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Reference Evapotranspiration Estimation With kNN and ANN Models Using Different Climate Input Combinations in the Semi-arid Environment

Sevim Seda YAMAÇ[a*]

[a]*Department of Plant Production and Technologies, Faculty of Agriculture and Natural Sciences, Konya Food and Agriculture University, Konya, TURKEY*

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Corresponding Author: Sevim Seda YAMAÇ, E-mail: sevim.yamac@gidatarim.edu.tr
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ABSTRACT

The absolute prediction of reference evapotranspiration (ET_o) is an important issue for global water balance. Present study demonstrated the performance of k-Nearest Neighbour (kNN) and Artificial Neural Network (ANN) models for prediction of daily ET_o using four combinations of climatic data. The kNN and ANN models were studied four combinations of daily climate data during 1996-2015 in the Middle Anatolia region. The findings of ET_o estimation with kNN and ANN models were classed with the FAO Penman Monteith equation. The outcomes of ET_o values demonstrated that the kNN had higher performances than the ANN in all combinations. The statistical indicators of the kNN model showed ET_o values with MSE, RMSE, MAE, NSE and R^2 ranging from 0.541-0.031 mm day^{-1}, 0.735-0.175 mm day^{-1}, 0.547-0.124 mm day^{-1}, 0.937-0.997 and 0.900-0.994 in the testing subset. Thus, the kNN can be used for the prediction of reference evapotranspiration with full and limited input meteorological data.

Keywords: Evapotranspiration, Penman-Monteith, K-nearest neighbour, Artifical neural network

1. Introduction

Evapotranspiration (ET) can be described as water loss into the atmosphere via plant transpiration and soil evaporation (Landeras et al. 2008; Fan et al. 2018). Water resources are significantly reduced in semi-arid and arid environments due to the consequences of increasing climate change. In these regions where water shortage is a major problem, it is essential to estimate water loss by ET. Therefore, precise prediction of ET is an imperative step for managing water activities, especially in the area which faces water scarcity.

Numerous methods to estimate ET have been recommended but each method has benefits and limitations due to their activities. However, methods which are depending on measurement are high-cost and also have usage difficulties. Therefore, a more economical and practical alternative application to this method is developing tools which are depending on mathematical models using climate variables measured from meteorological stations.

The Penman-Monteith equation is frequently applied method due to recommendation of the Food and Agriculture Organization of the United Nations as a standard method (FAO PM) for reference evapotranspiration (ET_o) estimation. In literature (Lopez-Urrea et al. 2006; Ali & Shui 2009; Pereira et al. 2015), the method was evaluated under different time steps and environmental conditions. For calculation of ET_o, the method requires many climatic input parameters (Feng et al. 2017), which is a big disadvantage of this equation. Moreover, the prediction of ET is a complicated process dependent on a huge and good quality of climatic parameters; therefore, it is difficult to represent all these complicated processes in an empirical model. Especially in developing countries, the meteorological data are very limited. This problem brings another obstacle of using FAO PM method. Therefore, simplified empirical methods with less climatic input variables are getting interested for ET_o estimation (Trabert 1896; Priestley & Taylor 1972; Hargreaves & Samani 1985). However, these methods obtain less accurate results for daily ET_o estimation than on a weekly and monthly (Torres et al. 2011).

Interest in the machine learning method in ET_o estimation has increased over the last two decades (Kisi & Cimen 2009; Feng et al. 2016; Tangune & Escobedo 2018) because these non-parametric methods can work without specific knowledge about the variables that are used for the models (Gocić et al. 2015; Kişi 2015; Yamaç & Todorovic 2020). Among the machine learning methods for prediction of ET_o, one of the most common methods is the artificial neural network (ANN) model. Ferreira et al. (2019) investigated the ANN and support vector machine (SVM) to predict ET_o in Brazil, using different climatic variables. The findings showed that the ANN gives the best result for the temperature and relative humidity-based models. Antonopoulos &

