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OPTIMIZATION OF PLANT DENSITY AND NITROGEN LEVELS IN BT AND NON-BT COTTON USING THE CROPGRO-COTTON MODEL ON ALFISOLS OF THE SOUTHERN TELANGANA ZONE

Nagender T[1], Raji Reddy D[2], Sreenivas G[3], Leela Rani P[4] and Pallavi C H[5]*

[1]*Department of Agronomy, College of Agriculture, Professor Jayashankar Telangana State Agricultural University, Rajendranagar, Hyderabad-500 030, India*
[2]*Ex-Director of Extension, Administrative Building, Professor Jayashankar Telangana State Agricultural University, Rajendranagar, Hyderabad-500 030, India*
[3]*Regional Agricultural Research Station, Jagtial-505 327, India*
[4]*Agro Climate Research Centre, Agricultural Research Institute, Rajendranagar, Hyderabad-500 030, India*
[5]*The District Agricultural Advisory and Transfer of Technology Centre, Agricultural Research Station, Tornala-502 114, India*

ABSTRACT

A field experiment was conducted at the Agricultural Research Institute, Rajendranagar, during the *kharif* seasons of 2015 and 2016 to calibrate and validate the CROPGRO-Cotton model. The study evaluated two cotton cultivars (MRC 7201 BG II and WGCV-48), three plant densities (18,518, 55,555, and 1,48,148 plants ha^{-1}), and three nitrogen levels (120, 150, and 180 kg ha^{-1}). After calibration and validation, the model was used to determine optimal plant densities and nitrogen levels for cotton production under semi-arid conditions using DSSAT v4.6›s seasonal analysis tool. The model simulated seed cotton yield across nine plant densities (18,518 to 1,48,148 plants ha^{-1}) and eight nitrogen levels (110 to 180 kg N ha^{-1}) based on 30 years of historical weather data (1986-2015). Results indicated that the optimal plant density for MRC 7201 in Telangana's semi-arid conditions was 55,555 plants ha^{-1}, with a nitrogen application rate of 120 kg N ha^{-1}, resulting in the best economic performance. Further validation with long-term datasets is suggested to improve the model's accuracy and applicability.

Keywords: CROPGRO-Cotton model, Plant density, Nitrogen, Telangana

Cotton (*Gossypium hirsutum* L.) is one of India's major cash crops, often referred to as 'white gold' and the 'king of fibers.' It plays a crucial role in the livelihoods of approximately 60 million people engaged in agriculture, processing, and textiles, contributing around 29% to the national GDP (Khadi *et al.*, 2010). India ranks first globally in cotton acreage, with 12.069 million hectares under cultivation, accounting for approximately 36% of the world's total cotton area of 33.3 million hectares. About 67% of India's cotton is cultivated in rainfed areas, while the remaining 33% is grown under irrigation. In the 2021-22 cotton season, India led the world in production with 36.218 million bales (6.16 million metric tonnes), representing 23% of global cotton production (155.5 million bales or 26.44 million metric tonnes). However, India's average cotton yield is 510 kg ha^{-1}, which is below the global average of 778 kg ha^{-1}. In Telangana, cotton is cultivated on 4.6 million hectares, producing 2.508 million tonnes with a productivity of 545 kg ha^{-1} during the 2021-22 season. Crop models have become invaluable tools for researchers and policymakers worldwide, providing critical insights into the impacts of climate change, management practices, and irrigation strategies on crop yields (Thorp *et al.*, 2014). Field experiments in these areas can be challenging to implement due to their resource-intensive nature. In this context, calibrated and validated crop simulation models present a viable alternative, offering outcomes comparable to field trials. The Decision Support System for Agrotechnology Transfer (DSSAT) crop models (Hoogenboom *et al.*, 2015) are sophisticated tools that require numerous input parameters to conduct in-depth assessments of crop growth, development, and the dynamics of water and nutrient management. The Cropping System Model (CSM) CROPGRO-Cotton model, in particular, simulates crop growth and development in response to weather conditions, soil properties, cultivar characteristics, and crop management practices.

The CSM-CROPGRO Cotton model has demonstrated robust capabilities in simulating cotton growth and yield, responding appropriately to factors such as water deficit, nitrogen deficiency, planting density, and CO_2 enrichment (Thorp *et al.*, 2017). The model has proven effective in predicting seed cotton yield, closely aligning with observed data, and accurately forecasting phenological stages, as evidenced by high

*Corresponding author: pallavireddy8990@gmail.com
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R^2 and d-statistic values. These results suggest that the model can be reliably utilized for yield prediction of cotton hybrids under varying nitrogen levels (Wajid *et al.*, 2014). Spatial optimization of the CROPGRO model has been successful in simulating key parameters such as leaf area index (LAI), canopy height, seed cotton yield, and evapotranspiration (ET) at a planting density of 22.0 plants m^{-2} (Anapalli *et al.*, 2016). Additionally, the seasonal analysis tool within the CROPGRO-Cotton model has shown that higher above-ground biomass, seed cotton yield, and nitrogen productivity are achieved when irrigation is scheduled at 40% depletion of available soil moisture (Mahadevappa *et al.*, 2020). Furthermore, modeling studies in the Texas Rolling Plains have identified effective deficit irrigation strategies for growing cotton, providing valuable insights for relatively new cotton-growing regions such as western Kansas (Modala *et al.*, 2015). Collectively, these studies highlight the importance of calibrating the CSM-CROPGRO-Cotton model for specific cultivars and regional growing conditions to ensure successful model implementation.

