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Predicting water and nitrogen requirements for maize under semi-arid conditions using the CSM-CERES-Maize model

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ABSTRACT

Crop models can be useful tools for optimizing irrigation water and fertilizer management to improve crop productivity. The goal of this study was to assess the performance of the Cropping System Model (CSM)-CERES-Maize for its capability to simulate soil moisture content in relation to plant growth, development and grain yield and to determine optimum irrigation and fertilizer inputs under semiarid conditions. The model simulations were compared with the observed results from field trials that were conducted during 2009 and 2010 with a combination of three irrigation regimes (full irrigation, water deficit at vegetative and at reproductive stage) and five nitrogen (N) rates using a split plot design for a total of 15 treatments. To determine the most appropriate combination of nitrogen fertilizer and irrigation, a combination of three irrigation regimes and five N rates ranging from 100 to 300 kg N ha^{-1} for a total of 15 scenarios were simulated for 35 years of historical daily weather data. The model was calibrated with an optimum treatment from the 2010 experiment, while the remainder of the data were used for model evaluation. The results showed that the model successfully predicted (R^2 = 0.98) soil moisture content throughout the growing season. The observed (calibrated) mean percentage differences (MPD) for the numbers of grains per ear, leaf area index (LAI) and total dry matter (TDM) were 5.98, 11.4, and 4.85%, respectively. The MPD was zero for yield, anthesis and maturity days. The normalized root mean square error (nRMSE) for grain yield was 10.4% and 11.4% in 2009 and 2010, respectively. Based on the economic analysis, the management scenario with an N fertilizer application rate of 300 kg N ha^{-1} in three splits and total irrigation of 525 mm was dominant with the highest mean grain yield (7973 kg ha^{-1}) and a gross margin of US $ 548 ha^{-1}. The outcomes of this study can be used for determining the optimum water and N requirements for maize production under semi-arid conditions. The modeled genetic coefficients might be helpful for plant breeders to develop maize cultivars for semi-arid regions that may give the optimum yield under above recommended N and water management practices.

1. Introduction

Crop simulation models can be very useful for assessing soil–plant-atmosphere relationships for cropping systems using various types of models through seasonal and spatial analysis (Thornton et al., 1997; Tsuji et al., 1998; Bergez et al., 2010; Leenhardt et al., 2016). Simulation models are now so progressive that they can be used as a multipurpose tool with trial data for numerous crop applications (Maton et al., 2007; Soltani and Sinclair, 2012; Bao et al., 2017). One of the main goals of a crop simulation model is to estimate crop production and environmental impact as a function of local weather and soil conditions (Boote et al., 1996, 2010; Hoogenboom, 2000; Bannayan et al., 2003; Jones et al., 2003; White et al., 2011; Holzworth et al., 2015). Numerous researchers have used different crop models for simulating crop growth and yield. For example, Chen et al. (2010) simulated water management for wheat and maize in the North China Plain using the APSIM (Agricultural Production Systems Simulator) model. Abedinpour et al. (2012) simulated the growth yield potential of

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maize using the Aqua Crop model under various water availability scenarios in the Bolivian Altiplano area. The Soil Water Balance Model (SWBM) was used in order to simulate soil nitrate leaching in Australia (Van der Laan et al., 2010). Similarly, many researchers have reported that the Decision Support System for Agrotechnology Transfer (DSSAT) model is to be well suited for simulating agricultural practices for different environments (Mavromatis et al., 2001; Jones et al., 2003; Liu et al., 2011a; Ahmad et al., 2012; Hoogenboom et al., 2015; Kadiyala et al., 2015; Soltani and Sinclair 2015; Mubeen et al., 2016; Araya et al., 2017).

The DSSAT software encompasses several crop models that can be used for yield trend simulation under diverse soil and climatic conditions (Aggarwal and Kalra, 1994; Jagtap and Jones, 2002; Bannayan et al., 2003; Soltani et al., 2004; Potgieter et al., 2005; White et al., 2011). The DSSAT software (Tsuji et al., 1994; Hoogenboom et al., 2011, 2015) includes the Cropping System Model (CSM) CERES-Maize (Ritchie et al., 1998; Jones et al., 2003) that has been widely and successfully used throughout the world (Jones et al., 2003; Hoogenboom et al., 2009) to dynamically simulate crop growth, nutrient uptake and water requirements, and to predict crop yield and other plant characteristics (Boote et al., 2010; Abbas et al., 2017). For instance, Duchon (1986) used the CSM-CERES-Maize to predict maize growth and yield in Illinois. Solar et al. (2007) demonstrated that the CERES-Maize Model can be applied to simulate the impact of water deficit on maize in a subtropical environment of Piracicaba, Brazil. The model was also evaluated under temperate scenarios characterized by moisture stress in North America (Piper and Weiss, 1990); Ben Nouna et al. (2003) used the model to test its performance in predicting crop response to Mediterranean region's environments. Liu et al. (2011b) presented a successful application of the model to predict maize yield and N cycling for a 50-year maize production in southwestern Ontario, Canada.

Water shortage is a chronic problem in semi-arid areas of the world where agriculture cannot exist without supplemental irrigation water. Maize can obtain high yield under semi-arid regions but with high irrigation water requirements (Hammad et al., 2011; Hammad et al., 2012). However, in many of the semi-arid regions this is an important restriction due to water scarcity (Ibáñez et al., 2008; Mansouri-Far et al., 2010; Hammad et al., 2015; Hammad et al., 2016). The drought stress index is one of numerous outputs of the CSM–CERES–Maize model that can be used as guidance for scheduling irrigation management decisions that conserve water and maximize yield (Solar et al., 2007; Quiring and David, 2008; Anothai et al., 2013; Kadiyala et al., 2015). Many studies have assessed growth and yield response of the CSM CERES–Maize model under various irrigation regimes (Dogan et al., 2006; Solar et al., 2007; Anothai et al., 2013). However, the crop modeling literature has very few studies that have made an extensive use of combined experimental and modeling approaches to study the irrigation regimes and N effect simultaneously at various maize production stages for semi-arid environments. A newer version of the CSM–CERES–Maize model (V 4.6) developed by Hoogenboom et al. (2015) requires further evaluation for a range of irrigation and N applications for semi-arid conditions. Therefore, the objectives of this study were i) to evaluate the performance of the CSM-CERES-Maize for simulating growth and yield of maize under different irrigation water regimes and nitrogen rates ii) to assess the economic impact of water and nitrogen for maize production in semi-arid environments, using Punjab-Pakistan as a case study.

2. Materials and methods

2.1. Field site and soil type

The field site was located at the Agronomic Research Farm of the University of Agriculture, Faisalabad, Pakistan (Latitude 31° 26′ N and Longitude 73° 06′ E), which represents a semi-arid environment. The soil at the experimental site was alluvial deposits mixed with loess having calcareous characteristics, making it very fertile (Abbas, 2013). The soil physical properties (i.e. bulk density, organic matter, soil pH, nitrogen (N) phosphorus (P) and potassium (K) of the upper (0–20 cm) and lower (20–40 cm) depths) were obtained from soil core samples. Soil bulk density, saturated moisture content, permanent wilting point, field capacity and saturation values for each soil layer was calculated from measured soil core samples data by following standard procedures (Saxton and Rawls, 2006) (Table 1). Because of its high evapotranspiration, Faisalabad features a semiarid to arid climate with a summer maximum temperature of 50 °C, a maximum winter temperature of 22 °C, and an average summer precipitation of 175 mm and an average winter precipitation of 93 mm (Abbas et al., 2014).

