Agricultural and Forest Meteorology 263 (2018) 41–48

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

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

Modelling reference evapotranspiration using a new wavelet conjunction heuristic method: Wavelet extreme learning machine vs wavelet neural networks

Ozgur Kisi[a], Meysam Alizamir[b,*]

[a] Ilia State University, Faculty of Natural Sciences and Engineering, Tbilisi, Georgia
[b] Young Researchers and Elite Club, Hamedan Branch, Islamic Azad University, Hamedan, Iran

ARTICLE INFO

Keywords:
Evapotranspiration
Estimation
Discrete wavelet transform
Extreme learning machine
Neural networks

ABSTRACT

Evapotranspiration is an important parameter in linking ecosystem functioning, climate and carbon feedbacks, agricultural management, and water resources. This study investigates the applicability of wavelet extreme learning machine (WELM) model which uses discrete wavelet transform and ELM methods in estimating daily reference evapotranspiration (ET_0). Various combination of climatic data of temperature, solar radiation, relative humidity and wind speed from two stations, Ankara and Kirikkale, located in central Anatolia region of Turkey were used as inputs to the WELM models. The WELM estimates were compared with wavelet artificial neural networks (WANN) and single artificial neural network (ANN), ELM and online sequential ELM (OS-ELM) models. The results indicate that the models comprising four input variables as inputs provide better accuracy than the models with less inputs. Solar radiation was found to be the most effective variable on ET_0. Wavelet conjunction models (e.g. WELM and WANN) generally show better accuracy compared to the single models and WELM model is found to be the best model in estimating ET_0. The root mean square error and mean relative error accuracies of the ELM, ANN and WANN models were improved by 28–25%, 32–32% and 27–26% for the Ankara Station and by 14–14%, 58–58% and 32–36% for the Kirikkale Station.

1. Introduction

Evapotranspiration is the principal component of the hydrological cycle which affects water requirements for irrigation and it also has an important effect on planning and management of water resources. Evapotranspiration can be obtained either directly (experimentally) or indirectly (mathematically). It can be directly measured by utilizing a lysimeter in a controlled crop area. However, the main disadvantages of this method are its difficulty, high cost and time-consuming procedure (Gavilan et al., 2007; Yassin et al., 2016). Accurately estimation of reference evapotranspiration (ET_0) is very important for irrigation water requirements and optimizing irrigation scheduling, crop quality and productivity. ET_0 represents the evapotranspiration from a hypothetical reference surface and indicate the evaporative demand of the atmosphere independent of management practices, crop type and development (Marti and Zarzo, 2012).

Researchers have developed lots of estimating the ET_0 over the last five decades. Selection of the method is dependent on the availability of observed climatic variables such as air temperature, relative humidity, wind speed and solar radiation. The FAO Penman–Monteith (FAO 56 PM) method was accepted as a standard method for estimation of ET_0 and it is commonly used in agricultural and environmental researches. The main disadvantage of this method is that it needs a high number of climatic data which may be unavailable or missing in some locations especially in developing countries. Therefore, alternative approaches that requires less weather inputs are needed (Yassin et al., 2016).

In recent years, successful applications of soft computing approaches such as Extreme Learning Machine (ELM), Artificial Neural Networks (ANN) and Online Sequential Extreme Learning Machine (OS-ELM) has received a great deal of attention as efficient methods in prediction of complicated and complex time series in hydrology and water resources. ELM is a novel training algorithm for single-hidden layer neural networks proposed by Huang et al. (2006). Şahin et al. (2014) studied capability of ELM as a predictive model to estimate solar radiation from satellite data in Turkey and found that it gave better results compared to ANN. Lima et al. (2015) investigated accuracy of OS-ELM as a non-linear regression model in environmental sciences and

* Corresponding author.
E-mail address: Meysamalizamir@gmail.com (M. Alizamir).

https://doi.org/10.1016/j.agrformet.2018.08.007
Received 13 March 2018; Received in revised form 11 August 2018; Accepted 13 August 2018
0168-1923/

it was found to be better than the online sequential multiple linear regression. Abdullah et al. (2015) developed a reference evapotranspiration predicting model based on ELM and found better results compared to ANN. Shiri et al. (2016) investigated ability of ELM, Genetic programing (GP) and ANN to predict the Urmia Lake level. The results of the study showed significant performance of ELM compared with other methods. Rezaie-Balf and Kisi (2017) estimated streamflow in three stations using ELM and showed the superior accuracy of this method to ANN. Heddam and Kisi (2017) applied ELM for modeling dissolved oxygen concentration and obtained more accurate results compared to ANN. Alizamir et al. (2017) applied ELM to predict groundwater level fluctuations. The results of the study revealed superiority of ELM compared to ANN, radial basis function (RBF) and autoregressive moving average approaches.

