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# Utilizing the CROPGRO Simulation Model to Optimize Management Practices for Achieving High Soybean Yields

**Ankita Negi[1], Kuldeep Rana[2] and Rajeev Ranjan[3]**

[1]Krishi Vigyan Kendra Baghpat, Sardar Vallabhbhai Patel University of Agriculture & Technology, Meerut, Uttar Pradesh (250 110), India

[2]Forestry and Ecology Department, Indian Institute of Remote Sensing, Dehradun, Uttarakhand (248 001), India

[3]Dept. of Agrometeorology, Govind Ballabh Pant University of Agriculture & Technology, Pantnagar, Uttar Pradesh (263 145), India

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**Corresponding** negi1996ankita@gmail.com

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## ABSTRACT

A study was conducted during the *kharif* (June–September) season of 2018 at G.B.P.U.A.&T., Pantnagar, Uttarakhand, India to calibrate and validate the CROPGRO-soybean model for Terai region and determine the optimal management practices for soybean variety PS1347. The experiment followed a Two Factorial Randomized Block Design, involving two fertilizer treatments with three sowing dates replicated thrice. The CROPGRO model was calibrated and validated using the field data of 2018 and 2017, respectively. The RMSE% between the observed and simulated values of different crop stages and yield indicators were between 3.24% and 14.22%. Subsequently, the crop yield for different management practices was also simulated. The model encompassed yield simulations for various management practices *viz.*, six tillage methods, five fertilizer treatments, nine sowing dates, and six irrigation levels. To achieve error minimization, soybean yield was simulated for four consecutive years (2015–2018) under various management practices, and the data was averaged. The simulation results indicated that the optimal management practices for achieving the highest soybean yield include sowing the seeds on the 20$^{th}$ June after implementing a tillage regimen involving three ploughings and two harrowing operations and further nourishing the crop with fertilizer dose of N:P:K:S::25:60:40:20 and applying 90 mm of irrigation. These findings will aid in optimizing management practices and developing sustainable and efficient approaches to achieve higher soybean yields with minimal inputs.

**KEYWORDS:** CROPGRO-Soybean model, calibration, crop management practices, validation

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***Data Availability Statement:*** Legal restrictions are imposed on the public sharing of raw data. However, authors have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

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## 1. INTRODUCTION

Soybean (*Glycine max* L. Merr.) is a highly productive, nutritional and profitable legume crop with diverse applications worldwide (Yoosefzadeh-Najafabadi et al., 2021). It plays a vital role in global vegetable oil production and serves as a valuable protein source for both humans and livestock (Choudhary et al., 2015; Das et al., 2016; Yusefi-Tanha et al., 2023). This versatile crop not only offers high protein content but also has the ability to enhance soil fertility, making it valuable in addressing nutritional security (Dass and Bhattacharyya, 2017). Furthermore, soybean seeds contain essential amino acids and important micronutrients such as zinc, iron, and manganese (Kobraee et al., 2013), making it a well-rounded food choice in Indian diets (Dass et al., 2022).

Meeting the escalating demands for food, feed, and bioenergy relies heavily on agricultural productivity (Spiertz and Ewert, 2009). Although there has been notable progress in terms of coverage and overall production, sustainability of high soybean productivity continues to face various constraints related to climate, soil conditions, production factors, and technological aspects (Agarwal et al., 2013). To ensure sustainable production and maximize soybean yield, it is imperative to adopt advanced approaches that optimize management strategies while minimizing environmental impacts (Balasundram et al., 2023). Maximizing crop yield necessitates the meticulous selection and optimization of management practices like irrigation (Roy et al., 2019), sowing date (Bateman et al., 2020), tillage and fertilization (Young et al., 2021). The interdependence of these practices implies that the outcome of one practice can be influenced by others. While a single practice may yield favorable results when assessed individually, its performance can be compromised when integrated with other practices, leading to reduced output. Consequently, it is crucial to identify the most effective combination of management practices, while minimizing inputs, in order to optimize crop yield within specific conditions.

