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Using artificial neural networks to predict the reference evapotranspiration

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Abstract: Artificial neural network models (ANNs) were used in this study to predict reference evapotranspiration (ET_o) using climatic data from the meteorological station at the test station in Kafr El-Sheikh Governorate as inputs and reference evaporation values computed using the Penman–Monteith (PM) equation. These datasets were used to train and test seven different ANN models that included different combinations of the five diurnal meteorological variables used in this study, namely, maximum and minimum air temperature ($T_{\max}$ and $T_{\min}$), dew point temperature (T_{dw}), wind speed (u), and precipitation (P), how well artificial neural networks could predict ET_o values. A feed-forward multi-layer artificial neural network was used as the optimization algorithm. Using the tansig transfer function, the final architected has a 6-5-1 structure with 6 neurons in the input layer, 5 neurons in the hidden layer, and 1 neuron in the output layer that corresponds to the reference evapotranspiration. The root mean square error (*RMSE*) of 0.1295 mm·day^{-1} and the correlation coefficient (r) of 0.996 are estimated by artificial neural network ET_o models. When fewer inputs are used, ET_o values are affected. When three separate variables were employed, the *RMSE* test values were 0.379 and 0.411 mm·day^{-1} and r values of 0.971 and 0.966, respectively, and when two input variables were used, the *RMSE* test was 0.595 mm·day^{-1} and the r of 0.927. The study found that including the time indicator as an input to all groups increases the prediction of ET_o values significantly, and that including the rain factor has no effect on network performance. Then, using the Penman–Monteith method to estimate the missing variables by using the ET_o calculator the normalised root mean squared error (*NRMSE*) reached about 30% to predict ET_o if all data except temperature is calculated, while the *NRMSE* reached about of 13.6% when used ANN to predict ET_o using variables of temperature only.

Keywords: climate data, ET_o calculator, feed-forward artificial neural networks, Penman–Monteith method, reference evaporation, root mean squared error

INTRODUCTION

Even if the data set just comprises the maximum ($T_{\max}$) and minimum ($T_{\min}$) air temperatures, reliable estimations of the ET_o for ten days or per month can be obtained (FAO, 2009). Córdova *et al.* (2015) found that wind velocity data estimation has no significant effect on calculated ET_o, but that if estimated the solar radiation data the calculations may be wrong by up to 24%; if relative humidity data is estimated, the error may reach 14%; and if all data except the estimated temperatures are estimated, the errors may be higher than 30% calendar. Artificial neural networks (ANN), which are mathematical models similar to biological neural networks, have attracted great interest in the domains of water science and technology in recent decades (Heddam, 2014). They can learn from examples, spot patterns in data, adjust solutions over time, and quickly process data the more input variables, the ANN model was more efficient (Yamina, Marouf and Amireche, 2020). The ability of the ANN to learn and generalize correlations in complex data sets is a key property that broadens its use (Wu, Dandy and Maier, 2014). Artificial neural networks (ANN) are effective tools for modelling nonlinear systems that require little input (Sudheer, Gosain and

