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ORIGINAL ARTICLE

Estimating Daily reference Evapotranspiration using Artificial Intelligence and Empirical models under Various Scenarios (temporal, local and external) of Meteorological data Management in Semi-arid areas

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ABSTRACT
Evapotranspiration (ET), as a major component of the hydrological cycle, is an important issue in water resources management. In most indirect methods to calculate ET, it is necessary to estimate at first the reference evapotranspiration (ET_O) at first. In this study, three different meteorological data management scenarios (temporal-local, temporal-local-external and temporal-external) were examined to estimate the ET_O by employing adaptive neuro-fuzzy inference system (ANFIS), FAO-Peman-Montieth (FPM) and three empirical models (Hargreaves, Priestley-Taylor and Makkink) under semi-arid conditions. In this investigation, 18 synoptic weather stations data (16 stations around the Shiraz city in south west, one station in center and another station in the north east of Islamic Republic of Iran) were used. Shiraz station was assumed as the main station. The results showed that Hargreaves model with temporal-local scenario produced an acceptable ET_O estimation (NRMSE= 21.5%). With the temporal-local-external scenario, stations located at the distance less than 150km from the main station, all models resulted in an acceptable ET_O estimations (10%<NRMSE≤20). At the distances farer (greater) than 150 km, the wind speed and aridity index were the two dominant climate variables on the estimation accuracy. Under the temporal-external scenario, the PT_{calib}, FPM, $ANFIS_{HR}$ and $ANFIS_{PT\ or\ MK}$ models could estimate the ET_O more accurately amongst the remaining models in some near stations (<150 km). $ANFIS_{HR}$ for all stations (<150 km) provided an acceptable ET_O. At the stations located between150 to 300km, the PT_{calib} model for 5 stations from 9 stations presented the reasonable ET_O estimation.
Key words: Reference evapotranspiration, FAO-56 Penman- Monteith, ANFIS model, Empirical models and Empirical models calibrated.

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INTRODUCTION

Evapotranspiration (ET) is the process of water loss to the atmosphere by the combined processes of evaporation and transpiration. Accurate estimation of ET is needed for computation of crop water requirement, irrigation scheduling, water resources management and planning, water allocation and water budget determination, especially in arid and semi-arid regions where water resources are scarce and fresh water is quite limited. Therefore, reliable estimation of ET is of great importance. Water requirement should be estimated by taking into account the climatic conditions [1]. ET may be measured directly by water balance or estimated indirectly using various approaches (energy balance, mass transfer, combination, temperature, radiation, humidity, etc.) methods [2 ,3]. In general the indirect methods at first step estimate the reference evapotranspiration (ET_O) and then multiplying it by plant factor (K_C) to obtain the ET. The term reference ET_O was introduced and elaborated by the United

Nations Food and Agriculture Organization (FAO) as a methodology for computing ET [4]. The interdependence of many factors affecting the ET makes the study of the evaporative demand of the atmosphere regardless of crop type, its stage of development and its management to be difficult. The ET_0 represents the evapotranspiration from a hypothesized reference crop (height 0.12 m, surface resistance 70 $s.m^{-1}$ and albedo 0.23) steadily kept fully moisture [5]. Obviously accurate estimation of ET_0 is the prime base for reliable calculation of ET [6 ,7]. There are some empirical models (e.g., Thornthwaite [8], Blaney and Criddle [9], Turc [10], Jensen and Haise [11], Priestley and Taylor [12], Makkink [13], Hargreaves and Samani [14], and FAO-56 Penman Monteith [5]) that employ measured climatic data as independent variables for ET_0 estimation. In the recent past, the FAO-56 Penman Monteith (FPM) model has been adopted as a reference equation for estimating the ET_0 and calibrating the other ET_0 – Estimating models [5]. The FPM model has two important advantages: (i) it can be applied to a great variety of environments and climate scenarios without need for the local calibration and (ii) it has been validated at many locations by using lysimeters under a wide range of climatic conditions [15]. On the other hand, the need for the full number of climatic variables (air temperature, relative humidity, solar radiation and wind speed) is a major disadvantage. Many weather stations are equipped with sensors for air temperature detection, but the presence of sensors necessary for the detection of the remaining climate variables may not be feasible and the data quality provided by them is also sometimes poor [16]. These constraints (absence of meteorological sensors) may be overcome by employing physically based models of the estimation of the climate variable, such as the air temperature-based estimation of radiation and relative humidity [5]. The application of ET_0 models with fewer climate variable requirements {e.g.; Hargreaves (HR), Priestley-Taylor (PT) and Makkink (MK) models} is also recommended under these situations [16]. Another alternative is the application of artificial intelligence (AI) based models (e.g.; artificial neural networks or ANN, adaptive neuro-fuzzy inference system or ANFIS and genetic programming or GP) [15 ,17]. In the recent years, ANN, ANFIS and GP approaches have been applied in hydrology and water resources engineering issues. Recent experiments have indicated that ANN, ANFIS and GEP may offer some promising results in hydrology and water resources engineering [18,19,20,15, 21]. Research studies on ET_0 estimates show that artificially based intelligence models (ANN, ANFIS and GEP) as compared to empirical models usually have led to better results [19,22, 23,17]. Research shows that among the artificial intelligence models, depending on the scenario used estimating accuracy would be different (e.g. [1,17]). ANFIS model is preferred because of the computation speed and stability of the results. ANFIS is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s is a combination of an adaptive neural network and a fuzzy inference system (FIS). The adaptive neural network is a superset of all kinds of feed-forward neural networks [24]. The parameters of the FIS are determined by the ANN learning algorithms. Since this system (ANFIS) is based on the FIS, reflecting extensive knowledge, an important aspect is that the system should always be interpretable in terms of fuzzy IF-THEN rules. ANFIS is capable of approximating any real continuous function on a compact set [25]. Pour-Ali Baba et al. [26] Estimated daily ET_0 using both available and calculated climatic data by ANFIS and ANN in South Korea. Dogan [27] examined the capability of the ANFIS technique to estimate daily ET_0 by performing a sensitivity analysis of the applied input parameters. Kisi and Ozturk [23] used the ANFIS computing technique for daily ET_0 estimation. Aytek [28] modeled daily ET_0 using a co-active ANFIS. Shiri et al.[17] a temporal-external-local and temporal-external scenarios to the comparison between AI and emprical models to estimate daily ET_0 was used. Kisi [22] compared with temporal-external between ANN, MLR, HR, Turc [10] and penman [29] models (for estimating ET_0) used in three weather stations in Los Angeles, California of USA. This paper investigates the performance ANFIS and the three conventional empirical model (MK, PT and HR) to daily ET_0 estimating under various scenarios temporal, local and external of meteorological data management by comparing them against the FPM model using data collected in a semi-arid condition (based on aridity Index).

