Artificial neural network for modeling reference evapotranspiration complex process in Sudano-Sahelian zone

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ABSTRACT

The major problem when dealing with modeling evapotranspiration process is its nonlinear dynamic high complexity. Researchers developed reference evapotranspiration (ET-ref) estimation models in rich and poor data situations. Thus, the well-known Penman–Monteith (PM) model always performs the highest accuracy results of ET-ref from a rich data situation. Its application in many areas particularly in developing countries such as Burkina Faso has been limited by the unavailability of the enormous climatic data required. In such circumstances, simple empirical Hargreaves (HARG) equation is often used despite of its non-universal suitability. The present study assesses the artificial neural network (ANN) performance in ET-ref modeling based on temperature data in Bobo-Dioulasso region, located in the Sudano-Sahelian zone of Burkina Faso. The models of feed forward backpropagation neural network (BFNN) algorithm type ANN and Hargreaves (HARG) were employed to study their performance by comparing with the true PM. From the statistical results, BFNN temperature-based models perform better than HARG. Beside, when wind speed is introduced into the neural network models, the coefficient of determination ($r^2$) increases significantly up to 9.52%. While, sunshine duration and relative humidity might cause only 3.51 and 6.69% of difference, respectively. Wind is found to be the most effective variable extremely required for modeling with high accuracy the nonlinear complex process of ET-ref in the Sudano-Sahelian zone of Burkina Faso.

Keywords: Evapotranspiration, Temperature data, Feed forward backpropagation, Hargreaves, Performance, Sudano-Sahelian zone

1. Introduction

In Sahelian zone where water resources scarcity is much constraining for agriculture, it is decisive to emphasize on its efficient use. To deal with the efficient use of agricultural water resources, Jabloun and Sahli (2008) stated on an accurate estimation of crop water and irrigation requirements for planning purpose. Options to increase water use efficiency rely on the accuracy of crop water and irrigation requirements which are strongly depending on evapotranspiration. Evapotranspiration assessment is essential to correctly quantify the crop water needs (Lovelli et al., 2008). According to Smith (2000), reference evapotranspiration (ET-ref) constitute a key element in developing strategies to optimize the use of water for crop production and to introduce effective water management practices. Also, understanding the ET-ref is essential for irrigation planning particular in arid regions (Wang et al., 2007). According to Stisen et al. (2008), ET-ref is a fundamental variable in the hydrological cycle and in any investigation of water and energy balances at the surface of the Earth.

ET-ref is constantly under the influence of several weather parameters including air temperature, relative humidity, wind velocity, sunshine duration, etc. Since there are so many factors affecting ET-ref, it is extremely difficult to formulate a simple equation that can produce accurate estimates values under different sets of climate condition. Although the importance of ET-ref has been widely reported in agriculture water resources management, the major problem to deal with modeling ET-ref process is its nonlinear dynamic high complexity. According to Kumar et al. (2002), ET-ref is a complex and nonlinear phenomenon, because it depends on the interaction of several climatic elements. The methods for measuring ET-ref require complex and very costly instrumental devices and are generally recommended only for specific research purposes (Kisi, 2007). Hence, the physically based complex Penman–Monteith (PM) equation is universally recommended by the Food and Agriculture Organization of the United Nations as the sole accurate method to calculate ET-ref (Allen et al., 1998). PM model incorporates thermodynamic and aerodynamic aspects, and has unanimously proved to be a relatively accurate method in both humid and arid climates (Smith et al., 1991; Yin et al., 2008). For
a country located in Sudano-Saharan zone where water efficient management has become a real challenge, the drawback for using PM is the large number of climatic data required that are not always available in many production sites. This has been indicated by Wang et al. (2008a) as a fundamental obstacle for agriculture water efficient management in Burkina Faso where irrigation remains a priority on the Government’s agenda.

In deed, there are several empirical equations around the world to compute ET-ref for instance the Hargreaves model which requires only the temperature data. The choice of any one method depends on the accuracy of the equation under a given condition and the availability of the required data. Most empirical methods do not show unanimous results regarding to the climatic condition. According to Shih (1984), an ideal method used for ET-ref estimation should be chosen based as minimally as possible on the input data variables without affecting the accuracy of estimation.