Ramasastri, 2003). ANNs can be used for forecasting reference evapotranspiration with high reliability (Trajkovic, Todorovic and Stankovic, 2003). Different ANN models techniques have been employed by several researchers to estimate evapotranspiration as a function of climate data, the multilayer perceptron (MLP) and radial basis functions neural networks (RBNN) techniques could be employed successfully in modelling the ET_o process (Kisi, 2008). Antonopoulos and Antonopoulos (2017) and Alsumaiei (2020) it was stated that the MLP model can have a relatively good performance in predicting evaporation in arid and very arid regions and cascade correlation algorithm has the ability to estimate the daily ET_o with reasonable accuracy (Diamantopoulou, Georgiou and Papamichail, 2011). Abbas (2017) it was stated that Feed-Forward Back Propagation (FFBP) with one hidden layer has a relatively good performance in predicting evaporation. ANNs were able to estimate ET_o properly when wind speed and solar radiation were unavailable (Dehbozorgi and Sepaskhah, 2012), and using only air temperature data as an input variable (Alves, De Souza Rolim and De Oliveira Aparecido, 2017). Trajkovic (2005) showed when radiation, relative humidity, and wind speed data are unavailable that an adaptive temperature-based RBF network can predict FAO-56 PM ET_o. The radial basis functions (RBF) network was viewed as emulating the FFBP in its performance and could be used effectively for ET_o prediction and, it is easier to build and much faster to train. That the network outputs are very highly correlated to estimated ET_o, especially when concerning all the climatic parameters (Awchi, 2008). The objectives of this study were: first, to study the possibilities of using FFBP networks to predict daily ET_o values using climatic data from the meteorological station at the test station in Kafr El-Sheikh Governorate as inputs to these networks and using the calculated ET_o data FAO-56 PM as an output for these networks. Second, reducing the FFBP input to the minimum weather data requirements required for estimating ET_o and its impact on acceptable accuracy. And third, comparing the ET_o values of FAO-56 PM ET_o computed under different levels of data availability using the ET_o calculator model with the ET_o computed in FFBP networks.

MATERIALS AND METHODS

The climate data used in this study consisted of daily observations of maximum ($T_{\max}$) and minimum ($T_{\min}$) air temperature (°C), dew point temperature (T_{dw}, °C), wind speed (u, m·s^{-1}) and precipitation (P, mm). All data was collected, for twenty years (from January 1, 2000 to December 31, 2020), from standard agricultural meteorological stations of the Agricultural Research Center in the tests station of Sakha, Kafer El-Shikh Governorate, Egypt, at latitude 31.09 N, and longitude 30.95 E, and mean altitude 2 m a.s.l.

These data were used as input to the artificial neural network (ANN) and the output was ET_o values were estimated using the Penman–Monteith (PM) method may be written as:

$$ET_o = \frac{0.408\Delta(R_n - G) + 900\ \gamma u_2(e_s - e_a)/(T + 273)}{\Delta + \gamma(1 + 0.34\ u_2)} \quad (1)$$

where: ET_o = reference evapotranspiration (mm·day^{-1}), R_n = net radiation (MJ·m^{-2}·day^{-1}), G = soil heat flux density (MJ·m^{-2}·day^{-1}), T = mean daily air temperature at 2 m height (°C), u_2 = wind speed at 2 m height (m·s^{-1}), e_s = saturation vapour pressure (kPa), e_a = actual vapour pressure (kPa), $e_s - e_a$ = saturation vapour pressure deficit (kPa), Δ = slope of the vapour pressure curve.

Which was proposed as the sole standard method for the computation of reference evapotranspiration (Trajkovic, Todorovic and Stankovic, 2003). The estimated ET_o values ware used as a standard for training and validation of various artificial neural network topologies. The Neural Network Toolbox (NN-Tool) in MATLAB (R2015a) is a tool for building multi-layer neural networks. In this study, the NN-Tool was used to train the network using the Feed-Forward Back Propagation (FFBP) algorithm.

To increase network training speed and efficiency, the Levenberg–Marquardt (L–M) algorithm was used with an early stopping criterion, as well as gradient descent (train GDX) with momentum and adaptive learning rate. All of the data was separated into three sets for the criterion (70% training, 15% validation, and 15% test) (Coulibaly, Anctil and Bobee, 2000).

Time, $T_{\min}$, $T_{\max}$, T_{dw}, u, and P are all nodes in the ANN model's input layer, while ET_o is represented by a single node in the output layer (calculated by the FAO-56 PM method). This study used one hidden layer with a varied number of hidden neurons to create networks because it can approximate any complex relationship. Trial and error were used to determine the number of neurons or nodes in the hidden layer, as well as model parameters. The number of hidden layer neurons ranged from two to five-step one. 1000, 1500, and 2000 epochs, learning rate from 0.001:0.005 step (0.001), and a momentum term of 0.9 were the model parameters that were fixed after numerous trials. In the hidden layer and output layer neurons, sigmoid and tanh activation functions were used, respectively. The optimal activation function was found through a trial-and-error procedure. The major selection criterion here was to improve the neural network's accuracy. Fig. 1 shown the model architecture.

