Comparing The Models SARIMA, ANFIS And ANFIS-DE In Forecasting Monthly Evapotranspiration Rates Under Heterogeneous Climatic Conditions

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Research Article

Keywords: Differential Evolution, ANFIS, Stochastic, ARIMA, Time series prediction, Reference Crop Evapotranspiration

Posted Date: August 17th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-781601/v1>

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Comparing the models SARIMA, ANFIS and ANFIS-DE in forecasting monthly evapotranspiration rates under heterogeneous climatic conditions

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Abstract

Reference crop evapotranspiration (ET₀) is one of the most important hydro-climatological components which directly affects agricultural productions, and its forecasting is critical for water managers and irrigation planners. In this study, adaptive neuro-fuzzy inference system (ANFIS) model has been hybridized by differential evolution (DE) optimization algorithm as a novel approach to forecast monthly ET₀. Furthermore, this model has been compared with the classic stochastic time series model. For this, the ET₀ rates were calculated on monthly scale during 1995-2018, based on FAO-56 Penman-Monteith equation and meteorological data including: minimum air temperature, maximum air temperature, mean air temperature, minimum relative humidity, maximum relative humidity & sunshine duration. The investigation was performed on 6 stations in different climates of Iran, including: Bandar Anzali & Ramsar (per-humid), Gharakhil (sub-humid), Shiraz (semi-arid), Ahwaz (arid) and Yazd (extra-arid). The models' performances were evaluated by the criteria percent bias (PB), root mean squared error (RMSE), normalized RMSE (NRMSE) and Nash-Sutcliffe (NS) coefficient. Surveys confirm the high capability of the hybrid ANFIS-DE model in monthly ET₀ forecasting; so that the DE algorithm was able to improve the accuracy of ANFIS, by 16% on average. Seasonal autoregressive integrated moving average (SARIMA) was the most suitable pattern among the time series stochastic models, and superior compared to its other competitors. Consequently, due to the simplicity and parsimony, the

SARIMA was suggested more appropriate for monthly ET₀ forecasting in all the climates. Comparison between the different climates confirmed that the climate type significantly affects the forecasting accuracies: it's revealed that all the models work better in extra-arid, arid and semi-arid climates, than the humid and per-humid areas.

Keywords: Differential Evolution; ANFIS; Stochastic; ARIMA; Time series prediction; Reference Crop Evapotranspiration

1. Introduction

The process of water parting the surface of moist soil is called evaporation, whereas this phenomenon from leaves' pores is called transpiration. Since recognizing these two phenomena on farms is not easy, they are to be considered as one integrated single variable referred to as "evapotranspiration". On the other hand, evapotranspiration is considered as the water requirement of plants, so its measurement is very important in all agricultural and irrigation projects. The amount of evapotranspiration is measured by a lysimeter. Due to the sensitivity of the lysimeter, there is a need for the presence of a technician expert on-site in order for the lysimeter to be continuously calibrated. Consequently, if good care is not taken, the recorded cases of lysimeter may have errors. As a remedy, the International Commission on Irrigation and Drainage (ICID) and World Meteorological Organization (WMO) have recognized the FAO-56 Penman-Monteith equation (FAO-56 PM), as a suitable alternative to the lysimeter (Allen et al., 1998); which can use several meteorological variables to estimate the evapotranspiration rate with an acceptable accuracy.

In recent years, despite the presence of some well-known mathematical models such as Penman-Monteith, Thornthwaite, Hargreaves-Samani, Blaney-Criddle, etc., the black-box artificial

intelligence (AI) models have been able to show acceptable accuracy in estimating evapotranspiration. For example, Mohammadi & Mehdizadeh (2020) and Ahmadi et al. (2021) by carrying out a survey on the arid and semi-arid regions of Iran found that in the complete absence of meteorological variables (which are required to use the Penman method), the AI models are able to estimate evapotranspiration with reasonable accuracy, by the least available meteorological variables. They also contended that integrating AI models with bio-inspired optimization algorithms can significantly increase the accuracy of evapotranspiration estimation. In Australia, AIs were able to provide an accurate estimate of evapotranspiration with only temperature and wind speed as available variables (Falamarzi et al., 2014); which in the absence of complete meteorological variables can be considered as suitable alternative for the FAO-56 PM model. Also, in cases such as Kumar et al. (2002), the validation of the estimated evapotranspiration from neural networks using lysimeter measured evapotranspiration values, and comparing them with the outputs of the FAO-56 PM model showed that AIs can be a better estimator for evapotranspiration. Reference crop evapotranspiration (ET_0) is one of the main components of the hydrological cycle associated with agricultural systems. Accurate estimation and prediction of ET_0 is very important in water resources management, irrigation planning, and determining the water needs of plants. Forecasting the evapotranspiration rates, through providing information on the future status of evapotranspiration at different time scales can be of great help in making appropriate decisions, planning as well as applying management methods of water resources. Data-driven models such as stochastic and artificial intelligence methods are efficient approaches that have shown good performance in modeling and predicting hydrometeorological variables in recent years (Aghelpour et al., 2021c; Mohammadi et al., 2020; Aghelpour et al. 2020b). Karbasi (2018) used AIs in forecasting ET_0 for 1, 2, 3, 7, 10, 14, 18, 24, and 30 days' horizons. Karbasi (2018) concluded that

