Neural Network Approach for Estimating Reference Evapotranspiration from Limited Climatic Data in Burkina Faso

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Abstract: - The well known Penman-Monteith (PM) equation always performs the highest accuracy results of estimating reference evapotranspiration (ETo) among the existing methods is without any discussion. However, the equation requires climatic data that are not always available particularly for a developing country such as Burkina Faso. ETo has been widely used for agricultural water management. Its accurate estimation is vitally important for computerizing crop water balance analysis. Therefore, a previous study has developed a reference model for Burkina Faso (RMBF) for estimating the ETo by using only temperature as input in two production sites, Banfora and Ouagadougou. This paper investigates for the first time in the semiarid environment of Burkina Faso, the potential of using an artificial neural network (ANN) for estimating ETo with limited climatic data set. The ANN model employed in the study was the feed forward backpropagation (BP) type using maximum and minimum air temperature collected from 1996 to 2006. The result of BP was compared to the RMBF, Hargreaves (HRG) and Blaney-Criddle (BCR) which have been successfully used for ETo estimation where there is not sufficient data. Based on the results of this study, it revealed that the BP prediction showed a higher accuracy than RMBF, HRG and BCR. The feed forward backpropagation algorithm could be potentially employed successfully to estimate ETo in semiarid zone.

Key-Words: - Evapotranspiration, estimating, limited climatic data, neural network, feed forward backpropagation, semiarid environment, water management

1 Introduction

Water resources management is a crucial requirement for increasing agricultural production in the arid regions where food insecurity is becoming a main concern. In Sub-Saharan Africa (SSA) particularly, according to [1], one third (34%) of population is undernourished, however, more than 70% of the population subsists from agriculture. One of the major reasons of food insecurity in SSA is the low agricultural productivity which is under the direct influence of climate pattern. It has been reported by [2] that, the water resources scarcity is becoming a main climate constraint for the agriculture production particularly in arid and semiarid zones. However, the impact of water scarcity on agriculture could be alleviated by an efficient management system. According to [3], the irrigated agriculture water efficient use is one of the most effective means of promoting income growth through the increasing of the crop productivity.

Therefore, Burkina Faso, an SSA country with a dry tropical climate where agriculture engages more than 85% of the population, is implementing in dry season the small scale irrigation project since 2001 throughout the country. Small scale irrigation has been popularly adopted by farmers and considered as a supplementary production strategy to overcome the low agricultural production of wet season. One of the difficulties is the high cost of water pumping due to lack of appropriate irrigation scheduling system.

However, reference evapotranspiration (ETo) identified as a key hydrological variable, could play an important role in establishing of appropriate irrigation scheduling [4, 5]. Its accurate estimation is of vital importance for computerizing crop water balance analysis. The sole recommended method for ETo computation is the physically-based complex Penman-Monteith (PM) equation using complete meteorological data [6]. The fundamental obstacle to widely applying the PM method in Burkina Faso is the numerous required data that are not always available in many production areas [7, 8]. As well, the weather data measurement equipment sensitivity requires a very good quality and regular costly maintenance for reliable ETo estimation.

Recently, to overcome the climatic data unavailability, a reference model for Burkina Faso (RMBF) using only temperature as input has been developed by [9, 10] for the irrigation scheduling purpose in two production sites, Banfora and Ouagadougou. Indeed, there are many empirical models such as Hargreaves (HRG) and Blaney-Criddle (BCR) which have been successfully used to predict ETo where there is not sufficient data [11, 12]. There is not universal consensus on the suitability of any given model for a given climatic environment. According to [13], the performances of most empirical methods have been found to vary from one climate to another. Hence, the small scale irrigation needs to be provided with the most accurate ETo estimation method based on minimum input data set.

Nowadays, artificial neural network (ANN) approach is successfully used for evapotranspiration estimation. According to [14, 15], evapotranspiration is a complex and nonlinear phenomenon to justify the use of the ANN technique; because it depends on several interacting climatological factors such as temperature, humidity, wind velocity, radiation, type and growth stage of the crop. The ANN is capable to model any arbitrarily complex nonlinear process that relates climate variables to evapotranspiration. According to [16], neural network technique seems to be very effective to identify a broad category of complex nonlinear systems when complete model information cannot be obtained. The emergence of ANN technology has provided many promising results in the field of hydrology and water resources simulation [14-22]. The ANN is a massively parallel distributed information processing system based on the concepts derived from research on the nature of human brains, and has many distinct advantages for hydrological modeling [23].