Crop simulation models have been created and utilized as instruments for identifying stringent management strategies specific to a given location by considering variables such as fertilizer application rates, plant density, sowing dates, and land use options (Boote et al., 1996; Ruiz-Nogueira et al., 2001; Bebeley et al., 2022). Among the various simulation models available, the CROPGRO model has gained widespread recognition as it aids decision-making for enhancing production by analyzing climate variability, management practices, and varietal selection under specific and future environmental conditions (Nath et al., 2017). The CROPGRO model, developed by the Decision Support System for Agrotechnology Transfer (DSSAT) initiative, has consistently shown good performance in simulating crop responses to detailed physiological processes and environmental factors (Bhatia et al., 2008; Bao et al., 2015a; Salmerón and Purcell, 2016; Hoogenboom et al., 2019). CROPGRO model has been widely used for simulation of crop yields of several agricultural crops like soybean, cotton, alfa alfa etc. (Malik et al., 2018; Dar et al., 2023). Previous studies have utilized the CROPGRO model to simulate soybean yield under various parameters and conditions, such as climate change scenarios (Bao et al., 2015b; Battisti et al., 2017; Nath et al., 2018; MacCarthy et al., 2022), sowing timings (Ruiz-Nogueira et al., 2001; Bebeley et al., 2022), and water management strategies (Dogan et al., 2007; Bhatia et al., 2008; Sharda et al., 2019). However, these studies were conducted focusing on specific factors. Meanwhile, the present study focuses on calibration and validation of CROPGRO model for optimizing soybean yield considering a diverse range of crop management practices, including tillage, irrigation, sowing date, and fertilization. Additionally, it aims to determine the optimal combination of these management practices that maximizes soybean yield. The findings of this study will provide valuable insights and recommendations for soybean growers, facilitating the development of sustainable and efficient practices that help in achieving better soybean yield using minimal inputs.

## 2. MATERIALS AND METHODS

### *2.1. Experimental site*

The experiment was conducted in the E4 plot (Latitude 29.08°N, Longitude 79.28°E, and Altitude 243.84 meters above mean sea level) within the Norman E. Borlaug Crop Research Centre of G.B.P.U.A.&T, Pantnagar in Uttarakhand, India. Pantnagar is situated in the Terai region of the Himalaya belt. The experiment took place during the *kharif* season (June–September) in the year 2018, specifically focusing on the soybean crop variety PS1347. The selected site, E4 plot, is characterized by sandy loam texture. The climate of the Pantnagar region is classified as humid subtropical, characterized by hot and dry summers and cool winters. The maximum temperature of Pantnagar during summer goes up to 42°C while winter temperature falls as low as 1°C. The month of May exhibits the highest recorded temperature of the year, while January typically experiences the lowest temperatures. The study area experiences a mean annual rainfall ranging from 1300 to 1400 mm. The monsoon season, spanning from June to September, accounts for approximately 80% of the annual rainfall. July and August are the wettest months, whereas the period from November to April is considered among the driest months of the year.

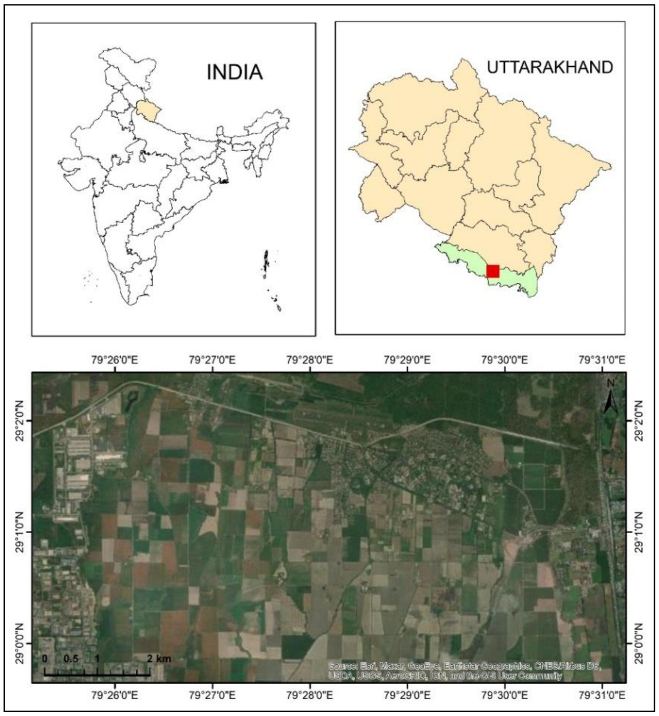


Figure 1: Study area map of experimental site at Pantnagar

*2.2. Calibration and validation of the CROPGRO model*

The primary objective of this study was to optimize soybean yield under various management practices utilizing the CROPGRO simulation model. The genotypic coefficient for soybean variety PS1347 generated for Pantnagar region was used in the study. The CROPGRO model was calibrated using the 2018 dataset, incorporating all observed values from the field. The model's simulation capability was assessed by examining its performance in predicting various observed field variables, including emergence, anthesis, physiological maturity, grain yield, biological yield, and harvest index. In order to verify the accuracy of the model, a comparison was made between the model simulated values and the observed values from the field. An iterative process of trial and error was implemented to reduce the error in the simulation. Model validation was performed by comparing the simulated dataset with the observed dataset obtained from field experiments conducted during the *kharif* (June–September) season of 2017. Simulated values within the projected confidence interval were considered valid for the simulation. To evaluate the model's performance, the root mean square error percentage (RMSE%) was calculated. Finally, after accomplishing the calibration and validation of CROPGRO model, it was employed to forecast the yield under different management practices.

