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Comparative analysis of reference evapotranspiration equations modelling by extreme learning machine

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ABSTRACT

This study presents an extreme learning machine (ELM) approach, for estimating monthly reference evapotranspiration (ET_0) in two weather stations in Serbia (Nis and Belgrade stations), for a 31-year period (1980–2010). The data set including minimum and maximum air temperatures, actual vapour pressure, wind speed and sunshine hours was employed for modelling ET_0 using the adjusted Hargreaves ($ET_{0,AHARG}$), Priestley–Taylor ($ET_{0,PT}$) and Turc ($ET_{0,T}$) equations. The reliability of the computational model was accessed based on simulation results and using five statistical tests including mean absolute percentage error (MAPE), mean absolute deviation (MAD), root-mean-square error (RMSE), Pearson correlation coefficient (r) and coefficient of determination (R^2). The validity of ELM modelled ET_0 are compared with the FAO-56 Penman–Monteith equation ($ET_{0,PM}$) which is used as the reference model. For the Belgrade and Nis stations, the $ET_{0,AHARG}$ ELM model with MAPE = 9.353 and 10.299%, MAD = 0.142 and 0.151 mm/day, RMSE = 0.180 and 0.192 mm/day, r = 0.994 and 0.992, R^2 = 0.988 and 0.984 in testing period, was found to be superior in modelling monthly ET_0 than the other models, respectively.

1. Introduction

Reference evapotranspiration (ET_0), introduced by the United Nations Food and Agriculture Organization (FAO) as a methodology for computing crop evapotranspiration (Doorenbos and Pruitt, 1977), can be measured using lysimeter, eddy covariance systems, bowen ratio-energy balance, scintillometer (Benli et al., 2006; Miranda et al., 2006; Williams and Ayars, 2005; Liu et al., 2013, 2012; Savage, 2009; Savage et al., 2009) or calculated using equations based on temperature, radiation or pan evapouration or combination-type equations. ET_0 is needed for the management of water resources, irrigation scheduling and agricultural production. Potential improvement of crop yields requires knowledge of supplementary irrigation and water balance model, in which one of the important components is evapotranspiration (Djaman and Irmak, 2013).

The FAO-56 Penman–Monteith (FAO-56 PM) equation (Allen et al., 1998) has been applied to be more superior in comparison with other ET_0 empirical models, and has been recommended as the reference equation (Gavilan et al., 2007; Lopez-Urrea et al., 2006; Pereira et al., 2015; Sentelhas et al., 2010). It can be validated using lysimeters under various climatic conditions. The FAO-56 PM requires a full-set of weather data i.e. such as minimum and maximum air temperatures, relative humidity, wind speed and radiation which are not available in the most of the stations. This is a major disadvantage of the FAO-56 PM equation (Gocic and Trajkovic, 2010; Todorovic et al., 2013; Valiantzas, 2015). Thus, the adjusted Hargreaves (Trajkovic, 2007), Priestley–Taylor (1972) and Turc (1961) equations were applied in this study because they do not require the full-set of weather data.

Computational intelligence (soft computing) methods can be used as alternative techniques in estimating and forecasting ET_0. For instance, the artificial neural network (ANN) has been applied in creating a model of evapotranspiration process (Sudheer et al., 2003; Kisi, 2007; Khoob, 2008; Kumar et al., 2011; Landeras et al., 2008; Cobaner, 2011). The adaptive neuro-fuzzy inference system (ANFIS) has been developed and applied to estimate ET_0 (Shiri et al., 2011; Kisi and Zounemat-Kermani, 2014; Citakoglu et al., 2014; Petkovic et al., 2015). Genetic programming (GP) is used for mathematical formulation of the ET_0 (Kisi and Cengiz, 2013; Traore and Guven, 2012; Shiri et al., 2014a). Support vector machine (SVM) and wavelet neural networks are one of the novel soft learning algorithms that has been applied in ET_0 modelling (Kisi and Cimen, 2009; Kisi, 2011; Cobaner, 2013; Shiri et al., 2014b; Gocic et al., 2015).

Recently, the Extreme Learning Machine (ELM) has been introduced as an algorithm for single layer feed forward neural network

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(Huang et al., 2004; Wang and Han, 2014; Tavares et al., 2015). It is capable to solve problems caused by gradient descent based algorithms like back propagation which applied in ANNs, and to decrease required time for training neural network. Several researchers applied ELM to solve the problems in different scientific fields. Nian et al. (2014) applied ELM towards dynamic model hypothesis in fish ethology research. The ELM can be used for prediction of non-stationary time series (Wang and Han, 2014), dynamic voltage stability status (Velayati et al., 2015), short-term load (Li et al., 2015) and bankruptcy (Yu et al., 2014) or in solving classification problems (Yin et al., 2015). The review of ELM trends can be found in Huang et al. (2015). Abdullah et al. (2015) applied ELM to predict Penman–Monteith ET_0 for three meteorological stations in Iraq, and concluded that ELM can be used on both complete and incomplete sets of weather data. Feng et al. (2016) used ELM, backpropagation neural networks optimized by genetic algorithm (GANN) and wavelet neural networks (WNN) models to estimate ET_0 and concluded ELM and GANN models were much better than WNN model.

