International Journal of Plant & Soil Science

Volume 35, Issue 18, Page 1880-1886, 2023; Article no.IJPSS.103353
ISSN: 2320-7035

Exploring DSSAT Model Genetic Coefficient Estimation Methodologies for Chickpea in Bundelkhand Region of Uttar Pradesh, India

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJPSS/2023/v35i183471

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/103353

Original Research Article

Received: 25/05/2023
Accepted: 29/07/2023
Published: 08/08/2023

ABSTRACT

In modern crop production, essential factors that contribute to narrowing yield gaps and minimizing production costs include making informed decisions about the selection of plant varieties, determining optimal sowing dates, determining appropriate plant populations, selecting suitable fertilizer rates, and implementing effective pest control methods. Two field experiments were conducted during the Rabi seasons of 2021 and 2022 at ICAR-Indian Institute of Pulses Research (IIPR), Kanpur using split-plot experimental design, where the main plots were three different sowing dates (20-25th October, November 10-15th, and 25th November-5th December), and the sub-plots were four chickpea cultivars (JG 16, RVG 202, IPC-07-66, and IPC-05-62), each with three

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replications. The genetic coefficients of the cultivars were estimated using both the iterative process (IP) and Generalized Likelihood Uncertainty Estimation (GLUE) methods in DSSAT v 4.7 to simulate the yields. Upon model validation, it was found that the average relative error (ARE) in predicting grain yield across the different sowing windows was between -25.7% to 29.1% when using the iterative process, while ARE was between -23.4% to 19% when using GLUE. The findings report more accurate simulations of chickpea growth and phenological development stages were recorded in normal sowings. And the model calibration suggest that GLUE provided superior estimates of genetic coefficients compared to the IP method. Therefore, it can be inferred that Glue is a more user-friendly and precise method.

Keywords: Chickpea; DSSAT; GLUE; iterative process.

1. INTRODUCTION

The DSSAT model is a widely used crop simulation system that allows for the evaluation of various factors impacting crop growth and yield, such as weather, soil water, genotype, soil, and crop nitrogen dynamics [1]. It enables researchers to simulate results in a matter of minutes, a process that could take years for an agronomist to carry out manually [2]. It is essential to develop a chickpea yield model for simulation that incorporates multiple processes of development and growth in order to assess the potential of new technologies or cultivars in varied circumstances. Singh and Virmani [3] developed the CHIKPGRO model, which is based on the PNUTGRO model. According to this model's genetic coefficients, each cultivar's growth and development characteristics must be specified [4] When a new cultivar is introduced and has to be evaluated for performance under various environmental and management practices, estimating genetic coefficients is very crucial [5].

The R language-based GLUE accessory is utilized to evaluate genetic coefficients in DSSAT, which can be both advantageous and disadvantageous. The computational intensity of the GLUE programme is one of its drawbacks. This intensity is influenced by the quantity of treatments chosen for estimate as well as the complexity of the genetic coefficients in a given crop module of DSSAT [6]. Alternatively, a trial-and-error or iterative process can be used, where different parameter values are manually tested until an acceptable fit to the data is obtained. Although crop simulation models and decision support systems can eliminate the need for expensive and time-consuming field experiments, it is essential to calibrate and assess these models in the particular environment of interest before using them to evaluate management options [7].

In India, the harvest of the rainy season crop, which starts in early October in southern parts and lasts until the second fortnight of November in the northern areas to avoid extreme low temperatures during the flowering stage, determines the schedule for planting chickpea. Chickpea crops grown in northern latitudes have a longer growing cycle compared to those in southern regions [8]. There is a need to generate genetic coefficients for chickpea cultivars in the Bundelkhand area of Uttar Pradesh. This study aims to evaluate the performance of different chickpea cultivars under varying sowing windows by estimating genetic coefficients using the CROPGRO-CHICKPEA (CHIKPGRO) model. The study hypothesizes that identifying the best genetic coefficient estimator will help to analyze yield gaps for chickpea in the region.

