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# Performance Evaluation of Artificial Neural Networks for Estimating Reference Evapotranspiration in Shahat, Libya using limited climatic data

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## Abstract

This study was conducted with the aim of evaluating the performance of artificial neural networks (ANNs) to estimate the reference evapotranspiration using limited climate data in Shahat region in Libya, compared to using the FAO Penman-Monteith equation (FPM), which requires temperature, wind speed, relative humidity and number of sunshine hours, which are rarely available in most meteorological stations in developing countries. In this study, we used the average temperature ($T_{mean}$) and the average relative humidity ($RH_{mean}$) obtained from Shahat meteorological station for the period from 1963 to 1999, and the extraterrestrial radiation ($R_a$), which can be calculated given the location and time of the day. These data are divided into two groups, from 1963 to 1988 and from 1989 to 1999 for the training and validation phases of the neural networks, respectively. This study concluded that using ($T_{mean}$), ($RH_{mean}$) and ($R_a$) gave the best agreement with the results calculated with the FAO Penman-Monteith equation, where the values of $R^2$ and RMSE are equal to 0.98 and 0.26, respectively.

**Keywords:** Reference Evapotranspiration, FAO Penman-Monteith Equation, Artificial Neural Networks

## INTRODUCTION

Evapotranspiration (ET) is a term used to describe the sum of evaporation and plant transpiration from the land surface to the atmosphere. It is the second most important variable in the hydrological cycle after rainfall and has an important role as a controlling factor of runoff volume or river discharge, irrigation water requirement and soil moisture contents (Mohan & Arumugam, 1996). Therefore, an accurate estimate of the ET is crucial for studies on the hydrologic water balance, irrigation system design and management, crop production, water resources planning and management and environmental assessment (Irmak et al., 2003),(Temesgen et al., 2005),(Kumar et al., 2011).

ET can be experimentally determined directly by lysimeters or estimated by indirect methods such as the aerodynamic method, energy balance method and combined method. Due to the high cost of lysimeters, installation and maintenance, this instrument is not widely used. Therefore, most users prefer indirect methods based on meteorological data (Kim & Kim, 2008),(Dinpashoh, 2006).

The Penman-Monteith FAO 56 (FPM) model is recommended as the sole method for calculation of ETo and it has been reported to be able to provide consistent ETo values in many regions and climates (Allen et al., 2005),(Allen et al., 2006). The main shortcoming of the FPM method is, however, that it needs a large number of climatic data and variables which are unavailable in many regions, especially in developing countries like Libya.

According to (Kumar et al., 2002), evapotranspiration is a complex nonlinear phenomenon because it depends on the interaction of several climatic factors, including solar radiation, wind speed, air humidity and temperature, as well as the type and growth stage of crops. The choice of a method for estimating evapotranspiration depends on several factors. One of these factors is the availability of meteorological data, because complex methods that require a large number of variables are only applicable when all necessary data are available.

Over the past decade, intelligent computational models have been developed as alternative methods for estimating the ETo, such as the artificial neural networks (ANNs) technique (Landeras et al., 2008). ANNs are effective tools for modeling nonlinear processes, as they require few inputs and are able to map input-output relationships without any understanding of the physical process involved (Haykin, 1999),(Sudheer et al., 2003).

Several types of research have been conducted using ANNs to estimate evapotranspiration as a function of climatic elements (Kumar et al., 2002),(Sudheer et al., 2003),(Odhiambo et al., 2001),(Trajkovic et al., 2003),(Achite et al., 2022),(Genaidy, 2020),(Heramb et al., 2023),(Rajput et al., 2023),(Abdel-Fattah et al., 2023),(Tunalı et al., 2023),(Ekhmaj, 2012) and (Ekhmaj et al., 2013). These researches found satisfactory results, compared with those obtained from the FPM method.

This study was carried out to investigate the estimation of the reference evapotranspiration (ETo) by using ANNs technique as a function of limited climatic data such as temperature (T) and relative humidity (RH) and calculated extraterrestrial radiation (Ra), for the region of Shahat, Libya.

