Agricultural Water Management 208 (2018) 140–151

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Reference evapotranspiration prediction using hybridized fuzzy model with firefly algorithm: Regional case study in Burkina Faso

Hai Tao[a], Lamine Diop[b], Ansoumana Bodian[c], Koffi Djaman[d], Papa Malick Ndiaye[c], Zaher Mundher Yaseen[e,*]

[a] Computer Science Department, Baoji University of Arts and Sciences, Shaanxi, China
[b] UFR S2ATA Sciences Agronomiques, de l'Aquaculture et des Technologies Alimentaires, Université Gaston Berger, BP 234, Saint Louis, Senegal
[c] Laboratoire Leïdi "Dynamique des territoires et développement", Université Gaston Berger (UGB), BP 234, Saint Louis, Senegal
[d] Department of Plant and Environmental Sciences, New Mexico State University, Agricultural Science Center at Farmington P.O. Box 1018, Farmington, NM 87499-1018, USA
[e] Sustainable Developments in Civil Engineering Research Group, Faculty of Civil Engineering, Ton Duc Thang University, Ho Chi Minh City, Vietnam

ARTICLE INFO

Keywords:
Reference evapotranspiration prediction
Firefly algorithm
Hybrid models
Agriculture management
Burkina Faso region

ABSTRACT

Reference Evapotranspiration (ETo) is one of the major components of the hydrological cycle that is very essential in water resources planning, irrigation and drainage management and several other hydrology processes. In irrigation system and design, the prediction of ETo is vital and indispensable for the quantification of crop water needs. This study investigates the capabilities of hybridized fuzzy model with firefly algorithm (ANFIS-FA) for predicting daily reference evapotranspiration over Burkina Faso region. Metrological information at Bobo Dioulasso, Bur Dedougou, and Ouahigouya stations, in Sahelian, Sudano-Sahelian, and Sudanian zone, are used for modelling development. Six different climatic input variable combinations corresponding to 6 models are inspected. The daily Penman-Monteith reference evapotranspiration for the time-period (1998–2012) are used to train and test the models. Several numerical indicators in addition to Taylor diagram are considered to evaluate the performance of the models. Results indicated that the hybrid ANFIS-FA model outperformed the classical ANFIS-based model for all three stations and the model with full inputs climatic data gave the best results. Furthermore, ANFIS-FA is performed the best for Bur Dedougou (Sahalian-Soudanian region) and less at Ouahigouya (sahalian region). In quantitative terms and for instance Bur Dedougou station, ANFIS-FA model increased the prediction accuracy remarkably (SI = 0.043, R^2 = 0.97, MAPE = 0.035 and RMSE = 0.24) compared with ANFIS-based model (SI = 0.068, R^2 = 0.89, MAPE = 0.037 and RMSE = 0.378). Results revealed the influence of utilizing nature-inspired firefly algorithm to substantially improve performance of the classical ANFIS model optimization for the applied application. Also, the applied modelling strategy can bring a trustful expert intelligent system for predicting reference evapotranspiration at the west desert of Africa.

1. Introduction

The improper use of water in most developing countries is the major cause of water scarcity, not necessarily deprivation of water resources. African region is experienced both arid and semi-arid weathers with a large chunk of its water use from irrigation and agriculture (Jung et al., 2010; Marshall et al., 2012; Schüttemeyer et al., 2007). The sustainability of irrigation, agricultural and even environmental aspects are mainly dependent on early ETo prediction, thereby presenting the need for the understanding of the accurate ETo prediction satisfies the optimal operational projects water use (Andam-Akorful et al., 2015; Sun et al., 2012). In addition, it is one of the major component of the hydrological processes that is very essential for water resources planning and other watershed sustainability (Kisi, 2007; Rana and Katerji, 2000; Trajkovic, 2005).

ETo can be determined using manual empirical formulation through direct micrometeorological information which is highly expensive (Abdullah et al., 2015) or the use of the Lysimeters which are difficult to manufacture in terms of time and expenses for research purposes (Wright, 1988). As alternatives to the direct methods, mathematical models which mainly employ estimated weather information (e.g., humidity, wind speed, temperature, solar radiation) that obtained locally at the meteorological stations of the watershed are developed (Feng et al., 2017; Kisi, 2016).

* Corresponding author.
E-mail address: yaseen@tdt.edu.vn (Z.M. Yaseen).

https://doi.org/10.1016/j.agwat.2018.06.018
Received 11 December 2017; Received in revised form 4 June 2018; Accepted 13 June 2018

In ETo prediction, several empirical methods have been used though the Food and Agriculture Organization (FAO) of the United Nation. FAO believes that a more accurate prediction could be achieved through a combination of energy balance/aerodynamics. They approved the FAO Penman-Monteith (P-M) equation as the standard equation for ETo estimation (Penman, 1948). In the last two decades, the application of soft computing models such as Artificial Intelligent (AI) models have been proposed to be implemented and solve this hydrological process (Abdullah et al., 2015; Fahimi et al., 2016). AI models are a programming technique mimics the biological brain nerve cells (neurons) performance in terms of interaction. AI models have been evidenced their capabilities in a wide range of application of science and engineering fields. The increase in science studies necessitated the development of mathematical models for handling the enormous volume of natural and artificial phenomena. Different categories of AI models such as artificial neural network (ANN), support vector machine (SVM) fuzzy logic (FL) and evolutionary computing (EC) approaches have been successfully used and are now seen as the best techniques of handling several scientific tasks of hydrology such as optimization, modelling, forecasting and prediction (Nourani et al., 2014; Yaseen et al., 2015b). The implementation of AI models is based on training, validation, and testing methodology. The training stage involves the optimal parameter determination which proceeds mainly in a similar way continues until the minimum error and norm weights are attained. The validation stage is accomplished during the training process to overcome the overfitting issues. The performance of the testing phase is regarded as the major process where the models are tested in terms of meeting predefined modelling objectives.

The popularity of AI models in scientific research has been evolved massively during this course of study and yet, more researches attention is being directed towards including hydrological studies (Adeloye et al., 2012; Kumar et al., 2011; Naoum and Tsanis, 2003). The efficiency of the AI models have been verified in river sedimentations (Afan et al., 2014; Nagy et al., 2002; Rezapour et al., 2010; Wieprecht et al., 2013; Yitian and Gu, 2003), river flow (Ch et al., 2013; Guo et al., 2011; Rasouli et al., 2010; Tayyab et al., 2016; Yaseen et al., 2016a, a; Yaseen et al., 2016b), precipitation modelling (Deo and Şahin, 2015; Krishna Kumar et al., 2005; Nourani et al., 2011; Wu and Chau, 2013), water quality (Hameed et al., 2016; Lee and Scholz, 2006; Liu et al., 2013; Maier et al., 2004; Parmar and Bhardwaj, 2014).

Evapotranspiration predictions have been received a massive attention by scholars in the last two decades. One of the earliest attempt of modelling ETo using the applications of AI conducted by (Trajkovic et al., 2003). The authors studied ANN model for predicting ETo using several metrological data in Serbia, the results showed a very successful modelling. The possibility of ETo prediction conducted using Multiple Layers Perception (MLP) (Kumar and Raghuwanshi, 2002). The FAO P-M equation compared with three conventional and AI methods in terms of achieving reliable ETo estimations using only temperature data (Trajkovic, 2005). The potential of generalized regression model in predicting ETo reported (Kisi, 2006). The accuracy of Adaptive Neuro-Fuzzy Inference System (ANFIS) on ETo modelling at the Santa Monika and Pomona stations compared to those obtained by FAO P-M using daily weather parameters collected over four years (Kisi and Ozturk, 2007). The performance of the ANFIS showed comparable results to the ANN models when compared with the traditional Hargreaves and Ritchie methods using the required weather parameters. The Radial Basis Function Neural Network (RBFNN) and Multilayer Perceptron (MLP) have been the most efficiently used ETo modelling methods in terms of the accuracy when compared to the other learning algorithms of ANN techniques (Kisi, 2008).

Based on the latest review research of AI-based ETo modelling, the semantic-based neural architecture has achieved a high level of accuracy for ETo modelling with respect to the forecasting and predictions (Kumar et al., 2011). Among all the AI models, the Adaptive Neuro Fuzzy Inference System (ANFIS) technique demonstrated an improved level of accuracy for reference evapotranspiration modelling (Abyaneh et al., 2011; Baba et al., 2013; Cai et al., 2004; Citakoglu et al., 2014; Cobaner, 2011; Karimaldini et al., 2012; Kisi et al., 2015; Ladlani et al., 2014; Patil and Deka, 2017; Shiri et al., 2012; Tabari et al., 2012). The ANFIS model has the potential of integrating the advantage of the fuzzy features in parallel with adaptive neural network system in processing non-linear and uncertainty problem (Jang, 1993). The ANFIS based model can benefit from the ability of the fuzzy logic system in handling the vagueness and imprecision in the predictor data set. However, ANFIS model was demonstrated some limitations due to the internal parameter optimization tuning. Hence, integrating this model with natural-inspired algorithm is the innovation solution to overcome these limitations. Most recently, the performance of hybrid systems has been enhanced in terms of precision for modelling hydrological and climatological application due to the integration of the good attributes of the components models into the hybrid model (Fahimi et al., 2016). The integration of several optimization algorithms in ETo modelling through embedment into a standalone AI-based model has improved the performance of the models as it allowed the deduction of the optimal solution for an estimation problem, and parallelly reduced the time of computation (Ghorbani et al., 2017). Much attention has been given to the nature-inspired metaheuristic optimization algorithms, enabling them to enhance the performance of other standalone AI models (Yang, 2010). Several 'wrapper' types of nature inspired optimization algorithms evidenced to enhance the predictability performance (Abdullah et al., 2014; Gromov and Shulga, 2012; Sudheer et al., 2013).

