Field Crops Research 277 (2022) 108420

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Effect of mineral N fertilizer and organic input on maize yield and soil water content for assessing optimal N and irrigation rates in Central Kenya

Stephen Okoth Aluoch [a], Zhuoting Li [b,c,*], Xiaoxin Li [a], Chunsheng Hu [a], David M. Mburu [d], Jingyi Yang [e], Qiangsheng Xu [b,c], Yuanzheng Yang [b,c], Hongxin Su [b,c]

[a] Key Laboratory of Agricultural Water Resources, Center for Agricultural Resources Research, Institute of Genetic and Developmental Biology, The Chinese Academy of Sciences, 286 Huaizhong Road, Shijiazhuang 050021, China
[b] Key Laboratory of Environment Change and Resources Use in Beibu Gulf, Ministry of Education, Nanning Normal University, 175 East Mingxiu Road, Nanning 530001, China
[c] Guangxi Key Laboratory of Earth Surface Processes and Intelligent Simulation, Nanning Normal University, 175 East Mingxiu Road, Nanning 530001, China
[d] Jomo Kenyatta University of Agriculture and Technology, 62000-00100 Nairobi, Kenya
[e] Harrow Research and Development Centre, Agriculture and Agri-Food Canada, 2585 County Road 20, Harrow, Ontario N0R 1G0, Canada

ARTICLE INFO

Keywords:
Maize grain yield
Soil water content
Fertilizer regime
DSSAT–CSM
Irrigation strategy

ABSTRACT

Maize (*Zea mays* L.) is an important food crop in Kenya, while low and erratic rainfall, and low nutrient input mainly result in low maize yield. This study were to assess optimal nutrient and irrigation management practice for maize in central Kenya based on field experiment combined with modeling simulation. On-farm experiment with four treatments including no fertilizer (N0), N applied at dose of 100 kg ha^{-1} only in the form of a chemical fertilizer (N100) or combined with animal manure (N100M) or straw (N100S) has been conducting since 2013 in central Kenya. The Decision Support System for Agro-technology Transfer–Cropping System Model (DSSAT–CSM) was firstly calibrated under the relative optimal treatment N100M, and it was then evaluated for the rest three treatments for 6 maize growing seasons from 2014 to 2018. The responses of grain yield to different irrigation and fertilizer regimes were simulated using the calibrated DSSAT–CSM. The combination of fertilizer and manure (N100M) resulted in the highest yield and that of fertilizer and straw (N100S), in the highest level of soil water content in each soil layer. The model (DSSAT-CSM) successfully predicted both grain yield (normalized root mean square error, or *nRMSE*, of 21–37% and the index of agreement, or *d*, of 0.89–0.93) and changes in water content of each soil layer (*nRMSE* < 20% and *d* > 0.70) in all treatments except N100S. The yield was most sensitive to any deficit in soil water content (dry spells) at the beginning of grain-filling stage, and the best regime for high yield, high water-use efficiency, and high agronomic efficiency comprised irrigation at 50–70 mm during that stage combined with fertilizer N at 100–120 kg ha^{-1}. The estimated magnitude yield gain with respect to optimal nutrition and irrigation ranged from 2 to 4 t ha^{-1} in different crop seasons. Optimal application of irrigation at the sensitive stage, fertilizer N, animal manure, and straw mulching holds great potential as an integrated farming practice for high grain yield and for efficient use of resources in maize cultivation in semi-arid parts of Kenya.

1. Introduction

Maize (*Zea mays* L.) is the staple food of 90% of Kenya's population (Ochieng et al., 2017). Maize is a suitable crop for warmer conditions but sensitive to water stress (Araya et al., 2015). Most of Kenya is either arid or semi-arid, characterized by highly variable weather including uneven distribution of rainfall and frequent droughts during critical stages of maize growth. Crop production is mainly rain-fed, irrigated area accounts for less than 2% of Kenya's total cultivated area (FAO, 2015), and also suffers from nutrient imbalance due to chronically low use of fertilizers, the latter being one of the major causes of low soil fertility in sub-Saharan Africa (Burke et al., 2019). Inadequate and erratic rainfall, lack of measures to conserve soil moisture, and degraded and infertile soil together with low nutrient inputs result in maize yields

* Corresponding author at: Key Laboratory of Environment Change and Resources Use in Beibu Gulf, Ministry of Education, Nanning Normal University, 175 East Mingxiu Road, Nanning 530001, China.
E-mail address: zhuotingli@nnnu.edu.cn (Z. Li).

https://doi.org/10.1016/j.fcr.2021.108420
Received 7 March 2021; Received in revised form 8 October 2021; Accepted 18 December 2021

in Kenya being very low (Tittonell et al., 2008; Mucheru-Muna et al., 2010, 2014; Ngetich et al., 2014) and the increasing frequency of extreme climatic events such as droughts and floods is bound to weaken food security in eastern Africa even further (Bryan et al., 2013; Rowell et al., 2015).

Climate-smart agriculture was suggested as an adaptation strategy to ensure food security in the face of climate change. In East Africa, climate-smart villages take many forms: they may be weather-smart (they get seasonal weather forecasts), water-smart (they practise such measures as rainwater harvesting), carbon-smart (they compost their organic waste to get manure), and so on (Ogada et al., 2020). Biazin et al. (2012) reviewed some commonly used rainwater-harvesting and management practices and reported that they hold a significant potential to increase rainwater-use efficiency and to sustain rain-fed agriculture in sub-Saharan Africa. Nyagumbo et al. (2019) reported that in-field water-harvesting technologies have the potential to increase soil water content and, consequently, maize yield in areas that face water shortage in semi-arid regions of Zimbabwe. Long-term measures aimed at soil and water conservation also tend to increase soil organic matter in farmlands of south-eastern Kenya (Saiz et al., 2016). In an on-farm experiment in semi-arid Kenya, growing maize using a ridges-and-furrows system and mulching with plastic film increased soil water content and grain yield (Mo et al., 2016). These two measures supplemented with balanced application of fertilizers could serve as a promising adaptive management practice to obtain higher yields from maize and to fix larger amounts of agricultural carbon in semi-arid eastern Africa (Mo et al., 2017). Other measures such as no tillage and residue retention, conventional tillage and manure, and the combination of both these measures increased maize yield substantially when compared to the yields from conventionally managed farms in both sub-humid and semi-arid agro-ecological zones and from both more fertile and less fertile soils in Kenya (Mutuku et al., 2020). Tully et al. (2015) reported that mineral fertilizers could increase maize grain yield in western Kenya, and Kiboi et al. (2019) reported that mineral fertilizers, with or without animal manure or crop residues, increased maize yield, and mulching with crop residue also increased soil water content in the central highlands of Kenya. In addition to rainwater harvesting, it is feasible to expand the area served by both dam-based and small-scale irrigation in Kenya (You et al., 2014). Nakawuka et al. (2018) reviewed the literature on trends, constraints, and opportunities related to smallholder irrigation in four East African countries, namely Ethiopia, Kenya, Tanzania, and Uganda, and reported that it is possible to increase the area under such irrigation despite many challenges. Augmenting rain-fed agriculture by rainwater harvesting not only lowers the risk of total crop failure due to dry spells but also increases the productivity of water and crops substantially (Biazin et al., 2012).

Besides on-farm trials, crop modeling has become an essential tool to evaluate optimal management strategies cost-effectively and quickly once the models are calibrated and their results compared against those from local on-farm experiments. Many models have been developed that simulate agro-ecosystems, and two most popular and widely used among them are APSIM (Agricultural Production Systems sIMulator; Holzworth et al., 2014) and DSSAT (Decision Support System for Agrotechnology Transfer; Jones et al., 2003), which are process-based crop growth simulation models. Some farming systems prevalent in Africa have also been modeled. For example, the DSSAT-CERES-Maize model predicted yields reliably from several sites in Kenya using such variables as plant population, cultivars, sowing dates, and the dose of nitrogen (N), predictions that enabled farmers to make decisions that were compatible with the farmers' socio-economic circumstances (Wafula, 1995). Whitbread et al. (2010) summarized the application of APSIM to simulate key soil and crop processes in highly constrained and low-yielding maize–legume systems in southern Africa. Zinyengere et al. (2013) investigated the impacts of climate change and agronomic practices on yields of various major food crops at specific locations in southern Africa using DSSAT. Araya et al. (2015) calibrated and evaluated the performance of both APSIM and DSSAT-CSM (cropping system model) in simulating maize growth and predicting yield in southwestern Ethiopia and found the predictions to be reliable, which enabled the authors to assess the impact of climate change on future maize yield. Corbeels et al. (2016) evaluated how well DSSAT could simulate the response of maize in Zambia to no tillage and mulching with crop residues. Seyoum et al. (2017) used APSIM to characterize the pattern of major droughts and their frequencies as they affected maize-based cropping systems in eastern and southern Africa. Araya et al. (2019) calibrated and validated DSSAT-CSM for predicting yield and biomass of wheat in northern Ethiopia under different combinations of the dose of N and the quantity of irrigation.

It was against this background that the current study was carried out in central Kenya with the following objectives to: (1) investigate the impact of N applied only in the form of a chemical fertilizer or combined with animal manure or straw or both on grain yield of maize and soil water content; (2) evaluate DSSAT-CSM for predicting grain yield and for simulating the dynamics of soil water by comparing the model's outputs with measured data; and (3) estimate optimal quantities of irrigation and N for maize based on the sensitivity of its yield to different irrigation and fertilizer regimes.

2. Materials and methods

2.1. Description of the site

2.1.1. Location

Data for this study were collected from an ongoing long-term field experiment set up in 2013 and continues to date. The site in Juja, about 35 km from Nairobi, the capital city of Kenya, is part of the large farm of Jomo Kenyatta University of Agriculture and Technology (1°05′ S, 37°01′ E) in Kiambu county in a semi-arid part of central Kenya with subtropical highland climate. The area is characterized by two main rainy seasons, the longer season from March to May and the shorter season from October to November. However, the shorter season sometimes extends to the first week(s) of December. Maize is grown in both seasons to benefit from this pattern of rainfall. Maize is planted in late current year and harvested in early next year in short rains. The region being dry for most part of the year, yields are low if farmers fail to sow at the onset of the short and unpredictable rainy season from March to May or from September to November. Juja is also characterized by a low water table, and the loose clay cotton soils are the main reason for the flooding in Juja in some years during the heavy rains that sometimes occur in April. The two extremes, namely long dry spells and the short but heavy rains accompanied by floods, require planning and better management practices to retain soil water, to carry out timely irrigation in optimal amounts, to apply fertilizers at optimal rates, and so on to maximize output.

2.1.2. Soil

The soil at the site is a chromic vertisol with poor drainage. Analysis of the top layer (0–20 cm) at the beginning of the long-term experiment showed that available N was 175 ppm, soil organic carbon was 17.7 g kg^{-1}, total nitrogen was 1.55 g kg^{-1}, and the soil comprised 62.9% clay, 23.6% sand, and 13.6% silt. Before the long-term experimental began, the site had been grassland with some small, scattered bushes mainly used by the university for grazing dairy cattle.

2.1.3. Layout of experiment

The general layout of the experimental field consisted of 81 randomized plots each measuring 80 m^2 (10 m × 8 m) grouped into nine blocks (labeled A to I), each block comprising nine plots, each plot representing a different treatment. The whole experiment thus encompassed nine treatments laid out in a randomized complete block design with three replications. For this study, four treatments, each with three replications (blocks A, B, and D), were chosen for comparing the

Table 1
Field management data for N0, N100, N100M and N100S treatments from 2016 to 2018 at the experimental site, Kenya.

