

Geospatial Approach to Chickpea Yield Estimation: DSSAT-CROPGRO Calibration in Bundelkhand, Uttar Pradesh

Kancheti Mrunalini^{1,2*}, Sellaperumal Pazhanivelan¹, Narendra Kumar², Ragunath Kaliaperumal¹,
S.P. Ramanathan¹, N. Srithasran¹ and A. Ragul¹

¹Tamil Nadu Agricultural University, Coimbatore-641003, Tamil Nadu, India.

²ICAR-Indian Institute of Pulses Research, Kanpur-208024, Uttar Pradesh, India.

(Corresponding author: Kancheti Mrunalini*)

(Received: 15 June 2023; Revised: 16 July 2023; Accepted: 30 July 2023; Published: 15 August 2023)

(Published by Research Trend)

ABSTRACT: In this research, the DSSAT model was utilized to simulate the growth, development, and yield of crops by effectively capturing the interactions between soil, plants, atmospheric conditions, and agricultural practices. Ensuring the timely and accurate prediction of crop yields proves pivotal for effective agricultural land management and the formulation of informed policy decisions. The study focused on estimating the spatial yield of chickpeas in seven districts of the Bundelkhand region in Uttar Pradesh using the DSSAT model. Genetic coefficients for different chickpea cultivars were evaluated during *rabi*, 2021–22 and were subsequently validated using crop data of 2022-23. The accuracy of the model's yield predictions was confirmed through comparison with observed yields obtained from crop cutting experiments conducted in farmers' fields. Statistical evaluations revealed excellent performance, with calibration yielding an R^2 , NRMSE, d and MAPE of 0.942, 0.107, 0.89, & 10.2 and with the validation phase also showed strong results, with values of 0.923, 0.149, 0.827, & 13.9 respectively.

The versatility of the DSSAT model and its crop simulation capabilities have led to its widespread application across various contexts. With successful calibration and validation for chickpea yields at a spatial level, the model is now well-positioned for further geospatial applications in the realm of natural resource management.

Keywords: CCE, Chickpea, CROPGRO, DSSAT, Spatial yield.

INTRODUCTION

India is the world's largest producer, accounting for nearly two-thirds of total output. India's chickpea farming covered roughly 10.7 million hectares in the agricultural year 2021-2022, yielding approximately 13.54 million metric tonnes (Indiastat, 2023). Proposed research area Bundelkhand in Uttar Pradesh state is a historically prominent chickpea-growing region (416,007 acres), producing approximately 148,408 tonnes of chickpea. It is the most important *rabi* pulse crop farmed in the Bundelkhand region of Uttar Pradesh, accounting for 67% of the total cropped area with an area.

With the global population expected to approach 9 billion by 2050, food demand is expected to climb by nearly 60%. To meet this increased demand, existing primary agricultural output must be significantly increased (FAO, 2009). It is expected that intensification efforts can produce around 80% of the desired increase. To meet this production target without resorting to large-scale land conversion for agriculture, crop intensification and annual crop productivity must be significantly increased. The assessment of yield gaps within existing cultivated lands reveals the possibility for increasing yields above current levels. Remote sensing

methodologies have substantially improved our understanding of farming practises at various scales and have revolutionised the evaluation of production gaps. Crop models must account for spatial heterogeneity when estimating crop yields across vast regions. Because of satellites' ability to acquire vast information over large areas with frequent revisits, the integration of remotely sensed data with crop simulation models has gained significance for agricultural yield estimation.

In this work, the DSSAT model was used to simulate crop growth, development, and yield by incorporating interactions between soil, plants, the atmosphere, and management practises. These models necessitate a wide range of inputs, including daily meteorological data, accurate soil surface and profile information, precise crop management plans, and genetic data relevant to the crops used. The adaptability of DSSAT and its crop simulation models has led to their use in a wide range of situations, from on-farm and precision management scenarios to broader regional analyses of the effects of yield estimation and climate change. The CSM-CROPGRO-Chickpea model has been used in recent studies to study the influence of climate change on chickpea output in Ethiopia (Mohammed *et al.*, 2017). The model has also been applied for yield prediction in Gujarat (Patil *et al.*, 2018) and Uttar Pradesh (Kumar *et*

al., 2018). This study employs the CROPGRO-chickpea model to predict chickpea yields across various locations in the study area, weather patterns, soil types, and management practices.

