Crop Yield Prediction based on Reanalysis and Crop Phenology Data in the Agroclimatic Zones

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Abstract

Crop yield and phenological stages are remarkably sensitive to not only environmental factors like atmospheric conditions and physical properties of soils but also agricultural activities. Accurate crop yield prediction plays a crucial role in food security and agricultural sustainability. There are several approaches that a wide range of researchers have tried to predict crop yield at different scales. In this study, we tested AgERA5 reanalysis product and crop phenological stage data to predict winter wheat yields in the agricultural lands of the agroclimatic regions of Turkey. The main objective is to propose a deep learning approach based on the combination of the reanalysis, which was extracted for the agricultural lands of the five most productive agroclimatic zones, and crop phenology data to predict winter wheat yields. Five performance indicators, such as normalized root mean squared error (NRMSE), mean absolute percentage error (MAPE), root mean squared error (RMSE), Nash-Sutcliffe Efficiency (NSE), and coefficient of determination (R^2), are chosen to test the model's accuracy and effectiveness. We have obtained promising findings and suggested that AgERA5 reanalysis data can be used as an input for the crop yield prediction of winter wheat with an error below 10% and a coefficient of determination above 0.9.

Keywords: Crop Yield Prediction, Multilayer Perceptron, Deep Neural Network, Winter Wheat, Agroclimatic Zones.

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1. Introduction

According to the United Nations (2017), the world's population is expected to reach 9.8 billion people in 2050. In addition, global food demand is expected to increase by 35-56 percent between 2010 and 2050 (van Dijk et al., 2021). Zero hunger, which is the second of the 17 most important sustainable goals of the United Nations, is only possible with sustainable agriculture (FAO et al., 2015) and agricultural investments (Mason-D'Croz et al., 2019). The COVID-19 pandemic has proven to the whole world how important sustainable food production is. It has exacerbated world hunger by affecting an additional 70-161 million people (United Nations, 2021). In addition, the increase in frequency and severity of weather and climate extremes such as flash droughts (Spinoni et al., 2019; Pendergrass et al., 2020) and floods (Hirabayashi et al., 2013; Haltas et al., 2021) has been experienced due to climate change, which is one of the main challenges in ensuring food supply (Fanzo et al., 2018). With the development of digital agriculture approaches, the destructive effects of climate change and human factors are targeted to be reduced (Basso and Antle, 2020).

Crop yield and grain quality are influenced by diverse variables like agroclimatic conditions, physical properties of soil, geography, and agricultural activities (Kukal and Irmak, 2018). Agroclimatic zones are based on the homogeneity of not only agricultural but also meteorological variables (Van Wart et al., 2013), such as time periods for crop growth, potential biomass and crop development, temperature range, and water requirements (Trnka et al., 2011). With the development of advanced computational techniques and algorithms (Yildirim and Demir, 2022) in environmental and agricultural sciences, many studies have been carried out to predict crop yield and biomass. These studies show us that crop yield and development are still dependent on many variables and have a complex structure (Schauberger et al., 2020). These prediction efforts have been conducted on a regional and large scale (Dang et al., 2021; Gómez et al., 2021) as well as on a field scale (Engen et al., 2021; Cao et al., 2021a) in diverse climates. To predict crop yield, crop growth simulation models (AquaCrop, DSSAT, WOFOST, EPIC, VIC, etc.) have been developed by diverse working groups and require a wide range of input data (Harou et al., 2021), which can sometimes be the most important limitation for researchers (Grassini et al., 2015; Constantin et al., 2019).

Besides, these simulation models are able to predict important variables such as crop water consumption (Ran et al., 2020), water footprints (Yeşilköy and Şaylan, 2020; 2021), and carbon sequestration (Yesilkoy et al., 2017; Nicoloso et al., 2020) as well as crop yield. Van Klompenburg et al. (2020) indicated that machine learning (ML) and deep learning (DL) algorithms have been widely used for prediction in crop yield for corn (Jiang et al., 2019; Khaki and Wang, 2019), wheat (Haider et al., 2019; Srivastava et al., 2022), soybean (Sun et al., 2019), rice (Chu and Yu, 2020), tomato and potato (Alibabaei et al., 2021; Fleisher et al., 2017) based on agroclimatic (Cao et al., 2021b), ERA5-reanalysis (Oses et al., 2020), crop phenology (Shook et al., 2021; Bakanoğulları et al., 2022), and remotely sensed (Nevavuori et al., 2019; Tian et al., 2021) data. In these studies, machine learning algorithms have been tried to predict crop yield not only with limited input data (meteorological) but also various input data (irrigation, crop phenology, soil properties). These studies show us that convolutional neural networks (CNN) and long short-term memory (LSTM) have been dominant approaches (Van Klompenburg et al., 2020) in crop prediction studies.

CNNs are designed to capture features or objects (Li and Demir, 2023) from images from any kind of source and data augmentation (Demiray et al., 2021; Sit et al., 2021) and synthetic image generation (Gautam et al., 2022). LSTMs are successful for predicting time series as they can learn long-term dependencies in complex multivariate sequences (Xiang et al., 2021). It is designed to solve the long-term dependency problem by means of short-term memory (Pak et al., 2018; Kratzert et al., 2018). Some studies tested the multi-layer perceptron (MLP) neural network and its ability to predict crop yields of winter wheat (Bhojani and Bhatt, 2020; Bazrafshan et al., 2022), blueberry (Sivanantham et al., 2022), and sunflower (Khalifani et al., 2022). They stated that activation functions in the neural network algorithms have an important impact on the model effectiveness of crop yield and other development variables. They help to improve the learning capacity of complex datasets (Kaleeswaran et al., 2020).