2. MATERIALS AND METHODS

2.1 Field Experiments

Two field experiments were conducted during the Rabi seasons of 2021 and 2022 at ICAR-Indian Institute of Pulses Research (IIPR), Kanpur. The first year's data was used for calibrating genetic coefficients while the second year's data was used for model validation. Four chickpea cultivars, namely JG 16, RVG 202, IPC-07-66, and IPC-05-62, which are recommended for the Bundelkhand region of Uttar Pradesh, were selected. The plant population was set at 3,33,333 plants ha^{-1} (30 cm × 10 cm) for each cultivar. The experiment was conducted in three different sowing windows, including early, normal, and late sowing, which reflected the prevalent chickpea cropping systems in the Bundelkhand region of Uttar Pradesh. The soil had a sandy loam texture and had a pH of 7.6, medium organic carbon content (0.30%), low available N value (115 kg/ha), medium available P content (16.8 kg/ha), and available K content (148 kg/ha). Standard agronomic management procedures were followed, including the weed and pests' management. Fig. 1 provided information on the typical weather patterns during the growth season.

2.2 Model Simulation Set-Up

In order to accurately simulate the growth, development, and yield, DSSAT depends mainly on genetic coefficients that are specific to cultivar. During the cropping season of 2021–2022, field observations of soil conditions, crop management, and meteorological factors were employed to calibrate the model. Leaf area index, days to flowering and physiological maturity, grain yield in 2021–22 were used to evaluate the genetic coefficients for chickpea cultivars. These coefficients were then validated using data from 2022-23. The default cultivars' genetic coefficients were previously integrated into the DSSATv4.7 genetic file (CHGRO047.CUL) for the DSSAT-CROPGRO model. The initial genetic coefficients were obtained from the default desi cultivar 990002, which was already included in DSSATv4.7. The crop-specific parameter values for the four cultivars examined in this study (JG 16, RVG 202, IPC-07-66, and IPC-05-62) were calculated and copied into the CHGRO047.CUL file to perform the simulation. This iterative process was conducted through a trial-and-error method, in which each factor's values were assigned to generate model results that closely matched the field conditions.

The first step in the calibration process was to set the duration between plant emergence and flower appearance (R1), using the default cultivar from the existing cultivar file. Next, the coefficient of days to anthesis was adjusted to minimize the RMSE between the simulated and observed values of days to anthesis. The days from anthesis to maturity were then adjusted to obtain the lowest RMSE between the simulated and observed days to maturity. Subsequently, R3, R5 and R7 were fine-tuned. The standard pod weight, including the grain, was adjusted based on the grain yield components until the lowest RMSE between the simulated and observed values for the final grain yield was achieved. Finally, R1, R3, R5, and R7 were readjusted simultaneously.

The genetic coefficients for different chickpea cultivars were generated using the GLUE program, which involves selecting a cultivar from the DSSATv4.7 database and defining treatments based on experiments where the cultivar was grown. The program was run separately for phenological and growth parameters, and the resulting parameters were incorporated into the cultivar file. This process was carried out following the methods of He et al [6], Ibrahim et al. [9], and Buddhaboon et al [7]. Model validation was performed by comparing simulated and observed data to ensure the calibrated model accurately represents the real situation. The accuracy of the model's predictions was evaluated using the absolute relative error (ARE; Eq. 1), which was calculated using observed and simulated variables such as grain yield and days to physiological maturity [10].

$$ARE = \frac{|\dot{X} - X|}{X} \times 100$$

Where, X is the actual value of the parameter and Ẋ is the predicted value of the parameter.

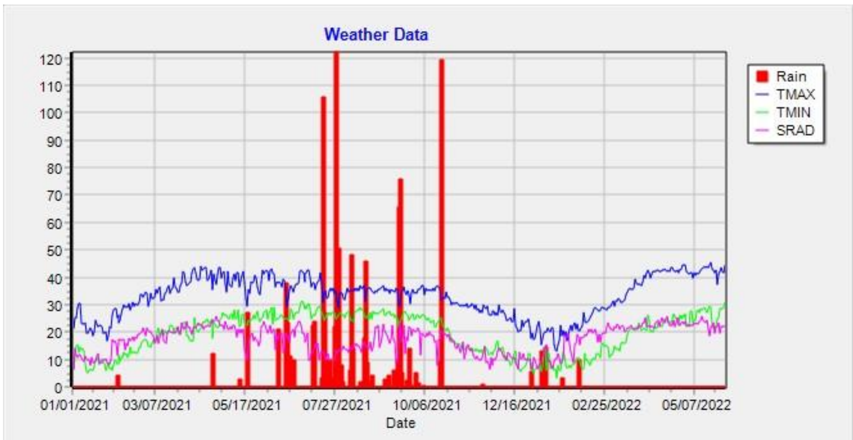

Fig. 1. Prevailing weather data generated in DSSAT during the study period (2021-22)

