Environmental Science and Pollution Research (2018) 25:28413–28430
https://doi.org/10.1007/s11356-018-2884-3

RESEARCH ARTICLE

Assessing the impact of climate variability on maize using simulation modeling under semi-arid environment of Punjab, Pakistan

Ishfaq Ahmed[1] · Muhammad Habib ur Rahman[2] · Shakeel Ahmed[3] · Jamshad Hussain[1] · Asmat Ullah[4] · Jasmeet Judge[5]

Received: 24 February 2018 / Accepted: 31 July 2018 / Published online: 7 August 2018

Abstract

Climate change and variability are major threats to crop productivity. Crop models are being used worldwide for decision support system for crop management under changing climatic scenarios. Two-year field experiments were conducted at the Water Management Research Center (WMRC), University of Agriculture Faisalabad, Pakistan, to evaluate the application of CERES-Maize model for climate variability assessment under semi-arid environment. Experimental treatments included four sowing dates (27 January, 16 February, 8 March, and 28 March) with three maize hybrids (Pioneer-1543, Mosanto-DK6103, Syngenta-NK8711), adopted at farmer fields in the region. Model was calibrated with each hybrid independently using data of best sowing date (27 January) during the year 2015 and then evaluated with the data of 2016 and remaining sowing dates. Performance of model was evaluated by statistical indices. Model showed reliable information with phenological stages. Model predicted days to anthesis and maturity with lower RMSE (< 2 days) during both years. Model prediction for biological yield and grain yield were reasonably good with RMSE values of 963 and 451 kg ha^{-1}, respectively. Model was further used to assess climate variability. Historical climate data (1980–2016) were used as input to simulate the yield for each year. Results showed that days to anthesis and maturity were negatively correlated with increase in temperature and coefficient of regression ranged from 0.63 to 0.85, while its values were 0.76 to 0.89 kg ha^{-1} for grain yield and biological yield, respectively. Sowing of maize hybrids (Pioneer-1543 and Mosanto-DK6103) can be recommended for the sowing on 17 January to 6 February at the farmer field for general cultivation in the region. Early sowing before 17 January should be avoided due to severe reduction in grain yield of all hybrids. A good calibrated CERES-Maize model can be used in decision-making for different management practices and assessment of climate variability in the region.

Research highlights
• CSM-CERES-Maize model under DSSAT v 4.6.1 was calibrated and evaluated with multi-year field experimental data.
• Model has potential to simulate phenology, growth, and yield of maize hybrids.
• Strategy and sensitivity analyses are helpful to optimize the maize planting time.
• Based on 36-year climate data, the optimum sowing date for spring maize hybrids was end of January in semi-arid environment.
• Climate variability results showed that yield would be reduced by 43% by increasing maximum and minimum temperatures of 4.4 and 2.3 °C, respectively.

Responsible editor: Philippe Garrigues

✉ Ishfaq Ahmed
ishfaq.ahmad@uaf.edu.pk

[1] Agro-climatology Laboratory, Department of Agronomy, University of Agriculture, Faisalabad, Pakistan

[2] Department of Agronomy, MNS-University of Agriculture, Multan, Pakistan

[3] Department of Agronomy, BZU, Multan, Pakistan

[4] Agronomic Research Station, Karor-Layyah, Punjab, Pakistan

[5] Center for Remote Sensing, Agricultural & Biological Engineering Department, University of Florida, Gainesville, FL, USA

Keywords CERES-Maize · Sowing date · Crop phenology · Grain yield · Climate variability

Introduction

Agricultural system is highly vulnerable to climate variability that significantly affected the growth and yield of crops. Changes in climate variability, frequency, and intensity of extreme events are due to climate change (Field 2012). Higher temperature accelerates the crop growth and development, which reduces the life cycle of crop that causes the reduction in yield (ur Rahman et al. 2018). Seasonal and interannual changes in cool and hot weather influence the crop yield (Craufurd and Wheeler 2009). It is projected that climate variability would increase due to warming of planet. The intensities of flood, drought, and heat stress will increase in the twenty-first century, which would have adverse effect on crop production (IPCC 2014). Assessment of climate variability provides insight in decision-making of climate-sensitive sector, such as agriculture (Abbas et al. 2017).

Maize is an important food crop in the world, feeding the human and livestock since ages. The prolonged exploit of maize in industry provide this crop a well-known position in farming financial system (Anderson et al. 2017). Maize is the 3rd main cereal/grain crop by area and produces raw material for range of numerous foodstuffs in Pakistan. Its contribution in value-added agriculture (VAA) and gross domestic product (GDP) is 2.2 and 0.4%, correspondingly in Pakistan. Total cultivated area in 2017 was 1.114 million hectares, and total production was 4.92 million tons in Pakistan (Government of Pakistan 2017). Cultivated area of maize crop was increased by 12% from 2015 to 2016. Development and growth of maize crop is probably be exaggerated by elevated environmental CO_2 and air temperature. Increased warming trend harmfully influences development, economic production, and quality of maize crop (Msowoya et al. 2016). High temperature during the growing season reduces the photosynthesis and accelerates the development and leaf senescence (Tubiello et al. 2007). The number of grains and grain weight is decreased when temperature is higher around anthesis stage (Ferris et al. 1998).

There are limited studies on the influence of increased CO_2 quantity and temperature interaction on this significant cereal crop under semi-arid conditions (Lobell et al. 2013). Crop phenological stage and phase processes are also driven by the joint influence of climatic variability and agronomic factors such as hybrid selection and management practices (Gabaldon Leal et al. 2015; Abbas et al., 2017; ur Rahman et al. 2017). On this basis, there is the need to assess the risks posed by climate variability on agriculture (Ureta et al., 2016).

Earth land cover of about 15% is semi-arid regions. More than 80% of Pakistan has an arid and semi-arid climate, where successful crop production is challenging due to increased temperatures and variability in rainfall (Naheed and Mahmood 2006). Change in temperature and minor shift in rainfall patterns in arid and semi-arid regions cause the huge reduction in crops yield (Huang et al. 2016). Maize is very sensitive to environmental stresses mainly temperature and water over reproductive period in semi-arid conditions. A significant reduction in gain yield at flowering stage was reported due to water shortage and uncertain rainfall patterns (Bergamaschi et al. 2004). A recent research revealed that exceeds in temperature from 30 °C decreased grain yield of maize by 1% under optimum growing circumstances and 1.7% under drought-stressed environment (Lobell et al. 2011). Most of the maize-cultivating regions in Pakistan and India are extremely susceptible to high temperature as well as drought stress. Optimum maize growing time is an essential choice for long-term scenario for intensifying and diversifying in South Asia, particularly in the higher and central regions of South Asia, which is prone to harsh heat stress during flowering/early grain-filling stages (Prasanna 2011; Nasim 2010).

Crop simulation models are essential for crop management decisions to minimize the risk associated with environment. Such models have been widely used to determine impact of climate variability for long-term scenarios (Bassu et al. 2014). Effect of weather variability on yield of crops can be assessed by various models because crop simulation models are run through weather data downscaled from general circulation models (GCMs). Differences in temporal and spatial scales of any crop and various climate models may introduce some uncertainties into assessments of effects of climate variability (Ngwira et al. 2014; Lin et al. 2015; ur Rahman et al. 2018).

The main goal of this research was to explore the impacts of climate variability on maize crop for the support of policy makers in decision making. The objectives of this study were as follows: (1) calibration and evaluation of CERES-Maize model with experimental dataset to develop robust genetic coefficient of maize hybrids, (2) optimization of sowing date by seasonal strategy analysis using CERE-Maize model, and (3) impact of climate variability on maize crop in semi-arid region of Pakistan.

Materials and methods

Description of the field experiment

A field experiment was conducted under arid to semi-arid climatic conditions of Punjab, Pakistan (31° 22′ N, 73°01 ′ E), during the two spring seasons for the years 2015 and 2016. An experiment was comprised of four sowing dates ($S_1 = 27$ January, $S_2 = 16$ February, $S_3 = 08$ March, $S_4 = 28$ March) and three maize hybrids (H_1 = pioneer-1543, H_2 = Mosanto-DK6103, H_3 = Syngenta-NK8711). An experiment was laid out in randomized complete block design with split plot arrangement. Four sowing dates were kept in main plot and three maize hybrids in subplot. Seed rate of 25 kg ha^{-1} was applied. Plant to plant distance of 20 cm and row to row distance of 75 cm were maintained. Each treatment was replicated three times. Based on soil analysis, recommended dose of 200 kg ha^{-1} of nitrogen in the form of urea, 125 kg ha^{-1} phosphorus in the form of ammonium phosphate, and 125 kg ha^{-1} potassium in the form of sulfate of potash were used. All phosphorus (P), potassium (K), and one third dose of nitrogen (N) fertilizers was applied before planting, while the remaining doses were applied in two splits, one at six-leaf (V6) stage and second at tasseling (VT). Other agronomic practices like weeds, pest, and disease control were kept constant for all treatments.

Data collection from the field experiment as input dataset for the model

Crop phenological data were recorded at different growth stages. Ten plants were tagged in the middle row of experimental unit to record the days to 50% tasseling, silking, and days to maturity. Vegetative samplings were taken fortnightly to record the data of leaf area index (LAI) and total dry matter (TDM). For LAI, three plants were harvested, fresh leaf and stem weight were recorded, and then 10 g subsample was used to record the LAI. However, for TDM of leaf, stem tassel and cob were oven-dried at 70 °C for 48 h, and then, dried weight was recorded. At maturity, half of plots were harvested to record grain yield and biological yield. Crop management data were used as input to create crop management file of the model. Days to anthesis, days to maturity, biological, grain yield, time series of TDM, and LAI were used to create experimental data files of a model.

Soil and weather dataset as input for model

The soil data was collected from the Soil Survey of Pakistan. Lyallpur soil series was found in the study region. Soil physical, chemical, and hydraulic properties are given in Table 1. According to USDA classification, the soil was coarse silty, mixed, hyperthermic, and typic calciargids. The soil was well drained with brown color. It was divided into nine profiles due to heterogeneity. It was alkaline; pH increases as depth is increased and had low total nitrogen of 0.04 which decreased to 0.01. The missing data of organic carbon was calculated from the organic matter divided by 1.7 (Bowman 1997). The data of soil layer, soil horizon, silt%, clay%, organic carbon%, pH in water, cation exchange capacity (cmol/kg), and total nitrogen in percentage were used as input dataset for soil file of model. The other parameters like drainage upper limit, lower limit, saturation%, bulk density (gcm^{-3}), saturated hydraulic conductance (cm h^{-1}), and root growth factor were estimated by methods provided by Rawls et al. (1982) and Baumer and Rice (1988).

Weather data such as maximum and minimum temperatures (°C), rainfall (mm), wind speed (km/h), and sunshine (h) for experiment were recorded from the observatory at WMRC during the years 2015 and 2016 as shown in Fig. 1. Daily weather data were used to create weather data input file in DSSAT.

