



Applicability of medium range weather forecasts for yield prediction of wheat (*Triticum aestivum*) using CERES-wheat model in south-western Punjab

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ABSTRACT

The study was carried out during the winter (*rabi*) season of 2021–22 at Punjab Agricultural University, Regional Research Station, Bathinda, Punjab to evaluate the predictability of wheat (*Triticum aestivum* L.) production using forecast scenarios that were gathered from the India Meteorological Department (IMD). CERES-wheat model was used to estimate crop phenology and wheat yield. The experiment was laid out in a split-plot design (SPD) with three replications. The main plot treatments included five sowing dates, viz. October 25, November 4, November 14, November 24 and December 4 with four sub-plot treatments of variety which were HD 3086, PBW 725, HD 2967 and PBW 658. The model's output with R²/RMSE for emergence, anthesis and maturity by using actual and forecasted data having 0.38/3.37 and 0.48/2.63, 0.56/4.28 and 0.70/8.48 and 0.71/8.30 and 0.49/2.63, respectively. Moreover, the wheat yield with R²/RMSE values of 0.85/148.31 kg/ha for the actual data and 0.86/140.50 kg/ha for the simulated data showed good agreement between simulated and observed data. Model validation showed that simulated emergence, anthesis and maturity were deviated over observed by 1–3 days, 1–8 days, and 1–20 days, respectively, whereas anthesis, maturity and yield were overestimated. Additionally, the simulated wheat yield differed from the observed yield by 0.5–12%. Phenology and yield were found to have greater RMSE values, wider deviations between simulated and actual values and less connection with delayed sowing. For the wheat growing season (2013–21), rainfall, T_{max} and T_{min} weather forecast were employed, which were to assess the likelihood of wheat production at various sowing periods. The medium-range weather forecast and the actual weather data closely matched each other for wheat phenology and yield. The annual fluctuation in observed wheat yields as well as treatment-wise variations was more or less effectively reflected by the daily medium-range weather forecast data. The findings of the study are extremely valuable for directing decisions in the study area, figuring out the best time to sow wheat crop, choosing appropriate wheat varieties based on predicted conditions, scheduling irrigation at critical growth stages and applying fertiliser optimally to increase crop productivity and resource efficiency.

Keywords: CERES-Wheat model, Phenology, Sowing dates, Varieties, Wheat yield

Wheat (*Triticum aestivum* L.) is a key global staple, ranking first in both area and production among cereals. It is highly sensitive to high temperatures during critical crop phases and the extent of loss depends on temperature variations, developmental stage and varieties. Globally, wheat spans 240 million hectares, yielding 779.87 million metric tonnes with a productivity of 3546.8 kg/ha. In India, the second-largest wheat producer, the figures stand at 31.7 Mha, 108.7 Mt and 3424 kg/ha, respectively. In Punjab during 2020–21, wheat covered 35.30 lakh hectares, producing 171.85 lakh tonnes at an average yield of 48.68 q/ha (Anonymous 2022).

Wheat adapts well to diverse climates, spanning from temperate to regions with heavy rainfall and warm humid

to dry cool environments. It is a long-day crop sensitive to temperature changes, with optimal planting temperature between 10°C and 15°C and maturity temperature ranging from 21°C–26°C. The ideal daylight duration for growth and development falls within 14–18 h (Ali *et al.* 2017, Mohan and Krishnappa 2020). Weather fluctuations, especially during the reproductive stage, impact wheat yield, with heat stress affecting different growth phases. In Punjab, extreme weather events like high temperatures, unseasonal rains and hailstorms during the reproductive stage contribute to wheat yield reduction. Effective crop management strategies like optimising sowing time, planning irrigation at critical development phases, choosing suitable wheat cultivars and applying fertilisers effectively to increase productivity and resource utilisation can help reduce output losses caused by erratic weather can help mitigate production losses from unpredictable weather (Kingra 2016).