MATERIALS AND METHODS

Aridity Index defined as:

$$I_A = \frac{P}{ET_0} \quad (1)$$

where P is precipitation (mm) and ET_0 (mm) is estimated by FPM model for a ten-year period (in this study). Classification of the station climate based on Aridity index [30] is given in table 1.

AI ET_0 models

Based on the input climate variable of the empirical models (HR, PT and MK) and FPM model, the three models of ANFIS ($ANFIS_{FPM}$, $ANFIS_{HR}$ and $ANFIS_{PT\ or\ MK)}$ designed and was used (table 3). Ten-year climate data were used to train (eight-year) and test (two-years=20% of total data) AI models (e.g. ANFIS, ANN AND GEP) to estimate ET_0. Recent studies in hydrology and water resources engineering show that researchers have used 20% to 40% of the total temporal data for testing models of AI [31,32, 33, 26 ,34] but the literature dose not propose information about the number (e.g. 3, 5, 7 , 10 , 12, etc) of appropriate years data. The preliminary tests of this study showed that 10 years is more appropriate for testing and training.

Physical and emprical models

-FPM model:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\left(\frac{900}{(\frac{T_{max} + T_{min}}{2}) + 273}\right)u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (2)$$

where ET_0 = reference evapotranspiration ($mm.day^{-1}$), Δ =slope of the daily saturation vapor pressure function ($kPa.^oC^{-1}$), γ = daily psychometric constant (($kPa.^oC^{-1}$), R_n= net radiation ($MJ.m^{-2}.day^{-1}$), G=soil heat flux density ($G_{day} \cong 0$)($MJ.m^2.day^{-1}$), $T_{max.}$=daily maximum air temperature (^oC) and $T_{min.}$=daily minimum air temperature (^oC), U_2= daily average 24 h wind speed at 2 m height ($m.s^{-1}$), e_a=daily saturation vapor pressure (kPa), and e_s =daily actual vapor pressure. R_n, γ and e_a were calculated based on sunshine hours, elevation and temperature-relative humidity (max. an min.) equation, respectively according to FAO-56 guideline [5].

-HR model:

$$ET_0 = 0.0023\,R_a\,(T_{max} - T_{min})^{0.5}(\frac{T_{max} + T_{min}}{2} + 17.8) \quad (3)$$

Where R_a is extraterrestrial radiation ($mm.day^{-1}$), and the other applied parameters were introduced before.

-PT model:

$$ET_0 = \frac{\alpha}{\lambda}\frac{\Delta}{\Delta + \gamma}(R_n - G) \quad (4)$$

Where α=1.26, λ =latent heat of the evaporation ($MJ.kg^{-1}$) and the other applied parameters were introduced before.

MK model:

$$ET_0 = 0.61\frac{\Delta}{\Delta + \gamma}\frac{R_s}{\lambda} - 0.12 \quad (5)$$

Where R_s is solar radiation ($MJ.m^{-2}.day^{-1}$) and the other applied parameters were introduced before.

Calibrated emprical models:

The following equation [5] was used to calibrate the applied empirical models (HR, PT and MK).

$$ET_0^{FPM} = a + bET_0^{M} \qquad (6)$$

in the 6 equation the superscript M stands for the HR, PT and MK as designated HR_{calib}., PT_{calib}. and MK_{calib}., respectively. In fact, this equation makes the emprical model results closer to the FPM model. To calibrate the empirical models, the combinations of 2, 4, 6, 8 and 10 years data were employed. The compound (compared to the FPM) which has the best estimation was used to test the calibrated model. Two-year of total data (10-year) were used to test the calibrated models (in order to coordinate with AI models).

Study area and available data:

The synoptic weather station of Shiraz city, south-west of Iran, located at semi-arid region based on I_A value (table 1) was selected as the main station (Fig. 1). Synoptic weather stations within 300 km distance (with similar or dissimilar I_A according to table 1) from the main station were specified as the "near stations" and beyond 300 km as the "far stations" stations. The near stations were divided to two groups: located at ≤150km (group 1) and at 150-300km (group 2) from the main station. Within each group, stations with complete data were (available for FPM-ET_0 computation for the 2000 to 2012 period) were selected (four and nine station for groups 1 and 2, respectively). The two stations with complete data as the far station were from center and north east of Iran. These stations were different wind speeds and similar in the aridity index. Totally 16 selected stations arrangement (fig. 1), mostly located at south west of Iran, allowed to examine the ET_0 estimation and its accuracy under the scenarios described subsequently in this section.

