MAUSAM, **74**, 3 (July 2023), 847-860

MAUSAM

DOI : https://doi.org/10.54302/mausam.v74i3.5598
Homepage: https://mausamjournal.imd.gov.in/index.php/MAUSAM

UDC No. 633.31 : 551.583 (560)

Estimation of Alfalfa (*Medicago sativa* L.) yield under RCP4.5 and RCP8.5 climate change projections with ANN in Turkey

MUHAMMET ALI PEKIN, NURDAN SAHIN DEMIRBAG*,

KHALID MAHMOOD KHAWAR and HALIT APAYDIN**

Research Department, Turkish State Meteorology Services, Ankara, Turkey

**Department of Field Crops, Faculty of Agriculture, Ankara University, Turkey*

***Department of Agricultural Engineering, Faculty of Agriculture, Ankara University, Turkey*

(*Received 23 June 2022, Accepted 12 December 2022*)

e mails : mapekin@mgm.gov.tr; nsahin@agri.ankara.edu.tr; bhatti@ankara.edu.tr; apaydin@ankara.edu.tr

सार — अल्फाल्फा दुनिया में सबसे व्यापक रूप से उगाई जाने वाली चारा फसलों में से एक है। अल्फाल्फा की खेती दुनिया भर में लगभग 35 **मिलियन हेक्टेयर भूमि पर की जाती है**, **जिसका वार्षिक उत्पादन** 255 **मिलियन टन है। अल्फाल्फा की खेती का औसत क्षेत्र लगभग** 637000 **हेक्टेयर है जिसमें से तुर्की में** 13 **मिलियन टन का उत्पादन और** 2200 **किग्राडीए**-1 **की उपज है। यह अपेक्षा की जाती है कि भविष्य में जलवायु परिवर्तन का इसके उत्पादन और उपज पर काफी प्रभाव पड़ेगा। इस अध्ययन का उद्देश्य** RCP4.5 **और** RCP8.5 **जलवायु परिवर्तन परिदृश्यों के अनुसार चयनित कृत्रिम तंत्रिका नेट वर्क** (ANN) **के माध्यम से अल्फाल्फा की उपज पर जलवायु परिवर्तन के प्रभाव का पूर्वानुमान करना है। इसलिए**, **सबसे पहले** 176 **विभिन्न एएनएन विकल्पों में से सर्वश्रेष्ठ एएनएन संरचना का चयन किया गया**, **जिसमें अल्फाल्फा उपज के पूर्वानुमान के लिए विभिन्न इनपुट पैरामीटर**, **सीखने की दर**, **क्षय और न्यूरॉन संख्याएं शामिल थीं। अध्ययन में प्रयुक्त एएनएन प्रशिक्षण/परीक्षण डाटासेट अल्फाल्फा की खेती के आँकड़ों**, **मिट्टी के मापदंडों और जलवायु संबंधी आँकड़ों से तैयार किया गया था। जलवायु परिवर्तन के अनुमानों** (HadGEM2-ES RCP4.5 **और** RCP8.5) **के अनुसार तुर्की के** 79 **प्रांतों में वर्ष** 2020-2060 **और** 2060-2100 **के लिए अल्फाल्फा उपज का अनुमान सर्वश्रेष्ठ** ANN **मॉडल का उपयोग करके लगाया गया है। एएनएन दृढ़ संकल्प के** 0.827 **गुणांक और** 0.813 **नैश-सटक्लिफ गुणांक के साथ अल्फाल्फा उपज की गणना करने में सक्षम था। यह ज्ञातव्य है कि अल्फाल्फा जलवायु परिवर्तन का प्रतिरोध कर सकता है और इसकी उपज उन क्षेत्रों में बढ़ती या घटती है**, **जहां जलवायु परिवर्तन के परिणामस्वरूप उसी क्रम में वर्षण में वृद्धि या कमी होती है। यह अनुमान लगाया गया है कि सबसे अधिक उपज वृद्धि आर्टविन** (6%) (**पूर्वी अनातोलिया क्षेत्र का एक प्रांत**) **में नोट की जाएगी और अधिकतम उपज में कमी सिएर्ट** (9%) (**दक्षिण पूर्वी अनातोलिया क्षेत्र का एक प्रांत**) **में नोट की जाएगी। इस शोध को अल्फाल्फा उपज अनुमान के लिए एक रचनात्मक पूर्वानुमान दृष्टिकोण माना जा सकता है।**

ABSTRACT. Alfalfa is one of the most widely cultivated forage crops in the world. Alfalfa farming is carried out on approximately 35 million ha of land worldwide with an annual production amounting to 255 million tons. The average alfalfa cultivated area is about 637000 ha with a production of 13 million tons and a yield of 2200 kgda^{-1} in Turkey. It is expected that climate change will have significantly different effects on its production and yield in the future. Therefore, the study aimed to predict the effect of climate change on the yield of alfalfa througha selected Artificial Neural Network (ANN) according to RCP4.5 and RCP8.5 climate change scenarios. Therefore, first of all, the best ANN structure among 176 different ANN alternatives consisting of various input parameters, learning rates, decay, and neuron numbers to predict alfalfa yield was selected. The ANN training/test dataset used in the study was composed of the alfalfa cultivation statistics, soil parameters and climatological data. Alfalfa yield for the years 2020-2060 and 2060-2100 in 79 provinces of Turkey is predicted by using the best ANN model, according to climate change projections (HadGEM2-ES RCP4.5 and RCP8.5). The ANN was able to calculate alfalfa yield with a 0.827 coefficient of determination and 0.813 Nash-Sutcliff coefficient. It is understood that the alfalfa can resist climate change and its yield tend to increase or decrease in regions, where there is an increase or decrease in precipitation in the same order as a result of climatic change. It is predicted that the highest yield increase will be noted in Artvin (6%) (a province of the Eastern Anatolia region) and the maximum yield decrease will be noted in Siirt (9%) (a province of the South Eastern Anatolia region). This research may be considered a creative prediction approach for the alfalfa yield estimation.

Key words – Forage farming, Meadows, Pastures, Artificial neural network, HadGEM2-ES, Time series, Plant growth model.

1. Introduction

Forage is provided from meadows, pastures and forage crops farming in Turkey; however, forage crop cultivation is insufficient, and their yield in meadows and pastures is low. Alfalfa and maize for silage constituted 54% of the cultivated area and 78% of the production during 2019. Forage needs are met largely with alfalfa farming (Karadas and Aksoy, 2019; Ozkan, 2020). About 33 million tons of forage is produced per annum in Turkey, which can meet just over one-half of the total needs (57 million tons) and is not able to meet the forage deficit. This results in an increase in the cost of beef and milk production at the national level (Alcicek *et al*., 2010; Ozkan and Sahin Demirbag, 2016; Eroglu *et al*., 2020). Alfalfa, silage corn, and oats are the most commonly farmed forage plants in Turkey (Kavut and Avcioglu, 2015; Tan and Yolcu, 2021).

Each plant has the minimum optimum climatic and soil conditions for its growth during the vegetation period. The alfalfa soil selectivity is low and develops better in deep, well-drained loamy-sandy soils with a sufficient amount of calcium, having a pH between 6.5 and 7.5. Alfalfa adaptation ability against varying climatic conditions is very strong and more than one harvesting can be taken in all vegetation periods. The growth of alfalfa slows down in periods when the air temperature reaches >30 °C and <10 °C with complete stoppage of growth occurring at temperatures <5 °C with optimum growth at ~ 25 °C. Adequate rainfall or irrigation evenly spread over the vegetation period increases yield and efficiency considerably. It can be cultivated without irrigation in regions with 350 to 450 mm of rainfall (MOE, 2012; Gokalp *et al*., 2017).

Yield prediction is to predict the crop yield and amount of production before harvesting (Simsek *et al*., 2007). The mathematical equation which expresses the plant's response to environmental factors is called the plant growth model and there are many plant growth models used for yield prediction. Crop growth models are divided into two subtitles empirical/corrective models and mathematical/explanatory models. Empirical/corrective models are simulated with only existing parameters, ignoring biological or physical effects and this approach is mostly used under stable conditions and could give good rapid estimates. Mathematical/explanatory models consist of mathematical equations which express the process of the crop growth stages. Plant growth is calculated across growing seasons with the weather, soil, and crop factors. These models are more efficient and this approach requires more detailed data analysis (Gowda *et al.*, 2013).

