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Wavelet neural networks and gene expression programming models to predict short-term soil temperature at different depths

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ABSTRACT

Soil temperature (ST), as one of the critical meteorological parameters, has great effects on many underground soil ecological processes. Due to the fact that accurate measuring of ST is costly because of launching field equipment, evolving predictive models to approximate ST is of great importance. Therefore, achieving accurate, reliable and easily attainable predictions of daily ST values is the main objective of the current research. To that end, the usefulness of three data-driven procedures containing artificial neural networks (ANN), wavelet neural networks (WNN) and gene expression programming (GEP) were examined for the estimation of ST at different soil depths at Tabriz synoptic station, north-west of Iran. In conformity with the correlation coefficients among ST and meteorological parameters, it was found that air temperature, Sunshine hours and radiation had the most and unquestionable effects on ST prediction at all considered depths. For evaluating the performance of these approaches, four different statistical error measures were used: coefficient of correlation (CC), mean absolute error (MAE), root mean squared error (RMSE) and Akaike's information criterion (AIC). Moreover, Taylor diagrams were employed for assessing the similarity between the observed and predicted ST values. Results revealed that the WNN in all considered depths had the best performance in ST prediction, but with increasing soil depth, the effect of meteorological parameters and estimation accuracy were reduced rapidly. As a conclusion, the lower values of RMSE and higher values of CC proved the effectiveness of WNN for predicting ST at the studied depths.

1. Introduction

Soil temperature is a vital meteorological parameter for ecological research and expertise, especially for solar energy applications (Bilgili, 2011). Additionally, ST plays an important role in climatological and hydrological modeling and in understanding environmental processes and climate change (Tabari et al., 2015), even though measured data of ST are not permanently accessible for exact locations. So, the goal of evolving predictive models is to associate ST to more simply measured parameters, e.g., air temperature (Lei et al., 2011). Therefore, there is a need to apply data-driven techniques for predicting ST at different soil depths (Kisi et al., 2014; Kim and Singh 2014). Kim and Singh (2014) assessed the abilities of two different methods including adaptive neuro–fuzzy inference system (ANFIS) and multilayer perceptron (MLP) in estimation of ST. They found that the MLP provided enhanced outcomes in contrast with ANFIS at different depths for both studied stations. In another study, the precision of three different neural networks techniques was evaluated by Kisi et al. (2014) for modeling ST values at Mersin Station, Turkey. They examined the influence of meteorological parameters and found that air temperature affected ST values, significantly. Tabari et al. (2015) scrutinized the capabilities of artificial neural networks (ANN) to predict ST at two weather stations of Iran. The outcomes for all the artificial neural networks ascertained that the ANN models could be used satisfactorily to forecast short-term ST values. Bilgili (2011) presented an ANN model for the goal of forecasting monthly ST by means of meteorological data of previous months including measured ST at different depths underneath the soil surface and the meteorological parameters in the time period of 2000–2007 at Adana Station, Turkey. Results specified that the ANN methodology was an effective and trustworthy model for the prediction of monthly ST values.

Recently, wavelet theory, which is a substitute data-preprocessing

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procedure, has been used in the field of hydrology (Wang and Ding, 2003). This methodology overcomes the basic weaknesses of the conventional Fourier transform such as, limited applicability for nonlinear and transient phenomena. Adamowski and Sun (2010) used joined neural networks with wavelet transform technique for flow estimation. They specified that the established combination method provided more accurate outcomes than simple neural networks. Wei et al. (2011) presented a hybrid wavelet neural network (WNN) approach for predicting monthly river flows and compared the gained results with the ANN models. Assessment of the results discovered that the WNN predictions were more trustworthy than those predicted by the ANN models.

Lately, another talented data-driven technique named gene expression programming (GEP) has been used broadly in predicting and estimating in different fields like hydraulics conductivity (Parasuraman et al., 2007), hydrological modeling (Koza, 1992), etc. GEP is a technique for population construction of models via evolutionary algorithms. The advantage of GEP models in contrast with regression and other artificial intelligent models is its capability to yield the explicit formulations without assuming any kind of existing relationship. In hydrology-related studies, GP-based methodologies have been used to model friction factor in irrigation pipes (Samadianfard et al., 2014), rainfall-runoff (Shoaib et al., 2015), evapotranspiration (Yassin et al., 2016), analysis of global warming effects on sea surface temperature (Samadianfard et al., 2016) and so on.