Model calibration and evaluation

This study used CERES-Maize model (Jones et al. 1986). CERES-Maize is under the shell of DSSAT (Decision Support System for Agro-Technology Transfer). DSSAT is a software program which comprised of dynamic crop growth models (Hoogenboom et al. 2016). Model simulates the

Table 1 Soil physical and chemical compositions and hydrological properties of experimental site used as soil input dataset in crop model

Depth	Clay (%)	Silt (%)	Organic carbon	pH in water	CEC (cmol/kg)	Total nitrogen (%)	Lower limit	Drained upper limit	Saturation	Bulk density (g cm^{-3})	Root growth factor
0–11	10	56	0.53	8.3	9.7	0.045	0.09	0.253	0.505	1.23	1.00
11–25	13	53	0.2	8.4	8.9	0.031	0.096	0.247	0.483	1.30	1.00
25–45	17	53	0.13	8.2	8.9	0.025	0.115	0.266	0.479	1.31	0.497
45–65	17	53	0.13	8.2	8.7	0.020	0.116	0.267	0.480	1.32	0.333
65–90	16	54	0.12	8.3	9.1	0.015	0.109	0.261	0.483	1.30	0.212
90–105	12	58	0.12	8.4	9.1	0.012	0.089	0.247	0.497	1.26	0.142
105–128	8	58	0.12	8.4	9.3	0.010	0.069	0.225	0.505	1.24	0.097
128–167	5	59	0.06	8.5	9.7	0.010	0.053	0.161	0.462	1.36	0.052
167–190	8	58	0.02	8.8	9.7	0.010	0.067	0.171	0.434	1.44	0.028

SLOC soil organic carbon, *SLHW* soil pH in water, *SLNI* soil total nitrogen concentration, *LL* lower limit, *DUL* drained upper limit, *SSAT* saturation, *SBDM* soil bulk density, *SBDM* soil bulk density, *SRGF* soil root growth factor

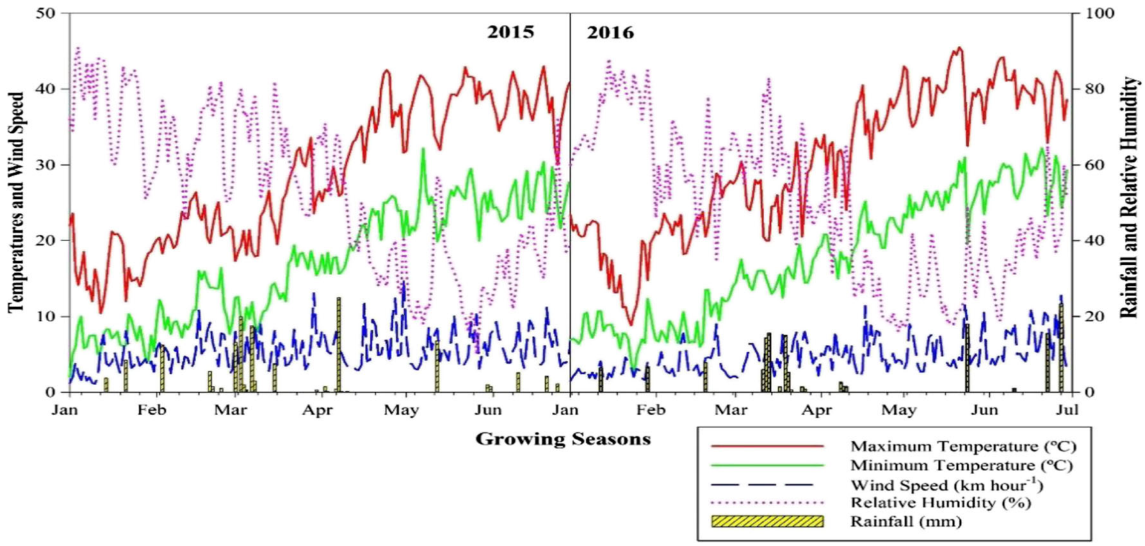


Fig. 1 Daily weather data at the experimental site during the growing seasons in 2015 and 2016

combined effect of plant genotype, soil type, management practices, and weather conditions on phenology, growth, and yield of maize (Jones et al. 2003). Genetic coefficients of CERES-Maize were adjusted by using generalized likelihood uncertainty estimation (GLUE) and sensitivity analysis tools built in DSSAT V4.6.1. CERES-Maize was calibrated with best sowing date of 27 January 2015 from field experiment for three maize hybrids. The GLUE was run with non-stressed treatment. It takes initial coefficients from the genotype file and at the end gives best combinations of phenology, growth, and yield parameters, which were then evaluated by different statistical indices (Hunt and Boote 1998). Similar approach for estimation of genetic coefficients using GLUE was also used by He et al. (2010).

After calibration, CERES-Maize was evaluated with other sowing dates in 2015 and 2016 maize-growing year. Accuracy of model and reliability of genetic coefficients were assessed by calculating the different statistical indices. Statistical indices described by Willmott (1981) were used to determine the differences between observed and simulated values.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{\mathrm{n}}\left|\mathrm{Y}_{Sim.} - \mathrm{Y}_{Obs.}\right| \qquad (1)$$

Mean absolute error (MAE) measures the magnitude of the errors in a set of estimates.

$$\mathrm{ME} = \frac{1}{\mathrm{n}}\sum_{i=1}^{\mathrm{n}}\left(\mathrm{Y}_{Sim.} - \mathrm{Y}_{Obs.}\right) \qquad (2)$$

Mean error (ME) is an observational error that refers to the average of all the errors in observed and simulated values.

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{\mathrm{n}}\sum_{\mathrm{i}=1}^{\mathrm{n}}\left(\mathrm{Y}_{Sim.} - \mathrm{Y}_{Obs.}\right)^2\right)} \qquad (3)$$

Root mean square error (RMSE) indicated the size of the error produced by the model, a model performance assessment criterion.

$$\mathrm{MAPE} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\frac{\left|Y_{Sim} - Y_{Obs.}\right|}{Y_{Obs.}} *100 \qquad (4)$$

The mean absolute percentage error (MAPE) shows that in relative terms the mistakes made by the estimates

$$d_r = 1 - \left[\frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum_{i=1}^{n}\left(\left|P_i'\right| - \left|O_i'\right|\right)^2}\right] \qquad (5)$$

Enhanced Willmott concordance index (d_r) shows the deviation between the observed and simulated values. The value of d_r ranged between 0 and 1. Value closer to 1 indicates the better simulation of model (Willmott et al. 2012). From all equations, n shows the number of variables, i shows the ith quantity of observed (obs.) and simulated (sim.).

Strategy analysis for the determination of optimum sowing date

Optimum planting date of spring maize was determined by CERES-Maize model using seasonal analysis in which multiple years are run with same initial conditions (Boote et al. 2016). Daily weather data of 36 years (1980–2016) were used to consider the temporal variation in strategy development of optimum sowing date. Nine treatments of sowing date were assessed with 10-day interval from the calibrated treatment (27 January). But, sudden decline in maize grain yield was observed for sowing on 7 January and earlier. Same is the case revealed for later sowing on 27 February and on ward sowing in the month of March. Six sowing dates result has been demonstrated in box and whisker plot instead of nine sowing dates. The model results were demonstrated in box and whisker plot of 25% quantile, median value of 50% quantiles, and 75% quantile. Results of three maize hybrids were presented in box and whisker plot at each sowing date, the mean percent difference (MPD) of each sowing date was calculated from the calibrated treatment.

Climate variability assessment

Seasonal analysis was done in CERES-Maize model to assess the climate variability. Observed daily climate data of maximum and minimum temperatures, solar radiations, rainfall, and wind speed for 36 years (1980–2016) was collected from the Pakistan Meteorological Department (PMD) and was used as input datasets. Crop management practices of best treatment (27 January 2015 with maize hybrid Poineer-1543) were used to create seasonal file in the model. The simulation of model started from 1 January 1980. The output from the seasonal analysis was used to make relationship with observed climate data. Average maximum and minimum temperatures of 36 years of climate data are shown in Fig. 2. Relationship of maximum and minimum temperatures were drawn with simulated phenology and yield through linear regression. Coefficient of determinant was calculated to show the strength of relationship between two variables. Confidence and prediction interval at 95% were also calculated to show the uncertainty between variables.

Results

Weather input data and climate variability

Daily values of maximum and minimum temperatures, solar radiation, precipitation, wind speed, and humidity were obtained from PMD weather observatory in Faisalabad Punjab, Pakistan. Weather variable data of maize-growing years of 2015 and 2016 were used as input data in the model. The climate of study area is arid/semi-arid with an average annual rainfall of 200 mm with uneven distribution. Seasonal daily weather data from Fig. 1 shows that year 2015 was warmer than 2016 with less rainfall. Mean maximum temperature of 31.3 and 33.1 °C and mean minimum temperature of 19.22 and 19.74 °C were recorded in 2015 and 2016, respectively. Total rainfall of 117.1 mm in 2015 and 91.8 mm in 2016 was recorded.

Historical climate data (1980–2016)

Climate variability revealed by 36-year historic data showed that variability and uncertainty were found in maximum and minimum temperature (Fig. 2). Mean maximum temperature ranged from 28 to 33.4 °C while mean minimum temperature ranged from 16 to 19.2 °C in historic climatic data. Highest peaks in mean maximum temperature were found in 1987, 1988, 1999, 2002, 2004, and 2009 maize crop-growing seasons. Mean maximum temperature was found lower in 2011, 2012, 2013, and 2015 while lowest (28 °C) was observed in 2015 maize-growing year. Lowest maximum temperature range was found among 36 years. Similar variation can be seen in mean minimum temperature of 36-year historic data. Highest mean minimum temperature (19 °C) was recorded in 2016 maize-growing year while lowest was recorded in 2015. Data clearly showed that there is variation and uncertain behavior of day and night temperature during maize-growing seasons which ultimately lead to variations in yield. Maize crop is sensitive to temperature changes, and bigger changes in both minimum and maximum temperature would lead to negative impact on maize yield.

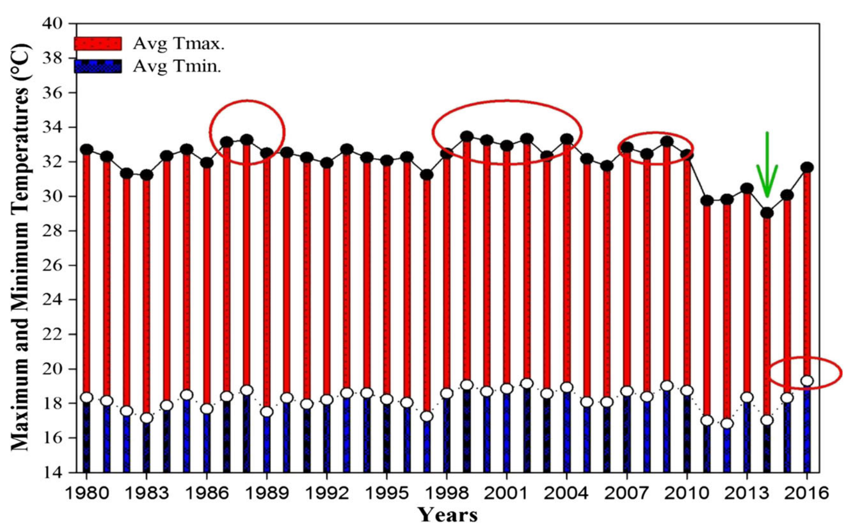


Fig. 2 Seasonal climate variability data 1980 to 2016. Average maximum and minimum temperature (yearly mean) data; circles represent the higher increase (changes) in maximum and minimum temperature while green downward arrow shows the decrease in maximum temperature in historic years

Soil input dataset and characteristics

Nine horizons (0–11, 11–25, 25–45, 45–65, 65–90, 90–105, 105–128, 128–167, and 167–190 cm) were recorded in soil due to heterogeneity in properties. The soil is brown in color, silty loam, well-drained, and strongly calcareous. Soil had 5 to 17% clay content in different soil horizons while silt percentage ranged 53 to 59 in the soil depths. Soil had low organic carbon in different horizons (0.53–0.02) due to oxidation promoted by high temperature in the studied region as high temperature is climate characteristics of the region. Soil is alkaline, and pH increases with depth reached up to 8.8 and soil is organic nitrogen deficient (0.045%) which is decreased in subsoil (0.01%). Soil samples to a depth of 190 cm were collected before maize sowing, and these samples were analyzed for physical, chemical, and hydrological properties. Soil samples were evaluated for all abovementioned parameters in Table 1.

