Performance evaluation of linear and nonlinear models for the estimation of reference evapotranspiration

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Abstract: In this study, the performance of linear and nonlinear models for the estimation of reference evapotranspiration was examined. To evaluate the performance of nonlinear models, we used the radial basis function (RBF) neural networks and genetic programming (GP), and the multiple linear regression (MLR) method was used for linear models. Using these three methods, monthly evapotranspiration was calculated for Isfahan region in a 26-year period. Comparison of the results for nonlinear and linear models showed that the GP3 model by the coefficient of determination of 0.99 and root mean square error (RMSE) of 0.21, has the best performance among the studied models. Instead, the RBF model training speed is higher than the GP model. Furthermore, the results showed that the MLR model has good performance in estimating evapotranspiration and there is no significant difference between the accuracy of the MLR and RBF method, but the accuracy of GP model is better than the RBF and MLR models. The results showed that the reference evapotranspiration could be estimated with high accuracy by both linear and nonlinear models for the study area.

Keywords: reference evapotranspiration; artificial neural networks; ANNs; genetic programming multiple linear regression; Penman-Monteith.


Biographical notes: Mustafa Goodarzi did his undergraduate work in Borujerd, Iran. He received his Bachelor of Science from Tehran University in 2006, his Master from Shahid Chamran University in 2008 and his PhD from Isfahan University of Technology in 2016.
1 Introduction

The process by which water is transferred from the land to the atmosphere by evaporation from the soil and other surfaces, and by transpiration from plants is called evapotranspiration (ET). Evaporation and transpiration occur simultaneously, and there is no simple way to distinguish between the two processes. Exact determination of evapotranspiration value is very important in different studies such as catchment modelling, agricultural water management, estimating the components of water balance, etc. Evapotranspiration can be measured with a lysimeter or water balance approach, or estimated from climatological data (Hou et al., 2013). However, the use of lysimeter to measure evapotranspiration is not always possible, because it is time-consuming and needs careful planning. Therefore, the indirect methods based on meteorological data are used to estimate the reference evapotranspiration. One of the methods that are widely used to estimate the reference evapotranspiration, is Penman-Monteith (PM) (Kumar et al., 2002). According to research conducted, PM is one of the most accurate methods to estimate evapotranspiration and can be used for different climates (Chiew et al., 1995).

In recent decades, many studies have been done on the development of methods to estimate evapotranspiration and to improve the existing ones, and the efforts in this area are still ongoing.

Evapotranspiration is a complex process because it is dependent on climatic factors such as temperature, humidity, wind speed, solar radiation, the type and stage of plant growth, etc. So, preparing a mathematical model which taking into account the climatic parameters, is difficult and may be associated with large errors. Also, climatic factors interact on each other which, this issue cannot be included in the mathematical models (Trajkovic et al., 2003). Thus, linear and nonlinear models are appropriate tools to determine evapotranspiration.

Artificial neural networks (ANN) are flexible mathematical models that can be applied in modelling complex systems (Yu Wu, 2008). Also, the ANNs by selecting the appropriate number of layers and neurons are able to select a nonlinear mapping between inputs and outputs (Karayiannis and Venetsanopoulos, 1993). The ANNs are models with complex functional relations learnable with training data, which is inspired from principles of data processing in the brain (Karayiannis and Venetsanopoulos, 1993).

In recent decades, the use of ANNs in water sciences has been increased. In the context of evapotranspiration estimation using neural network, different studies have been
conducted so far. Kumar et al. (2002) estimated the reference evapotranspiration by using ANNs. These values are then compared with the results of conventional methods, the PM, to evaluate the ANNs’ ability to predict the ET. Bruton et al. (2000) used ANNs and calculated daily evaporation from pan, using meteorological data, including rainfall, temperature, relative humidity, radiation and wind speed of cities around the world between 1992 and 1996, with an estimated error rate of 1.11 (mm/day).

Eslamian et al. (2012) estimated PM reference evapotranspiration using ANNs and genetic algorithm (ANN-GA). The results indicated that ANN-GA predicted PM ET$_0$ better than ANNs model. Soltani and Morid (2005), Zanetti et al. (2007), Rahimi Khooob (2008), Hou et al. (2013), Abdullah et al. (2015) and Yassin et al. (2016) also studied estimation of ET using ANN.

