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Research paper

Simulating Wheat (*Triticum aestivum* L.) Yield under Different Sowing Dates and Nitrogen Management Using CERES-Wheat Model in Tropical Highlands of Ethiopia

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ABSTRACT

This study assesses climate change impacts on wheat production in the tropical highlands of Ethiopia using the DSSAT-CERES-Wheat model. Field experiments were conducted across three locations (Bore, Kulumsa, Sinana) during 2023–2024, evaluating two wheat cultivars (Shaki, Boru) under nitrogen rates (0, 46, 69, 92 kg ha⁻¹) and sowing dates (early, normal, late). The model was calibrated and validated using phenological, growth, and yield data, showing strong agreement between simulated and observed values. For Shaki, grain yield calibration yielded an RMSE of 130 kg ha⁻¹, NRMSE of 3.4%, and a d-index of 0.91; for Boru, an RMSE of 140 kg ha⁻¹, NRMSE of 3.6%, and a d-index of 0.90. Biomass RMSE was 190 kg ha⁻¹ (Shaki) and 200 kg ha⁻¹ (Boru), with d-index >0.91. Anthesis date RMSE was 1.7–1.9 days (d-index >0.92), while LAI simulations had RMSE of 0.14–0.17. Validation results confirmed robust model performance for critical variables: anthesis date (RMSE: 1.9–2.0 days), LAI (RMSE: 0.15–0.18), biomass (RMSE: 187–197 kg ha⁻¹), and grain yield (RMSE: 127–137 kg ha⁻¹) for Shaki and Boru, respectively. Key findings indicate early planting with 92 kg N ha⁻¹ maximises yields, mitigating climate-driven losses. Confirms DSSAT's utility in guiding adaptive wheat management for Ethiopia's climate-vulnerable agriculture.

Keywords: CERES-Wheat model; Calibration; Validation; Nitrogen management; Planting dates; Simulation.

Climate change critically challenges 21st-century agriculture. The Intergovernmental Panel on Climate Change reports a 0.74 °C rise in global temperature over the past century, with a projected increase of 1.1–5.8 °C by 2100, plus more extreme events (IPCC, 2021). These changes reduce farming output and strain agricultural systems, particularly in subSaharan Africa, where Ethiopia is highly vulnerable, and Ethiopian agriculture strongly depends on seasonal climate patterns. Wheat is the world's most widely grown food crop, with high productivity and cultivated area (Singh *et al.*, 2023). In Ethiopia, wheat leads in national output and yield per hectare, though third in area. Its productivity declines due to poor genetics, moisture stress, frost, and limited agronomic practices (Tesfaye *et al.*, 2025). Climate change exacerbates these: rising temperatures and increasing rainfall variability (Tesfaye

et al., 2025) are projected to negatively affect wheat phenology, growth, and yield in Ethiopia and globally (Tesfaye *et al.*, 2025). The FAO advises integrating climate information into agronomic management, especially in subSaharan Africa (Wei, 2020).

Crop modelling quantitatively assesses agronomic practices, climate, soil, and genotype effects on crop growth, yield, resource efficiency, and environmental impact (Mamassi *et al.*, 2023). Traditional experiencebased research has limitations (Timaeus *et al.*, 2022); knowledgebased dynamic models are gaining popularity (Mouratiadou *et al.*, 2023). They integrate disciplines, simulate crop responses to various environments, and test management alternatives (Boote *et al.*, 2010; Sandhu *et al.*, 2016). Dynamic models help develop strategies for crop management, land use, and

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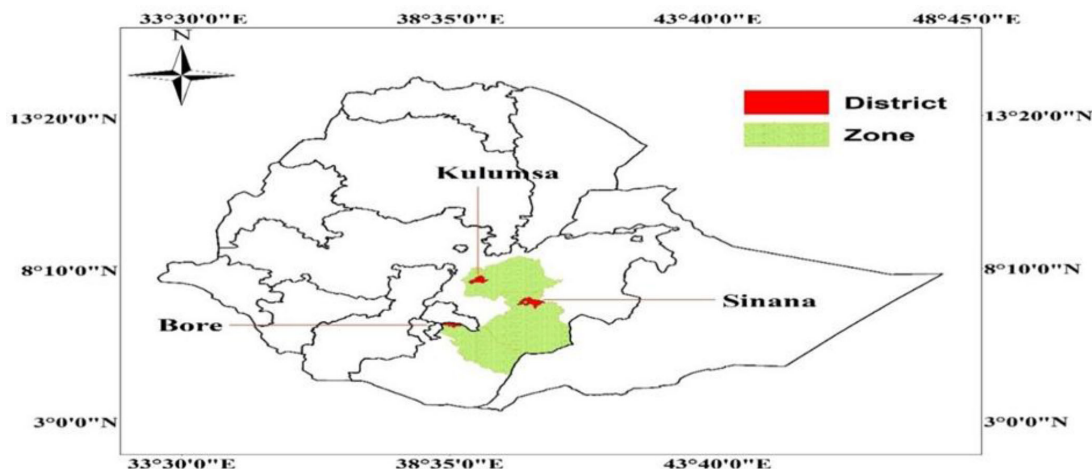


Fig. 1: Map of the study areas, Kulumsa, Bore, and Sinana in Ethiopia

water management, and identify knowledge gaps, test hypotheses, determine influential parameters, and facilitate communication (Pham *et al.*, 2021).

The DSSAT platform with its CERESWheat module is key for simulating climate change impacts on wheat yields. Research shows that climate-driven yield declines in Ethiopia can be offset by optimised planting dates and nitrogen application. DSSATCERESWheat simulates daily crop growth using solar radiation capture, canopy leaf area, temperature and photoperiod-driven phenological development (shorter phases and growing season at higher temperatures, reducing yield), soil moisture effects on nitrogen uptake and water status. Using radiation, temperature, and water inputs, the model simulates development, biomass, and grain yield, making it valuable for evaluating climate change impacts in Ethiopia. This study aims to: (a) calibrate and evaluate the DSSAT CERESWheat model, and (b) analyse climate change impacts on wheat production using DSSAT version 4.8.5, while assessing sowing dates and nitrogen fertilizer levels as mitigation strategies via sensitivity analysis.