Thivierge *et al*. (2016) examined changes in alfalfa yield in Canada according to climate change scenarios (RCP4.5 and RCP8.5). They reported that the yield may increase in the first harvest, and decrease in the second harvest due to water and heat stress. He *et al*. (2019) simulated the change in alfalfa yield in Canada with the DeNitrification-DeComposition model and RCP4.5 and RCP8.5 scenarios. They reported that increased carbon dioxide, increased rainfall and prolonged development period may positively affect the yield. Alemeyahu *et al*. (2020) examined the impact of climate change on alfalfa cultivation in Ethiopia using precipitation and temperature projections of three models (CCSM4, HadGEM2-AO and MIROC5) in their study. They predicted that land suitable for alfalfa cultivation will expand, in dry regions or the plateaus where precipitation and temperature are expected to increase. Furthermore, they pointed out that the rainfall deficit would increase and consequently the land suitable for alfalfa production will shrink significantly. Yang *et al*. (2020) examined five different cropping systems (continuous maize, winter wheat, continuous lucerne, maize-wheat-soybean rotation, and lucerne (4-years)-winter wheat (2-years) rotation) with APSIM based model using RCP4.5 and RCP8.5 scenarios. When the results were compared with the initial simulation, it was predicted that there might be a 6.7-37.7% decrease in corn yield, 1.7-23.6% decrease in wheat yield, and a 7.2-12.3% increase in lucerne yield.

An artificial neural network (ANN) is a sub-branch of artificial intelligence and is one of the most used artificial intelligence methods. While biological neural networks consist of many biological nerve cells connected to each other, ANN consist of many artificial neural cells connected to each other. ANN is also defined as computer systems that can learn. It is used quite frequently in many engineering fields (Uzundurukan *et al*., 2019). The use of ANN in the agricultural field has increased considerably in recent years.

Ji *et al*. (2007) investigated the estimation of rice yield by the ANN method. Consequently, they estimated the rice yield as R= 0.67. They also reported that the ANN method is more successful than the linear regression method. Zhang *et al*. (2009) conducted a study with ANN and statistical models, on the prediction of soybean growth and development under wet conditions. It was concluded that the ANN model is quite successful and can be used as a plant growth model. Zaefizadeh *et al*. (2011) used regression and the ANN method to predict barley yield. They recommended that the ANN method is more successful and that it can be used in yield estimation studies. Guler *et al*. (2017) studied to estimate the import amounts of some oilseed plants with integrated ARIMA and ANN methods. When comparing the success of the two models in this study, it was seen that the ANN method was more successful. Adisa *et al.* (2019) conducted a study to estimate the corn yield in four different provinces of South Africa with the ANN method. Normalized Difference Vegetation Index, Potential Evapotranspiration, precipitation, minimum temperature, maximum temperature, soil moisture, and size of land cultivated for maize production variables were used as input parameters in this study to estimate the corn yield in these provinces with adjusted R between 0.86 and 0.67. Ser and Bati (2019) conducted a study to find out the best classification model in deep neural networks. The physical properties of the mushroom are used as input parameters, to determine its poisonous characteristics. They concluded that Nadam, Adam, and Rmsprop optimization methods showed better performance and ReLU was the most successful activation function. Another result reached in the study is that the algorithms showed different performances according to the nature of the problem and the parameters used. Khaki and Wang (2019) estimated corn yield using the deep neural network method. As a result, they managed to predict the yield with an 11% error. Zhang *et al.* (2019) conducted a study to detect wheat yellow rust disease by ANN and random forest classifier (ROS) methods from high-resolution unmanned aerial vehicle images. They found that the ANN method detected the disease with 0.85 and the ROS method with 0.77 correlation efficiency.

In both scenarios based on climate change projections (RCP4.5 and RCP8.5), it is expected to see an increase in the air temperature in Turkey. It has been reported that towards the end of the century, the temperature increase may reach 4 °C according to the RCP4.5 scenario and 6 °C according to the RCP8.5 scenario. According to precipitation projections, it was reported that the precipitation regime would remain irregular (Akcakaya *et al.*, 2015). With industrial development, population growth, and change in human behavioral habits, the impact of humans on the environment becomes more and more every year due to the rapid spread of technology. Climate change, especially global warming, creates an important agenda and uncertainty with this effect. With the development in the field of computer software and hardware, artificial intelligence techniques are being used frequently to reach high accuracy in the unknown or predict the future.

It aimed to create an artificial intelligence model by analyzing the effects of climatological, crop and soil parameters on alfalfa yield, and to estimate the alfalfa yield between 2020-2060 and 2060-2100 according to optimistic and pessimistic climate change projections (RCP4.5 and RCP8.5 scenarios).

TABLE 1

List of the observation stations

Observation stations					
Adana	Bayburt	Elazığ	Kayseri	Osmaniye	K. Maraş
Kilis	Bilecik	Sinop	Kırıkkale	Sakarya	Çanakkale
Kars	Bingöl	Niğde	Kırklareli	Samsun	Eskişehir
Ağrı	Bitlis	Uşak	Kırşehir	Sivas	Gaziantep
Aksaray	Bolu	Tokat	Adıyaman	Şanlıurfa	Hakkari
Amasya	Burdur	Giresun	Kocaeli	Şırnak	Karabük
Ankara	Bursa	Hatay	Balıkesir	Tekirdağ	Karaman
Antalya	Ordu	Iğdır	Kütahya	Trabzon	Erzincan
Konya	Çankırı	Isparta	Malatya	Tunceli	Erzurum
Artvin	Çorum	İstanbul	Manisa	Gümüşhane	
Aydın	Denizli	İzmir	Mersin	Yalova	
Muş	Siirt	Van	Muğla	Yozgat	
Bartın	Düzce	A.Karahisar	Nevşehir	Zonguldak	
Batman	Edirne	Kastamonu	Ardahan	Diyarbakır	

2. Materials and methods

2.1. *Study area and data*

Turkey is located in the temperate zone and surrounded by seas on three sides and has highly variable elevations and geographic formations at short distances. Air masses affecting Turkey vary according to the location. The frequency of these air masses is also variable. Turkey lies on the transaction of Europe-Siberia, Iran-Turan and the Mediterranean eco-geographical zones. This geographical diversity has led to wide climatological and biological diversity in Turkey (Yilmaz and Cicek, 2016).

There is about 25 million ha of agricultural land in Turkey. 67% of the land is used for growing field crops, 18% as fallow land, 3% for vegetable production area, and 12% as fruit. Grain is grown in 70% of the agricultural land, legumes make 5%, industrial crops and 8%, oilseeds in 7%, tubers in 1% and forage crops in 9%. alfalfa and corn silage most widely grown forage crops. Corn silage and alfalfa are the most widely grown forage crops and the forage needs of a large proportion (74%) are met by these plants. Alfalfa forage quality and yield are high. It is one of the most important forages for livestock production (Karadas and Aksoy, 2019; Ozkan, 2020; Ozguvan *et al.*, 2010).