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Under this circumstance, a common tool for comprehending and forecasting crop growth, development and yield under various climatic and management circumstances is a crop simulation model. Crop simulation models are mathematical representations of crop growth, development and yield that use algorithms to mimic above and below ground interactions between the crop and its surroundings (Boote *et al.* 2018, Dhir *et al.* 2024). These models aid in evaluating how crop production is affected by agronomic techniques, soil conditions and weather variability. The most well-known of these for modelling wheat phenology and yield under various climatic conditions is DSSAT (Decision Support System for Agrotechnology Transfer) (Kundathil *et al.* 2023). Furthermore, its CERES-wheat module is a proven tool for modelling wheat production and phenology in a variety of climate conditions. In order to simulate wheat development and productivity, the CERES-wheat model needs inputs such as daily meteorological data, soil properties, crop genetic factors and management techniques. Under various agroclimatic circumstances, it may be widely used to optimise sowing dates, varietal selection, irrigation scheduling, fertiliser application etc. (Hoogenboom *et al.* 2010, Goswami and Dutta 2020, Kundathil *et al.* 2023). So, with the use of actual meteorological data and medium-range weather forecasts, the DSSAT-CERES-wheat model makes it easier to estimate wheat production and phenology under a variety of climatic conditions for a given area (Basso *et al.* 2016, Liu *et al.* 2019).

MATERIALS AND METHODS

Experimental details: The study was carried out during the winter (*rabi*) season of 2021–22 at Punjab Agricultural University, Regional Research Station, Bathinda (30°36'09" N, 74°28'55" E; at an elevation of 211 m amsl), Punjab. The study was laid out in a split-plot design (SPD) with three replications. The main plot treatments comprised of five sowing dates, namely October 25, November 4, November 14, November 24, and December 4, while the sub-plot treatments involved four varieties, viz. HD 3086, PBW 725, HD 2967, and PBW 658 as these varieties are mostly short duration, resistant to yellow and brown rust and high productivity making them popular choices among farmers in this region. Moreover, for the wheat growing seasons spanning from 2013–2021, weather forecast parameters including rainfall, T_{\max} and T_{\min} were utilized to evaluate the potential wheat production across different sowing periods. Bathinda is located in the state's south-western portion and is under 5th agro-climatic zone of Punjab. It has semi-arid type of weather. The average annual rainfall in the region is around 440 mm, with over 80% of that falling during the south-west monsoon season (first week of July to mid-September) and lasting far into the winter. The average maximum temperature in June is 40–45°C while the average lowest temperature is 4–5°C. Frosty evenings with chilly winds are typical in December–January when night temperatures approach 0°C and dust storms in May–June

when the temperature climbs above 47°C.

CERES-wheat model: It is a wheat crop simulation model that replicates daily phenological development and growth in response to soil and meteorological variables as well as crop management. The FORTRAN code runs for the Crop Environment Resource Synthesis (CERES)-Wheat model (Timsina and Humphreys 2006, Basso *et al.* 2016). It is a management-level model that simulates wheat crop growth, development and yield by taking into account the effects of weather, management, genetics, soil water, carbon and nitrogen (Mohanty *et al.* 2024). The wheat model considers daily meteorological information, soil water conditions, cultivar features and crop management while simulating wheat production. For this model, input data are required for crop management information, daily meteorological data precipitation (mm), maximum and minimum temperature (°C), and solar radiation (W/m²).

Model validation: In its most basic form, model validation is a comparison of simulated and observed output parameter values. If the simulated values fall within a certain range of the observed value, the predicted model is valid and can be utilised for crop research and management. The CERES-wheat model was validated by comparing highly calibrated genotypic coefficients from previously verified research, notably Grover and Pal (2018) for PBW 725 and PBW 658 and Sarabjit (2019) for HD 3086 and HD 2967 with experimental data of Bathinda during *rabi* 2021–22. They have derived genetic coefficients using inbuilt system in DSSAT module, namely Gencalc (genotype coefficient calculator) with the help of previous years' weather, crop, soil, etc. management data.

RESULTS AND DISCUSSION

Validation of CERES-wheat model for phenology and yield using actual weather emergence: The observed and simulated days required for wheat emergence for both actual and forecasted weather data is shown in Fig. 1. The data revealed a consistent pattern, indicating that the range of days needed for emergence falls within 3–11 days when using both actual and forecasted data for the year 2021. This suggests that the CERES-wheat model successfully captured the emergence timing, showcasing its ability to simulate this critical stage of wheat growth. The similarity between the observed and simulated results using both types of weather data further supports the model's reliability in predicting emergence, thereby demonstrating its potential as a valuable tool for wheat cultivation planning.