MATERIALS AND METHODS

Description of the study area

The study was carried out at three locations in Ethiopia, namely Bore (6°25' N 40°21' E), Kulumsa (8°01' N 39°16' E), and Sinana (7°06' N 41°21' E), which were selected for the present study (Fig. 1). The research focuses on key wheat-producing regions in the southeastern highlands of Ethiopia. Specifically, the areas of Bore, Kulumsa, and Sinana are located in the Guji, Arsi, and Bale zones of Oromia regional state, which fall under a highland climate classification (Fig. 1). These districts were chosen due to their favourable climate conditions for wheat cultivation and their significant production coverage. Classified as highland climates (Fig. 1), further site-specific details are summarised in Table 1. Most southeastern Oromia experiences bimodal rainfall (*Belg & Kiremt*), with most of the total precipitation in the study area occurring between June and September. April is the hottest month, while December is the coldest month of the year. Table 1 presents the annual total precipitation and average minimum and maximum

temperatures. The soils of the study sites were characterised as clay to clay loam to clay with medium drainage.

The average soil pH ranges from slightly acidic to near-neutral (5.5–7.2), which is most favourable for crop cultivation. Organic matter content varies from 1.5–6.0%, with Sinana the highest (3.0–6.0%) and Bore the lowest (1.5–3.5%). Total nitrogen levels range from 0.1–0.4%, and available phosphorus is low, especially in Sinana (3–10 ppm). The cation exchange capacity (CEC) is moderate to very high (15–45 cmol (+) kg⁻¹), with Sinana showing the highest values (25–45 cmol (+) kg⁻¹). Exchangeable potassium ranges from moderate to high (0.8–3.0 cmol (+) kg⁻¹), with Sinana also having the highest levels (1.5–3.0 cmol (+) kg⁻¹).

Description of DSSAT CERES-Wheat model

The DSSAT CERES-Wheat model is a process-based crop simulation tool within the Decision Support System for Agrotechnology Transfer (DSSAT) that predicts wheat growth, development, and yield by integrating daily weather, soil properties, management practices, and cultivar-specific genetic coefficients. It simulates phenology (germination to maturity) using thermal time, while dynamically accounting for soil water balance, nitrogen cycling, and biomass partitioning to quantify yield impacts from drought, heat, or nutrient deficits. In this study, DSSAT v4.8.5 was applied at Bore, Kulumsa, and Sinana (Ethiopia) to evaluate planting date and nitrogen management strategies using site-specific input data.

Field experiment and Crop management

The DSSAT-CERES-Wheat model was calibrated and evaluated using field experiments and crop management data collected during the main cropping season (June to September) of 2023 and 2024 under rainfed conditions at Bore, Kulumsa, and Sinana Agricultural Research Centres. Growth, phenology, and management data for two leading wheat bread wheat cultivars, Boru and Shaki, were utilised for this experiment. These cultivars, developed by the Kulumsa Agricultural Research Centre under the Ethiopian Institutes of Agricultural Research, are specifically bred for highland wheat-growing regions. The experiment involved

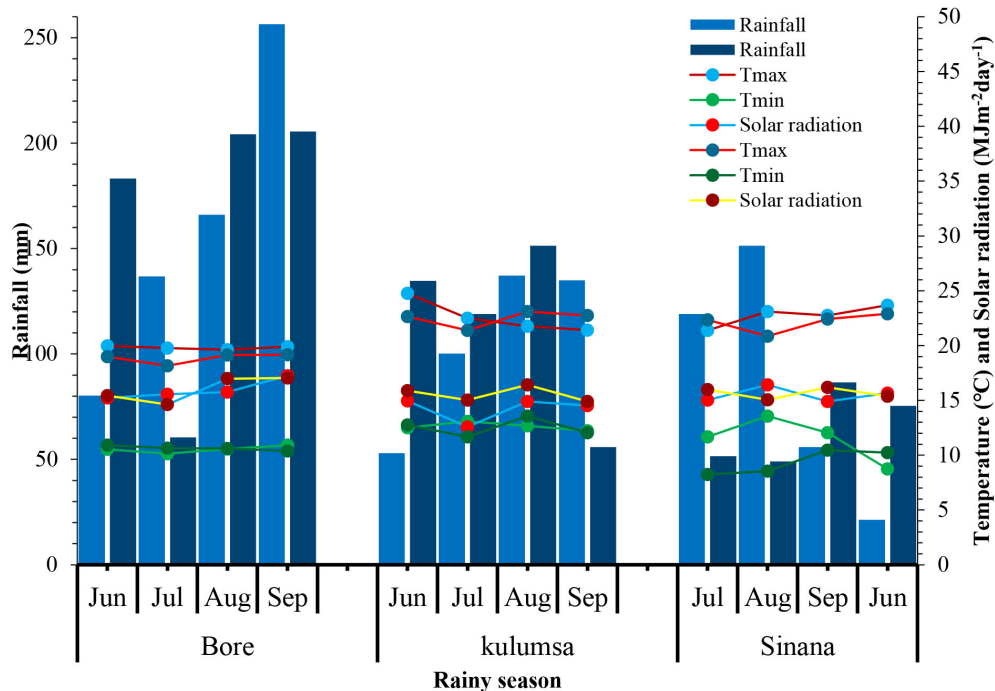


Fig. 2: Average monthly precipitation, maximum and minimum temperatures in Bore, Kulumsa, and Sinana over the growing season.

Table 1: Altitude, rainfall, minimum and maximum temperature of the study areas

Locations	Altitude (m)	Annual Rainfall (mm)	Annual Tmax (°C)	Annual Tmin (°C)
Bore	2671	1737	24.61	10.58
Kulumsa	2420	1083	25.77	9.60
Sinana	2442	1076	22.85	10.70

testing different combinations of nitrogen fertiliser rates and planting dates for two improved wheat varieties. A factorial experiment consisted of four different nitrogen rates (0, 46 (recommended), 69, and 92 N kg per hectare) and three different planting dates (early (01 July), mid (15 July), and late (30 July) with two varieties (Shaki and Boru). The experiment was conducted using a randomized complete block design, including three replications with each plot size 2.4 m by 2.5 m. Planting was performed manually, achieving this by using the recommended seed rate. The row planting spacing was set at 20 cm, and 3 cm was used for the depth of planting. Half of the nitrogen treatments were applied at planting, and the remaining half was applied 35 to 42 days after planting. The recommended fertiliser rate for wheat production in the study areas is 100 kg ha⁻¹ of di-ammonium phosphate, commonly applied for all treatments at sowing. Data on crop phenology and biophysical traits were gathered from a net plot area of 5 m².