One of the methods used to determine the correlation between ET and climatic factors is multiple linear regression (MLR). In this method evapotranspiration and various climatic factors are introduced as the dependent and independent variables in the model, respectively. The best model is the model that can better predict the dependent variable based on different independent variable. In this regard, several studies have been done that show the capabilities of this method to estimate evapotranspiration (Arabsolghar et al., 2011; Huo et al., 2012; Ladlani et al., 2014; Mosavi et al., 2009; Tabari et al., 2012).

In this study, the performance of linear and nonlinear models for the estimation of reference evapotranspiration was examined. To evaluate the performance of nonlinear models the radial basis function (RBF) neural networks and genetic programming (GP) model, and for linear models, the MLR method was used. The results of these models with each other and also with the values calculated by the PM were compared.

2 Materials and methods

In this study, monthly average maximum and minimum temperature, relative humidity, wind speed and solar radiation data of Isfahan synoptic station in central Iran over a period of 26 years (1980–2005) has been used in order to calculate the average monthly reference evapotranspiration. This station is located in 51° 52´ 00´´ E, 32° 40´ 00´´ N and 1,543 metres above sea level. Due to lack of access to lysimeter data over a long period and other limitations of lysimeters, PM method was used for estimating reference evapotranspiration. The PM method among different methods to estimate reference evapotranspiration has been the most accurate method, and this has been demonstrated in several studies (Azhar et al., 2014; Daliakopoulos et al., 2005; Eslamian et al., 2012; Huo et al., 2012; Karayiannis and Venetsanopoulos, 1993; Nourani and Sayyah Fard, 2012; Yassin et al., 2016). Therefore, in this study, the evapotranspiration values calculated by the PM method were used for the validation of models.

2.1 Penman-Monteith

In this study, PM equation as recommended by FAO (Allen et al., 1998) was used for estimation of reference evapotranspiration. The reference evapotranspiration was calculated using equation (1), based on climatic parameters, including the maximum temperature, minimum temperature, relative humidity, wind speed and sunshine (Allen et al., 1998).
\[ ET_0 = \frac{0.408\Delta (R_n - G) + \frac{888}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma (1 + 0.34u_2)} \] (1)

where \( ET_0 \) is reference evapotranspiration (mm/day); \( R_n \) is net radiation at the crop surface (MJ/m\(^2\)/day); \( G \) is soil heat flux density (MJ/m\(^2\)/day); \( T \) is mean daily air temperature at 2 m height (°C); \( u_2 \) is mean daily wind speed at 2 m height (m/s); \( e_s \) is saturation vapor pressure (KPa); \( e_a \) is actual vapour pressure (KPa); \( e_s - e_a \) is saturation vapour pressure deficit (KPa); \( \Delta \) is slope of vapour pressure curve (KPa/°C); and \( \gamma \) is psychrometric constant (kPa/°C).

2.2 RBF networks

Neural networks are massively parallel, distributed processing systems representing a new computational technology built on the analogy to the human information-processing system. These models are called intelligent systems because they are used to estimate the general governing rules of the phenomenon based on the calculations on numerical data (Daliakopoulos et al., 2005; Karayiannis and Venetsanopoulos, 1993).

Typically, the ANN models are formed of an input layer, a hidden layer and an output layer. Figure 1 shows the schematic of a three-layer neural network. In this study, the output layer contains a node that is the reference evapotranspiration. The input layer is composed of various combinations of input variables, minimum and maximum temperature (\( T_{\text{min}}, T_{\text{max}} \)), radiation (\( R_n \)), relative humidity (\( H \)) and wind speed (\( W \)). The numbers of nodes in the hidden layer are determined by the process of trial and error. To enhance the performance of the training process, the inputs and target data were normalised.
The difference between the various types of ANNs usually comes from the many different structures for the nodes (architecture) and the many ways to determine the weights and functions for training the network. In this study, RBF ANN, were used to forecast reference evapotranspiration using existing data. The RBF networks are nonlinear hybrid networks, which containing a single hidden layer. In this method, typically the transfer function in the middle layer is the Gaussian function and in the output layer is a linear function. The RBF networks’ training is generally divided into two parts. In the first part, which is mainly learning of unsupervised clustering methods, parameters and basic functions are determined. In the second part, which is a supervised learning, the weights between the hidden layer and output layer are determined using the reduce slope and linear regression methods (Daliakopoulos et al., 2005; Dehghani et al., 2009).

