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Wheat Yield Prediction for Turkey Using Statistical Machine Learning and Deep Learning Methods

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Forecasting agricultural product yield is quite an important and elaborate task for agriculture sector. Previous information about future enables all parties included in agriculture sector to take necessary precautions to alleviate any possible damage. Wheat is possibly the most important food ingredient for many people in the world. It provides daily nutrition needs throughout the world and is of strategical importance for the independence of many nations. The current study is carried out to analyze the applicability of various statistical, machine learning and deep learning methods on predicting wheat yield. For this purpose, weather and plant nutrient usage are used input variables and the wheat yield in the major producing provinces is considered as target output. The analysis results have demonstrated that all models are quite good at learning the relationship between the selected environment variables and wheat yield. However, models have achieved the highest accuracies in forecasting the wheat yield in Konya province. Furthermore, Random Forest ranked first in its prediction of wheat yield in Konya province. It is followed by CNN, Auto-Arima and LSTM methods.
Keywords: Yield forecast; CNN; random forest; LSTM; auto arima; statistical inference; wheat; seasonal autoregression

INTRODUCTION

Wheat is cultivated extensively across the globe, including Turkey. It holds significant importance due to its large producer base and its role as a fundamental ingredient in bread, a staple food for many (Behmand *et al.*, 2019). Within the cereal category, wheat encompasses two primary varieties, namely bread wheat and pasta wheat. With its remarkable adaptability to diverse regions, wheat ranks among the most crucial crops worldwide, contributing approximately half of the calories and protein consumed by a third of the global population (Erenstein *et al.*, 2022).

In the present era, the global population is consistently expanding, and life expectancy is constantly increasing thanks to the enhancing healthcare developments and increasing awareness among individuals (Fang *et al.*, 2020). Simultaneously, agriculture holds a significant position in the Turkish economy due to favorable climatic conditions and fertile soils (Altürk *et al.*, 2022). Given the escalating population and the agricultural commitment, the quality of wheat, which occupies the largest cultivation area in Turkey, including factors such as price and yield, has perpetually been a matter of consideration (Keyder and Yenal, 2011).

Particularly in the developing countries like Turkey, the consumption of wheat and its derived nutrients takes precedence in the realm of food consumption. With its remarkable adaptability, wheat stands as the most extensively grown cereal worldwide, with a production of 781 million tons across 225 million hectares (FAO, 2017). Notably, countries such as China, India, the United States, Russia, Australia, Canada, Ukraine, Turkey, and Kazakhstan hold the foremost positions in the global wheat production (FAO, 2017). Turkey, boasting a wheat cultivation area of 7 million hectares and a production volume of 19.8 million tons, holds a significant potential on the global scale (TUIK, 2022). All the abbreviations used throughout the paper are summarized in Table 1.

Despite fluctuations in wheat yield in Turkey, the average yield per unit area stood at 262 kg/da (TUIK, 2022), remaining below the global average of 351 kg/da (TMO, 2019). These yield fluctuations not only contribute to price volatility but also hinder the formulation of effective strategies for establishing a balance between wheat supply and demand (Kalkuhl *et al.*, 2016). Accurate estimates of future wheat yields, as one of the most cultivated cereal crops globally and a fundamental food source for numerous countries, hold significant importance in shaping agricultural

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policies and ensuring food security (Sasson, 2012). Furthermore, wheat serves as a crucial ingredient in international trade, making future yield forecasts essential for countries to plan their wheat exports and imports. Such forecasts also aid farmers and traders in predicting future prices and market trends (Veninga and Ihle, 2018).