The crop data collected included key phenological stages, growth parameters, and yield components. Days to 50% flowering were recorded visually when half the plants in a plot showed emerged heads, while days to 90% physiological maturity were determined upon a visual shift in stem color to yellowish/dark brown. At the maximum tillering stage, the Leaf Area Index (LAI) was measured using digital canopy photography. At full maturity, the number of

tillers per m² was counted from quadrants, and the final above-ground biomass yield was recorded from sun-dried samples. Grain yield was harvested from a defined net plot, threshed, cleaned, and weighed, with the final weight adjusted to 12.5% moisture content. Finally, the harvest index (HI), representing the partitioning efficiency to grain, was calculated as the ratio of grain yield to total above-ground biomass.

Climate and weather

For the baseline climate analysis, 34 years of daily meteorological records (1990-2024) were utilised, with precipitation and temperature data obtained from the Ethiopia Meteorological Institute (EMI) and solar radiation data acquired from the NASA POWER (Prediction of Worldwide Energy Resources) database. The Fig. 2 presents key climatic variables for the 2023 and 2024 cropping seasons. In 2023, the mean maximum and minimum temperatures during the rainy season (June - September) were recorded as 20 °C and 11 °C (Bore), 23 °C and 13 °C (Kulumsa), and 24 °C and 9 °C (Sinana). Corresponding total rainfall amounts for the same period (June - September) were 639.5 mm, 653.36 mm, and 247.77 mm, respectively. In contrast, the 2024 cropping season exhibited slightly lower temperatures, with mean maximum and minimum values of 18.86 °C and 10.63 °C (Bore), 22.47 °C and 12.52 °C (Kulumsa), and 22.12 °C and 9.37 °C (Sinana). Concurrently, seasonal rainfall increased to 653.36 mm (Bore), 460.82 mm (Kulumsa), and 262.33 mm (Sinana). The results (Fig. 2) illustrate an inverse correlation between temperature and rainfall trends across the study regions during 2023 and 2024.

Soil profile characteristics

Soil profile data were gathered from specific sites at the Bore, Kulumsa, and Sinana research stations one week before sowing.

Table 2: Soil physical and chemical characteristics for the study areas Bore, Kulumsa and Sinana

Location	SLD (cm)	LL (cm ³ cm ⁻³)	UL (cm ³ cm ⁻³)	SAT (cm ³ cm ⁻³)	RGF	SSC (cm h ⁻¹)	BD (g cm ⁻³)	OC (%)	CL (%)	SI (%)	LHW (pH)	CEC (cmol kg ⁻¹)	%TN
Bore	30	0.323	0.51	0.53	1	0.06	1.12	3.01	43	28	5.1	23.12	0.33
	60	0.325	0.506	0.527	0.407	0.06	1.13	2.91	44	26	5.29	26	0.52
	80	0.335	0.513	0.527	0.223	0.06	1.13	2.5	46	24	6.5	29	0.51
	120	0.315	0.472	0.503	0.122	0.06	1.21	2.0	47	24	6.9	29	0.51
	150	0.315	0.464	0.496	0.067	0.06	1.23	1.97	47	21	7.1	31	0.06
	180	0.298	0.419	0.462	0.037	0.06	1.34	0.98	49	18	7.3	31.5	0.06
Kulumsa	30	0.24	0.37	0.45	0.85	0.15	1.15	2.97	40.4	27.9	6.6	45.3	0.09
	60	0.26	0.39	0.46	0.70	0.12	1.18	2.37	43.1	26.9	6.7	43.9	0.12
	80	0.27	0.40	0.47	0.50	0.09	1.23	1.26	45.4	25.8	6.8	45.9	0.03
	120	0.27	0.40	0.47	0.38	0.09	1.29	1.31	45.4	25.1	7.0	46.2	0.03
	150	0.26	0.39	0.46	0.05	0.10	1.34	1.42	44.0	24.7	7.2	46.1	0.04
	180	0.26	0.39	0.46	0.05	0.10	1.34	0.23	44.0	24.7	7.2	46.1	0.04
Sinana	30	0.351	0.534	0.541	1	0.06	1.12	2.76	50	27	6.6	45	0.65
	60	0.332	0.492	0.512	0.407	0.06	1.19	1.7	52	28	7.7	44	1.07
	80	0.3	0.452	0.495	0.223	0.06	1.24	1.6	46	27	6.6	46	1.12
	120	0.309	0.454	0.492	0.122	0.06	1.25	1.4	49	25	7.75	46	0.117
	150	0.313	0.449	0.484	0.067	0.06	1.28	0.98	52	25	7.4	47.3	0.10
	180	0.309	0.426	0.464	0.037	0.06	1.35	0.28	55	23	7.45	47.4	0.113

Note. Soil bulk density (BD), clay content (CL), silt content (SI), and layer depth (SLD). Saturated hydraulic conductivity (SSC), Upper Limit (UL) and lower moisture limits (LL), and saturation level (SAT). Soil organic carbon (OC), cation exchange capacity (CEC), and pH in water (LHW), Root growth factor (RGF).

A pit was excavated to examine the soil profile, which was assessed up to 1.8 m depth. Initial soil samples were collected at intervals of 30 cm (0-30, 30-60, 60- 90, 90-120, 120-150, and 150-180 cm). Soil pH (1:2.5 water suspension), total nitrogen (Kjeldahl), and organic carbon (Walkley–Black), were determined using standard methods validated for agricultural soils. Bulk density was measured by the oven-dry weight method (Blake & Hartge, 1986). Organic carbon (OC) was measured by Walkley–Black, cation exchange capacity (CEC) by ammonium acetate (pH 7.0) (Chapman, 1965), and soil pH in water (LHW) at a 1:2.5 ratio (Thomas, 1996). Root growth factor (RGF) was estimated from bulk density and texture, indicating physical constraints to root development (Jones & Kiniry, 1983). Soil hydraulic properties, saturated hydraulic conductivity (SSC), upper (UL) and lower (LL) moisture limits, and saturation (SAT) were determined using standard laboratory methods (constant head, pressure plate) (Klute & Dirksen, 1986; Richards, 1941) at the Horticoop Soil and Water Laboratory in Bishoftu, Ethiopia. The analysed results of soil profile data of the experimental area were summarised and displayed in Table 2.