Antonopoulos (2017) examined the prediction of ET_o comparing the ANN model and empirical equations in Greece. They pointed out that the performance metrics of the ANN model was higher than empirical equations. Landeras et al. (2008) studied the prediction of ET_o using empirical equations and the ANN in Spain. The ANN is better than the empirical equations. Traore et al. (2010) applied the ANN model for ET_o estimation in the Sudano-Sahelian zone. The model showed that the ANN can be used as an alternative model for prediction of ET_o. Khoob (2008) compared the Hargreaves-Samani (1985) equation and ANN to estimate ET_o in Iran. The result demonstrated that the ANN estimated better than the Hargreaves-Samani equation. Moreover, the recent study was done by Feng & Tian (2020). They compared nearest neighbor algorithms and empirical methods in China. The findings demonstrated that kNN method is more accurate than empirical methods. However, very few studies have used machine learning methods for estimation of ET in Turkey. Citakoglu et al. (2014) evaluated the estimation of monthly ET_o using adaptive network based fuzzy inference system (ANFIS) and ANN models in Turkey. The ANFIS estimated slightly higher performance than the ANN. Kisi (2016) investigated M5 Model Tree (M5Tree), multivariate adaptive regression splines (MARS) and least square support vector regression (LSSVR) methods in Turkey. The overall result indicates that the LSSVR observed the best results with local output and input variables while the MARS model performed the best results in estimating ET_o in the lack of local output and input data.

The goal of the study is to make a comparison of kNN and ANN models with a standard method of FAO PM using four combinations of meteorological data for the prediction of ET_o. In this way, the paper was purposed to understand the accurate modelling performance for prediction of ET_o in semi arid environment of Turkey comparing one recognized and widely used model (ANN) with recently used model (kNN) from first combination to fourth combination which is from less to more meteorological data.

2. Material and Methods

2.1. Study area and dataset description

The area under study is Konya in the Middle Anatolia region of Turkey. The meteorological station is placed at 1030 m altitude, 38° 14′ N latitude and 32° 40′ E longitude. The daily weather data was taken from the Turkish Meteorological Organization in Turkey. The climatic data was recorded from 1996 to 2015 (20 years). The collected data was maximum and minimum air temperature (°C), maximum and minimum relative humidity (%), solar radiation (MJ m^{-2}) and wind speed (m s^{-1}). Table 1 shows the statistical characteristics of the meteorological parameters. The climate of study region is a semi-arid (Kottek et al. 2006) and the average yearly precipitation is 548 mm. Figure 1 presents total annual precipitation variables for 20 years (1996-2015).

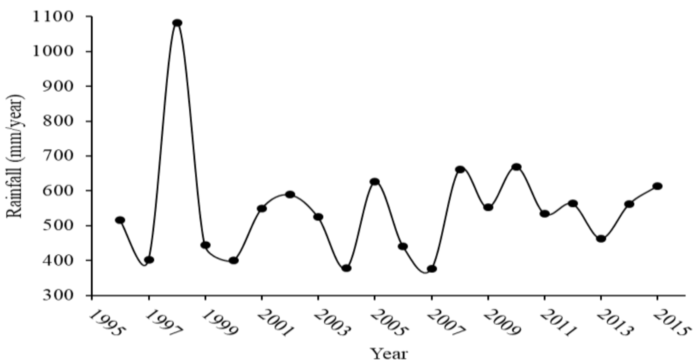

Figure 1- The total annual precipitations for 20 years (1996-2015)

Table 1- Statistical parameters of the used dataset

Variables	T_{min} (°C)	T_{max} (°C)	R_n (MJ m^{-2})	RH_{min} (%)	RH_{max} (%)	U_2 (m s^{-1})	ET_o (mm day^{-1})
Maximum	22.10	39.60	30.64	88.31	100.00	7.20	10.91
Minimum	-18.90	-9.20	0.10	9.83	24.83	0.10	0.37
Mean	6.64	18.85	16.57	37.63	74.08	2.56	3.77
Standard deviation	7.28	9.77	7.62	14.99	22.49	1.01	2.33
Skewness	-0.04	-0.16	-0.05	0.66	-0.16	0.28	0.44
Kurtosis	-1.04	-1.07	-1.12	0.22	-1.46	0.00	-0.89

