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Comparison of ELM, GANN, WNN and empirical models for estimating reference evapotranspiration in humid region of Southwest China

Yu Feng [a], Ningbo Cui [b,c,*], Lu Zhao [b], Xiaotao Hu [d], Daozhi Gong [a,1]

[a] State Engineering Laboratory of Efficient Water Use of Crops and Disaster Loss Mitigation/MOA Key Laboratory for Dryland Agriculture, Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agriculture Sciences, Beijing, China
[b] State Key Laboratory of Hydraulics and Mountain River Engineering & College of Water Resource and Hydropower, Sichuan University, Chengdu, China
[c] Provincial Key Laboratory of Water-Saving Agriculture in Hill Areas of Southern China, Chengdu, China
[d] Key Laboratory of Agricultural Soil and Water Engineering in Arid and Semiarid Areas, Ministry of Education, Northwest A&F University, Yangling, Shaanxi, China

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SUMMARY

Reference evapotranspiration (ET_0) is an essential component in hydrological ecological processes and agricultural water management. Accurate estimation of ET_0 is of importance in improving irrigation efficiency, water reuse and irrigation scheduling. FAO-56 Penman–Monteith (P–M) model is recommended as the standard model to estimate ET_0. Nevertheless, its application is limited due to the lack of required meteorological data. In this study, trained extreme learning machine (ELM), backpropagation neural networks optimized by genetic algorithm (GANN) and wavelet neural networks (WNN) models were developed to estimate ET_0, and the performances of ELM, GANN, WNN, two temperature-based (Hargreaves and modified Hargreaves) and three radiation-based (Makkink, Priestley–Taylor and Ritchie) ET_0 models in estimating ET_0 were evaluated in a humid area of Southwest China. Results indicated that among the new proposed models, ELM and GANN models were much better than WNN model, and the temperature-based ELM and GANN models had better performance than Hargreaves and modified Hargreaves models, radiation-based ELM and GANN models had higher precision than Makkink, Priestley–Taylor and Ritchie models. Both of radiation-based ELM (RMSE ranging 0.312–0.332 mm d^{-1}, E_{ns} ranging 0.918–0.931, MAE ranging 0.260–0.300 mm d^{-1}) and GANN models (RMSE ranging 0.300–0.333 mm d^{-1}, E_{ns} ranging 0.916–0.941, MAE ranging 0.2580–0.303 mm d^{-1}) could estimate ET_0 at an acceptable accuracy level, and are highly recommended for estimating ET_0 without adequate meteorological data.

1. Introduction

As the only term that appears in both water balance and surface energy balance equations (Xu and Singh, 2005), evapotranspiration (ET) is an essential component in hydrological and ecological processes, and plays a key role in agricultural water management. Reference evapotranspiration (ET_0) represents the ET from a hypothetical reference surface and is introduced to express the evaporative demand of the atmosphere independent of management practices, e.g. crop type and development (Martí et al., 2015), and it is frequently used to quantify ET. Thus, accurate estimation of ET_0 is important in improving irrigation efficiency, water reuse and drainage controlling (Shiri et al., 2014a). ET_0 can be measured by experimental techniques, which are the most common approaches. However, the methods of experimental techniques are expensive. ET_0 can express the evaporating power of the atmosphere at a specific location and time of the year and does not consider crop characteristic and soil factor (Torres et al., 2011). Allen et al. (1998) mentioned that the only factor affecting ET_0 is climatic variable, so ET_0 can be assessed by empirical and semi-empirical equations from meteorological data.

Many methods based on climatic data have already been proposed, the FAO-56 Penman–Monteith (P–M) established based on the principles of aerodynamic and energy balance has taken all factors influencing ET_0 into consideration, and it is introduced as the sole method to estimate ET_0 (Allen et al., 1998). Numerous results in different climate regions have proved the reliability of FAO-56 P–M method, so it is used as a standard method to evaluate other ET_0 other methods (Tabari et al., 2012, 2013). However, when computing ET_0 by FAO-56 P–M model, lots of climatic variables, including wind speed, solar radiation, humidity, and temperature are

* Corresponding author at: College of Water Resource and Hydropower, Sichuan University, 610065 Chengdu, China.

E-mail addresses: cuiningbo@126.com (N. Cui), gongdaozhi@caas.cn (D. Gong).

[1] Co-corresponding author at: Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agriculture Sciences, 100081 Beijing, China.

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needed and the calculation process is complex. Sometimes these variables are incomplete or not available in a given meteorological station, especially in developing countries (Traore et al., 2010). Hence it is imperative to develop a simpler approach which could compute ET_0 with high precision.

Numerous empirical models for estimating ET_0 with less climatic data can be classified as temperature-based, radiation-based, pan evaporation-based, mass transfer-based and combination type (Tabari et al., 2013). Thornthwaite (1948) firstly introduced the temperature-based Thornthwaite model for calculating the potential evapotranspiration; and Penman (1948) derived a model for estimation of evaporation from open surfaces by the combination of energy balance with mass transfer methods. Priestley and Taylor (1972) proposed the radiation-based Priestley–Taylor model, which was a simplification of the Penman model. Hargreaves and Samani (1985) introduced the maximum, minimum temperature and extraterrestrial radiation to calculate solar radiation, and then they proposed the temperature-based Hargreaves model, which was one of the simplest method. Almorox et al. (2015) assessed 11 temperature-based ET_0 methods for estimating ET_0 in 4362 meteorological stations worldwide, and it was found the Hargreaves method provided the most accurate global average performance in arid, semiarid, temperate, cold and polar climates.

