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Crop water use estimation of drip irrigated walnut using ANN and ANFIS models

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RESUMEN

Los nogales, así como sus frutos, representan un sector importante de la industria agrícola y su cultivo contribuye significativamente a la economía global. Hay muchos problemas relacionados con el riego, que es un factor clave en el cultivo de la nuez. El más importante está relacionado con la estimación precisa de la necesidad de agua de riego. En este estudio, el uso de agua de nuez se estimó a través de dos métodos de inteligencia artificial: redes neuronales artificiales (ANN, por su sigla en inglés) y el sistema de inferencia neuro-difusa adaptativa (ANFIS), utilizando los datos meteorológicos del oeste de Turquía, que tiene condiciones climáticas semiáridas. Los modelos ANN y ANFIS se aplicaron mediante escenarios probables de datos meteorológicos disponibles que incluyen temperatura máxima, mínima y media, velocidad del viento y horas de sol para los años 2016-2019, y se evaluó su desempeño para estimar la evapotranspiración de la nuez. Los resultados indican que el rendimiento óptimo de los modelos se observa en el cuarto escenario con R = 0.90 y dos parámetros climáticos, a saber, duración de la luz solar y temperatura media para los modelos ANN y ANFIS, respectivamente. Ambos modelos pudieron predecir el uso de agua de los cultivos con alta correlación y el menor número de parámetros climáticos. Sin embargo, se encontró que el poder predictivo del modelo ANFIS era mayor, con el MSE más pequeño (0.36 para entrenamiento y 0.29 para pruebas), en comparación con el modelo ANN.

ABSTRACT

Walnut trees, as well as their fruits, represent an important sector of the agricultural industry and their cultivation significantly contributes to the global economy. Irrigation is a key factor in walnut cultivation and its most important problem is related to accurately estimating the need for irrigation water. Walnut water use was estimated in this study through artificial intelligence methods, namely artificial neural networks (ANN) and the adaptive neuro-fuzzy inference system (ANFIS) using meteorological data in western Turkey, which has semi-arid climatic conditions. Probabilistic scenarios based on maximum, minimum and average temperature, wind speed and sunshine hours over the period 2016-2019 were developed and tested with ANN and ANFIS to estimate walnut evapotranspiration. Results indicate that the optimum performance in the training and testing for ANN and ANFIS was obtained from the fourth scenario with R = 0.95 and two climate parameters: sunshine duration and mean temperature. Both ANN and ANFIS were able to predict crop water use obtaining a high correlation and the minimum number of climatic parameters. Nevertheless, the ANFIS model had a higher predictive capacity, with smaller MSE (0.36 for training and 0.29 for testing) compared to the ANN model.

Keywords: artificial intelligence, data analysis, evapotranspiration, semi-arid climate, irrigation.

1. Introduction

Due to its high economic value, walnut cultivation has been steadily increasing across the world in recent years, with about 1.3 million ha and an average yield of 4.5 million t. Turkey ranks third in the world due to its annual walnut production of nearly 225 000 t (FAO, 2019). Walnut trees can easily adapt to various soil and climate conditions. Walnuts require cool enough weather in winter and autumn to satisfy the need for cooling and a temperature of 25-35 ºC in spring and summer, which is enough to support normal growth and maturing. Although it takes a long time to grow, walnut is one of the most widespread fruit species in the world, with a cooling requirement of 400-1800 h. In general, walnut trees adapt more easily to valleys that are sun-drenched in the summer and moderately warm in winter, protected from the wind. In certain regions, late frosts in the spring are among the most important factors which cause inefficiency in walnut trees.

Irrigation and the correct choice and application of the irrigation method are too among the most important factors. A total minimum annual precipitation of 500 mm is sufficient for walnut cultivation; however, it is of great importance that the precipitation is regular. Especially in the summer, there should be enough water and humidity in the soil. According to many studies that have examined crop yield response to irrigation of walnut trees, their annual water demand is around 750-1500 mm (Goldhamer et al., 1982, 1984; Fulton et al., 2003; Chauvin et al., 2005; FAO, 2012; Goldhamer and Beede, 2015). There are many studies about irrigation modernization, as well as various irrigation project designs (Fukui et al., 1980; Andrade and Allen, 1999; Ortega et al., 2004; Rocamora et al., 2013; Zapata et al., 2013). The topics of drip irrigation and the quality of irrigation water for good crop production were studied by Ayers and Wescott (1985), Grattan et al. (2004), Master et al. (2007), Díaz and Grattan (2009).

The estimation of walnut crop evapotranspiration (ET) is of great relevance for improved water management, especially in arid and semi-arid regions where irrigation is needed to stabilize and increase agricultural production. ET is a vital variable for hydrological and agrometeorological studies and, particularly, for the optimization of water use in agricultural crop cultivation. A particular attention is given to the estimation of crop evapotranspiration (ET_c) in arid and semi-arid regions, under water scarcity, and when crops are exposed to different kinds of abiotic stress (water, salinity, etc.). However, modeling ET_c is a complex process due to its non-linear structure and the intricate relationship between meteorological and crop parameters. Moreover, the measurements of crop ET are tedious and prone to errors due to difficulties in adequately considering numerous factors that affect the uniformity and stability of the soil-plant-atmosphere continuum (Allen et al., 2011). Consequently, the investigation of the most appropriate and accurate methodology for ET estimation remains a priority topic for the planning and management of water resources, on-farm irrigation scheduling, crop growth simulations, and climate change studies. There are different methods and techniques for measuring or estimating ET. Each of them has advantages and disadvantages based on their usage and data requirements. Many researchers have investigated the direct and indirect measurement of ET using lysimeters and other tools; however, this is a time consuming and expensive method (Campbell and Norman, 1998; Dinpashoh, 2006; Ali and Shui, 2009; Ding et al., 2010; Abyaneh et al., 2011; Aghajanloo et al., 2013; Jovanovic et al., 2018).