Model calibration

Model calibration is the process of comparing a model to a real system by running the model interactively and making necessary revisions. This involves adjusting a basic set of model parameters, especially through cultivar coefficients, to describe the system being studied more accurately. The goal is to ensure that the simulated values closely align with the observed ones. The calibration procedure starts by adjusting genetic coefficients to

achieve a better match between the predicted and measured data (Hooogenboom *et al.*, 2020). The DSSAT-CERES-Wheat model was calibrated to utilise minimal data sets, including 30 years of daily weather data for a baseline period, soil profile data on relevant parameters, and crop data collected (phenology, growth, yield, and yield-related factors) from field experiments at Bore, Kulumsa, and Sinana research sites during the 2023 cropping season. The model's seven wheat cultivar-specific parameters were optimised using crop growth and phenology data gathered according to established procedures by the generalised likelihood uncertainty estimation (GLUE) technique within the DSSAT model environment (Table 3). The cultivar genetic coefficients, formulated in thermal time (degree-days) and photoperiod response units, enable the accurate simulation of varietal performance under the region's specific environmental conditions. This calibration process allowed the model to capture the distinct phenological development patterns and yield potential of each wheat cultivar presented in Table 3.

Model evaluation

Before using a model to study crop growth, it is crucial to adjust the cultivar genetic coefficients and evaluate the model to ensure accurate results. The model's specifications were fine-tuned utilising observed field data. After calibration, the model was evaluated using data collected from the Bore, Kulumsa, and Sinana sites during the 2024 main cropping season. Evaluation of model reliability was done using R², RMSE, NRMSE, and Willmott's index of agreement (d-stat) statistical indices. High R² values and low RMSE and NRMSE values indicate good model performance.

Table 3: Cultivar-specific genetic parameters used for calibrating the DSSAT-CERES-Wheat model for Boru and Shaki varieties.

Genetic Coefficient	Description	Value	
		Shaki	Boru
P1V	Vernalization sensitivity coefficient (days)	50	55
P1D	Photoperiod sensitivity coefficient (% reduction/day)	60	65
P5	Grain filling duration coefficient (degree days)	500	520
G1	Kernel number per unit canopy weight at anthesis	20	22
G2	Standard kernel size under optimum conditions (mg)	40	42
G3	Standard stem weight at maturity (g/plant)	2.5	2.7
PHINT	Phyllochron interval (degree days)	80	85

The model's performance is considered good if R^2 and d-stat values approach one, while RMSE approaches zero. Two kinds of data were utilised for model evaluation: average data that includes days to flowering, days to maturity, and yield; and time-series data that includes dry weights of biomass and LAI collected over time. For average observation, RMSE was used to assess the accuracy between simulated and measured values. For the time series data, R^2 and the index of agreement (d) were used to evaluate the goodness of fit. RMSE shows a variation of the simulated values from the measured ones and describes the prediction error relative to actual values. To maximise model accuracy, RMSE should be minimised. RMSE is always positive, and a good simulation should have an RMSE as close to zero as possible (MacCarthy *et al.*, 2012).

The RMSE was determined using the following formula:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2}$$

The normalised Root Mean Square Error (nRMSE) quantifies the relative deviation between simulated and observed values, expressed as a percentage. Performance thresholds classify simulations as: excellent (<10% nRMSE), good (10-20%), fair (20-30%), or poor (>30%) (Rani *et al.*, 2016).

The nRMSE was computed using the following equation:

$$nRMSE = \frac{1}{\sigma} MSRE \times 100$$

The coefficient of determination (R^2) quantifies the ratio of variance in the dependent variable explained by the model's independent variables. Ranging from 0 to 1, higher R^2 values indicate better model fit, with values above 0.5 generally considered statistically acceptable (Balderama *et al.*, 2016). The R^2 is computed from the linear regression of simulations versus the observations graph (Balderama *et al.*, 2016).

$$R^2 = 1 - \frac{RSS}{TSS}$$

where RSS is the sum of squares of residuals, and TSS is the total sum of squares. R^2 is always less than or equal to 1.

Willmott's index of agreement (d-stat) measures prediction accuracy, ranging from 0 (no agreement) to 1 (perfect fit) (Willmott, 1984). A value close to 1 indicates strong model performance.

The d-stat was computed using this equation:

$$d = 1 - \left[\frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (P_i + O_i)^2} \right] \quad 0 \leq d \leq 1$$

Where: n = number of observations, P_i and O_i denote the simulated and measured values, respectively, for the i^{th} observation

Finally, the yield gap is then estimated by subtracting the experimental yield from the climate potential yield and expressed as $t \text{ ha}^{-1}$ (Yasin *et al.*, 2021). The mean per cent deviation quantifies the relative difference between predicted and measured values, where negative values indicate systematic underestimation and positive values reflect overestimation by the model.

The E (%) was computed using the equation (Yasin *et al.*, 2021):

$$\%X = \frac{X_{\text{Simulated}} - X_{\text{Observed}}}{X_{\text{Observed}}} \times 100$$

Where X = any variable of interest.

In this study, the model's performance was evaluated by comparing the predicted mean values of days to anthesis, days to physiological maturity, grain yield (kg ha^{-1}), and LAI against the measured values.

RESULTS AND DISCUSSION

Model calibration

The genetic coefficients were acquired using the Generalised Likelihood Uncertainty Estimation tool (Table 3). There was substantial variation between the two wheat varieties across all measured traits. The statistical indices used to calibrate the predicted and measured values demonstrated high precision for crop phenology, yield attributes, and yield for tested cultivars, as shown in Table 4. For cultivar Shaki and Boru, the estimated statistical indices (RMSE, nRMSE, d-Stat, and R^2) for all tested parameters, including anthesis date, maturity date, leaf area index, number of tillers, grain yield, biomass yield, and harvest index, were averaged across three locations in 2023. The model specifications for all tested parameters were deemed acceptable for both cultivars, Shaki and Boru, as presented in Table 4.