Table 1
Physical and chemical characteristics of the soil at the experimental site.

	2009		2010	
Soil properties	0–0 cm	20–40 cm	0–20 cm	20–40 cm
Field capacity ($cm^3\ cm^{-3}$)	0.32	0.39	0.33	0.38
Permanent wilting point ($cm^3\ cm^{-3}$)	0.13	0.17	0.12	0.17
Bulk density ($g\ cm^{-3}$)	1.32	1.51	1.32	1.54
Organic matter (%)	1.08	0.34	0.98	0.35
Soil pH	7.64	7.44	7.58	7.37
Total soil nitrogen ($g\ kg^{-1}$)	0.73	0.29	0.68	0.23
Total soil phosphorous ($g\ kg^{-1}$)	7.11	4.21	7.30	4.35
Total soil potassium ($g\ kg^{-1}$)	20.25	7.53	20.56	8.45

2.2. Crop husbandry and treatment

The maize hybrid Pioneer 31R88 was planted on August 1, 2009 and August 2, 2010. The experimental treatments were assigned into main plots, consisting of three irrigation regimes I_1 (Irrigation at V2, V6, V12, V16, VT, R1 and R3 stage), I_2 (Irrigation at V6, V12, VT, R1 and R3 stage) and I_3 (Irrigation at V2, V6, V12, V16, VT and R3 stages); where V is the vegetative growth stage and # is the number of fully expanded leaves on the main stem, R is the reproductive growth stage, and R1 is silking, VT is tasseling and R3 milk stage. The irrigation applications were scheduled according to the individual treatments by observing the number of leaf stages as described by Ritchie and Hanway (1993). The depth of irrigation water was maintained with a 0.75 m × 0.90 m size Cut-Throat flume. The following formula was used for calculation of the duration of each irrigation application:

$$t = \frac{(A \times d)}{Q} \tag{1}$$

where t is time to irrigate a given area (second), A is area to be irrigated (m^2), d is depth of water applied (mm) and Q is discharge measured through a Cut-Throat flume ($m^3\ s^{-1}$).

A buffer plot was designed among the plots to avoid a moisture effect of neighboring plots. Five N rates (100, 150, 200, 250, and 300 kg ha^{-1}) including optimum dose 250 kg ha^{-1} on the basis of experimental soil analysis (Al-Kaisi and Yin., 2003) were applied in three splits in subplots that had a dimension of 3 m × 5 m. The optimal doses of P_2O_5 and K_2O (each at the rate of 125 kg ha^{-1}) were applied during seedbed preparation. Similar agronomic practices including weeding, hoeing, and earthing up were conducted in all plots. The crop was harvested on November 11, 2009 and November 13, 2010.

2.3. Crop measurement data

In each plot, 10 plants were randomly tagged to make daily crop phenology observations. Phenology of the crop was recorded by counting the number of leaves and the leaf collar appearance on a daily basis in each individual plot. The tasseling and silking stage was recorded when 50% tassels and silks appeared in each plot, respectively. Physiological maturity was determined by continually sampling ears

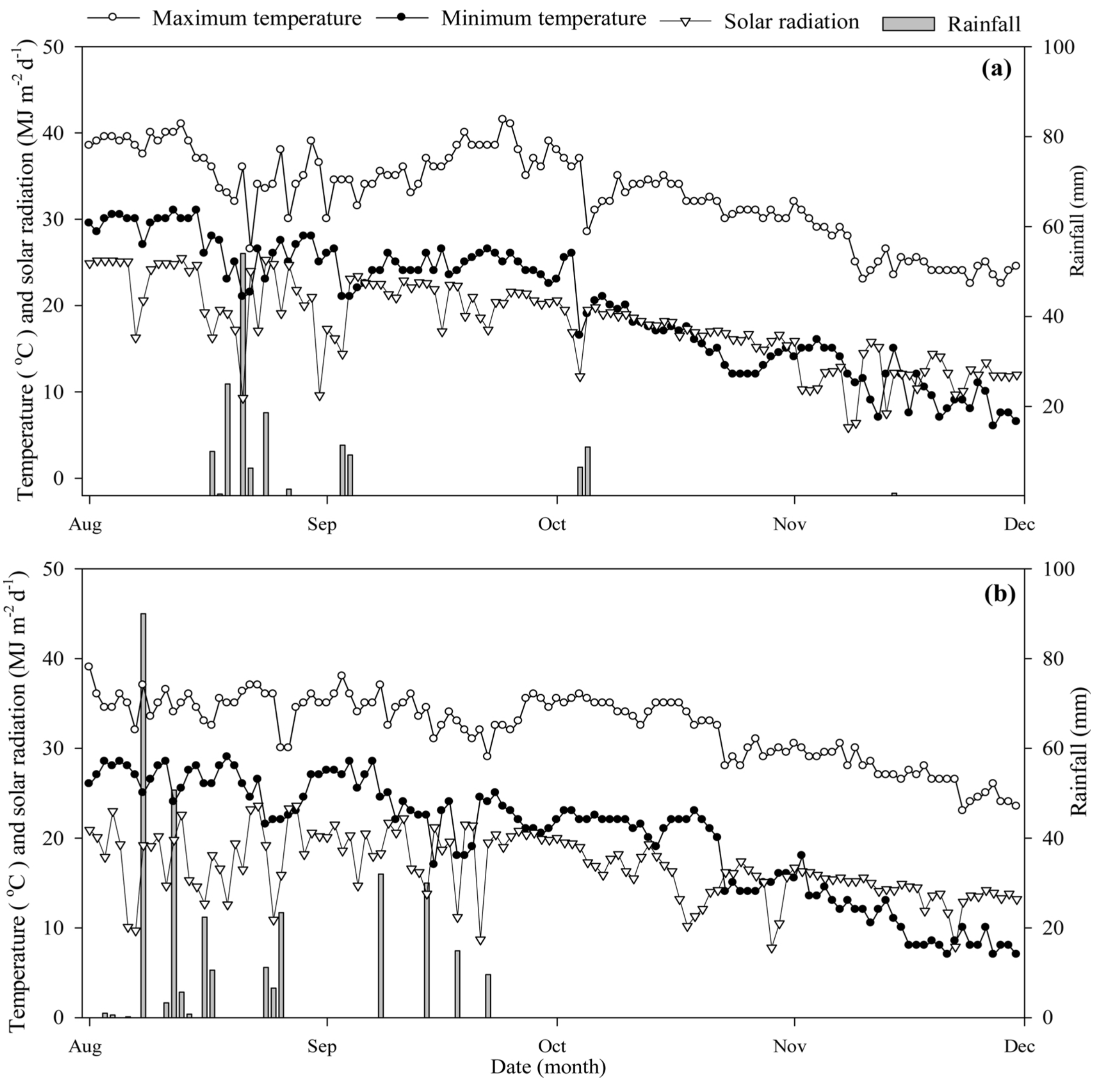

Fig. 1. Daily meteorological data recorded at the experimental site during the 2009 (a) and 2010 (b) growing seasons.

