

Development of Minimum Soil and Plant Data Set for DSSAT Crop Simulation Model for Pigeonpea Cultivars under Varied Dates of Sowing

Lingaraj Huggi, Shivaramu H. S., Thimmegowda M. N.,
 Manjunatha M. H.

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Abstract Traditional agronomic experiments conducted at particular points in time and space are site, season specific and time consuming. To overcome this, many computer based software have been developed called as Crop Simulation Models. Among the numerous crop growth models, the most widely used is the Decision Support for Agro Technology Transfer (DSSAT) model, which is designed to simulate growth, development, and yield of a crop along with changes in soil water, carbon and nitrogen under the system over time. An attempt was made to develop

minimum data set for two pigeonpea cultivars (BRG-1 and BRG-2) from the observations recorded by conducting an experiment at UAS, GKVK, Bengaluru during 2017-18 and 2018-19. The results of 2018 revealed that the model underestimated the yields under the crop sown during 30th May (-108.4%) and overestimated the yields under the crop sown during 10 and 24th August (54.2% and 15.1%, respectively). Among the two varieties, model overestimated the yields for BRG-1 (3.7%) compared to BRG-2 (-29.8%). During 2018-19, model underestimated the yield for 10th May and 1st June sown crop (-41.0% and -74.9%, respectively) as compared crop sown on 12th July (250.7%). Among the two varieties, BRG-2 recorded lower error (1.6%) as compared to BRG-1 (88.3%). Statistical evaluation of experimental yield using mean error (ME), root mean square error (RMSE), coefficient of residual mass (CRM) and modelling efficiency (EF) revealed that, simulation of BRG-1 grain yield was in good agreement with the observed values with comparatively low ME (3.6 and 46.0 during 2017-18 and 2018-19, respectively) indicating the variety is calibrated well among the two varieties. Minimum average RMSE (3511.2) values were recorded indicating less deviation of simulated values from observed values. Positive CRM (0.048) values were recorded indicating underestimation of yields by the model, requiring some more calibration by field experimentation.

Lingaraj Huggi*
 PhD Scholar, Department of Agronomy, UAS, GKVK, Bengaluru 560065, India

Shivaramu H. S.
 Prof and Head, AICRP on Arrometeorology, UAS, GKVK, Bengaluru 560065, India

Thimmegowda M. N.
 Senior Scientist, (Agronomy), AICRP for Dryland Agriculture, UAS, GKVK, Bengaluru 560065, India

Manjunatha M. H.
 Junior Agronomist, AICRP on Arrometeorology, UAS, GKVK, Bengaluru 560065, India
 e-mail: lingarajhuggi@gmail.com
 *Corresponding author

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Introduction

Information needs for agricultural decision making at all levels are increasing rapidly due to increased demands for agricultural products and increased pressures on land, water, and other natural resources. The generation of new data through traditional agronomic research methods are insufficient to meet these increasing needs. Traditional agronomic experiments are conducted at particular points in time and space, making results site and season-specific, time consuming and expensive. Unless new data and research findings are put into formats that are relevant and easily accessible, they may not be used effectively. In order to overcome these, many computer based software have been developed called as Crop Simulation Models. Crop Simulation Models integrate the effects of soils, weather, management, genetics and pests on daily growth and can be used to gain insight into spatial yield variability. Among the numerous crop growth models, the most widely used is the Decision Support for Agro Technology Transfer (DSSAT) model, which is designed to simulate growth, development and yield of a crop growing on a uniform area of land, as well as the changes in soil water, carbon and nitrogen that take place under the cropping system over time. DSSAT has been in use by researchers all over the world, for various purposes, including, climate change impact studies, sustainability research and precision agriculture, and is well validated for a number of regions and crops (Hoogenboom 2000). The data requirements include weather inputs, soils classification and crop management practices. There are different methods to use the DSSAT family of crop growth models to understand causes of spatial yield variability, conduct yield gap analysis for factors that limit yield and estimate the economic consequences of moving from uniform to spatially variable management. Though different workers have been evaluated the CROPGRO model for other crops viz. Suriharan et al. (2008), Patel et al. (2013) validated the CROPGRO model for groundnut. Bhatia et al. (2008) for soybean and Srivastava et al. (2016) for chickpea. There is limited work on CROPGRO Pigeonpea modelling so in this paper we are making an attempt to discuss methodologies for the preparation of necessary input files for DSSAT to be used to simulate spatially variable

Table 1. Dates of sowing of pigeonpea.