The CSM-CROPGRO Cotton model has been applied in several studies for crop management and decision support. It has been used to assess growth, development, and seed cotton yield under varying nitrogen levels and planting dates for different genotypes (Wajid *et al.*, 2014; Ali *et al.*, 2016; Mishra *et al.*, 2021). The model has also been tested for its performance under different environmental conditions (Paz *et al.*, 2012), as well as for evaluating water and irrigation use efficiency (Garcia y Garcia *et al.*, 2010; Rahman *et al.*, 2019; Li *et al.*, 2020). Additionally, the DSSAT model has been explored for various crops, including maize (Rani *et al.*, 2016; Pallavi *et al.*, 2021), cotton (Mahadevappa *et al.*, 2020), and soybean (Mahesh *et al.*, 2017) in the Southern Telangana region of India. Despite these advancements, comprehensive model parameterization using high-quality, extensive field data remains limited globally for cotton. Moreover, few studies have investigated cotton growth, development, and yield responses to different plant densities and nitrogen dosages.

Data collection through field experimentation is both time-consuming and costly over extended periods. Given that farmers in the Southern Telangana region are economically disadvantaged and heavily dependent on variable rainfall patterns, these challenges are exacerbated. In such circumstances, a calibrated and validated cotton model can provide crucial support for making informed, tactical decisions, offering valuable assistance to extension specialists and policymakers in improving the livelihoods of cotton farmers. Therefore, there is a clear need to identify optimal plant populations and nutrient management strategies for cotton producers in the region, using crop simulation models validated against experimental data specific to Telangana State. Therefore, the present study was conducted keeping in view the following objectives: (a) To calibrate and validate the CROPGRO-Cotton model for both Bt and non-Bt cotton under varying nitrogen levels and plant population densities. (b) To apply the validated model across different plant densities and nitrogen levels through seasonal analysis, with the aim of optimizing crop management practices.

MATERIALS AND METHODS

A field experiment was conducted at the Agricultural Research Institute, Professor Jayashankar Telangana State Agricultural University, Rajendranagar, Hyderabad, during the *kharif* seasons of 2015 and 2016. The experiment was designed as a randomized block design (factorial), replicated three times, with two cotton cultivars (MRC 7201 BG II and WGCV-48), three plant densities (P_1: 18,518 plants ha^{-1}, P_2: 55,555 plants ha^{-1}, and P_3: 1,48,148 plants ha^{-1}), and three nitrogen levels (N_1: 120 kg ha^{-1}, N_2: 150 kg ha^{-1}, and N_3: 180 kg ha^{-1}). Observations were made on various parameters, including plant height, phenological stages, leaf area index, above-ground biomass production, irrigation water use, yield attributes, and seed cotton yield. The CSM-CROPGRO-Cotton model was selected for this study due to its successful application in different cropping systems under diverse climatic conditions, as demonstrated by various researchers globally. The CSM-CROPGRO-Cotton model functions by calculating rate variables on a daily time step, integrating the state variables over time, and updating them accordingly (Jones *et al*., 2003).

Weather input data were obtained from the agrometeorological observatory at the Agricultural Research Institute, Rajendranagar. Soil samples were collected from the experimental field to assess the physical and chemical characteristics of the soil, which were then incorporated into the model as soil input parameters.

Calibration of the CSM-CROPGRO-Cotton model was carried out by iteratively adjusting the model's parameters to match observed values from the field study. A manual calibration approach was employed, where sensitive model parameters were systematically modified, and their impacts on simulated crop growth and yield were evaluated by visually comparing the simulated results with observed data. This process also involved the assessment of model performance through various statistical measures. Three statistical parameters were used to evaluate model performance: root mean square error (RMSE) (Willmott, 1982), normalized root mean square error (NRMSE)

(Loague and Green, 1991), and the coefficient of agreement (Willmott, 1981). These metrics provided a quantitative basis for assessing the accuracy of the model's predictions. The calibration process followed an iterative, trial-and-error approach (Hanson, 2000; Hanson *et al.*, 1999), wherein the genetic coefficients for both cotton cultivars were calibrated to optimize the model's predictive accuracy.

To assess the accuracy of the model simulations, the calibrated CROPGRO-Cotton model was validated using data recorded for plant densities and nitrogen level treatments during the 2015 and 2016 cropping seasons, under varying weather conditions. During the validation process, the observed data for key parameters, including anthesis date, maturity date, yield components, leaf area index, seed cotton yield, and total crop biomass, were compared with the simulated values. If the calibrated models perform well in validation with independent data sets, they can be considered reliable tools for supporting operational, tactical, and strategic decision-making in crop management (Matthews *et al.*, 2002). Once calibrated and validated for a specific environment, the model can be used to evaluate alternative management strategies.

Using the seasonal analysis tool in DSSAT v4.6, an effort was made to develop alternative management strategies by adjusting plant densities and nitrogen levels under the semi-arid environment of Telangana State. This analysis utilized 30 years of historical daily weather data from 1986 to 2015.

In this study, seasonal analysis was conducted by modifying the experimental file within the model to include nine plant densities, ranging from 18,518 plants ha^{-1} to 1,48,148 plants ha^{-1}. The specific plant densities tested were: P_1 (18,518 plants ha^{-1}), P_2 (24,691 plants ha^{-1}), P_3 (37,037 plants ha^{-1}), P_4 (37,037 plants ha^{-1}), P_5 (55,555 plants ha^{-1}), P_6 (1,11,111 plants ha^{-1}), P_7 (49,382 plants ha^{-1}), P_8 (74,074 plants ha^{-1}), and P_9 (1,48,148 plants ha^{-1}). Additionally, eight nitrogen levels were simulated, ranging from 110 kg N ha^{-1} to 180 kg N ha^{-1}, with an optimal dosage of 150 kg N ha^{-1} and incremental increases of 10 kg N ha^{-1}, yielding the following nitrogen treatments: N_1 (110 kg N ha^{-1}), N_2 (120 kg N ha^{-1}), N_3 (130 kg N ha^{-1}), N_4 (140 kg N ha^{-1}), N_5 (150 kg N ha^{-1}), N_6 (160 kg N ha^{-1}), N_7 (170 kg N ha^{-1}), and N_8 (180 kg N ha^{-1}). These nitrogen levels were simulated across all nine plant densities to evaluate their effects on cotton growth and yield.