In the literature, there are studies for predicting crop yield by using crop growth simulation models like AquaCrop (Gobin et al., 2017; Yeşilköy and Şaylan, 2020), WOFOST (Caldag et al, 2017), DSSAT (Vanli et al., 2019; Yeşilköy and Şaylan, 2021), and ensemble mean (Palosuo et al., 2011) for different parts of Turkey. As we mentioned before, simulating these models needs a wide range of input data and requires interdisciplinary work. Fully connected feed-forward DNNs have been applied to crop yield prediction with spatiotemporal (Dang et al., 2021), ground (Khaki and Wang, 2019; Bhojani and Bhantt, 2020), remotely-sensed (Jin et al., 2020; Sagan et al., 2021), and a combination of sequential and non-sequential (Cao et al., 2021) data. A limited number of ML and DL approaches to predict crop yield were conducted in Turkey. Çakır et al. (2014) used the artificial neural network (ANN) algorithm to predict winter wheat yield with meteorological data in the southeastern region. Yalcin (2019) utilized field images to estimate sunflower yield using CNN. Bregaglio et al. (2021) hybridized the ML and process-based algorithm to predict hazelnut yield with phenology and meteorological data. Mateo-Sanchis et al. (2021) tested the ML algorithm for yield estimation of the three major cereals (maize, barley, and wheat) in Europe, including Turkey. These studies show that meteorological variables, crop phenology, and vegetation-related indices have provided better results.

In recent years, some studies have indicated that DL approaches can perform better in comparison with machine learning approaches and crop growth simulation models. Nevertheless, there is limited research about crop yield prediction with any DL technique. To address this knowledge gap, we used fully connected multilayer perceptron neural networks (FCMLPNN) to predict crop yields in the major agroclimatic regions growing winter wheat in Turkey. The most important feature that distinguishes this study from others is to create neural network algorithm with AgERA5 reanalysis and crop phenological stages datasets.

Winter wheat is considered as a strategic crop and contains an important amount of calories and protein for the food supply (Hawkesford et al., 2013). According to FAOSTAT (2022), Turkey produces 20 million tons of winter wheat and ranks 10^{th} among producers in the world and 3^{rd} in Europe, behind France and Germany. In addition, due to its location in the Mediterranean Basin, which is an important hotspot (Spinoni et al., 2020), it is one of the countries where the effects of climate change will be felt most intensely in agriculture and its related sectors like public health and food supply (Hayes et al., 2018; Linares et al., 2020). Moreover, these five agroclimatic regions were chosen based on the following aspects: (1) The residents of the study area earn their livings through agricultural activities. (2) According to TurkStat (2022), these agricultural areas correspond to 57.7% of the production in Turkey. (3) Agricultural lands in these agroclimatic zones have the highest crop yields and production values in Turkey.

The purpose of this study was (1) to explore the performance of the MLP approach for the winter wheat yield prediction with AgERA5 reanalysis data according to phenological stages as input and (2) to provide usability information of the reanalysis data in agricultural lands of the agroclimatic regions for crop yield prediction. To the best of our knowledge, this is the first study to predict with AgERA5 reanalysis and crop phenology data in the agroclimatic zones.

The manuscript was structured as follows: Section 2 describes the study area and AgERA5 reanalysis and crop phenology data, presents the details of the MLP approach and its activation functions, and gives the formulation of performance criteria. Section 3 presents the properties of the agroclimatic regions' winter wheat yield prediction results with performance indicators. In Section 4, results were discussed with related studies, and some suggestions were provided for future works as a conclusion.

2. Materials and Methods

2.1. Study Area

The study area covers the agricultural lands of the five most productive agroclimatic regions in Turkey (Figure 1). Turkey is located in the southeastern part of Europe and has diverse agroclimatic zones (TAGEM and DSİ, 2017), which provide for the production of endemic plants. CORINE Land Cover Version 2018 data were downloaded from the European Environmental Agency (EEA, 2018) by extracting winter wheat cultivation areas from the 2.1.1 (non-irrigated arable land), 2.1.2 (permanently irrigated land), 2.4.2 (complex cultivation patterns), and 2.4.3 (land principally occupied with agriculture) classes. These growing areas have the highest crop yield values in Turkey. Also, these lands account for 57.7% of the winter wheat production of Turkey (TurkStat, 2022). We selected five agroclimatic zones, where agriculture is the major economic driver for residents. As previously stated, winter wheat can be considered as the prevailing crop for these agroclimatic zones responsible for the main winter wheat production.

2.2. Data

Increased data availability, which is a result of advancements in observation systems and computation resources, gives a wealth of information for conducting precise temporal and spatial assessments. In this study, we used the most advanced gridded meteorological datasets according to their spatiotemporal resolution. We used daily AgERA5 (Boogaard et al., 2020), based on the ECMWF (European Centre for Medium-Range Weather Forecasts) ERA5 gridded data at surface level Atmospheric Reanalysis, with 0.1-degree spatial resolution. ERA5 reanalysis data have been scientifically well-accepted and used as critical data source in diverse research fields like energy assessments (Gualtieri, 2021), river discharge (Harrigan et al., 2020), extreme weather events (Rodríguez and Bech, 2020), precipitation (Bandhauer et al., 2021; Nacar et al., 2022), drought conditions (Kelebek et al., 2021), agricultural water requirements (Rolle et al., 2022), and crop yield forecasts for operational use (Araghi et al., 2022; Bojanowski et al., 2022).