Date of sowing	Year	
	2017-18	2018-19
D ₁	30 May	16 May
D ₂	10 August	1 June
D ₃	24 August	12 July

crop development.

Materials and Methods

The input data required for running the Crop Simulation Model (CROPGRO-Pigeonpea) of DSSAT (version 4.6.1) includes crop data, daily weather data, soil data and crop specific genetic coefficients.

Crop data (management data)

To evaluate the model, field experiments were conducted at ZARS, GKVK, UAS, Bengaluru (Latitude 13° 05' N and Longitude 77° 34' E and altitude of 924 meters above MSL) with three dates of sowing (Table 1) and two cultivars (V₁ : BRG-1 and V₂ : BRG-2) during *khariif* seasons of 2017-18 and 2018-19. Soil and crop management practices are same for all treatments as per UAS, Bengaluru package of practices.

For generation of genetic coefficients, observations were made in order to record the number of days taken for attaining a particular phenological stage. Later genetic coefficients were calculated according to the description given in the model (Table 2) repeated interactions are done until a close match between simulated and observed phenology and yield was obtained in respective treatments.

Weather data

The model required maximum temperature (T_{max}), minimum temperature (T_{min}), rainfall (RF) and solar radiation (SRAD). The daily weather data from 2017-18 to 2019-2018-18 were collected from agrometeorology observatory situated nearby (within 100 meter) the experimental plots. Sunshine hours (h) were converted to SRAD (MJ/m²/d) using the filling missing value technique available in the weatherman module present within the model.

Table 2. Genetic coefficients used for calibration of the model.

Coeff	Definitions	Values	
VAR#	Identification code or number for a specific cultivar	GKVK 02	GKVK 03
VAR-name	Name of cultivar	BRG-1	BRG-2
EXPNO	Number of experiments used to estimate cultivar parameters	PP0002	PP0002
ECO#	Code for the ecotype to which this cultivar belongs (see *eco file)	-	-
CSDL	Critical short day length below which reproductive development progresses with no day length effect (for short day plants) (hour)	12.89	12
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (1/h)	0.56	0.35
EM-FL	Time between plant emergence and flower appearance (R_1) (photo thermal days)	29.3	29.3
FL-SH	Time between first flower and first pod (R_2) (photo thermal days)	9.10	9.10
FL-SD	Time between first flower and first seed (R_3) (photo thermal days)	25.8	25.8
SD-PM	Time between first seed (R_4) and physiological maturity (R_5) (photo thermal days)	29.01	29.01
FL-LF	Time between first flower (R_1) and end of leaf expansion (photo thermal days)	23.23	23.23
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 ppm CO ₂ and high light (mg CO ₂ /m ² /s)	0.9	1.1
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm ² /g)	320.0	320.0
SIZLF	Maximum size of full leaf (three leaflets) (cm ²)	171.4	172.4
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.81	0.8
WTPSD	Maximum weight per seed (g)	0.26	0.14
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photo thermal days)	63.2	45.0
SDPDV	Average seed per pod under standard growing conditions (#/pod)	5.0	5.0
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photo thermal days)	11.3	22
THRSH	Threshing percentage. The maximum ratio of (seed/(seed+shell)) at maturity. Causes seeds to stop growing as their dry weight increases until shells are filled in a cohort	76.0	70.0
SDPRO	Fraction protein in seeds (g (protein)/g (seed))	0.223	0.225
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.015	0.015

Soil data

The layer wise soil physical composition (sand, silt and clay percentage), textural class, physical constrains (bulk density), soil chemical properties (soil pH, cation exchange capacity, organic carbon content and total N content) and soil albedo from the experimentation site studied and were recorded as indicated below (Table 3).

Model evaluation

The statistical approach of model evaluation, involved the use of the following model evaluators as proposed by Loague and Green (1991) : The relative mean error (ME) percentage, root mean square error (RMSE), coefficient of residual mass (CRM) and modelling efficiency (EF).

Table 3. Soil profile parameters used for calibration of the model.