The meteorological data consisted of 13 years (2000–2012) of daily records of air temperature (max. and min.), sunshine hours, wind speed (mean) and relative humidity (max. and min.) were used. For all of stations were estimated ET_0 by FPM, HR, PT, MK, HR_{calib}., PT_{calib}., MK_{calib}., $ANFIS_{FPM}$, $ANFIS_{HR}$ and $ANFIS_{PT\ or\ MK}$ models.

Scenarios

Temporal-Local scenario:

In this scenario, it was assumed that the main station lacked the required climate variables for FPM models. So the three empirical models with the local data were employed and ET_0 were estimated for the two-year from 2011 to 2012. The results were compared (based on accuracy estimating criteria) with FPM model (table 4).

By temporal, it is meant the use of meteorological data related to different years (ten-year in the study) and by local is define as the use of meteorological data of main station (Shiraz) to estimate ET_0 at the same station.

Temporal-Local-external scenario:

In this scenario, it was assumed that the main station lacked the required climate variables for FPM models. The empirical models were calibrated in near or far stations (15 stations) and then were tested in the main station (Shiraz). ANFIS ($ANFIS_{HR}$ and $ANFIS_{PT\ or\ MK}$) models were trained (eight-year from 2003 to 2010) in the near or far stations and were tested by two-year data from 2011 to 2012, in the main station (table 5).

By external (Non-local), it is meant the use of the data of near or far the stations to train the of ANFIS model or to calibrate the emprical models.

Temporal-external scenario:

In this scenario, it was assumed that the area (the place where the main station was located) lacks the synoptic weather station or has station with incomplete data. For ET_0 estimation the external (near or far) data of 15 stations were used and then (i): the three empirical models were calibrated and tested at the near or far stations (ii): The ANFIS models ($ANFIS_{FPM}$, $ANFIS_{HR}$ and $ANFIS_{PT\ or\ MK}$) were trained (eight-year from 2003 to 2010) and tested (two-year from 2011 to 2012) at near or far weather stations and (iii) the ET_0 was estimated by empirical and physical models (HR, PT, MK and FPM). The ET_0 estimated with all of models then were compared (based on accuracy estimating criteria) with FPM model at the main weather station (Shiraz).

Accuracy estimation criteria

Four accuracy indices were calculated to assess the models' performance, namely, root mean square error (RMSE), normalized root mean square error (NRMSE), Nash–Sutcliffe efficiency (NSI) and mean biased error (MBE). They were computed from the following equations [35, 36, 37].

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}\left(\mathrm{ET}_{0i}^{M}-\mathrm{ET}_{0i}^{FPM}\right)^{2}}{N}} \tag{7}$$

$$NRMSE\%=\frac{RMSE}{\overline{ET}_{0}^{FPM}}\times 100 \tag{8}$$

$$\mathrm{NSE}\%=\left(1-\frac{\sum_{i=1}^{n}(\mathrm{ET}_{0i}^{FPM}-\mathrm{ET}_{0i}^{M})^{2}}{\sum_{i=1}^{n}(\mathrm{ET}_{0i}^{FPM}-\overline{\mathrm{ET}}_{0}^{FPM})^{2}}\right)\times 100 \tag{9}$$

$$\mathrm{MBE}=\frac{\sum_{i=1}^{n}(\mathrm{ET}_{0i}^{M}-\mathrm{ET}_{0i}^{FPM})}{N} \quad 10)$$

where ET_{0i}^{FPM} and ET_{0i}^{M} are the ET_0 values computed at the i-th time step from FPM and from the selected models (HR, PT and MK), N is number of time steps, $\overline{\mathrm{ET}}_{0}^{FPM}$ is mean value of the FPM-ET_0 values. The RMSE can take value from 0 to +∞, the closer to zero the greater the accuracy. The NRMSE can also give a good insight for comparing the performances of various models. Rating are: excellent, NRMSE<10%; Good 10% < NRMSE<20%; Fair 20 %< NRMSE<30% and poor with NRMSE>30% [37, 38]. According to Allen et al. [5], the NRMSE 0 up to 20% may be considered as an acceptable value. The NSE indicates how well the plot of observed versus simulated data fits the 1:1 line. It ranges between ∞ and 1.0 (1 inclusive); with NSE =1 being the optimal value. Whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value, which indicates unacceptable performance [37]. The MBE is usually intended to indicate average model 'bias'; that is, over all over or under estimation. The MBE can convey useful information, but should be interpreted cautiously since it is inconsistently related to typical-error magnitude, other than being an under estimate (MBE ≤ RMSE) [35].

RESULTS AND DISCUSSION

The value RMSE, NRMSE, MBE, NSE and Rating NRMSE related to three scenarios meteorological data management for estimating ET_0 are shown in Tables 4 to 6.

Temporal-local scenario

Table 4 shows that HR model (NRMSE= 21.5%) can be alternative to FPM model for estimating ET_0. But PT and MK models with NRMSE 27% to 30% are not acceptable. For Boroojen, Gonbad Kawoos, Karaj, sad Doroudzan and Abadeh (approximate wind speed between 1.3 to 2 m .s^{-1}) stations with I_A similar to main station also NRMSE is close to 20%. One reason why HR model is the good rate is because this model has been developed in the Davis station as the same as the main station [39]. Tabari [40] during an investigation to compare some empirical models (HR, MK, PT and Turc) for estimating ET_0 with FPM model and concluded that in arid and semi-arid climate HR model may be more efficient. Kisi [22] compared HR, Turc[10] and penman [29] models to the FPM model in semi-arid climate and concluded that HR model (for estimate ET_0) is more accurate than other models.