Model Performance Evaluation

The DSSAT-CERES-Wheat model was validated using an independent dataset from three locations during the 2024 growing

Table 4: Model error analysis for phenology, growth and yield pooled across 2022/2023 and 2023/2024 seasons

Varieties	Crop characteristic	Mean value		RMSE	nRMSE (%)	dstat	R ²
		Observed	Simulated				
Shaki	Anthesis date (days)	75.5	75.5	1.8	2.4	0.92	0.94
	Maturity date (days)	120.5	120.5	2.2	1.8	0.93	0.95
	Leaf Area Index (LAI)	4.25	4.15	0.15	3.5	0.90	0.91
	Number of tillers	362.5	352.5	16.0	4.4	0.91	0.92
	Grain yield (kg/ha)	4037.5	3975	127.5	3.2	0.91	0.92
	Biomass yield (kg/ha)	8525	8425	187.5	2.2	0.92	0.93
	Harvest index	0.445	0.435	0.02	4.5	0.89	0.90
	Anthesis date (days)	77.5	77.5	2.0	2.6	0.91	0.93
Boru	Maturity date (days)	122.5	122.5	2.4	2.0	0.92	0.94
	Leaf Area Index (LAI)	4.35	4.25	0.18	4.0	0.89	0.90
	Number of tillers	372.5	362.5	18.0	4.8	0.90	0.91
	Grain yield (kg/ha)	4137.5	4075	137.5	3.3	0.90	0.91
	Biomass yield (kg/ha)	8625	8525	197.5	2.3	0.91	0.92
	Harvest index	0.455	0.445	0.03	6.6	0.88	0.89

season, which was not included in the initial cultivar coefficient calibration. Model outputs, including phenological stages (anthesis and maturity), growth parameters (leaf area index and tiller number), and yield components (grain yield, biomass yield, and harvest index), were compared against measured field data for the Shaki and Boru cultivars. Results are presented numerically in Table 4 and visually in Fig. 4a-g (Shaki) and Fig. 5a-g (Boru). The calibrated cultivar parameters demonstrated strong predictive accuracy, with close alignment between predicted and measured values for crop phenology, yield attributes, and final grain yield. Simulated crop traits (phenology, growth, and yield) showed good agreement with observations (Tables 4; Fig. 4 & 5), confirming robust performance across cultivars (Shaki and Boru), 2023 and 2024-year average data.

Model Performance in Simulating Growth and Yield Parameters

The CERES-Wheat model was evaluated for its ability to predict the phenology, growth, and yield parameters of two wheat varieties (Shaki and Boru) across different planting dates and nitrogen rates during the calibration phase (2022–2023) and the evaluation phase (2024). The results indicate a high statistical association between the predicted (Sim) and observed (Obs) values, with only minor deviations. The phenology, growth, and yield parameters were analyzed and discussed separately.

Grain Yield

The data in Table 4 display the CERES-Wheat model's evaluation results for various factors, including anthesis date, maturity date, leaf area index, number of tillers, grain yield, biomass yield, and harvest index for the Shaki and Boru wheat varieties. During the model calibration process, the absolute RMSE for grain yield was 0.13 t ha⁻¹ for the Shaki variety and 0.14 t ha⁻¹ for the Boru variety. In the evaluation phase, the RMSE was 0.125 t ha⁻¹ for Shaki and 0.135 t ha⁻¹ for Boru. The data in Table 4 reveal notable variations between the RMSE, nRMSE, the D index, and the coefficient of determination (R²) during the calibration and evaluation process of the model. Particularly, the nRMSE for grain yield was 3.4% for Shaki 3.6% for Boru during calibration, and 3.2% for Shaki and

3.3% for Boru at evaluation. The model's D index, which measures the accord between observed and predicted values, was 0.91 for Shaki, 0.90 for Boru during calibration, and 0.91 for Shaki, and 0.90 for Boru during evaluation. Table 4 demonstrates a high association between the predicted and measured grain yield results, supported by Fig. 3e and 4e, which show a regression coefficient of 0.99, indicating a strong association between predicted and observed values. For each variable analysed in the evaluation predictions, as detailed in Table 4, grain yields were exactly fitted and matched with standard deviation (SD) and RMSE. The predicted and measured values for four nitrogen fertiliser rates (0, 46, 69, and 92 kg N ha⁻¹) and three planting dates (Early, Normal, and Late) showed deviations ranging from -1.92% to -1.00% and -1.96% to -1.01% during calibration and evaluation for the Boru variety. In comparison, the Shaki variety displayed deviations from -2.00% to 1.02% and -1.96% to -1.01% during calibration and evaluation, respectively. Results indicate higher grain yields were achieved with early planting dates and increased nitrogen fertilisation (92 kg N ha⁻¹). Significant impacts on grain yields of the wheat varieties under different planting dates and levels of nitrogen fertiliser. The benefits of the CERES-Wheat model in predicting bread wheat yields under different management conditions.

Above-ground biomass yield

The aboveground biomass yield (Table 4) highlights the impact of planting dates and nitrogen (N) fertiliser rates. The results reveal that for the wheat cultivars Shaki and Boru, the root mean square error (RMSE) values for biomass yields were 0.19 t ha⁻¹ and 0.20 t ha⁻¹ during calibration, and 0.18 t ha⁻¹ and 0.19 t ha⁻¹ during evaluation, respectively. Under varying planting dates and nitrogen fertiliser rates, the normalised RMSE (nRMSE) for biomass yields was 2.7% and 2.9% during calibration, and 2.2% and 2.3% during evaluation. The D index values were measured at 0.92 and 0.91 for the calibration phase, and 0.92 and 0.91 during evaluation, indicating a reasonable fit between the predicted and measured values at harvest. A comparison of the predicted and actual biomass yield values, as presented in Table 4, shows that the model accurately represents actual biomass production. Regression