RESULTS AND DISCUSSION

Calibration

The model demonstrated strong performance in simulating growth, phenology, seed yield, and biomass (Table 1) during the calibration process, across all plant densities and nitrogen levels for the two cultivars, MRC 7201 BGII and WGCV-48. Calibration results indicated that the model predicted flowering dates with a high degree of accuracy, showing only a one-day difference between observed and simulated flowering days for the MRC 7201 BGII cultivar, with a root mean square error (RMSE) of 0.5 days. Similarly, for the WGCV-48 cultivar, the observed and simulated flowering days differed by only 0.5 days, with RMSE values of 0.5 days across different plant densities and nitrogen levels. Additionally, the CROPGRO-Cotton model accurately simulated the number of days from planting to physiological maturity for both cultivars, with an RMSE of 0.9 days.

Calibration of the CROPGRO-Cotton model provided genetic coefficients for both Bt and non-Bt cultivars, MRC 7201 and WGCV-48, in relation to total biomass (kg ha^{-1}). The results showed that for the MRC 7201 (Bt) cultivar, the coefficient of determination (R^2) was 0.96, with a root mean square error (RMSE) of 635.5 kg ha^{-1} and a *d*-statistic of *0.86*. For the WGCV-48 (non-Bt) cultivar, the corresponding values were $R^2 = 0.85$, RMSE = 307.2 kg ha^{-1}, and *d*-statistic = *0.85*. Additionally, boll weight at maturity (kg ha^{-1}) was also simulated accurately, with R^2 values of *0.81* and *0.89* for MRC 7201 and WGCV-48, respectively. The RMSE values for boll weight at maturity were 208.2 kg ha^{-1} for MRC 7201 and 129.6 kg ha^{-1} for WGCV-48, while the *d*-statistic values were *0.92* and *0.96*, respectively, indicating high model accuracy. The results of the calibration, including the genetic coefficients for seed cotton yield for both cultivars, are presented in Table 1.

Validation

The calibrated CSM-CROPGRO-Cotton model was validated using an independent data set (not used in the calibration process) collected during the years 2015 and 2016, covering a range of plant density and nitrogen level treatments under variable weather conditions. For the MRC-7201 cultivar, the model's prediction of maximum leaf area index (LAI) under different plant densities and nitrogen levels was considered excellent (Fig. 1a). The model achieved a normalized root mean square error (NRMSE) of 9.4%, with a root mean square error (RMSE) of 0.50 and a coefficient of residual mass (CRM) of 1.1. The positive CRM value indicated that the model tended to slightly underpredict the LAI by 1.1%. For the WGCV-48 cultivar, the CROPGRO-Cotton model closely predicted the maximum LAI values, with simulated values showing a strong correlation with observed values (Fig. 1b). The model performed with an RMSE of 0.4, NRMSE of 9.2%, and a CRM of 3.4, indicating that the model slightly underpredicted the LAI by 3.4% across varying plant densities and nitrogen levels.

Table 1. Calibration of the CROPGRO-Cotton model: Observed vs. predicted phenology, yield attributes, seed yield, and total biomass

Variable Name	Cultivars	Observed	Simulated	R^2	RMSE	*d*-Stat
Flowering (days)	MRC 7201 BGII	51	52	*0.82*	0.5	*0.86*
	WGCV-48	56	56	*0.82*	0.5	*0.86*
Physiological maturity (days)	MRC 7201 BGII	104	104	*0.96*	0.87	*0.96*
	WGCV-48	114	114	*0.97*	0.86	*0.97*
Total biomass (kg ha^{-1})	MRC 7201 BGII	10001	9491	*0.96*	635.5	*0.86*
	WGCV-48	8635	8390	*0.85*	307.2	*0.85*
Seed cotton yield (kg ha^{-1})	MRC 7201 BGII	3428	3449	*0.96*	49.7	*0.98*
	WGCV-48	2495	2581	*0.83*	169.4	*0.92*
Boll weight at maturity (kg ha^{-1})	MRC 7201 BGII	5587	5683	*0.81*	208.2	*0.92*
	WGCV-48	3920	3876	*0.89*	129.6	*0.96*

