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EVALUATING THE IMPACT OF SOWING DATES AND CULTIVAR SELECTION ON WHEAT YIELD UNDER CLIMATE VARIABILITY: A GLUE-CALIBRATED DSSAT MODEL APPROACH

RIZWAN ABID *
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.
*Corresponding Author Email: rizwanabidrizvi@gmail.com

SYED AFTAB WAJID
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.

FATIMA SIDDIQA
Department of Climate Change, Institute of Soil and Environmental Sciences, University of Agriculture, Faisalabad, Pakistan.

NAVEEDULLAH
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.

AMINA RASHID
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.

AHSAN RASHID CHUGHATTA
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.

ZAINAB FATIMA
Department of Agronomy, University of Agriculture, Faisalabad, Pakistan.

Abstract

Wheat productivity is often constrained by suboptimal sowing times and inappropriate cultivar selection, leading to reduced yields under varying environmental conditions. Identifying the best sowing dates and suitable cultivars can enhance growth performance and yield outcomes. A field experiment was conducted at the Agronomic Research Area, University of Agriculture, Faisalabad, to evaluate the effects of four sowing dates (November 5th, November 20th, December 5th, and December 20th) and four wheat cultivars (Arooj-22, Subhani-21, Nawab-21, and Sadiq-21) on wheat growth and yield. The experiment followed a Randomized Complete Block Design (RCBD) with split arrangements and three replications. Results indicated that early sowing, particularly on November 20th, led to the highest grain yield (4932.25 kg ha^{-1}) and a maximum number of productive tillers (373 m^2). Among cultivars, Arooj-22 and Subhani-21 exhibited superior performance, with Arooj-22 yielding 4574.26 kg ha^{-1} and Subhani-21 achieving the highest Leaf Area Index (4.05). The DSSAT model was calibrated and evaluated using the field data, showing strong agreement between observed and simulated values. Model calibration produced low root mean square error (RMSE) values for key parameters, including days to anthesis (RMSE = 1-2), LAI (RMSE = 0.4-0.7), and grain yield (RMSE = 2-85). Model evaluation across different treatments yielded RMSE values of 314.14 to 673.18 for grain yield and 0.22 to 1.89 for LAI, indicating acceptable prediction accuracy. The rise in temperature significantly impacts wheat yield, with varying effects across different varieties. Arooj-22 saw a 1.20% yield decrease at 2.5°C, rising to 26.28% at 4.5°C. Subhani-21's yield dropped by 8.32% at 2.5°C and 30.86% at 4.5°C. Nawab-21 was the most affected, with a 16.33% yield reduction at 2.5°C and 38.84% at 4.5°C, while Sadiq-21 and Arooj-22 showed greater resilience. These results highlight the importance of optimal sowing time and cultivar selection, as well as the reliability of the DSSAT model for simulating wheat growth under varying environmental conditions.

Keywords: Wheat Yield, Sowing Dates, Cultivar Performance, Climate Variability, DSSAT Model, GLUE Calibration, Crop Simulation.

1. INTRODUCTION

Wheat plays a crucial role in ensuring Pakistan's food security and strengthening its economy. It has the second highest position among crops in the nation, behind rice (Rehan *et al*., 2024). It is a fundamental meal that constitutes 60% of the typical Pakistani's daily diet, with an average intake of around 125 kg per year, which is one of the highest rates globally. Pakistan ranks seventh globally in terms of wheat production, mostly attributed to its extensive arable lands, particularly in the province of Punjab (Khan *et al.*, 2020).

Climate change is causing temperatures to rise, which is the biggest threat to crop production worldwide. Sustainable wheat production in Pakistan faces challenges due to climate variability and climate change, which cause a serious threat to food security. The temperature increase projected by the end of the century presents a significant hazard to the agriculture industry. There could be potential reductions in grain yield in semi-arid regions of Pakistan of around 30% (Hussain *et al*., 2021). Crop output is being hampered by rising temperatures. When the temperature is above the ideal, the wheat crop suffers. Wheat yield fell to 6% as the average seasonal temperature rose by 1°C (Asseng *et al.,* 2015).

Pakistan aims to attain self-sufficiency in wheat production, and the introduction of 31 wheat varieties since 2021 would enhance the productivity, climatic resilience, and disease resistance of the country's farmed wheat fields. Nevertheless, Pakistan's reliance on foreign supply has grown significantly, with the country importing around two to three million tons, which accounts for roughly 10% of its total need, in recent years (Jha *et al.*, 2024).

Approximately 36% of the global population relies on wheat as a primary food source. Wheat cultivation is adaptable to many climates and soil conditions. Although Pakistan has a wide range of wheat types with excellent potential, the average yield per acre is much lower compared to other wheat-producing nations. Several factors contribute to the reduced crop production in the nation, such as incorrect timing of planting, fluctuating temperatures, inadequate variety selection, and a lack of site-specific and modern technologies. Moreover, the insufficiency of irrigation water and inputs, the high costs of inputs, the harm caused by pests, the uneven use of fertilizers, and the obstacles in marketing are all contributing to a decrease in the average yield of wheat (Janjua and Aslam, 2024). The primary factor contributing to this gloomy situation is the high degree of fluctuation in weather conditions. Choosing the appropriate cultivar and planting it in a certain place is essential in order to get a greater grain production (Pandey, 2023).