The main aim of this study is to apply ELM approach in modelling of monthly ET_0 using the following models: adjusted Hargreaves, Priestley–Taylor and Turc methods. These methods are selected because they require the minimum weather data in their calculation. The performance of ELM models is compared with the FAO-56 PM equation. The value of the ET_0 calculated with mean monthly weather data is very similar to the average of the daily ET_0 values calculated with daily average weather data for that month (Allen et al., 1998).

2. Studied region and used data

The monthly set of meteorological data of two meteorological stations in Serbia, Belgrade (latitude 44°48′N, longitude 20°28′E, elevation 132 m) and Nis (latitude 43°20′N, longitude 21°54′E, elevation 204 m), were used in this study.

The data sample covers 31 years (1980–2010) of monthly records of maximum (T_{max}) and minimum (T_{min}) air temperatures, actual vapour pressure (e_a), wind speed (U_2) and sunshine hours (n). Mean annual values of the meteorological variables for the selected stations used in this study during the period 1980–2010 are presented in Fig. 1. The mean monthly n is 172.1 and 163.1 h for Belgrade and Nis, respectively. The selected data were used in calculating ET_0 that is applied on the study area for management of water resources and irrigation scheduling.

3. Methodology

3.1. Methods for estimating reference evapotranspiration

3.1.1. FAO-56 Penman–Monteith equation

The FAO-56 Penman–Monteith (PM) equation (Allen et al., 1998) is used to estimate reference evapotranspiration:

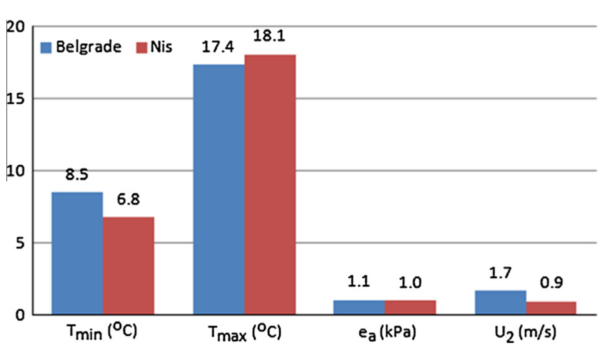

Fig. 1. Mean annual values of the meteorological variables for two selected stations during the period 1980–2010.

$$ET_{0,PM} = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \tag{1}$$

where $ET_{0,PM}$ is reference evapotranspiration (mm day^{-1}), Δ is slope of the saturation vapour pressure function (kPa °C^{-1}), R_n is net radiation (MJ m^{-2} day^{-1}), G is soil heat flux density (MJ m^{-2} day^{-1}), γ is psychrometric constant (kPa °C^{-1}), T is mean air temperature (°C), U_2 is average 24-h wind speed at 2 m height (m s^{-1}), e_s is saturation vapour pressure (kPa); e_a is actual vapour pressure (kPa), and $e_s - e_a$ is vapour pressure deficit (kPa).

3.1.2. Adjusted Hargreaves equation

Trajkovic (2007) developed the adjusted Hargreaves equation that provides close agreement with FAO-56 PM estimates at humid locations, which can be written as:

$$ET_{0,AHARG} = 0.0023R_a(T_{max} - T_{min})^{0.424}\left(\frac{T_{max} + T_{min}}{2} + 17.8\right) \tag{2}$$

where $ET_{0,AHARG}$ is ET_0 estimated by the adjusted Hargreaves equation (mm day^{-1}), T_{max} and T_{min} are maximum and minimum air temperatures (°C), respectively, and R_a is extraterrestrial radiation (mm day^{-1}).

3.1.3. Priestley–Taylor equation

Priestley and Taylor (1972) proposed a simplified version of the Penman equation for use when surface areas are wet:

$$ET_{0,PT} = \alpha\frac{\Delta}{\Delta + \gamma}(R_n - G) \tag{3}$$

where α is empirical constant (α = 1.26), Δ is slope of the saturation vapour pressure curve (kPa °C^{-1}), γ is psychrometric constant (kPa°C^{-1}), R_n is net radiation (MJ m^{-2} day^{-1}), and G is soil heat flux (MJ m^{-2} day^{-1}). Net radiation, the psychrometric constant and the slope of the saturation vapour pressure curve were calculated using the FAO-56 procedure and the soil heat flux was assumed to be 0 based on Allen et al. (1998).

3.1.4. Turc equation

Turc equation (Turc, 1961) is one of the most accurate empirical equations used to estimate ET_0 under humid conditions (Jensen et al., 1990; Trajkovic and Kolakovic, 2009):

$$ET_{0,T} = 0.013\left(23.88\left(0.25 + 0.5\frac{n}{N}\right)R_a + 50\right)T(T + 15)^{-1} \tag{4}$$

where N is maximum possible duration of sunshine (h), T is mean air temperature (°C), n is actual duration of sunshine (h), and R_a is extraterrestrial radiation (MJ m^{-2} day^{-1}).

3.2. Extreme learning machine

Extreme Learning Machine (ELM) as a tool of learning algorithm, has been introduced for single layer feed-forward neural network (SLFN) architecture (Annema et al., 1994; Huang et al., 2004, 2006a). ELM chooses the input weights randomly and determines the output weights of SLFN analytically. ELM algorithm has more favourable general capability with faster learning speed and does not require too much human intervention, and can run much faster than the conventional algorithms. It is capable to determine all the network parameters analytically, which prevents trivial human intervention. ELM is an efficient algorithm with numerous advantages including ease of use, quick learning speed, higher performance, and suitability for many nonlinear activation and kernel functions (Huang et al., 2004, 2006a).