NEURAL NETWORK FORMULATION FOR EVAPOTRANSPIRATION MODELLING IN SWAZILAND

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Abstract: Evapotranspiration is one of the most significant components in the context of water resources management, especially in the planning and management of irrigation practices. The irrigation sector in Swaziland is the largest consumer of water, using about 96% of the available water, while livestock, domestic and industry shares the remaining 4%. Hence, its accurate estimation is essential to ensure sustainability in our scarce resource, water. The FAO-56 Penman-Monteith (PM) method has remained the sole standard method of estimating the reference evapotranspiration (ET_o). However, the numerous meteorological variables required have been a major setback for most developing countries like Swaziland. Temperature based models including Blaney-Criddle (BCR) and Hargreaves (HRG) are used instead despite their limited accuracy. The present study proposes the use of multilayer perceptron (MLP) neural networks to estimate ET_o under limited data conditions. Neural networks have gained popularity over the years in hydrologic applications due to their ability to model non-linear processes with greater accuracy. Daily climatic data collected from 2004 to 2011 at Malkerns research station, Swaziland, are used for the investigation. The data sets were divided to four based on the four different seasons of the country; autumn, spring, summer and winter. This was done to counter effect the proneness of over estimation and under estimation of ET_o by the temperature based models. The performance of the models seasonally was compared with their performance on annual basis. The different climatic parameters collected; relative humidity (RH), solar radiation (R_s), sunshine hours (u) and wind speed (U) were individually combined in the MLP with minimum (T_{min}) and maximum temperatures (T_{max}) to identify the most sensitive parameters in the different seasons. Coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) were used to test performance of the different models. Results have shown that MLP temperature based models improves ET_o estimation when compared to BCR and HRG by as high as 30%; with FAO-56 PM as the reference. Hargreaves method came second and BCR method, last. After introducing the different climatic parameters in the MLP-temperature based model, the coefficient of determination increased significantly. The most sensitive parameters to the estimation of ET_o in the autumn, spring, summer and winter were U ($R^2 = 0.688$), RH ($R^2 = 0.877$), R_s ($R^2 = 0.911$) and U ($R^2 = 0.781$), respectively. When season is not considered, annual estimations indicate that solar radiation is the most sensitive parameter, and this might decrease the estimations of ET_o since seasonal estimations show R_s to be most crucial in the summer season. Our findings indicate that MLP can be successfully used to improve ET_o estimations in Swaziland, consequently, improving the overall water use efficiency and sustainability.

Keywords: evapotranspiration, limited climatic data, multilayer perceptron networks, Swaziland, water management

INTRODUCTION

Evapotranspiration (ET) is defined as the combined process in which water is lost from soil (evaporation) and plants (transpiration). It is an important component of the hydrologic cycle and its accurate estimation is essential for both engineers and researchers in many fields such as crop production, irrigation design and management and water resources planning. ET quantification is frequently preceded by the estimation of reference evapotranspiration (ET_o). Allen et al. [1], defines ET_o as evapotranspiration from a reference surface, not short of water. The reference surface is a hypothetical grass reference crop with an assumed crop height of 0.12m, a fixed surface resistance of $70sm^{-1}$ and an albedo of 0.23. In Swaziland where about 96% of the available water is used by the irrigation sector, precise estimation is essential, otherwise inefficient use of water may counter effect the means of ensuring food security in the agriculture dependant country. In an effort to revitalize agriculture in Swaziland and enhance food security, the Swazi government (SG), European Union (EU) and Food and Agriculture Organization (FAO) have helped about 20000 small holder (in 2013) or subsistence farmers to move towards commercial farming. In commercial farming, adequate and proper utilization of water resources in order to cut irrigation costs cannot be escaped. ET is obtained from mainly three methods, and these are; lysimeters, water balance methods and through climatic parameters (empirical means). Direct measurements of ET_o using lysimeters requires more time and needs adequate and careful experience, hence, it is not always possible in field measurements. Due to their simplicity, empirical methods are preferred compared to the other methods [2]. The choice of an empirical method to use lies on several factors, amongst which is the availability of meteorological data. If all required data is available, the sole method used to date (2014) is the Penman Monteith (PM) method recommended by the Food and Agriculture Organisation (FAO). It has been accepted globally by scientists, engineers and other practitioners as the most accurate method to estimate ET_o. In many regions, however, the practicability of the FAO56-PM method is limited mainly due to the numerous parameters required. The FAO56-PM requires the following inputs to compute ET_o; minimum and maximum temperatures (T_{min} and T_{max}), relative humidity (RH), wind speed (U) and sunshine hours (n). Besides the numerous inputs, the FAO56-PM uses complicated unit conversions and lengthy calculations [3]. Furthermore, the radiation term and aerodynamic term as used in the FAO56-PM is cumbersome and needs expertise to determine [4]. Hence, due to its complexity other alternatives are sought like the temperature based models, which requires mainly temperature to compute ET_o. These include but not limited to, Blaney-Criddle (BCR) and Hargreaves (HRG) methods. BCR requires mean temperature and the percentage of annual daytime hours according to the latitude. On the other hand, HRG require minimum, maximum and mean temperatures together with extraterrestrial radiation. Several researchers [5, 6, 7] have found that in many regions the accuracy of these methods is questionable as they are most suitable in the countries in which they were developed. Furthermore, Alexandris et al. [8] in their study in Greece reported that these temperature based methods are often unable to capture some climatic variables crucial to the estimation of ET_o.