MATERIAL AND METHODS

A. Study Area

The Bundelkhand region of Uttar Pradesh encompasses the state's southern half. Bundelkhand is located in central India, between 25.1448° and 25.7502° North latitudes and 78.4182° to 80.8577° East longitudes, bordered by the Yamuna River to the north, the Chambal River to the west, the Bagelkhand region of Madhya

Pradesh to the south, and the Vindhya Range to the east. The Bundelkhand region has a subtropical climate, with hot summers and comparatively cool winters. Monsoon rains are critical for agricultural activity in the region. Despite its arid and semi-arid climate, agriculture is an important economic activity in Bundelkhand. Wheat, Pulses, oilseeds, and jowar are commonly grown here. The study area includes seven districts in Uttar Pradesh: Jalaun, Hamirpur, Mahoba, Jhansi, Banda, Lalitpur, and Chitrakoot (Fig. 1). The Bundelkhand region of Uttar Pradesh is comprised of these seven districts.

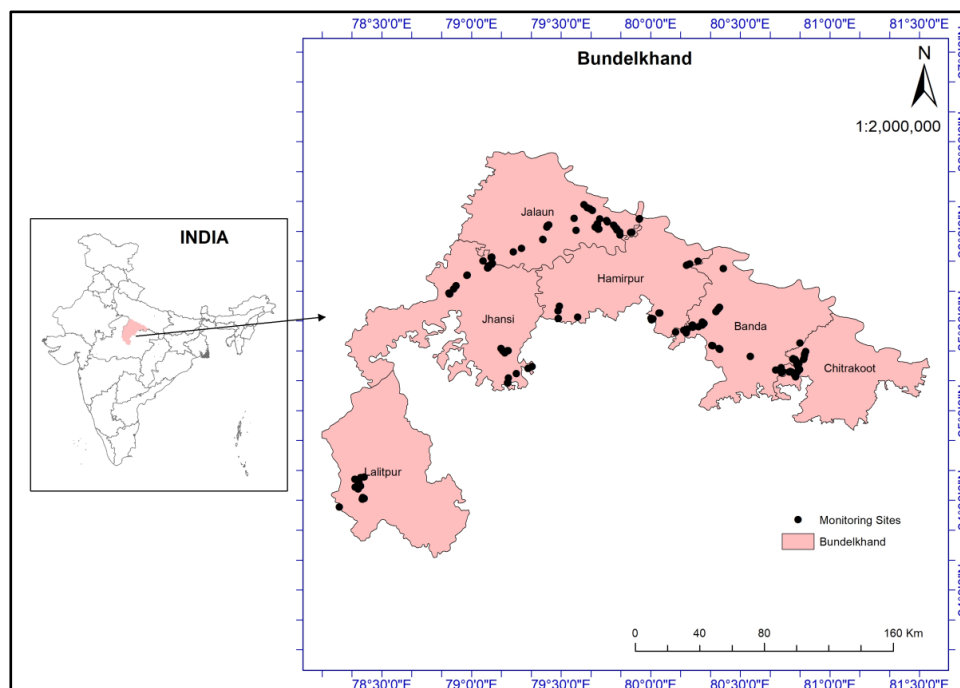


Fig. 1. Monitoring sites in Bundelkhand Region of Uttar Pradesh.

B. Experiment and Crop Simulation Model

Two field experiments were conducted during the Rabi seasons of 2021-22 and 2022-23 at different locations of study area. 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. A total of 325 ground truth points corresponding to chickpea and 76 points representing other crops were collected during the comprehensive ground survey in Bundelkhand region of Uttar Pradesh. These points were obtained using a random stratified sampling method, contributing to the training and validation process. Among the collected chickpea points, 15-20 points from each district were meticulously chosen as monitoring sites for the training of the DSSATv4.7 model.

The genetic coefficients for different varieties of chickpea were derived using the GLUE software. This involved selecting a chickpea variety from the DSSATv4.7 database and defining experimental conditions based on actual growth trials of the chosen

variety. This procedure closely followed the methodologies outlined in the works of He *et al.* (2010); Buddhaboon *et al.* (2018). To ensure the accuracy of the calibrated model in representing real-world scenarios, a validation process was conducted by comparing simulated results to observed data.