(ET_o: reference evapotranspiration, T_{min}: minimum air temperature, T_{max}: maximum air temperature, R_n: solar radiation, RH_{min}: minimum air relative humidity, RH_{max}: maximum air relative humidity, U_2: wind speed).

2.2. FAO Penman-Monteith

The FAO PM equation (Allen et al. 1998) was used for prediction of daily ET_o;

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34\ U_2)} \tag{1}$$

Where; ET_o, is the reference evapotranspiration (mm day^{-1}), Rn is the net solar radiation (MJ m^{-2} day^{-1}); G, is the soil heat flux density (MJ m^{-2} day^{-1}), T, is the mean daily air temperature (°C); Δ, is the slope of the saturated vapour pressure curve (kPa °C^{-1}); γ , is the psychometric constant (0.066 kPa °C^{-1}), es is saturation vapour pressure (kPa)and ea is actual vapour pressure (kPa) and U_2 is the mean daily wind speed (m s^{-1}). T and U_2 was measured at 2m height.

The e_s was estimated as:

$$e_s = \frac{e^0(T_{max}) + e^0(T_{min})}{2} \tag{2}$$

Where; e^0 (T), is the saturation vapour pressure (kPa), and T_{min} and T_{max} are minimum and maximum daily air temperature (°C), respectively. The $e^0(T)$ was calculated as:

$$e^0(T) = 0.6108\ exp\ \left[\frac{17.27\ T}{T+237.3}\right] \tag{3}$$

The e_a was calculated as:

$$e_a = \frac{RH_{mean}}{100}\left[\frac{e^0(Tmax) + e^0(Tmin)}{2}\right] \tag{4}$$

Where; RH_{mean}, is the mean daily relative humidity.

2.3. k-Nearest neighbour

The kNN is the simple classification method, presented by Cover & Hart (1967), which is widely used machine learning methods (Wu et al. 2008). It is non-parametric which is easy to implement and which obtains efficient and competitive results. This advantage makes method much more significant than many other machine learning methods.

Figure 2 shows the kNN schematic illustration for 2 classes of k=1 and k=3. In Figure 1a, a known sample (-), nearest to the sample X, is used for categorization of sample X; in Figure 2b, three nearest (+) samples to X are employed for categorization. The present study was applied Euclidian distance equation (Equation 2) . It can be written as:

$$x(a,b) = \sqrt{\sum_{n=1}^{N}(a_i - b_i)^2} \tag{5}$$

Where; x, is the Euclidian distance, a and b are the data including to N dimensions. n is an index number.