Season sequence	Year	Rainy season	Crop	Tillage date	Planting date	Row space (cm)	Harvest date	N0	N100	N100M		N100S	
								Fertilizer	Fertilizer	Fertilizer	Manure	Fertilizer	Straw residue
								(Kg N ha^{-1})					
1	2014	Long rains	Maize	29-Mar-14	31-Mar-14	70	30-Jul-14	0	100	100	60	100	25
2	2015	Long rains	Maize	8-Apr-15	9-Apr-15	70	20-Jul-15	0	100	100	60	100	25
3	2016	Long rains	Maize	2-Apr-16	4-Apr-16	70	17-Aug-16	0	100	100	60	100	25
4	2017	Long rains	Maize	19-Mar-17	22-Apr-17	70	12-Sep-17	0	100	100	60	100	25
5	2017	Short rains	Maize	31-Oct-17	2-Nov-17	70	27-Mar-18	0	100	100	60	100	25
6	2018	Long rains	Maize	2-Apr-18	5-Apr-18	70	8-Aug-18	0	100	100	60	100	25

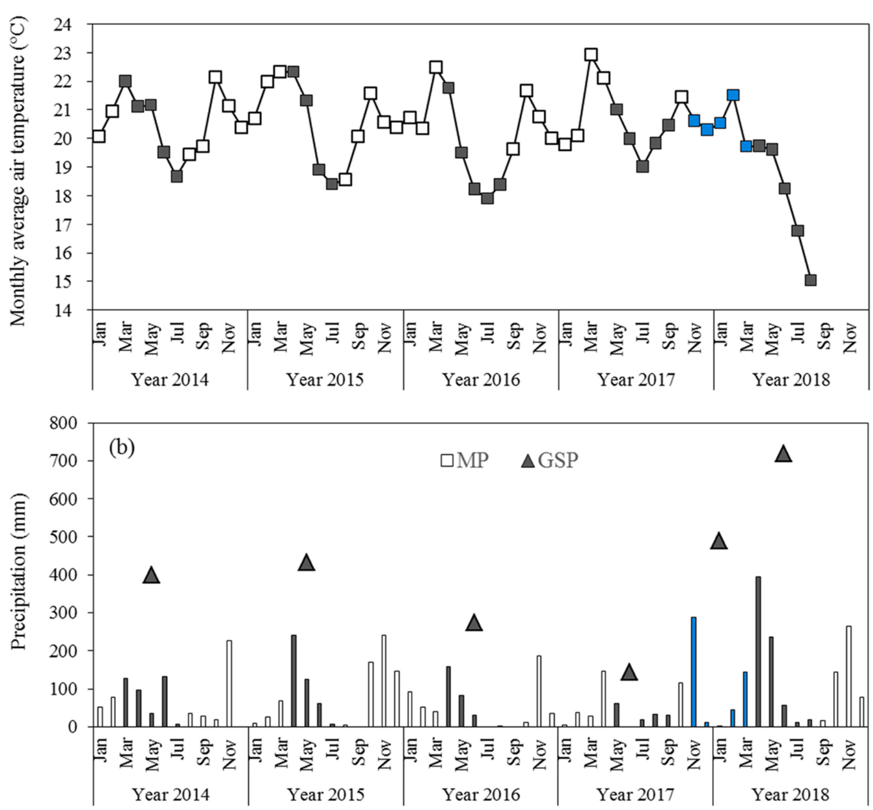

Fig. 1. Weather data, 2014–2018: (a) monthly average air temperature (black or blue marks indicate growing seasons) and (b) monthly precipitation (MP) in each year (black or blue bars indicate growing seasons) and cumulative precipitation during each growing season (GSP).

experimental data with outputs from the DSSAT model. The four treatments were as follows: (1) no nitrogen (N0), (2) N at 50 kg ha^{-1} given as a basal dose using diammonium phosphate (DAP) following by another dose of N at 50 kg ha^{-1} as topdressing using urea (N100), which is the recommended practice, (3) N100 along with 3 t ha^{-1} of cattle manure containing 2.0% N (N100M), and (4) N100 along with 5 t ha^{-1} of maize straw containing 0.5% N (N100S).

This study was carried out over 5 consecutive years (2014–2018) during which all the treatments and other management practices remained unchanged except those that depended on the weather (see below). Even the manure was obtained from the same source throughout to ensure uniformity. Although, as mentioned earlier, two crops of maize were taken each year, most of the time the crops raised during the short rainy season failed because of either dry spells or floods, which is why the experimental data consist of data for all the five crops grown during the long rainy season and for only one crop grown during the shorter rainy season (Table 1). Data on the dynamics of soil water were collected during only three seasons, namely November 2016 to February 2017, May–September 2017, and April–August 2018. Changes in the weather affected some operations; for instance, heavy rains at the beginning of some seasons and the consequent water-logging meant that the application of fertilizers and manures had to be delayed to minimize the possible leaching of N.

The field was usually plowed using a tractor-mounted disc plow (20–30 cm deep) a little before the onset of the seasonal rains and the soil allowed to dry for at least two days before harrowing to break up large lumps. The whole field was then marked and divided into plots as given above, with one-meter-wide paths between the plots for easy

Table 2
Soil profile data[a] of the experimental field.

Soil depth (cm)	Lower limit (cm^3 cm^{-3})	Drained Upper limit (cm^3 cm^{-3})	Saturation (cm^3 cm^{-3})	Saturated hydraulic conductivity (cm h^{-1})	Bulk density (g cm^{-3})	Organic carbon (g kg^{-1})	Clay (< 0.002 mm) (%)	Silt (0.05–0.002 mm) (%)	Total nitrogen (g kg^{-1})	pH in water	Cation exchange capacity (cmol kg^{-1})
0–10	0.200	0.302	0.413	0.37	1.13	17.7	62.9	13.6	1.55	5.5	36.5
10–20	0.200	0.324	0.416	0.37	1.13	17.6	66.0	18.0	1.58	5.5	36.5
20–30	0.200	0.324	0.420	0.37	1.13	6.3	66.0	18.0		5.5	43.3
30–40	0.200	0.338	0.426	0.46	1.13	6.3	66.0	14.0		5.9	43.3
40–60	0.218	0.336	0.438	0.63	1.13	6.3	68.0	12.0		5.9	43.3
60–80	0.218	0.332	0.451	0.67	1.27	8.4	70.0	10.0		6.0	55.5
80–100	0.218	0.340	0.472	0.68	1.38	5.5	71.0	10.0		6.2	47.0

[a]The data on topsoil bulk density, content of organic carbon, total N, and proportions of clay and silt were obtained from the measurements and analyses of the soil samples collected at the beginning of the experiment. The other data were obtained from Kenya soil survey report in 1978.

movement, which was further facilitated by alternating the inter-row spacing between 40 cm and 70 cm. Maize seeds were sown manually using a string to mark each row. Within each row, spacing was maintained at 30 cm using a stick of the same length and sharpened at one end for digging. Seeds were sown 2.5 cm deep, two seeds to a hole, and carefully covered with loose soil, which was then compacted slightly to facilitate proper germination. Each plot accommodated 15 rows, with 33 plants on average in each row, the average density was 500 plants per plot.

2.2. Harvest and sampling

The crop was harvested manually by cutting each plant close to the ground. Some stalks were cut into smaller pieces using a tractor-mounted cutting machine and stored in sacks until required for the treatment N100S; the rest of the lot was used by the university as cattle feed. The cobs were air-dried for weeks before being shelled and weighed when completely dry. For the data on biomass (dry matter), plant height, and the number of leaves, plants were selected at random. Dry weight was recorded after drying in an oven at 70 °C for 48 h.

Soil samples were collected before and after the rains from all the treatments at seven depths along the soil profile: 0–10 cm, 10–20 cm, 20–30 cm, 30–40 cm, 40—60 cm, 60–80 cm, and 80–100 cm. Soil was retrieved using an auger to drill the soil samples, packed into labeled self-sealing (Ziplock) polythene bags, weighed, repacked into smaller paper bags, dried in an oven at 105 ℃ for 24 h, and weighed again to calculate the water content. Other soil properties measured included pH, bulk density, content of soil organic carbon, and percentages of silt and clay: all were determined using appropriate field and laboratory methods.

2.3. Weather data

Data on the main weather parameters required to calibrate and run the model, such as daily maximum and minimum air temperatures, daily solar radiation, and daily precipitation, were collected from an automated weather station (ET107, Campbell Scientific, Logan, Utah) installed in the field in November 2016. However, the DSSAT model requires daily values of the weather parameters throughout the year for each year. Therefore the missing weather data, for the period from January 2014 to November 2016, were obtained from the Kenya Agricultural and Livestock Research Organization weather station in Thika town 18 km from the experimental site. The weather data were downloaded weekly from the automated weather station to monitor the changes in daily temperature and rainfall to manage the irrigated plots accordingly.

The highest and the lowest annual average air temperatures during the 5 years were 27.3 °C and 13.8 °C. Monthly average temperatures ranged from 18.4 °C, in March, to 22.9 °C in July (Fig. 1a). Annual rainfall ranged from 771 mm to 1409.2 mm and monthly rainfall, from 0 mm to 395.3 mm. Most of the rainfall occurred from March to May and from October to November (Fig. 1b) although drought was frequent in January and from July to August (Fig. 1b). Rainfall during the six cropping seasons ranged from 143 mm in 2017 to 719 mm in 2018, both the extremes being in the long rainy season (Fig. 1b).

2.4. Simulation

2.4.1. Data for model input

The Crop Estimation through Resource and Environment Synthesis (CERES)-Maize (Jones and Kiniry, 1986) is one of the cropping system models (CSMs) embedded in DSSAT. The CERES-Maize module and the CENTURY-based soil module in DSSAT (version 4.6.1) (Jones et al., 2003; Hoogenboom et al., 2010, 2014) were used for simulations. The model runs with a daily time step and simulates crop growth, development, and yield of specific cultivars based on the effects of weather, soil, and management practices (Jones et al., 2003). The model requires data on crop management, daily weather, initial soil conditions, cultivar, and soil profile. Data on crop management included the method of tillage and date, date of sowing, row spacing, plant density, fertilizers and manures (dates and amounts), and other details. The relevant information on crop management during all six seasons is summarized in Table 1. The straw was cut into small pieces (about 2–5 cm) and used as mulch for all the plots under N100S, applied immediately after sowing. The straw served as mulch and, after its decomposition, as a source of soil organic matter. For the rest of the treatments (N0, N100, N100M), all the plant biomass was cut and totally cleared from the field after harvesting or before plowing for the next season. The field was plowed to a depth of 20 cm in March or April (for the first season of the year) and in October (for the second season of the year) in all the years except for the second season in 2017, when the field was plowed in December. The field was left fallow between the harvest of a crop and sowing the next crop.

The minimum daily weather data required to run the DSSAT model included daily maximum and minimum temperatures (°C), daily solar radiation (MJ m^{-2}), and daily precipitation (mm). The data on soil bulk density, content of organic carbon, total N, and proportions of clay, silt, and sand were obtained from the measurements and analyses of the soil samples. The measured initial content of organic carbon in the topsoil was 17.7 g kg^{-1}, total N was 1.55 g kg^{-1}, and soil pH was 5.5 (Table 2). The other data including the drained upper limit (field capacity), soil water lower limit (wilting point), degree of saturation, and saturated hydraulic conductivity were obtained from published data collected by Jomo Kenyatta University of Agriculture and Technology during the detailed survey of the university's soil.

2.4.2. Calibration for the cultivar

The DSSAT model has to be calibrated for the cultivar coefficients under the optimum conditions, namely minimum nutrient contents stress and weather stress for the given region. Such calibration is

Table 3
The calibrated cultivar coefficients of maize for the experimental field using CERES-Maize in DSSAT-CSM (v4.6).

Cultivar	Calibrated coefficients		
Calibration year	2014–2015	2016	2017–2018
Cultivar name	KE0001	KE0002	KE0003
P1 Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above a base temperature of 8 deg.C) during which the plant is not responsive to changes in photoperiod	110	160	110
P2 Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above the longest photoperiod at which development proceeds at a maximum rate (which is considered to be 12.5 h)	0.75	0.75	0.75
P5 Thermal time from silking to physiological maturity (expressed in degree days above a base temperature of 8 deg.C)	550	500	850
G2 Maximum possible number of kernels per plant	750	400	750
G3 Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1})	9.5	9.0	9.5
PHINT Phylochron interval; the interval in thermal time (degree days) between successive leaf tip appearances	65	55	60

necessary because cultivar coefficients control the stages of crop growth, which can vary with the weather (Jones et al., 2003). The calibration was carried using trial and error: the value of each parameter was changed by ± 5%, and the root mean square error (*RMSE*) between the simulated and the measured grain yield was used for determining the values that offered the best match. In calibrating for cultivar coefficients, in addition to grain yield, three phenological stages were also considered: seedling emergence, flowering, and grain filling. The calibrated cultivar coefficients in this study were based on adjusting earlier calibrated cultivars available in the model database. The study used a total of three cultivars: one in 2014 and 2015, one in 2016, and one in 2017 and 2018. Based on the field experimental observations, N100M treatment obtained the highest grain yield was under relative optimum nutrition in this study. Therefore, the parameters for all the three cultivars were calibrated using the relative optimum N100M treatment and the actual local weather and soil conditions (Table 3). The simulated phonological stages (e.g., emergence, flowering, and grain filling days) under the calibrated cultivar coefficients were roughly in the same phonological stages as field crops in this region. The simulated grain yields N100M were evaluated to ensure the predicted yields matched the actual yields very well. The model outputs were validated using other three different treatments.

The simulation was carried out through the DSSAT Sequence Analysis program to make it possible for the dynamics of soil water and of soil nutrients to be transferred continuously from the beginning to the end of the simulation. A total of four management files in the DSSAT readable format, namely SQX, were created for each of the four treatments based on the input data described earlier. A graphics software package, namely EasyGrapher, was used for data visualization and statistical evaluation of the model's output. The focus was on evaluating the model by comparing the simulated or predicted grain yield and soil water dynamics with actual values measured during the experimental years.

2.4.3. Statistical analysis

A number of statistical analyses were carried out, aimed at different aspects of the model's performance. To address all the aspects satisfactorily, five deviation statistics were used: root mean square error (*RMSE*), mean error (*E*), normalized *RMSE* (*nRMSE*), index of agreement

Table 4
The combination of different irrigated water amounts and timing of irrigation applied for each irrigation strategy scenario during dry seasons in 2017 and 2018.