Other approaches which have captured researchers attention in the past decades are the artificial neural networks (ANNs) applied in various fields of hydrology engineering including classification, forecasting and modeling problem. ANN application in hydrology due to its high nonlinear functional characteristic has provided rapidly many advantages in river flows extrapolation (Cigizoglu, 2003), rainfall-runoff modeling (Firat, 2003; Keskin and Terzi, 2006; Parasuraman et al., 2007; Dogan, 2008; Kim and Kim, 2008), Sudheer et al. (2003) and Zanetti et al. (2002) in their ET-ref estimation, simplified the ANN inputs data to air temperature, extraterrestrial solar radiation and daily light hours. Recently, Khoob (2008a) and Landeras et al. (2008) used similar data set without the daily light to estimate successfully the ET-ref. By observing the study sites of the above-mentioned studies, it is found that there is no study conducted under the climatic condition of the Sudano-Saharan zone.

Therefore in this study, the potential of the multilayer feed forward backpropagation neural network algorithm type ANN is investigated for modeling the ET-ref nonlinear complex process using limited climatic data in Bobo-Dioulasso located in the Sudano-Saharan zone of Burkina Faso. Feed forward backpropagation neural network (BPNN) and Hargreaves (HARG) were employed to study their performances in Bobo-Dioulasso where important climatic data have been collected. BPNN algorithm is the most commonly used ANN in hydrological predictions (Govindaraju and Rao, 2000). Basically, BPNN has provided better performance than generalized regression neural network in hydrology modeling (Wang and Traore, 2009; Wang et al., 2009). Its performance in ET-ref estimation has been reported by Wang et al. (2008c) in two other regions of Burkina Faso. In addition, in a worldwide scale, BPNN capability for estimating ET-ref has also been widely reported in Chauhan and Shrivastava (2008) and Khoob (2008a,b) studies. In some areas (e.g., developing countries), the available data may be the air temperature and solar radiation due to the difficulty in obtaining the data of other parameters, therefore BPNN model suits for ET-ref estimation (Kisi, 2009). Since the purpose of this study was to evaluate the ability of the neural network for ET-ref modeling in Sudano-Saharan zone from limited climatic data, the inputs were prior set to air temperature data for determining the best network configuration. Using a low input requirement model for ET-ref estimation is an important step which cannot be overlooked in the areas where there is limited meteorological data.

2. Methodology

2.1. Study area description

The area under study is Bobo-Dioulasso, located in the Western region of Burkina Faso in Sudano-Sahelian zone. The decadal climatic data used for this study were recorded from 1996 to 2006. The data were comprised of maximum and minimum air temperature (°C), precipitation (mm), relative humidity (%), wind velocity (km day⁻¹) and sunshine duration (h). Bobo-Dioulasso is located at 460 m altitude, 11° 17’ N latitude and 4° 32’ W longitude (Fig. 1). The region has two seasons; a rainy season from May to October, and a dry season from November to April. Based on the data collected, the annual rainfall is 980.60 mm. In the region, 85.50% of rainfall occurs between May and September with a peak in August (258.57 mm). The annual averages of the minimum and maximum air temperature are ranged from 19.64 to 25.24 °C and 29.60 to 37.62 °C, respectively. The relative humidity means are 33.82% in dry season and 73.81% in rainy season with an annual average of 53.81%. Wind velocity recorded at 2m above the ground has an annual average of 205 km day⁻¹.

2.2. Reference evapotranspiration models

- Penman–Monteith (PM) equation for calculation of the ET-ref is given by Allen et al. (1998) as following:

\[ \text{ET-ref} = \frac{0.408 \Delta (R_n - G) + \gamma (900/(T + 273)) u_2 (e_a - e_s)}{\Delta + \gamma (1 + 0.34 u_2)} \]  \hspace{1cm} (1)

where ET-ref is the reference evapotranspiration (mm day⁻¹); R_n is the net radiation at the crop surface (MJ m⁻² day⁻¹); G is the soil heat flux density (MJ m⁻² day⁻¹); T is the mean daily air temperature at 2 m height (°C); u_2 is the wind speed at 2 m height (m s⁻¹); e_a is the saturation vapour pressure (kPa); e_s is the actual vapour pressure (kPa); e_a - e_s is the saturation vapour pressure deficit (kPa); Δ is the slope vapour pressure curve (kPa °C⁻¹); γ is the psychrometric constant (kPa °C⁻¹).
- Hargreaves (HRG) equation used is given as

\[ \text{ET-ref} = C_0 (T_{\text{max}} - T_{\text{min}})^{0.5} (T_{\text{mean}} + 17.8) R_a \]  \hspace{1cm} (2)

where \( T_{\text{mean}} \) stands for the mean temperature (°C); \( T_{\text{max}}, T_{\text{min}} \) and \( C_0 \) stand for the maximum temperature (°C), minimum temperature (°C) and conversion coefficient which is 0.0023, respectively, and \( R_a \) stands for the extraterrestrial radiation (mm day⁻¹).