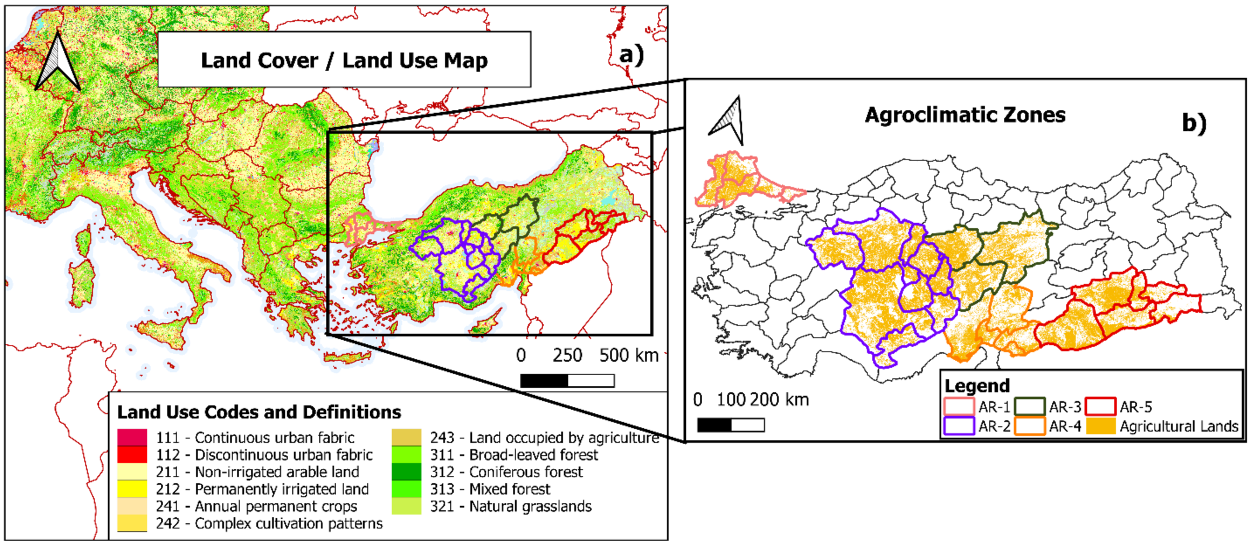

Figure 1. a) The figure contains the location, land cover/land use of the study. Yellow, green, and red colors are associated with agricultural lands, forests, and urban lands, respectively. The red line represents the country boundaries; b) There are five major agroclimatic zones, and each zone has different colors. Agricultural lands are illustrated in orange color. The black line represents the boundaries of the provinces of Turkey.

Daily air temperature (maximum: T_{max}, minimum: T_{min}; mean: T_{mean} (°C)) and daily mean dew point temperature (T_{dew} (°C)), daily mean global solar radiation (R_s (KJm^{-2})), daily total precipitation (P (mm)), and daily mean wind speed (WS (m s^{-1})) were obtained from the ECMWF Copernicus Climate Change Service from 2004 to 2021. These spatiotemporal data were overlaid with the agricultural lands of each agroclimatic zones, and time series for each meteorological variable were extracted by using a spatially weighted mean due to the shape of the earth. Data manipulation, extraction, and visualization were performed using QGIS (version 3.10) and Climate Data Operators (CDO, version 1.9.9).

A crop water requirement guide for Turkey, published by the General Directorate of Agricultural Research and Politics and State Hydraulic Works (2017), was used to obtain winter wheat crop phenological data. Yields and production of winter wheat for each province between the years 2004 and 2021, were provided from the Turkish Statistical Institute (TurkStat, 2022).
Date of the crop phenological stages can be varied in the agroclimatic regions. Even though their phenological periods are the same, different crop cultivars are sowed in the agroclimatic zones and can have different climate demands and impacts on regional and seasonal climate (Bakanoğulları et al., 2022). The Phenology data of winter wheat includes growing periods (tillering, stem extension, heading, and ripening) and is illustrated in Figure 2 (TAGEM and DSİ, 2017).

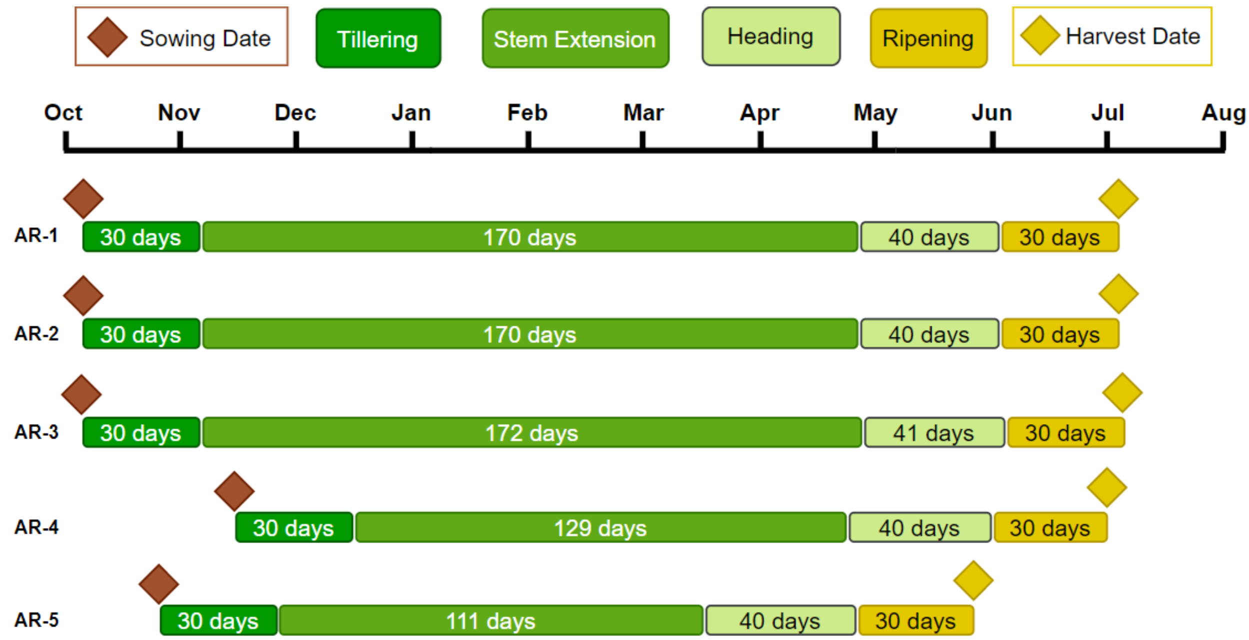

Figure 2. represents the phenological stages of the winter wheat. ARs stand for agroclimatic regions. Four main crop phenological stages were considered. The length of the phenological stages in days can be found in the colored boxes.