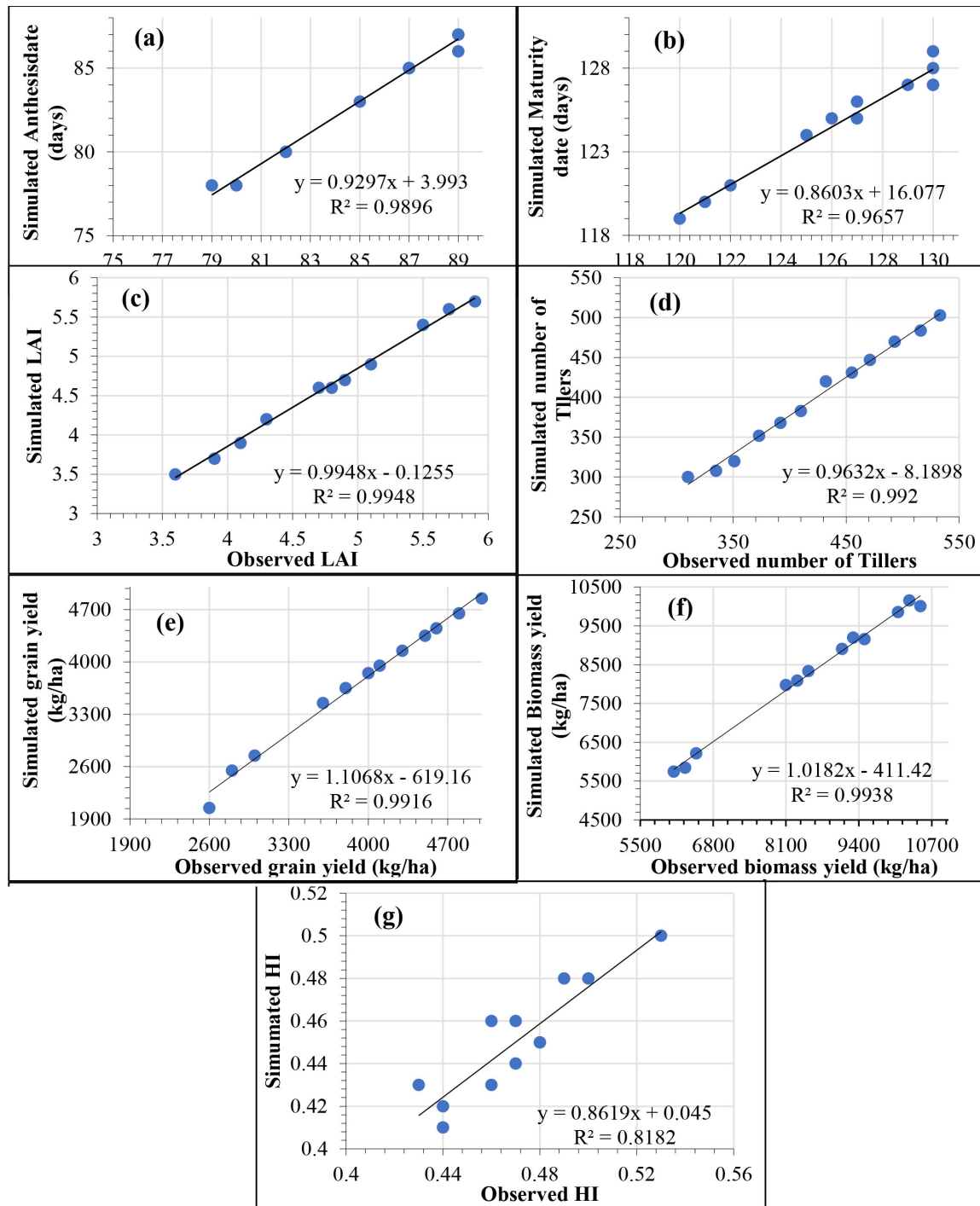


Fig. 3: Association between measured and simulated value of days to anthesis (a), and days to maturity (b), leaf area index(c), number of tillers(d), grain yield (e), biomass yield (f), and harvest index (g) of Boru bread wheat variety

analysis, illustrated in Fig. 3a to 3f, reported a high coefficient of determination (R^2) of 0.818 to 0.995, indicating a higher association between the predicted and observed values. The percentage variance between the predicted and measured biomass yields varied during both the calibration and evaluation phases, depending on nitrogen application rates and planting dates. For Shaki, the analogy ranged from -1.67% to -0.96% during calibration and -1.65% to -0.96% during evaluation. For Boru, the ranges were -1.64% to -0.95%

during calibration and -1.64% to -0.96% during evaluation.

Leaf Area Index (LAI)

The impacts of planting time and nitrogen (N) fertiliser rates on the leaf area index (LAI) of the wheat varieties Shaki and Boru were evaluated using the CERES-wheat model (Table 4). The results show that the root mean square error (RMSE) values for LAI at calibration were 0.14 for Shaki and 0.17 for Boru, while during

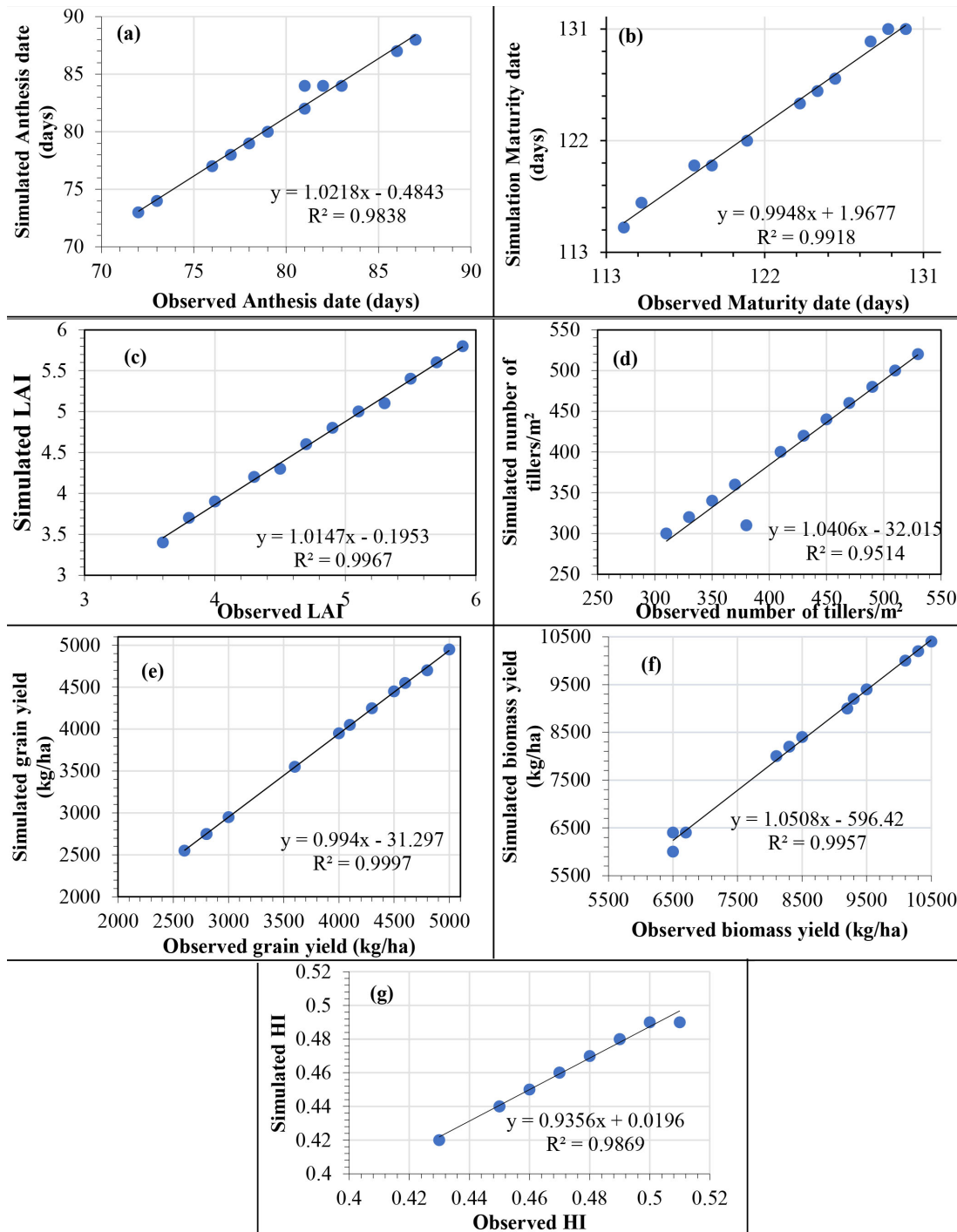


Fig. 4: Association between measured and predicted values of days to anthesis (a), and days to maturity (b), leaf area index(c), number of tillers (d), grain yield (e), aerial dry biomass yield(f), and harvest index (g) of Shaki bread wheat variety