3. RESULTS AND DISCUSSION

The yield components and development factors were evaluated using field data, model output with IP coefficients, and GLUE coefficients. The cultivar coefficients produced by the two techniques are shown in Table 1, and among the date-specific coefficients, the cultivar's specific leaf area under ideal growth circumstances had a significant standard deviation ranging from 30.9 to 34.15 for different varieties. This might account for the little discrepancy in predicted leaf area towards harvesting. The difference in standard deviation between the initial seed and physiological maturity was considerable and ranged from 0.7 to 5.4 days, which may help to explain how changes in weather conditions might affect the sensitivity of model prediction that when crop will reach physiological maturity. All other date-specific coefficients, however, had standard deviations of less than two days, including EMFL, FLSH, and FLSD. GLUE exhibits less variability in simulating yield when compared to observed data based on the individual performance of the cultivar coefficients with respect to the primary growth and development variables and the time-sequence growth traits of the crop among different varieties (Table 1 and Fig. 2). This shows that the GLUE-generated coefficients often converge to a set of cultivar coefficients that are close to optimum.

With respect to the physiological maturity days in early sowing conditions, the GLUE cultivar coefficients slightly overpredicted with an average error of (ARE) of -3.3 to 1.7% with difference of 0, 2 and 1 days, respectively for all three varieties (JG 16, RVG 202, and IPC-05-62). Whereas for IPC-07-66, GLUE had underprediction of 4 days compared to observed values. However, IP generated coefficients showed underprediction of all four varieties with a range of -4 to -6 days with an error of -5.2 to -3.3%. Similar results were observed with respect to physiological maturity days within a range of +2 days for GLUE with average error of -1.7 to 1.8% and -4 to -8 days for IP generated coefficients. Boote et al [11] also pointed out this error and reported that model could not accurately simulate the physiological maturity especially in the irrigated situations. This may be due to the effect of thermal and moisture regime in combination or separately, which determines the phenological development of chickpea, while the model only accounted for thermal environmental changes. In contrast to these, late showed more variation in simulating physiological maturity days within the range of -5 to +8 and -10 to +2 days respectively with GLUE and IP methods in comparison to observed values (Table. 2). The model did not accurately simulate the rainfall impact and hence there were large differences in physiological maturity days, which was observed during late sowing window. Yadav et al [12] evaluated the PNUTGRO model for groundnut at Gujarat and reported similar findings. According to the study, the CHIKPGRO model tended to overestimate the days to first pod in timely sown treatments and underestimate it in late sown treatments. However, the GLUE-generated cultivar coefficients were found to predict the development variables more accurately than the IP coefficients, as they had a lower difference in simulated values compared to observed values. The evaluation of the model against measured values showed that the GLUE simulation model could predict the days to physiological maturity very closely to the observed results for all varieties and sowing windows, with an R2 value of 0.72 compared to 0.62 for IP. Therefore, the GLUE-generated coefficients were considered to have a good fit and were able to predict the appropriate days to physiological maturity of chickpea across different sowing windows and varieties. Fig. 2 also shows the performance of the GLUE-generated coefficients in comparison to the observed data.

In this study we utilized coefficients from IP and GLUE to simulate yields in the DSSAT model, it was found that the R^2 values for observed and simulated yield were 0.71 and 0.79 respectively for IP and GLUE coefficients (Fig. 2). GLUE generated coefficients resulted in simulated yields that were closer to observed yield values with good model fit across all sowing windows, compared to IP generated coefficients. However, there was notable variation between simulated and observed chickpea yields, with the least variation observed in normal sowing scenarios where the model predicted yields with an average relative error ranging from 1.1 to 5.1. In early sowing scenarios, the model tended to overpredict yields, with an average relative error of 19.5 to 29.1, while in late sowing scenarios, the model tended to underpredict yields, with simulated values ranging from 808 to 1490 kg/ha and observed values ranging from 1467 to 1700 kg/ha. The study also found that temperatures above 30 °C during the end of the reproductive phase had a negative impact on chickpea biomass and seed yield. This suggests that the model may overestimate the severity of thermal