the predictions' accuracy was desirable and showed that with increasing the forecast horizon, the forecasting accuracy decreases. A comparison between stochastic and artificial intelligence methods in Spain revealed that both model types predicted weekly evapotranspiration effectively (Landeras et al., 2009). Lucas et al. (2020) compared the Seasonal Autoregressive Integrated Moving Average (SARIMA) stochastic model with the Convolutional Neural Network (CNN) model in order to predict daily evapotranspiration in Brazil. They concluded that the CNN model is able to provide a more accurate prediction of evapotranspiration than the SARIMA model. In opposite, in the Tamil Nadu of India, a comparison was made between artificial intelligence and stochastic methods and stochastic models were introduced more appropriate for predicting ET₀ (Kishore & Pushpalatha, 2017). Predicting evapotranspiration especially in areas such as Iran which facing limited water resources, is doubly important for the determination of the cultivation pattern, and proper management of water and soil resources. In Iran, these two types of numerical models (stochastics and AIs) have been used to predict ET₀. Ashrafzadeh et al. (2020) used the SARIMA, Group Method of Data Handling (GMDH), and Support Vector Machine (SVM) models, to predict ET₀ in humid areas of the Caspian Sea's southern margin. They evaluated the accuracy of the models and showed that the mentioned models are able to predict the ET₀ value for the next 2 years, with the same suitable accuracy as the train-test period.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) model is one of the most efficient AI methods that has been used in both simple and hybridized forms, for hydrological and meteorological modeling. ANFIS model showed its acceptable performances, in solar radiation estimation (Üstün et al., 2020; Benmouiza & Cheknane, 2019; Halabi et al., 2018; Khosravi et al., 2018), pan evaporation estimation (Adnan et al., 2019; Guven & Kisi, 2013; Keskin et al., 2009), drought forecasting (Aghelpour et al., 2021a; Aghelpour et al., 2021b; Aghelpour et al., 2020a;

Aghelpour et al., 2020c; Kisi et al., 2019), river flow forecasting (Aghelpour & Varshavian, 2020; Allawi et al., 2018), rainfall forecasting (Mekanik et al., 2016; Yaseen et al., 2018; Aghelpour et al., 2021d) and wind speed forecasting (Maroufpoor et al., 2019). However, they are rarely used in evapotranspiration prediction studies. The combination of bio-inspired optimization algorithms has improved the performances of AIs in most cases, significantly (Deo et al., 2018; Aghelpour et al., 2019; Paham et al., 2021; Aghelpour & Varshavian, 2021; Mohammadi et al., 2021). These algorithms that use complex evolutionary methods can optimally enhance the parameters of AIs, and significantly increase the accuracy of estimates and predictions (Moazenzadeh & Mohammadi, 2019; Ashrafzadeh et al., 2019; Ashrafzadeh et al. al., 2020; Aghelpour et al., 2020c).

The present study intends to use the ANFIS model to predict the reference evapotranspiration and compare it with the classical SARIMA stochastic model. Moreover, as a novelty, the Differential Evolution (DE) algorithm (a bio-inspired algorithm) which is hybridized with the ANFIS model, has been used as ANFIS-DE to optimize and improve the ANFIS's prediction accuracy. In this study, stations from different climates (from extra-arid to per-humid) are studied and for the first time, the effect of climate type is also investigated on the accuracy of the models predicting ET₀; which is another novelty aspect of the current research.

2. Materials and methods

2.1.Data and areas under investigation

Iran is located in the Middle East, on the dry belt of the earth. Consequently, it is facing limited water resources in human life's different sectors, such as agriculture. According to De-Martonne climatic zoning, Iran has 28 different climatic classes (Rahimi et al., 2013; Aghelpour et al., 2020a). The majority of regions of Iran have arid (central desert, southwest, and southwest of the

country) and semi-arid climates (The Zagros Mountains in the west and northwest of the country as well as northeastern regions), and only small areas of Iran have humid climates (Southern shore of the Caspian Sea in the north). The rate of evapotranspiration, which is affected by different meteorological factors, varies in different climatic zones. For example, in arid regions such as Ahwaz, the range of ET₀ is between 40 and 350 mm per month, while in humid climates like Ramsar, the ET₀ varies between 20 and 158 mm per month. This paper aims to investigate the effect of the type of the climate on the accuracy of models predicting evapotranspiration. For this, six synoptic stations from different climates of Iran are considered (Figure 1).

<Figure 1. here>

Three stations were selected from humid and sub-humid areas of northern Iran (on the southern margin of the Caspian Sea), and the other three stations were selected from arid and semi-arid areas in central and southwestern parts of Iran. Most of the agricultural lands in the northern humid areas are under rice cultivation and the horticultural lands in this area are often under citrus cultivation. In arid and semi-arid regions of the southern parts of Iran, the main agricultural crops include wheat and maize, and the important horticultural crops are grapes and pistachios. A summary of information on the climatic zones in this study, stations, and common products in them is shown in Table 1.

<Table 1. here>

The data used in this paper include monthly meteorological data and belong to the period 1995-2018. These data include minimum air temperature (T_{min}), maximum air temperature (T_{max}), mean air temperature (T_{mean}), minimum relative humidity (RH_{min}), maximum relative humidity (RH_{max}) and sunshine duration (SSD), which are prepared on a monthly scale of the Iranian

Meteorological Organization (IRIMO). Using these data and FAO-56 PM model, the amount of monthly evapotranspiration was estimated in the 6 mentioned stations. The “Evapotranspiration” package in R software was used to estimate the evapotranspiration rates, based on the FAO-56 PM method. For modeling, the period under study was divided into two parts of training and testing, which include 75% (the first 18 years) and 25% (the remaining 6 years), respectively. The characteristics of the meteorological data as well as the estimated evapotranspiration data are shown in Table 2.