Neural network approaches have been successfully applied to a number of different climate parameters combinations to model the ETo process. Studies have used the neural networks to model the evapotranspiration as a function of climatic variables required [14, 19, 24-27]. By simplifying the climatic variables to air temperature, extraterrestrial solar radiation and daily light hours, [15, 28] found satisfactory results. [29] removed the daily light hours and found better ETo prediction by using only air temperature and extraterrestrial solar radiation as input variables of the network. So, there is no doubt that the artificial neural network is a powerful computation tool for ETo estimation in the areas where few data are available. Due to the ability of ANN to identify and learn the input-output patterns without being explicitly programmed to do so, it has become a prospective research area with great potential.

However, the application of ANN to evapotranspiration estimation in Sub-Saharan Africa is limited in literature. To the knowledge of the authors, no work has been reported in the literature on ETo estimation using ANN technique in Burkina Faso. In order to address the difficulty of climatic data unavailability, this paper was motivated to evaluate for the first time in Burkina Faso the potential of using the ANN for ETo estimation based only on limited climatic data set. In this study, the ANN algorithm feed forward backpropagation (BP) type was selected for ETo estimation as a function of the minimum and maximum air temperature, and extraterrestrial radiation, for Ouagadougou and Banfora regions. Only minimum and maximum air temperature are collected, the extraterrestrial radiation can be determined for a certain day and location as described by [6]. The performances of the temperature-based models ANN, RMBF, HRG and BCR were compared to the one estimated by PM method.

2 Material and Methods

2.1 Investigation Areas

Ouagadougou and Banfora explored in the present study are located in the North Sudano-Sahelian region and South Sudano region of Burkina Faso, respectively (Figure 1). The data sets were collected from the meteorological stations located in both regions. In North Sudano-Sahelian region at 800 mm isohyets, Ouagadougou Airport Meteorological station located at $12^o37'$N latitude, $-1^o52'$W longitude and 306 m altitude. In South Sudano region at isohyets 1200 mm, National Sugar Company Agro-meteorological station (SN-SOSUCO) located in Banfora, Western part of Burkina Faso at $10^o63'$N latitude, -4^o77W longitude and 302 m altitude. The decadal weather data composed of precipitation (mm), relative humidity (%), wind speed (m/s), maximum and minimum temperature (^{o}C) were collected from 1996 to 2006 in both locations for this study.

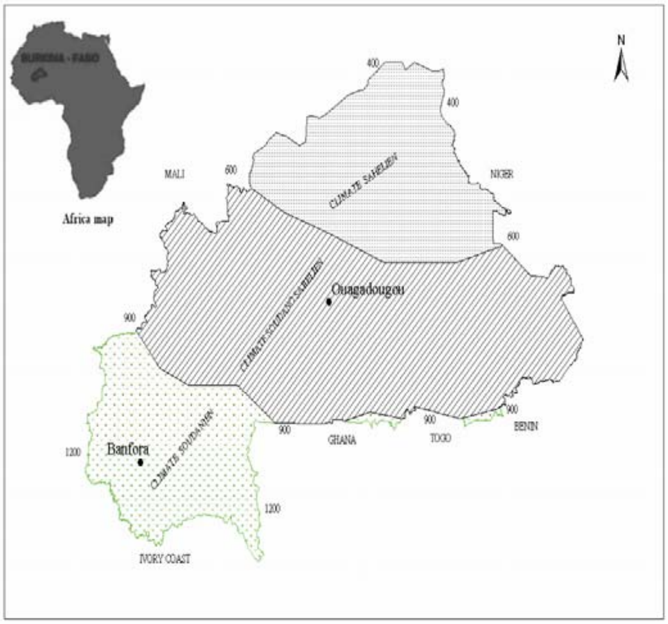


Figure 1. Sketch of the investigation areas

2.2 Estimation of Reference Evapotranspiration

The Penman-Monteith equation for calculation of the reference evapotranspiration proposed by [6] is stated as the following:

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

Where ETo is the reference evapotranspiration [mm day^{-1}]; R_n the net radiation at the crop surface [MJ m^{-2} day^{-1}]; G the soil heat flux density [MJ m^{-2} day^{-1}]; T the mean daily air temperature at 2 m height [°C]; u_2 the wind speed at 2 m height [m s^{-1}]; e_s the saturation vapour pressure [kPa]; e_a the actual vapour pressure [kPa]; e_s - e_a the saturation vapour pressure deficit [kPa]; Δ the slope vapour pressure curve [kPa °C^{-1}]; and γ the psychrometric constant [kPa °C^{-1}].