Table 1. Abbreviation Glossary

TUIK	Turkish Statistical Institute
FAO	United Nation Food and Agriculture Organization
ARIMA	Autoregressive Integrated Moving Average Model
SARIMA	Seasonal Autoregressive Integrated Moving-Average Model
SARIMAX	Seasonal Autoregressive Integrated Moving-Average with Exogenous Regressors Model
CNN	Convolutional Neural Networks
RNN	Recurrent Neural Networks
LSTM	Long-Short Term Memory Neural Networks
XGBoost	Extreme Gradient Boosting Algorithm

Time series analysis is a widely employed methodology for predicting future outcomes based on historical data (Idrees *et al.*, 2019). The statistical approach explores the temporal variations of a variable and aims to forecast its future behavior. Time series data consists of regularly measured observations (Jebb *et al.*, 2015). The primary objective of time series analysis is to make predictions by utilizing available data, with statistical models utilized to discern past trends, patterns, and seasonal effects (Bontempi *et al.*, 2013). Traditional models such as ARIMA and SARIMAX have conventionally been employed in time series analysis (Siami-Namini *et al.*, 2019). However, with advancements in technology, machine learning and deep learning algorithms have emerged, encompassing models such as CNN, RNN, LSTM, and Random Forest, and have found applications in time series analysis across diverse domains (Siami-Namini *et al.*, 2018).

Models like ARIMA and SARIMA rely on mathematical formulas to predict future values based on their relationships with previous values (ArunKumar *et al.*, 2022). As a result, these models possess limited learning capacity and may struggle to capture complex relationships compared to deep learning models (Zhong *et al.*, 2019). Additionally, models like ARIMA and SARIMA often require the data to possess specific statistical properties, such as stationarity, normal distribution, and constant variance (Khashei *et al.*, 2012). Consequently, the implementation of these models may necessitate prior data transformations or preparatory steps. In contrast, deep learning models are generally more flexible and impose fewer assumptions on the data (Pichler *et al.*, 2020). Moreover, ARIMA and SARIMA models may encounter challenges in adapting to new data once the learning process is complete. Updating the model may require retraining or adjusting parameters (Khashei *et al.*, 2012). Conversely, deep learning models exhibit adaptability to new data, thanks to their inherent flexibility (Buslaev *et al.*, 2020).

In this study, important wheat production areas are determined. In order to predict the wheat yield of the determined areas, weather parameters and plant nutrient usage have been collected considering the planting and harvesting times of wheat product. Curated dataset consists of 43 input variables and 1 output variable (wheat yield). The current study makes important contributions to the policy makers, traders, producers and consumers of wheat product through robustly forecasting future trends of wheat production and enabling them to take precautions beforehand. A recent review which has curated the studies in literature carried out between 2019 and 2022 on wheat yield prediction emphasized the lack of public dataset as a major challenge (Debelee *et al.*, 2023). The dataset and codes pertaining to the models employed in the study are shared in a public github repository (https://github.com/cevher/wheat-yield-estimation). This is another important contribution of the study, which makes researchers to further analyze the methods and dataset in depth.

MATERIAL AND METHODS

Initially, the main wheat production areas of Turkey were determined according to 2022 wheat production amounts (TSI). Accordingly, Konya, Edirne, Çorum, Şanlıurfa, and Eskişehir ranked the top 5 cities in Turkey. Wheat yield data is obtained from the public plant production database of Turkish Statistical Institute. This data covers the period between 2004 and 2022. Fertilizers and plant nutrition products are directly effective on yield. Therefore, the amounts of Nitrogen –N, Phosphorus- P_2O_5, Potash-K_2O) used in each city were collected for 2004 and 2022 from the records of Turkish Ministry of Agriculture and Forestry. Weather is another important factor that affects the harvest and yield of any agricultural product. Wheat is planted between September-October and harvested during June and July in Turkey. For this reason, weather parameters were collected for from the records of Turkish State Meteorological Services. The selected weather parameters include monthly average minimum temperature, monthly average temperature, monthly average wind speed and monthly precipitation. These parameters were collected for the periods between October and June. In summary, a total of 43 input variables are used to predict the yield output for each city.

Auto Arima, Convolutional Neural Network, Long Short-Term Memory and Random Forest Algorithms are chosen as forecast models. Pmdarima, a Python statistical library, was used to perform Auto Arima model. Auto ARIMA (Auto-Regressive Integrated Moving Average) is a popular algorithm used for time series forecasting. It is an extension of the ARIMA model that automatically determines the optimal values for the order of differencing (d), the order of the autoregressive term (p), and the order of the moving average term (q) based on the characteristics of the input data. Tensorflow and Keras frameworks were used to construct CNN and LSTM architectures, and Scikit Learn python framework was used to implement Random Forest estimator. All models are well known and widely used for various purposes. Simplest possible architectures are chosen for CNN and LSTM models.