from each plot to assess the appearance of black layers at the base of the grains. From each sub plot an area of 0.2 m^2 was harvested by cutting the plants at the ground level at 15-day intervals. There were seven destructive samplings throughout the growing period and the final sample was for determining grain yield. A subsample of 10 g fresh leaf from each of the harvested samples (an area of 0.2 m^2) was taken and used for measuring leaf area with a Laser Leaf Area Meter (Model CI-203, CID Bio-Science). The measured leaf area of 10 g fresh leaf was further used to calculate leaf area m^{-2} based on weight. The sub-sample's leaf area index was calculated and scaled up for the ratio of leaf area to land area as:

$$LAI = \frac{\text{Leafarea}}{\text{Groundarea}} \tag{2}$$

A sub-sample (20 g) of each shoot fraction was taken for measuring dry matter production. The samples were oven-dried at 70 °C for 72 h to achieve constant dry weight. Plants were then separated into leaves, stems, tassels, and ears. The number of grains per ear was counted for three ears taken from each plot. The remaining area (3 m^2) of each experimental plot was used for determining final grain yield.

2.4. Soil moisture content

The soil moisture content of the upper (0–20 cm) and lower (20–40 cm) layers of the soil were measured seven times during the 2009 and 2010 growing seasons. Before each irrigation, the soil moisture content of each individual experimental plot was measured with Time Domain Reflectometry (MiniTrase ELE 514-190 UK). The soil moisture measurements were compared with the simulated soil moisture content by the CSM-CERES-Maize model.

2.5. Model description and evaluation

In this study the CSM-CERES-Maize Model, which is one of the crop growth modules in the DSSAT software, was used to simulate maize growth and yield. The model requires soil surface and soil profile properties, planting date information, plant population, row spacing, daily precipitation, maximum and minimum air temperature, solar radiation and air humidity data. The weather data were collected by a meteorological station approximately at a distance of 300 m from the study site (Fig. 1).

The long term observed weather data, crop management and the observed crop data were used as input for the model (Soltani and Hoogenboom, 2007). The cultivar coefficients of hybrid Pioneer 31R88 were estimated by using a so-called 'grid search approach' established by Mavromatis et al. (2002). A non-stress standard treatment (I_1N_4 of 2010) was used to estimate the genetic coefficients (Zheng et al., 2017). Six genetic coefficients (P1, P2, P5, G2, G3 and PHINT) are used in CSM-CERES-Maize to simulate growth, development and yield of maize (Table 2).

Table 2
Calibrated values of the cultivar coefficients of the maize hybrid Pioneer 31R88 for the CSM-CERES-Maize model.

Cultivar coefficients	Value
P1(°C day)	311
P2(day h^{-1})	0.840
P5(°C day)	752.0
G2 (kernel $plant^{-1}$)	725.2
G3 (mg d^{-1})	10.60
PHINT (°C day)	42.50

P1: Thermal time from crop seedling emergence to the end of the juvenile stage.
P2: Degree to which development is delayed for each hour rise in photoperiod above the critical photoperiod (12.5 h for CERES) at which development proceeds at maximum rate. P5: Thermal time from silking to physiological maturity. G2: Maximum possible number of kernel per plant. G3: Grain filling rate under optimum conditions (mg day^{-1}). PHINT: Phyllochron interval; the interval in thermal time between two successive leaf tip emergences.

2.6. Model calibration

The observed weather data (2009 and 2010), the soil series data for the experimental site, crop management and the observed crop data were used for calibration of the model and to determine the genetic coefficients. The cultivar coefficients for the hybrid (Pioneer 31R88) were determined through trial and error by comparing simulated data with observed data using the so-called 'grid search approach' as defined by Jagtap et al. (1993) and Mavromatis et al. (2002)

Once each of the genetic coefficients (e.g P1) was individually estimated, the model was run with a different value of G2 to closely match the simulated and observed values. This process was then repeated for G3 (keeping PI, P2, P5 G2 and PHINT unchanged) so that the estimated values closely matched with the observed values. Each of the replications was calibrated individually.

2.7. Economic analysis

The strategy analysis tool of DSSAT was run for a range of management options to determine the effect of water and N on crop productivity. The three irrigation regimes (I_1, I_2 and I_3) and five N rates (100, 150, 200, 250 and 300 kg ha^{-1}) were also evaluated using the Mean-Gini Dominance Analysis (Thornton and Hoogenboom, 1994; Tsuji et al., 1998). Gross margin ($ ha^{-1}) for each treatment was determined by the following formula

$$\text{Gross Margin} = \{(Y \times P) - (IN \times C)\} - V \tag{3}$$

where Y is simulated maize grain (kg ha^{-1}), P is price of yield (0.30 $ kg^{-1}), I is supplemental irrigation water (mm ha^{-1}), N is nitrogen fertilizer application rate (kg ha^{-1}), C is the cost of I and N fertilizer (0.05 $ mm^{-1} ha^{-1} and 0.35 $ kg^{-1}, respectively) and V is the base production costs (240 $ ha^{-1}) for all treatments. The inputs prices were obtained from the Pakistan Economic Survey (GOP, 2012).

2.8. Model statistics

For calibration and evaluation of the model, the simulated days to emergence, days to anthesis, and days to maturity as well as yield values were compared with the observed data. Various CSM-CERES-Maize statistical indices were recorded, including mean percent difference (MPD) and the normalized root mean square error (nRMSE) given in percent, determined according to Yang et al. (2014) with

$$MPD = \frac{\left[\sum_{i=1}^{n}\left(\frac{|O_i - P_i|}{O_i}\right)100\right]}{n} \tag{4}$$

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{n}} \times \frac{100}{M} \tag{5}$$

where n is the number of observations, Pi and Oi mean to predicted and observed values respectively, e.g., days from emergence to anthesis and physiological maturity, LAI, TDM, yield and its components while M is the mean of the observed variable. The model simulation is considered excellent when the MPD and nRMSE < 10%, good if the MPD and nRMSE > 10 and < 20%, and fair if the MPD and nRMSE is > 20% and < 30% (Jamieson et al., 1991). The Index of Agreement (d) as proposed by Willmott et al. (1985) was also calculated (Eq. (5)). According to the d-statistic, the closer the index value to 1, the best the agreement between the simulated and observed variables (Timsina and Humphreys, 2006; Yang et al., 2014).

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(Pi - Oi)^2}{\sum_{i=1}^{n}(|P'i| - |O'i|)^2}\right] \tag{6}$$

where, n is number of observations, Pi is productive value, Qi is mean observation value, $P\acute{i} = Pi - M$ and $O\acute{i} = Oi - M$ is a measured observation.