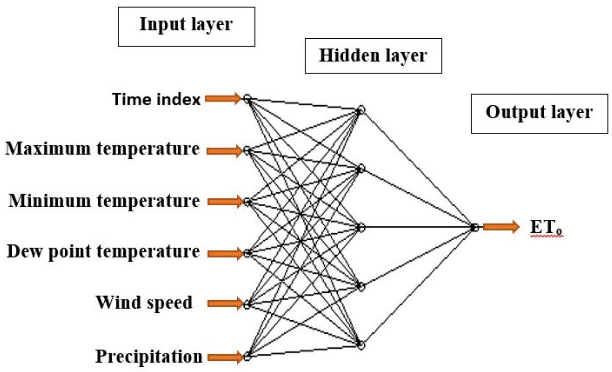

Fig. 1. The optimal model architecture; ET_o = reference evapotranspiration; source: own elaboration

Then, to investigate the effect of the time parameter, it was cancelled from input and the best model was trained without a time index.

The study analysed multiple groups of climatic variables as inputs to ANN models to measure the degree of influence of ET_o values with each of these inputs. Thus, the groups of inputs investigated in this study are:
1) $T_{\max}$, $T_{\min}$, T_{dw}, u, P;
2) $T_{\max}$, $T_{\min}$, T_{dw}, u;

3) $T_{\max}$, $T_{\min}$, T_{dw};
4) $T_{\max}$, $T_{\min}$;
5) $T_{\max}$, $T_{\min}$, u, P;
6) $T_{\max}$, $T_{\min}$, T_{dw}, P;
7) $T_{\max}$, $T_{\min}$, u

and effect an additional input node representing the add time index (month number throughout the year) has been incorporated in each of the previously discussed input structures, and the networks have been re-trained while keeping the spread and a maximum number of nodes the same in all cases.

Then compare the ANN results in cases 3, 4, and 7 with the ET_o calculator software developed by the FAO's Land and Water Division. Its main purpose is to calculate FAO-recommended reference evapotranspiration (ET_o).

Root mean square error (*RMSE*), normalised root mean square error (*NRMSE*), and Nash–Sutcliffe efficiency (*NSE*) were applied to assess and compare the accuracy of the methods and scenarios of the ANN models used and to identify the best way for predicting evapotranspiration. Performance indicators, correlation coefficient (r), coefficient of determination (R^2), and *RMSE*, were used for the validation period (Wang *et al.*, 2012). The expressions for the statistical parameters indicated above are given below.

- The correlation coefficient (r): the degree of linear connection and the direction between observed and predicted/simulated values is represented by this indicator; it is written as:

$$r = \frac{\sum_{i=1}^{n}\left[\left(h_{pi}-\bar{h}_p\right)\left(h_{oi}-\bar{h}_o\right)\right]}{\sqrt{\left[\left\langle\sum_{i=1}^{n}\left(h_{pi}-\bar{h}_p\right)^2\right\rangle\left\langle\sum_{i=1}^{n}\left(h_{oi}-\bar{h}_o\right)^2\right\rangle\right]}} \tag{2}$$

where: h_{oi} = observed ET_o at i the time, h_{pi} = predicted ET_o at i the time, n = total number of observations, $\bar{h}_o$ = mean of the observed ET_o, $\bar{h}_p$ = mean of the predicted ET_o.

Better models tend to have r values close to 1.