The study was carried out in 79 out of 81 Turkish provinces; where alfalfa is cultivated widely. The meteorological data were obtained from the observatories of the Turkish State Meteorology Service (TSMS). The

TABLE 2

Statistical features of parameters used

Par.	Description	Unit	Mean	Std. Dev.	Min	Max
MT_1	Jan. mean temperature	°C	2.8	4.7	-14.2	13.1
MT_2	Feb. mean temperature	°C	4.8	5.0	-14.9	14.8
MT_3	Mar. mean temperature	°C	8.1	3.8	-7.9	17.6
MT_4	Apr. mean temperature	°C	12.6	3.2	4.0	20.5
MT_5	May. mean temperature	°C	17.3	2.9	9.4	25.1
MT_6	June mean temperature	°C	22.0	3.2	13.2	30.8
MT_7	July mean temperature	°C	24.6	2.8	15.7	33.4
MT_8	Aug. mean temperature	°C	24.9	2.7	15.8	32.8
MT_9	Sep. mean temperature	°C	21.1	3.1	10.4	28.9
MT_10	Oct. mean temperature	°C	15.1	3.6	5.0	25.1
MT_11	Nov. mean temperature	°C	9.4	4.3	-5.3	20.1
MT_12	Dec. mean temperature	°C	4.5	4.9	-13.5	14.7
MT_Y	Annual mean temperature	°C	13.9	3.2	4.1	21.1
T30D	Number of days T>30 C	Days	56.7	30.1	0.0	140.0
T5D	Number of days T<5 C	Days	118.6	55.5	0.0	232.0
PR_1	Jan. total precipitation	mm	91.7	72.0	0.0	556.7
PR_2	Feb. total precipitation	mm	59.7	49.0	0.0	336.6
PR_3	Mar. total precipitation	mm	64.8	41.3	0.0	335.9
PR_4	Apr. total precipitation	mm	54.0	40.7	0.0	383.4
PR_5	May. total precipitation	mm	60.9	35.8	0.0	218.4
PR_6	June total precipitation	mm	46.1	40.6	0.0	283.5
PR_7	July total precipitation	mm	17.7	27.4	0.0	183.8
PR_8	Aug. total precipitation	mm	17.9	30.7	0.0	269.8
PR_9	Sep. total precipitation	mm	26.7	37.4	0.0	280.6
PR_10	Oct. total precipitation	mm	62.8	55.7	0.0	396.6
PR_11	Nov. total precipitation	mm	45.9	41.4	0.0	276.2
PR_12	Dec. total precipitation	mm	84.9	74.8	0.0	503.5
PR_Y	Annual total precipitation	mm	633.1	258.6	162.4	1743.4
HGT	Station height	m	702.5	551.4	4.0	1827.0
LAT	Station latitude	Degree	39.3	1.5	36.2	42.0
LON	Station longitude	Degree	35.0	5.0	26.4	44.1
AWT_T_S	Area weighted topsoil carbon content	kg cm^{-2}	4.5	0.8	2.8	6.9
T_B_D	Topsoil bulk density	kg dm^{-3}	1.4	0.1	1.3	1.7
T_C	Topsoil carbon content	kg cm^{-2}	3.8	1.2	1.7	5.6
T_C_C	Cation exchange capacity of the clay fraction in the topsoil	cmol per kg	56.4	25.8	16.0	108.0
T_CLAY	Topsoil clay fraction	% weight	27.2	12.0	6.0	55.0
T_GRAVEL	Topsoil gravel content	% vol.	9.4	6.6	2.0	26.0
T_OC	Topsoil organic carbon	% weight	0.9	0.3	0.4	1.4
T_PH_H2O	Topsoil pH	-log(H+)	7.2	1.0	4.6	8.3
T_R_B	Topsoil reference bulk density	kg dm^{-3}	1.4	0.1	1.2	1.7
T_SAND	Topsoil sand fraction	% weight	39.8	13.6	16.0	83.0
T_SILT	Topsoil silt fraction	% weight	33.0	7.7	11.0	45.0
MY	Mean yield	kg da^{-1}	2666.1	1408.3	393.0	5740.5
MPT	Mean plantation	ha	82715.0	155868.0	612.3	941776.5
Y	Yield	kg da^{-1}	2664.0	1533.5	200.0	7908.0

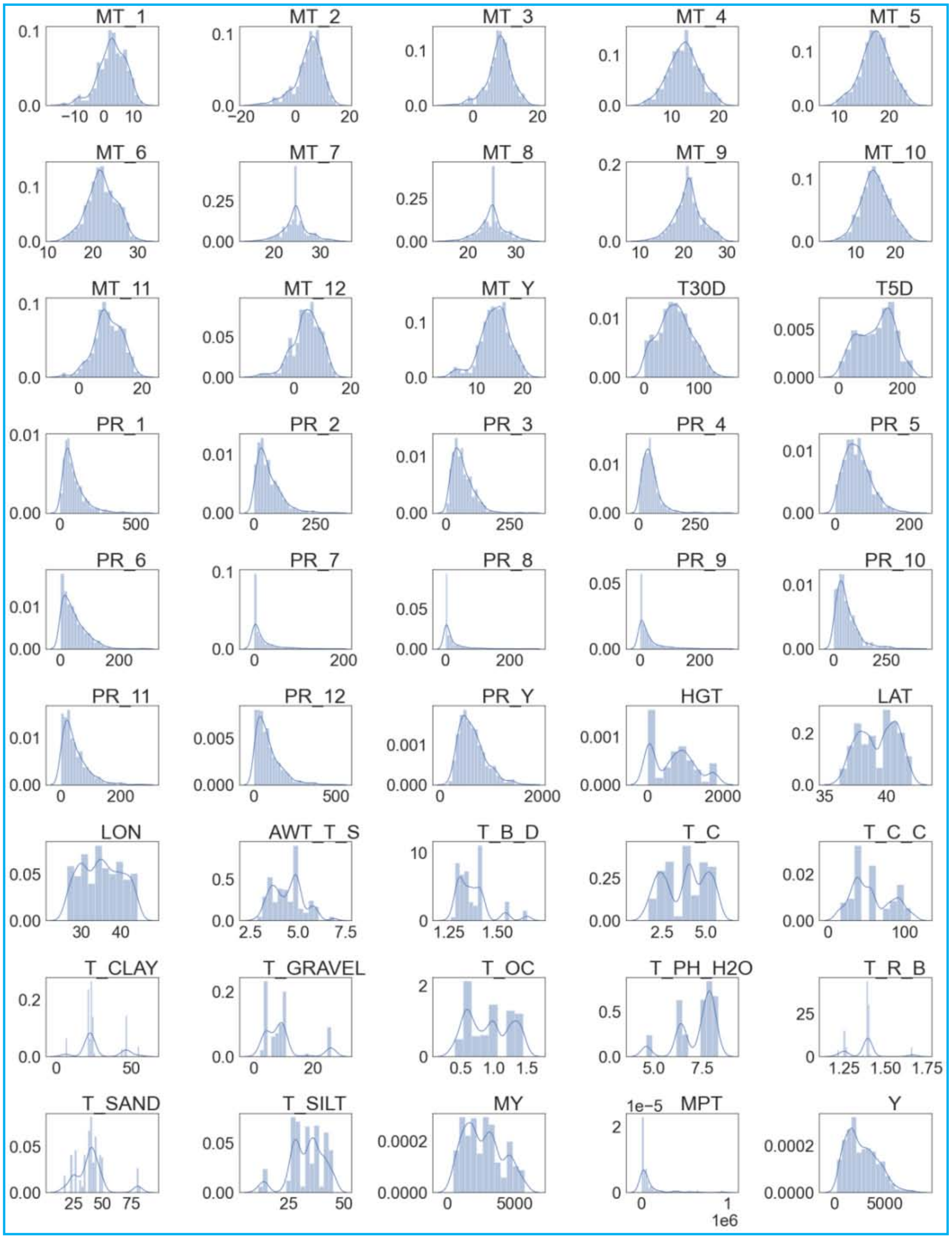

Fig. 1. Distribution of the parameters

locations of these observation stations are given in Table 1. Alfalfa cultivation statistics were obtained from the Turkish Statistical Institute (TSI). Soil data were extracted from the Regridded Harmonized World Soil Database v1.2 (RHWSD v1.2) which was distributed by "The Distributed Active Archive Center (DAAC)" (Wieder *et al.*, 2014).

Statistical features of parameters used in the ANN train/test section are given in Table 2 and the distribution of parameters is given in Fig. 1.

Alfalfa is a perennial plant. Meteorological conditions occurring throughout the year can affect its yield. Therefore, the average temperature and

TABLE 3

Representative Concentration Pathways (RCPs) were used in this study (Demircan *et al*., 2017a; IPCC, 2007; TSMS 2015)

Name of RCP's	Radiative Forcing	Time	Pathway Shape	Concentration	Emissions
RCP 8.5	>8.5 Wm^{-2}	in 2100	Rising	> ~1370 ppm at 2100	rising continues until 2100
min	2	2000-2100		350	7
max	8.5			1400	28
RCP 4.5	~4.5 W m^{-2}	at stabilization after 2100	stabilization without overshoot	~ 650 ppm (stabilization after 2100)	A decline from the mid-century
min	2	2000-2100		350	7
max	4.5			570	11

precipitation parameters for twelve months of the year were included in the study. When the air temperature rises above 30 °C and falls below 5 °C, the clover stops growing. Artificial data (pertaining to T30D and T5D) expressing this situation was included in the study for perfection. Alfalfa has little soil selectivity and some properties of the soil can be controlled by cultural techniques. On the other hand, it is known that the roots of alfalfa develop better in neutral, deep, and silt soils. Soil variables related to these conditions were also included in the study. Sunshine duration and altitude are other factors known to affect plant growth. Latitude, longitude, and station height variables are also included in the study to express these conditions (Gokalp *et al*., 2017; MOE, 2012).