3. Results and discussion

3.1. Cultivar coefficients

The final values for the six cultivar coefficients that control vegetative *(P1, P2, and P5)* and reproductive (*G2*, *G3*, and *PHINT*) crop growth and development are shown in Table 2. The value for coefficient *P*1 (thermal time from seedling appearance to the end of the juvenile phase) was 311 °C day, corresponding to a medium to late flowering hybrid. The values for *P*2 (range to which development is delayed for every hour increase in photoperiod beyond the critical photoperiod) was set to 0.840 day per hour, however, no response to photoperiod was simulated since the day length throughout the growing season was less than 12.5 h (critical photoperiod). The value for *P*5 (which is thermal time from flowering to physiological maturity) was calibrated to 752 °C day, corresponding to a shorter maturity duration hybrid. The values for *G*2 (maximum number of kernel per plant) was calibrated to 725.2. The *G*3 (kernel filling rate) was calibrated to 10.60 mg day^{-1}. The values of *G2* (kernel per plant) and *G3* (grain filling rate) illustrated that this was a high yielding hybrid for semi-arid environments. The PHINT (phyllochron interval) was set as 42.5 °C day for the hybrid pioneer 31R88. Solar et al. (2007) set PHINT to 42.3 °C day and the values for our cultivar coefficients were within the range of their findings.

3.2. Soil moisture content

To assess the performance of the soil water balance of the model for various irrigation regimes, the simulated water content was compared to the observed values for two soil depths during both years: 0–20 cm and 20–40 cm. To avoid the overlapping of curves only the simulated and observed soil water content for the three irrigation regimes with the N application rate (250 kg ha^{-1}) are shown (Figs. 2 and 3). The simulated soil water content for the 0–20 cm depth showed a good agreement with the observed water content, with a d-statistic of 0.88 and 0.89 for 2009 and 2010, respectively. Similarly, a good agreement was observed for the 20–40 cm soil depth for the normal irrigation

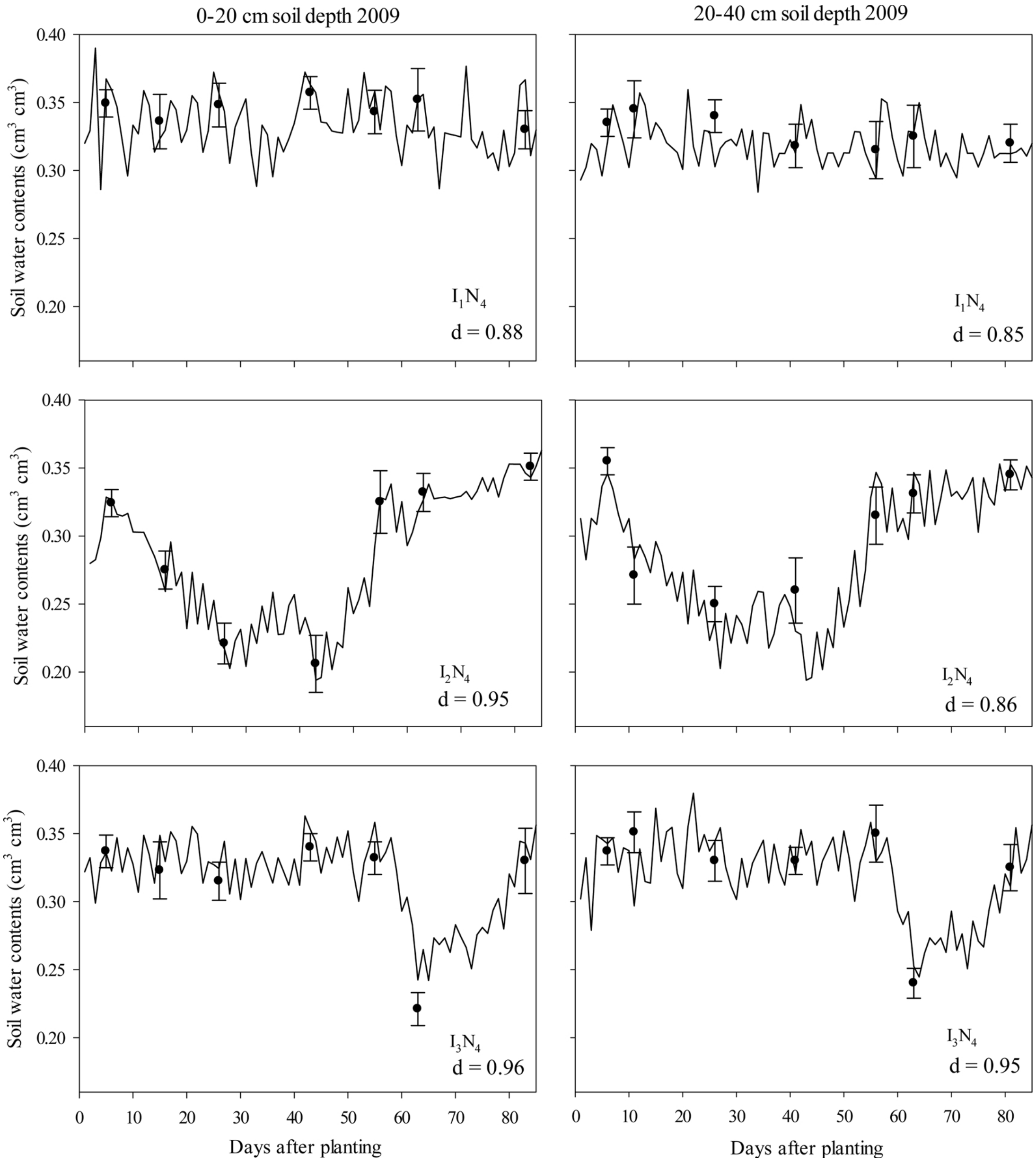

Fig. 2. Simulated (−) and observed (•) soil moisture content at soils depths of 0–20 cm and 20–40 cm during 2009 for full irrigation (I_1), water stress during the vegetative stage (I_2) and water stress during the reproductive stage (I_3) with optimum nitrogen rate (N_4).

regime (I_1), with a d-statistic of 0.85 and 0.86 for 2009 and 2010, respectively (Figs. 2 and 3). In treatment I_1, an adequate moisture content was observed for both soil depths at all growth stages. The model also gave good agreement of soil moisture content between simulated and observed values for the treatment I_1 at both soil depths (d-statistic ranged 0.85–0.89 for 0–20 cm and 20–40 cm). The model simulated a moisture deficit during the vegetative stage (treatment I_2) showing a decrease in soil moisture content during the early growth stages for both soil depths (d-statistic ranged 0.86–0.95 for both growing seasons). When stress was applied during the reproductive stage (treatment $I_3 \times N_4$) the soil moisture content decreased for both soil depths, which was also well simulated by the model. The model simulated soil moisture content well for the treatment $I_3 \times N_4$ for 0–20 cm and 20–40 cm soil depths, and the d-statistic ranged from 0.94 to 0.97. The decrease in soil moisture content during the reproductive stage was less than during the vegetative stage (Figs. 2 and 3). Anothai et al. (2013) also found that soil water contents were estimated well by the CSM–CERES–Maize model. They concluded that the model was able to accurately simulate soil water content in response to different irrigation regimes under semi-arid conditions for Greeley, Colorado. Based on the outcome of our study and the Anothai et al. (2013) study it can be concluded that the model has the potential to be employed as a water management tool under water-deficit conditions. Similarly, Liu et al. (2011a) concluded that the CERES-Maize and CROPGRO-Soybean modules of DSSAT v4.6 model can be a useful tool for simulating soil moisture content for a fine-textured soil in southwestern Ontario, Canada.