The RBF hidden layer neurons attached to each of the input neurons by weight parameters, which are centres of neurons. The output of each hidden layer neuron is a function of the distance between the input vector, \( \mathbf{x} = [x_1, x_2, \ldots, x_n] \), and radial vector, \( \mathbf{W} = [w_{1i}, w_{2i}, \ldots, w_{ni}] \), Which is calculated as follows:

\[
\delta_i = \sqrt{\sum_{j=1}^{n} (x_i - x_{ij})^2}
\]  

(2)

The output of hidden layer neurons can be calculated in different ways. The main transfer function for this purpose is Gaussian function, which is described as follows:

\[
f(\delta_i) = \exp(-\lambda \delta_i^2)
\]  

(3)

where \( \lambda \) is a constant coefficient. Finally, the outputs of the output layer are calculated by the following equation:

\[
z_k = \sum_{j=1}^{f} b_{jk} y_j
\]  

(4)

where \( b_{jk} \) is weight coefficients between \( f^{th} \) hidden layer neurons and \( k^{th} \) output layer neuron and \( y_j \) is \( j^{th} \) output of the hidden layer neurons. The training of ANNs are based on a trial and error process until the best architecture are provided by changing the number of hidden layers and their neurons, transfer function, and learning algorithms for estimating the output value.

The decision-making criteria for selecting the best network are the root mean square error and the coefficient of determination (\( R^2 \)), which are calculated as follows:

\[
RSME = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - y_0)^2}
\]  

(5)

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y_0)^2}{\sum_{i=1}^{N} y_i^2 - \frac{1}{n} \sum_{i=1}^{N} y_0^2}
\]  

(6)
where \( y_0 \) is observed data, \( y_t \) calculated data and \( n \) the number of observations (Bruton et al., 2000).

### 2.3 Genetic programming

GP, introduced by Koza (1992), belongs to a class of evolutionary algorithms (EA), which are based on the Darwin’s theory of evolution (Khu et al., 2001). GP is a relatively new EA to other algorithms such as evolutionary programming (Fogel et al., 1966), genetic algorithms (Holland, 1975) and evolution strategies (Schwefel, 1981). The above-mentioned algorithm defines an objective function in terms of the quality criteria and compares different solutions in a step by step process to apply correct data structure, and finally, provide the right answer. The GP method has been used by researchers in various fields of water engineering. Some of the studies which have been done by GP are including the works by Farboudfam et al. (2010) and Guven (2009) for river flow prediction, Khu et al. (2001) for in real-time runoff forming, Aytek and Kisi (2008) for suspended sediment modelling, Ghorbani et al. (2010) for flood routing, Zahiri and Azamathulla (2014) for predicting flow discharge in compound channels, Parasuraman et al. (2007) and Yassin et al. (2016) for estimating reference evapotranspiration.

In this study, the following steps were considered for modelling of the monthly reference evapotranspiration. First step was to select appropriate fitting function that in this study the root mean square error was selected as the fitness function. The second step was to select the total input variables and functions in order to produce the chromosomes. In this study, a set of meteorological data were considered as input variables. Also, the four main operational functions that include \{+ , − , ×, ÷\} and mathematical functions \{\(X^2, X^3, \sqrt{X}, \frac{1}{X}, \log(X), \sin(X), \cos(X)\}\} were used to produce the chromosomes. The third step involves selecting the structure and architecture of the chromosomes. The length of each vertex and the number of genes were selected based on the number of input variables. The fourth step was to choose the crossover function. Finally, mutation operators are determined. Detailed descriptions about the GP method are provided by Koza (1992), Babovic and Keijzer (2000) and Parasuraman et al. (2007).

### 2.4 Multiple linear regression

MLR are used to model the relationship between two or more independent variables and a dependent variable by fitting a linear equation to observed data. In these models, the researcher is faced with a large number of variables that the relationship between them is not well known and, the goal is to create a predictive model based on the variables. In MLR method, variables that are best fitted to model are chosen based on a step by step assessment. The MLR format is generally as follows:

\[
Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \ldots + \beta_pX_p
\]

where \( i \) is observation index, \( X \) predictor variable (independent), \( Y \) predicted variable (dependent), \( \beta \) coefficient of independent variables (Alexopoulos, 2010). In this study, meteorological parameters were considered as independent variables and reference evapotranspiration was considered as the dependent variable for the model. Using backward and forward methods and based on sensitivity of parameters, different MLR models were developed.
2.5 Sensitivity analysis

