Using Genetic Algorithms and Gene Expression Programming to Estimate Evapotranspiration with Limited Meteorological Data

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Abstract

In this study, genetic algorithm (GA) was employed to detect the most important variables for estimating ETo among mean temperature (Tmean), maximum temperature (Tmax), minimum temperature (Tmin), sunshine hours (n), relative humidity (RH), and wind speed (WS). The results show that Tmean and WS are the most important meteorological variables to model evapotranspiration in Iran. Then, we selected gene expression programming (GEP) to model ETo based on Tmean and WS historical data. The results indicate that the GEP has good performance for semiarid and Mediterranean climates compared to very humid and some arid regions. In addition, GEP is an effective solution when there is insufficient meteorological data available.

Introduction

Modeling reference evapotranspiration (ETo) using hybrid artificial intelligence techniques is emerging. These methods are useful since evapotranspiration plays undeniable role in hydrological cycle, water resources management, food and water security, and sustainable agriculture (Ahmad et al. 2019; Shiri et al. 2012, 2014; Parasuraman et al. 2007). Although several methods have been developed to predict ETo in around the world, there is a limited number of models to estimate ETo where meteorological data is restricted or insufficient (Shiri et al. 2012, 2014). Some investigations claimed greater accuracy of the GA & GEP rather than the artificial neural network (ANN) (Kim and Kim 2008; Eslamian et al. 2012), Support Vector Regression (SVR) (Kisi and Guven 2010; Wang et al. 2014), Adaptive Neuro-Fuzzy Inference System (ANFIS) (Shiri et al. 2012, 2013, 2014), and empirical models (Shiri et al. 2012; Marti et al. 2015).

This study aims to model ETo in 18 regions of Iran to recognize the parameters with the most significant roles in ETo. The results of this study are useful in different parts of the world, where there is insufficient meteorological data due to the lack of synoptic stations or other limitations.

Materials and Methods

In this study, various functions of the maximum temperature (Tmax), mean temperature (Tmean), minimum temperature (Tmin), relative humidity (RH), wind speed (WS), and sunshine hours (n) were defined and then combined by using summation and multiplying functions (Table 1). The goal is to minimize the difference between the current functions with the FAO-Penman–Monteith (FPM; Allen et al. 1998) as a base model to estimate ETo. To this end, a GA program was coded in MATLAB environment based on the functions presented in Table 1. The monthly averages of meteorological data from 1961 to 2010 were collected from the Islamic Republic of Iran Meteorological Organization (IRIMO). These data contain mean, minimum, and maximum daily air temperature (Celsius), saturated vapor pressure deficit (kPa), mean and minimum relative humidity (%), wind speed (m/s) and direction, rainfall (mm/month), cloudy days, and sunshine hours (hr/month). Table 2 shows the position of all 18 synoptic stations employed in this study and their climates.

Table 1. Structure of genetic algorithm (GA) designed in this study

Base	Formula
Mean Temperature	$ETo = a_1(T_{mean})^{a_2} + a_3$
Differential Temperature	$ETo = b_1(T_{\max} - T_{\min})^{b_2} + b_3$
Relative Humidity	$ETo = c_1(RH)^{c_2} + c_3$
Wind Speed	$ETo = e_1(WS)^{e_2} + e_3$
Solar Radiation	$ETo = f_1(n)^{f_2} + f_3$
Total (Summation)	$(ETo)_{GA} = \sum_{i=1}^{5} ETo_i$
Total (Multiplying)	$(ETo)_{GA} = \prod_{i=1}^{5} ETo_i$
Goal Function	$Minimize[(ETo)_{GA} - (ETo)_{FPM}]$