Table 1. Genetic coefficients generated by iterative process and with GLUE for different chickpea cultivars

Genetic Parameter	Default Coefficients	JG 16			RVG 202			IPC-06-77			IPC-05-62		
		IP	GLUE	SD	IP	GLUE	SD	IP	GLUE	SD	IP	GLUE	SD
CSDL	11.0	11.00	11.00	0	11.00	11.00	0	11.00	11.00	0	11.00	11.00	0
PPSEN	-.143	-.143	-.143	0	-.143	-.143	0	-.143	-.143	0	-.143	-.143	0
EM-FL	37.00	31.00	37.84	3.42	36.00	41.14	2.57	36.00	35.66	0.17	40.00	37.77	1.115
FL-SH	8.0	5.5	8.6	1.55	7.5	6.5	0.5	7.0	6.1	0.45	8.0	8.180	0.09
FL-SD	15.0	13.0	14.9	0.95	13.0	14.5	0.75	14.5	14.4	0.05	16.0	14.2	0.9
SD-PM	38.00	30.50	26.05	2.225	30.50	33.22	1.36	31.50	33.02	0.76	27.50	38.33	5.415
FL-LF	42.00	34.00	34.00	0	36.00	36.00	0	36.00	36.00	0	42.00	42.00	0
LFMAX	1.000	0.950	1.000	0.025	1.000	1.001	0.0005	1.000	1.004	0.002	1.040	1.002	0.019
SLAVR	200.	200.	135.1	32.45	200.	131.7	34.15	200.	137.6	31.2	200.	138.2	30.9
SIZLF	10.00	10.00	10.00	0	10.00	10.00	0	10.00	10.00	0	10	10.00	0
XFRT	0.96	0.96	0.960	0	0.96	0.960	0	0.96	0.960	0	0.96	0.960	0
WTPSD	0.283	0.170	0.194	0.012	0.200	0.227	0.0135	0.165	0.200	0.0175	0.165	0.186	0.0105
SFDUR	29.0	22.0	22.0	0	22.0	22.0	0	22.0	22.0	0	22.0	22.0	0
SDPDV	1.00	1.20	1.20	0	1.60	1.60	0	1.60	1.60	0	1.60	1.600	0
PODUR	18.0	18	18.0	0	18.0	18.0	0	18.0	18.0	0	18.0	18.0	0
THRSH	85.0	82.0	82.0	0	82.0	82.0	0	85.0	85.0	0	85.0	85.0	0
SDPRO	.216	.216	0.216	0	.216	0.216	0	.244	0.244	0	.262	0.262	0
SDLIP	0.48	0.48	0.48	0	0.48	0.48	0	0.48	0.48	0	0.48	0.48	0

Abbreviations: SD: Standard Deviation CSDL: Critical Short-Day Length below which reproductive development progresses WITH daylength effect (for long day plants) (hour); PPSEN: Slope of the relative response of development to photoperiod with time (negative for long day plants) (1/hour); EM-FL: Time between plant emergence and flower appearance (R1) (photothermal days); FL-SH: Time between first flower and first pod (R3) (photothermal days); FL-SD: Time between first flower and first seed (R5) (photothermal days); SD-PM: Time between first seed (R5) and physiological maturity (R7) (photothermal days); FL-LF: Time between first flower (R1) and end of leaf expansion (photothermal days); LFMAX: Maximum leaf photosynthesis rate at 30 C, 350 vpm CO2, and high light (mg CO2/m2 s); SLAVR: Specific leaf area of cultivar under standard growth conditions (cm2/g); SIZLF: Maximum size of full leaf (three leaflets) (cm2); XFRT: Maximum fraction of daily growth that is partitioned to seed + shell; WTPSD: Maximum weight per seed (g); SFDUR: Seed filling duration for pod cohort at standard growth conditions (photothermal days); SDPDV: Average seed per pod under standard growing conditions (#/pod); PODUR: Time required for cultivar to reach final pod load under optimal conditions (photothermal days); THRSH: The maximum ratio of (seed/(seed+shell)) at maturity; SDPRO: Fraction protein in seeds (g(protein)/g(seed)); SDLIP: Fraction oil in seeds (g(oil)/g(seed))

Table 2. Absolute relative error (%) between simulated and observed values of Seed Yield (SY) (Kg/ha) and Physiological Maturity (PM) (days) using iterative process and GLUE

Cultivars	JG 16		RVG 202		IPC-06-77		IPC-05-62	
Parameters	**SY**	**PM**	**SY**	**PM**	**SY**	**PM**	**SY**	**PM**
Early sowing								
Observed	1980	115	1756	120	1850	122	1962	122
IP (sim)	2556	109	2209	114	2378	116	2784	118
ARE	29.1	-5.2	25.8	-5.0	28.5	-4.9	41.9	-3.3
GLUE (sim)	2366	115	2056	122	2270	118	2472	123
ARE	19.5	0.0	17.1	1.7	22.7	-3.3	26.0	0.8
Normal sowing								
Observed	2082	110	1886	119	2056	119	2060	121
IP (sim)	2188	106	2351	111	2534	114	2377	116
ARE	5.1	-3.6	24.7	-6.7	23.2	-4.2	15.4	-4.1
GLUE (sim)	2105	112	2063	120	2371	117	2177	122
ARE	1.1	1.8	9.4	0.8	15.3	-1.7	5.7	0.8
Late sowing								
Observed	1467	106	1700	114	1568	115	1650	110
IP (sim)	1090	100	1296	104	1182	107	808	112
ARE	-25.7	-5.7	-23.8	-8.8	-24.6	-7.0	-51.0	1.8
GLUE (sim)	1123	106	1418	117	1306	110	1490	118
ARE	-23.4	0.0	-16.6	2.6	-16.7	-4.3	-9.7	7.3

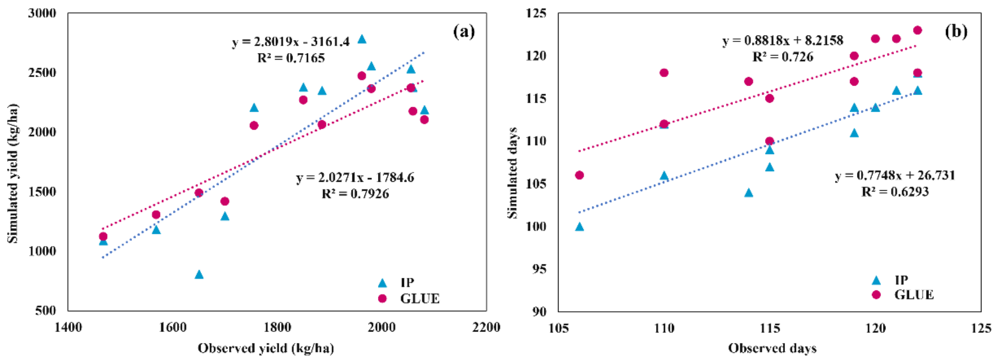

Fig. 2. (a) Comparison of observed and simulated yield of chickpea varieties; (b) Comparison of observed and simulated physiological maturity days of chickpea varieties for different sowing windows

stress conditions [13]. Leport et al [14] observed a significant reduction in the number of seeds of chickpea plants due to terminal drought. Pedersen et al [15] evaluated the CROPGRO-Soybean model was found that model underestimated total biomass and grain yield at harvest. Agrawal [16] found that all chickpea genotypes sown in December in the Jabalpur region of Madhya Pradesh had reduced yields, suggesting that the model may overestimate the severity of thermal stress in actual field conditions. Delayed sowing of chickpea may result in depletion of residual soil moisture and eventual exposure of the crop to terminal drought, which can cause a reduction in grain yield [2].

4. CONCLUSIONS

In the study, the DSSAT model was used to determine effect of the growth and yield of chickpeas under various sowing windows. DSSAT model was found to simulate chickpea yield from normal sowing with minimum absolute relative error. According to the study's results, the GLUE method outperformed the conventional iterative/trial and error approach in terms of optimization efficiency and accuracy. These findings encourage the broader use of GLUE of DSSAT model in agricultural research.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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