Irrigation strategy	Irrigated water (mm)	Irrigation date		Growing stage
		Julian day in 2017	Julian day in 2018	
IR0	0			
IR1	10	173 (June 22, 2017)	1 (January 1, 2018)	Silking begining
IR2	30			
IR3	50			
IR4	70			
IR5	90			
IR6	10	180	8	
IR7	30			
IR8	50			
IR9	70			
IR10	90			
IR11	10	188 (July 7, 2017)	15(January 15, 2018)	Grain filling begining
IR12	30			
IR13	50			
IR14	70			
IR15	90			
IR16	10	195	22	
IR17	30			
IR18	50			
IR19	70			
IR20	90			
IR21	10	202	29	
IR22	30			
IR23	50			
IR24	70			
IR25	90			
IR26	10	209		
IR27	30			
IR28	50			
IR29	70			
IR30	90			
IR31	10	216		
IR32	30			
IR33	50			
IR34	70			
IR35	90			
IR36	10	173	1	
	10	188	8	
	10	195	15	
	10	202	22	
	10	209	29	
IR37	20	173	1	
	20	188	8	
	20	195	15	
	20	202	22	
	20	209	29	
IR38	30	173	1	
	30	188	8	
	30	195	15	
	30	202	22	
	30	209	29	
IR39	40	173	1	
	40	188	8	
	40	195	15	
	40	202	22	
	40	209	29	
IR40	50	173	1	
	50	188	8	
	50	195	15	
	50	202	22	
	50	209	29	

(*d*), and modeling efficiency (*EF*). The features of each deviation statistics are described in detail in our earlier publications (Yang et al., 2014; Li et al., 2015a, 2015b). Each deviation statistic addresses only one specific aspect; however, using each of the five indexes helped us to quantify the overall performance. The five deviation statistics were calculated using the following equations:

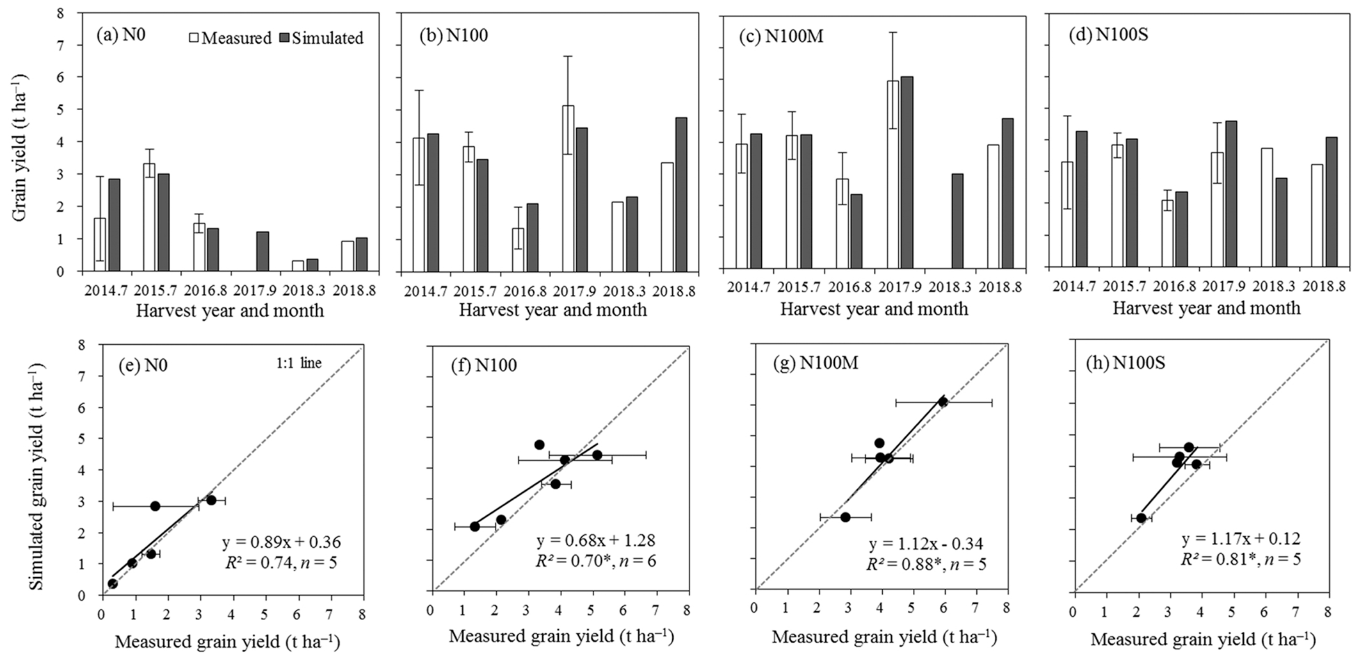

Fig. 2. Predicted (black bars) and actual (blank bars) grain yield of maize from four treatments, namely (a) 0 kg ha^{-1} of N (the control, or N0), (b) 100 kg ha^{-1} of N (N100), (c) 100 kg ha^{-1} of N combined with manure (N00M), and (d) 100 kg ha^{-1} of N combined with mulching with straw (N100S). Correlation and regression between predicted and actual grain yield: (e) from N0; (f) from N100; (g) from N00M; and (h) from N100S. The slope without "* " indicates not significant difference with 1 at 0.05 probability level. The intercept without "* " indicates not significant difference with 0 at 0.05 probability level. R^2 marked with "* " indicates significant correlation at 0.05 probability level. Error bars represent standard deviation ($n = 3$).

$$E = \frac{\sum_{i=1}^{n} (S_i - M_i)}{n} \tag{1}$$

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

$$nRMSE = \frac{RMSE}{\overline{M}} \times 100 \tag{3}$$

$$d = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (|S_i - \overline{M}| + |M_i - \overline{M}|)^2} \tag{4}$$

$$EF = 1 - \frac{\sum_{i=1}^{n} (S_i - M_i)^2}{\sum_{i=1}^{n} (M_i - \overline{M})^2} \tag{5}$$

where S_i is the simulated or predicted value, M_i is the actual or measured value, n is the number of values, and $\overline{M}$ is the average of the measured values.

In addition, the paired-t-test was used to ascertain whether differences between the simulated and measured values were statistically significant. The relationship between the simulated and measured values was also fitted by a linear regression ($y = bx + a$, where y and x represent the simulated and measured data, respectively) to evaluate model performance. The slope of the linear regression indicates the extent of systematic bias. The significances of the slope, intercept and the coefficient of correlation were tested.

2.4.4. Sensitivity of model

Sensitivity analysis is a fundamental tool for understanding and building simulation models (Confalonieri et al., 2010) and provides very useful information on the performance and general behavior of a model. In this study, the dry period from late June to August 2017 and that in January 2018 occurred during the critical stages of silking and grain filling, while the early critical stages such as flowering (Saddique et al., 2019) and heading (Araya et al., 2019) did not encounter drought period during experiment running from 2014 to 2018. Therefore, the irrigation strategy was designed for the dry periods in both the seasons involving the longer and the shorter rainy seasons in 2017 (Table 4). The irrigation strategy consisted of a combination of different times and quantities of irrigation; the crop was irrigated from the beginning of the silking stage to the late grain-filling stage at intervals of 7 days, and the quantities ranged from 10 mm to 90 mm at intervals of 20 mm. The sensitivity of grain yield to these combinations was simulated for the two seasons in 2017 under different doses of N including N0, N100, and N100M to assess the optimal irrigation strategy. Treatment N100S was excluded because that soil water content under that treatment could not be captured reliably. A total of six management files in the DSSAT readable format, namely MZX, were created for the two seasons and for the three treatments, namely N0, N100, and N100M. The responses of grain yield and irrigation water productivity (IWP) to irrigation regimes were evaluated. The productivity of irrigation water (kg ha^{-1} mm^{-1}) was calculated using the equation given by Zhang et al. (1999), Howell (2001), and Araya et al. (2019):

$$IWP = \frac{(GY_I - GY_R)}{I} \tag{6}$$

where GY_I is grain yield (kg ha^{-1}) from the irrigated crop; GY_R is the corresponding yield (kg ha^{-1}) obtained from the rain-fed crop; and I is the amount of irrigation (m^3 ha^{-1}).

In addition, the precipitation use efficiency (PUE) (kg ha^{-1} mm^{-1}) of maize grain yield was also calculated as the ratio of grain yield under rain-fed condition to precipitation in crop growth period using the following equation (Ojeda et al., 2018; Srivastava et al., 2019):

$$PUE = \frac{GY_R}{P} \tag{7}$$

where GY_R is grain yield (kg ha^{-1}) under rain-fed condition; and P is the

Table 5
Statistical evaluation of simulated maize grain yields, and precipitation use efficiency against measured values.

Treatment	Measured	Simulated	Sample No.	*E*	*RMSE*	*nRMSE* (%)	*d*	*EF*	Paired-*t* (*p*)
Grain yield (t ha^{-1})									
N0	1.52 (1.13)[a]	1.71 (1.16)	5	0.18	0.57	37.37	0.93	0.72	0.53
N100	3.33 (1.38)	3.55 (1.13)	6	0.23	0.73	21.92	0.89	0.67	0.50
N100M	4.18 (1.12)	4.34 (1.34)	5	0.16	0.46	11.04	0.96	0.81	0.51
N100S	3.21 (0.67)	3.87 (0.87)	5	0.66	0.75	23.49	0.73	-0.55	0.02
Entire data	3.07 (1.42)	3.38 (1.45)	21	0.30	0.64	20.97	0.95	0.78	0.03
Precipitation use efficiency (kg ha^{-1} mm^{-1})									
N0	5.22 (4.23)	6.35 (6.20)	5	1.12	3.08	59.05	0.89	0.33	0.48
N100	14.59 (13.88)	14.50 (11.56)	6	-0.09	2.64	18.06	0.99	0.96	0.94
N100M	19.16 (15.68)	19.58 (16.18)	5	0.42	1.34	7.01	1.00	0.99	0.54
N100S	13.86 (9.06)	17.03 (12.04)	5	3.17	4.23	30.52	0.95	0.73	0.09
Entire data	13.27 (11.95)	14.37 (12.13)	21	1.10	2.99	22.53	0.98	0.93	0.09

[a] Values in brackets are the S.D. for each treatment.

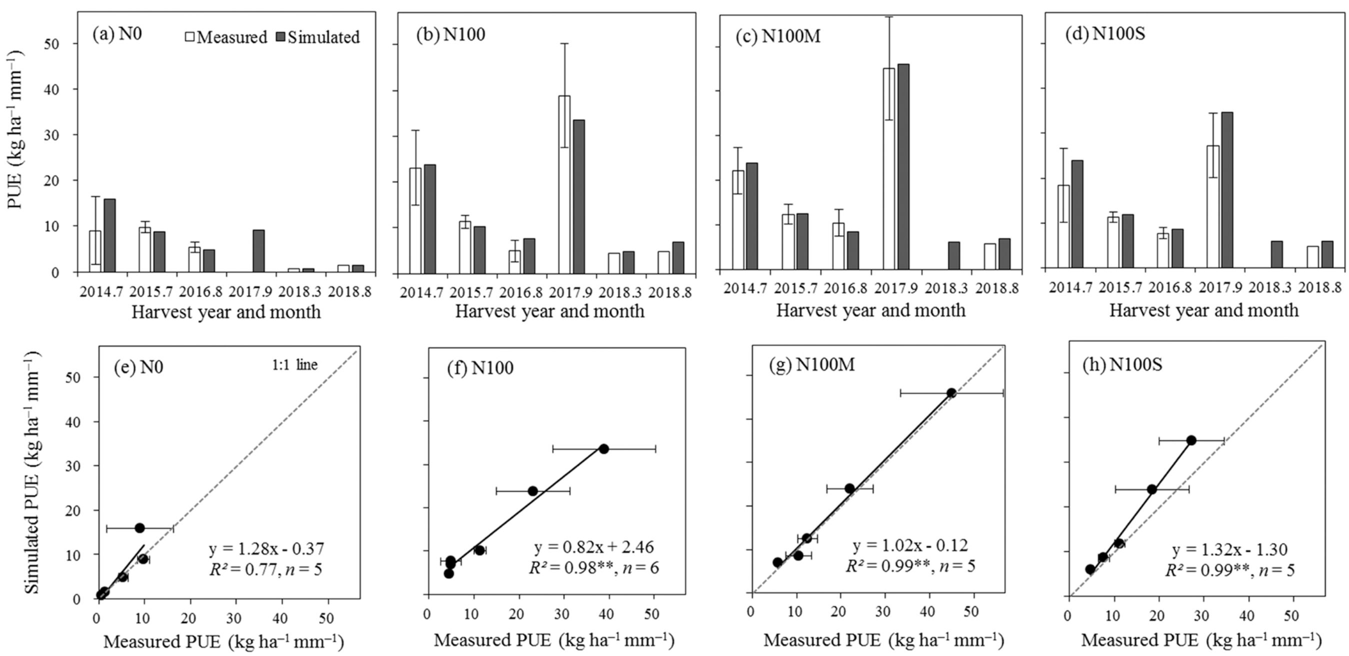

Fig. 3. Predicted (black bars) and actual (blank bars) PUE (precipitation use efficiency) of maize grain yield from four treatments of N0 (a), N100 (b), N00M (c), and N100S (d) (see Fig. 2 for explanation of the abbreviations of the treatment). Correlation and regression between predicted and actual PUE: (e) from N0; (f) from N100; (g) from N00M; and (h) from N100S. R2 marked with "* " indicates significant correlation at 0.05 probability level. Error bars represent standard deviation (n = 3).

amount of precipitation in crop growth period (mm).

