Temperature-Based Feed-Forward Backpropagation Artificial Neural Network For Estimating Reference Crop Evapotranspiration In The Upper West Region

Ibrahim Denka Kariyama

Abstract –The potential of modeling the FAO Penman-Monteith (FAO-56 PM) method for computing reference crop evapotranspiration (ET_o) using feed-forward backpropagation artificial neural networks (FFBANN) with minimal measured climate data such as with the air temperature (maximum and minimum) was investigated using local climatic data from the Wa Meteorological weather station. Three FFBANN models were developed and trained with the Levenberg-Marquardt algorithm and the early stopping approach. These three FFBANN models are temperature-based models and have the same input variable as the established temperature-based empirical methods; the Hargreaves, Blaney-Criddle and the Thornthwaite methods. A comparative study was carried to see how these FFBANN models performed relative to the other three established temperature-based empirical methods using the FAO-56 PM method as the benchmark. In general, the FFBANN models outperformed these established methods in estimating the ET_o and should be preferred where only measured air temperature (maximum and minimum) is the variable available for estimating the reference crop evapotranspiration.

Index Terms – *Reference crop evapotranspiration, Feed-Forward backpropagation artificial neural network.*

1 INTRODUCTION

The reference crop evapotranspiration is a component of the hydrological cycle and hence an important parameter in the field of hydrology and other disciplines. The Food and Agricultural Organization (FAO) defines reference crop evapotranspiration (ETo) as the rate of evapotranspiration from a hypothetic crop with an assumed crop height of 12 cm, a fixed canopy resistance of 70 sm-1 and albedo of 0.23, closely resembling the evapotranspiration from an extensive surface of green grass of uniform height, actively growing, completely shading the ground and not short of water [1, 2]. The FAO [2, 3] recommended that where needed climatological variables are available reference crop evapotranspiration should be computed using FAO-56 Penman-Monteith (FAO-56 PM), as the calibrated empirical methods may still not give accurate results [4]. However, determining the radiation term and aerodynamic term as used in the FAO-56 PM is cumbersome and needs expertise. The FAO-56 PM also requires four measured climatic data; the air temperature, air relative humidity, wind speed and the sunshine hour or solar radiation. These data are not always available in most weather stations and where available the reliability of some of the data are questionable and sometimes with missing data.

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Therefore, although the FAO-56 PM is the most accurate and accepted standard method, its application is often limited. Empirical methods are often used instead, based on the fact that meteorological variables necessary for the application of the FAO-56 PM are always not available [5]. Empirical methods requires less measured climate data and are simple to use but are most suitable in the location and climatic conditions in which there were developed. Their suitability in different locations is enhanced by calibration using local climatological data. The calibrations of these empirical methods with the FAO-56 PM as the benchmark, may still not give accurate results [4]. Temperature-based empirical methods estimate the ET_o using only measured maximum and minimum air temperatures as the minimum set of climate data necessary to estimate ET_o and astronomical data which depends on the location and date (day and month of the year). Computer Modelling of the reference crop evapotranspiration using minimal climatic data that mimic established empirical methods are gaining prominence in the quest to find an accurate and suitable method for computing ET_o with minimal climate data requirement. The FAO-56 PM method for computing reference crop evapotranspiration exhibits complex non-linear relationship with the climate data therefore artificial intelligence (AI), neural computing techniques that are able to accurately map complex, non-linear input-output relationships such as the reference crop evapotranspiration therefore offers a useful alternative to the complex FAO-56 PM and the established empirical methods. The main advantage of artificial intelligence approach over other traditional methods is that it does not require information about the complex nature of the underlying process under consideration to be explicitly described in mathematical form [6]. This paper therefore used feed-forward backpropagation artificial neural network (FFBANN) to develop temperature-based models for estimating the ET_o. The FFBANN is a supervised artificial neural network that uses input-output mapping capabilities to find function approximation for complex nonlinear relationships. Once the model learns to predict the reference crop evapotranspiration using the input-output exemplars, the model is then stored and used to predict reference evapotranspiration in the future using new inputs variables only. Comparisons are made with three established temperature-based empirical methods; the Hargreaves, Blaney-Criddle and the Thornthwaite methods using the FAO-56 PM as the benchmark.