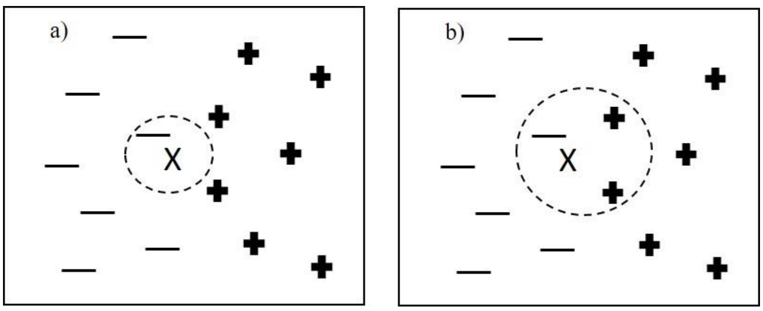

Figure 2- The k-nearest neighbour (kNN) schematic illustration

2.4. Artificial neural network

The ANN model based on numerical model that was developed and designed in order to analyse the performance of a biological neural system. The structure of ANN models is similar as biological brain with numerous layers of connected neurons. (Landeras et al. 2008). In recent decades, the ANN has been applied in hydrological and agricultural studies (Kumar et al. 2011). The general architecture of the ANN is shown in Figure 3. The model has the capability to learn, memorize and create relationships between weighted neurons from a training dataset. When the testing data is implemented into the system, the model realises the relationships between neurons and assigns the data to the appropriate class. The well known structure of an ANN model is formed of an input layer, where the data is entered; hidden layer(s), where the data is processed; and output layer, where it gives the results (Yamaç et al. 2020).

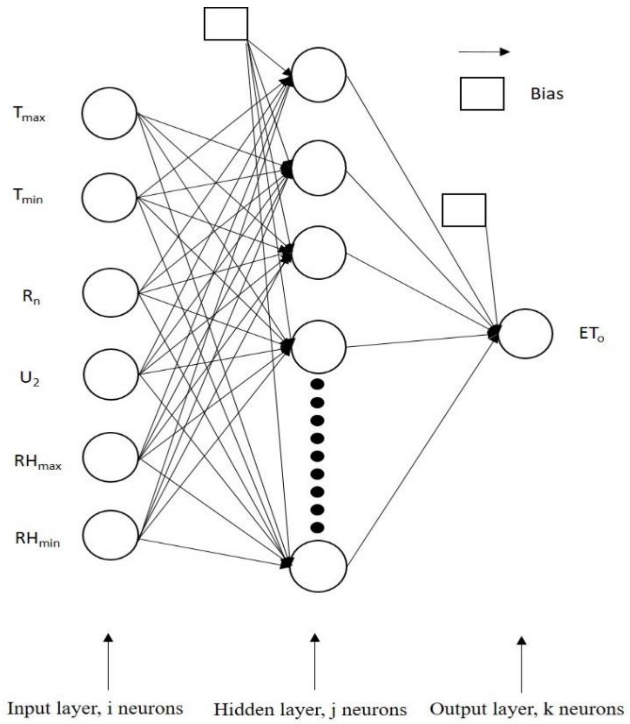

Figure 3- The general architecture of the artificial neural networks

2.5. Model development and performance evaluation

The kNN and ANN models were developed to simulate and estimate the daily ET_o in a semi-arid environment. To establish kNN and ANN models, six climatic variables (wind speed, solar radiation, minimum-maximum relative humidity and minimum-maximum air temperature) were employed as inputs, while ET_o was employed as the output variable. Correlations between these climatic variables and ET_o have been shown in Table 2. The reason of development of the correlation matrix was to understand which climatic variables have the best relations with ET_o. According to correlation matrix, the next nearest correlation was added for development of combinations. Table 3 shows different input combinations for the models.

Table 2- Correlation matrix between ET_o and climatic data

Variables	T_{min}	T_{max}	R_n	RH_{min}	RH_{max}	U_2	ET_o
T_{min}	1.000						
T_{max}	0.914	1.000					
R_n	0.687	0.839	1.000				
RH_{min}	-0.349	-0.691	-0.732	1.000			
RH_{max}	-0.700	-0.784	-0.665	0.580	1.000		
U_2	-0.031	-0.035	0.039	0.019	0.026	1.000	
ET_o	0.819	0.915	0.913	-0.680	-0.779	0.185	1.000

Before the models run, all the variables are standardized ranging between 0 to 1. The standardization equation is defined as:

$$z = \frac{x - \mu}{\sigma} \tag{6}$$

Where; σ is the standard deviation, μ is the mean value and x is the original data.