<Table 2. here>

2.2.Time series model

A time series is a set of recorded observations of a variable such as X_i overtime in the form of $X_1, X_2, X_3, \dots, X_N$ between which the time interval is equal (Gutam & Sinha, 2016). Time series models are kind of stochastic models that work based on regression coefficients and use the time lags of the target variable, as the model’s input variable. These models include Autoregressive (AR), Integrated (I), and moving average (MA) components. They are shown in an integrated state known as Autoregressive Integral Moving Average (ARIMA). The Seasonal ARIMA (SARIMA) model is a model that can be used for numerical simulation of the stochastic behavior of periodic time series. In other words, SARIMA is a linear parametric stochastic model which can be used to model and predict variables, which have seasonal autocorrelations. The cross form of this model is shown as $SARIMA(p, d, q) \times (P, D, Q)_\omega$; in which ω is the periodicity; $p, d,$ and q are the non-seasonal degrees of autoregressive, differencing and moving average, respectively; $P, D,$ and Q are the seasonal degrees of autoregressive, differencing and moving average, respectively. The general form of this model is shown below: (Salas et al, 1980):

$$\text{Eq. 1} \quad \Phi_p(B^\omega)\phi_p(B)\nabla_\omega^D\nabla^dX_t = \theta_q(B)\Theta_Q(B^\omega)\varepsilon_t$$

177 In this formula X_t is a stochastic variable as the target and ε_t is a normal random variable with
 178 mean μ and variance σ_ε^2 , as a residual. Parameters of B including $\Phi, \phi, \nabla_\omega^D, \nabla^d, \Theta, \theta$, represent the
 179 backward operators associated with seasonal autoregressive, non-seasonal autoregressive,
 180 seasonal differencing and non-seasonal differencing, seasonal moving average and non-seasonal
 181 moving average, respectively. Whose equations are described in equations 2 to 7 (Salas et al,
 182 1980).

$$\text{Eq. 2} \quad \Phi_p(B^\omega) = (1 - \phi_1 B^{\omega \times 1} - \dots - \phi_p B^{\omega \times p})$$

183

$$\text{Eq. 3} \quad \phi_p(B) = (1 - \phi_1 B^1 - \dots - \phi_p B^p)$$

184

$$\text{Eq. 4} \quad \nabla_\omega^D = (1 - B^\omega)^D$$

185

$$\text{Eq. 5} \quad \nabla^d = (1 - B)^d$$

186

$$\text{Eq. 6} \quad \Theta_Q(B^\omega) = (1 - \theta_1 B^{\omega \times 1} - \dots - \theta_Q B^{\omega \times Q})$$

187

$$\text{Eq. 7} \quad \theta_q(B) = (1 - \theta_1 B^1 - \dots - \theta_q B^q)$$

188 In this research, the Minitab software and the SARIMA model have been used to simulate and
 189 predict evapotranspiration time series.

2.3. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS model has the ability to make relationships between input and output data using fuzzy rules and to learn from a neural network in order to generate input structure for a system. ANFIS model designs and creates non-linear maps to define relationships between input and output spaces by employing Artificial Neural Network (ANN) and fuzzy logic, which is known as a neuro-fuzzy system. Fuzzy systems include three different parts, namely fuzzification, inference engine, and defuzzification. Fuzzy rules are achieved by utilizing fuzzy inference systems. A Fuzzy inference system consists of two different inferences, namely Mamdani and Sugeno. They both work in an excellent fashion when they are combined with an optimization algorithm and adaptive techniques (Khosravi et al., 2018). In this paper, we use Sugeno inference. Figure 2 shows the structure of the ANFIS model.

<Figure 2. here>

These two equations are the base rules of Sugeno inference:

$$\text{Eq. 8} \quad \text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$

$$\text{Eq. 9} \quad \text{Rule 2: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2$$

ANFIS model contains different layers. Layer one, in this model, is the fuzzification layer. Each node receives a signal and then transfers it to the next layer. The following equation describes the cells outputs (O_1^i) (Khosravi et al., 2018; Haznedar and Kalinli, 2016):

$$\text{Eq. 10} \quad O_1^i = \mu_{A_i}(x); \quad i = 1, 2$$

μ_{A_i} is related to Membership Function (MF). A_i is linguistic variable and it is related to node function. The following equation shows the common formula for μ_{A_i}

$$\text{Eq. 11} \quad \mu_{A_i}(x) = \exp \left\{ - \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i} \right\}$$

209 In this equation, x is input and a_i , b_i , c_i are premise parameters. Layer 2 is called the rule layer
 210 which is obtained by membership degrees. All the output nodes establish the firing strength of a
 211 fuzzy rule.

$$\text{Eq. 12} \quad O_2^i = w_i = \mu_{A_i}(x) \bullet \mu_{B_i}(y); \quad i = 1, 2$$

212 Layer 3 is the normalization layer. In this layer, all the nodes are fixed and they are tagged with
 213 N. The rule's firing strength to the sum of all rules' firing strengths is the ratio that is calculated by
 214 the i^{th} node in the normalization layer.

$$\text{Eq. 13} \quad O_3^i = \bar{w}_i = \frac{w_i}{w_1 + w_2}; \quad i = 1, 2$$

215 The defuzzification layer is the layer 4 of ANFIS model. Each rule uses the value of the previous
 216 layer to compute the output value.

$$\text{Eq. 14} \quad O_4^i = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i); \quad i = 1, 2$$

217 In this equation, $\bar{w}_i$ comes from the previous layer, namely layer 3. $\bar{w}_i$ is a normalized firing
 218 strength and p_i , q_i , and r_i are the consequent parameters. Layer 5 is called the sum layer. By
 219 summing the output values of the rules that come from the previous layer, the final output of the
 220 ANFIS model is calculated.

$$\text{Eq. 15} \quad O_5^i = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad i = 1, 2$$

221 To implement the ANFIS model, MATLAB software is used in this study.

222 To summarize, the ANFIS model contains two sets of parameters: premise parameters and
 223 consequence parameters. Premise parameters are input parameters of MFs and their aim is to

specify the shape and the location of the input MFs (parameters of input MFs). Consequence parameters are output parameters of MFs (parameters of output MFs) (Jang, 1993). To estimate these parameters, classical ANFIS uses the least square (LS) methods. However, in the current research, we have developed a novel ANFIS-DE model, which uses the meta-heuristic Differential Evolution (DE) algorithm to estimate ANFIS's sets of parameters.