Late-sown crops showed more emergence days from November 24 and December 5 with both actual and predicted data, after which there was an increase in emergence days due to a decrease in temperature. Additionally, with delayed sowing compared to normally sown crop, more days were needed for emergence due to the dropping temperatures at the time, which increases the number of days needed for emergence. The model showed results that were almost always underestimated when using actual data to determine the sowing time and varieties. A similar pattern was observed

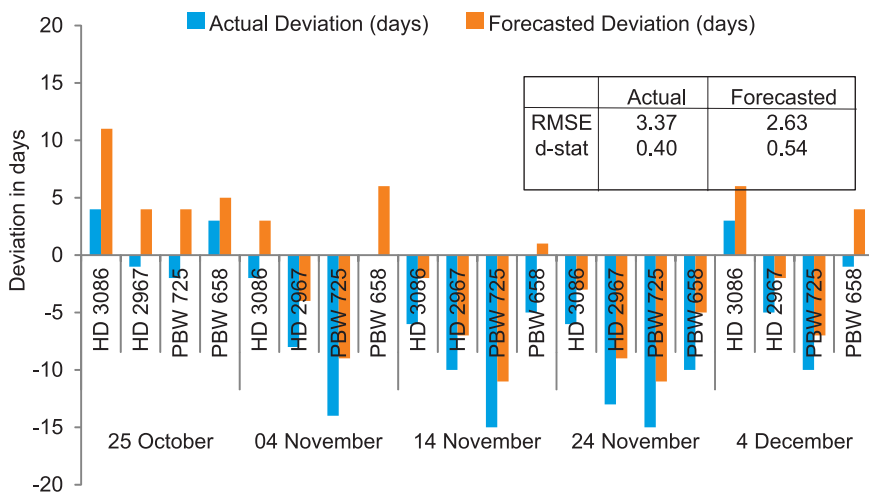


Fig. 1 Comparison between actual and simulated emergence (DAS) of wheat as affected by sowing time and varieties using actual and forecasted weather data.

when using forecasted data. Since, the maturity period is longer for HD 3086, it took more days for emergence when actual and predicted data were used. Actual and forecasted data were recorded with RMSE values of 3.37 and 2.63; D-Stat value of 0.40 and 0.54, and R^2 values of 0.38 and 0.48, respectively, for each treatment, showing less error between actual and simulated days needed to complete wheat emergence (Fig. 1). Reasonable level of accuracy for wheat crop emergence, as indicated by acceptable RMSE and moderate R^2 values, revealed that it can suggest appropriate planting time. This information leads to better sowing decisions and contribute to improve the uniformity in crop stand under varying climatic conditions.

It was also discovered that the model was unable to predict emergence well in accordance with observed with RMSE values of 6 and 5 days for Bathinda, respectively. Furthermore, the model predictions should be underestimated the emergence.

Anthesis: The observed and simulated days required for anthesis with both actual and forecasted weather data for given planting dates and varieties are shown in Fig. 2. When real data and forecasted data from 2021–22 were used, the range of simulated days to attain anthesis was determined to be between 92 and 116 and 92 to 127 DAS, respectively.

The simulated days taken for anthesis were highest for the early sown crop (October 25), followed by the mid and late sown crops (November 4, November 14, November 24, December 4) with both actual and forecasted weather data. When the crop was sown on October 25 and November 4, the model overestimated the result, but when the crop was sown on November 14, November 24, and December 4, the model underestimated the result using actual weather and the

forecasted weather data. Furthermore, utilising forecasted data, the model achieved outcomes that were both overestimated and underestimated in the November 14 and December 4 seeded crop. The main reason for the inflated results was that the model only took a few elements into account, such as lowest temperature, maximum temperature, rainfall, date of sowing, date of simulation, and so on. But, on some aspects, such as biotic stress and insect pest attack, could not be included. Using actual and forecasted data, the variance was determined in between 3–6 and 6–17 days, 1–8 and 8–14 days, 1–7 and 2–8 days, 1–4 days and 3–4 days, and 3–6 and 1–2 days

for crops sown on October 25, November 4, November 14, November 24, and December 4, respectively.