Delay in sowing wheat leads to low yield of crop in cropping systems of rice-wheat due to unfavorable temperature conditions. Sub-optimal temperatures affect seed growth and development, leading to poor crop establishment and lower plant population, causing reduced yield. High temperatures during the reproductive growth stage cause resulting in smaller grain size, reduced yield, and lower quality of harvested produce. Extreme temperatures cause early maturation leading to a shorter grain-filling period and further reducing the yield (Sattar *et al.*, 2010). Each government sets a target for wheat production. Failure to achieve the target can lead to a breakdown in the system for agriculture professionals, policymakers, and specialists, resulting in food scarcity (GOP, 2022).

Pakistan has a variety of wheat cultivars, but the yield per acre is considerably lower than other countries that produce wheat. The major reasons for this yield reduction include inadequate sowing time, temperature fluctuations, inadequate selection of cultivars, insufficient use of current technologies, a lack of site-specific inputs and irrigation water, and rising input costs due to pesticide damage (Joshi *et al*., 2011).

Wheat phenology refers to the series of transformations that take place from its emergence from the soil to its maturation and is impacted by the choice of sowing dates and cultivars. The length and phases of these variations are significant indications of the potential yield of the crop. To achieve optimum production, it is essential to use recommended sowing dates and improved cultivars, which play a crucial role in dual purpose system of wheat which is used for forage purpose and grain production. (Arzadun *et al*., 2006; Amrawat *et al*., 2013). The low productivity of wheat can be attributed to its shorter favorable growing period. In recent years, the mid-February temperature has surged, resulting in a shorter cool spell during its growing season, with more temperature fluctuations that hamper productivity of crop. Phenology of crop is greatly affected by temperature, and each species has its own optimal temperature, base temperature, and upper-temperature limit that decides how well it will grow (Hatfield *et al*., 2011

Crop models are used for both geographical and temporal uncertainty analysis in agricultural production (Hoogenboom, 2000). To understand the link between environmental variability, agronomic methods, and crop improvement, statistical models are not sufficient. However, crop growth models like DSSAT and APSIM can replicate this interaction (Abbas *et al.,* 2017;Hoogenboom *et al.,* 2017; Tariq *et al.,* 2018). One aspect can be studied in isolation from others (Abbas *et al.,* 2017). Climate warming, crop management, and cultivar changes in rice and wheat phenology can all be studied separately using the DSSAT crop simulation model (Ahmad *et al.,* 2019).

To evaluate crop management alternatives, DSSAT is a comprehensive model. They use physiological mechanisms to model the crop’s reaction to changes in soil and atmospheric conditions. In Pakistan and other South Asian nations, DSSAT has been extensively utilized to model the combined impacts on genetics, input methods, climatic parameters, and soil health on wheat and rice yield (Ahmad *et al.,* 2012). Management methods, environmental variables, and daily weather data are all basic requirements to start up the crop models. In X build (crop management information) and cultivars file (cultivar-specific coefficients) are needed in DSSAT model. With the sensitivity analysis feature of DSSAT, we used an iterative method to estimate the cultivar coefficients. Using daily time steps, the model mimics phenological development as well as total dry matter accumulation from planting to harvest (Ahmad *et al.,* 2011).

Genetic modification that results in longer grain filling periods, improved heat tolerance and delayed wheat crop phenology may be one approach for dealing with climate change's detrimental impacts (Nelson *et al.,* 2009). Climate impact studies benefit greatly from simulation modeling because it takes into account a wide range of weather variables and their interaction with plant growth, development, and yield climate-sensitive production processes (Challinor *et al.,* 2014). Several climate studies have utilized crop simulation models, the most frequent related to crop production (Rosenzweig *et al.,* 2014).

2. MATERIALS AND METHODS

Experimental Site and Design

The experiment was carried out at the Agronomic Research Area of the University of Agriculture, Faisalabad (31.4504° N, 73.1350° E). A Randomized Complete Block Design (RCBD) with a split arrangement was used, including three replications to avoid difficulties. The treatments were randomized using a factorial design. Each plot had a net size of 6m x 1.8m, with a row-to-row distance of 22.5 cm, and contained 8 rows. The treatment factors included two components: Factor A (Sowing Dates: S) in the main plot, with four levels—S_1 (5th November), S_2 (20th November), S_3 (5th December), and S_4 (20th December); and Factor B (Cultivars: V) in the subplot, consisting of four cultivars—V_1 (Arooj-22), V_2 (Subhani-21), V_3 (Nawab-21), and V_4 (Sadiq-21).

Crop Growth Observations

Each plot was sown with eight lines and divided into two equal halves. Half of the area was allocated for destructive sampling, which involved measuring biomass and leaf area. The remaining half was let to grow and was eventually harvested to yield the ultimate grain harvest. Pegs were used to demarcate a one-square-meter area in order to ensure impartiality during the final harvest.

Sampling

Sampling was undertaken biweekly during the months of low temperature (November, December, January, and February). Due to accelerated phenology, the sampling frequency was raised to every 10 days when the temperature rose in March and April. A single foot length was collected from each plot at ground level, ensuring that sampling was not done from the first rows to minimize any boundary effects. The sample's entire fresh weight was measured promptly after it was harvested. During the initial phases, a smaller portion of the sample was collected to determine the weight of the leaves and stems. However, in the later stages, when the plant had started flowering, the weights of the leaves, stems, and spikes were measured individually. The subsequent parameters were computed using this sampling.

