Estimation of Daily Pan Evaporation for Lake Abaya using Artificial Neural Networks

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ABSTRACT
Pan evaporation and its estimation is important in lake hydrology. Artificial Neural Network is used for estimation of pan evaporation by designing a causal network where pan evaporation is estimated from rainfall, sunshine hours, wind speed, relative humidity and temperature.

General Terms
Artificial Neural Networks

Keywords
Lake hydrology, pan evaporation, rainfall, sunshine hours, relative humidity, wind speed, temperature, Artificial Neural Networks.

1. INTRODUCTION
Proper estimation of evaporation from an open water body is vital for efficient water resource planning and management for any watershed. The class A pan is used for the direct measurement of lake evaporationwhich is normally based on the measurements from a small pan near to large open water bodies. Also, the pan evaporation measurements are often subjected to discontinuity. In this situation, Artificial Neural Networks are useful for estimation of pan evaporation.

1.1 Area of Study
Data from January 2005 to December 2005 obtained from the Arba Minch Weather Station near Lake Abaya are used for the study. Lake Abaya is situated in the Great Rift Valley in the southern region in Ethiopia. Lake Abaya is approximately 60 km long and 20 km wide with a surface area of 1162 sq.km with an average depth of 7.1m., located around latitude and longitude 6°26' N and 37°53' E respectively with maximum depth 13.1 m and is at an elevation of 1285m from mean sea level.

Figure1. Map of Study Area

1.2 Artificial Neural Network (ANN)
ANN is a tool coming under soft computing techniques. It is a massively parallel processing system and derives its name from its similarity with the human brain[1]. Similar to human neurons, the nodes in this network are called artificial neurons. These receive data from all adjoining neurons as inputs and by processing it according to the processing function used, produce a single output which is carried forward from each node. There are many architectures of ANN[2]. We have used PURELIN, TANSIG and LOGSIG architectures. These are available in the software MATLAB.

1.3 Software used
The softwares used are MS Windows7, nntool from toolboxes of Matlab a2010R, MS Excel, MS word.

1.4 Procedure
The data were arranged in proper format in Excel tables so that it can be imported in Matlabnntool. The variables rainfall, wind speed, sunshine hours, relative humidity and temperature were treated as independent variables affecting the Pan Evaporation which was treated as the single dependent variable[3].

In matlab, the “nntool” Graphical User Interface was used to create ANNs with TANSIG, LOGSIG and PURELIN architectures and varying the number of neurons from 1 to 10, as beyond 10, significant improvement was not seen in the preliminary trials and in some cases the error increased disproportionately. Thus a total of 30 networks were built up. The nomenclature for the network was as follows: LS for LOGSIG architecture, PL for PURELIN architecture and TS for TANSIG architecture. 1n, 2n ---10n representing the number of neurons in the hidden layer. Thus, PL5n means a network with PURELIN architecture having 5 neurons.

2. DATA DIVISION
Two-third data were used for training the networks and validating the networks. In training, the target data supplied reference for calculation and back propagation of error in the training process [4]. The same data were simulated without target values for validation stage. The remaining one-third data were used for testing the networks as these were previously unseen by the network [5].

2.1Performance criteria
Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) were used as criteria for evaluation of performance of the networks.

2.2 Choice of Network Architecture
The chart below shows the comparison of predictions by various networks as per the RMSE (Root Mean Square Error) and MAPE (Mean Average Percentage Error) values. As seen

here **LS4n** network gives the minimum errors in both criteria. Thus 5-4-1 architecture i.e. 5 inputs, 4 hidden neurons and 1 output, with LOGSIG activating function gives the best network configuration for prediction of pan evaporation in this case.

However it must be remembered that the ANN is site specific data driven model and will be useful solely for this site.