## MATERIALS AND METHODS

### Study area

The climatic data used in this study were obtained from Shahat weather station located of the longitude of 21° 51′E, the latitude of 32° 49′N, and a mean altitude is 621 meters above sea level. The Shahat region is characterized by a Mediterranean climate (hot, dry, summer, warm, rainy, winter), the rainiest month is January with a value of 121.1 mm, and the least rainy month of the year is July, with a precipitation of 0.5 mm, the total annual precipitation is 557.4 mm, and the coldest month of the year is the month January, with an average temperature of 9.5 ° C, while the hottest month is August, with an average temperature of 23.26 ° C, and the average temperature of 16.6 ° C.

The historical data series includes average monthly maximum ($T_{max}$), minimum ($T_{min}$) and mean air temperature ($T_{mean}$)(° C), mean relative humidity ($RH_{mean}$) (%), and wind speed ($U_2$) (m.s$^{-1}$), which covered the period from 1945 to 1999. Because of the lack of a connected series of this data, the beginning was taken from 1963 and the missing data within this period has been processed. Table (1) shows the statistical parameters of meteorological variables at Shahat weather station. The map of the study area and the location of the meteorological station are shown in Figure (1).

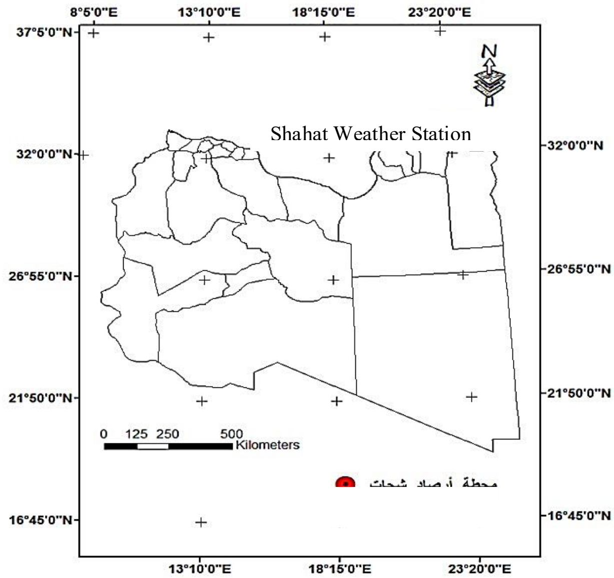



**Figure:(1).** location of the meteorological station

**Table:(1).** Statistical parameters of meteorological variables at Shahat weather station

| Parameter | $T_{max}$ (°C) | $T_{min}$ (°C) | $T_{mean}$ (°C) | $RH_{mean}$ (%) | $U_2$ ($m.s^{-1}$) | Sun (hr) | FPM ($mm.d^{-1}$) |
|---|---|---|---|---|---|---|---|
| Mean | 20.9 | 12.3 | 16.6 | 67.8 | 4.7 | 8.0 | 4.0 |
| Standard Error | 0.3 | 0.2 | 0.2 | 0.4 | 0.1 | 0.1 | 0.1 |
| Standard Deviation | 5.9 | 4.7 | 5.2 | 9.3 | 1.6 | 2.5 | 1.7 |
| Range | 22.1 | 17.9 | 19.8 | 50.0 | 8.0 | 11.1 | 6.7 |
| Maximum | 31.1 | 21.2 | 25.9 | 89.0 | 10.0 | 13.0 | 7.8 |
| Minimum | 9.0 | 3.3 | 6.2 | 39.0 | 2.1 | 1.9 | 1.1 |
| Count | 444 | 444 | 444 | 444 | 444 | 444 | 444 |