Leaf Area Index (LAI)

The Leaf Area Index is the ratio of leaf area to land area. The SunScan Canopy Analysis System type SS1 model was employed to measure the leaf area index. The sun scanner was placed at three distinct positions inside each plot and the average value was calculated from these measurements. The Leaf Area Index (LAI) was subsequently determined using the methodology outlined by Watson (1952). This indicator is crucial for comprehending the arrangement of the uppermost layer of vegetation and the capacity for photosynthesis of the crops being examined. The formula for LAI is as follows:

LAI = leaf area / land area

Plant Height (cm):

The height of five randomly selected plants from each experimental unit was measured. Measurements were taken from the base at ground level to the top of the plant, recorded in centimeters. An average plant height was then calculated for each experimental unit for further analysis.

Number of Productive Tillers (m^{-2}):

In each plot, the number of productive tillers (spike-bearing) was counted within a defined area of 1 square meter.

1000-Grain Weight (g):

A sample of 1000-grains was counted and weighed. The weight was recorded using a precision scale, providing the 1000-grain weight in grams.

Grain Yield (kg ha^{-1}):

Grain yield was determined by harvesting and threshing a portion (half) of each experimental unit. The harvested grains were then weighed, and the yield per hectare was calculated.

Harvest Index (%):

The harvest index was calculated as the ratio of grain yield to the total biological yield (grain plus straw). This index is expressed as a percentage, indicating the efficiency of the plant in converting total biomass into grain.

Statistical Analysis

Fisher's Analysis of Variance technique was employed for data analysis. Treatment means were differentiated using Tukey’s Honest Significance Difference (HSD) test at a $P \leq 0.05$ probability level (Steel *et al.,* 1997).

Crop Growth Modeling

The CERES-Wheat models are invaluable tools in agriculture for exploring various cultural adaptations, such as cultivar type, sowing date, irrigation, and fertilizer management. These models effectively analyze whole farm systems, pasture sequences, and rotations, aiding in the development of both strategic and tactical planning (Andarzian *et al.,* 2015).

Model Calibration

Model parameters were adjusted during calibration to account for local circumstances. Obtaining genetic coefficients for novel cultivars utilized in modeling research is crucial. Data gathered from treatments that performed the best in field testing was used to calibrate the model. In order to implement the best-performing treatment, genetic coefficients and soil properties have to be changed.

The Generalized Likelihood Uncertainty Estimation (GLUE) method was applied to calibrate four wheat cultivars in DSSAT, focusing on optimizing sowing time to manage uncertainty in key model parameters. This involved generating and simulating a range of parameter sets for each cultivar under different sowing times. The outputs were compared to observed data, with likelihoods calculated using metrics like RMSE. GLUE provided a distribution of likely parameter sets, offering insights into variability in model predictions. This approach improved the reliability of predictions by systematically addressing uncertainty across all cultivars and sowing times.

Model Elements and Input Data

The CERES-Wheat model relies on a limited number of explicit parameters and primarily straightforward input variables, which are either commonly used or can be easily determined. The system stores files for climate, crops, soil, and management on its hard drive, allowing for easy modification through the user interface. A range of graphs and schematics in the menu helps users in understanding the impact of different input choices.

Climatic Data

For the CERES-Wheat model, which predicts crop development daily, accurate daily data on air temperature and rainfall is crucial. Climate data, used in the DSSAT model by default from 1901 to 2099, assists in determining crop development and phenology. It also adjusts biomass production during periods of extreme temperatures. The data includes measurements of the mean annual atmospheric CO_2 concentration from Hawaii's Mauna Loa Observatory. The University of Agriculture, Faisalabad's meteorological observatory, located 100 meters from the experimental site, recorded all climatic data.

Model Evaluation

For model evaluation, observed growth data was compared with simulated data. The model ran against all treatments except those used in the calibration process. Subsequently, simulation results were compared with statistical results**.** Where,

$$\mathrm{R\,M\,S\,E} = \left[\sum_{i=1}^{n} \frac{(P_i - O_i)^2}{n} \right]^{0.5}$$

$$\mathrm{d} = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(|p_i'| + |o_i'|)^2}\right], d \leq 1$$

$$\mathrm{M\,P\,D} = \left[\sum_{i=1}^{n}\left(\frac{|O_i - P_i|}{O_i}\right)100\right]/n$$

$$R^2 = 1 - \left[\frac{\sum_i (O_i - P_t)^2}{\sum_i (O_i - \bar{O})^2}\right]$$

MDP = Mean predicted deviation

n = number of observations

RMSE = root mean square

D = index of agreement

O_i = observed values of the variable under study

R^2 = coefficient of determination

P_i = predicted values of the variable under study

DSSAT can also be further utilized for validation purposes using observed data from the second year, without altering the crop coefficient. Following a successful validation process, DSSAT can then be employed for sensitivity analysis.

Environmental Modification

After calibration, the DSSAT model was used to simulate the effects of increased temperatures on the environment. Specifically, temperature increases of 2.5°C and 4.5°C were applied using the environmental modification window in the X build. The model was adjusted accordingly to reflect the impact of climate change on grain yield.

3. RESULTS

Leaf Area Index (LAI)

LAI was significantly influenced by both sowing date and cultivar (Table 1). The maximum LAI was observed on November 5th (4.52), while the lowest was on December 20th (3.35). Among cultivars, Subhani-21 had the maximum LAI (4.05), and Sadiq-21 had the minimum (3.80).

