International Journal for Multidisciplinary Research (IJFMR)

E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Calibrating DSSAT CERES-Rice Model to Assess Management Practices And Climate Change Impacts on Rice Yield in Dapoli, Maharashtra.

Shahenaz Mulla[1], Sudhir Kumar Singh[2], Prashant Narayan Vishwakarma[3], Shailendra Rai[4], Mamta Rana[5]

[1]Meteorologist, IMD
[2]Associate Professor, University of Allahabad
[3]Research Scholor, University of Allahabad
[4]Professor, University of Allahabad
[5]Associate Professor, Satyawati College, Delhi University.

Abstract

Rice is a globally significant staple crop, yet its production is increasingly threatened by climate variability and shifting agronomic conditions. This study employs the Decision Support System for Agrotechnology Transfer (DSSAT) CERES-Rice model to simulate and assess rice yield dynamics in the Dapoli region of Maharashtra. Calibration and validation were conducted using historical datasets from the 2011 Kharif season and tested against observed yields from 2020 and 2021. Key input parameters, including daily weather records, soil properties, crop management practices, and genetic coefficients, were incorporated to enhance simulation accuracy. Results demonstrate that an optimal planting density of two plants per hill maximized yield potential, while densities exceeding this threshold resulted in yield declines due to intensified resource competition. Furthermore, strategic irrigation interventions substantially improved productivity, particularly for rain-fed Karjat-3 rice varieties. The findings underscore the critical interplay between planting density and irrigation strategies in optimizing rice production under varying climatic conditions. This research provides valuable insights for farmers and policymakers, advocating for precision agriculture and adaptive management practices to bolster climate resilience and sustainable rice cultivation in coastal agro-ecosystems.

1 Introduction

Rice is a crucial food crop that supports over half of the global population, but climate change threatens its production, particularly in regions like Dapoli, Maharashtra, which rely heavily on monsoonal rainfall. Increasing temperatures, erratic rainfall, and a growing frequency of extreme weather events, such as tropical cyclones, create significant challenges for sustainable rice farming (Geethalakshmi et al., 2011; Bowden et al., 2023). The frequency of tropical cyclones in the Arabian Sea has risen by 52% between 2001 and 2019, with Very Severe Cyclonic Storms (VSCS) nearly tripling and cyclone duration increasing by 80% (Deshpande et al., 2021). Rising sea surface temperatures and enhanced tropical cyclone heat

potential (Balaguru et al., 2015) have led to increased cyclone intensity, energy, and lifetime maximum strength, despite a decrease in overall frequency (Murakami et al., 2020).
Given Dapoli's location on Maharashtra's west coast, it is highly vulnerable to these climatic hazards, which could adversely impact rice yields. Calibrating the CERES-Rice model within the DSSAT framework offers an effective way to simulate rice growth and assess the impact of climate variables like temperature, rainfall, and extreme events on yield. The model is widely used for predicting crop performance and evaluating the impact of management strategies, such as irrigation and planting density (Goswami & Dutta, 2020; Singh et al., 2016). However, its application in specific agroecological zones, such as coastal Maharashtra, remains limited (Bowden et al., 2023).
This research aims to calibrate the CERES-Rice model for the Dapoli region, focusing on the effects of climatic variability and management practices on rice yields. By refining the model for this location, the study seeks to develop strategies to ensure sustainable rice production in the face of climate change.

2 Materials and Method

2.1 Study Area

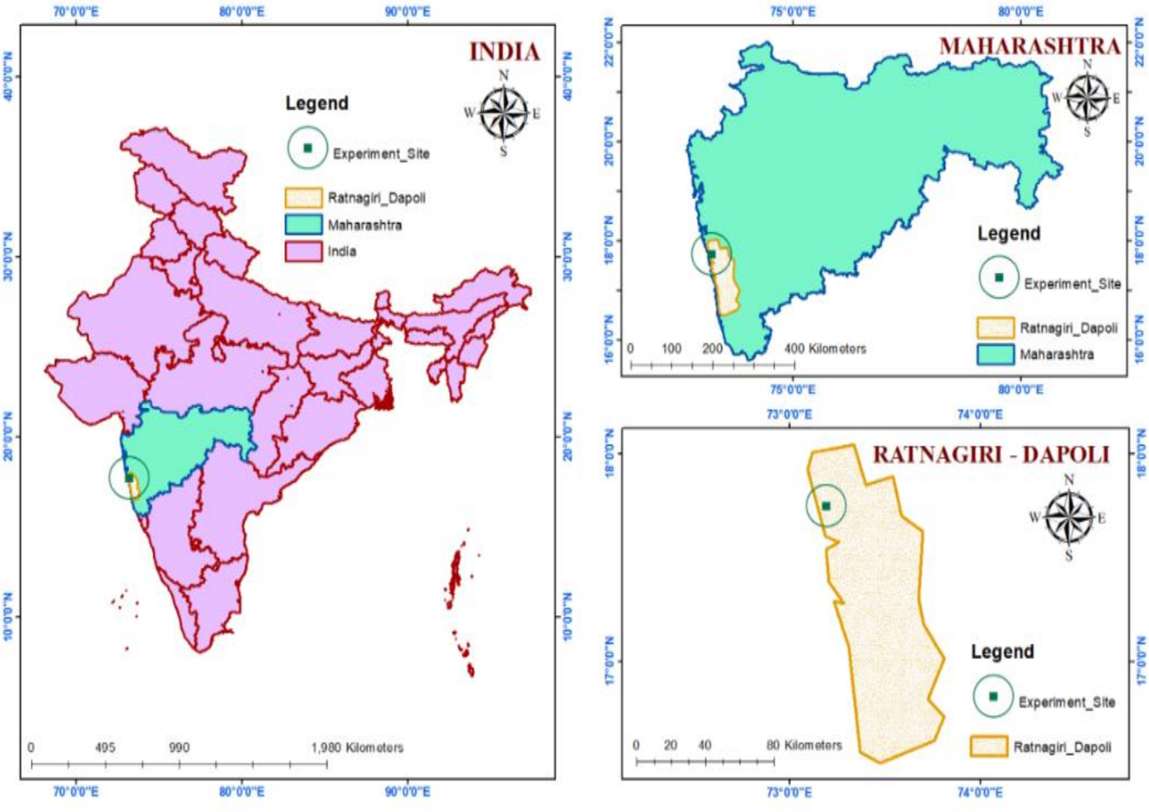

Fig. 1 Study Area Map of Dapoli (Prepared using Q-GIS)