The recently developed firefly algorithm (FA) optimization technique is gaining research interest as several studies have reported a favourable enhancement in the accuracy of their modelling (Yaseen et al., 2017). In comparison with other optimization approaches, FA is more robust and reliable due to the possibility of simultaneously and effectively resolving both the global and local optima in the learning process of the AI models. Despite the robustness of the FA, its application in evapotranspiration process prediction forecasting is yet to be explored. Hence, and for the best knowledge of the authors, this is the first implementation of the hybridized data-intelligent model (i.e., ANFIS-FA) for reference evapotranspiration over Burkina Faso region, west Africa. The current research question is: what is the potential of the hybrid ANFIS-FA model to mimic the physical mechanism between the climatological information and reference evapotranspiration? The developed hybrid intelligent model investigated over three different metrological stations characterized with diverse climatological features "this is to explore the generalization capacity of the predictive model". The finding of this research is very capital for the agricultural and irrigation prospective as an alternative modelling strategy and particularly within the context of Africa where there is a serious problem in data monitoring and metrological data availability.

2. Case study and data description

In this study, three meteorological stations data (daily time scale) of Bobo Dioulasso, Bur Dedougou, and Ouahigouya stations, situated in the sudanian, sahelian-sudanian, and sahelian of Burkina Faso, respectively, were used to build the hybrid intelligent model for evapotranspiration prediction. Fig. 1 displays the location of the three stations.

The daily minimal and maximal temperature, maximal relative humidity, solar radiation, wind speed and vapor pressure deficit between 1998 and 2012, with no gap, collected from Africa rice Center were used as predictor variables. Table 1 shows the daily values of the predictor variables over the study period. It can be seen that the Bobo Dioulasso station presents the lowest temperature (maximal and minimal), followed by Bur Dedougou, and Ouahigouya station, respectively; suggesting an increasing gradient of the temperature from sudanian to sahelian zone. Also, it can be observed the same pattern for

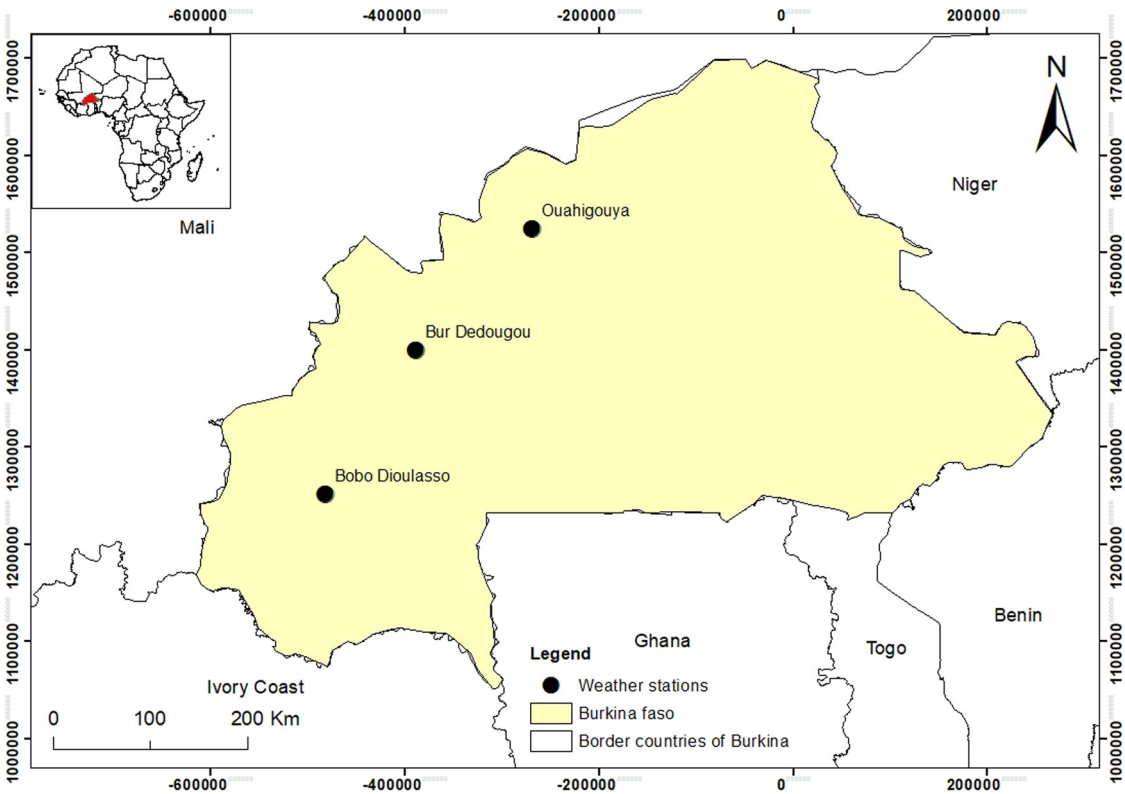

Fig. 1. The location of the investigated metrological stations.

the relative humidity as well. Concerning the daily mean wind speed, we have noticed an opposite trend: Bobo Dioulasso (1.7 m/s), Bur Dedougou (1.5 m/s), and Ouahigouya (1.1 m/s). It is worth to state, the selection of the current region to be study due to the lack of reliable meteorological data monitoring. In addition, to have a detailed and comprehended vision of the predictability of soft computing models on this region.

3. Methodology

3.1. Adaptive neuron fuzzy inference system (ANFIS)

Among several machine learning models, ANFIS model which is based on fuzzy set theory applied in several multiple disciplinary field of science and engineering. ANFIS combines fuzzy systems and the learning skill of neural networks (Cortés et al., 2012; Ho et al., 2011; Lohani et al., 2012). Three main types models of ANFIS are broadly recognized which are presenting in the following: Mamdani, Sugeno, and Tsumoto (Kaur and Kaur, 2012; Mayilvaganan and Naidu, 2011). In general, Sugeon's model is the predominant used over the other types (Takagi and Sugeno, 1985). Theoretically, the membership function controls the input attributes of the fuzzy logic model (Çekmiş et al., 2014). Nodes and rules are represented the normal ANFIS architecture. On the other hand, the rules certificate the mimicking processes among the inputs and targeted output.

Various types of MFs (e.g., Gaussian, triangular, trapezoidal) used for training ANFIS model. However, in the current research Gaussian MF is selected due to its flexibility (Awadallah et al., 2009). MF (U_{Ni}) can be formulated as follows:

$$U_{\mathrm{Ni}} = \frac{\exp(-(x-c_i)^2)}{2\sigma_j^2} \tag{1}$$

where x defines the input matrix at i and (σ_j and c_i) are the provisional quantitative parameters.

The ANFIS model is subjected to the fuzzy based rules (i.e., IF-THEN). The rules are formulated as explained in Eq. 2 and 3 with two input variables and one output:

$$\text{Rule 1: IF } x \text{ is } P_1 \text{ and } y \text{ is } Q_1\text{, then } f_1 = p_1x + q_1y + r_1 \tag{2}$$

$$\text{Rule 2: IF } x \text{ is } P_2 \text{ and } y \text{ is } Q_2\text{, then } f_2 = p_2x + q_2y + r_2 \tag{3}$$

P_i and Qi are fuzzy sets and fi represents the output within the fuzzy region. p_i, q_i, and r_i are the parameters used for designing the network training processes. A general description of the ANFIS model is demonstrated in Fig. 2a.

The modeled reference evapotranspiration problem is subjected to several hydrological and climatological factors and thus the nature of

Table 1
Mean daily values of the predictor variables for the investigated time-period 1998 to 2012.

Stations	Lat (°C)	Long (°C)	Alt (m)	T_{max} (°C)	T_{min} (°C)	HR_{max} (%)	U2 (m/s)	R_s (MJ/m^2)	VPD (KPa)
Bobo Dioulasso	11.17	−4.32	445	33.7	22.6	67.1	1.7	20.7	2.2
Bur Degoudou	12.35	−1.52	305	35.5	22.8	60.2	1.5	21.1	2.6
Ouahigouya	13.57	0.20	315	36	23.5	51.1	1.1	21.5	3.0

*Lat: latitude, Long: Longitude, Alt: altitude, T_{max}: maximal temperature, T_{min}: minimal temperature, HR_{max}: maximal relative humidity, U2: wind speed at 2 m height, Rs: Solar Radiation, VPD: vapor pressure deficit.