Master horizon	Depth (cm)	Clay %	Silt %	Stone %	Organic carbon %	pH in water	CEC (cmol/kg)	Total nitrogen (%)
A _p	0-12	22.00	10.60	1.00	0.45	5.03	9.71	0.079
A _z	12-24	31.58	10.20	0.50	0.40	5.00	11.23	0.078
B _t	24-42	41.40	10.70	1.00	0.36	5.82	11.20	0.077
B _{t1}	42-70	42.30	11.80	1.00	0.46	6.36	12.19	0.077
B _{t2}	70-108	44.60	12.60	1.00	0.30	6.84	13.17	0.077
B _{t3}	108-36	40.70	13.50	1.00	0.26	7.25	13.04	0.077
BC	136-176	44.40	17.10	1.00	0.21	7.92	15.00	0.077
B _c C	176-210	57.50	16.80	1.00	0.21	8.54	17.07	0.077

Mean error (ME) percentage

It is calculated as :

$$ME = 100 \frac{\left(\frac{1}{n} \sum_{i=1}^n (P_i - O_i) \right)}{\bar{O}}$$

Coefficient of residual mass (CRM)

The CRM is a measure of the tendency of the model to over estimate or under estimate the measurements. Positive values for CRM indicate that the model under estimates the measurements and negative values for CRM indicate a tendency to over estimate. The CRM is defined by :

$$CRM = \left(\frac{\sum_{i=1}^n (O_i) - \sum_{i=1}^n (P_i)}{\sum_{i=1}^n (O_i)} \right)$$

Root mean square error (RMSE)

The RMSE values show how much the simulations over estimate or underestimate the measurements. RMSE tests the accuracy of the model and set of RMSE values were calculated. A smaller RMSE indicated less deviation of the simulated from the observed values.

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

Modelling efficiency (EF)

The EF value compares the simulated values to the average value of the measurements. A negative EF value indicates that the average value of the measurements gives a better estimate than the simulated values.

$$EF = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})^2 - \sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \right)$$

Where, P_i = Yield predicted by the model, O_i = Yield observed, \bar{O} = Mean of all O_i values, n = Number of samples.

Results and Discussion

The seed yield of two cultivars BRG-1 and BRG-2, three dates of sowing (D_1 , D_2 and D_3 with two years (2017-18 and 2018-19) model under estimated compared to the observed yield (Table 4).

During 2017-18 model under estimated the yields under the crop sown during first date of sowing (negative values of error, -108.4%) and over estimated the yields under the crop sown during second and third dates of sowing (positive value of error, 54.2% and 15.1% for D_2 and D_3 , respectively). Among the two varieties, model over estimated the yields for BRG-1 variety (V_1 , 3.7%) compared to BRG-2 variety (V_2 , -29.8%). Among the interactions, BRG-2 variety sown during August-24 recorded least error (D_3V_2 , 14.3%) compared to all other treatments (Table 5).

During 2018-19, model under estimated the yield for 1st and second date of sowing (-41.0% and -74.9% error for D_1 and D_2 , respectively) as compared to third date of sowing (250.7%). Among the two varieties sown, BRG-2 recorded lowest error (1.6%) as compared to BRG-1 (88.3%). Among the interactions, BRG-2 variety sown on July-12 recorded least error (D_3V_2 , 224.7%).

These results were due to the genetic coefficients are not yet stabilized. Because, Process of stabilization requires minimum of four to five years experimental data under normal weather situation. Similar results are found for rice by Sreenivas and Reddy (2013). Yadav et al. (2016), Singh et al. (2014) also observed that the yield and yield attributes of groundnut as simulated by PNUTGRO model showed lesser efficiency when number of experimental years were minimum. Having said this, first year of research period being drought hit added to the lower efficiency of the model. Srivastava et al. (2016) observed that the crop models were calibrated for unlimited water conditions. However, such results need to be

Table 4. Seed yield of two varieties under three dates of sowing.

Year	Variety	Date of sowing					
		D ₁		D ₂		D ₃	
		Observed yield (kg/ha)	Simulated yield (kg/ha)	Observed yield (kg/ha)	Simulated yield (kg/ha)	Observed yield (kg/ha)	Simulated yield (kg/ha)
2017-18	V ₁	2141.0	1492.0	176.5	1023.0	85.38	377.7
	V ₂	2145.6	874.7	183.6	673.3	34.01	304.3
2018-19	V ₁	2870.4	2725.7	2716.0	2641.3	495.04	1581.7
	V ₂	2561.7	1339.3	2569.4	1312.0	306.62	871.0

used cautiously as the model has its inherent error in simulation.

