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Full Length Research Paper

Computational performance of reference evapotranspiration in semiarid zone of Africa

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Evapotranspiration is a major component of hydrologic cycle and its accurate estimation is essential for agricultural water management. The Penman-Monteith (PM) equation is the universal accurate method for estimating reference evapotranspiration (ET_ref). Its drawback is the large climatic data required which are unavailable in many African semiarid regions such as Burkina Faso. The Hargreaves (HRG) conventional method which requires few data is still used despite of its non-universal accuracy often reported due to the model inability to capture the effect of some important climatic parameters. Therefore, this study assessed the performance of an artificial neural network (ANN) for computing ET_ref in Dédougou region, located in the Soudano-Sahelian zone of Burkina Faso. This study employed ANN and HRG models in order to evaluate their performance by comparing with the true PM. From the statistical comparison results, ANN showed a good performance than HRG which overestimated ET_ref for the observed condition. Furthermore, wind speed has been found as an important factor in ANN accuracy improvement. Using ANN under semiarid zone climatic condition of Africa for computing ET_ref is highly superior to the conventional method.

Key words: Agricultural water management, evapotranspiration, models performance, Sahelian zone, temperature data.

INTRODUCTION

The hydrological models currently used in several studies around the world including the modeling of climate change (Thodsen, 2007), yield function (Wang et al., 2008a), water budget (Sepaskhah et al., 2006), irrigation scheduling (Clarke et al., 1998) and rainfall index (Wang et al., 2007) all require the evapotranspiration. Suyker and Verma (2008) stated on the importance of evapotranspiration as a major component of agricultural water management due to the persistence of the water resources rarity and growing of the world population.

Water management is vital for a country such as Burkina Faso located in a dry tropical climate of Western Africa where crops are constantly under the influence of low rainfall and high temperature. Hence, efficient use of water becomes extremely a major challenge for Burkinabe farmers. Efficient water management requires an accurate reference evapotranspiration (ET_ref) which can be derived from the meteorological variables. Fisher et al. (2005) indicated that ET_ref is a major component in terrestrial water balance and net primary productivity models, but it is difficult to measure and predict. The most common Penman-Monteith (PM) equation has been recommended by the Food and Agriculture Organization of the United Nations as universally accurate method for estimating ET_ref. According to Alexandris et al. (2006), PM is now widely used by agronomists, irrigation engineers and other scientists in the field-practice and research. However, the large number of weather input data required by the PM equation is often difficult and expensive to obtain for practical applications in many countries

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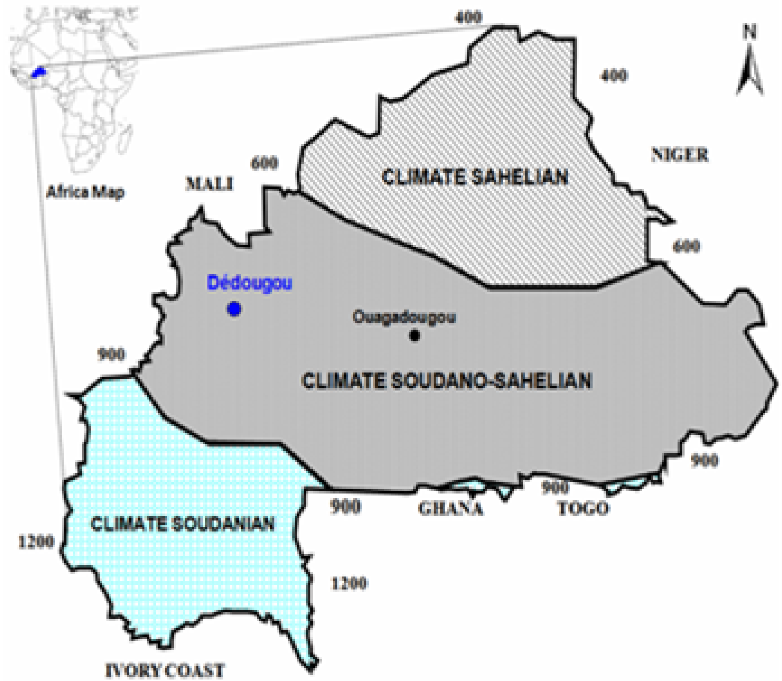

Figure 1. Location of the study area in Burkina Faso.

of the world.