ET_o is a non linear phenomenon relying on several climatic variables. Artificial neural networks (ANN) has gained popularity over the last few years in the fields of hydrology and water resources modelling due to their ability to model complex and non linear processes. It has been successfully applied in hydrology related areas such as rainfall-runoff modelling [9, 10]; stream flow forecasting [11, 12]; ground water modelling [13] and reservoir operations and modelling [14]. The success in using ANNs in the above fields suggests an effective way for the modelling of ET_o in Swaziland. This paper investigates the potential of using ANNs for the first time in Swaziland to model the evapotranspiration process.

MATERIALS AND METHODS

Study area

Fig. 1 show the study area where all the climatic parameters used in this study were obtained. Data were obtained from the only agriculture research centre in Swaziland, i.e. the Malkerns research station. Swaziland climate is mainly subtropical and has four main agro ecological zones; Highveld, Middleveld, Lubombo and the Lowveld. Altitude within these zones varies between 200 and 1300 m. Rainfall varies between 500mm to 1000mm The Highveld has the highest elevation with annual rains of about 1200mm. The Middleveld come second in altitude (average of 700m) and also in annual rainfall amounts (average of 900mm) and the lowest altitude and rain amounts are in the Lowveld, with an annual average rainfall of 500mm. Malkerns research station is located in the Middleveld ecological zone. Data collected from this station includes daily minimum and maximum temperatures, relative humidity (RH), wind speed (U) and sunshine hours (n) for a period of 8 years (2004 to 2011). A summary of the climatic variables for the period is given by Table 1.

Reference evapotranspiration models: FAO-56 PM

The FAO-56 PM model is described by the equation;

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

Where ET_o is evapotranspiration (mm/day), R_n is net radiation (MJ m^{-2} day^{-1}), G is soil heat flux (MJ m^{-2} day^{-1}), γ is the psychrometric constant (kPa °C^{-1}), e_s is the saturation vapour pressure, e_a is the actual vapour pressure (kPa), and Δ is the slope of the saturation vapour pressure-temperature curve (kPa °C^{-1}), T is the average daily air temperature (°C), and U_2 is the mean daily wind speed at 2m (m s^{-1})

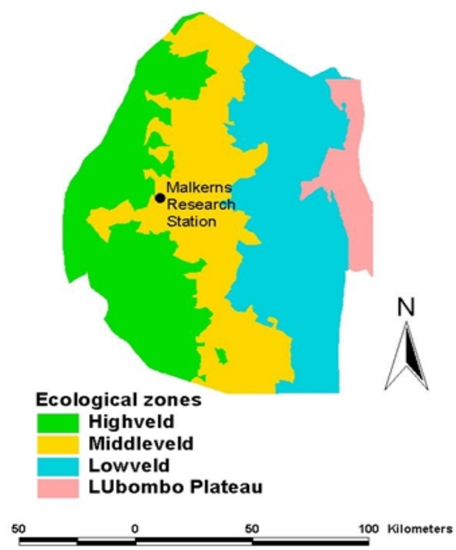

Figure 1: The location of Malkerns research station and the ecological zones of Swaziland.