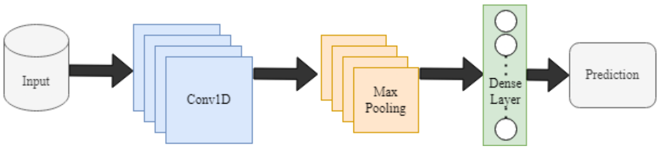


Figure 1. Convolutional Neural Network (CNN) architecture employed in the analysis

Conv1D layer contains 63 neurons, Max-pooling layer implemented with pool size 2, Dense Layer contains 50 neurons, Output layer contains 1 neurons

The CNN architecture is composed of 1 Conv1D layer with 63 neurons, 1 MaxPooling with pool size 2, 1 Dense Layer with 50 neurons and 1 Dense layer as output (Figure 1). On the other hand, LSTM architecture contains 1 LSTM layer with 50 neurons and 1 Dense layer as output (Figure 2). ReLu is chosen as activation and Adam is used as optimizer with a learning rate of 0.005, and both models were trained for 1000 epochs.

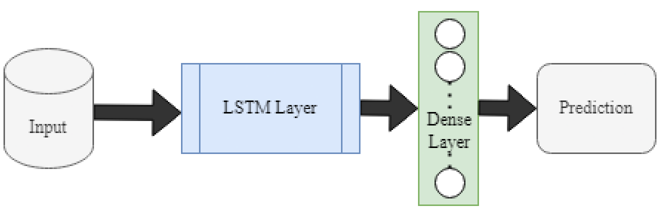


Figure 2. Long Short-Term Memory Network (LSTM) architecture employed in the analysis. LSTM layer contains 50 neurons, Dense Layer contains 1 neuron as output.

RESULTS

Wheat yield can be affected by many factors. Some of the main factors affecting wheat yield can be listed as weather conditions, soil quality, fertilization, diseases and pests. Indeed, weather conditions have a significant effect on wheat yield. Appropriate temperature, rainfall and sunlight affect the growth and yield of the wheat plant. Adverse weather conditions such as extreme heat, drought or heavy rainfall can reduce wheat yield. On the other hand, well-drained soils, appropriate pH level, the right nutrient content, and soils rich in organic matter support wheat plant growth. Soil salinity, acidity or unproductive soils can negatively affect wheat yield. Fertilization is another important factor. Using the right fertilizer can increase the growth and yield of the wheat plant. It is important to provide adequate amounts of essential nutrients such as nitrogen, phosphorus and potassium. In addition, deficiencies of other trace elements (e.g. zinc, iron) can affect wheat yield. Lastly, diseases affecting the wheat plant (eg rust, mildew) and pests (eg insects, nematodes) can cause yield loss. Therefore, appropriate agricultural practices and measures should be taken to control diseases and pests. Agricultural practices such as planting time, seeding density, irrigation methods and weed control can also affect wheat yield. Proper farming methods and timing can increase plant growth and yield in optimum conditions. These factors are the main factors affecting wheat yield, but this list is not complete. There are many other factors that affect wheat yield. In addition, other variables such as variety selection, genetic factors and agricultural technologies may also have an impact on wheat yield.

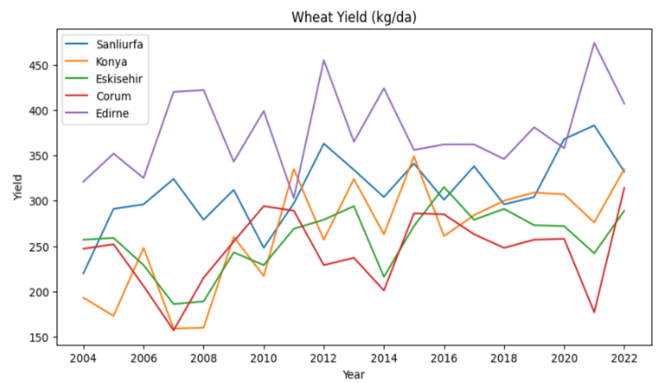


Figure 3. Wheat yield (kg/da) by major wheat producing cities in Turkiye. The top 5 provinces that produce the highest wheat product are determined by the production amounts recorded in 2022.