*2.3. Crop management practices*

The sowing of the soybean crop was carried out using two fertilizer treatments: Site-Specific Nutrient Management (SSNM) $F_1$- N:P:K:S::25:50:50:30, and Nitrogen Omission $F_2$- P:K:S::50:50:30. Each treatment was replicated thrice and implemented on three different sowing dates viz., $D_1$ (29$^{th}$ June), $D_2$ (9$^{th}$ July), and $D_3$ (19$^{th}$ July). The experiment was conducted following a two Factorial Randomized Block Design. The plant growth and development parameters were recorded for *kharif* (June–September) season of 2018. Weather data for the entire season was collected from the Agrometeorological Observatory of C.R.C. G.B.P.U.A.&T, Pantnagar.

In the process of selecting the best management practices, different practices like six tillage treatments, five fertilizer options, nine sowing dates, and six irrigation levels were compared to determine the combination that would produce the highest soybean yield at a low cost. The CROPGRO model was employed to calculate the simulated yield for four consecutive years, namely 2015, 2016, 2017, and 2018, for each treatment. Subsequently, the four-year average of the simulated yield was computed for each treatment with the aim to minimize the error in the simulations. The obtained results were then analyzed and interpreted to determine the optimal combination of management practices that can maximize soybean yield.

*2.3.1. Tillage treatments*

Table 1 presents various tillage treatments, including their dates, operations, and implements used. The treatments differ in terms of the number of operations conducted, implements employed, and ploughing depths. Some treatments involved multiple operations such as ploughing and harrowing, while others focused on specific implements like the chisel plough, harrow tine, or cultivator field. Additionally, variations in yield against different ploughing depths (10 cm, 20 cm and 30 cm) were tested. These differences in tillage treatments demonstrate the range of approaches evaluated in the study, highlighting the potential impact of different tillage strategies on yield of soybean crop. The four-year average yield (2015–2018) results obtained under different tillage treatments were analyzed to obtain the best tillage treatment that can produce maximum yield under a given fertilizer treatment on a specific sowing date.

*2.3.2. Fertilizer doses*

A total of five fertilizer doses were used to simulate the soybean crop yield (Table 2). The differences in the fertilizer doses mainly lie in the relative proportions of nitrogen (N), phosphorus (P), potassium (K), and sulfur (S). These variations in nutrient ratios can have significant impacts on plant nutrition, growth, and development. Choosing the appropriate fertilizer dose with the desired nutrient composition is crucial for optimizing plant productivity and achieving specific agricultural goals. The best fertilizer treatment was selected after evaluating the simulated yield of soybean crop for different treatments ($f_1$, $f_2$, $f_3$, $f_4$, and $f_5$)

Table 1: Tillage treatment combinations used to simulate soybean yield

| Treat-ments | Date | Tillage operation | Implements used |
|---|---|---|---|
| Tillage 1 ($T_1$) | June 22nd | Ploughing | Chisel plough straight point (30 cm) |
| | June 26th | Ploughing | Cultivator field (20 cm) |
| Tillage 2 ($T_2$) | June 25th | Ploughing | Chisel plough straight point (30 cm) |
| | June 26th | Harrowing | Harrow tine (10 cm) |
| | June 27th | Ploughing | Cultivator field (20 cm) |
| Tillage 3 ($T_3$) | June 25th | Ploughing | Chisel plough straight point (30 cm) |
| | June 26th | Harrowing | Harrow tine (10 cm) |
| | June 27th | Harrowing | Harrow tine (10 cm) |
| | June 28th | Ploughing | Cultivator field (15 cm) |
| | June 29th | Ploughing | Cultivator field (15 cm) |
| Tillage 4 ($T_4$) | June 25th | Ploughing | Chisel plough straight point (30 cm) |
| | June 26th | Harrowing | Harrow tine (10 cm) |
| | June 27th | Harrowing | Harrow tine (10 cm) |
| | June 28th | Ploughing | Cultivator field (20 cm) |
| | June 29th | Ploughing | Cultivator field (20 cm) |
| Tillage 5 ($T_5$) | June 29th | Ploughing | Cultivator field (20 cm) |
| Tillage 6 ($T_6$) | June 29th | Ploughing | Cultivator field (15 cm) |

using CROPGRO simulation model.