The Penman-Monteith (PM) equation is one of the most widely used methods to assess reference grass evapotranspiration (ET_o) based on weather variables. It is recommended by the Food and Agriculture Organization (FAO) of the United Nations as a standard method (FAOPM) for ET_o estimation (Allen et al., 1998). This method was tested against many other equations under different climatic conditions and for various time steps adopted for ET estimation (Todorovic, 2006; Pereira et al., 2015).

There are some alternative machine learning techniques that can be used for ET estimation as more economical and less time-consuming methodologies. However, these methods are difficult to develop due to the non-linear dynamic complexity of the ET process, which depends on the interaction of several meteorological and crop variables (Martí and Gasque, 2010; Traore et al., 2010). Moreover, the accuracy of ET estimation by mathematical approaches depends on the number of available meteorological parameters, as well as the quality of measured input data. Since the beginning of this century, machine learning algorithms have been increasingly applied in modeling ET (Kumar et al., 2002, 2011; Trajkovic et al., 2003; Pal and Deswal, 2009; Martí and Gasque, 2010; Kisi et al., 2015; Yassin et al., 2016; Mattar, 2018; Mehdizadeh, 2018; Sattari et al., 2020). Antonopoulos and Antonopoulos (2017) studied the estimation of daily ET_0 using artificial neural networks (ANN) and empirical methods in northern Greece. Their results demonstrated that the application of ANN yielded a satisfactory performance (Kisi, 2016; Dou and Yang, 2018). Tabari et al. (2013) studied the adaptive neuro-fuzzy inference system (ANFIS) and support vector machines (SVM) for modeling potato ET_c in northwest Iran. The results demonstrated that the ANFIS and SVM techniques simulated better potato ET_c than all empirical methods.

This study was aimed at identifying the best model to estimate crop-walnut ET based on scenarios including meteorological data and to compare it with a well-known and frequently used method.

2. Materials and methods

2.1 Study site

The study was performed in the walnut orchards in the district of Gölcük, Kocaeli, Western Turkey (40º 43' 36.5" N 29º 48' 23.8" E) as shown in Figure 1. All the orchards where walnuts were cultivated had been set up according to the cultivators' own knowledge and experience. While some of the orchards were set up on the plain, others were set up on high lands within the forest, approximately 500-800 masl. The district is under the influence of the Black Sea climate, but it also exhibits the semi-arid climate properties of the Marmara region. When average climatic values measured throughout many years (1950-2015) are studied, it is seen that the average temperature is 23.8 ºC, while the highest average temperature has been measured in July as 29.6 ºC. The lowest average temperature has been measured in January as 3.3 ºC. The average number of rainy days has a maximum of 17.4 in January and a minimum of 5.2 in August. The annual average rainfall in the region is 768 mm. Total monthly precipitation has been recorded to be highest in December, with an average of 110.0 kg m^{-2}, and lowest in July, with an average of 37.1 kg m^{-2} (TSMS, 2017). The four-year climate data of the region used in the models were obtained from the General Directorate of Meteorological Service.

The local walnut species cultivated in the research area are Şebin and Bilecik, while Chandler and Pikan are the foreign species that provide high efficiency

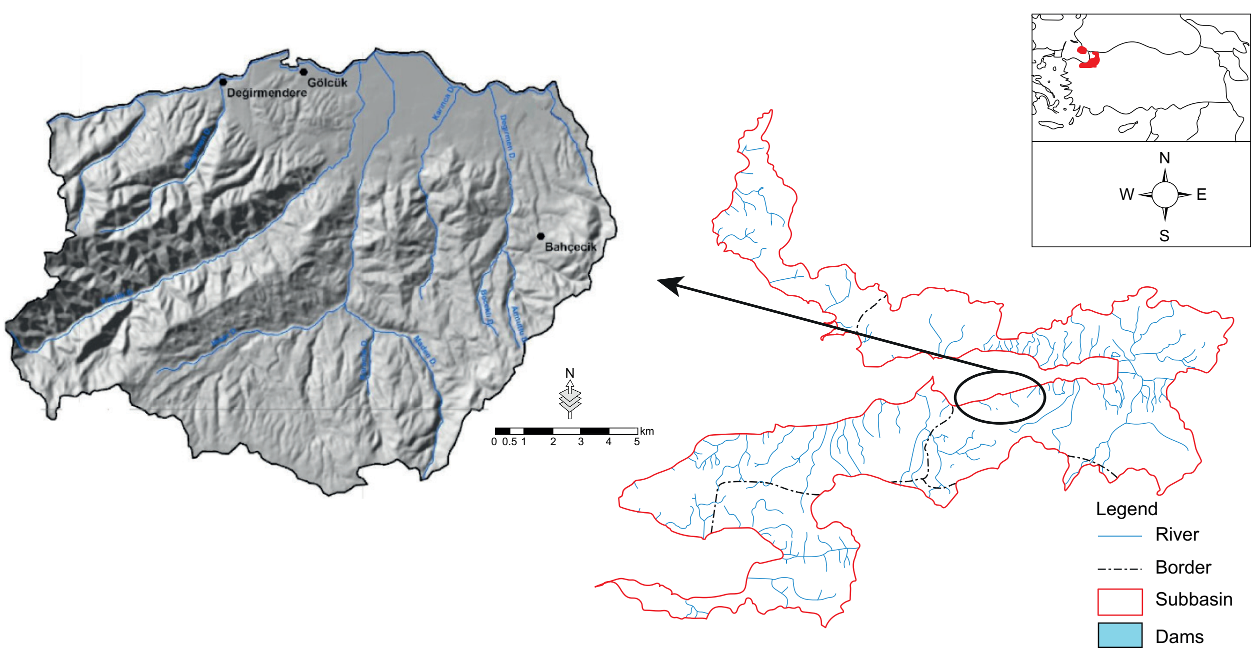

Fig. 1. Study area in the Marmara Region of Turkey.

