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Research Paper

Use of ERA5-L reanalysis datasets to derive heat units and predict the maturity period of wheat crop in central Punjab

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ABSTRACT

The ERA5-L reanalysis dataset, produced by ECMWF is the latest and most advanced global climate reanalysis datasets available with high spatial and temporal resolution. To assess the applicability of ERA5-L reanalysis data, a field experiment was conducted to predict the onset of maturity period of wheat crop based on heat units derived by ERA5-L data at the University research farm in Ludhiana. The wheat variety Unnat PBW-550 was sown under two dates of sowing (D_1: 27th October and D_2: 17th November) during three consecutive seasons (2020–21, 2021–22, and 2022–23). The phenological observations revealed that the October sown wheat took a greater number of days (153-154 days) to attain maturity as compared to November sown (139-142 days) crop. When heat units were derived from ERA5-L dataset, accumulated GDD (R^2:0.95) and accumulated PTU (R^2:0.95) displayed higher maturity prediction accuracy compared to HTU (R^2:0.32) in all three *rabi* seasons. Ground observed and ERA5-L information were employed to estimate the beginning of maturity for wheat. For this, the accumulated heat units were calculated from sowing to booting stage of wheat crop. Our findings provided intriguing prospects for using ERA5-L reanalysis data as a different data source to predict crop phenology far in advance.

Keywords: Heat units, Solar radiation, Phenology, ERA5-L reanalysis, Maturity prediction

The study of the periodic biological events in relation to the seasonal shifts is called the phenology which helps in understanding the dynamics of ecosystems and how they react to climatic changes. One can estimate the potential yield and schedule harvesting of crops in advance by tracking the various phenological events like, anthesis, grain filling and physiological maturity. Accurate prediction of phenology is required to manage crops more efficiently in terms of controlling pest and diseases, effective utilization of water resources and breeding activities and adapting to climate change and also from the perspective of food security and effective market planning. The role of climate change impact on natural systems is now widely recognized, which makes phenology prediction very crucial which not only will enable researchers, decision makers and land managers to effectively foresee but also to reduce the consequences of climate change on agriculture and its biodiversity. Temperature is the most important weather parameter that influences the growth and development of the crop, particularly phenology and yield as it controls many of the physical and chemical processes (Kaur *et al.,* 2019). Another important climatic factor influencing agricultural output is solar radiation, which is mainly required for transpiration and photosynthesis (Phakamas *et al.,* 2013). Significant variations in climatic parameters have been recorded in the study region (Kaur *et al.,* 2016). Damage to the crop phenological stages like heading, anthesis and grain filling stages were possible, if the highest temperature exceeds 22 °C, 32 °C and 34 °C respectively during these stages (Singh *et al.,* 2022). If temperature rises during reproductive stage of a crop, it results in reduction of pollen viability, fertilization, grain filling and seed development (Mishra *et al.,* 2015; Dubey *et al.,* 2014).

The agroclimatic indices such as growing degree days (GDD), helio-thermal units (HTU) and photothermal units (PTU) are useful in evaluating the effects of agrometeorological factors at various crop growth stages (Khichar *et al.,* 2019). The idea of heat unit system is based on the understanding that crops have specific temperature requirement that must be met to attain specific phenological stage in their growth cycle. Due to strong correlation

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Table 1: Statistical indicators used in the study

Statistical indicators	Formula
Root mean square error (RMSE)	$\sqrt{\left(\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}\right)}$
Nash Sutcliffe efficiency (NSE)	$1-\frac{\sum_{i=1}^{n}(O_i-P_i)^2}{\sum_{i=1}^{n}(O_i-\bar{O})^2}$
Index of Agreement (DR)	$1-\left[\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{\sum_{i=1}^{n}(\lvert P_i-\bar{O}\rvert+\lvert O_i-\bar{O}\rvert)^2}\right]$
Mean absolute percent error (MAPE)	$\frac{1}{n}\sum_{i=1}^{n}\frac{\lvert O_i - P_i\rvert}{O_i}$

between crop development and temperature, GDD are commonly employed to evaluate crop development. The utilization of HTU facilitates the examination of how temperature and the duration of the sunshine hours impact the development of phenological stages in a crop, while PTU represents the combined influence of photoperiod *i.e.* day length and temperature on crop development. It is a concept that is used to study how the interaction between light and temperature influence the time of occurrence of phenological stages. For deriving agroclimatic indices, the weather parameter data are important (Chen *et al.,* 2011). Such meteorological data is however, not readily available due to the limitations in agro-meteorological observatories in all the locations. Specially, solar radiation data is not available from many meteorological stations due to high cost of data acquisition, expensive equipment and difficulty in sensor calibration (Fodor and Mika, 2011). Such limitations in the data acquisition may hamper studies related to land-surface processes and can become a problem in application of crop growth simulation models (Phakamas *et al.,* 2013).