2.4. Differential Evolution (DE) optimization algorithm

Although Differential Evolution (DE) uses basic optimized operations such as mutation, crossover, and selection, it is an impressive and powerful optimization algorithm. One of the privileges of this algorithm is that it has parallel search methods and uses NP and also it has D-dimensional vectors of parameters. The advantage of these vectors is that they do not change during the minimization procedure. DE performs a population process for each generation G. First, one population vector is randomly initialized including the parameters and this probability distribution is uniformed. When preliminary solution is achieved, DE algorithm calculates the difference between the weights of two population vectors and assigns it to the third vector in order to produce new parameter vectors, which is known as the mutation operation (Halabi et al., 2018):

$$\text{Eq. 16} \quad v_{i,G+1} = x_{i,G} + F(x_{r2,G} - x_{r3,G})$$

According to $v_{i,G+1}$, these mutant vectors, x_i , G and $i = 1, 2, 3, \dots, NP$ are created, while $r1$, $r2$, and $r3$ are randomly integers and NP is selected from this distribution: integers $\in [1, 2, 3, \dots, NP]$. Moreover, I and F are real values and they are different from each other $\in [1, 2, 3, \dots, NP]$.

During the mixing process which is also called crossover operation, parameters of the mutated vector are mixed with other vector parameters to create the trial vector. The following equations describe this mixing process:

$$\text{Eq. 17} \quad u_{i,G+1} = (u_{1i,G+1}, u_{2i,G+1}, \dots, u_{di,G+1})$$

$$\text{Eq. 18} \quad u_{ji,G+1} = \begin{cases} v_{ji,G+1}; & \text{if } randb(j) \leq CR \text{ or } j = rnbr(i) \\ x_{ji,G+1}; & \text{if } randb(j) > CR \text{ or } j \neq rnbr(i) \end{cases}$$

In this equation, $u_{i,G+1}$ is the trailer and $x_{i,G}$ is the target vector, where $u_{i,G+1}$ and $x_{i,G}$ are the trailer and target vectors, respectively. $randb(j)$ is the J^{th} uniform random evaluation $\in [0.1]$, $rnbr(i)$ is a random value index $\in [1, 2, 3, \dots, d]$ and CR is crossover constant which is determined by users. The selection operation is the last operation. The trial vector costs a lower cost function than the target vector. Therefore, the selection operation uses the trial vector as a target value for the next generation. NP competitions are considered like one generation procedure as each population vector has to serve once as the target vector. Complementary descriptions about the DE optimization algorithm can be found in Storn & Price (1997) and Halabi et al. (2018). The DE algorithm flowchart is illustrated in Figure 3.

<Figure 3. here>

In this paper, the DE algorithm is implemented by coding in MATLAB software's environment. The trial and error method is used to choose the best operators of DE to optimize the ANFIS model. They are illustrated in Table 3.

<Table 3. here>

2.5. Evaluating the accuracy of the predictions

This study uses six criteria to evaluate the performance of the models: Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Percent Bias (PB), Pearson correlation coefficient (R), coefficient of determination (R^2), and Nash- Sutcliff coefficient (NS). In general, these criteria are

264 used to compare the accuracy of different models with each other. Furthermore, they are used to
 265 compare the accuracy of models in different climates. To calculate them, we need two series of
 266 predicted and observed evapotranspiration data. Their equations are as follows.

$$\text{Eq. 19} \quad RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (ETO_i - ETP_i)^2}; \quad 0 < RMSE < +\infty$$

267

$$\text{Eq. 20} \quad PB = \sum_{i=1}^n \left(\frac{ETO_i - ETP_i}{ETO_i} \right); \quad -\infty < PB < +\infty$$

268

$$\text{Eq. 21} \quad R = \frac{\sum_{i=1}^n (ETO_i - \overline{ETO}) (ETP_i - \overline{ETP})}{\sqrt{\sum_{i=1}^n (ETO_i - \overline{ETO})^2} * \sqrt{\sum_{i=1}^n (ETP_i - \overline{ETP})^2}}; \quad -1 < R < 1$$

269

$$\text{Eq. 22} \quad R^2 = \left[\frac{\sum_{i=1}^n (ETO_i - \overline{ETO}) (ETP_i - \overline{ETP})}{\sqrt{\sum_{i=1}^n (ETO_i - \overline{ETO})^2} * \sqrt{\sum_{i=1}^n (ETP_i - \overline{ETP})^2}} \right]^2; \quad 0 < R^2 < 1$$

270

$$\text{Eq. 23} \quad NRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (ETO_i - ETP_i)^2}}{ETO_{max} - ETO_{min}}; \quad 0 < NRMSE < +\infty$$

271

$$\text{Eq. 24} \quad NS = 1 - \frac{\sum_{i=1}^n (ETO_i - ETP_i)^2}{\sum_{i=1}^n (ETO_i - \overline{ETO})^2}; \quad -\infty < NS < 1$$

ETO_i shows the amount of observed evapotranspiration of the i^{th} month, ETP_i is the amount of evapotranspiration predicted in the i^{th} month, $\overline{ETO}$ shows the mean of observational evapotranspiration, $\overline{ETP}$ represents the average of the predictive evapotranspiration, ETO_{max} is the maximum of the observational evapotranspiration, and finally ETO_{min} is the minimum of the observational evapotranspiration. According to the defined range for these criteria, the closer the RMSE, PB and NRMSE are to zero, and the closer NS, R, and R^2 are to one, the better the model performance is. Another point about NRMSE is that it has 4 intervals in terms of evaluating the quality of models: 1) $NRMSE > 0.3$ poor performance, 2) $0.2 < NRMSE < 0.3$ average performance 3) $0.1 < NRMSE < 0.2$ good performance and 4) $0 < NRMSE < 0.1$ excellent performance.