Model evaluation

Statistical evaluation of experimental yield using ME, RMSE, CRM and EF are presented (Table 5). Simulation of BRG-1 grain yield was in good agreement with the observed values with comparatively low ME (3.6

and 46.0 during 2017-18 and 2018-19, respectively) indicating the variety is calibrated well among the two varieties. Minimum average RMSE (3511.2) values were recorded indicating less deviation of simulated values from observed values. Positive CRM (0.048) values were recorded indicating under estimation of yields by the model, requiring some more calibration by field experimentation. The treatments also showed positive modelling efficiency of 1 (average of 2 years) indicating simulated values are giving better estimates

Table 5. The relative mean error (ME) percentage, root mean square error (RMSE), coefficient of residual mass (CRM) and modelling efficiency (EF) of DSSAT CROPGRO Pigeonpea model.

Treatments	2017-18			2018-19			Pooled		
	Observed yield (kg/ha)	Simulated yield (kg/ha)	Error (%)	Observed yield (kg/ha)	Simulated yield (kg/ha)	Error (%)	Observed yield (kg/ha)	Simulated yield (kg/ha)	Error (%)
Dates of sowing									
D ₁	2143.3	1183.3	-108.4	2716.0	2032.5	-41.0	2429.7	1607.9	-74.7
D ₂	180.0	848.2	54.2	2642.7	1976.7	-74.9	1411.4	1412.4	-10.4
D ₃	59.7	341.0	15.1	400.8	1226.3	250.7	230.3	783.7	132.9
Varieties									
V ₁	801.0	964.2	3.7	2027.2	2316.2	88.3	1414.1	1640.2	46.0
V ₂	787.7	617.4	-29.8	1812.6	1174.1	1.6	1300.2	895.8	-14.1
Interaction (DoS × Var)									
D ₁ V ₁	2141.0	1492.0	-80.8	2870.4	2725.7	-8.0	2505.7	2108.8	-44.4
D ₁ V ₂	2145.6	874.7	-136.1	2561.7	1339.3	-74.0	2353.7	1107.0	-105.1
D ₂ V ₁	176.5	1023.0	75.9	2716.0	2641.3	-3.8	1446.3	1832.2	36.1
D ₂ V ₂	183.6	673.3	32.4	2569.4	1312.0	146.0	1376.5	992.7	-56.8
D ₃ V ₁	85.4	377.7	16.0	495.0	1581.7	276.6	290.2	979.7	146.3
D ₃ V ₂	34.0	304.3	14.3	306.6	871.0	224.7	170.3	587.7	119.5
RMSE		3141.4			3881.1			3511.2	
CRM		0.004			0.091			0.048	
Modelling efficiency		1.0			1.0			1.0	

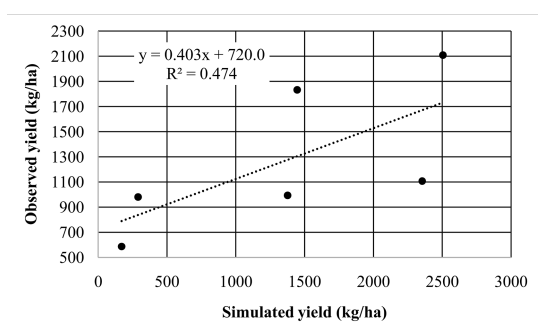


Fig. 1. Observed vs simulated yields of pigeonpea cultivars under different dates of sowing.

as compared to observed values. Figure 1 also shows relationship between observed and simulated values.

DSSAT model has proved to be robust and valuable tool for predicting yield CROPGRO Pigeonpea was started in 2015. As an attempt, experimental results of two years are used for generation of genetic coefficient. Further these generated coefficients are evaluated statistically. The yield was under estimated by the DSSAT model. Since the present research data base is very less, the process of calibration is incomplete and it has to be fine-tuned. The validated DSSAT model has wide range of applications from improving and evaluating the current growth and management practices for prediction of crop growth, phenology, potential and actual yield, performance of pigeonpea under climate change.

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