Soil hydrological properties such as field capacity (drained upper limit (DUL)), permanent wilting point (lower limit (LL)), saturated hydraulic conductivity (SSKS), and soil bulk density (SBDM) were computed while details of all these studied parameters can be seen in Table 1. Soil root growth factor (SRGF) was assessed in the model, and it ranged 1 to 0.028 to adjust the maize root growth in deeper soil layers. No runoff was observed due to better irrigation practices, and environmental conditions were not in the favor of runoff during growing seasons; therefore, runoff curve number (SLRO) was adjusted to 25 to simulate zero runoff. Although soils are deficit in nitrogen due to high decay of soil organic carbon because of high temperature in the region, proper nitrogen is being used for maize growth and yield; a soil fertility factor (SLPF) of 0.92 was used. It is an important model input parameter which directly affects the crop growth rate by altering the canopy photosynthesis rate.

Maize genetic coefficients

Maize crop phenology and growth-related parameters were calibrated first in ecotype file. Thermal time or days taken for the completion of different phenological events like thermal time from seedling emergence to end of juvenile phase and silking to physiological maturity are crucial in phenology module of CERES-Maize (Table 2). Monsanto-DK6103 is a long-day hybrid that took more number of degree days (274) from seedling emergence to the end of juvenile phase (P1) above a base temperature of 8 °C than other two hybrids. Syngenta-NK8711 took lower thermal time (219) from seedling emergence to the end of juvenile phase (P5); it seemed to be a short-duration hybrid. The same case was found for thermal time from silking to physiological maturity of hybrids; Monsanto-DK6103 took more number of degree days (766) to reach physiological maturity while Syngenta-NK8711 took minimum degree days (702). Comparison of phenological parameters P1 and P5 showed that more number of degree days was taken by hybrid Monsanto-DK6103 while minimum number of degree days was achieved by Syngenta-NK8711 than others. More maximum possible number of kernels per plant (770.7) was recorded in hybrid Pioneer-1543 than others while kernel filling rate during grain filling stage under optimum conditions was found non-significant among hybrids. Phylochron interval between successive leaf tip appearances in degree days (°C days) was found lower (18.90) in Pioneer-1543 than other two hybrids (22). Details of genetic coefficients can be seen in Table 2. A lower RMSE and linear regression between measured and simulated parameters, a slope close to 1, and close to unity values of "*d*" mean a good fitted model.

Table 2 Genetic coefficients of hybrids adjusted during CERES-Maize model calibration

Cultivar	P1	P2	P5	G2	G3	PHINT
Pioneer-1543	265	0.683	736	770.7	24	18.90
Monsanto-DK6103	274	0.751	766	751.0	23	22.00
Syngenta-NK8711	219	0.490	702	611.0	25	22.00

P1 thermal time from emergence to end of juvenile phase (days), *P2* photoperiod sensitivity (0–1), *P5* thermal time from silking to physiological maturity (days), *G2* potential kernel per plant, *G3* kernel growth rate under optimum condition (mg/day), *PHINT* thermal time from leaf tip to emerge (°C/day)

Calibration of CERES-Maize model

Monsanto-DK6102 and Poineer-1543 accumulated more number of photothermal days (75 and 76; 115 and 114) from sowing to anthesis and maturity, respectively. These hybrids finally contributed higher growth and grain yield and other related parameters than Syngenta-NK8711 (Table 3). Close fit between observed and simulated phenology parameters was found with highest error percent of 2.63 and 2.80 for anthesis and maturity, respectively, among all studied hybrids (Table 3). Model generally undersimulated the peak LAI for all hybrids, and percent difference ranged − 3.14 to − 6.75%. Close fit was recorded between observed and simulated time series LAI with higher values of *d*-index (0.97 to 0.99) and lower RMSE (0.44 to 0.50) among all hybrids for calibrated treatment (27 January 2015) (Fig. 3a, b). Comparison of observed and simulated aboveground biomass (kg ha^{-1}) of hybrid revealed the closer fit while percent error ranged 0.075 to 0.89 (Table 3). Simulated and observed time course of tops weight comparison of three hybrids during model calibration revealed the best fit with reasonably high values of d-index (0.99) while RMSE was 449 to 1172 kg ha^{-1} (Fig. 7). Comparison of simulated and observed grain yield hybrids during model calibration showed the best fit with percent error of − 1.08 to 4.94 only. Monsanto-DK6102 and Poineer-1543 are long-duration hybrids producing higher grain yields (9380

Table 3 Comparison of observed and simulated variables of maize hybrids related to phenology, growth, and grain yield during model calibration (27 January 2015)

Parameters	Poineer-1543				Monsanto-DK6103				Syngenta-NK8711			
	Obs.	Sim.	%Error	Abs. error	Obs.	Sim.	%Error	Abs. error	Obs.	Sim.	%Error	Abs. error
Days to anthesis (days)	76	78	2.63	2	74	75	1.35	1	71	69	− 2.81	2
Days to maturity (days)	114	114	0	0	113	115	1.77	2	107	110	2.80	3
Leaf area index	6.081	5.89	− 3.14	0.19	6.265	6.05	− 3.43	0.21	5.748	5.36	− 6.75	0.38
Grain yield (kg ha^{-1})	9380	9463	0.89	83	9036	9046	0.11	10	7990	7996	0.075	6
Biological yield (kg ha^{-1})	21,364	22,331	4.53	967	22,850	22,604	− 1.08	246	19,051	19,994	4.94	943

and 9036 kg ha^{-1}) than Syngenta-NK8711 (7990 kg ha^{-1}). Performance of CERES-Maize model revealed the best fit between observed and all simulated studied parameters.

Crop growth, development, and grain yield response of CERES-Maize

Duration of major phenological events

The model simulations for major phenological events sowing to anthesis and grain maturity revealed the good predictions for all hybrids over sowing dates. The model slightly underestimated both days to anthesis and maturity for few sowing dates in hybrids while generally simulations revealed the marginally over-prediction. There is no defined trend of undersimulation and oversimulations about sowing dates for phenological parameters. Generally, the model did not typically predict high variations in maize crop phenological development among sowing dates during model evaluation, and precise simulation of phenological events are crucial in crop models as these influence model performances based on real field data. There was no significant difference between observed days to anthesis and maturity for the two growing years (2015 and 2016). Genotypic variations also existed, and hybrids had different crop growth cycle as model well predicted the variations in phenological development; Syngenta-NK8711 is a short-duration hybrid than others. Statistical indices were found quite well during both growing years for phenological events. Percent error (PE) for days to anthesis ranged − 10.71 to 8.20% and − 4.08 to 5.71% in 2015 and 2016 maize-growing years, respectively, when all hybrids and sowing dates were evaluated. Similarly, lower PE was recorded for days to maturity of different hybrids at different sowing dates. The PE ranged − 3.30 to 2.80% and − 3.09 to 4.55% in 2015 and 2016 growing years, respectively. In model evaluation, simulated days to anthesis were too good with *d*-index values close to unity (0.97) and RMSE of 2.73 days for all treatments during two growing years (2015 and 2016) (Fig. 3a). Relationship between observed and simulated days to maturity of all studied treatments ($n = 24$) in both growing years (2015 and 2016) revealed the overall good performance [(RMSE = 2.44, $d = 0.97$) (Fig. 3b). These results confirmed the ability of CSM-CERES-Maize model for simulating the duration of phenological events of promising hybrids sown at various dates under semi-arid climatic conditions of Faisalabad.

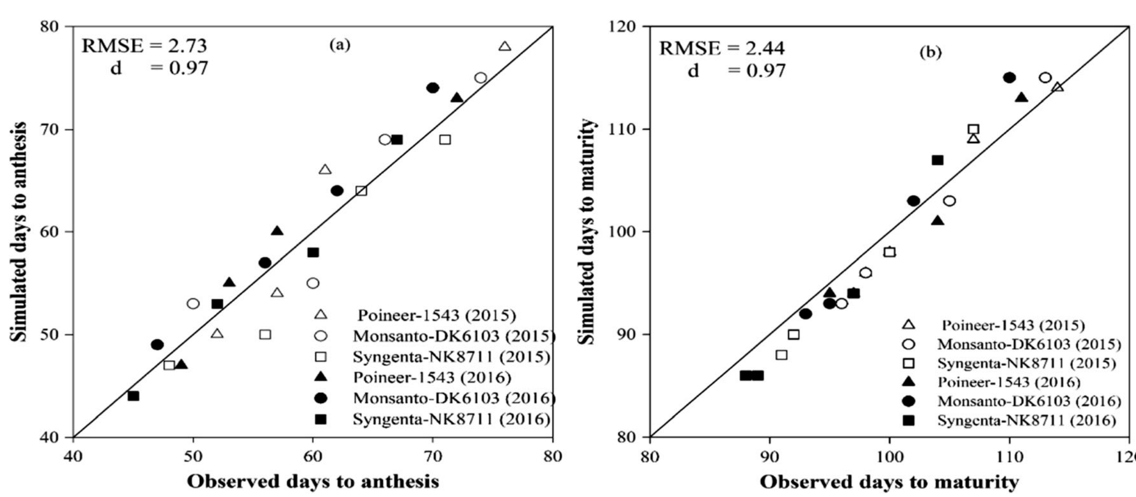


Fig. 3 CERES-Maize performance in phenology. **a** Days to anthesis. **b** Days to maturity of hybrids sown at various dates (27 January to 28 March) during both growing years (2015 and 2016)

CERES-Maize model response to maize growth (leaf area index and biomass)

Leaf area index (LAI)

The CERES-Maize model evaluation response for maize hybrids regarding time course LAI predicted well with good statistical indices during growing seasons for different hybrids at different sowing dates. Generally, model evaluation of peak LAI was good at all sowing dates during both growing years, but PE ranged − 8.45 to 4.80% in 2015 while it ranged − 14.34 to 5.96% in 2016 growing years. Overall, model showed undersimulation of LAI for majority of the sowing dates but its statistical indices lie in acceptable range (Table 3). Early season LAI was well predicted up to peak (55 DAS), then undersimulated during late season especially for 16 February and 8 March sowing dates with all hybrids during both growing years. But, model slightly oversimulated time series LAI for all hybrids at sowing dates of 28 March (Figs. 4 and 5). The model evaluation revealed the good prediction for LAI in 2015 growing year for all hybrids studied. High *d*-index was computed (0.96 to 0.98) for all planted dates and maize hybrids in 2015, while it ranged 0.92 to 0.98 in 2016 maize-growing year for all hybrids (Figs. 4 and 5). CERES-Maize model simulated time series of LAI fairly well for all hybrids during evaluation with reasonable good values of *d*-index 0.90 and lower RMSE (0.304) when all studied treatments were considered. It revealed the potential of CERES-Maize to simulate LAI (Fig. 6).