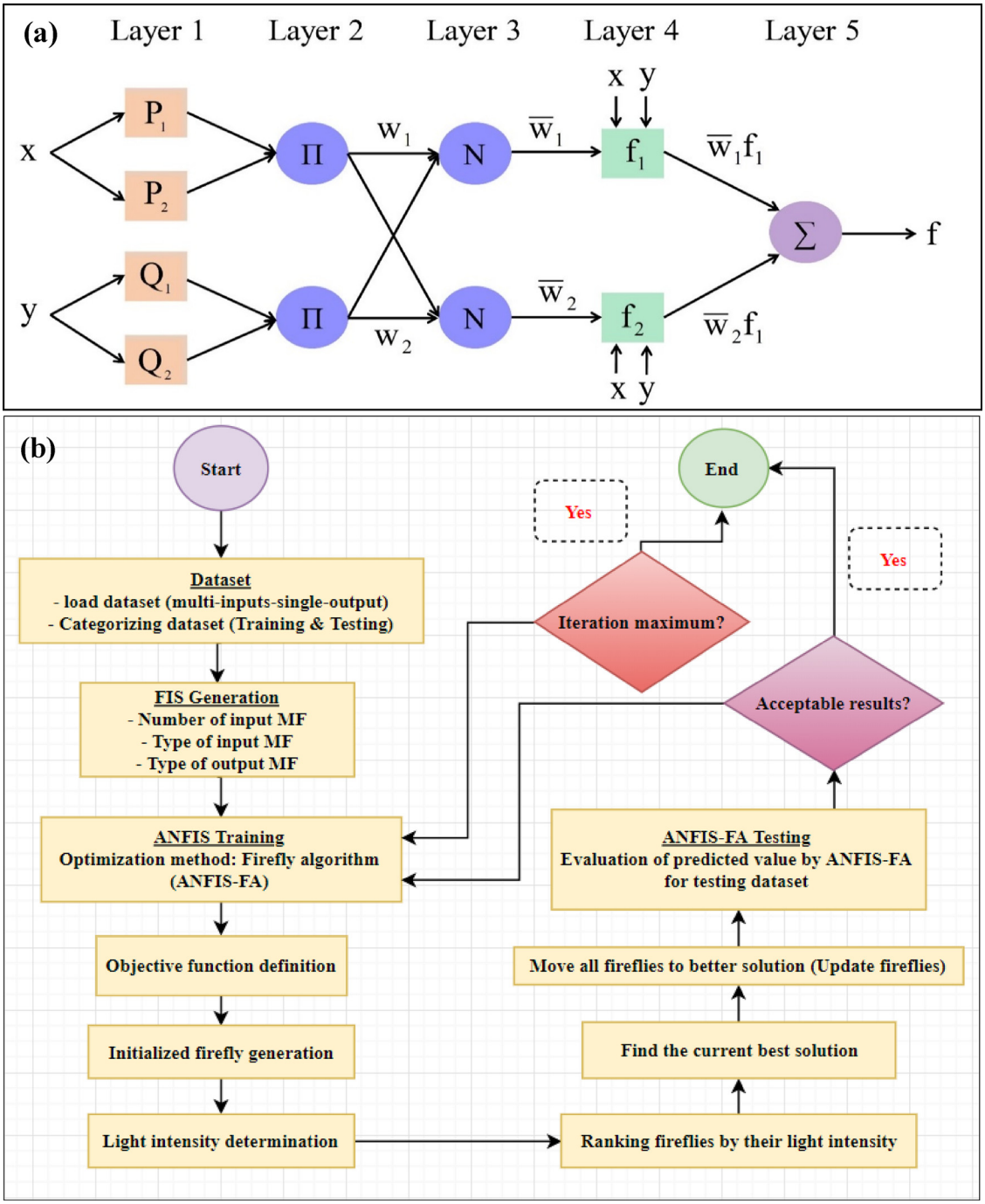

Fig. 2. a) ANFIS predictive model structure, b) The scheme of the hybrid predictive model by integrating ANFIS model with FA learning algorithm.

this problem is highly non-linear and non-stationary. To solve this, the ANFIS model is used perceptively in order to extract information and convert it to fuzzy systems. The optimality of modelling ANFIS model relies on tuning the internal parameters (*i.e.* σj and cj) of the Gaussian membership function. Hence, new evolutionary nature-inspired optimization algorithm called Firefly Optimization Algorithm (FA) is adopted to determine the internal parameters of ANFIS membership function.

3.2. Hybrid model based on ANFIS-FA

The social behaviour of fireflies (light flashing) inspired the development of the Firefly optimization algorithm (FA) (Yang, 2010). The characteristic behaviour of the fireflies, irrespective of their gender gave rise to three essential rules in the FA structure. These rules are based on the fact that fireflies are presumed to be unisex with a distinctive attribute of attracting each order, the rate of attraction of one firefly to the order depends on the intensity of the light flashed by the attracting firefly, and the intensity of the light emitted by the fireflies is directly related to the amount of light it is emitting. With regard to these stipulated rules, the function of the FA model is related to the brightness and intensity of light emitted by the firefly. Equations 4 and 5 present the mathematical representation of the intensity and attractiveness of a firefly respectively. The ability of any firefly to attract another firefly depends on its unique intensity β (Yang, 2010).

$$I = I_0 e^{-\gamma r^2} \tag{4}$$

$$w(r) = w_0 e^{-yr^2} \tag{5}$$

where the light intensity is represented by I and attractiveness at a distance is represented by $w(r)$. I_0 and W_0 represent the intensity of the emitted light and the attractiveness at a distance $r = 0$ from the firefly. y represents the light absorption coefficient. Eq. (6) provides the distance r between any two fireflies i and j (Yang, 2010):

$$r_{ij} = \|x_i + x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})} \tag{6}$$

where x_i and x_j are the location of fireflies i and j in a Cartesian coordinate system. As mentioned, firefly is attracted by another and vice-versa, thus the movement of firefly a by another firefly b is represented in Eq. (7) (Yang, 2010).

$$\Delta_{xi} = \beta_0 e^{-yr^2} \tag{7}$$

where $\alpha\varepsilon i$ and $\beta_0 e^{-yr^2}$ are the randomized and attraction terms, respectively, $\alpha \wedge \varepsilon i$ represents the randomization coefficient and random number vector, respectively. The value of α lies within 0 and 1. From Eq. (7), the movement of the next firefly is at its position $_i + \Delta_{xi}$.

The optimal design of the ANFIS-FA model requires the adjustment of some FA parameters such as the movement and light absorption coefficients (α and γ respectively), as well as the attraction coefficient base (β_0). The values of γ, β_0 and α in this paper were set at 1, 1.8 and 0.5 respectively. These values were determined after a series of trial and error processes. The details of the FA procedure are provided by Yang (2010).

Table 2 showed a series of input combinations put together based on the information obtained from metrological data. All the input combinations were targeted at one response, which is the reference evapotranspiration. Prior to the application of the ANFIS model, the range of membership function (MF) parameters required for its optimization was defined. During the training process, the root mean square error (RMSE) was determined and used as the yardstick for the monitoring of the accuracy of the ANFIS-FA model. During the proper optimization process, the FA scheme was used to optimize the antecedent parameters of the ANFIS model, consisting mainly of the MF parameters. To initiate the first ANFIS-FA iteration, a generation of an initial population of Firefly was randomly employed in a way that each firefly is represented in the ANFIS set(s). The light intensity of the fireflies was the basis for the computation of their degree of attractiveness, thereby collectively comparing the attractiveness of the fireflies. Having compared the attractiveness of all the fireflies, the particular firefly with the maximum brightness is selected and other fireflies are naturally attracted to it. Similarly, the performance of the ANFIS-FA was further evaluated by determining the RMSE which is regarded as a fitness function in the hybrid model. The ANFIS-FA was continuously trained until either of a maximum number of iterations or an acceptable fitness function value is achieved. The proposed flowchart of the hybrid ANFIS-FA model is illustrated in Fig. 2b. For appropriate data division, 80% of the data were used to train the models and the remaining 20% for model testing for each of the three stations.

Table 2
Input combinations based on the included metrological information variables.

Input no.	Input combinations models	Output
M1	T_{max}	ETo
M2	T_{max}, R_s	
M3	T_{max}, RH_{max}, R_s	
M4	T_{max}, T_{min}, RH_{max}, R_s	
M5	T_{max}, T_{min}, RH_{max}, R_s, $U2$	
M6	T_{max}, T_{min}, RH_{max}, R_s, $U2$, VPD	

3.3. Penman-Monteith empirical approach

Daily reference evapotranspiration was computed using the Penman-Monteith formula (Jensen et al., 1990):

$$ETo = \frac{0.408\Delta(Rn - G) + \gamma \frac{Cn}{T+273} U2(es - ea)}{\Delta + \gamma(1 + CdU2)} \tag{8}$$

where: ETo is the reference evapotranspiration (mm day^{-1}), Δ is the slope of saturation vapor pressure versus air temperature curve (kPa °C^{-1}), Rn is the net radiation at the crop surface (MJ m^{-2} d^{-1}), G is the soil heat flux density at the soil surface (MJ m^{-2} d^{-1}), T is the mean daily air temperature (°C), U2 is the daily wind speed at 2 m height (m s^{-1}), es is the saturation vapor pressure (kPa), ea is the actual vapor pressure (kPa), es-ea is the saturation vapor pressure deficit (kPa), γ is the psychrometric constant (kPa °C^{-1}), Cn and Cd are constants with values of 900 and 0.34, respectively.

4. Application and prediction discussion

The capability of the new hybrid ANFIS-FA model was evaluated to predict reference evapotranspiration using various input combinations. ANFIS-FA was verified against ANFIS-based model. Fig. 2a and b give the ANFIS structure and the flow chart serving the development of the hybrid ANFIS-FA, respectively.

Six different input combinations corresponding to six models (M1, M2, …, M6) defined in Table 2, used to build the developed predictive models. The combinations are (M1: T_{max}), (M2: T_{max} and R_s), (M3: T_{max}, RH_{max} and R_s), (M4: T_{max}, T_{min} RH_{max} and R_s)), (M5: T_{max}, T_{min}, RH_{max} and R_s, U2) and (M6: T_{max}, T_{min}, RH_{max} and R_s, U2, VPD). The first input combination (M1) includes only the maximum temperature owing to the fact that this climatological variable is the main trigger for the ETo amount (Hargreaves and Samani, 1985).

