APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT REFERENCE EVAPOTRANSPIRATION IN FAMAGUSTA, NORTH CYPRUS

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ABSTRACT:

Accuracy in reference evapotranspiration (ETo) estimation is required for agricultural production, water resources management and planning. To this effect, a three layered Feed Forward Neural Network (FFNN) trained with Back Propagation (BP) algorithm was employed to predict monthly ETo in Famagusta region of Northern Cyprus for the period 2017 – 2050. The models were trained with 2, 3, and 4 inputs, the most dominant parameter was obtained and the results were compared to Multilinear Regression (MLR) Model results. Penman-Monteith (PM) method was used to estimate the past ETo. The results deduced that FFNN models can accurately predict ETo with higher efficiency than MLR models. Also in view of the obtained results, wind speed (U_2) is the most dominant between the input parameters.

1. INTRODUCTION

Evapotranspiration (ET) is among the crucial elements of hydrologic water cycle and is of magnificent value to the management of water resources. It can be measured instrumentally or by applying reference evapotranspiration calculations (Gocić et al., 2015). ETo is regarded as the basis for ascertaining crop evapotranspiration (ETc) in addition to crop irrigation water requirements computation (Dai et al., 2009). The equation for modified Penman-Monteith (PM) has been recognized worldwide for varied time steps comprising monthly, daily, and hourly for ETo evaluation and is considered the best method for ETo determination by Food and Agricultural Organization of United Nations (FAO) (Allen et al., 1998).

Artificial Neural Networks (ANNs) for the past decades have been given substantial attention in numerous field, including Hydrology, System modeling, Financial forecasting, Fault diagnosis and control, and Pattern recognition (Coulibaly, 2003). However, in recent years, applications of ANN

were utilized in estimating evapotranspiration, and the results suggested that ANN have more prediction accuracy than conventional method (Dai et al., 2009).

The objectives of this study are to predict monthly ETo for Famagusta meteorological region of Northern Cyprus for the period of 33 years (2017 – 2050), determine the most dominant input parameter, and finally, perform multilinear regression (MLR) model to compare with the obtained ANN results.

2. MATERIALS AND METHODS

2.1 Study area and data

Famagusta is also called Gazimagusa (in Turkish) located in Northern Cyprus, lies between the Eloea and Greco on the Eastern coast. It occupies the deepest harbor in Cyprus (http://www.whatson-northcyprus.com/towns/famagusta.htm). Famagusta have a latitude of $35^0$11`N, longitude $33^0$95`E and altitude 20m, average annual precipitation is 404mm. The study region location is given in Figure 1.

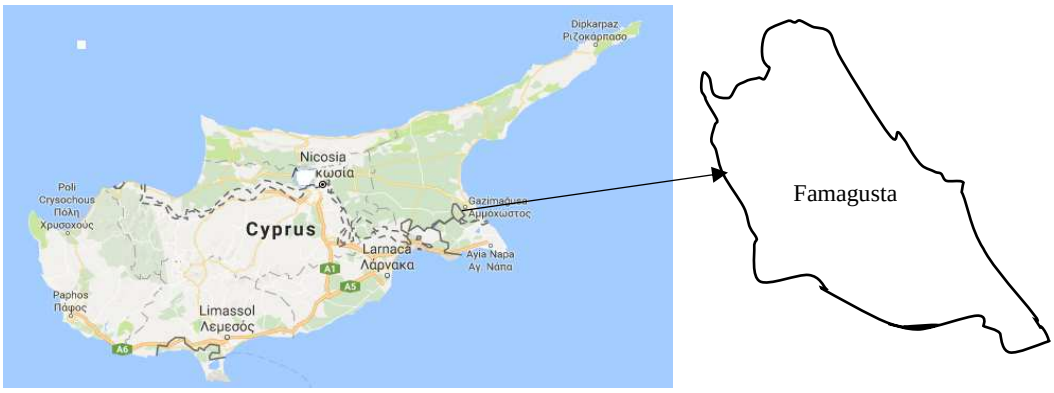

Figure1: Study region location in Cyprus

A total of 408 monthly meteorological data comprising of minimum and maximum temperatures (T_{min}, T_{max}), wind speed (U_2) and relative humidity (R_h) from 1983 – 2016 were collected from NASA Prediction of Worldwide Energy resource (POWER), Climatology Resources for Agroclimatology.