Biomass (kg ha^{-1})

A close fit between time series observed total dry matter (TDM) and simulated was found at all studied sowing dates and hybrids. Statistical indices showed the best

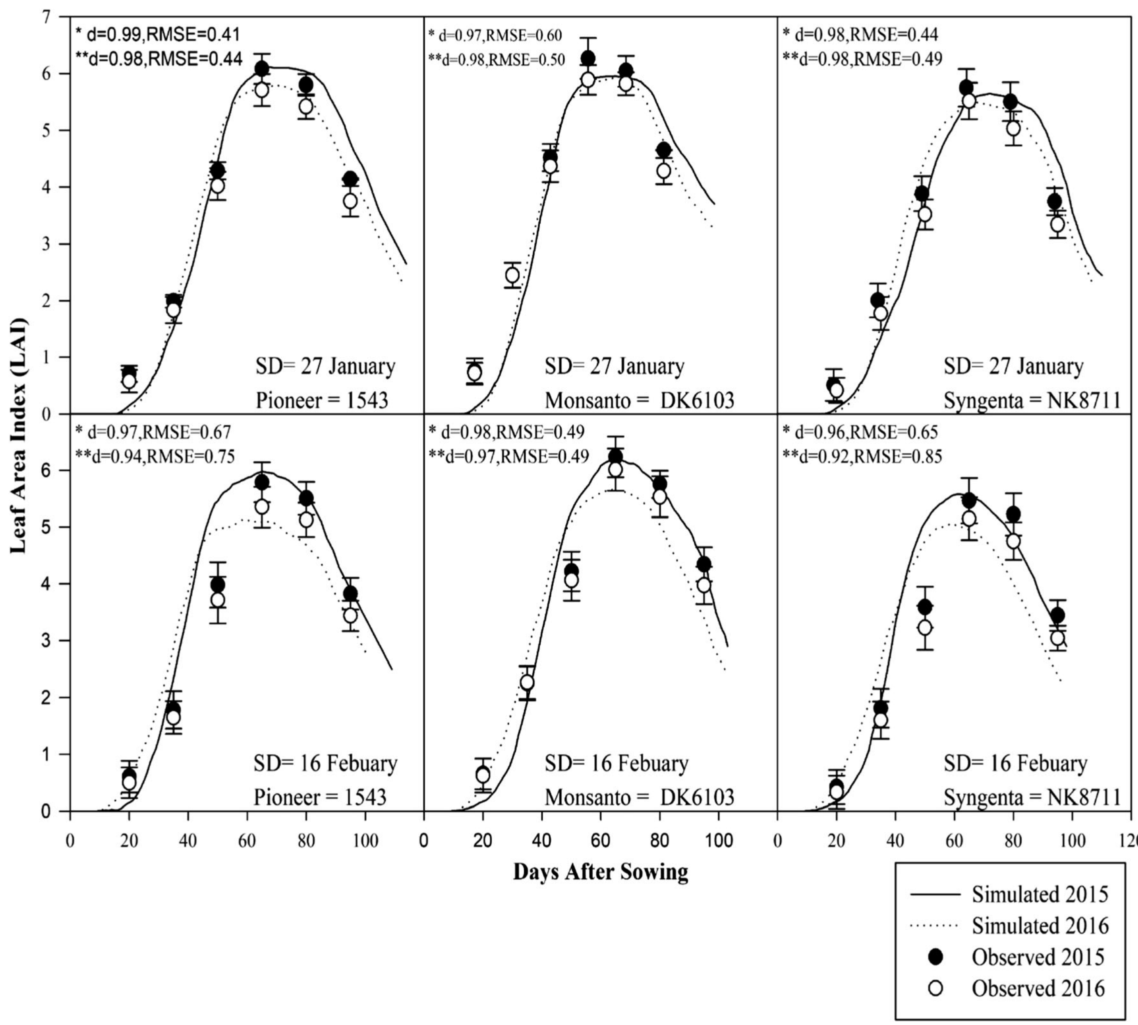


Fig. 4 CERES-Maize performance in time series LAI of hybrids at sowing dates of 27 January and 16 February during both growing years (2015 and 2016). Where, SD = sowing dates, *d = 2015, **d = 2016. Note: 27 January in 2015 growing year was used for calibration while other dates of sowings are used for model evaluation

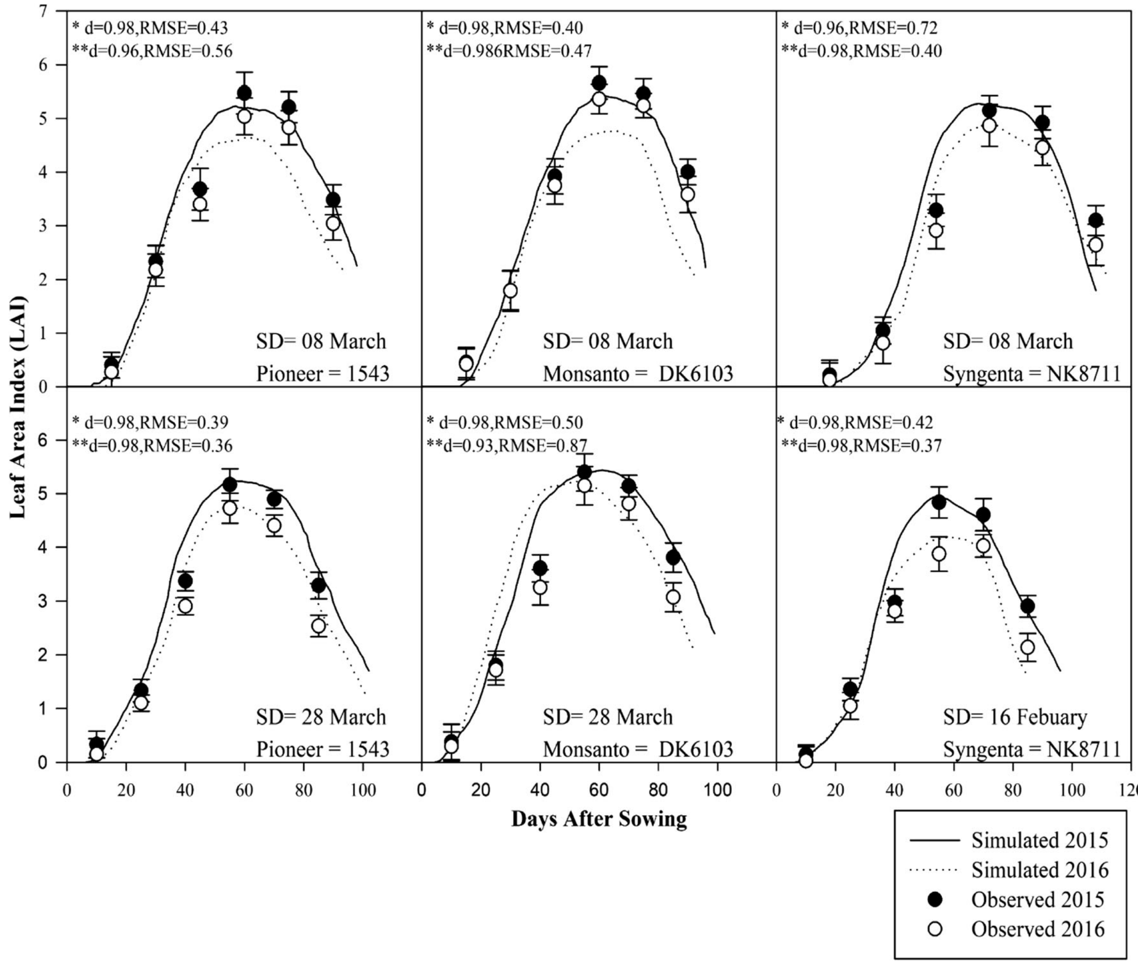
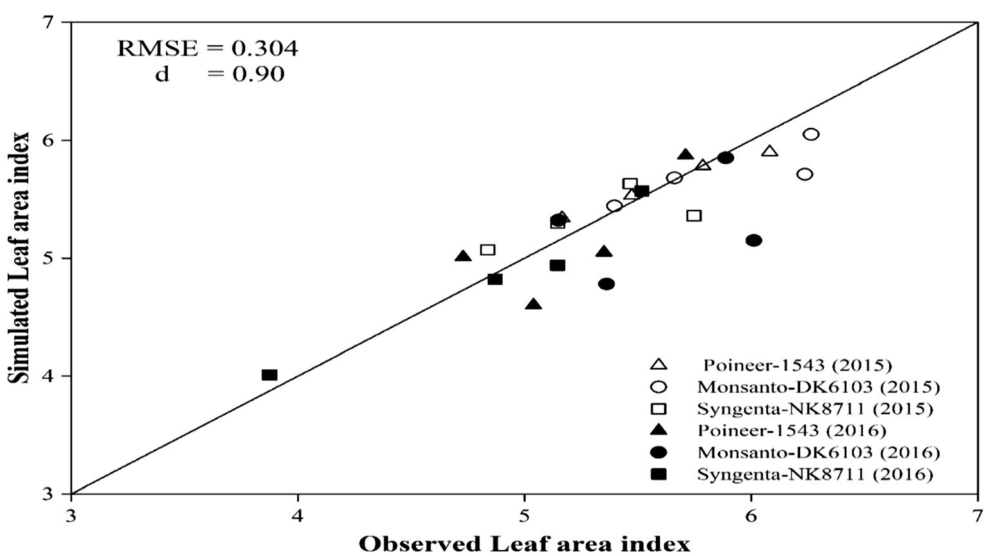


Fig. 5 CERES-Maize performance in time series LAI of hybrids at sowing dates of 8 March and 28 March during both growing years (2015 and 2016) during model evaluation (similar observation as in the previous figure). Where SD = sowing dates, $*d = 2015$, $**d = 2016$

prediction of models for TDM during both maize-growing years (2016 and 2016). Close fit was found up to 60 days after sowing for three hybrids in all sowing dates during 2015 and 2016. Model slightly overpredicted after

Fig. 6 CERES-Maize performance for leaf area index of hybrids sown at various dates (27 January to 28 March) during both growing years (2015 and 2016) (similar observation as in the previous figure)



100 days of planting in Poineer-1543 and Syngenta-NK-8711 at 27 January sowing date during 2015. However, model slightly undersimulated in all hybrids during 2016 (Figs. 7 and 8). Model evaluation revealed the good prediction for TDM during both growing year for all hybrids studied. Higher values of *d*-index (0.99) for time series TDM was computed in Pioneer-1543 and Monsanto DK-1630 by considering all sowing dates in both years while it ranged 0.98 to 0.99 for Syngenta NK-8711 (Figs. 7 and 8). Lower values of RMSE was computed in hybrids for TDM by considering all sowing dates during both years; it ranged 194 to 924[1], 449 to 815, and 404 to 1172 kg ha^{-1} for Pioneer-1543, Monsanto DK-6103, and Syngenta NK-8711, respectively (Figs. 8 and 9). Generally, model evaluation of TDM at harvest was good at all sowing dates during both growing years, but PE ranged − 5.79 to 5.03% in 2015 while it ranged − 10.46 to 7.48% in 2016 growing years for all hybrids studied. Overall, the model showed oversimulation for majority of the sowing dates but undersimulated in few sowing dates, however, statistical indices lie in acceptable range (Table 3). Hybrid produced biomass in both growing years by adopting this order Monsanto DK-6103 > Pioneer-1543 > Syngenta NK-8711. Denser canopy and biomass were developed by hybrid Monsanto DK-6103 than others. A best fit between simulated and observed biological yield at harvest was found among all treatments ($n = 24$) tested in model during both growing seasons (Fig. 9), with lower RMSE values of 963 kg ha^{-1} and reasonably good values of *d*-index (0.94).

