Pak. J. Bot., 54(3): 835-842, 2022. DOI: http://dx.doi.org/10.30848/PJB2022-3(40)

SIMULATING THE GROWTH AND YIELD OF PEANUT CULTIVARS UNDER TEMPORAL VARIATION USING CROPGRO-PEANUT (DSSAT) MODEL

ADEEL AHMAD[1*], AFTAB WAJID[1], MUHAMMAD HAMZAH SALEEM[2], MEMOONA SHEHZADI[3], MUHAMMAD REHAN[1], MUHAMMAD HUSSAAN[4], MUHAMMAD FAHEEM [5,6], M. TARIQ JAVED[4], MOHAMED A. EL-SHEIKH[7], HUDA ALSHAYA[8], AND SHAFAQAT ALI[9,10*]

[1]*Department of Agronomy, University of Agriculture, 38000 Faisalabad, Pakistan*
[2]*College of Plant Science And Technology, Huazhong Agricultural University, Wuhan 430070, China*
[3]*Agronomic Research Station Farooqabad, 39500, Punjab, Pakistan*
[4]*Department of Botany, Government College University, Allama Iqbal Road, 38000 Faisalabad, Pakistan*
[5]*School of Agricultural Equipment Engineering, Jiangsu University, Zhenjiang, China*
[6]*Department of Farm Machibery and Power, University of Agiculture, Faisalabad 38000, Pakistan*
[7]*Botany and Microbiology Department, College of Science, King Saud University, Riyadh, Saudi Arabia*
[8]*Cell and Molecular Biology, University of Arkansas, Fayetteville 72701, United States of America*
[9]*Department of Environmental Sciences and Engineering, Government College University Allama Iqbal Road, 38000 Faisalabad, Pakistan*
[10]*Department of Biological Sciences and Technology, China Medical University, Taichung 40402, Taiwan*
**Correspondening author's email: adeelahmad772@gmail.com; shafaqataligill@gcuf.edu.pk*

Abstract

Crop models are widely used in developing crop management strategies for sustainable production especially under changing climatic conditions. The impact of sub-optimal climatic conditions on peanut production can be explored with the aid of such models. Peanut being the king of oilseeds, enjoys itself a prime position amongst all other cash crops and has the potential to narrow the gap between production and consumption of edible oil. The study was undertaken to simulate the growth and yield of peanut cultivars under temporal variation using CROPGRO-Peanut (DSSAT) model. The model calibration was done with phenology (days to anthesis and days to maturity), growth (leaf area index and total dry matter) and yield data of both cultivars with 15-April planting date. The submodules such as Sensitivity Analysis and Generalized Likelihood Uncertainty Estimation (GLUE) were used to adjust the genetic coefficients. Simulations of physiology, phenology and yield were found well with good indices. Model simulated the days to anthesis and maturity accurately with d-index (>0.92 and >0.92), and the indices of biomass and leaf area index were simulated well with lower RMSE (349.34-497.14 and 0.86-0.69), respectively during model evaluation. Pod yield was also predicted well with lower RMSE (266.31-341). Both cultivars performed well with greater yield at 15-April sowing primarily due to optimum growing conditions. The sub-optimal growing period at delayed planting (15-June) resulted in poor growth and development due to temperature stress ultimately, caused 27% pod yield penalty. Model also predicted the genotypes developments at different sowing times and higher yield was observed at 15-April sowing. Peanut sowing at mid-April can be recommended for the farmers to avoid environmental stress and appropriate use of available resources for sustainable yield. Results depicted the potential of model for selection of appropriate genotype, planting dates and other peanut management practices in the region.

Key words: Calibration, Evaluation, CROPGRO-Peanut, DSSAT, Temporal variations.

Introduction

Peanut (*Arachis hypogaea* L.) is rich in oils and high value cash crop, considered as an alternative adaptation strategy for farmers. It is a leguminous plant native to South America. Archealogist explored that it introduced in Peru, probably from the eastern Andes, 8500 years ago (Hammons *et al.*, 2016). It is grown in tropical and sub tropical regions. Peanut crop has great significance in the world grain market. The world production of peanut was 49.66 million metric tons, with a planted area of 29.71 million ha (Anon., 2021). Peanut contain 45-50 percent oil content, 25-30 percent protein, vitamins and essential minerals (Ahmad & Rahim, 2007). The peanut is used in making peanut snacks, butter, roasted peanut and candies. The peanut kernel is also converted into cake and oil in world major peanut growing countries like China (Ortega & Ochoa, 2003). To meet the requirements, Pakistan had to import edible oil of value US$ 3.063 billion (Anon., 2017) which are exhausting our economy day by day.

Crop yield is determined by its adaptability to weather conditions of a region (Saleem *et al.*, 2019a,b,c,d,e). Qasim *et al.*, (2016) reported that the uncertain periodic events of climate are more frequent in the region. The configuration of planting time with its environmental variables are extremely important to maximize crop yield (Tiwari *et al.*, 2014). From sowing to harvesting, crop productivity is affected by any variation in weather variables. High temperature exposure of groundnut, cause a significant loss in peanut yield (Craufurd *et al.*, 2002). The increase in temperature has a great impact of crop development stages. Consequently, the influence of changing temperature in terms of thermal and photo-thermal time is important to study. According to (Khosravi *et al.*, 2010) to maximize crop yield, selection of optimum sowing time and variety is important. The planting times and genotypes influenced the phenological phenophases, and growth (Damahe, 2018).