The general process of modeling and predicting the evapotranspiration time series in this paper is shown as a flowchart in Figure 4.

<Figure 4 here>

3. Results

3.1. Modeling and evaluating the predictions

In this study, ET_0 's monthly time lags were considered as input to the models. Therefore, Autocorrelation Function (ACF) diagrams for different stations were considered (Figure 5), which show the extent and significance of the correlation of the variable with its previous steps' amounts.

<Figure 5. here>

As can be seen from Figure 5, the ET_0 data in all 6 stations have a significant seasonal trend. The ET_0 time series are periodic and have a 12 months' periodicity. To moderate this seasonal trend, several degrees of seasonal differentiation with a lag of 12 months (equal to the periodicity) were considered. Investigations showed that seasonal differentiation of order "one" has the best

consistency with ET0 data. As a result, the SARIMA model is modified as the SARIMA pattern SARIMA (p, 0, q)(P, 1, Q)₁₂. Moreover, when the time lag increases, the significance threshold of correlation (dashed line) increases and more than three return periods (36 months), it reaches a point that is practically logical not to use them as inputs. Therefore, a maximum lag of 36 months is considered as inputs for all models. In the SARIMA model, this includes seasonal autoregressive and moving average degrees (P & Q), which is equal to 1, 2, and 3. These degrees and also the non-seasonal degrees of autoregressive and moving average (p & q) were all tested, and their best performance was selected for each station and reported in Table 4. Simple and hybrid ANFIS models (ANFIS & ANFIS-DE) were implemented based on the fuzzy c-means (FCM) clustering method. Lags of 1, 6, 12, 18, 24, 30, and 36 months were also considered as inputs to these AI models.

<Table 4. here>

In Table 4, the predictions of all three models were evaluated by the mentioned evaluation metrics. Since the test section actually shows the validity of the models, the test section is also discussed in the interpretations of this section. At first, it can be seen that in all stations, the R coefficients are very high, which indicates the optimal performance of the models in predicting monthly ET0 (the minimum value of R is equal to 0.949, which belongs to the simple ANFIS model in Ramsar station). Additionally, the amount of PB in all cases is very small (close to zero); which confirms the lack of significant under/overestimation and consequently the excellent performance of the models. According to Table 4, in all stations, the SARIMA linear model has superior performance than the other two models, and the weakest performance among the models belongs to the simple ANFIS model. The DE algorithm in combination with the ANFIS model (ANFIS-DE), was able to increase the prediction accuracy for ANFIS by an average of 15.8%. The lowest prediction error

belongs to the SARIMA model at Shiraz station with $RMSE = 7.918 \frac{mm}{month}$. The highest prediction error is reported in Ahwaz station with $RMSE = 16.906 \frac{mm}{month}$, which belongs to the simple ANFIS model.

3.2.Comparison between the models

Scatter plots are used for graphical illustration of the correlation between the predicted and actual values of monthly ET0 (figure 6).

<Figure 6. here>

In Figure 6, the horizontal axis of the graphs represents the observed ET0 data, and the vertical axis represents the predictions presented by the models. This figure shows that at all stations, the slope of the fitted regression line between the observed-predicted data samples is very small associated with the $X = Y$ line. The points are well concentrated around their regression line, and this concentration is more on the diagrams related to the SARIMA model than the other two models. On the other hand, the R^2 coefficient shows that the SARIMA linear model offers a better prediction than the other two nonlinear and complex models, ANFIS and ANFIS-DE. Also, ANFIS-DE predictions show better correlations compared to simple ANFIS. The diagrams in Figure 6 show that the weakest performance belongs to the predictions of ANFIS in Ramsar ($R^2 = 0.901$), and the best performance belongs to the predictions of SARIMA at Yazd station ($R^2 = 0.984$). In order to compare the models, the Taylor diagram is also represented for each station (Figure 7).

<Figure 7. here>

This diagram (Figure 7) is able to simultaneously check the correlation, the error, and also to compare their standard deviations, between the outputs of several models vs their observational values. In these diagrams, point O is an indicator of observational data, and points A, B, and C are the indicators of the SARIMA, ANFIS, and ANFIS-DE models, respectively. At all stations, point A is located the closest to point O, confirming the superiority of the SARIMA model. After that, ANFIS-DE (point C) and ANFIS (point B) models are in the second and third places, respectively. The best position of points A, B, and C belongs to Shiraz station, where these points are located between two circles $RMSE = 5 \frac{mm}{month}$ and $RMSE = 10 \frac{mm}{month}$, and around the radius $R = 0.99$. At Yazd station, a similar situation to Shiraz is observed. The weakest points' position can belong to Bandar Anzali station; where points A, B and C are farthest from point O, between circles of $RMSE = 10 \frac{mm}{month}$ and $RMSE = 15 \frac{mm}{month}$, and between two radii of $R = 0.99$ and $R = 0.95$. Furthermore, comparing the standard deviations between outputs and the observations, reveals that the points of the models, especially point A, are in a very good position relative to the quadrant close to point O. This shows that the models, especially SARIMA, have been able to show good ability in estimating the standard deviation of actual ET0 values.

3.3.Comparison of ET0 prediction accuracy among different climates

In general, the comparison between the stations in Figure 7 represents that the humid stations are located in weaker ranges of error and correlation, than the arid stations. Also, according to Figure 6, in humid and sub-humid climates, the R^2 value resulted from the SARIMA model is in the range of 0.95 - 0.96, while in arid and semi-arid regions, it is in the range of 0.97 - 0.98. Therefore, it is evident that ET0 is slightly better predicted in arid areas. However, due to the different range of

ET0 data in different climates (Table 2), it is better to consider the normalized RMSE (NRMSE) criterion at stations for evaluation (Figure 8).

<Figure 8. here>

In Figure 8, the NRMSE and NS criteria for the test period were plotted together as a combo-graph. This diagram is drawn separately for all models at all stations. At first, it can be seen that all models have a NS value greater than 0.9, which confirms the very good prediction of ET0 by the models. Moreover, the NRMSE value in all stations is less than 0.1. According to the quality classes defined for NRMSE (Aghelpour & Varshavian, 2020), the predictions for all climates in this study are considered very reasonable. The visible trend of NS and NRMSE is similar across stations. Both criteria indicate a better prediction of ET0 in arid and semi-arid climates. In other words, if the NS level is increased at a station, the NRMSE level will decrease at the same station (which is well illustrated in the combo-graph). Therefore, it can be said that both criteria achieved similar results in comparing the accuracy of ET0 prediction among the climates. For example, in the ANFIS-DE model for humid and sub-humid stations, the NRMSE is between 0.07 - 0.09 and the NS is between 0.93 - 0.95, while for arid and semi-arid stations, NRMSE is between 0.04 - 0.06 and NS is between 0.97 - 0.98. In the combo-graph belonging to the SARIMA model, the NRMSE value for humid and sub-humid areas is between 0.06 - 0.08 and the NS value is between 0.94 - 0.96, while for arid and semi-arid areas, the NRMSE is between 0.04 - 0.05 and the NS is between 0.98 - 0.99. The comparison of the models is similar to the previous diagrams and tables; which reported the SARIMA model more appropriate. The predictions provided by the models can also be graphically seen in time-series plots (Figure 9), to see the overlaps.

<Figure 9. here>

4. Discussion

Research on the use of AIs to estimate and predict the reference evapotranspiration, as in this paper, have evaluated the results of these models as favorable (Ahmadi et al., 2021; Ashrafzadeh et al., 2020; Adamala et al., 2018; Abrishami et al., 2019). Also, the desirability of the accuracy of time series models in the current study is similar to the research of Gautam & Sinha (2016), Landaras et al. (2009), Psilovikos & Elhag (2013), Mossad & Alazba (2016), and Bouznad et al. (2020), that have been conducted in different climatic regions. The superiority of time series models over AIs in ET₀ forecasting in Iran, has also been reported in Ashrafzadeh et al. (2020); however, their study only addressed the humid northern climate. Additionally, Ashrafzadeh et al. (2020) used non-hybridized models of artificial intelligence; while the current research showed that the novel hybrid ANFIS-DE model can significantly increase the accuracy of the simple ANFIS model. In Brazil, however, AIs provided a relatively more accurate prediction of ET₀ than time series models did (Lucas et al., 2020), which contradicts the results of the current study. The reason for this contradiction could be due to the differences between the climatic conditions of the studies' regions.

In comparison, between the climates of the present study, the geographical location as well as the physical systems involved can be factors influencing the accuracy of ET₀ prediction. For example, the humid regions of northern Iran are affected by Caspian atmospheric systems and various western systems such as the Black Sea and the Mediterranean Sea; while the western and southwestern regions of Iran (such as Shiraz, and Ahwaz) are only weakly affected by the two systems of Saudi Arabia's high-pressure and Sudan's low-pressure. Susceptibility to a large number of systems can disrupt the order of time series, reduce autocorrelation and consequently lead to a poor prediction. This difference in the order of the ET₀ series in different climates is

depicted in the diagrams of Figure 9. On the other hand, these three stations of Shiraz, Ahwaz and Yazd, are located near the Subtropical High-Pressure Belt (SHPB) (latitude 30 degrees), which can stabilize the weather regime in these areas and thus make the ET0 series more regular. By moving away from the SHPB and approaching the latitudes of the northern humid regions, the effects of the irregularity of the annual regime become more obvious and can eventually lead to a relative increase in the prediction errors in these areas.

5. Conclusion

Studies have been shown that the water requirement of plants can be predicted with very good accuracy by using the time lags of the evapotranspiration variable. The currently used data-driven approaches could provide acceptable predictions of ET0, regardless of the various atmospheric and physical factors that affect it. This result is similar in all currently studied climates. Despite the significant improvement (about 16%) of the ANFIS model in combination with the Differential Evolution optimization algorithm, it still fails to compete with the SARIMA linear model. The reason may be as Ashrafzadeh et al. (2020) has reported, the linear autocorrelation is stronger than nonlinear autocorrelation in the ET0 time series. Finally, the present study proposes time series models to better predict ET0 for two reasons: 1) higher accuracy 2) the simplicity of use. Another important conclusion of this paper is that the type of climate in a region significantly affects the accuracy of predictor models of ET0: In the arid and semi-arid climates of southern Iran, ET0 was predicted more accurately than the humid and sub-humid regions of northern Iran. Due to the high accuracy and promising results of the present study, the use of these data-driven models to predict the water needs of plants in other geographical areas is recommended. Moreover, the use of the current models especially SARIMA and the hybrid ANFIS-DE has research value for long-term and multi-ahead years prediction of monthly ET0. The use and comparison of stochastic, artificial

intelligence, and metaheuristic models in predicting ET0 on a daily scale can be an interesting topic for study, suggested to future researchers in this field.

Funding Statement

This work was supported by the Bu-Ali Sina University Deputy of Research (Grant numbers 99-277).

Author's Contribution

Conceptualization, Pouya Aghelpour; methodology, Pouya Aghelpour, Vahid Varshavian; software, Pouya Aghelpour, validation, Pouya Aghelpour, Vahid Varshavian, and Zahra Hamed; investigation, Pouya Aghelpour, and Vahid Varshavian; resources, Zahra Hamed; data curation, Pouya Aghelpour; writing—original draft preparation, Vahid Varshavian, Pouya Aghelpour, and Zahra Hamed; writing—review and editing, Vahid Varshavian, Pouya Aghelpour; visualization, Zahra Hamed; supervision, Vahid Varshavian. All authors have read and agreed to the published version of the manuscript.

Ethics approval

Not applicable, because this article does not contain any studies with human or animal subjects.

Consent for publication

The Authors hereby consents to publication of the Work in any and all Springer publications

Data & Code Availability

The data & Code used to support the findings of this study are available from the first and corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Table 1. The studied stations' location, climate (according to extended De-Martonne classification [Rahimi et al., 2013]) and the main agricultural/horticultural products of their regions

Province	Station	Coordinates			Climate (based on extended De- Martonne method)	Main products	
		Latitude - northern (degree)	Longitude - eastern (degree)	Elevation (m)		Agricultural	Horticultural
Gilan	Bandar Anzali	37.47	49.47	-26.2	Per humid(B) - Moderate	rice cultivars; tobacco; watermelon	tea; olive; citrus; kiwi; plum
Mazandaran	Ramsar	36.90	50.67	-20.0	Per humid(A) - Moderate	rice cultivars; wheat; soy; rapeseed	citrus; kiwi; ornamental flower; plants
	Gharakhil	36.45	52.77	14.7	Sub-humid - Moderate		
Khuzestan	Ahwaz	31.33	48.67	22.5	Arid - Warm	wheat; barley; maize; legumes; rapeseed	vegetable; cucurbits; potato; onion
Fars	Shiraz	29.53	52.60	1484.0	Semi arid - Moderate	wheat; barley; sugar beet; maize	almonds, grapes, pomegranates, damask rose; figs
Yazd	Yazd	31.90	54.28	1237.2	Extra arid - Cold	sorghum, fodder maize, millet, legumes, alfalfa	pistachios, pomegranates, apricots, saffron

Table 2. Specifications of the meteorological data used and the calculated ET0 on monthly scale

Station	Variable	Training period				Testing Period			
		Min.*	Max.	Average	STD.	Min.	Max.	Average	STD.
Bandar Anzali	Tmin (°C)	0.80	25.40	14.41	6.85	3.10	26.10	14.80	6.84
	Tmax (°C)	5.30	31.80	19.24	7.14	8.40	32.80	20.12	7.57
	Tmean (°C)	3.00	28.40	16.82	6.99	5.80	29.30	17.46	7.18
	RHmax (%)	81.20	96.90	92.21	3.09	81.50	96.50	91.68	3.73
	RHmin (%)	54.80	84.10	73.11	5.72	53.90	84.40	71.76	7.04
	SSD ($\frac{hr}{month}$)	28.50	337.60	161.74	73.68	40.40	339.70	163.78	82.92
	ET0 ($\frac{mm}{month}$)	20.60	174.30	74.39	43.57	22.70	170.30	80.42	49.65
Ramsar	Tmin (°C)	0.90	24.90	13.77	6.82	2.90	25.40	14.34	6.85
	Tmax (°C)	7.10	31.50	19.93	6.86	9.20	32.50	20.43	7.23
	Tmean (°C)	4.00	28.20	16.86	6.82	6.10	28.90	17.39	7.03
	RHmax (%)	80.60	97.30	89.85	3.33	80.30	95.10	90.18	3.80
	RHmin (%)	56.50	84.20	69.07	4.83	56.70	82.70	69.61	5.82
	SSD ($\frac{hr}{month}$)	39.00	289.20	139.53	51.16	52.80	309.70	140.29	58.79
	ET0 ($\frac{mm}{month}$)	20.90	158.50	71.52	37.90	23.20	151.70	72.77	42.10
Gharakhil	Tmin (°C)	-1.30	23.80	12.76	7.14	1.50	24.20	13.03	7.20
	Tmax (°C)	8.10	34.80	21.98	7.14	11.70	34.70	22.58	7.35
	Tmean (°C)	3.40	28.80	17.37	7.11	6.60	29.20	17.80	7.26
	RHmax (%)	89.40	98.90	95.40	2.04	89.20	97.00	94.16	2.07
	RHmin (%)	46.50	76.90	62.45	5.59	47.60	73.50	62.27	5.41
	SSD ($\frac{hr}{month}$)	40.30	310.20	170.11	49.43	73.30	317.60	169.54	53.09
	ET0 ($\frac{mm}{month}$)	23.40	164.40	78.10	40.16	20.20	169.70	80.22	44.70
Ahwaz	Tmin (°C)	6.20	31.50	19.44	7.86	7.40	31.40	19.79	8.02
	Tmax (°C)	14.70	48.10	33.60	10.59	17.40	48.90	34.15	10.24
	Tmean (°C)	10.40	39.80	26.52	9.20	13.40	39.90	26.98	9.10
	RHmax (%)	28.10	95.80	60.09	19.00	27.80	96.30	62.35	18.27
	RHmin (%)	6.80	67.10	23.85	14.67	7.80	64.70	25.46	13.46
	SSD ($\frac{hr}{month}$)	162.40	383.60	273.79	58.02	163.60	370.30	272.99	58.36
	ET0 ($\frac{mm}{month}$)	40.20	354.50	169.06	93.21	44.80	310.50	161.89	85.55
Shiraz	Tmin (°C)	-2.00	24.20	10.95	7.46	-1.10	22.30	10.46	7.29
	Tmax (°C)	9.40	40.10	26.33	9.17	11.70	40.10	26.90	8.85
	Tmean (°C)	4.80	32.10	18.64	8.26	5.60	31.10	18.68	8.04
	RHmax (%)	30.00	91.90	58.33	17.96	27.80	90.90	58.51	18.24
	RHmin (%)	6.60	54.50	20.86	11.01	4.30	49.50	17.51	10.04
	SSD ($\frac{hr}{month}$)	208.50	372.30	296.88	40.68	222.70	370.30	294.97	40.10
	ET0 ($\frac{mm}{month}$)	37.90	251.40	133.79	64.01	44.70	224.50	129.44	60.15
Yazd	Tmin (°C)	-4.40	28.30	13.24	8.74	1.10	27.40	14.32	8.46
	Tmax (°C)	4.80	42.60	27.33	9.62	12.40	41.80	27.87	9.05
	Tmean (°C)	0.20	35.50	20.29	9.16	6.80	34.60	21.10	8.74
	RHmax (%)	15.50	87.70	41.06	19.22	12.60	80.40	38.11	17.38
	RHmin (%)	5.10	57.60	16.25	9.96	4.90	39.60	14.49	7.54
	SSD ($\frac{hr}{month}$)	209.80	376.80	292.77	47.08	200.40	383.00	296.97	47.65
	ET0 ($\frac{mm}{month}$)	34.00	289.10	156.13	73.86	55.30	273.50	155.87	70.35