The actual yield of chickpea or the attainable yield achieved by farmers during the Rabi season of 2022-23 was determined. This was accomplished by conducting Crop Cutting Experiments (CCEs) at different monitoring sites within the seven districts of Bundelkhand region of Uttar Pradesh. At each monitoring site, four separate CCEs were conducted. These experiments were carried out in randomly selected areas, each measuring 5x5 meters. The average yield obtained from these four CCEs at each monitoring site was then extrapolated to yield per hectare (ha), serving as the actual yield value for that specific site. The gathered yield data was subsequently used as the basis for estimating the attainable yield, which in turn serves as a benchmark for measuring the yield gap experienced in chickpea production.

C. Calibration and Validation

The model performance was evaluated by using the statistical indices include the coefficient of determination (R^2), Normalized Root Mean Square Error (NRMSE), Index of Agreement (d) and Mean Absolute Percentage Error (MAPE).

Coefficient of determination (R^2): Pearson's correlation coefficient is denoted as "r," while R-squared (R^2) is the squared value of Pearson's correlation coefficient.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}$$

where, r: Correlation coefficient; n: number in the given dataset; x: first variable in the context; y: second variable

Normalized Root Mean Square Error (NRMSE): The normalized root-mean-square error (NRMSE) can be understood as a proportion of the total range that is typically captured by the model.

$$NRMSE = \frac{RMSE}{\bar{O}}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{model,i})^2}{n}}$$

Where, X(Obs,i) is the observation value and X(model, i) is the forecast value.

Index of Agreement (d): The index of agreement signifies the relationship between the mean square error and the potential error, expressed as a ratio.

$$d = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (|P_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

Where, O_i : observation value; P_i is the forecast value; \bar{O} : average observation values; \bar{P} : average forecast values.

Mean Absolute Percentage Error (MAPE): The Mean Absolute Percentage Error (MAPE) quantifies the magnitude of errors in terms of percentage.

$$MAPE = 100 \times \frac{1}{n} \times \sum_{i=1}^n \left| \frac{Obs_i - Model_i}{Obs_i} \right|$$

Where, Obs is the observation value and Model is the forecast value.

RESULTS AND DISCUSSION

A. Chickpea Genetic Coefficients

The genetic coefficients for four different varieties JG 16, RVG 202, IPC-07-66, and IPC-05-62 of chickpea were generated using the GLUE software in DSSATv4.7 as discussed in the methodology (Table 1). The GLUE program was separately executed for both phenological and growth parameters. The resulting parameter values were then integrated into the specific cultivars profile.

Table 1: Genetic coefficients generated by GLUE tool for different chickpea cultivars.

Genetic Parameter	JG 16	RVG 202	IPC-06-77	IPC-05-62
CSDL	11.00	11.00	11.00	11.00
PPSEN	-.143	-.143	-.143	-.143
EM-FL	37.84	41.14	35.66	37.77
FL-SH	8.6	6.5	6.1	8.180
FL-SD	14.9	14.5	14.4	14.2
SD-PM	26.05	33.22	33.02	38.33
FL-LF	34.00	36.00	36.00	42.00
LFMAX	1.000	1.001	1.004	1.002
SLAVR	135.1	131.7	137.6	138.2
SIZLF	10.00	10.00	10.00	10.00
XFRT	0.960	0.960	0.960	0.960
WTPSD	0.194	0.227	0.200	0.186
SFDUR	22.0	22.0	22.0	22.0
SDPDV	1.20	1.60	1.60	1.600
PODUR	18.0	18.0	18.0	18.0
THRSH	82.0	82.0	85.0	85.0
SDPRO	0.216	0.216	0.244	0.262
SDLIP	0.48	0.48	0.48	0.48

Abbreviations: SD: Standard Deviation CSDL: Critical Short-Day Length below which reproductive development progresses WITH day length 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 ppm 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))

B. Yield Estimation with Crop Simulation Models

The DSSAT CROPGRO-chickpea model was executed to estimate yields using different weather, soil and

management files for the points in the study area. The simulated yields ranged from 1279 to 2198 kg ha⁻¹, while the observed yields produced in the farmers' fields

ranged from 1024 to 2084 kg ha⁻¹. For all varieties in study area, the simulated yield fitted well with the observed yield although the simulated yield was slightly higher than the observed values. Slight overestimation in simulation of biomass yield than observed yield in DSSAT-CERES-Wheat DSSAT was reported by Attia *et*

al. (2016). The observed yield and simulated yield are compared, and their deviation is calculated. It indicates that the deviation is 64 to 378 kg ha⁻¹ for all varieties of chickpea in 47 experimental locations of seven districts (Table 2).