Total Dry Matter (TDM)

TDM was significantly affected by sowing date, but there was no significant effect of cultivar (Table 1). The November 5th sowing produced the maximum TDM (1404.82 g m^{-2}), while the December 20th resulted minimum TDM (1016.78 g m^{-2}). Among cultivars, though not statistically significant, Subhani-21 had the highest TDM (1287.72 g m^{-2}), and Sadiq-21 the lowest (1241.60 g m^{-2}).

Number of Tillers

The number of tillers was significantly influenced by both sowing date and cultivar (Table 1). The maximum number of tillers was recorded for the November 20th (372.98 m^2), and the minimum was observed on December 20th (263.28 m^2). Among cultivars, Subhani-21 produced the highest number of tillers (335.66 m^2), while Nawab-21 had the lowest (319.01 m^2).

Plant Height (PH)

Plant height was significantly affected by both sowing date and cultivar (Table 1). The November 5th sowing resulted in the tallest plants (106.27 cm), while the shortest plants were recorded on December 20th (82.73 cm). Among cultivars, Arooj-22 had the maximum plant height (93.33 cm), and Nawab-21 had the minimum (93.30 cm).

1000-Grain Weight (GW)

1000-grain weight (g) was significantly influenced by both sowing date and cultivar (Table 1). The highest grain weight was recorded for the November 5th sowing (41.58 g), while the lowest was observed on December 20th (32.25 g). Among cultivars, Arooj-22 had the maximum grain weight (39.87 g), and Nawab-21 recorded the minimum (35.85 g).

Grain Yield (GY)

Grain yield was significantly affected by both sowing date and cultivar (Table 1). The highest yield was recorded for the November 20th sowing (4932.25 kg ha^{-1}), while the lowest yield was observed for the December 20th sowing (3531.19 kg ha^{-1}). Among cultivars, Arooj-22 produced the highest yield (4574.26 kg ha^{-1}), while Sadiq-21 recorded the lowest yield (4070.06 kg ha^{-1}).

Harvest Index (HI)

The harvest index was significantly influenced by both sowing date and cultivar (Table 1). The December 5th sowing resulted in the highest HI (35.70%), and the lowest HI was recorded for the November 5th sowing (31.67%). Among cultivars, Subhani-21 exhibited the highest HI (35.95%), while Sadiq-21 had the lowest (32.79).

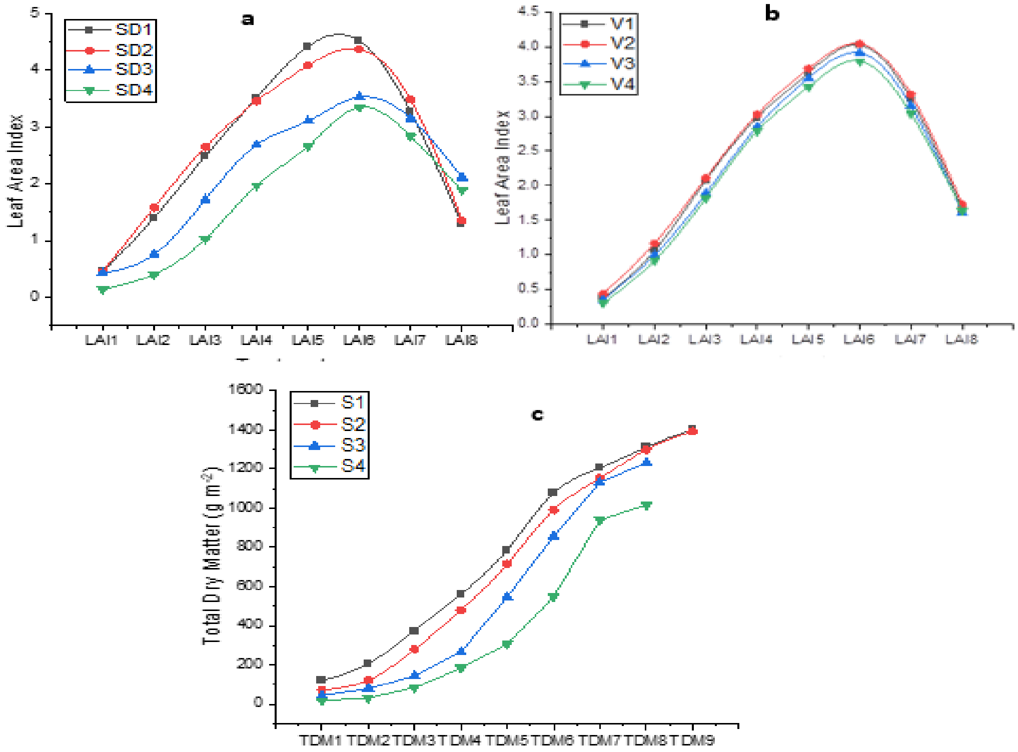

Figure 1: Time Course Changes in LAI for Planting Dates (a), Varieties (b) and total dry matter (c)

Table 1: Influence of sowing date as effected by wheat cultivars on growth and yield component

