Modeling Reference Evapotranspiration by Generalized Regression Neural Network in Semiarid Zone of Africa

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Abstract: - This paper investigates for the first time in Burkina Faso, the potential of using an artificial neural network (ANN) for reference evapotranspiration (ETo) estimation. The ANN algorithm generalized regression neural network (GRNN) was selected for its ability to model the ETo from minimum climatic data. The irrigation management in Burkina Faso still faced to climatic data unavailability for estimating the ETo with the recommended Penman-Monteith (PM) equation. Recently, to overcome the climatic data unavailability difficulty, a reference model for Burkina Faso (RMBF) using only temperature as input has been developed for irrigation management purpose in two production sites, Banfora and Ouagadougou. In this study, four alternative methods to PM, including GRNN, RMBF, Hargreaves (HRG) and Blaney-Criddle (BCR) were employed to study their performances in three production sites, Dori, Bogande and Fada N'gourma. The minimum climatic data were set to the maximum and minimum air temperature as input variables collected from 1996 to 2006. The results revealed that, RMBF, HRG and BCR overestimated the ETo and showed poor performance. In addition, GRNN performance was higher than RMBF, HRG and BCR. Finally, wind has been determined as a sensitive parameter in the ETo estimation for the areas studied. Obviously, using GRNN with minimum climatic variables for ETo estimation is more reliable than the other alternative methods. It is possible to estimate ETo by using ANN in semiarid zone of Africa.

Key-Words: - Evapotranspiration, estimating, GRNN, minimum climatic data, semiarid zone, irrigation management.

1 Introduction

Evapotranspiration determination is a key factor for water balance analysis and irrigation scheduling [1, 2]. In general, the reference evapotranspiration (ETo) estimation in the developing countries has been stated as a major constraint for irrigation development [3]. Accurate estimation of ETo, especially in semiarid regions such as Burkina Faso, has a great importance for irrigation water management. Penman–Monteith combination method is one of the most accurate methods to evaluate ETo at different time steps. However, it requires numerous weather variables such as air temperature, relative humidity, wind speed and solar radiation, which are not always available in many production sites particularly in developing countries. Accordingly, ETo is still estimated by the alternative empirical methods such as Hargreaves (HRG) and Blaney-Criddle (BCR) despite their inaccuracy in many areas [4].

The ETo importance is evident in many water resources management technologies such computer based simulation models developed during the last past decade. The application of a number of computer technologies [5, 6] in Burkina Faso for water management is limited by the wide range of climatic data required for ETo estimation with the sole recommended Penman-Monteith (PM) equation. However, using computer based simulation models can revolutionize the irrigation water management practice in Burkina Faso. In recents studies, it has been reported that the difficulty for applying such technology in Burkina Faso is the unavailability of complete climatic data in many production sites for computing ETo [7, 8].

Moreover, [9, 10] suggest the temperature methods of Hargreaves (1985) and Blaney-Criddle (1990) as suitable to the study area where the complete data required for PM ETo estimation is not available. The performance of different alternative equations has been evaluated under different climate conditions [11, 12]. But, there is no universal consensus on the suitability of any given model for a given climate. According to [4], the empirical formula are limited by their inherent characteristics. However, a very few studies reported on the evapotranspiration estimation in Burkina Faso. Efficient water management based on simple and accurate ETo estimation method is urgently necessary for the different production sites in Burkina Faso. Hence, to overcome the climatic data limitation, a previous study done by [1] developed a reference model (RMBF) for ETo estimation in two production sites, Ouagadougou and Banfora.

In last few years, another alternative method is the application of the artificial neural networks (ANNs) for estimating the ETo. ANN is a mathematical model based on the biological neural networks, able to model any arbitrarily complex nonlinear process that relates climatic variables to ETo. According to [13], the ANN modeling technique has been rapidly gaining attention in many scientific and engineering fields in recent years. ANNs have recently been applied in several areas of hydrological research, including rainfall estimation [14], flow forecasting [15], rainfall–runoff processes [16], river sediment flux modeling [17] and evapotranspiration process modeling [18]. Indeed, ANN ability to estimate ETo has been widely investigated and outstanding results have been reported by several studies [19, 20]. According to [21], the main advantage of ANNs in comparison to the conventional methods is that ANNs do not require detailed information on the physical processes of the system to be modeled, as this one is explicitly described under the mathematical form (input-output model).