Temporal-local-external scenario

Table 5 shows that the near stations (similar or dissimilar) in group1 (< 150 km) (Yasouj, Fassa, Sad doroudzan and Zarghan) seem produced resonable ET_0 estimation for the examined models (10% < NRMSE≤20%). According to the climate variables presented in table 2, especially wind speed, distance, I_A, and altitude of group1 stations, it seems that none of the climate variables had a significant effect on changing in the value of the estimate ET_0 of the models in the domain of 10 to 20%. Therefore stations with distance 150 km around of main station (shiraz) the estimated ET_0 could be alternative to FPM models (the good rate) based on the NRMSE index.

At the 150 to 300 km, the good rate accuracy was rather influenced by the wind speed and aridity index depends. At Dogonbadan station, the PT_{calib} and MK_{calib} models were good because of the aridity index similarity to the main station (though wind speed is different). For Boroojen station $PT_{calib.}$, $HR_{calib.}$ and $MK_{calib.}$ models are recommended (table 3) because their aridity index and wind speed are close to the main station. In Behbahan and Lar stations, all models except $ANFIS_{PTor\ MK}$ seem acceptable probably because their wind speed is similar to the main station (though aridity index is different). However, $PT_{calib.}$ model in Hasanabad Darab station is one exception (wind speed and aridity index is different than the main station). The NRMSE related to Boroojen, Lar and Behbahan stations shows that wind speed is more effective than the aridity index on estimated ET_0. Marvast, Omidiyeh Aghajari, Bushehr, Eizadkhast and Shahrbabak stations (table 2) with dissimilar aridity index and wind speed (2.28-3.1 $m.s^{-1}$) are different than the main station (1.30 $m.s^{-1}$) and the estimated ET_0 are not suitable (NRMSE> 22%).

For the far stations (Karaj and Gonbade Kawoos), according to the results of Tables 2 and 5, estimated ET_0 of all models at the Gonbade Kawoos station (based on NRMSE) is good. It may be because of similarity of the I_A index and wind speed of Gonbade Kawoos station with the main station. At Karaj station two models ($PT_{calib.}$ and $MK_{calib.}$) may be recommended. It may be because of the dissimilarity of the wind speed of Karaj station with the main station (wind speed=1.96 $m.s^{-1}$). In general, similarity in the wind speed among the far stations seems more influential on estimate ET_0 than the aridity index; however, more weather stations are required to generalize this finding. Shiri et al. (2013) by using the temporal-external-local scenario were compared between AI (ANFIS and GEP) and emprical (HR, MK and Turc) models in five weather stations (Bam, Kerman, Esfahan, Semnan and Shahrood) in Iran (the arid climate based on I_A). Their results showed estimating of ET_0 by the ANFIS model was performed better than the GEP model.

Temporal-external scenario

Table 6 shows at near stations (similar or dissimilar) belonging to the group1 station (≤150 km); (i) the $PT_{calib.}$ model in Zarghan, Yasouj, and Fassa weather station; (ii) the FPM model in Zarghan and Yasouj stations; (iii) the $ANFIS_{HR}$ model in Zarghan, Yasouj, Sad Doroudzan and Fassa stations and (iv) the $ANFIS_{PTor\ MK}$ model in Zarghan, Yasouj and Fassa produced acceptable ET_0 estimation (NRMSE≅ 20%). The $ANFIS_{HR.}$ model for all stations is presented admissible ET_0 estimation (NRMSE between 16.9% to 19.5%). However, HR model in Shahrbabak station is one exception. At greater than 150 km, the PT_{calib} model for five stations (Lar, Hasanabad Darab, Dogonbadan, Bushehr and Abadeh) from out of 9 stations is manufactured suitable ET_0 estimation (NRMSE between 17.1 to 21.4%). Kisi [22] compared with temporal-external between ANN, MLR, HR, Turc [10] and penman[29] models (for estimating ET_0) used in three synoptic stations (Claremont, Pomona and Santa Monica) in Los Angeles, California of USA (the semi-arid climate). Two applications were employed. In the first application, the input data of Claremont station are used as inputs to in the ANN (two different types of input climate variables), MLR (multi-linear regression), Penman [29], HR and Turc [10] models to estimate ET_0 in Pomona station. In the second application the ET_0 in the same station was estimated using the input data of Claremont and Santa Monica stations. The ANN model with input of solar radiation, wind speed, air temperature, and relative humidity performed better than the other models (as compared to FPM model). However, the HR model showed better performance than the ANN model. The HR model also seems to have more accurate estimates than the Penman, Turc and MLR models. Among the models using the ANN with input of solar radiation and air temperature, it had been the maximum accuracy.

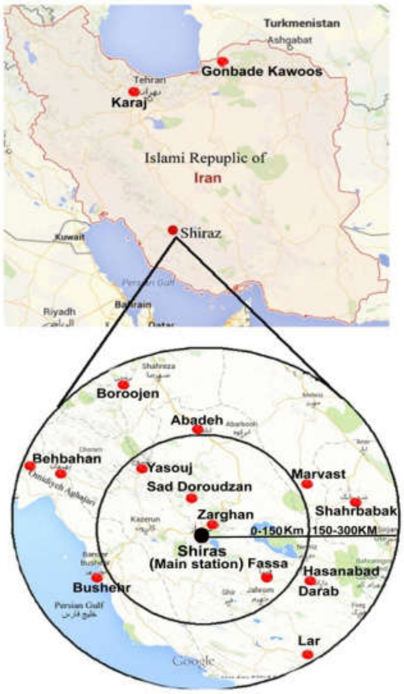

Fig.1: The main selected area (Shiraz) and the location around within 0-300km distance (near weather stations) along with far station locations on the Iran map.