The developed hybrid ANFIS-FA and the classical ANFIS models compared through the prediction skills using different statistic metrics (Eqs. (9)–(17)) including absolute error criteria, best-of-goodness, scatter index (SI), mean absolute percentage error (MAPE), root mean square error (RMSE), root mean square relative error (RMSRE), mean relative error (MRE), mean absolute errors (MAE), BIAS, determination coefficient (R^2) and relative error (RE) metrics.

$$SI = \frac{\sqrt{\frac{\sum_{i=1}^{n}(ETo_{Ci} - ETo_{pi})^2}{n}}}{E\acute{T}o_{Ci}} \tag{9}$$

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{ETo_{Ci} - ETo_{pi}}{ETo_{Ci}}\right| \tag{10}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(ETo_{Ci} - ETo_{pi})^2}{n}} \tag{11}$$

$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{ETo_{Ci} - ETo_{pi}}{ETo_{Ci}}\right)^2} \tag{12}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{ETo_{Ci} - ETo_{pi}}{ETo_{Ci}}\right)(7) \tag{13}$$

$$MAE = \frac{\sum_{i=1}^{n}|ETo_{Ci} - ETo_{pi}|}{n} \tag{14}$$

$$BIAS = \frac{\sum_{i=1}^{n}(ETo_{Ci} - ETo_{pi})}{n} \tag{15}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(ETo_{Ci} - E\acute{T}o_{Ci})(ETo_{pi} - E\acute{T}o_{pi})}{\sqrt{\sum_{i=1}^{n}(ETo_{Ci} - E\acute{T}o_{Ci})^2 \sum_{i=1}^{n}(ETo_{pi} - E\acute{T}o_{pi})^2}}\right]^2 \tag{16}$$

Table 3
The statistical performance indicators for the testing period of Bobo Dioulasso metrological station using ANFIS and ANFIS-FA models. The bold line presents the best input combination.

Input Combinations	SI	MAPE	RMSE	MAE	RMSRE	MRE	BIAS	R^2
ANFIS								
M1	0.159492	0.124226	0.846385	0.609842	0.186043	0.03018	−0.02752	0.47
M2	0.137301	0.090255	0.728621	0.474018	0.136421	0.008914	0.02331	0.61
M3	0.102984	0.069672	0.546513	0.358576	0.110091	0.020392	−0.05814	0.77
M4	0.096355	0.068582	0.51133	0.353615	0.101822	0.019058	−0.05233	0.80
M5	0.070745	0.042046	0.375426	0.214912	0.075326	0.010361	−0.03186	0.89
M6	0.062065	0.040311	0.329361	0.205763	0.067494	0.00995	−0.03013	0.91
ANFIS-FA								
M1	0.139568	0.110268	0.740653	0.54323	0.162719	0.0207	0.006001	0.58
M2	0.111316	0.08642	0.590727	0.448827	0.11087	0.034918	−0.11716	0.74
M3	0.083786	0.060405	0.444631	0.31999	0.083215	0.016396	−0.03984	0.85
M4	0.082465	0.060201	0.43762	0.317452	0.081511	0.014717	−0.02947	0.85
M5	0.048049	0.039433	0.254983	0.201758	0.05095	0.005244	0.011014	0.96
M6	0.045754	0.038281	0.242805	0.196133	0.04803	0.004635	0.012255	0.96

$$RE = \frac{\sum_{i=1}^{n} (ETo_{Ci} - ETo_{pi})}{\sum_{i=1}^{n} (ETo_{Ci} - \acute{ETo}_{Ci})} \tag{17}$$

where ETo_{Ci} is the actual daily evapotranspiration (Penman-Monteith), ETo_{pi} is the daily predicted evapotranspiration by the applied models, $\acute{ETo}_{Ci}$ and $\acute{ETo}_{pi}$ are the mean values of the actual and predicted ETo, and n is the length of the data series. The pertinence of using several statistic metrics justified by the fact that each metric summarizes a large number of data into a single value, Thus, stressing only a certain aspect of the error characteristics of the model performance (Chai and Draxler, 2014).

Tables 3–5 tabulate the prediction performance of the classical ANFIS and the hybrid ANFIS-FA predictive models over the testing phase for Bobo Dioulasso, Bur Dedougou, and Ouahigouya, respectively. For Bobo Dioulasso station, the RMSE (MAE) values ranged between 0.846 (0.609) to 0.375 (0.215) mm and 0.741 (0.543) to 0.255 (0.202) mm for ANFIS and ANFIS-FA models, respectively.

Based on the tabulated results, ANFIS-FA model outclassed ANFIS-based model with respect to SI, MAPE, RMSRE, MRE, and BIAS metrics. The best accuracy achieved for the sixth input combination (M6) through including all the available climatological information. Whereas, M1 that integrated only the daily maximum temperature attained the worst prediction results. This is best can be explained due to the high correlation of the ETo to multiple climate information. Note that every additive climatological variable enhances the prediction accuracy as clearly indicated using the R_s (M2) up the last variable VPD (M6).

With more reliable numerical presentation and for the ANFIS and ANFIS-FA models, respectively. Bobo Dioulasso station achieves the SI (RMSE) values ranged between 0.159-0.062 (0.846-0.329) and 0.139-0.045 (0.740-0.242); MAE (BIAS) values are ranged between 0.609-0.205 (0.023-(-0.058)) and 0.543-0.196 (0.006-(-0.039)). Bur Dedougou station attains the SI (RMSE) values are ranged between 0.149-0.061 (0.827-0.343) and 0.143-0.043 (0.799-0.240), respectively; MAE (BIAS) values ranged between 0.635–0.189 (0.080-0.004) and 0.617-0.190 (0.060-0.038). The third metrological station "i.e., Ouahigouya station" presents the SI (RMSE) values are ranged between 0.208-0.096 (1.123-0.519) and 0.205-0.074 (1.106-0.401); MAE (BIAS) values ranged between 0.907-0.297 (0.292-(-0.155) and 0.891-0.319 (0.210-(-0.040)). What can be comprehended from these numerical results that the ANFIS-FA model exhibits more reliable prediction accuracy and satisfies the base research question.

Over all the three inspected metrological stations, the ANFIS-FA model attains the precise results and M6 input combination performed the best. On the other hand, the first input combination (M1) gave the poorest results. This is clearly indicating the necessity of initiating a monitoring station to maintain the data collection. However, the current available data perform an efficient intelligent predictive model. By comparing the hybrid ANFIS-FA with ANFIS results, the proposed ANFIS-FA model provides the best performance even though the similarity trend were observed when passing from one single input model to full climatic data information. This fact is suggesting that more inputs data will increase the performance of the model. From these results, it can be drawn that the modelling is more accurate at the station of Bur Dedougou (Sudanian-Sahelian area) and worst at Ouahigouya station (Sahelian zone). Thus, the climatic area influences the results of model

Table 4
The statistical performance indicators for the testing period of Bur Dedougou metrological station using ANFIS and ANFIS-FA models. The bold line presents the best input combination.

Input Combinations	SI	MAPE	RMSE	MAE	RMSRE	MRE	BIAS	R^2
ANFIS								
M1	0.148699	0.125131	0.826845	0.637529	0.196533	0.015037	0.080871	0.51
M2	0.128049	0.099097	0.712024	0.52623	0.143036	0.021184	−0.01387	0.63
M3	0.112527	0.086371	0.625712	0.462797	0.13157	0.008259	0.031844	0.71
M4	0.102779	0.079343	0.571505	0.424771	0.123701	0.006879	0.040497	0.76
M5	0.068061	0.037122	0.378454	0.193163	0.082806	0.002768	0.003967	0.89
M6	0.061733	0.035331	0.343268	0.189672	0.065602	0.000921	0.009168	0.91
ANFIS-FA								
M1	0.143826	0.11817	0.799753	0.616629	0.165169	0.01435	0.060983	0.54
M2	0.119423	0.096259	0.664054	0.518671	0.124355	0.034691	−0.10207	0.69
M3	0.104507	0.07792	0.581115	0.427826	0.107867	0.019813	−0.03671	0.76
M4	0.090569	0.067829	0.503612	0.376068	0.090425	0.009527	0.01183	0.82
M5	0.043914	0.035968	0.244187	0.192576	0.049264	5.59E-05	0.03937	0.97
M6	0.043172	0.035701	0.240061	0.190737	0.048956	7.03E-05	0.038763	0.97

Table 5
The statistical performance indicators for the testing period of Ouahigouya metrological station using ANFIS model. The bold line presents the best input combination.

Input Combinations	SI	MAPE	RMSE	MAE	RMSRE	MRE	BIAS	R^2
ANFIS								
M1	0.208759	0.177218	1.123556	0.907623	0.23167	0.007085	0.211257	0.39
M2	0.193723	0.143553	1.042629	0.778196	0.187932	−0.01832	0.292776	0.50
M3	0.179905	0.142457	0.968261	0.732395	0.192594	0.031096	0.039622	0.55
M4	0.157393	0.126096	0.847103	0.647849	0.169033	0.018507	0.057505	0.64
M5	0.101453	0.063975	0.546029	0.305106	0.116411	0.03774	−0.1559	0.86
M6	0.096457	0.062369	0.519137	0.297614	0.110542	0.035691	−0.14852	0.87
ANFIS-FA								
M1	0.205545	0.172677	1.106258	0.89103	0.221053	0.005506	0.210614	0.41
M2	0.181229	0.143938	0.975387	0.744221	0.188596	0.041173	−0.01861	0.54
M3	0.171172	0.13427	0.921258	0.693817	0.180898	0.03494	0.00438	0.60
M4	0.152709	0.122891	0.821892	0.631431	0.162969	0.033722	−0.01197	0.69
M5	0.076319	0.06733	0.410754	0.326786	0.091733	0.025579	−0.04392	0.94
M6	0.07462	0.06547	0.40161	0.319051	0.089043	0.024326	−0.04099	0.95

simulation or prediction. These results show obviously that modelling is site specific and depends on climate zone as mentioned by (Bodian et al., 2016; Lamine et al., 2015); thus, researchers and development agencies have to take precaution before generalizing model application.