2.3. Prediction Algorithm

DL approaches (Hinton and Salakhutdinov, 2006) have been recently implemented in agricultural and environmental research and have provided promising results and a significant potential (Muruganantham et al., 2022) for image processing, prediction, and data analysis (Li et al., 2022). Multilayer perceptron (MLP) is very efficient and the most common type of DL algorithm that has a supervised learning technique using the back-propagation method to obtain a model for complex phenomena. MLP can benefit three-layer structure, which includes input layer, hidden layer(s), and output layer. The input layer provides the external information, and the output layer solves the problem and produces the results. A hidden layer (one or more) is connected to the input and output layers. Each layer contains a number of neurons and nodes. Each neuron in this structure is fully connected to all neurons in the following layer or layers (Zhao et al., 2009; Khalifani et al., 2022) and has its own weight. Equation 1 represents the input function u, which computes the weighted sum of the input features:

$$u(x) = \sum_{i=1}^{n} \omega_i x_i \qquad \text{Eq. (1)}$$

where ω_i, weight; x_i, input. The result of this equation is passed on to the activation function.

Activation functions, training type, optimization functions, and rescaling methods play significant roles in the neural structure to solve different non-linear issues. These functions were selected based on the trial and error procedure for accurate crop yield predictions. The hyperbolic tangent ($\tan(h)$) function (Eq. 3) and gradient descent, aka vanilla gradient descent, algorithm is among the most widely used methods due to their fast-computing speed (Bi and Hu, 2021), and selected as the activation function and optimizer, respectively.

$$\tan(h) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \qquad \text{Eq. (2)}$$

This function can be defined as the ratio between hyperbolic sine and cosine functions at the points x and –x. The range of the activation function is between -1 and 1. Gradient descent (Eq. 3) attempts to minimize the error by improving the model's accuracy. The backpropagation method is performed by gradient descent as an optimizer to adjust the weight of the neurons.

$$\theta = \theta - \eta . \nabla_{\theta} J(\theta) \qquad \text{Eq. (3)}$$

In this study, the MLP algorithm was used to predict winter wheat yield. In Figure 3, each meteorological variable of the four phenological stages (mean temperature, maximum temperature, minimum temperature, dew point temperature, solar radiation, wind speed, and precipitation) was entered as input data in the MLP structure. The main challenge after our many trials of the DNN algorithm are to select activation functions, rescaling, and training methods. A fully connected MLP with two hidden layers was configured. The number of units in the layers (input, hidden, and output), activation functions, training functions, optimization algorithms of hidden layers, and rescaling methods in the input and output can be found in Table 1.

Table 1. Each row contains the parameters in the layers of the MLP algorithm for crop yield prediction. The agroclimatic region (AR) in which the methods are used, is written in parentheses.

Input Layer	Number of Independent Variables: 28 Method of Rescaling Covariates: Standardized (AR-1, AR-2, AR-3, AR-5) and Adjusted Normalized (AR-4)
Hidden Layer	Number of Hidden Layers: 2 Number of Units in the 1st Hidden Layer: 14 Number of Units in the 2nd Hidden Layer: 7 Type of Training: Batch (AR-1, AR-2, AR-5), Online (AR-3, AR-4) Optimization Algorithm: Gradient Descent Activation Function: Hyperbolic Tangent
Output Layer	Number of Units: 1 Activation Function: Hyperbolic Tangent Rescaling of Scale Dependent Variables: Adjusted Normalized Error Function: Sum of Squares

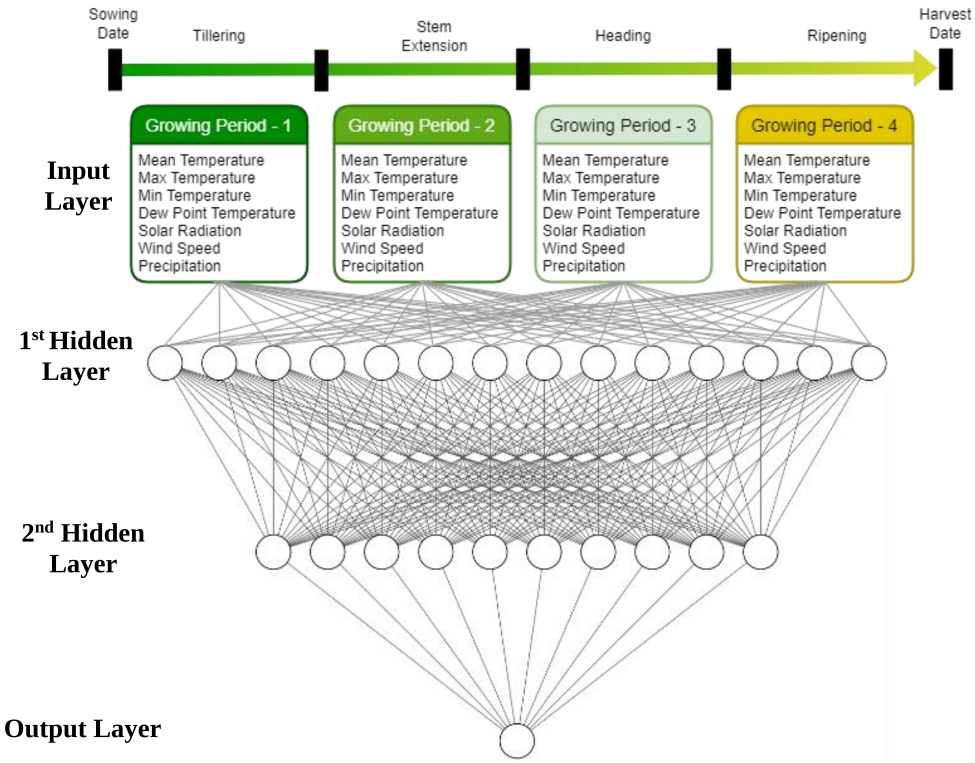

Figure 3. Structure of the MLP with two hidden layers for the crop yield prediction. Meteorological variables (see the boxes from green to yellow) in the crop phenological stages are defined as inputs. The 1st and 2nd hidden layers contain 14 and 7 nodes, respectively. The output layer is the crop yield.