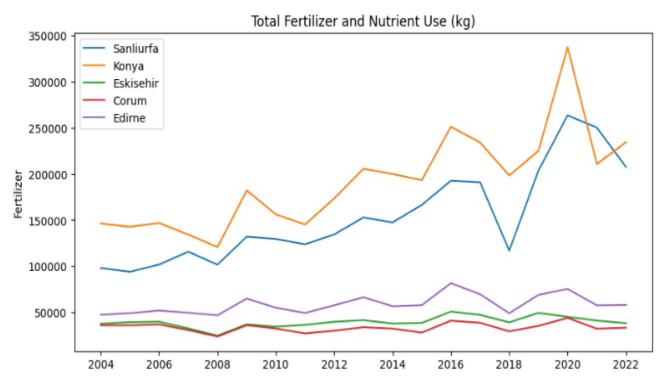
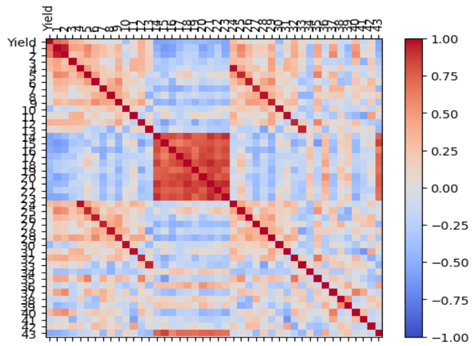


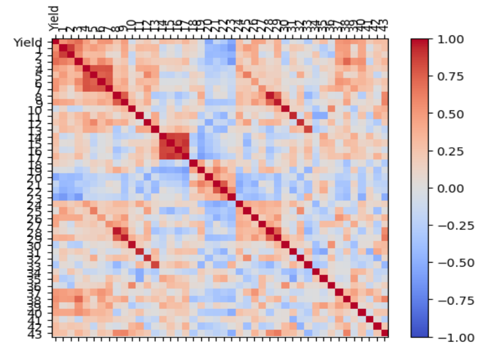
Figure 4. Fertilizer and plant nutrient use (kg) by major wheat producing cities in Turkiye. The total amount contains Nitrogenous (N), Phosphate (P_2O_2) and Potash (K_2O) usages.

Table 2. Correlation results between inputs and wheat yield by major wheat producing cities in Turkiye

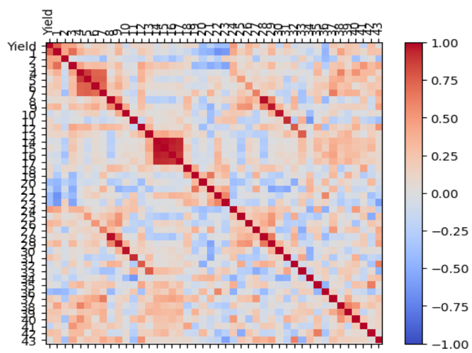
Şanlıurfa



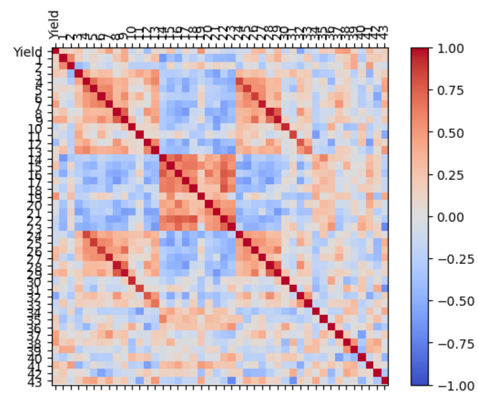
Konya



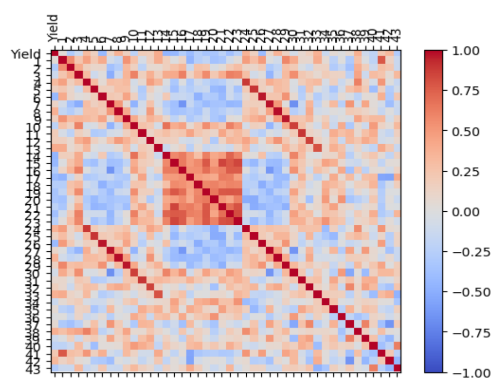
Eskişehir



Çorum



Edirne



The numbers 1 … 43 represent the meteorological and fertilization inputs. The correlation results change between -1 and 1. -1 indicates negative perfect correlation, while 1 indicates positive perfect correlation.