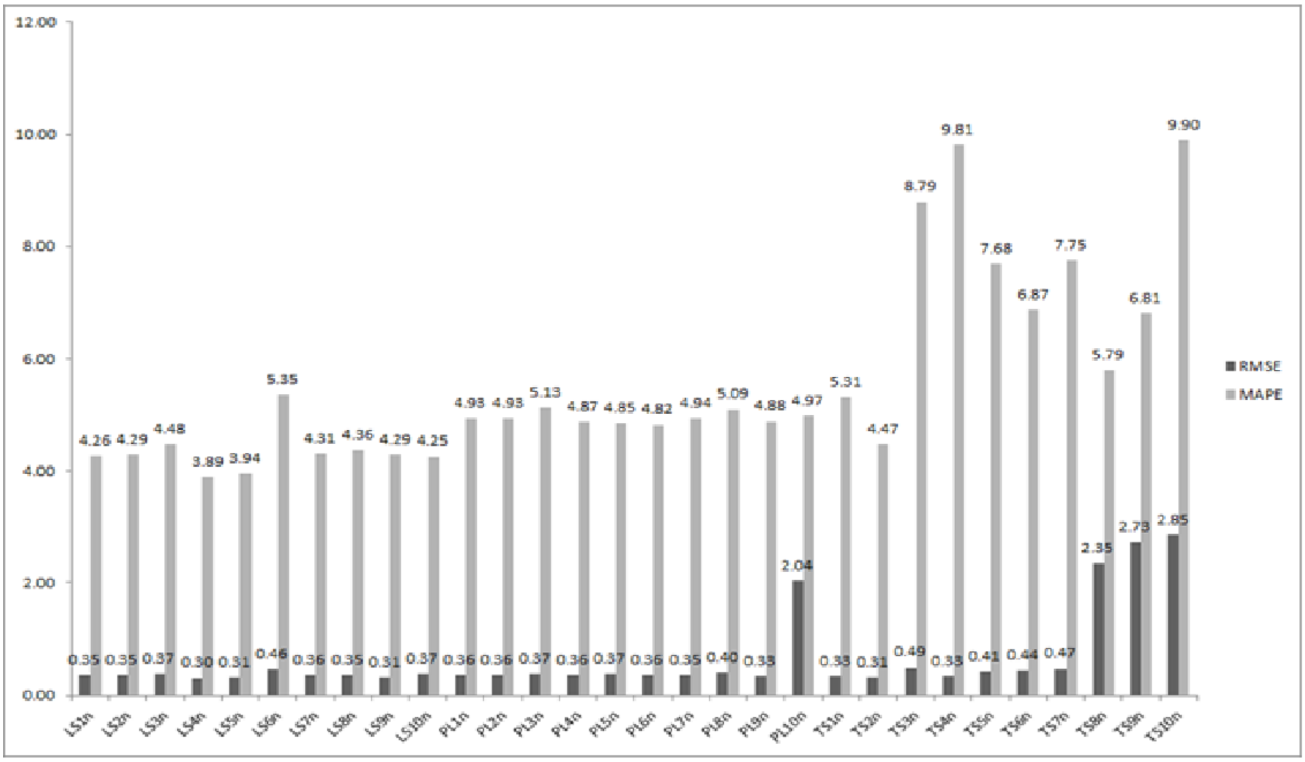

Figure2. Performance of Different ANNs

3. RESULTS

Penman'sequation is the most commonly used mathematical modeling tool for estimating pan evaporation[6]. It is as given below:

$$E = [\Delta/(\Delta+\Upsilon)]R_n + [\Upsilon/(\Delta+\lambda)][6.43(1+0.536u_2)(e_w - e_a)]*1/\lambda$$

Where

E :Evaporation in mm/day

Δ :The slope of saturation water vapor pressure vstemperatue curve

γ : The psychometric constant

λ : The latent heat of vaporization

u_2 : Wind speed at 2m above the ground in m/sec

e_w : Saturation vapor pressure of air at mean air temperature

e_a : Actual vapor pressure of air at mean air temperature

R_n : net radiation.

Thus it is seen here how complex it is to model a natural phenomenon mathematically. However this paper shows how the ANN black box can successfully track and model the phenomenon by simply providing the same inputs required for Penman's model[7]. Only selecting the correct network configuration is a non-trivial task and involves rigorous spade work, which, once in place, can be used for the same site in future. In this paper, the use of Artificial Neural Networks for estimation of pan evaporation is conclusively shown to be superior to Penman's model.

The selected network is used for the prediction and figures 3, 4 and 5 show the comparative predictions by Penman's equation and ANN against the actually observed values of lake evaporation.

It is seen that inspite of being a rigorously analytical method, Penman's equation is lacking in precision of prediction as compared to the prediction by ANN even though the input parameters given to both the models are the same.

4. CONCLUSIONS

As can be seen in figures 3, 4 and 5 the values of pan evaporation by Penman's equation do not model the actually observed values very closely but the values predicted by ANN match very closely with the actually observed values. Thus if forecasts of the five input parameters are given to the ANN of the chosen 5-4-1 configuration with LOGSIG as the activation function, it will predict the lake evaporation with desirable accuracy so as to be useful in the management of the lake hydrology. The additional figure 6 shows in greater resolution the comparative accuracy of Penman's model and ANN.