*2.3.3. Date of sowing*

The comparison of simulated soybean yield was done at nine different sowing dates taken at 10 day intervals from 30th May to 20th August *viz.*, 30th May, 10th June, 20th June, 30th June, 10th July, 20th July, 30th July, 10th August and 20th August.

Table 2: Different fertilizer doses used for yield optimization

| Symbols | Fertilizer doses |
|---|---|
| $f_1$ | N:P:K:S::25:60:40:20 |
| $f_2$ | N:P:K:S::25:80:40:20 |
| $f_3$ | N:P:K:S::20:60:40:20 |
| $f_4$ | N:P:K:S::25:80:50:20 |
| $f_5$ | N:P:K:S::20:80:40:20 |

*2.3.4. Irrigation*

A total of six irrigation levels viz., 40 mm, 50 mm, 60 mm, 70 mm, 80 mm, and 90 mm were used to determine the best irrigation level that would result in the highest soybean yield.

## 3. RESULTS AND DISCUSSION

### *3.1. Calibration and validation of CROPGRO model*

Various plant growth and development parameters, such as, emergence, anthesis, days to physiological maturity, grain yield, biological yield, and harvest index were observed and simulated for the year 2018. The observed and simulated data on the occurrence of different crop stages during the crop season are presented in Table 3. Regardless of the fertilizer treatment or sowing date, the observed field data shows that crop generally took around 4–5 days to emerge after sowing. Anthesis occurred after approximately 49–57 days, while physiological maturity ranged from 95–123 days after sowing. Upon examining the relation between observed and simulated values of different crop stages at various treatments and sowing dates, several patterns were observed. In general, there is a notable level of consistency

Table 3: Observed and simulated readings of different crop growth stages in relation to various fertilizer treatments and sowing dates

| Fertilizer treatments | Date of sowing | Crop growth stages | | | | | |
|---|---|---|---|---|---|---|---|
| | | Emergence (days after sowing) | | Anthesis (days after sowing) | | Physiological maturity (days after sowing) | |
| | | Observed | Simulated | Observed | Simulated | Observed | Simulated |
| SSNM | $D_1$ (29th June) | 5 | 5 | 57 | 59 | 123 | 104 |
| | $D_2$ (9th July) | 5 | 5 | 57 | 59 | 123 | 104 |
| | $D_3$ (19th July) | 4 | 4 | 54 | 53 | 100 | 96 |
| N Omission | $D_1$ (29th June) | 5 | 4 | 54 | 53 | 100 | 96 |
| | $D_2$ (9th July) | 4 | 4 | 49 | 47 | 95 | 90 |
| | $D_3$ (19th July) | 4 | 4 | 49 | 47 | 95 | 90 |
| RMSE (%) | | 9.07 | | 3.24 | | 10.92 | |

between the observed and simulated values across different crop stages for varying treatments, and sowing dates. This suggests that the simulation model is capable of accurately predicting the crop growth stages. The observed and simulated values of emergence (RMSE: 9.07%) and anthesis (RMSE: 3.24%), tend to closely align with each other across most treatments and sowing dates, indicating that the model performs well in capturing the timing of these key growth stages. However, in some instances, there are slight discrepancies between the observed and simulated values for the variable of physiological maturity (RMSE: 10.92%). The simulated values may deviate slightly from the observed values, suggesting a margin of error in predicting the completion of this growth stage.

By comparing the observed and simulated values across different fertilizer treatments and sowing dates, it is possible to assess the effects of these factors on crop growth stages. Under the SSNM treatment, both observed and simulated values of crop stages (emergence, anthesis, and physiological maturity) show consistency across different sowing dates. This indicates that the fertilizer application according to site-specific nutrient management has a positive impact on crop growth stages. In the N Omission treatment, the observed and simulated values of crop stages are slightly lower compared to the SSNM treatment. This suggests that the omission of nitrogen fertilizer has a slight negative impact on crop growth, leading to a delay in growth stages. For both fertilizer treatments, the observed and simulated values of crop stages are generally higher on $D_1$ (29$^{th}$ June) compared to the other sowing dates. This indicates that early sowing promotes faster crop growth and development. While, for both $D_2$ (9$^{th}$ July) and $D_3$ (19$^{th}$ July), the observed and simulated values of crop stages are slightly lower compared to the $D_1$ sowing date. The fertilizer treatments and sowing dates have a noticeable impact on the observed and simulated values of different crop stages. The SSNM treatment generally leads to better crop growth, while the omission of nitrogen fertilizer (N Omission treatment) results in slightly lower growth stages. Additionally, early sowing ($D_1$) tends to promote faster crop growth, while later sowing dates ($D_2$ and $D_3$) may cause a slight delay in crop development. These findings highlight the importance of appropriate fertilizer management and timely sowing practices to optimize crop growth. (Rathore et al., 2019) Overall, the relation between observed and simulated values indicates that the simulation model is generally reliable in predicting the crop growth stages. The simulation results from Yadav et al. (2012) demonstrated that the DSSAT model satisfactorily simulates anthesis (days after sowing), first pod (days after sowing), maturity (days after sowing), leaf area index, pod yield, harvest index, and shelling percentage. Boulch et al. (2021) evaluated the adaptation potential of soybean under different agro-climatic scenarios using CROPGRO model and obtained good simulation for different crop stages of soybean crop. Mishra et al. (2021) observed favorable model simulations for cotton cultivars across different sowing dates, specifically from anthesis to physiological maturity, indicating proficient predictive capabilities of CROPGRO model.