![Fig. 1. Location of the investigation area in Burkina Faso.](image-url)
2.3. ANN model development

This study used the latest version of the NeuroSolution software version 5.07 presented by the NeuroDimension. The artificial neural network (ANN) algorithm selected for this study was the feed forward backpropagation neural network (BPNN). The BPNN is a supervised learning technique used for training the artificial neural networks. Basically, it is a gradient descent technique to minimize some error criteria. The feed forward backpropagation neural network has been widely used in approximating a complicated nonlinear function. The neural network structure in this study consisted of an input layer, a hidden layer and an output layer (Fig. 2). In Fig. 2, $T_{\text{min}}$ and $T_{\text{max}}$ represent the minimum and maximum air temperature; while $R_a$ stands for the extraterrestrial radiation variable. The decadal data collected in Bobo-Dioulasso has a total of 396 patterns, and it was divided into three parts for the purpose of training (70%), cross validation (20%) and testing (10%). The training data (from January 1996 to December 2003) are used to train the network by minimizing the error data. The cross validation data (from January 2004 to December 2005) are used to find the network performance by monitoring the training and guard against overtraining. Then, the testing data (from January 2006 to December 2006) are used for checking the overall performance of trained and validated network.

The feed forward backpropagation neural network algorithm during the training process has two pass of propagation (forward/backpropagation) for calculating all the gradients. For the forward pass, the activation pattern of an input vector is propagated through the network to produce an output. Each input $x_i$ is multiplied by an adjustable constant $w_{ij}$ (weight) before being fed to the ith processing element (PE) in the output layer, yielding by Eq. (3). In this study, the network transfer function was the sigmoid which is one of the most commonly used transfer function. This function takes the input and squashes the output into the range 0–1. The sigmoid activation function is defined as $1/(1 + e^{-x})$ for the continuous and differential process. In the forward propagation, the computation of the output is carried out, layer by layer, from the input to the output in the forward direction, and the error $(E)$ between desired outputs and actual outputs is computed.

In the backpropagation pass, the adjustment of the interconnecting weights during training employs a method known as error backpropagation in which the weight associated with each connection is adjusted by an amount proportional to the strength of the signal in the connection and the total measure of the error. The total error at the output layer given in Eq. (4) is then reduced by redistributing this error value backwards through the hidden layers until the input layer is reached:

\[
y_i = f(\text{net}_i) = f\left(\sum_j w_{ij}x_j + b_i\right)
\]

where $f(\text{net})$ is the activation function with a transfer threshold defined by $[0, 1]$; $x_i$ is the input from unit $i$, $w_{ij}$ is the weight of connection from unit $i$ to unit $j$; $b_i$ is the bias term for each PE:

\[
e_i = -e_i + \sum_{j=1}^{n} w_{ij}\delta_j
\]

where $\delta$ is the summation index enforces $j > i$, and $e$ and $\varepsilon$ are the produces and injected error. The error is propagated from the output layer to the input layer for updating the weights of connections according to the following gradient equation:

\[
\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta y_i \delta_i
\]

and

\[
w_{ij}(n + 1) = w_{ij}(n) + \Delta w_{ij}(n)
\]

where the step size $\eta$ is called the learning rate, $\delta_i$ is a sum of local errors at each network output PE, scaled by the weights connecting the output PE to the ith PE. $\delta_i$ computes the total error reaching the ith PE from the output layer as $\delta_i(n) = f'(\text{net}_i(n)) \sum_j b_i w_{ij}(n)$. This process is repeated until the total error for all data sets is sufficiently small.

At the beginning of our study, the neural network was prior fed with the minimum and maximum air temperature adopted as the minimum input set represented by BPN1 temperature-based model for determining the optimum number of the network.
processing element (PE). Then, the best network configuration determined was used to train and test several other input combinations represented in Table 1 in order to apprehend the potential inputs variables affecting the ET-ref process in this Sudan-Sahelian zone of Africa studied. This may help to understand the weather influence on ET-ref. BPNN2 model has three input variables; minimum and maximum air temperature, and extraterrestrial radiation. The extraterrestrial solar radiation is not a collected data but determined for a certain day and location by the Allen et al. (1998) procedure.