3.3. Crop phenology

Anthesis day was reasonably well-simulated by the model (Table 3). The evaluation of the model for the period from sowing to silking with the experimental data for 2009 and 2010 showed good results. The average difference was 3 and 2 days for 2009 and 2010, respectively (Table 4) and nRMSE was 3.5% and 4.7% for 2009 and 2010, respectively. Similarly, the evaluation of the model for the period from

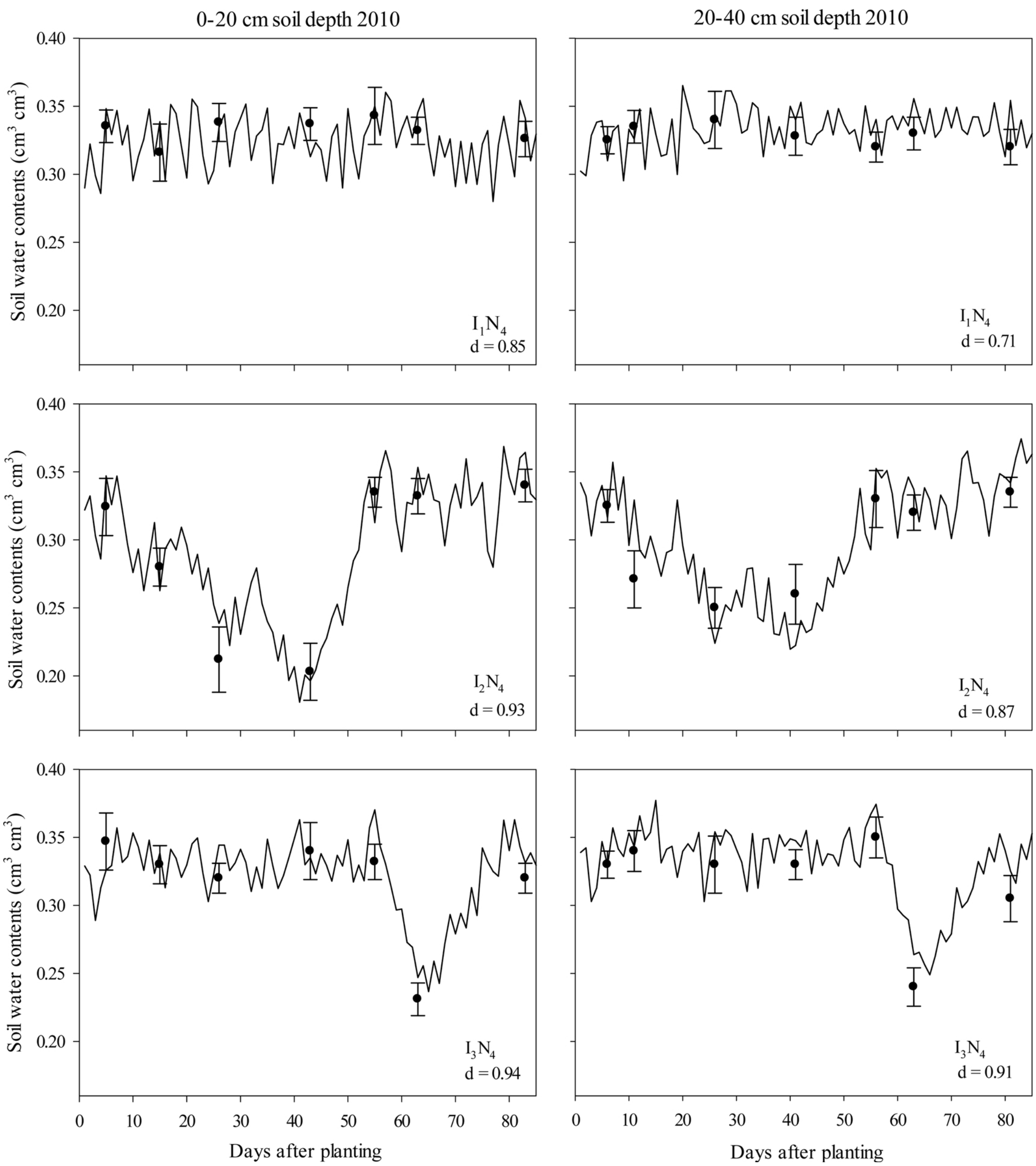

Fig. 3. Simulated (−) and observed (•) soil moisture content at soils depths of 0–20 cm and 20–40 cm during 2010 for full irrigation (I_1), water stress during the vegetative stage (I_2) and water stress during the reproductive stage (I_3) with optimum nitrogen rate (N_4).

Table 3
Summary of simulated and observed values during model calibration with data recorded from the standard treatment (I_1N_4) for 2010.

Variable	Simulated	Observed	[a]MPD
Planting to Anthesis (days)	58	58	0.00
Planting to Maturity (days)	103	103	0.00
Maximum LAI	4.82	5.36	10.1
Grains per ear (No.)	399	418	4.8
Total Dry Matter (kg ha^{-1})	17143	17665	1.8
Mat Yield (kg ha^{-1})	7973	7973	0.00

[a] Mean percentage difference.

planting to physiological maturity showed good results. The average difference between the observed and simulated values was 0 and 4 days for 2009 and 2010, respectively, and with nRMSE of 2.0% and 3.9% for 2009 and 2010, respectively. These results were similar to those of Solar et al. (2007) who conducted their research in subtropical area of Brazil. However, in our study under semiarid region the model did not predict phenology as well in 2010 as in 2009 with a significant difference in nRMSE during both years. This might be due to the variability of the weather conditions (Boote et al., 1998).

3.4. Crop growth

The model simulated the maximum LAI well with an MPD of 10.1% (Table 3) and a d-statistic of 0.80. During the early growth stages the model overestimated LAI during both years, while during the reproductive phase LAI was slightly underestimated for all treatments (Fig. 4). The underestimation of LAI could be due leaf senescence during the growing season. The d-statistic for LAI ranged from 0.71 to 0.96. Ben Nouna et al. (2003) reported that due to the variability of some hybrid characteristics such as leaf appearance, leaf area growth and leaf senescence, the model showed less response to LAI in the semi-arid Mediterranean environment of Bari, Italy. Solar et al. (2007) concluded that LAI of the four maize hybrids of their study was reasonably well simulated by CSM-CERES-Maize for the subtropical

Table 4
Observed (Obs) and simulated (Sim) number of days from plant emergence to anthesis and number of days from plant emergence to physiological maturity for model evaluation.

