Simulation of summer groundnut for yield and yield attributing traits using CROPGRO-Peanut model

Abstract

Field experiments were carried out at College farm, B. A. College of Agriculture, Anand Agricultural University, Anand.The DSSAT v 4.6 CROPGRO-Peanut model was used to predict the phenology of groundnut crop under combinations of three sowing dates and four groundnut cultivars. The model was calibrated with a 2015 dataset of growth and phenological parameters for estimating the genetic coefficients of all four cultivar and was validated with a 2016 dataset of the same parameters. Result found that the model was able to reasonably simulate the pod yield, kernel yield and haulm yield with per cent error ranging (± 10.06) between observed and simulated value for all cultivars under different sowing dates Simulations of yield and yield attributing characters using the calibrated model were found to be quite accurate.

Key words: Calibration, validation, groundnut, pod yield

Introduction

Crop growth simulation models are useful tools for considering the complex interactions between a range of factors that affect crop performance, including weather, soil properties and management. Crop modeling began with the computer age and the first models attempted to simulate individual processes within a plant such as light interception in crop canopies (Loomis and Williams, 1963). Subsequently different models were developed to simulate plant growth and development for many different crops. Individual crop models have been combined into comprehensive programs allowing modeling of various crops in rotation. Before a crop model can provide accurate and reliable results, a researcher must first ensure that the model has been calibrated and that it will accurately simulate what it was designed to predict. Also, the model must be validated to the conditions for which the researcher wants to simulate. (Boote *et al.,* 1996). One of the most widely used and researched systems is the Decision Support System for Agrotechnology Transfer (DSSAT) model. DSSAT is a result of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project supported by the U.S. Agency for International Development from 1983 to1993. DSSAT was designed so that users can input, organize, store data on crops, soils, and weather, can retrieve, analyze and display data, can calibrate and evaluate crop growth models and can evaluate different management practices at a site (Jones *et al.*, 1998). It provides users with easy access to data bases of soil, crop, and climatic data; individual crop models; weather generators; expert systems; strategy evaluation; and utility programs for formatting, retrieving, and graphing information (Singh, 1989). The model simulates the impact of the main environmental factors such as weather, soil type, and crop management on crop growth, development and yield. Input requirements for DSSAT include weather, soil condition, plant characteristics and crop management. The minimum weather input requirements of the model are daily solar radiation, maximum and minimum temperatures and precipitation. Soil inputs include albedo, evaporation limit, mineralization, photosynthesis factors, pH, drainage and runoff coefficients. Management input information includes plant population, planting depth, and date of planting. Latitude is required for calculating day length. The model simulates phenological development, biomass accumulation, partitioning, leaf area index, root, stem, leaf-growth, the water and N-balance from planting until harvest at daily or desire time steps. Under DSSAT there are various groups of models viz., CERES models for cereals (barley, maize, sorghum, millet, rice and wheat); the CROPGRO models for legumes (dry bean, soybean, peanut and chickpeamodels for root crops (cassava, potato) and other crops (sugarcane, tomato, sunflower and pasture). Hence, decision Support System for Agrotechnology Transfer (DSSAT) model has been found one of the most efficient decision support system (Hoogenboom *et al.*, 2004). The objective of the present study was to Calibration and validation of CROPGRO-peanut model for summer groundnut.

Material and methods

The field experiment on groundnut was carried during the summer season of 2015 and 2016 at Agronomy Farm, B. A. College of Agriculture, Anand Agricultural University, Anand (Latitude of $22^0$35'N and longitude of 72^0 55'E and at an elevation of 45.1m above mean sea level). The experimental site located near to the agrometeorological observatory and falls in the middle Gujarat Agro-ClimaticZone-III. The experiment was laid out in split plot design with four replications and the details of treatments consist of four varieties of groundnut *viz.*, GG-2, GG-20, GJG-31 and TG-26 were sown on three different dates *viz.*, D_1 early date (31^{th} January), D_2 normal date (15^{th} February) and D_3 late date (2^{nd}March). All their commended package practices for spring season were followed and care was taken against biotic stresses.

For calibration of the CROPGRO-Peanut model, data on plant growth and development, soil characteristics, weather and crop management were collected as required for determining the cultivar coefficients of V_1-GG-2, V_2-GG-20, V_3-GJG-26 and V4-TG-26and follow the procedures described in IBSNAT and Hoogenboom *et al.,* (1999). The genetic coefficients were calibrated based on collected data of from field experimental conducted during summer season of 2015 at Anand condition and validated with data set of summer seas on 2016. The cultivar coefficients were estimated by repeated iterations by running the GLUE coefficient calculator using the observed yield data for all the sowing environments until a close match between simulated and observed phenology and yield was obtained. Calibrated genetic coefficients of all four cultivars of groundnut given in table1.

Results and discussion

Pod yield (kg ha^{-1})

The observed and simulated value of pod yield under different dates of sowing and cultivars of groundnut are presented in (Table- 2). The results revealed that the observed value of pod yield under different dates of sowing were 1811 to 2123 kg ha^{-1} while the simulated value was 1641 to 2348 kg ha^{-1} with deviation ranging between -9.4 to 12.1 percent. The lowest deviation was observed in third dates of sowing. *i.e* 02nd March. In case of different cultivars close simulation is obtained *i.e* the observed pod yield was 1772 to 2110 kg ha^{-1} while model simulated 1853 to 2285 kg ha^{-1} with deviation ranging between 2.8 to 6.4 per cent. The average error as computed by r, MAE, MBE, RMSE and PE were 0.85, 19.38, 19.38, 171.74 and 8.75 respectively indicating a fairly good simulation. Similar result reported by Pandey *et al.* (2001) by CROPGRO model for *kharif* groundnut.