Penman-Monteith equation computes ET_ref using the minimum and maximum air temperature, relative humidity, wind velocity and sunshine hour data. The enormous data required by the equation has been indicated as constraining for irrigation information computerization in Burkina Faso (Traore et al., 2007; Wang et al., 2008a).

Hence, the conventional approach such as Hargreaves equation is still used for ET_ref estimation in many areas because of the advantage of its simplicity requiring only air temperature data. According to Smith et al. (1996), although the conventional methods use few weather data, they do not have a universal suitability. Alexandris et al. (2006) reported that they are often unable to capture the effect of some important climatic parameters which may affect ET_ref. According to Meza (2005), the conventional approaches miss the opportunity to incorporate some weather information.

In past decades, scientists paid considerable attention for another approach which is the artificial neural network (ANN) applied in diverse fields of hydrology engineering forecasting and modeling. Artificial neural network application in hydrology includes rainfall-runoff modeling (Firat, 2008); suspended sediment forecasting (Wang et al., 2008b) and evapotranspiration estimation (Kisi, 2006). Artificial neural network was potentially used to model ET_ref as a function of climatic variables. Sudheer et al. (2003) and Zanetti et al. (2007) in their ET_ref estimation simplified the neural network inputs data to air temperature, extraterrestrial solar radiation and daily light hours.

Recently, Khoob (2008a) used similar input sets but without the daily light data for estimating successfully ET_ref in Iran. From the outstanding results of above reported studies, the hypothesis in this present research is stated on the effectiveness of the ANN to model ET_ref better than conventional methods in semiarid zone of Africa when only temperature data are available.

Therefore, in this study, the minimum and maximum air temperature (°C), and extraterrestrial solar radiation (mm day^{-1}) were adopted as the input variables of the neural network. The present study employs the Generalized Regression Neural Network (GRNN) algorithm ANN type and Hargreaves (HRG) conventional method for ET_ref modeling in Dédougou region located in Burkina Faso an African semiarid country where climatic data have been collected from 1996 to 2006. The objective of the present paper is to assess the performances of the GRNN and Hargreaves (HRG) models for estimating ET_ref by comparison with the reference PM.

METHODOLOGY

Climate dataset

The decadal climatic data used for this study were recorded at the meteorological station of Dédougou from 1996 - 2006. Dédougou is located in the Soudano-Sahelian zone at 300 m altitude, 12°47'N latitude and 3°48'W longitude (Figure 1). The area has a semiarid climate with 809 mm annual average of rainfall. In the region, 80.5% of rainfall occurs between June and September with a peak in August (227 mm). The region has two seasons; a rainy season

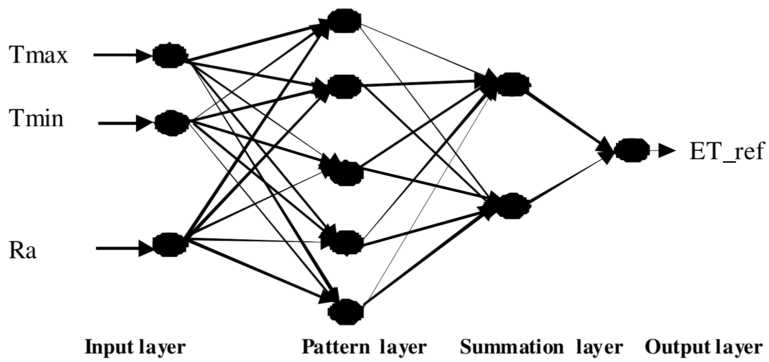

Figure 2. Schematic diagram of GRNN architecture.