As seen in Fig. 1, mean temperature (MT) and precipitation (PR) parameters in this study show normal distribution but others parameters (Soil and location) do not show a similar trend. Normally distributed data are not essential for artificial intelligence studies, but they can provide good results in classification studies (Sattari *et al*., 2020).

An expert meeting was held in 2007 by the World Meteorological Organization and IPCC to reveal the climate change scenarios. In this meeting, it was decided to create climate change data sets according to 4 representative emission/concentration scenarios (RCPs) (IPCC 2007). RCPs are used in the study were given in Table 3.

Hadley Global Environmental Models (HadGEM2) consists of a series of models developed by the Hadley Institute affiliated with the UK Meteorology Service. The HadGEM2-ES model is a 2nd generation global climate model in this model family and is the most comprehensive model in the HadGEM2 series. With the HadGEM2-ES model, climate projections can be made on a global scale according to emission/concentration scenarios (Akçakaya *et al*., 2015). Regional Climate Model System (RegCM) was developed by the American National Center for Atmospheric Research. RegCM-4.3 has been adapted as a regional climate model by the Department of Earth System Physics of the International Abdusselam Theoretical Physics Center. With this model, regional products can be prepared from global model outputs up to 10 km resolution (hydrostatic limit) (Akcakaya *et al*., 2015). TSMS started a study in 2011 to determine the possible adverse effects of climate change. For this purpose, TSMS conducted a dynamic downscaling study on global model outputs (HadGEM2-ES, MPI-ESM-MR, GFDL-ESM2M) based IPCC emissions/concentrations scenarios (RCP4.5 and RCP8.5). The dynamic downscaling process was done with RegCM the -4.3.4 model and 20 km resolution products were prepared. In this project, the period 1971-2000 has been taken as the reference period and a climate change projection has been made until 2100 (Akçakaya *et al*., 2015). The Intergovernmental Panel on Climate Change (IPCC) (2007) reported that the eastern Mediterranean basin will be one of the regions that will be most affected by climate change. Turkey is located in the eastern Mediterranean basin. The annual average temperature rises in Turkey; between 1.0 °C –and 2.0 °C for the period 2016-2040. It is foreseen to be between 1.5 °C - 4.0 °C for the period 2041-2070 and 1.5 °C - 5 °C for the last period 2071-2099. Instead of increasing and decreasing the amount of precipitation, it is predicted that the regime will be irregular (Demircan *et al*., 2017b). Agriculture is one of the sectors that is expected to be the most affected by climate change.

In the last section of the study, alfalfa yield change was predicted with the help of climate projection parameters produced by TSMS from HadGEM2-ES global model RCP4.5 and RCP8.5 output, and ANN.

2.2. *Methods*

The relationship between the variables used in the study and alfalfa green yield was measured by correlation analysis (R). In order to predict the change in alfalfa green yield, an ANN model was created and trained using measured alfalfa green yield, climatological data and modeled soil data. Different evaluation criteria were used to determine the best model and parameters. With the selected ANN model, based on the RCP4.5 and RCP8.5 climate change scenarios, alfalfa green yield was predicted for the periods of 2020-2060 and 2060-2100, and the changes in yield were revealed by comparing with the reference period (1971-2000).

2.2.1. *Artificial neural network (ANN)*

ANN is a sub-branch of AI and is one of the most used artificial intelligence applications. While biological neural networks consist of many biological nerve cells connected to each other, ANN consists of many artificial nerve cells connected to each other. ANN is also defined as learning computer systems. It is used quite frequently in many engineering fields (Uzundurukan *et al*., 2019). ANNs consist of three layers. These layers are input, hidden and output layers, respectively. The input layer is the layer where the data enters the ANN, the hidden layer is the layer where the data is processed, and the output layer is the layer where the model provides the outputs predicted. The number of neurons and the number of hidden layers are selected according to the problem in ANNs. They are generally determined by trial and error (Apaydin *et al*., 2020).

In ANNs input vectors (X1...Xn) and weights (W1...Wn) are used. Input vectors are multiplied by a weight, and then they are accumulated with bias. Finally, output (Y) is obtained by applying the activation function. ReLU, Sigmoid, and Soft max activation functions are the most used (Apaydin *et al*., 2020). In the study ReLU, (Equation 1) was used as an activation function.

$$f(y) = \begin{cases} 0, & y < 0 \\ y, & y \geq 0 \end{cases} \qquad (1)$$

It has to be trained for the proper working of the ANN model. First, the error values are obtained by comparing the results obtained during the training phase with the training data set. The optimization function is used to minimize these error values. In the study, the Adam optimization function is used. Adam is a successful optimization method and is also used in deep learning applications (Ser and Bati, 2019).

2.2.2. *ANN scenarios*

Determining the optimum input features and hyperparameters in ANN models is the most difficult and time consuming step. Running the model with optimum values allows for determining the best estimate. Following hyperparameter alternatives were used in the study: Two hidden layers with 100-50 and 200-100 neurons, 150 and 300 epochs, 1×10^{-3} and 1×10^{-4} learning rate (LR), 0.01 and 0.001 decay. Therefore, different alternative ANN structures were created according to the trial-error approach in the study.

In the study, input scenarios were created according to the climate and soil demands of alfalfa. The measurement of meteorological and soil parameters may be difficult and costly. So, it is naturally desirable to predict alfalfa yield with a minimum number of parameters. In the first scenario, all the features used in the study were included. The next ten scenarios were created with different features according to the climate and soil requirements of the alfalfa. ANN was trained with alternative hyper-parameters in all of the scenarios created and results were obtained. In total, 176 alternatives were tested to obtain the best ANN structure to predict alfalfa yield.

2.2.3. *Evaluation metrics*

The relationship between the train/test data with alfalfa yield was measured by correlation analysis (Equation 2).

$$R = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \qquad (2)$$

Coefficient of determination (R²), Nash-Sutcliff coefficient (NS), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used to evaluate the ANN model and these metrics are presented in Equations 3 to 6.

$$R^2 = \frac{n\left(\sum xy\right) - \left(\sum x\right)\left(\sum y\right)}{\sqrt{\left(n\sum x^2 - \left(\sum x\right)^2\right)\left(n\sum y^2 - \left(\sum y\right)^2\right)}} \qquad (3)$$

$$\mathrm{NS} = 1 - \frac{\sum (x_i - y_i)^2}{\sum (x_i - \bar{x})^2} \qquad (4)$$

$$\mathrm{MAPE} = \frac{1}{n} \sum \frac{|x - y|}{|x|} * 100 \qquad (5)$$

TABLE 4

Correlation coefficients of the variables in the training data set with alfalfa yield

Parameter	R	Parameter	R	Parameter	R
MT_1	0.216	PR_1	0.127	AWT_T_S	-0.092
MT_2	0.274	PR_2	0.067	T_B_D	0.025
MT_3	0.270	PR_3	-0.065	T_C	-0.219
MT_4	0.217	PR_4	-0.142	T_C_C	0.124
MT_5	0.236	PR_5	-0.205	T_CLAY	-0.189
MT_6	0.158	PR_6	0.001	T_GRAVEL	0.103
MT_7	0.194	PR_7	-0.158	T_OC	-0.213
MT_8	0.188	PR_8	-0.120	T_PH_H2O	0.105
MT_9	0.155	PR_9	-0.087	T_R_B	0.200
MT_10	0.128	PR_10	-0.044	T_SAND	0.207
MT_11	0.186	PR_11	-0.026	T_SILT	-0.071
MT_12	0.183	PR_12	0.014	MY	0.916
MT_Y	0.237	PR_Y	-0.066	MPT	-0.147
T30D	0.214	LAT	-0.141	HGT	-0.268
T5D	-0.148	LON	-0.498		

$$\text{RMSE} = \sqrt{\frac{\sum (y-x)^2}{n}} \quad (6)$$

Where x is the observation value, $\bar{x}$ is the mean observation value, y is the prediction parameter and n is the number of instances.

A closer R^2 value to 1 represents better performance. RMSE is one of the most useful evaluation metrics for ANN study. Closer RMSE values to 0 show better performance. According to Chiew *et al*. (1993), 0.90<NS represents that prediction is very acceptable; 0.90>NS>0.60 prediction is acceptable and 0.60>NS prediction is unacceptable. MAPE is one of the most popular ANN evaluation metrics. MAPE<10 represents highly accurate forecasting, 10<MAPE<20 is good forecasting, 20<MAPE<50 is reasonable forecasting, and MAPE>50 is weak forecasting (Hsu *et al*., 2008). R^2 and RMSE were considered as the main evaluation criteria in the study.

2.2.4. *Software's used*

Open source software and codes were used in this study. Descriptive statistics for input parameters were calculated with Jasp 0.14. Soil parameters were extracted from the RHWSD v1.2 database with the code written in NCL 6.4.0 programming language. The ANN model is coded with Python 3.8.0 programming language and Keras library. The success statistics of the ANN model were calculated with the codes written with Python's Scikit-learn and Hydro Eval libraries. The graphics were drawn with codes written in Python's Matplotlib library.

3. Results and discussion

3.1. *Initial analyses*

The correlation coefficients calculated in the training data set are given in Table 4 to reveal the relationship between environmental conditions and alfalfa yield statistically. According to Table 4, all of the correlations between monthly and yearly mean air temperatures (MT) and yield (Y) are positive. The correlations between January-June MT parameters and yield are higher than the correlation between July and later months. When the correlations between MT parameters and alfalfa yield were examined, the highest positive correlation was seen with MT_2 (R=0.274). It is seen that the correlation of T30D variable is positively contrary to expectations. The correlation of the T5D variable is negative. When the correlations between precipitation variables (PR) and yield were analyzed, positive correlations were observed

TABLE 5

Evaluation scores of the best performing models for every scenario

Alt.	InputSce.	Neron	Epoch	Lr	Decay	R^2 Train	R^2 Test	NS Train	NS Test	MAPE Train	MAPE Test	RMSE Train	RMSE Test
8	S1	100-50	300	$1x10^{-3}$	0.01	0.847	0.82	0.817	0.809	15.53	16.35	597.21	660.10
20	S2	100-50	150	$1x10^{-3}$	0.01	0.844	0.823	0.813	0.812	15.82	16.25	601.30	654.65
38	S3	100-50	300	$1x10^{-4}$	0.01	0.842	0.825	0.805	0.808	16.56	16.00	605.66	650.20
54*	S4	100-50	300	$1x10^{-4}$	0.01	0.834	0.827	0.758	0.777	20.33	19.23	620.57	647.21
78	S5	200-100	300	$1x10^{-4}$	0.01	0.827	0.822	0.751	0.774	21.03	18.98	632.28	655.79
94	S6	200-100	300	$1x10^{-4}$	0.01	0.834	0.823	0.780	0.796	19.04	17.17	621.17	653.12
102*	S7	200-100	300	$1x10^{-4}$	0.01	0.843	0.822	0.815	0.813	16.19	16.21	603.19	656.22
110*	S7	100-50	300	$1x10^{-4}$	0.01	0.841	0.827	0.798	0.807	17.31	16.41	608.52	646.29
122*	S8	100-50	150	$1x10^{-4}$	0.01	0.841	0.826	0.794	0.804	17.99	16.94	608.36	647.59
135	S9	200-100	300	$1x10^{-3}$	0.001	-0.011	-0.02	-4.046	-4.362	58.01	56.55	1533.11	1569.73
154*	S10	100-50	150	$1x10^{-4}$	0.01	0.831	0.827	0.755	0.782	20.53	18.48	626.47	646.48
163	S11	200-100	150	$1x10^{-3}$	0.001	-0.169	-0.189	-3.466	-4.211	62.17	60.13	1648.03	1694.66

* Most successful 5 models

with the months of January, February, June and December, while the others were negative in contrast to the expected. The correlations between precipitation and alfalfa yield is quite low. The correlation between alfalfa yield and longitude was calculated as -0.498 and the correlation with altitude as -0.268. When the correlations between soil variables and yield were examined, a positive and more significant correlation was observed with the T_SAND (0.207) and T_R_B (0.200) parameters. The correlations between the variables (T_C, T_OC) related to the carbon content of the soil and the yield were measured negatively. The correlation between average alfalfa yield (MY) and yield is quite high as expected.

3.2. *ANN results*

65% (492 rows) of the created data were selected as training data set, 15% (122 rows) as validation, and 20% (153 rows) as test data set. Evaluation scores of the best performing models of each input scenario which were obtained from combinations of different input parameters, epoch, learning rate, decay and neuron number are given in Table 5. Loss and scatter graphs are given in Fig. 2 for the top five models.

As the number of epochs increased, the amount of error decreased and similarly, the amount of validation error decreased in all 5 scenarios. The training and validation error curves become parallel to each other and flattened with the completion of the learning process. It is understood that the model estimation shows good regression with observed values according to the scatter graph.

Time series graphs are given in Fig. 3. According to time series graphs, it appears that the models are good at predicting the direction of change in alfalfa yield.

There was no significant difference in the success of these five models according to these results, however, “Alternative 154” can be said to be more useful than other models since fewer input parameters are used. “Alternative 154” can explain 83% of the data set variation (R^2 = 0.827) and also this model is in the "prediction acceptable" class according to the NS coefficient and in the "good prediction" class according to MAPE. Therefore, the next processes were carried out with this model.

3.3. *Alfalfa yield change prediction*

It is expected to increase the air temperature in Turkey in both scenarios based on climate change projections (RCP4.5 and RCP8.5). It has been reported that towards the end of the century, the temperature increase may reach 4°C according to the RCP4.5 scenario and 6°C according to the RCP8.5 scenario. According to precipitation projections, it has been reported that the