Grain yield (kg ha^{-1})

Maize grain yield was well simulated by the model for all hybrids during temporal variation (sowing dates) assessment in growing seasons (2015 and 2016) with lower RMSE (451 kg ha^{-1}) and higher *d*-index values of 0.97 during model evaluation (Fig. 10). Generally, model capability for maize grain yield simulations was found to be good with lower PD for hybrid Pioneer-1543 while slightly high undersimulations of 10.42 and 10.56% were recorded for Monsanto-DK-6103 and Syngenta-NK-8711, respectively, in 2016 (Table 4). Higher grain yield was produced at early sowing of 27 January in all hybrids, and decreasing trend of grain yield was found for late sowing while minimum yield was produced by delayed sowing of 28 March during both growing years (Fig. 11). Sowing dates adopted the following order in producing the grain yield during both years, 27 January > 16 February > 8 March > 28 March. Hybrid performance in relation with different sowing dates revealed higher grain yield production at early sowing then decline

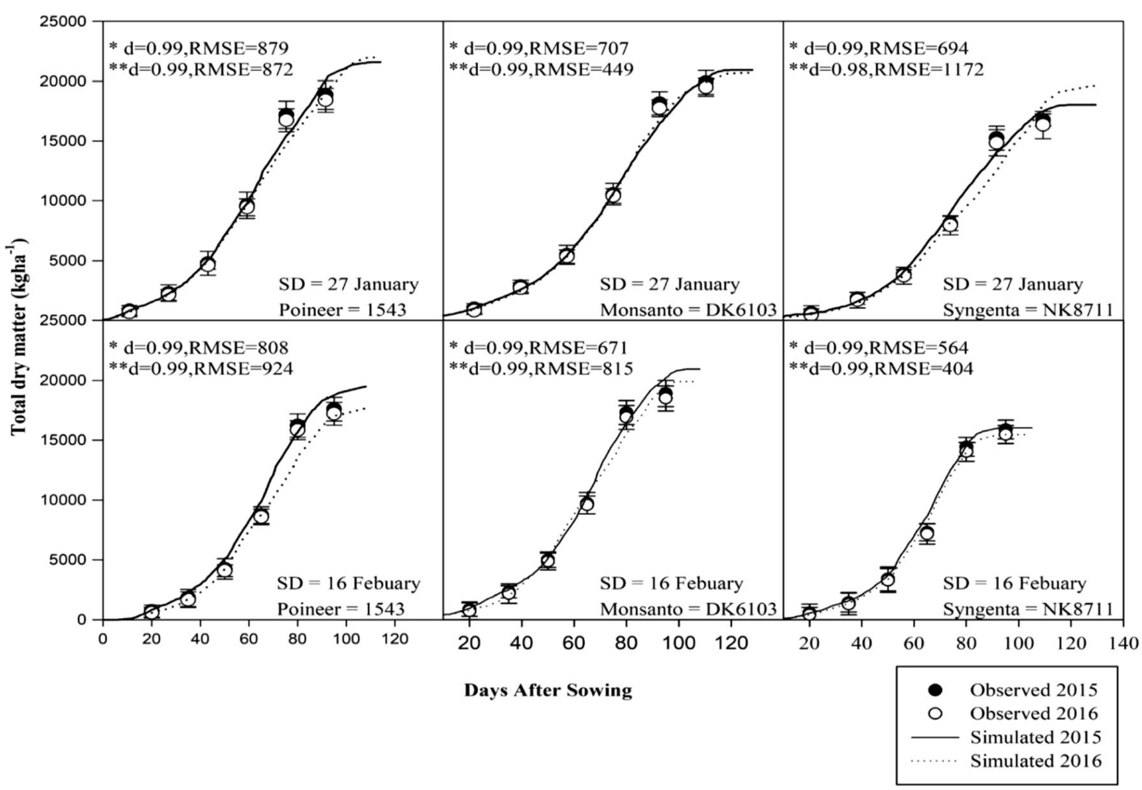


Fig. 7 CERES-Maize performance in time series total dry matter (TDM) of hybrids at sowing dates of 27 January and 16 February during both growing years (2015 and 2016). Note: 27 January in 2015 growing year was used for calibration while other date of sowings is used for model evaluation

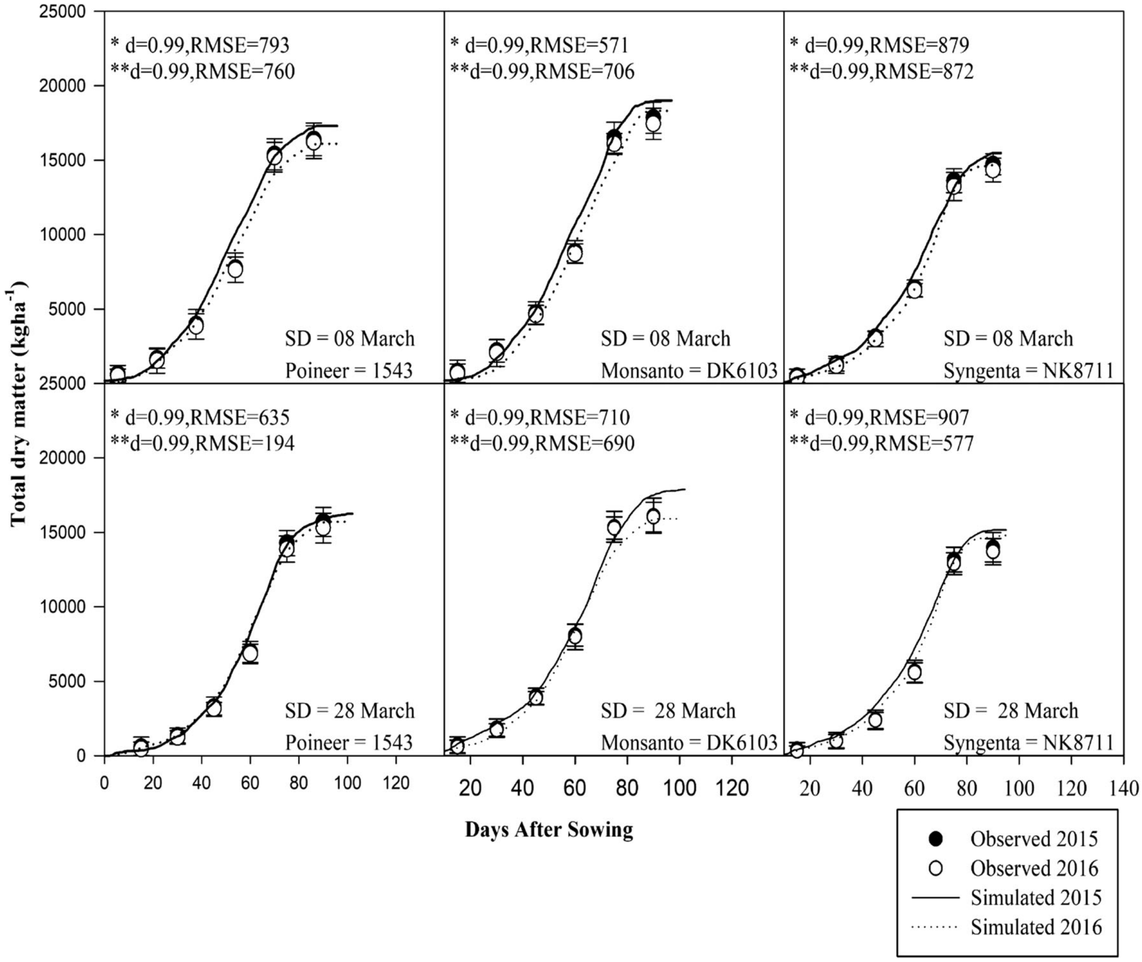
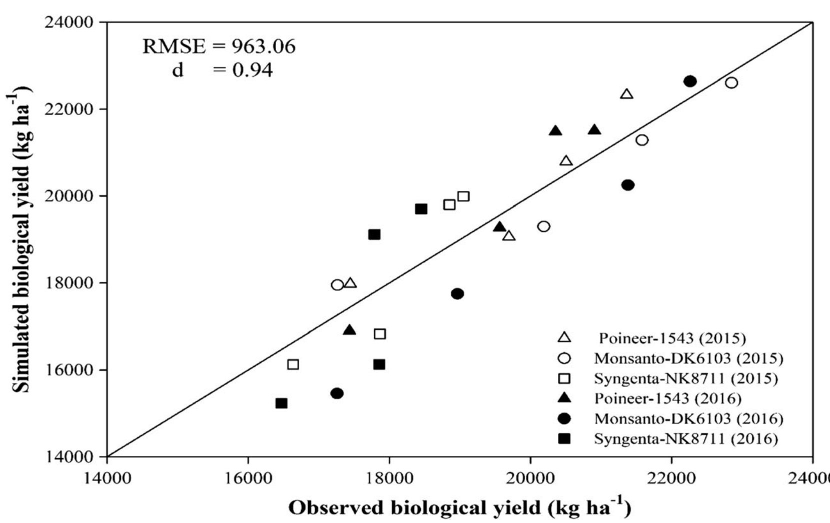


Fig. 8 CERES-Maize performance in time series total dry matter (TDM) of hybrids at sowing dates of 08 March and 28 March during both growing years (2015 and 2016) during model evaluation (similar observation as in the Fig. 7)

for later sowing. Generally, hybrids Monsanto-DK-6103 and Poineer-1543 performed reasonably good at early sowing (27 January) while Syngenta-NK-8711 produced more yield at later sowing (8 March and 28 March). Trend analysis of hybrids revealed that Syngenta-NK-8711 can also be recommended for late sowing while Monsanto-

Fig. 9 CERES-Maize performance for biological yield at harvest of hybrids sown at various dates (27 January to 28 March) during both growing years (2015 and 2016)



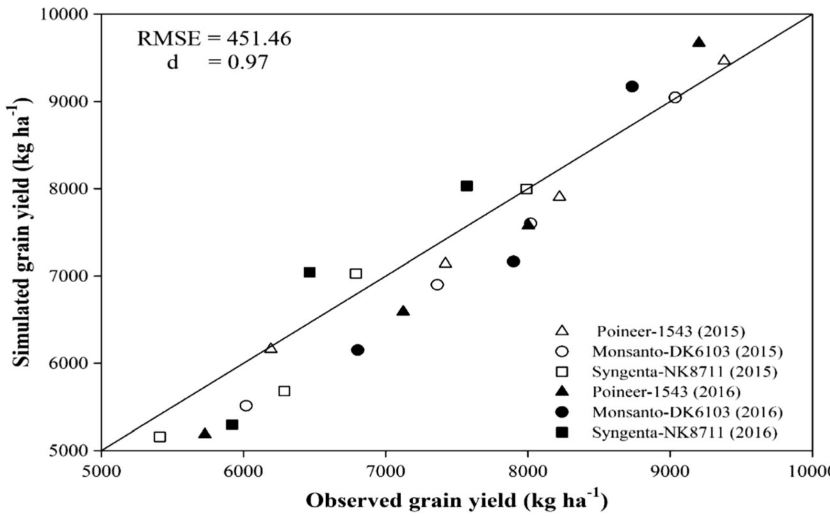


Fig. 10 CERES-Maize performance for grain yield of hybrids sown at various dates (27 January to 28 March) during both growing years (2015 and 2016)

DK-6103 and Poineer-1543 would be adopted for early sowing under semi-arid climatic conditions in the country (Fig. 12). Temporal variation analysis revealed that model fairly well simulated grain yield for early sowing for all hybrids but model underpredicted grain yield at 8 March and 28 March sowing dates during both growing years (Fig. 11). Generally, PD varied − 9.64 to 3.52% in 2015 while − 10.56 to 8.97% in 2016 growing year. Generally, model simulation was good but slightly undersimulated with marginal high difference for 8 March and 28 March sowing dates in both hybrids Monsanto-DK-6103 and Syngenta-NK-8711 in 2015 while difference was more pronounced in 2016 growing years for same hybrids and sowing dates due to differences in climatic conditions (Table 4).