Table 3- Input combinations of the kNN and ANN models

Models		*Inputs combinations*
kNN	*ANN*	
kNN1	ANN1	T_{max}, T_{min}
kNN2	ANN2	T_{max}, T_{min}, R_n
kNN3	ANN3	T_{max}, T_{min}, R_n, U_2
kNN4	ANN4	T_{max}, T_{min}, R_n, U_2, RH_{max}, RH_{min}

The total 20 years dataset (1996-2015), 70% of which was used for training and 30% for testing, was split randomly. For the training subset, k-fold cross-validation was applied to evaluate predictive models. The training dataset was separated into 10 folds. In this way, the kNN and ANN models were trained and tested 10 times and gave the results according to average of the 10 repetition.

The performance of kNN and ANN models were appraised using coefficient of determination (R^2), Nash-Sutcliffe model efficiency coefficient (NSE), mean absolute error (MAE), root means square error (RMSE) and the mean squared error (MSE) in the training and testing subsets. The good performance metrics of the models can be understood when MAE, RMSE and MSE values are smaller and NSE and R^2 are higher.

3. Results and Discussion

The kNN and ANN with four combinations of climatic input data were evaluate for training and testing subsets. The findings showed that the kNN and ANN models were able to describe the nonlinear relationships between meteorological variables to estimate daily ET_o values adequately. The performance metrics of the models, including MSE, RMSE, MAE and R^2 are presented in Tables 4 and 5 for the prediction of daily ET_o. As can be seen in Tables 4 and 5, all the applied kNN and ANN models presented accurate daily ET_o estimates during training and testing subsets. In general, the kNN4 showed the highest performance metrics. However, the ANN1 model has the lowest performance in the testing subset.

The best accuracy of the kNN under four climatic conditions to estimate daily ET_o over training and testing subsets was observed when the k was chosen as 5. Table 4 demonstrated the performance metrics of the kNN model to estimate daily ET_o during the training and testing subsets for four combinations of available climatic data. Employing four different climatic input combinations, the statistical indicators of daily ET_o using kNN presented that the lowest performance in the training and testing subsets was observed when ET_o was predicted only with maximum air temperature and minimum air temperature (kNN1). An appropriate improvement of model performance was observed for combination 2 with the reduction of statistical indicator in the testing subset. Among all combinations of kNN models, the highest performance was observed fourth combination (kNN4) in the testing subset.

Table 4- Performance metrics of the kNN models under four different climate input

	Training					*Testing*				
Model	*MSE (mm day^{-1})*	*RMSE (mm day^{-1})*	*MAE (mm day^{-1})*	*NSE*	*R^2*	*MSE (mm day^{-1})*	*RMSE (mm day^{-1})*	*MAE (mm day^{-1})*	*NSE*	*R^2*
kNN1	0.796	0.892	0.669	0.830	0.853	0.541	0.735	0.547	0.932	0.900
kNN2	0.350	0.591	0.429	0.920	0.936	0.232	0.482	0.349	0.961	0.957
kNN3	0.075	0.274	0.192	0.997	0.986	0.049	0.220	0.155	0.995	0.991
kNN4	0.048	0.220	0.154	0.981	0.991	0.031	0.175	0.124	0.997	0.994

For the ANN model, the 5 was identified for the number of neurons in the hidden layer. The best performance criteria was showed when ANN model has 2(3, 4, 6)-5-1 structure for daily ET_o estimation. This can be explained that the model occurs of 2 neurons for first, 3 neurons for second, 4 neurons for third and 6 neurons for fourth combinations in input layer, 1 in the output layer and 5 neurons in the hidden layer. For the activation function, the rectified linear unit function was employed for this study. Table 5 demonstrated the performance metrics of the ANN model to estimate daily ET_o during the training and testing subsets for four combinations of available climatic data. Among all ANN models, the ANN1 model demonstrated the lowest performance in training and testing subsets. From the first to the second combination, a relevant improvement of more than 30% ET_o estimate was observed for MSE, RMSE and MAE values when solar radiation is added together with minimum air temperature and maximum air temperature data (ANN2). It is noticeable that the ANN method had the highest performance for ANN4 model.