Note: Data of 2015 and 2016 was used for calibration of model

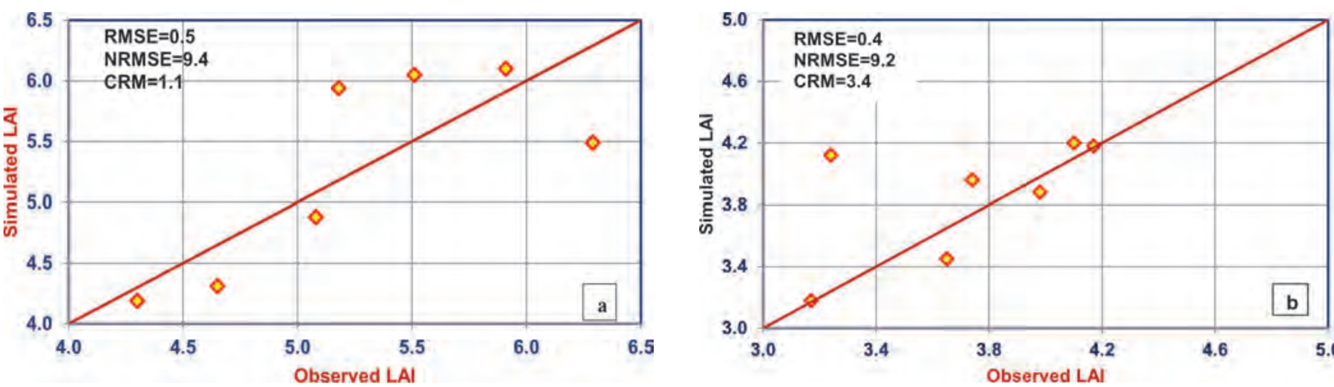

Fig. 1. Observed and simulated maximum Leaf Area Index (LAI) for (a) MRC-7201 and (b) WGCV-48 cultivars under varying plant densities and nitrogen levels, modeled using the CROPGRO-Cotton model

The observed and simulated seed cotton yield showed good agreement across various plant densities and nitrogen levels, with the model demonstrating reasonable accuracy. For the MRC-7201 cultivar, the root mean square error (RMSE) was 300 kg ha^{-1}, and the normalized RMSE (NRMSE) was 11%, while for the WGCV-48 cultivar, the RMSE was 350 kg ha^{-1}, and the NRMSE was 9% (Fig. 2a, 2b). The positive coefficient of residual mass (CRM) values indicated a slight underprediction of seed cotton yield by the model, with an underprediction of 5% for MRC-7201 and 4% for WGCV-48.

Model application for plant densities

The simulation results for varying plant densities were analyzed statistically and are presented in Table 2. The highest mean seed cotton yield was predicted for P_9 (1,48,148 plants ha^{-1}), which was significantly higher than P_1 (18,518 plants ha^{-1}) and P_2 (24,691 plants ha^{-1}). On the other hand, P_1 (18,518 plants ha^{-1}) exhibited the lowest seed cotton yield, significantly lower than the other plant densities. However, P_1 (18,518 plants ha^{-1}), P_2 (24,691 plants ha^{-1}), P_3 (37,037 plants ha^{-1}), P_4 (37,037 plants ha^{-1}), P_5 (55,555 plants ha^{-1}), P_6 (1,11,111 plants ha^{-1}), P_7 (49,382 plants ha^{-1}), and P_8 (74,074 plants ha^{-1}) were statistically similar, showing no significant difference in seed cotton yield among

Table 2. Tukey's HSD Test for mean seed cotton yield (kg ha^{-1}) at different plant densities

Plant densities	Mean seed cotton yield (kg ha^{-1})
P_9 (45x15cm) - 1,48,148 plants ha^{-1}	2760^{a*}
P_6 (60x15cm) - 1,11,111 plants ha^{-1}	2721^{ab}
P_8 (45x30cm) - 74,074 plants ha^{-1}	2714^{ab}
P_7 (45x45cm) - 49,382 plants ha^{-1}	2692^{ab}
P_5 (60x30cm) - 55,555 plants ha^{-1}	2689^{ab}
P_4 (60x45cm) - 37,037 plants ha^{-1}	2654^{ab}
P_3 (90x30 cm) - 37,037 plants ha^{-1}	2508^{ab}
P_2 (90x45cm) - 24,691 plants ha^{-1}	2478^{b}
P_1 (90x60 cm) - 18,518 plants ha^{-1}	2442^{b}

*Note: Means followed by the same alphabet do not differ significantly at *p≤0.05*

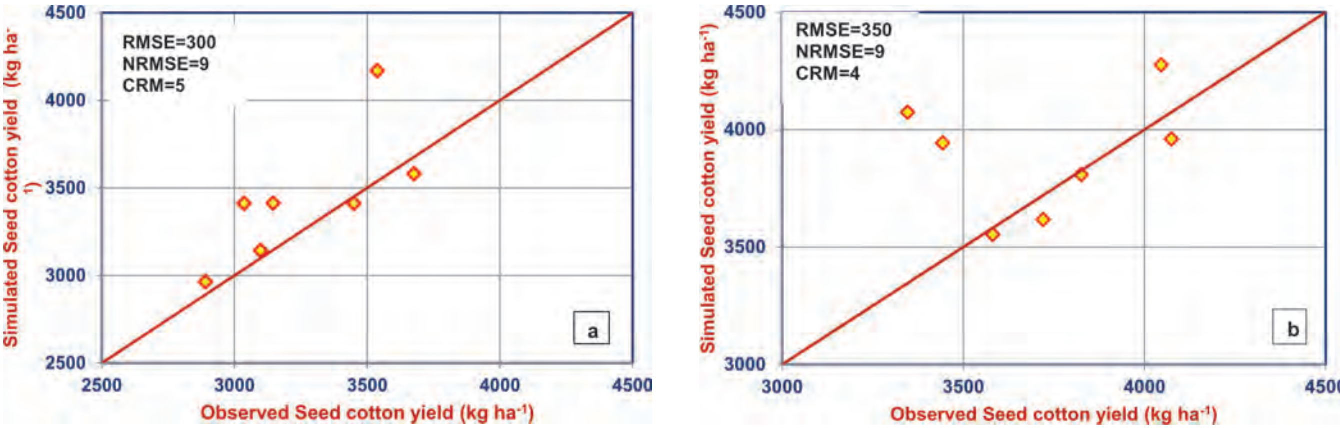

Fig. 2. Observed and simulated seed cotton yield (kg ha⁻¹) for (a) MRC-7201 and (b) WGCV-48 cultivars under varying plant densities and nitrogen levels, modeled using the CROPGRO-Cotton model

these densities. Given the extensive dataset, which includes nine plant densities over a 30-year period with a total of 270 simulation scenarios, the results were visualized using box plots and exceedance probability analysis to provide a clearer understanding of the distribution and variability of seed cotton yield across different plant densities.