Dr. Balasaheb Sawant Konkan Krishi Vidyapeeth (DBSKKV) is located at 17.77°N latitude, 73.19°E longitude, and 330 meters above sea level shown in **Fig. 1**. Ongoing studies, which began in 2011, investigate the impact of climatic variability on agriculture and water resource management. Dapoli, in Ratnagiri district, Maharashtra, is an agricultural powerhouse in the Konkan region known as the "Mini Mahabaleshwar" due to its cool climate and geographic location. Dapoli covers 866 square kilometers and is largely rural, with 144,084 residents and 34,256 in urban zones, according to the 2011 census. Dapoli's topography, located between the Sahyadri mountain range and the Arabian Sea, includes nutrient-rich laterite soils and a hydrological network defined by the Bharja, Vashishti, and Jog rivers, which enable substantial rice farming. Dapoli has a tropical climate (Köppen classification: Aw), with an average maximum temperature ranging from 28°C to 32°C, a minimum temperature between 16°C to 22°C, annual rainfall of about 2,500 mm to 3,500 mm, and bright sunshine hours averaging 6 to 8 hours per day, with significant variation during the monsoon season (IMD Report, 2020). Its proximity to the Arabian Sea creates great conditions for rice production. However, climate unpredictability presents issues in the Dapoli area, demanding study into adaptive, water resource management, and climate-resilient farming approaches.

2.2 Field Layout

Three experimental customized plots with Randomized Block Design(RBD) designs measuring 15.12 m^2 and transplanting, seed rate as 12 kg/ha with a 21-day seedling growth period were chosen.

2.3 DSSATv4.8, CERES Rice Model

This research calibrates the DSSAT CERES-Rice model (Jones et al., 2010) to simulate rice yield under varying management practices in Dapoli, Maharashtra, incorporating weather, soil, genetic coefficient, and crop management data. The model predicts crop development and yield, enabling better agricultural planning and resilience-building in the region. The model uses Priestley-Taylor/Ritchie-ET for evapotranspiration, the soil conservation service method for infiltration, and Ritchie's water balance approach for hydrology simulations.

2.4 Crop Selection: Karjat-3 Rice Variety

Karjat-3 Rice variety, developed by Waghmode and Dongale (2006), is a medium-tall cultivar suitable for rainfed and irrigated environments, having yield potential of 1.5 to 5 tonnes per ha, especially suitable for Konkan and Vidarbha regions. This variety, resistant to blast and moderately resistant to other diseases, suitable for the Konkan and Vidarbha regions. The selection of Karjat-3 is beneficial for a drought-resistant cultivar and reduces yield loss under varying climatic and soil conditions, particularly in Dapoli region.

2.5 Data Requirements for Calibration

Various datasets were collected and input into the model to ensure accurate rice growth simulation using the CERES-Rice model. These include:

Weather Data (2010-2022): Fig. 2, 3 & 4 represent the average of daily maximum and minimum temperatures, rainfall, and solar radiation data collected from the Agro-Meteorological Field Unit (AMFU) in Dapoli. The recorded mean values of maximum temperatures ranged from 24 to 41.7 °C, minimum temperature range from 14 to 29.5 °C, relative humidity ranges from 29.4 to 71.9%, average solar radiation 2.7 to 17.9 MJ/m^2/day and that of rainfall as 2511.5 mm.

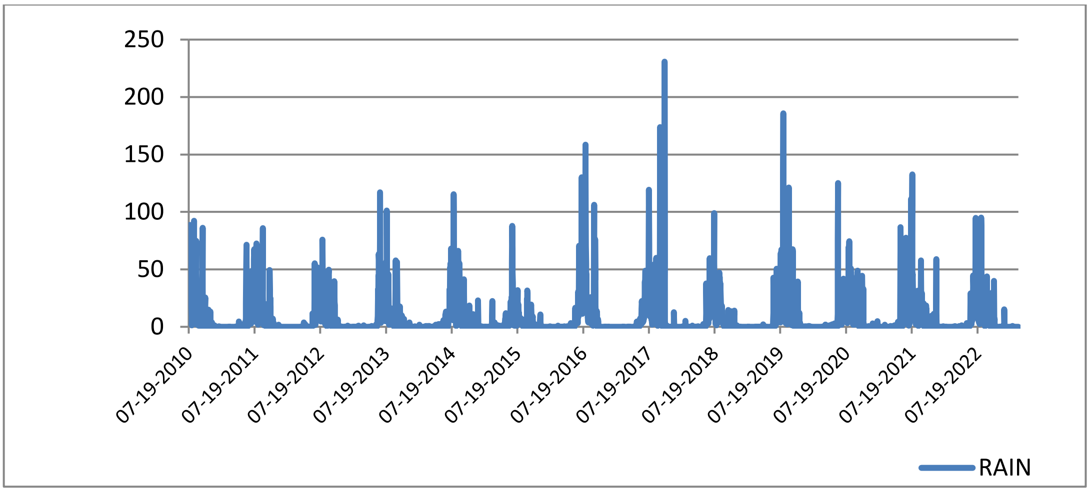

Fig. 2 Rainfall(mm) (2020-2022)

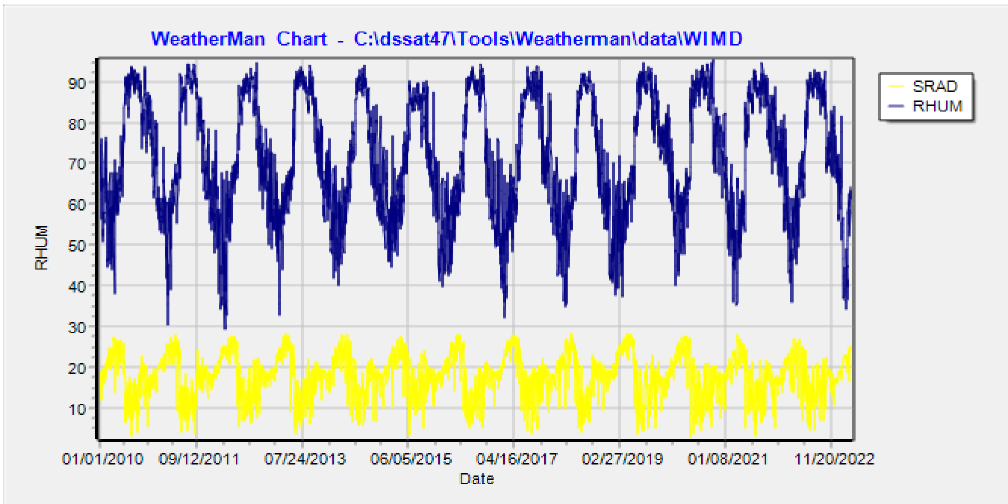

Fig. 3 Solar Radiation (MJ/m^2/day and Humidity(%) (2010-2022)