CROPGRO-Peanut model is an integrated part of DSSAT (Hoogenboom *et al.*, 2004). This model can be used to estimate various parameters such as canopy photosynthesis. It responds to daily weather inputs, soil water, cultivar choice and management practices dynamically. CROPGRO-Peanut dynamically responds to cultural practices, weather, soil water deficits and cultivar choice. CROPGRO-Peanut model has capability to predict phonology, development and yield of crop which are affected by climatic conditions, traits of cultivars and management practices provide an opportunity to use the model for increase in production of peanut by mitigating the problems related to environment, management practices and cultivars of crop. Halder *et al*., (2017) conducted an experiment on growth, development and yield of peanut by using DSSAT model. They found calibrated model quite accurate, for simulating the yield of peanut. Guled *et al*., (2012) concluded that the model predicted and recorded values were correspondingly closed to phenology and pod yield of peanut cultivars. Crop simulation models have potential for creating virtual crop cultivars, for further assisting the breeder's selection criteria and genetic enhancement of main characteristics contributing towards the yield improvement under various targeted environments (Hammer & Jordan, 2007).

Boote *et al*., (1987); Boote *et al*., (1992) developed PNUTGRO model that effectively predicts peanut growth, development and pod yield. PNUTGRO, crop simulation model was extensively assessed for evaluating the climatic conditions, cultivars, yield, and genetic coefficient (Boote *et al.*, 1992). Yadav *et al*., (2012) reported that CROPGRO-Peanut model can simulate the yield, days to anthesis, shelling percent. They suggested that the model can also be used to improve current management practices of peanut which ultimately resulted in more peanut production.

CROPGRO-Peanut parameterization with comprehensive and quality experimental data are still missing for peanut. Moreover, studies about testing peanut model for physiology and yield under temporal variation in semi-arid irrigated environment are still unavailable Therefore, the validation of CROPGRO-Peanut model for different genotypes under specific climatic conditions and developing appropriate management strategies is significant. The goals of study were to evaluate the CROPGRO-Peanut model for achieving potential production for different cultivars under temporal variation in Pakistan.

Material and Methods

Field experiment: The field trial was performed during Peanut growing period 2017 at research area, University of Agriculture, Faisalabad (73^0 E longitudes and 31^0N latitudes; 213 m altitude). Peanut cultivars and Planting dates were considered as key treatments in this experiment. The trail was arranged as split-plot with three replications. Peanut cultivars (BARI-2016 and BARD-479) were placed in subplot while sowing dates (15-April, 15-May, and 15-June) were kept in main plots.

Crop husbandry and input data measurement: Peanut was sown on flat beds by hand drill at 45 cm row-row distance at 100 kg ha^{-1} seed rate. Proper plant safety procedures were adopted to control weed and insect pest to avoid weed-crop and insect-crop competition through hoeing and chemical control. A basal amount of fertilizer added with the ratio of 20:40:40 kg ha^{-1} for NPK respectively.

Growth and development data were noted by randomly selecting five plants from each experimental unit to measure phenological events. These observed phonological phenophases were used as inputs for model parameterization. The time series and maximum leaf area index (LAID and LAIX) were used for model parameterization. Time series, final TDM and pod yield were observed for each experimental unit.

CROPGRO-Peanut model description: The CROPGRO-Peanut model (Hoogenboom *et al*., 2015) was used to evaluate the influence of cultivars and planting dates on phenology, growth and production of peanut to evaluate the possible management strategies under temporal variation due to its wide range application under changing climatic conditions for different regions worldwide. The model simulation is affected by edaphic and weather conditions. CROPGRO-Peanut model simulates growth and development on the bases of thermal heat unit accumulation or photo thermal time (Jones *et al*., 2003). Hedgerow model of leaf-level photosynthesis is used to simulate the light interception and canopy photosynthesis on the basis of canopy cover and peanut row structure (Boote & Pickering, 1994). Hydrological processes (daily soil water availability, evaporation and transpiration) can be simulated with Ritchie water balance (Ritchie, 1985). The model uses Penman-FAO method to assess the evapotranspiration (ET) (Doorenbos, 1975). Detailed explanation of structure, methodology and integration of all the DSSAT sub modules are discussed (Hoogenboom *et al*., 2015).

Model inputs

Meteorological data: Daily maximum and minimum temperature (ºC), relative humidity (%), daily solar radiation and rain fall (mm) were observed in weather station, University of Agriculture, Faisalabad, Pakistan. The model used these weather variables as input data set. The data of minimum, maximum and average temperatures, rainfall, daily sunshine hours and solar radiation for the growing period are presented in Figs. 1 and 2.

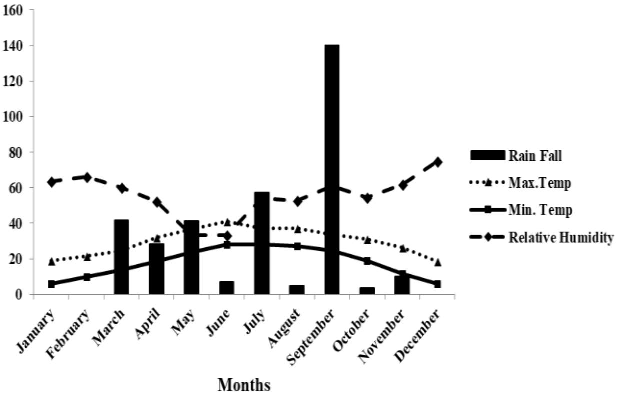

Fig. 1. Monthly average rainfall (mm), Max., Mini. Temperature (ºC) and relative humidity (%) during 2017.