BPNN1 and BPNN2 are designed as temperature-based models presenting similarity to the conventional methods selected in this study. The input structures of BPNN3, BPNN5, and BPNN7 are formed by inserting sunshine, relative humidity and wind into the BPNN1 combination, respectively. Then, the model of BPNN2 integrating sunshine, relative humidity and wind are presented by BPNN4, BPNN6 and BPNN8, respectively. Finally, having both relative humidity and wind together into BPNN1 and BPNN2 are illustrated by BPNN9 and BPNN10, respectively. The network was trained and tested for each combination summarized in Table 1.

2.4. Data normalization

The data used in this study such as minimum and maximum air temperature, extraterrestrial radiation, wind velocity and relative humidity were normalized for preventing and overcoming the problem associated to the extreme values. The decadal ET-ref values were computed using the different estimation models enumerated above. Decade time scale has been reported by Doorenbos and Pruitt (1977) and Hargreaves (1994) as suitable to estimate ET-ref. According to Zanetti et al. (2007), by grouping the daily values into averages, the ET-ref may be estimated due to their highest stabilization. For data normalization, the input and output data were scaled in the range of [0 1] using the following equation:

$$Y_{norm} = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}}$$

Table 1
Neural network input data structure.

<table>
<thead>
<tr>
<th>Model</th>
<th>Inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPNN1</td>
<td>$T_{max}, T_{min}$</td>
</tr>
<tr>
<td>BPNN2</td>
<td>$T_{max}, T_{min}, R_a$</td>
</tr>
<tr>
<td>BPNN3</td>
<td>$T_{max}, T_{min}, R_a, Sun$</td>
</tr>
<tr>
<td>BPNN4</td>
<td>$T_{max}, T_{min}, R_a, Sun$</td>
</tr>
<tr>
<td>BPNN5</td>
<td>$T_{max}, T_{min}, R_a, R_b, Sun$</td>
</tr>
<tr>
<td>BPNN6</td>
<td>$T_{max}, T_{min}, R_a, R_b, Wind$</td>
</tr>
<tr>
<td>BPNN7</td>
<td>$T_{max}, T_{min}, R_b, Wind$</td>
</tr>
<tr>
<td>BPNN8</td>
<td>$T_{max}, T_{min}, R_a, R_b, Wind$</td>
</tr>
<tr>
<td>BPNN9</td>
<td>$T_{max}, T_{min}, R_a, R_b, Warth$</td>
</tr>
<tr>
<td>BPNN10</td>
<td>$T_{max}, T_{min}, R_a, R_b, Warth$</td>
</tr>
</tbody>
</table>

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

2.5. Models evaluation

This study carried out a multicriterion performance evaluation by using the root mean square (RMSE), mean absolute error (MAE) and coefficient of determination ($r^2$). These statistical criteria are used to evaluate the performance between the alternative ET-ref models and PM as given by the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \bar{y})^2}{N}}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \bar{y}|$$

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

where $y_i$ represents the PM observed ET-ref, $y_i'$ is the estimated ET-ref for the ith values; $\bar{y}$ and $\bar{y}'$ represent the average values of the corresponding variable; $N$ represents the number of data considered. Additionally, a linear regression $y = \alpha_0 + \alpha_1 x$ is applied for evaluating the performance of ET-ref estimation, where $y$ is the dependent variable (alternative models); $x$ is the independent variable (PM); $\alpha_0$ is the intercept; $\alpha_1$ is the slope.

3. Results and discussion

3.1. Processing elements determination

This study adopted a hidden layer for the model construction since it is well known that one hidden layer is enough to represent the ET-ref nonlinear complex relationship (Kumar et al., 2002; Zanetti et al., 2007). The determination of the processing elements in the hidden layer providing the best testing results was the initial process of the training procedure. BPNN1 with only minimum and maximum air temperature was used to generalize the best neural network configuration. The number of node processing elements (PEs) in the hidden layer was varied between 1 and 20. The data set aside for the testing period were used to find the optimal number of PEs. More recently, in Iran, Khooob (2008a,b) trained the network with up to 30 processing elements using similar inputs set and found optimum results at six and nine PEs in Safiabad and Khuzestan plain, respectively. In this study, the optimum number of PEs in the hidden layer was found at nine based on the minimum RMSE and maximum coefficient of determination ($r$) as shown in Fig. 3 (a) and (b). The network configuration is denoted by BPNN (number of input-PEs-output). Hence, the configuration with nine

Fig. 3. Neural network accuracy under different number of processing elements during the ET-ref modeling process in Bobo-Dioulasso region: RMSE (a) and $r$ (b).
PES providing the best results when generalizing BPNN1 (2-9-1) was applied to model the ET-ref. Then the study compared the BPNN and Hargreaves (HARG) ET-ref estimated to the PM value.