For agriculture water management purpose, the reference model for ETo estimation has been developed for solving the difficulty of climatic data unavailability in Burkina Faso. This reference model determined by [10] can be written as the following:

$$ETo = p(0.23T_{mean} + 4.065) + \\ 0.0023(T_{max} - T_{min})^{0.5}(0.5T_{mean} + 8.9)R_a \quad (2)$$

where ETo is the daily reference evapotranspiration (mm/day); p is the mean daily percentage of annual daytime hours according to the latitude; T_{max} and T_{min} are the maximum and minimum temperature (^oC); T_{mean} is the mean temperature (^oC); and R_a is the extraterrestrial radiation (mm/day).

Hargreaves method (HRG) is used for ETo estimation when solar radiation data, relative humidity data and wind speed data are missing. This method estimates ETo using only the maximum and minimum air temperature with the following equation [6]:

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

Where ETo is the daily reference evapotranspiration (mm/day); T_{max} and T_{min} are the maximum and minimum temperature (^oC); T_{mean} is the mean temperature (^oC); R_a is the extraterrestrial radiation (mm/day); and Co is the conversion coefficient (^oC) (C_o =0.0023).

Blaney-criddle method (BCR) referred to the temperature mean values can be expressed as [30]:

$$ETo = p(0.46T_{mean} + 8.13) \quad (4)$$

Where ETo is the daily reference evapotranspiration (mm/day); T_{mean} is the mean daily temperature (^0C); and p is the mean daily percentage of annual daytime hours according to the latitude.

2.3 Neural Network and Models Evaluation

The neural network is trained with a series of inputs and desired outputs from the training data set [31]. The most commonly used ANN in hydrological predictions is the feed forward network with the BP training algorithm [32]. Feed forward backpropagation is a supervised learning technique used for training artificial neural networks. Basically, it is a gradient descent technique to minimize some error criteria. BP has been widely used in approximating a complicated nonlinear function. The neural network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer. Adjustable weights are used to connect the nodes between adjacent layers and optimized by training algorithm to get the desired classification results [33].

Further examination of the ETo estimation equations show that the ETo is mainly dependent on the climatic parameters. Consequently, this study considers the minimum and maximum air temperature, and extraterrestrial radiation as the inputs of the network. The ETo decade values are the output of the network. Figure 2 shows the typical configuration of a BP used in this study for modeling the ETo process.

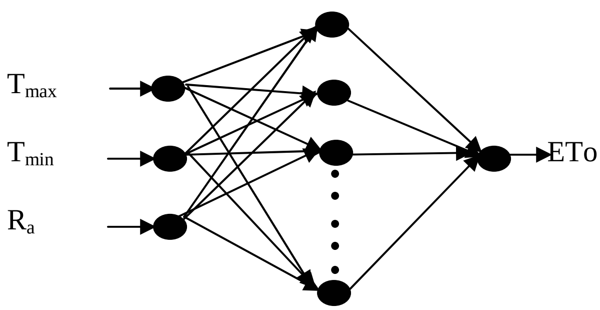


Figure 2. Structure of typical BP neural network model.

In this study, the network transfer function was the log-sigmoid. According to [34], log-sigmoid is one of the most commonly used transfer function. The log-sigmoid transfer function is commonly used in backpropagation networks because of it differentiable. This function can have any inputs value between plus and minus infinity, and squashes the output into the range 0 to 1. The mathematical equation of each layer may be written as following:

$$Y_o = \Phi(\sum W_{io} X_i - \theta_o) \qquad (5)$$

where Y_o is the output of the neuron o; W_{io} is the weight increments between i and o; X_i is the input signal generated for neuron i; θ_o is the bias term associated with neuron o; and the nonlinear activation function Φ is assumed to be a sigmoid function as $\Phi(x) = 1/(1+e^{-x})$ for the continuous and differential process. Beside, the Levenberg-Marquardt optimization was chosen for the network training function that updates weight and bias values.