Table1. Climate based on Aridity Index [30]

Aridity Index	Climate
<0.03	Hyper Arid
0.03-0.2	Arid
0.2-0.5	Semi-Arid
0.5-0.75	sub-humid
>0.75	Humid

Table 2. Summary of data in the studied weather stations

Station	Latitude (°N)	Longitude (°E)	Altitude (m)	P (mm)	ET_0(mm)	I_A	Ws ($m.s^{-1}$)	Distance to Shiraz (km)
Abadeh	31.11	52.40	2030.0	297.8	1528.0	0.20-SA	1.81	175
Behbahan	30.36	50.14	313.0	306.5	1745.4	0.17-A	1.26	247
Boroojen	31.57	51.18	2197.0	262.3	1275.0	0.20-SA	1.32	290
Bushehr	28.58	50.49	9.0	226.4	1766.3	0.13-A	2.33	171
Dogonbadan	30.26	50.46	699.5	408.1	1504.6	0.27-SA	0.95	169
Eizadkhast	31.32	52.07	2188.0	163.4	1735.4	0.09-A	3.10	216
Fassa	28.58	53.41	1288.3	277.8	1614.4	0.17-A	1.26	132
Gonbade kawoos	37.15	55.01	37.2	567.4	1222.0	0.46-SA	1.46	-
Hasanabad darab	28.47	54.17	1098.2	235.2	1520.7	0.15-A	0.86	202
Karaj	35.55	50.54	1312.5	301.7	1444.4	0.21-SA	1.96	-
Lar	27.42	54.75	792.0	158.3	1709.4	0.09-A	1.18	281
Marvast	30.30	54.15	1546.6	61.0	1945.4	0.03-A	2.37	193
Omidiyeh aghajari	30.46	49.40	27.0	231.0	2372.5	0.10-A	2.54	288
Sad doroudzan	30.11	52.27	1625.2	460.0	1651.1	0.28-SA	1.83	65
Shahrbabak	30.06	55.08	1834.1	125.5	1828.1	0.07-A	2.28	265
Shiraz (main Station)	**29.32**	**52.36**	**1484.0**	**307.3**	**1560.6**	**0.20-SA**	**1.30**	**-**
Yasouj	30.50	51.41	1831.5	824.8	1426.5	0.58-SH	1.37	150
Zarghan	29.47	52.43	1596.0	297.9	1399.5	0.21-SA	1.00	27

W_S: mean daily wind speed; P: average annual precipitation (ten-year); ET_0: annual ET_0 (ten-year); I_A: aridity Index; HA: hyper-arid; A: arid; SA: semi-arid; H: humid; SH: sub-humid (based on aridity index values, Table 1.).

Table 3. ANFIS models input climate variables based on the similarity to the main physical and empirical models.

Models	Daily input climate variables.
FPM	T_{mean}, R_S, $U_{2(mean)}$, RH_{mean}
PT	T_{max}, T_{min}, T_{mean}, R_S
MK	T_{max}, T_{min}, T_{mean}, R_S
HR	T_{max}, T_{min}, T_{mean}, R_a

Table 4. Temporal-local scenario: Estimating the ET_0 (for two-year, 2011-2012) by the emprical models and comparing to the FPM model in the main station

Models	RMSE mm.day^{-1}	NRMSE%	MBE mm.day^{-1}	NSE%	Rating*
HR	0.91	21.5	0.34	82.4	Fair
PT	1.15	27.4	-0.81	71.6	Fair
MK	1.27	30.1	-0.83	65.5	Poor

* based on classification of NRMSE.

Table 5. Temporal-local-external scenario: Estimating the ET_0 (two-year, 2011-2012) by ANFIS and the calibrated empirical models and comparing to the FPM model in the main station .

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Abadeh	N	S	$ANFIS_{HR}$	0.82	19.5	-0.27	85.6	Good
			$ANFIS_{PT\ or\ MK}$	0.72	17.1	-0.16	88.9	Good
			$HR_{Calib.}$	0.84	19.9	0.23	84.9	Good
			$PT_{Calib.}$	0.72	17.2	0.04	88.8	Good
			MK_{Calib}	0.78	18.5	0.06	87.1	Good
Behbahan	N	D	$ANFIS_{HR}$	0.89	21.1	-0.44	83.1	Fair
			$ANFIS_{PT\ or\ MK}$	1.00	24.1	-0.43	77.9	Fair
			$HR_{Calib.}$	0.87	20.5	-0.10	84.0	Fair
			$PT_{Calib.}$	0.75	17.8	0.11	88.0	Good
			MK_{Calib}	0.83	19.7	0.23	85.3	Good
Boroojen	N	S	$ANFIS_{HR}$	1.23	29.2	0.73	67.7	Fair
			$ANFIS_{PT\ or\ MK}$	1.85	43.9	0.95	26.9	Poor
			$HR_{Calib.}$	0.85	20.2	-0.18	84.5	Fair
			$PT_{Calib.}$	0.91	21.6	-0.45	82.2	Fair
			MK_{Calib}	0.92	21.9	-0.39	81.7	Fair
Bushehr	N	D	$ANFIS_{HR}$	1.90	45.0	0.41	23.3	Poor
			$ANFIS_{PT\ or\ MK}$	2.74	67.3	1.30	-72.0	Poor
			$HR_{Calib.}$	1.32	31.3	1.00	62.8	Poor
			$PT_{Calib.}$	0.90	21.4	-0.21	82.8	Fair
			MK_{Calib}	0.94	22.2	0.51	81.3	Fair
Dogonbadan	N	S	$ANFIS_{HR}$	0.99	23.6	-0.64	78.8	Fair
			$ANFIS_{PT\ or\ MK}$	1.10	26.1	-0.78	74.2	Fair
			$HR_{Calib.}$	0.94	22.4	-0.47	81.0	Fair
			$PT_{Calib.}$	0.73	17.3	-0.15	88.7	Good
			MK_{Calib}	0.78	18.5	-0.10	87.1	Good
Eizadkhast	N	D	$ANFIS_{HR}$	1.45	34.4	1.20	55.2	Poor
			$ANFIS_{PT\ or\ MK}$	1.49	35.4	1.26	55.2	Poor
			$HR_{Calib.}$	1.36	32.3	1.10	60.3	Poor
			$PT_{Calib.}$	0.96	22.7	0.61	80.5	Fair
			MK_{Calib}	1.10	25.4	0.74	75.4	Fair