The sensitivity of grain yield to various doses of N in the two dry seasons of 2017 and in the normal season in 2018 was simulated under rain-fed conditions and under optimal irrigation according to the results from the simulated responses of grain yield to different irrigation strategy scenarios. The dose of N was varied from 0 kg ha^{-1} to 160 kg ha^{-1} in increments of 20 kg. The responses of agronomic efficiency (AE) of fertilizer N, PUE and IWP to the different doses were investigated. Using the results from this sensitivity analysis, the optimum dose of N to simultaneously achieve high grain yield, high AE, and high IWP were identified for both dry and normal years. In addition, effects of the interaction between irrigation regime and the dose of N on grain yield were also investigated. Agronomic efficiency (kg kg^{-1}) was calculated using the following equation (Fageria and Baligar, 2005):

$$AE = \frac{(G_F \quad - \quad G_U)}{N} \tag{8}$$

where G_F is the grain yield (kg) from plots to which N had been applied, G_U is the grain yield (kg) from plots that had not received N, and N is the dose (kg) of N.

3. Results

3.1. Grain yield and precipitation use efficiency

Grain yield, as a function of the weather, cultivar coefficients, dose of N, and application of manure and of straw, varied markedly with the year and the treatment (Figs. 2a–2d). Averaged over the 5 years (2014–2018), the yield was 1.52 ± 1.13 (S.D.) t ha^{-1} in the control plots (N0), 3.33 ± 1.38 t ha^{-1} in plots that had received fertilizer N alone (N100), 4.18 ± 1.12 t ha^{-1} in plots supplied with fertilizer N and manure (N100M), and 3.21 ± 0.67 t ha^{-1} in those supplied with fertilizer N and straw (N100S) (Table 5). The average yield under N0, because of N deficiency, was significantly lower than that under any of the other three treatments ($p < 0.05$, *t*-test) but did not differ significantly among those three. The inter-annual variation in yield under any given treatment was mainly due to the different cumulative precipitation (GSP) as well as different distribution of rainfall during the growing season. Grain yield in both seasons from 2014 to 2016 reflected the trends in cumulative GSP whereas that in 2017 was not affected although the cumulative GSP was very low (132 mm; Fig. 1b) because rainfall in that year was evenly

Table 6
Statistical evaluation of simulated soil water contents in different soil layers at the 0–100 cm soil depth against measured values.

Treatment	Soil depth (cm)	Soil water content (cm^3 cm^{-3})							
		Measured	Simulated	Sample No.	*E*	*RMSE*	*nRMSE* (%)	*d*	*EF*
N0	0–10	0.294	0.275	41	-0.019	0.046	15.72	0.80	0.45
	10–20	0.300	0.281	41	-0.019	0.044	14.57	0.82	0.47
	20–30	0.313	0.288	41	-0.025	0.047	15.13	0.81	0.43
	30–40	0.316	0.302	41	-0.014	0.046	14.56	0.82	0.43
	40–60	0.307	0.306	41	-0.001	0.041	13.26	0.82	0.47
	60–80	0.286	0.305	41	0.019	0.039	13.68	0.79	0.10
	80–100	0.276	0.305	41	0.029	0.049	17.77	0.62	-1.24
N100	0–10	0.300	0.272	41	-0.029	0.057	19.00	0.77	0.31
	10–20	0.305	0.276	41	-0.029	0.060	19.64	0.74	0.25
	20–30	0.317	0.279	41	-0.037	0.063	19.72	0.70	0.05
	30–40	0.315	0.290	41	-0.026	0.059	18.73	0.72	-0.04
	40–60	0.305	0.291	41	-0.014	0.049	16.01	0.78	0.20
	60–80	0.292	0.289	41	-0.003	0.044	15.16	0.76	-0.05
	80–100	0.277	0.289	41	0.012	0.044	15.76	0.72	-0.08
N100M	0–10	0.305	0.277	41	-0.027	0.055	18.06	0.76	0.30
	10–20	0.311	0.282	41	-0.029	0.055	17.63	0.74	0.25
	20–30	0.315	0.286	41	-0.029	0.054	17.07	0.73	0.10
	30–40	0.315	0.299	41	-0.016	0.048	15.30	0.82	0.37
	40–60	0.315	0.300	41	-0.014	0.040	12.67	0.86	0.57
	60–80	0.296	0.298	41	0.001	0.038	12.77	0.80	0.14
	80–100	0.278	0.304	41	0.026	0.050	17.86	0.61	-0.75
N100S	0–10	0.328	0.284	41	-0.044	0.070	21.18	0.62	-0.18
	10–20	0.335	0.284	41	-0.051	0.077	22.89	0.53	-0.32
	20–30	0.336	0.283	41	-0.053	0.081	24.16	0.47	-0.59
	30–40	0.334	0.300	41	-0.033	0.072	21.68	0.60	-0.25
	40–60	0.327	0.307	41	-0.021	0.056	17.03	0.70	0.06
	60–80	0.309	0.305	41	-0.005	0.045	14.55	0.72	-0.08
	80–100	0.287	0.316	41	0.029	0.055	19.19	0.48	-2.01

Table 7
Statistical evaluation of the simulated soil water storage amounts in 0–100 cm soil depth against the measured values.

Treatment	Soil water storage in 0–100 cm soil depth (mm)							
	Measured	Simulated	Sample No.	*E*	*RMSE*	*nRMSE* (%)	*d*	*EF*
N0	209.25	206.15	41	-3.10	22.56	10.78	0.87	0.60
N100	211.14	198.55	41	-12.59	30.49	14.44	0.81	0.28
N100M	213.07	204.57	41	-8.50	25.92	12.17	0.84	0.43
N100S	225.69	207.88	41	-17.81	38.02	16.84	0.65	-0.45

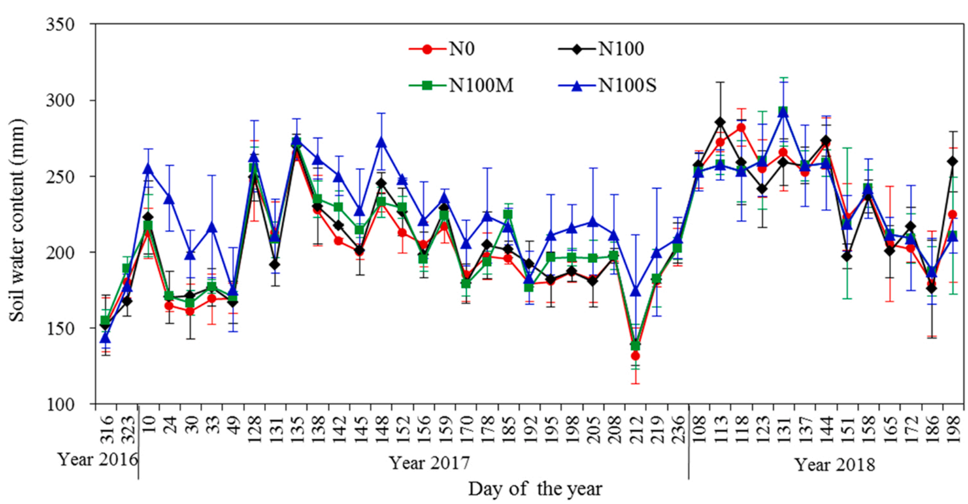

Fig. 4. Total soil water content in 0–100 cm profile under N0, N100, N00M, and N100S (see Fig. 2 for explanation of the abbreviations of the treatment). Error bars represent standard deviation ($n = 3$).

distributed. On the other hand, grain yield in the season 2017/18 was affected although the cumulative GSP was high because of the dry spell in January 2018. The average grain yield under N100S was almost equal to that under N100, although the inter-annual variation in N100S (S. D. = 0.67 t ha^{-1}) was much lower than that in N100 (S. D. = 1.38 t ha^{-1}). In seasons with dry spells, such as 2016 and 2017/18, grain yields under N100S were markedly higher than those under N100, probably because mulching, by retaining more soil moisture, offset to

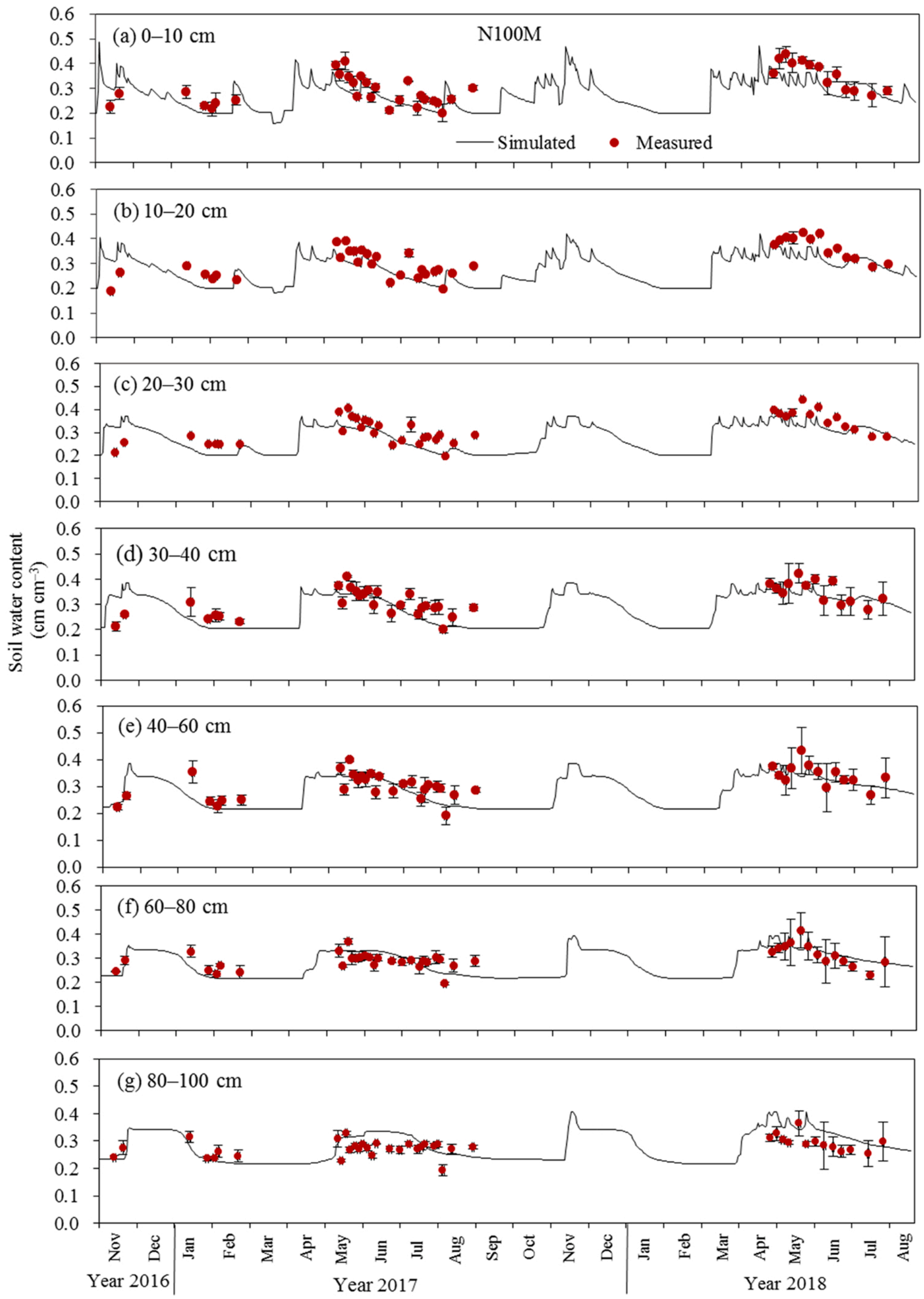

Fig. 5. Predicted and actual water content of different layers of soil in plots given N at 100 kg ha^{-1} combined with manure (N100M): (a) 0–10 cm, (b) 10–20 cm, (c) 20–30 cm, (d) 30–40 cm, (e) 40–60 cm, (f) 60–80 cm, and (g) 80–100 cm. Error bars represent standard deviation ($n = 3$).

some extent the adverse effects of the dry spells (data are shown in Section 3.2).

The precipitation use efficiency (PUE) of grain yield under rain-fed condition varied markedly with the year and the treatment (Figs. 3a–3d). The PUE ranged in 0.63–9.76 kg ha^{-1} mm^{-1}, 4.45–38.89 kg ha^{-1} mm^{-1}, 5.73–45.10 kg ha^{-1} mm^{-1} and 4.70–27.23 kg ha^{-1} mm^{-1}, with averages of 5.22 ± 4.23, 14.59 ± 13.88, 19.16 ± 15.68 and 13.86 ± 9.06 kg ha^{-1} mm^{-1} for N0, N100, N100M and N100S, respectively (Fig. 3, Table 5). The PUE in the treatments with fertilizer N applied were much higher than that in N0. The high inter-annual variation in PUE under any given treatment was mainly associated with the different cumulative precipitation during crop growing period.