The graphical representation of the simulation scenarios revealed a consistent increase in median seed cotton yield with the rise in plant densities. The box plots indicated that crop grown at higher plant densities, specifically P_9 (1,48,148 plants ha⁻¹) and P_6 (1,11,111 plants ha⁻¹), exhibited considerably less variability in yield compared to other plant densities (Fig. 3). This smaller variance was associated with more stable average yields for these densities. Furthermore, the

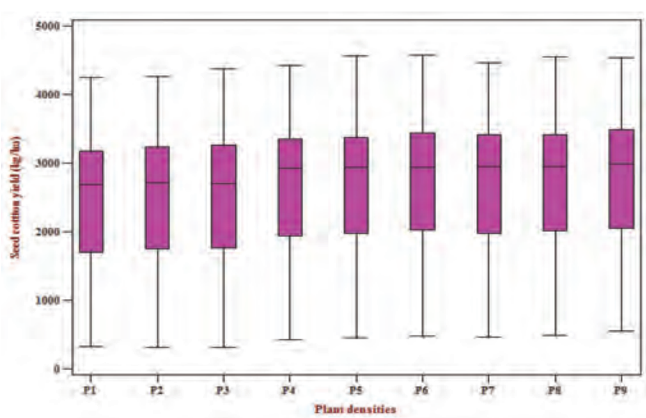

Fig. 3. Simulated seed cotton yield across varying plant densities. Box limits represent the 25th and 75th percentiles, the central line represents the median, and the whiskers indicate the minimum and maximum values. (P_1-18,518 plants ha⁻¹, P_2-24,691 plants ha⁻¹, P_3-37,037 plants ha⁻¹, P_4-37,037 plants ha⁻¹, P_5-55,555 plants ha⁻¹, P_6-1,11,111 plants ha⁻¹, P_7-49,382 plants ha⁻¹, P_8-74,074 plants ha⁻¹, P_9-1,48,148 plants ha⁻¹)

reduced variability shown in Fig. 4 suggested a lower risk of achieving minimum yields, with 90% of the years (27 out of 30) exceeding yields in the range of 1393 to 1425 kg ha⁻¹ when cotton was grown at plant densities of 1,11,111 to 1,48,148 plants ha⁻¹, with spacings of 60 x 15 cm and 45 x 15 cm, respectively. With the box plots and exceedance probability results, it was evident that plant densities of 1,11,111 to 1,48,148 plants ha⁻¹ resulted in minimal yield variability and the least risk of achieving higher yields. However, the model also indicated that while seed cotton yield generally increases with plant density, this trend may not always hold true under different environmental or management conditions.

Model application of nitrogen levels

The simulation results for different nitrogen levels were analyzed statistically and are presented in Table 3. The highest mean seed cotton yield was predicted for N_8 (180 kg N ha⁻¹), which was significantly superior

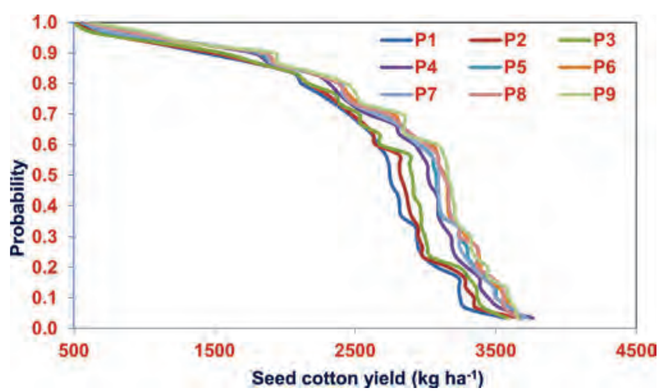

Fig. 4. Exceedance probability of seed cotton yield (kg ha⁻¹) across varying plant densities. (P_1-18,518 plants ha⁻¹, P_2-24,691 plants ha⁻¹, P_3-37,037 plants ha⁻¹, P_4-37,037 plants ha⁻¹, P_5-55,555 plants ha⁻¹, P_6-1,11,111 plants ha⁻¹, P_7-49,382 plants ha⁻¹, P_8-74,074 plants ha⁻¹, P_9-1,48,148 plants ha⁻¹)

Table 3. Tukey's HSD test for mean seed cotton yield (kg ha^{-1}) at different nitrogen levels

Nitrogen levels	Mean seed cotton yield (kg ha^{-1})
N_8 - 180 kg N ha^{-1}	2760^{a*}
N_7 - 170 kg N ha^{-1}	2735^{a}
N_6 - 160 kg N ha^{-1}	2713^{a}
N_5 - 150 kg N ha^{-1}	2682^{ab}
N_4 - 140 kg N ha^{-1}	2626^{ab}
N_3 - 130 kg N ha^{-1}	2563^{ab}
N_2 - 120 kg N ha^{-1}	2508^{ab}
N_1 - 110 kg N ha^{-1}	2442^{b}