Table 4 provides information on the relation between observed and simulated values of different crop yield indicators at various fertilizer treatments and sowing dates. The observed and simulated grain yield (RMSE: 7.2%), biological yield (RMSE: 8.62%), and harvest index (RMSE: 14.22%) values under both the SSNM and N Omission treatments are quite similar, indicating good agreement between the observed data and the simulation results. Under SSNM, the differences between the observed and simulated values are relatively small, suggesting that the simulation accurately represents the actual crop performance. However,

Table 4: Observed and simulated readings of different crop yield indicators in relation to various fertilizer treatments and sowing dates

| Fertilizer treatments | Date of sowing | Crop yield indicators | | | | | |
|---|---|---|---|---|---|---|---|
| | | Grain yield (kg ha$^{-1}$) | | Biological yield (kg ha$^{-1}$) | | Harvest Index (%) | |
| | | Observed | Simulated | Observed | Simulated | Observed | Simulated |
| SSNM | $D_1$ (29$^{th}$ June) | 2469 | 2466 | 6543 | 6564 | 38 | 39 |
| | $D_2$ (9$^{th}$ July) | 2074 | 2434 | 6272 | 6510 | 33 | 39 |
| | $D_3$ (19$^{th}$ July) | 2290 | 2313 | 6497 | 5940 | 35 | 38 |
| N Omission | $D_1$ (29$^{th}$ June) | 2275 | 2298 | 6152 | 5879 | 37 | 39 |
| | $D_2$ (9$^{th}$ July) | 2100 | 2205 | 6275 | 5163 | 33 | 43 |
| | $D_3$ (19$^{th}$ July) | 2074 | 2175 | 5124 | 5035 | 40 | 43 |
| RMSE (%) | | 7.2 | | 8.62 | | 14.22 | |

there are slightly larger differences in N Omission compared to the SSNM treatment, indicating a relatively higher level of uncertainty in the simulation results due to the absence of nitrogen fertilizer. The differences between observed and simulated values of crop yield indicators for $D_1$ (29th June) are relatively small, suggesting that the simulation accurately captures the crop performance for this sowing date. Whereas, the observed and simulated values for the later sowing dates ($D_2$: 9th July and $D_3$: 19th July) show slightly greater differences compared to the $D_1$ sowing date. Overall, the observed and simulated values of crop yield indicators demonstrate a reasonably close agreement, indicating that the simulation model is capable of capturing the general trends and patterns in crop performance. da Silva et al. (2021) also found that CROPGRO showed good agreement between simulated and observed results of soybean yield under climate change scenario. However, some differences between observed and simulated values exist, which can be attributed to various factors such as variations in field conditions, uncertainties in parameter estimation, limitations of the simulation model, biotic stresses, and factors not considered in the model (Liu et al., 2011; Quansah et al., 2020). But these differences are relatively smaller and can be taken care of while interpreting and utilizing the simulated results for decision-making purposes.

*3.2. Comparison of simulated yield with different management practices*

*3.2.1. Tillage treatment*

Table 5 highlights the influence of different tillage treatments and sowing dates on the simulated yields of the crops under investigation. In the SSNM experiment, the maximum simulated yield (2291.00 kg ha$^{-1}$) was observed under tillage treatment $T_4$ and sowing date $D_1$ (29th June). This combination yielded the highest simulated yield among all the options presented in the table. On the other hand, the minimum simulated yield (2041.25 kg ha$^{-1}$) in the SSNM experiment was observed under tillage treatment $T_4$ and sowing date $D_3$ (19th July). In the N omission experiment, the maximum simulated yield (2263.25 kg ha$^{-1}$) occurs under tillage treatment $T_2$ and sowing date $D_1$ (29th June). The minimum simulated yield (1989.50 kg ha$^{-1}$) in the N omission experiment was observed under tillage treatment $T_5$ and sowing date $D_3$ (19th July). The combination of tillage treatment $T_4$ and sowing date $D_1$ (29th June) consistently yielded the highest simulated yield in both the SSNM and N omission experiments. This combination shows promising results in terms of achieving higher crop yields compared to other combinations of tillage treatments and sowing dates presented in the table.