To overcome this, one such dataset that has gained prominence is the ERA5-L reanalysis dataset. It has been produced by the European Centre for Medium-Range Weather Forecasts (ECMWE) and is a long-term global atmospheric reanalysis dataset that provides detailed and consistent meteorological data of several decades including historical as well as future projected datasets. The utility of ERA5-L reanalysis datasets lies in their ability to provide high-resolution meteorological parameters including temperature, solar radiation, wind speed, precipitation, humidity etc. across large spatial and temporal scales. This dataset can be easily used by researchers to investigate crop growth, phenology, water balance and climate risk assessment (Vanella *et al.,* 2022). Amongst heat units, only GDD has been employed to estimate the accurate timing of occurrence of a specific growth stage at a particular location (Dar *et al.,* 2018). So, keeping this in view our study was based on following objectives: (1) To assess the applicability of ERA5-L reanalysis datasets for calculation of different heat units under different date of sowing and (2) To employ different heat units (GDD, HTU and PTU) to predict the crop maturity during different date of sowing

MATERIAL AND METHODS

Experimental site and observations

The field experiments were performed at research farm of Punjab Agricultural University, Ludhiana. A yellow rust resistant wheat variety Unnat PBW-550 was grown consecutively for three *rabi* seasons (2020-21, 2021-22 and 2022-23). The treatment consisted of two dates of sowing, 27th October (D_1) and 17th November (D_2) respectively. The site is located at 30.89° N and75.80°E at an elevation of 247m above mean sea level.

The days taken to attain a particular growth stage by the crop was determined through visual observations. The date of occurrence of booting, anthesis, milking and physiological maturity was noted when 50% of the plants attained that particular stage. When 50% or more tillers had inflated flag leaf bases and 50% of the panicles had visible anthers, booting and anthesis were detected respectively. While, milking stage was recorded when four out of five spikelets oozed out white liquid when squashed between thumb and fingers. Physiological maturity was recorded when the grains were difficult to crush and had moisture content of 30-50%.

The meteorological data was acquired for three crop growing season (*rabi)* viz. 2020-21, 2021-22, and 2022-23. The data comprised of daily maximum and minimum air temperature (°C), daily sunshine hours (hrs) and latitude (radians). They were acquired from surface agrometeorological observatory located at PAU, Ludhiana while, solar radiation (MJm^{-2}) was recorded from the crop field using Pyranometer.

ERA 5 Reanalysis datasets

In this study, hourly maximum and minimum air temperature (°C) and solar radiation (MJm^{-2}) datasets have been downloaded from Climate Change Service platform (https://cds.climate.copernicus.eu/cdsapp#!/ dataset/reanalysis-era5-single-levels) in NetCDF format for the study region for three crop growing years. For this ERA5 land hourly (ERA5-L) data on single level was used. ERA5-L dataset offers enhanced resolution (0.1° x 0.1°) with consistent view of land evolution characteristics over many decades. The ERA5-L dataset has been generated globally by replaying ECMWF ERA5 climate reanalysis land component. ERA 5 solar radiation data was used as an input in Angstrom formula (Allen *et al.,* 2006) to calculate actual bright sunshine hours for our study period.

The pre-processing of ERA5-L datasets were carried out with the help of a GIS software viz. ArcGIS 10.4. In this software multidimensional tool of ArcGIS was used for data visualization and the hourly datasets were extracted as a spreadsheet for further analysis. The hourly data was then combined to obtain data at a daily time step so that it could be compared to the ground observed data.

Computation of agro-meteorological indices

At a specific phenological stage, the daily growing degree days (GDD) were computed by subtracting the base temperature (4.5°C for wheat crop) from the daily mean temperature and the resulting values were added to obtain the accumulated GDD (Dar *et al.,* 2018). Further by multiplying the daily actual bright sunshine hours and day length with the daily GDD, helio-thermal (HTU) and photothermal units (PTU) were computed respectively (Kaur *et al.,* 2016). Calculations were made with both observed data and ERA5-L datasets.