Table 1: Monthly means of the main climatic variables at Malkerns research station during 2004 to 2011

Month	T_{min} (°C)	T_{max} (°C)	*RH* (%)	***U*** (km/day)	*n* (hours)	R_s (MJ/m²/day)	ETo (mm/day)
January	18.5	27.7	76	164	5.5	19.4	4.26
February	18.7	28.7	72	164	7.3	21.3	4.64
March	16.9	27.3	72	155	6.6	18.3	3.9
April	14.4	25.2	73	152	5.7	14.4	2.98
May	11.2	24.8	62	201	6.5	13	3.07
June	8.8	22.6	59	228	7.5	12.7	2.91
July	8.3	23.1	55	262	8.1	14	3.42
August	10.6	24.8	57	303	7.8	15.9	4.18
September	12.9	26.4	60	295	7.4	18.2	4.67
October	14.9	26.2	69	253	5.4	17.6	4.26
November	16.2	26.8	74	228	5.5	19.1	4.33
December	17.6	27.9	74	216	6	20.3	4.61

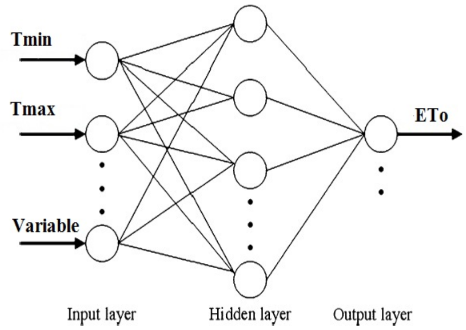

Figure 2: Structure of the MLP model.

Table 2: Conditions of the training performance variables for MLP

Training variables	Assigned value
Step size	1
Momentum	0.7
Iterations/Epochs	1000
Training threshold	0.001

FAO CROPWAT 8 computer software for windows is used to compute FAO56-PM ET_o and net radiation. The software computes ET_o based on the FAO guidelines for computing crop water requirements in their publication NO 56 of the Irrigation and Drainage series.

Blaney-Criddle method

$$ET_o = p(0.46T_{mean} + 8.13) \tag{2}$$

Where ET_o is evapotranspiration (mm/day), T_{mean} is the average daily temperature (°C) and p is the average daily percentage of annual day time hours according to the latitude.

Hargreaves method

$$ET_o = C_o(T_{max} - T_{min})^{0.5}(T_{mean} + 17.8)R_a \tag{3}$$

Where ET_o is evapotranspiration (mm/day), T_{max} and T_{min} are the maximum and minimum temperatures, T_{mean} is the average daily temperature (°C), R_a is the extraterrestrial radiation (mm/day) and C_o is the conversion coefficient (°C).

Artificial Neural Network

An Artificial Neural Network (ANN) is an information-processing paradigm inspired by biological nervous systems such as our brain [15]. Neural networks are composed of neurons as basic units. Each neuron receives input data, processes the input data, and transforms them into output forms. The input maybe pure data or the output results of other neurons and the output forms maybe the results of other neurons [16]. ANN is configured for a specific application through a learning process, which follows two types; supervised and unsupervised. In supervised, network acquires knowledge by comparing estimated output with known output. In unsupervised, network does not acquire knowledge of corresponding output. Supervised learning process is adopted in this study to compare the known evapotranspiration that is computed by the FAO56-PM to that of MLP. Through repeated epochs, the learning algorithm adjusts the connection strengths to give the optimum results. There are numerous algorithms available in neural networks, and the choice is purely trial and error based. In this study, however, multiple layer perceptron (MLP) algorithms is used following its wide and successful application in the field of hydrological modelling [17, 18, 19]. This algorithm is managed by Neurosolution software version 5.07 presented by the Neurodimension.

Fig. 2 provides a developed structure of the MLP with input combination 3, which is made of three layer neurons: input layer, hidden layer and an output layer. Minimum and maximum temperatures were the main and unchanged inputs in our model. The third input was altered among the available climatic parameters obtained from the weather station (RH, R_s, n, and U). The output response of each neuron is calculated based on the weighted sum of all its input according to the activation function employed. The MLP can have more than one hidden layer; however, studies have revealed that a single hidden layer is enough for ANN to approximate any complex non-linear function

[20]. Therefore, in this study one hidden layer MLP is used. MLP is trained using the many kinds of algorithms within the network.

Table 2 shows the condition of training performance variables for the MLP. The daily data collected was divided into three for the purposes of training (70%), cross validation (20%) and testing (10%) of the developed model. Training data are from January 2004 to December 2008. The training performance of neural network is iterated until the training error is attained to the training tolerance. Iteration refers to a one completely pass through a set of inputs and target data. Cross validation data (January 2009 to December 2010) are used to find network performance by monitoring training and avoid overtraining. Finally testing data (January to December 2011) are used to find the overall performance of the model.