2 RESEARCH METHODOLOGY

2.1 Artificial Neural Networks Models

A neural network (NN) model is a mathematical construct whose architecture is essentially analogous to the human brain. The highly interconnected processing elements (PEs) or neurons arranged in layers are similar to the arrangement of the human brain [7, 8]. Haykin [7] defines neural network viewed as an adaptive machine as follows: “A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two aspects: Knowledge is acquired by the network through a learning process. Interneuron connection strengths known as synaptic weights are used to store knowledge”. The procedure used to perform the learning process is called a learning algorithm. The manner in which the neurons of a neural network are combined is linked with the learning algorithm. A learning algorithm is a prescribed set of well-defined rules for the solution of a learning problem. Neural networks are trained to perform a particular function by adjusting the values of the connections (weights) between elements. The neural networks are adjusted or trained, so that a particular input leads to a specific target output. The network is adjusted based on a comparison of the output and the target, until the network output matches the target. Training is a procedure whereby a network is actually adjusted to do a particular job [9]. There are two approaches to training: supervised and unsupervised training. Supervised training involves a mechanism of providing the network with the desired output either manually, “grading” the network’s performance or by providing the desired outputs with inputs [10]. Unsupervised (also referred to as self-organization or adaption) is where the networks have to make sense of the inputs without outside help. Majority of networks utilize supervised training. Neural networks have been trained to perform complex function in various fields of application including pattern recognition, identification, classification, speech, vision and controls systems [10]. That is basically, most neural networks application can be classified into five categories: prediction, classification, data association, data conceptualization, and data filtering. Today neural networks have been broadly used in different disciplines (engineering, financial and other practical application). It can be trained to solve problems that are difficult for conventional computers or human beings. Artificial neural networks have been successfully used in evapotranspiration modelling [5, 6, 8, 11, 12, 13, 14, 15, 16, 17, 18, 19]. Parasuraman et al. [16] observe that the input-output functional relationship does not remain the same over the entire modeling domain, varying at different spatial and temporal scale. Therefore the need to use local data to model the ETo in the region. Artificial neural networks have input-output mapping capabilities for analyzing complex nonlinear relationships in many fields of study. The main advantage of ANNs approach over other traditional methods is that it does not require information about the complex nature of the underlying process under consideration to be explicitly described in mathematical form [6]. Evapotranspiration is a complex and nonlinear phenomenon because it depends on several interacting climatological factors such as temperature, humidity, wind speed, solar radiation, crop type and growth stage of the crop, soil moisture content, and a lot more [6, 8]. Artificial neural networks (ANNs) are effective tools to model nonlinear systems better than simple regression [20], numerical algorithms and other conventional statistical methods.

2.2 Neural Network Models and Architecture

Modelling reference crop evapotranspiration using artificial networks was achieved using MATLAB (Windows version 7.5.0 (R2007b), The Mathworks Inc., Natich, MA) with Neural Networks Toolbox 5.1, for the models simulations. There are multitudes of network types available for ANN applications and the choice of any network application depends on the problem and data. A feed-forward backpropagation often referred to as feed-forward multilayer perceptron (MLP) with a single hidden layer was considered to be best choice for this study. Perceptron are fast and reliable networks for problems they can solve [9]. There is considerable literature evidence that evapotranspiration can be modelled using single-hidden layer network [5, 6, 8, 13, 15, 19]. Feed-forward backpropagation (feed-forward multilayer perceptrons (MLP)) have been shown to have a computational superiority in comparison to other paradigms [21]. Feed-forward backpropagation networks consist of input, hidden, and output layers and each layer includes an array of processing element (neuron) as illustrated in Fig.1.