Model application for maize optimum sowing date assessment

Optimum sowing dates under semi-arid climatic conditions was assessed by the model. Delay in sowing than 06 February reduced the grain yield drastically for all hybrids. Mean grain yield decreased up to 29% when sowing was delayed 1 month from 27 January while 20 days early sowing (07 January) also suffered yield loss up to 26% in all hybrids studied (Fig. 12). Hybrid Poineer-1543 achieved mean

Table 4 Comparison of observed and simulated variables of maize hybrids related to phenology, growth, and grain yield during model evaluation at different sowing dates in growing years of 2015 and 2016

Hybrids name	Sowing dates	Days to anthesis		Days to maturity		LAI		Grain yield		Biological yield	
		2015 % Error	2016 % Error	2015 % Error	2016 % Error	2015 % Error	2016 % Error	2015 % Error	2016 % Error	2015 % Error	2016 % Error
Pioneer-1543	27 January	2.63	1.39	0.00	1.80	− 2.99	2.78	0.88	5.06	4.53	2.87
	16 February	8.20	5.26	1.87	− 2.88	− 0.12	− 5.63	− 3.87	− 5.34	1.39	5.55
	08 March	− 5.26	3.77	− 2.00	− 3.09	1.04	− 8.73	− 3.79	− 7.48	− 3.19	− 1.48
	28 March	− 3.85	− 4.08	− 2.04	− 1.05	3.37	5.96	− 0.50	− 9.50	3.06	− 3.09
Monsanto-Dk6103	27 January	1.35	5.71	1.77	4.55	− 3.43	− 0.65	0.11	4.99	− 1.08	1.68
	16 February	4.55	3.23	− 1.90	0.98	− 8.45	− 14.34	− 5.20	− 9.28	− 1.37	− 5.30
	08 March	− 8.33	1.79	− 2.04	− 2.11	0.32	− 10.87	− 6.30	− 9.61	− 4.40	− 6.43
	28 March	6.00	4.26	− 3.13	− 1.08	0.80	3.30	− 8.42	− 10.42	3.96	− 10.46
Syngenta-NK-8711	27 January	− 2.82	2.99	2.80	2.88	− 6.75	0.96	0.08	6.10	4.95	6.79
	16 February	0.00	− 3.33	− 2.00	− 3.09	3.00	− 4.00	3.52	8.97	5.03	7.48
	08 March	− 10.71	1.92	− 2.17	− 3.37	2.97	− 1.05	− 9.64	− 10.56	− 5.79	− 9.66
	28 March	− 2.08	− 2.22	− 3.30	− 2.27	4.80	3.48	− 4.68	− 7.76	− 3.08	− 7.54

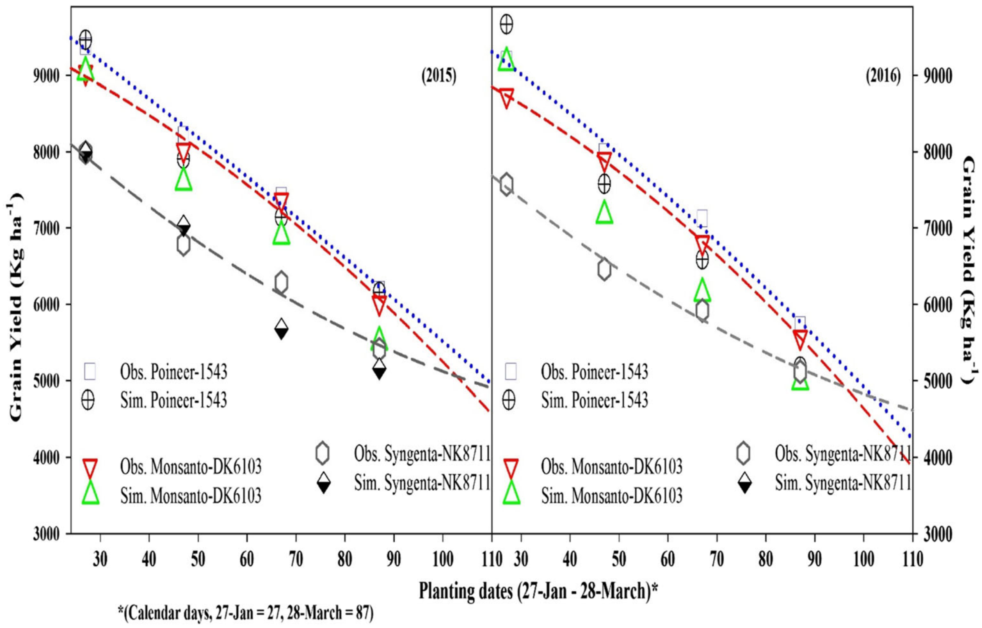


Fig. 11 Comparison of observed and simulated maize grain yield of hybrids, Pioneer-1543, Monsanto-DK6103, and Syngenta-NK8711 at multi-sowing dates (27 January to 28 March) with calendar days during model evaluation (dotted lines showed the trend of observed yield of maize hybrids)

maximum grain yield (9259 kg ha^{-1}) when planted at 27 January. Similar trends were observed for all hybrids at different sowing dates, but differences were found due to genotypic differences in thermal and photothermal time among sowing dates (Fig. 12). Field experiments also supported the model results regarding sowing date analysis, late sowing from 27 January revealed decline in grain yield, and significantly reduction after 16 February. Hybrid production showed decline in yield from first sowing (27 January) onward, earlier sowing trend than 27 January was computed by the model as it is crucial to know about early sowing of these hybrids in the region. All hybrids were found to be photoperiod sensitive as early sowing on 7 January suffered harshly, and yield reduced up to 26%. Variation between 10th and 90th percentiles was observed among maize sowing dates and hybrids as well. Decrease in median and 10th percentiles values were found when maize was sown too early on 7 January and too late (27 February). It is obvious from analysis that too early and too late planting had an increase in risk to getting lower maize grain yield, as results revealed that there was significant

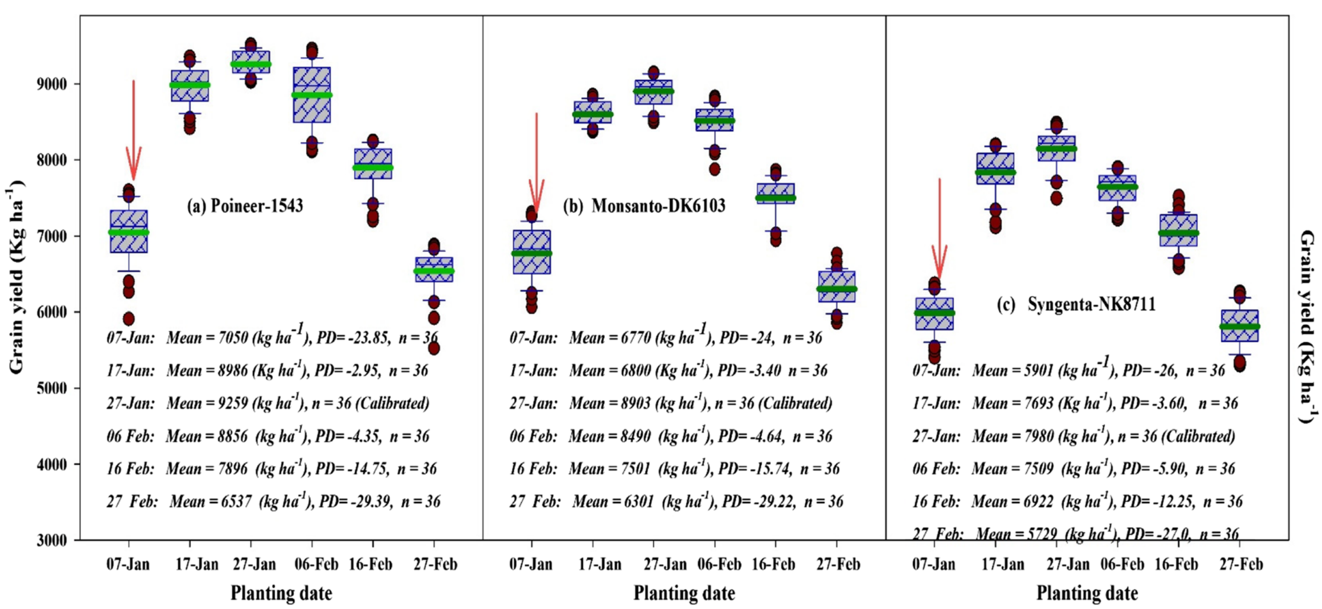


Fig. 12 Maize sowing date analysis (07 January to 27 February) under seasonal strategy analysis and model performance for different hybrids in 36 years of maize-growing seasons

impact of climatic conditions such as solar radiation, temperature, and precipitation variations and low photothermal units when planting was too early and too late (Fig. 12). These hybrids can be recommended to be sown between 17 January and 6 February on the farmer field in the region. Early sowing than 17 January showed severe reduction of grain yield in all hybrids due to lower night temperature and base temperature. Early planting than 17 January should be avoided for all hybrids while hybrid Syngenta NK-8711 performed better at later sowing up to 16 February; it may be recommended for late sowing as well.

Impact of climate variability on maize crop

Maize crop cycle and phenology

Climate variability in observed historic data (1980–2016) has strong negative relationship with all studied attributes of maize crop. As increasing trend in maximum and minimum temperatures was observed from 1980 to 2016, maize crop cycle was being shortened due to that increase and ultimately has negative impact on biological and grain yields. Maximum temperature has more pronounced impact on days to anthesis of maize crop than minimum temperature and reduced days of anthesis from 87 to 63. Strong negative relationship was observed with higher values of coefficient of regression (R^2 = 0.83) with negative intercept values of 0.1525 (Fig. 13a). Negative relationship was enhanced as maximum temperature shifts from 29 to 34 °C in different historic years. Similarly, minimum temperature also has negative relationship to increase in temperature, while coefficient of regression (R^2 = 0.65) was found above normal and intercept value was found − 7.8923. Days to anthesis of maize crop reduced as minimum temperature shifts from 16.8 to 19.2 °C (Fig. 13b). Increase in maximum and minimum temperature both exerts negative effect on maize crop cycle till maturity and shorten the overall crop cycle by early maturity of grain. Maize crop mature 8 days early (125 to 117) due to increase in maximum temperature of 29 to 34 °C, revealing the strong negative relationship with coefficient of regression values of 0.73 while intercept was found − 0.4203 (Fig. 13c). Negative relationship was also found between minimum temperature and days to maturity with R^2 values of 0.63. Generally, maximum temperature has more dominant negative impact on phenology and maize crop cycle than minimum temperature as temperature extremes cause more drastic effect on phenology and overall maize productivity in semi-arid region of the country (Fig. 13d).