Table 5: Comparison of four-year average of simulated soybean yield under different tillage treatments

| Fertilizer treatments | Date of sowing | Simulated yield (kg ha$^{-1}$) under different tillage treatments | | | | | |
|---|---|---|---|---|---|---|---|
| | | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_6$ |
| SSNM | $D_1$ (29th June) | 2281.75 | 2278.50 | 2289.75 | 2291.00 | 2279.75 | 2275.00 |
| | $D_2$ (9th July) | 2091.75 | 2091.75 | 2091.75 | 2093.75 | 2090.75 | 2093.50 |
| | $D_3$ (19th July) | 2041.50 | 2041.50 | 2041.50 | 2041.25 | 2041.50 | 2044.75 |
| N Omission | $D_1$ (29th June) | 2262.00 | 2263.25 | 2262.75 | 2262.00 | 2255.50 | 2247.50 |
| | $D_2$ (9th July) | 2064.50 | 2064.00 | 2064.75 | 2064.00 | 2064.00 | 2063.50 |
| | $D_3$ (19th July) | 1990.00 | 1990.00 | 1990.00 | 1990.00 | 1989.50 | 1989.75 |

The tillage treatments $T_5$ and $T_6$ in the experiment were similar, differing only in the tillage depth. However, despite this similarity, $T_5$ and $T_6$ produced different results in terms of simulated yield. Specifically, $T_5$ resulted in a higher simulated yield when sown on date $D_1$ (29th June) compared to $T_6$. However, for sowing dates $D_2$ and $D_3$, $T_5$ either produced equal or lower simulated yields compared to $T_6$. This finding underlines the significance of tillage depth as a factor influencing the yield of soybean crops. It suggests that variations in tillage depth within similar tillage treatments can lead to differences in crop productivity. Kombiok and Buah (2013) determined that escalating tillage depth leads to enhanced root nodulation in soybean crops, resulting in increased nitrogen fixation and subsequently augmenting soybean yield.

The specific combination of tillage treatment and sowing date affects the overall productivity of the crops, as demonstrated by the variation in simulated yields observed in the table. The tillage treatments, including cultivator field, harrow tine, and chisel plough straight point with varying depths, resulted in increased soybean yield. These findings indicate that the tillage method, timing of tillage operations, tillage depth, and the type of implement chosen can significantly affect the yield of soybean crop (Busscher et al., 2000; Vetsch et al., 2007; Adamic and Leskovsek, 2021).

*3.2.2. Fertilizer treatment*

Table 6 provides information on the simulated yields under

Table 6: Four-year average of simulated soybean yield under different fertilizer doses and sowing dates

| Date of sowing | Simulated yield (kg ha$^{-1}$) under different fertilizer doses | | | | |
|---|---|---|---|---|---|
| | $f_1$ | $f_2$ | $f_3$ | $f_4$ | $f_5$ |
| $D_1$ (29th June) | 2361.00 | 2361.00 | 2340.75 | 2361.00 | 2329.75 |
| $D_2$ (9th July) | 2165.00 | 2165.00 | 2158.50 | 2165.00 | 2159.50 |
| $D_3$ (19th July) | 2103.00 | 2103.00 | 2096.00 | 2103.00 | 2086.75 |

different fertilizer doses for three different sowing dates. For sowing date $D_1$ (29th June), the simulated yields ranged from 2329.75 kg ha$^{-1}$ to 2361.00 kg ha$^{-1}$ across different fertilizer doses. Fertilizer doses $f_1$, $f_2$, and $f_4$ yielded the highest simulated yield of 2361.00 kg ha$^{-1}$, whereas, $f_3$ resulted in a slightly lower simulated yield of 2340.75 kg ha$^{-1}$ for $D_1$ (29th June). For sowing date $D_2$ (9th July), the simulated yields ranged from 2158.50 kg ha$^{-1}$ to 2165.00 kg ha$^{-1}$ across different fertilizer doses. In case of sowing date $D_3$ (19thJuly), the simulated yields varied from 2086.75 kg ha$^{-1}$ to 2103.00 kg ha$^{-1}$for different fertilizer doses. All fertilizer doses, $f_1$, $f_2$, $f_3$, $f_4$, and $f_5$, resulted in similar simulated yields for $D_2$ and $D_3$.