Table 2: Comparison of observed and simulated yields of chickpea in the study area.

Latitude	Longitude	Observed Yield (kg ha ⁻¹)	Simulated Yield (kg ha ⁻¹)	Deviation (kg ha ⁻¹)
Variety I: JG 16				
26.01238	79.71164	1098	1365	267
26.14808	79.62718	1467	1548	81
25.58088	79.49028	1264	1421	157
26.03454	79.43108	1024	1402	378
25.50087	79.46531	1148	1279	131
25.51226	79.48461	1175	1293	118
25.51206	79.48457	1264	1416	152
25.25132	79.48534	1158	1367	209
25.51301	79.48507	1194	1342	148
26.00384	79.58352	1154	1400	246
26.07194	79.57198	1184	1358	174
25.54295	80.04598	1134	1462	328
Variety II: RVG 202				
25.79917	79.09445	1795	1892	97
25.80475	79.09332	1657	1735	78
25.81559	79.11227	1564	1700	136
25.81624	79.10976	1649	1789	140
25.81977	79.1159	1028	1320	292
25.81975	79.11615	1484	1678	194
25.15431	79.20195	1465	1605	140
25.15512	79.20266	1436	1589	153
24.62505	78.38076	1364	1512	148
Variety - IPC-06-77				
25.28431	80.80548	1595	1735	140
25.28939	80.79491	1458	1711	253
25.28588	80.79361	1539	1719	180
25.25821	80.82404	1364	1523	159
25.26217	80.82676	1687	1877	190
25.28518	80.85314	1364	1482	118
25.27167	80.12533	1958	2022	64
25.27267	80.12571	1546	1745	199
25.27315	80.12532	1853	2002	149
25.33477	80.27244	1984	2142	158
25.36187	80.34213	2084	2198	114
25.36129	80.34585	1549	1648	99
25.34532	80.38167	1684	1798	114
25.34119	80.38526	1982	2064	82
25.30065	80.55532	1842	1932	90
Variety - IPC-05-62				
25.41370	79.45471	1525	1673	148
25.40166	79.51277	1534	1687	153
25.37998	79.52686	1352	1702	350
25.36216	79.56621	1459	1567	108
25.32726	79.68988	1635	1832	197
25.31108	79.73334	1582	1763	181
25.15173	79.20108	1597	1729	132
24.62818	78.40111	1559	1812	253
24.60092	78.37177	1473	1569	96
24.59721	78.36765	2058	2137	79
24.57766	78.38059	1964	2096	132

C. Accuracy Assessment

In this study, various statistical metrics were employed to evaluate the model's performance against the actual

data for chickpea yield. The assessment utilized the coefficient of determination, Normalized Root Mean Square Error, Index of Agreement, and Mean Absolute

Percentage Error. When examining the model's performance against observed chickpea yield, the calibration results displayed an R^2 value of 0.942. This yielded smaller discrepancies between the model's simulations and the observed yields, as visualized in Fig. 2. The NRMSE for simulated yields was 0.107, indicating a favourable alignment between the model's predictions and actual data. Additionally, the simulated yields demonstrated an MAPE of 10.2%. These metrics collectively suggest that the model effectively captured the production of the four chickpea cultivars during the 2021-22 rabi season.

To gauge the accuracy of the model's predictions, the index of agreement (d) was employed, which ranges between 0 and 1. In the context of this experiment, a value of d greater than 0.9 was deemed excellent, while a value between 0.8 and 0.9 indicated a good fit between the simulated and observed data. Furthermore, a moderate agreement was identified for d values between 0.7 and 0.8 for CSM-CROPGRO-Soybean and CSM-CERES-Maize modules (Liu *et al.*, 2013). During the calibration phase of the CROPGRO-chickpea model, the calculated index of agreement exhibited strong concordance between the simulated and observed yield

data, with a value of 0.892. This outcome underscores that the calibrated model's performance was deemed acceptable.