2.4. Model Evaluation

To quantify the model's effectiveness, normalized root mean squared error (NRMSE), mean absolute percentage error (MAPE), root mean squared error (RMSE), Nash-Sutcliffe Efficiency (NSE), and coefficient of determination (R^2) were selected as performance indicators. Formulations of these indicator can be found in the below (Eq. 4-8), respectively.

$$NRMSE = \sqrt{\left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n\bar{O}^2}\right]} x\ 100 \qquad \text{Eq. (4)}$$

$$MAPE = 100\ x\ \frac{1}{n}\sum_{1}^{n}\left|\frac{O_i - P_i}{O_i}\right| \qquad \text{Eq. (5)}$$

$$RMSE = \sqrt{\left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}\right]} \qquad \text{Eq. (6)}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad \text{Eq. (7)}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}{O_i}^2} \qquad \text{Eq. (8)}$$

where n is the number of data, P_i and O_i are the predicted and observed values, respectively. Model performances is considered as excellent when NRMSE and MAPE with < 10%; good if 10-20%;

fair if 20-30%; poor if >30%. Model performance is described as very good if NSE > 0.75; good if 0.75-0.65; satisfactory if 0.65-0.50; satisfactory if < 0.50. A larger R^2 represents better model performance (Nevavuori et al., 2019; Dang et al., 2021; Fahad et al., 2022).

3. Results and Discussions

3.1. Agroclimatic Analysis for Winter Wheat Growing Season

For each of the agroclimatic regions of the winter wheat-growing areas, the mean, maximum, and minimum air temperatures (T_{mean}, T_{max}, and T_{min}, respectively) and total precipitation according to crop phenological stages (e.g., growing periods (GPs)) can be found in Figure 4 (a-e). In general, winter wheat has almost the same phenological stages, including sowing and harvest dates in the AR-1 and 3 zones. In the AR-4 zone, the sowing date of the winter wheat takes place approximately 40 days later than in the AR-1 and AR-3 zones. However, it can be observed that GP-3 and 4 have similar dates. This can be caused by the highest temperatures in the GP-3 and GP-4. In addition, it is well known that different crop cultivars can be sown among the regions and in the same growing areas. It was calculated to be 19.5°C and 2.5°C higher than the AR-1 and three zones' mean temperatures. Although AR-5 has the shortest crop development period (211 days), it is the second region with the most precipitation, which is calculated as 538.2 mm. This might be related to crop cultivar or agroclimatic properties. The agroclimatic zone with the highest precipitation is AR-1 with 573.1 mm. This region also has the highest crop yields (395.0 kg/da) among them.

In the tillering period (GP-1), the mean sea level of AR-1 is relatively lower than AR-2 and AR-3, and that causes a higher air temperature. The mean air temperature of AR-4 is the lowest among the regions due to the late sowing of winter wheat. Development of the crop root zone and germination takes place during this period. In the stem extension period (GP-2), which is the longest growing period of winter wheat, there is the coldest air temperature and the highest amount of precipitation. Crop height increases the most, which means the most precipitation occurs. Moreover, it is calculated that the minimum air temperature below 0°C in AR-3 and 4 as -0.8 and -3.4°C, respectively. In other agroclimatic zones (AR-1, AR-4, and AR-5), minimum temperatures are not experienced below 0°C. In the heading stage (GP-3), all agroclimatic zones have almost the same day length (40 days). The ripening period (GP-4) has the shortest growing period and the highest air temperature and lowest precipitation values.

Time series of the crop yield fluctuation is illustrated in Figure 5 (a-e). When focusing on the AR-1, it can be seen that crop yield has stayed below the mean crop yield for Edirne and Kırklareli between the years 2015-2020 and 2006-2012, respectively, whereas Istanbul had more production between 2015 and 2020 compared to the other cities. In the AR-2, while Aksaray and Konya had higher crop yields than the long-term mean, winter wheat yields in Karaman, Kırıkkale, and Ankara remained below the long-term mean. The AR-3 graph shows that Kayseri has an increasing yield trend. While Adana, which is located in the AR-4, yields above the mean and Kilis yields below the long-term mean, the crop yield tends to increase in Kahramanmaraş over the years. The decrease in yield in Kilis, especially in 2008, 2014, and 2016, was due to the drought occurrence.