## Reference Evapotranspiration (ETo)

The FPM equation was developed to describe ET of a reference grass crop, which is defined as the rate of evapotranspiration from a hypothetical crop with an assumed fixed height (12 cm), surface resistance (70 $s.m^{-1}$) and albedo (0.23), close resembling the evapotranspiration from an extensive surface of a disease-free green grass cover of uniform height, actively growing, completely shading the ground, and with adequate water and nutrient supply (Allen et al., 1998). The ETo was calculated using the standard equation (Eq1), recommended in the FAO 56 bulletin (Allen et al., 1998). This Equation takes the form:

$$ET_o = \frac{\left[0.408 \times \Delta(R_n - G) + \gamma\left(\frac{900}{T + 273} U_2(e_s - e_a)\right)\right]}{\Delta + \gamma(1 + 0.34\, U_2)} \qquad (1)$$

Where:

$ET_o$ : is the reference evapotranspiration [$mm.day^{-1}$];

$R_n$ : is the net radiation at the crop surface [MJ $m^{-2}$ $day^{-1}$];

$G$ : is the soil heat flux density [MJ $m^{-2}$ $day^{-1}$];

$T$ : is the mean daily air temperature at 2 m height [°C];

$U_2$ : is the wind speed at 2 m height [m.s$^{-1}$];
$e_s$ : is the saturation vapour pressure [kPa];
$e_a$ : is the actual vapour pressure [kPa];
$e_s - e_a$: is the saturation vapour pressure deficit [kPa];
$\Delta$ : is the slope vapour pressure curve [kPa.°C$^{-1}$]; and
$\gamma$ : is the psychrometric constant [kPa.°C$^{-1}$]

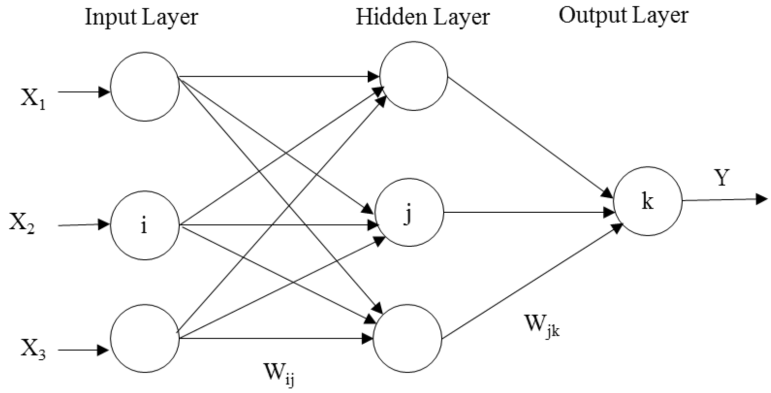
Due to the large amount of data needed for the calculation of ETo, the software REF-ET version 4.1, developed by (Allen, 2000) was used.

**Artificial neural network (ANN)**
An artificial neural network is a highly interconnected network of many simple processing units called neurons, which are analogous to the biological neurons in the human brain. Neurons having similar characteristics in an ANN are arranged in groups called layers. The neurons in one layer are connected to those in the adjacent layers, but not to those in the same layer. The strength of the connection between the two neurons in adjacent layers is represented by what is known as a ‘connection strength’ or ‘weight’. An ANN normally consists of three layers which are an input layer, a hidden layer and an output layer (Bishop, 1995).

In a feed forward network, the weighted connections feed activations is only in the forward direction from an input layer to the output layer. In a recurrent network additional weighted connections are used to feed previous activations back into the network. The structure of a feed-forward ANN is shown in figure 2. In figure 2, the circles represent neurons; the lines joining the neurons represent weights; the inputs are represented by X’s; Y represents the output; $W_{ij}$ and $W_{jk}$ represent the weights between input and hidden, hidden and output layers, respectively.

An important step in developing an ANN model is the training of its weight matrix. The weights are initialized randomly between a suitable range and then updated using a certain training mechanism (Minasny & McBratney, 2002) and (Jain & Kumar, 2006).

ANN is one of the non-parametric models that (do not need to any assumptions about the nature of the variables and their relationships with each other), discover nonlinear relations without the need of knowing the shape of this relationship. This is the reason for the power of ANN method. So the researchers focus on selecting the best network structure, best activation functions and best training algorithm which give the best results of the models. The implementation of such steps is very complicated. However, with the development of computers, it is easy to perform.