Table 5- Performance metrics of the ANN models under four different climate input

	Training					*Testing*				
Model	*MSE (mm day⁻¹)*	*RMSE (mm day⁻¹)*	*MAE (mm day⁻¹)*	*NSE*	*R^2*	*MSE (mm day⁻¹)*	*RMSE (mm day⁻¹)*	*MAE (mm day⁻¹)*	*NSE*	*R^2*
ANN1	0.724	0.851	0.653	0.883	0.867	0.695	0.834	0.635	0.893	0.872
ANN2	0.338	0.582	0.433	0.922	0.938	0.322	0.567	0.421	0.923	0.941
ANN3	0.097	0.311	0.225	0.989	0.982	0.106	0.325	0.237	0.968	0.981
ANN4	0.074	0.227	0.196	0.967	0.986	0.051	0.225	0.162	0.993	0.991

The scatter plot of predicted ET_o values by the kNN and ANN with four combinations of input climate variables, compared with the FAO PM equation during testing subset, are presented in Figures 4 and 5. In general, for all models, the fourth combination with maximum air temperature, minimum air temperature, solar radiation, maximum relative humidity, minimum relative humidity and wind speed correlated close to the line of 1:1. However, the first combination with maximum air temperature and minimum air temperature yielded more scattered ET_o values relative to the other climatic input combinations. The daily ET_o values estimated from kNN with first combination (kNN1) model were more close to the FAO PM equation values (Figure 4).