When actual and forecasted weather data were used for given varieties, PBW 658 took fewer days to anthesis because generally, its maturity period is shorter. When crop was sown on October 25, HD 3086 showed the most variation (6 and 17 days) followed by HD 2967 (5 and 15 days), PBW 725 (5 and 14 days), and PBW 658 (3 and 6 days), respectively with actual and forecasted weather. Similarly, when the crop was sown on November 4, the observed anthesis days ranged between 1 and 14 days for all varieties. In terms of statistical analysis, among the treatments, d-Stat was 0.63 and 0.60, R^2 - 0.56 and 0.70 and RMSE 4.28 and 8.48 for actual and forecasted data, respectively (Fig. 2). Low RMSE and high R^2 values showed that the model correctly predicted anthesis dates, indicating strong alignment with observed data. This increases the potential output by allowing for the appropriate timing of management practices like irrigation and fertilizer application throughout the flowering period.

For the growth and yield parameters of wheat, Pal *et*

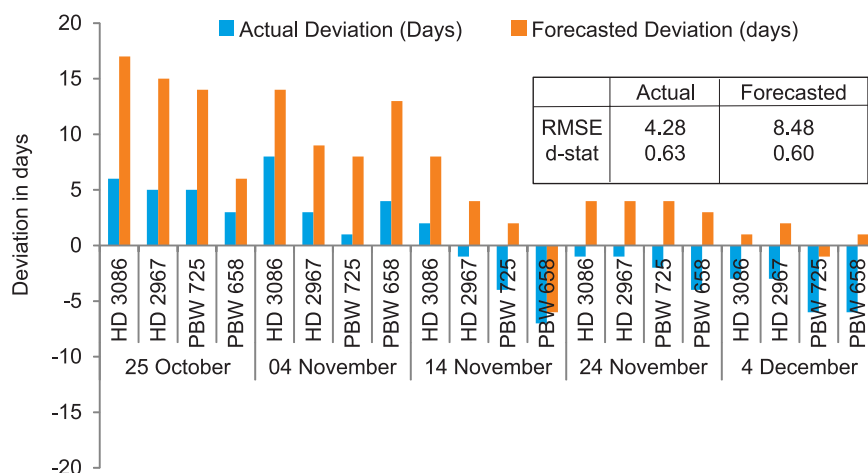


Fig. 2 Comparison between actual and simulated anthesis (DAS) of wheat as affected by sowing time and varieties during *rabi* 2021–22 using actual and forecasted weather.

al. (2015) calibrated and validated the CERES-wheat model. They found that the percent root mean square error (% RMSE) values ranged from 5.9–15.6% for the days to attain anthesis. In addition, they demonstrated a decrease in the simulated value of anthesis with delayed sowing. According to Kaur *et al.* 2022, strong agreement was seen between the simulated and observed results, with R^2 values for anthesis being 0.93 and 0.90 for the wheat crop anthesis. Endalew (2019) and Pal *et al.* (2012) also noted a great match between the actual and simulated anthesis dates.

Maturity: The number of observed and simulated days required to reach wheat maturity using actual and forecasted weather data in CERES-wheat crop model for various sowing dates and varieties is depicted in Fig. 3. For actual and predicted weather conditions, the simulated days to maturity ranged from 120–154 and 126–163, respectively. Using both actual and forecasted data on Dec 5. Furthermore, the crop planted on December 5, took a few days for it to mature because the days required to maturity were found to be maximum for the early sowing crop (October 25), and minimum for crop sown the temperature began to fall after this date. The model predicted an underestimated result for the crop sown on November 14 and November 24 and the crop sown on October 25, November 4 and December 4 produced model results that were both underestimated and overestimated. The model uses small number of parameters which includes the minimum and maximum temperature, rainfall, sowing and simulation dates, and other factors, was the primary reason for the overestimation. It could not, however, take into account other factors, such as biotic stress.

With the crop sown on October 25, the difference between the observed and forecasted results, using actual and predicted data, ranged from, -1–4 days and 4–11 days, respectively. Similarly, the variation in days for maturity of crops sown on November 4, November 14, November 24 and December 4 ranged from -14 to -2 days and -9 to 6 days, -15 to -5 days and -11 to 1 days, respectively for actual weather data whereas, -13 to -6 days, -11 to -3 days and -10 to 3 days and -7 to 6 days, respectively for forecasted weather data. Pal and Yadav (2018) conducted similar research that showed maturity decline with delayed planting. Additionally, it was discovered that the percent root mean square error (%RMSE) values took a very long time to mature between the observed and simulated values, ranging from 9.3–15.6%. In agreement with this, Kumar *et al.* (2017) also discovered a variation of 0.6–1.0 days between observed and simulated days taken to maturity. These results were also aligned with the results found by Pal and Murty (2013).