In addition, the ANNs can also model the ETo process by using only minimum climatic variables. Studies reported by [21] and [22] showed the ability of the ANNs to estimate the ETo by using air temperature, solar radiation and daily light hours. [23] used similar simplified climatic data, but by removing the daily light hours variable. So, there is no doubt about the computational ability of the ANN to estimate the ETo where only few climatic variables are available. However, not work has been reported yet on the ANNs application in Burkina Faso where there is a real need for ETo estimation. Therefore, this present study aims to explore for the first time in Burkina Faso, the potential of using the ANN for ETo estimation based on limited climatic variables in Dori, Bogande and Fada N'gourma. The ANN algorithm generalized regression neural network (GRNN) type was selected for ETo estimation as a function of the minimum and maximum air temperature, and extraterrestrial radiation collected from 1996 to 2006. Four alternative methods to PM, including GRNN, RMBF, Hargreaves (HRG) and Blaney-Criddle (BCR) are employed to study their performances.

2 Material and Methods

2.1 Study Area

Meteorological data required for the estimation of the ETo using the different selected models were collected from 1996 to 2006 in three meteorological stations. The three regions studied are located in two agro-climatic zones. Dori meteorological station located in the Sahelian zone, Fada N'gourma in the Soudano Sahelian zone, and Bogande in between (Figure 1). The Sahel where Dori is located, is the driest zone of Burkina Faso, with its lowest annual rainfall (483.56 mm). The weather data composed of precipitation (mm), relative humidity (%), wind speed (km/day), maximum and minimum temperature (^{o}C), and sunshine (hour) were collected in the study areas.

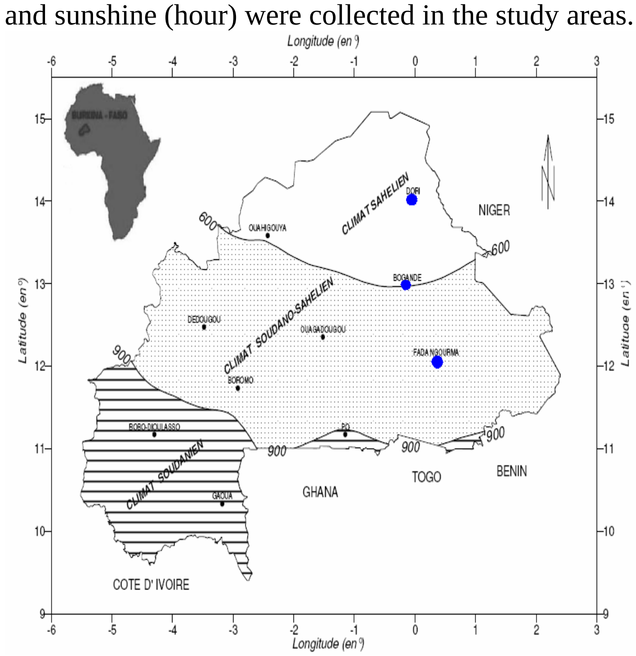

Figure 1. Sketch of the investigation areas.

2.2 Evapotranspiration Estimation Models

The reference evapotranspiration (ETo) was computed for the decade time step using different models selected in this study.

The Penman-Monteith equation for calculation of the reference evapotranspiration is given by [11] as following:

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

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 (RMBF) for ETo estimation has been developed to solve the difficulty of climatic data unavailability in Burkina Faso. This reference model determined by [1] can be written as the following:

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

Hargreaves (HRG) method 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 [11]:

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

Blaney-Criddle (BCR) method referred to the temperature mean values can be expressed as :

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

where ETo is the reference evapotranspiration (mm day^{-1}); 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 (^{o}C); T_{mean} is the mean temperature (^{o}C); R_a is the extraterrestrial radiation (mm day^{-1}); and C_o is the conversion coefficient (^{o}C) (C_o =0.0023).

