Optimizing Soybean Cultivation in Uttarakhand's Tarai Region Using the DSSAT CROPGRO Modeling Approach

Abstract:

Soybean (Glycine max) is a vital oilseed crop globally, but in India, its average grain yields remain relatively low despite the presence of high-yielding varieties. This study aimed to optimize soybean cultivation in the Tarai region of Uttarakhand, India, by exploring the impact of different sowing dates on crop growth and yield using the Decision Support System for Agrotechnology Transfer (DSSAT) CROPGRO model. The experiment was conducted in 2022 and 2023 at Pantnagar, Uttarakhand, using a split-plot design with three replications. The model was calibrated and validated for different sowing dates, and key parameters such as emergence days, physiological maturity days, grain yield, harvest index, and leaf area index were compared between simulated and observed values.During validation RMSE and R^2 was 48.44 and 0.90 for grain yield, 1.10 and 0.99 for physiological maturity, 0.042 and 0.99 for harvest index and 1.14 and 0.97 for LAI respectively.The results showed that adjusting sowing dates can significantly affect soybean growth and yield, with optimal sowing times resulting in higher yields and better crop performance. Specifically, sowing on July 22nd resulted in the highest grain yield, while sowing on August 21st led to the lowest. The DSSAT CROPGRO model proved to be a valuable tool for simulating soybean growth and predicting crop outcomes under varying environmental conditions.

Keywords: DSSAT, Model simulation, CROPGRO and

INTRODUCTION

Soybean (Glycine max (L.) Merrill) is basically recognized as a leguminous crop; however, it has emerged as a prominent oilseed crop globally. It contributes to over 50 percent of oilseed production and accounts for approximately 30 percent of the total vegetable oil supply. Despite the presence of numerous high-yielding soybean varieties, India continues to experience relatively low average grain yields.Soybeans are primarily categorized as an oilseed crop rather than a pulse crop, boasting a protein content of 40-42% and an oil content of 18-20% (Devi et al., 2012). Their remarkable nutritional profile has fuelled a growing demand for soy-based foods such as soymilk, soybean sprouts, soy nuts, various types of tofu, cottage cheese, and curd (Rao et al., 2002). In Uttarakhand, soybeans are predominantly cultivated during the kharif season. However, farmers often encounter practical challenges such as poor germination and inadequate crop growth, resulting in significantly low yields. Optimal temperatures ranging from 28-32°C are crucial for both germination and vegetative stages, while temperatures of 30-36°C are preferred during the reproductive phase.

Various soybean varieties exhibit sensitivity to environmental fluctuations in their respective cultivation areas. Like other cereal crops, soybean seeds begin to deteriorate in quality during harvesting, processing, and storage, consequently reducing plant stands and seed yields. Therefore, achieving rapid germination and uniform crop growth is imperative for maximizing seed yield potential (Yari et al., 2010). At the farmer's level, several factors limiting soybean seed production. Key among these is inappropriate sowing timing, unpredictable weather patterns, low germination rates, poor seed quality, and insufficient irrigation. Addressing these challenges necessitates a thorough exploration of diverse soybean varieties and agronomic strategies. By identifying suitable varieties and adopting proper agricultural practices, these constraints in soybean cultivation can be effectively mitigated. In northern India, soybean cultivation typically occurs during the Kharif rainy season, spanning from June to November. However, excessive moisture or waterlogging during the monsoon months presents unfavourable conditions for soybean growth. These conditions lead to diminished soil porosity, resulting in reduced soil aeration, reduced nodulation, inhibited root growth, and impaired nutrient uptake. These physiological and biochemical disruptions negatively impact the plant's productivity.Assessing the scale of such potential impacts has prompted the utilization of several process-based crop models. These models are designed to simulate the complex interplay between crops, their environment like weather and soil conditions, management practices, and performance under projected future climate conditions (Ahmed & Hassan, 2011). One widely employed model in this regard is Crop Growth (CROPGRO), developed by Jones et al. (2003).Many calibration and validation investigations conducted on CROPGRO-soybean have confirmed the model's capacity to accurately replicate crop growth stages and observed seed yields across various climatic conditions and regions (Batchelor et al., 1993; Tsuji et al., 1998; Lal et al., 1999; Southworth et al., 2002; Wang et al., 2003; Mera et al., 2006; Res et al., 2007).Achieving sustainable soybean production and maximizing yield requires the adoption of advanced methods that enhance management strategies while mitigating environmental impacts (Balasundram et al., 2023). Optimizing crop yield entails careful selection and fine-tuning of management practices such as irrigation (Roy et al., 2019), planting schedules (Bateman et al., 2020), tillage, and fertilization (Young et al., 2021).The CROPGRO model, a product of the Decision Support System for Agrotechnology Transfer (DSSAT) initiative, has consistently demonstrated strong performance in replicating crop reactions to detailed physiological process and environmental variables (Bhatia et al., 2008; Bao et al., 2015a; Salmeron and Purcell, 2016; Hoogenboom et al., 2019).The CROPGRO model has found extensive application in simulating crop yields across various agricultural crops such as soybean, cotton, and alfalfa (Malik et al., 2018; Dar et al., 2023).It's crucial to sow soybeans at the recommended time to mitigate potential harm from insects, diseases. freezing, and weeds, Likewise, ensuring that flowering occurs under suitable temperature and day length conditions is paramount for achieving optimal yield. Delayed sowing of soybeans could result in reduced plant height, fewer branches, reduced harvest index, and lower grain yield (Khan et al., 2011). Utilizing resources, particularly light, water, and nutrients, which enhances the rate of vegetative growth and development, especially influencing factors such as leaf area index (LAI) and plant height. These aspects are significantly influenced by planting density and row spacing (Holshouser and Whittaker, 2002).