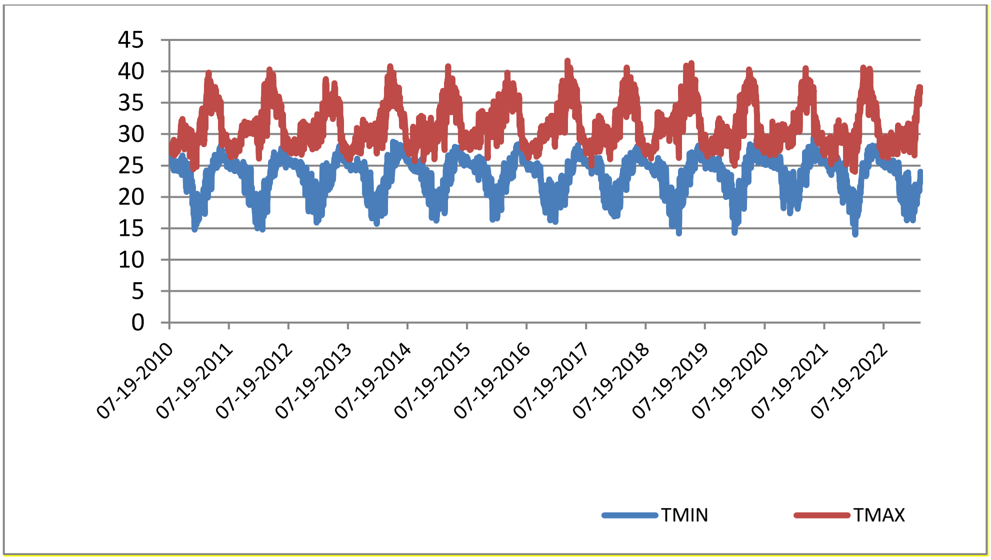

Fig. 4 Temperature(°C) (Maximum, Minimum (2010-2022)

Soil Data: Tables 1 & 2 provide soil details in the study region. The soil profile at Dapoli is characterized by lateritic composition, moderate sediment component, high iron and aluminum oxide content. It has medium-to-fast permeability, low organic carbon, and a slightly acidic pH. The soil texture is consistent, with 26-41% clay content, and is moderately susceptible to erosion, especially during heavy rainfall periods due to its composition and permeability (Nandgude et al., 2014). Soil texture, nutrient availability, and hydraulic conductivity are important inputs for modeling crop response under varying moisture conditions.

Table 1: Soil Profile of Dapoli, Ratnagiri District, Maharashtra, India

Depth Bottom (cm)	Master Horizon	Clay (%)	Silt (%)	Stone (%)	Organic Carbon	pH in Water	Cation Exchange Capacity
5	O	41.4	17.4	-99	0.65	6.5	-99
15	A	26.6	18.4	-99	0.16	6.5	-99
30	E	26.6	18.4	-99	0.16	6.5	-99
45	B	26.6	18.4	-99	0.16	6.5	-99
60	C	26.6	18.4	-99	0.16	6.5	-99

*-99= No Data found (Default value)

Table 2 : Soil Hydraulic and Physical Properties

Depth Bottom (cm)	Lower Limit	Drainage Upper Limit	Saturation	Bulk Density	Saturated Hydraulic Conductivity cm/hr	Root Growth Factor
5	0.251	0.358	0.425	1.45	0.06	1
15	0.163	0.252	0.389	1.56	0.43	1
30	0.163	0.252	0.389	1.56	0.43	0.638
45	0.163	0.252	0.389	1.56	0.43	0.472
60	0.163	0.252	0.389	1.56	0.43	0.35

Crop Management Data: Karjat-3 seedlings were manually transplanted at a density of 30 per m² into puddled soil. The applied fertilizer rates were 100:50:50 kg of NPK per acre. Crop management data includes planting dates, irrigation, fertilizer, pest control, and other agronomic procedures and helps to simulate the agronomic management practices.

Crop Data and Phenology: Yield-related data such as panicles per square meter, tillers, grain weight, and phenological stages like anthesis, panicle initiation, and maturity were used to calibrate the model. These parameters are crucial for evaluating how different management practices affect crop outcomes.

2.6 Calibration of Genetic Coefficients

Table 3: Genetic Coefficients for Crop Growth

Genetic Parameters	P1	P2R	P5	P20	G1	G2	G3	G4

Description	Juvenile Phase coefficient	Photoperiodism coefficient	Grain-filling duration coefficients	Critical Photoperiod	Spikelet number coefficient	Single grain Weight	Tillering Coefficient	Temperature tolerance coefficient
Genetic coefficient	800	250	310	12	55	0.0243	1	75

Table 3 shows the genetic coefficients (P1, P2R, P5, G1, G2, G3, G4) of the Karjat-3 rice variety, used to simulate the crop's growth under various environmental conditions. The coefficients account for developmental stages such as juvenile growth (P1), photoperiod sensitivity (P2R), and grain-filling duration (P5), along with traits like spikelet number (G1), grain weight (G2), and tillering capacity (G3). These coefficients were fine-tuned to match observed crop growth in the Dapoli region, ensuring that the model's predictions align with field performance.