Table 2: Number of days taken by the crop to attain different phonological stages under different dates of sowing three years

Years/ season	Booting		Anthesis		Milking		Maturity	
	D_1	D_2	D_1	D_2	D_1	D_2	D_1	D_2
2020-21	68	87	88	104	110	114	154	142
2021-22	73	82	93	97	112	116	154	137
2022-23	75	81	102	94	116	108	153	139
Mean	72	83	94	98	112	113	153	139

Table 3: Statistical analysis of ERA 5-L and ground observed weather datasets during wheat growing seasons

Years	Maximum temperature (T_{max})		Minimum temperature (T_{min})		Solar radiation (S_{rad})	
	R^2	RMSE (° C)	R^2	RMSE (° C)	R^2	RMSE (MJm^{-2})
2020-21	0.95	1.50	0.86	1.83	0.77	2.71
2021-22	0.97	1.31	0.94	1.54	0.85	2.35
2022-23	0.94	1.47	0.92	1.49	0.69	3.18

Statistical analysis

Utilising several statistical indicators (Table 1), comparisons were made between observatory and reanalysis based agro-meteorological indices produced from ERA-5 L. The statistical analysis was carried out using R-software.

RESULTS AND DISCUSSION

Phenology

Table 2 represents the data on the different growth stages (booting, anthesis, milking, and maturity) of wheat over a three-year period for two dates of sowing, D_1 (27th October) and D_2 (17th November). The results showed that the delay in wheat sowing decreased the number of days taken to achieve physiological maturity. In contrast to this it experienced enhanced growth period and delayed maturity when sown in advance, hence accumulating more number of days to reach maturity (Table 2). On an average, D_1 took 72 days to attain booting, 94 days for anthesis, 112 days for milking and 153 days to attain physiological maturity. While, D_2 took 11 days, 4 days and 1 more day to attain booting, anthesis and milking respectively. It took 14 days less to attain maturity than D_1. Studies of Brar *et al.,* (2022) also reported that 25th November sown wheat reached maturity 20 days earlier than wheat sown on October 25. Similar were the results of Dar *et al.,* (2018) for 25th October and 10th November sown wheat.

Comparison of ERA5-L data with observed

The statistical performance (R^2 and RMSE) after comparing the ERA 5-L reanalysis datasets and ground observed daily weather variables (T_{max}, T_{min} and S_{rad}) for three wheat seasons are presented in Table 3. The results show that ERA5-L T_{max} and T_{min} were very closely related to observed values with R^2 of 0.94-0.97 and 0.86-0.94 respectively while S_{rad} was slightly less related (R^2 of 0.69-0.85).

Accumulated growing degree days (AGDD)

The accumulated GDD computed from the observed data under two sowing dates D_1 and D_2 were compared with those computed with ERA5-L datasets (Fig. 1). The results indicated that the ERA5-L datasets were quite similar in accordance with the observed data. The coefficient of determination (R^2) for AGDD derived from observed and ERA5-L datasets was 0.99 for both sowing dates (Fig. 1).

Accumulated helio-thermal units (AHTU)

The HTU needed to attain a particular growth phase varied with the date of sowing. AHTU derived from observed and ERA5-L datasets showed the similar results. The R^2 for AHTU derived from observed and ERA5-L datasets was 0.96 and 0.97 for D_1 and D_2 respectively (Fig. 2).

Accumulated photothermal units (APTU)

The relationship developed between observed and ERA5-L derived APTU under two dates of sowing are presented in Fig. 3. The R^2 for APTU derived from observed and ERA5-L datasets was 0.99 for both the dates of sowing.

Prediction of wheat maturity

As the ERA5-L reanalysis data and derived heat units were very close to the observed values, an attempt was made to predict the number of days taken to attain maturity of wheat crop using accumulated heat units (AGDD, AHTU and APTU) from sowing to different phenological stages (booting, anthesis and milking) using ERA5-L reanalysis data. The regression models for predicting maturity from ERA5-L derived heat units for both the sowing dates have been given in Table 4.

