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ARTICLE

A mixture neural methodology for computing rice consumptive water requirements in Fada N'Gourma Region, Eastern Burkina Faso

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Abstract Crop consumptive water requirement (Crop-ET) is a key variable for developing management plans to optimize the efficiency of water use for crop production particularly in semiarid zone. In Burkina Faso, the unfavorable climatic conditions characterized by the low and unevenly distribution of rainfall have pushed water resources management to the forefront of the crop production issue. Crop-ET is extremely required in rainwater effective management for mitigating the impact of water deficit on the crops. Basically, Crop-ET determination involves reference evapotranspiration (ETo) and crop coefficient (Kc) which required complete climatic data and specific site crop information, respectively. ETo estimation with the recommended FAO56 Penman–Monteith (PM) equation is limited in Burkina Faso due to the numerous meteorological data required which are not always available in many production sites. In such circumstances, research to compute directly Crop-ET as an alternative to the two-step approach of calculating ETo and determining site specific Kc, seems desirable. Therefore, this study aims to evaluate the performance of a mixture principal component analysis neural network (PCANN) model for computing rice Crop-ET directly from temperatures data in Fada N'Gourma region located in Eastern Burkina Faso, Africa. From the statistical results, rice Crop-ET can be successfully computed by using PCANN methodology, when only temperatures data are available in this African semiarid environment. Thus, in poor data situation, Crop-ET direct computation can be rapidly addressed through PCANN model for agricultural water management in African semiarid regions.

Keywords Neural network · Rice consumptive water requirements · Water management plans · Semiarid regions

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Introduction

Agricultural water resources scarcity in semiarid zone of Africa affects directly the crop productivity and accordingly aggravates the food deficit problem for million of people. In Burkina Faso, rice crop is submitted to rainwater shortage due to the country typical unfavorable dry tropical climatic conditions characterized by a low and unevenly distribution of rainfall. The vast majority of rice production in Africa is rainfed and therefore exposed to the climatic risks. Study done by Nwite et al. (2008) in Nigeria, West Africa, indicated that the poor water management is among the key problems faced by rice farmers under rainfed systems. According to Panigrahi et al. (2007), in many dry regions and other places in the world, where irrigation water is a scarce commodity, there is no other alternative than a better and more effective use of rain to increase food production. To mitigate the impact of rainwater deficit on any crop, crop consumptive water requirement (Crop-ET) can be used as a key component for developing effective water management plans. In Burkina Faso, water insufficiency has been considered as a serious limitation for rice production, and hence the focus has been set on the rice seeds improvement for drought and pest tolerance. Optimizing the water use efficiency has been neglected in the country. However, Crop-ET computation can provide several management options such as suitable cropping calendar determination, yield modeling and rainwater efficient management strategy development.

In fact, Crop-ET is an indispensable variable in rainwater effective management for computerizing the crop water balance analysis. Options to increase the efficiency of water use rely on the accuracy of crop water requirements. According to Pereira et al. (2003) and Wang et al. (2009a), Crop-ET accurate estimation is an important path to the efficient management of water. Inaccurate estimates of Crop-ET can lead to inefficient use of water and fatal crop stress. The correct estimation of crop water requirements is therefore an important step towards the development of efficient water management policies (Meza 2005). Basically, Crop-ET direct measurement requires instruments which are costly and time consuming for developing worlds. Its computation is strongly depending on the physically based complex evapotranspiration and crop information. From Allen et al. (1998), the crop consumptive water requirements can be expressed as the product of a crop coefficient (Kc) and a reference evapotranspiration (ETo). Study done by Gavilan and Castillo-Llanque (2009) reported that, the most frequently used method for computing consumptive use of water by crops is a two-step approach that quantifies the atmospheric demand through the calculation of the ETo and characterizes the crop growth through a Kc. According to Li et al. (2008), disposal of ETo and Kc is important for managing water-saving. The product of these two parameters provides an estimation of the crop consumptive water requirement as Crop-ET = ETo*Kc which has become the widely accepted standard procedure of calculation (Doorenbos and Pruitt 1977).