It is worth to discuss the influence of the VPD in addition to the other variables of the sixth input combination in comparison with the individual maximum temperature information (M1). For instance at Bobo Dioulasso, there is a noticeable augmentation in the prediction precision presented by 67% for the root mean square error using the hybrid ANFIS-FA model. It is moderate percentage evidenced the variability of the vapor pressure deficit integrated with other variables as predictors for the ETo.

The scatter plots of the optimal ANFIS and ANFIS-FA models over the testing period for all stations presented in Fig. 3. The determination coefficient (R^2) and the slope of the different regressions are used to evaluate the agreement between the actual and predicted reference evapotranspiration. Results show the superiority of the ANFIS-FA for all three stations. $R^2 = 0.9661$ (0.9183); 0.972 (0.9159); and 0.9502 (0.8783) for ANFIS-FA (ANFIS) at Bobo Dioulasso, Bur Dedougou, and Ouahigouya station, respectively. The slopes of the different regression equations exhibit also the same pattern, suggesting the significance of the FA optimization algorithm for the ANFIS model optimization. Results indicate that estimates of hybrid ANFIS-FA models closer to the manual calculation of Penman-Monteith evapotranspiration and ANFIS-FA superior to the classical ANFIS.

Fig. 4 displays the percentage of relative error distribution of predicting ETo values. The percentage errors depended on the model and location. For the best model and location (ANFIS-FA model 6 at Bobo Dioulasso), the absolute percentage error value found to be around ± 10%. Some higher absolute percentage error values noticed but not significant compared to the whole testing period. When considering ANFIS (M6) and the same location, it can be noticed a more important percentage relative error exceeds ± 20% with several peak events reached 40% suggesting that ANFIS-FA improved substantially the prediction of the reference evapotranspiration by reducing drastically the committed errors. The same conclusions can be drawn to the other investigated metrological stations (i.e., Bur Dedougou, and Ouahigouya) in terms of the ANFIS-FA superiority in giving less error when predicting ETo.

Further analysis, Taylor diagram (TD) (Taylor, 2001) is examined for the developed predictive models. TD uses standard deviation and the coefficient of correlation (r) of observed and simulated data to make classification. The best model is the one with (r = 1) and presenting the same amplitude of variation than the observed data. Fig. 5 presents the Taylor diagrams for all investigated input combinations of ANFIS and ANFIS-FA and for all stations (Bobo Dioulasso, Bur Dedougou, and Ouahigouya).

Overall, the integration of the nature inspired Firefly optimizer with ANFIS improved substantially the performance of the modelling by increasing the best-fit-of-goods and reducing the absolute error measurements. The M6 gave the best results and over all the stations with remarkable modelling outcomes for Bur Dedougou station. These findings confirmed the importance of all climate variables in predicting or computing the reference evapotranspiration. Each of the climate variables might impact positively or negatively the variation of evapotranspiration. Therefore, efforts need to be made in order to monitor all climate variables. In case of scarce data in this area, the third input combination (M3) gave an acceptable result and can be used as an alternative. The applied modelling strategy gives a standard and reliable predictive model that can be used for the West Africa area that can be extremely valuable for water management authorities.

Over the past decade, the classical ANFIS model was used to estimate the evaporation or reference evapotranspiration; afterward certain hybrid ANFIS models (Wavelet-ANFIS, ANFIS-SC, ANFIS-GP, etc.) established to improve its modelling capability and results showed the improvement of results. Recently a novel optimizer method: the firefly method used to improve the capability of artificial intelligent method and valuable results achieved. For example, Ghorbani et al. (2017) compared the traditional Multilayer Perceptron (MLP) and support vector machine (SVM) models to the MLP-FA for predicting pan evaporation in the north of Iran. They concluded that MLP-FA model outperformed the classical MLP and SVM models; suggesting the role played by Firefly method in optimizing results of the classical models. This study as demonstrated by Ghorbani et al. (2017) confirms the power of the Firefly method to improve the accuracy of the AI modelling.

5. Conclusion

Prediction of reference evapotranspiration for better evaluation of crop water needs, is a remarkable responsibility for agriculture and irrigation engineers and agronomist. Thus, providing and exploring a robust intelligent model to increase the accuracy of classical models is the passionate of the new trend researches. In this research, a new adaptive neuro-fuzzy inference system integrated with firefly optimization algorithm was developed and tested for the prediction of reference evapotranspiration in Burkina Faso region, West Africa. Data of three climatic stations (Bobo Dioulasso, Bur Dedougou, and Ouahigouya) was utilized to build the hybrid predictive model ANFIS-FA and the benchmark model. Various input combinations including maximum temperature, minimum temperature, maximum relative humidity, solar radiation, wind speed and vapor pressure deficit were considered in this study. Based on these variables, six models were defined to establish the forgoing predictive models. The most accurate

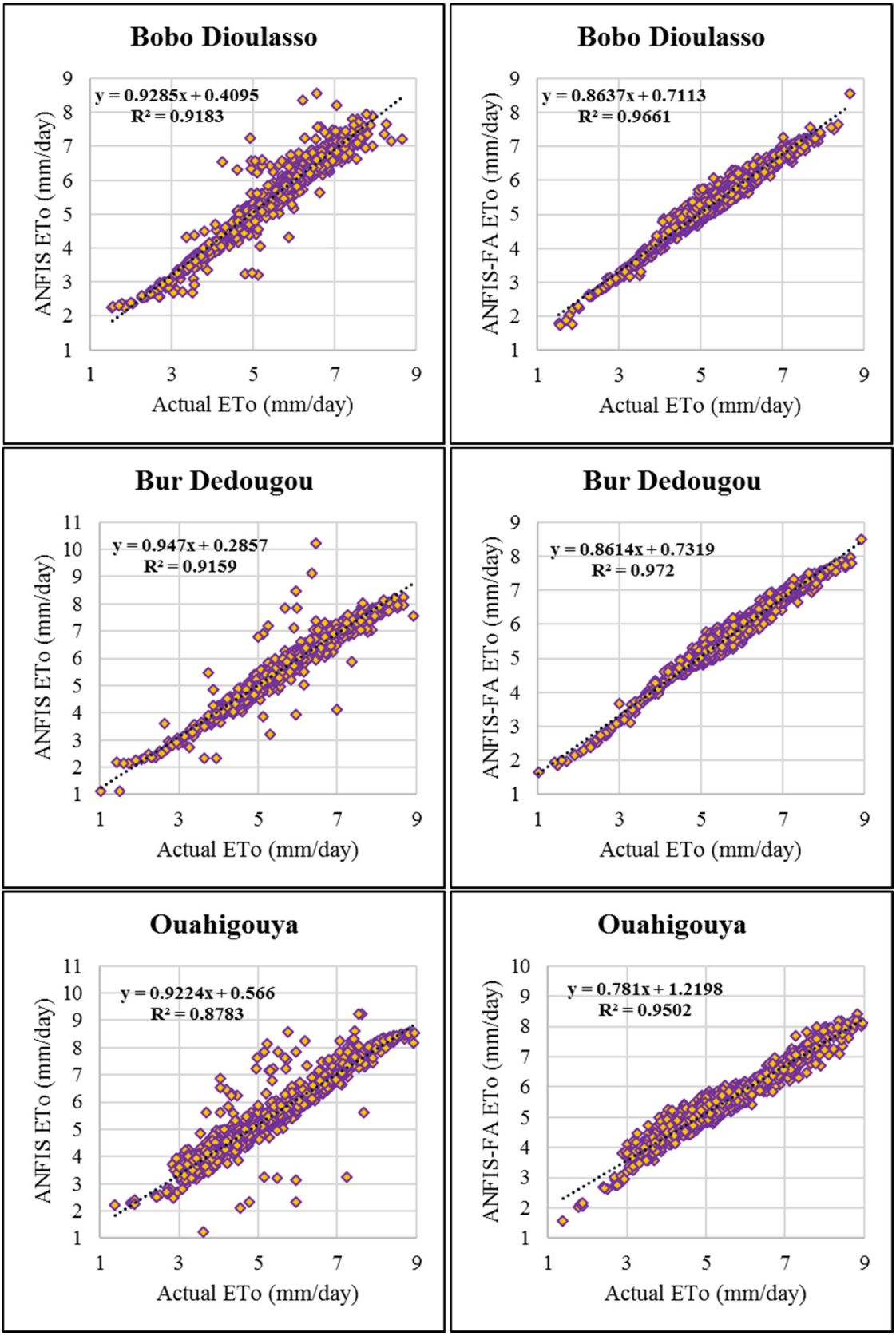

Fig. 3. Scatterplots of the predicted versus actual reference evapotranspiration over the testing period for the three inspected stations, Bobo Dioulasso station, Bur Degoudoua, and Ouahigouya.