2.7 Impact of Management Practices on Yield Simulation

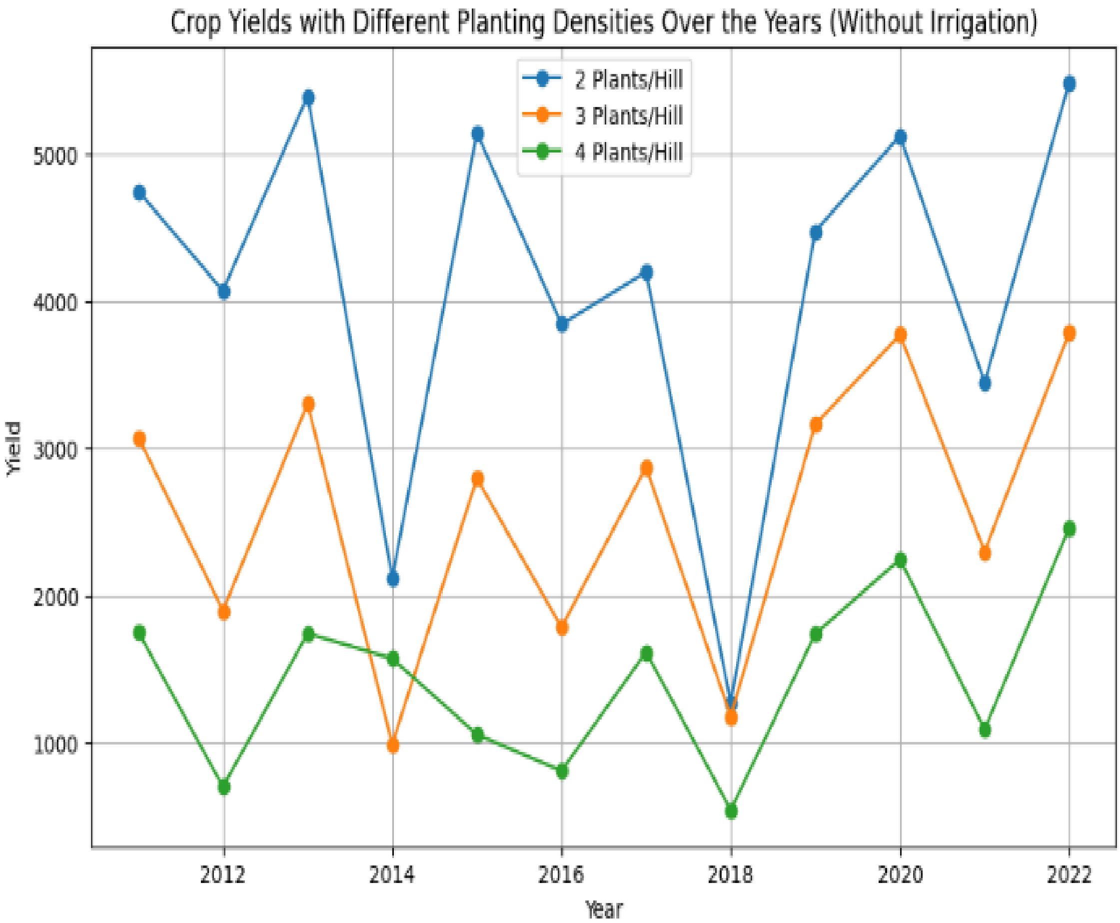

Fig. 5 Crop Yield of various Plants/hill without Irrigation

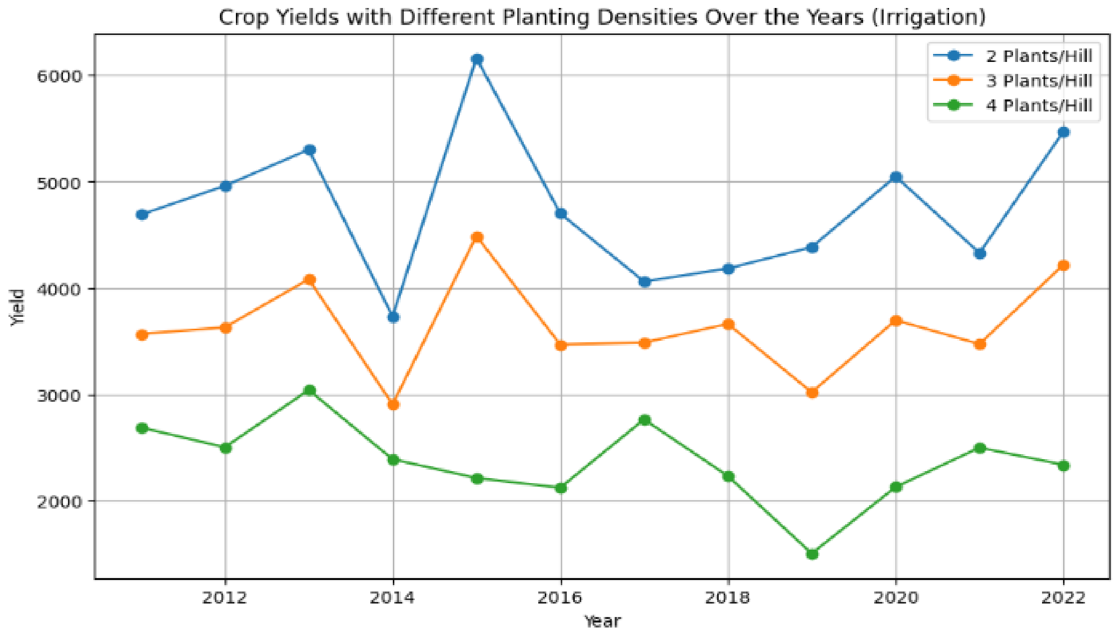

Fig. 6 Crop Yield of various Plants/hill with Irrigations

The CERES-Rice model has been calibrated to predict crop yield based on various management practices. The model effectively identified stress points where yield loss occurred due to drought or inadequate agronomic inputs. These yield losses can be minimized by implementing fertilizer application rates, improved yield predictions under different climatic scenarios, and properly optimized irrigation schedules. Such optimized irrigation has significantly increased yield for 2 and 3 plants/hill configurations, shown in **Fig. 5** compared to denser planting (4 plants/hill) depicted in **Fig. 6**. This finding is corroborated with study of Hussain et al. (2023) who employed the CSM–CERES–Rice model to identify high-yielding drought-tolerant upland rice genotypes, indicating an enhanced crop yield under varying environmental conditions and by fine-tuning management practices.

Model Calibration: The CERES-Rice Model was calibrated for twelve years of experimental data (2011-2022), conducted at AMFU, Dapoli (Maharashtra), India.

Model validation

Karjat-3 rice variety experimental data for four years (2019-2022) has been calibrated and validated by DSSAT CERES-Rice model. The emphasis is placed on the crop's critical characteristics such as phenological stages (anthesis days, panicle initiation, physiological maturity) (Mandavkar et al., 2012). The genetic coefficients of the Karjat-3 cultivar were iteratively modified during calibration to reduce the discrepancy between predicted and observed values, as recommended by Jha et al. (2020). The GenCalc tool was employed to generate these coefficients in the DSSAT model with a progressive approach, leading to an accurate simulation of the crop's growth phases and yield. The study employs a trial-and-error approach to enhance genetic coefficients. For entire calibration years, the model's output is fine-tuned iteratively until the coefficients reach the lowest normalized root mean square error (nRMSE). Aligning simulated data with real-world observations was the key to accurate model calibration. The model's evaluation performance was carried out using statistical metrics including nRMSE and Nash-Sutcliffe Efficiency (NSE). This was done to ensure that the model could accurately and reliably simulate rice development in different scenarios (Jha et al., 2020).