Models evaluation

The performance of the temperature based models in this study is evaluated using three standard statistical indexes (Eq. 4 to 6). These include; root mean square error (RMSE), mean absolute error (MAE) and coefficient of correlation (R). The RMSE is a measure of the residual variance. MAE measures how close estimations are to eventual outcomes. R is a measure of accuracy and is generally used for comparison of alternative models.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - y_i')^2}{N}} \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - y_i'| \tag{5}$$

$$R = \frac{\sum_{i=1}^{N}(y_i - \bar{y})(y_i' - \bar{y})}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{6}$$

where y_i represents the FAO56-PM ET_o, y_i' is the alternative methods estimated ET_o; $\bar{y}$ and $\bar{y}'$ represent the averages values of the corresponding variable; and *N* represents the number of data considered. Additionally, a linear regression y = α1x+α0 is applied for evaluating the models' performance statistically, where y is the dependent variable (FAO56-PM ET_o); x is the independent variable (alternative methods); α1 the slope and α0 the intercept.

RESULTS AND DISCUSSION

To obtain the best results from the ANN architecture, processing elements (PE) in the single hidden layer adopted should be first determined. According to Kim et al. [21], determining the processing elements (PE) is one of the difficult tasks in neural network model formulation. In addition, it is an important factor, which affects the performance of the trained network. In this study, processing elements were varied between 1 and 12. Optimum processing elements yielding higher R^2 and minimum RMSE were found by trial and error method after comparing output with that of FAO56-PM. The activation function was set to tanh after trial and error with other activation functions like sigmoid and linear functions. The number of epochs or iterations was varied from 1000 with increments of 1000 up to 5000 and optimum results were obtained with 1000 iterations as illustrated by the conditions of MLP training shown in Table 2. ET_o was calculated according to the four different seasons of the country (autumn, spring, summer and winter) and on annual basis. The optimum processing elements together with a summary of the statistical analysis findings of the ANN model is summarised in Table 3. For the different seasons and on annual basis, optimum processing elements were different. ANN analysis revealed the most sensitive parameters (indicated by a red colour in Table 3) for the calculation of ET_o. The bold colour represents all the climatic parameters collected. It should be noted, however, that the emphasis of the study is on finding a less complex method, requiring less climatic data inputs and yet improve the accuracy of ET_o estimation. Different climatic data proved sensitive in the different seasons. In the four seasons; autumn, spring, summer and winter, the most sensitive parameters were U (R^2 = 0.687, RMSE = 0.664 mm/day), RH (R^2 = 0.878, RMSE = 0.639 mm/day), R_s (R^2 = 0.912, RMSE = 0.375 mm/day) and RH (R^2 = 0.814, RMSE = 0.605 mm/day), respectively. When season was not considered, annual estimations indicate that solar radiation is the most sensitive parameter. The annual findings might be misleading and can be the genesis of poor estimations of ET_o as different parameters affect ET_o in the different seasons.

Table 3: Statistical performance evaluation for the ANNs model with different inputs

Season	Model	PE	RMSE	MEA	R^2
Autumn	T_{min} and T_{max}	12	0.687	0.530	0.411
	T_{min}, T_{max} and RH	12	0.523	0.386	0.677
	T_{min}, T_{max} and R_s	5	0.615	0.493	0.591
	T_{min}, T_{max} and n	12	0.593	0.476	0.621
	T_{min}, T_{max} and U	4	0.664	0.539	0.687
	T_{min}, T_{max}, RH, Rn, n and U	10	0.261	0.192	**0.947**
Spring	T_{min} and T_{max}	11	0.906	0.700	0.709
	T_{min}, T_{max} and RH	2	0.639	0.480	0.878
	T_{min}, T_{max} and R_s	8	0.774	0.538	0.792
	T_{min}, T_{max} and n	11	0.793	0.545	0.781
	T_{min}, T_{max} and U	8	0.884	0.664	0.752
	T_{min}, T_{max}, RH, Rn, n and U	5	0.275	0.156	**0.978**
Summer	T_{min} and T_{max}	11	0.758	0.624	0.629
	T_{min}, T_{max} and RH	11	0.666	0.542	0.733
	T_{min}, T_{max} and R_s	10	0.375	0.273	0.912
	T_{min}, T_{max} and n	6	0.443	0.314	0.908
	T_{min}, T_{max} and U	11	0.703	0.567	0.676
	T_{min}, T_{max}, RH, Rn, n and U	11	0.163	0.103	**0.984**
Winter	T_{min} and T_{max}	5	0.984	0.713	0.491
	T_{min}, T_{max} and RH	7	0.605	0.454	0.814
	T_{min}, T_{max} and R_s	7	1.012	0.723	0.516
	T_{min}, T_{max} and n	7	1.024	0.746	0.506
	T_{min}, T_{max} and U	5	0.661	0.466	0.781
	T_{min}, T_{max}, RH, Rn, n and U	9	0.248	0.152	**0.968**
Annual	T_{min} and T_{max}	1	0.769	0.620	0.508
	T_{min}, T_{max} and RH	12	0.657	0.529	0.667
	T_{min}, T_{max} and R_s	6	0.581	0.438	0.739
	T_{min}, T_{max} and n	7	0.656	0.514	0.654
	T_{min}, T_{max} and U	9	0.633	0.501	0.677
	T_{min}, T_{max}, RH, Rn, n and U	12	0.132	0.099	**0.987**