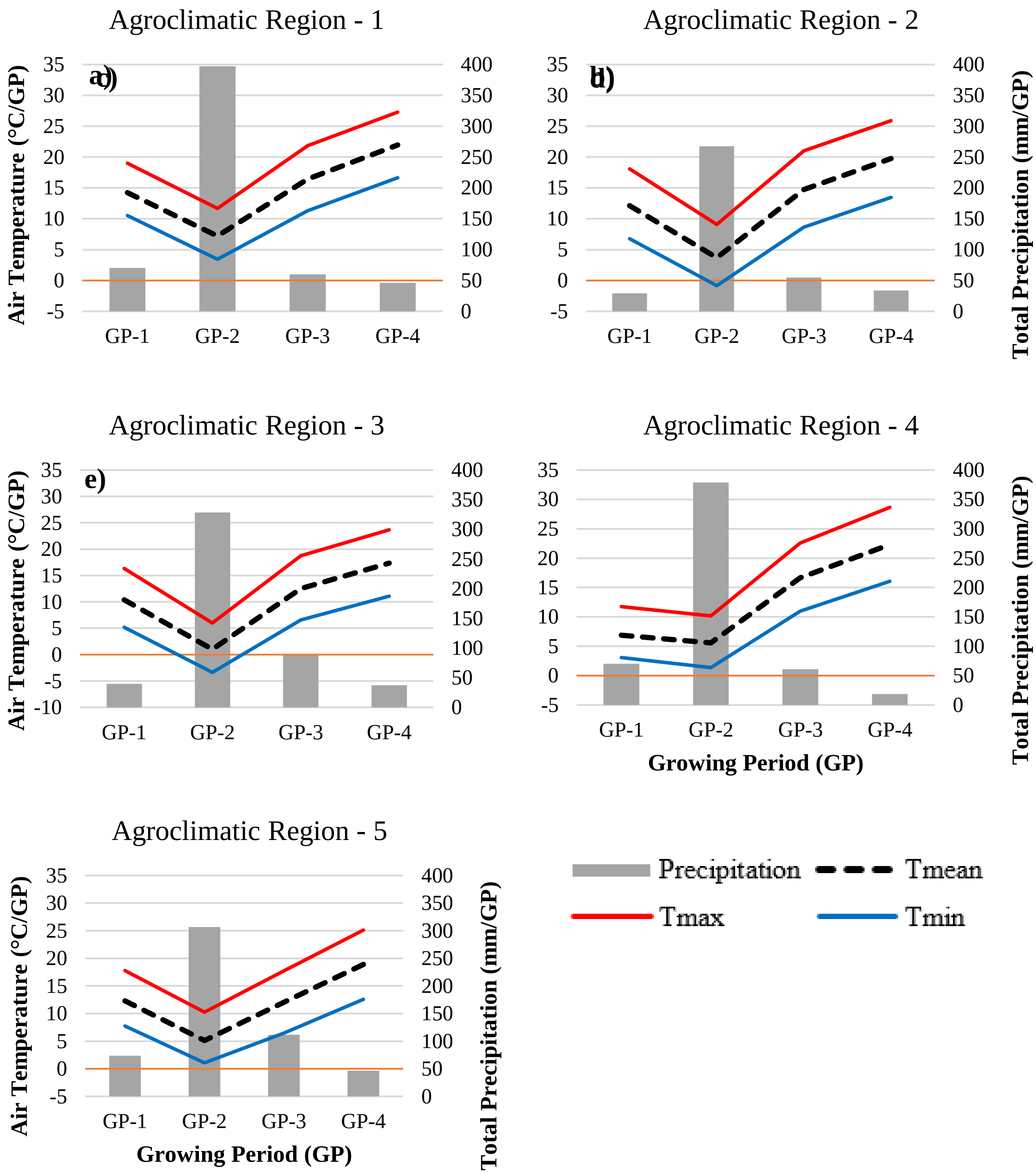

Figure 4. (a-e). Lines (red, black dashed, and blue) and gray column bars represent the air temperature (maximum, mean, and minimum) and precipitation in the growing period of the winter wheat, respectively. Orange horizontal line represents the 0°C. The left and right sides of the visuals show the air temperature and total precipitation, respectively.