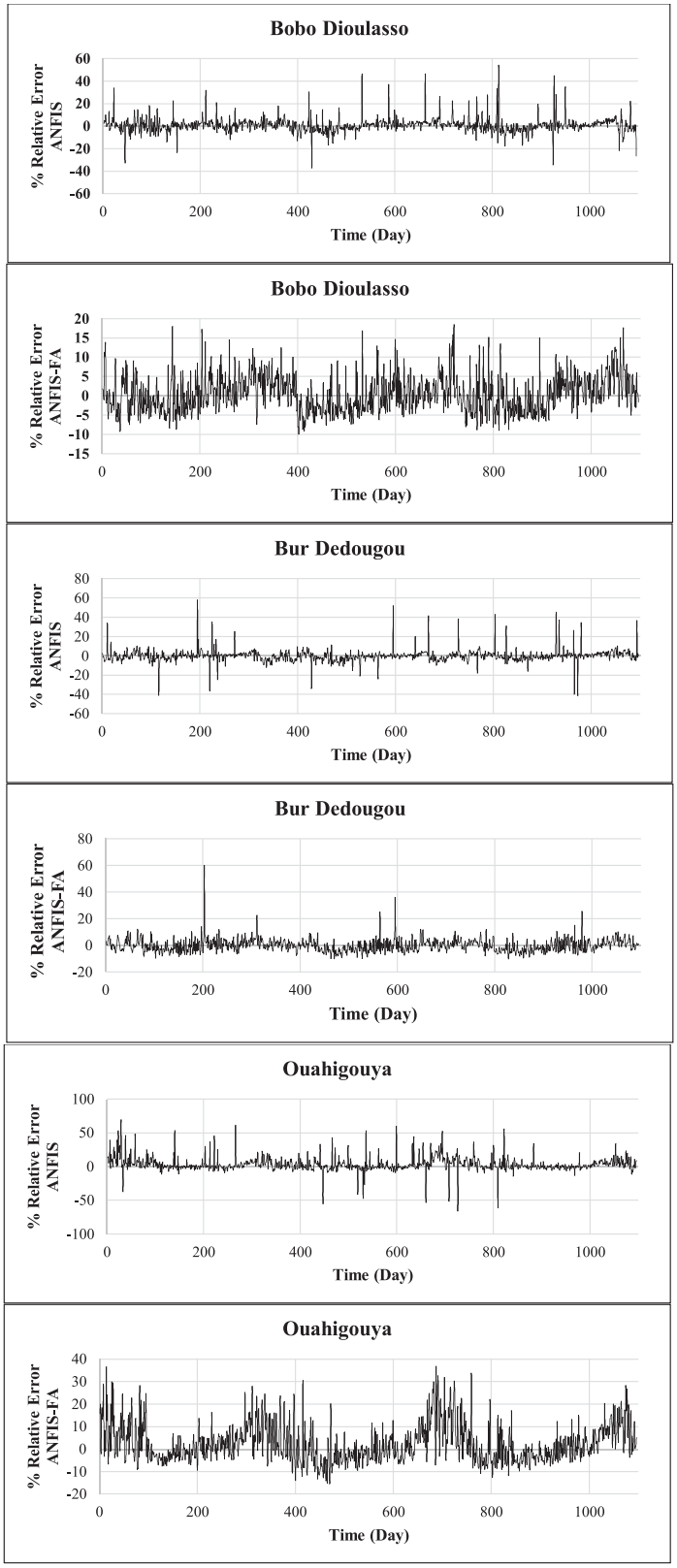

Fig. 4. Relative distribution error indicator over the testing period for the three investigated stations.

results were achieved by using all of the variables as input combination for both ANFIS-FA and ANFIS. This is best can be explained due to the complexity pattern on the ETo that required informative attributes. Furthermore, the results corroborated the superiority of the ANFIS-FA model compared with the classical ANFIS model and showed the potential value of an integrated ANFIS-Firefly optimized model to improve the capability of the ANFIS-based model significantly. The results of this study showed that the performance of the modelling depends on climate zone; therefore, similar studies in other regions of varying climatic conditions need to be explored in order to reinforce the finding of

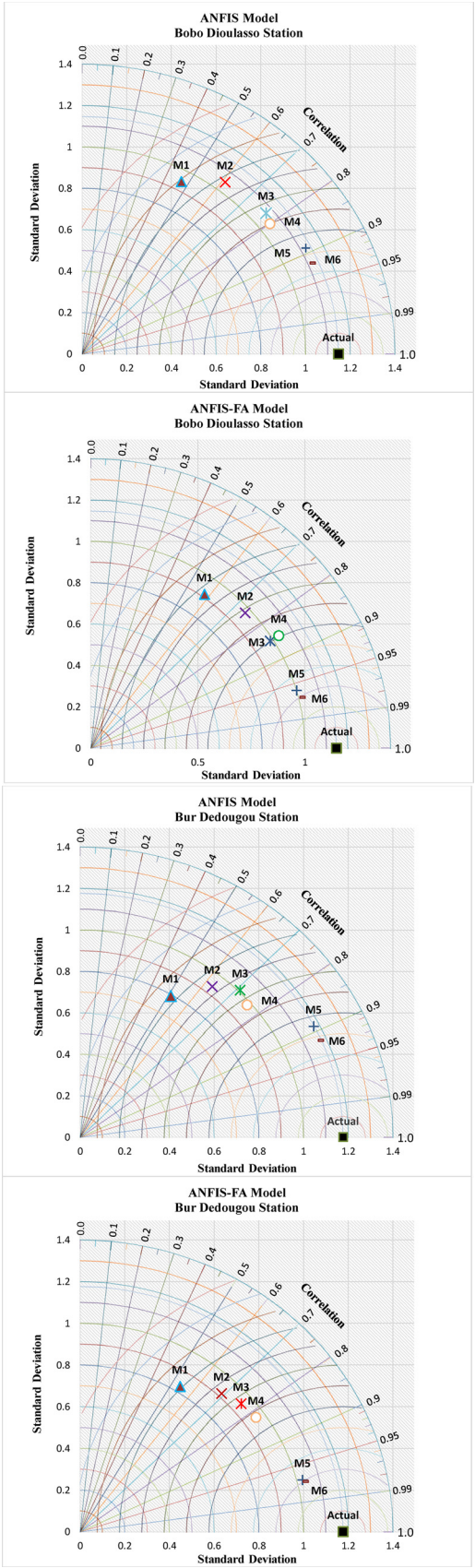

Fig. 5. Taylor diagram of the predicted reference evapotranspiration over the testing period for the three investigated stations.

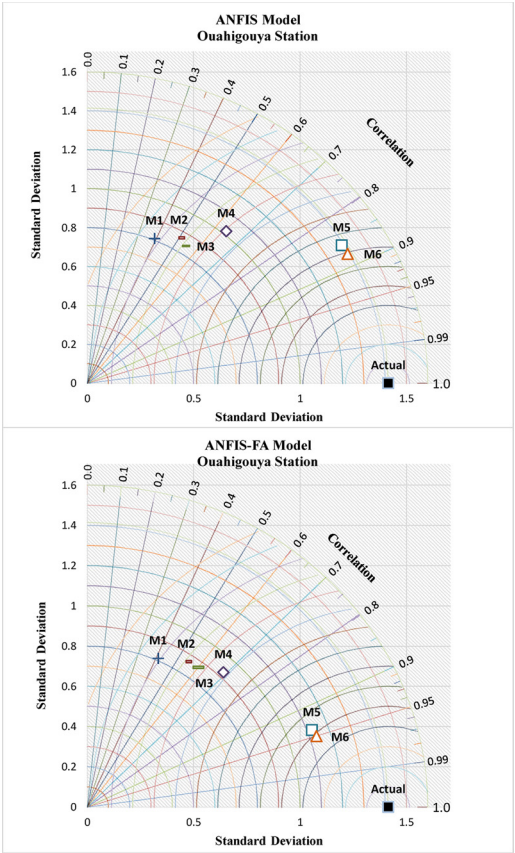

Fig. 5. (*continued*)

this study. Furthermore, the implemented hybrid model for the ETo prediction exhibited the motivation to explore on other climatological and agricultural processes such as temperature, solar radiation and crops productivity prediction.

References

Abdullah, S.S., Abdul Malek, M., Mustapha, A., Aryanfar, A., 2014. Hybrid of artificial neural network-genetic algorithm for prediction of reference evapotranspiration (ET0) in arid and semiarid regions. J. Agric. Sci. 6, 191–200. http://dx.doi.org/10.5539/jas.v6n3p191.

Abdullah, S.S., Malek, M.A., Abdullah, N.S., Mustapha, A., 2015. Feedforward back-propagation, genetic algorithm approaches for predicting reference evapotranspiration. Sains Malaysiana 44, 1053–1059.

Abyaneh, H.Z., Nia, A.M., Varkeshi, M.B., Marofi, S., Kisi, O., 2011. Performance evaluation of ANN and ANFIS models for estimating garlic crop evapotranspiration. J. Irrig. Drain. Eng. 137, 280–286. http://dx.doi.org/10.1061/(ASCE)IR.1943-4774.0000298.

Adeloye, A.J., Rustum, R., Kariyama, I.D., 2012. Neural computing modelling of the reference crop evapotranspiration. Environ. Model. Softw. 29, 61–73. http://dx.doi.org/10.1016/j.envsoft.2011.10.012.