Further, the obtained models were compared based on the various statistical parameters for both dates of sowing in both the seasons. A highly significant correlation (at 0.05% level) was obtained between the days taken to achieve maturity and the accumulated heat units. In case of D_1, the coefficient of

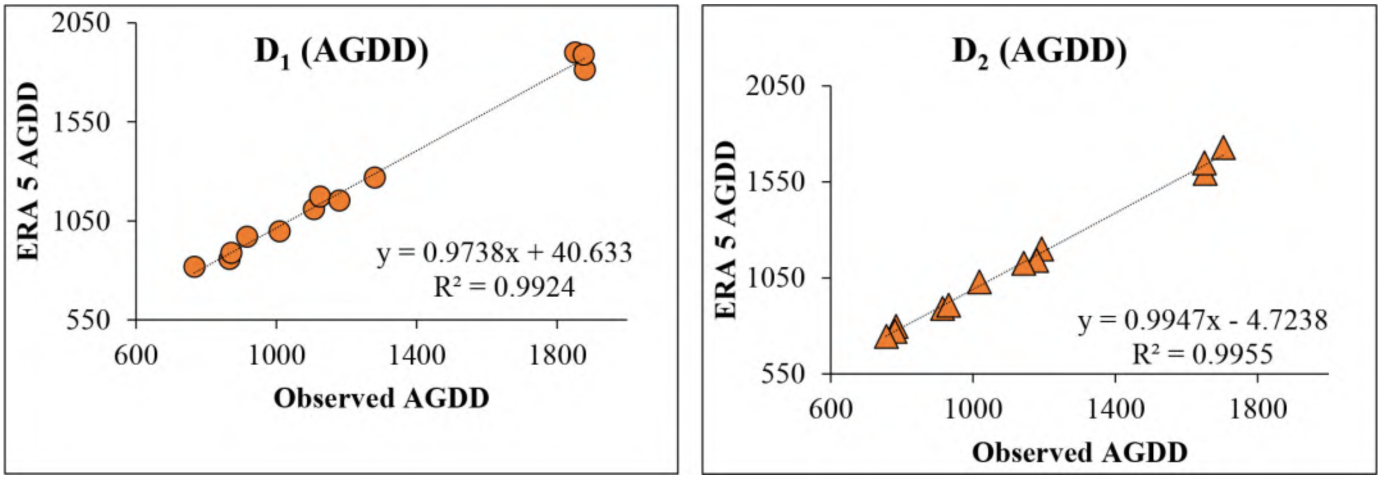

Fig. 1: Relationship between observed and ERA5-L derived AGDD under two dates of sowing

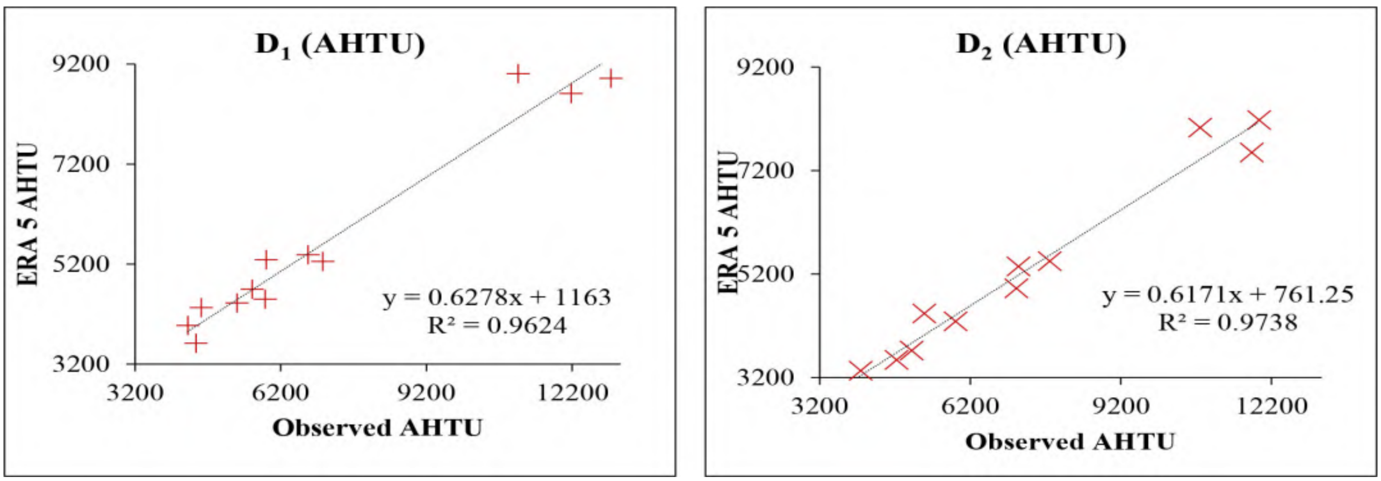

Fig. 2: Relationship between observed and ERA5-L derived AHTU under two dates of sowing