2.3 Artificial Neural Network

GRNN was preferred instead of the multilayer networks for the reasons that, it does not require an iterative training procedure as the multilayer percepton neural networks model, and then the local minimum problem was not faced in the GRNN modeling and its performances have been reported by [20]. The GRNN consists four layers: input layer, pattern layer, summation layer and output layer. Figure 2 shows a schematic diagram of generalized regression neural network architecture. The number of input units in the first layer is equal to the total number of parameters. The first layer is fully connected to the second, pattern layer, where each unit represents a training pattern and its output is a measure of the distance of the input from the stored patterns. Each pattern layer unit is connected to the two neurons in the summation layer.

The GRNN can be treated as a normalized radial basis function network in which the hidden unit is centered at every training case. These radial basis function units are usually probability of density functions such as the Gaussian. GRNN is a method for estimating the joint probability density function of input and output, given only a training set. Since the probability density function is derived from the data with no preconceptions about its form, the system is perfectly general. By definition, the regression of a dependent variable (output) on an independent (input) estimates the most probable value for output, given input and a training set. This study considers the minimum and maximum air temperature and extraterrestrial radiation as the inputs and ETo values are the output of the network.

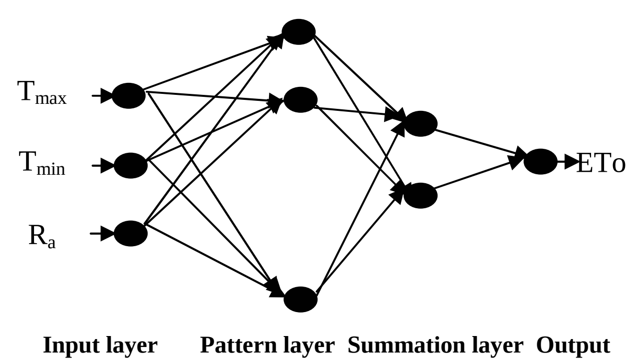

Figure 2. Schematic diagram of GRNN architecture.

Suppose that $f(x, y)$ represents the joint probability density function of a vector random variable x (input), and a scalar random variable y (output). The most probable predicted value of y which is also conditional mean of y given x (regression of y on x) is expressed by:

$$E(y/x) = \hat{y}(x) = \frac{\int_{-\infty}^{+\infty} yf(x, y)dy}{\int_{-\infty}^{+\infty} f(x, y)dy} \tag{5}$$

The density function can be estimated from the training set using the Parzen's nonparametric estimator [24]:

$$f(x, y) = \frac{1}{n(2\pi)^{\frac{p+1}{2}} \sigma(p+1)} \sum_{i=1}^{n} e^{-d(x,x_i)} e^{-d(y,y_i)} \tag{6}$$

Where $d(x, x_i) = \sum_{j=1}^{p} [(x_j - x_{i_j})/(\sigma_j)]^2$ and $d(y, y_i) = [(y - y_i)/(\sigma_y)]^2$ the number of training patterns and the number of independent variables are denoted n and p, respectively. The density function $f(x, y)$ is therefore estimated by a weighted sum of the "Kernel function" [25]. The parameter σ represents the smoothing parameter the width of the "Kernel function".

The estimator $f(x, y)$ is asymptotically unbiased and consistent [26]. An interpretation of the probability estimate $f(x, y)$ is that it assigns sample probability of width σ for each i th value of x and y. The indicated integration yields as the following:

$$\hat{y}(x) = \frac{\sum_{i=1}^{n} y_i e^{-d(x,x_i)}}{\sum_{1=i}^{n} e^{-d(x,x_i)}} \tag{7}$$

The predictor (3) is a weighted sum over all the training patterns. It is directly applicable to problems involving numerical data. Each training pattern is weighted exponentially according to its Euclidean distance to the unknown pattern x and also according to the smoothing factors. This predicator was mapped into a neural network, which includes the four layers that are the input layer, pattern layer, summation layer and output layer.

2.4 Data Preparation

The neural network was fed with few data including of minimum and maximum air temperature, and extraterrestrial radiation fixed as 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 [22], 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 Dori, Bogande and Fada N'gourma had a total of 396 patterns divided in two parts for the purpose of training and testing. The training data (from January 1996 to December 2005) is used to train the network by minimizing the error data and the testing data (from January 2006 to December 2006) used for checking the overall performance of trained network. Generally, the agriculture activities in Burkina Faso are yearly planned. Hence, in this study, the one year data equivalent to 10% of the total data set was used for testing the models. To overcome the problem associated with the extreme values, the input and output data set were scaled in the range of [0 1] using the following equation [27]:

$$y_{\text{norm}} = \frac{y_{\text{i}} - y_{\min}}{y_{\max} - y_{\min}} \tag{8}$$

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.