Treat.	Anthesis (day)						Physiological Maturity (day)					
	2009			2010			2009			2010		
	Sim	Obs	[a]SE	Sim	Obs	[a]SE	Sim	Obs	[a]SE	Sim	Obs	[a]SE
I_1N_1	54	51	2.90	56	52	3.10	98	97	2.08	102	98	2.52
I_1N_2	54	53	3.36	56	54	3.98	99	98	3.61	102	99	3.00
I_1N_3	54	54	3.06	56	55	1.62	99	99	3.61	102	100	3.00
I_1N_4	54	56	0.35	56	58	1.85	99	101	2.65	102	103	0.58
I_1N_5	54	55	3.80	56	56	2.15	99	102	1.00	102	103	1.00
I_2N_1	53	49	0.46	54	50	2.31	98	95	1.53	103	96	2.65
I_2N_2	53	50	0.91	54	51	2.59	98	96	2.08	103	98	3.00
I_2N_3	53	52	0.75	54	52	2.35	98	98	3.00	103	99	3.51
I_2N_4	53	53	1.31	54	54	2.31	98	99	3.06	103	101	2.52
I_2N_5	53	53	3.29	54	53	2.56	98	101	2.52	103	101	2.17
I_3N_1	54	51	0.93	56	51	2.52	97	94	1.00	101	94	1.00
I_3N_2	54	53	3.90	56	53	2.61	97	95	2.00	101	95	1.53
I_3N_3	54	53	3.66	56	54	3.16	97	96	2.00	101	98	3.61
I_3N_4	54	54	1.67	56	55	2.64	97	98	2.00	101	99	3.89
I_3N_5	54	55	3.09	56	55	2.50	97	99	3.00	101	99	3.00
Average	54	51	2.23	55	53	2.55	98	98	2.34	102	98	2.52
[b]nRMSE (%)	3.5			4.7			2.0			3.9		
[c]MPD (%)	3			8.5			2.1			4.3		

[a] Standard error (from three replication).
[b] Normalized root mean square error.
[c] Mean percentage differences.

environment of Brazil.

The model correctly simulated TDM with an MPD of 1.8% (Table 3). The nRMSE ranged from 3 to 5%, while the d-statistic for TDM ranged from 0.97 to 0.99 (Fig. 5). During model evaluation, TDM was very close to the observed data for the normal irrigation (treatment I_1) for all N application rates for both 2009 and 2010. However, for 2010 the predicted values for TDM during the reproductive phase were slightly higher than the observed values for the application of 300 kg N ha^{-1}

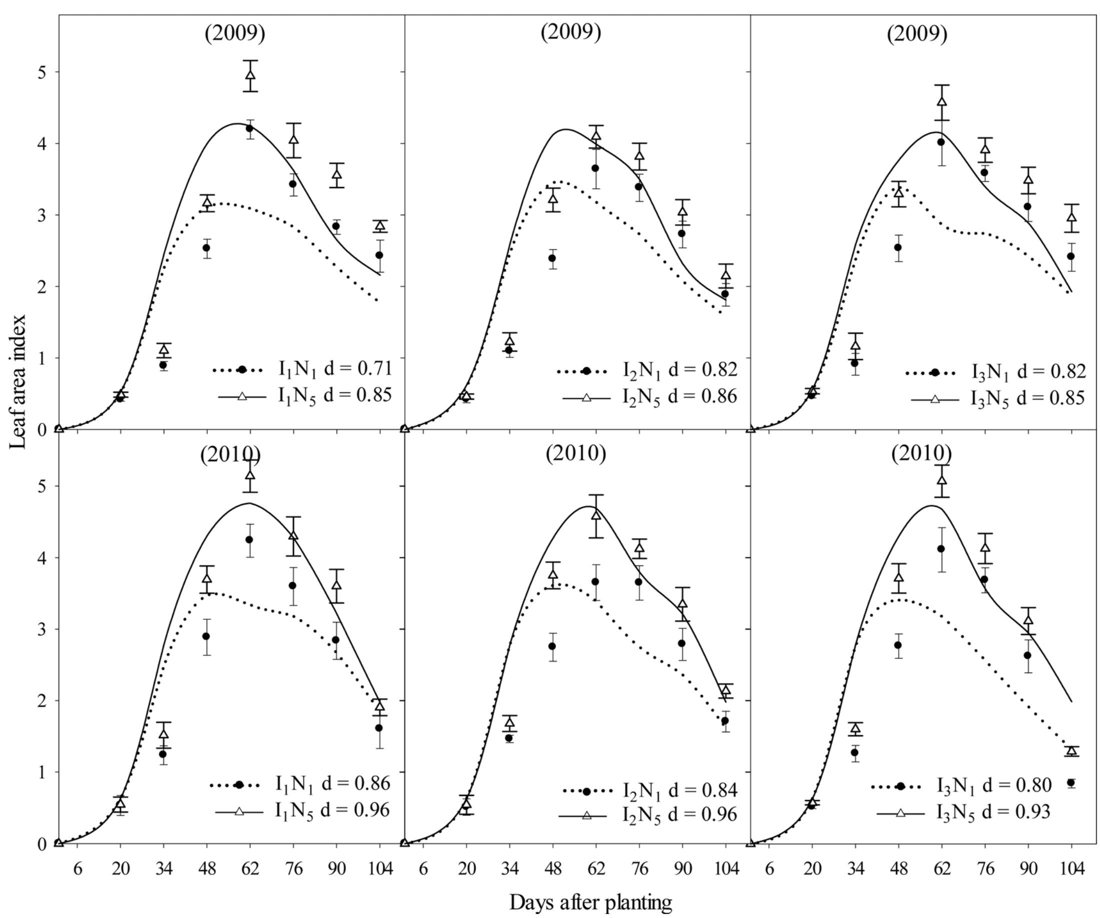

Fig. 4. Comparison of simulated (− −, ….) with observed (Δ, •) leaf area index for full irrigation (I_1), water stress at vegetative stage (I_2) and water stress at reproductive stage (I_3) with the minimum (N_1 = 100 kg ha^{-1}) and maximum (N_5 = 300 kg ha^{-1}) nitrogen rate for 2009 and 2010.