Kernel yield (kg ha^{-1})

The observed and simulated kernel yield (kg ha^{-1}) under different dates of sowing and cultivars are shown in (Table-2). It is found that the model simulated value to kernel yield was 1350 to 1580 (kg ha^{-1}) were very close to the observed value 1234 to 1439 kg ha^{-1} under different dates of sowing. Among the cultivars close simulation is obtained *i.e.* the observed kernel yield were range between 1232 to 1455 (kg ha^{-1}) while model simulated 1396 to 1556 (kg ha^{-1}) with deviation ranging between 7.0 to 13.3 per cent. The average error as computed by r, MAE, MBE, RMSE and PE were 0.96, 10.26, 10.26, 99.33 and 6.77 respectively.

Haulm yield (kg ha^{-1})

The observed and simulated haulm yield (kg ha^{-1}) under different dates of sowing and cultivars are presented in (Table-2). It is found that the model simulated haulm yield under different dates of sowing were ranging between 3959 to 4711(kg ha^{-1}) the observed haulm yield were 4684 to 5263 (kg ha^{-1}) with deviation ranging between -10.5 to -15.6 per cent.

Among the cultivars observed value of haulm yield were 4576 to 5423 (kg ha^{-1}), while model simulated 3868 to 4706 (kg ha^{-1}) with deviation ranging between -11.7 to -15.6 per cent. The model has overestimated haulm yield under most of the treatments except. The average error as computed by r, MAE, MBE, RMSE and PE were 0.96, 57.50, -57.50, 500.84 and 10.06 respectively.

Harvest index

The comparison between observed and simulated value of harvest index under different dates of sowing and cultivars of groundnut are presented in (Table-2). The results revealed that the observed value harvest index under different dates of sowing were 28.0 to 28.7 per cent while the simulated value was 34.0 to 38.8 percent with deviation ranging between 21.5 to 35.5 per cent. In case of different cultivars observed value to harvest index were 27.5 to 29.7 % while model simulated 34.0 to 37.3 % with deviation ranging between 17.6 to 33.7 per cent. The model was found to overestimate the harvest index under most of the treatments except. The statistical test criteria computed by r, MAE, MBE, RMSE and PE were 0.23,0.63, 0.63, 5.72 and 20.20 respectively.

Conclusions

Overall results shows that the calibrated CROPGRO- Peanut model performance was somewhere underestimated or overestimated but found within quite acceptable limits for simulation of yield and yield attributing characters (*viz.*, pod yield, kernel yield and haulm yield) with error percent less than 10.06. but for model performance for prediction of harvest index was not good with error percent more than 20.0. Hence, this model can be used for simulating the pod yield, kernel yield and haulm yield of groundnut cultivars.

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Details of the AI usage are given below:

1.

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Table 1: Genetic coefficients for cultivars GG 2, GG 20, GJG 31 and TG 26

Parameter	GG-2	GG-20	GJG-31	TG-26
CSDL	11.84	11.84	11.84	11.84
PPSEN	0.00	0.00	0.00	0.00
EM-FL	19.5	19.5	18.5	18.5
FL-SH	11.0	10.0	8.0	11.0
Fl-SD	20.0	19.0	18.0	18.0
SD-PM	40.00	39.00	35.00	36.00
FL-LF	89.00	87.00	80.00	80.00
LFMAX	1.50	1.50	1.48	1.40
SLAVR	270	260	240	240
SIZLF	16.0	16.0	16.0	16.0
XFRT	0.84	0.84	0.84	0.80
WTPSD	0.155	0.200	0.200	0.200
SFDUR	24.0	22.0	24.0	22.0
SDPDV	1.46	1.65	1.46	1.55
PODUR	3.0	4.0	4.0	4.0
THRSH	76.0	74.0	74.0	80.0
SDPRO	.270	.270	.270	.270
SDLIP	.510	.510	.510	.510

(Mote, *et al* .2018)

Table 2: Test criteria in evaluation of model with respect to yield and yield components

Treatment	Pod yield (kg ha^{-1})			Kernel yield (kg ha^{-1})			Haulm yield (kg ha^{-1})			Harvest index		
	Obs.	Sim.	D (%)	Obs.	Sim.	D (%)	Obs.	Sim.	Er. (%)	Obs.	Sim.	D (%)
D_1 (31st January)	1953	2184	12.1	1325	1444	9.0	4978	4221	-15.2	28.3	34.4	22.1
D_2 (15th February)	2123	2348	10.7	1439	1580	10.0	5263	4711	-10.5	28.7	38.8	35.5
D_3 (02nd March)	1811	1641	-9.4	1234	1350	9.6	4684	3959	-15.6	28.0	34.0	21.5
V_1 (GG 2)	2021	2084	2.8	1346	1475	9.4	5323	4706	-11.7	27.5	34.0	23.7
V_2 (GG 20)	2110	2208	4.4	1455	1556	7.0	5423	4644	-14.4	28.1	36.7	30.6
V_3 (GJG 31)	1945	2285	6.4	1297	1404	8.5	4576	3969	-13.4	29.7	35.0	17.6
V_4 (TG 26)	1772	1853	4.2	1232	1396	13.3	4577	3868	-15.6	28.0	37.3	33.7
r	0.85			0.96			0.96			0.23		
MAE	19.38			10.26			57.50			0.63		
MBE	19.38			10.26			-57.50			0.63		
RMSE	171.74			99.33			500.84			5.72		
PE	8.75			6.77			10.06			20.20		

Where, Obs: observed, Sim: simulated, D: deviation. (%), r: correlation coefficient, MAE: mean absolute error, MBE: mean bias error, RMSE: root mean square error, PE: % error.