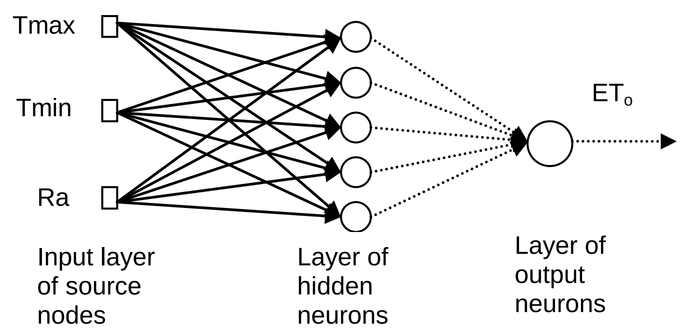

Fig. 1. Schematic of feed-forward backpropagation ANN1 with single hidden layer and one output layer

The feed-forward backpropagation network was trained under supervision with the Levenberg-Marquardt (LM) algorithm (TRAINLM) [22, 23] and learned with adaption learning function “backpropagation with momentum” (LEARNGDM) which is preferable to standard backpropagation algorithm [5]. Levenberg-Marquardt uses the Newton’s method for approaching the minimum of the error function. The error is the mean square error as express below.

$$MSE = \frac{\sum_{i=1}^{N}\left(y_{PM-ET_o,i} - y_{ANN,i}\right)^2}{N} \quad (1)$$

Where $y_{PM-ET_o,i}$ is ET_o estimated by the FAO-56 PM, $y_{ANN,i}$ is ETo estimated by the ANN models, and N is number of observations. The use of the LM algorithm in network training is relatively new [24]. Coulibaly et al. [25] reported that about 90% of the applications of ANNs in hydrology over the last few years make use of multilayer feed-forward neural networks trained by the standard back-propagation algorithm. However, the standard back-Propagation has several drawbacks, namely that the algorithm is very slow, requires much off-line training, exhibits temporal instability (can oscillate) and has a tendency to become stuck at local minima. On the contrary, the LM algorithm has been proved to have the fastest convergence on networks which contain up to a few hundred's weights [9]. The tan-sigmoid activation function was chosen for the layer of hidden neurons and the output neurons. The tan-sigmoid function is preferred to the log-sigmoid function because according to [7], a multilayer perceptron may converge faster (in terms of the number of epochs required) when the sigmoid function is symmetric than when it is asymmetric. In order to implement the LM algorithm, the default values of the training parameters were used: the epochs was set at 100, goal at 0, max_fail at 5, mem_reduc 1, min_grad at 1e-010, mu at 0.001, mu_dec 0.1, mu_inc 10, mu_max 1010, show 25 and the time set at Inf. The training stops if the number of iterations exceeds the epochs, if the performance function drops below the goal, if the magnitude of the gradient is less that min_grad, or if the training time is longer than the set time seconds [9]. Also, the parameter mu is multiple with mu_dec whenever the performance function is reduced by a step and it is multiple by mu_inc whenever a step would increase the performance function. If the mu becomes larger than mu_max, the algorithm is stop. The parameter mem_reduc is used to control the amount of memory used by the algorithm. As reported by Demuth and Beale [9], the default parameter values normally perform adequately for algorithms such as the LM. One of the major advantages of neural networks is their ability to generalize, perceptron have the ability to generalized from its training vectors (inputs and target/output) and learn from initially randomly distributed connections. To improve the generalization of the models, the early stopping rule was used [9, 26, 27]. The use of early stopping rule reduced the training time significantly [28] and it provided better and more reliable generalization performance than the use of the LM algorithm alone. For early stopping the climatic data were divided into three parts: A training set (657 exemplars), used to determine the network parameters, weights and biases; validation set (219 exemplars), used to estimate the network and performance and decide when the training is stopped; and a test set (219 exemplars), used to verify the effectives of the stopping criterion and to estimate the expected performance in the future. The validation set is normally passed to the training function; therefore the validation set forms part of the network. The training using the LM was stopped when the mu (μ) became larger than 0.001, when the number of epochs reaches 100 or when the validation performance started to decrease.