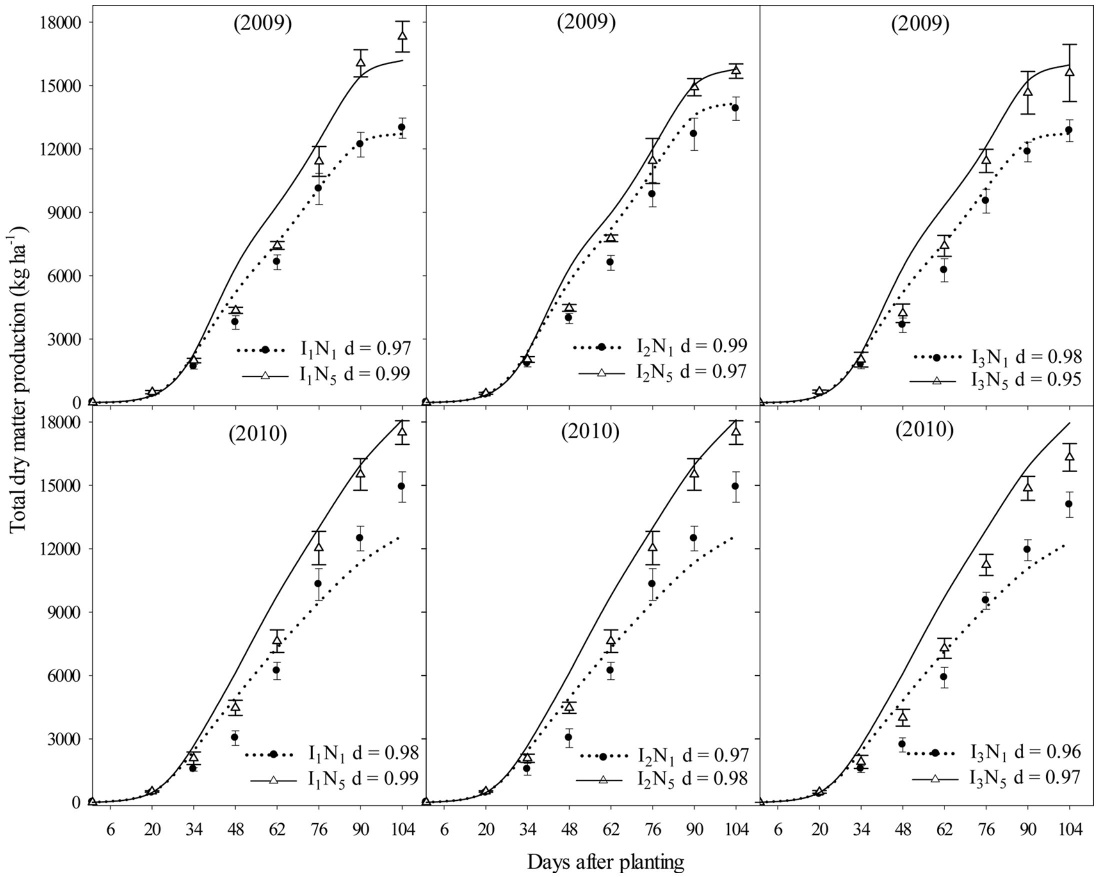

Fig. 5. Comparison of simulated (– –, ...) with observed (Δ, •) of total dry matter production (kg ha^{-1}) for full irrigation (I_1), water stress at vegetative stage (I_2) and water stress at reproductive stage (I_3) with the minimum (N_1 = 100 kg ha^{-1}) and maximum (N_5 = 300 kg ha^{-1}) nitrogen rate for 2009 and 2010.

Table 5
Observed (Obs) and simulated (Sim) number of grains per ear and grain yield for model evaluation.

Treat.	Number of grain (per ear)						Grain yield (kg ha^{-1})					
	2009			2010			2009			2010		
	Sim	Obs	[a]SE	Sim	Obs	[a]SE	Sim	Obs	[a]SE	Sim	Obs	[a]SE
I_1N_1	347	370	20	363	375	26	6089	5380	223	6944	5693	378
I_1N_2	361	376	16	378	386	23	6016	5983	161	7668	6136	441
I_1N_3	388	395	15	395	398	19	6853	7030	214	7963	7216	431
I_1N_4	390	406	12	399	418	24	6754	7683	237	7973	7973	377
I_1N_5	385	398	10	399	410	14	6712	7450	250	7630	7680	404
I_2N_1	330	335	26	345	339	15	5545	4983	275	5603	5063	400
I_2N_2	341	352	28	380	354	19	5573	5293	190	5969	5340	386
I_2N_3	343	362	8	397	367	12	5462	6033	208	5946	6103	441
I_2N_4	327	368	11	398	380	11	5848	6533	301	5956	6700	469
I_2N_5	322	356	18	399	372	20	5901	6380	270	5848	6380	484
I_3N_1	269	329	25	316	331	22	4619	4766	355	4662	4803	371
I_3N_2	270	345	15	325	345	25	4721	4983	275	4909	5030	350
I_3N_3	276	340	20	345	356	28	4709	5433	379	5077	5440	436
I_3N_4	277	357	15	339	363	22	4725	5733	257	5124	5870	459
I_3N_5	277	355	29	323	358	32	4737	5623	372	4997	5773	363
Average	327	363	18	367	370	21	5618	5952	260	6151	6080	410
[b]nRMSE (%)	10.4			5.2			10.4			11.1		
[c]MPD (%)	10.2			4.8			9.2			9.4		

[a] Standard error (from three replication).
[b] Normalized root mean square error.
[c] Mean percentage differences.

for I_3 irrigations regimes with a d-statistic of 0.97. The small differences between predicted and observed values may be due to the conditions that were not taken into account by the model, such as pest, disease, and weed control (Dzotsi et al., 2003).

3.5. Crop yield

The CSM-CERES-Maize simulated the number of grains per ear well with a nRMSE of 10.4% and 5.2% for 2009 and 2010, respectively

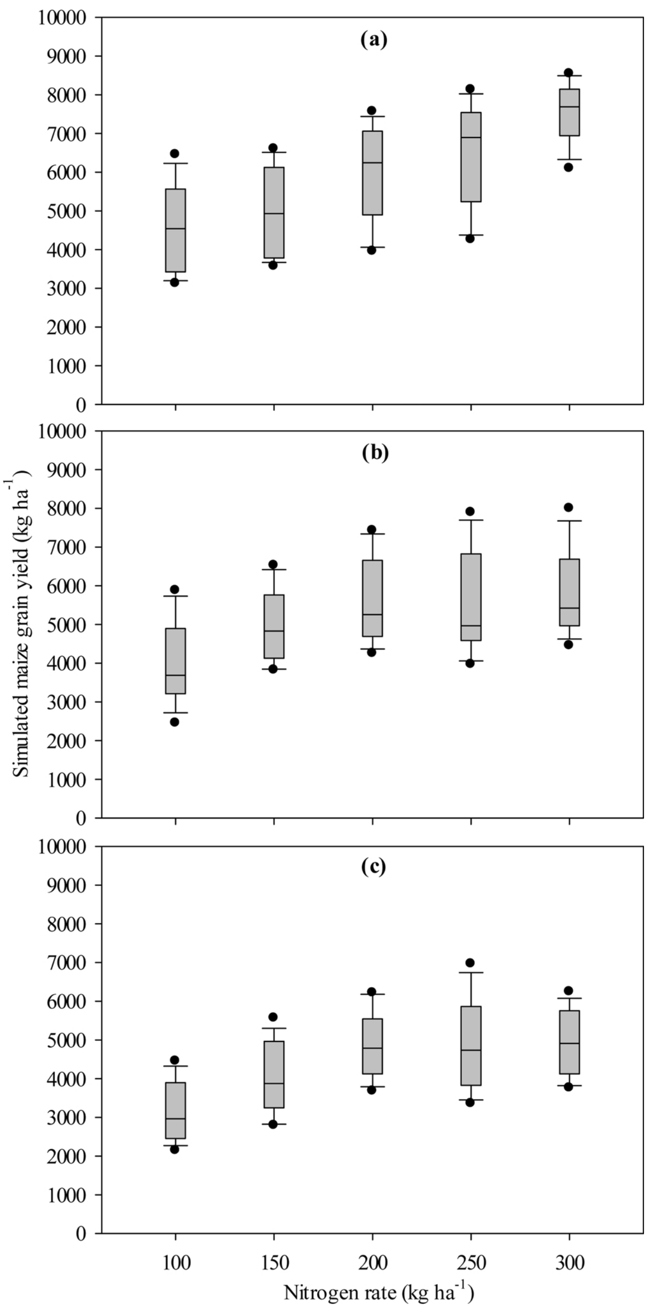

Fig. 6. Simulated grain yield for maize at normal irrigation (a), drought stress during the vegetative stage (b) and drought stress during the reproductive stage (c) for five N application rates. The box limits represent the 25th and 75th percentiles, the box central line shows the median, and outliers illustrate the maximum and minimum values at the variable irrigation regimes and N rates.