In recent time,scientists are paying more attention to predicting crop yields to produce more food, there has been a growing focus within the research community on crop yield prediction to increase food production(Dwaram and Madapuri,2022). Machine learning (ML) played a crucial for Crop Yield Prediction, serving as a decision-making tool. It assists in determining which crops to cultivate and provides guidance throughout the growing period. There are Many different ways of using computers to predict crop yieldusing, random forests, K-nearest neighbors and neural networks. Scientists have also tried lots of other machine learning methods to make predictions better. Some popular ones are long short-term memory (LSTM) networks, convolutional neural networks (CNNs)and deep neural networks (DNNs) (Dwaram and Madapuri,2021, 27-29)

The research aimed to assess how altering the sowing date affects the duration of soybean vegetation, the length of individual growth stages, and ultimately, the size of the seed yield. Adjusting the sowing date according to the specific location of soybean cultivation and the prevailing weather conditions can significantly impact the thermal conditions and day length during the soybean's growth period. Although the sowing date is not typically considered a direct input factor in cultivation practices, it can play a strategic role in addressing yield challenges faced in the climatic conditions of Tarai region of Uttarakhand.

Materilalsand Methods

The field experiment was conducted at plot number D6, Norman E. Borlaug Crop Research Centre of Govind Ballabh Pant University of Agriculture and Technology, Pantnagar, U.S Nagar (Uttarakhand) during *kharif* season of 2022 and 2023. Pantnagar is situated in the *Tarai* belt, about 30km southward of foothills of the Shivalik ranges of Himalayas at 29.02^{o}N latitude, 79.28^{o}E longitude and at an altitude of 243.80 m above the mean sea level.The climate of Pantnagar comprises of sub-humid to sub-tropical with hot dry summer and cool winters. Generally, the monsoon sets in around third week of June and lasts up to September end.The mean annual rainfall is 1400 mm. May is the hottest month of the year and temperature generally rises to 45.5±1.5°C. However, minimum temperature can be low as 1.5±1.0°C in the month of January.

Soil characteristics

The physico-chemical properties of the experimental soil were determined by adopting standard analytical methods. The soil was sandy loam in texture, neutral in reaction (pH 7.2), low in available nitrogen (220 kg ha^{-1}), high in available phosphorus (35.40 kg ha^{-1}), medium in available potassium (170.69 kg ha^{-1}) and low in organic carbon (0.32%).

AGRONOMIC PRACTICES ADOPTED:

Land was prepared thoroughly to obtain fine soil tilth. Pre sowing irrigation was given at about 10 days prior to sowing of the experimental crop. First ploughing was done by tractor drawn soil turning plough in order to get field free from weeds and crop stubbles. After 3-4 days, two ploughings were given deeply by tractor drawn cultivator.The fertilizer was applied as 20:60:40:30kg/h in the form of N: P: K: S. Apart this 5kg Zn per ha was applied in the form of ZnSO4. Urea (46% N), single super phosphate (18% P_2O5, 12% S), Murate of Potash (60% K_20 and ZnSO4 were used as a source of nitrogen, phosphorous, potassium, Zinc and sulphur. During sowing rows were opened to a depth of 4-5cm with the help of furrow opener as per row distance of treatment. One manual weeding was also done at 45 DAS. Thimet was used as an insecticide. Harvesting was done as per maturity of genotypes. The crop was harvested when crop look straw colored, and seeds were hard enough containing 15-17% moisture. The harvesting of each net plot was done separately and left in the same plots for three to four days for sun drying. Later on, seeds from harvested produce of each plot were separated by manual threshing and then seeds were stored properly.

Experimental detail

There was a total of nine treatments laid out in a split plot design. The treatments were replicated three times, giving a total of 27 plots and a net experimental area of 259.47 m^2.Randomly selected three plants plot^{-1} were tagged for collecting data on emergence (days), LAI (maximum) and yield at harvest maturity (kg/h),physiological maturity day and harvest index were recorded on three randomly selected plant. Leaf area index was measured by Ceptometer (CEPTOMETER LP-80), emergence was observed by day to taking in emergence and physiological maturity was observed from germination to its physiological maturity days, after threshing the whole produce, the seed yield was obtained from each plot, weighed in kg m-^{2} and then converted to kg ha-1 for recording data. Harvest index is the yield of the plants part of the economic interest (economic yield) as percentage of total biological yield in terms of dry matter and calculated by using following formula:

$$\text{Harvest index (\%)} = \frac{grain\ yield\,(\frac{kg}{ha})}{biological\ yield\ (\frac{kg}{ha})} \text{ X } 100$$

Decision Support System for Agrotechnology Transfer (DSSAT)

The following five input files were created to run the model:

WEATHER FILE (FILE.WTH) with annual daily solar radiation, maximum air temperature, minimum air temperature, and precipitation,

SOIL FILE (FILES) with soil properties of the area under study

SOYBEAN MANAGEMENT FILE (FELEX) this contains the details of all inputs (observed field data) to the models for each simulation.