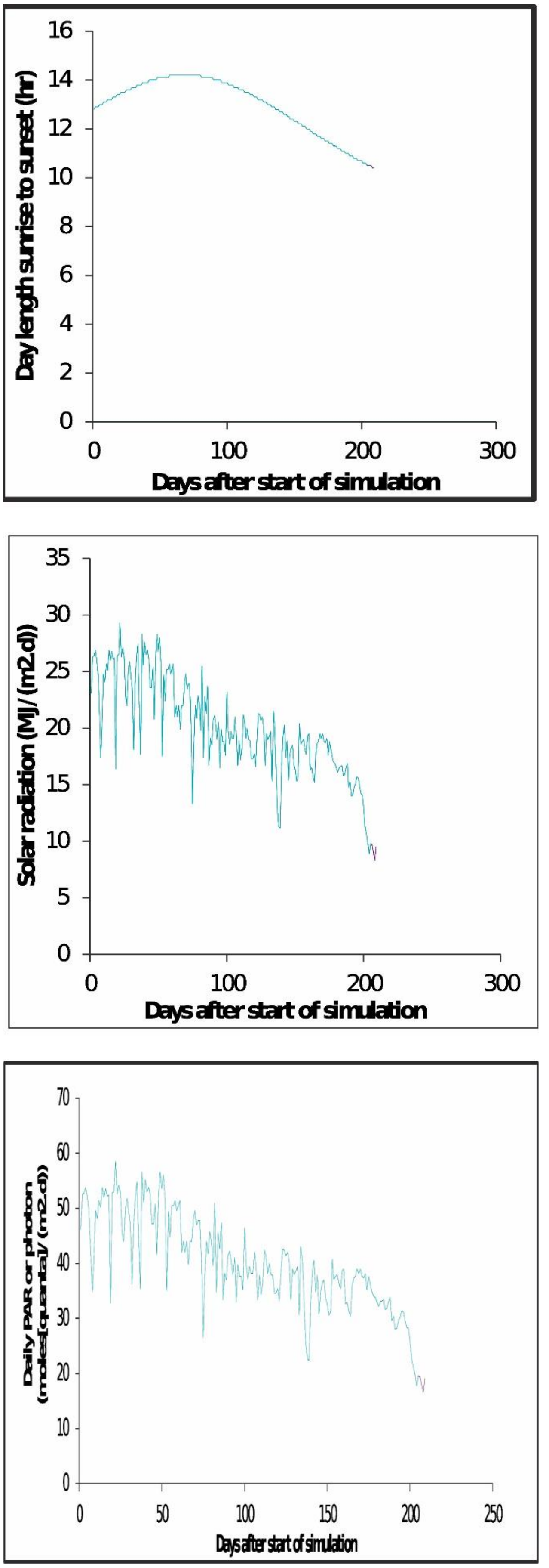

Fig. 2. Weather data (day length sunshine, daily solar radiation and daily PAR) for the growing season.

Input data and attributes of soil: The experimental site's soil was calcareous, well drained and silty loam with low organic matter (0.6–0.10). Soil was deficient in nitrogen (0.04%-0.01%) decreased in low horizon and alkaline in nature. Soil samples were collected following the standard methods and its physico-chemical properties were analyzed. Due to changing soil physio-chemical properties, the profile was divided into five partitions (0-11, 11-25, 25-65, 65-90 and 90-125 cm). Soil hydraulic properties like SRGF, SSKS, DUL, SSAT and LL were calculated using an extension in DSSAT (Table 1).

CROPGRO-Peanut model execution

Model parameterization: The model parameters are categorized with local conditions in model parameterization. The ecotype, species and cultivar files have specific information of each parameter like growth and yield. The model was validated for each treatment under study. Crop management data were recorded during the experiment for model input including planting times, nutrient application, tillage and irrigation information.

Model calibration and evaluation process

Model calibration: CROPGRO-Peanut model CROPGRO-Peanut model calibration was done on final data of peanut crop. Genetic coefficient of both cultivars BARI-2016 and BARD-479 were adjusted in the model. Estimation of genetic coefficient requires growth, phenology and yield data. Sub module GLUE and sensitivity analysis was used to select the finest crop coefficient. The model adjustment was done by matching the observed values of crop development and yield with the predicted values. Therefore, the information of phenological events (anthesis and maturity days), yield components such as LAI, Tops weight, pods yield was used for model calibration. Combination of genetic coefficient having low error was selected.

The CROPGRO-Peanut model was calibrated with 15-April sowing data which optimally utilized the resources. Model evaluation was done by running the model with remaining treatment. The model simulation was done with measured data by using GLUE sub module to drive the first subsequent parameter distribution of input data. Furthermore, the resulted distribution was used as an input to generate an ultimate posterior distribution. Genetic coefficients were adjusted within 5-20% from observed value range. Crop coefficients were adjusted one by one; it was started with anthesis and maturity days followed by growth, biomass and yield parameters (Hunt & Boote, 1998). Genetic coefficients were also evaluated by sensitivity analysis. The model predictions were compared with measured data to manually adjust the genetic coefficients. All the observed and simulated parameters were compared with the help of statistical indices to assess the model performance.

Model evaluation: Genetic coefficients of calibrated model were assessed by comparing the measured and predicted data to evaluate the reliability and accuracy of calibrated genetic coefficients. The model was run with rest of treatments to test the performance of genetic coefficients. The precision of genetic coefficients was also tested by the predicted deviation (PD), root mean square error (RMSE) and index of agreement (d).

$$\mathrm{PD} = \frac{(O_i - P_i)}{O_i} \times 100$$

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(|p'_i| + |o'_i|\right)^2}\right]$$

$$\mathrm{RMSE} = \left[\sum_{i=1}^{n}\frac{(P_i - O_i)^2}{n}\right]^{0.5}$$

where: n = number of observations, O_i= observed values, P_i= predicted values.