2.5 Models Evaluation

The model performances were assessed by the root mean square error (RMSE), the mean absolute error (MAE) and the coefficient of correlation. RMSE and MAE indicate the predictive ability of the models. The square value of coefficient of correlation (r) is used to measure the accuracy of the neural network models in order to select the best architecture during the training period. These statistical evaluations are defined as the following:

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(y_i-y'_i)^2}{N}} \tag{9}$$

$$\mathrm{MAE}=\frac{1}{N}\sum_{i=1}^{N}\left|y_i-y'_i\right| \tag{10}$$

$$r=\frac{\sum_{i=1}^{N}(y_i-\bar{y}_i)(y'_i-\bar{y}'_i)}{\sqrt{\sum_{i=1}^{N}(y_i-\bar{y}_i)^2\sum_{i=1}^{N}(y_i-\bar{y}'_i)^2}} \tag{11}$$

where y_i represent the PM observed ETo, y'_i is the alternative methods estimated ETo for the *i*th values; $\bar{y}_i$ and $\bar{y}'_i$ represent the average values of the corresponding variable; and N represents the number of data considered. Additionally, a single linear regression $y=b_0+b_1x$ is applied for evaluating the models' performance statistically, where y is the dependent variable (PM); x the independent variable (alternative methods); b_0 the intercept; and b_1 the slope.

3 Results and Discussion

3.1 Reference Evapotranspiration Estimation

The inputs for the generalized regression neural network (GRNN) were set to the minimum and maximum air temperature, and extraterrestrial radiation. GRNN performance analysis was carried out by trying different smoothing parameters in order to obtain the best architecture. The networks were tested using different input and output values that were not given for training previously. The network structure which provided the best training results was selected based on the coefficient of correlation, and then applied to the testing data. The network structure GRNN (3, 0.1, 1) with 3 inputs, smoothing parameter =0.1 and 1 output gave for the training stage, the highest coefficient of correlation. Its performances were evaluated during the testing period and compared to the other methods.

Table 1 showed the estimation accuracy obtained by the GRNN, HRG, RMBF and BCR in Dori, Bogande, and Fada N'gourma. The statistical performances in these three regions were ranged between 0.367 to 0.907, 0.356 to 1.845 and 0.291 to 1.668 for the r^2, RMSE and MAE, respectively. From Table 1, GRNN provided the highest r^2, (0.907) and lowest RMSE (0.356) and MAE (0.291). The performances of GRNN were higher in Dori (r^2=0.799, RMSE=0.356 mm day^{-1}, MAE=0.291 mm day^{-1}), Bogande (r^2=0.836, RMSE=0.393 mm day^{-1}, MAE=0.313 mm day^{-1}) and Fada N'gourma (r^2=0.907, RMSE=0.378 mm day^{-1}, MAE=0.321 mm day^{-1}).

Table 1. Statistical performances for the different models.

Location	Model	b_0	b_1	r^2	RMSE (mm/day)	MAE (mm/day)
Dori	GRNN (3-0.1-1)	1.059	0.777	0.799	0.356	0.291
	HRG	1.856	0.835	0.598	1.185	1.046
	RMBF	2.419	0.784	0.486	1.509	1.357
	BCR	2.981	0.733	0.367	1.845	1.668
Bogande	GRNN (3-0.1-1)	1.863	0.652	0.836	0.393	0.313
	HRG	1.115	0.811	0.781	0.420	0.341
	RMBF	0.989	0.878	0.734	0.579	0.446
	BCR	0.863	0.946	0.649	0.832	0.655
Fada N'gourma	GRNN (3-0.1-1)	2.325	0.511	0.907	0.378	0.321
	HRG	0.548	1.037	0.791	0.824	0.726
	RMBF	0.291	1.142	0.706	1.116	0.971
	BCR	0.033	1.248	0.613	1.428	1.218

Based on these highest performances, the difference in ranking number from the statistical evaluation placed GRNN at the top followed by HRG, RMBF and BCR.