5. FUTURE SCOPE

Artificial Neural Networks can be used in estimating lake evaporation more accurately than traditional analytical or mathematical models.

Complex natural phenomena dependent on large number of variables which are not easy to measure accurately can be treated with ANN if past few years observed data is available giving sufficiently accurate predictions to control and manage these natural phenomena.

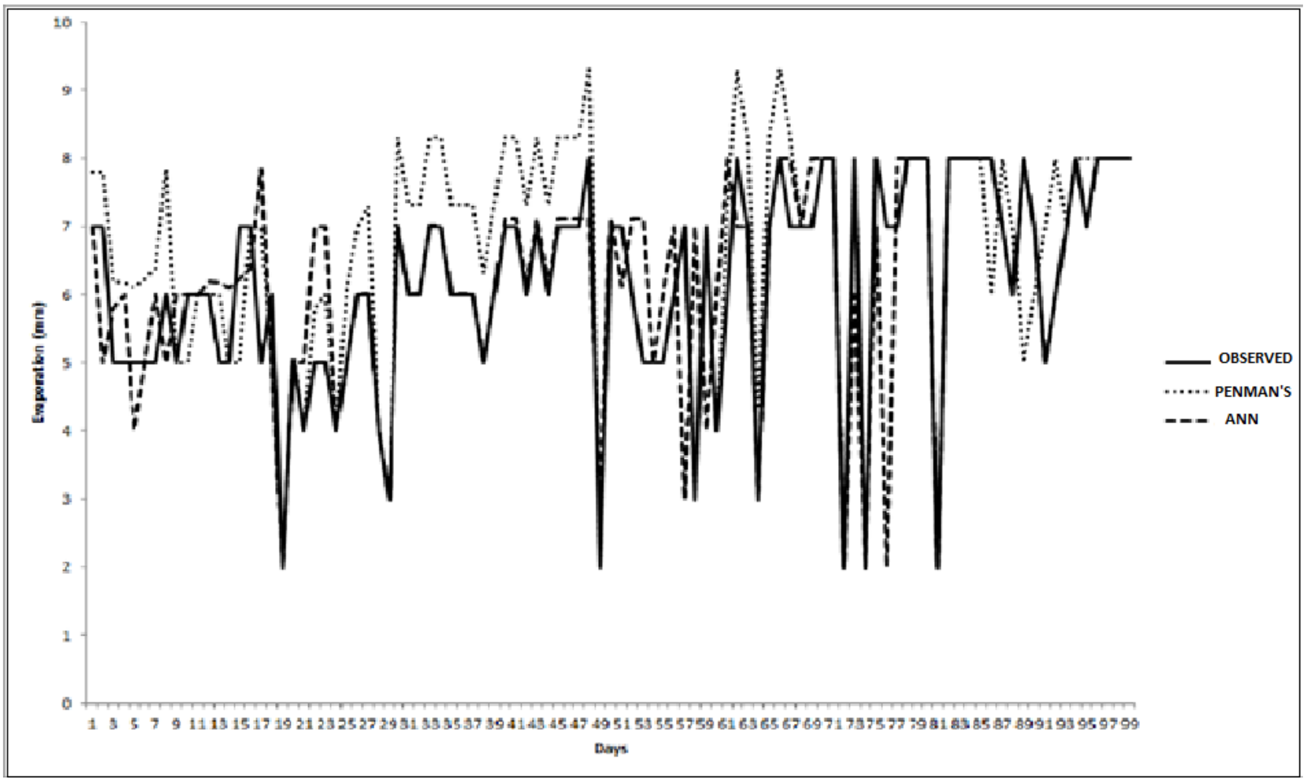

Figure 3. Pan Evaporation Prediction Days 1 to 99

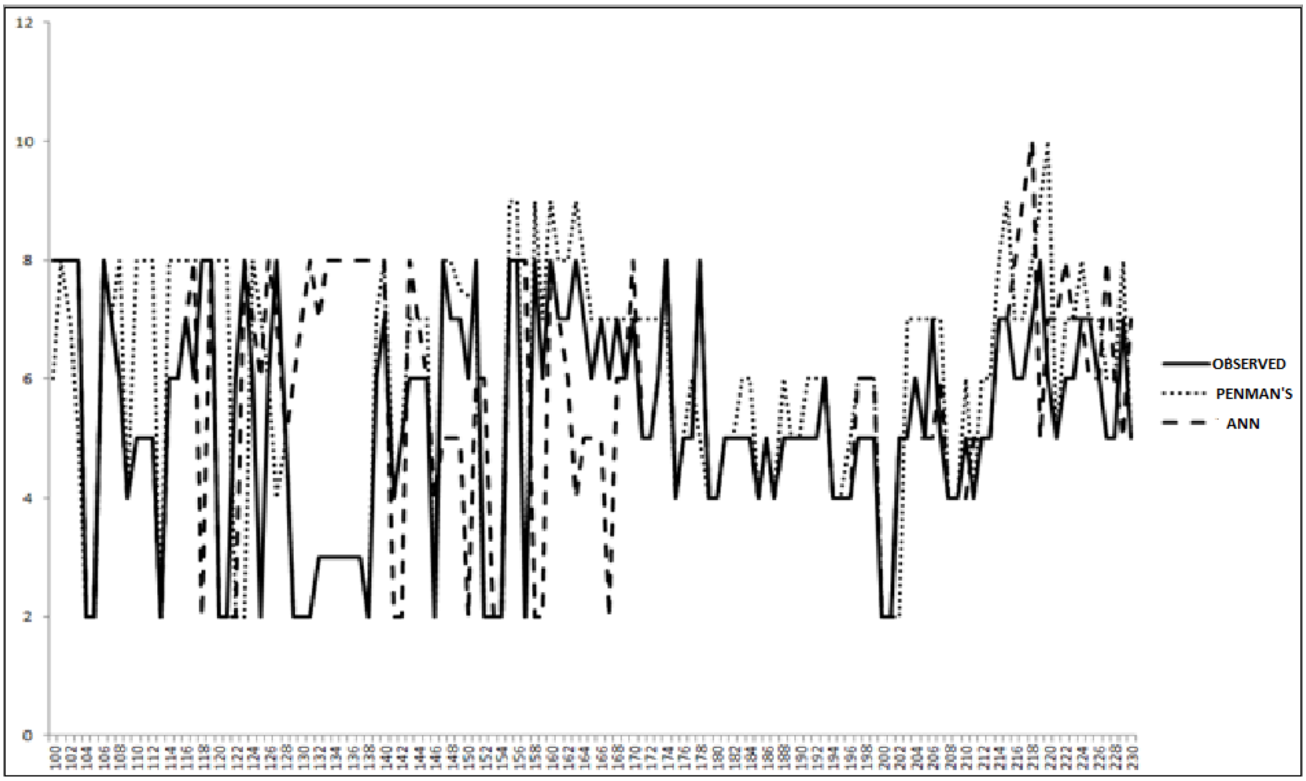

Figure 4. Pan Evaporation Prediction Days 100 to 230

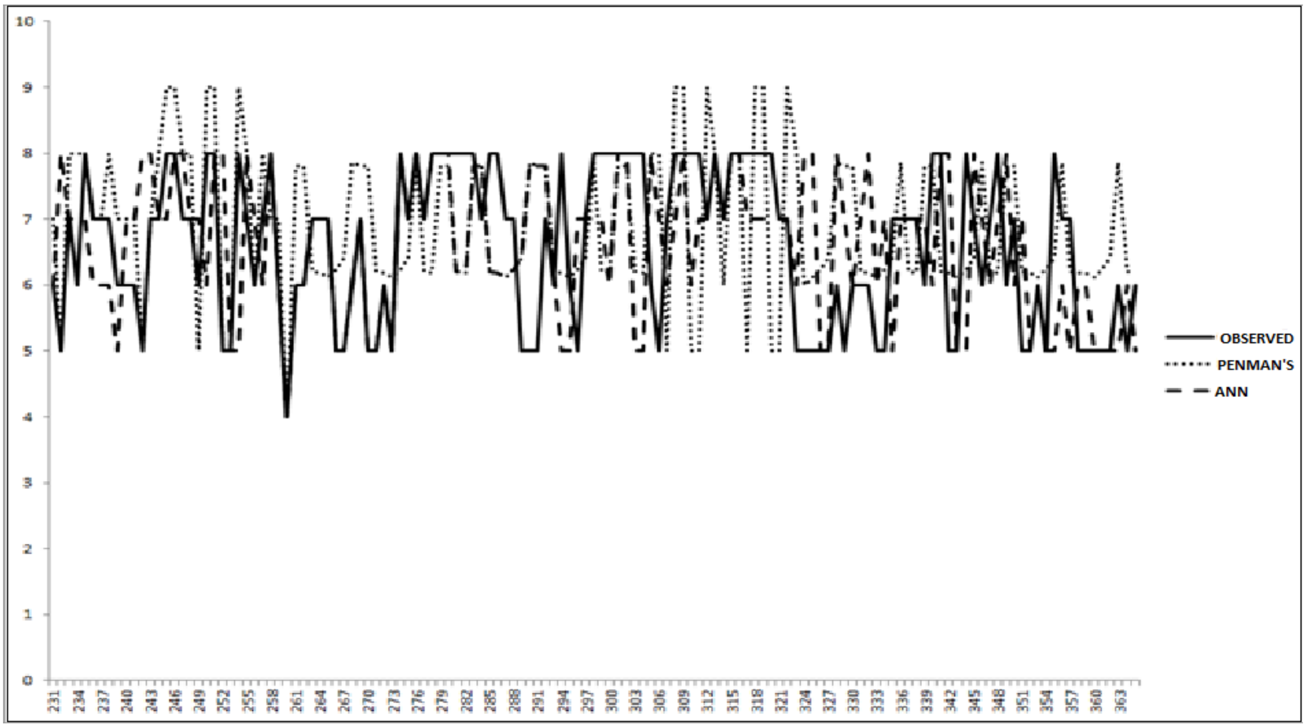

Figure5. Pan Evaporation Prediction Days 231 to 365

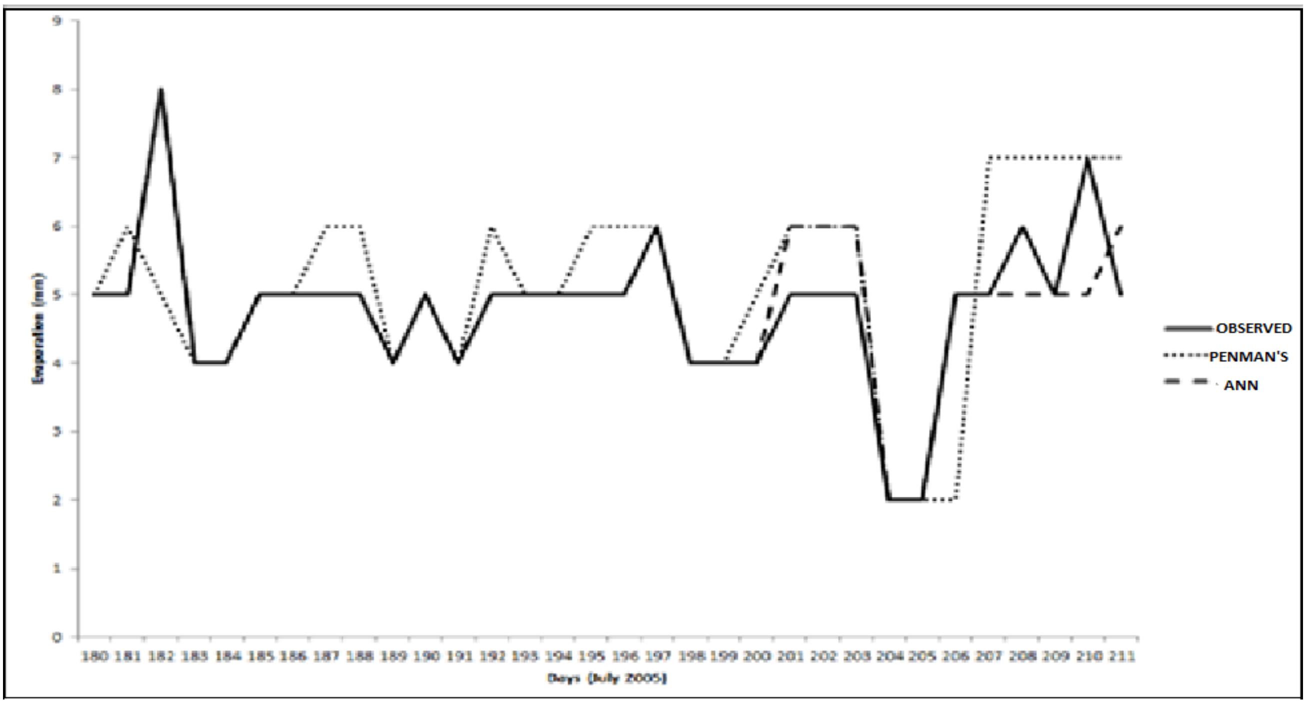

Figure 6. Predictions for July 2005

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