Results

Peanut genetic: Peanut growth and phenological variables in ecotype file were calibrated as thermal heat units to estimate accurate period between sowing and emergence with measured data. The EM-FL Parameter was critical for predicting the anthesis process. The predicted phenology was noted within the range of observed days. A linear regression (slope close to 1) and lower RMSE value between simulated and observed parameters and "d" value approaching to unity indicate a good fitted model. BARI-2016 cultivar accumulated higher amount of thermal heat units from sowing to maturity and ultimately, produced higher yield than other (Table 2). A peanut genetic coefficient associated with photosynthesis rate of leaf (LFMAX) was found responsive as it influences carbon accumulation and leaf photosynthesis hence; it was assessed in wide range for better prediction. LFMAX influence simulation of canopy growth, LAI and evapotranspiration, accordingly after considering no stress of water, nutrients, it was adjusted to 2.78 and 1.78 (mg CO_2/m^2 s^1) for BARI-2016 and BARD-479 respectively (Table 2). During model calibration the predicted and measured LAI and biomass (kg ha^{-1}) of genotypes were compared with their simulated absolute error and root mean square error (Table 3). SLAVR was adjusted at 245 cm^2/g which affects specific leaf area and LAI simulations. Measured and predicted time course LAI and TDM assessment of two genotypes during calibration confirmed good fit with convincingly high d-index (0.80-0.99) whereas, absolute error was (-0.16 to -1.19) and (-313 to -445 kg ha^{-1}) for leaf area index and biomass, respectively (Fig. 3). Moreover, RMSE values were found well (0.51-1.19 and 313-445 kg ha^{-1}) for LAI and biomass for both genotypes during peanut growth season respectively (Fig. 3).

Table 1. Physio-chemical composition and hydraulic characteristics of soil used as model input.

Depth (cm)	SLCL (%)	SLSI (%)	DUL (cm cm^{-1})	SLHW	SSAT (cm cm^{-1})	SLOC (%)	SBDM (g cm^{-3})	SSKS (cm h^{-1})	SLNI (%)	LL (cm cm^{-1})	SRGF
0–11	10	56	0.18	8.3	0.341	0.91	1.19	0.68	0.04	0.067	1
11–25	13	53	0.168	8.4	0.323	0.34	1.28	0.68	0.02	0.066	1
25–65	17	53	0.189	8.2	0.340	0.23	1.29	0.68	0.02	0.082	0.407
65-90	16	54	0.186	8.3	0.340	0.20	1.29	0.68	0.02	0.078	0.212
90-125	12	58	0.176	8.4	0.350	0.20	1.25	0.68	0.01	0.064	0.001

SLCL = Clay contents in soil, SLSI = Silt contents in soil, DUL = Drained upper limit, SLHW = Soil pH in water, SLOC = Soil organic carbon, SBDM = Soil bulk density, SSKS = Saturated hydraulic conductivity, SLNI = Soil total nitrogen concentration, LL = Lower limit, SSAT = Saturation, SRGF = Soil root growth factor

Table 2. Adjusted Genetic coefficients of cultivars during CSM-CROPGRO-Peanut model calibration.

	Cultivar coefficients description	Calibrated value		Testing range	Default value
		BARI-2016	BARD-479		
	Peanut phenology and development				
EM-FL	The time between plant emergence and flower appearance (R1) (photothermal days)	10.4	10.4	10–30	17
FL-SH	The time between the first flower and first pod (R3) (photothermal days)	7	7	7–17	7
FL-SD	The time between the first flower and first seed (R5) (photothermal days)	30.5	30.5	17–30	17
SD-PM	The time between the first seed (R5) and physiological maturity (R7) (photothermal days)	77	77	60–80	74
FL-LF	The time between the first flower (R1) and the end of leaf expansion (photothermal days)	90	90	70–90	70
	Peanut growth				
LFMAX	Maximum leaf photosynthesis rate at 30 °C, 350 vpm CO_2, and high light (mg CO_2/m^2 S^{-1})	2.78	1.78	0.7–2.8	1.10
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^{-2}g^{-1})	245	245	245–285	245
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	16	16	16–20	18
	Peanut yield				
XFRT	The maximum fraction of daily growth that is partitioned to seed + shell	1.04	1.04	0.56–1.04	0.74
SFDUR	Seed filling duration for pod cohort at standard growth conditions	34	34	22–44	38
PODUR	The time required for cultivar to reach final boll load under optimal conditions	6	9.5	6–30	15
THRSH	The maximum ratio of (seed/(seed + shell)) at maturity	98	80	72–98	78

Table 3. Calibration of the model for observed and simulated variables of phenology, growth, and yield at (15-April).