The best ANN architecture in the different seasons were then compared with ET_o calculated by the two temperature based methods (Blaney-Criddle and Hargreaves), with FAO56-PM being the reference model. Values of ET_o estimated by the different models are shown in Fig. 3 to 7.

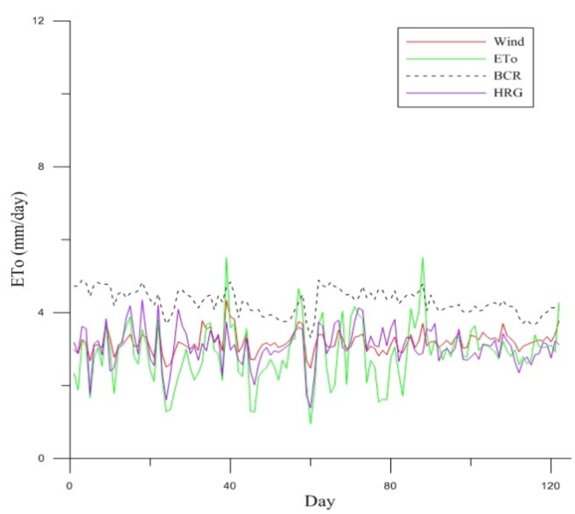

Figure 3: Variation in evapotranspiration estimates with different models in autumn.

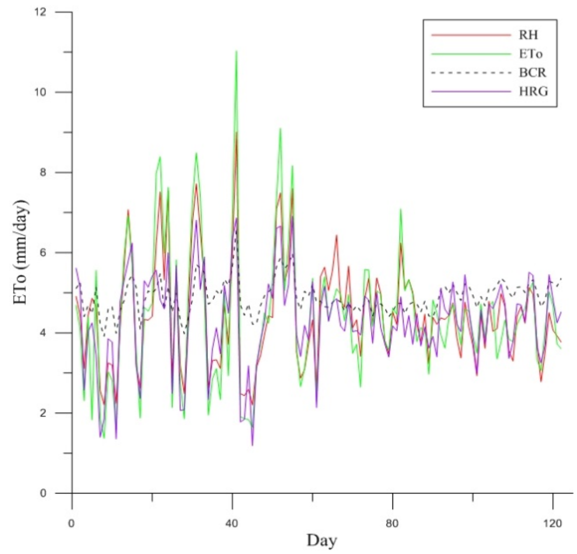

Figure 4: Variation in evapotranspiration estimates with different models in spring.

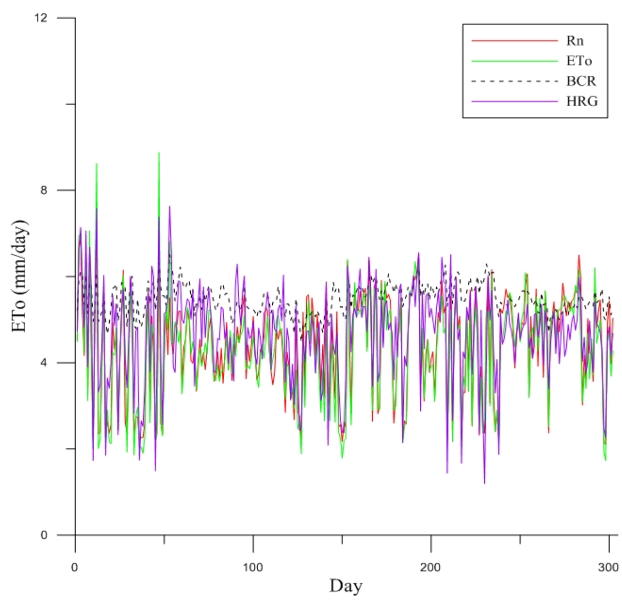

Figure 5: Variation in evapotranspiration estimates with different models in summer.