EXPERIMENTAL DATA FILE (FILEA) this contains observed values of experimental performance of the crop, which can be used for comparison with the simulated outputs of the model runs. The information provided includes anthesis date, physical maturity, yield, seed weight, seed number, panicle number, maximum LAI and dry matter.

GENETIC COEFFICIENTS FILE (FILEC) there are number of coefficients that can be adjusted in the CROPGRO-Soybean model depending upon the variety under consideration. The 'genetic coefficients' describe the phenology and grain yield components of a particular variety. Cultivar specific genotypic coefficient of soybean cultivars was derived from the experimental data with the help of GENCALC software.

Table 1: Genotypic coefficient developed for modeling of PS 1347 cultivar:

S.No.	Parameter	Definition of trait	Genetic coefficient (PS1347)
1	CSDL	Critical short day length below which reproductive development progresses not affected by day length	14.45
2	PPSEN	The slope of the relative response of development to photoperiod with time	0.49
3	EM-FL	Time between plant emergence and flower appearance (photothermal days)	20.9
4	FL-SH	Time between first flower and first pod (photothermal days)	5.5
5	FL-SD	Time between first flower and first seed (photothermal days)	10.3
6	SD-PM	Time between first seed and physiological maturity (photothermal days)	16.50
7	FL-LF	Time between first flower and end of leaf expansion (photothermal days)	17.00

8	LFMAX	Maximum leaf photosynthesis rate at 30°C, 350 ppm CO_2, and high light (mg CO_2/(m^2 s)	1.200
9	SLAVE	Specific leaf area of cultivar under standard growth conditions (cm^2/g)	300
10	SIZELF	Maximum size of the full leaf (three leaflets) (cm^2)	400
11	XFRT	The maximum fraction of daily growth that is partitioned to seed + shell	1.00
12	WTPSD	Maximum weight per seed (g)	0.12
13	SFDUR	Seed filling duration for pod at standard growth conditions (photothermal days)	19.00
14	SDPDV	Average seed per pod under standard growing conditions	2.15
15	PODUR	Time required for cultivar to reach final pod load under optimal conditions	32.0

MODEL TESTING

Model testing is the process to evaluate its performance under a specific set of soil and weather conditions. Model testing involves calibration, verification, validation and sensitivity analysis. Before the use of any model, adequate validation or assessment of magnitude of errors that may result through its use is necessary.Validation is the comparison between simulated data and the observed dataset from field experiments. Model can be considered valid and useful even though there may be some difference between experimental data and simulated output. If the simulated values lie within the projected confidence band, then the model can be considered valid. Thus, validation is used as an evaluation of model for its usefulness.

RESULTS AND DISCUSSION

Calibration of the DSSAT CROPGRO Model for Different Sowing Dates of Soybean Crop

DSSAT 4.8 model was calibrated for the Pantnagar*tarai* region with the help of actual or measured data and simulated data of the year 2022 for the calibration of DSSAT CROPGRO model and error statistics calculated for the same were represented in Table 1.

Days to taken emergence.

Data from the validation of simulated days required for emergence compared to observed data in soybean crops sown at various dates in 2022 were present in Table 2. Observed emergence times ranged from 6.3 to 4.6 days, while model simulations showed a range of 5-5 days. Error percentages and Root Mean Square Error (RMSE) were calculated to assess the disparities between simulated and observed soybean emergence. The RMSE, MAPE obtained between the observed and simulated emergence were 1.48 and 0.17 respectively.

Days taken to physiological maturity.

The physiological maturity closely approximated observed values, with a root mean square error (RMSE) of 4.48 days. Observed time to physiological maturity ranged from 59.55 to 72.88 days, while model simulations indicated a range of 57-69 days. The coefficient of determination (R^2) between observed and simulated values was 0.93 (Fig.1).

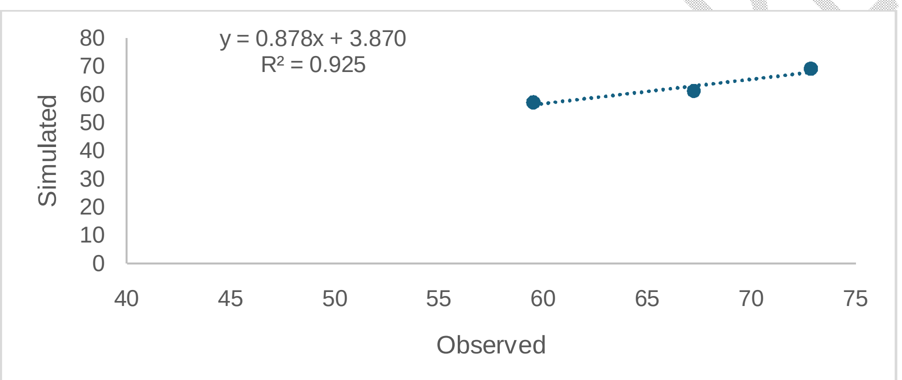

Fig. 1.Simulated and Observed Physiological maturity day calibration.

Grain Yield (kg ha^{-1})

The grain yield, as simulated by the model and observed, ranged from 1070 to 1342 kg/ha and 1074.67 to 1304.77 kg/ha, respectively. The root mean square error (RMSE) was determined to be 22.33, and the coefficient of determination (R^2) between observed and simulated values was 1.0 (Fig. 2).