Variables	BARI-2016				BARD-479			
	Obs.	Sim.	Abs. Err.	RMSE	Obs.	Sim.	Abs. Err.	RMSE
Days to flowering	32	32	0	0	28	28	0	0
Days to maturity	157	157	0	0	154	154	0	0
Leaf area index	6.03	5.52	-0.51	0.51	5.57	4.38	-1.19	1.19
Biomass (kg ha^{-1})	9845	9532	-313	313	8865	8420	-445	445
Pod yield (kg ha^{-1})	3243	3102	-141	141	2642	2498	-144	144

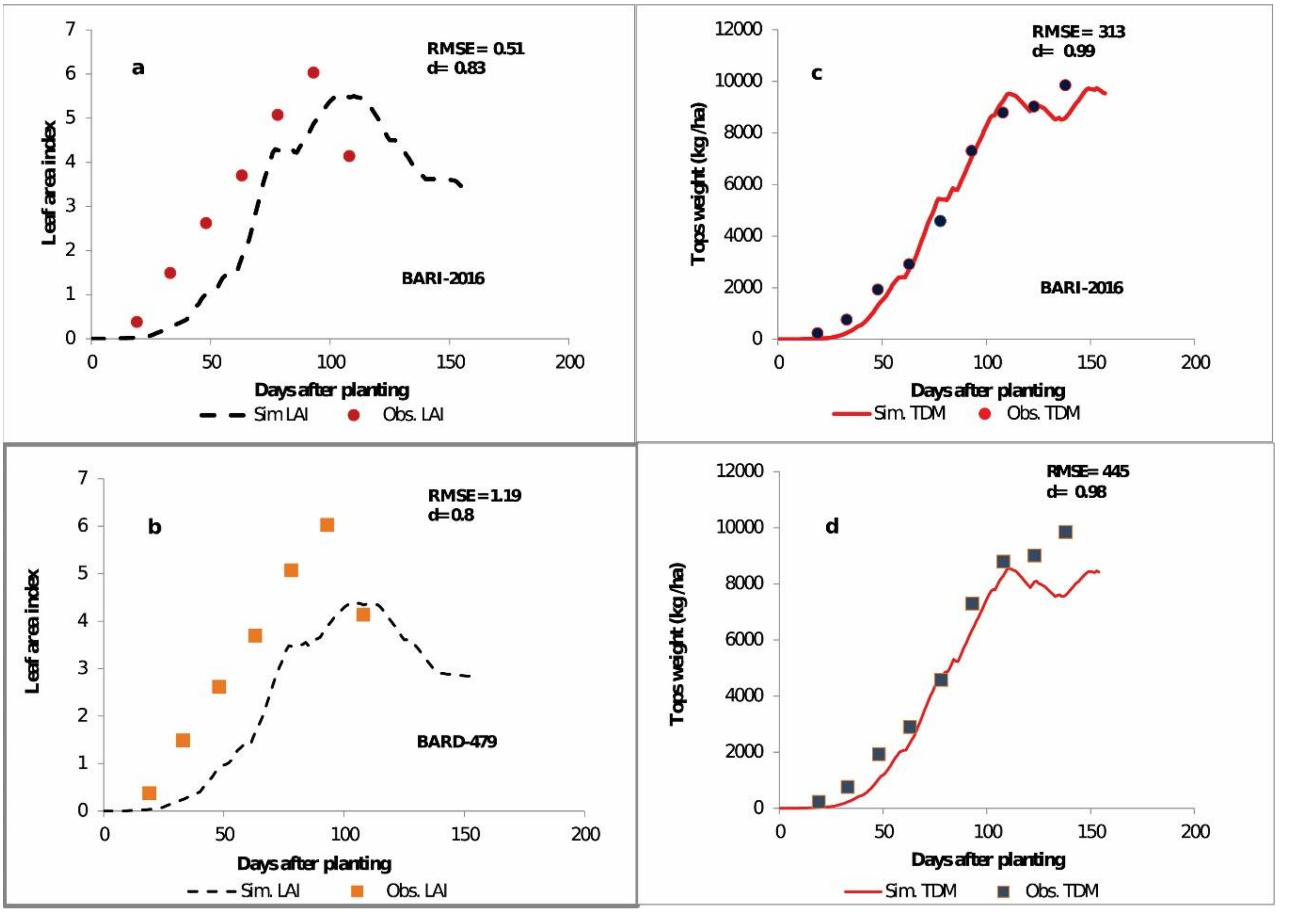

Fig. 3: Observed and simulated time series LAI (a, b), TDM (c, d) of cultivars, BARI-2016, and BARD-479 during model calibration (15 April planting).

Table 4. Comparison of observed and predicted time series biomass and leaf area index for different genotypes under temporal variation.

Treatments	Planting dates	Total dry matter (kg ha^{-1})	LAI
Cultivars		RMSE	RMSE
BARI-2016	15-April	313	0.51
	15-May	60	0.10
	15-June	489	1.22
BARD-479	15-April	445	1.19
	15-May	312	0.44
	15-June	628	0.87

Crop phenology and growth response of CROPGRO-Peanut

Model response to phenological phenophases: CROPGRO-Peanut prediction for anthesis and maturity depicted good simulations for all genotypes over temporal variation. The model under predicted the days to flowering and maturity at different sowing times for both cultivars whereas, over simulated for 15-May sowing for BARI-2016. Statistical indices were found accurate for phenological development as values of d-index were projected to unity (0.67–0.93) for days to anthesis whereas, (0.99-1) for maturity in all the treatments (genotypes and sowing times). The measured and predicted days to anthesis and maturity for all the treatments showed good fit with RMSE ranged (1.41-0.71) and (0-1), respectively (Table 4). These outcomes confirmed capability of CROPGRO-Peanut model for predicting the phenological developments of genotypes over temporal variations.