Moreover, the need of accurate ETo values to predict Crop-ET has been widely reported by several authors (Allen 1996; Cob and Juste 2004). Penman–Monteith (PM) equation is universally recommended by the Food and Agriculture Organization of the United Nations as the sole accurate method to calculate ETo (Allen et al. 1998). Nevertheless, the drawback for using PM is the large number of climatic data required such as air temperature, relative humidity, wind speed, and sunshine duration data that are not always available in many production sites in Burkina Faso. Consequently, it becomes very hard to compute Crop-ET in poor data condition in semiarid regions. In addition, computing Crop-ET became also complex since it depends on the ETo physical nonlinear complex phenomenon and the crop site specific Kc. Therefore, a computing technique to estimate directly Crop-ET as an option to the two-step approach of calculating ETo and determining site specific Kc, seems desirable.

Furthermore, other approaches which have captured researchers attention nowadays are the artificial neural networks (ANNs) applied for solving the nonlinear complex system. Nonlinear system theory recognition and control have been made possible through the ANN. ANN has many advantages in the field of advance nonlinear model identification and representation. Outstanding results have been reported using several ANN algorithms in diverse fields including backprogapagion network for Modeling waterbird diversity in irrigation ponds (Fang et al. 2009), time-lagged recurrent network for river sedimentation forecasting (Wang and Traore 2009), adaptive neuro fuzzy for climate change impact assessments (Tung et al. 2009), radial basic function for hydro-meteorological data modeling (Alp and Cigizoglu 2007), self-organizing feature map network for water resources analysis and application (Kalteh et al. 2008), and generalized regression neural network for evapotranspiration computation (Kişi 2006). Most of these reported studies have used either the unsupervised or supervised network and also they have been applied in the areas different from the semiarid environment condition of Africa.

Indeed, there is a mixture of unsupervised and supervised network called principal component analysis neural network (PCANN) which is a powerful hybrid network. The results of Rattan and Hsieh (2005) showed that PCANN has a high ability to capture the nonlinear complex phenomenon process. From the above reported studies, it is observed that no research has been reported yet using this hybrid PCANN for computing crop consumptive water requirements. Beside, the employment of ANN in Africa for modeling the crop consumptive water demand nonlinear complex system is very poor in literature. Therefore, PCANN computing technique ability in estimation of rice consumptive water requirements (Crop-ET) is investigated in this article. The main objective of this study is to evaluate the neural network performance for computing rice Crop-ET directly from temperatures data in Fada N'Gourma region located in Eastern Burkina Faso, Western Africa. The purpose of this study was to evaluate the ability of the neural network; therefore, the network was fed with the meteorological data adopted as inputs variables, and Crop-ET as output variable.

Materials and methods

Study area description

The area under study is Fada N'Gourma region located in semiarid zone in Eastern Burkina Faso. Indeed, the country has three large climatic zones which are the Sudanian, Sudano–Sahelian, and the Sahelian zones. Fada N'Gourma is located in Sudano–Sahelian zone at 309 m altitude, 12°03′N latitude and 0°37′W longitude (Fig. 1). The region has two seasons; a rainy season from May to September, and a dry season from October to April. The decadal climatic data used for this study were recorded from 1996 to 2007. The data were comprised of maximum and minimum air temperature (°C), precipitation (mm), relative humidity (%), wind velocity (km day^{-1}) and sunshine duration (h). Based on the data collected, the annual rainfall is 800.41 mm. In the region, 79.8% of rainfall occurs between June and September with a peak in August (202.45 mm). The annual averages of the minimum and maximum air temperature are ranged from 18.20 to 26.81°C and 30.66 to 40.12°C, respectively. The relative humidity means are 34.59% in dry season and 71.40% in rainy season with an annual average of 50.38%. Wind velocity recorded at 2 m above the ground has an annual average of 90 km day^{-1}.

Crop-ET computation procedure

Rice Crop Information

The duration of the rice growing stages are estimated with the help of the extension agents of the Regional Direction of the Ministry of Agriculture, Hydraulic and Fisheries Resources of Burkina Faso. As the growing period heavily depends on the local circumstances, Brouwer and Heibloem (1986) suggested to always obtain these data locally. The growing season is divided into four main development stages that include the initial, development, mid-season, and late-season stages. The traditional direct sowing date for the rice crop in the region, i.e., June 1st is chosen in this study.