*Min. = Minimum; Max. = Maximum; STD = Standard deviation

Table 3. The operators of differential evolution Algorithm

Operator	Value
Population	100
Maximum Number of Iterations	200
Crossover probability	0.1
Scaling factor lower bound	0.2
Scaling factor upper bound	0.8

Table 4. Evaluating the models' predictions by evaluation criteria

Station	Model	Train			Test		
		RMSE ($\frac{mm}{month}$)	PB	R	RMSE ($\frac{mm}{month}$)	PB	R
Bandar Anzali	SARIMA(1,0,0)(2,1,2)₁₂*	9.436	-0.026	0.977	10.078	-0.042	0.982
	ANFIS	8.177	-0.014	0.983	12.767	0.035	0.970
	ANFIS-DE	10.492	-0.019	0.971	10.532	-0.018	0.977
Ramsar	SARIMA(1,0,2)(3,1,3)₁₂	8.973	-0.011	0.973	9.711	-0.028	0.975
	ANFIS	8.130	-0.011	0.977	13.257	-0.013	0.949
	ANFIS-DE	11.171	-0.015	0.957	10.998	-0.013	0.965
Gharakhil	SARIMA(1,0,0)(3,1,1)₁₂	10.909	-0.013	0.963	9.713	-0.041	0.979
	ANFIS	9.624	-0.014	0.971	12.569	-0.018	0.960
	ANFIS-DE	12.300	-0.018	0.953	10.711	-0.005	0.970
Ahwaz	SARIMA(1,0,1)(2,1,3)₁₂	14.844	-0.003	0.987	12.789	0.020	0.990
	ANFIS	12.597	-0.008	0.991	16.906	-0.021	0.983
	ANFIS-DE	16.134	-0.008	0.984	14.533	-0.020	0.985
Shiraz	SARIMA(1,0,1)(2,1,2)₁₂	8.364	-0.004	0.991	7.918	0.013	0.992
	ANFIS	6.281	-0.004	0.995	9.920	-0.007	0.986
	ANFIS-DE	10.408	-0.009	0.987	9.077	-0.014	0.988
Yazd	SARIMA(2,0,0)(3,1,3)₁₂	10.142	-0.007	0.991	8.897	0.005	0.994
	ANFIS	8.858	-0.008	0.993	10.537	0.007	0.989
	ANFIS-DE	11.224	-0.011	0.989	9.548	0.000	0.991

*Bold rows specify the best fitted model in each station.

Figure 1. Location of the stations under investigation on the country

Figure 2. The schematic structure of an ANFIS model with two inputs

Figure 3. Flowchart of the optimization process based on differential evolution algorithm

Figure 4. General flowchart of the evapotranspiration modeling, prediction and evaluation processes

Figure 5. Autocorrelation plots for the monthly ET0 time series; the alphabets within the brackets refer to the stations: (a) Bandar Anzali, (b) Ramsar, (c) Gharakhil, (d) Ahwaz, (e) Shiraz, (f) Yazd

Figure 6. Scatter plots to investigate the models' predictions against their simultaneous observed values; the alphabets within the brackets refer to the stations: (a) Bandar Anzali, (b) Ramsar, (c) Gharakhil, (d) Ahwaz, (e) Shiraz, (f) Yazd

Figure 6. Continued

Figure 7. Taylor diagrams to compare the models in the stations; the diagram of each station is specified by its own name

Figure 8. Combo-graph of NRMSE and NS criteria to make a comparison between the different climates

Figure 9. Multiple time series plots of the observed monthly evapotranspiration beside the models' predictions