By definition, sensitivity analysis shows the effects of changing a parameter on the other parameter (McCuen, 1974). Changes in climate parameters directly affect evaporation, and it has a different environmental impact. In hydrological studies, different sensitivity coefficients have been used including Babajimopoulos et al. (1992), McCuen (1974), Saxton (1975), Coleman and DeCoursey (1976), Beven (1979), Gong et al. (2006) and Ambas and Baltas (2012). In this study, the new method for calculating the sensitivity coefficient provided by Ambas and Baltas (2012), was used to determine the sensitivity of different climatic parameters on evapotranspiration for the three methods (RBF, GP, MLR) used in this study. In this method, Ambas and Baltas used standard deviation of the parameters and proposed a new sensitivity coefficient which is calculated as follows:

\[ K_{Sp} = \frac{\partial M}{\partial \sigma P} \]  

where \( K_{Sp} \) is relative sensitivity coefficient, \( M \) is evaluated dependent variable, \( P \) is independent affecting variable and \( \sigma_P \) is standard deviation of the parameter \( P \). In this study, \( K_{Sp} \) represents the changes in evapotranspiration due to the change of meteorological parameters.

3 Results and discussion

3.1 Results of RBF method

In this study, the climate data over a period of 26 years (1980–2005) were used to build the RBF model. For this purpose, the data from the period 1980–2000 were used for training, and the period 2000–2005 were used for verification of the model. In the RBF model, eight different configurations were defined for the parameters and different networks with different architectures and parameters for estimating reference evapotranspiration. The number of neurons in hidden layer and overall network architectures for RBF method was determined by trial and error, and assessment of different modes. Then, for each of the eight models, the optimal structure was chosen as the best architectures. After determining the best structure for each case, they were arranged according to the RMSE and \( R^2 \) values which are summarised in Table 1. According to the results, in the RBF1 mode when all parameters are chosen as input the best estimate of reference evapotranspiration is obtained, and the model shows acceptable accuracy in estimating \( \text{ET}_0 \). In the RBF method when the network architectures were (5-12-1) (the numbers in the parentheses are the number of nodes in input, hidden and output layers, respectively) the best performance was achieved by a coefficient of determining of 0.96 and RMSE 0.46. The results also showed that between all parameters, the temperature has the greatest influence on estimating evapotranspiration, that it is consistent with other studies findings (Huo et al., 2012; Jain et al., 2008). The scatter plot of RBF vs PM for calculated values of \( \text{ET}_0 \) for the optimal structure (RBF1) is shown in Figure 2. Also, in Figure 3 the predicted values of reference evapotranspiration by RBF compared with the PM method for 2002. As it can be seen, this method is in good agreement with the values of the PM.
### Table 1  
Statistical results for the different models of RBF method

<table>
<thead>
<tr>
<th>Model</th>
<th>Input parameters</th>
<th>Optimised architecture</th>
<th>Testing $R^2$</th>
<th>RMSE</th>
<th>Training $R^2$</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>RBF1</td>
<td>$T_{\text{max}}, T_{\text{min}}, W, H, R_n$</td>
<td>(5-12-1)</td>
<td>0.96</td>
<td>0.49</td>
<td>0.96</td>
<td>0.46</td>
</tr>
<tr>
<td>RBF2</td>
<td>$T_{\text{max}}, T_{\text{min}}, W, R_n$</td>
<td>(4-9-1)</td>
<td>0.95</td>
<td>0.61</td>
<td>0.95</td>
<td>0.51</td>
</tr>
<tr>
<td>RBF3</td>
<td>$T_{\text{ave}}, W, H, R_n$</td>
<td>(4-9-1)</td>
<td>0.94</td>
<td>0.54</td>
<td>0.94</td>
<td>0.58</td>
</tr>
<tr>
<td>RBF4</td>
<td>$T_{\text{max}}, T_{\text{min}}, W, H$</td>
<td>(4-9-1)</td>
<td>0.93</td>
<td>0.61</td>
<td>0.93</td>
<td>0.65</td>
</tr>
<tr>
<td>RBF5</td>
<td>$T_{\text{max}}, T_{\text{min}}, W$</td>
<td>(3-9-1)</td>
<td>0.92</td>
<td>0.75</td>
<td>0.92</td>
<td>0.78</td>
</tr>
<tr>
<td>RBF6</td>
<td>$T_{\text{max}}, T_{\text{min}}, R_n$</td>
<td>(3-9-1)</td>
<td>0.91</td>
<td>0.88</td>
<td>0.92</td>
<td>0.80</td>
</tr>
<tr>
<td>RBF7</td>
<td>$T_{\text{max}}, T_{\text{min}}, H$</td>
<td>(3-9-1)</td>
<td>0.90</td>
<td>0.85</td>
<td>0.91</td>
<td>0.87</td>
</tr>
<tr>
<td>RBF8</td>
<td>$T_{\text{max}}, T_{\text{min}}$</td>
<td>(3-9-1)</td>
<td>0.91</td>
<td>0.92</td>
<td>0.90</td>
<td>0.97</td>
</tr>
</tbody>
</table>