In the case of varieties, simulated maturity varied

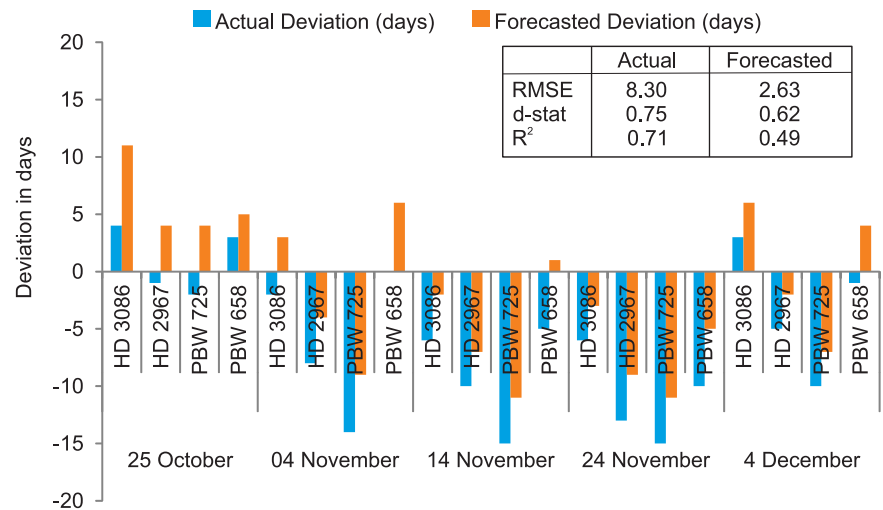


Fig. 3 Comparison between actual and simulated maturity days of wheat as affected by sowing time and varieties during *rabi* 2021–22 using actual and forecasted weather.

between -15 and 4 days when actual weather was used, whereas it ranged between -11 to 11 when forecasted weather data was used. Regarding statistical analysis, the values of d-Stat, R^2 and RMSE for actual and forecasted data across treatments were 0.75 and 0.62, 0.71 and 0.49, and 8.30 and 2.63, respectively (Fig. 3). The model's adequate RMSE and R^2 values showed that it was accurate in predicting maturity. This makes it possible to schedule harvests more effectively and lowers post-maturity risks like weather-related damage or loss of grain quality.

Yield: The simulated wheat yield using CERES-wheat model by using actual as well as forecasted weather data of experimental year 2021–22 is shown in Fig. 4.

For the various treatments, the simulated wheat yield varied from 2723–4383 kg/ha for the actual weather data and from 2723–4466 kg/ha for the predicted weather, respectively. The yield simulated for early sown wheat (October 25) revealed highest grain yield in a range of 4009 to 4613 kg/ha using actual weather data whereas using forecasted data, model simulated highest yield for 4 November in a range of 4532–4848 kg/ha when compared to mid and late-sowing wheat (November 14, November 24 and December 4). Furthermore, utilising actual and predicted meteorological data, the crop sown on November 14 produced wheat yields of 4405 kg/ha and 4721 kg/ha, respectively. Furthermore, when the sowing date was delayed, the yield of the simulated wheat yield showed decreasing trend. Bisht *et al.* (2023) validated very good agreement between simulated and observed values under five, four and three irrigations regimes as compared to lower irrigation regimes for wheat crop by using CERES-wheat model. Moreover, Dhir *et al.* (2021) simulated seed cotton yield for Bathinda and Faridkot, respectively and found the results in good agreement with observed yield having higher value of d-stat (0.84 for Bathinda and 0.89 for Faridkot) and R^2 (0.75 for Bathinda and 0.83 for Faridkot).

For crops sown on October 25, November 4, November 14, November 24 and December 4, the percent deviation