Based on these findings, the combination of sowing date $D_1$ (29th June) and fertilizer doses $f_1$, $f_2$, and $f_4$ consistently produced the highest simulated yields, reaching 2361.00 kg ha$^{-1}$. This indicates that these fertilizer doses are more effective in promoting crop growth and yield compared to the other doses. Conversely, the combination of sowing date $D_1$ (29th June) and fertilizer dose $f_5$ resulted in the lowest simulated yield of 2329.75 kg ha$^{-1}$. This suggests that $f_5$ may be less optimal for achieving higher crop yields compared to the other fertilizer doses. It is important to note that for sowing dates $D_2$ and $D_3$, the simulated yields across all fertilizer doses are relatively similar, with no clear distinction between the doses in terms of better or worse results.

The comparative evaluation of all five treatment conditions demonstrated the prominent contribution of nitrogen and phosphorus to soybean yield. Specifically, in the fertilizer treatments $F_1$, $F_2$, and $F_4$, where the nitrogen dosage was consistent, the soybean yield remained highest and stable despite variations in other fertilizer doses. This substantiates the significant role of nitrogen in determining crop yield. Begum et al (2015) also reported the highest yield of soybean crop with nitrogen fertilizer followed by phosphorous. Also, the optimal fertilizer dose among these treatments can be selected based on cost-effectiveness and minimal environmental impact. Considering this, $f_1$ (N:P:K:S::25:60:40:20) treatment was found to be better than $f_2$ (N:P:K:S::25:80:40:20) and $f_4$ (N:P:K:S::25:80:50:20) due to lesser fertilizer consumption in $f_1$. These findings provide valuable insights into optimizing fertilizer management practices for enhancing soybean productivity.

### *3.2.3 Date of sowing*

Figure 2 provides information on the simulated yields under two different conditions: SSNM (Site-specific Nutrient Management) and N omission, for various sowing dates. Overall, the key findings emphasize the influence of sowing date and the chosen condition (SSNM or N omission) on the simulated yields, with different sowing dates resulting in varying levels of crop yield under different conditions.

The simulated yields under SSNM range between 1644.5–2406 kg ha$^{-1}$ across different sowing dates. The highest simulated yield of 2406 kg ha$^{-1}$ was observed for the sowing date of 20th June under SSNM, while the lowest simulated yield of 1644.5 kg ha$^{-1}$ was observed for the sowing date of 20th August. The simulated yields under N omission ranged from 1523.5 kg ha$^{-1}$ to 2410.75 kg ha$^{-1}$ across different sowing dates. Maximum simulated yield (2410.75 kg ha$^{-1}$) was observed for the sowing date of 10th June, whereas, the minimum simulated yield (1523.5 kg ha$^{-1}$) was observed for the sowing date of 20th August. Furthermore, the table shows that the simulated yields decrease as the sowing dates progress towards the end of the season, with lower yields observed for the sowing dates of 20th July, 30th July, 10th August, and 20th August. Based on these findings, the combination of sowing date 20th June and SSNM consistently produced the highest simulated yields, reaching 2410.75 kg ha$^{-1}$. This indicates that this combination resulted in the best outcome in terms of crop yield among all the options presented in the table. On the other hand, the combination of sowing date 20th August and condition N omission yielded the lowest simulated yield of 1523.5 kg ha$^{-1}$. This suggests that this particular combination was less effective in promoting crop growth and yield compared to

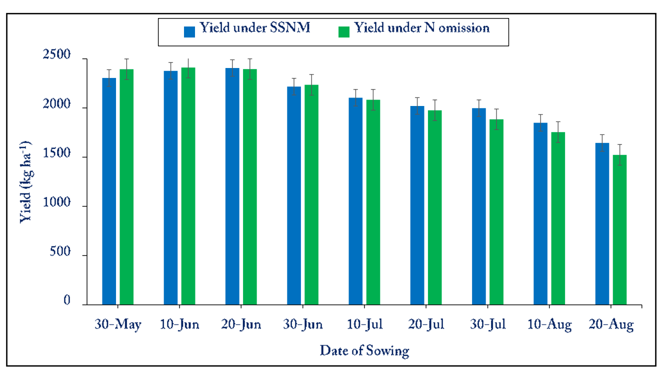


Figure 2: Four-year average of CROPGRO simulated yield under various date of sowing

the other combinations.