In the validation phase for the rabi season of 2022-23, the comparison between simulated and observed yields yielded a favourable R^2 value of 0.923, showcasing a strong correlation. The agreement was even higher with an index of agreement (d) of 0.827. However, in terms of error assessment, the model displayed good alignment with a NRMSE of 0.147 and an MAPE of 13.9% (Fig. 3). The analysis of these calculated statistical metrics for both model calibration and evaluation implies that the crop simulations accurately captured the trends seen in the observed data. Consequently, the model, which has been calibrated and evaluated, is deemed suitable for conducting scenario analyses and making predictions about future outcomes. Notably, the statistical parameters derived from this study are consistent with findings from other investigations employing the DSSAT CROPGRO-chickpea model (Patil and Patel 2017; Hajishabani *et al.*, 2020) and for CROPGRO-Cotton (Srinivasan *et al.*, 2021).

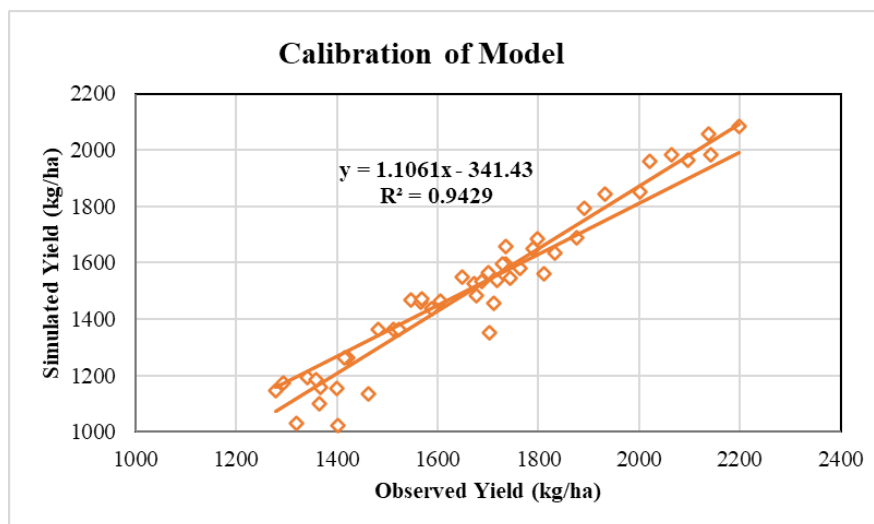


Fig. 2. Calibration of DSSAT model with simulated and observed yields.

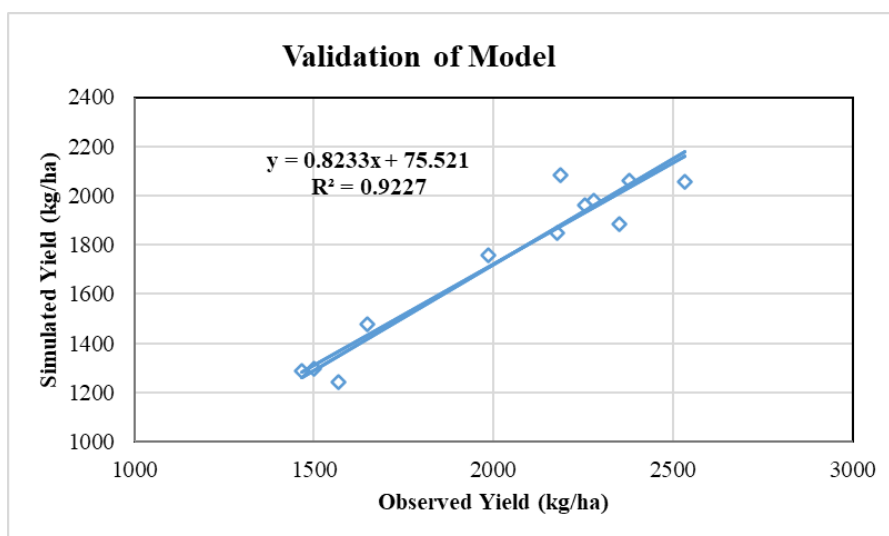


Fig. 3. Validation of DSSAT model with simulated and observed yields.

CONCLUSIONS

The effectiveness of the DSSAT model in predicting chickpea yield has been established, signifying its utility as a valuable predictive tool. The incorporation of the CROPGRO module allows for spatial yield simulations under varying conditions of soil, weather, and management practices, thereby enhancing chickpea production prospects. In essence, the model's proficiency in rainfed environments is evident as the study area Bundelkhand region of Uttar Pradesh falls under rainfed zone.