The spatiotemporal variability of daily ST data is affected by geographical parameters such as latitude, altitude and topography. So, precise ST measurement needs to gauge at several stations, whereas the more stations require the more equipment and expenses. Therefore, the objective of this study is to evaluate the capabilities of WNN in estimating ST using meteorological parameters at different soil depths and comparing its predictive results with outputs of GEP and ANN methods. The obtained predictions from the models should be compared with the equivalent observed values using statistical parameters.

2. Material and methods

2.1. Artificial neural networks

The ANNs are successfully used to exploit the immense parallel local processing and the scattered storage properties present in the human brain (Huo et al., 2012). Their capability to recognize the complex nonlinear affiliations among input and output datasets can be considered as their key benefit. The ANNs have turned up to be beneficial and proficient modeling tools, particularly for problems whose characterization processes might be hard to define through physically or statistically established equations. The network topology is composed of neurons associated by links and commonly structured in a number of layers. Weighted input from a previous layer is received and treated by each layer node whose output is then delivered to the nodes in the following layers through a transfer function. Most ANNs involve of three layers of input, output and one or more hidden layers (Senthil Kumar et al., 2005). A back propagation algorithm was implemented for estimating the network parameters. The data are typically scaled to lie in a fixed range of 0 to 1, as the activation function is a sigmoid. Determination of a suitable architecture for a neural network for a definite problem is an imperative factor as the network topology straight fully affects the complexity of computations. In the current research, the quantity of hidden neurons is specified by different trials. The trial and error technique initiates with two hidden neurons at first. Then, it is increased to 20 with a step size of 1 at each trial. The available data is separated into two sets of training and testing and the mentioned technique is continued until there is no substantial enhancement in lowering the estimation error. The model is then verified by investigating the accuracy of the test data set. The structure with a minimum prediction error was designated as the concluding ANN model.

Table 1
Parameters of the GEP model.

Parameter	Value
Function set	+, −, ×, /, *Ln(x), Exp, Power, Sin, Cos, Tan*
Chromosomes	30
Head size	8
Number of Genes	3
Linking Function	Addition (+)
Mutation Rate	0.044
Inversion Rate	0.1
One-Point Recombination Rate	0.3
Two-Point Recombination Rate	0.3
Gene Recombination Rate	0.1
Gene Transposition Rate	0.1

2.2. Wavelet analysis

The Wavelet Transforms (WT) has lately been developed in signal processing and has been applied extensively in astronomy, communications and other engineering fields (Si and Zeleke, 2005; Hu and Si, 2016) since its academic expansion by Grossman and Morlet (1984). It is established on conveying signals as sums of little waves. The capability of wavelets to provide the precise locality of any variations in the forms of the sequence, and the ability of wavelet transforms for applying to any time series has made them a beneficial tool (Goyal, 2014). The WT can be applied in a continuous form (CWT) as well as in a discrete (DWT) form. Lark and Webster (2004) analyzed soil variation in two dimensions with the DWT. The outcomes showed the advantages of DWT over conventional geostatistical techniques for the study of complex regions. For the WT, the fundamental functions are translations and dilations of one function called the mother wavelet. The mother wavelet function can be defined as:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{1}$$

The DWT requires less calculation time and straightforwardly can apply to different types of datasets. Therefore, these advantages make it extensively used among scholars. In the DWT, two sets of functions observed as low and high-pass filters, decompose the original time series and consequently turn them into approximation and details components, respectively. The high frequencies of the time series are analyzed by the high-pass filters, while the low frequency contents of the same data are analyzed by low-pass filters. The high scale low frequency elements are recognized as approximation and provide the background information. On the other hand, the low scale high frequency elements are identified as details and present the slight characteristics of descriptive value in data (Nourani et al., 2009). The DWT scales and positions are based on power of two (dyadic scales and positions) and can be defined for a discrete time series f(t), which occurs at any time t as:

$$DWT_{a,b} = {a_0}^{-j/2} \int_{j=0}^{j=1} \psi^*({a_0}^{-j/2} - kb_0)f(t)dt \tag{2}$$

where * corresponds to the complex conjugate of ψ, and real numbers, j and k are the integers that control the wavelet scales and positions, respectively. The most common and simplest choice for the parameters a_0 and b_0 introduced by Mallat (1998) is two and one time steps, respectively. Therefore with putting $a_0 = 2$ and $b_0 = 1$ in the above equation, the dyadic wavelet can be written in more compact notation as:

$$DWT_{a,b} = 2^{-j/2} \int_{j=0}^{j=1} \psi^*(2^{-j/2} - k)f(t)dt \tag{3}$$