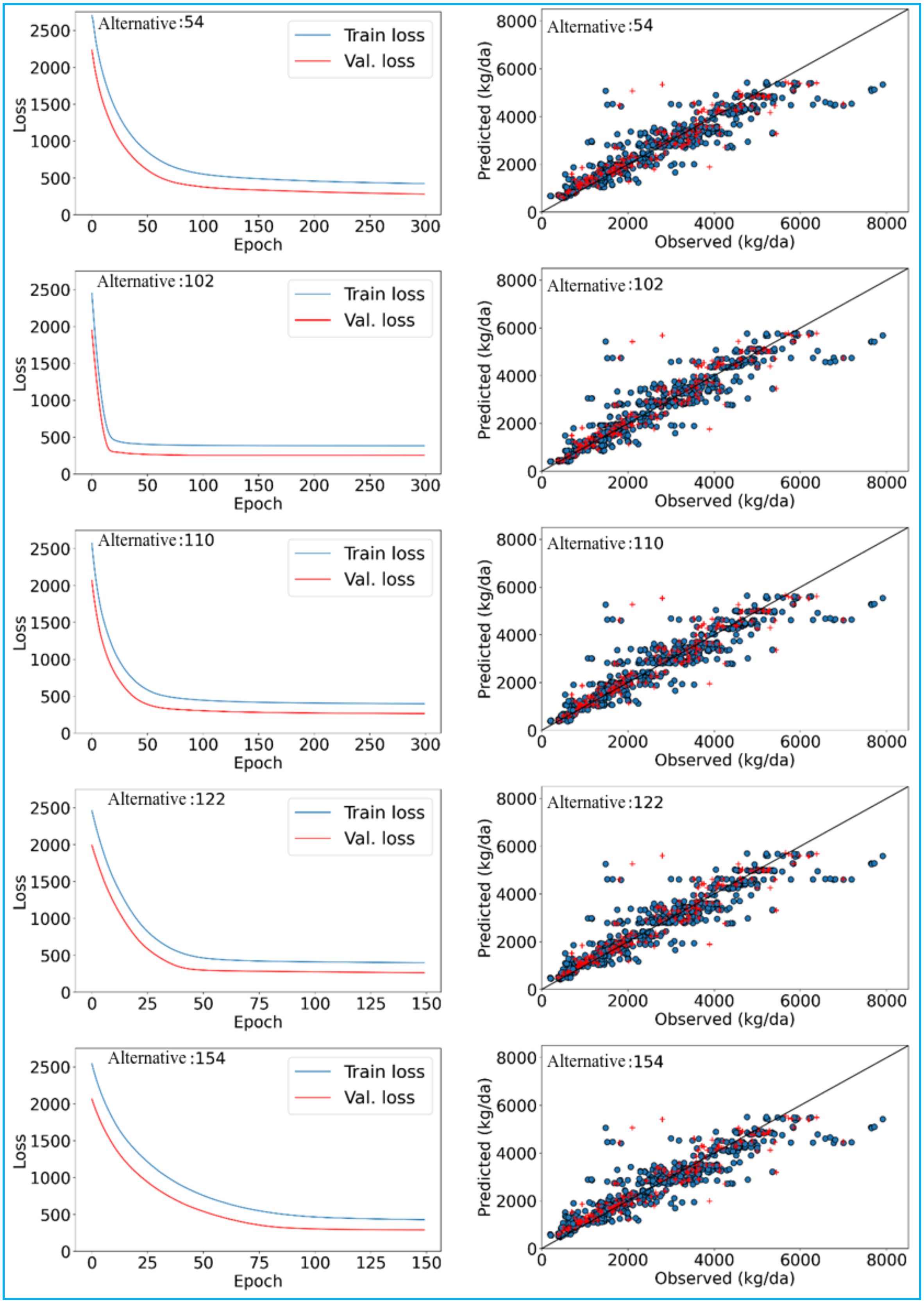

Fig. 2. Loss and scatter graphs of top five models

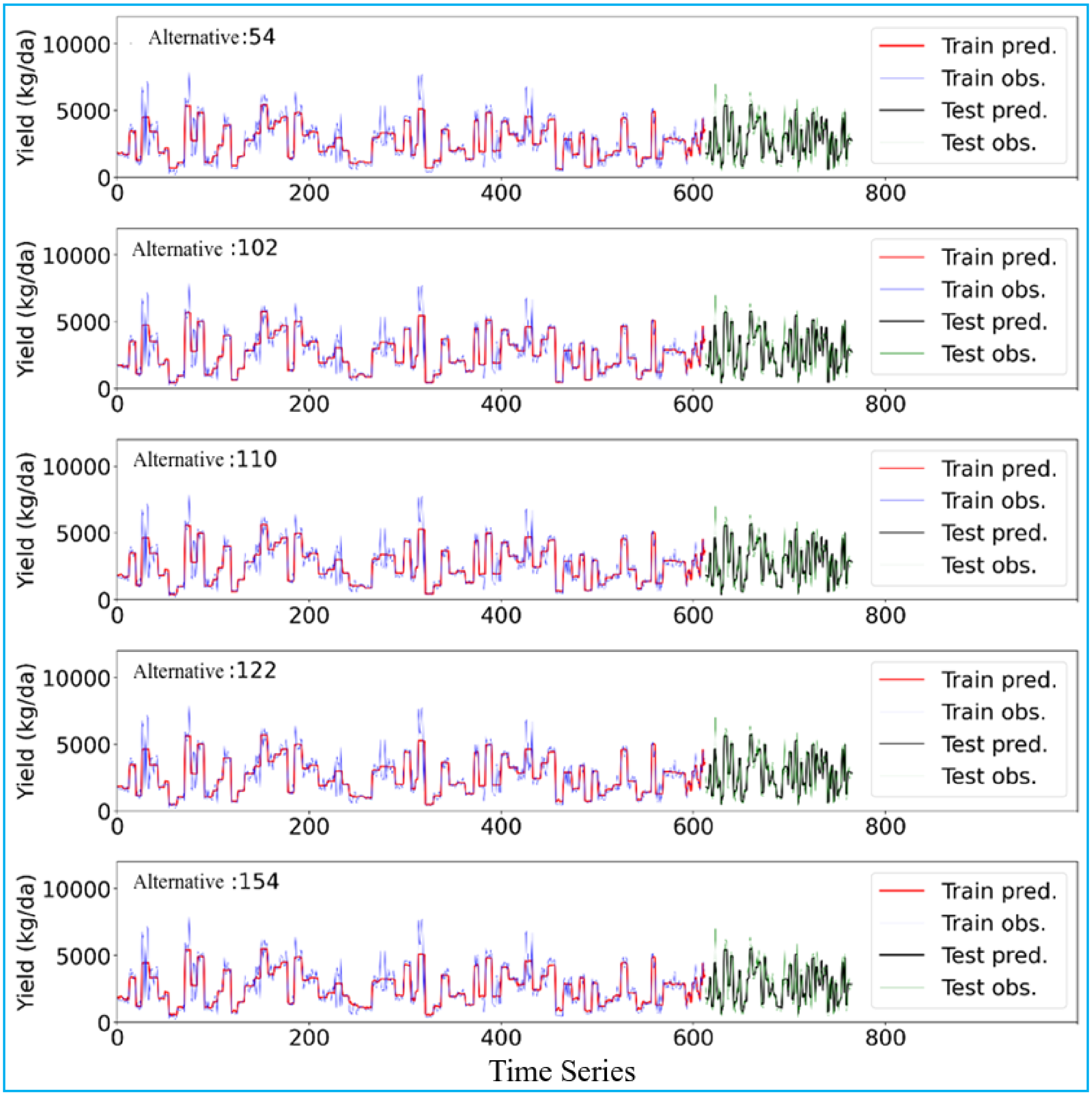

Fig. 3. Time series graphs

rainfall regime will become irregular rather than a decreasing trend in both scenarios. It is predicted that there may be great differences, especially when examined seasonally (Akçakaya *et al*., 2015).

Alfalfa yield was predicted *via* “Alternative 154”. Therefore, alfalfa yields for the reference period (1979-2000) of 79 provinces within the scope of the study were calculated. In the second stage, alfalfa yield changes were estimated with both RCP4.5 and RCP8.5 climate projections for the periods 2020-2060 and 2060-2100 of the 79 provinces within the scope of the study. These alfalfa yield projections were compared to the reference period yield in terms of the percentage change.

Alfalfa yield changes are given in Table 6. When these results are evaluated together with the climate change projections, it is understood that there may be an increase in productivity in the provinces where a significant increase in precipitation is predicted, and there may be a decrease in the yield in the provinces where a significant decrease in precipitation is predicted. Changes in the alfalfa yield of the majority of Turkey are estimated to be less than 1%.

TABLE 6

Alfalfa yield changes (%)