In general, it was found a poor agreement between PM and the HRG, RMBF and BCR methods for ETo estimation in Dori, Bogande and Fada N'gourma (Table 1). Despite this poor agreement, HRG method's performs better in Dori (r^2=0.598, RMSE=1.185 mm day^{-1}, MAE=1.046 mm day^{-1}), Bogande (r^2=0.781, RMSE=0.420 mm day^{-1}, MAE=0.341 mm day^{-1}) and Fada N'gourma (r^2=0.791, RMSE=0.824 mm day^{-1}, MAE=0.726 mm day^{-1}) than RMBF and BCR. BCR gave a very poor performance in Dori (r^2=0.367, RMSE=1.845 mm day^{-1}, MAE=1.668 mm day^{-1}) and Bogande (r^2=0.649, RMSE=0.832 mm day^{-1}, MAE=0.655 mm day^{-1}) and Fada N'gourma (r^2=0.613, RMSE=1.428 mm day^{-1}, MAE=1.218 mm day^{-1}). Figure 3 shows the decade ETo estimated from selected methods. GRNN produced the closest ETo values to PM in the regions studied when compared to the other alternatives methods. The deviation between GRNN and PM estimates ETo values is less than 1.00 mm day^{-1}. More recently, [28] have obtained better results by using the GRNN model for ETo estimation. Precision of ANN model was higher than some temperature-based methods and could be used to predict ETo when only temperature was available [29]. From the results of this study, it could be concluded that by using the GRNN model, it is possible to estimate the ETo based on minimum climatic data in the semiarid zone of Africa.

Further analysis using the ETo estimation rate between PM and the HRG, RMBF and BCR showed an overall estimation. The minimum overestimation was obtained by HRG in Dori (21.27%), Bogande (1.88%) and Fada N'gourma (15.17%). The maximum overestimation was produced by BCR in Dori (33.92%), Bogande (10.63%) and Fada N'gourma (25.45%). The RMBF less overestimated the ETo values when compared to BCR in Dori (27.60%), Bogande (6.26%) and Fada N'gourma (20.31%). [30] and [31] found an overestimation with BCR model in semiarid zones. [32] stated that, the low performance of BCR in semiarid climates is obviously due to the lowest degrees of correlation between temperature variables and ETo. As mentioned above, in general, this present study shows an overestimation with RMBF, BCR and HRG. However, it has been reported by [23, 33, 34] that, HRG under-predicted ETo in the semiarid regions. This overestimation of HRG could