**Artificial Neural Net Work Development**

In this study, the input variables to the ANN model include $T_{mean}$, $RH_{mean}$ and extraterrestrial radiation $R_a$, while the output of the model produced predicted ETo. The extraterrestrial solar radiation is not measured data but is estimated for a certain day and location. One of the outputs of the REF-ET model version 4.1 is extraterrestrial radiation ($R_a$) (Allen, 2000).

The extraterrestrial radiation, for each day of the year and different latitudes can be estimated from the solar constant, the solar declination and the time of the year by:

$$R_a = \frac{24\,(60)}{\pi}\, G_{sc}\, d_r \left[\omega_s \sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_{s)}\right] \qquad (2)$$

Where:
$R_a$: Extraterrestrial radiation [MJ $m^{-2}$ $day^{-1}$],
$G_{sc}$ : Solar constant = 0.0820 [MJ $m^{-2}$ $min^{-1}$],
$d_r$ : Inverse relative Earth-Sun,
$\omega_s$ : Sunset hour angle [rad],
$\varphi$ : Latitude [rad],
$\delta$ : Solar declination [rad],

The data were divided into two groups. The first group 70% (311) is called the training set and 30% (133) is called validating datasets. Thus, the training data (from January 1963 to December 1988) were used to train the network and validating data (from January 1989 to December 1999) to validate the network.

The data used in this study were normalized for preventing and overcoming the problem associated with the extreme values. ANN models with 5 hidden layers have been tried for the present study. The output of the network is the values of predicted ETo. Training and validation of the networks are accomplished by ANNdotNET V 1.3 (Hrnjica, 2020). ANN models are trained using Feedforward network that uses a back propagation learning algorithm with Stochastic Gradient Decent (SGD) learner and 0.01 learning rate. The hyperbolic tangent (TanH) activation function was adopted.

The best ANN architecture for prediction of average FPM are selected on the basis of statistical parameters like root mean square error (RMSE), Coefficient of determination ($R^2$) and Nash-Sutcliffe (NSE).

## Performance criteria:

The performance of the models was evaluated by a set of test data using root mean square error (RMSE)، coefficient of determination ($R^2$) (Kennedy & Neville, 1986), and Nash-Sutcliffe efficiency (NSE) (Nash & Sutcliffe, 1970), between measured and predicted values. These statistics parameters are defined as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(ET_{ANN} - ET_{FPM})^2}{\mathrm{n}}} \qquad (3)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(ET_{ANN} - \overline{ET}_{ANN}\right)\left(ET_{FPM} - \overline{ET}_{FPM}\right)\right]^2}{\sum_{i=1}^{n}\left(ET_{ANN} - \overline{ET}_{ANN}\right)^2 \sum_{i=1}^{n}\left(ET_{FPM} - \overline{ET}_{FPM}\right)^2} \qquad (4)$$

$$\mathrm{NSE} = 1 - \frac{\left[\sum_{i=1}^{n}(ET_{FPM} - ET_{ANN})\right]^2}{\sum_{i=1}^{n}\left(ET_{FPM} - \overline{ET}_{FPM}\right)^2} \qquad (5)$$

Smaller values of RMSE and higher values of $R^2$ indicate higher model performance. The Nash-Sutcliffe (NSE) efficiency is used to evaluate the predictive power of the model and varies from -∞ to 1, with 1 being the perfect fit between the data estimated by the model and the measured data.

Where:
$ET_{FPM}$ : FPM , (mm.day$^{-1}$),
$ET_{\mathrm{ANN}}$ : Predicted evapotranspiration, (mm.day$^{-1}$),
$\overline{ET}_{FPM}$ : Average FPM, (mm.day$^{-1}$),
$\overline{ET}_{ANN}$ : Average predicted evapotranspiration, (mm.day$^{-1}$),
$n$ : Total number of samples.

A summary of the statistical description of the data used as inputs in the Neural Network model is presented in the table (2).