Table 2. Location and climate of the stations

Station Name	North Latitude	East Longitude	Climate
Ahvaz	31° 20´	48° 40´	Arid
Arak	34° 6´	49° 46´	Semiarid
Bushehr	28° 58´	50° 49´	Arid
Esfahan	32° 37´	51° 40´	Arid
Hamedan	34° 52´	48° 32´	Semiarid
Jiroft	28° 35´	57° 48´	Arid
Kerman	30° 15´	56° 58´	Arid
Mashhad	36° 16´	59° 38´	Semiarid
Moghan	39° 39´	47° 55´	Semiarid
Qazvin	36° 15´	50° 3´	Semiarid
Rasht	37° 19´	49° 37´	Very humid
Sanandaj	35° 20´	47° 0´	Mediteranean
Shahrekord	32° 17´	50° 51´	Semiarid
Shiraz	29° 32´	52° 36´	Semiarid
Tabriz	38° 5´	46° 17´	Semiarid
Urmia	37° 40´	45° 3´	Semiarid
Yazd	31° 54´	54° 17´	Arid
Zabol	31° 2´	61° 29´	Arid

The authors have used the last five years (2006-2010) as the testing period and the rest of the data (1961-1005) as training period. In this study, a hybrid data-driven machine learning technique (considering both GA and GEP) was developed to model ETo in four climates. Figure 1 shows a general structure of GEP. To evaluate the accuracy of the models Equation (1) was used. Where, Xi and Yi are the ith observed and estimated values, respectively; and N is the total numbers of data.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_i - Y_i)^2}{N}} \quad (1)$$

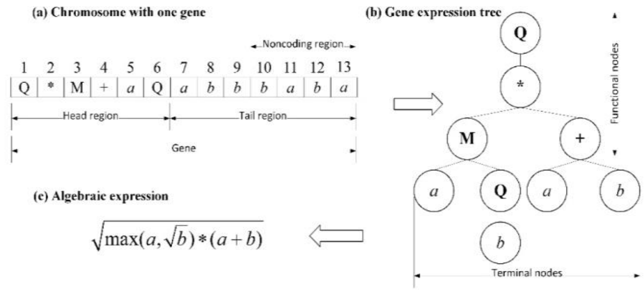

Figure 1. General structure of a GEP model

Results and Discussions

The results of GA demonstrate that a function of Tmean and WS may predict ETo with good accuracy (Table 3). Therefore, this result is the basis for the development of the genetic models using the GEP. However, Tmean is the first variable to be measured in each station or region. Hence, Tmean is considered as the input variable for all GEP models in this study.

Table 3. Performance of genetic algorithm (GA) for different meteorological variables

Model	Variables	RMSE (mm/day)
GA1	Tmean	0.68
GA2	Tmean, Tmin, Tmax	0.50
GA3	Tmean, RH	0.57
GA4	Tmean, n	0.62
GA5	Tmean, WS	0.33
GA6	Tmean, WS, RH	0.31
GA7	Tmean, WS, n	0.32
GA8	Tmean, WS, RH, n	0.30