Afan, H.A., El-Shafie, A., Yaseen, Z.M., Hameed, M.M., Wan Mohtar, W.H.M., Hussain, A., 2014. ANN based sediment prediction model utilizing different input scenarios. Water Resour. Manag. 29, 1231–1245. http://dx.doi.org/10.1007/s11269-014-0870-1.

Andam-Akorful, S.A., Ferreira, V.G., Awange, J.L., Forootan, E., He, X.F., 2015. Multi-model and multi-sensor estimations of evapotranspiration over the Volta Basin, West Africa. Int. J. Climatol. 35, 3132–3145. http://dx.doi.org/10.1002/joc.4198.

Awadallah, M.A., Bayoumi, E.H.E., Soliman, H.M., 2009. Adaptive deadbeat controllers for brushless DC drives using PSO and ANFIS techniques. J. Electr. Eng. 60, 3–11.

Baba, A.P.A., Shiri, J., Kisi, O., Fard, A.F., Kim, S., Amini, R., 2013. Estimating daily reference evapotranspiration using available and estimated climatic data by adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN). Hydrol. Res. 44, 131–146. http://dx.doi.org/10.2166/nh.2012.074.

Bodian, A., Dezetter, A., Deme, A., Diop, L., 2016. Hydrological evaluation of TRMM rainfall over the Upper Senegal River Basin. Hydrology 3, 15. http://dx.doi.org/10.3390/hydrology3020015.

Cai, J.B., Liu, Q.X., Liu, Y., 2004. Predicting of daily reference evapotranspiration via adaptive neuro-fuzzy inference system (ANFIS). L. Water Manag. Decis. Tools Pract. 1 (2), 485–489.

Çekmiş, A., Hacihasanoğlu, I., Ostwald, M.J., 2014. A computational model for accommodating spatial uncertainty: predicting inhabitation patterns in open-planned spaces. Build. Environ. 73, 115–126. http://dx.doi.org/10.1016/j.buildenv.2013.11.023.

Ch, S., Anand, N., Panigrahi, B.K., Mathur, S., 2013. Streamflow forecasting by SVM with quantum behaved particle swarm optimization. Neurocomputing 101, 18–23. http://dx.doi.org/10.1016/j.neucom.2012.07.017.

Chai, T., Draxler, R.R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature. Geosci. Model. Dev. 7, 1247–1250. http://dx.doi.org/10.5194/gmd-7-1247-2014.

Citakoglu, H., Cobaner, M., Haktanir, T., Kisi, O., 2014. Estimation of monthly mean reference evapotranspiration in Turkey. Water Resour. Manag. 28, 99–113. http://dx.doi.org/10.1007/s11269-013-0474-1.

Cobaner, M., 2011. Evapotranspiration estimation by two different neuro-fuzzy inference systems. J. Hydrol. 398, 292–302. http://dx.doi.org/10.1016/j.jhydrol.2010.12.030.

Cortés, E., Algredo-Badillo, I., García, V.H., 2012. Performance analysis of ANFIS in short term wind speed prediction. IJCSI Int. J. Comput. Sci. (9), 9.

Deo, R.C., Şahin, M., 2015. Application of the artificial neural network model for prediction of monthly standardized precipitation and evapotranspiration index using hydrometeorological parameters and climate indices in eastern Australia. Atmos. Res. 161–162, 65–81. http://dx.doi.org/10.1016/j.atmosres.2015.03.018.

Fahimi, F., Yaseen, Z.M., El-shafie, A., 2016. Application of soft computing based hybrid models in hydrological variables modelling: a comprehensive review. Theor. Appl. Climatol. 1–29. http://dx.doi.org/10.1007/s00704-016-1735-8.

Feng, Y., Cui, N., Gong, D., Zhang, Q., Zhao, L., 2017. Evaluation of random forests and generalized regression neural networks for daily reference evapotranspiration modelling. Agric. Water Manag. 193, 163–173. http://dx.doi.org/10.1016/j.agwat.2017.08.003.

Ghorbani, M.A., Deo, R.C., Yaseen, Z.M.H., Kashani, M., Mohammadi, B., 2017. Pan evaporation prediction using a hybrid multilayer perceptron-firefly algorithm (MLP-FFA) model: case study in North Iran. Theor. Appl. Climatol. http://dx.doi.org/10.1007/s00704-017-2244-0.

Gromov, V.A., Shulga, A.N., 2012. Chaotic time series prediction with employment of ant colony optimization. Expert Syst. Appl. 39, 8474–8478. http://dx.doi.org/10.1016/j.eswa.2012.01.171.

Guo, J., Zhou, J., Qin, H., Zou, Q., Li, Q., 2011. Monthly streamflow forecasting based on improved support vector machine model. Expert Syst. Appl. 38, 13073–13081. http://dx.doi.org/10.1016/j.eswa.2011.04.114.

Hameed, M., Sharqi, S.S., Yaseen, Z.M., Afan, H.A., Hussain, A., Elshafie, A., 2016. Application of artificial intelligence (AI) techniques in water quality index prediction: a case study in tropical region, Malaysia. Neural Comput. Appl. 1–13. http://dx.doi.org/10.1007/s00521-016-2404-7.

Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99. http://dx.doi.org/10.13031/2013.26773.

Ho, W.H., Chen, J.X., Lee, I.N., Su, H.C., 2011. An ANFIS-based model for predicting adequacy of vancomycin regimen using improved genetic algorithm. Expert Syst. Appl. 38, 13050–13056. http://dx.doi.org/10.1016/j.eswa.2011.04.109.

Jang, J.S.R., 1993. ANFIS: adaptive-network-based fuzzy inference system. IEEE Trans. Syst. Man Cybern. 23, 665–685. http://dx.doi.org/10.1109/21.256541.

Jensen, M.E., Burman, R.D., Allen, R.G., 1990. Evapotranspiration and Irrigation Water Requirements. ASCE.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S.I., Sheffield, J., Goulden, M.L., Bonan, G., Cescatti, A., Chen, J., de Jeu, R., Dolman, A.J., Eugster, W., Gerten, D., Gianelle, D., Gobron, N., Heinke, J., Kimball, J., Law, B.E., Montagnani, L., Mu, Q., Mueller, B., Oleson, K., Papale, D., Richardson, A.D., Roupsard, O., Running, S., Tomelleri, E., Viovy, N., Weber, U., Williams, C., Wood, E., Zaehle, S., Zhang, K., 2010. Recent decline in the global land evapotranspiration trend due to limited moisture supply. Nature 467, 951–954. http://dx.doi.org/10.1038/nature09396.

Karimaldini, F., Shui, L.T., Mohamed, T.A., Abdollahi, M., Khalili, N., 2012. Daily evapotranspiration modelling from limited weather data by using neuro-fuzzy computing technique. J. Irrig. Drain. Eng. 138, 21–34. http://dx.doi.org/10.1061/(Asce)Ir.1943-4774.0000343.

Kaur, A., Kaur, A., 2012. Comparison of mamdani-type and sugeno-type fuzzy inference systems for air conditioning system. Int. J. Soft Comput. Eng. 2, 323–325.

Kisi, Ö., 2006. Generalized regression neural networks for evapotranspiration modelling. Hydrol. Sci. J. 51, 1092–1105.

Kisi, O., 2007. Evapotranspiration modelling from climatic data using a neural computing technique. Hydrol. Process. 21, 1925–1934. http://dx.doi.org/10.1002/hyp.6403.

Kisi, O., 2008. The potential of different ANN techniques in evapotranspiration modelling. Hydrol. Process. 22, 2449–2460. http://dx.doi.org/10.1002/hyp.6837.

Kisi, O., 2016. Modelling reference evapotranspiration using three different heuristic regression approaches. Agric. Water Manag. 169, 162–172. http://dx.doi.org/10.1016/j.agwat.2016.02.026.

Kisi, Ö., Ozturk, O., 2007. Adaptive neurofuzzy computing technique for evapotranspiration estimation. J. Irrig. Drain. Eng. 133, 368–379.

Kisi, O., Sanikhani, H., Zounemat-Kermani, M., Niazi, F., 2015. Long-term monthly evapotranspiration modelling by several data-driven methods without climatic data. Comput. Electron. Agric. 115, 66–77. http://dx.doi.org/10.1016/j.compag.2015.04.015.

Krishna Kumar, K., Hoerling, M., Rajagopalan, B., 2005. Advancing dynamical prediction of Indian monsoon rainfall. Geophys. Res. Lett. 32, 1–4. http://dx.doi.org/10.1029/2004GL021979.

Kumar, M., Raghuwanshi, N., 2002. Estimating evapotranspiration using artificial neural network. J. Irrig. 454–457.

Kumar, M., Raghuwanshi, N.S., Singh, R., 2011. Artificial neural networks approach in evapotranspiration modelling: a review. Irrig. Sci. http://dx.doi.org/10.1007/s00271-010-0230-8.

Ladlani, I., Houichi, L., Djemili, L., Heddam, S., Belouz, K., 2014. Estimation of daily reference evapotranspiration (ET0) in the North of Algeria using adaptive neuro-fuzzy inference system (ANFIS) and multiple linear regression (MLR) models: a comparative study. Arab. J. Sci. Eng. 39, 5959–5969. http://dx.doi.org/10.1007/s13369-014-1151-2.

Lamine, D., Ansoumana, B., Dior, D., 2015. Use of atmometers to estimate reference evapotranspiration in Arkansas. Afr. J. Agric. Res. 10, 4376–4383. http://dx.doi.org/10.5897/AJAR2015.10332.