Provinces	Ref.Y	RCP4.5	RCP8.5	RCP4.5	RCP8.5	Provinces	Ref.Y	RCP4.5	RCP8.5	RCP4.5	RCP8.5
		2020-2060		2060-2100				2020-2060		2060-2100	
Adana	1809	0.254	0.276	0.102	0.652	A.Karahisar	3335	0.001	0.026	-0.134	-0.139
Kilis	4232	-0.104	-0.032	-0.233	-0.251	Kastamonu	1126	-0.031	0.541	1.164	1.691
Kars	595	1.798	3.793	4.002	5.949	Kayseri	3534	-0.139	-0.075	-0.239	-0.249
Ağrı	1184	0.449	1.073	0.792	1.374	Kırıkkale	1896	0.006	0.460	0.213	0.305
Aksaray	4453	-0.033	0.101	-0.083	-0.081	Kırklareli	2047	0.218	0.116	0.291	0.380
Amasya	3337	-0.038	0.223	0.091	0.322	Kırşehir	1301	-0.347	0.121	-0.414	-0.079
Ankara	1785	-0.314	0.095	-0.256	-0.199	Adıyaman	1700	-0.981	-0.725	-1.809	-1.672
Antalya	2710	3.427	-0.886	-3.139	-3.767	Kocaeli	1859	0.361	0.010	0.127	0.643
Konya	4800	-0.021	0.119	0.058	-0.108	Balıkesir	2692	0.405	0.427	0.332	0.477
Artvin	1377	1.112	2.813	4.080	3.927	Kütahya	1897	0.025	0.063	-0.063	-0.031
Aydın	5428	0.384	0.292	0.200	0.190	Malatya	4116	-0.087	0.016	-0.235	-0.224
Muş	2417	-0.147	0.072	-0.044	-0.086	Manisa	3190	0.605	0.511	0.446	0.395
Bartın	4828	0.473	0.616	0.885	0.860	Mersin	2683	0.467	0.793	0.616	0.906
Batman	1170	-2.252	-2.794	-2.983	-3.176	Muğla	4648	0.758	0.070	0.137	-0.172
Bayburt	1572	0.063	0.162	0.563	0.083	Nevşehir	3482	-0.103	0.033	-0.154	-0.055
Bilecik	2346	0.255	0.214	0.416	0.214	Ardahan	763	0.047	3.574	5.031	4.411
Bingöl	3901	-0.406	-0.073	-0.399	-0.523	Osmaniye	3238	-1.756	-1.155	-2.278	-2.334
Bitlis	774	0.111	0.257	-0.283	-0.443	Sakarya	1620	0.423	0.231	0.332	0.679
Bolu	1566	-0.680	-0.743	-0.050	0.088	Samsun	3388	-0.688	-0.321	-0.744	-0.538
Burdur	2733	-0.033	-0.210	-0.463	-0.651	Sivas	1203	-0.751	-0.193	-0.779	-0.448
Bursa	3249	0.134	0.245	0.069	0.303	Şanlıurfa	1604	-0.831	-0.609	-1.228	-1.032
Ordu	812	-3.247	-0.681	-2.358	-3.723	Şırnak	1966	-1.127	-0.829	-1.018	-1.509
Çankırı	3568	-0.020	0.136	0.125	0.256	Tekirdağ	4432	0.861	0.569	0.622	0.825
Çorum	4097	0.062	0.249	0.155	0.380	Trabzon	1225	-2.571	1.271	0.767	-3.081
Denizli	4437	0.129	0.096	-0.024	-0.113	Tunceli	1516	-0.950	0.297	-1.697	-1.969
Siirt	954	-6.550	-5.791	-6.798	-8.847	Gümüşhane	1187	-0.638	-0.187	1.012	0.021
Düzce	4827	0.038	0.099	0.148	0.305	Yalova	2916	0.386	0.183	0.024	0.117
Edirne	3090	0.340	0.165	0.372	0.392	Yozgat	2826	-0.300	-0.062	-0.385	-0.234
Elazığ	3387	-0.284	-0.190	-0.526	-0.562	Zonguldak	2736	0.428	0.628	0.794	0.967
Sinop	2899	0.082	0.767	0.550	1.209	Diyarbakır	1378	-0.564	-0.665	-0.996	-0.890
Niğde	4271	-0.182	0.033	-0.155	-0.236	K.Maraş	1674	-1.051	-0.873	-1.510	-1.523
Uşak	4838	0.008	-0.073	-0.218	-0.331	Çanakkale	5630	0.518	0.480	0.533	0.279
Tokat	2225	-0.083	0.289	0.225	0.469	Eskişehir	2918	0.118	0.190	0.241	0.122
Giresun	1444	-4.953	-2.082	-3.569	-5.653	Gaziantep	1990	-0.718	-0.802	-1.207	-1.534
Hatay	3365	-0.974	0.236	-0.940	-2.575	Hakkari	1004	-1.291	-1.361	-1.086	-1.358
Iğdır	3263	0.105	0.217	0.260	0.454	Karabük	2365	-0.039	0.329	0.693	0.754
Isparta	3213	0.036	-0.102	-0.379	-0.493	Karaman	5079	-0.039	0.018	-0.111	-0.188
İstanbul	1988	2.644	1.619	2.007	2.641	Erzincan	1868	0.013	0.287	0.186	0.147
İzmir	4339	0.500	0.630	0.471	0.302	Erzurum	2214	0.007	0.236	0.070	0.081
Van	1289	0.886	0.396	0.368	0.426						

4. Conclusion

A novel approach to predicting future alfalfa yield based on climate change and ANN is presented in the study. The relationship between the factors of alfalfa cultivated area, average alfalfa yield, climate (28 parameters), soil (11 parameters), and location (3 parameters) with alfalfa yield was analyzed by correlation analysis first for this purpose. The highest correlation with yield was measured with Lon (-0.498), HGT (-0.266) and MY (0.916) parameters. When the correlation of soil and climate parameters is examined, the correlation between mean air temperature and efficiency is more obvious.

In the second phase, to find the best ANN structure that can predict alfalfa yield, 176 different ANN alternatives consisting of, various input parameters, learning rates, decay, and neuron numbers were tested. ANNs were formed in two hidden layers. ANN was able to predict the yield of alfalfa with the highest test scores of R^2=0.827, NS=0.813, MAPE=16.00 and RMSE=646.29 according to the results obtained. It can be said that ANN can be used as a successful yield estimation model.

In the last phase, alfalfa yield changes were estimated according to RCP4.5 and RCP8.5 scenarios. It is predicted that there may be a yield decrease in regions where precipitation decrease is expected according to the results, there may be a yield increase in regions where precipitation increase is expected, and in large parts of Turkey limited yield change is predicted rather.

Acknowledgments

We would like to thank TSMS for meteorological data, TSI for alfalfa data, DAAC for soil data. The article was developed from the MSc thesis of Muhammet Ali PEKİN.

Authors' contributions : Conceptualization, NSD, and MAP; Data curation, MAP; Formal analysis, MAP; Investigation, MAP, NSD, and HA; Methodology, MAP, HA and KMK; Project administration, NSD; Software, MAP; Supervision, NSD, and HA; Validation, MAP and HA; Visualization, MAP; Writing, MAP, NSD, HA and KMK; Technical-English evaluation, KMK. All authors have read and agreed to the published version of the manuscript.

Funding : This research received no external funding.

Conflict of interest : The authors declare no conflict of interest.

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

References

Adisa, O. M., Botai, J. O., Adeola, A. M., Hassen, A., Botai, C. M., Darkey, D. and Tesfamariam, E., 2019, "Application of Artificial Neural Network for Predicting Maize Production in South Africa", *Sustainability*, **11**, 4, 1145. doi : https://doi.org/10.3390/su11041145.

Akcakaya, A., Sumer, U. M., Demircan, M., Demir, O., Atay, H., Eskioglu, O., Gurkan, H., Yazici, B., Kocaturk, A., Sensoy, S., Boluk, E., Arabaci, H., Acar, Y., Ekici, M., Yagan, S. and Cukurcayir, F., 2015, "Turkey's climate projections and climate change with new scenarios", TR2015-CC. General Directorate of Meteorology, p149. Ankara.

Alcicek, A., Kilic, A., Ayhan, V. and Ozdogan, M., 2010, "Forage production and problems in Turkey", Turkey Agricultural Engineering VII. Technical Congress, 11-15 January, Ankara.

Alemayehu, S., Ayana, E. K., Dil, Y. T., Demissie, T., Yimam, Y., Girvetz, E., Aynekulu, E., Solomon, D. and Worqlul, A. W., 2020, "Evaluating Land Suitability and Potential Climate Change Impacts on Alfalfa (Medicago sativa) Production in Ethiopia", *Atmosphere*, **11**, 10, 1124. doi : https://doi.org/10.3390/atmos11101124.

Apaydin, H., Feiz, H., Sattar, M. T., Colak, M. S., Shamshirband, S. and Chau, K., 2020, "Comparative Analysis of Recurrent Neural Network Architectures for Reservoir Inflow Forecasting", *Water*, **12**, 150. doi : https://doi.org/10.3390/w12051500.

Chiew, F., Stewardson, M. J. and Mc Mohan, T., 1993, "Comparison of Six Rainfall-runoff modelling approaches", *J. Hyrdrol*., **147**, 1-36. doi : https://doi.org/10.1016/0022-1694(93)90073-I.

Demiïrcan, M., Gurkan, H., Eskiïoglu, O., Arabaci, H. and Coskun, M., 2017a, "Climate Change Projections for Turkey : Three Models and Two Scenarios", *Turkish Journal of Water Science and Management*, **1**, 1, 22-43. doi : 10.31807/tjwsm.297183.

Demircan, M., Turkoglu, N. and Cicek, I., 2017b, "Climate Change: From Model to Sectorial Applications (in Turkish)", In: Proceeding of the International Congress on 75th Anniversary of Turkish Geography Society; Ankara, Turkey, 147-162.

Eroglu, E. N., Bozoglu, M. and Bilgiïc, A., 2020, "The Impact of Livestock Supports on Production and Income of the Beef Cattle Farms : A Case of Samsun Province, Turkey", *Journal of Agricultural Sciences*, **26**, 1, 117-129. doi : 10.15832/ankutbd.487493.

Gowda, Y. P., Satyareddi, S., Manjunatha, S. B., 2013, "Crop Growth Modelling : A Review", *Research and Reviews : Journal of Agriculture and Allied Sciences*, **2**, 1.

Gokalp, S., Yazici, L., Cankaya, N. and İspirli, K., 2017, "Determination of Forage Yield and Quality Performance of Some Alfalfa (*Medicago sativa* L.) Cultivars in Tokat-Kazova Ecological Conditions",*Journal of Agricultural Faculty of Gazi Osman Paşa University*, **34**, 3, 114-127. doi : 10.13002/jafag4332.

Guler, D., Saner, G. and Naseri, Z., 2017, "Forecasting of Import Quantities of Oil Seed Plants by ARIMA and Neural Networks Methods", *Balkan and Near Eastern Journal of Social Sciences*, **3**, 1, 60-70.

He, W., Grant, B., Smith, W., Vander Zaag, A., Piquette, S., Qian, B., Jing, Q., Rennie, T., Bélanger, G., Jégo, G. and Deen, B., 2019, "Assessing alfalfa production under historical and future climate in eastern Canada: DNDC model development and application", *Environ. Model. Softw*., **122**. doi : https://doi.org/10.1016/j.envsoft.2019.104540.

Hsu, L. and Wang, C. I., 2008, "Applied multivariate forecasting model to tourism industry", *Tourism : An International Interdisciplinary Journal*, **56**, 2, 159-172. Preuzeto s https://hrcak.srce.hr/36609.

IPCC, 2007, Climate Change 2007 - The Physical Science Basis Contribution of Working Group I to the Fourth Assessment Report of the IPCC.

Ji, B., Sun, Y., Yang, S. and Wan, J., 2007,"Artificial neural networks for rice yield prediction in mountainous regions", *Journal of Agricultural Science*, **145**, 249-261. doi : 10.1017/S0021859606006691.

Kara, H., Donmez Sahin, M. and Ay, S., 2010, "The Effect of Climate Changes on Agricultural Products in Usak Province", *BIBED*, **3**, 1, 39-46.

Karadas, K. and Aksoy, E., 2019, "Alfalfa Production and Economic Importance in Iğdır Province", In : Proceeding of the 2nd International Zeugma Conference on Scientific Researches; Gaziantep, Turkey, 334-343.

Kavut, Y. and Avcioglu, R., 2015, "Yield and quality performances of various alfalfa (*Medicago Sativa* l.) cultivars in different soil textures in a mediterranean environment", *Turkish Journal of Field Crops*, **20**, 1, 65-71. doi : 10.17557/.04500.

Khaki, S. and Wang, L., 2019, "Crop Yield Prediction Using Deep Neural Networks", *Front. Plant Sci*., **10**, 621. doi : 10.3389/fpls.2019.00621.

MOE, 2012, "Forage crop cultivation (621bhy125)", Turkish Ministry of National Education, p60, Ankara.

Ozkan, U. and Sahin Demirbağ, N., 2016, "Status Quo of Quality Roughage Resources in Turkey", *Turkish Journal of Scientific Reviews*, **9**, 1, 23-27.

Ozkan, U., 2020, "Comparative Overview and Evaluation of Turkey's Forage Crops Agriculture", *Turkish Journal of Agricultural Engineering Research (TURKAGER)*, **1**, 1, 29-43.

Ozguven, M. M., Turker, U. and Beyaz, A., 2010, "Agricultural Structure and Mechanization Level of Turkey", *GOU Journal of the Faculty of Agriculture*, **27**, 2, 89-100.

Sattari, M.T., Apaydin, H. and Shamshirband, S., 2020, "Performance Evaluation of Deep Learning-Based Gated Recurrent Units (GRUs) and Tree-Based Models for Estimating ETo by Using Limited Meteorological Variables", *Mathematics*, **8**, 6, 972. doi: https://doi.org/10.3390/math8060972.

Ser, G. and Bati, C. T., 2019, "Determining the Best Model with Deep Neural Networks: Keras Application on Mushroom Data", *YYU Journal of Agricultural Science*, **29**, 3, 406-417. doi : 10.29133/yyutbd.505086.

Simsek, O., Mermer, A., Yildiz, H., Ozaydin, K. A. and Cakmak, B., 2007, "Estimation of Wheat Yield for Turkey Using Agro Met Shell Model", *Journal of Agricultural Sciences*, **13**, 3, 299-307. doi : 10.1501/Tarimbil_0000000552.

Uzundurukan, S. and Saplioglu, K., 2019, "Investigation of Artificial Intelligence Applications and Trends Used in Scientific Studies", *DUMF Journal of Engineering*, **10**, 1, 249-262. doi : https://doi.org/10.24012/dumf.394591.

Tan, M. and Yolcu, H., 2021, "Current Status of Forage Crops Cultivation and Strategies for the Future in Turkey : A Review", *Journal of Agricultural Sciences*, **27**, 2, 114-121. doi : 10.15832/ankutbd.903732.

Thivierge, M. N., Jégo, G., Bélanger, G., Tremblay, G., Rotz, C. A. and Qian, B., 2016, "Predicted Yield and Nutritive Value of an Alfalfa-Timothy Mixture under Climate Change and Elevated Atmospheric Carbon Dioxide", *Agronomy Journal*, **108**, 1-19. doi : 10.2134/agronj2015.0484.

TSMS, 2015, "Climate Projections and Climate Change in Turkey with New Scenarios", Ankara, Turkey.

Wieder, W. R., Boehnert, J., Bonan, G. B. and Langseth, M., 2014, "Regridded Harmonized World Soil Database v1.2.Data set", Available on-line [http://daac.ornl.gov] from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, USA. doi : http://dx.doi.org/10.3334/ORNLDAAC/1247

Yang, X., Li, Z., Cui, S., Cao, Q., Deng, J., Lai, X. and Shen, Y., 2020, "Cropping system productivity and evapotranspiration in the semiarid Loess Plateau of China under future temperature and precipitation changes: An APSIM-based analysis of rotational vs. continuous systems", *Agricultural Water Management*, 229, 105959. doi : https://doi.org/10.1016/j.agwat.2019.105959.

Yilmaz, E. and Cicek, I., 2016, "Thornthwaite Climate Classification of Turkey", *Journal of Human Science*, **13**, 3, 3973-3994.

Zaefizadeh, M., Jalili, A., Khayatnezhad, M., Gholaminand, R. and Mokhtari, T., 2011, "Comparison of Multiple Linear Regressions (MLR) and Artificial Neural Network (ANN) in Predicting The Yield Using Its Components in The Hulless Barley", *Advances in Environmental Biology*, 109.

Zhang, J., Zhang, L., Zhang, M. and Watson, C., 2009, "Prediction of Soybean Growth and Development Using Artificial Neural Network And Statistical Models", *ActaAgronomicaSinica*, **35**, 2, 341-347. doi : https://doi.org/10.1016/S1875-2780(08)60064-4.

Zhang, X., Han, L., Dong, Y., Shi, Y., Huang, W., Han, L., González-Moreno, P., Ma, H., Ye, H. and Sobeih, T., 2019, "A Deep Learning-Based Approach For Automated Yellow Rust Disease Detection From High-Resolution Hyperspectral UAV Images", *Remote Sensing*, **11**, 1554, 1-16. doi : https://doi.org/10.3390/rs11131554.