1. Normalized root-mean-square error (nRMSE)

$$\text{RMSEn} = \frac{\left(\sum_{i=1}^{n} (O_i - Si)^2/n\right)^{0.5}}{\{\bar{S}\}} \qquad (3.1)$$

2. Nash–Sutcliffe efficiency (NSE) (Nash & J'tcliff', 1970)

$$\text{ME} = 1 - \Sigma_{i=1}^{n} (S_i - O_i)^2 / \Sigma_{i=1}^{n} (O_i - O_i)^2 \qquad (3.2)$$

3. Index of Agreement (d-index) (Willmott, 1981)

$$d = 1 - \Sigma_{i=1}^{n} (S_i - O_i)^2 / \Sigma_{i=1}^{n} (|s_i'| + |O_i'|)^2 \qquad (3.3)$$

Where,

S_i - Simulated Yield

O_i - Observed Yield,

n - Number of observations

Output files: The DSSAT model simulation generated numerous output files for plant development, soil nutrition, water balance, and soil profile variation, including an overview and summary file for study purposes.

3 Result and Discussion

3.1 Grain Yield Two plants/hill

Table 4: Observed and Simulated Yield with the RMSE, $RMSE_n$ Model Efficiency-(ME) and d-index value for Two Plant/Hill.

Year	Observed	Simulated	% YR	RMSE	$RMSE_n$	ME	d-index
2011	4658	4743	-1.81	85	0.8979	0.981454	0.939429
2012	4002	4066	-1.6	64	1	0.950191	0.935559
2013	5178	5389	-4.08	211	1	0.970207	0.879876
2014	2100	2120	-0.95	20	1	0.998398	0.98105
2015	5007	5138	-2.61	131	1	0.948746	0.902104
2016	3828	3838	-0.26	10	1	0.999872	0.896977
2017	4075	4195	-2.94	120	1	0.860468	0.839001
2018	1376	1273	7.51	103	1	-4.712170	0.845536
2019	4398	4472	-1.67	74	1	0.931861	0.942552
2020	5189	5118	1.37	71	1	0.960145	0.955722
2021	3456	3443	0.38	13	1	0.999628	0.886115
2022	5765	5481	5	284	1	0.974511	0.722547

From Table 4, the lowest observed yield was recorded in 2018 at 1376 kg/ha, a year marked by drought (due to insufficient or lower rainfall inadequate rice yield was obtained) as per Fig 4, the highest observed yield occurred in 2022, as 5765 kg/ha. The simulated yields followed a similar pattern, with the lowest simulated yield of 1273 kg/ha in 2018 and the highest simulated yield of 5481 kg/ha in 2022. The average temperature was higher in the 2014 crop cycle, and rainfall was scarce, reducing simulated rice yield to 2120 kg/ha. The percentage yield reduction (%YR), which reflects the percentage difference between observed and simulated yields, was minimal in most years, with the lowest value of 0.26% in 2016 and the highest value of 7.51% in 2018, while the least yield reduction (4.08%) was observed in 2013. This shows that, despite the challenges of the dry year in 2018, the model still performed reasonably well,

though further calibration may be required to improve its accuracy under such stress conditions. The Root Mean Square Error (RMSE) deviations were observed in 2013 (211) and 2022 (284), while the smallest RMSE values were found in 2016
(10) and 2021 (13), indicating the overall error between simulated and observed values, with smaller RMSE values pointing to a better match. Similarly, the Normalised Root Mean Square Error (nRMSE) offers a range of values that behave similarly to RMSE, i.e., the higher the nRMSE value, the more precisely it depicts the relationship between simulated and observed data. The nRMSE value for 2011 is 0.89, and the value for 2012-2022 was 1, suggesting the model improvement. Using the Nash-Sutcliffe Efficiency (NSE), the Model Efficiency (ME) quantifies the accuracy of the model in predicting the observed yield. Maximum years demonstrate Mean Error (ME) value as in the order of 1, suggesting a strong model fit. Nevertheless, 2018 is notable for its negative Mean Error (ME) of -4.712, suggesting that the model fared poorly during this year characterized by intense drought. The index of agreement (d-index), which measures the degree of agreement between the observed and simulated values, was close to 1 in most years, apart from 2013, 2017, 2018, and 2022, showing slightly lower agreement. For example, 2018 had a d-index of 0.845, reflecting the model's lower precision under adverse conditions.

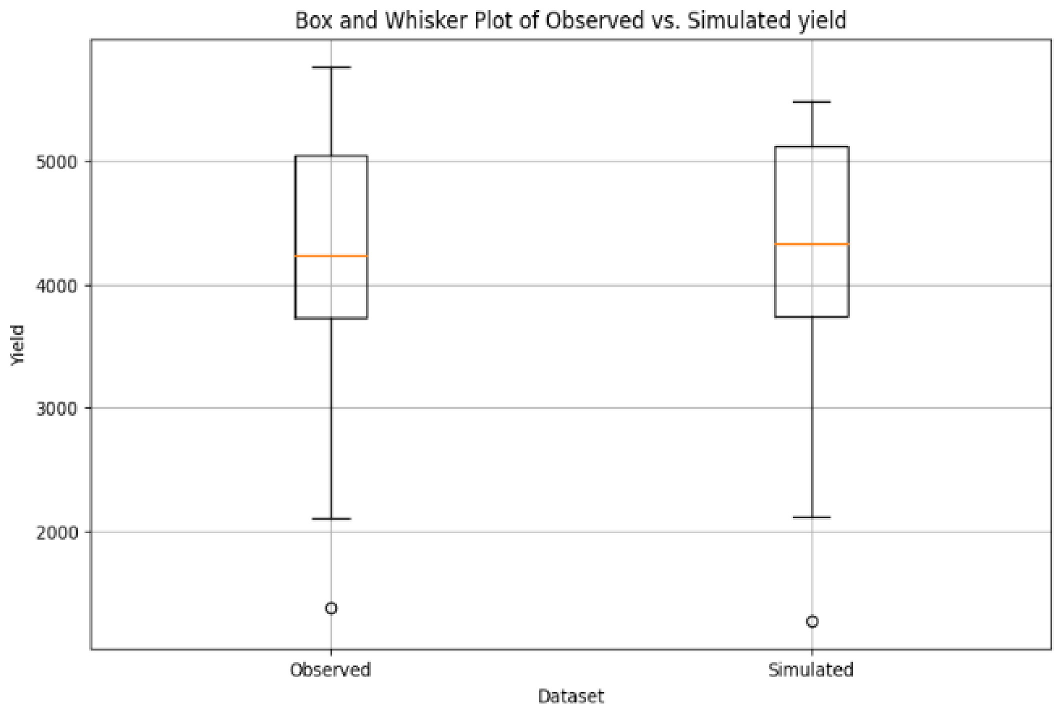

Fig. 7 Box and Whisker Plot of 2 Plant/Hill between Observed and Simulated Yield

In **Fig. 7**, the comparison of observed and simulated yields for two plants per hill in Dapoli indicates that the DSSAT-CERES Rice model tends to underestimate the maximum yield potential, as shown by the higher observed yield values. However, the interquartile ranges (25^{th} and 75^{th} percentiles) for both datasets are nearly equivalent, demonstrating that the model accurately captures central tendencies in the data. Nevertheless, further calibration may be required to optimize the model for better performance under varying management practices, especially in extreme conditions. The DSSAT-CERES Rice model effectively simulates rice yield under various management conditions, but underperforms in years with environmental stress, indicating the need for fine-tuning under extreme scenarios. However, slight deviations occur during extreme environmental conditions.