	LAI	TDM (gm^{-2})	No. of tillers	PH (cm)	GW (g)	GY (kg ha^{-1})	HI
Factor A Sowing Date							
05th Nov.	4.52A	1404.82A	356.35A	106.27A	41.58A	4449.62B	31.67B
20th Nov.	4.38A	1392.82A	372.98A	99.43B	39.00B	4932.25A	35.41A
05th Dec.	3.53B	1232.00B	311.84B	91.86C	37.99B	4399.93B	35.70A
20th Dec	3.35C	1016.78C	263.28C	82.73D	32.25C	3531.19C	34.75A
HSD	0.15	50.18	20.95	6.08	2. 36	176.59	1.43
Significance	**	**	**	**	**	**	**
Factor B Cultivars							
Arooj-22	4.03A	1271.23	328.67AB	93.33B	39.87A	4574.26A	35.95A
Subhani-21	4.05A	1287.72	315.66B	93.37B	37.50AB	4349.41AB	33.88BC
Nawab-21	3.92AB	1245.88	319.01AB	93.30B	35.85B	4319.26B	34.92AB
Sadiq-21	3.80B	1241.60	341.11A	100.30A	37.60AB	4070.06C	32.79C
HSD	0.22	70.55	22.20	6.41	2.53	241.18	1.89
Significance	**	NS	*	**	**	**	**

LAI = Leaf Area Index, TDM = Total Dry Matter, PH= Plant Height, GW= 1000-Grain Weight, GY= Grain Yield, HI= Harvest Index
** = Highly Significant, * = Significant, NS = Non-Significant

Crop Growth Modeling

Estimation of Genetic Coefficients for CERES-Wheat under DSSAT

The CERES-Wheat model needs a set of seven genetic cultivar coefficients in order to allow the modelling of phenology, growth, and cultivar yield. Every cultivar was assigned a unique coefficient that was determined using an iterative procedure. The observed and simulated data for phenology, growth, and yield were compared using the CERES-Wheat model in order to show strong agreement between the two sets of data.

This was done to give each cultivar the greatest possible care. Accurate data replication in a model necessitates the right cultivar genetic coefficients. Equating the CERES-Wheat model with treatments S_2V_1, S_2V_2, S_2V_3, and S_2V_4 proved to be effective. The varieties Arooj-22, Subhani-21, Nawab-21, and Sadiq-21 were sown for these treatments on 20th November.

Seven cultivar coefficients control the wheat crop's phenology and reproductive phase, including the ideal vernalization temperature in days (P1V) and photoperiod response. Table 2 displays these coefficients, which are P5, G1, G2, and PHINT.

The model was calibrated using a treatment that demonstrates strong performance under real-world settings. The model also exhibits strong performance in terms of phenology, growth, and yield. The wheat cultivars Arooj-22, Subhani-21, Nawab-21, and Sadiq-21 required specific vernalization values, namely P1V (7.028, 5.028, 6.110 and 5.520 days) correspondingly. The photoperiod response (PID) for cultivars Arooj-22, Subhani-21, Nawab-21, and Sadiq-22 was measured as 6.640, 6.340, 1.240 and 2.260 respectively, indicating their sensitivity to changes in day length.

The regulation of the reproductive phase during the growth season was governed by four genetic coefficients, namely G1, G2, G3, and PHINT. During anthesis, the maximum number of kernels per unit canopy weight (G1) was calculated to be 20.11, 20.11, 15.75 and 18.55 for the varieties Arooj-22, Subhani-21, Nawab-21, and Sadiq-21, respectively. The standard kernel size under optimal conditions (G2) is an indicator of the grain's boldness. It is a genetic trait that can also be modified by environmental pressures throughout the reproductive period.

The highest values (45.51, 40.51, 50.31 and 44.91) were documented for the following varieties: Arooj-22, Subhani-21, Nawab-21, and Sadiq-21, respectively. The coefficient G3 represents the weight of non-stressed standard tillers, including grain weight. The values for these cultivars were 0.827, 0.550, 0.505 and 0.950. The phyllochron interval (PHINT) is the time period between the appearances of the leaf tip. The values for Arooj-22, Subhani-21, Nawab-21, and Sadiq-21 were 146.8, 138.8, 102.8 and 170.8, respectively.

Table 2: Genetic wheat coefficient under CERES-Wheat model used for model calibration

Cultivars	P1V	P1D	P5 (°C.d)	G1 (#/g)	G2 (mg)	G3 (Gdwt)	PHINT (°C.d)
Arooj-22	7.028	6.640	932.5	20.11	45.51	0.827	146.8
Subhani-21	5.028	6.340	907.5	20.11	40.51	0.550	138.8
Nawab-21	6.110	1.240	850.5	15.75	50.31	0.505	102.8
Sadiq-21	5.520	2.260	985.5	18.55	44.91	0.950	170.8

PIV: Days, optimum vernalizing temperature, required for vernalization

PID: Photoperiod response (% reduction in rate/10 h drop in pp)

P5: Grain filling (excluding lag) phase duration (oC.d)

G1: Kernel number per unit canopy weight at anthesis (#/g)

G2: Standard kernel size under optimum conditions (mg)

G3: Standard non-stressed mature tillers weight (including grain) (g dwt)

PHINT: (Phyllochron interval) Interval between successive leaf tip appearances (°C.d)

Model Calibration

The data revealed that the model predicted the phenological, physiological, and yield attributes closely with the observed values (Table 4). The phenological event of days to anthesis was simulated accurately across all varieties, with RMSE values of 1 for Arooj-22, Nawab-21, and Sadiq-21, and 2 for Subhani-21. Similarly, the days to maturity were well predicted, with RMSE values of 1 to 2 across the varieties. The simulation of Maximum LAI was also close to the observed values, with RMSE values ranging from 0.4 to 0.7 across the varieties. Grain yield predictions were also in close alignment with the observed values, with RMSE values ranging from 2 to 85. The biological yield showed good simulation accuracy, with RMSE values ranging from 8 to 286 across the different varieties. Overall, the model provided a robust prediction of the studied attributes.