2.2 Artificial neural network (ANN)

ANNs are flexible methods of modeling that requires input and output sets of data to simulate system altitude (Mehr et al., 2015). ANN is comprise of a number of sample processing elements (called neurons/nodes) that are interconnected with characteristics information processing of an adorable attribute, including parallelism, learning, noise tolerance, nonlinearity, and generalization capability. Nowadays, the widespread and most widely used ANN is Feed Forward Neural Network (FFNN) trained by Back Propagation (BP) algorithm (Nourani and Kalantari, 2010). A typical FFNN is shown in Figure 2 below;

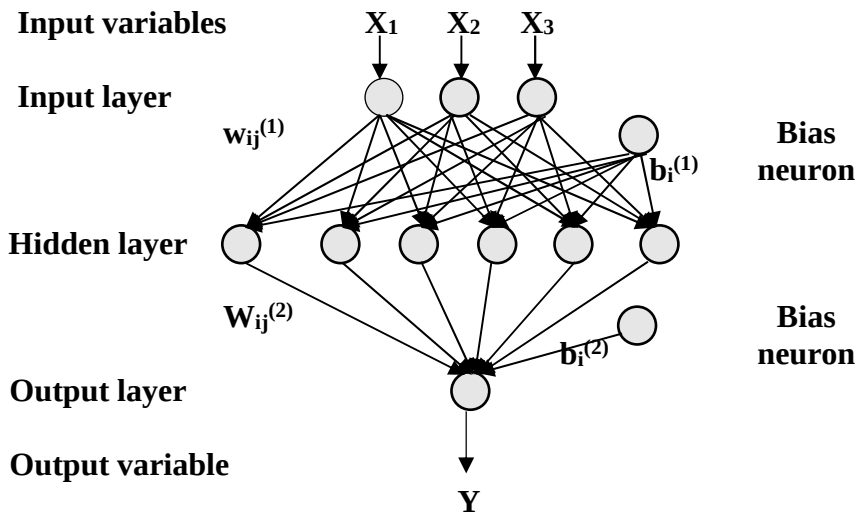

Figure 2: A schematic architecture of FFNN with 3 input parameters

2.3 Data normalization and performance evaluation criteria

To eliminate dimensions of variables input – output, the data were normalized to fall between 1 to 0 by using the following formula;

$$E_n = \frac{E_i - E_{min}}{E_{max} - E_{min}} \tag{1}$$

Where E_{min}, E_{max}, E_n, E_i are the minimum, maximum, normalized, actual values used, respectively. Determination Coefficient (DC or R^2) and Root Mean Square Error (RMSE) were used to determine the models efficiency in accordance to Nourani et al., (2012a), given by

$$DC = 1 - \frac{\sum_{i=1}^{N}(E_i - \hat{E}_i)^2}{\sum_{i=1}^{N}(E_i - \bar{E})^2} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(E_i - \hat{E}_i)^2}{N}} \tag{3}$$

Where N, $\bar{E}$, $\hat{E}_i$, E_i are the number of data used, average observed data, model computed value, and observed value, respectively.

2.4 Multilinear regression (MLR)

MLR is among the most used statistical techniques in modeling linear relationship between dependent and independent variables. The MLR methodology is given in equation 4 below according to Parmar and Bhardwaj, (2015);

$$y = b_0 + b_1 x_1 + b_2 x_2 + \cdots b_i x_i \tag{4}$$

Where x_i is the ith predictor value, b_0 is the constant of regression, and b_i is the ith predictor coefficient.

2.5 Reference evapotranspiration (ETo)

The reference evapotranspiration approach was proposed to determine atmospheric demand of evapotranspiration independent of management practice, crop development, and crop type. Several methods are used in computing ETo but the best method is PM (Allen et al., 1998). The PM equation is given by;

$$ETo = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (5)$$

Where
ETo = Reference evapotranspiration (mm/day), Δ = slope vapour pressure curve (kpa/^{0}C, R_n= net radiation at the crop surface (MJ/m^2/day), G = soil heat flux density (MJ/m^2/day), T = Air temperature at 2m height (^{0}C), U_2 = wind speed at 2m height (m/s), e_s = saturation vapour pressure (kpa), e_a = actual vapour pressure (kpa), $e_s - e_a$ = saturation vapour pressure deficit (kpa), γ = psychrometric constant (kpa/^{0}C).

3. Results and Discussion

ANN architecture identification is the fundamental and primary aspect to consider in modeling, because improper architecture can cause overfitting, computational overload and underfitting (Nourani et al., 2012b). To have ANN model free from the aforementioned problems, a three layered FFNN trained by Levenberg Marquardt optimization algorithm was employed for the ANN modeling. However, Tangent sigmoid was used as the transfer function of both output and hidden layers neurons. A total of 408 monthly meteorological data samples were considered for the study and were divided in to 75% (306) and 25% (102) for training and validation, respectively. Statistical analysis of the parameters used for the training and validation is given in Table 1.

Table 1: Statistical analysis of the data used

Variable	Data set	Min	Max	Mean (U_2)	Standard Deviatn.	Skewness (C_S)	Kurtosis (C_K)
T_{min} (^{0}C)	Training	5.7	28.4	17.65	6.42	0.11	-1.39
	Validation	10.4	27.2	18.75	5.2	0.05	-1.43
T_{max} (^{0}C)	Training	11.1	34.9	23.23	6.52	0.08	-1.39
	Validation	14.4	38.3	25.28	6.93	0.14	-1.23
R_h (%)	Training	42	77	59.16	8.14	0.0001	-0.99
	Validation	49	79	61.94	6.75	0.39	-0.54
U_2 (m/s)	Training	1.84	4.58	2.76	0.51	0.73	0.003
	Validation	1.58	4.58	2.81	0.59	0.49	0.06

The models were trained using 2, 3, and 4 inputs. The input parameters to the developed models are given in Table 2.