*Note: Means followed by the same alphabet do not differ significantly at *p≤0.05*

to all other nitrogen levels, including N_5 (150 kg N ha^{-1}), N_4 (140 kg N ha^{-1}), N_3 (130 kg N ha^{-1}), N_2 (120 kg N ha^{-1}), and N_1 (110 kg N ha^{-1}). On the other hand, N_1 (110 kg N ha^{-1}) exhibited the lowest seed cotton yield, which was significantly lower than the other nitrogen treatments. However, nitrogen levels N_1 (110 kg N ha^{-1}), N_2 (120 kg N ha^{-1}), N_3 (130 kg N ha^{-1}), N_4 (140 kg N ha^{-1}), and N_5 (150 kg N ha^{-1}) were statistically similar, showing no significant difference in seed cotton yield among these treatments. Additionally, nitrogen levels N_8 (180 kg N ha^{-1}), N_7 (170 kg N ha^{-1}), N_6 (160 kg N ha^{-1}), N_5 (150 kg N ha^{-1}), N_4 (140 kg N ha^{-1}), N_3 (130 kg N ha^{-1}), and N_2 (120 kg N ha^{-1}) were also on par with each other, indicating no significant variation in yield among these levels. These findings suggest that while higher nitrogen levels (particularly N_8) resulted in

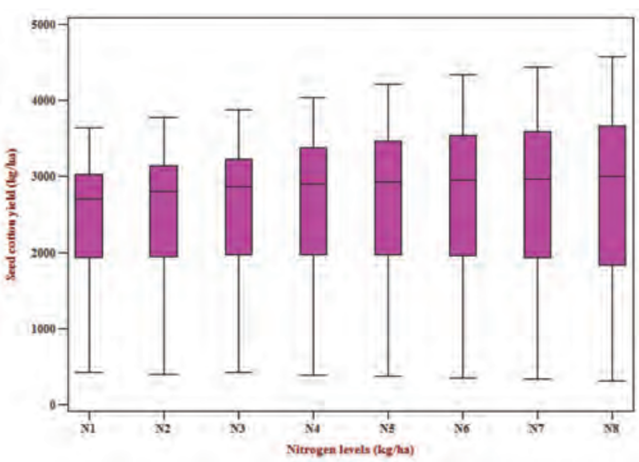

Fig. 5. Simulated seed cotton yield under varying nitrogen levels. Box limits represent the 25th and 75th percentiles, the central line indicates the median, and the whiskers show the minimum and maximum values. (N_1-110 kg N ha^{-1}, N_2-120 kg N ha^{-1}, N_3-130 kg N ha^{-1}, N_4-140 kg N ha^{-1}, N_5-150 kg N ha^{-1}, N_6-160 kg N ha^{-1}, N_7-170 kg N ha^{-1}, N_8-180 kg N ha^{-1})

superior seed cotton yields, nitrogen levels from 120 to 150 kg N ha^{-1} produced similar yields.

The graphical representation of the simulation scenarios demonstrated a consistent increase in median seed cotton yield with rising nitrogen (N) levels. The box plots (Fig. 5) revealed that the crop's response to the nitrogen level of 180 kg N ha^{-1} showed significantly less variability compared to other nitrogen levels, as the smaller variance was associated with a more stable average yield. Furthermore, the reduced variability shown in Fig. 6 indicated the least risk of achieving minimum yields, with 90% (27 out of 30) of the years exceeding yields in the range of 1379 to 1426 kg ha^{-1} when cotton was grown with nitrogen levels between 150 kg N ha^{-1} and 180 kg N ha^{-1}.

The response to nitrogen (Fig. 6) exhibited a classic response curve, where yield increased with the application of nitrogen up to 120-130 kg N ha^{-1}. However, the yield increase showed diminishing trend with each additional increment of 10 kg N ha^{-1}, extending up to 180 kg N ha^{-1}. Beyond 120 kg N ha^{-1}, additional nitrogen application was unlikely to provide significant economic benefits. The spread of the whiskers on the box plots further indicated that yield variability increased with each added increment of nitrogen, highlighting that higher nitrogen inputs led to greater uncertainty in yield outcomes. Seasonal analysis for different plant densities revealed that the model was more sensitive to reduced plant densities. However, under real field conditions, this was not entirely true, as the present hybrid cultivars exhibited higher leaf area index (LAI) and dry matter production (DMP) due to their canopy architecture and soil conditions. The model assumes that with an increase in plant density, biomass and ultimately yield would increase, but this may not always be the case. Among the various plant densities, the model predicted

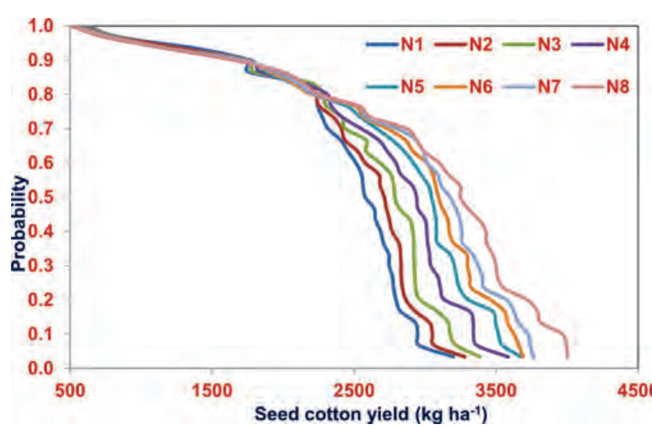

Fig. 6. Exceedance probability of seed cotton yield (kg ha^{-1}) under varying nitrogen levels. (N_1-110 kg N ha^{-1}, N_2-120 kg N ha^{-1}, N_3-130 kg N ha^{-1}, N_4-140 kg N ha^{-1}, N_5-150 kg N ha^{-1}, N_6-160 kg N ha^{-1}, N_7-170 kg N ha^{-1}, N_8-180 kg N ha^{-1})