evaluation, the RMSE values were 0.15 for Shaki and 0.18 for Boru. The NRMSE at the peak tillering stage was 3.7% and 4.1% during calibration, and 3.5% and 4.0% during evaluation for the Shaki and Boru cultivars, respectively. The D index was 0.90 for Shaki and 0.89 for Boru during calibration and evaluation, respectively (Table 4 and Fig. 3c & 4c). The regression coefficient (R^2) of 0.99 suggests a very close agreement between the predicted and observed LAI values. The findings suggest that early planting and a boost in the nitrogen fertiliser rate to 92 kg N ha⁻¹ result in a higher LAI

in the studied locations. The deviations between the predicted and observed LAI results under different nitrogen fertiliser rates (0 to 92 kg N ha⁻¹) and planting times (early to late) at calibration rates from -2.78% to -1.69% for Boru and from -2.86% to -1.72% for Shaki. During evaluation, the deviations ranged from -2.82% to -1.21% for Boru and -2.82% to -1.71% for Shaki. The model successfully simulated LAI responses to different nitrogen application rates and planting dates, though minor discrepancies with observed data persist. These deviations reflect the biological complexity of crop-

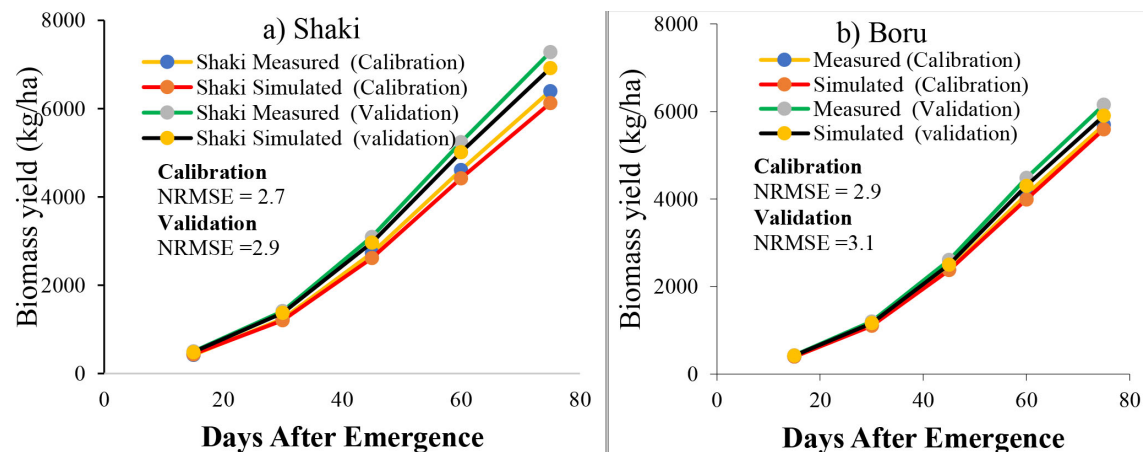


Fig. 5: Comparison of simulated and measured biomass production of *Shaki* and *Boru* wheat varieties

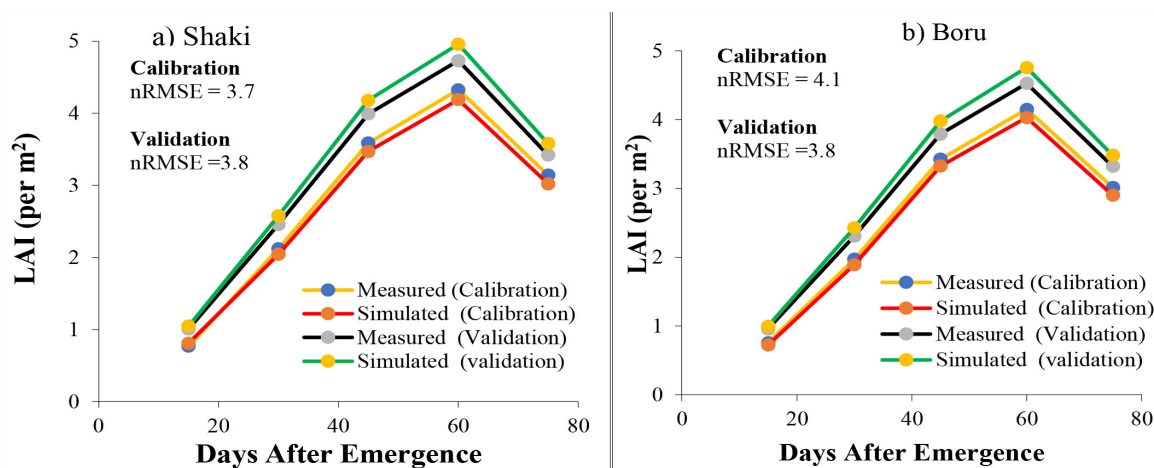


Fig. 6: Comparison of simulated and measured LAI of *Shaki* and *Boru* wheat varieties

environment dynamics and inherent field variability.