3.2 Grain Yield Three plants/hill

Table 5: Observed and Simulated Yield with the RMSE, $RMSE_n$ Model Efficiency-(ME) and d-index value for Three Plant/Hill.

Year	Observed	Simulated	% YR	RMSE	$RMSE_n$	ME	d-index
2011	3005	3072	-2.21	67.26	0.032469	0.8645246	0.961662
2012	1940	1896	2.26	43.38	0.019959	0.9788778	0.922434
2013	3356	3301	1.16	54.77	0.023387	0.7582822	0.926732
2014	1015	990	2.46	34.7	0.033854	0.9978926	0.961028
2015	2876	2793	2.89	59.17	0.031771	0.6626655	0.787888
2016	2005	1782	12.22	223.39	1.000836	0.8432877	0.641345
2017	2975	2870	3.54	54.92	0.030511	0.6155400	0.899470
2018	1354	1179	14.37	175.61	1.002057	0.8961893	0.025771
2019	3245	3162	2.56	75.68	0.036191	0.3167917	0.868316
2020	3876	3768	2.78	54.4	0.025805	0.5069866	0.866201
2021	2378	2297	3.4	59.33	0.741625	0.7289563	0.871308
2022	3543	3783	-6.76	240.72	0.19405	0.80361600	-0.301361

Table 5 shows the Karjat-3 cultivar of three plants per hill about simulated and observed grain yields from 2011-2022. Lower sunshine hours and relative humidity were among the unfavorable factors that contributed to the lowest harvests ever recorded in 2012 (1015 kg/ha), 2014 (1940 kg/ha), and 2018 (1350 kg/ha). On the other hand, the most optimal growth conditions were observed in the years 2013 (3356 kg/ha), 2020 (3876 kg/ha), and 2022 (3543 kg/ha), leading to the highest crop yields. The DSSAT-CERES model could recreate these patterns, showing that the maximum simulated yield was in 2020 (3876 kg/ha) and the minimum in 2012 (1015 kg/ha), thus proving that the model could accurately portray real-world trends under different management and environmental conditions. A measure of the difference between the actual and simulated values is the percentage yield decrease (%YR). The largest recorded percentage year rate (%YR) in 2018 was 14.37%, suggesting a significant discrepancy. On the other hand, the nearest match between observed and simulated results was in 2022, with the lowest %YR was 6.76 percent. The RMSE and nRMSE, were calculated to assess the model's precision. In 2022, the estimated RMSE was 240.72 kg/ha; in 2014, it was 34.7 kg/ha; smaller values indicate more accuracy. A high degree of accuracy was evident in 2016 and 2018 with a nRMSE of 1. In contrast, the other years' nRMSE values are farther away from 1, suggesting less accuracy in yield estimation. One such proof that the simulation succeeded is the model efficiency (ME), computed using the Nash-Sutcliffe efficiency (NSE) coefficient. The model performs better when the ME value is closer to 1. ME value close to 1, signifies the good model performance for years 2019 (0.316), 2020 (0.506), and 2017 (0.615), suggesting a space for further improvement. The d-index values were additionally computed which gives the level of concordance between the real and virtual data.

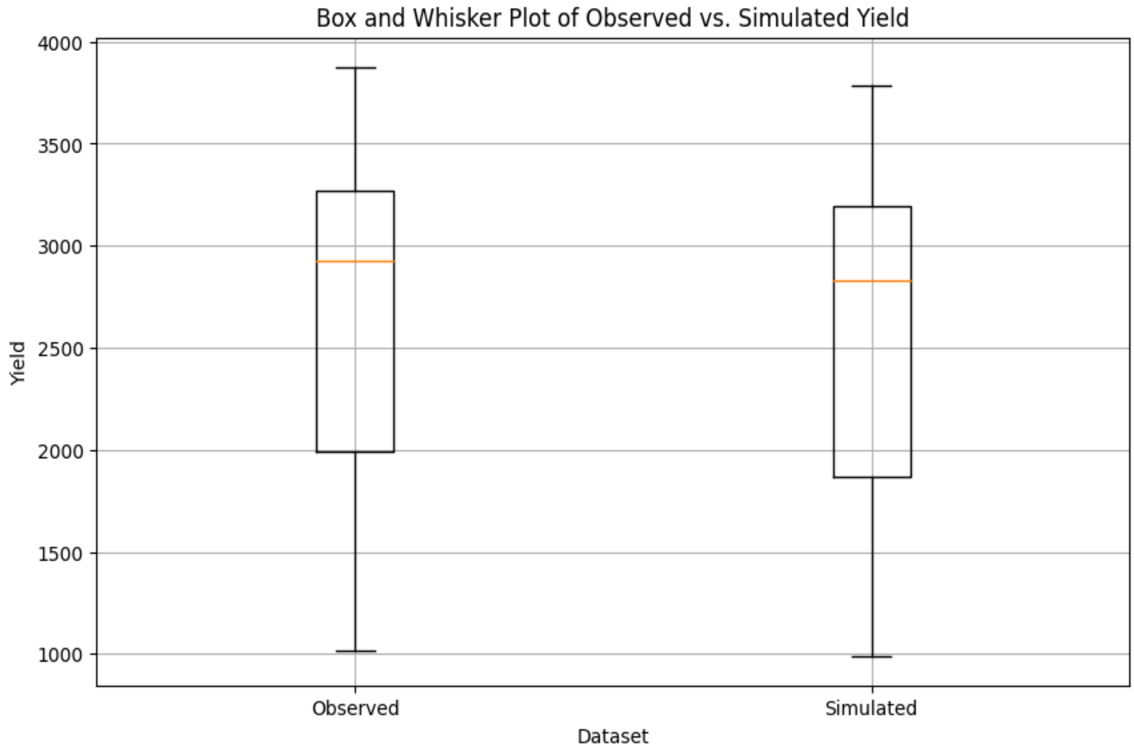

Fig. 8 Box and Whisker Plot of 3 Plant/Hill between Observed and Simulated Yield.