3.2. Temperature-based models

The performance statistics results of BPNN1 temperature-based were 0.882, 0.403 mm day\(^{-1}\) and 0.285 mm day\(^{-1}\) for \(r^2\), RMSE and MAE, respectively. While, the results with the second neural network temperature-based model BPNN2 were \(r^2\) (0.904), RMSE (0.353 mm day\(^{-1}\)) and MAE (0.277 mm day\(^{-1}\)). HARG model produced the poorest performance with a \(r^2\), RMSE and MAE equal to 0.693, 0.714 mm day\(^{-1}\) and 0.581 mm day\(^{-1}\), respectively. Based upon \(r^2\), RMSE and MAE, it can be concluded that both BPNN1 and BPNN2 temperature-based perform better than HARG. Additionally, it was observed that BPNN2 performance in ET-ref modeling for this Sudano-Sahelian Zone studied is superior to BPNN1. By looking only at its combination, the performance of BPNN2 is due to the presence of extraterrestrial radiation (C_{0}) variable into the model. If a model of low input data required is to be constructed for ET-ref modeling, BPNN2 should be considered as the R_{0} is not a collected variable. Fig. 4(a) and (b) shows the comparison plot and scatter of decades ET-ref estimated by the temperature-based of BPNN1, BPNN2 and HARG models during the testing period in Bobo-Dioulasso.

These results indicated that the neural network has a better generalization ability in ET-ref modeling when compared to the conventional Hargreaves temperature-based method under the climatic condition of Bobo-Dioulasso. Recently, Khoob (2008b) and Kumar et al. (2008) reported also that the performance of BPNN is better than the conventional HARG method.

Beside the poor performance of HARG, it shows an underestimation in dry season and an overestimation in rainy season. Trajkovic (2005) reported that, Hargreaves mostly underestimated or overestimated ET-ref obtained from the FAO-56 Penman–Monteith method. Cob and Juste (2004) found HARG equation overestimated the ET-ref between 14 and 20% in the semiarid condition, and Temesgen et al. (1999) explained this overestimation by the wind in the atmosphere that decreases the temperature during the daytime and increases it during the nighttime. Since it is well known that the wind deteriorates the performance of the temperature-based models; this could explain the poor results obtained with the HARG method in this study. According to Alexandris et al. (2006), HARG equation is often unable to capture the effect of some important climatic parameters which may affect the ET-ref. The performance of the temperature-based models may strongly dependent of climatic condition. However, the sensitivity study of ET-ref under the specific climatic conditions of Burkina Faso is still unexplored. By checking the Penman–Monteith equation, it is function of air temperature, sunshine, relative humidity and wind speed, which means these variables are important in ET-ref estimation. This method considers almost all parameters that are reported to have an influence on ET-ref (Sudheer et al., 2003). Therefore, we consider these variables as additional inputs into the neural network temperature-based models for apprehending the key potential variable susceptible to improve the BPNN accuracy.

3.3. Climatic effects

Under the consideration of the weather effect on ET-ref, the neural network accuracy might be improved by capturing the