After calibrating the performance of DSSAT-CSM under N100M to ensure that the predicted yields would match the actual yields closely (*nRMSE* = 11.04%, *d* = 0.96, and *EF* = 0.81), the model was validated and the results showed that the model indeed performed well in predicting the yields under N0 (*nRMSE* = 37.37%, *d* = 0.93, *EF* = 0.93) and those under N100 (*nRMSE* = 21.92%, *d* = 0.89, *EF* = 0.89) (Table 5), although it overestimated the yields under N100S. In addition, a strong linear regression was seen between the predicted and the actual yields in every treatment (Fig. 2, e–h). The slope of the regression (0.68–1.17) in none of the treatments was statistically different from 1 ($p > 0.05$), and the intercepts of all the treatments were not statistically different from 0 ($p > 0.05$). The predicted yields were significantly positively correlated with measurements in any of the treatments ($p < 0.05$) except N0

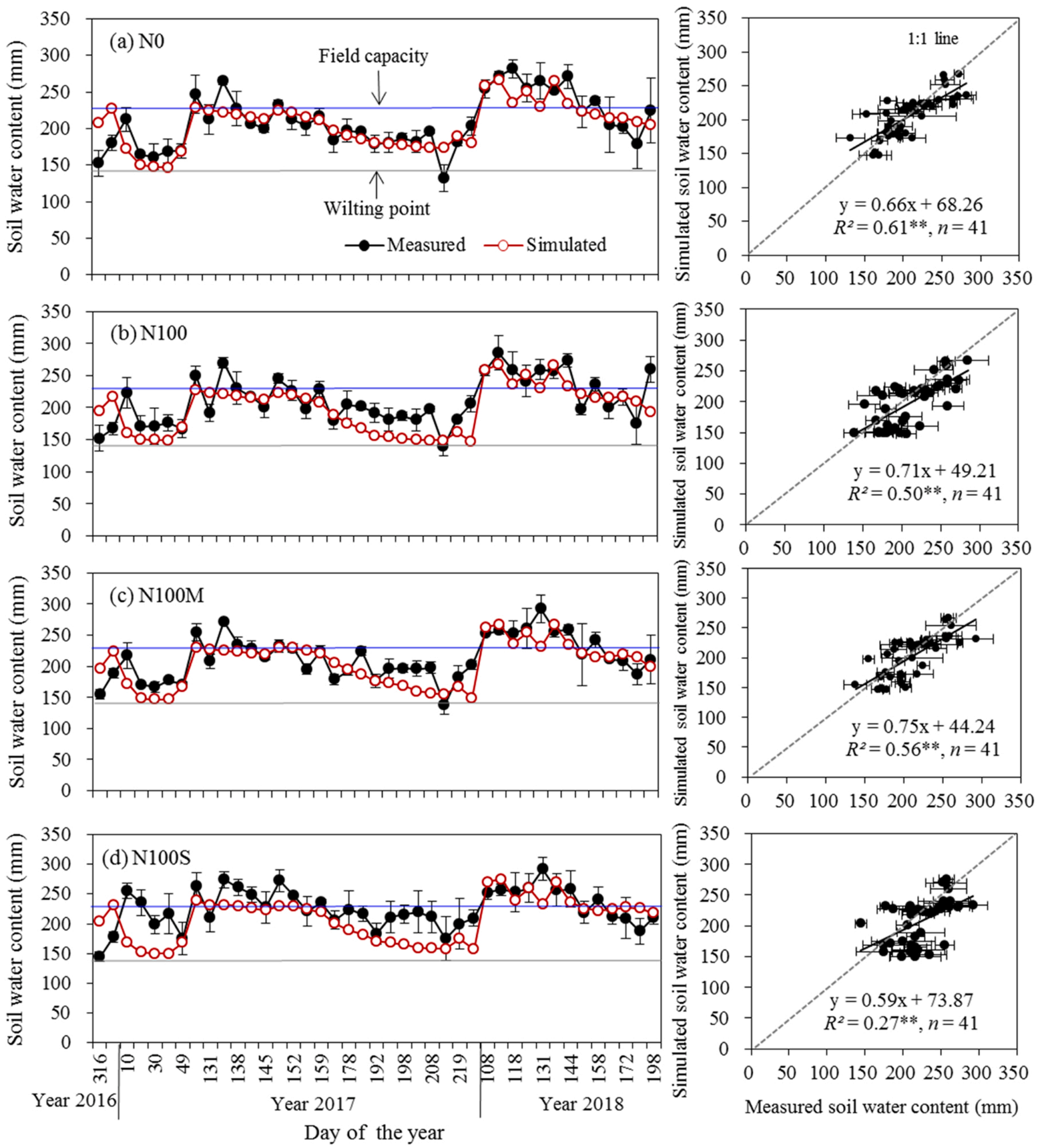

Fig. 6. Predicted and actual total soil water content (0–100 cm) under (a) N0, (b) N100, (c) N00M, and (d) N100S (see Fig. 2 for explanation of the abbreviations of the treatment). Linear regression and correlation between predicted and actual values; R^2 marked with "* *" indicating significant correlation at the 0.01 probability level. Error bars represent standard deviation ($n = 3$).

($p = 0.06$). The paired-t-test showed that the predicted yields were not statistically different from the actual yields in any of the treatments ($p > 0.50$) except N100S (Table 5). The model also predicted the PUE of grain yield quite well (Fig. 3, Table 5).

3.2. Soil water content

The four treatments differed markedly in soil water content. Overall, and across the entire profile, the average soil water content was the highest under N100S and decreased progressively from N100M to N100 to N0 (Tables 6 and 7). The paired t-test showed that the average soil water content in each soil layer and across the 0–100 cm profile under N100S was significantly higher than that in any of the other treatments ($p < 0.01$) but not significantly different among them except that in the layers 0–10 cm, 10–20 cm, and 60–80 cm; across the profile, it significantly higher under N100M than that under N0 ($p < 0.05$). The water content showed similar patterns of temporal changes in each layer and in each treatment (changes across the profile are shown in Fig. 4) although in absolute terms the levels under N100S were markedly higher than those under any of the other three treatments, especially during the dry spells in January and July 2017 (Fig. 4). These findings indicated that mulching with straw was effective in raising the water retention capacity of soil, and this greater capacity contributed to maintaining grain yields in seasons with dry spells.

In each layer of soil, the daily soil water content throughout the model ran from 2014 to 2018 and the daily water content as measured fluctuated greatly. The pattern of the fluctuations was similar across all the treatments throughout the model (the fluctuations under N100M in each layer are shown as an example in Fig. 5, a–g). The pattern closely matched the pattern of rainfall distribution (Fig. 1b). For instance, soil

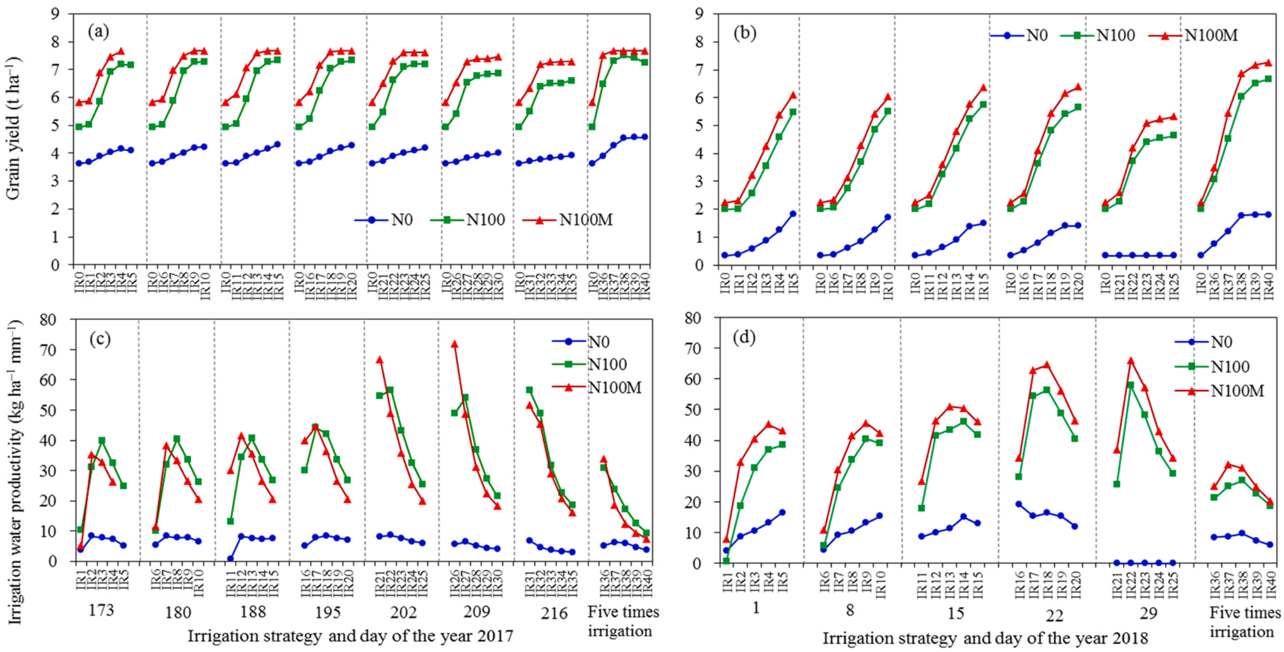

Fig. 7. Predicted response of grain yield of maize and irrigation water productivity to different irrigation regimes (see Table 4 for explanation of the abbreviations of the irrigation strategy) under N0, N100, and N100M (see Fig. 2 for explanation of the abbreviations of the treatment) during long rainy season (a, c) and short rainy season (b, d) in 2017.

water content was generally higher in the rainy season, that was from March to May and from October to November, and generally lower during the dry periods in January and from June to August. By comparing the predicted soil water contents to the measured values from late 2016–2018, we found that the model generally captured the dynamics well, despite some deviations (Fig. 5, a–g and Table 6). The predicted contents for each layer up to the depth of 80 cm matched the measured values very well under N0 ($nRMSE$ = 13.3–15.7%, d = 0.79–0.82, EF = 0.10–0.47), and the performance was moderate to good for each soil layer right up to 100 cm under both N100 and N100M (Table 6). However, the predictions were underestimates in the case of N100S for every layer except the deepest layer (80–100 cm) (Table 6).

Although overall the predicted levels closely matched the actual levels (Fig. 6, a–d), those for the dry periods, especially during July to August 2017 under all treatments except N0, were marked underestimates (Fig. 6, a–d), mainly because of underestimating the water content of layers up to a depth of 60 cm. On the other hand, the predicted *cumulative* soil water contents at all depths matched the actual measurements quite well under all treatments except N100S, as can be seen from the extent of deviation shown in Table 7 ($nRMSE$ < 15%, d > 0.8, EF > 0.28). The total soil water content under N100S was significantly underestimated (Table 7). Although the average soil water content was predicted to be the highest under N100S throughout the run from 2014 to 2018, the model failed to predict the actual water retention capacity resulting from mulching with straw.

3.3. Sensitivity analysis

3.3.1. Sensitivity of grain yield to irrigation

The predicted soil water contents of each soil layer increased greatly as the volume of irrigation increased, and over several weeks the contents remained higher than those in solely rain-fed plots. Soil water contents in the upper soil layers (0–50 cm) were more sensitive than the deeper soil layers to irrigation. The predicted grain yields were significantly and positively correlated to the volume of irrigation at all times and under N0, N100, and N100M in both the two dry seasons (Fig. 7a and b). The predicted yields showed a typical linear but diminishing return curve when plotted against the volume of irrigation. The predicted yields were generally more sensitive to the volume of irrigation during the shorter rainy season of 2017 than during the longer rainy season of the same year.

In the longer rainy season of 2017, the predicted yields were markedly higher, by as much as 2.0 t ha^{-1}, when the volume of irrigation increased from 0 mm to 50 mm, applied during silking starting on June 22, 2017 (i.e., Julian day 173 in 2017) to early grain filling on July 14, 2017 (Julian day 195) under both N100 and N100M, but decreased progressively as the volume increased beyond 50 mm (Fig. 7a). The magnitude of increase in yield as the volume of irrigation increased was much lower under N0 than under N100 or N100M, because of N deficiency experienced in N0. However, the increase in yield from more frequent irrigation (IR 36–40) was comparable to that when the plots were irrigated only once. The response of IWP to the volume of irrigation showed typical parabolic curves when irrigation was given from silking to early grain filling (IR 1–20) whereas IWP showed a linear and negative relationship with the volume of irrigation when it was given from early grain filling to mid grain filling (IR 21–35; Fig. 7c). The irrigation water productivity also responded negatively to volume of irrigation when the crop was irrigated multiple times. IWP peaked at around 40 kg ha^{-1} mm^{-1} in scenarios IR 1–20 under both N100 and N100M but at 57 kg ha^{-1} mm^{-1} under N100 and at 71 kg ha^{-1} mm^{-1} under N100M in scenarios IR 21–30. Under N100M, peak IWP was reached under lower volumes of irrigation compared to that under N100. The optimal volume was 30 mm for N100 and 50 mm for N100M, which led to high yield and high IWP in the longer rainy season of 2017.