The performance of different models is evaluated based on the criteria of the root mean square errors (RMSE) and square value of coefficient of correlation (r) between temperature-based ETo and PM ETo. These two statistical parameters used for the performance evaluation are given as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_p - Y_e)^2}{N}} \qquad (6)$$

$$r = \frac{\sum_{i=1}^{N}(Y_p - \overline{Y}_p)(Y_e - \overline{Y}_e)}{\sqrt{\sum_{i=1}^{N}(Y_p - \overline{Y}_p)^2 \sum_{i=1}^{N}(Y_e - \overline{Y}_e)^2}} \qquad (7)$$

where Y_p and Y_e represent PM method and temperature-based models ETo estimated for the *i*th values; $\overline{Y}_p$ and $\overline{Y}_e$ represent the average values of the corresponding variable; and N represents the number of observations. Additionally, a single linear regression ($y=b_0+b_1x$) was accomplished for each estimation, by considering the ETo values from PM and alternative methods as the independent variable and the dependent variable respectively. The results were analyzed by using the coefficients (b_0 , b_1, and r^2) of the equations.

2.4 Data Normalization

Data set were comprised of minimum and maximum air temperature, and extraterrestrial radiation fixed as the neural network minimum input set. The decade values were used in order to obtain a network that has a high estimation capacity in the investigation areas. According to [28], by grouping the daily values into averages, the ETo may be estimated due to their highest stabilization. The decade data set collected from 1996 to 2006 in Ouagadougou and Banfora had a total of 394 patterns divided in three parts for the purpose of training (70%), validation (20%) and testing (10%). The training data (from January 1996 to December 2003) is used to train the network by minimizing the error data; the validation data (from January 2004 to December 2005) used to find the network performance and then the testing data (from January 2006 to December 2006) used for checking the overall performance of trained and validated network. For preventing an overcome problem associated to the extreme values, the input and output data set were scaled in the range of [0 1] using the following equation [14, 35]:

$$Y_{norm} = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \quad (8)$$

where, Y_{norm} is the normalized dimensionless variable; Y_i is the observed value of variable; then Y_{min} and Y_{max} are the minimum and the maximum value of the observed variable.

3 Discussion of Results

The architectures with a hidden layer were adopted in this study based on the fact, an ANN with just only a hidden layer is enough to represent the nonlinear relationship between the climatic elements and the corresponding ETo [14, 28, 36]. The determination of the nodes in the hidden layer providing the best training results was the initial process of the training procedure. The numbers of nodes in the hidden layer were varied between 5 and 20 and the correlation statistics were used to evaluate the best architecture during the training and validation stages. Once the training stage was completed, the final and most important step in this work of neural networks is to test the programs designed. The networks were tested using different input and output values that were not given for training previously. The performance criteria, RMSE and r^2 were calculated using the tested data to find the optimal number of the hidden nodes.

Decade ETo estimated from reference model for Burkina Faso (RMBF); Hargreaves (HRG), Blaney-Criddle (BCR) and the feed forward backpropagation network (BP) were compared to Penman-Monteith (PM) considered as true ETo. The performances of these four temperature-based models present different trends in ETo estimation.

The results from the statistical criteria found in Ouagadougou indicated a high performance of RMBF (RMSE=0.193 mm day^{-1}; r^2=0.910) when compared to HRG (RMSE=0.294 mm day^{-1}; r^2=0.860) and BCR (RMSE=0.295 mm day^{-1}; r^2=0.840). Similarly to Ouagadougou, in Banfora, RMBF (RMSE=0.150 mm day^{-1}; r^2=0.968) performs better than HRG (RMSE=0.224 mm day^{-1}; r^2=0.961) and BCR (RMSE=0.383 mm day^{-1}; r^2=0.909). There is a difference in rank number derived from these statistical performances. Therefore, based on the lowest RMSE and highest r^2, the ETo estimates comparison across the models indicated that RMBF ranked first followed by HRG and BCR in second and third place, respectively. It was observed generally in Ouagadougou and Banfora, BCR overestimates and HRG underestimated the ETo. The performance of these two alternative methods may strongly dependent of climate condition. [37] concluded that, the accuracy of Blaney-Criddle and Hargreaves models varies with climatic conditions. Similar results have been reported in semiarid conditions that, Hargreaves generally under-predicted ETo [38], and Blaney-Criddle over-predicted ETo [37]. In the dry tropical climate context of Burkina Faso, the results obtained from RMBF, HRG and BCR in this study agreed with those previously studied by [10]. HRG model shows superiority over BCR for these two sites located in a semiarid environment. The low performance of BCR in semiarid climates is evidently due to the lowest degrees of correlation between temperature variables and ETo [39]. According to [13], at the semiarid location, Hargreaves was overall best than Blaney-Criddle. In the present study for both Ouagadougou and Banfora, RMBF was more close to PM than HRG and BCR. These results agree with the conclusion drawn by [10] that, the RMBF offers a satisfactory alternative to the standard PM for Ouagadougou and Banfora regions and could be used when complete climatic data are not available.