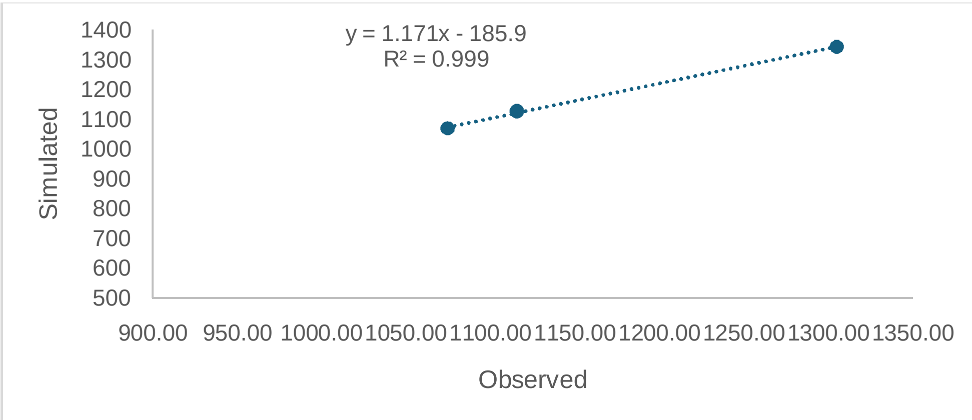

Fig 2. Simulated and Observed Grain yield (kg/h) during calibration.

Harvest Index

The observed and simulated harvest index values exhibited closely related ranges, from 0.36 to 0.45 and 0.38 to 0.46, respectively. The root mean square error (RMSE) for both simulated and observed values was calculated as 0.014. The coefficient of determination (R^2) of 0.88 was found between simulated and observed data (Fig. 3).

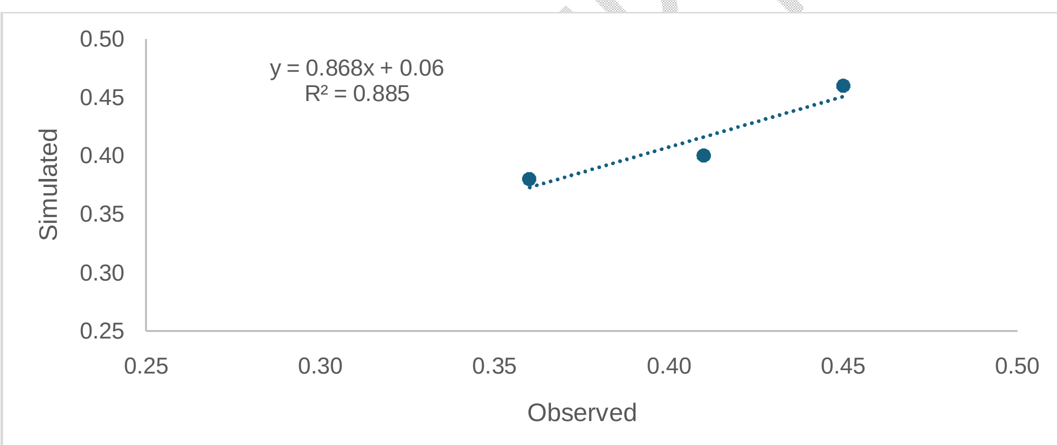

Fig. 3. Simulated and Observed Harvest indexcalibration.

Leaf Area Index

The leaf area index exhibited a range of 4.56 to 5.7 for simulated values and 3.07 to 5.05 for observed values. The root mean square error (RMSE) between simulated and observed values was calculated as 0.09. Furthermore, the coefficient of determination (R^2) between simulated and observed values was determined to be 1.00 (Fig. 4).

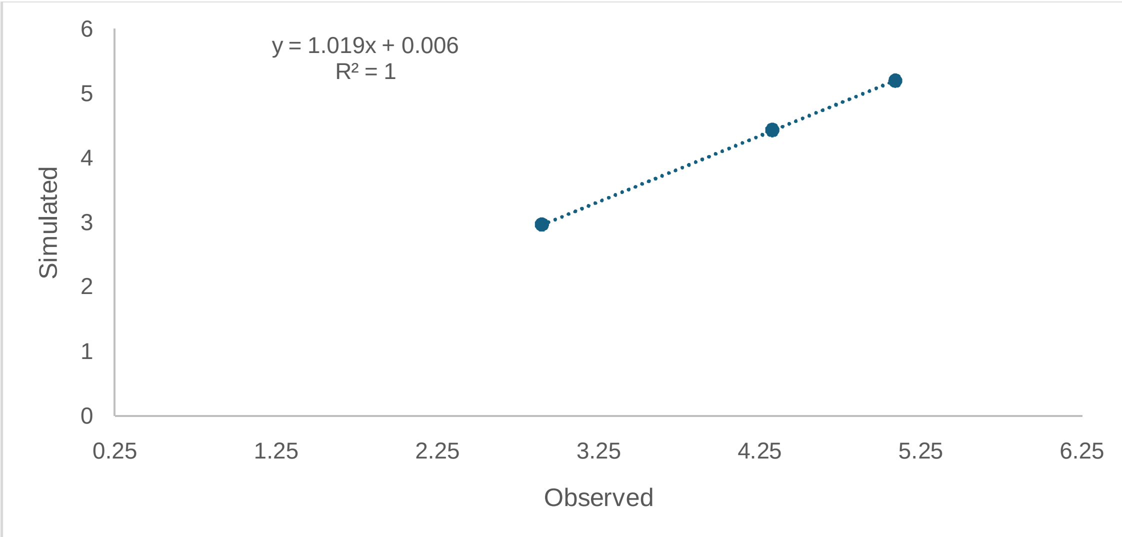

Fig. 4. Simulated and Observed Leaf area index during calibration.