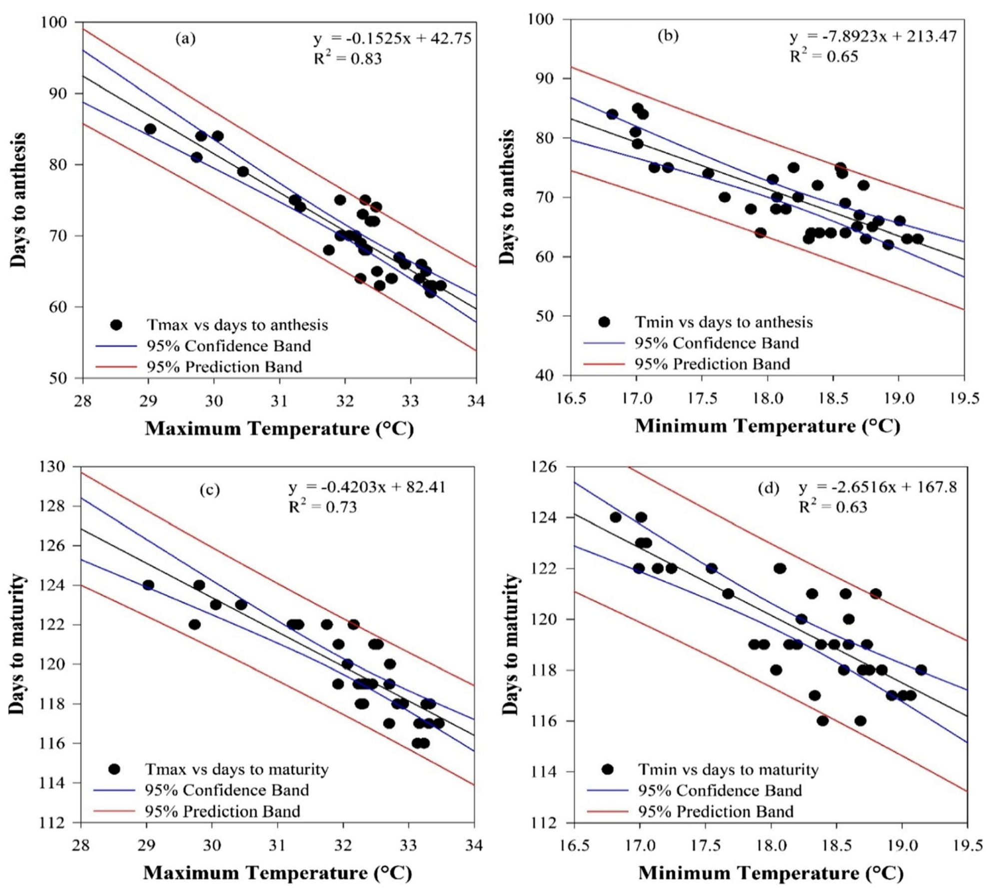


Fig. 13 Relationships of seasonal historic temperature (1980–2016) with **a** days to anthesis with T_{max}, **b** days to anthesis with T_{min}, **c** days to maturity with T_{max}, and **d** days to maturity with T_{min}

Maize biological yield and grain yield (kg ha^{-1})

Crop phenology and short crop cycle have direct impact on biological yield and ultimately effect final grain yield. As crop cycle reduced by decreasing the number of days to anthesis and maturity, it will affect the radiation interception by reducing crop cycle and crop canopy. Minimum temperature has more pronounced impact maize biological yield than maximum temperature and reduced biological yield 25,000 to 22,000 kg ha^{-1}. Strong negative relationship was observed with high values of coefficient of regression ($R^2 = 0.72$) with negative intercept values of 0.0008 (Fig. 14b). Negative relationship was enhanced as minimum temperature shifts from 16.8 to 19.2 °C in different historic years. Similarly, maximum temperature also has negative relationship to increase in temperature, while coefficient of regression ($R^2 = 0.67$) was found above normal and intercept value was found − 1381 (Fig. 14b).

Short life cycle of maize crop affect the grain yield of hybrids studied. Increase in maximum and minimum temperature both exerts negative effect on maize crop cycle and grain yield. Maximum temperature has more significant negative impact on grain yield, as strong negative relationship was observed between maximum temperature and grain yield with higher values of coefficient of regression (0.89) with negative intercept values of 0.0009 (Fig. 14c). Negative relationship was also found between minimum temperature and grain yield with R^2 values of 0.73 (Fig. 14d). Maximum temperature has more negative effects on growth and yield of maize as compared to minimum temperature.

Discussion

The CERES-Maize model is a comprehensive computer model in DSSAT which simulate the phenology, crop growth biomass, and grain yield in response to different environmental conditions (Chisanga et al. 2015a). The CERES-Maize model was well parameterized and showed a good performance in simulations of phenology, growth, and yield attributes of various maize hybrids. Similar findings were reported by Liu et al. (2015) and Mubeen et al. (2016). Genetic parameters during calibration were estimated by Bayesian approach using the GLUE by providing actual field data of phenology, physiology, morphology, growth, yield, and yield components. The minimum and maximum values of maize hybrid

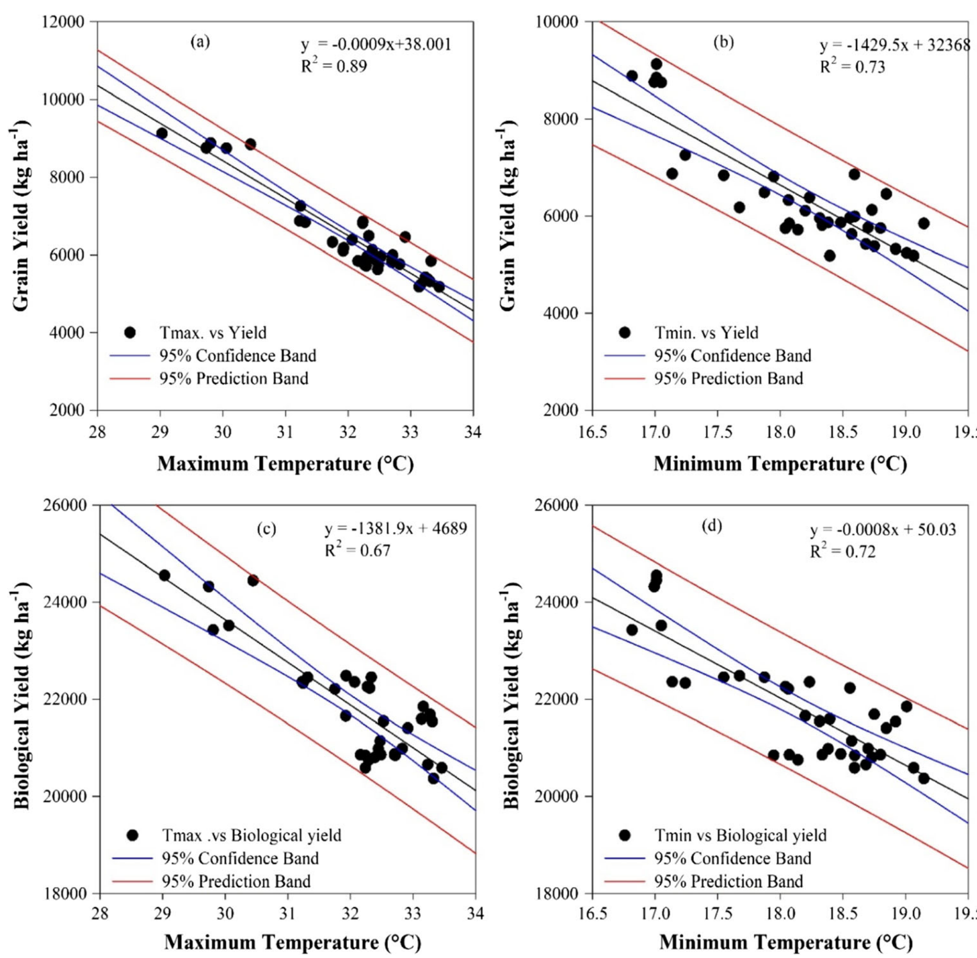


Fig. 14 Relationships of seasonal historic temperature (1980–2016) with **a** grain yield (kg ha^{-1}) with T_{max}, **b** grain yield (kg ha^{-1}) with T_{min}, **c** biological yield (kg ha^{-1}) with T_{max}, and **d** biological yield with T_{min}

coefficient in CERES-Maize were P1 (140–365), P2 (0.0–0.1), P5 (600–990), G2 (500–908), and G3 (5–25) computed. It is a well-defined approach being used for many crops especially maize and soybean genetic coefficient estimation (Jones et al. 2011). Cultivar coefficient estimated in this study is within the range as it was reported by Jones et al. (2003). Genetic coefficients of CERES-Maize were estimated by GLUE program of Abdrabbo et al. (2013), showing a good accuracy in simulating the days to anthesis and maturity.

In the current study, days to anthesis decreased due to delayed planting from January to the end March. The possible reason could be the high temperature in late planting, decreasing the growing degree days which lead to early maturity of crop. Another reason might be high temperature in late sowing affect the pollination and silk viability. In case of maize hybrids, results showed that Poineer-1543, Monsanto DK 6103, and Syngenta NK8711 completed life cycle at 114, 113, and 110 days after planting at the end January sowing. Model simulated the life cycle of maize hybrids with a difference of 1–2 days. Photoperiodic response of hybrids is associated with early and late sowing. Phenology, days to anthesis, and maturity phases of maize hybrids were simulated well by the model, attaining a reasonable good values of statistical indices (RMSE = 2.73 and 2.44; $d = 0.97$) during evaluation with all treatments during both years ($n = 24$). Although, 1- to 2-day differences were exited among hybrids due to genotypic variations. Generally, model performance was found good at all planting dates with hybrids, showing the model ability to simulate phenology well. Soler et al. (2007) found the close prediction of days to anthesis and maturity with 0- to 2-day difference between observed and simulated values. Chisanga et al. (2015b) reported that CERES-Maize model predicted days to anthesis (-2 ± 1) and maturity (-4 ± 1) very well.

In field experiment, maximum days to LAI and biomass were recorded in the first sowing date (27 January), while among maize hybrids, higher biomass and LAI was recorded in Monsanto-DK 6103. The reason of more biomass in Monsanto (DEKALB) hybrids could be due to staygreen character till the end of season which increased the tolerance of osmotic stress (Popelka 2012). The CERES-Maize model predicted the peak LAI at flowering stage and decreased at physiological maturity. The reduction in LAI at maturity was due to inhabitation of LAI development and acceleration of leaf senescence. The dry matter accumulation was linearly increased by model and decline, 15 days after silking to maturity. Higher dry matter accumulation was due to increase in solar radiation flux and leaf photosynthetic activity. Lower dry matter at maturity was due to reduction in incident radiation. Model slightly undersimulated the LAI and TDM at latter stages in late sowing dates. Dogan et al. (2006) reported that the model undersimulate the LAI at reproductive stages of crop due to rapid senescence of leaves in the model.

Higher grain yield was recorded in Poineer-1543 for end January sowing due to favorable climatic conditions with long growth cycle attaining higher solar radiation. Grain yield gradually decreased from January to end March sowing. Similar trend was observed in biological yield. Higher grain yield in early sowing might be due to longer growth cycle and favorable temperature especially at grain filling stage. Model also simulated the less yield and final biological yield for late sowing maize hybrids. The reason could be the lowest thermal time and solar radiation in late sowing limit the photosynthetic activity in the model, which can reduce the transfer of assimilate to grains, that limit the yield in late sowing. Another reason found by Sangoi (2001) is that higher temperature increases the growth rate and reduces the time for kernel filling which ultimately reduces the grain yield. Our results are in conformity with Chisanga et al. (2015b) who evaluated the CERES-Maize model on different sowing dates and nitrogen at Zambia. Statistical indices showed a good performance in prediction of days to anthesis ($\geq -3 \leq +1$), days to maturity ($\geq -4 \leq 3$), and grain yield with nRMSE of 21%. Similar results were reported by Saseendran et al. (2005), who evaluated the model at different sowing dates found a close agreement between observed and simulated phenology and grain yield.