2.3 Data Set for Networks

The data for the networks consists of daily climatic data from the Wa Meteorological station latitude 10°.04' N and altitude 322.7 m from 2009-2011. A total of 1095 exemplars were generated for the networks training, validation and testing. The first 657 daily climatic data were used for the models training and the remaining 438 was then divided into two for models validation (219 exemplars) and testing (219 exemplars). The first network ANN1 consists of only measured air temperature (maximum and minimum), computed extraterrestrial radiation which depends on the position of the sun and hence is a function of location (latitude) and date (month) [5]. ANN1 resembles the combination used in Hargreaves temperature-based ET_o approach [29]. The second network ANN2, consists of only measured air temperature (maximum and minimum) and maximum possible sunshine hours (N) which depends on the position of the sun and hence is a function of location (latitude) and date (month) [15]. ANN2 therefore resembles ET_o approach by Blaney-Criddle [30] and [31], since the ratio of actual daytime hours to annual mean daily daytime hours (%) (p), in the Blaney-Criddle method is calculated from N and the mean air temperature in both approaches is the mean of the maximum and minimum. The third network ANN3 consists of only measured air temperature (maximum and minimum), computed extraterrestrial radiation and maximum possible sunshine hours (N) which depends on the position of the sun and hence is a function of location (latitude) and date (month) [5]. ANN3 also resembles the combination used in Hargreaves and Samani [29] temperature-based ET_o approach, since, N is just a function of location and coefficients used in Hargreaves are location dependent. The outputs for the three networks are the ET_o computed using the FAO-56 PM method (PM-ET_o). These inputs-outputs mapping were used for the networks training, validation and testing. The networks were trained in order to obtain the best minimum ANN architecture in terms of performance. For each ANN architecture, the number of nodes in the input and output layer were fixed at three inputs and one output for ANN1 and ANN2 and four inputs and one output for ANN3. The numbers of nodes (neurons) in the hidden layer were varied from 5-10 neurons. In all six models were developed for each network and the model architecture with the best performance was then chosen based on the statistical criterion that were used for models performance analyses. These statistical methods were the correlation coefficient (R) and the mean square error (MSE).

2.4 Brief Overview of Temperature-Based Methods

Temperature-based ET_o methods employ only measured maximum and minimum air temperatures as the minimum set of climate data necessary to estimate ETo and astronomical data which depends on the location (latitude) and date (day and month of the year). Three of such methods – Hargreaves, Blaney-Criddle and Thornthwaite considered in this paper are briefly discussed below. The Hargreaves method [29] for estimating reference crop evapotranspiration is recommended by the FAO consultation group, than any other temperature-based method for measuring reference evapotranspiration. Hargreaves method uses the maximum and minimum temperature and extraterrestrial radiation as the main data for computing reference crop evapotranspiration (Table 1). The differences in maximum and minimum temperatures may be successfully correlated with humidity conditions as well as net radiation [1] and can be used where only temperature data are recorded for computing reference crop evapotranspiration. The method is empirical and therefore need to be calibrated using local climatological data to obtain accurate and reliable result. The Blaney-Criddle method [30] is a simple empirical method that uses only temperature for estimating evapotranspiration. The method is inaccurate when used in climatic conditions other than Western United States where it was developed [32]; however, the method can give reasonable estimates when calibrated using local data. The Blaney-Criddle method presented in FAO-24 by Doorenbos and Pruitt [32] is more accurate than the original Blaney-Criddle method of the US Soil Conservation Service [30]. However, the coefficients of the FAO-24 method are difficult to estimate using the empirical relationships developed for its estimation and therefore not considered in this paper. The original Blaney-Criddle method [30] for estimating reference crop evapotranspiration is presented in Table 1. Thornthwaite [31], and Thornthwaite and Manther's [33] method is also empirical; the only factors taken into account for estimating potential evapotranspiration which is now considered as the reference crop evapotranspiration are the mean air temperature and hours of daylight. The estimates are based upon a 12-hour day (amount of daylight) and a 30-day month. The adjusted estimates of reference crop evapotranspiration for any month with number of days different from 30 and number of sunshine hours/day different from 12 is presented in Table 1 and the unit is in mm/day. The Thornthwaite method often overestimates the reference crop evapotranspiration when applied outside East-Central USA where it was developed.