With respect to Table 3, WS is introduced as the most important factor to control the variations of ETo under insufficient meteorological data conditions. Therefore, in the next step, ETo is estimated in all 18 stations using the Tmean, and WS then compared with the FPM (Table 4). Table 4 shows the best performance of the GEP belongs to Shahrekord (RMSE=0.0650 mm/day) with semiarid climate, while, the worst accuracy is reported for Kerman (RMSE=0.4177 mm/day) with arid climate. In 83% of regions the GEP resulted with a RMSE<0.20 mm/day. Furthermore, the natural logarithm (ln) function is used more than sinus, cosines, and particularly exponential functions in the GEP structures. In all regions (except for Rasht), the accuracy was improved compared to the GEP models based on the Tmean, Tmin, and Tmax (Table S1). Therefore, in highly humid climates, it is recommended to use a temperature–based GEP model versus wind speed–based GEP model. It may correspond to minimum diurnal temperature rate (DTR) in very humid regions compared to other climates (role of relative humidity and saturated vapor pressure). However, wind speed based GEP models forecasted ETo in arid, semiarid and Mediterranean climates more accurate than the other models. It should be noted that the arctan has not acceptable accuracy compared to other functions. In addition, the results illustrate that ln and exp functions have a better performance than sine and cosine functions. Doing a further analysis, ETo is estimated using Tmean, Tmin, and Tmax (Table 5). The best performance of the GEP belongs to Rasht (RMSE=0.0884 mm/day), while the worst accuracy is seen for Zabol (RMSE=0.8020 mm/day) as is presented in table 5. In 61% of regions the GEP efficiency is lower than RMSE<0.30 mm/day. Furthermore, sine and cosine functions were employed more than the natural logarithm (ln) and particularly exponential functions in the GEP structures. In all regions, the accuracy was improved compared to the GEP models based on the Tmean only (Results of GEP for Tmean has not been shown in this paper). The results of the GA revealed that use of the RH and n do not increase accuracy of the GEP significantly (Table 3). This is also confirmed by the GEP. For instance, Table 6 shows the performance of a GEP model with Tmean, WS, and RH as input parameters. According to Table 6, the best performance of the GEP belongs to Esfahan (RMSE=0.0730 mm/day), while, the worst accuracy is reported for Kerman (RMSE=0.4252 mm/day). In 89% of regions the GEP resulted with a RMSE<0.20 mm/day. Furthermore, sinus and cosines functions are employed more than the natural logarithm (ln) and particularly exponential functions in the GEP structures. Moreover, plus and minus functions were used more than multiplication sign and specially division. A comparison of Tables 4 and 6 indicates that adding the RH as input parameter not only did not increase the GEP's accuracy, but also led to the reduction in the accuracy of 56% of the regions. It is worth mentioning that the best structures of the GEP are not a function of the RH in 44% of the regions (Arak, Bushehr, Mashhad, Moghan, Qazvin, Sanandaj, Shahrekord, Shiraz, Tabriz, and Yazd). It is an important result and confirms that the Tmean and WS are more valuable to be used as input variable for the GEP compared to RH.

Conclusion

In this research, the performance of both GA and GEP is assessed using 50-year time series data under 18 regions in Iran with arid, semiarid, very humid, and Mediterranean climates. The GA results suggested that use of a double-parameter basis including the Tmean and WS may model ETo with good accuracy in arid, semiarid, and Mediterranean regions. However, in very humid regions, temperature-based models (Tmean, Tmax, and Tmin) are better alternatives to reduce uncertainty. In future studies, a further analysis of the effects of climate extremes in humid climates will be assessed. This study could serve as the basis for the modeling of ETo in Mediterranean climates, especially when the availability of input data is limited. The next step of this study is to train the GA & GEP using ETo calculated at one site with all the meteorological variables available. Then, use the resulting functions to estimate ETo at a site where there are insufficient meteorological variables.

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Table 4. Performance of gene expression programming (GEP) for mean temperature (Tmean) and wind speed (WS) as input data.