(short) from May to September, and a dry season (long) from October to April. The annual average air temperatures are ranged from 22.2 - 38.8℃ and 18.3 - 40.3℃ in rainy and dry season, respectively. The relative humidity means are 33% in dry season and 69% in rainy season with an annual average of 48%. Wind velocity recorded at 2 m above the ground has an annual average of 147 km day^{-1}. The wind speed annual averages in rainy and dry season are 141 - 150 km day^{-1} respectively. The data for this study were comprised of maximum and minimum air temperature (℃), precipitation (mm), relative humidity (%), wind velocity (km day^{-1}) and sunshine duration (hours).

Reference evapotranspiration (ET_ref) estimation methods

Penman-Monteith (PM) equation used in this study is given as the following:

$$\mathrm{ET\_ref} = \frac{0.408\,\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \tag{1}$$

where ET_ref 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 (℃); u_2 the wind speed at 2 m height (m s^{-1}); e_s the saturation vapor pressure (kPa); e_a the actual vapor pressure (kPa); e_s - e_a the saturation vapor pressure deficit (kPa); Δ the slope vapor pressure curve (kPa ℃$^{-1}$); and γ the psychrometric constant (kPa ℃$^{-1}$).

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

$$\mathrm{ET\_ref} = \mathrm{Co}(T_{max} - T_{min})^{0.5}(T_{mean} + 17.8)R \tag{2}$$

where T_{max} and T_{min} are the maximum and minimum temperature (°C); T_{mean} is the mean temperature (°C); R_a is the extraterrestrial radiation (mm day^{-1}); and Co is the conversion coefficient (°C) (Co = 0.0023).

Artificial neural network

The artificial neural network (ANN) is a mathematical mode l so called black-box in which the network takes only the input and output data for learning the complex relationship, and then produces approximately a new output from the input data. The present study employs the generalized regression neural networks (GRNN) algorithm for ET_ref computation. Generalized regression neural network is preferred instead of the multilayer networks due to its performances (Kim and Kim, 2008), it does not also require an iterative training procedure as the multilayer percepton neural networks model, and then the local minimum problem is not faced in the GRNN modeling. Figure 2 shows a schematic diagram of generalized regression neural network architecture.

Generalized regression neural network consists four layers: input layer, pattern layer, summation layer and output layer. 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 data for this study collected from 1996 - 2006 were divided in three sets for the purpose of training, cross-validation and testing.

The generalized regression neural network 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. Generalized regression neural network 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 (Tmin) and maximum (Tmax) air temperature and extraterrestrial radiation (Ra) as the inputs and ET_ref values are the output of the network.

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:

$$E(y/x) = \hat{y}(x) = \frac{\int_{-\infty}^{+\infty} y f(x,y)dy}{\int_{-\infty}^{+\infty} f(x,y)dy} \tag{3}$$

The density function can be estimated from the training set using the Parzen's nonparametric estimator (Chtioui et al., 1999):

$$f(x,y)=\frac{1}{n(2\pi)^{\frac{p+1}{2}}\sigma(p+1)}\sum_{i=1}^{n}e^{-d(x,x_i)}e^{-d(y,y_i)} \tag{4}$$

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 as n and p respectively. The density function $f(x,y)$ is therefore estimated by a weighted sum of the "Kernel function" (Firat, 2008). The parameter σ represents the smoothing parameter.

The estimator $f(x,y)$ is asymptotically unbiased and consistent (Scott, 1992). 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:

$$\hat{y}(x)=\frac{\sum_{i=1}^{n}y_i e^{-d(x,x_i)}}{\sum_{1=i}^{n}e^{-d(x,x_i)}} \tag{5}$$

The predictor (5) is a weighted sum over all 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.

Data preparation

The data used in the neural network for the ET_ref computation were normalized in order to overcome the problem associated with extreme values. Hence, the input and output data sets were scaled in the range of [0 1] using the following equation (Kumar et al., 2002):

$$y_{\mathrm{norm}}=\frac{y_{\mathrm{i}}-y_{\min}}{y_{\max}-y_{\min}} \tag{6}$$

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 values of the observed variable.