<table>
<thead>
<tr>
<th>Table 2</th>
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<tbody>
<tr>
<td>Summary of models statistical performances during the testing period in Bobo-Dioulasso.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Inputs</th>
<th>(\alpha_1)</th>
<th>(\alpha_0)</th>
<th>(r^2)</th>
<th>RMSE (mm day(^{-1}))</th>
<th>MAE (mm day(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>HARG</td>
<td>T_{\text{max}}, T_{\text{min}}, C_{0}, R_0</td>
<td>0.448</td>
<td>2.737</td>
<td>0.693</td>
<td>0.714</td>
<td>0.581</td>
</tr>
<tr>
<td>BPNN1</td>
<td>T_{\text{max}}, T_{\text{min}}</td>
<td>0.805</td>
<td>0.903</td>
<td>0.882</td>
<td>0.403</td>
<td>0.285</td>
</tr>
<tr>
<td>BPNN2</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0</td>
<td>0.779</td>
<td>1.204</td>
<td>0.904</td>
<td>0.333</td>
<td>0.277</td>
</tr>
<tr>
<td>BPNN3</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, Sun</td>
<td>0.702</td>
<td>1.571</td>
<td>0.851</td>
<td>0.442</td>
<td>0.338</td>
</tr>
<tr>
<td>BPNN4</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, Sun</td>
<td>0.889</td>
<td>0.579</td>
<td>0.900</td>
<td>0.333</td>
<td>0.216</td>
</tr>
<tr>
<td>BPNN5</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, C_{0}</td>
<td>1.026</td>
<td>-0.180</td>
<td>0.941</td>
<td>0.273</td>
<td>0.219</td>
</tr>
<tr>
<td>BPNN6</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, R_0</td>
<td>1.071</td>
<td>-0.269</td>
<td>0.940</td>
<td>0.317</td>
<td>0.196</td>
</tr>
<tr>
<td>BPNN7</td>
<td>T_{\text{max}}, Wind</td>
<td>0.918</td>
<td>0.348</td>
<td>0.966</td>
<td>0.220</td>
<td>0.176</td>
</tr>
<tr>
<td>BPNN8</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, Wind</td>
<td>0.931</td>
<td>0.416</td>
<td>0.981</td>
<td>0.158</td>
<td>0.125</td>
</tr>
<tr>
<td>BPNN9</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, Wind</td>
<td>0.951</td>
<td>0.086</td>
<td>0.969</td>
<td>0.258</td>
<td>0.208</td>
</tr>
<tr>
<td>BPNN10</td>
<td>T_{\text{max}}, T_{\text{min}}, R_0, R_0, Wind</td>
<td>0.992</td>
<td>0.047</td>
<td>0.998</td>
<td>0.048</td>
<td>0.033</td>
</tr>
</tbody>
</table>
key climatic variables in the ET-ref modeling process. In order to verify such statement, a sensitivity study with eight additional combinations incorporating wind velocity, relative humidity and sunshine are conducted. This is a major step for understanding the relative importance of climatic variables to the variation of ET-ref. According to Aksoy et al. (2007), the results from sensitivity analysis are of great importance to determine the change in ET-ref due to input variables. Such quantification is also necessary to determine the accuracy required when measuring the climatic variables used as input into mathematical models (Irmak et al., 2006). The performances obtained with the neural network models by consider-

Fig. 5. Comparison plots and scatters of decades ET-ref estimated by incorporating sunshine (a and b), relative humidity (c and d) and wind speed (e and f) into the neural network temperature-based models during the testing period in Bobo-Dioulasso, Burkina Faso.
ing additional input variables were presented in Table 2. They ranged between 0.851–0.998, 0.048–0.442 and 0.033–0.338 for $r^2$, RMSE and MAE, respectively. The models with sunshine duration variable BPNN3 ($r^2 = 0.851$, RMSE = 0.442 mm day$^{-1}$, MAE = 0.338 mm day$^{-1}$) and BPNN4 ($r^2 = 0.900$, RMSE = 0.333 mm day$^{-1}$, MAE = 0.216 mm day$^{-1}$) do not perform better than BPNN1 and BPNN2, respectively. The comparison results show significant improvement of the accuracy of BPNN1 and BPNN2 temperature-based when either relative humidity or wind velocity is inserted into the models as additional input variables. Indeed, it might be observed that the relative humidity when taking into account increases the accuracy of the neural network not as wind. It can be clearly seen in Table 2 that the presence of relative humidity represented by BPNN5 ($r^2 = 0.941$, RMSE = 0.273 mm day$^{-1}$, MAE = 0.219 mm day$^{-1}$) and BPNN6 ($r^2 = 0.940$, RMSE = 0.317 mm day$^{-1}$, MAE = 0.196 mm day$^{-1}$) do not perform higher than wind models. The evidence of wind effect on ET-ref in Bobo-Dioulasso is showed by BPNN7 ($r^2 = 0.966$, RMSE = 0.220 mm day$^{-1}$, MAE = 0.176 mm day$^{-1}$) and BPNN8 ($r^2 = 0.981$, RMSE = 0.158 mm day$^{-1}$, MAE = 0.125 mm day$^{-1}$).

Furthermore, the $r^2$ increases drastically from 0.882 to 0.966, i.e. 9.52% of increasing when wind speed is incorporated into the BPNN1 represented by BPNN7 model. While, sunshine duration and relative humidity into the BPNN1 given by BPNN3 and BPNN5 might caused in absolute value only 3.51 and 6.69%, respectively. The integration of wind speed in BPNN2 model illustrated by BPNN8 increases the $r^2$ from 0.904 to 0.981, i.e. at least 6.86% of increasing. Sunshine duration and relative humidity variables inserted into BPNN2 which are represented by BPNN4 and BPNN6 change the $r^2$ for 0.44 and 3.98%, respectively.

In general, it is observed that all models integrating wind velocity such as BPNN7, BPNN8, BPNN9 and BPNN10 reduce significantly the RMSE and MAE and increase the $r^2$. The reduction of RMSE and MAE and increasing of $r^2$ obtained with relative humidity were smaller than those from wind. The performances of the models integrating wind speed are ranged between 0.966–0.998, 0.048–0.258 and 0.033–0.208 for $r^2$, RMSE and MAE, respectively. The high sensitivity of ET-ref to wind velocity is also established throughout the models of BPNN9 and BPNN10. By looking back the models of BPNN5 and BPNN6 which are different from BPNN9 and BPNN10 only by the absence of wind speed, their performances are not good as with the presence of wind. However, BPNN9 and BPNN10 in term of $r^2$ do change significantly and their intercepts $a_{0}$ almost reach 0 and slopes $a_1$ are very close to 1. This remark on wind as a powerful variable is truly strengthened when comparing also BPNN5 and BPNN6 to BPNN7 and BPNN8, respectively. Fig. 5(a, b), (c, d) and (e, f) shows the comparison plots and scatters of decades ET-ref estimated by incorporating sunshine, relative humidity and wind speed into the network input sets during the testing period, respectively.

These results arrive at a solid conclusion that wind is the most effective and required variable for modeling with high accuracy the nonlinear complex process of ET-ref in this Sudano-Saharan zone of Burkina Faso. Kigi and Ozturk (2007) by using the neural network found that the relative humidity and wind speed were more effective for estimating ET-ref with the temperature-based method. According to Popova et al. (2005), the impact of wind speed on the ET-ref results is relatively smaller except for arid windy areas. Hupet and VanclouSter (2001) found that, the solar radiation and wind speed are the most sensitive factors in the analysis of ET-ref. Li and Beswick (2005) reported that, the wind speed is a much serious source of errors than solar radiation on the ET-ref. ET-ref is sensitive to wind (Fisher et al., 2005) and its performance may be also influenced (Xiaoying and Erda, 2005). It has been observed in the East Arid Zone of Nigeria in West Africa a positive correlation between ET-ref and wind speed (Hess, 1998). In summary, based upon statistical performances evaluation, it can be concluded that wind speed is the most effective variable and is highly recommended to be into the model. Li and Beswick (2005) stated that, due to the importance of wind, it has to be available for the ET-ref calculation. Therefore, in the specific climatic condition of this Sudano-Saharan zone, wind has to be regarded as a necessary variable for modeling the ET-ref with high accuracy.

4. Summary and conclusions

Accurate estimates of evapotranspiration are needed in agricultural water resources efficient management. The PM is a universal physical based model requiring enormous climatic data which are missing particularly in developing country such as Burkina Faso. It is concluded that when taking into account just air temperatures and extraterrestrial radiation data, it is possible to estimate ET-ref in Bobo-Dioulasso using the artificial neural network. The results showed that the artificial neural network temperature-based model has a better performance when compared to the empirical Hargreaves method.

Furthermore, relative humidity and wind velocity were found to improve the neural network accuracy when applied into the models inputs. Indeed, it was observed that the relative humidity is less effective than wind in ET-ref modeling in Bobo-Dioulasso. From the models performances analysis, it can be concluded that wind speed is the most effective variable than relative humidity and sunshine. Therefore, wind speed is highly recommended for modeling with high accuracy the nonlinear complex process of ET-ref in the Sudan-Sahelian zone of Burkina Faso.

ET-ref constitutes a key element of efficient management of agriculture water resources. Therefore, artificial neural network approach may open a new opportunity for rapid estimation of accurate ET-ref in Burkina Faso. The availability of accurate ET-ref will facilitate the application of a number of water balance computer-based simulation programs for agricultural water resources management and planning in Burkina Faso.

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