Validation of DSSAT 4.8 Model for Different Sowing date of Soybean

Days Taken toEmergence

Data from the validation of simulated days required for emergence compared to observed data in soybean crops sown at various dates in 2023 were presented in Table 2. With a root mean square error (RMSE) of 1.136 days. Observed emergence times ranged from5.3 to6.7 days, while model simulations showed a range of 5-6 days. The coefficient of determination (R^2) between observed and simulated values was 0.52 (Fig.5).

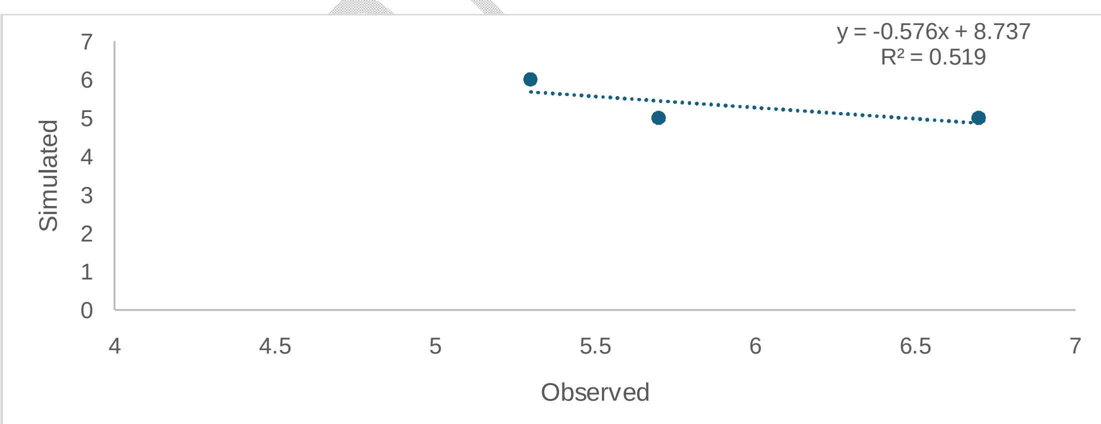

Fig. 5. Simulated and Observed Emergence Day during validation.

Days for Physiological Maturity

The difference between simulated and observed physiological maturity was ranges 57-69 and 57.11-70.11 respectively. The RMSE between observed and simulated value are 1.10 days. The coefficient of determination (R^2) between observed and simulated values was 0.99 (Fig. 6).

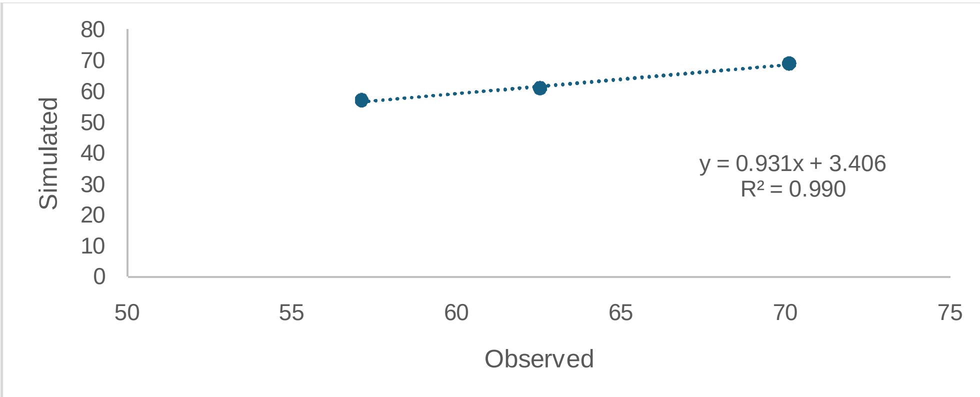

Fig. 6. Simulated and Observed Physiological maturity day during validation.

Grain Yield (kg ha^{-1})

Simulated and observed grain yield of soybean were presented in table 2. The difference between the simulation and observed grain yield ranges from 1155 to 1211 kh/ha andn1127.45 to 1285.68 kg/ha, respectively. The root mean square error (RMSE) was determined to be 48.44, and the coefficient of determination (R^2) between simulation and observed values was 0.90 (Fig.7).