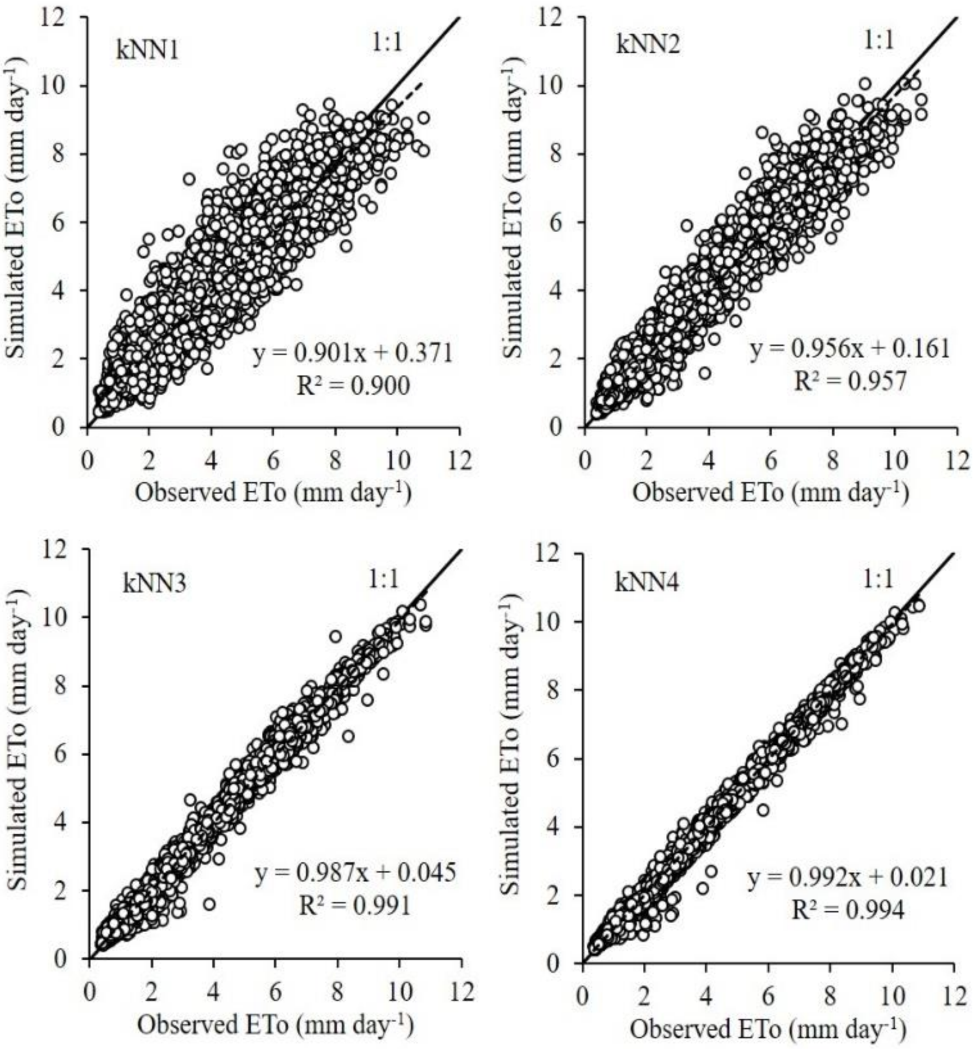

Figure 4- Scatter plots of the kNN models under four different climate input for testing subset

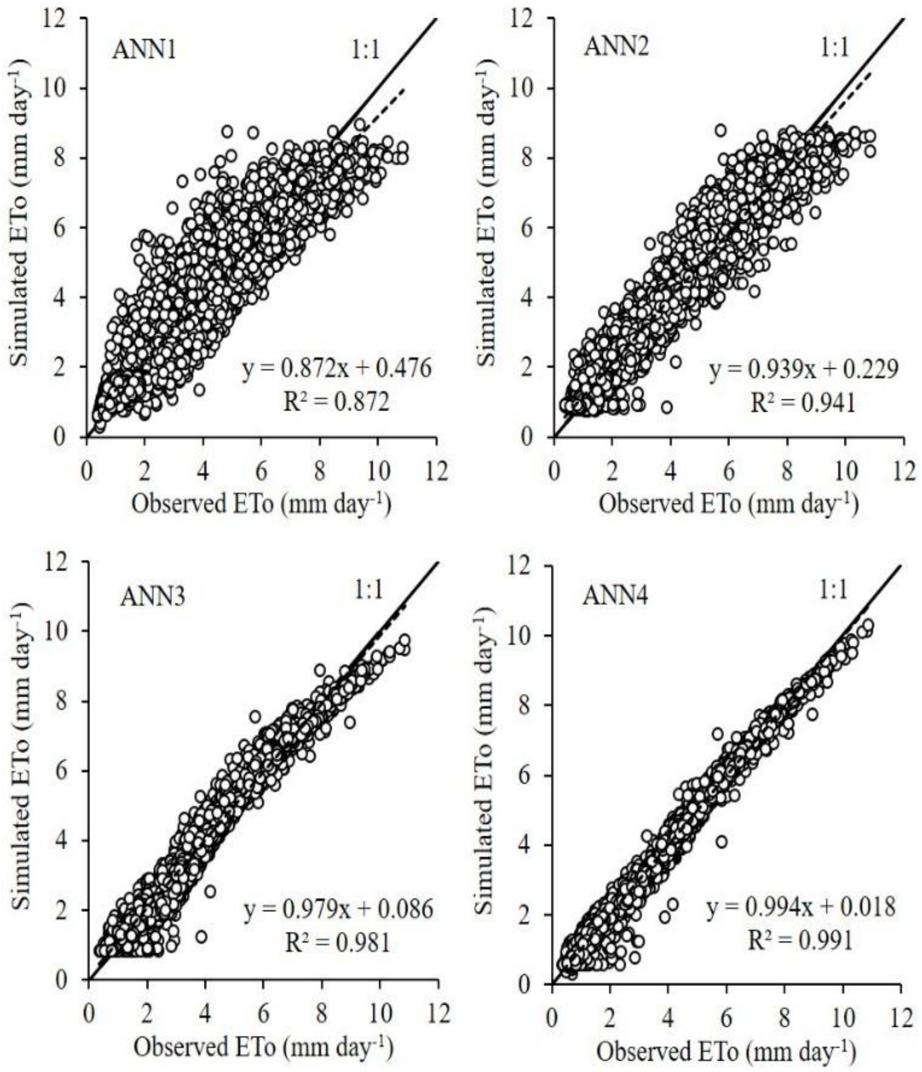

Figure 5- Scatter plots of the ANN models under four different climate input for testing subset