Statistical analysis

Three statistical indicators were used for comparing the models performances, namely, root mean squared error (RMSE), mean absolute error (MAE) and coefficient of determination (r^2), expressed as a percentage of the arithmetic mean of observed values:

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(y_{\mathrm{i}}-y'_{\mathrm{i}})^2}{\mathrm{N}}} \tag{7}$$

$$\mathrm{MAE}=\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left|y_{\mathrm{i}}-y'_{\mathrm{i}}\right| \tag{8}$$

$$\mathrm{r}=\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(y_{\mathrm{i}}-\bar{y}_{\mathrm{i}})(y'_{\mathrm{i}}-\bar{y}'_{\mathrm{i}})}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}}(y_{\mathrm{i}}-\bar{y}_{\mathrm{i}})^2\sum_{\mathrm{i}=1}^{\mathrm{N}}(y_{\mathrm{i}}-\bar{y}'_{\mathrm{i}})^2}} \tag{9}$$

Where y_{i} represents the PM observed ET_ref, y'_{i} is the alternative methods estimated ET_ref for the *i*th values; $\bar{y}_{\mathrm{i}}$ and $\bar{y}'_i$ represent the average values of the corresponding variable; and N represents the number of data considered. Additionally, a linear regression $y=\alpha_0+\alpha_1 x$ is applied for evaluating the models' performance statis-tically, where y is the dependent variable (PM); x the independent variable (alternative methods); α_0 the intercept; and α_1 the slope.

RESULTS DISCUSSION

ET_ref estimation

The data collected between 1996 and 2006 in Dédougou region had a total of 396 patterns divided in three parts for the purpose of training from January 1996 to December 2003, cross-validation from January 2004 to December, 2005, and testing from January 2006 to December 2006. The training data are used to train the network by minimizing the error data, the cross-validation used to find the network performance and guard against over-training, and then the testing data used for checking the overall performance of the trained network. The testing data used were not given during the training phase previously. The present study used the decade time step data since it is well documented by Doorenbos and Pruitt (1977) and Droogers and Allen (2002) as a suitable step for ET_ref computation when using the temperature-based models. The Hargreaves conventional method be-haves best for decades predictions although some accurate ET_ref daily estimations have been reported in the literature of Hargreaves and Allen (2003). According to James (1998), the temperature-based models are not accurate as the PM for period less than 5 days.

In this study, ET_ref was estimated with the Gene-ralized Regression Neural Networks (GRNN) and Har-greaves (HRG). In the GRNN approach, very few user decisions are required. Among the decisions that are required is the selection of the appropriate smoothing factors (α) to be applied to each of the model inputs. The success of the GRNN depends heavily on this smoothing factor (Kişi and Ozturk, 2007). The smoothing factor (α) producing the best estimation results in this study has been found at 0.01. The statistical evaluation results obtained with HRG are 0.850, 0.429 mm day^{-1} and 0.363