**Figure 2**  
Scatter plot of the RBF method compared with PM

**Figure 3**  
$E_T$ values predicted by RBF1 compared with PM for 2002 (see online version for colours)
3.2 Results of GP method

In the GP method similar to RBF method, the climate data over a period of 26 years (1980–2005) were used to build the GP model. In this method, in order to avoid the complexity of the patterns and involved in memory, eight different patterns were assessed as model. Statistical comparison of the results each model is provided in Table 2. According to these results, we can conclude that over all the performance of the GP in the prediction of evapotranspiration was good and can calculate evapotranspiration with very high accuracy. Based on the results, the GP3 with a coefficient of determination of 0.99 and RMSE 0.2 is the best model among the GP models. The scatter plot of GP3 vs PM for calculated values of ET$_0$ is shown in Figure 4. In addition, the predicted values of reference evapotranspiration by GP3 and PM method for 2002 are shown in Figure 5. The GP models gave the most accurate estimates, and also they are easier to use than RBF, as they calculate the ET using explicit algebraic equations.

Table 2  Statistical results for different models of GP method

<table>
<thead>
<tr>
<th>Model</th>
<th>Input parameters</th>
<th>Testing</th>
<th>Training</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$R^2$</td>
<td>RMSE</td>
</tr>
<tr>
<td>GP1</td>
<td>$T_{ave}$, $W$, $R_n$</td>
<td>0.96</td>
<td>0.42</td>
</tr>
<tr>
<td>GP2</td>
<td>$T_{ave}$, $W$, $H$</td>
<td>0.96</td>
<td>0.43</td>
</tr>
<tr>
<td>GP3</td>
<td>$T_{ave}$, $W$, $H$, $N$</td>
<td>0.99</td>
<td>0.21</td>
</tr>
<tr>
<td>GP4</td>
<td>$T_{ave}$, $R_n$</td>
<td>0.92</td>
<td>0.65</td>
</tr>
<tr>
<td>GP5</td>
<td>$T_{max}$, $T_{min}$, $W$</td>
<td>0.95</td>
<td>0.49</td>
</tr>
<tr>
<td>GP6</td>
<td>$T_{max}$, $T_{min}$, $R_n$</td>
<td>0.91</td>
<td>0.84</td>
</tr>
<tr>
<td>GP7</td>
<td>$T_{max}$, $T_{min}$, $H$</td>
<td>0.92</td>
<td>0.75</td>
</tr>
<tr>
<td>GP8</td>
<td>$W$, $H$, $R_n$</td>
<td>0.92</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Figure 4  Scatter plot of the GP method compared with PM

![Figure 4](https://via.placeholder.com/150)
3.3 Results of MLR method

In this model, all climatic data for the period 1980–2005 were used to develop MLR models. In order to create MLR models different combinations of independent variables, including the minimum temperature ($T_{\text{min}}$), maximum temperature ($T_{\text{max}}$), radiation ($R_n$), relative humidity ($H$) and wind speed ($W$), were used to estimate ET as the dependent variable. The summary of results, for the MLR modelling is presented in Table 3. According to the presented results in the table, it is clear that the best performance is when all parameters are included in the model (MLR1) in which the coefficient of determination and RMSE are 0.97 and 0.59, respectively. This reflects the good performance of the model to estimate reference evapotranspiration, which is consistent with other research findings (Arabsolghar et al., 2011; Azizi et al., 2009; Tabari et al., 2012; Ladlani et al., 2014). The optimum MLR model (MLR1) for the study area and the coefficients of the model are provided in equation (9) [the units in this equation are same as the equation (1)]. The scatter plot for MLR1 is shown in Figure 6. Moreover, the predicted values of reference evapotranspiration by MLR1 and PM method for 2002 are compared as shown in Figure 7. In general, the performance of the model shows that this model can predict the reference evapotranspiration in the study area with good accuracy. However, this method has some limitations, including the need for large amounts of data to build the model, and the model works well only in the range of the data so cannot be used for other regions.