**Table:(2).** Statistical parameters of the climatic variables used for training and validation processes.

| Statistical parameters | Climatic Variables | | |
|---|---|---|---|
| | $T_{mean}$ (°C) | $RH_{mean}$ (%) | $R_a$ (MJ m$^{-2}$ day$^{-1}$) |
| Training processes | | | |
| Maximum | 25.2 | 89 | 41.46 |
| Minimum | 6.2 | 39 | 17.99 |
| Mean | 16.44 | 68.05 | 30.66 |
| Standard Deviation | 5.11 | 9.47 | 8.38 |
| Count | 311 | 311 | 311 |
| Validation processes | | | |
| Maximum | 25.9 | 83 | 41.46 |
| Minimum | 7.7 | 43 | 17.99 |
| Mean | 16.99 | 67.27 | 30.53 |
| Standard Deviation | 5.57 | 8.93 | 8.45 |
| Count | 133 | 133 | 133 |

## RESULTS AND DISSCUSSION

Table (3) refers to the number of input, hidden and output nodes of each ANN model. Furthermore, Table (3) presents the statistical results of the optimum ANN models using different input combinations to estimate the FPM. In the training process, the ANN1 model, where only the mean temperature ($T_{mean}$) was used as an input to this model, the values of RMSE, $R^2$ and NSE were 0.84, 0.74 and 0.74 respectively. In the validation process, the performance metrics of the ANN1 model, were 0.74, 0.81 and 0.80 for RMSE, $R^2$ and NSE respectively.

**Table:(3).** Performance criteria of the ANN models during training and validation

| Model | Input variables | Structure | Training | | | Validation | | |
|---|---|---|---|---|---|---|---|---|
| | | | RMSE | $R^2$ | NSE | RMSE | $R^2$ | NSE |
| ANN1 | $T_{mean}$ | 1-5-1 | 0.84 | 0.74 | 0.74 | 0.74 | 0.81 | 0.80 |
| ANN2 | $T_{mean}$, $R_a$ | 2-5-1 | 0.50 | 0.90 | 0.90 | 0.40 | 0.94 | 0.94 |
| ANN3 | $RH_{mean}$ | 1-5-1 | 0.94 | 0.68 | 0.68 | 0.96 | 0.68 | 0.66 |
| AAN4 | $RH_{mean}$, $R_a$ | 2-5-1 | 0.49 | 0.91 | 0.91 | 0.52 | 0.90 | 0.90 |
| ANN5 | $T_{mean}$, $RH_{mean}$ | 2-5-1 | 0.39 | 0.94 | 0.94 | 0.46 | 0.94 | 0.92 |
| ANN6 | $T_{mean}$, $RH_{mean}$, $R_a$ | 3-5-1 | 0.23 | 0.98 | 0.98 | 0.26 | 0.98 | 0.97 |

The scatter plot of predicted ETo values by the ANN1 model, compared with the FPM during the validation process, is presented in Figures (3). ANN2 model was performed better than ANN1. It can be observed that the presence of some of the input variables, such as extraterrestrial radiation ($R_a$) significantly affects the model's performances. Where RMSE, $R^2$ and NSE were 0.40, 0.94 and 0.94 respectively, i.e. a 16.05% increase in $R^2$. The scatter plot of predicted ETo values by the ANN2 model, compared with FPM is shown in Figure (4).