TABLE1
SUMMARY OF THREE TEMPERATURE-BASED METHODS FOR ESTIMATING ET_o [MM/DAY]

Model	Description of the Model	Remarks
Hargreaves	$ET_o = 0.0023(T_{mean} + 17.8)(\delta_T^{0.5})R_a$	Ra is the extraterrestrial radiation [mm/day] (water equivalent); $\delta_T = T_{\max} - T_{\min}$; T_{mean} is the mean daily temperature; $T_{\max}$, $T_{\min}$ are the maximum and minimum air temperature respectively [^{o}C]
Thornthwaite	$ET_o = \frac{N}{360} 16\left(\frac{10T_{mean}}{I}\right)^{\alpha}$ $I = \sum_{k=1}^{12}(0.2T_k)^{1.514}$ $\alpha = 0.016I + 0.5$	T_{mean} is mean air temperature, I is the annual heat index; and N the maximum possible sunshine hours [h]
Blaney-Criddle	$ET_o = p(0.46Tmean + 8.13)$	p is ratio of actual daytime hours to annual mean daily daytime hours (%); T_{mean} is mean air temperature [^{o}C]

2.5 FAO-56 Penman-Monteith (FAO-56 PM)

The FAO-56 PM equation for the hypothetical reference crop evapotranspiration is expressed as [2] below.

$$PM - ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

Where $PM - ET_o$ ET_o estimated by the FAO-56 PM [mm/day]; R_n net radiation at the crop surface [MJ m^2/day]; G soil heat flux density [MJ m^2/day]; T mean daily air temperature [^{o}C]; u_2 daily wind speed at 2 m height [m/s]; e_s saturation vapour pressure [kPa]; e_a actual vapour pressure [kPa]; $e_s - e_a$ vapour pressure deficit [kPa]; Δ slope of the saturation vapour pressure temperature curve [kPa/^{o}C]; and γ psychrometric constant [kPa/^{o}C].

The terms in the numerator on the right-hand side of the expression in (2) are the energy term (radiation term) and the aerodynamic term respectively. This is why the method is called a combination method because it combines both the energy and aerodynamic aspect in calculating the reference crop evapotranspiration. The inputs measured climatological data for estimating the radiation term and the aerodynamic term where daily: air temperature (maximum and minimum), sunshine hours, wind speed and air relative humidity (maximum and minimum).

2.6 Calibrations of the models

Calibration of the empirical temperature-based ET_o methods using the FAO-56 PM as the recommended standard method [34], were achieved using linear regression analysis as shown in the equation below:

$$PM - ETo = a + b\left(ET_{o,TB}\right) \qquad (3)$$

Where a and b are parameters determined by linear regression [-], $ET_{o,TB}$ is estimate of reference crop evapotranspiration by any of the temperature-based methods (ANN models and existing temperature-based models). The performance of the empirical temperature-based methods and their calibrated versions were statistically analysed and evaluate against the standardized method (the FAO-56 PM). The performance evaluation involved the correlation coefficient (R) and mean sum of square error (MSE). The mean sum of square error (MSE) was the basis for evaluating their performance. The lower the MSE value, the better the agreement. The values of the MSE was compared to the ANN models and discussed.

3. Results and Discussions

In other to select the network architecture with the best performance out of the six models that were developed, the correlation coefficient, MSE and model with minimal architecture during the testing set was used. The statistical summary of the selected models during training, validation and testing sets of artificial neural networks for the three networks models are shown in Tables 2.