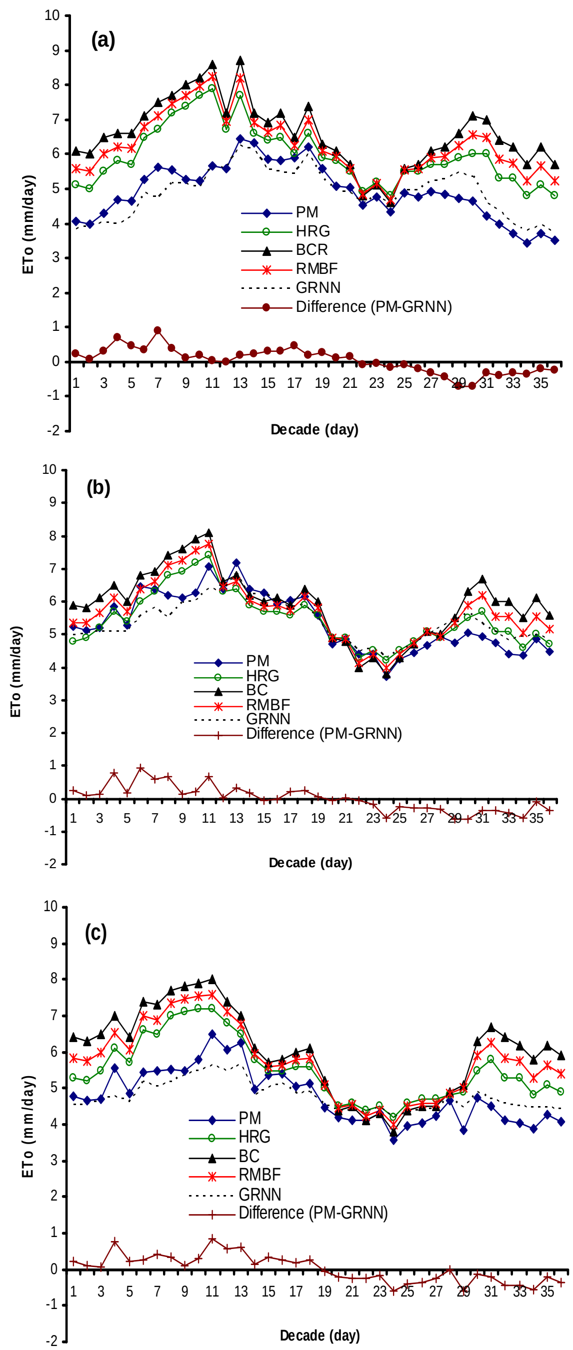

Figure 3. Plot of decade ETo estimated from the limited input data set for Dori (a), Bogande (b) and Fada N'gourma (c) in Burkina Faso.

be probably due to the influence of the specific weather condition of Dori, Bogande and Fada N'gourma particularly, the high temperature variation and high wind velocity. According to [35] also reported that, HRG method mostly underestimated or overestimated ETo obtained from PM. This present study found an overestimation with HRG, as well as RMBF and BCR methods. Similar conclusion was reported by [36] that HRG method overestimated 23.1% of evapotranspiration by PM method in semi-arid region of Karnal, India. [37] found that HRG overestimated the ETo in the semiarid regions of north China. This implies that the climatic conditions impact the level of agreement between ETo methods. The results obtained with RMBF do not suggest the application of this method for an accurate decade ETo estimation by considering only a yearly climatic data in Dori, Bogande and Fada N'gourma.

The factor such as wind velocity documented by [38] occurred an important variation of ETo computed from the temperature-based methods. Further analysis done by [39] indicated that wind in the atmosphere decreases the temperature during the daytime and increases it during the nighttime, this could explain at some extent the different behavior of the HRG equation at the non-windy and windy regions. Therefore, for these semiarid regions investigated in this study high wind speed might affect the performance of the ETo estimated from the alternatives methods. It has been reported by [40, 41] that the alternatives methods are very dependent on local climate condition. However, no study examined yet the sensitivity analysis of the specific weather condition on the ETo estimation in Burkina Faso.

3.2 Sensitivity Analysis

The wind velocity has been determined by [42] has a serious source of error on the ETo estimation. According to [43], high wind speed could affect the ETo value in arid regions. The impact of wind speed on the ETo results is relatively smaller except for arid windy areas [44]. Under these considerations, the ETo process has been modeled by considering the wind velocity as a new input variable added to the minimum and maximum air temperature, and extraterrestrial radiation. The results from Table 2 showed a very good agreement between GRNN and PM in Dori (r^2=0.990, RMSE=0.083 mm day^{-1}, MAE=0.069 mm day^{-1}) and Bogande (r^2=0.971, RMSE=0.161 mmday^{-1}, MAE=0.120 mm day^{-1}) and Fada N'gourma (r^2=0.982, RMSE=0.116 mm day^{-1}, MAE=0.089 mm day^{-1}). Therefore, when wind velocity is introduced to the network input, the performances of the GRNN in the three regions improved significantly. Figure 4 shows the comparison between GRNN and PM estimates ETo when wind velocity is added into the network input. The deviation between GRNN and PM estimates ETo values is less than 0.50 mm day^{-1}. In the East Arid Zone of Nigeria in West Africa, [45] observed a positive correlation between ETo and wind speed. ETo is sensitive to wind [46] and its performance may be also influenced [47]. The influence of wind speed on the ETo could explain probably the poor performance of HRG, RMBF and BCR models found in the above results in Dori, Bogande and Fada N'gourma. It has been documented at least by [11, 39] that, the climate parameters such as wind velocity simultaneously results by deteriorating ETo from temperature-based methods. The sensitivity analysis of ETo to wind showed that, in the specific weather condition of Burkina Faso, the wind speed has to be regarded as a necessary climatic variable for these semiarid zones. Therefore, it was possible to improve significantly the accuracy of ANN prediction by adding the wind speed parameter to the network input data previously defined. As ETo is relatively important for the crop water requirement accurate estimation, it is urgent to ensure reliable and accurate data of wind velocity.

Table 2. Statistical performances during the testing period when the wind velocity is added into the network input.