The feed forward backpropagation algorithm (BP) using only the minimum and maximum air temperature, and extraterrestrial radiation was trained for the determination of the best architecture. The BP network structure providing the best training results was applied to the testing data. Table 1 shows different networks and their performance during the training and validation stages for Ouagadougou and Banfora. BP algorithm using the 10 nodes (FFBP 3-10-1) gave the highest coefficient of correlation in Ouagadougou (r^2=0.981) and Banfora (r^2=0.982) during the training stage. During the testing stage, this BP configuration (FFBP 3-10-1) provided the very close estimates to PM in both Ouagadougou and Banfora when compared to the others temperature-based methods. [40] also obtained a better result with BP than empirical alternative methods.

The summary of statistic performances for the different temperature-based models is presented in Table 2. BP network with ten nodes in hidden layers has the highest performances criteria in Ouagadougou (RMSE=0.112 mm day^{-1} and r^2=0.961) and Banfora (RMSE=0.148 mm day^{-1}; and r^2=0.980). In spite of the good results of RMBF, BP produces the closest ETo values to PM. In term of the methods performance and yielded ETo, BP ranked at the top when compared to the others. More recently, [29] used similar data set configuration as input and found the best results with nine nodes in the hidden layer. By using minimum climates data set, [28] concludes that, it is possible to estimate ETo by BP approach. Precision of BP model was higher than some temperature-based methods and could be used for the prediction of ETo when only temperature was available [41]. Several models have been developed according the number of the inputs data and the type of the ANN algorithm. In general, studies have reported that, artificial neural networks may offer a promising alternative for estimation of reference evapotranspiration [24, 42-44].

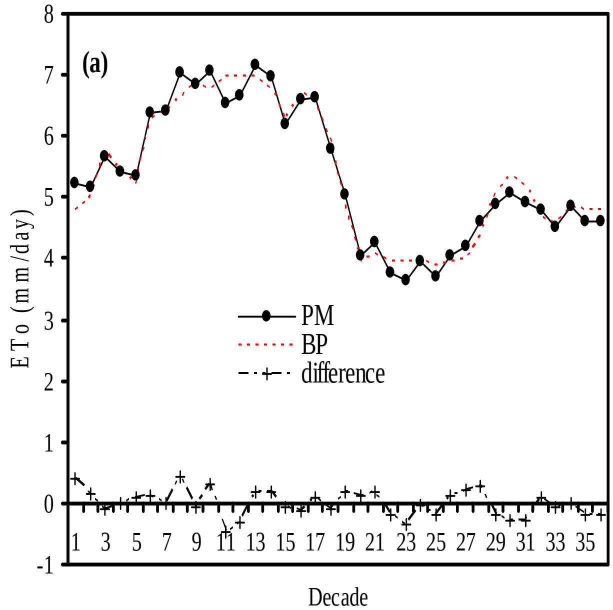
In order to see the model estimation performance, Figures 3a and b plotted BP ETo estimates with ten nodes configuration and PM ETo. It can be seen that, BP estimated ETo values agreed closely with the PM and followed the same trend. In both Ouagadougou and Banfora, the deviation in ETo values were less

Table 1. Neural network architectures and their coefficient of correlations for the training and validation periods in Ouagadougou and Banfora.

Region	ANN configuration	Nodes in Hidden layer	r^2	
			Training	Validation
Ouagadougou	FFBP (3-5-1)	5	0.964	0.945
	FFBP(3-10-1)	10	0.981	0.928
	FFBP(3-15-1)	15	0.986	0.948
	FFBP(3-20-1)	20	0.988	0.858
Banfora	FFBP (3-5-1)	5	0.916	0.881
	FFBP(3-10-1)	10	0.982	0.759
	FFBP(3-15-1)	15	0.972	0.901
	FFBP(3-20-1)	20	0.966	0.881

Table 2. Summary of statistical performances for the different models during the testing period (January 2006 to December 2006) in Ouagadougou and Banfora.