in simulated wheat yield over observed ranged between 0.23–7.28%, -7.34–9.10%, -2.25–5.73%, 6.77–26.11% and -3.55–11.07%, respectively with actual data whereas -5.44–19.04% and -0.24–3.16% and -15.22–21.33% and -2.90–2.46% and 15.46–20.27%, respectively with forecasted weather data. It was found that forecasted data can also be utilised to estimate yield with high accuracy because the discrepancy between simulated and observed data was smaller when the weather was predicted. Regarding varieties, the differences between simulated and observed wheat yields were found to range from -2.25–11.07%, -2.90–3.54%, 0.89–7.28%, and -3.55–2.46% for actual weather and from -7.34–20.29%, -5.50–21.33%, -5.44–15.89%, and 9.10–56.11% for forecasted weather for HD 3086, HD 2967, PBW 725, and PBW 658, respectively. Regarding statistical analysis, the values for the treatments for the actual and forecasted data were 0.80 and 0.79, respectively for d-Stat and 0.85 and 0.80, respectively for R², with RMSE values of 148.3kg/ha and 140.5 kg/ha, respectively (Fig. 4). The model's high R² and low RMSE values demonstrated its excellent yield simulation capability. This accurate yield forecast aids in efficient resource management and empowers farmers to make well-informed choices that optimise profits.

Pal *et al.* (2015) used the CERES-wheat model to simulate grain production and showed that the model was useful for predicting wheat grain yield with %RMSE and t-values ranging from 5.7–12.2% (t = -4.5 to 1.8). They also found that the delayed sowing crop resulted in a lower grain yield. Additionally, according to Rani *et al.* (2017), crop simulation model DSSAT was able to accurately estimate wheat's grain production (R² = 0.759), biomass yield (R² = 0.728), and N uptake (R² = 0.883).

Harvest index: For the various treatments studied, the simulated harvest index (HI) varied from 0.30–0.40 for the actual weather and from 0.29–0.55 for the predicted weather. The harvest index was observed to be high with both actual and forecasted weather data for two dates of sowing i.e. November 4 (0.29–0.57) and Nov 14 (0.30–0.57) followed by other dates i.e. October 25, November 24 and December 4. In actual data among all the varieties HD 2967, HD 3086, PBW 725 and PBW 658, the harvest index was maximum in HD 2967 which varied from 0.30–0.40. Whereas in

forecasted data harvest index was more in two varieties that is PBW 725 and PBW 658 than other two varieties HD 2967 and HD 3086 (Fig. 5).

With actual data, HI varied from -5.00–8.11% and in forecasted, it was from 21.75–41.08% for date 25 October. On the other hand, HI for November 4 with actual data varied from 2.70–10.53% and in forecasted, it was from 23.68–55.95%. For crops sown on November 24, HI varied from 6.06–11.11% and in forecasted it was from 16.22–66.67% and for December 04 in actual data, it varied from 3.23–18.75% and in forecasted it was from 2.5–89.31%. Comparing different varieties of wheat, in HD 3086 HI varied from 2.70–18.75% in actual data and in forecasted data it ranged from 2.50–23.68%. In HD 2967, HI varied from 5–16.67% in actual data and in forecasted data it ranged from 27.75–76.33%. In variety PBW 725 with actual data, per cent deviation in HI varied from 3.23–10.53% and in

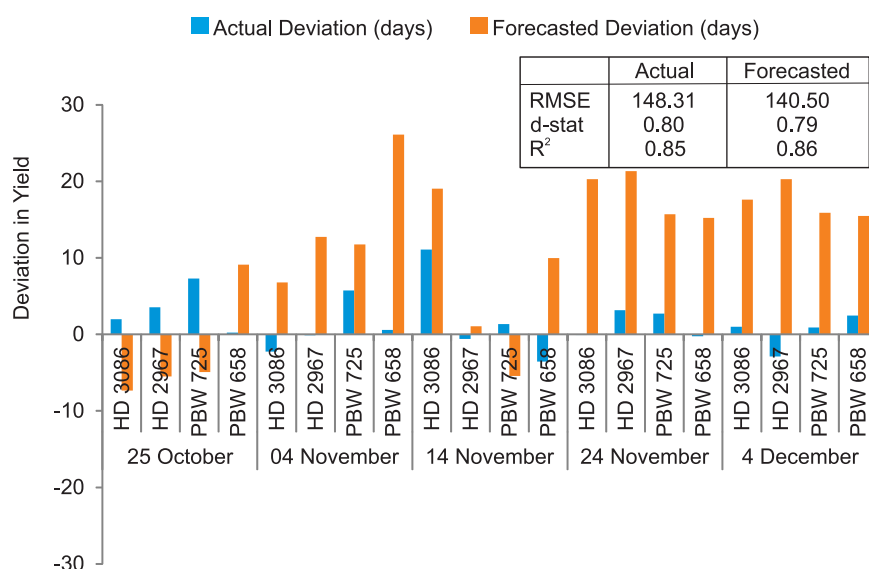


Fig. 4 Comparison between observed and simulated yield of wheat as affected by sowing time and varieties during *rabi* 2021–22 using actual and forecasted weather.