In general, the statistical indicators demonstrated that the fourth combination provides by far the best performance for kNN and ANN models with complete meteorological data while the poorest performance was obtained with the first combination fed with maximum and minimum temperature. In general, the findings are in agreement with literature (Torres et al. 2011; Tabari et al. 2012), concluding that more climatic input variables commonly increase modelling accuracy. This result is in accordance with Fan et al. (2018) who also indicated that machine learning models with temperature, relative humidity, wind speed and solar radiation inputs have the best performances comparing with the less meteorological variables in the semi-arid environment. Moreover, the findings showed that the kNN and ANN with maximum/minimum temperature, combined with solar radiation (second combination), have a better performance than the kNN and ANN models with minimum and maximum temperature in a semi-arid region. In that case, for testing subset, the kNN2 model, R^2 was 0.957, NSE was 0.961, MSE was 0.232, RMSE was 0.458 and MAE was 0.349. For ANN2 model, R^2 was 0.941, NSE was 0.923, MSE was 0.322, RMSE was 0.567 and MAE was 0.421 in the testing subset. These results demonstrated that the solar radiation input was more substantial than wind speed and relative humidity upon maximum/minimum temperatures in a semi-arid region. According to statistical indicators, with the kNN and ANN models based on solar radiation and maximum/minimum temperature (kNN2 and ANN2), meteorological input variables can also produce satisfactory ET_o estimates in the semi-arid environment of Turkey where other meteorological variables are not easily accessible.

Previous studies indicated that employing all meteorological input variables provided the best performances for predicting ET_o. Feng et al. (2017) predicted daily ET_o with random forests (RF) and generalized regression neural networks (GRNN) models using different meteorological variables concluding that the models with complete meteorological data is preferable than the combination which is added less meteorological variables. A similar result was pointed out also by Traore et al. (2010) when the ANN was used to predict daily ET_o variables in Sudano-Sahelian zone.

The kNN model showed the best performances in all combinations when compared to the ANN model. This could be explained by the fact that the kNN model concentrating on the characteristic of the nearest neighbours similar to the behaviour of applied climatic variables and their correlation with the ET_o. Comparing result from previous study, larger RMSE and MAE were mentioned by (Feng & Tian 2020) using the kNN model. From this comparative analysis, it may be concluded that it is suitable to estimate ET_o employing kNN model in semi-arid environment of Turkey.

4. Conclusions

This paper presented an application of the kNN and ANN models for the accurate estimate of daily ET_o with full and limited meteorological data in a semi-arid environment of Turkey. To identify the optimal results to estimate daily ET_o in the mentioned semi-arid region, the kNN and ANN models with four different combinations of meteorological input variables were proposed. The recently used kNN model was implemented to estimate daily ET_o for analysing the performance metrics of different combinations of climatic input data and to compare with a well-known ANN model. This ANN was applied in many previous studies, therefore; it is used as a comparison model in order to evaluate the performance of kNN model in this study.

The statistical performance in the testing and training subsets was improved by adding one climatic parameter to each combination (from 1 to 4), which demonstrated positive correlations with the number of input variables to the kNN and ANN models. Among all the combinations, the kNN model offered better predictional accuracy and stability than the well-known ANN model. Therefore, the results advocated that the kNN has a high potential for ET_o prediction in the semi-arid region of Turkey, even possibly in other regions of the world with presenting similar environments. In addition, the overall results showed that less meteorological input combinations may be a suitable alternative solution where full meteorological data sets are not available. This finding is especially important for agricultural lands in developing countries, where meteorological data are missing to estimate ET_o.

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