Region	Model	b_0	b_1	r^2	RMSE
Ouagadougou	FFBP(3-10-1)	0.012	0.993	0.961	0.112
	BCR	0.599	0.867	0.840	0.295
	HRG	-0.747	1.186	0.860	0.294
	RMBF	-0.368	1.071	0.910	0.193
Banfora	FFBP(3-10-1)	0.212	0.955	0.980	0.148
	BCR	-0.765	1.179	0.909	0.383
	HRG	0.784	0.828	0.961	0.224
	RMBF	0.010	1.003	0.968	0.150



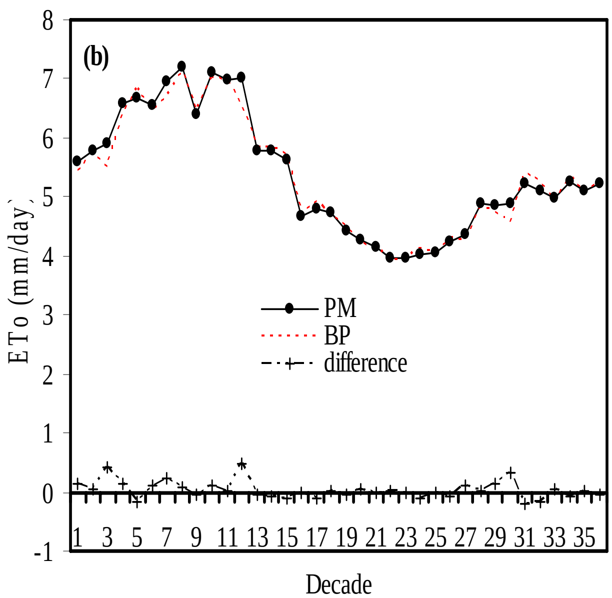


Figure 3. Comparison between decades ETo calculated by the proposed BP network and PM methods for Ouagadougou (**a**) and Banfora (**b**).

than 1 mm/day. From this closest agreement of BP with PM, it could be concluded that, neural network is a powerful ETo estimation tool for a country where complete climate data for PM application are not available. Thus, the neural network temperature-based could be suggested for reliable ETo estimation in the investigation areas. Since air temperature is a widely available variable, Burkina Faso needs ANN technique for the improvement of irrigation management in the small scale irrigation areas.

4 Implication of this Study

This present study explores only in two regions the neural network methodology as an alternative for solving the difficulty of climatic data availability in Burkina Faso. The country has three agro-climatic zones, which are the Soudano, Soudano-Sahelien and Sahelien zones. It is known that, the regional climatic difference may affect the ETo estimation. Thus, the network architecture found in this study for Ouagadougou and Banfora could not be extrapolated to the other regions. So, there is a need to evaluate the potential of using the artificial neural network in the other regions of Burkina Faso. It is difficult to find a universal simple mathematical model for an accurate ETo estimation for different locations. Thus, the neural network could provide reliable estimation models for the different production sites of small scale irrigation in Burkina Faso. The neural network will have to be tested with data sets from widely varying climatic and geographical regions.

5 Conclusions

Climatic data unavailability is one of the major constraints of irrigation management due to the difficulty of reference evapotranspiration estimation by the PM recommended method. However, the development of irrigation sector and its planning system improvement as part of the small scale irrigation project activities are a big challenge for the government of Burkina Faso. There is therefore, a necessity for establishing an estimation methodology for Burkina Faso with high accuracy. Most of the alternatives methods accuracy is influenced by the climate condition which limits their universal application. From the results of this study, the reference model (RMBF) previously developed only for Banfora and Ouagadougou gave a satisfactory result for evapotranspiration estimation when compared to Hargreaves (HRG) and Blaney-Criddle (BCR). But, it has been found that, the neural network provides the closest agreement with Penman-Monteith when compared to RMBF, HRG and BCR. This present study has demonstrated the potential of using the neural network with limited climatic data for reliable reference evapotranspiration estimation in semiarid environment of Burkina Faso. Obviously, using the ANN for ETo estimation is more reliable than the other alternative methods. This approach may help rapidly the small scale irrigation project to overcome the data limitation constraint throughout the country. Neural network can help to improve significantly the efficiency of irrigation management in Burkina Faso when the relative humidity, wind velocity and sunshine data are not available. Farmers could reduce the high cost of water pumping by benefiting of an accurate irrigation scheduling system.

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