Crop consumptive water requirement

Decadal rice crop consumptive water requirement (Crop-ET) is calculated from reference evapotranspiration using a stage dependent crop coefficient according to the following equation (Allen et al. 1998):

$$\text{Crop - ET} = \text{Kc} * \text{ETo} \tag{1}$$

where Kc stands for the crop coefficient and ETo stands for the reference evapotranspiration (mm day^{-1}). The values of Crop-ET for rice are computed by using the latest version of CROPWAT_8 software developed by the Food and Agriculture Organization of the United Nations.

Crop coefficient

The values of crop coefficient are obtained from FAO56 procedure (Allen et al. 1998). An accurate determination of Kc is highly required since it affects the crop water requirements. The crop coefficients were derived by the numerical determination approach and then adjusted as described by Allen et al. (1998):

$$\text{Kc}.i = \text{Kc}_{\text{prev}} + \left[\frac{i - \sum(L_{\text{prev}})}{L_{\text{stage}}}\right](\text{Kc}_{\text{next}} - \text{Kc}_{\text{prev}}) \tag{2}$$

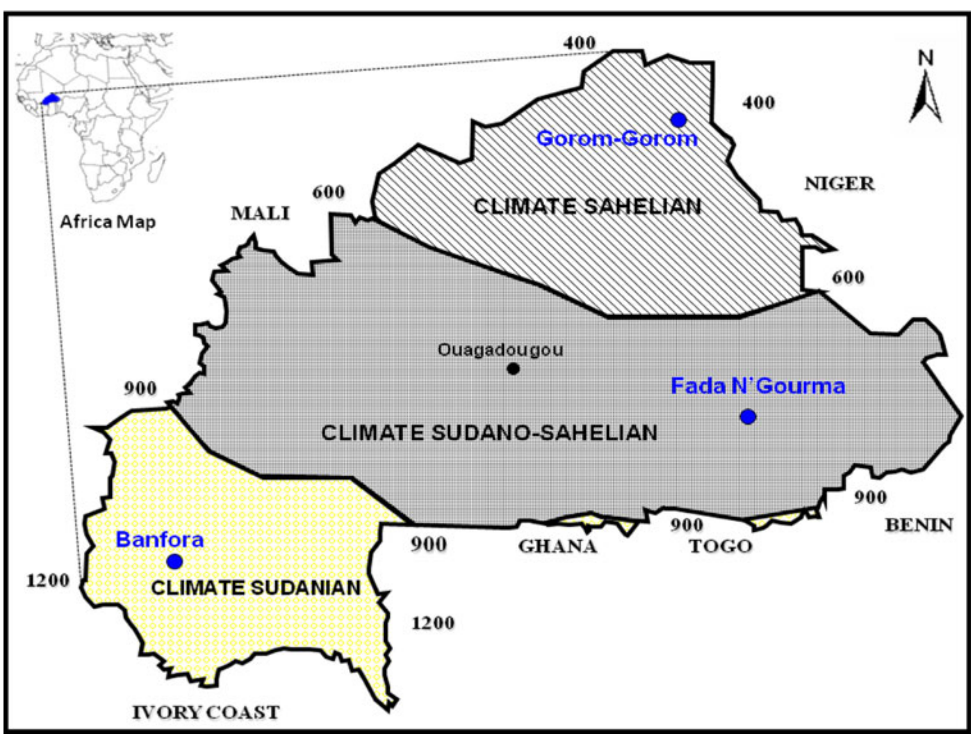


Fig. 1 Location of the study area in Burkina Faso

where i is the day number within the growing season, Kc.i crop coefficient on day i, L_{stage} is the length of the stage under consideration (days), Kc_{prev} is the crop coefficient at the previous stage, Kc_{next} is the crop coefficient at the next stage, $\sum(L_{prev})$ is the sum of the length of all previous stages (days).