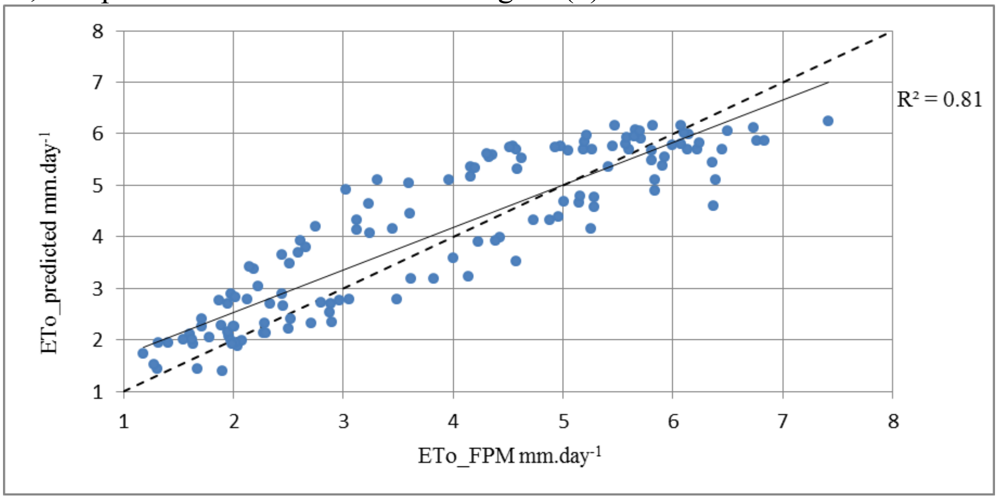



**Figure: (3).** scatter plot of predicted ETo values by the ANN1 model, compared with FPM during validation.

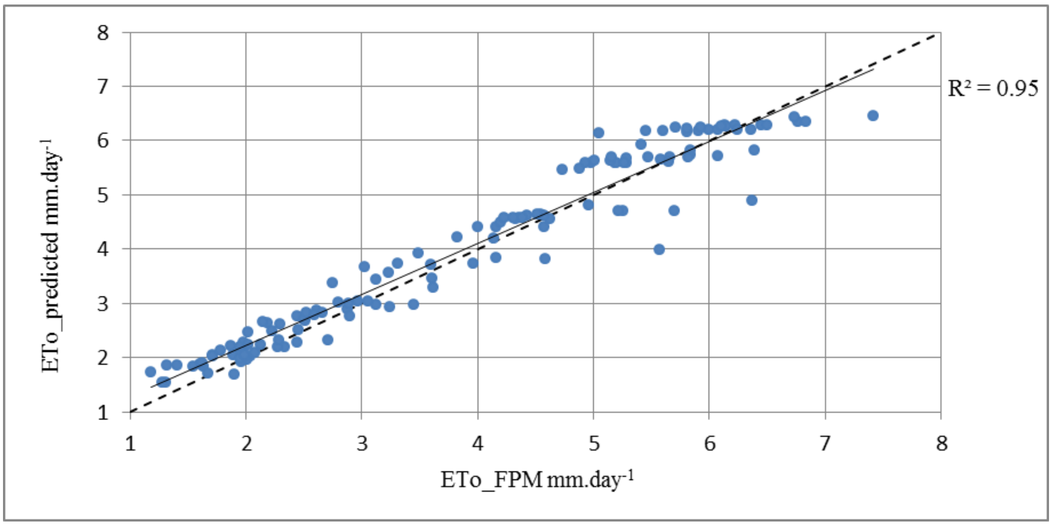



**Figure: (4).** scatter plot of predicted ETo values by the ANN2 model, compared with FPM during validation.

ANN3 model has the lowest performance compared with other combinations. In this model, only the mean relative humidity ($RH_{mean}$) was used. Figure (5) shows the scatter plot of this relationship. Figures from (6) to (8) show the scatter plot of predicted ETo values by the ANN4, ANN5 and ANN6 respectively compared with the FPM during the validation process. Where, ($RH_{mean}$+ $R_a$), ($T_{mean}$+ $RH_{mean}$) and ($T_{mean}$+ $RH_{mean}$+ $R_a$) were used for ANN4, ANN5 and ANN6 respectively.

Among all combinations of ANN models, the highest performance was with ANN6 model. Where the values of RMSE, $R^2$ and NSE were, 0.26, 0.98 and 0.97 respectively. These results correspond to the results of (Genaidy, 2020),(Heramb et al., 2023),(Rajput et al., 2023),(Abdel-Fattah et al., 2023),(Tunalı et al., 2023).