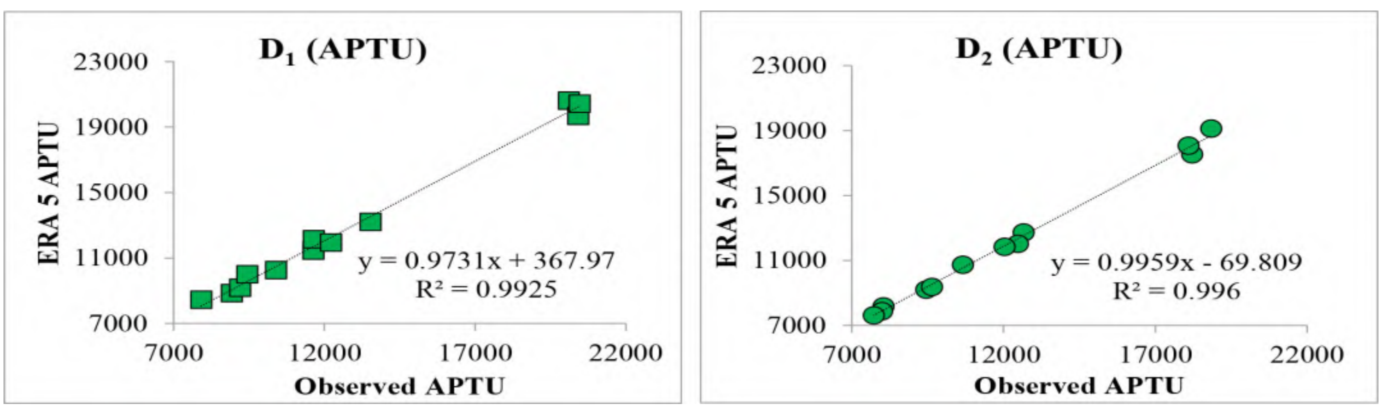

Fig. 3: Relationship between observed and ERA5-L derived APTU under two dates of sowing

determination obtained was at par when prediction was made using AGDD and APTU, unlike AHTU, where differences were observed in the magnitude. Focusing on the coefficient of determination (R^2) and root mean square error (RMSE) to compare D_1 and D_2, it is evident that D_1 consistently outperforms D_2. The higher absolute values of R^2 for D_1 in case of $AGDD_B$ and $APTU_B$ (0.95, 0.95), $AGDD_A$ and $APTU_A$ (0.97, 0.98), $AGDD_M$ and $APTU_M$ (0.86, 0.86) indicated a stronger linear relationship between the number of days taken to attain maturity and accumulated heat units compared to D_2. Additionally, D_1 exhibits lower RMSE values across all models, suggesting that D_1 has less error in predictions than D_2 further highlighting superior predictive accuracy of heat units in case of D_1 (Table 5).

Comparing the performance of the ATHU models with AGDD and APTU models for D_1 and D_2 revealed distinct differences in predictive accuracy and correlation. For D_1, the AHTU models generally show weaker performance compared to the AGDD models, as indicated by lower R² values (0.32 for $AHTU_B$, 0.48 for $AHTU_A$ and 0.51 for $AHTU_M$ models). The RMSE values for AHTU models

Table 4: Regression equation for different prediction model derived from ERA5-L data for D_1 and D_2

Prediction Models	D_1	D_2
$AGDD_B$	Days = 190-0.120*$AGDD_B$	Days = 110-0.071 $AGDD_B$
$AGDD_A$	Days = 180-0.120*$AGDD_A$	Days = 73-0.034 $AGDD_A$
$AGDD_M$	Days = 110-0.058*$AGDD_M$	Days = 76-0.040 $AGDD_M$
$AHTU_B$	Days = 130-0.013*$AHTU_B$	Days = 90-0.011 $AHTU_B$
$AHTU_A$	Days = 180-0.027*$AHTU_A$	Days = 69-0.0066 $AHTU_A$
$AHTU_M$	Days = 150-0.020*$AHTU_M$	Days = 62-0.0063 $AHTU_M$
$APTU_B$	Days = 190-0.012*$APTU_B$	Days = 110-0.0066 $APTU_B$
$APTU_A$	Days = 180-0.011*$APTU_A$	Days = 70-0.003 $APTU_A$
$APTU_M$	Days = 110-0.0053*$APTU_M$	Days = 48-0.0021 $APTU_M$