$$ET_0 = 5.05 \times 10^{-2}T_{\text{min}} + 0.1235T_{\text{max}} + 6.6 \times 10^{-3}W$$
$$+ 0.12861R_n - 3.39 \times 10^{-3}H - 2.168$$

(9)
### Table 3
Statistical results for different models of MLR method

<table>
<thead>
<tr>
<th>Model</th>
<th>Independent variables</th>
<th>$R^2$</th>
<th>RMSE</th>
<th>Dependent variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLR1</td>
<td>(Constant), $R_n$, $W$, $T_{max}$, $H$, $T_{min}$</td>
<td>0.97</td>
<td>0.59</td>
<td>ET$_0$</td>
</tr>
<tr>
<td>MLR2</td>
<td>(Constant), $T_{max}$, $W$, $R_n$, $T_{min}$</td>
<td>0.95</td>
<td>0.62</td>
<td>ET$_0$</td>
</tr>
<tr>
<td>MLR3</td>
<td>(Constant), $T_{max}$, $W$, $R_n$</td>
<td>0.95</td>
<td>0.67</td>
<td>ET$_0$</td>
</tr>
<tr>
<td>MLR4</td>
<td>(Constant), $T_{max}$, $W$</td>
<td>0.93</td>
<td>0.88</td>
<td>ET$_0$</td>
</tr>
<tr>
<td>MLR5</td>
<td>(Constant), $T_{max}$</td>
<td>0.90</td>
<td>0.97</td>
<td>ET$_0$</td>
</tr>
</tbody>
</table>

### Figure 6
Scatter plot of the MLR method compared with PM

- $R = 0.96$
- $RMSE = 0.46$

### Figure 7
ET$_0$ values predicted by MLR1 compared with PM for 2002 (see online version for colours)
The sensitivity analysis for all parameters of the models presented in this study, including the maximum temperature, minimum temperature, average temperature, relative humidity, wind speed and radiation, was performed and the $K_{S_p}$ for each parameter was calculated. In Table 4, the calculated multiple linear response ($K_{S_p}$) for each parameter in the three models is presented. As can be seen, the average temperature and relative humidity are the most and the least sensitive parameters of the three methods, respectively. Our results are in agreement with many researches, including Ambas and Bltas (2012), Dinpashoh and Sharifi (2012), Rohina et al. (2013) and Hou et al. (2013) but with this difference that in this study, the wind speed shows more sensitivity than other researches.

Table 4 The sensitivity of the reference evapotranspiration to the meteorological variables

<table>
<thead>
<tr>
<th>Parameter-method</th>
<th>RBF</th>
<th>GP</th>
<th>MLR</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{\text{max}}$</td>
<td>0.54</td>
<td>0.56</td>
<td>0.65</td>
</tr>
<tr>
<td>$T_{\text{min}}$</td>
<td>0.37</td>
<td>0.37</td>
<td>0.41</td>
</tr>
<tr>
<td>$T_{\text{ave}}$</td>
<td>0.72</td>
<td>0.88</td>
<td>0.82</td>
</tr>
<tr>
<td>$W$</td>
<td>0.29</td>
<td>0.34</td>
<td>0.58</td>
</tr>
<tr>
<td>$H$</td>
<td>-0.03</td>
<td>-0.08</td>
<td>-0.015</td>
</tr>
<tr>
<td>$R_n$</td>
<td>0.64</td>
<td>0.48</td>
<td>0.68</td>
</tr>
</tbody>
</table>

4 Conclusions

In this study, the performance of linear and nonlinear models was examined for the estimation of reference evapotranspiration in Isfahan, Iran. For this propose, the RBF and GP were used as nonlinear models and MLR as the linear model. Considering the values of PM as prediction goal and using meteorological data of Isfahan station in a 26-year period (1980–2005), different patterns were evaluated for each model. Results from comparison of nonlinear models showed that the GP models have better performance than RBF, but development and training of RBF models are easier and tend to learn much faster. Furthermore, results indicate that performance of MLR model is satisfactory and can predict the evapotranspiration with good accuracy. However, due to the advantages offered by the RBF and GP models, including the ability to filter out the noises, outliers and missing data and the abilities to update the model with new data are preferable to MLR models. Results from the study indicate that the GP3 model has the best performance among all models, and it can predict the evapotranspiration values with high accuracy. Results from the study indicate that both linear and nonlinear models proved to be capable of producing reliable predictions for the reference evapotranspiration. Therefore, the conclusion that which model is better for the region and chosen for application, depend on expert opinion about the conditions and availability of climate data.
References


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