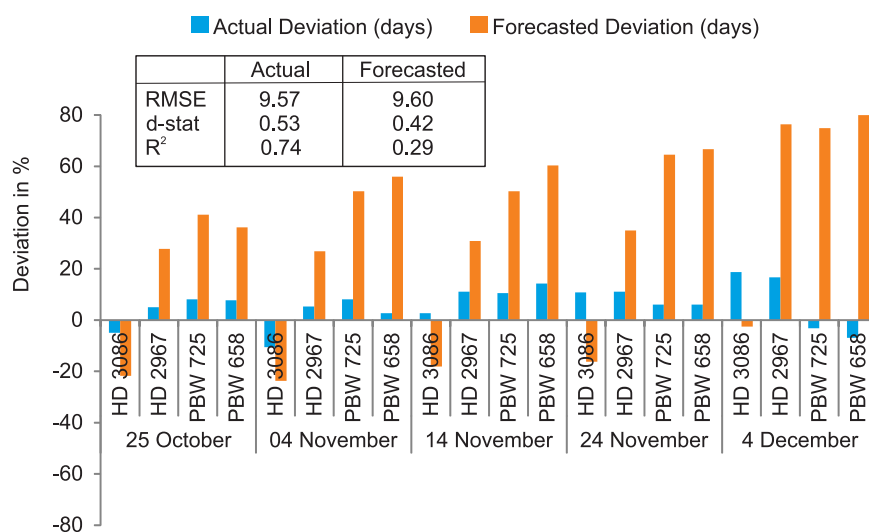


Fig. 5 Comparison between actual and simulated harvest index of wheat as affected by sowing time and varieties during *rabi* 2021–22 using actual and forecasted weather.

forecasted data, it was from 41.03–74.84%. In variety PBW 658 with actual data, % HI varied from -6.90–14.29% and in forecasted, it varied from 36.15–89.31% (Fig. 5).

Regarding statistical analysis, the values for the treatments were 0.53 and 0.42 for d-Stat and 0.74 and 0.29 for R^2 , with RMSE values of 9.57 and 9.60, respectively, for the actual and forecasted data (Fig. 5). According to the model's modest R^2 values and acceptable RMSE, harvest maturity predictions were made with good accuracy. This degree of accuracy is enough for supporting timely harvest planning, reducing post-maturity loss and maximising grain quality.

Statistics between actual and simulated value of wheat phenology and yield using actual and forecasted weather of 2021: Table 1 shows the statistical analysis of the actual and simulated wheat phenology values. In terms of crop phenology, variation in days between observed and simulated days for emergence, anthesis and maturity was only 03 days, 01 days, and 05 days, respectively, when using actual weather with the help of the CERES-wheat model. Using forecasted weather data model showed variations of 03 days, 06 days, and 01 days for emergence, anthesis and maturity, respectively. As shown in Table 1, the model performed better than expected, as indicated by lower variance in the predicted wheat production and higher values of d-Stat. (0.97 for observed weather and 0.91 for forecasted weather) and R^2 (0.94 for actual weather and 0.89 for forecasted weather). Pal *et al.* (2016) reported similar findings, noting RMSE of 193.29 kg/ha and a strong correlation (0.979) between observed and simulated wheat yield at Bathinda (Punjab). The effectiveness of CERES-wheat model was also confirmed by Arshad *et al.* (2017) with an above-ground biomass RMSE ranging from 273–581 kg/ha. Additionally, Andarzian *et al.* (2015) revealed normalised RMSE's for anthesis date, maturity date, grain yield and biomass were 3%, 2%, 11.8%, and 3.4%, respectively. Thorp *et al.* (2014) discovered that the CERES-wheat model successfully predicted wheat yields of 105–1107 kg/ha within 3–28%

of root mean square error (RMSE).