The decline in soybean yield observed both before and after mid-June can be attributed to the absence of favorable conditions for crucial crop events such as pod formation, fruit maturity, and seed development. The inadequate pod formation, the production of fewer seeds per pod, and a reduced seed index collectively contribute to the decrease in yield before and after the optimum sowing time. The unfavorable conditions aroused by delayed sowing tends to shorten the soybean flowering and seed set period, thereby, resulting in reduced yields during this period (Egli et al., 1987). Singh et al. (2010) observed that in the soybean cultivar PK416, delayed sowing led to a reduction in yield attributes such as pods per plant, 100-seed weight, and seed per pod. Similar trends of decrease in soybean yield with delay in date of crop sowing were obtained by Zhang and Gao (2010) and Kumar and Pande (2012).

*3.2.4. Irrigation*

Table 7 presents the simulated yields under different irrigation levels for two treatments, SSNM and N omission, across three different sowing dates. The simulated yields vary depending on the treatment, sowing date, and irrigation level combination. Generally, higher irrigation levels tend to result in higher simulated yields. The combination of SSNM treatment, sowing date $D_1$ (29$^{th}$ June), and an irrigation level of 90 mm yielded the highest simulated yield of 2172.25 kg ha$^{-1}$. This combination outperformed all others in terms of crop productivity. On the other hand, the combination of N omission treatment, sowing date $D_3$ (19$^{th}$ July), and an irrigation level of 70 mm resulted in the lowest simulated yield of 1627.70 kg ha$^{-1}$.

It was observed that earlier sowing dates (such as $D_1$ on 29$^{th}$ June) tend to result in higher simulated yields compared to later sowing dates (such as $D_3$ on 19$^{th}$ July). This suggests that timely sowing plays a crucial role in achieving higher crop yields. In most cases, the simulated yields under the SSNM treatment are slightly higher than those under the N omission treatment. This indicates that proper nutrient management, as implemented in the SSNM treatment, can have a positive impact on crop productivity. Higher irrigation levels, such as 90 mm, often correspond to higher simulated yields compared to lower irrigation levels. Adequate water supply is essential for optimal crop growth and development. Overall, the general trend in the table suggests that earlier sowing dates,

along with appropriate treatment and higher irrigation levels, tend to result in better simulated yields. It is important to note that specific combinations of factors may yield different results, and other factors not captured in the table, such as weather conditions and soil quality, can also influence crop yield. The study revealed that accurate simulation results regarding optimum irrigation necessitate comprehensive knowledge of soil type, crop requirements, and the availability of irrigation water specific to the selected region. Furthermore, the findings indicated that as irrigation increased, there was an observed upward trend in yield according to the DSSAT model. These results are consistent with the findings of Sweeney et al. (2003), Garcia y Garcia et al. (2010) and Sharda et al. (2019) which found that increase in supplemental irrigation augmented the soybean yield.

Table 7: Four-year average of simulated soybean yield under different irrigation levels

| Treatments | Date of sowing | Simulated yield (kg ha$^{-1}$) under different irrigation levels | | | | | |
|---|---|---|---|---|---|---|---|
| | | 40 mm | 50 mm | 60 mm | 70 mm | 80 mm | 90 mm |
| SSNM | $D_1$ (29$^{th}$ June) | 1756.20 | 1759.30 | 1758.00 | 1783.20 | 1757.70 | 2172.25 |
| | $D_2$ (9$^{th}$ July) | 1676.50 | 1667.20 | 1686.00 | 1675.00 | 1677.00 | 1995.00 |
| | $D_3$ (19$^{th}$ July) | 1641.00 | 1636.50 | 1645.00 | 1638.00 | 1640.00 | 1883.25 |
| N Omission | $D_1$ (29$^{th}$ June) | 1713.50 | 1726.50 | 1726.25 | 1746.70 | 1725.70 | 2106.75 |
| | $D_2$ (9$^{th}$ July) | 1670.70 | 1669.25 | 1676.50 | 1739.70 | 1668.50 | 1979.50 |
| | $D_3$ (19$^{th}$ July) | 1637.50 | 1631.75 | 1635.25 | 1627.70 | 1631.00 | 1870.70 |

## 4. CONCLUSION

CROPGRO model performed good in predicting the occurrence of crop growth stages and crop yield indicators with RMSE values between simulated and observed values ranging from 3.24% and 14.22%. The simulation results demonstrate that the optimal management practices for maximizing soybean yield entail implementing a tillage regimen involving three ploughings and two harrowing operations, sowing the seeds on the 20th of June, fertilizing the crop with a ratio of N:P:K:S::25:60:40:20, and providing 90 mm of irrigation.

## 5. FURTHER RESEARCH

The study could be expanded to include more years of data collection to enhance the accuracy of the simulations. Additionally, research efforts could investigate the impact of other agronomic practices, such as pest and weed management on soybean yield. By refining and expanding the knowledge base, future research can provide farmers with more precise recommendations for maximizing soybean production and improving agricultural sustainability in the Pantnagar region.

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