Location	Model	b_0	b_1	r^2	RMSE (mm/day)	MAE (mm/day)
Dori	GRNN (4-0.1-1)	0.197	0.959	0.990	0.083	0.069
Bogande	GRNN (4-0.1-1)	0.536	0.902	0.971	0.161	0.120
Fada N'gourma	GRNN (4-0.1-1)	0.483	0.899	0.982	0.116	0.089

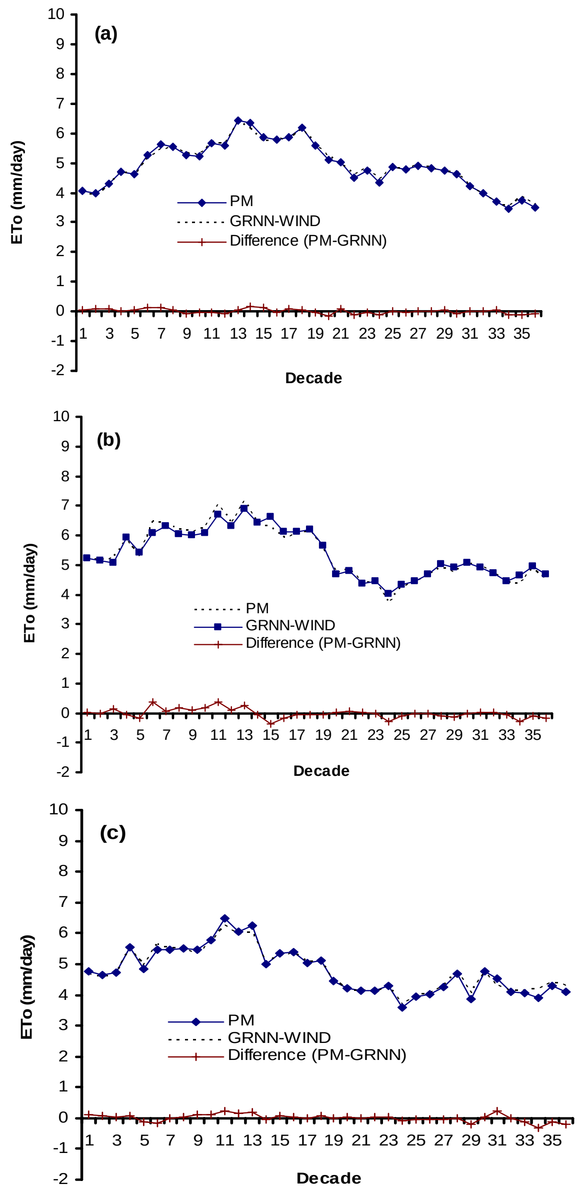

Figure 4. Plot of decade estimated ETo (January to December 2006) from the limited input data set including wind velocity for Dori (**a**), Bogande (**b**) and Fada N'gourma (**c**) in Burkina Faso.

4 Conclusions

The present work focused on the ability of the generalized neural network to estimate reference evapotranspiration using limited climatic data at decade time steps. An accurate determination of the reference evapotranspiration from minimum climatic data could help for efficient irrigation management through computer-based water balance simulation techniques. The results of this study showed in general an overestimation of ETo estimated with RMBF, BCR and HRG. The results obtained with RMBF do not suggest the application of this method for an accurate decade ETo estimation with only one year climatic data in Dori, Bogande and Fada N'gourma. GRNN produced the closest ETo values to PM in these regions studied when compared to the other alternatives methods. Based on the highest performances, the difference in ranking number from the statistical evaluation placed GRNN at the top followed by HRG, RMBF and BCR. From the results of this study, it could be concluded that by using the GRNN model, it is possible to estimate the ETo based on minimum climatic data in Afican semiarid zones. By introducing the wind velocity to the network input, the performances of the GRNN in these three regions improved significantly. ETo is sensitive to wind velocity, therefore this parameter has to be regarded as a necessary climatic variable for the semiarid zones of Africa.

5. Acknowledgments

The authors are thankful to the International Cooperation and Development Fund (TaiwanICDF) for the financial support provided during this study. In addition, the authors wish to acknowledge the Department of Irrigation Development of Ministry of Agriculture, Hydraulic and Fishery Resources of Burkina Faso for collecting and providing the data used in this study.

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