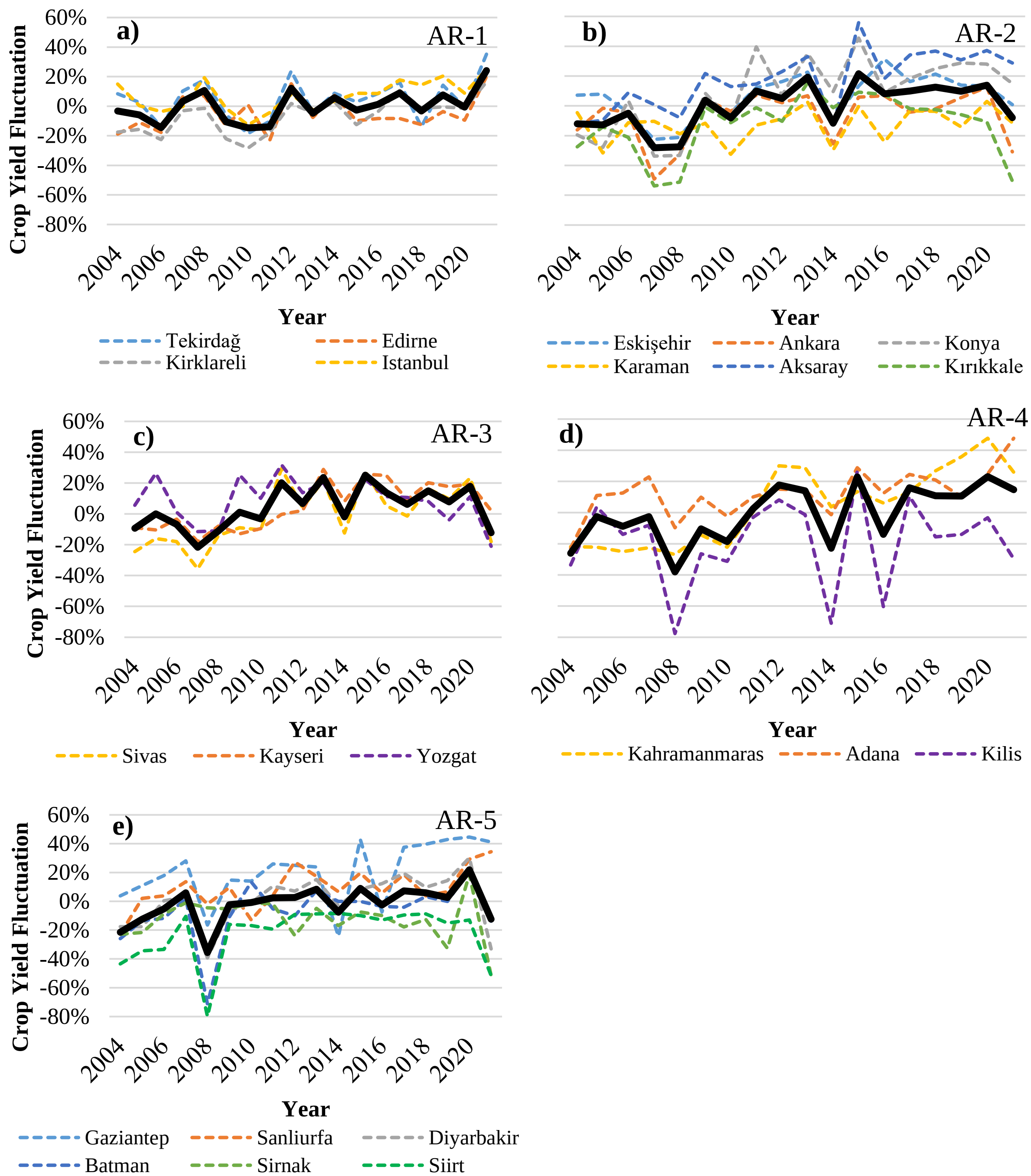

Figure 5. Time series of the crop yield fluctuations of the ARs by years can be seen. Dashed, colorful lines and black, solid lines represent the provincial and regional mean crop yield fluctuations, respectively.

Finally, there was a significant decrease in the crop yield in Siirt and Batman in the AR-5. In addition, Gaziantep and Şanlıurfa show an increase in crop yield during this period. All the graphics in Figure 6 show us that although crop yield has regionally similar characteristics, changes in farmers' production habits (i.e., fertilizer use and disease control) and micro-scale meteorological events (such as convective precipitation, hail) have a significant impact on yield and may cause these fluctuations. Also, agricultural and hydrological droughts occurred in the major parts of Turkey in the 2007-2008, 2013-2014, and 2015-2016 episodes. Especially, southeastern part of Turkey may be more vulnerable than other regions, which clearly impacted crop yield.

In general, crop yield anomaly values showed similar characteristics. The most parts of Turkey, which includes the major agricultural lands, experienced severe agricultural and hydrological drought in the 2007-2008, 2013-2014, and 2015-2016 episodes (Yeşilköy and Şaylan, 2022). Concordantly, agricultural yields and production dramatically decreased. Because agricultural production principally depends on climatic condition (aka rainfed agriculture). Besides, some agroclimatic regions (i.e., AR-4) may be more vulnerable to dry conditions, which causes a critical decrease in yields and production. Specifically, crop yield reduction during these three drought episodes was found to be around 25%.

3.2. Prediction Results

Scatterplots and boxplots of actual and predicted crop yield can be seen in Figure 6 (a-e). According to these visuals and numerical results, it can be said that the winter wheat yield was successfully predicted. The standard deviation of the predicted yield is lower than the standard deviation of the yields and was calculated as 40.2 and 48.6 kg/da, respectively. Besides, mean values of performance indicators (MAPE, NRMSE, RMSE, NSE, and R^2) were calculated as 4.0%, 5.2%, 15.1 kg/da, 0.91 and 0.93, respectively. All performance indicator results in Table 2 state that our proposed approach has a considerable capacity to predict winter wheat yield for each AR. All NRMSE and MAPE values were calculated with a lower error than 10%. Also, RMSE of the predicted are considerably lower than mean observed yields. According to our model evaluation criteria, our results showed that the effectiveness of the model can be considered “excellent”.

According to box plots, no significant difference can be found between the actual and predicted crop yield. Moreover, model was able to capture not only the distribution and mean of the actual data when focusing on the interquartile range (IQR=upper quartile – lower quartile) of the boxplots but also median values. In the AR-4, it can also be seen that crop yield was predicted with relatively higher error values. The agricultural lands of this AR may be more vulnerable to agricultural drought than the other regions. Therefore, winter wheat yields may be reduced in the 2007-2008, 2013-2014, and 2015-2016 growing periods in the AR-5. Furthermore, lower yield values were overestimated and higher values were underestimated with our prediction approach. Nevertheless, our findings are promising.

Our results were compared with other studies in literature. A limited number of studies were found on predicting winter wheat yield using DNN and other DL algorithms with meteorological and phenological data. Bhojani and Bhatt (2020) predicted winter wheat yield using multilayer perceptron (MLP) in West India with meteorological variables. They tested different activation functions for prediction and a wide range of MAPE values between 0.1 and 22%. Cao et al. (2021) predicted winter wheat yield from the field to the county scale in China using ML, Google Earth Engine, and DL algorithms, including DNN. They used a wide range of data (meteorology, soil, vegetation indices, soil parameters, and remotely sensed). Their DNN prediction performance was determined to be 0.87 in R^2. DNN shows good performance at the field and county level among algorithms.