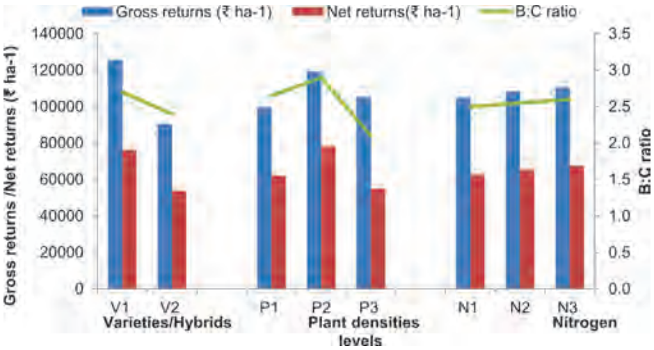

Fig. 7. Gross returns, net returns, and benefit-cost (B:C) ratio of cotton as influenced by cultivars, plant densities, and nitrogen levels. (V_1-MRC 7201 BGII, V_2-WGCV-48; P_1-90 cm × 60 cm, P_2-60 cm × 30 cm, P_3-45 cm × 15 cm; N_1-120 kg N ha^{-1}, N_2-150 kg N ha^{-1}, N_3-180 kg N ha^{-1})

the highest yield for a density of 1,11,111 plants ha^{-1} with a spacing of 60 x 15 cm. However, for different nitrogen levels, the model was not sensitive to nitrogen applications beyond 120 kg N ha^{-1}, which aligns with observations from field experiments.

Economics

The economic indicators, including gross returns, net returns, and the benefit-cost (B:C) ratio, were calculated and are presented in Fig. 7. Among the cultivars, the highest gross returns (₹1,25,513 ha^{-1}), net returns (₹76,370 ha^{-1}), and B:C ratio (2.7) were recorded for the MRC 7201 BGII cultivar, followed by the WGCV-48 cultivar. Among the plant densities, the highest gross returns (₹1,19,286 ha^{-1}), net returns (₹78,177 ha^{-1}), and B:C ratio (2.9) were observed with P_2 (60 cm x 30 cm, 55,555 plants ha^{-1}). This was followed by P_3 (45 cm x 15 cm, 1,48,148 plants ha^{-1}) and P_1 (90 cm x 60 cm, 18,518 plants ha^{-1}). Interestingly, the effect of nitrogen levels did not show a significant influence on gross returns, net returns, or the B:C ratio, suggesting that other factors such as plant density and cultivar selection played a more crucial role in determining the economic outcomes.

Based on the experimental data and model integration, an optimum plant density of 55,555 plants ha^{-1} at a spacing of 60 cm x 30 cm, along with an optimal nitrogen dose of 120 kg ha^{-1}, was found to be economically feasible for the MRC 7201 hybrid under the semi-arid conditions of the Southern Telangana Zone. Additionally, plant densities can be adjusted for emerging high-density cotton lines, and genetic coefficients with slight modifications could be used to test other cotton cultivars across the entire Telangana region. Furthermore, the delineation of potential production zones within the Telangana region, coupled with targeted strategies for increasing yields in these zones, could provide valuable insights for policymakers at the regional level.

In the near future, there is a critical need for continuous monitoring of changes in land quality over time, particularly in response to various land management practices, using sustainable modeling approaches. This will enable a more accurate understanding of how land management decisions influence soil health and productivity. Additionally, assessing the impact of climate change on cotton growth and productivity is essential. This can be achieved through the use of crop models to evaluate the potential effects of shifting climatic patterns on yield and growth. Moreover, identifying possible mitigation strategies to counteract adverse effects, including changes in pest incidence and other climate-related challenges, will be crucial for ensuring long-term cotton production sustainability. By integrating climate models, pest management practices, and adaptive land management strategies, cotton farming systems can be made more resilient to the challenges posed by climate change.

CONCLUSION

In conclusion, this study successfully calibrated and validated the CSM-CROPGRO-Cotton model for two cotton cultivars, MRC 7201 BGII and WGCV-48, under various plant densities and nitrogen levels in the semi-arid conditions of Southern Telangana. The model demonstrated its potential in simulating cotton growth, phenology, yield, and biomass with a high degree of accuracy, providing valuable insights for optimizing crop management practices. The results indicated that an optimal plant density of 55,555 plants ha^{-1} (60 cm x 30 cm spacing) and a nitrogen dose of 120 kg ha^{-1} were economically feasible for achieving higher seed cotton yields in the region. Additionally, the study revealed that while nitrogen levels above 120 kg ha^{-1} did not show significant economic benefits, plant density adjustments can significantly impact yield outcomes. The integration of field experiments and crop modeling highlighted the importance of considering both genetic and environmental factors, such as canopy architecture and soil conditions, when determining the best agronomic practices. The study also emphasized the need for further research into emerging high-density cotton lines and the application of model adjustments to test other cultivars in the region. Moreover, the findings suggest the potential for developing regional strategies based on delineated production zones, which could help policymakers optimize resource use and enhance cotton productivity across Telangana.

Looking ahead, continuous monitoring of land quality and productivity under different management practices will be essential, particularly in the face of climate change. Assessing the impacts of changing climatic conditions and pest dynamics on cotton farming, alongwith identifying effective mitigation strategies, will be critical for ensuring the long-term sustainability of cotton production in the region. The results of this study provide a foundation for informed decision-making in cotton farming and can contribute to the development of resilient agricultural systems in Southern Telangana and beyond.

Authors' contribution

Conceptualization and designing of the research work (DR, GS); Execution of field/lab experiments and data collection (TN, CP); Analysis of data and interpretation (TN, GS, PL); Preparation of manuscript (CP, TN).

Conflicts of interest

The authors declare that they have no conflicts of interest.

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LITERATURE CITED

Ali N, Zada A, Ali M and Hussain Z 2016. Isolation and identification of *Agrobacterium tumefaciens* from the galls of peach tree. *J Rural Dev Agric* **1**: 39-48.