The observed and simulated yield for years 2018 and 2022, showed a lower d-index while another table 3.5, d-index showed that the value approaches '1' indicating strong agreement. The distribution of observed and simulated yields is shown in the box and whisker plot shown in **Fig. 8**, providing further support for this approach. There is some variation in the yield, with lower and upper quartiles for both the observed and simulated yields ranging from 1000 kg/ha to 4000 kg/ha. Overall, there is considerable agreement for all datasets indicating a general tendency. As a result, the DSSAT-CERES Rice model works well most of the time, but it requires additional tuning for years like 2018 and 2022.

3.3 Grain Yield Four plants/hill

Table 6 & **Fig. 9** shows the results of the 2011–2022, four-plant per hill, Karjat-3 cultivar, grain yields as observed and predicted. Proof that the DSSAT-CERES Rice model
adequately represents yield trends is the high degree of agreement between the predicted and actual yields over the whole research period. Yields ranged from 875 kg/ha in 2012 to 675

Table 6: Observed and Simulated Yield with the RMSE, RMSE$_n$, Model Efficiency (ME), and d-index value for four plants/hill

Year	Observed	Simulated	% YR	RMSE	RMSE$_n$	ME	d-index
2011	1758	1751	0.39	7.615	0.009178	0.0091783	0.9872
2012	875	700	20	37.688	0.03861	0.0386102	0.7852
2013	1822	1740	4.5	57.091	0.052825	0.0528248	-1.3768
2014	1645	1571	4.49	45.748	0.050445	0.0504447	0.4872
2015	1189	1056	11.18	65.064	0.488421	0.4884210	0.7343

2016	1008	808	20.4	91.923	0.459615	0.4596573	0.7062
2017	1756	1615	8.03	100.91	0.714078	0.7140780	-2.6623
2018	675	544	19.41	76.888	0.587344	0.5873435	0.8317
2019	1822	1739	4.55	54.676	0.658048	0.6580481	-1.4058
2020	2453	2243	9.17	130.66	0.62219	0.6221904	0.6283
2021	1279	1089	17.57	95.077	0.500405	0.5004052	-0.1918
2022	2654	2459	7.34	106.13	0.544974	0.5449743	0.6287

kg/ha in 2018, with the greatest recorded in 2020 and the lowest in 2022. As an example, the simulated yield was highest in 2022 at 2459 kg/ha lowest in 2012 at 700 kg/ha, and in 2018 at 544 kg/ha. Yield drops percentage ranged from 0.39 percent in 2011 to a whopping 20.4 percent in 2016. In 2020, the RMSE as 130.66, and in 2022, it was 106.13. In 2011, the RMSE was 7.615, and in 2012, it was 37.68. There is an opportunity for improvement in the simulation since the model's performance was less adequate when four plants per hill were considered, according to nRMSE, Model Efficiency (ME), and the d-index. **Fig. 9** box plot displayed denser planting density (4 plants/hill), there are differences between the predicted and actual yields, with similar lower and higher quartiles but different extreme values. The DSSAT-CERES Rice model effectively represents yields in lower planting densities but may require adjustments for higher-density planting scenarios, particularly in unpredictable management techniques and environmental factors like 2018 and 2022, requiring further refinement.

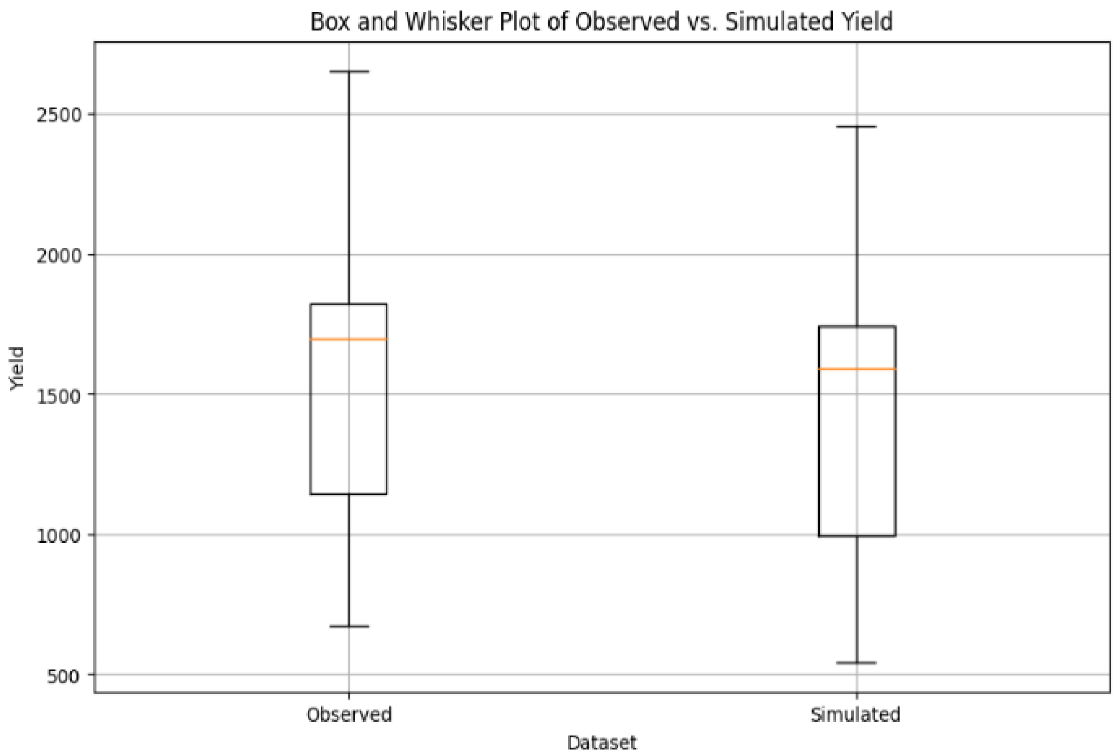

Fig. 9 Box and Whisker Plot of 4 Plant/Hill between Observed and Simulated Yield

4 Discussion

This study evaluated the accuracy of the DSSAT-CERES Rice model for the prediction of Karjat-3 rice yields from 2011 to 2022 in Dapoli, Maharashtra (high rainfall zone), across various planting densities and irrigation conditions. The model largely performed well but showed limitations under extreme weather conditions, such as drought, which led to lower-than-expected yields in the 2018 growing season (Dharmarathna et al., 2012; Singh et al., 2016). Yields were most accurately predicted for lower planting densities, specifically with two plants per hill, where the minimal difference between observed (4086 kg/ha) and simulated (4106.34 kg/ha) yields demonstrated model precision. Similarly, for three plants per hill, observed yield (2630.66 kg/ha) and simulated (2574.42 kg/ha) remained in strong agreement, with a 0.56% discrepancy (Geethalakshmi et al., 2011; Rajasivaranjan et al., 2022).