- The coefficient of determination (R^2) is the square of Pearson's correlation coefficient r and denotes the fraction of the overall variation in the observed data that the model can explain. The values of R^2 range from 0 to 1. The closer the values are to 1 indicating better agreement between observed and predicted/simulated values (Willmott, 1984). It is expressed as:

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left[\left(h_{pi}-\bar{h}_p\right)\left(h_{oi}-\bar{h}_o\right)\right]}{\sqrt{\left[\left\langle\sum_{i=1}^{n}\left(h_{pi}-\bar{h}_p\right)^2\right\rangle\left\langle\sum_{i=1}^{n}\left(h_{oi}-h_o\right)^2\right\rangle\right]}}\right]^2 \tag{3}$$

The root mean square error (*RMSE*): is used to measure the difference between model values predicted and the observed actual values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{\mathrm{obs},i}-X_{\mathrm{model},i}\right)^2}{n}} \tag{4}$$

where: $X_{\mathrm{obs},\,i}$ = the observation value, $X_{\mathrm{model},\,i}$ = the predicted value.

- The normalised root mean square error (*NRMSE*): relates the *RMSE* to the observed range of the variable. Thus, the overall range is resolved by the model. Can be observed as simulation (modelling) was excellent if it was smaller than 10% statistical indicator, good if between 10 and 20%, medium quality if it was between from 20 to 30%, and bad if it was greater than 30%.

$$NRMSE = \frac{RMSE}{\bar{O}} \tag{5}$$

where: $\bar{O}$ = the average observation value.

- The Nash–Sutcliffe efficiency (*NSE*): is a normalised statistic that compares the residual variance to the observed data variance (Nash and Sutcliffe, 1970).

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(OBS_i - SIM_i\right)^2}{\sum_{i=1}^{n}\left(OBS_i - \overline{OBS}\right)^2} \tag{6}$$

where: OBS_i = the observation value, SIM_i = the forecast value, and the $\overline{OBS}$ = the average observation value.

RESULTS AND DISCUSSION

This research aims to see how well FFBP networks can predict daily ET_o values using five different climate variables. Because there are no clear standards for determining propagation values and the number of concealed nodes, the trial-and-error method is used to estimate them. A massive number of tests were carried out using various nodes and the combinations that produced the best network performance. Two statistical methods were used to evaluate performance: maximizing the correlation coefficient (r) and minimization of the root mean squared error (*RMSE*). Both the training and verification phases have their *RMSE* values displayed.

The first experiment of the neural network model with gradient descent (GDX) (train algorithm) discovered that the architecture optimal model was (6-5-1), the transfer function of the hidden layer is sigmoid and the output layer was tansing, 2000 epoch, and learning rate 0.005, while correlation coefficient (r = 0.994) and root mean squared error (*RMSE* train = 0.07, *RMSE* validation = 0.17) was shown as Table 1.

Table 1. Training and validation of best FFBP networks due to gradient descent (GDX)

Transfer function		*r*				*RMSE*	
hidden layer	output layer	train	validation	test	all data	validation	train
Sigmoid	tansing	0.994	0.994	0.994	0.994	0.178	0.073
Tansing	tansing	0.992	0.992	0.992	0.992	0.200	0.066

Explanations: r = correlation coefficient, *RMSE* = root mean squared error.
Source: own study.

Table 2 and Figure 2 showed the optimal ANN (6-5-1) when using the Levenberg–Marquardt (L–M) algorithm with 2000 epoch, transfer function of hidden layer and output layer is tansing, whereas correlation coefficient (r = 0.996) and root mean squared error (*RMSE* train = 0.018 and *RMSE* validation = 0.14).

Table 2. Training and validation of best FFBP networks due to Levenberg–Marquardt (L–M)

Transfer function		*r*				*RMSE*	
hidden layer	output layer	train	validation	test	all data	validation	train
Sigmoid	tansing	0.996	0.996	0.995	0.996	0.142	0.043
Tansing	tansing	0.997	0.996	0.996	0.996	0.135	0.018

Explanations: r = correlation coefficient, *RMSE* = root mean squared error.
Source: own study.