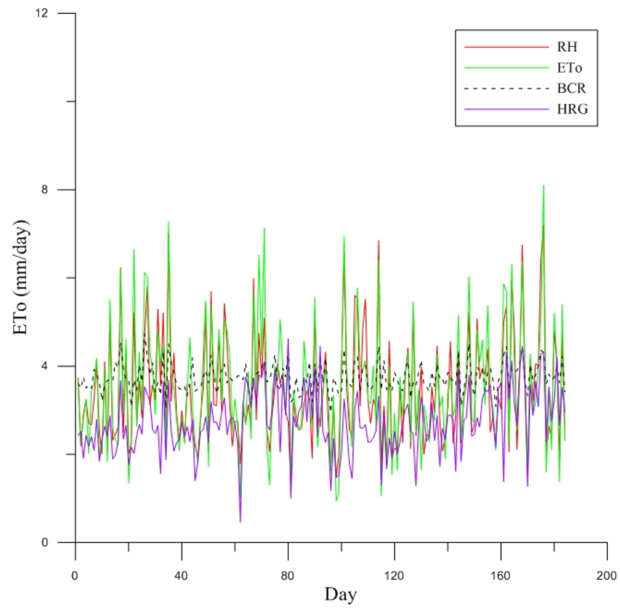

Figure 6: Variation in evapotranspiration estimates with different models in winter.

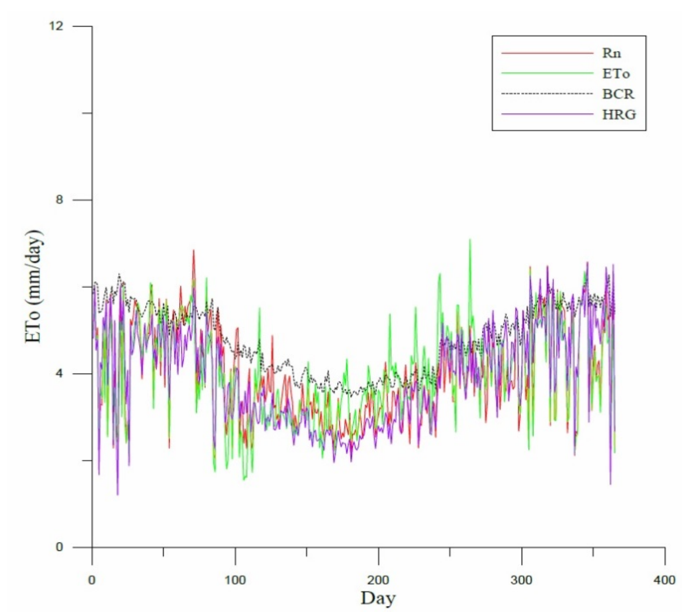

Figure 7: Variation in evapotranspiration estimates with different models annually.

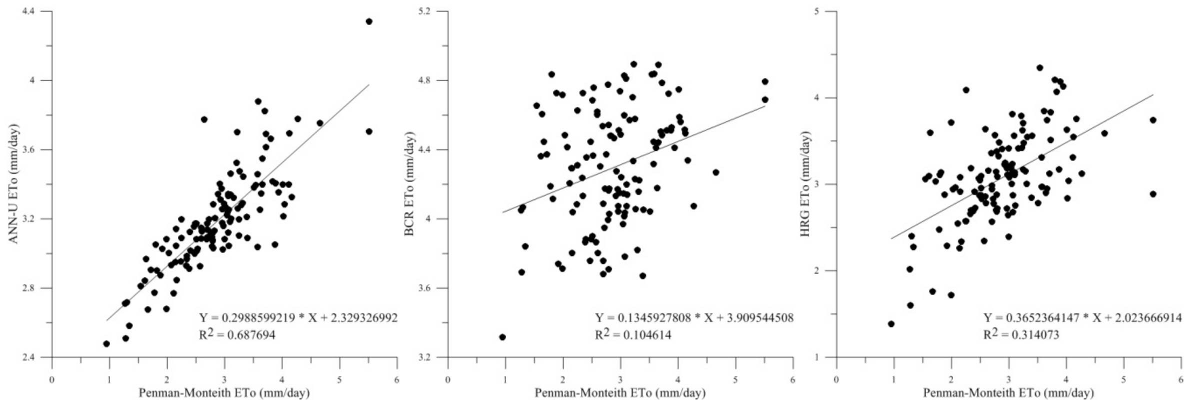

Figure 8: Scatter of daily ET_o estimated by MLP, BCR and HRG in autumn.