N: near; F: Far; S: similar; D: dissimilar

Table 5 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Fassa	N	D	$ANFIS_{HR}$	0.77	18.3	-0.03	87.3	Good
			$ANFIS_{PT\ or\ MK}$	0.71	16.9	0.01	89.2	Good
			$HR_{Calib.}$	0.82	19.4	-0.04	85.7	Good
			$PT_{Calib.}$	0.70	16.7	-0.04	89.7	Good
			MK_{Calib}	0.77	18.4	-0.03	87.1	Good
Gonbade kawoos	F	S	$ANFIS_{HR}$	0.88	20.8	-0.17	83.6	Fair
			$ANFIS_{PT\ or\ MK}$	0.83	19.6	-0.17	85.4	Good
			$HR_{Calib.}$	0.81	19.3	-0.07	85.8	Good
			$PT_{Calib.}$	0.84	19.9	-0.25	84.9	Good
			MK_{Calib}	0.81	19.2	0.19	86.0	Good
Hasanabad Darab	N	D	$ANFIS_{HR}$	0.91	21.6	-0.50	82.2	Fair
			$ANFIS_{PT\ or\ MK}$	1.05	25.0	-0.73	76.2	Fair
			$HR_{Calib.}$	0.93	22.0	-0.43	81.6	Fair
			$PT_{Calib.}$	0.81	19.1	-0.38	86.0	Good
			MK_{Calib}	1.00	23.5	-0.47	78.9	Fair
Karaj	F	S	$ANFIS_{HR}$	0.93	22.1	0.41	86.5	Fair
			$ANFIS_{PT\ or\ MK}$	1.17	27.7	0.63	71.0	Fair
			$HR_{Calib.}$	0.97	23.0	0.46	80.0	Fair
			$PT_{Calib.}$	0.71	16.8	0.05	89.2	Good
			MK_{Calib}	0.89	21.2	0.44	83.0	Fair
Lar	N	D	$ANFIS_{HR}$	0.82	19.5	-0.16	85.5	Good
			$ANFIS_{PT\ or\ MK}$	0.83	19.6	-0.32	85.4	Good
			$HR_{Calib.}$	0.89	21.1	-0.31	83.1	Fair
			$PT_{Calib.}$	0.72	17.1	-0.11	88.9	Good
			MK_{Calib}	0.81	19.1	-0.09	86.1	Good
Marvast	N	D	$ANFIS_{HR}$	1.35	32.2	1.10	60.7	Poor
			$ANFIS_{PT\ or\ MK}$	1.33	31.4	1.10	62.3	Poor
			$HR_{Calib.}$	1.15	27.2	0.80	71.9	Fair
			$PT_{Calib.}$	1.32	31.2	1.11	62.9	Poor
			MK_{Calib}	1.22	28.9	0.93	68.3	Fair

N: near; F: Far; S: similar; D: dissimilar

Table 5 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Omidiyeh Aghajari	N	D	$ANFIS_{HR}$	1.23	29.1	072	62.7	Fair
			$ANFIS_{PT\ or\ MK}$	1.84	43.7	0.94	27.5	Poor
			$HR_{Calib.}$	1.20	28.4	0.70	69.2	Fair
			$PT_{Calib.}$	1.84	43.7	1.5	27.5	Poor
			MK_{Calib}	2.2	52.1	1.90	-3.24	Poor
Sad Doroudzan	N	S	$ANFIS_{HR}$	0.82	19.4	-0.28	85.6	Good
			$ANFIS_{PT\ or\ MK}$	0.72	17.1	-0.17	88.9	Good
			$HR_{Calib.}$	1.00	24.2	0.53	77.8	Fair
			$PT_{Calib.}$	0.72	16.9	-0.02	89.1	Good
			MK_{Calib}	0.79	18.8	0.17	86.5	Good

Shahrbabak	N	D	$ANFIS_{HR}$	1.35	31.9	1.00	61.3	Poor
			$ANFIS_{PT\ or\ MK}$	1.32	31.3	1.05	62.8	Poor
			$HR_{Calib.}$	1.28	30.3	0.85	65.0	Poor
			$PT_{Calib.}$	1.10	25.2	0.75	75.8	Fair
			MK_{Calib}	1.14	27.1	0.77	72.1	Fair
Yasouj	N	D	$ANFIS_{HR}$	0.75	17.9	0.03	87.9	Good
			$ANFIS_{PT\ or\ MK}$	0.72	17.1	0.14	88.9	Good
			$HR_{Calib.}$	0.81	19.3	0.00	85.9	Good
			$PT_{Calib.}$	0.76	18.1	-0.19	87.5	Good
			MK_{Calib}	0.78	18.6	-0.06	86.9	Good
Zarghan	N	S	$ANFIS_{HR}$	0.82	19.5	-0.28	85.5	Good
			$ANFIS_{PT\ or\ MK}$	0.72	17.1	-0.17	88.8	Good
			$HR_{Calib.}$	0.97	22.9	-0.49	80.0	Fair
			$PT_{Calib.}$	0.85	20.2	-0.42	84.5	Fair
			MK_{Calib}	0.82	19.4	-0.27	85.7	Good

N: near; F: Far; S: similar; D: dissimilar

Table 6.: Temporal-External Scenario in the main station: Estimating the ET_0 (two-year, 2011-2012) by ANFIS, emprical and calibrated empirical models and comparing to the FPM model in the main Station.