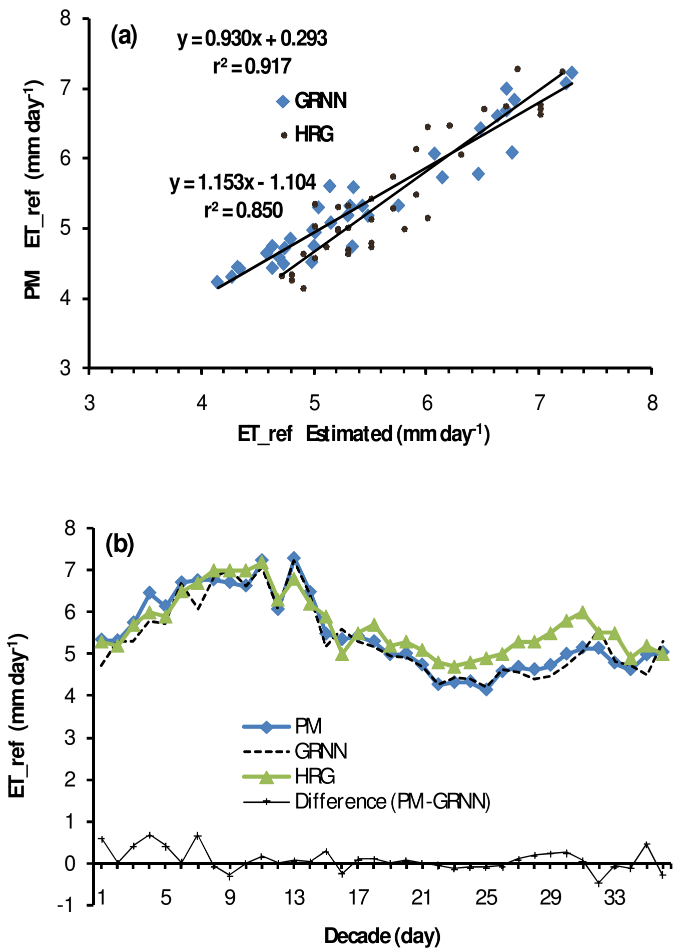

Figure 3. Models scatter (a) and plot (b) comparison during the testing period.

mm day^{-1} for r^2, RMSE and MAE, respectively. While with GRNN, the results are 0.917, 0.272 mm day^{-1}, and 0.193 mm day^{-1} for r^2, RMSE and MAE, respectively.

The generalized regression neural network produces the best result based on the r^2, RMSE and MAE. The good performances of GRNN in comparison with PM can be seen from the scatter and plot representation given in Figures 3a and b, respectively. In Figure 3b, the deviation between GRNN model and PM estimates ET_ref values are ranged between -0.46 to 0.68 mm day^{-1} which are less 1 mm per day. More recently, Khoob (2008b) also obtained good results by using similar input data sets with the neural network.

The Hargreaves model shows clearly poor performance results in comparison with GRNN. The ET_ref comparison results between Hargreaves and PM taken as reference values showed an overestimation from the nineteen decade (July) of the year. This overestimation is most pronounced during the rainy season as shown in Figure 3b. In general, the conventional methods due to their models simplicity are unable to capture the effect of some important climatic parameters which affect ET_ref. The behavior of the HRG could be explained by the influence of other parameters such as wind which is not considered into the model. The weather conditions of the study area characterized by a low rainfall, high temperature variation and high wind speed, might affect the accuracy of the temperature-based estimates ET_ref. Alexandris et al. (2006) also found an overestimation with HRG up to 28%. Singandhupe and Sethi (2005) observed an overestimation with HRG in the arid region of India. According to Trajkovic (2005), Hargreaves method mostly underestimated or overestimated the ET_ref obtained from the PM method. The performance of the HRG conventional method may strongly dependent of climatic condition. George et al. (2002) indicated that, the accuracy of this method varies with climatic conditions.

There is therefore a consensus that, the performances of most alternative methods have been found to vary from one climate to another (Nandagiri and Kovoor, 2006). Since the GRNN showed high performance than the HRG temperature-based method, this algorithm can be considered as a potential alternative approach for estimating the ET_ref in the semiarid zone of Africa. The accuracy of the GRNN might be improved by considering other parameters such as wind velocity which has affected significantly the temperature-based ET_ref in many other arid areas. In order to understand the influence of wind on ET_ref in this semiarid environment, the sensitivity analysis was carried out by considering wind speed as an additional input variable of the neural network.

ET_ref sensitivity analysis

Under the consideration of wind into the neural network input data sets, the ET_ref has been estimated. The scatter and plot of ET_ref estimated when wind velocity is incorporated into the network are given in Figures 4a and b respectively. For this windy region, GRNN accu-racy improves significantly with wind velocity (r^2 = 0.970, RMSE = 0.025 mm day^{-1}, MAE = 0.124 mm day^{-1}). The wind speed increased significantly the coefficient of determination (r^2) of GRNN from 0.917 - 0.970.

Furthermore, the wind changes drastically the r^2 with 5.30% of increasing, and also reduces significantly the RMSE and MAE. These good results show the evidence of the high sensitivity of ET_ref for the wind speed under the Dédougou weather condition. ET_ref is sensitive to wind (Fisher et al., 2005) and its performance may be also influenced (Xiaoying et al., 2005).