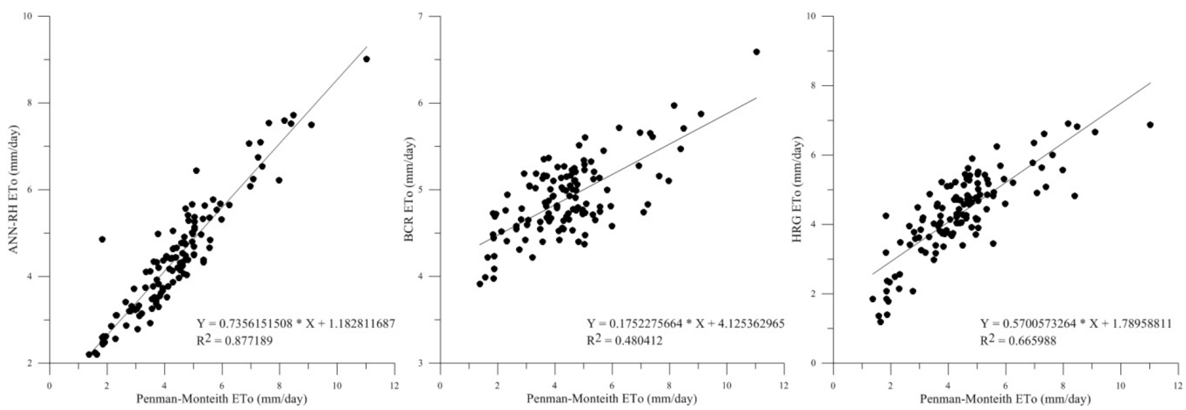

Figure 9: Scatter of daily ET_o estimated by MLP, BCR and HRG in spring.

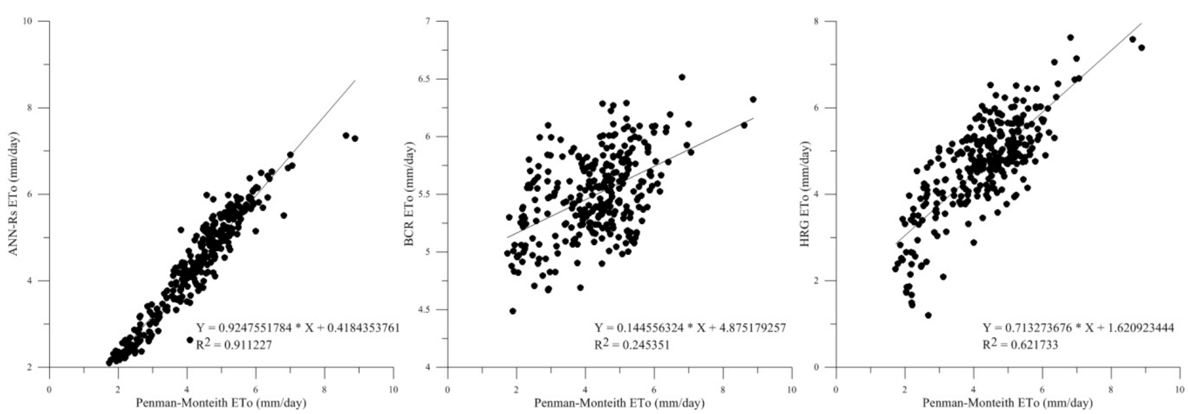

Figure 10: Scatter of daily ET_o estimated by MLP, BCR and HRG in summer.

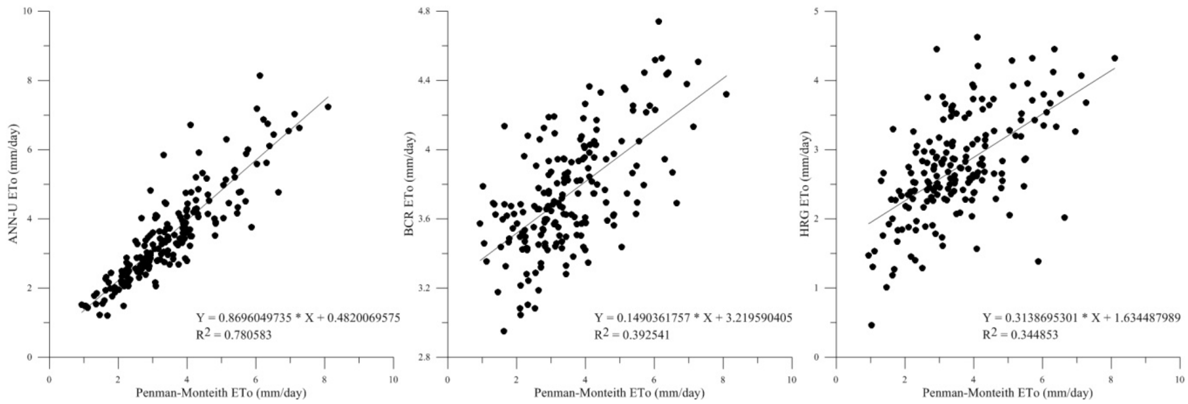

Figure 11: Scatter of daily ET_o estimated by MLP, BCR and HRG in winter.