When a time index is added to the input, the r and *RMSE* values improve significantly when compared to the results of situations without a time index this corresponds to (Awchi, 2008). Although adding the additional parameter may not affect all cases equally, it is noticeable that the effect is stronger as more input parameters are given. The reduction in *RMSE* values for the validation phase owing to integrating the time index varied from 29.8% (case 4) to 70.1% (case 1), while validation r values increased from 3.84% for case 1 to 10.4% for case 4.

Three networks were chosen from the seven investigated examples to investigate the impact of integrating daily rainfall data as an input to the network as shown in Tables 3 and 4. Networks 1, 6, and 5 were compared to networks 2, 3, and 7 in terms of performance respectively. The findings demonstrate that incorporating rainfall data has no meaningful impact on network performance improvement. As a result, using rainfall data for ET_o prediction is not recommended. Importantly, the time index parameter was employed to increase network performance.

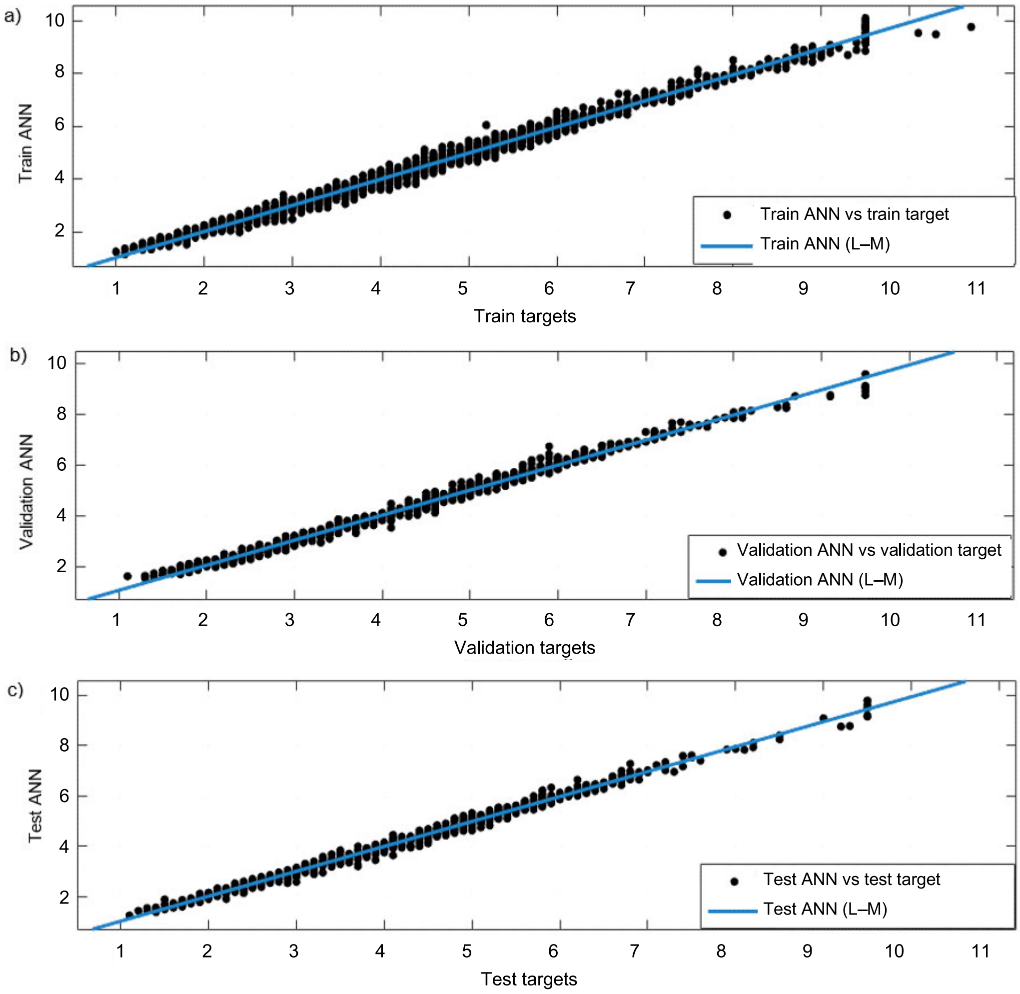

Fig. 2. Comparison of the ET_o predicted by the best FFBP networks (ANN) and observed values at: a) training, b) cross-validation, c) testing phases; source: own study

The second experiment of the neural network model (5-5-1) was without the time index to study the effect of time. The result was correlation coefficient (r = 0.96) and root mean squared error (*RMSE* train = 0.05, *RMSE* validation = 0.5).