In the shorter rainy season of 2017, the predicted yields increased linearly in all the treatments as the volume of irrigation increased from 0 mm to 70 mm, applied during silking starting on January 1, 2018 (Julian day 1 in 2018) to grain filling starting on January 15, 2018 (Julian day 15 in 2018) (Fig. 7b). When the crop was irrigated during early grain filling (Julian day 22 in 2018), grain yields increased rapidly as the volume of irrigation increased from 0 mm to 50 mm but more slowly when it increased beyond 50 mm. Late irrigation (Julian day 29 in 2018) was less effective than early irrigation in increasing yield under both N100 and N100S but had no effect on yield under N0. Broadly, irrigation increased grain yield by 1.0 t ha^{-1} under N0, by 3.5 t ha^{-1} under N100, and by 4.0 t ha^{-1} under N100M as the volume increased

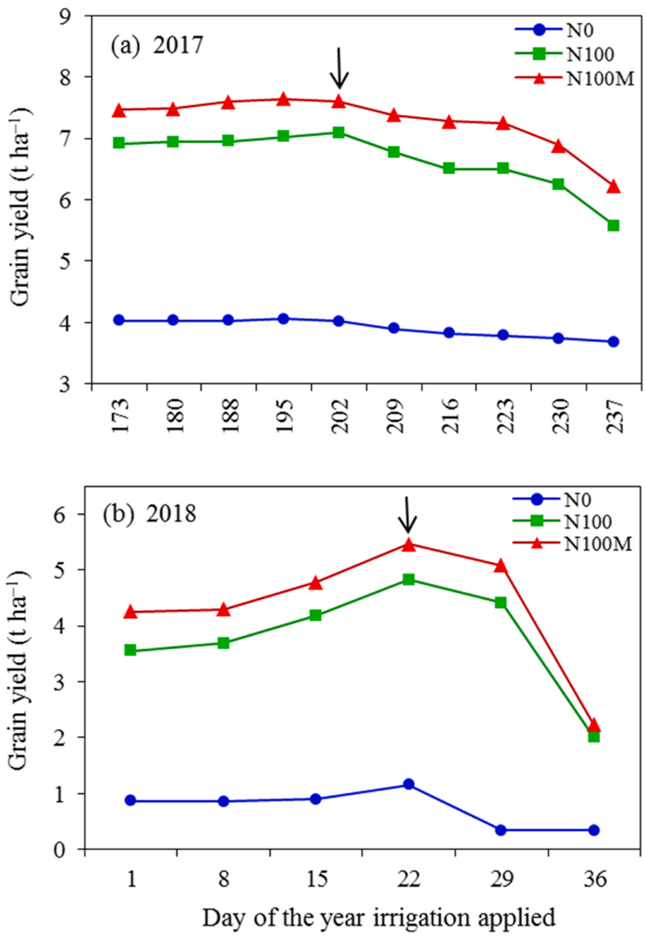

Fig. 8. Differences in predicted grain yield of maize as influenced by the time of irrigation with optimal volumes of irrigation under N0, N100, and N100M (see Fig. 2 for explanation of the abbreviations of the treatment) during long rainy season (a) and short rainy season (b) in 2017. The arrows indicate the optimum irrigation time with the highest grain yield.

from 0 mm to 70 mm. More frequent irrigation (IR 36–40) increased grain yield rapidly, by 1.5 t ha^{-1} under N0, by 4.0 t ha^{-1} under N100, and by 4.5 t ha^{-1} under N100M when the volume of irrigation increased from 0 mm to 150 mm. The response of IWP to the volume of irrigation traced a typical parabolic curve for each irrigation date under both N100 and N100S (Fig. 7d). The highest IWP was about 55 kg ha^{-1} mm^{-1} under N100 and 65 kg ha^{-1} mm^{-1} under N100M when irrigated at 30–50 mm during early grain filling (Julian days 22–29 in 2018). The once-only irrigation scenario with irrigation volume ranging from 50 mm to 70 mm was optimal for both high grain yield and high IWP in the shorter rainy season of 2017.

Under the optimal one-time irrigation scenario with 50 mm of water, grain yields varied depending on the date on which the crop was irrigated under all treatments in the two seasons in all years (Fig. 8, a and b). In the longer rainy season of 2017, grain yields were higher when the crop was irrigated during silking to early grain filling than when irrigation was delayed further. The highest grain yield was achieved when the crop was irrigated within two weeks of the beginning of grain filling. Grain yield was lower when the crop was irrigated later, that is from mid grain filling onwards. In the short rainy season of 2017, grain yields increased as the date of irrigation was delayed during silking to early grain filling period and peaked when the crop was irrigated 1 week after the beginning of grain filling, whereas grain yields decreased when irrigation was delayed beyond that time. Therefore, the optimal time of irrigation is the early grain filling period, that is within 2 weeks of the beginning of grain filling.

3.3.2. Sensitivity of grain yield to nitrogen dose

The predicted grain yield showed clear but varying responses to increasing doses of N in the dry spells during both the rainy seasons of 2017 and in the normal long rainy season of 2018, under both no irrigation and optimal irrigation (Fig. 9, a–c). The curve showing the response of grain yield to fertilizer N was either linear with a plateau or showed the typical diminishing returns.

In the long rainy season on 2017, grain yield increased linearly from 3.6 t ha^{-1} to 4.9 t ha^{-1} as the dose of N increased from 0 kg ha^{-1} to 60 kg ha^{-1} and then levelled off when no irrigation was given, whereas under optimal irrigation, grain yield increased linearly from 4.0 t ha^{-1} to 7.0 t ha^{-1} as the dose increased from 0 kg ha^{-1} to 100 kg ha^{-1} and then levelled off (Fig. 9a). In the shorter rainy season of 2017, grain yield increased rapidly from 0.3 t ha^{-1} to 2.0 t ha^{-1} as the dose of N increased from 0 kg ha^{-1} to 100 kg ha^{-1} and then levelled off in absence of irrigation, whereas under optimal irrigation, grain yield increased exponentially from 1.4 t ha^{-1} to 4.5 t ha^{-1} as the dose of N increased from 0 kg ha^{-1} to 60 kg ha^{-1}; the rate of increase in grain yield then slowed down to reach 6.0 t ha^{-1} at 140 kg N ha^{-1} (Fig. 9b). In the normal rainy season of 2018, grain yield increased from 1.6 t ha^{-1} to 4.7 t ha^{-1} as the dose of N increased from 0 kg ha^{-1} to 100 kg ha^{-1} and then levelled off, regardless of whether the crop had been irrigated or not (Fig. 9c). Thus under normal rainfall, irrigation contributed little to increasing grain yield, which was only slightly higher with irrigation than that without irrigation as the dose of N increased from 20 kg ha^{-1} to 80 kg N ha^{-1} (Fig. 9c).

The agronomic efficiency of fertilizer N differed in its response to the dose of N depending on irrigation and the season (Fig. 9, d–f): AE was much higher under irrigation in both the rainy seasons of 2017 because they were marked by dry spells, which meant that the rain-fed crop was under water stress. In the longer rainy season of 2017, AE remained at approximately 32 kg kg^{-1} even when the dose of N increased from 40 kg ha^{-1} to 80 kg ha^{-1} but declined as the dose increased beyond 100 kg ha^{-1} under irrigation (Fig. 9d): AE was thus negatively correlated to the dose of N in absence of irrigation in the long rainy season of 2017. In the shorter rainy season of that year, however, AE increased rapidly as the dose of N increased, peaking at 52 kg kg^{-1} when the dose was 60 kg ha^{-1}, but decreased at doses greater than 60 kg ha^{-1} under irrigation (Fig. 9e). In the absence of irrigation, AE responded positively to the dose of N from 20 kg ha^{-1} to 100 kg ha^{-1}, and then decreased as the dose increased beyond 100 kg N ha^{-1} (Fig. 9e). In the longer rainy season of 2018, which was marked by normal rainfall, AE responded negatively to the dose of N regardless of irrigation (Fig. 9f).

Precipitation use efficiency (PUE) of grain yield under rain-fed condition responded positively to the dose of N in both the rainy seasons of 2017 and the normal season of 2018 (Fig. 10a): in the longer rainy season of 2017, PUE increased linearly from 27 to 37 kg ha^{-1} mm^{-1} as the dose of N increased from 0 kg ha^{-1} to 60 kg ha^{-1} but level off at higher doses; in the shorter rainy season of 2017, PUE increased exponentially to 4 kg ha^{-1} mm^{-1} at doses of N up to 100 kg ha^{-1} but the increase slowed down at higher doses; in normal rainfall season of 2018, PUE increased linearly from 2 to 7 kg ha^{-1} mm^{-1} as the dose of N increased from 0 kg ha^{-1} to 100 kg ha^{-1} but level off at higher doses. Irrigation water productivity (IWP) also responded positively to the dose of N in both the rainy seasons of 2017 (Fig. 10b): in the longer rainy season, IWP increased exponentially to 40 kg ha^{-1} mm^{-1} as the dose of N increased from 0 kg ha^{-1} to 100 kg ha^{-1} but the increase slowed down at higher doses; in the shorter rainy season, IWP increased linearly to 50 kg ha^{-1} mm^{-1} at doses of N up to 60 kg ha^{-1} but the increase slowed down at rates greater than 60 kg ha^{-1}. The IWP was not responsive to the dose of N in normal rainfall season of 2018. These results indicated that the dose of N should be lowered to 60–80 kg ha^{-1} in the dry season for rain-fed maize, and increased to 100–120 kg ha^{-1} in humid seasons and even in dry seasons if optimal irrigation is possible, to achieve not only high yield but also high AE, high PUE and high IWP.

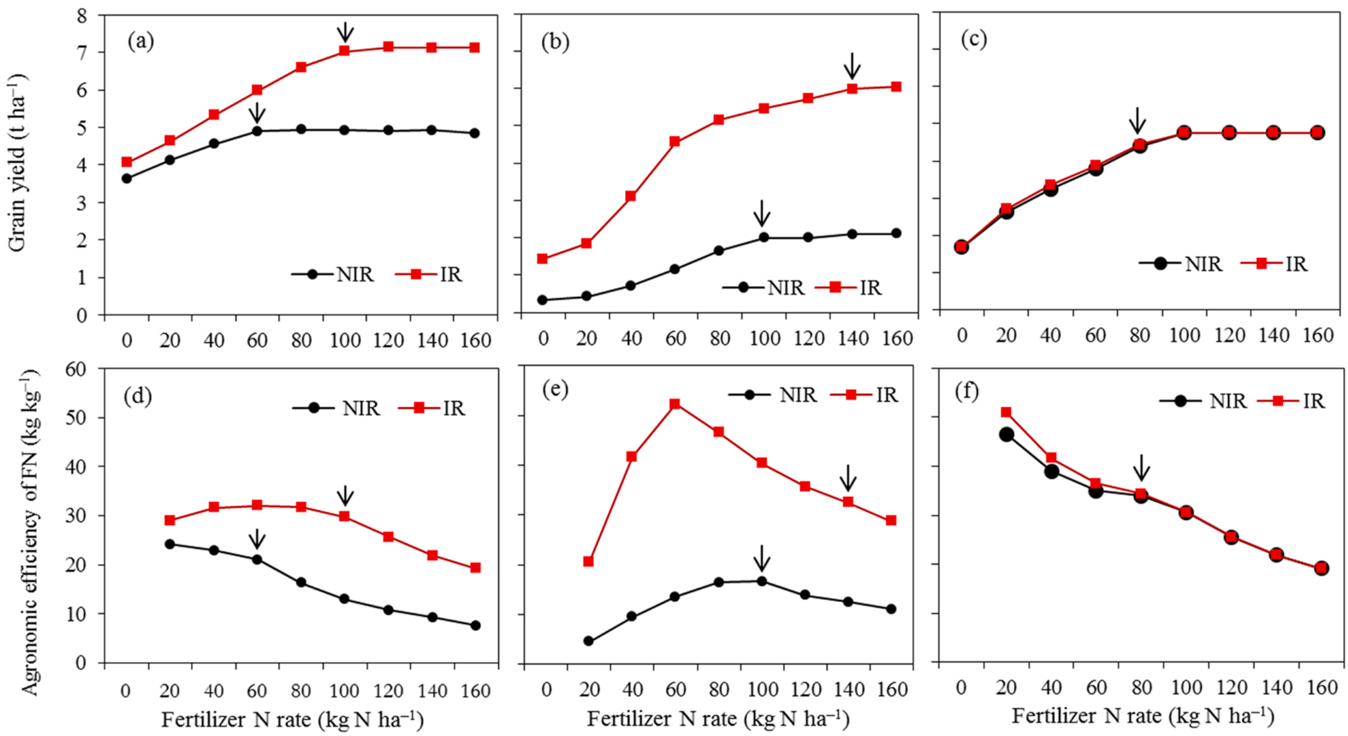

Fig. 9. Differences in predicted grain yield of maize and agronomic efficiency of fertilizer N (FN) as influenced by different doses of N without irrigation (NIR) and with optimal irrigation (IR) during dry spells in the longer rainy season (a, d) and shorter rainy season (b, e) in 2017 and during normal weather in the longer rainy season of 2018 (c, f). The arrows indicate the optimum doses of N with high grain yield.