In top 5 wheat producing cities of Turkiye, wheat yield has demonstrated fluctuating and slowly increasing trend (Fig. 3) and there is no noteworthy spike in wheat yields.

Total amount of fertilizer usage increased in Sanliurfa and Konya provinces and it remained slightly the same in the other three provinces (Figure 4). Considering the Figure 3, wheat yield is lower in Konya and Sanliurfa in 2004 and becomes slightly higher than those in Corum and Eskisehir, which could be attributed to the increasing use of fertilizers.

The dataset curated for the study includes monthly observations between 2004 and 2022. As inputs, 43 variables including weather parameters, plant fertilizer and nutrients are used as input variables to forecast wheat yield in top 5 provinces in Turkiye. The correlations between input variables and yield are demonstrated in Table 1, in which the color is gray if there is no correlation between variables (when correlation is 0 or near 0), while the color is dark red if there is a perfect positive correlation and the color is dark blue if

Table 3. Prediction accuracy of models given by MAE, MSE and RMSE metrics

Models	Metrics	Şanlıurfa	Konya	Eskişehir	Çorum	Edirne
Auto Arima	MAE	0.46347	0.17063	0.37779	0.34611	0.37748
	MSE	0.45162	0.04028	0.17397	0.14276	0.20178
	RMSE	0.67202	0.20072	0.41710	0.37784	0.44920
CNN	MAE	0.29517	0.18750	0.27323	0.19638	0.34822
	MSE	0.12645	0.03518	0.08864	0.05203	0.22495
	RMSE	0.35560	0.18756	0.29772	0.22811	0.47429
LSTM	MAE	0.26276	0.18974	0.33034	0.22401	0.46094
	MSE	0.07551	0.05079	0.14233	0.10365	0.33445
	RMSE	0.27479	0.22538	0.37727	0.32195	0.57832
Random	MAE	0.38513	0.12879	0.21804	0.2916	0.27399
Forest	MSE	0.16715	0.02327	0.07153	0.12260	0.10563
	RMSE	0.40884	0.15256	0.26745	0.35015	0.32501

MAE: Mean Absolute Error, MSE: Mean Squared Error, RMSE: Root Mean Squared Error. The lower values indicate higher accuracy.

there is a perfect negative correlation between variables. Table indicated the high correlations among variables. However, correlation strength shows variety in cities. For instance, there is relatively higher correlation between yield and Nitrogen fertilizer usage in Eskisehir (0.74) and Sanliurfa (0.78) than Corum (0.26), Edirne (0.38) and Konya (0.52). And the correlation between yield and Phosphor and Potash fertilizers is higher in Konya (0.79-0.72) and Sanliurfa (0.73-0.74) than Eskisehir (0.54-0.53), Edirne (0.30-0.42) and Corum (0.21-0.33). It is also noteworthy that there is a positive correlation between yield and high average minimum and average temperature from September to February in all cities, while there is a negative correlation between yield and average wind speed in all months.

The statistical model Auto-Arima is applied using PmdArima python library. This method requires data to be stationary. For this purpose, Augmented Dickey-Fuller test is performed, and the non-stationary data series is differenced to establish stationarity. Furthermore, Min-Max Scaler is performed to standardize the variables to eliminate any bias that can be caused by the larger data series. The statistical (auto-arima), machine learning (Random Forest) and deep learning (CNN and LSTM) models are applied for each province, respectively. In order to evaluate the accuracy results of the models, Mean Absolute Error, Mean Squared Error and Root Mean Squared Error metrics are employed. The results of the evaluation metrics are given in Table 2.