Then, using various combinations of these parameters as inputs, seven networks were created. The output of all networks provided is the daily ET_o value evaluated using the PM method. Tables 3 and 4 listed these groups, which contained seven separate cases. To make the process of analysing network performance easier, these scenarios were grouped by the number of input parameters and the type of parameters.

For all cases with the time index input, the scatterplots of the observed vs predict values of the reference evapotranspiration ET_o of the FFBP with the L–M algorithm, R^2 values ranging from 0.992 in ANN 1 to 0.859 in ANN 4 and are displayed in Figure 3.

Table 3. Result of training and validation of best FFBP networks due to different inputs of climatic parameter without time index

ANN no.	Inputs	*r*				*RMSE*	
		train	validation	test	all data	validation	train
1	T_{max}, T_{min}, T_{dw}, u, P	0.958	0.959	0.956	0.958	0.453	0.052
2	T_{max}, T_{min}, T_{dw}, u	0.958	0.954	0.952	0.956	0.481	0.024
3	T_{max}, T_{min}, T_{dw}	0.906	0.909	0.903	0.906	0.677	0.002
4	T_{max}, T_{min}	0.852	0.838	0.860	0.851	0.857	0.001
5	T_{max}, T_{min}, u, P	0.931	0.932	0.924	0.930	0.586	0.001
6	T_{max}, T_{min}, T_{dw}, P	0.907	0.901	0.910	0.907	0.682	0.013
7	T_{max}, T_{min}, u	0.928	0.932	0.923	0.928	0.588	0.001

Explanations: r = correlation coefficient, *RMSE* = root mean squared error, T_{max} = maximum temperature (°C), T_{min} = minimum temperature (°C), T_{dw} = dew point temperature (°C), u = wind speed ($m \cdot s^{-1}$), P = precipitation (mm).
Source: own study.

Table 4. Result of training and validation of best FFBP networks due to different inputs of climatic parameters including a monthly time index

ANN no.	Inputs	*r*				*RMSE*	
		train	validation	test	all	validation	train
1	Mon, T_{max}, T_{min}, T_{dw}, u, P	0.9966	0.9962	0.9960	0.9964	0.1353	0.0183
2	Mon, T_{max}, T_{min}, T_{dw}, u	0.9956	0.9962	0.9952	0.9956	0.1429	0.0002
3	Mon, T_{max}, T_{min}, T_{dw}	0.9717	0.9689	0.9712	0.9712	0.3964	0.0618
4	Mon, T_{max}, T_{min}	0.9288	0.9255	0.9219	0.9272	0.6007	0.0003
5	Mon, T_{max}, T_{min}, u, P	0.9676	0.9607	0.9669	0.9665	0.4348	0.0003
6	Mon, T_{max}, T_{min}, T_{dw}, P	0.9725	0.9715	0.9684	0.9717	0.3760	0.0164
7	Mon, T_{max}, T_{min}, u	0.9662	0.9640	0.9662	0.9659	0.4061	0.0003

Explanations: Mon = monthly time index, other symbols as in Tab. 3.
Source: own study.

Then comparing the ET_o values of FAO-56 PM ET_o computed under different levels of data availability using the ET_o calculator model with the ET_o computed in FFBP networks.