Year-wise and treatment-wise comparison of simulated wheat yield (kg/ha) using actual weather data and forecasted weather during 2013–2020: Comparison of the simulated wheat yield (kg/ha) year-wise and treatment-wise for each year between 2013–2020 using actual weather and forecasted weather data are given in Supplementary Table 1 and 2. When using actual weather data, R^2 , d-Stat and RMSE values between 0.12 and 0.43, 0.46–0.86, and 675.5–1283, respectively and wheat yield ranged from 3526–4689 kg/ha throughout the years from 2013–2020, and the difference in simulated wheat yield over actual ranged from 2.26–26.61%. While using predicted data for the years 2013–2020, the per cent deviation in simulated wheat yield ranged from 17.50–50.37 kg/ha, with R^2 between 0.23 and 0.35, d-Stat between 0.36 and 0.59 and RMSE between 1025 and 1397 (Supplementary Table 1). Similarly, simulated wheat yield ranged from 2893–5554 kg/ha (11.03–36.76% variance) using forecasted weather and from 2893 to 4832 kg/ha (7.70–22.76% deviation) using actual weather data from 2013–2020.

Additionally, using actual weather, the values of R^2 , d-Stat., and RMSE varied from 0.25–0.74, 0.38–0.86 and 507.16–1448 kg/ha, respectively, while using forecasted weather, the values were 0.21–0.67, 0.24–0.57 and 488–1647 kg/ha. When using actual weather data, variety PBW 658 showed the largest deviation (22.76%), while variety HD 3086 showed the lowest deviation (8.95%). In addition, when using forecasted data, variety PBW 658 showed the highest deviation (36.56%), while HD 3086 showed the lowest deviation (14.10%) (Supplementary Table 2).

The trend line of the forecasted and observed data was found to be extremely close to each other when the observed and simulated wheat production was compared. The R^2 score for the actual data was 0.56, while the R^2 for the predicted data was 0.44. As a result, the medium-range weather forecast and the observed weather data for wheat yield were very similar. The daily medium-range weather

Table 1 Statistics between actual and simulated value of wheat phenology and yield using actual and forecasted weather

Variable Name	Actual	Simulated	Std. Dev. actual	Std. Dev. Simulated	R^2	RMSE	d-Stat	Total Observation
Using actual weather data								
Emergence (DAS)	6	3	0.894	0	0.08	3.13	0.27	20
Anthesis (DAS)	105	104	5.91	9.04	0.64	5.62	0.85	20
Maturity (DAS)	142	137	11.05	11.55	0.72	8.31	0.87	20
Yield (kg/ha)	3679	3785	566.15	664.17	0.94	211.35	0.97	20
Harvest index	0.35	0.46	0.03	0.11	0.08	0.12	0.17	20
Using forecasted weather data								
Emergence (DAS)	6	3	0.89	0.40	0.08	3.376	0.24	20
Anthesis (DAS)	105	111	5.91	9.41	0.64	8.48	0.72	20
Maturity (DAS)	142	141	11.04	11.73	0.717	6.46	0.92	20
Yield (kg/ha)	3679	4150	566.15	680.91	0.89	680.58	0.91	20
Harvest index	0.36	0.48	0.03	0.10	0.06	0.16	0.19	20

forecast data demonstrated more or less considerable effectiveness to capture treatment-specific variability in observed wheat yield as well as year-to-year variation. In light of this, we conclude that the research's findings are very beneficial for decision-making in the study area, including selecting the ideal time to plant wheat as well as other input management and farm operations (Table 1).

The validation of the CERES-wheat model for phenology and yield using actual and forecasted weather data provided valuable insights. The model demonstrated reasonable accuracy in simulating wheat emergence, anthesis, maturity, yield, and harvest index. However, it consistently underestimated emergence and overestimated anthesis and maturity, indicating the need for further improvements and consideration of additional factors such as biotic stress. The model's performance varied among different sowing dates and wheat varieties, with early-sown crops generally yielding higher grain production. The utilization of forecasted weather data showed potential for estimating yield with higher accuracy compared to actual weather data. Overall, while the CERES-wheat model shows promise, refinement and expansion of its parameters are necessary for more reliable predictions in wheat cultivation. Therefore, the results suggest that in order to increase wheat grain production, optimum planting dates and appropriate wheat cultivar should be given priority. Forecasted weather information should be included into pre-season preparation by farmers and decision-makers to increase the accuracy of production estimation. To improve the predicted dependability of the CERES-wheat model, it is recommended that it be further refined, notably by including biotic stress parameters such as pests and diseases. Finally, depending on model results, management strategies should be modified, paying special attention to optimising critical phenological stages like emergence and maturity.

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