DISCUSSION

Wheat is one of the most important cereal crops and the main food ingredient for most of the people in the world and it plays a crucial role in countries independence. Therefore, accurate prediction of the wheat yield is quite an important task for sustainable food security (Debelee *et al.*, 2023). Convolutional Neural Network has been used in comparison with several machine learning methods using various meteorological, soil and management practices. A single dimension CNN is reported to outperform Deep Neural Network and XGBoost algorithms (Srivastava *et al.*, 2022). In another study, multisource data is acquired to improve wheat yield prediction accuracy (Cao *et al.*, 2020). They employed monthly meteorological observations and satellite images on county level across China. Ridge Regression, Random Forest and Light Gradient Boosting are reported to achieve the highest accuracies with R-square between 0.68 and 0.75. However, all the studies have employed the rather conventional approaches using either climate or satellite data. They all lack the certain additional factors like socio-economic factors, irrigation conditions, fertilization and pesticide usages. For this reason, this study gathered the widest possible dataset for each provinces combining climate, fertilization and pesticide usages. The dataset is publicly open to researchers in a Github repository given in the material section.

The analysis results revealed that all models performed well in all provinces. Considering the three metrics (MAE, MSE, RMSE) the model performance is found relatively higher in Konya. However, no final decision can be concluded about which model should be preferred. For instance, LSTM performed better in Sanliurfa province compared to Corum, Edirne and Eskisehir. In general, it can be said that model performance tends to be better for Konya province. Random Forest ranked first by providing the lowest error rates in Konya (MAE: 0.12879, MSE: 0.02327, RMSE: 0.15256), which is consistent with the previous studies findings. This is followed by CNN prediction for Konya (MAE: 0.18750, MSE: 0.03518, RMSE: 0.18756), and Auto-Arima prediction (MAE: 0.17063, MSE: 0.04028, RMSE: 0.20072), for Konya provinces. It is noteworthy that all the highest prediction accuracies were obtained for Konya province, which can be attributed to the higher correlation among selected input variables and wheat yield for Konya province and Konya province has a long history in wheat production, known as granary of Turkey. The government gives higher subsidies for wheat production in this region of the country. It can be also concluded that wheat production in Konya is more prone to the effects of weather and fertilization compared to the other cities. The results indicate that wheat yield estimation is generally harder for Sanliurfa and Edirne provinces. Sanliurfa province is located in the southeast border of Turkey. This part of the country generally has arid soil and more prone to drought. The largest irrigation project was constructed in the region. However, local studies have reported that farmers in the region have shifted to more profitable products in irrigatable fields and wheat production is confined to the areas with harsh soil conditions (Cikman *et al.* 2017; TEPGE, 2022). On the other hand, Edirne is located in the northwest edge of Turkey and wheat production is mainly made in non-irrigated soils in the province. The winter rainfall directly affects wheat yield. And with climate change, rainfall amount greatly fluctuates from year to year, making it harder to predict the production amount and yield of wheat.

***Conclusion*:** In this study, a comparative analysis is made to predict wheat yield using statistical, machine learning and deep learning methods. The top 5 provinces that produce the highest amount of wheat are determined and wheat yield information is obtained from Turkish Statistical Institute. As input variables, monthly meteorological observations have been collected from the State Meteorological Services database. The selected variables cover the periods between September and July of 2004-2022. In addition, fertilizer usage amounts have been collected from the Ministry of Agriculture and Forestry for each province. The analysis results indicate that all models yield quite good prediction accuracy for each province. However, the models except from LSTM provided slightly better results for predicting wheat yield in Konya province. This can be attributed that wheat production is more prone to environment factors such as weather and fertilization, and therefore, higher wheat can be obtained if these parameters are given further importance. Models' performance varied in other provinces. For instance, LSTM performed well in Sanliurfa, Eskisehir and Edirne. But, in general, models tended to perform poorer in Edirne province. The curated dataset and model application codes are shared in a public github repository. Further studies can be implemented using more advanced architectures and other methods on the dataset.

***Conflict of interest*:** No potential conflict of interest was reported by the authors.

***Authors' Contribution Statement*:** Cevher Ozden curated, designed and implemented the analysis. Nurgul Karadogan reviewed the previous studies and wrote the discussion section.

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