The relative impact of climate on crop required the adjustment of Kc. For specific adjustment of Kc mid and late season in climates where relative humidity differs from 45% or where wind speed (u_2) is larger or small than 2.0 m/s, the procedure is given by Allen et al. (1998) as

$$\mathrm{Kc.mid} = \mathrm{Kc.mid(Tab)} + [0.04(u_2 - 2) - 0.004(\mathrm{RH}_{min} - 45)]\left(\frac{h}{3}\right)^{0.3} \quad (3)$$

where Kc.mid(Tab) is the value for Kc mid season taken from Table 12 (FAO56), u_2 is the value of wind at 2 m height, RH_{min} is the value of relative humidity, and h is the plant height during the mid-season. The tabulated Kc values listed in Table 12 for initial, mid, and end seasons for various agricultural crops are given in FAO56 to assist in the Kc determination. The coefficients integrate the effects of both transpiration and evaporation over time. The values for Kc in Table 12 are for non stressed and well-managed crops, they are only approximations and could be used for estimating Crop-ET during preliminary or planning studies (Allen et al. 1998).

Penman–Monteith ETo

The FAO56 Penman–Monteith (PM) equation for computing ETo is given by Allen et al. (1998) as following:

$$\mathrm{ETo} = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (4)$$

where ETo 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_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa), $e_s - e_a$ is the saturation vapour pressure deficit (kPa), Δ is the slope vapour pressure curve (kPa °C^{-1}), and γ is the psychrometric constant (kPa °C^{-1}).

Mixture neural network model

Model theoretical summary

The artificial neural network algorithm selected for this study is the principal component analysis neural network (PCANN). PCANN is a mixture of unsupervised and supervised networks. In this hybrid supervised–unsupervised network, the control parameters must be set for both supervised and unsupervised segments of the network. The unsupervised segment of the network performs the feature extraction and the supervised segment of the network performs the nonlinear of these features using a multilayer perceptron (MLP). In supervised learning, the goal is to predict one or more target variables from one or more input variables. Principal component analysis is a well known method of orthogonalizing data. The advantages for using PCANN are that it trains faster without the possibility of losing important input information, and the MLP is able to train easily. PCANN is a data reduction method, which condenses the input data down to a few principal components. Note that during the training process in this study, the unsupervised parameter is set to the input data dimensional level and the supervised MLP is trained with the backpropagation algorithm. Principal component neural network can be viewed as a hybrid network with three layers (Fig. 2). The independent variables are the input layer, and the principal components of the independent variables are the hidden, unsupervised layer. The predicted values from regressing the dependent variables on the principal components are the supervised output layer.

For the unsupervised learning, all components in that family can be functionally described through a weight update function $\Delta_{ij}(t)$in the form of the equation below.

$$\Delta_{ij}(t) = f(x, y, w, \eta) \quad (5)$$

where x, y, w, and η stand for the network input, output, weight, and the step size specified within the learning rate, respectively. The objective is to find a low dimensional representation of the data which captures most of the variance since the main application is to reduce the dimensionality (the number of variables) of the data by

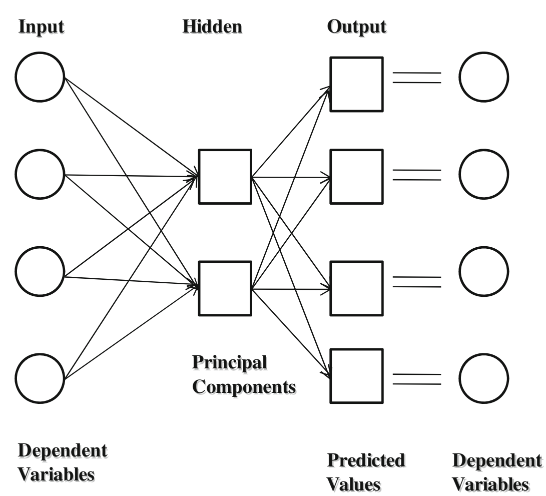


Fig. 2 Principal component analysis model typology

extracting component. The output can be extended to m multiple output units, yielding:

$$y_i(n) = \sum_{i=0} w_{ij}(n)x_i(n) \quad j = 0, 1, \ldots m - 1 \tag{6}$$

In this study, a very effective normalization of the Hebbian rule proposed by Oja has been selected read below as the weight update function in which i, j, and k are set for network layers indices from input to output layer:

$$\Delta w_{ij} = \eta y_i (x_j - \sum_{k \in o} y_k w_{kj}) \tag{7}$$

For the supervised learning, the MLPs are trained with the backpropagation algorithm. Two important characteristics of the multilayer perceptron are processing elements (PEs) nonlinearity and their massive interconnectivity. The error between desired outputs and actual outputs is computed, the backpropagation rule propagates the errors through the network for adjusting the weight. The total error at the output layer given in Eq. 8 is then reduced by redistributing this error value backwards through the hidden layers until the input layer is reached. The error signal is equal to:

$$e_j(n) = d_j(n) - y_j(n) \tag{8}$$

where $e_j(n)$ is an instantaneous error, $d_j(n)$ is the jth component of the desired response, and $y_j(n)$ is the system response at iteration n for a given input pattern.

Using the theory of gradient descent learning, each weight in the network can be adapted by correcting the present value of the weight with a term that is proportional to the present input and error at the weight, i.e.,

$$\Delta w_{jk} = -\eta \frac{\partial \mathrm{E}}{\partial w_{jk}} = -\eta y_k \delta_j \tag{9}$$

and

$$w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n) \tag{10}$$

where δ_j is a sum of local errors at each network output PE, scaled by the weights connecting the output PEs to the jth PE. The local error $\delta_j(n)$ can be directly computed from $e_j(n)$ at the output PE or can be computed as a weighted sum of errors at the internal PEs.

δ_j computes the total error reaching the jth PE from the output layer as$\delta_j(n) = f'(\mathrm{net}_j(n)) \sum_k \delta_k w_{kj}(n)$. This process is repeated until the total error for all data sets is sufficiently small. This study used during the process the tan-sigmoid activation function $[f = (e^x - e^{-x})/(e^x + e^{-x})]$ bounded between [−1, 1]. Since it is very easy for training process to get trapped in a local minimum with the back-propagtion, the momentum term to the weight change is added. The momentum coefficient (α) keeps the network moving and stabilizes its convergence. In momentum learning, the change of weight is computed as follows:

$$\Delta w_{jk}(n+1) = -\eta y_k \delta_j + \alpha \Delta w_{jk}(n) \tag{11}$$

Model data preparation

The data used in this study were normalized for preventing and overcoming the problem associated to the extreme values. The neural network was fed with minimum and maximum air temperatures, and extraterrestrial solar radiation. Note that the extraterrestrial radiation is not a collected data but determined for a certain day and location according to the FAO56 procedure described by Allen et al. (1998). The decades Crop-ET values were yearly computed during the rice normal growing period for 12 years from 1996 to 2007 using the climatic data of the region under study. The Crop-ET decadal data have a total of 169 patterns divided in three parts for the purpose of training (70%), cross-validation (20%), and testing (10%) in order to reach the best generalization. The testing data correspond to the Crop-ET estimated during the rice normal growing period in rainy season for the year 2007. The training data are used to train the network by minimizing the error. The cross-validation data are used to find the network performance by monitoring the training and guarding against overtraining. Then, the testing data are used for checking the overall performance of the trained and validated network. This study used the latest version of the NeuroSolution 5.0 software presented by the NeuroDimension, Inc. Intelligence software solution.

Model performance measures

The performances evaluation criteria were the mean squared errors (MSE), normalized mean squared errors (NMSE), mean absolute errors (MAE), and the coefficient of determination (r) between estimated and observed Crop-ET. These statistical criteria are given by the following equations:

$$\mathrm{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(y_i - y_i'\right)^2 \tag{12}$$

$$\mathrm{NMSE} = \frac{\sum_{i=1}^{N} (y_i - y_i')^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{13}$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{i=1}^{N} \left| y_i - y_i' \right| \tag{14}$$

$$r = \frac{\sum_{i=1}^{N} (y_i - \bar{y})\left(y_i' - \bar{y}'\right)}{\sqrt{\sum_{i=1}^{N} (y_i - \bar{y}^2) \sum_{i=1}^{N} (y_i - \bar{y}')^2}} \tag{15}$$

where y_i and $\bar{y}$ stand for the ith observed values and mean of the observed data, respectively, and y_i' and $\bar{y}'$ stand for the ith estimated output and mean of the estimated output data, respectively, and N stands for the number of observation in the data. In addition, a linear regression ($y = \alpha_1 x + \alpha_0$) analysis was accomplished between estimated Crop-ET as dependent variable (y) and observed Crop-ET as the independent variable (x); α_1 the slope and α_0 the intercept.

Results and discussion

Model configuration

The initial step of the principal component analysis neural network (PCANN) process is the determination of an appropriate configuration for the hybrid supervised–unsupervised architecture network. Since this study aims to compute rice consumptive water requirements from few climatic data, the minimum and maximum air temperature, and extraterrestrial solar radiation variables are used as input to generalize the best neural network configuration. The number of principal component required by the unsupervised network is set to the input data dimensional level. For the supervised multilayer, the determination of the optimum processing elements (PEs) in the hidden layer providing the best results is carried out. According to Parasuraman et al. (2007), one of the important issues in the development of neural networks model is the determination of the optimal number of processing elements that can satisfactorily capture the nonlinear relationship existing between the input and the output variables. There are no fixed rules for developing a neural network model with predefined optimum number of PE. Since no clear-cut guidelines are available (Vemuri 1992), therefore, the trial-and-error method was decided. The normalized mean square error (NMSE) and coefficient of determination (r) were chosen as the criteria for the selection of the PE optimum number. Various PEs between 1 and 20 have been tried in this study, and the optimum values were found with eight PEs as shown in Fig. 3a and b. Hence, the configuration with eight PEs providing the best result was adopted in this study. Also, this study adopted a single hidden layer since it is well known that one hidden layer is enough to represent the nonlinear complex process of evapotranspiration (Kumar et al. 2002; Zanetti et al. 2007), which is strongly involved in Crop-ET computation.

Rice Crop-ET computation

Rice crop consumptive water requirements (Crop-ET) are computed using principal component analysis neural network based on air temperature and extraterrestrial radiation data. Table 1 summarizes the performances results of the employed neural network in this study during the training, cross-validation and testing periods. The statistical performances during the training period are 0.9435, 0.0350 mm day^{-1}, 0.0566 mm day^{-1}, and 0.1551 mm day^{-1} for r^2, MSE, NMSE, and MAE, respectively. In the cross-validation period, the performances are r^2 (0.9589), MSE (0.0251 mm day^{-1}), NMSE (0.0424 mm day^{-1}) and MAE (0.1323 mm day^{-1}). Figure 4a and b shows the scatter plots between observed and estimated outputs during the network training and cross-validation periods, respectively. It is observed during the training and cross-validation periods that the computed outputs by the model fit well the observed values and the mean square errors are less than 5%. Obviously, the model employed is capable to establish the relationship between rice Crop-ET and climate factors effectively. These performances results tell us that the network has a better ability to learn the complex relationship between rice consumptive water requirements and meteorological variables in the semiarid zone studied here.

During the testing period, the accuracies of the neural network are 0.9639, 0.0392 mm day^{-1}, 0.0394 mm day^{-1}, and 0.1697 mm day^{-1} for r^2, MSE, NMSE, and MAE,

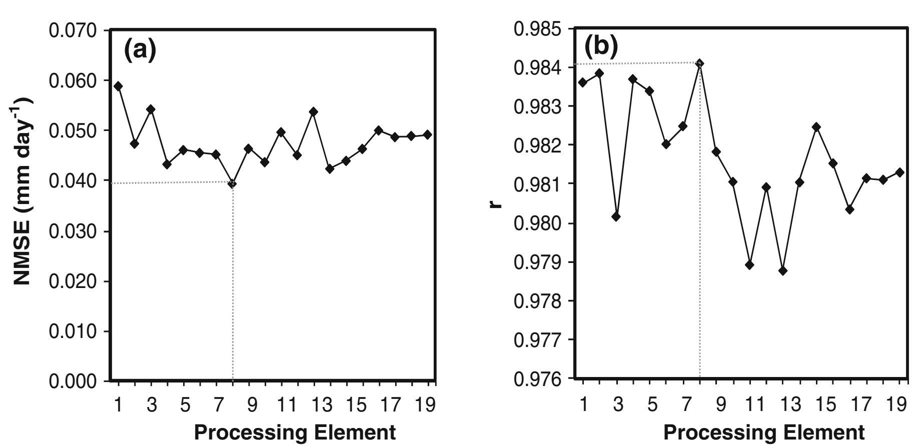


Fig. 3 Accuracy of the principal component analysis neural network under the processing elements number variation for computing rice Crop-ET in Fada N'Gourma: NMSE (**a**) and r (**b**)

Table 1 Statistical performances of principal component analysis neural network model for computing rice Crop-ET during the training, cross-validation and testing periods in Fada N'Gourma region

Period	α_1	α_0	r^2	MSE (mm day^{-1})	NMSE (mm day^{-1})	MAE (mm day^{-1})
Training	0.9439	0.2687	0.9435	0.0350	0.0566	0.1551
Cross-Validation	0.9751	0.1354	0.9586	0.0251	0.0424	0.1323
Testing	0.9226	0.3256	0.9639	0.0392	0.0394	0.1697

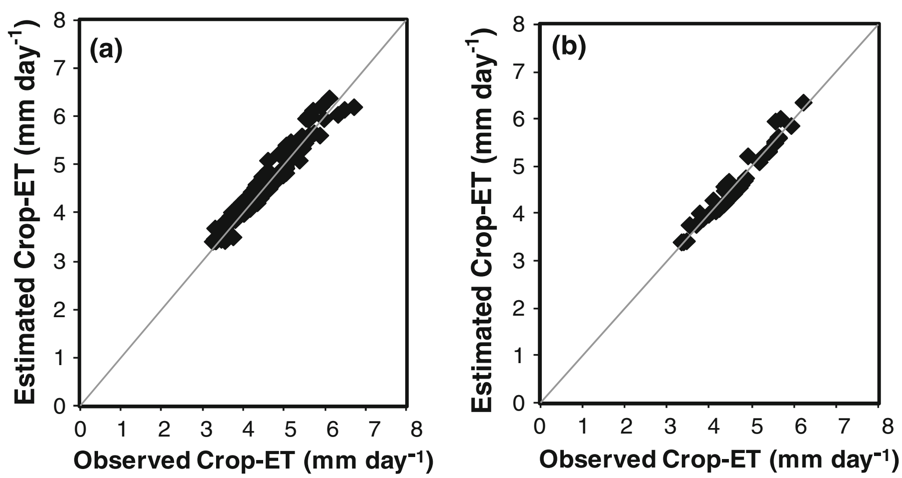


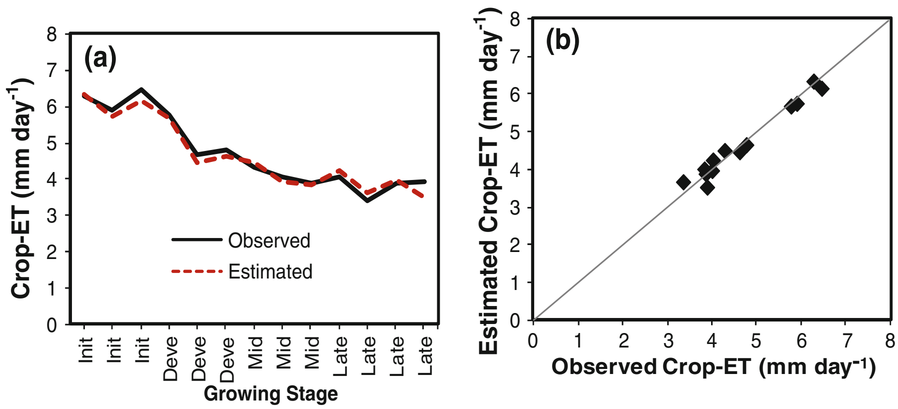
Fig. 4 Scatter plots between observed and estimated values of rice Crop-ET during the training (**a**) and cross-validation (**b**) periods in Fada N'Gourma region

respectively. These statistical values indicate clearly that the model performance was satisfactory for computing the rice consumptive water requirements in Fada N'Gourma region. From the statistical point of view, the estimates errors of the testing period are satisfactory with a mean square error and a normalized mean square error less than 5%, despite of the highest value observed for the mean absolute error. The plot and scatter between observed and estimated values of rice Crop-ET are provided in Fig. 5a and b for better representation, respectively. From Fig. 5a, it can be clearly seen that PCANN model produced a very close estimated Crop-ET values to the observed values during the rice growing stages. It can also be observed from Fig. 5b that the points are less scattered and the points on the fit line are closer to the exact (45) line with a high coefficient of determination r^2 (0.9639) and a satisfactory slope (>90). Sudheer et al. (2003) achieved remarkable success for computing rice crop water requirements by using artificial neural network based on temperature data. In their study, they reported that it is reasonable to believe that neural network can offer reliable estimation values of crop water needs.

The results of this study show that in semiarid zone of Africa, it is possible to successfully compute crop consumptive water requirements by using artificial intelligent neural network model from climatic data basis. In fact for agricultural water resources management, several studies have focused the employment of artificial neural networks on reference evapotranspiration process modeling (Zanetti et al. 2007; Khoob 2008; Traore et al. 2008a, b; Wang et al. 2009b). Note that the neural networks application for computing crop consumptive water requirement is very limited in literature even on a worldwide scale. However, the need to predict crop consumptive water requirements and their change in a period of time is highly sought. From the dataset of climate and observed crop consumptive water requirements, the PCANN is able to model rice Crop-ET in Burkina Faso. This could provide several management options such as determination of suitable cropping pattern, rainwater efficient planning, and supplementary irrigation option development. Agricultural systems are more nonlinear, changeable and complex, and the control of agriculture system is more complicated but can be partially solved by artificial intelligent methodology. An accurate prediction of crop water demand is a prerequisite for effective control of agricultural system.

As evidenced in this study, PCANN algorithm is a powerful tool for modeling the crop consumptive water requirements complex process. Therefore, this hybrid network can be suggested for solving part of difficulty of ETo and Kc availability by directly estimating the Crop-ET in African semiarid zone. Neural network computing technique can overcome the meteorological data unavailability which has been reported by Traore et al. (2007) and Wang et al. (2008a, b) as a basic obstacle for agricultural water resources management in Burkina Faso. Suitable water management is highly needed in this region because of the decreasing of water resources and as a result compromising

Fig. 5 Evolution plot (**a**) and scatter (**b**) of observed and estimated values of rice Crop-ET using principal component analysis neural network in Fada N'Gourma region



the food security challenge that top the government's agenda.

Further comparison of rice Crop-ET estimated shows a variation between the three climatic zones in Burkina Faso. Crop-ET varies according to the location with as case study Banfora, Fada N'Gourma, and Gorom–Gorom regions located in the Sudanian, Sudano–Sahelian, and Sahelian zones, respectively. Crop-ET were higher in Gorom–Gorom (658 mm) followed by Fada N'Gourma (610.9 mm) and Banfora (531.5 mm). These differences in Crop-ET could be associated with regional agro-ecological variations between regions with Banfora at 1,200 mm isohyets, Fada N'Gourma at 800 mm isohyets, and Gorom–Gorom at 400 mm isohyets. It has been documented at least by Izaurralde et al. (2003) and Goyal (2004) that the geographical difference in the temperature and precipitation could explain such differences in crops water demands. Hence, Banfora in the South Sudanian zone with a low Crop-ET potentially has the most favorable agricultural conditions compared to Fada N'Gourma and Gorom–Gorom in the East Sudano-Sahelian and North Sahelian zones, respectively. A study coordinated by the CEEPA for the World Bank in Burkina Faso, reported that, the crop water demands varies with the climate pattern, i.e., Crop-ET increases from Southwestern area towards Northeastern Sahelian conditions (Perret 2006).

Conclusion

Crop-ET estimation is a promising approach in water resources management for a country where most of required data are not always available. Computing crop consumptive water requirement is an important step forward in water resources effective management and planning in poor data situation. In this study, a mixture principal component analysis neural network model was employed with limited climatic data to compute rice crop water requirements in Fada N'Gourma, Eastern Burkina Faso. From the results of the study, it is found that by using only air temperature and extraterrestrial radiation variables, it is possible to estimate reliable Crop-ET values. Therefore, the principal component analysis neural network computing technique can be suggested as a powerful tool for agricultural water resources management strategy development in rice production areas in Burkina Faso. Neural network computing technique can overcome the data unavailability constraint in the issue of water resources efficient management in African semiarid regions.

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