(AHU_B; accumulated heat unit from booting, AHU_A; accumulated heat unit from anthesis, $AHTU_M$; accumulated heat unit from milking)

Table 5: Statistical analysis of the prediction models obtained from ERA 5-L weather datasets for D_1 and D_2

Statistical parameters	$AGDD_B$		$AGDD_A$		$AGDD_M$	
	D_1	D_2	D_1	D_2	D_1	D_2
R^2	0.95	0.72	0.97	0.55	0.86	0.50
r	-0.97	-0.85	-0.99	-0.74	-0.93	-0.71
RMSE (° C)	1.08	1.59	1.42	2.02	1.40	1.53
NSE	0.95	0.72	0.97	0.55	0.86	0.50
d	0.92	0.73	0.93	0.61	0.79	0.76
MAPE (%)	0.86	2.46	1.99	4.42	3.13	3.10

	$AHTU_B$		$AHTU_A$		$AHTU_M$	
Statistical parameters	D_1	D_2	D_1	D_2	D_1	D_2
R^2	0.32	0.65	0.48	0.62	0.51	0.42
r	-0.57	-0.80	-0.69	-0.79	-0.72	-0.65
RMSE (° C)	6.19	2.12	5.29	1.76	2.92	1.93
NSE	0.32	0.65	0.47	0.62	0.51	0.42
d	0.60	0.70	0.69	0.65	0.65	0.73
MAPE (%)	7.04	3.59	7.96	3.61	6.61	4.23

	$APTU_B$		$APTU_A$		$APTU_M$	
Statistical parameters	D_1	D_2	D_1	D_2	D_1	D_2
R^2	0.95	0.71	0.97	0.55	0.86	0.38
r	-0.97	-0.84	-0.98	-0.74	-0.93	-0.62
RMSE (° C)	1.12	1.61	1.48	2.01	1.39	1.18
NSE	0.95	0.71	0.97	0.55	0.86	0.38
d	0.91	0.73	0.93	0.61	0.79	0.55
MAPE (%)	0.93	2.48	2.05	4.40	3.10	4.50

(AHU_B; accumulated heat unit from booting, AHU_A; accumulated heat unit from anthesis, $AHTU_M$; accumulated heat unit from milking)

are significantly higher, particularly for $AHTU_B$ and $AHTU_A$, where D_1 has RMSE of 6.19 days and 5.29 days, respectively. For D_2, the AHTU models show relatively better performance compared to D_1, with higher R^2 values (0.65). Additionally, the RMSE values for AHTU models in D_2 are significantly lower (ranging from 1.76 to 2.12 days), suggesting improved prediction accuracy compared to D_1. Overall the predictions for D_1 were better shown by model (AGDD and APTU) derived from anthesis stage, while for D_2, booting stage derived AHTU model showed better prediction.

CONCLUSION

This study examined the effectiveness of ERA5-L data in representing the heat units (GDD, HTU, and PTU) obtained for *rabi* season from 2020-21 to 2022-23, in comparison to observed ground datasets for Ludhiana, Punjab. In case of first and second date of sowing heat units accumulated from sowing to booting are enough to predict the onset of maturity for wheat using ground observed and ERA5-L datasets. These findings contribute to enhancing our comprehension of the sources of uncertainty in reanalysis data across diverse climate conditions. Furthermore, these results offer encouraging prospects for utilizing ERA5-L reanalysis data as an alternative data source to estimate the crop phenology well in advance. This presents a valuable solution to overcome the scarcity of observed agro-meteorological data in numerous regions.

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***Conflict of Interest*:** There is no conflict of interest from the authors.

Data availability: The weather data are available with Department of Climate Change and Agricultural Meteorology, PAU, Ludhiana. The ERA5-L reanalysis datasets are available at Climate Change Service platform (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels) in NetCDF format.

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