Hess (1999) found a positive correlation between ET_ref and wind speed in the East Arid Zone of Nigeria in Africa. It is well documented at least by Allen et al. (1998) and Temesgen et al. (1999) that, the climatic parameters such as wind velocity simultaneously results by deteriorating ET_ref from temperature-based me-thods. Kisi and Ozgur (2007) by using the ANN found that the wind speed is the most effective variable in estimating ET_ref with the temperature-based method. According to

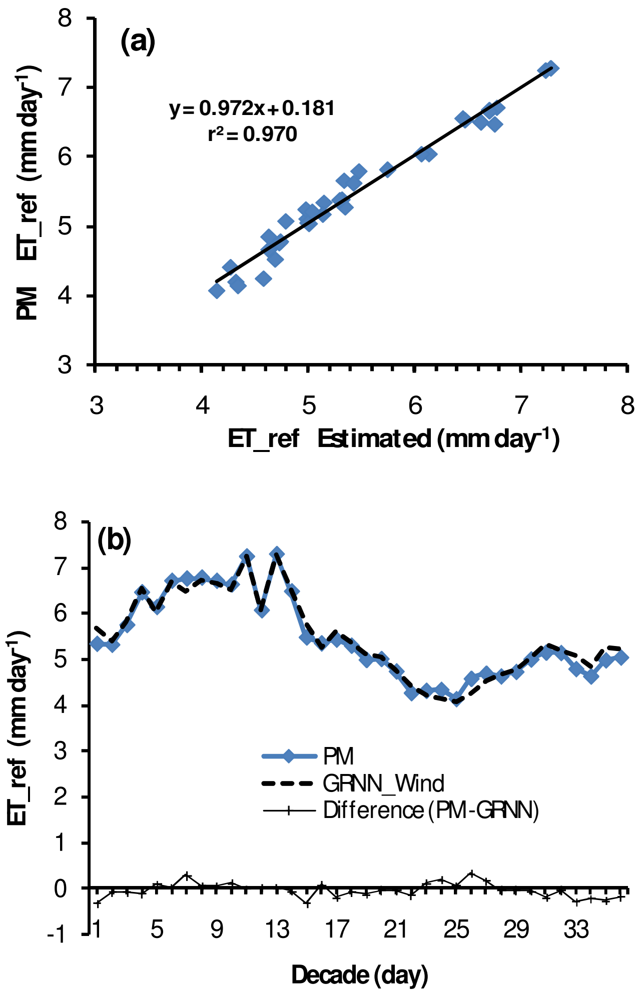

Figure 4. GRNN scatter (a) and plot (b) during the testing period when wind speed is integrated into the neural network model.

Popova et al. (2005), the impact of wind speed on the ET_ref results is relatively smaller except for arid windy areas. From Figure 4b, the deviation bet-ween GRNN wind model and PM estimates ET_ref values are ranged between -0.32 - 0.33 mm day^{-1}. This indicates that the GRNN wind model produces a very close value to PM with a small error margin.

Wind speed is extremely required to be in the model for the neural network accuracy improvement in this African semiarid zone. When wind data is not available, ET_ref can still be better estimated with the GRNN than HRG using air temperature and extraterrestrial radiation data. It could be concluded that, the wind velocity is an important source for improving the network accuracy in ET_ref estimation for the semiarid zone of Africa.

Conclusion and Recommendation

The accurate estimation of evapot ranspiration is crucial for an efficient agriculture water management in the area where there is water resources rarity problem. Since it is well known that the large numbers of meteorological data required for PM are not always available in Africa, this study adopted an approach using few input variables. It was clearly showed from the ET_ref modeling results that, HRG performs less than GRNN. Beside, HRG over-estimated the ET_ref under the weather condition of this semiarid zone studied. GRNN produced the best esti-mation values close to the PM ET_ref. Using ANN with only temperature data under semiarid zone climatic con-dition of Africa for estimating ET_ref is highly superior to the conventional method. It has been observed that the accuracy of the GRNN improves significantly when wind speed is considered into the neural network model. For high efficient of agricultural water management which involves accurate ET_ref, wind speed is an important variable and extremely recommended to be taken into account in the model for this semiarid zone of Africa.

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