Model Evaluation

The model was evaluated using the remaining treatments of the experiment. The results for various parameters are detailed as follows:

Grain Yield

The simulated and observed grain yield data were compared for the cultivars Arooj-22, Subhani-21, Nawab-21, and Sadiq-21 across different treatment dates. The model's performance in predicting grain yield showed acceptable accuracy with RMSE values of 314.14 for Arooj-22, 437.19 for Subhani-21, 576.12 for Nawab-21, and 673.18 for Sadiq-21. The d-statistics also ranged from 0.55 to 0.91, indicating a moderate to high degree of agreement between observed and simulated values, as shown in Table 5.

Leaf Area Index (LAI)

The leaf area index (LAI) values, both observed and simulated, are in moderate agreement for the different cultivars. The RMSE values for LAI ranged from 0.22 to 1.89, with Nawab-21 showing the best fit with an RMSE of 0.22 and d-stat of 0.96, indicating a very high degree of agreement. However, Sadiq-21 exhibited the highest RMSE of 1.89 and a lower d-stat of 0.413, indicating less accuracy in simulation for this cultivar, as presented in Table 6.

Total Dry Matter

The model evaluation for total dry matter indicated varying levels of accuracy. The RMSE values were 2331.42 for Arooj-22, 1983.07 for Subhani-21, 1598.89 for Nawab-21, and 3203.43 for Sadiq-21. The d-stat values ranged from 0.56 to 0.81, showing that the model performed relatively better for Subhani-21 and Nawab-21, while its accuracy was lower for Sadiq-21, as shown in Table 7.

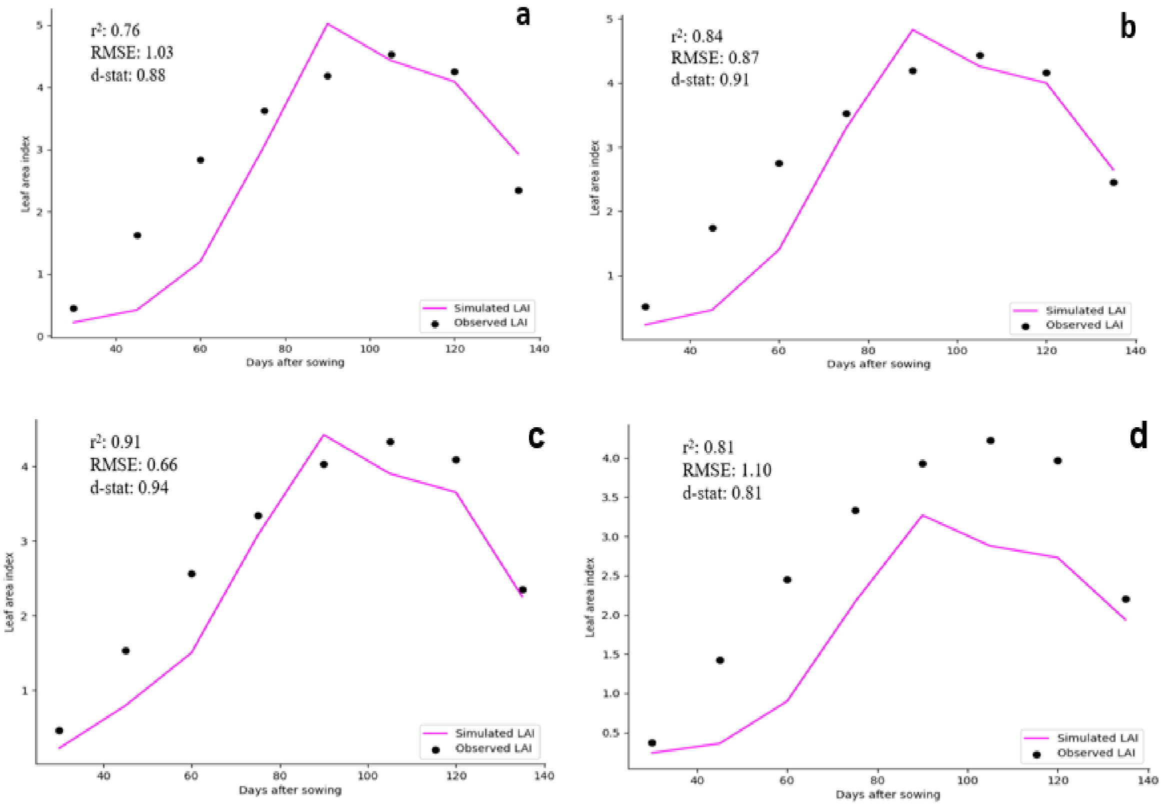

Figure 2: Calibrated time-series leaf area index on 20th November sowing for Arooj-22 (a), Subhani-21 (b), Nawab-21 (c) and Sadiq-21