Anapalli S S, Fisher D K, Reddy K N, Pettigrew W T, Sui R and Ahuja L R 2016. Vulnerabilities and adapting irrigated and rainfed cotton to climate change in the lower Mississippi Delta region. *Climate* **55**: 1-20.

Garcia y Garcia A, Persson T, Paz J O, Fraisse C and Hoogenboom G 2010. ENSO-based climate variability affects water use efficiency of rainfed cotton grown in the southeastern USA. *Agric Ecosyst Environ* **139**: 629-35.

Hanson J D 2000. Generic crop production model for the root zone water quality model. **In**: *The root zone water quality model*, Ahuja L R (ed.). Water Resource Publishing, Highland Ranch, Colorado, pp. 145-56.

Hanson J D, Rojas K W and Shaffer M J 1999. Calibrating the root zone water quality model. *Agronomy J* **91**: 171-77.

Hoogenboom G, Jones J W, Wilkens P, Porter C, Boote K J, Hunt L A, Singh U, Lizaso J L, White J W, Uryasev O, Royce F S, Ogoshi R, Gijsman A J, Tsuji G Y and Koo J 2015. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.5. Honolulu, Hawaii: University of Hawaii.

Jones J W, Hoogenboom G, Porter C H, Boote K J, Batchelor W D, Hunt L and Ritchie J T 2003. The DSSAT cropping system model. *European J Agron* **18**: 235-65.

Khadi B M, Santhy V and Yadav M S 2010. Highlights the advances in cotton biotechnology, the benefits and socioeconomic impacts. Zehr U B (Ed.), *Cotton Biotechnological Advances* XVI, 245p.

Li M, Du Y, Zhang F, Fan J, Ning Y, Cheng H and Xiao C 2020. Modification of CSM-CROPGRO-Cotton model for simulating cotton growth and yield under various deficit irrigation strategies. *Comput Electron Agric* **179**: 105843.

Loague K and Green R E 1991. Statistical and graphical methods for evaluating solute transport models: Overview and application. *J Contam Hydrol* **7**: 51-73.

Mahadevappa S G, Sreenivas G, Reddy D R, Madhavi A and Rao S S 2020. Application of CROPGRO-Cotton model to optimize irrigation scheduling in *Bt* cotton on alfisols of Southern Telangana. *J Agrometeorol* **22**: 390-93.

Mahesh N, Sreenivas G, Rani P L, Gupta A, Sreekanth P D and Madavi A 2017. Influence of sowing dates and plant densities on dry matter production and nitrogen uptake of soybean under South Telangana agro climatic zone of Telangana State. *Int J Curr Microbiol Appl Sci* **6**: 2061-66.

Matthews R B, Stephens W, Hess T, Middleton T and Graves A 2002. Applications of crop/soil simulation models in Tropical Agricultural Systems. *Adv Agron* **76**: 31-124.

Mishra S K, Kaur V and Singh K 2021. Evaluation of DSSAT-CROPGRO cotton model to simulate phenology, growth and seed cotton yield in north-western India. *Agronomy J* **113**: 3975-90.

Modala N R, Ale S, Rajan N, Munster C L, DeLaune P B, Thorp K R, Nair S S and Barnes E M 2015. Evaluation of the CSMCROPGRO-Cotton model for the Texas rolling plains region and simulation of deficit irrigation strategies for increasing water use efficiency. *Trans ASABE* **58**: 685-96.

Pallavi C, Sreenivas G, Yakadri M, Biswal A, Madhavi A, Sreekanth P D and Laxman B 2021. Assessing the maize (*Zea mays* L.) crop performance using spectral indices under different sowing dates and irrigations schedules. *Int J Curr Microbiol Appl Sci* **12**: 319-31.

Paz J O, Woli P, Garcia y Garcia A and Hoogenboom G 2012. Cotton yields as influenced by ENSO at different planting dates and spatial aggregation levels. *Agric Syst* **111**: 45-52.

Rahman M H, Ahmad A, Wajid A, Manzoor H, Fahd R, Wajid I, Md A I, Vakhtang S, Muhammad A, Asmat U, Abdul W, Syeda R S, Shah S, Shahbaz K, Shah F, Saddam H and Wajid N 2019. Application of CSM-CROPGRO-cotton model for cultivars and optimum planting dates: Evaluation in changing semi-arid climate. *Field Crops Res* **238**: 139-52.

Rani P L, Sreenivas G and Reddy D R 2016. Calibration and validation of CERES-maize model for hybrid maize under variable plant densities and nitrogen levels in Southern

Telangana Zone of Telangana State, India. *Int J Bio-resource Stress Manag* **7**: 212-17.

Thorp K R, Hunsaker D J, Bronson K F, Andrade-Sanchez P and Barnes E M 2017. Cotton irrigation scheduling using a crop growth model and FAO-56 methods: Field and simulation studies. *Trans ASABE* **60**: 2023-39.

Thorp K, Ale S, Bange M, Barnes E, Hoogenboom G, Lascano R, McCarthy A C, Nair S, Paz J O, Rajan N, Reddy K R, Wall G W and White J W 2014. Development and application of process-based simulation models for cotton production: A review of past, present, and future directions. *J Cotton Sci* **18**: 10-47.

Wajid A, Ahmad A, Hussain M, Rahman M H, Khaliq T, Mubeen M, Rasul F, Bashir U, Awais M, Iqbal J, Sultana S R and Hoogenboom G 2014. Modelling growth, development and seed cotton yield for varying nitrogen increments and planting dates using DSSAT. *Pakistan J Agric Sci* **51**: 641-49.

Willmott C J 1981.On the validation of models. *Phy Geography* **2**: 184-94.

Willmott C J 1982. Some comments on the evaluation of model performance. *Bull Amer Met Soc* 63: 1309-13.