Only cases 2, 3, 4, and 7 from ANN were compared with the ET_o calculator, which uses no rain quantity between its inputs to generate the reference evapotranspiration, to test the ET_o calculation's accuracy when compared to the standard FAO-56 PM method. The previously mentioned *NRMSE* and *NSE* performance appraisal scales were used to evaluate ET_o estimation methodologies.

Table 5 refers to a statistical analysis comparing the performance of an artificial neural network (ANN) method and an ET_o calculator method for calculating reference evapotranspiration (ET_o) in cases where certain data are missing. The study found that when wind speed data are unavailable (case 3), T_{dw} data are unavailable (case 7), or only temperature data are available (case 4), the ANN method generally performed better than the ET_o calculator method in terms of *RMSE*, *NSE* and the *NRMSE*. However, in case 2, the ET_o calculator method performed better.

Then comparing the ET_o values of FAO-56 PM ET_o computed under different levels of data availability using the ET_o calculator model with the ET_o computed in FFBP networks.

Only cases 2, 3, 4, and 7 from ANN were compared with the ET_o calculator, which uses no rain quantity between its inputs to generate the reference evapotranspiration. The study also found that as the number of missing variables increased, the accuracy of ET_o calculations decreased for both methods.

The study found that in case 2, when using an ANN with a time index input, the calculations were excellent. In case 3, when wind data was unavailable, the ANN method produced excellent calculations while the ET_o calculator method produced good results. In case 7, when T_{dw} data was unavailable, the ANN method with a time index input performed excellently, while the ET_o calculator method performed moderately with a potential error rate of 25% if dew point temperature data were estimated. In case 4, when only T_{max} and T_{min} data were available, the ANN method with a time index input performed well with an error rate of 13.6%, but the ET_o calculator method performed poorly with an error rate of more than 30%. These results are similar to those found by Córdova *et al.* (2015).