and high-quality full fruits inside thin shells, thus yielding high income. The walnut orchards in the research area vary between 5 and 10 ha in size. The young trees in the orchards are generally planted within 9 × 9 and 10 × 10 m spaces.

All the information that was needed for the planning of the irrigation system, the sizing of the system elements, and the configuration and operation of the system were obtained through terrain analyses. Following these efforts, the drip irrigation project was prepared and set up in the orchard. The drip irrigation system consisted of the water source, pumping unit, control unit, pipelines and drippers. Irrigation water was filtered taking care not to clog the drippers and then mixed with the necessary nutrients. After the pressure and flow rate checks, it was distributed to the research plots. The control unit was made up of a fertilizer tank, a strainer filter and manometers for pressure control. Soil samples were taken and analyzed according to Blake (1965) and Benami and Diskin (1965). The soil texture was measured with a hydrometer as explained in Bouyoucos (1962). Irrigation water quality analyses were performed in the laboratory, in accordance with USDA (1954). The actual value of infiltration rate was identified (Criddle et al., 1956) by double ring infiltrometer measurements.

2.2 Data collection, description and analysis

The raw data set (Table I) to be used in the model includes the parameters of maximum, minimum and average temperatures (T_{max}, T_{min} and T_{avg}, respectively), wind speed (u_2) and sunshine hours (n). The reference dataset in this study was the calibrated climate data from regional weather stations for the period 2016-2019, provided by the Turkish State Meteorological Service (TSMS, 2022). The averages of annual temperature, wind speed, and the sunshine duration recorded between the first and last frost dates were 20.50 ºC, 1.92 m s^{-1}, and 6.9 h, respectively, while the highest values of maximum and minimum temperatures were 40.7 and 31.9 ºC, and the lowest values 12 and 2.5 ºC. The extreme values for all meteorological parameters were observed during these years. Therefore, the raw data set was subjected to quality control by removing 5% of noisy data from the data set.

The reference evapotranspiration was calculated based on the PM-FAO method in Eq. (1), using meteorological data (Allen et al., 1998).

$$ET_0 = \frac{0.408\,\Delta\left(R_n - G\right) + \gamma \frac{900}{T+273} u_2 \left(e_s - e_a\right)}{\Delta + \gamma\left(1 + 0.34\, u_2\right)} \tag{1}$$

where ETo is the reference ET (mm d^{-1}), Rn is the net radiation (MJ m^{-2} d^{-1}), G is the soil heat flux density (MJ m^{-2} d^{-1}), T is the mean daily air temperature (ºC), Δ is the slope of the saturation vapor pressure function (kPa $ºC^{-1}$), γ is the psychometric constant (kPa $ºC^{-1}$), e_s is saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), and u_2 is the mean daily wind speed (m s^{-1}).

The crop evapotranspiration is calculated by multiplying the reference crop evapotranspiration by a walnut crop coefficient and described as:

Table I. Ranges of the raw dataset based on statistic terms across the study region for 2016-2019.

Parameters	Data statistics				Units
	Maximum	Minimum	Mean	SD	
T_{avg}	32.7	6.6	20.5	5.058	ºC
n	12.8	0.0	7.0	3.769	h
T_{max}	40.7	12.0	26.8	5.706	ºC
T_{min}	31.9	2.5	15.8	5.002	ºC
u_2	4.6	1.1	1.9	0.432	m s^{-1}
ET_c	7.9	0.5	3.7	2.059	mm day^{-1}

SD: Standard deviation.

$$ET_c = ET_0 \, k_c \tag{2}$$

where ET_c is the crop evapotranspiration (mm d^{-1}), k_c is the crop coefficient (dimensionless), and ET_0 is the reference crop evapotranspiration (mm d^{-1}).

The growing season was observed regularly in the field throughout the study period from the first frost on April 15 to the last frost on November 10. During this period, four major growing stages were distinguished as the initial, crop development, mid-season and late season stages. Accordingly, the corresponding K_c values were adopted from investigations by the General Directorate of Agricultural Research and Policies for a specific region in Kocaeli as K_{cini} = 0.41, K_{cmid} = 1.17 and K_{cend} = 0.77.

The data were normalized from 0 to 1 based on Eq. (3) to ensure they remained within a certain range and the statistical distribution was uniform when scaling.

$$X' = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{3}$$

where X_i is raw data, X_{min} is the minimum value of X, X_{max} is the maximum value of X, and Y is the standardized data value.

2.3 Probabilistic scenarios

The ReliefF feature selection algorithm, which is a filter feature selection method modified by Kira and Rendell (1992), was used to filter the data and sort them according to their weight values between –1 (worst) and +1 (best). The processing procedure was repeated for each attribute and the weight value of each attribute was calculated at the end (Köksal, 2020; Sattari et al., 2021). A series of probabilistic scenarios based on ReliefF results were created to be used in the artificial intelligence models. Matlab R2016a was used to implement ANN and ANFIS models and Weka 3.9.4 modules were used to implement ReliefF.