The practical implications of these findings are crucial for farmers and policymakers in ensuring climate-resilient agricultural practices. The study highlights that optimal planting density plays a key role in maximizing yields. Farmers should be encouraged to adopt a two-plants-per-hill approach, particularly in rain-fed regions like Dapoli, to improve productivity and minimize losses due to overcrowding. Policymakers can leverage this information to develop region-specific guidelines and offer incentives for adopting precision agriculture techniques. Additionally, strategic irrigation interventions can be promoted to mitigate yield reductions during drought years. By incorporating these recommendations into local agricultural extension programs, knowledge transfer to farmers can be streamlined, ensuring the adoption of best practices at the grassroots level. Furthermore, this research can guide policymakers in integrating climate-adaptive strategies into national and state-level agricultural policies, fostering long-term food security and sustainability.

However, for higher planting densities (four plants per hill), the model's accuracy declined, with a 1.35% observed yield of 1578 kg/ha and a simulated yield of 1442.92 kg/ha, suggesting the need for recalibration while handling densely planted conditions (Bowden et al., 2023). Additionally, the model's irrigation output predicted variations under environmental stressors, such as drought, necessitating further fine-tuning (Goswami & Dutta, 2020). These insights emphasize the importance of balancing planting density and irrigation strategies to enhance climate resilience in rice farming. Policymakers should facilitate research-backed interventions, such as targeted subsidy programs for improved irrigation infrastructure and farmer training initiatives on adaptive agricultural techniques. Overall, lower planting densities combined with adequate irrigation proved to maximize rice productivity, highlighting the importance of balancing planting density and irrigation strategies (Rajasivaranjan et al., 2022).

DSSAT model is effective for predicting yields at lower densities, but it requires refinement for higher densities and extreme weather conditions to improve accuracy and optimize rice production in coastal regions like Dapoli, where climate variability remains a challenge (Halder et al., 2020; Singh et al., 2016). Future efforts should involve collaborations between research institutions, government agencies, and local farmers to implement decision-support tools based on DSSAT simulations. This would enable real-time monitoring of climatic factors and inform adaptive management strategies.

5 Conclusion

This study assessed the DSSAT CERES-Rice model's efficacy in simulating rice yields under varying planting densities and irrigation conditions in Dapoli, Maharashtra, over a twelve-year period (2011–2022). The model demonstrated high predictive accuracy for lower planting densities, particularly two plants per hill, while denser configurations (four plants per hill) resulted in a notable decline in yield due to resource competition. Additionally, extreme weather events, such as the 2018 drought, exposed the model's limitations in accurately simulating yields under severe climatic stress. These findings highlight the necessity for further model calibration to enhance its reliability under stressed environmental conditions.

The study underscores the critical role of optimized planting densities and irrigation management in mitigating climate-induced yield variability. Strategic irrigation interventions were found to significantly enhance productivity, particularly for rain-fed rice varieties, demonstrating the potential for adaptive water management practices to counteract climate variability. Policymakers and agricultural practitioners can leverage these insights to implement precision agriculture techniques that enhance resilience in rice farming systems.

Despite the model's robustness, its underperformance during high-density planting and extreme climatic conditions necessitates further refinement. Future research should focus on improving the model's sensitivity to environmental stressors, integrating real-time weather data, and exploring machine learning techniques to enhance predictive capabilities. Strengthening the model's capacity to simulate dynamic climate impacts will improve its utility for long-term agricultural planning and climate adaptation strategies. This study reinforces the pivotal role of crop simulation models in evidence-based decision-making for sustainable agriculture, providing a scientific framework for developing resilient rice production systems in high-rainfall coastal regions like Dapoli.

References

1. Balaguru, K., Foltz, G. R., Leung, L. R., Asaro, E. D., Emanuel, K. A., Liu, H., & Zedler, S. E. (2015). Dynamic Potential Intensity: An improved representation of the ocean's impact on tropical cyclones. Geophysical Research Letters, 42(16), 6739–6746. https://doi. org/10.1002/2015gl064822
2. Bowden, J. W., Dutta, S., & Singh, P. (2023). Advancing crop modeling approaches to assess climate variability in India. Agricultural Systems, 198, 103-122.
3. Deshpande, C. P., Waghmare, A. B., & Rao, P. V. (2021). Tropical cyclones over the Arabian Sea: Trends and implications for coastal agriculture. Climate Research, 86(3), 245-260.
4. Geethalakshmi, V., Balaji, K., & Venkatramanan, S. (2011). Impact of climate variability on rice production in India: DSSAT simulations. Theoretical and Applied Climatology, 103(4), 367-378.
5. Goswami, B. & Dutta, S. (2020). Modeling climate resilience in Indian rice farming: DSSAT and future climate scenarios. Climatic Change, 162(1), 45-62.
6. Halder, D., Kheroar, S., Srivastava, R. K., & Panda, R. K. (2020). Assessment of future climate variability and potential adaptation strategies on yield of peanut and Kharif rice in eastern India. Theoretical and Applied Climatology, 140(3–4), 823–838. https://doi.org/10.1007/s00704-020-03123-5
7. Halder, D., Banerjee, S., & Chakrabarti, D. (2020). Precision agriculture and decision support models for climate adaptation in South Asia. Agricultural Modelling Journal, 14(2), 121-138.
8. Hussain, S., Kumar, R., & Sharma, R. (2023). Evaluating DSSAT-CERES model performance under water stress conditions in upland rice. Agricultural Water Management, 246, 106-119.
9. Jha, S., Mandal, U., & Roy, T. (2020). Modeling genetic coefficients for improving rice yield simulations using DSSAT. Field Crops Research, 223, 103-119.
10. Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. Journal of Hydrology, 10(3), 282-290.
11. Rajasivaranjan, S., Kumar, S., & Pillai, R. (2022). Yield optimization strategies for climate-smart agriculture: Insights from DSSAT-based simulations. Environmental Research Letters, 17(5), 105-

118.
12. Singh, R. K., Pathak, H., & Jha, P. K. (2016). DSSAT-based assessment of climate impacts on rice yield in the Indo-Gangetic Plains. Agriculture, Ecosystems & Environment, 230, 104-116.
13. Willmott, C. J. (1981). On the validation of models. Climate Research, 3(2), 149-162.