TABLE 2
STATISTICAL SUMMARY OF SELECTED ANN MODELS ARCHITECTURE DURING TRAINING, VALIDATION’ AND TESTING”

ANN models	Models architecture	R	MSE $(mm/day)^2$
		0.79	0.5403
ANN1	3-5-1	0.64’	0.6120
		0.79”	0.3035
		0.80	0.5200
ANN2	3-9-1	0.66’	0.6423
		0.80”	0.3005
		0.78	0.5717
ANN3	4-7-1	0.71’	0.5189
		0.80”	-0.3074

Considering the correlation coefficients (R-values), R of close to 1 is preferred hence generally the ANN models performance was not the best to be desired. This shows that there are noises in the data sets which the ANN models could not best explain. This supports the work by Adeloye et al. [19], that when there are noises in the data sets, FFBANN models do not perform best and higher ANN models may be tested. The noise in the data sets are as result of the fact that only measured air temperature was used in all the models as input data sets whereas the target was computed using measured air temperature (T_{max} and T_{min}), air relative humidity (RH_{max} and RH_{min}), sunshine hours (n) and wind speed at 2 m height (U_2). This also support the fact that FFBANN do not perform best when fewer inputs data are provided and it also explain the fact that the other variables such as the air relative humidity, sunshine hours and wind speed are important in determining the reference crop evapotranspiration (Table 3).

TABLE 3
CROSS-CORRELATION MATRIX OF THE CLIMATE VARIABLES AND THE PM-ETO

	T_{max}	T_{min}	U_2	RH_{max}	RH_{min}	n	PM -ET_o
T_{max}	1.00						
T_{min}	0.39	1.00					
U_2	0.06	0.20	1.00				
RH_{max}	-0.56	0.18	-0.06	1.00			
RH_{min}	-0.79	0.06	-0.04	0.84	1.00		
n	0.63	0.03	0.04	-0.33	-0.58	1.00	
PM -ET_o	0.70	0.42	0.52	-0.33	-0.53	0.73	1.00

The ANN3 model which contained four input variables performed better than the two other models using the MSE as the performance criteria during the testing since the best generalized models using the independent testing is desired for future estimations (Table 2). It must be noted that in determining the radiation-term in the FAO-56 PM method both the computed maximum possible sunshine hours (N) and the extraterrestrial radiation (Ra) are required when using measured sunshine hours instead of incident radiation. The combination of the N and Ra in the ANN3 makes the model superior to the two other models showing that the more useful information fed into the network, the better the performance of the network. The ANN2 also performed better than the ANN1 (Table 2). The linear regression models presented in the Fig. 2-4 below show the correlation coefficients and the models calibrations parameters.