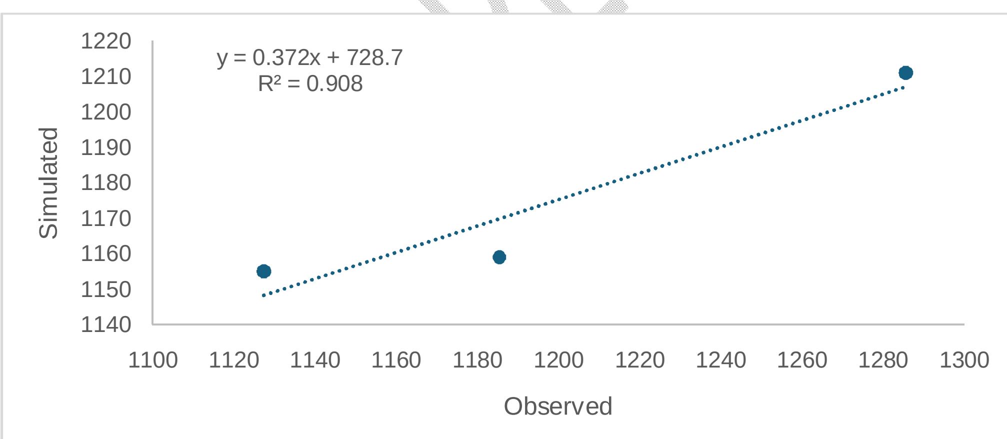

Fig. 7. Simulated and Observedgrain yield (kg/h) during validation.

Harvest Index

The difference between observed and simulated harvest index values are closely related ranges, from 0.40 to 0.44 and 0.33 to 0.45, respectively. The root mean square error (RMSE) for both simulated and observed values was calculated as 0.042. The R^2 valuewas of 0.99 found between simulated and observed data (Fig. 8).

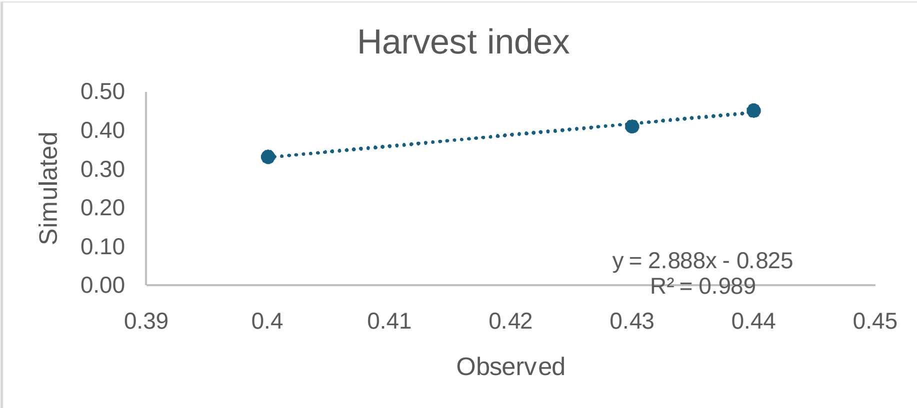

Fig. 8. Simulated and Observed Harvest index during validation.

Leaf Area Index

The leaf area index exhibited a range of 4.56 to 5.7 for simulated values and 3.07 to 5.05 for observed values. The root mean square error (RMSE) between simulated and observed values was calculated as 1.14. The coefficient of determination (R^2) between simulated and observed values was determined to be 0.97 (Fig. 9).Calibration and validation of crop growth models play pivotal roles in their development, evaluation, and practical application. This rigorous process ensures the reliability, accuracy, and applicability of the models across varied environmental conditions.

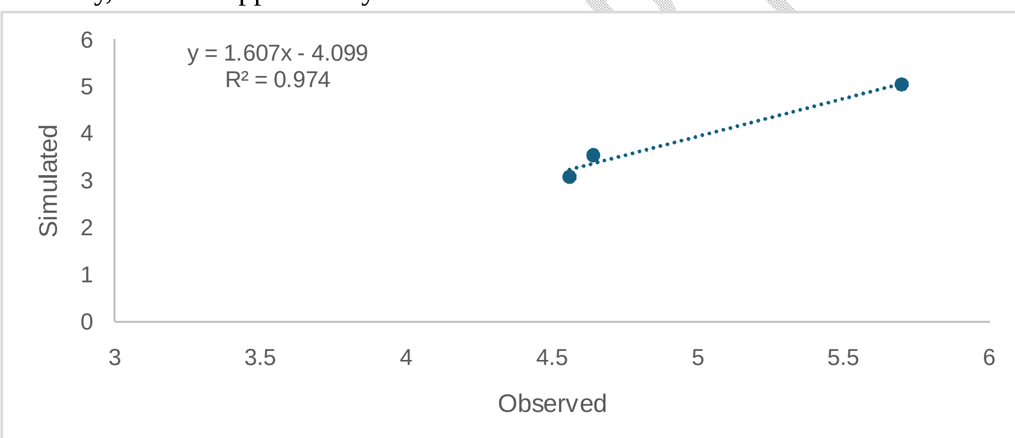

Fig. 9.Simulated and ObservedLeaf area index during validation.

Table 2.Calibration of DSSAT CROPGRO model for three sowing dates (D1= Jul. 22, D2= Aug. 6, D3= Aug. 21) of soybean crop during kharif season 2022.

DOS	EDAP		MDAP		HWAM		HIAM		LAIX	
	O	S	O	S	O	S	O	S	O	S
D1	6.3	5	72.88	69	1304.77	1242	0.36	0.38	5.09	5.19
D2	5.3	5	67.22	61	1115.76	1125	0.41	0.40	4.33	4.43
D3	4.6	5	59.55	57	1074.67	1070	0.45	0.46	2.9	2.96

DOS= date of sowing, EDAP= Emergence Day after sowing, MDAP= physiological maturity day after sowing, HWAM= yield at harvest maturity, HIAM= harvest index at maturity, LAIX= leaf area index maximum.

Parameter	RMSE	NRMSE	MBE	R2	MAPE
EDAP	1.48	0.023	-1.3	NaN	0.17
MDAP	4.48	0.067	-4.21	0.925	0.014
HWAM	22.33	0.019	13.93	0.999	3.5%
HIAM	0.014	0.035	0.007	0.886	0.081
LAIX	0.089	0.022	0.087	1	22.7%

Table 3. Validation ofDSSAT CROPGRO model for three sowing dates (D1= Jul. 22, D2= Aug. 6, D3= Aug. 21) of soybean crop during kharif season 2023.

DOS	**EDAP**		**MDAP**		**HWAM**		**HIAM**		**LAIX**	
	O	**S**	**O**	**S**	**O**	**S**	**O**	**S**	**O**	**S**
D1	6.7	5	70.11	69	1285.68	1211	0.4	0.33	5.7	5.05
D2	5.7	5	62.55	61	1185.5	1159	0.43	0.41	4.64	3.53
D3	5.3	6	57.11	57	1127.45	1155	0.44	0.45	4.56	3.07

DOS= date of sowing, EDAP= Emergence day after sowing, MDAP= physiological maturity day after sowing, HWAM= yield at harvest maturity, HIAM= harvest index at maturity, LAIX= leaf area index maximum.

PARAMETERS	RMSE	NRMSE	MBE	R2	MAPE
EDAP	1.136	0.193	-0.567	0.519	0.17
MDAP	1.103	0.017	-0.923	0.991	0.014
HWAM	48.437	0.04	-24.543	0.909	3.5%
HIAM	0.042	0.1	-0.027	0.992	0.081
LAIX	1.136	0.299	-1.083	0.974	22.7%

CONCLUSION

The study highlights the importance of choosing the right sowing date for soybean cultivation in the Tarai region of Uttarakhand to maximize yield potential. The DSSAT CROPGRO model was successfully calibrated and validated for different sowing dates, demonstrating its effectiveness in predicting soybean growth and yield. The results indicate that the optimal date of sowing for soybean cultivation in the Tarai region of Uttarakhand is July 22nd. Sowing on this date resulted in the highest grain yield compared to other sowing dates, with a mean yield of 1304.77 kg/ha in the calibration year (2022) and 1285.68 kg/ha in the validation year (2023). This suggests that sowing soybeans around late July can lead to better crop performance and higher yields in this region.Farmers and policymakers can use these findings to optimize soybean cultivation practices, improve crop management strategies, and enhance overall agricultural productivity in the region. Further research could focus on expanding the model to other regions and crops to facilitate sustainable agricultural practices and food security.

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REFERENCES

1. Devi KN, Singh LNK, Singh MS, Singh SB, Singh KK. Influence of sulphur and boron fertilization on yield, quality, nutrient uptake and economics of soybean (*Glycine maxL.*) under upland conditions. Journal of Agricultural Science.2012; 4 1-9.
2. Rao M, Bhagsari A, Mohamed A. Fresh green seed yield and seed nutritional traits of vegetable soybean genotypes. Crop Science.2002; 42: 1950-1958.
3. Yari LM, Aghaalikhani M, Khazaei F. Effect of Seed priming duration and temperature on seed germination behavior of bread wheat (*Triticum aestivumL.*). ARPN Journal of Agricultural and Biological Science. 2010; 5(1).
4. Ahmed M, Hassan F. APSIM and DSSAT Models as Decision Support Tools. In 19th International Congress on Modelling and Simulation (pp. 1174-1180). Perth, 12-16 December 2011.
5. Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ. DSSAT Cropping System Model. European Journal of Agronomy, 18, 235-265. https://doi.org/10.1016/S1161-0301(02)00107-7.