Potentially climate variability is inducing the risk with yield gap analysis and can be managed by providing decision support with the aid of crop models (Coumou and Rahmstorf 2012). Simulated days to anthesis and maturity by CERES-Maize model were negatively correlated with increase in temperatures. The relationship of maximum and minimum temperatures with grain and biological yields showed a negative relationship with reasonable high values of R^2 (Fig. 14a, b). The reason could be the increase in maximum and minimum temperatures, which accelerate crop growth and shorten the grain-filling period. Another reason could be the increase in temperatures which lead to reduction in photosynthetic activity, senescence of leaves, pollen viability, seed abortion, and less seed setting, which ultimately reduce the grain yield. Lin et al. (2015) also reported that increase in maximum and minimum temperatures shorten the duration of flowering and maturity. Asseng et al. (2013) found that high temperature reduced the chlorophyll content and grain weight of crop, which lead to decrease in grain yield. Cicchino et al. (2010) and Bassu et al. (2014) reported similar findings that higher temperature delayed the anthesis and also increase the number of male sterile plant. Our results are according to the finding of Yin et al. (2015), who reported that increase in maximum temperature above 30 °C negatively affects the grain yield of maize. However, in cases of this study, maximum temperature was 32 °C which significantly lead to reduction in grain yield. Hatfield and Prueger (2015) also found similar results that grain yield has negative relationship with temperature.

Conclusion

The CERES-Maize model was well calibrated with observed field experimental data of phenology, growth, and yield component. Model simulated days to anthesis and maturity with RMSE less than 2 days during both years. Model performance for biological yield and grain yield was good with RMSE values of 963 and 451 kg ha^{-1}, respectively. Study results showed that grain yield gradually decreased by delayed planting from January to end of March. Strategy analysis showed that early sowing before 17 January faced the severe reduction in grain yield of all hybrids. Climate variability results revealed that phenology and grain yield were negatively affected by fluctuation in temperatures. Days to anthesis and maturity decreased by 5 days with temperatures above 32 °C. Climate variability results showed that yield would be reduced by 43% by increase in maximum and minimum temperatures of 4.4 and 2.3 °C, respectively. To mitigate the negative impacts of climate variability, it is recommended that maize hybrid Poineer-1543 should be planted at the end of January on farmer field under semi-arid to arid climatic conditions of Punjab, Pakistan.

References

Abbas G, Ahmad S, Ahmad A, Nasim W, Fatima Z, Hussain S, Rehman MH, Khan MA, Hasanuzzaman M, Fahad S, Boote KJ, Hoogenboom G (2017) Quantification the impacts of climate change and crop management on phenology of maize-based cropping system in Punjab, Pakistan. Agric For Meteorol 247:42–55

Abdrabbo MAA, Hashem FA, Elsayed ML et al (2013) Evaluation of CSM-CERES-maize model for simulating maize production in northern delta of Egypt. Life Sci J 10:3179–3192

Anderson CL, Cronholm A, Biscaye P (2017) 14 Do changes in farmers' seed traits align with climate change? A case study of maize in Chiapas, Mexico. Handb Behav Econ Smart Decis Ration Decis within Bounds Reason 251

Asseng S, Ewert F, Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburn PJ, Rötter RP, Cammarano D, Brisson N, Basso B, Martre P, Aggarwal PK, Angulo C, Bertuzzi P, Biernath C, Challinor AJ, Doltra J, Gayler S, Goldberg R, Grant R, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Kersebaum KC, Müller C, Naresh Kumar S, Nendel C, O'Leary G, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Semenov MA, Shcherbak I, Steduto P, Stöckle C, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, Wallach D, White JW, Williams JR, Wolf J (2013) Uncertainty in simulating wheat yields under climate change. Nat Clim Chang 3:827–832

Bassu S, Brisson N, Durand J et al (2014) How do various maize crop models vary in their responses to climate change factors? Glob Chang Biol 20:2301–2320

Baumer O, Rice J (1988) Methods to predict soil input data for Drainmod, ASAE paper 88-2564. American Society of Engineers, St. Joseph, Michigan

Bergamaschi H, Dalmago GA, Bergonci JI, Bianchi CAM, Müller AG, Comiran F, Heckler BMM (2004) Water supply in the critical period of maize and the grain production. Pesqui Agropecuária Bras 39: 831–839

Boote KJ, Porter C, Jones JW et al (2016) Sentinel site data for crop model improvement—definition and characterization. Improv Model Tools Assess Clim Chang Eff Crop Response:125–158

Bowman RA (1997) Field methods to estimate soil organic matter. Conservation tillage fact sheet# 5-97. USDA-ARS and NRCS, Akron. Available: www.akron.ars.usda.gov/fs_field.html. Accessed Jan 2018

Chisanga CB, Phiri E, Shepande C, Sichingabula H (2015a) Evaluating CERES-Maize model using planting dates and nitrogen fertilizer in Zambia. J Agric Sci 7:1–19. https://doi.org/10.5539/jas.v7n3pxx

Chisanga CB, Phiri E, Shepande C, Sichingabula H (2015b) Evaluating CERES-Maize model using planting dates and nitrogen fertilizer in Zambia. J Agric Sci 7:79

Cicchino M, Edreira JI, Otegui ME (2010) Heat stress during late vegetative growth of maize: effects on phenology and assessment of optimum temperature. Crop Sci 50:1431–1437

Coumou D, Rahmstorf S (2012) A decade of weather extremes. Nat Clim Chang 2:491–496

Craufurd PQ, Wheeler TR (2009) Climate change and the flowering time of annual crops. J Exp Bot 60:2529–2539

Dogan E, Clark GA, Rogers DH et al (2006) On-farm scheduling studies and CERES-maize simulation of irrigated corn. Appl Eng Agric 22: 509–516

Ferris R, Ellis RH, Wheeler TR, Hadley P (1998) Effect of high temperature stress at anthesis on grain yield and biomass of field-grown crops of wheat. Ann Bot 82:631–639

Field CB (2012) Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press

Gabaldon Leal C, Lorite IJ, Minguez Tudela MI et al (2015) Strategies for adapting maize to climate change and extreme temperatures in Andalusia, Spain. Clim Res 65:159–173

Government of Pakistan (2017) Economic survey of Pakistan. Econ Advis Wing Financ Div Govt Pakistan:29–30

Hatfield JL, Prueger JH (2015) Temperature extremes: effect on plant growth and development. Weather Clim Extrem 10:4–10

He J, Jones JW, Graham WD, Dukes MD (2010) Influence of likelihood function choice for estimating crop model parameters using the generalized likelihood uncertainty estimation method. Agric Syst 103: 256–264

Hoogenboom G, Porter CH, Shelia V, et al (2016) Decision support system for agrotechnology transfer (DSSAT) version 4.7 (https://DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA

Huang J, Ji M, Xie Y, Wang S, He Y, Ran J (2016) Global semi-arid climate change over last 60 years. Clim Dyn 46:1131–1150

Hunt LA, Boote KJ (1998) Data for model operation, calibration, and evaluation. Understanding options for agricultural production. Springer, In, pp 9–39

IPCC (2014) Climate change 2014: mitigation of climate change. Cambridge University Press

Jones CA, Kiniry JR, Dyke PT (1986) CERES-maize: a simulation model of maize growth and development. Texas A& M University Press

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT (2003) The DSSAT cropping system model. Eur J Agron 18:235–265

Jones JW, He J, Boote KJ et al (2011) Estimating DSSAT cropping system cultivar-specific parameters using Bayesian techniques. Methods Introd Syst Model Agric Res:365–394

Lin Y, Wu W, Ge Q (2015) CERES-Maize model-based simulation of climate change impacts on maize yields and potential adaptive measures in Heilongjiang Province, China. J Sci Food Agric 95:2838–2849. https://doi.org/10.1002/jsfa.7024

Liu X, Andresen J, Yang H, Niyogi D (2015) Calibration and validation of the hybrid-maize crop model for regional analysis and application over the US Corn Belt. Earth Interact 19:1–16
Lobell DB, Bänziger M, Magorokosho C, Vivek B (2011) Nonlinear heat effects on African maize as evidenced by historical yield trials. Nat Clim Chang 1:42–45
Lobell DB, Hammer GL, McLean G, Messina C, Roberts MJ, Schlenker W (2013) The critical role of extreme heat for maize production in the United States. Nat Clim Chang 3:497–501
Msowoya K, Madani K, Davtalab R, Mirchi A, Lund JR (2016) Climate change impacts on maize production in the warm heart of Africa. Water Resour Manag 30:5299–5312
Mubeen M, Ahmad A, Wajid A, Khaliq T, Hammad HM, Sultana SR, Ahmad S, Fahad S, Nasim W (2016) Application of CSM-CERES-Maize model in optimizing irrigated conditions. Outlook Agric 45: 173–184
Naheed G, Mahmood A (2006) Water requirement of wheat crop in Pakistan. Pakistan J Meteorol 6:89–97
Nasim W (2010) Modeling the impact of climate change on nitrogen use efficiency in sunflower (helianthus Annuus L.) under different agroclimatic conditions of Punjab-Pakistan. Diss. Faculty of Agriculture/University of Agriculture, Faisalabad
Ngwira AR, Aune JB, Thierfelder C (2014) DSSAT modelling of conservation agriculture maize response to climate change in Malawi. Soil Tillage Res 143:85–94
Popelka M (2012) Genetic architecture of stay-green in maize. Purdue University, USA, pp 100–240
Prasanna BM (2011) Maize in Asia-trends, challenges and opportunities. Addressing Climate Change Effects and Meeting Maize Demand for Asia; Asian Maize Conference, 11; Book of Extended Summaries; Nanning, Guangxi (China); 7-11 Nov. 2011. In: ^ TAddressing Climate Change Effects and Meeting Maize Demand for Asia; Asian Maize Conference, 11; Book of Extended Summaries; Nanning, Guangxi (China); 7-11 Nov. 2011^ AZaidi, PH Babu, R. Cairns, J. Jeffers, D. Kha, LQ Krishna, GK Krishna, V. McDonald
Rawls WJ, Brakensiek DL, Saxtonn KE (1982) Estimation of soil water properties. Trans ASAE 25:1316–1320
Sangoi L (2001) Understanding plant density effects on maize growth and development: an important issue to maximize grain yield. Ciênc Rural 31:159–168
Saseendran SA, Ma L, Nielsen DC, Vigil MF, Ahuja LR (2005) Simulating planting date effects on corn production using RZWQM and CERES-Maize models. Agron J 97:58–71
Soler CMT, Sentelhas PC, Hoogenboom G (2007) Application of the CSM-CERES-Maize model for planting date evaluation and yield forecasting for maize grown off-season in a subtropical environment. Eur J Agron 27:165–177
Tubiello FN, Soussana J-F, Howden SM (2007) Crop and pasture response to climate change. Proc Natl Acad Sci 104:19686–19690
Rahman MH, Ahmad A, Wajid A, et al (2017) Application of CSM-CROPGRO-Cotton model for cultivars and optimum planting dates: evaluation in changing semi-arid climate. Field Crop Rese. https://doi.org/10.1016/j.fcr.2017.007
Rahman MH, Ahmad A, Wang X et al (2018) Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan. Agric For Meteorol 253:94–113
Ureta C, Martinez-Meyer E, Gonzalez EJ, Alvarez-Buylla ER (2016) Finding potential high-yield areas for Mexican maize under current and climate change conditions. J Agric Sci 154:782–794
Willmott CJ (1981) On the validation of models. Phys Geogr 2:184–194
Willmott CJ, Robeson SM, Matsuura K (2012) A refined index of model performance. Int J Climatol 32:2088–2094
Yin XG, Wang M, Kong QX, Wang ZB, Zhang HL, Chu QQ, Wen XY, Chen F (2015) Impacts of high temperature on maize production and adaptation measures in Northeast China. Ying yong sheng tai xue bao= J Appl Ecol 26:186–198