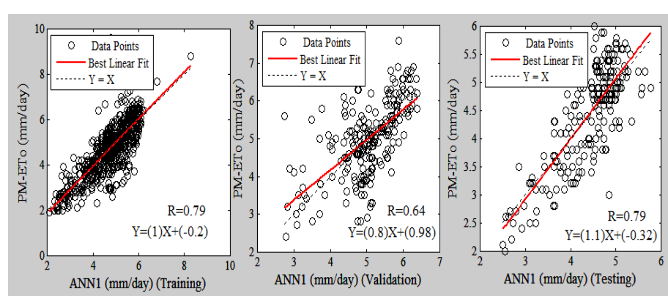

Fig.2. Linear regression model of ANN1 during training, validation and testing

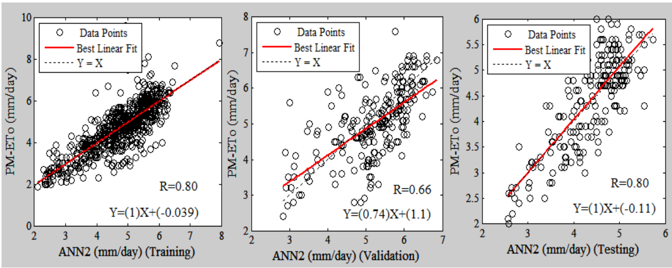

Fig.3. Linear regression model of ANN2 during training, validation and testing

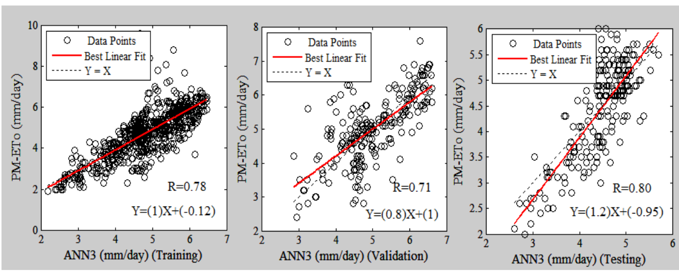

Fig.4. Linear regression model of ANN3 during training, validation and testing

Comparing the performance of the three ANN models to that of the three temperature-based methods, the ANN models outperformed the traditional temperature-based models considered in this study. This is not surprising given what has been noted previously about ANNs which are able to model any complex function even when such functions are not specified explicitly. The results are perhaps an indication that the three traditional temperature-based models considered in this study are incomplete or relatively inadequate for computing the complex reference crop evapotranspiration process. Of the three empirical temperature-based methods, performance was ranked; Hargreaves, Thornthwaite and Blaney-Criddle. The result confirms the results of many works that, the Hargreaves method performs better than other empirical temperature-based methods and that good results can be obtained using maximum and minimum temperature as the main parameters for modelling reference crop evapotranspiration [2]. The calibrations of the Hargreaves, Thornthwaite and Blaney-Criddle methods are achieved using the linear regression results (Fig.5). The calibrated versions showed some improvements in the performances using the MSE (Table 4). The ANN models also outperformed the calibrated versions of the three existing temperature-based methods (Table 2 and Table 4). This confirmed the fact that the calibrated versions still does not give an accurate estimation of the reference crop evapotranspiration in the region [4].

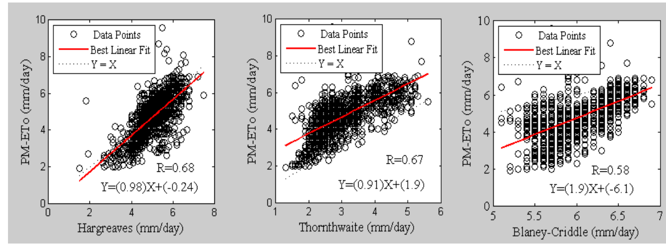

Fig.5. Linear regression model of Hargreaves, Thornthwaite and Blaney-Criddle

TABLE 4
THE PERFORMANCE CRITERIA FOR THE ORIGINAL AND CALIBRATED EXISTING TEMPERATURE-BASED ETO METHODS

Method	R	MSE (mm/day)^2
Hargreaves	0.68	0.7681
Hargreaves-calibrated	0.69	0.672
Thornthwaite	0.67	3.427
Thornthwaite - calibrated	0.67	0.6809
Blaney-Criddle	0.58	2.1363
Blaney-Criddle-calibrated	0.58	0.8882

4. CONCLUSIONS AND RECOMMENDATIONS

The superiority of the ANN for modeling reference crop evapotranspiration using minimal data such as the air temperature (maximum and minimum) over the existing empirical temperature-based methods was confirmed. Although the FFBANN models employed in this paper did not performed as desired as a result of noise in the data sets, the cross correlation matrix confirms the fact that only air temperature (maximum and minimum) will not give an accurate estimation of the reference crop evapotranspiration in the region. The FFBANN models when compared with the original and calibrated versions of the three temperature-based (Hargreaves, Thornthwaite and Blaney-Criddle), the FFBANN models presented better performance. Therefore, where the needed climatic data are not available for the application of the combinations methods, the reference crop evapotranspiration can be modeled successfully with FFBANN using minimum climatic data, with maximum and minimum air temperature as the main measurable input variables. Also other higher learning non-linear ANN models suitable for fewer inputs could be investigated, such as the radial basis ANN and self organizing map.

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