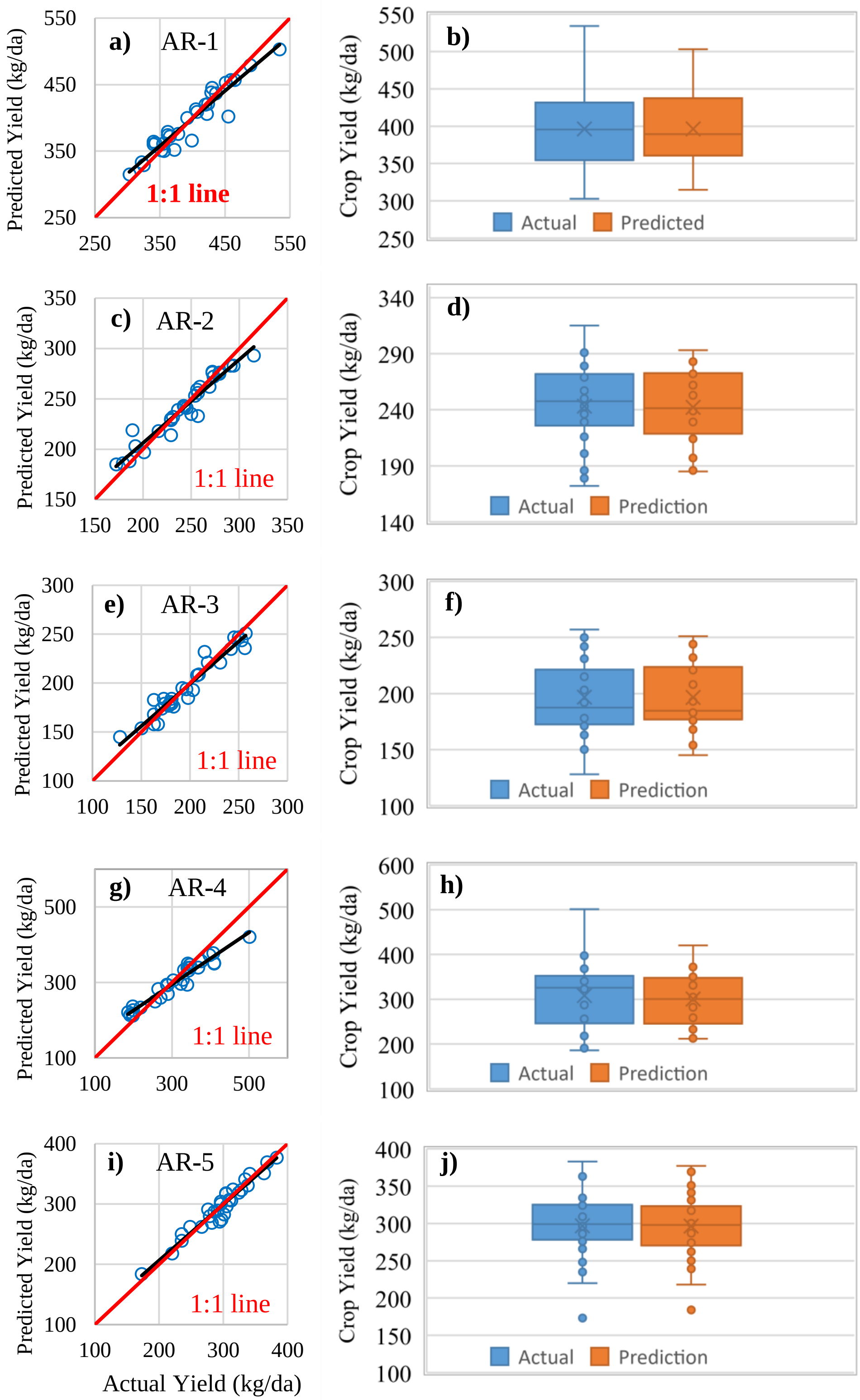

Figure 6. (a-j). Scatterplots and boxplots of actual and predicted crop yield. The reference line (1:1) and best fit line are represented by red and black lines, respectively.

Table 2. Performance indicators of the proposed approach.

Region	**MAPE (%)**	**NRMSE (%)**	**RMSE (kg/da)**	**NSE**	$\mathbf{R^2}$
AR-1	3.06	4.20	16.65	0.90	0.91
AR-2	2.96	4.20	10.20	0.92	0.93
AR-3	3.51	4.46	8.78	0.93	0.94
AR-4	7.39	9.43	29.06	0.86	0.94
AR-5	3.06	3.60	10.67	0.94	0.94

Mateo-Sanchis et al. (2021) investigated the main drivers, including monthly ERA5-renalysis data, of crop yield prediction using ML for winter wheat and other major cereals. They found the most dominant factors for winter wheat as 0.85±0.03 R^2 values. Çakır et al. (2014) used MLP to predict winter wheat yield using some agrometeorological indicators in southeastern part of Turkey. Their RMSE values were higher than our findings. Wolanin et al. (2020) used meteorological variables, vegetation indices, and crop fraction data to predict wheat yield with CNN, which is a popular DL approach. Their highest NSE value (0.87) was lower compared to our NSE values. Tian et al. (2021) created LSTM networks to predict wheat yield using remotely sensed and meteorological data and found R^2 as 0.83.

4. Conclusion

In summary, the aim of this study was to test the effectiveness of the scientifically accepted and publicly available AgERA5 gridded reanalysis, based on ERA5 reanalysis and crop phenological stage data, for the yield prediction of winter wheat. We approached the prediction method, which was a widely-used DNN (MLP with 2 hidden layers) algorithm, by using both crop phenology and AgERA5 data. We extracted the meteorological variables for the five productive ARs' agricultural lands in Turkey for the phenological stages of the winter wheat and defined them as input data for the prediction model. We calculated the model effectiveness with the widely used performance indicators to compare to other related studies. The determination coefficients of the predictions performed for each region are 90% and above, and the error values were calculated as being below 10%. It was quantified that our approach provides higher accuracy for estimating winter wheat yield than the performance indicators provided by other studies.

According to our findings, we have several suggestions for future studies as follows: (a) For large-scale studies, crop yield predictions should be conducted in agroclimatic zones for better model accuracy; (b) In crop yield prediction studies, crop phenological stages should be considered an important input; (c) AgERA5 reanalysis data extracted from agricultural lands can be defined as input for crop yield prediction. Lastly, agricultural production or farmers can benefit from studies about quantifying the drought susceptibility of agricultural lands and successful drought management plans, which can contain educational materials with efficient irrigation practices and increased awareness of the climate crisis.

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