Agricultural Water Management 169 (2016) 162–172

Contents lists available at ScienceDirect

Agricultural Water Management

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

Modeling reference evapotranspiration using three different heuristic regression approaches

Ozgur Kisi

Canik Basari University, Architectural and Engineering Faculty, Civil Eng. Dept., Samsun 55080, Turkey

ARTICLE INFO

Article history:
Received 16 December 2015
Received in revised form 23 February 2016
Accepted 24 February 2016
Available online 4 March 2016

Keywords:
Reference evapotranspiration
Heuristic regression approaches
Least square support vector regression
Multivariate adaptive regression splines
M5 model tree
Modeling

ABSTRACT

Modeling reference evapotranspiration (ET_0) is important in reservoir management, planning regional water resources and evaluation of drinking-water supplies. The study investigates the ability of three different heuristic regression approaches, least square support vector regression (LSSVR), multivariate adaptive regression splines (MARS) and M5 Model Tree (M5Tree) in modeling ET_0. The first part of the study focused on testing the accuracy of the LSSVR, MARS and M5Tree models in estimating the ET_0 data of Antalya and Isparta stations located in Mediterranean Region of Turkey. Cross-validation method was utilized in the applications. The LSSVR models were observed to be better than the MARS and M5Tree models in estimating ET_0 of Antalya and Isparta stations with local input and output data. The accuracy of the applied methods was investigated in estimation of ET_0 using air temperature, solar radiation, relative humidity and wind speed inputs from nearby station in the second part of the study (cross-station application without local input data). The results showed that the MARS models provided better accuracy than the LSSVR and M5Tree models with respect to SI, mean absolute error (MAE) and determination coefficient (R^2). In the third part of the study, the accuracy of the applied models was investigated in ET_0 estimation using input and output data from nearby station. The results showed that the M5Tree models outperformed the other models with respect to SI, MAE and R^2. The overall results showed that the LSSVR could be successfully used in estimating ET_0 by using local input and output data. In case of without local inputs, however, the MARS model performed better than the LSSVR and M5Tree models while the M5Tree was observed to be the best alternative for estimating ET_0 in the absence of local input and output data.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

Accurately estimation of evapotranspiration (ET) has great importance in many studies such as hydrologic water balance, design and management of irrigation system, crop yield simulation, planning and management of water resources. ET estimation is also very important for explaining many theoretical problems in field of hydrology and meteorology. ET data are used as the source for assessing the acreage of numerous crops that can be irrigated with the given water amount in the development of irrigation projects (Chauhan and Shrivastava, 2008).

In last decades, soft computing methods (e.g. artificial neural networks, support vector machine) have been successfully applied for modeling ET_0 (Marti et al., 2015; Shiri et al., 2013; Shiri et al., 2014; Shiri et al., 2015). Kisi (2006) developed two different feed-forward neural network models for estimation of daily reference evapotranspiration from climatic data. Kumar et al. (2008) used artificial neural network (ANN) for modeling reference crop evapotranspiration and compared with empirical methods. They found that the ANN models gave better closeness to FAO-56 Penman–Monteith (PM) ET_0 than the empirical methods. Gonzalez-Camacho et al. (2008) used a feed-forward back propagation ANN to estimate ET_0 from weather data of air temperature, solar radiation, relative humidity, and wind velocity. They showed that ANN models were good alternative prediction tools to statistical models such as linear and nonlinear regression models.

Dogan (2009) investigated the potential of a neuro-fuzzy (ANFIS) method for modeling daily grass crop ET_0 obtained using FAO-56 PM equation. Various combinations of daily climatic data were used as inputs to the ANFIS in order to evaluate the degree of effect of each variable on daily FAO-56 PM ET_0. The ANFIS technique comprising inputs of solar radiation, air temperature, relative humidity and wind speed provided the best accuracy. Kisi and Cimen (2009) investigated the accuracy of support vector machines (SVM), in modelling ET_0 utilizing daily meteorological data of solar

E-mail address: okisi@basari.edu.tr

http://dx.doi.org/10.1016/j.agwat.2016.02.026
0378-3774/© 2016 Elsevier B.V. All rights reserved.

List of symbols

The symbols used in the study are

ABC	Artificial bee colony
ANN	Artificial neural network
ANFIS	Neuro-fuzzy
EPR	Evolutionary polynomial regression
ET_0	Reference evapotranspiration
FAO-56 PM	FAO-56 Penman-Monteith
GP	Genetic programming
GRNN	Generalized regression neural networks
LSSVR	Least square support vector regression
MAE	Mean absolute error
MARS	Multivariate adaptive regression splines
M5Tree	M5 Model Tree
R^2	Determination coefficient
RBNN	Radial basis neural network
SI	Scatter index
SVM	Support vector machines.

radiation, air temperature, relative humidity and wind speed. They compared SVM with empirical methods and concluded that SVM could be successfully employed in modelling the ET_0 process. El-Baroudy et al. (2010) compared the accuracy of three different data-driven methods, evolutionary polynomial regression (EPR), ANNs and Genetic Programming (GP) in modeling ET_0. They found EPR to be comparable to the models of GP and ANNs. Wang et al. (2010) utilized ANN for modeling evapotranspiration process in arid region of Africa. They found that the ANN provided better accuracy than the empirical models. Ozkan et al. (2011) investigated the ability of ANN with artificial bee colony (ABC) algorithm in daily reference evapotranspiration modeling based on daily climatic data of solar radiation, air temperature, relative humidity, and wind speed from two stations, Pomona and Santa Monica, in Los Angeles, USA. They reported that the ANN-ABC and ANN with Levenberg–Marquardt were found to be superior alternative to the ANN with standard back-propagation models. Cobaner (2011) compared accuracy of two different ANFIS methods, grid partition based neuro-fuzzy and subtractive clustering based neuro-fuzzy, in ET_0 estimation and reported that the subtractive clustering based ANFIS model yielded good accuracy with fewer amounts of computations as compared to the grid partition based ANFIS and ANN models. Kumar et al. (2011) reviewed studies related to modeling ET_0 with ANN approach. They discussed 26 studies in this topic.

Ladlani et al. (2012) compared generalized regression neural networks (GRNN) and radial basis neural network (RBNN) in estimating reference ET_0 for the first time in Algeria by using various daily climatic data. Comparison results indicated that the GRNN performed better than the RBFNN, Priestley–Taylor and Hargreaves–Samani models. Karimaldini et al. (2012) investigated the accuracy of ANFIS models for daily reference evapotranspiration estimation under arid conditions from limited weather data. They indicated that when similar climatic inputs were used, the ANFIS models performed better than the Hargreaves, Priestley–Tailor, Makkink, and Blaney–Criddle models. Baba et al. (2013) estimated daily ET_0 using available and estimated climatic data by ANFIS and ANN. According to our knowledge, there is not any published study in the literature related to application of least square support vector regression (LSSVR), multivariate adaptive regression splines (MARS) and M5 Model Tree (M5Tree) models for estimating ET_0.

The aim of this study is to investigate the ability of LSSVR, MARS and M5Tree methods in (i) locally modeling of monthly ET_0 of Antalya and Isparta stations, (ii) estimating ET_0 of Isparta Station using input data of Antalya Station and (iii) estimating ET_0 of Isparta Station utilizing the data of Antalya Station without local input and output data.

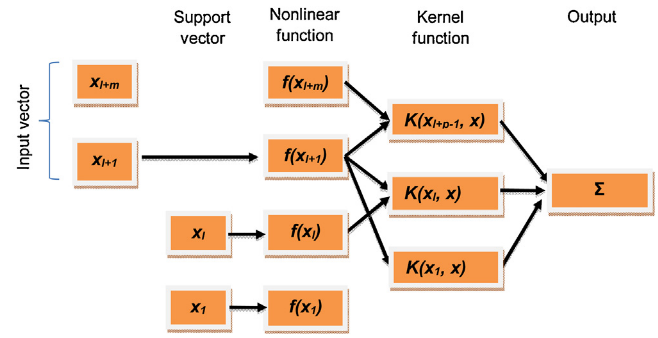

Fig. 1. The structure of an LSSVR.

2. Methods

2.1. Least square support vector regression

The LSSVR initially proposed by Suykens and Vandewalle (1999) is an productive tool for tackling non-linear issues, classification and function estimation (Kisi, 2015b; Kumar and Kar, 2009). Fig. 1 exhibits the system of an LSSVR. By involving inputs x_i (climatic data) and output y_i (Evapotranspiration) time series, the nonlinear LSSVR function can be expressed as

$$f(X) = w^T f(X) + b \tag{1}$$

where w = m-dimensional weight vector, f = mapping function and b = bias term (Shu-gang et al., 2008).

By including function estimation error, the regression problem can be characterized seeing structural minimization standard as

$$\min J(w, e) = \frac{1}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^{m} e_i^2 \tag{2}$$

which subject to following constraints

$$y_i = w^T f(x_i) + b + e_i \quad (i = 1, 2, \ldots, m) \tag{3}$$

where γ = regularization constant and e_i = training error corresponding to x_i.

To illuminate the w and e (solving Eq. (2)), the Lagrange multiplier optimal programming method is utilized. By changing the constraint problem into an unconstraint problem, the objective function is gotten. The Lagrange function L can be characterized as

$$L(w, b, e, \alpha) = J(w, e) - \sum_{i=1}^{m} \alpha_i \left\{ w^T f(x_i) + b + e_i - y_i \right\} \tag{4}$$

where α_i = the Lagrange multipliers.

By considering the Karush–Kuhn–Tucker (Flecher, 1987), the ideal conditions are gotten by taking the partial derivatives of Eq. (4) regarding w, b, e and α, separately as

$$\begin{cases} w = \sum_{i=1}^{m} \alpha_i \phi(x_i) \\ \sum_{i=1}^{m} \alpha_i = 0 \\ \alpha_i = \gamma e_i \\ w^T f(x_i) + b + e_i - y_i = 0 \end{cases} \tag{5}$$

Download English Version:

https://daneshyari.com/en/article/4478288

Download Persian Version:

https://daneshyari.com/article/4478288

Daneshyari.com