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Abadeh	N	S	$ANFIS_{FPM}$	1.15	27.2	0.36	71.8	Fair
.			$ANFIS_{HR}$	1.10	25.6	-0.66	75.1	Fair
			$ANFIS_{PT\ or\ MK}$	0.97	23.1	-0.51	79.8	Fair
			$HR_{Calib.}$	0.85	20.1	0.02	84.6	Fair
			$PT_{Calib.}$	0.80	19.0	0.19	86.3	Good
			MK_{Calib}	0.89	21.2	0.18	82.9	Fair
			FPM	0.89	21.2	0.28	82.9	Fair
			HR	0.92	21.9	-0.35	81.8	Fair
			PT	1.38	32.8	-1.10	59.1	Poor
			MK	1.49	35.3	-1.00	52.6	Poor
Behbahan	N	D	$ANFIS_{FPM}$	1.67	39.6	0.72	40.4	Poor
			$ANFIS_{HR}$	1.19	28.3	0.54	69.6	Fair
			$ANFIS_{PT\ or\ MK}$	1.27	30.1	0.49	65.6	Poor
			$HR_{Calib.}$	1.31	31.1	0.58	63.1	Poor
			$PT_{Calib.}$	1.44	34.1	0.83	55.9	Poor
			MK_{Calib}	1.58	37.3	0.84	47.0	Poor
			FPM	1.64	38.9	0.73	42.6	Poor
			HR	1.44	34.2	0.95	55.6	Poor
			PT	1.20	28.5	-0.74	69.2	Fair
			MK	1.37	32.4	-0.79	60.2	Poor
Boroojen	N	S	$ANFIS_{FPM}$	1.12	26.5	-0.10	73.4	Fair
			$ANFIS_{HR}$	1.61	38.1	-0.45	44.7	Poor
			$ANFIS_{PT\ or\ MK}$	3.44	81.4	0.97	-152	Poor
			$HR_{Calib.}$	1.37	32.5	-0.95	59.7	Poor
			$PT_{Calib.}$	1.16	27.5	-0.77	71.3	Fair
			MK_{Calib}	1.27	30.0	-0.77	65.7	Poor
			FPM	0.98	23.1	-0.21	79.7	Fair
			HR	1.15	27.3	-0.64	71.6	Fair
			PT	1.44	34.2	-1.13	55.5	Poor
			MK	1.59	37.8	-1.15	45.8	Poor

N: near; F: Far; S: similar; D: dissimilar

Table 6 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Bushehr	N	D	$ANFIS_{FPM}$	1.29	30.6	0.66	64.5	Poor
			$ANFIS_{HR}$	1.10	25.8	0.63	74.6	Fair
			$ANFIS_{PT\ or\ MK}$	1.21	28.8	0.64	68.5	Fair
			$HR_{Calib.}$	1.31	31.0	0.47	63.4	Poor
			$PT_{Calib.}$	0.91	21.5	-0.20	82.5	Fair
			MK_{Calib}	1.28	30.3	0.62	65.0	Poor
			FPM	1.21	28.7	0.61	68.8	Fair
			HR	1.27	30.0	-0.28	65.7	Poor
			PT	0.94	22.4	-0.10	80.9	Fair
			MK	1.46	34.7	-0.80	54.3	Poor
Dogonbadan	N	S	$ANFIS_{FPM}$	1.17	27.6	0.00	71.0	Fair
			$ANFIS_{HR}$	0.82	19.4	-0.11	85.7	Good
			$ANFIS_{PT\ or\ MK}$	0.91	21.6	-0.13	82.3	Fair
			$HR_{Calib.}$	0.95	22.6	-0.14	80.5	Fair
			$PT_{Calib.}$	0.97	22.9	-0.38	80.1	Fair
			MK_{Calib}	1.00	24.6	-0.03	77.1	Fair
			FPM	1.1	25.8	-0.03	74.7	Fair
			HR	1.27	30.1	0.71	65.6	Poor
			PT	1.41	33.4	-0.99	57.6	Poor
			MK	1.34	31.7	-0.78	61.7	Poor
Eizadkhast	N	D	$ANFIS_{FPM}$	1.44	27.1	0.49	72.1	Fair
			$ANFIS_{HR}$	1.00	23.7	0.46	78.6	Fair
			$ANFIS_{PT\ or\ MK}$	1.00	24.0	0.49	78.0	Fair
			$HR_{Calib.}$	0.93	22.0	0.32	81.6	Fair
			$PT_{Calib.}$	0.93	22.1	0.51	81.4	Fair
			MK_{Calib}	1.00	24.9	0.50	76.5	Fair
			FPM	1.10	25.6	0.48	75.0	Fair
			HR	1.10	25.7	-0.64	74.9	Fair
			PT	1.37	32.5	-1.00	59.9	Poor
			MK	1.55	36.8	-1.10	48.7	Poor