6. Batchelor WD, Jones JW, Boote KJ, Pinnschmidt HO. Extending the Use of Crop Models to Study Pest Damage. Transaction of the ASAE.1993; 36, 551-558. https://doi.org/10.13031/2013.28372.
7. Tsuji GY, Hoogenboom G, Thornton PK. Understanding Options for Agricultural Production. Berlin: Springer.1998; https://doi.org/10.1007/978-94-017-3624-4.
8. Lal M, Singh K, Srinivasan G, Rathore L, Naidu D, Tripathi C. Growth and Yield Responses of Soybean in Madhya Pradesh, India to Climate Variability and Change. Agricultural and Forest Meteorology.1999; 93, 53-70. https://doi.org/10.1016/S0168-1923(98)00105-1.
9. Southworth J, Pfeifer RA, Habeck M, Randolph JC, Doering OC, Johnston JJ, Rao DG. Changes in Soybean Yields in the Midwestern United States as a Result of Future Changes in Climate, Climate Variability, and CO2 Fertilization. Climatic Change. 2002; 53, 447-475. https://doi.org/10.1023/A:1015266425630.
10. Wang F, Fraisse CW, Kitchen NR, Sudduth KA. Site-Specific Evaluation of the CROPGRO-Soybean Model on Missouri Claypan Soils. Agricultural Systems. 2003; 76, 985-1005. https://doi.org/10.1016/S0308-521X(02)00029-X.
11. Mera RJ, Niyogi D, Buol GS, Wilkerson GG, Semazzi FHM. Potential Individual versus Simultaneous Climate Change Effects on Soybean (C3) and Maize (C4) Crops: An Agrotechnology Model Based Study. Global and Planetary Change. 2006; 54, 163-182. https://doi.org/10.1016/j.gloplacha.2005.11.003.
12. Res C, Brassard JP, Singh B. Effects of Climate Change and CO2 Increase on Potential Agricultural Production in Southern Québec. Climate Change. 2007; 34, 105-117. https://doi.org/10.3354/cr034105.
13. Balasundram SK, Shamshiri RR, Sridhara S, Rizan N. The role of digital agriculture in mitigating climate change and ensuring food security: an overview. Sustainability. 2023; 15(6), 5325. https://doi. org/10.3390/su15065325.
14. Roy PC, Guber A, Abouali M, Nejadhashemi AP, Deb K, Smucker AJ. Crop yield simulation optimization using precision irrigation and subsurface water retention technology. Environmental Modelling & Software. 2019; 119, 433–444. https://doi.org/10.1016/j.envsoft.2019.07.00
15. Bateman NR, Catchot AL, Gore J, Cook DR, Musser FR, Irby JT. Effects of planting date for soybean growth, development, and yield in the southern USA. Agronomy. 2020; 10(4), 596. https://doi. org/10.3390/agronomy10040596.
16. Young MD, Ros GH, de Vries W. A decision support framework assessing management impacts on crop yield, soil carbon changes and nitrogen losses to the environment. European Journal of Soil Science. 2019; 72(4), 1590–1606. https://doi.org/10.1111/ejss.13024
17. Bhatia VS, Singh P, Wani SP, Chauhan GS, Rao AK, Mishra AK, Srinivas K. Analysis of potential yields and yield gaps of rainfed soybean in India using CROPGRO-Soybean model. Agricultural and Forest Meteorology 148(8-9), 1252–1265. https://doi.org/10.1016/j.agrformet.2008.03.004.
18. Bao Y. Hoogenboom G, McClendon R, Urich P. Soybean production in 2025 and 2050 in the southeastern USA based on the SimCLIM and the CSM-CROPGRO-Soybean models. Climate Research. 2015a; 63(1), 73–89. https://doi.org/10.3354/ cr01281.

19. Salmerón M, Purcell LC. Simplifying the prediction of phenology with the DSSAT-CROPGROsoybean model based on relative maturity group and determinacy. Agricultural Systems. 2016; 148, 178–187. https://doi.org/10.1016/j.agsy.2016.07.016
20. Hoogenboom G, Porter CH, Boote KJ, Shelia V, Wilkens PW, Singh U, White JW, Asseng S, Lizaso, JI, Moreno LP, Pavan W, Ogoshi R, Hunt LA, Tsuji GY, Jones JW. The DSSAT crop modeling ecosystem. In K. J. Boote (Ed.), Advances in Crop Modelling for a Sustainable Agriculture. Burleigh Dodds Science Publishing. 2019; 173–216.
21. Malik W, Boote KJ, Hoogenboom G, Cavero J, Dechmi F. Adapting the CROPGRO model to simulate alfalfa growth and yield. Agronomy Journal. 2018; 110(5), 1777–1790. https://doi.org/10.2134/ agronj2017.12.0680.
22. Dar EA, Hoogenboom G, Shah ZA. Meta analysis on the evaluation and application of DSSAT in South Asia and China: Recent studies and the way forward. Journal of Agrometeorology. 2023; 25(2), 185–204. https://doi.org/10.54386/jam.v25i2.2081
23. Khan AZ, Shah P, Khan H, Nigar S, Perveen S, Shahand MK, Zubair M. Seed quality and vigour of soybean cultivars as influenced by canopy temperature. Pakistan Journal of Botany. 2011; 43:642-648.
24. Holshouser DL, Whittaker JP. Plant population and row spacing effects on early soybean production systems in the Mid Atlantic USA. Agronomy Journal. 2002; 94:603- 611.
25. Dwaram JR, Madapuri RK. Crop yield forecasting by long short-term memory network with Adam optimizer and Huber loss function in Andhra Pradesh, India, Concurrency and Computation: Practice and Experience, https://doi.org/10.1002/cpe.7310.
26. Dwaram JR, Madapuri RK. Crop Yield Prediction using Machine Learning Algorithm . 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), doi:10.1109/ICICCS51141.2021.9432236.
27. Akinola, O. A., Olufayo, A. A., &Oguntunde, P. G. (2014). Dynamic Crop Water Production Model of Plantain Yield Response to Water. Journal of Experimental Agriculture International, 4(12), 1544–1556. https://doi.org/10.9734/AJEA/2014/9319
28. Adeosun, E. O., Awe, B. S., & Ajewole, P. O. (2018). The Use of Model to Determine Ecological Variables Responsible for Soil Organic Carbon Sequestration in Derived Savanna Soils of Southwestern Nigeria. Archives of Current Research International, 15(1), 1–12. https://doi.org/10.9734/ACRI/2018/43932
29. Garibay VM, Kothari K, Ale S, Gitz III DC, Morgan GD, Munster CL. Determining water-use-efficient irrigation strategies for cotton using the DSSAT CSM CROPGRO-cotton model evaluated with in-season data. Agricultural Water Management. 2019 Aug 20;223:105695.