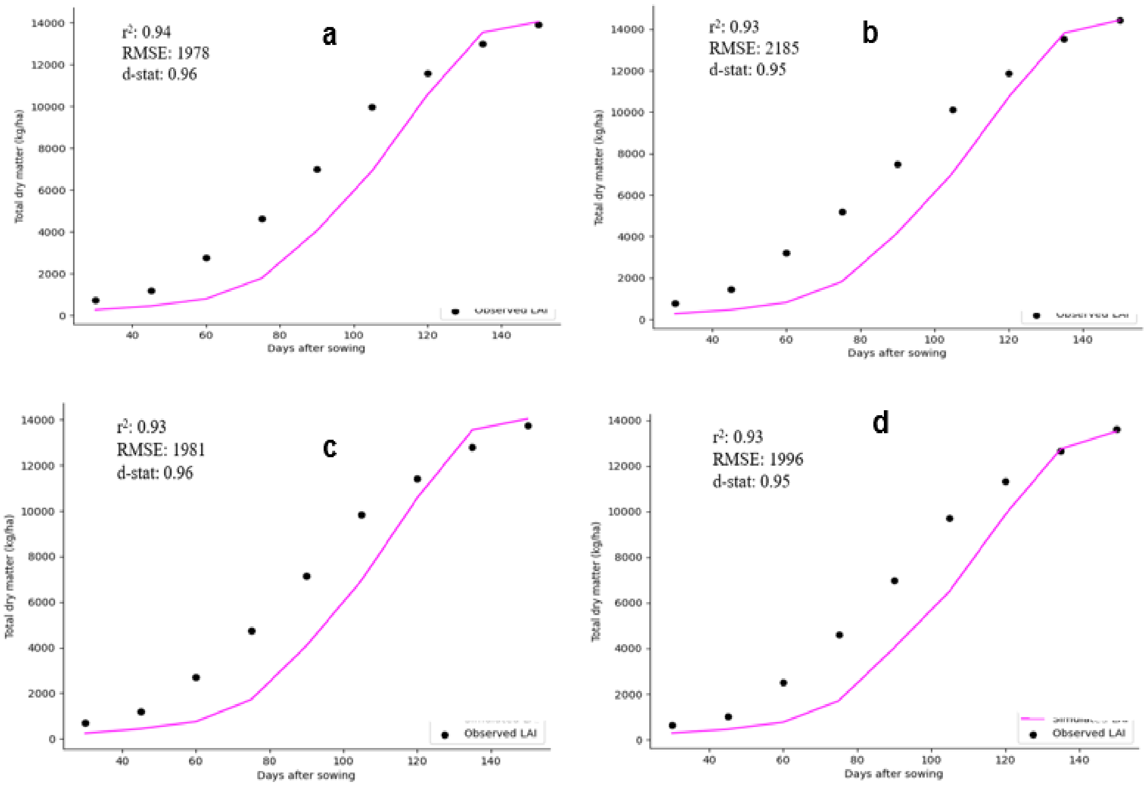

Figure 3: Calibrated time-series total dry matter on 20th November sowing for Arooj-22 (a), Subhani-21 (b), Nawab-21 (c) and Sadiq-21

Impact of climate change on wheat cultivars under different sowing dates using DSSAT

The increase in temperature has a significant impact on wheat yield, as shown by the percentage decrease across different varieties under temperature rises of 2.5°C and 4.5°C (Table 3). The results indicate the potential effects of climate change on crop production. Arooj-22 showed a yield decrease of 1.20% at 2.5°C, which significantly increased to 26.28% at 4.5°C. Subhani-21 experienced a yield reduction of 8.32% at 2.5°C and 30.86% at 4.5°C.

Nawab-21 saw the most significant impact, with a yield decrease of 16.33% at 2.5°C and 38.84% at 4.5°C, making it the most vulnerable variety to temperature increases. On the other hand, Sadiq-21 and Arooj-22 showed more persistence, with relatively smaller yield decreases under the temperature changes compared to the other varieties. These findings underscore the significance of temperature rise due to climate change could adversely affect wheat yield.

Table 3: Impact of Climate Change on Reduction (%) in grain yield under different sowing dates using DSSAT

	Increase in temperature	
Cultivars	**2.5 ^{0}C**	**4.5 ^{0}C**
Arooj-22	1.20	26.28
Subhani-21	8.32	30.86
Nawab-21	16.33	38.84
Sadiq-21	2.80	29.49

Table 4: Summary of observed and simulated results during calibration of varieties

Treatments	Arooj-22			Subhani-21			Nawab-21			Sadiq-21		
	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE	Obs.	Sim.	RMSE
Days to Anthesis (Days)	100	101	1	102	100	2	100	99	1	100	99	1
Days to Maturity (Days)	145	147	2	143	144	1	140	142	2	145	147	2
Maximum LAI	4.5	5.2	0.7	4.4	5.1	0.7	4.3	4.7	0.4	4.2	3.5	0.7
Grain Yield (kg ha^{-1})	5232	5247	15	4987	5072	85	4832	4868	36	4676	4678	2
Biological Yield (kg ha^{-1})	13925	14049	124	14423	14431	8	13758	14044	286	13605	13506	99

Obs. = Observed, Sim. = Simulated, RMSE = Root mean square error

Table 5: Model Evaluation by Simulated and Observed Values for grain yield

Treatments	Arooj-22			Subhani-21			Nawab-21			Sadiq-21		
	Sim.^{a}	Obs.^{b}	E(%)^c	Sim.^{a}	Obs.^{b}	E(%)^c	Sim.^{a}	Obs.^{b}	E(%)^c	Sim.^{a}	Obs.^{b}	E(%)^c
5th November	4770	4817	0.98	4607	4512	-2.11	4203	4343	3.22	4050	4124	1.79
5th December	4090	4632	11.7	3689	4432	16.76	3430	4320	20.6	3102	4213	26.37
20th December	3623	3614	-0.25	3353	3464	3.2	3351	3780	11.35	2919	3265	10.6
Average	4161	4354.33		3883	4136		3661.33	4147.67		3357	3867.33	
Statistical Indices	**RMSE = 314.14**			**RMSE = 437.19**			**RMSE = 576.12**			**RMSE = 673..18**		
	d-stat = 0.91			**d-stat = 0.83**			**d-stat =0.55**			**d-stat = 0.64**		

a = Simulated, b = Observed, c = Error percentage

Table 6: Model Evaluation by Simulated and Observed Values for leaf area index

Treatments	Arooj-22			Subhani-21			Nawab-21			Sadiq-21		
	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]
5th November	6.1	4.6	-32.61	6	4.8	-25	4.8	4.5	-6.67	4.6	4.2	-9.52
5th December	2.6	3.6	27.78	2.8	3.6	22.22	3.6	3.5	-2.86	1.2	3.5	65.71
20th December	1.5	3.4	55.88	1.6	3.4	52.94	3.5	3.3	-6.06	1	3.3	69.7
Average	3.4	3.87		3.47	3.93		3.97	3.77		2.27	3.67	
Statistical Indices	**RMSE = 1.51**			**RMSE = 1.33**			**RMSE = 0.22**			**RMSE =1.89**		
	d-stat = 0.64			**d-stat = 0.72**			**d-stat = 0.96**			**d-stat =0.413**		

Table 7: Model Evaluation by Simulated and observed values for total dry matter

Treatments	Arooj-22			Subhani-21			Nawab-21			Sadiq-21		
	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]	Sim.[a]	Obs.[b]	E(%)[c]
5th November	13335	14055	5.12	13585	14553	6.65	12356	13868	10.9	12476	13715	9.03
5th December	9476	12553	24.51	9844	12383	20.5	10165	12235	16.92	7850	12107	35.16
20th December	7801	10315	24.37	8048	10149	20.7	8924	9972	10.51	6898	10234	32.6
Average	10204	12307.7		10492.3	12361.7		10481.7	12025		9074.67	12018.7	
Statistical Indices	**RMSE =2331.42**			**RMSE = 1983.07**			**RMSE = 1598.89**			**RMSE =3203.43**		
	d-stat =0.73			**d-stat = 0.81**			**d-stat = 0.78**			**d-stat = 0.56**		

a = Simulated, b = Observed, c = Error percentage

4. DISCUSSION

The results of this study are consistent with previous research, showing that delayed planting significantly impacts wheat's leaf area index (LAI). Like the findings of Wu *et al.* (2013) and Pal *et al.* (2012), late sowing leads to reduced LAI due to senescence, which is confirmed by the data for December 20th sowing. Nikzad *et al.* (2024) also observed that early sowing results in higher dry matter accumulation, as was the case in this study, with November 5th sowing producing the highest total dry matter (TDM).

This supports Chauhan *et al.* (2020) and Pandey (2023) who emphasized the importance of dry matter in yield formation. The current study aligns with Keshav *et al.* (2024), who found that early sowing results in taller plants, consistent with the increased plant height recorded on November 5th in this experiment. Heat stress and a shorter growing season may explain the reduced plant height observed with late sowing, as noted by Khan *et al*. (2024).

Additionally, Jatana *et al.* (2020) and Roy *et al.* (2024) reported fewer tillers in late-sown wheat, which matches the lower tiller count seen with the December 20th sowing. Sowing time also significantly influenced grain weight and yield. The results corroborate those of Shalaby *et al*. (2023) and Dubey *et al.* (2019), who found that early sowing enhances grain weight, a trend confirmed by the November 5th sowing in this study.

These outcomes are similar to the findings of Ul-Allah *et al.* (2021) and Dhaliwal *et al.* (2020), who reported that early sowing leads to higher grain yield, as observed in this experiment with the highest yield recorded for November 20th sowing. Additionally, the study supports findings from Spink *et al*. (2000) and Ahmad *et al.* (2023), indicating that delayed sowing reduces yield and harvest index (HI).

5. CONCLUSION

The experiment revealed that both sowing date and cultivar had a significant impact on key agronomic traits, including LAI, TDM, number of tillers, plant height, 1000-grain weight, and grain yield. Early sowing, particularly on November 5th and 20th, led to higher growth and yield, with November 5th showing the best overall results. Arooj-22 and Subhani-21 outperformed the other cultivars in most traits. Model calibration and evaluation showed strong agreement between observed and simulated values, especially for days to anthesis and grain yield, though some discrepancies were observed in simulating TDM and LAI for specific cultivars. Additionally, the results underscore the potential adverse effects of climate change, with increased temperatures leading to significant reductions in wheat yield, particularly in more vulnerable varieties like Nawab-21. These findings highlight the importance of considering both agronomic practices and climate change impacts to ensure sustainable wheat production.

Conflict of Interest

The authors declare that there is no conflict of interest.

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