The calculation of ET_0 can be considered as a complicated non-linear regression process depending on several climatic factors, so more researchers have put forward the ET_0 models based on soft computing techniques. Shiri et al. (2012) proposed ET_0 models based on gene expression programming (GEP) and adaptive neuro-fuzzy inference system (ANFIS) in northern Spain, compared these two models with Priestley–Taylor and Hargreaves models for estimating ET_0, and suggested that the GEP model was the best model in computing ET_0. Tabari et al. (2012) investigated the potential of support vector machines (SVM), ANFIS, multiple linear regression (MLR), multiple non-linear regression (MNLR), four temperature-based and eight radiation-based equations in ET_0 modeling in a semi-arid highland environment in Iran, and found that the SVM and ANFIS models were better than those of the regression and climate based models. Kisi (2013) investigated the applicability of Mamdani fuzzy genetic (MFG) and Sugeno fuzzy genetic (SFG) approaches in modeling daily ET_0 in Turkey, and indicated that the SFG method was faster and had better accuracy than the MFG method in modeling daily ET_0. Abdullah et al. (2015) found the ELM was proved to be efficient and of high speed, and had a very good generalization performance in modeling ET_0 in Iraq. The estimation accuracy of ET_0 in data scarce area was significantly improved with the establishment of computing models. These models showed strong adaptability around the world (Trajkovic, 2009; Landeras et al., 2008; Shiri et al., 2014a,b; Falamarzi et al., 2014). Although the model types, training data and climate characteristics of the study area may affect the accuracy of the models, they performed better than other empirical models under the same condition.

Recently a severe drought occurred in Southwest China during the period from the autumn of 2009 to the spring of 2010, which affected more than 60 million people (Yan et al., 2013). The Ministry of Civil Affairs of China revealed that the direct economic loss exceeded 23.66 billion CNY (Feng et al., 2014a). Water resources in Southwest China are vulnerable under the impacts of climate change and human activities, and the precise estimation of ET_0 is the first firm step in saving water (Abdullah et al., 2015). Developing models for accurately estimating ET_0 is highly needed in Southwest China. The main objectives of the current study are (I) to develop 3 computing models, ELM, artificial neural networks optimized by genetic algorithm (GANN) and wavelets neural networks (WNN), for modeling ET_0 in humid area of Southwest China (II) to compare the performances of ELM, GANN, WNN and empirical models in estimating ET_0 with limited data at different spatio-temporal scales.

2. Materials and methods

2.1. Study area and dataset

The weather data were obtained from 13 meteorological stations located in Hilly Area of Central Sichuan (HACS), Southwest China. HACS is a typical irrigated area, with an area of 84 thousand km^2. The geographical locations of the study area are shown in Fig. 1. The study area has a warm and humid climate, with frost-free days of 280–350 a year, mean annual temperature of 18 °C, mean annual precipitation of about 1041 mm and mean annual sunshine duration of 1150 h. Annul means of main climatic variables at each station during 1994–2013 were shown in Table 1.

Daily meteorological data during 1994–2013, including maximum and minimum air temperature, wind speed, relative humidity, sunshine duration, were collected from the National Climatic Centre of the China Meteorological Administration. The daily data during 1994–2008 of all related stations were used to train the ELM, GANN and WNN, and the rest of the data were used for validation.

All inputs to the ELM, GANN and WNN are normalized to fall between 0 and 1 to minimize the influence of absolute scale. The normalization scheme is as follows (Wen et al., 2015):

$$x_{\text{norm}} = \frac{x_0 - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

where x_{norm}, x_0, $x_{\min}$, and $x_{\max}$ are normalized value, real value, minimum value, and maximum value, respectively.

The stations of Bazhong, Suining, Xuyong and Yibin were selected to conduct detailed evaluation of the models since the geographic, geomorphic and meteorological conditions are relatively uniform. And the data of all 13 stations were used to analyze the spatial differences of the models.

2.2. Penman–Monteith model

ET_0 values computed by P–M model were used to evaluate the performance of other models. The P–M model could be the standard approach in modeling ET_0 in HACS due to its applicability (Zhao et al., 2012; Feng et al., 2014b). P–M model is expressed as the follows:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{\text{mean}}+273} U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \tag{2}$$

where ET_0 is reference evapotranspiration (mm d^{-1}), R_n is net radiation (MJ m^{-2} d^{-1}), G is soil heat flux density (MJ m^{-2} d^{-1}), T_{mean} is mean air temperature (°C), e_s is saturation vapor pressure, kPa; e_a is actual vapor pressure, kPa; Δ is slope of the saturation vapor pressure function (kPa °C^{-1}), γ is psychometric constant (kPa °C^{-1}), U_2 is wind speed at 2 m height (m s^{-1}). The calculation of all data required in estimating ET_0 followed the method and procedure in FAO-56 (Allen et al., 1998).

2.3. Empirical models

Two temperature-based models which only require maximum and minimum air temperature as the input data were selected to compute ET_0, including Hargreaves model (Hargreaves and Samani, 1985) and modified Hargreaves model (Hu et al., 2011).

Hargreaves model (Hargreaves and Samani, 1985):

$$ET_0 = 0.000939R_a(T_{\text{mean}} + 17.8)(T_{\max} - T_{\min})^{0.5} \tag{3}$$