2.4 Artificial intelligence methods

2.4.1 Artificial neural networks

An ANN model was created for each probabilistic scenario obtained from the ReliefF algorithm. Once the probabilistic scenarios were created as model input, the entire dataset was randomly split. The reason for the random division of the data was the increase and decrease of climatological parameters during the development period (Yu et al., 2020; Pandey and Pandey, 2020). Different percentages of data sets (training, validation, and testing) were applied at a rate from 75 to 85% for training, 0 to 10% for validation, and 15 to 20% for testing in each ANN model. There is no specific and accepted methodology for the network architecture created to determine the best performance of ANN (Wu et al., 2014; Antonopoulos et al., 2015). Therefore, neuron numbers were determined by trial and error for the best performance in all probabilistic scenarios. The performance of each model was evaluated according to R^2 and MSE (Sagi and Jain, 2020; Adeloye et al., 2012), and the best scenario was selected.

2.4.2 Adaptive neuro-fuzzy inference system

The model was run with the five input parameters (T_{max}, T_{min}, T_{avg}, u_2, and n) using the Matlab R2016a module to implement ANFIS. In the model, different membership functions were used to minimize each parameter's error. The dataset was implemented between 60-80% for training and 20-40% for testing.

3. Results

3.1 Results of data analysis and probabilistic scenarios

The real data set consists of 879 rows with the five meteorological parameters covering the growth periods of 2016-2019. When the dataset was examined after the data analysis, the mean T_{avg} remained approximately constant, while the standard deviation decreased from 5.058 to 4.46. In addition, three outliers were removed from the dataset because unexpected records could create a bias in the model. As a result, the maximum and minimum values of T_{avg} for four years were prepared for the model as 28.9 and 9 ºC, respectively.

According to the analysis results for maximum and minimum temperatures, the four peak values and the three lowest maximum temperature values were removed from the dataset, and it was found that T_{max} decreased from 40.7 to 37.4 ºC. In addition, it was found that while the mean maximum temperature value increased, the standard deviation value decreased from 5.706 to 4.853. On the other hand, it was determined that the average minimum temperature value increased from 15.8 to 16.3 ºC.

Following this, there was a decrease in the minimum temperature deviation from the mean.

As can be seen in Figure 2, the wind speed set does not show a uniform distribution, but there are a few values above 3 m s^{-1}. When these data are removed (see Fig. 3), the maximum and minimum wind speeds are 2.9 m s^{-1} and 1.1 m s^{-1}, respectively, and a uniform distribution is formed with 1.89 m s^{-1}.

No specific data was observed in the sunshine duration data, so it was removed from the dataset. However, due to the other parameters that were removed, the dataset was positively affected. For this reason, the average mean sunshine duration increased from 6.69 to 7.32 h, but the standard deviation value decreased from 3.769 to 3.563.

In summary, from the set of 891 data, 57 were removed, corresponding to 6% percent of the total dataset. Of the 879 datasets, 45 were reserved for verification and not included in the models. Therefore, 834 datasets were used in the training, validation and testing stages. According to the data analysis results, it was concluded that the standard deviation value decreased in all parameters and the mean values remained approximately constant.

The aim of proposing these scenarios was mainly to determine whether there was a high correlation with models that have descending probabilistic input parameters. The ReliefF algorithm was used to rank the five selected input parameters to estimate the output parameter of each AI model.

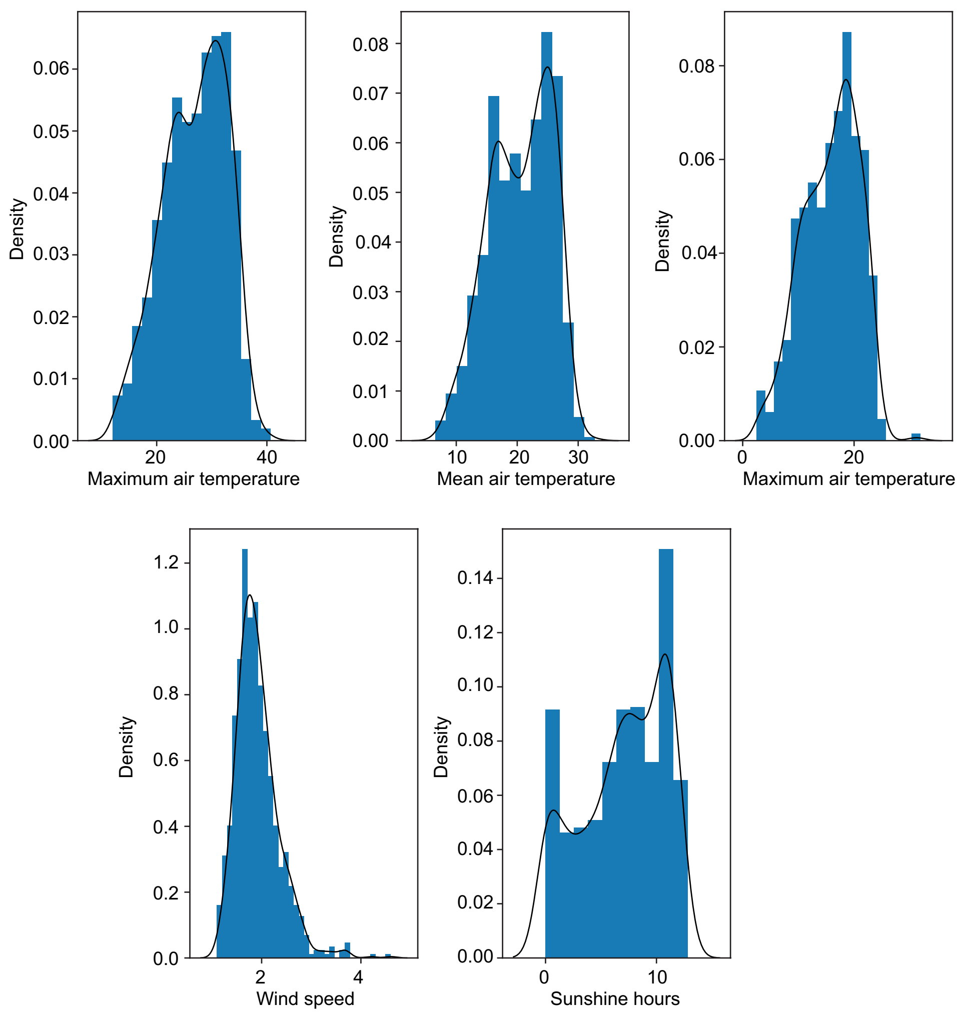

Fig. 2. Density of the raw dataset.

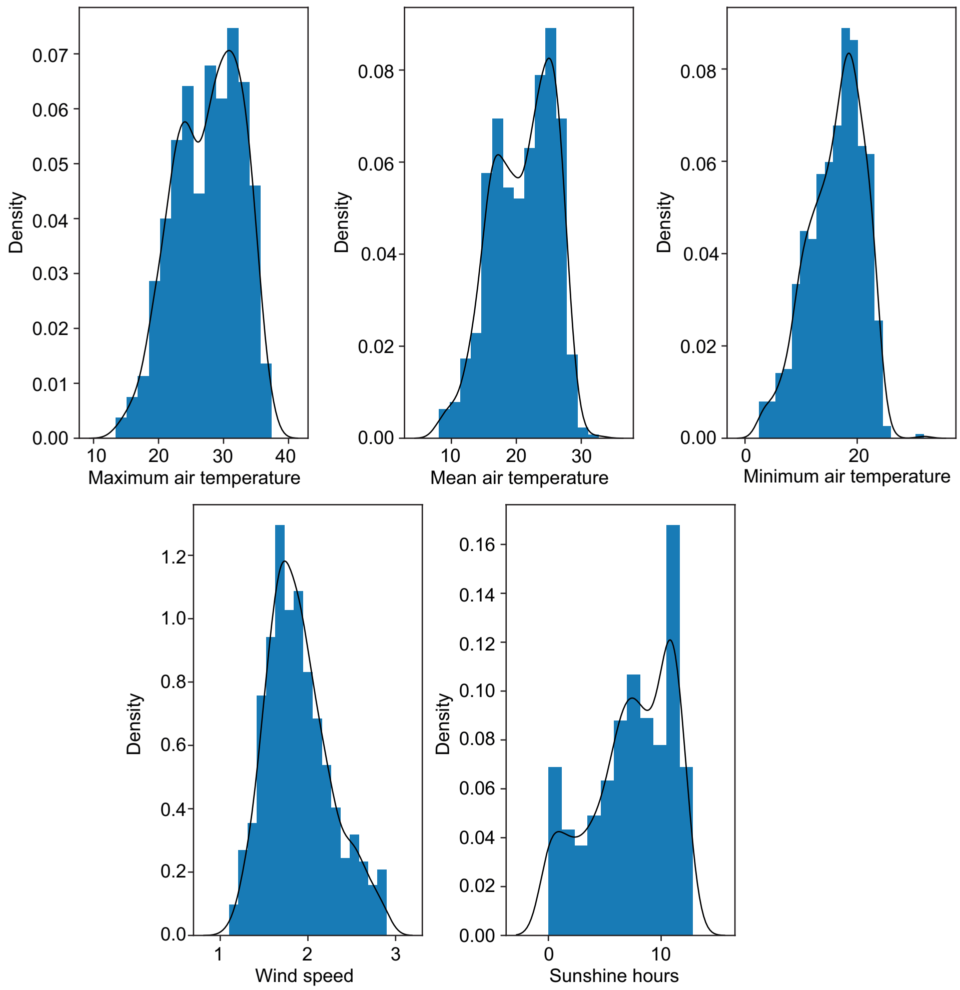

Fig. 3. Density of the dataset.

The algorithm results for all input parameters are shown in Table II.

According to the results of the relief algorithm, the input parameters were arranged in order of importance and various scenarios were created by reducing the number of parameters one by one (i.e., starting with six parameters and then reducing them to five, four, etc.). In the new scenarios generated in this

Table II. Ranges of the dataset based on statistic terms across the experimental region for 2016-2019 and ReliefF ranking.

Parameters	Maximum	Minimum	Mean	SD	ReliefF-ranked attributes	Units
T_{avg}	28.9	9.0	21.1	4.460	0.002422	ºC
n	12.8	0.0	7.3	3.563	0.001214	h
T_{max}	37.4	15.3	27.7	4.853	0.001021	ºC
T_{min}	24.3	3.1	16.3	4.602	0.000719	ºC
u_2	2.9	1.1	1.9	0.356	0.000371	m s^{-1}
ET_c	7.5	0.9	3.9	1.943	-	mm day^{-1}

SD: Standard deviation.

manner, the accuracy of the model may increase or decrease. This reduction model can be expected to be at an acceptable level of performance (see Table II). Table III shows different inputs based on alternative scenarios. In the first scenario, the model is run using all input parameters. Then, in each scenario, the accuracy of the model was reassessed with one missing parameter.

Table III. Probabilistic scenarios of different inputs based on ReliefF ranking.

Output parameter	Scenario	Input parameters				
	1	T_{avg}	n	T_{max}	T_{min}	u_2
	2	T_{avg}	n	T_{max}	T_{min}	
ETc	3	T_{avg}	n	T_{max}		
	4	T_{avg}	n			
	5	T_{avg}				

3.2 Crop water use estimation by artificial neural networks

Various training functions and different numbers of neurons were used to investigate the best performance. A trial and error approach was adopted to find the optimum number of neurons. The randomization of the hidden layer's neurons was found to be between six and three neurons in parallel with the input parameter. In the hidden layer, the values with the best number of nodes and lowest error were used.

In the models created with ANN, the MSE and R^2 values were obtained by running each model 15 times on average. As shown in Table IV, over-learning was detected in scenarios 1, 2 and 3 despite optimizing the number of neurons. To solve this problem, 5% of the dataset was used for the validation part. It was concluded that the best training performance of the models was in the first scenario with an R^2 of 0.91. However, it was concluded that R^2 and MSE values remained constant when the wind speed, and the maximum and minimum temperatures were removed in other scenarios. Accordingly, when Scenario 4 was examined, it was seen that the R^2 values for training and testing were 0.90 and 0.89, and MSE values for training and testing were 0.9324834 and 0.9306326 mm day^{-1}, respectively. On the other hand, due to the fact that the value of R^2 with a single

Table IV. Performance of each scenario based on the ANN model for training, validation and testing.

Output parameter	Scenario	Performance								
		Training (%)	Validation (%)	Testing (%)	MSE			R^2		
					Training	Validation	Testing	Training	Validation	Testing
ETc	1	80	5	15	0.9279886	0.9096128	0.9410764	0.92	0.95	0.89
	2	80	5	15	0.9275259	0.9271293	0.9349952	0.91	0.92	0.88
	3	80	5	15	0.9326156	0.9227667	0.9398205	0.90	0.91	0.88
	4	**80**	**-**	**20**	**0.9324834**	**-**	**0.9306326**	**0.90**	**-**	**0.89**
	5	80	-	20	0.9930310	-	0.9824550	0.80	-	0.77

MSE: mean square error; R^2: coefficient of determination.

parameter was 0.78 in Scenario 5 and the errors in the estimation increased, it was not considered appropriate for the model estimation. As a result, Scenario 4, which had the highest correlation, minimum mean square error, and minimum input parameter was considered to be the best model.

Even when high correlation is found throughout the network training, testing and validation phases, the models still need to be verified to prove that they perform accurate estimations. The 45 datasets that were not used in the training, validation and testing of the ANNs model were separated as one value for each month and used in verification. Each probabilistic scenario was used while verifying the model. The graphs between the predicted and observed values for all parameters are shown in Figure 4.

3.3 Crop water use estimation by ANFIS

In the generated probabilistic scenarios, the data sets were manually distributed as 80 and 20% for training and testing, respectively. Membership functions (MF) that are used in training ANFIS models are functions used to determine the classes of values. The MF type is of great importance in training the network. For this reason, "gaussmf" and "gauss2mf" functions with the lowest error margin were selected by trial and error for all applied MF types.

It was found that the smallest MSE in the ANFIS model was 0.209896 mm day^{-1} in Scenario 1 with five input parameters (T_{avg}, n, T_{max}, T_{min} and u_2), and 0.701142 mm day^{-1} in Scenario 5 with only one input (T_{avg}). It was concluded that R^2 values of scenarios 1, 2, 3, and 4 remained constant despite the decrease

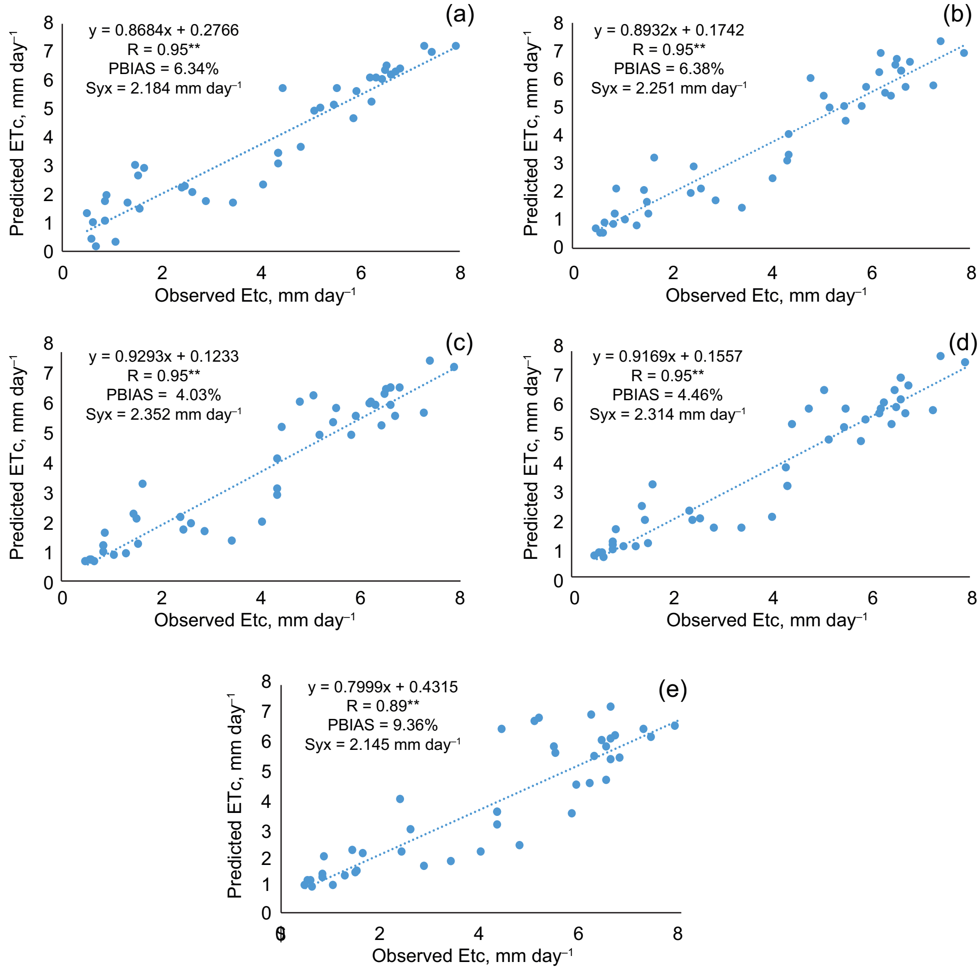

Fig. 4. Verification of results based on the ANN model: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, (e) Scenario 5.

in parameter numbers. It was found that values for Scenario 4 were 0.364975 and 0.294885 mm day^{-1} for training and testing, respectively, while in Scenario 5 these values increased to 0.701142 and 0.898864 mm day^{-1}. On the other hand, while values for R^2 were 0.90 for both training and testing in Scenario 4, it was found to be 0.81 for training and 0.79 for testing in Scenario 5. Therefore, it was concluded that Scenario 4 was more successful in estimating crop water use (see Table V).

3.3.1 Model verification

The same 45 data sets used in ANN models were also used for the verification of ANFIS models. The most advantageous aspect of the model verification dataset is the presence of parameters that are not trained by the model. For example, while the highest and lowest model-trained ETc values were 7.49 and 0.88 mm day^{-1}, the highest and lowest ETc values in the validation dataset were 7.92 and 0.51 mm day^{-1}. In other words, ANFIS models can predict even the highest and lowest values in all scenarios which they have not encountered before with the lowest rate of error. Figure 5 shows the observed and estimated crop water use values.

3.4 Performance of the Penman Monteith approach for crop water use

ETc values obtained from the Penman approach, considering multiple climate parameters and plant characteristics, were plotted in Figure 6 together with the verification results used for the scenario proposed in the models. As seen in the figure, the results of the model obtained with a few parameters are in parallel with Penman's results, and the ANFIS and ANN models have the highest statistical correlation (–0.349 and –0.361, respectively) according to the comparison (two-simple t test) .

Considering the predicted ETc, rainfall and also the 2-year phenological follow-ups, it was determined that irrigation must be initiated at the beginning of April when walnut trees are forming leaves and blossoming, and continued through October. If the trees are unable to get enough water during this period, growth and vegetation will slow down and there will be decreases in quality and efficiency, since fruits will not be able to grow enough meat. It is prescribed that in walnut areas with similar climate

Table V. Performance of each scenario based on the ANFIS model for training, validation and testing.

Output parameter	Scenario	Performance											
		Training (%)	Testing (%)	Number of MFs	MF type	Epochs	Number of nodes	Non-linear parameters	Fuzzy Rules	MSE		R^2	
										Training	Testing	Training	Testing
	1				gaussmf	41	524	30	243	0.209896	0.355707	0.94	0.88
	2				gauss2mf	49	193	48	81	0.277951	0.258986	0.92	0.91
ETc	3	80	20	3	gaussmf	90	78	18	27	0.337374	0.296796	0.90	0.90
	4				**gaussmf**	**123**	**35**	**12**	**9**	**0.364975**	**0.294885**	**0.90**	**0.90**
	5				gauss2mf	73	16	12	3	0.701142	0.898864	0.81	0.79

MF: membership functions; MSE: mean square error; R^2: coefficient of determination.