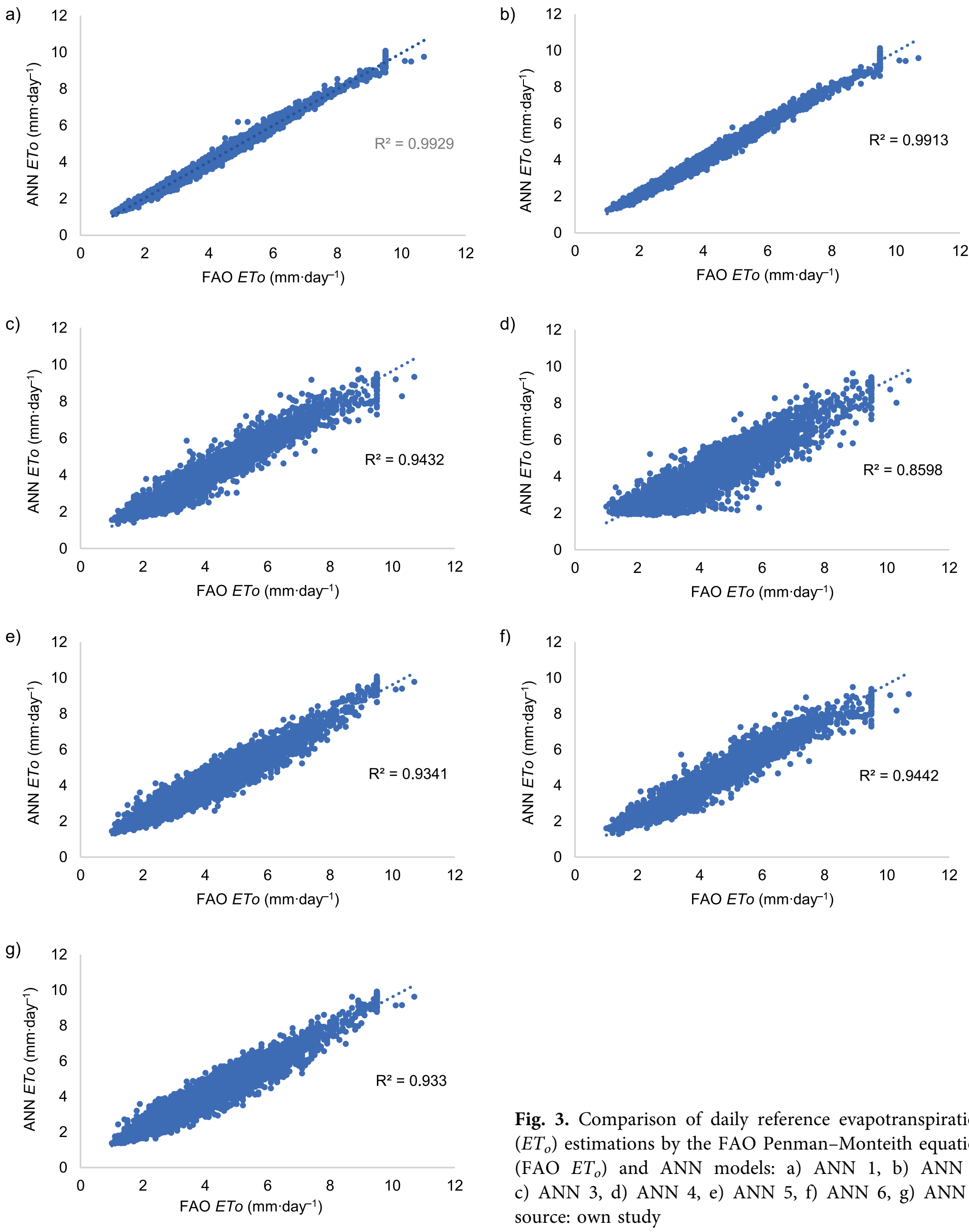

Fig. 3. Comparison of daily reference evapotranspiration (ET_o) estimations by the FAO Penman–Monteith equation (FAO ET_o) and ANN models: a) ANN 1, b) ANN 2, c) ANN 3, d) ANN 4, e) ANN 5, f) ANN 6, g) ANN 7; source: own study

Table 5. The performance indices of artificial neural network (ANN) and the ET_o calculator method for the cases of missing variables were analysed

Case no.	ANN with time index			ET_o calculator		
	RMSE	*NRMSE* (%)	*NSE*	*RMSE*	*NRMSE* (%)	*NSE*
2	0.148	3.4	0.991	0.093	2.1	0.997
3	0.379	8.6	0.943	0.873	19.9	0.698
4	0.595	13.6	0.86	1.345	30.6	0.284
7	0.411	9.4	0.933	1.109	25.2	0.513

Explanations: *RMSE* = root mean square error, *NRMSE* = normalised root mean square error, *NSE* = Nash–Sutcliffe efficiency.
Source: own study.

CONCLUSIONS

This paper aims to investigate the potential of ANN in estimating daily ET_o in the Sakha district of Kafr El-Sheikh Governorate in Egypt. Networks using various input sets of available climatic data were trained using the FFBP network to predict daily ET_o values using different climatic data. Analysis of the study results indicated that FFBP networks with the use of L–M training algorithms and sigmoid activation function can predict ET_o values. ANN 1 model was presented with inputs of maximum and minimum air temperature, precipitation, wind speed and dew point temperature, and a single component hidden layer. Of five neurons the best architecture among the many that were tested. It gave the best ET_o estimates among the input groups tried in the study. The best results are obtained when all studied climatic parameters are included as inputs to the network. Using only air temperature inputs gave bad ratings. In addition, no significant improvement in network performance was observed when precipitation was incorporated as an input to the network. It was seen that there is a valuable effect of including the time index of the inputs, which resulted in a clear improvement in all studied cases. Therefore, the use of time indicators is highly recommended for future research work. The results also showed that using FFBP networks for both maximum and minimum temperature data is better than using ET_o calculator to predict ET_o at the study site.

From a practical point of view, ANN models can be considered more suitable to serve as a tool for ET_o estimation when the input climate variables are insufficient.

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