Duration of peanut growth (Leaf area index and biomass): The CROPGRO-Peanut predicted times series LAI and biomass with good fit during crop growing period for genotypes at various planting windows. Low variations were noted in BARI-2016 with lower RMSE but both cultivars had low values of RMSE (Tables 5 and 6). Model assessment revealed good simulation for leaf area index of both cultivars; RMSE was found lower (0.865-0.696) for both genotypes under all planting windows (Table 3). The model simulated RMSE value for leaf area index was (0.865) with degree of agreement (0.97) for cultivar BARI-2016 in second and third sowing times (Table 5). The model simulated RMSE value for LAI was (0.696) of genotype BARD-479 in second and third planting with d-stat value of (0) (Table 6). CSM-CROPGRO-Peanut predicted time course TDM accumulation quite well for both genotypes. Model estimated the simulated and observed time course biomass with good indices during planting times for both genotypes particularly BARI-2016 with low value (349.33) of RMSE (Table 5). A best fit between measured and predicted final biomass was observed with all treatments tested in model (Tables 5 and 6).

Table 5. Comparison of observed and simulated Pod yield (PY) for peanut cultivars under model evaluation.

Variables	Pod yield (Kg ha^{-1})					
Treatments	BARI-2016			BARD-479		
	Obs.	Sim.	PD	Obs.	Sim.	PD
15-April	3243	3102	-141	2642	2498	-144
15-May	2743	2935	192	2280	2192	-88
15-June	2385	1990	-395	1925	1359	-566
Statistical Indices	RMSE = 266.31, E =-114.67, d = 0.89			RMSE = 341, E =-266, d = 0.82		

Peanut pod yield: Pod yield (PY) was well predicted by CROPGRO-Peanut for genotypes during different planting windows with lower RMSE (266.31–341 kg ha^{-1}) at final harvest (Table 4). CROPGRO-Peanut simulation for pod yield was found well with good d-index (0.89 and 0.82) for genotypes BARI-2016 and BARD-479, respectively for all experimental treatments (Table 6). Simulated PY matched with observed.

Table 6. Simulated and observed phenology, LAI and biomass of genotype BARI-2016 and BARD-479 under evaluation of CROPGRO-Peanut model.

Cultivars	Treatments											
	Days to flowering			Days to maturity			LAI maximum			Tops wt. (kg/ha)		
	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE
BARI-2016	30	32	1.414	149	149	0	5.53	6.1	0.865	8640	8917	349.334
BARD-479	27	28	0.707	145	146	1	4.55	4.78	0.696	7692	7854	497.136

Discussion

CROPGRO-Peanut model was well parameterized with field data. Model estimated the cultivar coefficients of genotypes predicted crop phonological phenophase, growth and pod yield good with good indices. Optimum growing period and superior genetic characteristic of cultivar BARI-2016 consumed more photo thermal days and depicted high LFMAX value from sowing to maturity and showed higher growth and yield than BARD-479. Lack of appropriate growing conditions was a reason for lower yield in BARD-479 (Tables 2 and 3). SFDUR, XFRT, PODUR and THRESH genetic coefficient provided a good fit for yield and generated good simulation showed the good performance of model during calibration for all observed parameters. The genetic coefficients had variations among genotypes under temporal variation (Modala *et al.*, 2015; Paz *et al.*, 2012). The model performed well during calibration (Fig. 1 and Table 2) with low RMSE and absolute error whereas d-index had unity value (1) depicted low variation between simulated and observed data which confirmed good fit model during calibration. Genetic coefficient provided a good fit for pod yield and generated a good simulation showed that the model perform good during calibration for all the studied parameters similar to (Guled *et al.*, 2012; Halder *et al.*, 2017; Yadav *et al.*, 2012).

CROPGRO-Peanut predicted the phonological phenophases logically well with good statistical indices during evaluation (Table 5). The predicted values of model for phenological stages of peanut cultivars were close to the observed values (Guled *et al.*, 2012). Yadav *et al*., (2012) concluded that PEANUTGRO model perfectly simulated days to anthesis. The model simulation was good for BARI-2016. Degree of agreement ranges for maturity days indicated satisfactory model performance (Samui *et al.*, 2006). DSSAT model was also tested for different crops under temporal variation locally (Ahmad *et al.*, 2017; Amin *et al.*, 2017; Mubeen *et al.*, 2013; Nasim *et al.*, 2016; Samui *et al.*, 2006).

Mostly, the model simulated the time course leaf area index very well, but it over predicted for all cultivars beyond 100 days after sowing, this was during the reproductive phase. Gilbert *et al*., (2002) investigated over simulation of model at later stages for PEANUTGRO model.

The model simulated the growth and yield parameters well for BARI-2016 cultivar. Gilbert *et al*., (2002) reported that the PNUTGRO founds to be most appropriate as a predictor of good peanut leaf area index. Model predicted biomass and economic yield well for both genotypes showed the capability of CROPGRO-Peanut for assimilates transfer in plant parts. Moreover, good model indices for biomass simulation during evaluation confirmed that the model ability of predicting the partitioning the bioassimilates to different plants parts (Table 3). Anothai *et al*., (2008) conducted peanut simulation studies revealed that simulated tops weight at final harvest was fairly close to observed value and found in good agreement with CSM-CROPGRO-Peanut.

Peanut pod yield was simulated well for both genotypes under different plantings. Peanut cultivar BARI-2016 planted 15-April showed good response to environmental conditions exhibiting excellent growth and pod yield. CROPGRO-Peanut also showed good simulation with the observed range of pod yield (Table 3).

Generally, model simulated well for temporal variations for pod yield, as good simulation of the CROPGRO-Peanut was also reported by (Halder *et al.*, 2017), they reported an accurate prediction of model for yield at maturity in an experiment. It exhibits that CROPGRO-Peanut model can accurately predict the yield under broad range of temporal variations.

Conclusions

CROPGRO-Peanut model was well calibrated by broad range of observation as growth, phonological phases and yield and tested with other observed data for model accuracy assessment and evaluation of genetic coefficients. The CROPGRO-Peanut was found capable for simulating all tested parameters of genotypes under wide range of plating dates during evaluation. The model simulates the peanut phenology, growth and pod yield. Model predicted reasonably well to biomass and yield changes however the model under predicted yield for all the sowing times except one (15-May) for BARI-2016. Results showed the CROPGRO-Peanut have potential and ability to develop management strategies for decision support and model also suggested appropriate sowing time for better decision aid to improve peanut production. Cultivars BARI-2016 and BARD-479 performed well with higher yield at 15-April sowing primarily due to optimum growing period by utilizing appropriate environmental conditions, showed good growth at phenological development. Delayed sowing (15-June) resulted in 27% pod yield penalty and poor growth indices due to sub optimal and short growing period. Model confirmed the cultivars growth at different sowing times and higher yield was obtained at 15-April sowing. It is suggested for the farmers to cultivate the peanut crop at mid-April for better yield and sustainable production. In future, calibrated CROPGRO-Peanut model can be used for developing appropriate adaptation and management strategies under future impact of climate change.

Acknowledgements

The authors would like to extend their sincere appreciation to the Researchers Supporting Project Number (RSP-2022/182), King Saud University, Riyadh, Saudi Arabia.

References

Ahmad, N. and M. Rahim. 2007. Evaluation of promising groundnut (*Arachis hypogaea* L.) varieties for yield and other characters. *J. Agri. Res*., 45: 185-189.

Ahmad, S., Q. Abbas, G. Abbas and Z. Fatima. 2017. Quantification of climate warming and crop man-agement impacts on cotton phenology. *Plants*, 6**(1): 7.**

Amin, A., W. Nasim, M. Mubeen, M. Nadeem, L. Ali, M. Rehman, H. Hammad, S. Wajid and S. Fahad. 2017. Evaluating the performance of CSM-CROPGRO-cotton model for phosphorus use in cotton crop under climatic conditions of Southern Punjab, Pakistan. *Environ. Sci. Pollut. Res*., 24: 5811-5823.

Anonymous. 2017. Economic Survey of Pakistan 2016-17. Ministry of Food, Islamabad, editor. Government of Pakistan.

Anonymous. 2021. Peanut area, yield and production. United States Foreign Agricultural Services, editor. USDA.

Anothai, J., A. Patanothai, S. Jogloy, K. Pannangpetch, K. Boote and G. Hoogenboom. 2008. A sequential approach for determining the cultivar coefficients of peanut lines using end-of-season data of crop performance trials. *Field Crops Res*., 108: 169-178.

Boote, K., J. Jones, G. Hoogenboom, G. Wilkerson and S. Jagtap. 1987. PNUTGRO v1. 0, Peanut crop growth and yield model. *Technical documentation. Department of Agronomy and Agricultural Engineering, University of Florida, Gainesville, FL*.

Boote, K., J. Jones and P. Singh. 1992. Modeling growth and yield of groundnut.

Boote, K. and N. Pickering. 1994. Modeling photosynthesis of row crop canopies. *Hort. Sci*., 29: 1423-1434.

Craufurd, P., P. Prasad and R. Summerfield. 2002. Dry matter production and rate of change of harvest index at high temperature in peanut. *Crop Sci*., 42: 146-151.

Damahe, A.R., S.B. Satpute and N.D. Parlawar. 2018. Growth and yield of cotton as influenced by different date of sowing and varieties *Int. J. Curr. Microbiol. App. Sci.,* 6: 2622-2628.

Doorenbos, J. 1975. Guidelines for predicting crop water requirements. *Food and Agriculture organization. Rome, Irrig. Drain. pap.* 24.

Gilbert, R., K. Boote and J. Bennett. 2002. On-farm testing of the PNUTGRO crop growth model in Florida. *Peanut Sci*., 29: 58-65.

Guled, P., A. Shekh, H. Patel, V. Pandey and G. Patel. 2012. Validation of CROPGRO-peanut model in middle Gujarat agroclimatic region. *J. Agrometeorol*., 14: 154-157.

Halder, D., R.K. Panda, R.K. Srivastava and S. Kheroar. 2017. Evaluation of the CROPGRO-Peanut model in simulating appropriate sowing date and phosphorus fertilizer application rate for peanut in a subtropical region of eastern India. *The Crop J*., 5: 317-325.

Hammer, G. and D. Jordan. 2007. An integrated systems approach to crop improvement. *Drought Front. in Rice*, 189-207.

Hammons, R.O., D. Herman and H.T. Stalker. 2016. Origin and early history of the peanut. In: Peanuts. *Elsevier*, 1-26.

Hoogenboom, G., J. Jones, P. Wilkens, C. Porter, W. Batchelor, L. Hunt, K. Boote, U. Singh, O. Uryasev and W. Bowen. 2004. Decision support system for agrotechnology transfer version 4.0. *University of Hawaii, Honolulu, HI (CD-ROM).*

Hoogenboom, G., J. Jones, P. Wilkens, C. Porter, K. Boote, L. Hunt, U. Singh, J. Lizaso, J. White and O. Uryasev. 2015. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6. DSSAT Foundation, Prosser, Washington.

Hunt, L. and K. Boote. 1998. Data for model operation, calibration, and evaluation. In Understanding options for agricultural production. Springer, 9-39.

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

Khosravi, V., G. Khajoie-Nejad, G. Mohammadi-Nejad and K. Yousefi. 2010. The effect of different sowing dates on yield and yield components of wheat (*Triticum aestivum* L.) cultivars. *Int. J. Agron. Plant Prod.,* 1: 77-82.