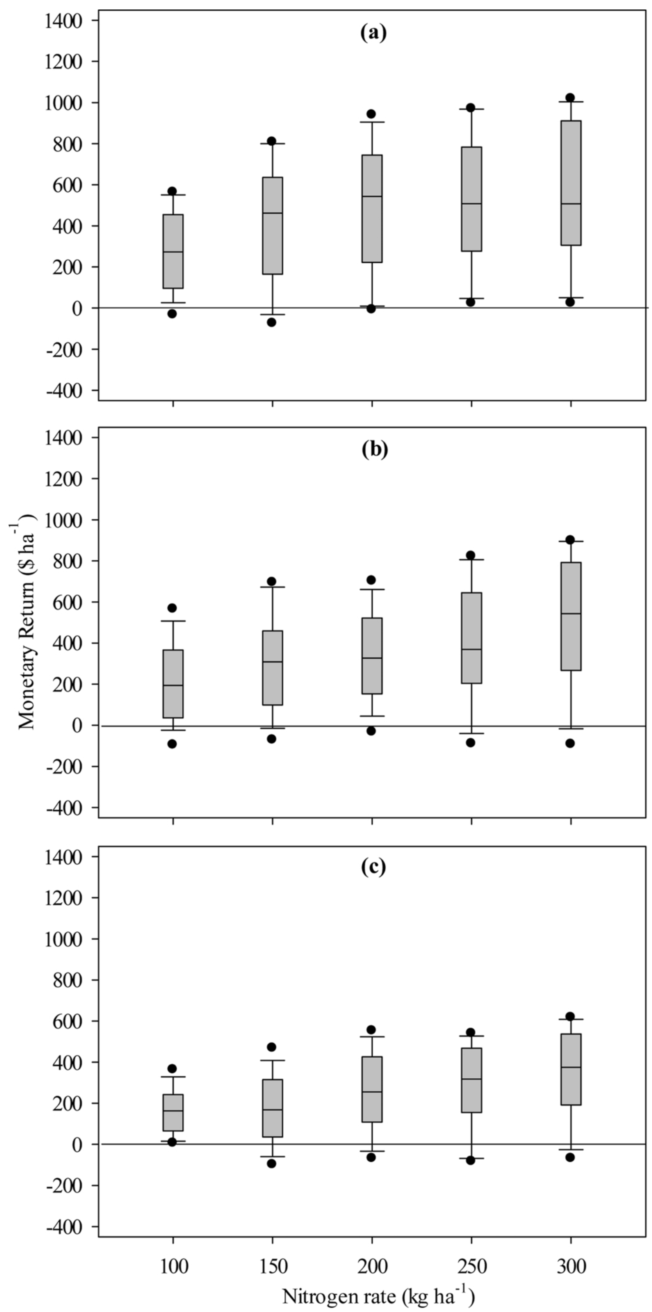

Fig. 7. Monetary return (US $ ha^{-1}) percentiles for three irrigation water regimes (normal (a), drought stress during the vegetative stage (b) and drought stress during the reproductive stage (c)) for five N application rates. The box limits represent the 25th and 75th percentiles, the box central line shows the median, and outliers illustrate the maximum and minimum values at the variable irrigation regimes and N rates.

(Table 5). Similarly, the model showed a low MPD for number of grains per ear (10.2% and 4.8% for 2009 and 2010, respectively). In some cases the model showed a trend to compensate between grains per ear and grain yield, which could explain the good prediction of yield (Solar et al., 2007). In this study the mean observed final grain yield increased when the N rate increased from 100 to 300 kg ha^{-1} with normal irrigation. A water deficit significantly decreased the grain yield. However, a water deficit during the reproductive stage caused a larger decrease in yield than during the vegetative stage (Table 5). The final grain yield was also well simulated with a nRMSE of 10.4% and 11.1% for 2009 and 2010, respectively. The CSM-CERES-Maize showed acceptable MPD (9.2% and 9.4% for 2009 and 2010, respectively) for grain yield indicating that the model was able to simulate grain yield well within the limits of experimental uncertainty. The increase in grain yield MPD during 2010 might be due to the weather (Fig. 1).

The simulated maize grain yield ranged from 3183 to 8124 kg ha^{-1}, with an average yield of 7531 kg h^{-1} for the 15 scenarios (Fig. 6). The results from this study showed that the highest mean grain yield was obtained with the irrigation regime I_1 with 300 kg N ha^{-1}. The model predicted that grain yield decreased during periods with a water deficit even with a higher N application rate. The grain yield reduction was higher when the crop was subjected to water deficit during the reproductive stage. This demonstrated that under water-limited condition the crop should be irrigated during the reproductive stage. The simulation scenarios also showed that the farmers should give adequate irrigation with optimum N rates to achieve a higher grain yield. Other studies which have performed crop model simulations of regional yields report similar findings (Chipanshi et al., 1999; Steven and Legates, 2008). These model results were also supported with earlier studies that have shown that the CSM-CERES-Maize can simulate yield accurately for a wide range of subtropical regions (Ritchie and Alagarswamy, 2003; Solar et al., 2007).

3.6. Model application and monetary returns

An economic analysis of the 15 different scenarios of irrigation regimes and N rates was conducted to determine monetary return for maize production using crop simulations under irrigated conditions. The monetary return ha^{-1} for all scenarios that were analyzed is presented in Fig. 7. The effects of inputs (water, N and basal costs) were analyzed with DSSAT using the seasonal analysis tool (Thornton and Hoogenboom, 1994) and the prices of the inputs showed clear differences in the results. The mean monetary return ranged from 57 to 912 US \$ ha^{-1} among the 15 scenarios that were analyzed. The application of 300 kg N ha^{-1} in three split applications with supplemental irrigation applications (280 mm during the entire growing season) was dominant with the highest mean return (Fig. 7). The model predicted the lowest mean monetary return value when the crop was subjected to water deficit during the reproductive stage (I_3) as compared to the water deficit at vegetative stage (I_2) and normal irrigation regime (I_1). The application of systems analysis which combines both the crop modeling and experimental field research to determine best management practices has become more common. Anothai et al. (2013) simulated evapotranspiration approaches with the CSM–CERES–Maize model under different irrigation strategies and the effect on maize growth, and development for semi-arid environments of Colorado, while Solar et al. (2007) applied the crop simulation CSM-CERES-Maize for determining optimum planting dates for maize in Brazil. With experimentation become more challenging due to increased labor and input costs, and to account for variable weather conditions across environments, systems analysis provides a promising alternative.

4. Conclusion

The CSM-CERES-Maize model accurately simulated phenological development, grain yield and final biomass production of maize under various water regimes and nitrogen rates. Leaf area index and total dry matter production were reasonably well-simulated by the model. Economic analysis of the inputs with respect to crop yield showed credible responses of simulated grain yields to nitrogen fertilizer application rates under various irrigation water regimes. Thus, the model provided reliable economic information on crop output based on various interactions between irrigation water and N management strategies. The results of this study support the potential of using the CSM-CERES-Maize model for determining the best management strategies for maize production under the semi-arid conditions.

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