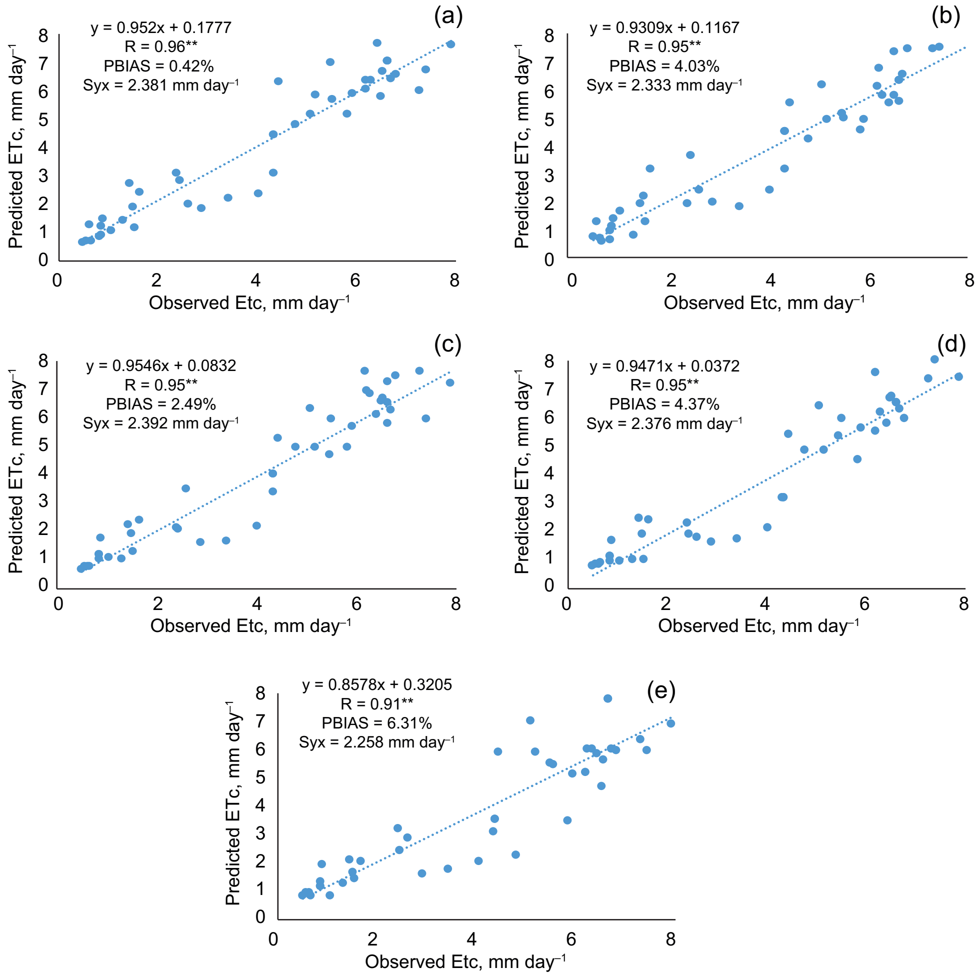

Fig. 5. Verification of results based on the ANFIS model: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, (d) Scenario 4, (e) Scenario 5

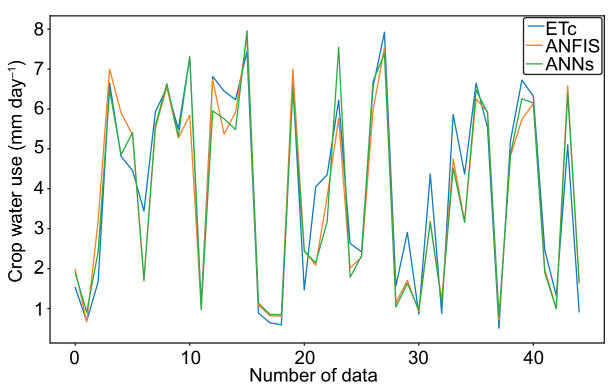

Fig. 6. Crop water use changes obtained by empirical and predicted model consisting of ANN and ANFIS.

and soil characteristics as the study area, irrigation can be performed every 3-4 days in the summertime.

4. Discussion

Many studies explain that ANN, ANFIS, and other machine learning methods can outperform traditional computational methods on the prediction of evaporation and evapotranspiration to explain the effect on agricultural water use (Adeloye et al., 2012; Kisi et al., 2015; Abrishami et al., 2018; Sanikhani et al., 2019; Yamaç and Todorovic, 2020; Elbeltagi et al., 2020; Petković et al., 2020; Yamaç, 2021; Sattari et al., 2021). Al-Mukhtar (2021) and Goyal et al. (2014) proposed and predicted E with high accuracy using these models and performance. In this study, the estimation results of plant water use were evaluated using the artificial intelligence methods of ANN and ANFIS with few parameters, including average temperature (T_{avg}) and sunshine duration (n). Terzi and Keskin (2005) predicted daily panevaporation using the ANN model with six meteorological variables in the Eğirdir lake region. Deswal and Pal (2008) used ANN to investigate the impact of various collections of meteorological parameters on water surface evaporation. They found that the most effective parameter in probabilistic scenarios created for the model is average temperature. Through scientific studies, it has been demonstrated that maximum, minimum and average temperatures are more successful than other climate parameters in estimating evapotranspiration using artificial intelligence models (Abyaneh et al., 2011; Tabari et al., 2013; Aghajanloo et al., 2013; Yamaç and Todorovic, 2020; Sattari et al., 2021).

According to the ANN and ANFIS results in this study, these models had an acceptable performance with high accuracy R and low mean square error to estimate ET. It was also concluded that ANFIS has a better performance than ANN. Likewise, Karimi et al. (2012) stated that the ANFIS model gave better results than ANN.

Numerous studies sustain that the results of various machine learning methods (including ANN and ANFIS) are more certain and accurate regarding crop water consumption and evaporation compared to empirical methods. Many researchers have used artificial intelligence models to predict evapotranspiration, finding that they give better results (Abyaneh et al., 2011; Feng et al., 2017; Nourani et. al., 2019; Hashemi and Sepaskhah, 2020; Yamaç and Todorovic, 2020; Gao et al., 2021; Hadadi et al., 2022). Also, our results are in accordance with Kisekka and Peddinti (2022) , who observed a statistically strong relationship with similar models between walnut ETc and different input variables.

5. Conclusion

The application of ANN and ANFIS in the fields of hydrology, water management, and environmental and agricultural studies, including agriculture and ET estimates, has increased in the last years. In this study, ANN and ANFIS were introduced to predict ET and investigate their modeling performance with different scenarios of meteorological input data availability. In this context, estimated ET was simulated by different machine learning methods and was compared to detailed empirical data. This methodology allowed to quickly produce statistically reliable predictions with less data, which in turn allowed to determine the evapotranspiration of walnut trees and their fruits in the Marmara basin of Turkey. These results will also assist in the determination of crop ET under limited water supply and stress conditions in terms of irrigated agriculture and efficient water use.

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