Modala, N.R., S. Ale, N. Rajan, C.L. Munster, P.B. DeLaune, K.R. Thorp, S.S. Nair and E.M. Barnes. 2015. Evaluation of the CSM-CROPGRO-Cotton model for the Texas rolling plains region and simulation of deficit irrigation strategies for increasing water use efficiency. *Transac. ASABE*. 58: 685-696.

Mubeen, M., A. Ahmad, A. Wajid, T. Khaliq and A. Bakhsh. 2013. Evaluating CSM-CERES-Maize Model for Irrigation Scheduling in Semi-arid Conditions of Punjab, Pakistan. *Int. J. Agri. & Biol*., 15.

Nasim, W., A. Ahmad, H. Belhouchette, S. Fahad and G. Hoogenboom. 2016. Evaluation of the OILCROP-SUN model for sunflower hybrids under different agro-meteorological conditions of Punjab, Pakistan. *Field Crops Res*., 188: 17-30.

Ortega, R. and R. Ochoa. 2003. El cacahuate y supotencialproductivoen México [The peanuts and their potential production in Mexico]. *Claridades Agropecuarias*, 4: 3-15.

Paz, J.O., P. Woli, A.G.Y. Garcia and G. Hoogenboom. 2012. Cotton yields as influenced by ENSO at different planting dates and spatial aggregation levels. *Agri. Sys*., 111: 45-52.

Qasim, M., M. Khalid, A. Sayyed, I. Din, K. Hayat and S.A. Jan. 2016. Phytochemical potentials and medicinal uses of twenty-four selected medicinal plants from Swabi, Pakistan. *J. Pure & Appl. Agri*., 1: 49-58.

Ritchie, J. 1985. Description and performance of CERES wheat: A user-oriented wheat yield model. *ARS Wheat Yield Project*, 159-175.

Saleem, M.H., S. Ali, M.F. Seleiman, M. Rizwan, M. Rehman, N.A. Akram, L. Liu, M. Alotaibi, I. Al-Ashkar and M. Mubushar. 2019. Assessing the correlations between different traits in copper-sensitive and copperresistant varieties of jute (*Corchorus capsularis* L.). *Plants*, 8(12): 545.

Saleem, M., S. Ali, M. Rehman, M. Rana, M. Rizwan, M. Kamran, M. Imran, M. Riaz, M. Hussein, A. Elkelish and L. Lijun. 2020a. Influence of phosphorus on copper phytoextraction via modulating cellular organelles in two jute (*Corchorus capsularis* L.) varieties grown in a copper mining soil of hubei province, Xhina. *Chemosphere*. DOI 10.1016/j.chemosphere.2020.126032.

Saleem, M.H., S. Fahad, M. Adnan, M. Ali, M.S. Rana, M. Kamran, Q. Ali, I.A. Hashem, P. Bhantana, M. Ali and R.M. Hussain. 2020b. Foliar application of gibberellic acid endorsed phytoextraction of copper and alleviates oxidative stress in jute (*Corchorus capsularis* L.) plant grown in highly copper-contaminated soil of china. *Environ. Sci. & Pollut. Res*., Available from https://doi.org/10.1007/s11356-020-09764-3. DOI 10.1007/s11356-020-09764-3.

Saleem, M.H., S. Fahad, S.U. Khan, S. Ahmar, M.H.U. Khan, M. Rehman, Z. Maqbool and L. Liu. 2020c. Morphophysiological traits, gaseous exchange attributes, and phytoremediation potential of jute (*Corchorus capsularis* L.) grown in different concentrations of copper-contaminated soil. *Ecotoxicol. & Environ. Safety*, 189: 109915.

Saleem, M.H., S. Fahad, S.U. Khan, M. Din, A. Ullah, A.E.L. Sabagh, A. Hossain, A. Llanes and L. Liu. 2020d. Copperinduced oxidative stress, initiation of antioxidants and phytoremediation potential of flax (*Linum usitatissimum* L.) seedlings grown under the mixing of two different soils of china. *Environ. Sci. & Pollut. Res*., 27(5): 5211-5221. Available from https://doi.org/10.1007/s11356-019-07264- 7. DOI 10.1007/s11356-019-07264-7.

Saleem, M.H., M. Kamran, Y. Zhou, A. Parveen, M. Rehman, S. Ahmar, Z. Malik, A. Mustafa, R.M.A. Anjum and B. Wang. 2020e. Appraising growth, oxidative stress and copper phytoextraction potential of flax (*Linum usitatissimum* L.) grown in soil differentially spiked with copper. *J. Environ. Manag*., 257: 109994.

Samui, R., R. Balasubramanian, P. Kulkarni, A. Shekh and P. Singh. 2006. Use of PNUTGRO model for optimization of sowing date and plant spacing to maximize yield of groundnut (*Arachis hypogaea* L.). *Mausam*, 57: 307.

Tiwari, K., S. Rayamajhi, R. Pokharel and M. Balla. 2014. Determinants of the climate change adaptation in rural farming in Nepal Himalaya. *Int. J. Multidiscip. & Curr. Res*., 2: 234-240.

Yadav, S., H. Patel, G. Patel, M. Lunagaria, B. Karande, A. Shah and V. Pandey. 2012. Calibration and validation of PNUTGRO (DSSAT v4. 5) model for yield and yield attributing characters of kharif groundnut cultivars in middle Gujarat region. *J. Agrometeorol., Special*: 24-29.

(Received for publication 20 July 2021)