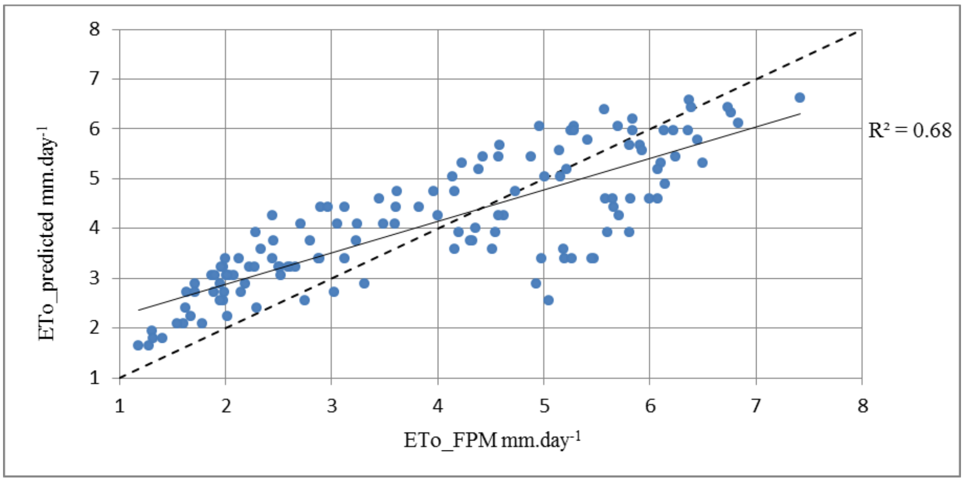



**Figure: (5).** scatter plot of predicted ETo values by the ANN3 model, compared with FPM during validation.

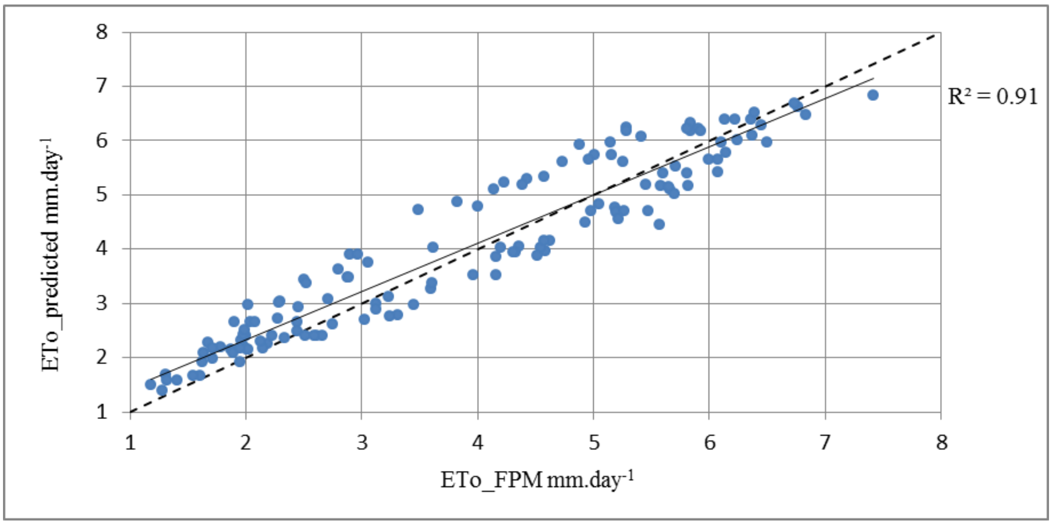



**Figure: (6).** scatter plot of predicted ETo values by the ANN4 model, compared with FPM during validation.

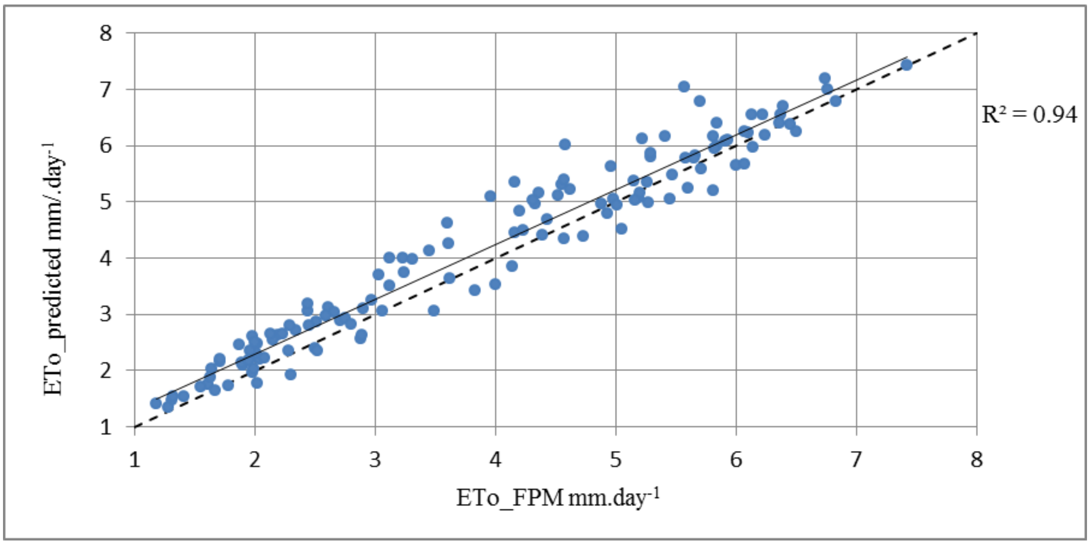



**Figure: (7).** scatter plot of predicted ETo values by the ANN5 model, compared with FPM during validation.

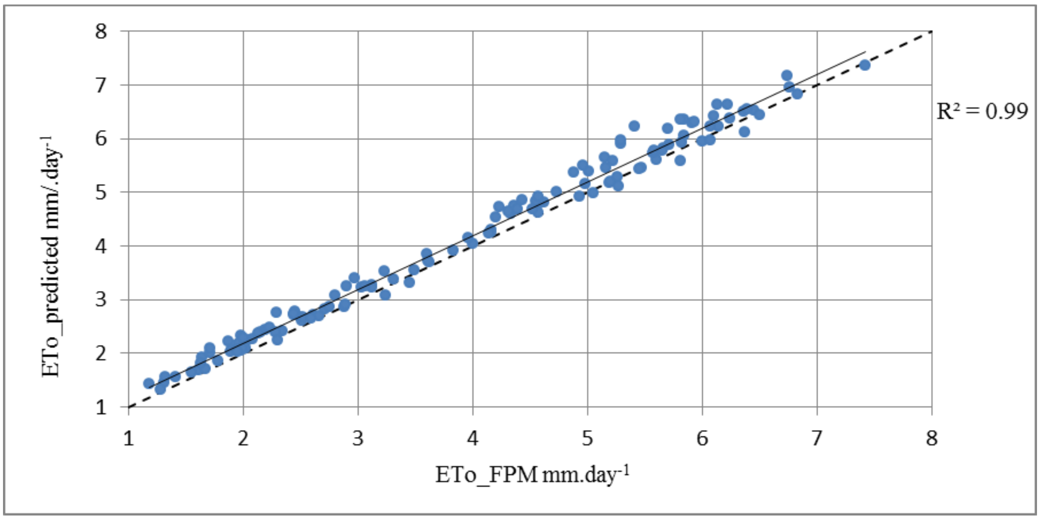



**Figure: (8).** scatter plot of predicted ETo values by the ANN6 model, compared with FPM during validation.

## CONCLUSION

From the previous discussion it is clearly seen that depending on the number of climatic variables available to calculate the reference evapotranspiration (ETo) using artificial neural networks (ANNs), It can recommend using the mean temperature ($T_{mean}$) with the extraterrestrial radiation ($R_a$) or using the mean relative humidity ($RH_{mean}$) with the extraterrestrial radiation. The best result obtained was using the average temperature ($T_{mean}$), the average relative humidity ($RH_{mean}$), and the extraterrestrial radiation ($R_a$).

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**Author contributions:** All Authors contributed equally to this manuscript.

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