FUTURE SCOPE

The validated DSSAT model holds potential for diverse applications, including forecasting crop growth, phenology, potential and actual yield, as well as assessing chickpea performance under climate change scenarios. Furthermore, the model's capabilities extend to refining and evaluating current practices related to chickpea cultivation and management.

Conflict of Interest. None.

REFERENCES

- Attia, A., Rajan, N., Xue, Q., Nair, S., Ibrahim, A., & Hays, D. (2016). Application of DSSAT-CERES-Wheat model to simulate winter wheat response to irrigation management in the Texas High Plains. *Agricultural Water Management*, 165, 50-60.
- Buddhaboon, C., Jintrawet, A., & Hoogenboom, G. (2018). Methodology to estimate rice genetic coefficients for the CSM-CERES-Rice model using GENCALC and GLUE genetic coefficient estimators. *The Journal of Agricultural Science*, 156(4), 482-492.
- Food and Agriculture Organization of the United Nations (FAO) (2009). High Level Expert Forum—How to Feed the World in 2050.
- Hajishabani, H., Mondani, F., & Bagheri, A. (2020). Simulation effects of sowing date on growth and yield of rainfed Chickpea (*Cicer arietinum* L.) by CROPGRO-CHICKPEA model. *Iranian Journal of Field Crops Research*, 18(2), 197-212.
- He, J., Porter, C. H., Wilkens, P. W., Marin, F., Hu, H., Jones, J. W., & Tsuji, G. Y. (2010). Generalized likelihood uncertainty analysis tool for genetic parameter estimation (GLUE Tool). *Decision Support System for Agrotechnology Transfer Version*, 4, 21-32.
- Indiastat (2023). Area, Production and Productivity of Gram in India (1950–51 to 2022–2023-3rd Advance Estimates). Available at URL <https://www.indiastat.com/table/agriculture/area-production-productivity-gram-india-1950-1951-/17325>
- Kumar, N., Singh, A. K., Mishra, S. R., Mishra, A. N., Chaudhari, R., & Singh, P. K. (2018). Performance & growth of chickpea (*Cicer arietinum* L.) cultivars on Dssat simulation model. *Journal of Pharmacognosy and Phytochemistry*, 7(2), 3397-3400.
- Liu, S., Yang, J. Y., Zhang, X. Y., Drury, C. F., Reynolds, W. D., & Hoogenboom, G. (2013). Modelling crop yield, soil water content and soil temperature for a soybean–maize rotation under conventional and conservation tillage systems in Northeast China. *Agricultural water management*, 123, 32-44.
- Mohammed, A., Tana, T., Singh, P., Korecha, D., & Molla, A. (2017). Management options for rainfed chickpea (*Cicer arietinum* L.) in northeast Ethiopia under climate change condition. *Climate Risk Management*, 16, 222-233.
- Pandey, V., Singh, A. K., Mishra, S. R., Singh, G., Deo, K., & Mishra, A. (2019). Evaluation of crop simulation modeling in chickpea crop using DSSAT model under agroclimatic conditions of eastern UP. *The Pharma Innovation Journal*, 8(4), 1139-1142.
- Patil, D. D., & Patel, H. R. (2017). Calibration and validation of CROPGRO (DSSAT 4.6) model for chickpea under middle GUJARAT agroclimatic region. *International Journal of Agriculture Sciences*.
- Patil, D. D., Karande, B. I., Satpute, S. B., & Patel, H. R. (2018). Sensitivity analysis to study the impact of climate change on chickpea using DSSAT (4.6) CROPGRO model over middle Gujarat Agroclimatic region. *A Peer-Review. Multi-Disciplinary Int. J.*, 223.
- Srinivasan, G., Pazhanivelan, S., Krishnasamy, S. M., Sudarmanian, N. S., Rajeswari, S., & Kannan, B. (2021). Deriving Genetic Coefficients for Cotton using the DSSAT CROPGRO-Cotton Model. *Biological Forum – An International Journal*, 13(4), 1077-1081.

How to cite this article: Kancheti Mrunalini, Sellaperumal Pazhanivelan, Narendra Kumar, Ragnath Kaliaperumal, S.P. Ramanathan, N. Sritharan and A. Ragul (2023). Geospatial Approach to Chickpea Yield Estimation: DSSAT-CROPGRO Calibration in Bundelkhand, Uttar Pradesh. *Biological Forum – An International Journal*, 15(8a): 203-208.