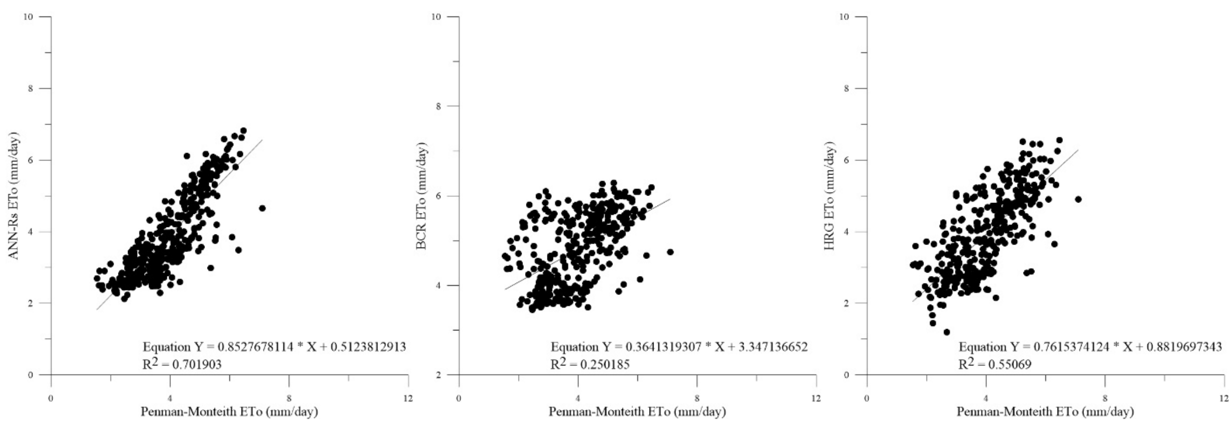

Figure 12: Scatter of daily ET_o estimated by MLP, BCR and HRG annually.

It is seen from the above figures that both temperature based models adopted overestimates and underestimates ET_o. In autumn (Fig. 3), BCR (indicated by dotted lines) performed worse as it overestimated ET_o by great magnitude, followed by Hargreaves (purple line). ET_o estimated by MLP fluctuates within the range of FAO56-PM. The poor performance of BCR is also illustrated by Fig. 8, which shows a lower R^2 value (0.105), followed by HRG with R^2 of 0.314. MLP yielded high R^2 value compared to the 2 by having 0.688. A similar pattern in performance is observed in all the seasons and on annual basis (Fig. 9 to 13), MLP performed better, followed by HRG and lastly BCR. In spring, only in a few cases does BCR underestimates ET_o, otherwise it generally overestimates. The findings differ from that observed by [22] and [23], who observed that HRG underestimated ET_o and BCR overestimated ET_o. This is likely due to the different climatic conditions experienced in the different regions as their studies were conducted in semi arid areas and Swaziland experiences a subtropical climate. Several authors [24, 25] have indicated that HRG generally under predicts ET_o and BCR overestimates. However, in the case of our study it is not the case except during the winter season.

CONCLUSION

In this study an attempt has been made to find an alternative method for estimating daily ET_o in the absence of required variables for FAO56-PM application. A comparison made between MLP, BCR and HRG indicated that MLP provided the best ET_o estimates. Optimum processing elements for calculating ET_o were different in the different seasons. The study further revealed that it may not be necessary to collect all the variables in the different seasons when one wants to compute ET_o using ANN. Instead only those sensitive parameters can be collected. The most sensitive parameters for calculating ET_o in autumn, spring, summer, winter and on annual basis were wind, relative humidity, solar radiation, relative humidity and solar radiation, respectively. We further suggest calculating ET_o seasonally as it yielded better results to when ET_o was computed on annual basis. Our findings indicate that MLP can be successfully used to improve ET_o estimations in Swaziland, consequently, improving the overall water use efficiency and sustainability.

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