Table 2: Input parameters used for the models

Model	Model Structure	Model Inputs
M1	2-4-1	T_{min} , T_{max} ,
M2	3-6-1	T_{min} , T_{max} , R_h
M3	3-6-1	T_{min} , T_{max} , U_2
M4	4-8-1	T_{min} , T_{max} , R_h , U_2

Four models were trained and by process of trial and error the best were selected. The obtained MLR and ANN models are presented in Table 3 below;

Table 3: Results of the best ANN models and MLR models

			ANN				MLR			
			Training		Validation		Training		Validation	
Model	Model Structure	Epoch	DC	RMSE	DC	RMSE	DC	RMSE	DC	RMSE
M1	2-4-1	109	0.9462	0.069	0.8841	0.1055	0.9146	0.0874	0.873	0.1111
M2	3-6-1	138	0.9568	0.0618	0.9121	0.0918	0.9317	0.0783	0.8823	0.1076
M3	3-6-1	199	0.9562	0.0623	0.9524	0.0676	0.9216	0.0839	0.9494	0.0705
M4	4-8-1	161	0.9591	0.0602	0.9728	0.0511	0.9347	0.0767	0.9519	0.0691

As seen in Table 3, M4 with 4 input parameters, 8 hidden layer neurons, one output, and 161 Epoch is the best model as it has the highest DC close to 1 and lowest RMSE close to 0 for both training and validation. However, it is obvious from Table 2 and 3 that wind speed (U_2) is the most dominant input with DCs 0.9562, 0.9524 and RMSE 0.0623, 0.0676 for training and validation, respectively. Moreover, Table 3 showed that ANN models have higher prediction accuracy than MLR models considering the obtained results for DCs and RMSEs for training and validation. The scatter plots and time series for the best model are given in Figure 3.

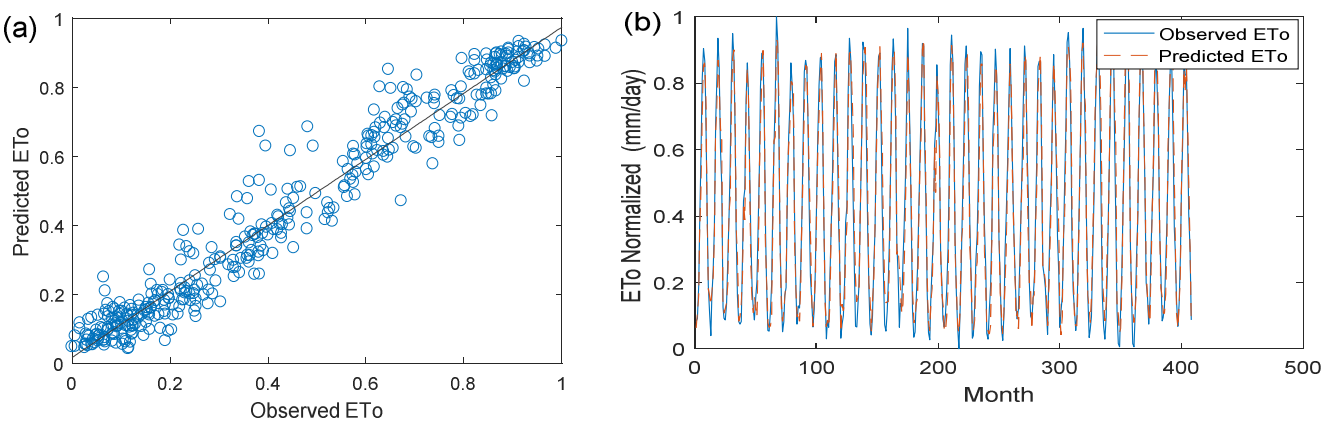

Figure 3: Observed and Predicted ETo for (a) Scatter plot (b) Time series

4. CONCLUSION

Considering the significance of reference evapotranspiration (ETo) in hydrologic water cycle and for proper estimations of crop water requirements and irrigation water requirements especially in the arid and semi-arid regions where water resources is scanty, accurate modeling of ETo would lead to better management of water resources. As a result, a three layered Feed Forward Neural Network (FFNN) with Back Propagation (BP) optimization algorithm was applied in this study to predict monthly ETo in Famagusta region of Northern Cyprus from 2017 – 2050. Moreover, Multilinear Regression Model (MLR) was used and compared to the results obtained by ANN. The results revealed that ANN can accurately forecast ETo in the study region and it possesses higher prediction efficiency in comparison to MLR. However, the results indicated that the accuracy of prediction was higher when 4 input parameters were used with wind speed (U_2) as the most dominant parameter.

In this study, ANN-based forecasting modeling was only considered to estimate ETo, hence, for further studies, other soft computing modeling tools should be employed inorder to strengthen the results and to have a better prediction of ETo in the study region.

5. REFERENCES

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