Recently, wavelet analysis is found to be a useful tool in modeling and predicting complex hydrological time series. This technique by overcoming the drawbacks of Fourier analysis, can provide sub-series of time series to improve accuracy of a forecasting model by extracting significant information at various levels. Numerous studies have been presented successful application of wavelet transform in noisy phenomena. Rajaee (2010) investigated performance of a conjunction model based on wavelet technique and neuro-fuzzy method for estimating suspended sediment load. Results showed that the combined model can provide more accurate outputs compared to multi linear regression and the conventional sediment rating curve. Wang et al. (2011) applied the combination of wavelet and neural network in the flood simulation. Based on comparisons, the model showed strong ability to predict the flood event. Kisi and Cimen (2012) predicted daily rainfall of two stations in Turkey using wavelet-support vector machines hybrid model. Results revealed superiority of the model compared to ANN and support vector machines. Xu and Liu (2013) applied wavelet ANN (WANN) for forecasting water quality. The WANN performed better than the back propagation and Elman neural networks. Falamarzi et al. (2014) estimated evapotranspiration by WANN and obtained more accurate results compared to ANN. Partal et al. (2015) studied the prediction of daily precipitation by combination of wavelet transform and neural network models. They found WANN to be better than the ANN, RBF and generalized regression neural network. Barzegar et al. (2017) applied wavelet extreme learning machine (WELM) for estimating water quality. Results illustrated that the WELM had a stronger predicting accuracy than the wavelet neuro fuzzy models. Samadianfard et al. (2018) estimated soil temperature using WANN, genetic programming and neural network. Results demonstrated that WANN model forecasted soil temperature more accurately than the other models.

Previous studies showed that the integration of wavelet analysis and ELM approaches might be beneficial in modeling ET_0. There is no study reported in the literature related to application of WELM in modeling ET_0. The aims of this study are i) to apply WELM in modeling ET_0 using various climatic variables as inputs and ii) to compare the accuracy of WELM with those of the WANN, OS-ELM, ELM and ANN models.

2. Materials and methods

2.1. Case study

Daily climatic data of minimum air temperature (T_{min}), maximum air temperature (T_{max}), solar radiation (SR), mean relative humidity (RH) and wind speed (W) from two stations, Ankara (latitude 39° 58′N and longitude 32° 51′E altitude 891 m) and Kirikkale (latitude 39° 50′N and longitude 33° 31′E altitude 751 m) located in Central Anatolia Region (CAR) were employed in this study. The data which have a period of 1985–2005 (20 years) were obtained from the Turkey State Meteorological Service. The location of the stations can be seen from Fig. 1. The annual average total precipitation for CAR is over 800 mm (Kahya and Karabork, 2001). The region has a flat topography surrounded by highlands and a semi-arid climate. It has hot and dry summers, and cold and rainy-snowy winters (Atalay, 1994; Akkemik and Aras, 2005).

2.2. Extreme learning machine

Huang et al. (2006) proposed a new training algorithm for single-hidden layer feedforward neural networks (SLFNNs) to overcome drawbacks of traditional learning approaches such as the gradient descent-based training algorithms. The ELM has several significant and interesting advantages compared to conventional learning methods such as back-propagation algorithms, including 1) the ELM is faster than other training algorithms, 2) the network can meet better generalization performance by employing the ELM, 3) all parameters of the network can be tuned iteratively by more accuracy, 4) the ELM can prevent the network from over-fitting or local minima, 5) the ELM can apply non-differentiable transfer functions to train SLFNNs, 6) the ELM can randomly generate network weights in the hidden layer and it can determine the output weights analytically.

The standard SLFNN with N hidden nodes can be defined as:

$$\sum_{i=1}^{N} \beta_i g(x_k, ;c_i a_i) = y_k,\ k = 1, 2, \ldots, M \tag{1}$$

where $g(.)$, c_i and β_i are transfer function, randomly specified bias and weight vector connection the hidden nodes to output nodes. The Eq. (1) can be written as:

$$H\beta = Y \tag{2}$$

where

$$H = \begin{bmatrix} g(x_1; c_1, w_1) & \cdots & g(x_1; c_m, w_M) \\ g(x_N; c_1, w_1) & \cdots & g(x_N; c_M, w_M) \end{bmatrix}_{N*M} \tag{3}$$

$$H\beta = (\beta_1^T \beta_2^T, \ldots, \beta_L^T)^T_{m*M} \tag{4}$$

The output weights can be found by least square solutions by employing the Moore–Penrose generalized inverse (H^+) of the hidden layer matrix.

$$\beta = H^+ Y \tag{5}$$

The ELM has been utilized widely as a robust and accurate non-linear regression model in various fields including hydrology and water resources (Alizamir et al., 2017; Shamshirband et al., 2016; Sokolov-Mladenović et al., 2016).

2.3. Online sequential extreme learning machine (OS-ELM)

OS-ELM is a robust and reliable online sequential modeling approach for SLFNNs that can learn the training data one by one or chunk by chunk by removing redundant data (Liang et al., 2006). It applies additive and radial basis function (RBF) hidden nodes (Eq. (6) and (7)). For additive hidden node by applying sigmoid activation function, the output of hidden node can be described as:

$$G(a_i, b_i, x) = g(a_i . x + b_i) \tag{6}$$

where a_i is the weight matrix linking input layer to the hidden node and b_i is the bias in the hidden node. For RBF hidden node by employing Gaussian transfer function, the output of hidden node can be described as:

$$G(a_i, b_i, x) = g(b_i \,||x - a_i||) \tag{7}$$

where a_i and b_i are the center and impact factor of RBF node. Also, in the OS-ELM, H^+ of Eq. (5) is given by:

$$H^+ = (H^T H)^{-1} H^T \tag{8}$$

By substituting Eq. (8) into Eq. (5), β can be defined: