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INTERACTION BETWEEN CONTINENTAL WATERS AND THE ENVIRONMENT

Comparison Between Gene Expression Programming and Traditional Models for Estimating Evapotranspiration under Hyper Arid Conditions[1]

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Abstract—Gene Expression Programming (GEP) was used to develop new mathematical equations for estimating daily reference evapotranspiration (ET_{ref}) for the Kingdom of Saudi Arabia. The daily climatic variables were collected by 13 meteorological stations from 1980 to 2010. The GEP models were trained on 65% of the climatic data and tested using the remaining 35%. The generalised Penman-Monteith model was used as a reference target for evapotranspiration (ET) values, with h_c varies from 5 to 105 cm with increment of a centimetre. Eight GEP models have been compared with four locally calibrated traditional models (Hargreaves-Samani, Irmak, Jensen-Haise and Kimberly-Penman). The results showed that the statistical performance criteria values such as determination coefficients (R^2) ranged from as low as 64.4% for GEP-MOD1, where the only parameters included (maximum, minimum, and mean temperature and crop height), to as high as 95.5% for GEP-MOD8 with which all climatic parameters included (maximum, minimum and mean temperature; maximum, minimum and mean humidity; solar radiation; wind speed; and crop height). Moreover, an interesting founded result is that the solar radiation has almost no effect on ET_{ref} under the hyper arid conditions. In contrast, the wind speed and plant height have a great positive impact in increasing the accuracy of calculating ET_{ref}. Furthermore, eight GEP models have obtained better results than the locally calibrated traditional ET_{ref} equations.

Keywords: arid conditions, reference evapotranspiration, gene expression programming, traditional models

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INTRODUCTION

Water has been labeled “blue gold”, and it is specified to be the critical issue of the 21st century [24]. Globally, irrigation is responsible for 75–80% of the world-wide consumption of water [37]. The knowledge of the amount and variation of evaporative losses is a key factor. Therefore, evapotranspiration (**ET**) is an essential parameter in water and energy balances on the earth’s surface [32]. It can be determined either experimentally (directly) or mathematically (indirectly). It can be measured directly by using either a lysimeter or a water balance in a controlled crop area [15]. However, this approach is difficult, time-consuming and expensive. Evapotranspiration can be calculated indirectly using a crop coefficient (K_c) as determined by the crop type, stage of growth, canopy cover and density and soil moisture, multiplied by a reference evapotranspiration (ET_{ref}) value [4]. The generalised Penman-Monteith (**PMG**) method is widely used in agricultural and environmental research to estimate the ET_{ref} and it coincides well with field observations. Many researchers acknowledge that the PMG model is the most promising standardised method for estimating the ET_{ref}. However, it requires a significant amount of climatic data, which may be unavailable or not be reliable in certain locations, especially when dealing with developing countries. In these cases, alternative methods that rely on fewer weather inputs are necessary. Soft computing techniques, including artificial neural networks (**ANN**), fuzzy logic (**FL**), neuro-fuzzy systems (**NFS**), and gene expression programming (**GEP**) and so on can be used as an alternative method to a physical model especially for complex non-linear systems [30].

GEP was invented by Ferreira [12] and is the natural development of genetic algorithms and genetic programming. GEP has been applied in fields as diverse as artificial intelligence, artificial life, engineering and science, financial markets, industrial, chemical and biological processes and mechanical

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models. It has been used to solve problems such as symbolic regression, multi-agent strategies, time series prediction, circuit design and evolutionary neural networks [33].

GEP has been used in various engineering science applications. For instance, in environmental engineering, Seckin et al. [35] investigated GEP's ability to estimate the methane yield and effluent substrate produced by two anaerobic filters. They found that the GEP approach predicted the performance of both anaerobic filters much better than the Stover-Kincannon model.

In civil engineering, Saridemir [34] successfully used GEP techniques to predict the compressive strength of concretes containing rice husk ash. Recently, Gandomi et al. [14] developed a GEP model for predicting the strength of concrete under triaxial compression loading and Mollahasani et al. [28] developed new empirical models to predict soil deformation moduli using GEP.

GEP has been used in a number of hydrological and hydraulic modelling problems. Guven et al. [18] used a GEP approach to model the stage-discharge relationship and compared the results with conventional methods. They found that the explicit algebraic formulations resulting from the GEP approach gave the best results. In a similar study, Azamathulla et al. [8] developed mathematical models to estimate the stage-discharge relationship for the Pahang River based on GP and GEP techniques.

Ghani et al. [17] used GEP to model the functional relationships of sediment transport in sewer pipe systems. More recent, Azamathulla et al. [7] used GEP to predict the transverse mixing coefficient in open channel flows. Zahiri et al. [42] used GEP to predict the flow discharge in compound channels.

Furthermore, Fernando et al. [10] introduced an innovative method for combining estimated outputs from a number of rainfall-runoff models using GEP to perform a symbolic regression. The results showed that the GEP combination method was able to combine the model outcomes from less accurate individual models and produce a superior river flow forecast. Azamathulla [6] used GEP to predict the friction factor for southern Italian rivers.

Of the many published studies on the application of GEP in hydrological modelling, only a few studies have examined the applicability and durability of GEP for modelling evapotranspiration. Shiri et al. [36] introduced a new GEP model for estimating the daily ET_{ref} at four weather stations in northern Spain between 1999 and 2003. The GEP model was compared with the adaptive neuro-fuzzy inference system and the Priestley–Taylor and Hargreaves–Samani models, using the PMFAO equation as a reference. The GEP model was found to perform better than the other models. Traore et al. [40] evaluated a GEP model's ability to estimate the ET_{ref} of the tropical seasonally dry regions of West Africa using routing meteorological data from Burkina Faso. The results revealed that the GEP model was a fairly promising approach. It provided successful, simple algebraic formulas that were easy to use and did not require the full set of meteorological data to accurately estimate the ET_{ref} in sub-Saharan Africa regions.

On the other hand, other Genetic programming techniques have been applied in modelling of evapotranspiration process. Parasuraman et al. [31] evaluated the performance of the genetic programming (**GP**) model, ANN models and the hourly PMFAO method in estimating the ET_{ref}. They found that both of the data driven models, GP and ANN, performed better than the PMFAO method. However, the GP model and ANN model performed comparably.

Moreover, Aytek et al. [5] presented GP as a new tool for estimating the ET_{ref} using daily climatic variables obtained from the California Irrigation Management Information System database. The results obtained were compared to seven conventional ET_{ref} models. They found that the new model produced satisfactorily results and could be used as an alternative to the conventional models. However, [23] investigated the accuracy of linear genetic programming, which is an extension of the GP technique, in modelling the daily ET_{ref} using the PMFAO equation. The linear genetic programming model was found to perform more accurately than the support vector regression model, artificial neural network and four empirical models.

The objectives of this study are to: (1) develop daily ET_{ref} models using the GEP technique from limited variables, and (2) assess the accuracy of the developed GEP models with four traditional models.

MATERIALS AND METHODS

Geographical Situation and Climatic Data Characterization

This study has been carried out in the Kingdom of Saudi Arabia (**KSA**) situated in the far southwest corner of Asia (Fig. 1), between latitudes 16°22′46″ N and 32°14′00″ N and longitudes 34°29′30″ E and 55°40′00″ E. It is the largest country in Arabia. The KSA occupies about 70% of the area of the Arabian Peninsula with an approximate area of 1950 thousand km^2. It is divided into thirteen provinces, as shown in Fig. 1. This study considers all of the provinces. The provinces are arranged by area in descending order in Table 1.

The KSA's climate varies from region to region, depending on the terrain. The climate is generally characterized by hot summers, cold winters and winter rainfall. The central areas experience hot, dry summers and cool, dry winters. The coastal areas experience high humidity. The air temperature falls moderately with the onset of autumn, which lasts from

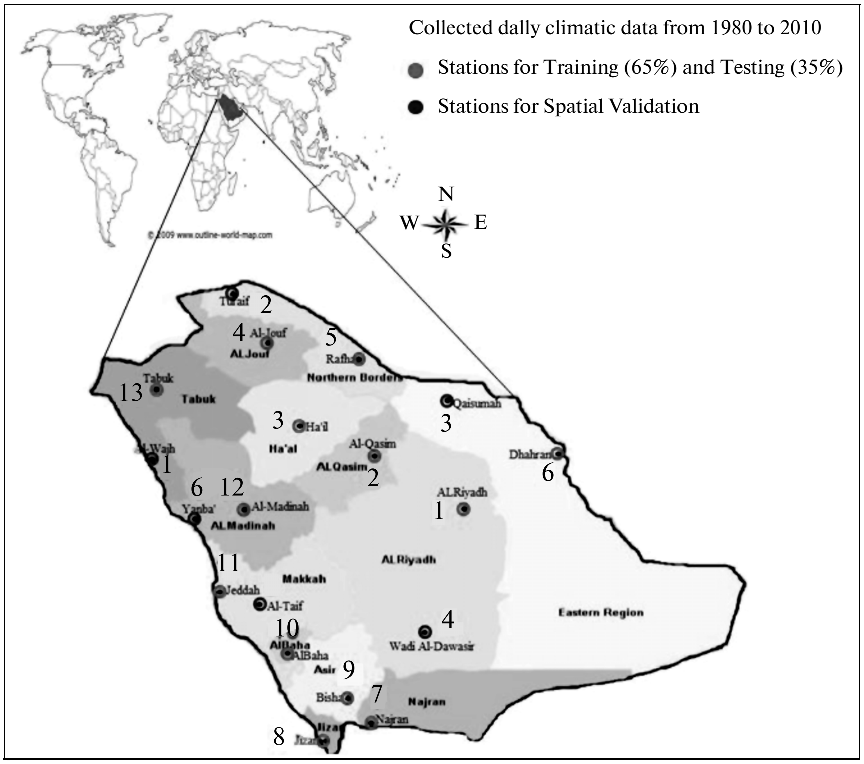

Fig. 1. Map of the KSA, showing its provinces and meteorological stations.

September 23 to December 21. The lowest air temperatures are reported in the northern regions (3–7°C). Later in the year, temperatures significantly decline in other areas. Temperature variations are noted daily and vary from region to region.

For this study, climatic data was recorded at 19 meteorological stations selected from the 13 KSA provinces. The spatial distribution of the selected stations within the provinces is shown in Fig. 1. Each province is represented by two stations, except for the provinces of Najran, Ha'il, Al-Jouf, Bisha, Al-Qasim, Jizan and Al-Baha, which are only represented by one station. The Presidency of Meteorology and Environment provided the data. The study's climatic data covers 31 years of daily meteorological information recorded from 1980 to 2010. The recorded data for all of the stations includes the maximum, minimum and mean air temperatures (T_x, T_n, and T_a) (°C); maximum, minimum and mean relative humidity (Rh_x, Rh_n and Rh_a) (%); wind speed at 2 m height (U_2) (m/s) and solar radiation (R_s) (MJ/m^2/d). Table 1 describes the meteorological stations and lists the annual averages of the climatic data from each station.

The GEP models take at most nine input variables, T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, U_2, R_s and the reference crop height (h_c) (m), which varies from 5 to 105 cm. This range is selected to cover both grass (10 to 15 cm) and alfalfa (30 to 80 cm). A random h_c value is chosen during training. The ET_{ref} is the output variable. The input variables are divided into three sets. The training set for the GEP models is composed of 65% of the daily data collected by 13 of the weather stations, Riyadh (North), A-Qasim, Ha'il, Al-Jouf, Rafha, Dhahran, Najran, Jizan, Bisha, Al-Baha, Jeddah, Al-Madina and Tabuk, from 1980 to 2007. The training set is used to find the patterns present in the data. The testing set for the GEP models is composed of the remaining 35% of the data from the same weather stations and period as the training set. It is used to evaluate the generalisation abilities of the trained models.

Output/Targeted Data of the GEP Models

The performances of the GEP models are compared to the PMG method. The PMG method is considered the standard procedure when measured lysimeter data is not available [16, 20]. The PMG method gives optimal results over all climatic zones [1, 16, 19, 20, 29] and has advantages over many other mathematical equations. It can be used globally without any local calibrations due to its physical basis, is well-documented and has been validated with a significant amount of lysimeter data [38]. Many researchers [9, 21, 22, 25, 26, 39, 41, 43] have used the PMG equation as a reference and standard equation to evaluate the results of their mathematical models. The daily ET_{ref} values from the PMG equation are used as the output/target variables in the GEP models. A general-

Table 1. Meteorological station sites and climatic parameters

Provinces	Areas*, km^2	Stations	Location			T_x, °C	T_n, °C	T_a, °C	Climatic parameters			U_2, m/s	R_s, $(MJ/m^2/d)$
			longitude, deg	latitude, deg	altitude, m				Rh_x, %	Rh_n, %	Rh_a, %		
Eastern Region	540	Qaisumah	46.13	28.31	355	32	19	25	77	30	50	2.6	21
		Dhahran	50.20	26.30	17	33	20	26	75	29	52	4.2	20
Al–Riyadh	380	Riyadh (North)	46.72	24.93	614	33	20	26	38	16	31	3.9	15
		Wadi Al–Dawasir	45.20	20.50	617	35	22	28	35	17	26	3.4	18
Al–Madinah	150	Al–Madina	39.60	24.47	619	33	25	19	56	29	44	4.2	26
		Yanba'	38.10	24.10	1	29	22	17	78	23	50	3.2	29
Makkah	137	Jeddah	39.17	21.40	12	34	28	22	81	37	60	2.6	23
		Al–Ta'if	40.50	21.50	1449	35	29	23	60	29	39	3.2	27
Tabuk	136	Tabuk	36.58	28.38	770	29	14	22	53	17	32	2.9	33
		Al–Wajh	36.50	26.20	20	28	10	18	70	22	45	2.2	29
Najran	130	Najran	44.40	17.60	1214	35	29	25	60	33	44	3.5	28
Ha'il	120	Ha'il	41.70	27.40	1013	34	28	22	81	37	60	2.3	14
Northern Borders	104	Turaif	38.65	31.68	854	35	29	23	60	29	39	3.3	29
		Rafha	43.50	29.60	447	29	14	22	53	17	32	2.9	22
Al–Jouf	85	Al–Jouf	40.10	29.80	689	30	14	22	48	18	31	3.11	25
Asir	80	Bisha	42.60	20.00	1157	33	17	25	47	15	29	2.4	28
Al–Gasim	73	Al–Qasim	43.80	26.30	650	32	18	25	44	30	18	2.9	27
Jizan	13	Jizan	42.60	16.88	3	36	30	25	61	34	44	3.3	36
Al–Bahah	12	Al–Baha	41.60	20.30	1656	29	16	22	56	22	38	1.3	28

* Saudi Geological Survey (2012), King Saudi Arabia: Facts and Numbers.

Table 2. List of empirical models and main variables needed for each model (T_a—average temperature, T_n—minimum temperature, T_x—maximum temperature, U_2—wind speed at level 2 m, R_s—solar radiation, Rh_n—minimum Rh, Rh_x—maximum Rh, Rh_a—average Rh, C_T—0.025, T_{xm}—−3, e_a—actual vapour pressure, e_s—saturation vapour pressure deficit, G—soil heat flux, γ—psychrometric constant, Δ—slope of the saturation vapour pressure-temperature curve, λ—latent heat of vaporisation, R_n—net radiation, W_f—wind function)

Model	Formula	Input variables	Based on
Hargreaves–Samani (1985)	$ET_o = 0.0023(T_a + 17.8)(T_x - T_n)^{0.5} R_a$	T_x, °C; T_n, °C; T_a °C	Grass
Irmak (2003)	$ET_o = -0.611 + 0.149R_s + 0.079T_a$	T_a, °C; R_s, MJ m^{-2} d^{-1}	Grass
Jensen–Haise (1963)	$ET_r = \frac{C_T(T_a - T_{xm})R_s}{\lambda}$	T_a, °C; R_s, MJ m^{-2} d^{-1}	Alfalfa
Kimberly–Penman (1972)	$ET_r = \frac{1}{\lambda}\left[\frac{\Delta}{\Delta+\gamma}(R_n - G) + \frac{\gamma}{\Delta+\gamma}6.43W_f(e_s - e_a)\right]$	T_x, °C; T_n, °C; T_a, °C; Rh_x, %; Rh_n, %; Rh_a, %; U_2, m s^{-1}, R_s, MJ m^{-2} d^{-1}	Alfalfa

ized form of the Penman-Monteith model can be written as [2]:

$$ET_{\text{ref}} = \lambda^{-1}\left[\frac{\Delta}{\Delta+\gamma^*}(R_n - G) + \frac{\gamma}{\Delta+\gamma^*}K(e_s - e_a)\right], \quad (1)$$

where λ is the latent heat of vaporiszation (MJ kg^{-1}), Δ is the slope of the saturation vapour pressure-temperature curve at the mean air temperature (kPa °C^{-1}), γ is the psychometric constant (kPa °C^{-1}), R_n is the net radiation (MJ m^{-2} day^{-1}), G is the soil heat flux (MJ m^{-2} day^{-1}), γ^* is the modified psychometric constant (kPa °C^{-1}), K is the parameter equal to $1.854 \times 10^5 \frac{\lambda/r_a}{T + 273}$ (MJ m^{-2} day kPa), r_a is the aerodynamic resistance (s m^{-1}), T is the air temperature (°C), e_s is the saturation vapour pressure at the air temperature (kPa), and e_a is the actual vapour pressure (kPa).

Empirical ET_{ref} Models

The GEP models are compared with four empirical models that represent the common strategies for calculating the ET_{ref}. The details of the models, a temperature-based model (Hargreaves–Samani), two radiation-based models (Jensen–Haise and Irmak) and a combination-based model (Kimberly–Penman), are shown in Table 2.

Gene-Expression Programming

GEP is a new evolutionary artificial intelligence technique developed by Ferreira [11]. According to [11, 12] the primary difference between GEP and its predecessors, genetic algorithms (**GAs**) and genetic programming (**GP**), stems from the nature of the individuals: in GAs, the individuals are linear strings of fixed length (chromosomes). In GP, the individuals are nonlinear entities of different sizes and shapes (parse trees). In GEP, the individuals are encoded as linear strings of fixed length (chromosomes) that are expressed as nonlinear entities of different sizes and shapes.

GEP uses chromosomes, which are usually composed of more than one gene of equal length, and expression trees or programmes, which are the expressions of the genetic information encoded in the chromosomes [13]. The chromosomes are composed of multiple genes, each gene encoding a smaller sub-programme. In GEP, the linear chromosomes represent the genotype and the branched expression trees represent the phenotype [12]. Figure 2 shows the organisation of a standard GEP model.

GEP is a complete genotype/phenotype system in which the genotype is totally separate from the phenotype. In contrast, in GP, the genotype and phenotype constitute one entangled mess, more formally referred to as a simple replicator system. As a result, GEP's genotype/phenotype system surpasses the GP system by a factor of 100–60000 [11, 12].

GEP models encode their information in linear chromosomes, which are later translated or expressed in expression trees. These computer programmes are usually developed to solve a particular problem and are selected according to their ability to solve that problem [18]. Figure 3 illustrates the general structure of a GEP modelling procedure.

Developing the GEP Model

The training set was selected from the whole data set and the remaining data was used as the testing set. GEP model development consisted of five major steps [11, 12]:

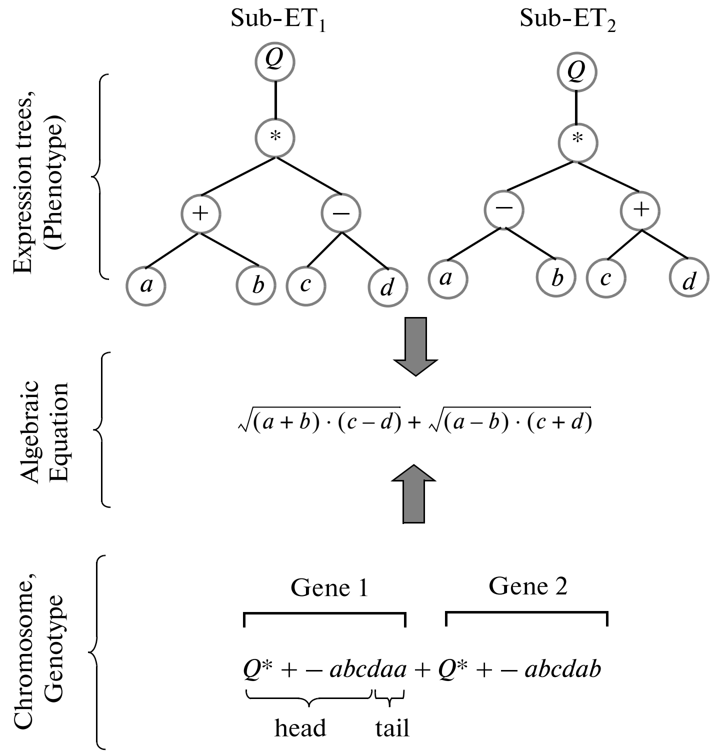

Fig. 2. GEP model of a chromosome with two genes and their phenotypes [36].

1—Select the fitness function. The fitness (f_i) of an individual program (i) is measured by:

$$f_i = \sum_{j=1}^{C_t} \left(M - \left| C_{(i,j)} - T_{(j)} \right| \right), \tag{2}$$

where M is the selection range, $C_{(i,j)}$ is the value returned by the individual chromosome i for fitness case j (out of C_t fitness cases) and T_j is the target value for fitness case j. If $|C_{(i,j)} - T_j|$ (the precision) ≤ 0.01, then the precision is 0 and $f_i = f_{\max} = C_t M$. The advantage of this fitness function is that the system can find the optimal solution by itself.

2—Choose the set of terminals (T) and the set of functions (F) to create the chromosomes. For instance, the terminal set includes the following variables: T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, R_s, U_2 and h_c. The choice of functions depends on the user. In this study, different mathematical functions were used, such as $+, -, \times, \div, \sqrt{\ }, \sqrt[3]{\ }$, ex and sin. Eight input combinations were tested, as listed in Table 3.

Table 3. The input variables combinations used in the GEP models

Model	Input Parameters								
	temperature, °C			Relative Humid, %			U_2, m/s	R_s, MJ/m^2/d	h_c, m
	T_x	T_n	T_a	Rh$_x$	Rh$_n$	Rh$_a$			
GEP–MOD1	✓	✓	✓						✓
GEP–MOD2	✓	✓	✓	✓	✓	✓			✓
GEP–MOD3	✓	✓	✓				✓		✓
GEP–MOD4	✓	✓	✓					✓	✓
GEP–MOD5	✓	✓	✓	✓	✓	✓	✓		✓
GEP–MOD6	✓	✓	✓	✓	✓	✓		✓	✓
GEP–MOD7	✓	✓	✓				✓	✓	✓
GEP–MOD8	✓	✓	✓	✓	✓	✓	✓	✓	✓

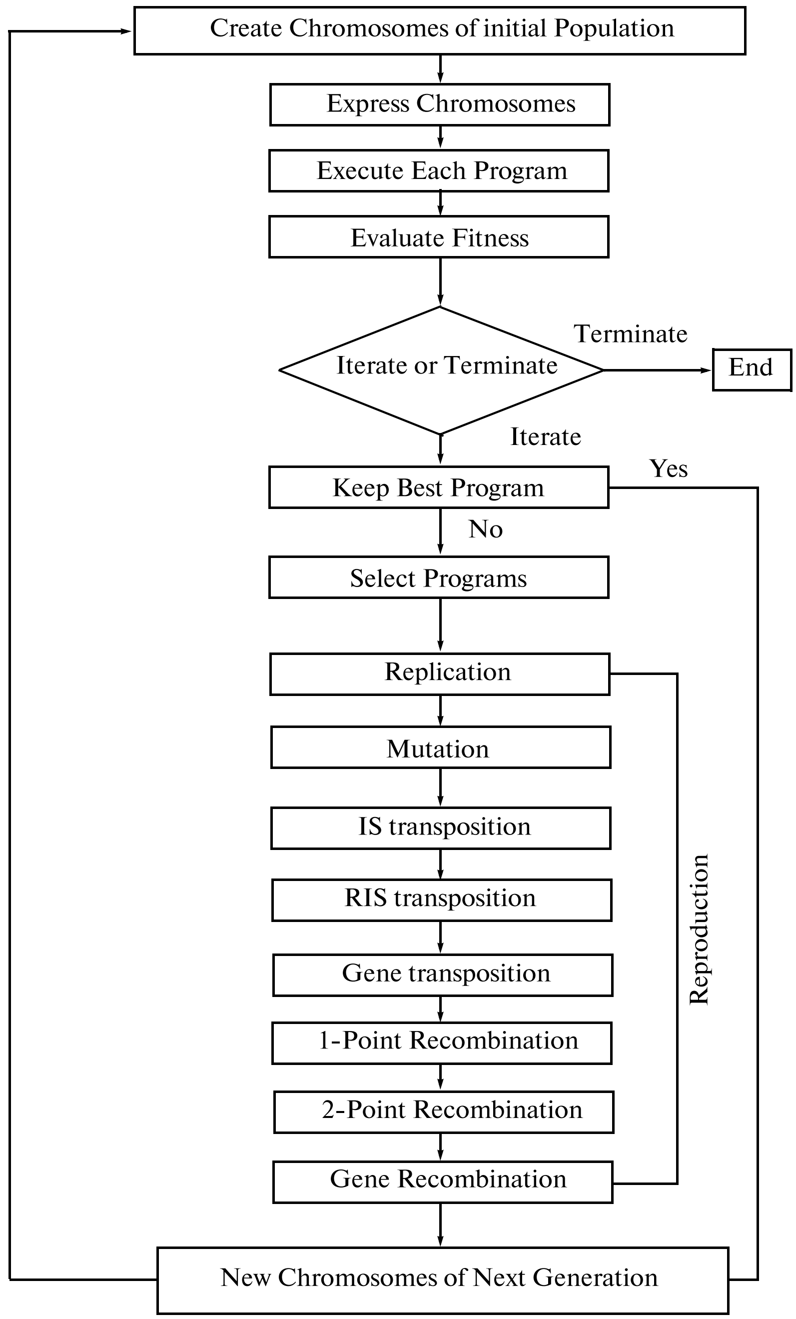

Fig. 3. Flow chart of the Gene Expression Algorithm [12].

3—Choose the chromosomal architecture. A single gene and two head length was initially used. The number of genes and heads were increased one after another during each run and the training and testing performance of each model was monitored.

4—Choose the linking function. Only addition or multiplication linking functions could be chosen for algebraic sub-trees.

5—Select the set of GEP operators from mutation, transposition and recombination. This process was repeated for a pre-specified number of generations or until a solution was found.

In the present work, the GeneXpro program is used to estimate the daily evapotranspiration. Figure 3 illustrates the general GEP modelling procedure.

The Input Combinations

The five climate factors could not be simultaneously collected in some regions. An empirical model that used a small amount of climate data to estimate the ET_{ref} was thus important. Several combinations of the input parameters were used as inputs to estimate the daily ET_{ref} using the GEP models. The input parameter combinations are listed in Table 3.

Eight GEP models were developed to test the performance of different combinations of input parameters, including climatic parameters and a reference crop height chosen randomly during the training process. The three temperature elements (maximum, minimum and mean temperature) and crop height were included in all of the combinations.

The first combination used the three temperature elements and crop height. It was a temperature-based model similar to the Hargreaves–Samani model, the details of which are listed in Table 2. The second combination added the three humidity elements (maximum, minimum and mean humidity) to the first combination. The third combination added wind speed to the first combination. The fourth combination added solar radiation to the first combination. The fourth combination was similar to the radiation-based models and has the same inputs as the Jensen–Haise model.

The fifth combination was formed by inserting wind speed into the second combination. The sixth combination was formed by inserting solar radiation into the second combination. The seventh combination consisted of all inputs parameters except the relative humidity data. The eighth combination consisted of all the input parameters and is an identical set to that used by the Kimberly–Penman model, as shown in Table 2.

Performance Criteria

After training the GEP models and validating the data set, the ET_{ref} values were estimated and compared to the daily values from the PMG model and four ET_{ref} models. The comparisons were made using the following statistical parameters.

$$R^2 = \frac{\left(\sum_{i=1}^{n}(E_i - \bar{E})(C_i - \bar{C})\right)^2}{\sum_{i=1}^{n}(E_i - \bar{E})^2 \sum_{i=1}^{n}(C_i - \bar{C})^2}, \quad (3)$$

$$OI = \frac{1}{2}\left(1 - \frac{RMSE}{E_{\max} - E_{\min}} + ME\right), \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i - C_i)^2}{n}}, \quad (5)$$

$$MAE = \frac{\sum_{i=1}^{n}\left|E_i - C_i\right|}{n}, \quad (6)$$

where E_i is value of ET_{ref} estimated by the PMG, C_i is corresponding value calculated by mathematical ET_{ref} models, n is number of observations, $\bar{E}$ is average of the estimated values, $\bar{C}$ is average of the calculated values, $E_{\max}$ is maximum estimated value, and $E_{\min}$ is minimum estimated value.

The coefficient of determination (R^2) measures the degree of correlation between the estimated and calculated values, where values approaching 1.0 indicate a good correlation. The root mean square error (**RMSE**) expresses the error in the same units that describe the variable [27]. The lower the RMSE is, the better the matching is. The overall index of the model performance (**OI**) combines the normalised RMSE and the model efficiency value. An OI value of 1.0 indicates a perfect fit between a model's estimated and calculated values [3]. The mean absolute error (**MAE**) is the average value of the absolute differences between the estimated and calculated values. A low MAE implies good model performance.

RESULTS AND DISCUSSION

Models Development Using Gene Expression Programming (GEP)

The main purpose of developing the GEP models was to generate the mathematical functions to use for predicting the ET_{ref}. The input parameters of the GEP models are given in Table 3. A set of preparatory model runs were carried out to test the performance of the models using four possible function sets. One function set is selected for continued use. All of these procedures were performed on GEP-MOD1, which contained the least variables, using the RMSE fitness function and the addition linking function. The results of the function selection investigation are presented in Table 4.

The results in Table 4 show that the operator function set *F*4 outperformed the other structures. The superiority of the *F*4 function set confirms the results of Shiri et al. [36], as these authors concluded that the GeneXpro default operator function set (*F*4) performed better than other applied function sets for estimating the daily ET_{ref} at four weather stations in Basque country, northern Spain and for estimating the daily suspended sediment load at two stations in Cumberland River, USA. Despite these results, the *F*3 function set was used in the GEP models, to develop less complicated mathematical equations and avoid the use of trigonometric functions. There were also only slight differences between the *F*3 and *F*4 function sets.

The maximum number of generations and best fitness generated during training were 209208 and 781.89 for GEP–MOD1, 260672 and 793.51 for GEP–MOD2, 20789 and 790.77 for GEP–MOD3,

Table 4. Preliminary selection of the basic functions used in the expression tree, using a scatter index

	Functions	R^2, %	RMSE, mm/d
*F*1	+, −, ×, ÷	61.3	3.45
*F*2	+, −, ×, ÷, sqrt, exp	63.2	3.23
*F*3	+, −, ×, ÷, sqrt, exp, Ln, X^2	64.4	3.10
*F*4	+, −, ×, ÷, sqrt, 3Rt, exp, Ln, X^2, X^3, sin(x), cos(x), arctan(x)	65.7	2.94

Table 5. Parameters of GEP models

Parameter	Description of parameter	Parameter setting
*P*1	Number of chromosomes	30
*P*2	Number of genes	3 (GEP–MOD1 to GEP–MOD7), 4 (GEP–MOD8)
*P*3	Head size	8 (GEP–MOD1 to GEP–MOD7), 10 (GEP–MOD8)
*P*4	Function set	+, −, ×, ÷, sqrt, exp, Ln, X^2
*P*5	Linking function	Addition
*P*6	Fitness function	Mean squared error
*P*7	Mutation rate	0.00206
*P*8	Inversion rate	0.00546
*P*9	One-point recombination rate	0.00277
*P*10	Two-point recombination rate	0.00277
*P*11	Gene recombination rate	0.00277
*P*12	Gene transposition rate	0.00277

170031 and 804.77 for GEP–MOD4, 202825 and 830.76 for GEP–MOD5, 104139 and 814.45 for GEP–MOD6, 199602 and 845.31 for GEP-MOD7 and 12447 and 915.36 for GEP–MOD8, respectively. The parameters used in training the eight models are given in Table 5.

The program was run until there was no longer a significant improvement in the performance of the models. The algebraic equations that best estimate the ET_{ref} and the expression trees are given in Table 6.

Gene Expression Programming (GEP) Models Performance Training and Testing Processes

The R^2, RMSE, OI and MAE statistics of each GEP model during training and testing are given in Table 7. GEP–MOD1 (whose inputs were the three air temperature variables and crop height) had the smallest R^2 (64.4%) and OI (92.2%) values and the highest RMSE (3.10 mm/day) and MAE (2.29 mm/day) values in training. Thus, GEP–MOD1 gave poor estimates. The relative humidity variables seem to have

Table 6. Statistical performance of the optimized GEP models during training and testing

Model	Inputs	Training				Testing			
		R^2, %	OI, %	RMSE, mm/d	MAE, mm/d	R^2, %	OI, %	RMSE, mm/d	MAE, mm/d
GEP–MOD1	T_x, T_n, T_a, h_c	64.4	92.2	3.10	2.29	63.6	77.9	3.19	2.40
GEP–MOD2	T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, h_c	72.2	93.1	2.85	2.07	71.0	81.0	2.94	2.17
GEP–MOD3	T_x, T_n, T_a, U_2, h_c	76.1	93.9	2.64	1.98	76.8	84.2	2.65	1.98
GEP–MOD4	T_x, T_n, T_a, R_c, h_c	68.3	92.9	2.92	2.11	67.9	80.4	2.99	2.21
GEP–MOD5	T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, U_2, h_c	97.8	96.1	1.98	1.46	89.3	89.6	2.09	1.53
GEP–MOD6	T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, R_c, h_c	77.5	94.5	2.48	1.73	77.6	85.6	2.52	1.81
GEP–MOD7	T_x, T_n, T_a, U_2, R_s, h_c	82.2	95.4	2.20	1.64	82.6	88.6	2.21	1.63
GEP–MOD8	T_x, T_n, T_a, Rh_x, Rh_n, Rh_a, U_2, R_s, h_c	95.5	98.1	1.12	0.83	95.4	96.3	1.14	0.83

been the most effective in estimating the ET_{ref}, as adding relative humidity to GEP–MOD1 (GEP–MOD2) significantly increased the performance, giving the largest R^2 increase (18%) and RMSE decrease (8%) in the training process.