Region	The best structure	RMSE (mm/day)
Ahvaz	$ETo = 3.189 - \sqrt{WS - 2 + Tmean} + \sqrt{7 + Tmean}$	0.2128
Arak	$ETo = \ln\left(\sqrt{\sqrt{2.197 \ln\ 2Tmean\quad Tmean - 4\ WS}\ + 1.386}\right)$	0.1079
Bushehr	$ETo = \ln\ 17.167WS + 137.339\ - \dfrac{\exp\left(\cos\dfrac{1}{Tmean}\right)}{\exp\ WS\ + \cos\ WS \times Tmean} - \dfrac{\exp\left(\cos\left(4 - Tmean - \dfrac{WS}{8}\right)\right)}{WS + \exp\ \ln\ WS\ - 0.8}$	0.1640
Esfahan	$ETo = \sqrt{Tmean} - \cos\ WS\ - 0.006 - \ln\ \sqrt[4]{2 - \cos\ WS}$	0.0925
Hamedan	$ETo = 5 - \exp\left(\exp\left(\dfrac{Tmean\sqrt{Tmean}}{12}\right)\right) - 0.518^{\frac{WS^{3.5}}{11+\frac{8}{WS}}}$	0.1457
Jiroft	$ETo = WS + 3.001 - \dfrac{\exp\ \sqrt{5^{\sin\ Tmean}}}{WS - 13}$	0.1401
Kerman	$ETo = \sqrt[4]{WS} \times \sqrt{\ln\left(WS + \dfrac{Tmean}{5}\right)} \times \ln\left(Tmean + \dfrac{\sqrt{Tmean} \times \ln\ WS}{5}\right)$	0.4177
Mashhad	$ETo = \exp\left(\dfrac{Tmean}{28}\right) + \ln\left(\dfrac{0.571\ Tmean + WS}{-\ln\left(\dfrac{WS}{7}\right)}\right)$	0.1725
Moghan	$ETo = \ln\ \sqrt{0.303 \ln\ Tmean\ \times Tmean \times WS} \times \ln\ \ln\ 9WS\ \times\ Tmean - \cos\ Tmean$	0.0906
Qazvin	$ETo = \ln\ WS\ + \sqrt{\ln\ WS\ + Tmean - \ln\ Tmean\ + 3}$	0.1079
Rasht	$ETo = \sqrt{\sin\ 0.745Tmean\ + \sqrt{5.064\ \sin\ WS\ + 4 + WS}}$	0.0961
Sanandaj	$ETo = \sqrt{Tmean \times\ \sqrt{WS} + 0.745}$	0.1287
Shahrekord	$ETo = 0.705 \times\ \sqrt{\ Tmean + 7}\ + \ln\ WS\ - 1 - \cos\ \ln\ 2 + 2Tmean$	0.0650
Shiraz	$ETo = \sqrt{\cos\ 2WS + Tmean + 26\ + \cos\ Tmean + 5\ + 2WS + \exp\ \sqrt{WS + 6}}$	0.1403
Tabriz	$ETo = \ln\ \exp\ \sin\ Tmean\ \ + 6 + Tmean + \sin\ \sin\ Tmean\ \ - \dfrac{\sin\ Tmean}{\ln\ 5 + WS} + 22025.465^{\ WS-7\ \ \sin\ WS\ +8}$	0.1620
Urmia	$ETo = \cos\left(\dfrac{WS - 6.135}{Tmean}\right) + \cos\left(\dfrac{12.96}{0.75 + WS + Tmean}\right) + \exp\left(\sqrt{\dfrac{WS}{5}}\right) - \dfrac{3}{Tmean}$	0.1158
Yazd	$ETo = \sqrt[4]{\dfrac{Tmean^2 - 8Tmean}{2}}\ \sqrt{\ WS + 0.008}$	0.1738
Zabol	$ETo = 5.016 - \dfrac{WS}{WS - 1} - \dfrac{0.246 - \dfrac{WS - 2}{3}}{2.273 - \cos\ Tmean}$	0.3612

Table 5. Performance of gene expression programming (GEP) for mean temperature (Tmean), maximum temperature (Tmax), and minimum temperature (Tmin) as input data.

Region	The best structure	RMSE (mm/day)
Ahvaz	$ETo=\frac{\sin\ Tmean+T\min-T\max}{\frac{\sin\ 6-T\min}{\cos\ Tmean\ -1}+\frac{\sin\ T\min}{5+T\min}+\cos\ T\max-T\min\ +5}+5.146+\cos\ \sin\ T\min+6$	0.6090
Arak	$ETo=\sqrt{T\max-T\min-\ln\ T\max-T\min-5\ -0.412-\ln\left(\frac{3-\ln\ Tmean}{\sin\ T\max-T\min}\right)}$	0.2540
Bushehr	$ETo=4+0.367\sin\left(4+\sin\ Tmean\ +\sin\left(\frac{T\min}{T\max-T\min}\right)\right)$	0.2186
Esfahan	$ETo=\cos\ \cos\ \sin\ Tmean+T\min-T\max\ +2.583+\cos\ \cos\ \cos\ Tmean\ +T\max-T\min+0.914$	0.3226
Hamedan	$ETo=\frac{T\max}{5}-0.227+0.123\cos\left(\frac{Tmean}{5}\times\sin\ T\min\right)+\frac{\cos\left(\frac{T\min^{T\min}}{25}\times\sin\ Tmean\right)}{\frac{T\max}{5}+0.5+\frac{0.4}{T\max}+\frac{0.136}{4+\frac{1}{T\max-T\min}}}$	0.2571
Jiroft	$ETo=\sin\ \sqrt{2\ T\min-2\ +\sin\ T\max-T\min\ +\sqrt{Tmean}-\sqrt{Tmean+T\max-T\min}}\ +4.987$	0.2738
Kerman	$ETo=\sqrt{T\max-1.632\cos\ 2Tmean\ -\cos\ T\min^{2.5}-\cos\ 0.5T\max-T\min-8}$	0.4867
Mashhad	$ETo=\frac{\cos\left(\cos\left(\frac{T\min+Tmean\ \ T\max-T\min}{7}\right)\right)+Tmean}{\frac{4\cos\ \cos\ 3+Tmean}{\cos\ \cos\ T\max-T\min\ +Tmean}}$	0.2698
Moghan	$ETo=\sqrt{8+\sin\sqrt{7^{Tmean}}+\sin\ T\max^{T\min}}$	0.3028
Qazvin	$ETo=0.412\ 10-\cos\ T\min\ -0.723\ln\ Tmean+T\min-T\max+4$	0.3306
Rasht	$ETo=\left(\cos\left(\frac{\cos\ \exp\ T\max-T\min}{2-Tmean}\right)\right)^5\times\left(\cos\left(\cos\left(\frac{Tmean}{2-Tmean}\right)\right)\right)^{\exp\ \sin\ T\max-T\min}\times\frac{T\max}{9}$	0.0884
Sanandaj	$ETo=\sqrt{Tmean}-\frac{\cos\ Tmean^4}{Tmean-3.5}-\frac{1.5^{\sin\ T\max-T\min-6}}{Tmean+0.793}-\frac{\cos\left(T\max-6-\frac{T\max-T\min}{T\min}+\frac{0.145}{T\min+6}\right)}{\frac{T\min\times\cos\ T\max-T\min}{6}+Tmean-7.8}$	0.2556
Shahrekord	$ETo=\sqrt{T\max-T\min}\times\sin\ \ln\ \sqrt{T\max-T\min}\ -\sin\ \ln\ 7-\sin\ Tmean\ -\sin\ T\min\times T\max$	0.2139
Shiraz	$ETo=\ln\ \ Tmean+\cos\ 5T\max\ \times\ \cos\ T\min+Tmean\ +5.753\ +\cos\ 5T\max\ +2\cos\ T\min+5$	0.2849
Tabriz	$ETo=\ -\sin\ \ln\ Tmean\ +403.428\ \times\cos\ 77.909+\ln\ T\max-T\min\ +\ 0.279\ -\sin\ T\max\ \times\cos\ -T\max$ $+\ln\ \ln\ 4Tmean\ \times Tmean$	0.2659
Urmia	$ETo=\ln\ \cos\ 2T\max+\cos\ Tmean\ +2\ T\max-T\min\ +\sin\ T\max-T\min+6\ +\cos\ 2T\max+Tmean+8\ -9.989$	0.1830
Yazd	$ETo=\sqrt{Tmean+\sin\ T\min\ +\sin\ 2T\min\ +\sin\ 2T\min-6-Tmean-T\max}\ +$ $\cos\ \sin\ \cos\ Tmean\ +T\max-T\min-2-\sqrt{Tmean+T\min}$	0.5039
Zabol	$ETo=0.125\ 4T\max-54-2\cos\ T\min\ -\cos\ -2Tmean+7.459$	0.8020

Table 6. Performance of gene expression programming (GEP) for mean temperature (Tmean), wind speed (WS), and relative humidity (RH) as input data.

Region	The best structure	RMSE (mm/day)
Ahvaz	$ETo=\cos\left(\frac{WS}{Tmean+8}\right)+\frac{1+WS}{1.609^{WS\times RH}+\cos\;Tmean\;+WS+RH}+\cos\left(\frac{RH+3}{WS+Tmean}\right)+2.449+WS$	0.1756
Arak	$ETo=3.002-\sin\left(\frac{4}{Tmean}-0.279\right)-\left(\sin\;7-WS\;+\frac{4}{Tmean}-\exp\;-0.039\;WS+1\;\right)$	0.1244
Bushehr	$ETo=\sin\;\sin\;\cos\;WS\;-2.236\;+\cos\;WS\;\;+\sin\;0.408WS\;+\sin\;-\sqrt{WS}\;+6$	0.1739
Esfahan	$ETo=\ln\left(9.178^{\cos\left(\ln\left(\frac{RH}{4}\right)\right)}\right)+\sqrt{4WS-\sin\;Tmean+6\;\;\cos\left(\frac{1.732}{WS+5}\right)}$	0.0730
Hamedan	$ETo=\sqrt{\frac{\frac{Tmean}{WS}+Tmean+8}{0.755WS\times RH}}+\sin\left(\sin\left(\sqrt{\frac{Tmean}{RH}}\right)\right)+\sin\;\sqrt{WS}$	0.1113
Jiroft	$ETo=\left(\frac{6WS^2}{RH}\right)^{\sin\;216RH\;+2.397}+\sin\left(\frac{32WS}{RH}\right)+3\exp\left(\frac{WS}{6}\right)$	0.1428
Kerman	$ETo=\left(2+WS+\sin\left(\frac{5-WS}{5^{WS}}\right)\right)\left(2+WS+\sin\left(\frac{RH}{5}\right)\right)^{0.035\;\sin\;\sin\;WS\;\;-\cos\;2-Tmean}$	0.4252
Mashhad	$ETo=\sqrt{\exp\;\sqrt{WS}+1.098}\;+\cos\;\ln\;\ln\;4^{RH}\;\;+66.230$	0.1584
Moghan	$ETo=\sqrt{\exp\;\sqrt{WS}}\;+\;\cos\;\cos\;WS^{\;\;\sin\;\sin\;6+WS}$	0.1070
Qazvin	$ETo=\exp\;\cos\;0.914-\sqrt{Tmean}\;\;+\;\sqrt[4]{Tmean}\times\sqrt{WS}$	0.1084
Rasht	$ETo=\sqrt{\sin\;2WS+RH-5\;+\ln\;7.841-WS\;+3\sqrt{WS}+\sin\;1-Tmean}$	0.0881
Sanandaj	$ETo=\sqrt{\sqrt{7Tmean\times WS-0.412Tmean}-\sin\;2.449WS-\sin\;WS-Tmean}$	0.1160
Shahrekord	$ETo=\sqrt{\ln\;WS+\exp\;WS\;\;-0.91}\;+\sqrt{\ln\left(\frac{Tmean}{3}+7\right)}+\frac{\sqrt{\sqrt{WS}+\frac{Tmean}{4}}}{4}$	0.0756
Shiraz	$ETo=\sqrt{\exp\;\ln\;\sqrt{WS}\;+\cos\;Tmean+8+\sqrt{Tmean}\;\;+\sqrt{2Tmean+WS}+WS\times\sqrt{2Tmean}}$	0.1261
Tabriz	$ETo=\sqrt{1.25+\ln\;8+WS\;\;-\sin\;WS+Tmean-0.141}\;+\sqrt{1.338+WS}$	0.1660
Urmia	$ETo=3+\frac{1}{3-Tmean-\frac{Tmean}{3}}-\frac{\sin\;8+WS}{3-\frac{WS}{3}-\frac{\sin\;RH}{6}}-\frac{\sin\left(-1.794-\frac{Tmean}{4}\right)}{3-\frac{5}{Tmean}-\sin\left(\frac{Tmean}{4}\right)-0.514\sin\;RH-4}$	0.1082
Yazd	$ETo=-\frac{\sin\;\sqrt{2Tmean}}{\frac{WS}{11}-1}-\frac{0.308}{5-WS}+2.828+WS$	0.1684
Zabol	$ETo=\frac{\sin\left(\frac{11.666+RH}{7.483}\right)}{-0.454\ln\;Tmean\;\left(\frac{0.656}{Tmean}+1\right)}+\frac{\sin\left(\frac{WS}{2}\right)}{\frac{5}{RH}+\;8WS^{\;\;0.54}}+\frac{Tmean}{RH}+\;8WS^{\;\;0.54}$	0.3234