Lee, B.H., Scholz, M., 2006. A comparative study: prediction of constructed treatment wetland performance with K-nearest neighbors and neural networks. Water Air. Soil. Pollut. 174, 279–301. http://dx.doi.org/10.1007/s11270-006-9113-2.

Liu, S., Tai, H., Ding, Q., Li, D., Xu, L., Wei, Y., 2013. A hybrid approach of support vector regression with genetic algorithm optimization for aquaculture water quality prediction. Math. Comput. Model. 58, 458–465. http://dx.doi.org/10.1016/j.mcm.2011.11.021.

Lohani, A.K., Kumar, R., Singh, R.D., 2012. Hydrological time series modelling: a comparison between adaptive neuro-fuzzy, neural network and autoregressive techniques. J. Hydrol. 442–443, 23–35. http://dx.doi.org/10.1016/j.jhydrol.2012.03.031.

Maier, H.R., Morgan, N., Chow, C.W.K., 2004. Use of artificial neural networks for predicting optimal alum doses and treated water quality parameters. Environ. Model. Softw. 19, 485–494. http://dx.doi.org/10.1016/S1364-8152(03)00163-4.

Marshall, M., Funk, C., Michaelsen, J., 2012. Examining evapotranspiration trends in Africa. Clim. Dyn. 38, 1849–1865. http://dx.doi.org/10.1007/s00382-012-1299-y.

Mayilvaganan, M.K., Naidu, K.B., 2011. ANN and fuzzy logic models for the prediction of groundwater level of a watershed. Int. J. Comput. Sci. Eng. 3, 2523–2530.

Nagy, H.M., Watanabe, K., Hirano, M., 2002. Prediction of sediment load concentration in rivers using artificial neural network model. J. Hydraul. Eng. 128, 588–595. http://dx.doi.org/10.1061/(ASCE)0733-9429(2002)128:6(588).

Naoum, S., Tsanis, I.K., 2003. Hydroinformatics in evapotranspiration estimation. Environ. Model. Softw. 18, 261–271. http://dx.doi.org/10.1016/S1364-8152(02)00076-2.

Nourani, V., Kisi, Ö., Komasi, M., 2011. Two hybrid artificial intelligence approaches for modelling rainfall-runoff process. J. Hydrol. 402, 41–59. http://dx.doi.org/10.1016/j.jhydrol.2011.03.002.

Nourani, V., Hosseini Baghanam, A., Adamowski, J., Kisi, O., 2014. Applications of hybrid wavelet-artificial intelligence models in hydrology: a review. J. Hydrol. 514, 358–377. http://dx.doi.org/10.1016/j.jhydrol.2014.03.057.

Parmar, K., Bhardwaj, R., 2014. Water quality management using statistical analysis and time-series prediction model. Appl. Water Sci. 4, 1–10. http://dx.doi.org/10.1007/s13201-014-0159-9.

Patil, A.P., Deka, P.C., 2017. Performance evaluation of hybrid wavelet-ANN and wavelet-ANFIS models for estimating evapotranspiration in arid regions of India. Neural Comput. Appl. 28, 275–285. http://dx.doi.org/10.1007/s00521-015-2055-0.

Penman, H.L., 1948. Natural evaporation from open water, bare soil and grass. Proc. R. Soc. Lond. Ser. A Math. Phys. Sci. 193, 120–145. http://dx.doi.org/10.1098/rspa.1948.0037.

Rana, G., Katerji, N., 2000. Measurement and estimation of actual evapotranspiration in the field under Mediterranean climate: a review. Eur. J. Agron. 13, 125–153. http://dx.doi.org/10.1016/S1161-0301(00)00070-8.

Rasouli, K., Hsieh, W.W., Cannon, A.J., 2010. Short lead-time streamflow forecasting by machine learning methods, with climate variability incorporated. World Environ. Water Resour. Congr. 2010, 4608–4619. http://dx.doi.org/10.1061/41114(371)468.

Rezapour, O.M., Shui, L.T., Ahmad, D.B., 2010. Review of artificial neural network model for suspended sediment estimation. Aust. J. Basic. Appl. Sci. 4, 3347–3353.

Schüttemeyer, D., Schillings, C., Moene, A.F., de Bruin, H.A.R., 2007. Satellite-based actual evapotranspiration over drying semiarid terrain in West Africa. J. Appl. Meteorol. Climatol. 46, 97–111. http://dx.doi.org/10.1175/JAM2444.1.

Shiri, J., Kişi, Ö., Landeras, G., López, J.J., Nazemi, A.H., Stuyt, L.C.P.M., 2012. Daily reference evapotranspiration modelling by using genetic programming approach in the Basque Country (Northern Spain). J. Hydrol. 414–415, 302–316. http://dx.doi.org/10.1016/j.jhydrol.2011.11.004.

Sudheer, C., Maheswaran, R., Panigrahi, B.K., Mathur, S., 2013. A hybrid SVM-PSO model for forecasting monthly streamflow. Neural Comput. Appl. 1–9. http://dx.doi.org/10.1007/s00521-013-1341-y.

Sun, Z., Gebremichael, M., Ardö, J., Nickless, A., Caquet, B., Merboldh, L., Kutschi, W., 2012. Estimation of daily evapotranspiration over Africa using MODIS/Terra and SEVIRI/MSG data. Atmos. Res. 112, 35–44. http://dx.doi.org/10.1016/j.atmosres.2012.04.005.

Tabari, H., Kisi, O., Ezani, A., Hosseinzadeh Talaee, P., 2012. SVM, ANFIS, regression and climate based models for reference evapotranspiration modelling using limited climatic data in a semi-arid highland environment. J. Hydrol. 444–445, 78–89. http://dx.doi.org/10.1016/j.jhydrol.2012.04.007.

Takagi, T., Sugeno, M., 1985. Fuzzy identification of systems and its applications to modelling and control. IEEE Trans. Syst. Man Cybern SMC-15, 116–132. http://dx.doi.org/10.1109/TSMC.1985.6313399.

Taylor, K.E., 2001. Summarizing multiple aspects of model performance in a single diagram. J. Geophys. Res. Atmos. 106, 7183–7192. http://dx.doi.org/10.1029/2000JD900719.

Tayyab, M., Zhou, J., Zeng, X., Adnan, R., 2016. Discharge forecasting by applying artificial neural networks at the Jinsha River Basin, China. Eur. Sci. J. 12, 1857–7881. http://dx.doi.org/10.19044/esj.2016.v12n9p108.

Trajkovic, S., 2005. Temperature-based approaches for estimating reference evapotranspiration. J. Irrig. Drain. Eng. 131, 316–323. http://dx.doi.org/10.1061/(ASCE)0733-9437(2005)131:4(316).

Trajkovic, S., Todorovic, B., Stankovic, M., 2003. Forecasting of reference

evapotranspiration by artificial neural networks. J. Irrig. Drain. Eng. 129, 454–457. http://dx.doi.org/10.1061/(ASCE)0733-9437(2003)129:6(454).

Wieprecht, S., Tolossa, H.G., Yang, C.T., 2013. A neuro-fuzzy-based modelling approach for sediment transport computation. Hydrol. Sci. J. 58, 587–599. http://dx.doi.org/10.1080/02626667.2012.755264.

Wright, J.L., 1988. Daily and seasonal evapotranspiration and yield of irrigated Alfalfa in Southern Idaho. Agron. J. 80, 662. http://dx.doi.org/10.2134/agronj1988.00021962008000040022x.

Wu, C.L., Chau, K.W., 2013. Prediction of rainfall time series using modular soft computingmethods. Eng. Appl. Artif. Intell. 26, 997–1007. http://dx.doi.org/10.1016/j.engappai.2012.05.023.

Yang, X.-S., 2010. Firefly algorithm, stochastic test functions and design optimization. Int. J. Bio-Inspired Comput 2 (2), 78–84. http://dx.doi.org/10.1504/IJBIC.2010.032124.

Yaseen, Z.M., El-Shafie, A., Afan, H.A., Hameed, M., Mohtar, W.H.M.W., Hussain, A., 2015a. RBFNN versus FFNN for daily river flow forecasting at Johor River, Malaysia. Neural Comput. Appl. http://dx.doi.org/10.1007/s00521-015-1952-6.

Yaseen, Z.M., El-shafie, A., Jaafar, O., Afan, H.A., Sayl, K.N., 2015b. Artificial intelligence based models for stream-flow forecasting: 2000–2015. J. Hydrol. 530, 829–844. http://dx.doi.org/10.1016/j.jhydrol.2015.10.038.

Yaseen, Z., Kisi, O., Demir, V., 2016a. Enhancing long-term streamflow forecasting and predicting using periodicity data component: application of artificial intelligence. Water Resour. Manag. http://dx.doi.org/10.1007/s11269-016-1408-5.

Yaseen, Z.M., Allawi, M.F., Yousif, A.A., Jaafar, O., Hamzah, F.M., El-Shafie, A., 2016b. Non-tuned machine learning approach for hydrological time series forecasting. Neural Comput. Appl. 1–13. http://dx.doi.org/10.1007/s00521-016-2763-0.

Yaseen, Z.M., Ebtehaj, I., Bonakdari, H., Deo, R.C., Mehr, A.D., Hanna, W., Wan, M., Diop, L., El-shafie, A., Singh, V.P., 2017. Novel approach for streamflow forecasting using a hybrid ANFIS-FFA model. J. Hydrol.

Yitian, L., Gu, R.R., 2003. Modelling flow and sediment transport in a river system using an artificial neural network. Environ. Manage. 31, 122–134. http://dx.doi.org/10.1007/s00267-002-2862-9.