GEP–MOD3 added wind speed and performed better than GEP–MOD1. In contrast, GEP–MOD4, which replaced solar radiation with the relative humidity variables, performed poorly, with $R^2 = 68.3\%$ and RMSE = 2.92 mm/day. GEP–MOD7 added solar radiation to GEP–MOD3 and performed better than GEP–MOD3, increasing the R^2 from 76.1 to 82.2% and the OI from 93.9 to 95.4% and decreasing the RMSE from 2.64 to 2.2 mm/day and the MAE from 1.98 to 1.64 mm/day. Replacing humidity with wind speed resulted in a worse performance by GEP–MOD6 than GEP–MOD7. Conversely, replacing humidity with solar radiation resulted in a better performance by GEP–MOD5 than GEP–MOD7.

Furthermore, it can be seen from Table 7 that GEP–MOD8 outperformed the other models by all of the performance criteria. GEP–MOD8 ranked best in the training process. This was expected, as GEP–MODS8 considered all of the variables that have an influence on the ET_{ref}.

During testing, the GEP models had R^2 values ranging from 63.2 to 95.4%, OI values from 77.3 to 96.1%, RMSE values from 1.14 to 3.2 mm/day and MAE values from 0.83 to 2.42 mm/day. It can be observed from Table 7 that the GEP models with high R^2 and OI values and low RMSE and MAE values were able to predict the target values with an acceptable degree of accuracy. Furthermore, GEP–MOD1 statistics were R^2 = 63.6%, OI = 77.9%, RMSE = 3.19 mm/day and MAE = 2.40 mm/day. Table 7 give the results of adding the relative humidity variables (GEP–MOD2), wind speed (GEP–MOD3) or solar radiation (GEP–MOD4). GEP–MOD2 (R^2 = 71.0%, OI = 81.0%, RMSE = 2.94 mm/day and MAE = 2.17 mm/day) and GEP-MOD3 (R^2 = 76.8%, OI = 84.2%, RMSE = 2.65 mm/day and MAE = 1.98 mm/day) produced better results, whereas GEP–MOD4 (R^2 = 67.9%, OI = 80.4%, RMSE = 2.99 mm/day and MAE = 2.21 mm/day) performed slightly worse. This result indicates the slight effect of solar radiation on modelling the ET_{ref}, as the R^2 only increased by 6.76% when solar radiation was added to GEP–MOD1. The relative humidity seemed to be more effective than solar radiation in modelling the ET_{ref}, as the R^2 increased by 11.63% when relative humidity was added to GEP–MOD1. Adding wind speed into the input combination improved the estimation accuracy significantly, due to its advection effects on evapotranspiration.

Table 7. Statistical performance of the uncalibrated (HS) and calibrated (CAL–HS) Hargreaves models, uncalibrated (IM) and calibrated (CAL–IM) Irmak models, GEP–MOD8, using the data collected from 1980 to 2010 by six weather stations

Models	R^2, %	OI, %	RMSE, mm/d	MAE, mm/d
GEP–MOD8–12	92.0	92.3	0.97	0.77
HS	66.0	23.5	3.45	2.84
CAL–HS	66.0	78.7	1.73	1.24
IM	68.7	53.3	2.66	1.87
CAL–IM	68.7	78.4	1.75	1.36

Table 8. Statistical performance of the uncalibrated (JH) and calibrated (CAL–JH) Jensen–Haise models, uncalibrated (KP) and calibrated (CAL–KP) Kimberly–Penman models, GEP–MOD8, using the data collected from 1980 to 2010 by six weather stations

Models	R^2, %	OI, %	RMSE, mm/d	MAE, mm/d
GEP–MOD8–50	97.6	96.9	0.75	0.55
JH	66.7	67.8	3.22	2.26
CAL–JH	66.7	76.9	2.65	1.98
KP	93.9	90.2	1.59	1.23
CAL–KP	93.9	94.2	1.13	0.86

A similar procedure was applied to add either wind speed or solar radiation to GEP–MOD2. The R^2 increased drastically by 25.77%, from 71.0 to 89.3%, when wind speed was added to GEP–MOD2. However, the addition of solar radiation to GEP–MOD2 did not result in a significant increase in R^2 (9.29% increase). Furthermore, solar radiation slightly increased the R^2 by 7.55% when it was added to GEP–MOD3. This result indicates that solar radiation had an insignificant effect on the modelling of the ET_{ref}. GEP–MOD8 outperformed the other models by all of the performance criteria.

The developed GEP models were compared with the results obtained from PMG model. Figure 4 compares the results on the training data set, using a scatter plot of the estimated ET_{ref} values with the 45° exact model line. Figure 5 similarly compares the results on the testing data set. It is obvious from Figs. 4 and 5 that the GEP–MOD8 estimates were closer to the corresponding ET_{ref} values estimated by the PMG model than those of the other GEP models. Most of the GEP models underestimated the

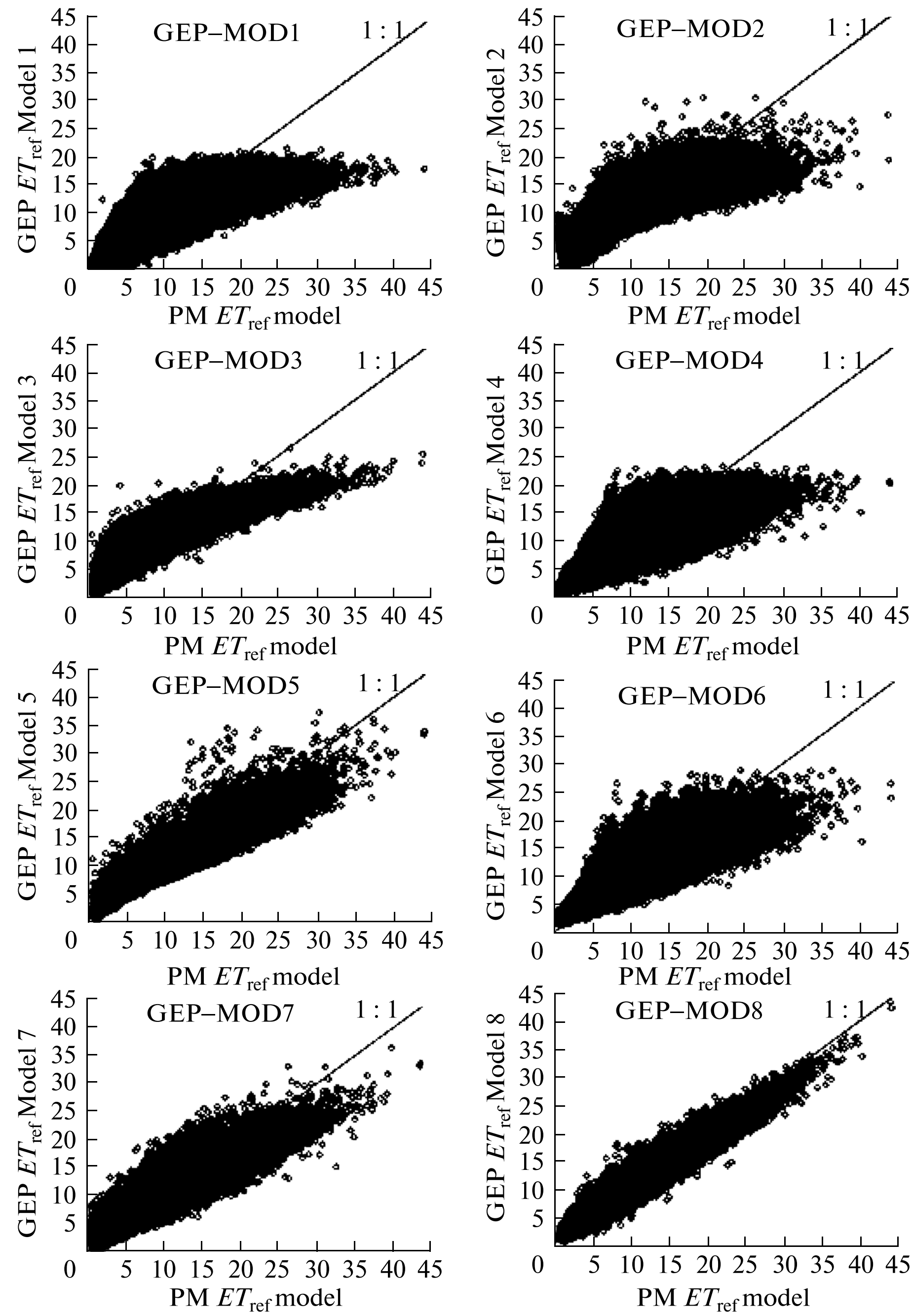

Fig. 4. Comparison of the daily ET_{ref} values estimated by the GEP models with different input combinations and by the PMG equation during training, using 65% of the data collected from 1980 to 2010 by 13 weather stations.

PMG ET_{ref} values when the values are greater than approximately 20 mm/day.

Comparison of the GEP and Empirical Models Grass-Based Comparison

The performances of the GEP–MOD8 models on grass are compared to the calibrated and uncalibrated versions of the Hargreaves and Irmak methods. The input variables used for each model are given in Tables 2 and 3. Table 8 and Fig. 6 showed that GEP–MOD8 outperformed the other models ($R^2 = 92.0\%$, OI = 92.3%, RMSE = 0.97 mm/day and MAE = 0.77 mm/day).

The R^2 for the Hargreaves model was 66% both before and after calibration, which indicates that there

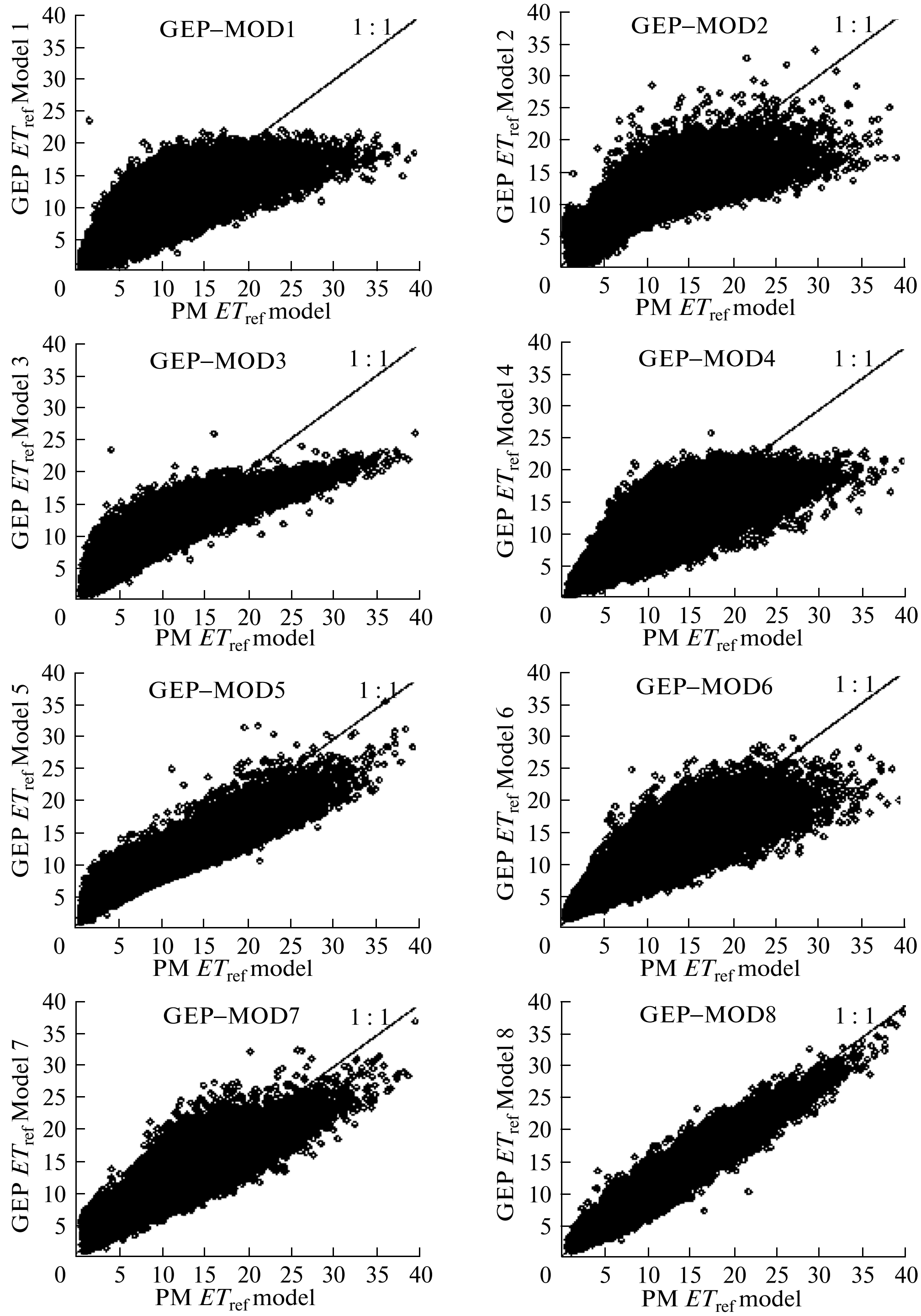

Fig. 5. Comparison of the daily ET_{ref} values estimated by the GEP models with different input combinations and the PMG equation during testing, using 35% of the data collecting from 1980 to 2010 by 13 weather stations.

is no improvement between the calibrated and uncalibrated models. However, the uncalibrated Hargreaves model statistics were OI = 78.7%, RMSE = 1.74 mm/day and MAE = 1.24 mm/day, whereas the calibrated Hargreaves model statistics were OI = 23.5%, RMSE = 3.45 mm/day and MAE = 2.84 mm/day. The calibration of the empirical model significantly increased the estimation accuracy, as measured by the OI, RMSE and MAE.

Table 8 also shows the comparison with the Irmak method, a grass reference method whose inputs are the average temperature and solar radiation. As men-

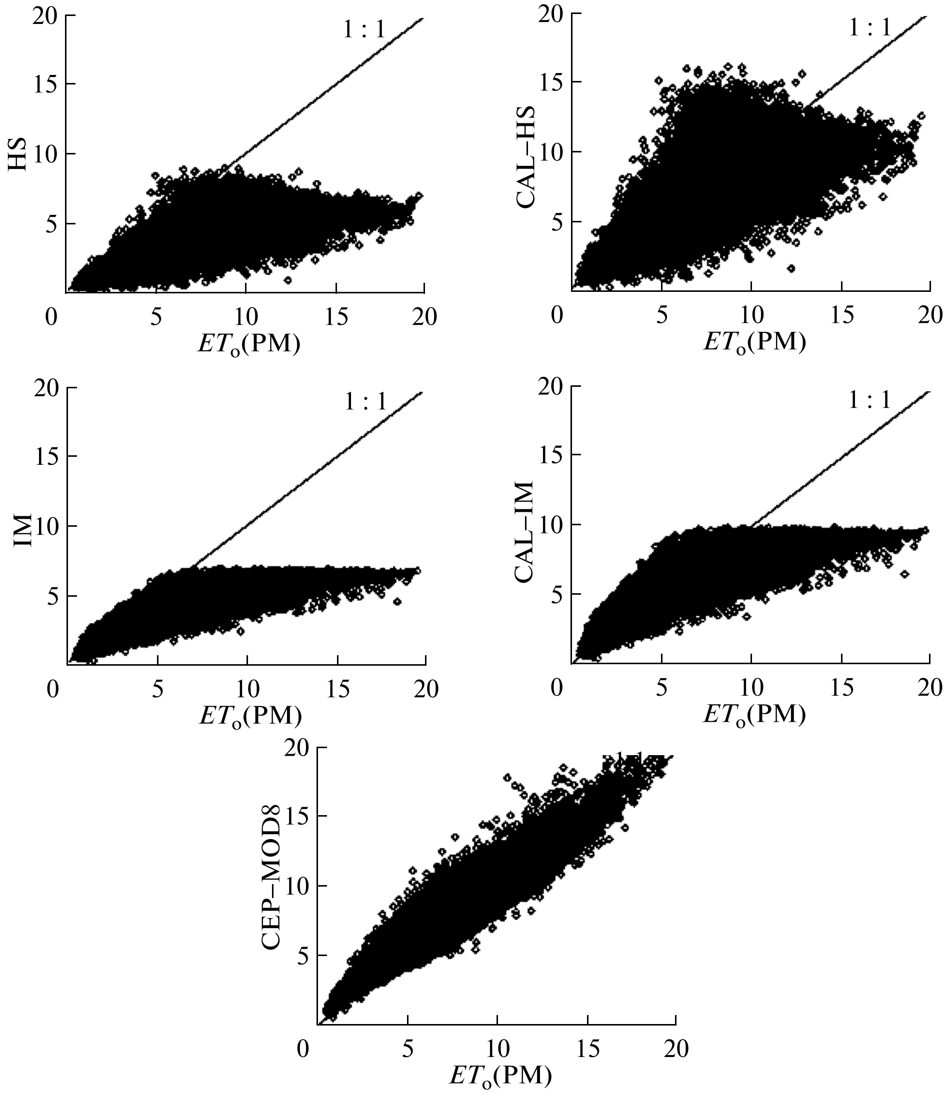

Fig. 6. Comparison of the grass ET_{ref} (ET_o) estimates by the uncalibrated (HS) and calibrated (CAL–HS) Hargreaves models, uncalibrated (IM) and calibrated (CAL–IM) Irmak models and GEP–MOD8.

tioned previously, GEP–MOD8 performed best. Like the Hargreaves models, the Irmak model had no difference in its R^2 value before and after calibration (68.7%). The uncalibrated Irmak model statistics were OI = 53.3%, RMSE = 2.66 mm/day and MAE = 1.87 mm/day. The calibrated Irmak model statistics were OI = 78.4%, REMSE = 1.75 mm/day and MAE = 1.36 mm/day.

Alfalfa-Based Comparisons

The performance of the GEP–MOD8 model on alfalfa was compared to the calibrated and uncalibrated versions of the Jensen-Haise and Kimberly-Penman methods. Table 9 and Fig. 7 showed that GEP-MOD8 performed best (R^2 = 97.6%, OI = 96.9%, RMSE = 0.75 mm/day and MAE = 0.55 mm/day). The Jensen-Haise model before (R^2 = 66.7%, OI = 67.8%, RMSE = 3.22 mm/day and MAE = 2.26 mm/day) and after calibration (R^2 = 66.7%, OI = 76.9%, RMSE = 2.65 mm/day and MAE = 1.98 mm/day) performed worst. The Kimberly–Penman models both before (R^2 = 93.9%, OI = 90.2%, RMSE = 1.59 mm/day and MAE = 1.23 mm/day) and after calibration (R^2 = 93.9%, OI = 94.2%, RMSE = 1.13 mm/day and MAE = 0.86 mm/day) performed the worst.

Therefore, the GEP models are a good alternative to the empirical models to some extent. This agrees with Shiri et al. [36], who stated that the main advantage of GEP models over other models (e.g., the adaptive neuro-fuzzy inference system) is their ability to explicitly express the relationship between the dependent and independent variables.

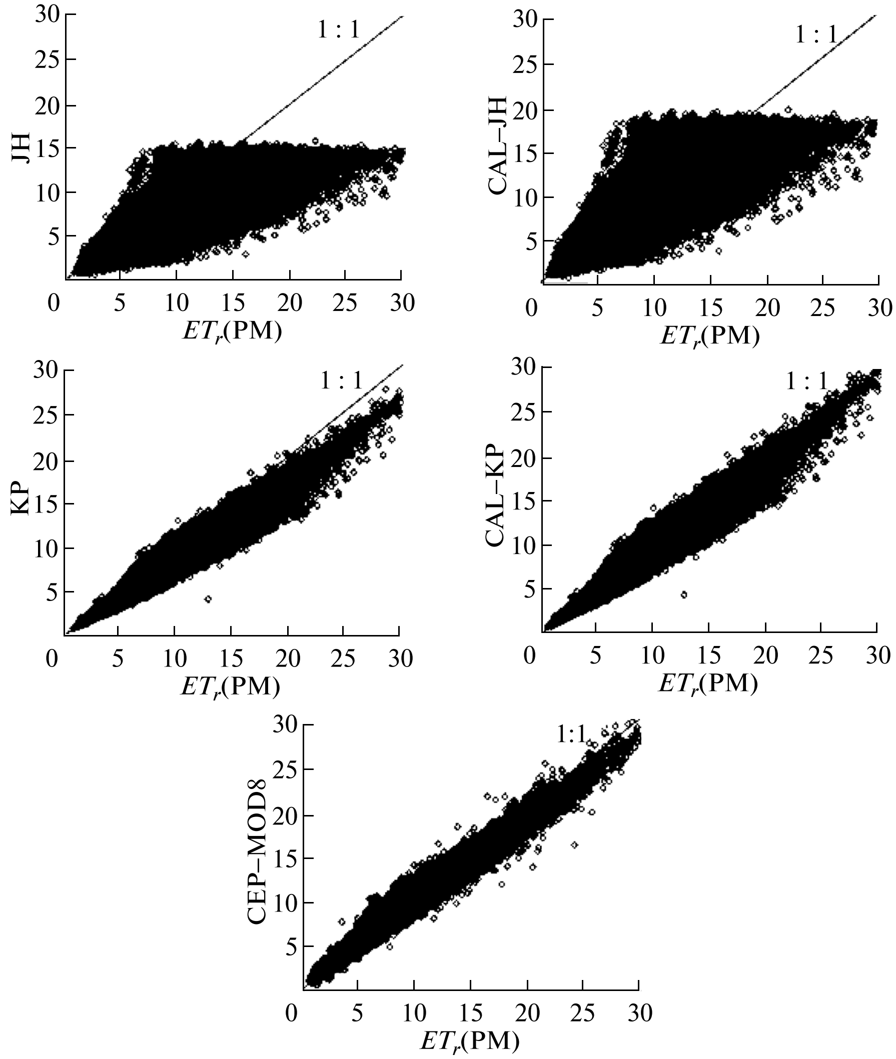

Fig. 7. Comparison of the alfalfa ET_{ref} (ET_r) estimates made by the uncalibrated (JH) and calibrated (CAL–JH) Jensen–Haise models, uncalibrated (KP) and calibrated (CAL–KP) Kimberly–Penman models, ANN–MOD8 and GEP–MOD8.

CONCLUSIONS

The ability of GEP technique for the estimation of reference evapotranspiration using climatic variables has been investigated in this study. Eight combinations of the daily climate variables, maximum, mean, and minimum air temperature; maximum, mean, and minimum relative humidity; wind speed; solar radiation; and crop height, were used as inputs for the GEP technique. The ET_{ref} was estimated from the standard PMG equation and used as a target variable. Nineteen meteorological stations were chosen from all regions of the KSA, representing all of the climatic conditions, Al-Qasim, Ha'il, Al-Jouf, Rafha, Dhahran, Najran, Jizan, Bisha, Al-Baha, Jeddah, Al-Madina, Tabuk, Turaif, Al-Wajh, Qaisumah, Yanba', Al-Ta'if and Wadi Al-Dawasir. Their daily climatic data collected from 1980 to 2010. The results showed that the GEP models' determination coefficients (R^2) ranged from 64.4 to 95.5% and RMSE values ranged from 1.13 to 3.1 mm/day. Therefore, an interesting result of the current study revealed that the developed GEP models should be used if meteorological stations supply an incomplete data set, through the lack or loss of some climatic variables, as the models gave estimated ET_{ref} values that were very close to the standard ET_{ref} values for the Saudi Arabian climatic conditions.

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REFERENCES

1. Alazba, A.A., Estimating palm water requirements using Penman–Monteith mathematical model, *J. King Saud Univ.*, 2004, vol. 16, no. 2, pp. 137–152.

2. Alazba, A.A., Comparison of the ASCE standardized and other Penman Monteith type equations under hyper-arid area, *ASABE Annual Meeting*, Michigan: Am. Soc. of Ag. Biol. Eng., St. Joseph, 2004.
3. Alazba, A., Mattar, M.A., El-Nesr, M.N., and Amin, M.T., Field assessment of friction head loss and friction correction factor equations, *J. Irrig. Drain. Eng.*, ASCE, 2012, vol. 138, no. 2, pp.166–176.
4. Allen, R.G., Pereira, L.S., Raes, D., and Smith, M., Crop evapotranspiration guidelines for computing crop water requirements, *FAO Irrigation and Drainage*, Rome, 1998, no. 56.
5. Aytek, A. and Kişi, O., Genetic programming approach to suspended sediment modelling, *J. Hydrol.*, 2008, vol. 351, no. 3–4, pp. 288–298.
6. Azamathulla, H.Md., Gene-expression programming to predict friction factor for Southern Italian Rivers, *Neural Comput. Appl.,* 2012, doi: 10.1007/s00521-012-1091-2.
7. Azamathulla, H.Md. and Ahmad, Z., Gene-expression programming for transverse mixing coefficient, *J. Hydrol.*, 2012, vol. 434–435, pp. 142–148.
8. Azamathulla, H.Md., Ghani, A.A., Leow, C.S., Chang, K.C., and Zakaria, N.A, Gene-expression programming for the development of a stage-discharge curve of the Pahang River, *Wat. Res. Manag.*, 2011, vol. 25, pp. 2901–2916.
9. Dai, X., Shi, H., Li, Y., Ouyang, Z., and Huo, Z., Artificial neural network models for estimating regional reference evapotranspiration based on climate factors, *Hydrol. Process.*, 2009, vol. 23, pp. 442–450.
10. Fernando, A.K., Shamseldin, A.Y., and Abrahart, R.J., Use of gene expression programming for multimodel combination of Rainfall-Runoff models, *J. Hydrol. Eng.*, 2012, vol. 17, no. 9, pp. 975–985.
11. Ferreira, C., *Gene Expression Programming in Problem Solving, 6th Online World Conference on Soft Computing in Industrial Applications, 2001.*
12. Ferreira, C., Gene expression programming: a new adaptive algorithm for solving problems, *Complex Syst.*, 2001, vol. 13, no. 2, pp. 87–129.
13. Ferreira, C., *Gene Expression Programming: Mathematical Modeling by an Artificial Intelligence*, Germany: Springer-Verlag, 2006.
14. Gandomi, A.H., Babanajad, S.K., Alavi, A.H., and Farnam, Y., Novel approach to strength modeling of concrete under triaxial compression, *J. Mater. Civ. Eng.*, 2012, vol. 24, no. 9, pp. 1132–1143.
15. Gavilan, P., Berengena, J., and Allen, R.G., Measuring versus estimating net radiation and soil heat flux: impact on Penman–Monteith reference ET estimates in semiarid regions, *Agr. Wat. Manag.*, 2007, vol. 89, pp. 275–286.
16. Gavilan, P., Lorite, I.J., Tornero, S., and Berengena, J., Regional calibration of Hargreaves equation for estimating reference ET in a semiarid environment, *Agr. Wat. Manag.*, 2006, vol. 81, pp. 257–281.
17. Ghani, A.A. and Azamathulla, H.Md., Gene-expression programming for sediment transport in Sewer Pipe Systems, *J. Pipeline Syst. Eng. Pract.*, 2011, vol. 2, no. 3, pp. 102–106.
18. Guven, A. and Aytek, A., A new approach for stage-discharge relationship: gene-expression programming, *J. Hydrol. Eng.*, 2009, vol. 14, no. 8, pp. 812–820.
19. Hupet, F. and Vanclooster, M., Effect of the sampling frequency of meteorological variables on the estimation of the reference evapotranspiration, *J. Hydrol.*, vol. 243, pp. 192–204.
20. Irmak, S., Irmak, A., Allen, R.G., and Jones, J.W., Solar and net radiation based equations to estimate reference evapotranspiration in humid climates, *J. Irrig. Drain. Eng.*, ASCE, 2003, vol. 129, no. 5, pp. 336–347.
21. Jain, S.K., Nayak, P.C., and Sudhir, K.P., Models for estimating evapotranspiration using artificial neural networks, and their physical interpretation, *Hydrol. Process.*, 2008, vol. 22, no. 13, pp. 2225–2234
22. Kisi, O. and Ozturk, O., Adaptive neuro-fuzzy computing technique for evapotranspiration estimation, *J. Irrig. Drain. Eng.*, ASCE, 2007, vol. 133, no. 4, pp. 368–379.
23. Kisi, O. and Guven, A., Evapotranspiration modeling using linear genetic programming technique, *J. Irrig. Drain Eng.*, 2010, vol. 136, no. 10, pp. 715–723.
24. Kumar, R., Jat, M.K., and Shankar, V., Methods to estimate irrigated reference crop evapotranspiration—a review, *Water Science Technology*, IWA Publishing, 2012, vol. 66, no. 3, pp. 525–535.
25. Kumar, M., Raghuwanshi, N.S., Singh, R., Wallender, W.W., and Pruitt, W.O., Estimating evapotranspiration using artificial neural network, *J. Irrig. Drain. Eng.*, ASCE, 2002, vol. 128, no. 4, pp. 224–233.
26. Landeras, G., Barredo, A.O., and Lopez, J.J., Comparison of artificial neural network models and empirical and semi-empirical equations for daily reference evapotranspiration estimation in the Basque Country (Northern Spain), *Agr. Wat. Manag.*, 2008, vol. 95, pp. 553–565.
27. Legates, D.R. and McCabe, J., Evaluating the use of "goodness-of fit" measures in hydrologic and hydroclimatic model validation, *Wat. Resour. Res.*, 1999, vol. 35, no. 1, pp. 233–241.
28. Mollahasani, A., Alavi, A.H., and Gandomi, A.H., Empirical modeling of plate load test moduli of soil via gene expression programming, *Comput. Geotechnics*, 2011, vol. 38, pp. 281–286.
29. Naoum, S. and Tsanis, K.I., Hydroinformatics in evapotranspiration estimation, *Environ. Modelling Software*, 2003, vol. 18, pp. 261–271.
30. Nazari, A., Prediction performance of PEM fuel cells by gene expression programming, *Int. J. Hydrogen Energy*, 2010, vol. 37, pp. 18972–18980.
31. Parasuraman, K., Elshorbagy, A., and Carey, S., Modeling the dynamics of the evapotranspiration process using genetic programming, *Hydrolog. Sci. J.*, 2007, vol. 52, no. 3, pp. 563–578.
32. Rivas, R. and Caselles, V., A simplified equation to estimate spatial reference evaporation from remote sensing-based surface temperature and local meteorological data, *Remote Sensing Environ.*, 2004, vol. 93, pp. 68–76.
33. Samadianfard, S., Gene expression programming analysis of implicit Colebrook–White equation in turbulent

flow friction factor calculation, *J. Petroleum Sci. Eng.*, 2012, vol. 92–93, pp. 48–55.

34. Saridemir, M., Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash, *Construction Building Mater.*, 2010, vol. 24, pp. 1911–1919.

35. Seckin, G., Yilmaz, T., Guven, A., Yuceer, A., Basibuyuk, M., and Ersu, C.B., Modeling the performance of up flow anaerobic filters treating paper-mill wastewater using gene-expression programming, *Ecol. Eng.*, 2011, vol. 37, pp. 523–528.

36. Shiri, J., Kisi, O., Landeras, G., Lopez, J.J., Nazemi, A.H., and Stuyt, L., Daily reference evapotranspiration modeling by using genetic programming approach in the Basque Country (Northern Spain), *J. Hydrology*, 2012, vol. 414–415, pp. 302–316.

37. Steve, R.G., Kirkham, M.B., and Brent, E.C., Root uptake and transpiration: from measurements and models to sustainable irrigation, *J. Agr. Wat. Manag.*, 2006, vol. 86, pp. 165–176.

38. Trajkovic, S., Testing hourly reference evapotranspiration approaches using lysimeter measurements in a semiarid climate, *Hydrology Res.*, 2010, vol. 41, no. 1, pp. 38–49.

39. Trajkovic, S. and Kolakovic, S., Comparison of simplified pan-based equations for estimating reference evapotranspiration, *J. Irrig. Drain. Eng.*, 2010, vol. 136, no. 2, pp. 137–140.

40. Traore, S. and Guven, A., Regional-specific numerical models of evapotranspiration using gene-expression programming interface in Sahel, *Wat. Res. Manag.*, 2012, vol. 26, pp. 4367–4380.

41. Traore, S., Wang, Y., and Kerh, T., Artificial neural network for modeling reference evapotranspiration complex process in Sudano-Sahelian Zone, *Agr. Wat. Manag.*, 2010, vol. 97, pp. 707–714.

42. Zahiri, A. and Eghbali, P., Gene expression programming for prediction of flow discharge in compound channels, *J. Civil Eng. Urbanism,* 2012, vol. 2, no. 4, pp. 164–169.

43. Zanetti, S.S., Sousa, E.F., Oliveira, V.P.S., Almeida, F.T., and Bernardo, S., Estimating evapotranspiration using artificial neural network and minimum climatological data, *J. Irrig. Drain. Eng.*, ASCE, 2007, vol. 133, no. 2, pp. 83–89.