4. Discussion

4.1. Grain yield and soil water content

Our experimental findings on the effects of different fertilizer regimes on grain yield and soil water content were consistent with those reported by Tully et al. (2015), Mo et al. (2016), Kiboi et al. (2019), Mutuku et al. (2020), and Zeweld et al. (2020). The yield increased significantly when N was supplied as a mineral fertilizer under normal rainfall in western Kenya (Tully et al., 2015), and both grain yield and water use efficiency were higher in plots mulched with grass straw than in those that were not mulched (Mo et al., 2016). Application of mineral fertilizer, either by itself or combined with manure or crop residue, consistently increased maize yield, which was generally maximum if chemical fertilizers and organic manure were combined, followed by that obtained from mineral fertilizer alone, and minimum in the absence of either (control) (Kiboi et al., 2019). Application of organic inputs such as crop residues and manure, either singly or in combination, has the potential to enhance soil water content in the central highlands of Kenya (Kiboi et al., 2019). Mutuku et al. (2020) also reported that grain yield in maize was higher with mineral fertilizers combined with manure than in the control (with neither mineral fertilizers nor manure) in low-fertility fields in the sub-humid and semi-arid regions of Kenya. Sustainable farming practices (such as retention of crop residues and use of manure) increase crop production and household income, and should be promoted especially in drought-prone, degraded, and water-stressed areas (Zeweld et al., 2020). In this study, average grain yield under N100M was higher than that under N100 because of the more balanced nutrient input from the manure. Mulching with maize straw (N100S) led to much higher soil water content than that in any of the other treatments, especially during dry spells, because the mulch protected the soil from direct heat from of the sun that would have otherwise increased the evaporation of soil water. It was the greater soil water content that contributed to higher grain yield in seasons with dry spells compared to that in N100; however, such mulching did not result in higher grain yield in the absence of any dry spells. Addition of manure (N100M) also led to higher soil water content than that in the treatment without manure or straw (N100) or that in the treatment without external application of N (N0), probably because the manure also resulted in higher levels of soil organic matter (Mutuku et al., 2020). Thus, the combination of mineral fertilizer, manure, and mulching with crop residue (straw) is recommended as a promising practice for higher grain yield and water conservation in semi-arid parts of Kenya.

Following its calibration based on cultivar parameters under N100M, the DSSAT-CSM made reliable predictions of grain yield under both N0 and N100, the predictions proved less satisfactory for N100S probably because the model underestimated soil water content especially during dry spell. The overall good performance of the model in predicting grain yield in this study was comparable with that reported earlier by Araya et al., (2015, 2019) and Corbeels et al. (2016). Araya et al. (2015) calibrated DSSATCSM using the data set from optimal management, evaluated the model for predicting yield without optimal management in south-western Ethiopia, and found that the model performance was moderate (*RSME* = 1.1 t ha^{-1} and d = 0.77). Corbeels et al. (2016) reported that, in Zambia, DSSAT was equally successful (*nRSME* = 10–31%) in predicting maize grain yield, whether under conservation agriculture (no tillage) or under conventional tillage. Araya et al. (2019) reported that DSSAT predicted wheat yield satisfactorily (*nRSME* = 10.16% and d = 0.97) under different levels of N and irrigation in northern Ethiopia. In addition, DSSAT-CSM generally captured the trends in temporal changes in soil water content of soil layers at different depths for all treatments except N100S in this study, and this good performance was comparable to that reported by Anothai et al. (2013) and Dokoohaki et al. (2017): the model was accurate in simulating soil water content over time at different depths under different levels of irrigation under semi-arid conditions (Anothai et al., 2013). Dokoohaki et al. (2017) also reported that DSSAT-CSM simulated soil water content accurately for a wide range of soil conditions and irrigation regimes in maize in semi-arid conditions. Therefore, DSSAT-CSM can be used as an effective tool to predict grain yield in maize and soil water content in its

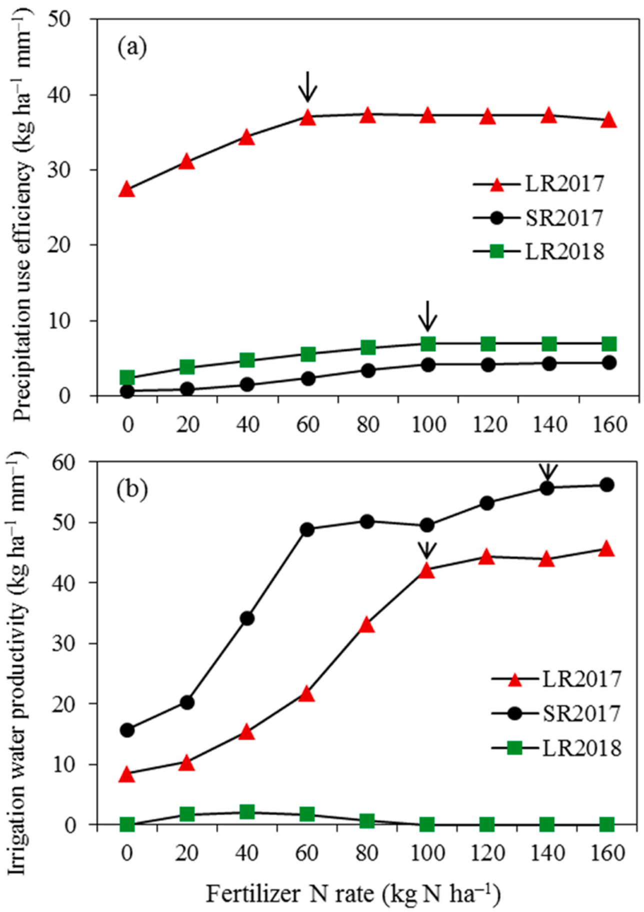

Fig. 10. Response of precipitation use efficiency under rain-fed condition (a) and irrigation water productivity under optimal irrigation (b) to different doses of N during the longer (LR) and shorter (SR) rainy seasons in 2017, and the longer (LR) rainy seasons in 2018. The arrows indicate the optimum doses of N with high precipitation use efficiency and high irrigation water productivity.

root zone under various farming practices in semi-arid regions.

4.2. Response of grain yield to irrigation and fertilizer nitrogen

Many studies have reported the characteristics of predicted grain yield of maize as affected by irrigation strategies (including the timing and volume of irrigation), dose of fertilizer N, and combinations of irrigation strategies and the dose of fertilizer N as affirmed by experimental results (Biazin et al., 2012; Tully et al., 2015; Pardo et al., 2020; van Dijk et al., 2020; Xu et al., 2019; Zamora-Re et al., 2020; Zou et al., 2020; Yan et al., 2021) and by modeling studies (Folberth et al., 2013; Kaur and Arora, 2018; Araya et al., 2019; Malik et al., 2019). Pardo et al. (2020) reported that barley responded positively to higher volumes of irrigation, although the highest average IWP was achieved under water deficit rather than under copious irrigation in semi-arid conditions. In western Kenya, grain yield of maize increased significantly as the dose of externally supplied N increased from 0 kg ha^{-1} to 161 kg ha^{-1} in 2012, which was a year with relatively normal rainfall, whereas N inputs had little impact in 2013, which was a drier year (Tully et al., 2015). Simulation using GIS-based EPIC predicted highest yields, 8–10 t ha^{-1}, in eastern and southern Africa if three improved management practices are combined (high doses of nutrients, liberal irrigation, and high-yielding cultivars) (Folberth et al., 2013). Another model, namely DSSAT-CERES-Maize, was used for identifying better irrigation and N-management practices: the model predicted that lowering both volume of irrigation and dose of N by the right amounts would lower the amount of N being lost through leaching *without* significant reduction in grain yield of irrigated maize grown under semi-arid conditions (Malik et al., 2019). The same model was also used to identify appropriate irrigation strategies for sustainable maize production in the arid and semi-arid regions of Guanzhong in China: the optimum irrigation was 200 mm applied during flowering and grain filling (Saddique et al., 2019). Simulation using DSSAT-CSM also showed a positive effect of both irrigation and N on wheat yield, biomass, and IWP and a strong and positive interdependence between irrigation and the dose of N as well as the time of irrigation (Araya et al., 2019). The above results indicate a significant effect of the interaction between the volume of irrigation and the amount of fertilizers on yield, which is why irrigation and fertilizer regimes should aim at optimal grain yield, IWP, and N-use efficiency and minimal losses of N through leaching instead of focusing on grain yield alone (Xu et al., 2019; Zamora-Re et al., 2020; Zou et al., 2020; Yan et al., 2021). Xu et al. (2019) suggested that for maize, the optimal dose of N was 140 kg ha^{-1} coupled with the recommended irrigation strategy considering the interactive effects of water and N on yield in north-western China. Based on the simulations of the various scenarios in this study, irrigation in amounts ranging from 50 mm to 70 mm during early parts of grain filling together with N at 100–120 kg ha^{-1} is recommended as the optimal regime for not only high grain yield but high N-use efficiency and high IWP as well.

In addition, the significant positive response of grain yield to the volume of irrigation and the dose of fertilizer N in this study points to the large scope to increase yield by appropriate management practices in eastern and southern Africa (Seyoum et al., 2017). Biazin et al. (2012) noted that in sub-Saharan Africa, it was possible to increase crop yields six-fold that achieved through traditional practices by supplemental irrigation (from rainwater harvesting) to rain-fed crops and application of fertilizers. The yield gap between actual yield and water-limited potential yield is caused by a combination of constraints such as genotype low improvement (tolerance to insects, diseases, herbicides, etc.), and low fertilizer input being the main cause (Affholder et al., 2013; van Dijk et al., 2020). The results of the simulations obtained in this study will help in more informed decision-making on irrigation and application of fertilizers to increase productivity and efficient use water and fertilizers.

5. Conclusions

Field observations over six maize-growing seasons from 2014 to 2018 showed that the highest average grain yield was obtained when N was combined with manure, and the highest soil water content of each soil layer was achieved when N was combined with straw mulching. The combination of mineral N, manure, and mulching is recommended as a promising practice to achieve higher grain yield and to retain more soil water in semi-arid areas of Kenya.

When calibrated under N100M, DSSAT-CSM predicted the grain yield well. The model generally captured the dynamics of soil water contents accurately in all layers of soil in all the treatments except in the case of N combined with mulching Overall, DSSAT-CSM is recommended for maize grown in semi-arid regions for predicting grain yield and soil water content in the root zone as influenced by the dose of fertilizers.

The simulated responses of grain yields to different irrigation regimes and fertilizer N rates showed that both N and water were critical and interacted to influence grain yield. The recommended strategy is to irrigate rain-fed maize only once, at 50–70 mm, during the early part of grain filling in combination with fertilizer N at 100–120 kg ha^{-1} to ensure optimal amounts of both irrigation and N. The results of the simulation will help in devising optimal irrigation and fertilizer regimes to achieve not only high grain yield but also high N use efficiency and high water use efficiency at the same time in semi-arid regions.

Declaration of Competing Interest

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.

Acknowledgments

This work was financially supported by the Sino-Africa Joint Research Project (grant no. SAJC201603); the National Natural Science Foundation of China (grant no. 31860144); the Natural Science Foundation of Guangxi (grant no. 2018GXNSFBA281177); the "One Hundred Talents" Project of Guangxi (grant no. 6020303891350); and the Guangxi Science and Technology Base and Talent Special Project (grant no. AD19110143). We also thank International Science Editing (http://www.internationalscienceediting.com) for editing the English language across this manuscript.

References

Affholder, F., Poeydebat, C., Corbeels, M., Scopel, E., Tittonell, P., 2013. The yield gap of major food crops in family agriculture in the tropics: assessment and analysis through field surveys and modelling. Field Crops Res. 143, 106–118.

Anothai, J., Soler, C.M.T., Green, A., Trout, T.J., Hoogenboom, G., 2013. Evaluation of two evapotranspiration approaches simulated with the CSM–CERES–Maize model under different irrigation strategies and the impact on maize growth, development and soil moisture content for semi-arid conditions. Agric. For. Meteorol. 176, 64–76. https://doi.org/10.1016/j.agrformet.2013.03.001.

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K.M., Kisekka, I., Martorano, L.G., 2015. Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. Agric. For. Meteorol. 214–215, 252–265. https://doi.org/10.1016/j.agrformet.2015.08.259.

Araya, A., Prasad, P.V.V., Gowda, P.H., Afewerk, A., Abadi, B., Foster, A.J., 2019. Modeling irrigation and nitrogen management of wheat in northern Ethiopia. Agric. Water Manag. 216, 264–272. https://doi.org/10.1016/j.agwat.2019.01.014.

Biazin, B., Sterk, G., Temesgen, M., Abdulkedir, A., Stroosnijder, L., 2012. Rainwater harvesting and management in rainfed agricultural systems in sub-Saharan Africa – a review. Phys. Chem. Earth Parts A/B/C. 47–48, 139–151. https://doi.org/10.1016/j.pce.2011.08.015.

Bryan, E., Ringler, C., Okoba, B., Koo, J., Herrero, M., Silvestri, S., 2013. Can agriculture support climate change adaptation, greenhouse gas mitigation and rural livelihoods? Insights from Kenya. Clim. Change 118 (2), 151–165. https://doi.org/10.1007/s10584-012-0640-0.

Burke, W.J., Frossard, E., Kabwe, S., Jayne, T.S., 2019. Understanding fertilizer adoption and effectiveness on maize in Zambia. Food Policy 86, 101721. https://doi.org/10.1016/j.foodpol.2019.05.004.

Confalonieri, R., Bellocchi, G., Bregaglio, S., Donatelli, M., Acutis, M., 2010. Comparison of sensitivity analysis techniques: a case study with the rice model WARM. Ecol. Model. 221, 1897–1906.

Corbeels, M., Chirat, G., Messad, S., Thierfelder, C., 2016. Performance and sensitivity of the DSSAT crop growth model in simulating maize yield under conservation agriculture. Eur. J. Agron. 76, 41–53. https://doi.org/10.1016/j.eja.2016.02.001.

Dokoohaki, H., Gheysari, M., Mousavi, S.F., Hoogenboom, G., 2017. Effects of different irrigation regimes on soil moisture availability evaluated by CSM-CERES-Maize model under semi-arid condition. Ecohydrol. Hydrobiol. 17 (3), 207–216. https://doi.org/10.1016/j.ecohyd.2017.06.001.