Harvest Index

The impacts of nitrogen (N) fertiliser rates and planting dates on the harvest index of wheat, as evaluated using the CERES-Wheat model, are outlined in Table 4. During the calibration and evaluation times, the absolute root mean square error (RMSE) for the harvest index was found to be 0.02 for *Shaki* and 0.03 for *Boru*. The normalised RMSE (NRMSE) and D index values for both times indicated a substantial agreement between the predicted and measured harvest indices. The NRMSE values were 4.4% and 4.9% for calibration, and 4.5% and 6.6% for evaluation. The D index values were 0.89 and 0.88 for *Shaki* and *Boru*, at calibration and evaluation phases, respectively. The regression analysis (Fig. 3g & 4g) reveals near-perfect agreement ($R^2 = 0.81$ and 98) between modelled and measured harvest indices, validating the CERES-Wheat model's reliability in predicting wheat responses to varying N fertiliser levels and sowing dates. The data indicate that increasing the N fertiliser rate to 92 kg N ha⁻¹ and using an earlier planting date resulted in a higher harvest index. The variations between modeled and observed result for N fertilizer rates (ranging from 0 to 92 kg N ha⁻¹) and planting dates (from late to early) ranged from -2.38% to

-2.0% and -2.33% to -1.96% for calibration, and -2.33% to -1.96% and -2.38% to -2.0% for evaluation, as briefly indicated in Fig. 3g and 4g. The observed variations validate the model's sensitivity to nitrogen and planting date modifications, establishing its reliability for harvest index simulation under varying field conditions.

Estimation of the seasonal progress of wheat LAI and biomass yield

The time-series comparison of simulated and measured LAI and biomass yield for the *Shaki* and *Boru* wheat varieties (Fig. 5 & 6) provides critical insights into the DSSAT model's performance in replicating crop growth dynamics. For LAI, close alignment between simulated and observed data would indicate robust calibration of canopy development parameters, such as phyllochron interval (PHINT) and leaf expansion rates, as demonstrated by Bhatt & Nain, (2024), who reported strong LAI correlations ($R^2 > 0.85$) in wheat models but noted underestimations during late senescence due to imperfect physiological ageing algorithms. Discrepancies in peak LAI might reflect unaccounted environmental stressors, such as water deficits or nutrient limitations, a finding echoed by Su *et al.*, (2025), who emphasised the need for site-specific soil moisture calibration to improve accuracy.

For biomass yield, a strong match suggests effective parameterisation of radiation use efficiency (RUE) and assimilate partitioning, as observed by Keller *et al.*, (2021), where genotype-specific coefficients (G1–G3) reduced biomass prediction errors (NRMSE < 15%). However, deviations could arise from field-scale variability, such as pest damage or microclimate effects not captured by the model, consistent with Naresh Kumar, (2023), who identified initial soil conditions (e.g., organic carbon) as key uncertainty sources. Varietal differences, e.g., *Shaki* fitting better than *Boru*, may highlight gaps in cultivar-specific parameters (e.g., P1V, P5) or stress responses, aligning with Tesfaye *et al.*, (2025), who found Ethiopian wheat varieties exhibited distinct sensitivities to heat and drought.

This study employed the Generalised Likelihood Uncertainty Estimation (GLUE) and sensitivity analysis within the CERES-Wheat model to assess the impact of varying planting dates and nitrogen fertiliser rates on bread wheat growth and yield in southeastern Oromia. The model effectively simulated key parameters, including anthesis date, maturity date, leaf area index (LAI), tiller count, grain yield, aboveground biomass, and harvest index for the cultivars *Shaki* and *Boru*. Consistent with Tefera *et al.*, (2024), our use of GLUE ensured accurate estimation of soil and genetic coefficients, reinforcing the reliability of our findings for highland wheat production systems. Following Maniruzzaman *et al.*, (2017), we systematically calibrated genetic coefficients across six growth and development categories. The model demonstrated strong performance, with grain yield simulations yielding RMSE values of 130 and 140 kg ha⁻¹ (NRMSE: 3.4 and 3.6%; *d*-index: 0.91 and 0.92) during calibration for *Shaki* and *Boru* wheat cultivars and comparable accuracy in evaluation (RMSE: 125 and 135 kg ha⁻¹; NRMSE: 3.6 and 3.8%; *d*-index: 0.90 and 0.91). Similar precision was observed for anthesis date, maturity date, biomass yield, tiller count, and LAI, aligning with previous studies (Tari *et al.*, 2017). For instance, biomass yield exhibited RMSE values of 190 and 200 kg ha⁻¹ (NRMSE: 2.7 and 2.9%), while tiller count and LAI showed deviations within acceptable ranges (RMSE: 16 and 18 tillers; 0.14 and 0.18 LAI units).

Our results are further supported by comparisons with previous studies. For instance, Sandhu *et al.*, (2020) demonstrated the reliability of the CERES-Wheat model in predicting wheat grain yield, reporting strong agreement between simulated and observed data with an NRMSE of 10.68%. Likewise, our model calibration yielded accurate predictions for multiple traits across the tested cultivars. These findings align with Maldonado-Ibarra *et al.*, (2015), who evaluated genetic coefficients for three spring wheat varieties using the DSSAT model. Their study reported NRMSE values for days to anthesis ranging from 3.5% to 9.7%, depending on the variety. They also confirmed that the DSSAT model provides reliable calibration and accurate yield predictions, reinforcing the validity of our results. Maniruzzaman *et al.*, (2017) also reported grain yield RMSE of 1.3 t ha⁻¹ for CERES-Rice simulations. Minor overestimations in biomass and yield may stem from uncertainties in soil-water dynamics or input parameter assumptions. In our study, deviations in grain yield across planting dates and nitrogen rates remained narrow (-2.0% to -1.01%), with late planting and higher nitrogen (92 kg ha⁻¹) maximising yields (4.34–4.47 t ha⁻¹). These

findings corroborate Maniruzzaman *et al.*, (2017), who reported biomass deviations of -4.3–14.6%, and Tari *et al.*, (2017), where Aqua Crop replicated biomass more accurately than grain yield. Overall, the model's robust performance underscores its utility for optimising wheat management in Ethiopian highlands, though careful consideration of soil-water interactions may further refine predictions.

CONCLUSIONS

This study evaluated the effects of climate change on wheat production in the tropical highlands of Ethiopia using the DSSAT-CERES-Wheat model. The results demonstrated that climate variability significantly influences wheat yield, with planting dates and nitrogen application rates playing key roles in productivity. The model exhibited strong calibration and validation performance, as evidenced by low RMSE values for grain yield, biomass, and phenological stages, confirming its reliability for wheat growth prediction under varying conditions. These findings underscore the need to integrate climate data into agricultural planning to enhance climate resilience. To enhance climate resilience in wheat production, stakeholders should adopt predictive modelling tools like DSSAT-CERES-Wheat for optimised crop management, invest in research on climate-adaptive varieties and practices, provide farmer training on climate-smart agriculture, implement supportive policies for agricultural technology, and establish continuous monitoring systems to refine adaptation strategies. These measures will strengthen food security under changing climatic conditions.

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