Fageria, N.K., Baligar, V.C., 2005. Enhancing nitrogen use efficiency in crop plants. Adv. Agron. 88, 97–185.

FAO, 2015. AQUASTAT database.⟨⟨http://www.fao.org/nr/water/aquastat/main/index.stm⟩⟩. (Accessed 29 July 2020).

Folberth, C., Yang, H., Gaiser, T., Abbaspour, K.C., Schulin, R., 2013. Modeling maize yield responses to improvement in nutrient, water and cultivar inputs in sub-Saharan Africa. Agric. Syst. 119, 22–34. https://doi.org/10.1016/j.agsy.2013.04.002.

Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., Brown, H., Whish, J.P.M., Verrall, S., Fainges, J., Bell, L.W., Peake, A.S., Poulton, P.L., Hochman, Z., Thorburn, P.J., Gaydon, D.S., Dalgliesh, N.P., Rodriguez, D., Cox, H., Chapman, S., Doherty, A., Teixeira, E., Sharp, J., Cichota, R., Vogeler, I., Li, F.Y., Wang, E., Hammer, G.L., Robertson, M.J., Dimes, J.P., Whitbread, A.M., Hunt, J., van Rees, H., McClelland, T., Carberry, P.S., Hargreaves, J.N.G., MacLeod, N., McDonald, C., Harsdorf, J., Wedgwood, S., Keating, B.A., 2014. APSIM - Evolution towards a new generation of agricultural systems simulation. Environ. Model. Softw. 62, 327–350.

Hoogenboom, G., Jones, J.W., Porter, C.H., Wilkens, P.W., Boote, K.J., Hunt, L.A., Tsuji, G.Y. (Eds.), 2010. Decision Support System for Agrotechnology Transfer Version 4.5, vol. 1: Overview. University of Hawaii, Honolulu, HI.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.I., White, J.W., Uryasev, O., Ogoshi, R., Koo, J., Shelia, V., Tsuji, G.Y., 2014. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6. DSSAT Foundation, Prosser, Washington. ⟨www.DSSAT.net⟩.

Howell, T.A., 2001. Enhancing water use efficiency in irrigated agriculture. Agron. J. 93, 281–289.

Jones, C.A., Kiniry, J.R., 1986. CERES-Maize: A Simulation Model of Maize Growth and Development, CERESMaize a Simulation Model of Maize Growth and Development. Texas A&M University Press, Texas.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265.

Kaur, R., Arora, V.K., 2018. Assessing spring maize responses to irrigation and nitrogen regimes in north-west India using CERES-Maize model. Agric. Water Manag. 209, 171–177. https://doi.org/10.1016/j.agwat.2018.07.022.

Kiboi, M.N., Ngetich, K.F., Fliessbach, A., Muriuki, A., Mugendi, D.N., 2019. Soil fertility inputs and tillage in fluence on maize crop performance and soil water content in the Central Highlands of Kenya. Agric. Water Manag. 217, 316–331. https://doi.org/10.1016/j.agwat.2019.03.014.

Li, Z.T., Yang, J.Y., Drury, C.F., Hoogenboom, G., 2015a. Evaluation of the DSSAT-CSM for simulating yield and soil organic C and N of a long-term maize and wheat rotation experiment in the Loess Plateau of Northwestern China. Agric. Syst. 135, 90–104. https://doi.org/10.1016/j.agsy.2014.12.006.

Li, Z.T., Yang, J.Y., Smith, W.N., Drury, C.F., Lemke, R.L., Grant, B., He, W.T., Li, X.G., 2015b. Simulation of long-term spring wheat yields, soil organic C, N and water dynamics using DSSAT-CSM in a semi-arid region of the Canadian prairies. Nutr. Cycl. Agroecosystems 101 (3), 401–419. https://doi.org/10.1007/s10705-015-9688-3.

Malik, W., Isla, R., Dechmi, F., 2019. DSSAT-CERES-maize modelling to improve irrigation and nitrogen management practices under Mediterranean conditions. Agric. Water Manag. 213, 298–308. https://doi.org/10.1016/j.agwat.2018.10.022.

Mo, F., Wang, J.Y., Xiong, Y.C., Nguluu, S.N., Li, F.M., 2016. Ridge-furrow mulching system in semiarid Kenya: a promising solution to improve soil water availability and maize productivity. Eur. J. Agron. 80, 124–136. https://doi.org/10.1016/j.eja.2016.07.005.

Mo, F., Wang, J.Y., Zhou, H., Luo, C.L., Zhang, X.F., Li, X.Y., Li, F.M., Xiong, L.B., Kavagi, L., Nguluu, S.N., Xiong, Y.C., 2017. Ridge-furrow plastic-mulching with balanced fertilization in rainfed maize (Zea mays L.): an adaptive management in east African Plateau. Agric. For. Meteorol. 236, 100–112. https://doi.org/10.1016/j.agrformet.2017.01.014.

Mucheru-Muna, M., Pypers, P., Mugendi, D., Kung'u, J., Mugwe, J., Merckx, R., Vanlauwe, B., 2010. A staggered maize-legume intercrop arrangement robustly increases crop yields and economic returns in the highlands of Central Kenya. Field Crops Res. 115, 132–139. https://doi.org/10.1016/j.fcr.2009.10.013.

Mucheru-Muna, M., Mugendi, D., Pypers, P., Mugwe, J., Kung'u, J., Vanlauwe, B., Merckx, R., 2014. Enhancing maize productivity and profitability using organic inputs and mineral fertilizer in central Kenya small-hold farms. Exp. Agric. 50, 250–269. https://doi.org/10.1017/S0014479713000525.

Mutuku, E.A., Roobroeck, D., Vanlauwe, B., Boeckx, P., Cornelis, W.M., 2020. Maize production under combined conservation agriculture and integrated soil fertility management in the sub-humid and semi-arid regions of Kenya. Field Crops Res. 254, 107833 https://doi.org/10.1016/j.fcr.2020.107833.

Nakawuka, P., Langan, S., Schmitter, P., Barron, J., 2018. A review of trends, constraints and opportunities of smallholder irrigation in East Africa. Glob. Food Secur. 17, 196–212. https://doi.org/10.1016/j.gfs.2017.10.003.

Ngetich, K.F., Diels, J., Shisanya, C.A., Mugwe, J.N., Mucheru-muna, M., Mugendi, D.N., 2014. Effects of selected soil and water conservation techniques on runoff, sediment yield and maize productivity under sub-humid and semi-arid conditions in Kenya. CATENA 121, 288–296. https://doi.org/10.1016/J.CATENA.2014.05.026.

Nyagumbo, I., Nyamadzawo, G., Madembo, C., 2019. Effects of three in-field water harvesting technologies on soil water content and maize yields in a semi-arid region of Zimbabwe. Agric. Water Manag. 216, 206–213. https://doi.org/10.1016/j.agwat.2019.02.023.

Ochieng, J., Kirimi, L., Makau, J., 2017. Adapting to climate variability and change in rural Kenya: farmer perceptions, strategies and climate trends. Nat. Resour. Forum 41, 195–208.

Ogada, M.J., Rao, E.J.O., Radeny, M., Recha, J.W., Solomon, D., 2020. Climate-smart agriculture, household income and asset accumulation among smallholder farmers in the Nyando basin of Kenya. World Dev. Perspect. 18, 100203 https://doi.org/10.1016/j.wdp.2020.100203.

Ojeda, J.J., Caviglia, O.P., Irisarri, J.G.N., Agnusdei, M.G., 2018. Modelling inter-annual variation in dry matter yield and precipitation use efficiency of perennial pastures and annual forage crops sequences. Agric. For. Meteorol. 259, 1–10.

Pardo, J.J., Martínez-Romero, A., Léllis, B.C., Tarjuelo, J.M., Domínguez, A., 2020. Effect of the optimized regulated deficit irrigation methodology on water use in barley under semiarid conditions. Agric. Water Manag. 228, 105925.

Rowell, D.P., Booth, B.B.B., Nicholson, S.E., Good, P., 2015. Reconciling past and future rainfall trends over East Africa. J. Clim. 28, 9768–9788. https://doi.org/10.1175/JCLI-D-15-0140.1.

Saddique, Q., Cai, H., Ishaque, W., Chen, H., Chau, H., Chattha, M., He, J., 2019. Optimizing the sowing date and irrigation strategy to improve maize yield by using CERES (Crop estimation through resource and environment synthesis)-maize model. Agronomy 9 (2), 109. https://doi.org/10.3390/agronomy9020109.

Saiz, G., Wandera, F.M., Pelster, D.E., Ngetich, W., Okalebo, J.R., Rufino, M.C., Butterbach-Bahl, K., 2016. Long-term assessment of soil and water conservation measures (Fanya-juu terraces) on soil organic matter in South Eastern Kenya. Geoderma 274, 1–9. https://doi.org/10.1016/j.geoderma.2016.03.022.

Seyoum, S., Chauhan, Y., Rachaputi, R., Fekybelu, S., Prasanna, B., 2017. Characterising production environments for maize in eastern and southern Africa using the APSIM

Model. Agric. For. Meteorol. 247, 445–453. https://doi.org/10.1016/j.agrformet.2017.08.023.
Srivastava, A.K., Mboh, C.M., Gaiser, T., Kuhn, A., Ermias, E., Ewert, F., 2019. Effect of mineral fertilizer on rain water and radiation use efficiencies for maize yield and stover biomass productivity in Ethiopia. Agric. Syst. 168, 88–100.
Tittonell, P., Corbeels, M., Van Wijk, M.T., Vanlauwe, B., Giller, K.E., 2008. Combining organic and mineral fertilizers for integrated soil fertility management in smallholder farming systems of Kenya: explorations using the crop-soil model FIELD. Agron. J. 100, 1511–1526. https://doi.org/10.2134/agronj2007.0355.
Tully, K.L., Wood, S.A., Almaraz, M., Neill, C., Palm, C., 2015. The effect of mineral and organic nutrient input on yields and nitrogen balances in western Kenya. Agric., Ecosyst. Environ. 214, 10–20. https://doi.org/10.1016/j.agee.2015.08.006.
van Dijk, M., Morley, T., van Loon, M., Reidsma, P., Tesfaye, K., van Ittersum, M.K., 2020. Reducing the maize yield gap in Ethiopia: decomposition and policy simulation. Agric. Syst. 183, 102828 https://doi.org/10.1016/j.agsy.2020.102828.
Wafula, B.M., 1995. Applications of crop simulation in agricultural extension and research in Kenya. Agric. Syst. 49 (4), 399–412. https://doi.org/10.1016/0308-521x(95)00033-2.
Whitbread, A.M., Robertson, M.J., Carberry, P.S., Dimes, J.P., 2010. How farming systems simulation can aid the development of more sustainable smallholder farming systems in southern Africa. Eur. J. Agron. 32 (1), 51–58 doi:10.1016/j.eja.2009.05.004.
Xu, J., Cai, H., Wang, X., Ma, C., Lu, Y., Ding, Y., Wang, X., Chen, H., Wang, Y., Saddique, Q., 2019. Exploring optimal irrigation and nitrogen fertilization in a winter wheat-summer maize rotation system for improving crop yield and reducing water and nitrogen leaching. Agric. Water Manag. 228, 105904 https://doi.org/10.1016/j.agwat.2019.105904.
Yan, F., Zhang, F., Fan, X., Fan, J., Wang, Y., Zou, H., Wang, H., Li, G., 2021. Determining irrigation amount and fertilization rate to simultaneously optimize grain yield, grain nitrogen accumulation and economic benefit of drip-fertigated spring maize in northwest China. Agric. Water Manag. 243, 106440.
Yang, J.M., Yang, J.Y., Liu, S., Hoogenboom, G., 2014. An evaluation of the statistical methods for testing the performance of crop models with observed data. Agric. Syst. 127, 81–89.
You, L., Xie, H., Wood-Sichra, U., Guo, Z., Wang, L., 2014. Irrigation potential and investment return in Kenya. Food Policy 47, 34–45. https://doi.org/10.1016/j.foodpol.2014.04.006.
Zamora-Re, M.I., Dukes, M.D., Hensley, D., Rowland, D., Graham, W., 2020. The effect of irrigation strategies and nitrogen fertilizer rates on maize growth and grain yield. Irrig. Sci. 38, 461–478. https://doi.org/10.1007/s00271-020-00687-y.
Zeweld, W., Van Huylenbroeck, G., Tesfay, G., Azadi, H., Speelman, S., 2020. Sustainable agricultural practices, environmental risk mitigation and livelihood improvements: empirical evidence from Northern Ethiopia. Land Use Policy 95, 103799. https://doi.org/10.1016/j.landusepol.2019.01.002.
Zhang, H., Wang, X., You, M., Liu, C., 1999. Water–yield relations and water-use efficiency of winter wheat in the North China Plain. Irrig. Sci. 19, 37–45.
Zinyengere, N., Crespo, O., Hachigonta, S., 2013. Crop response to climate change in southern Africa: a comprehensive review. Glob. Planet. Change 111, 118–126. https://doi.org/10.1016/j.gloplacha.2013.08.010.
Zou, H., Fan, J., Zhang, F., Xiang, Y., Wu, L., Yan, S., 2020. Optimization of drip irrigation and fertilization regimes for high grain yield, crop water productivity and economic benefits of spring maize in Northwest China. Agric. Water Manag. 230, 105986.