N: near; F: Far; S: similar; D: dissimilar

Table 6 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Fassa	N	D	$ANFIS_{FPM}$	1.10	26.2	0.38	74.0	Fair
			$ANFIS_{HR}$	0.81	19.2	0.19	85.9	Good
			$ANFIS_{PT\ or\ MK}$	0.85	20.1	0.22	84.6	Fair
			$HR_{Calib.}$	0.92	21.9	0.33	81.8	Fair
			$PT_{Calib.}$	0.84	19.9	0.34	84.9	Good
			MK_{Calib}	0.99	23.4	0.41	79.2	Fair
			FPM	0.98	23.3	0.35	79.3	Fair
			HR	1.10	26.0	0.66	74.3	Fair
			PT	1.19	28.3	-0.79	69.6	Fair
			MK	1.25	29.6	-0.69	66.7	Fair
Gonbade kawoos	F	D	$ANFIS_{FPM}$	1.69	40.1	-0.92	39.0	Poor
			$ANFIS_{HR}$	1.56	37.0	-0.90	47.9	Poor
			$ANFIS_{PT\ or\ MK}$	1.61	38.1	-0.85	44.8	Poor
			$HR_{Calib.}$	1.52	35.9	-0.92	50.9	Poor
			$PT_{Calib.}$	1.38	32.7	-0.84	59.3	Poor

			MK_{Calib}	1.64	38.9	-0.84	42.4	Poor
			FPM	1.66	39.2	-0.94	41.5	Poor
			HR	1.38	32.8	-0.58	59.1	Poor
			PT	1.64	38.8	-1.21	42.7	Poor
			MK	2.13	50.5	-1.63	3.10	Poor
Hasanabad Darab	N	D	$ANFIS_{FPM}$	1.10	25.2	-0.05	75.2	Fair
			$ANFIS_{HR}$	0.82	19.4	-0.07	85.8	Good
			$ANFIS_{PT\ or\ MK}$	0.87	20.6	-0.09	83.9	Fair
			$HR_{Calib.}$	0.87	20.6	-0.14	83.8	Fair
			$PT_{Calib.}$	0.75	17.9	-0.02	87.9	Good
			MK_{Calib}	0.99	23.4	-0.08	79.2	Fair
			FPM	1.00	24.3	-0.03	77.6	Fair
			HR	1.11	26.2	0.66	73.9	Fair
			PT	0.99	23.5	-0.53	79.0	Fair
			MK	1.17	27.7	-0.56	70.9	Fair

N: near; F: Far; S: similar; D: dissimilar

Table 6 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Karaj	F	S	$ANFIS_{FPM}$	1.37	32.5	-0.23	60.0	Poor
			$ANFIS_{HR}$	1.10	25.8	-0.32	74.7	Fair
			$ANFIS_{PT\ or\ MK}$	1.17	27.8	-0.31	70.6	Fair
			$HR_{Calib.}$	1.13	26.8	-0.44	72.7	Fair
			$PT_{Calib.}$	1.00	24.5	-0.24	77.2	Fair
			MK_{Calib}	1.19	28.3	-0.20	69.6	Fair
			FPM	1.33	31.4	-0.27	62.5	Poor
			HR	1.18	28.0	-0.62	70.1	Fair
			PT	1.45	34.4	-1.14	55.0	Poor
			MK	1.74	41.3	-1.34	35.3	Poor
Lar	N	D	$ANFIS_{FPM}$	1.10	25.3	0.31	75.6	Fair
			$ANFIS_{HR}$	0.97	23.0	0.53	80.0	Fair
			$ANFIS_{PT\ or\ MK}$	1.00	23.9	0.52	78.2	Fair
			$HR_{Calib.}$	0.87	20.7	0.28	83.7	Fair
			$PT_{Calib.}$	0.88	20.9	0.29	83.3	Fair
			MK_{Calib}	0.92	21.8	0.17	81.9	Fair
			FPM	1.00	24.7	0.30	76.8	Fair
			HR	1.35	32.0	1.05	61.2	Poor
			PT	1.06	25.1	-0.51	76.1	Fair
			MK	1.19	28.2	-0.48	69.8	Fair
Marvast	N	D	$ANFIS_{FPM}$	1.44	34.2	0.76	55.6	Poor
			$ANFIS_{HR}$	1.41	33.3	1.18	57.8	Poor
			$ANFIS_{PT\ or\ MK}$	1.41	33.4	1.10	57.7	Poor
			$HR_{Calib.}$	1.16	27.5	0.82	71.2	Fair
			$PT_{Calib.}$	1.24	29.4	0.98	67.1	Fair
			MK_{Calib}	1.27	30.2	0.94	65.4	Poor
			FPM	1.45	34.4	0.72	55.1	Poor
			HR	0.91	21.6	0.35	82.3	Fair
			PT	1.29	30.5	-0.94	64.6	Poor
			MK	1.33	31.4	-0.83	62.5	Poor

N: near; F: Far; S: similar; D: dissimilar

Table 6 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Omidiyeh Aghajari	N	D	$ANFIS_{FPM}$	3.30	78.3	2.53	-133	Poor
			$ANFIS_{HR}$	2.79	66.0	2.25	-65.6	Poor
			$ANFIS_{PT\ or\ MK}$	2.87	68.1	2.28	-76.3	Poor
			$HR_{Calib.}$	2.65	62.7	2.10	-49.3	Poor
			$PT_{Calib.}$	2.68	63.4	2.12	-52.9	Poor
			MK_{Calib}	2.85	67.6	2.31	-73.7	Poor
			FPM	3.27	77.4	2.50	-128.0	Poor
			HR	1.71	40.4	1.21	37.8	Poor
			PT	1.21	37.8	1.25	29.7	Poor
			MK	1.44	34.2	-0.81	55.2	Poor
Sad Doroudzan	N	S	$ANFIS_{FPM}$	1.97	46.7	-0.99	17.0	Poor
			$ANFIS_{HR}$	0.92	21.7	-0.34	82.1	Fair
			$ANFIS_{PT\ or\ MK}$	2.23	52.9	-1.46	-6.4	Poor
			$HR_{Calib.}$	0.99	23.5	0.44	79.0	Fair
			$PT_{Calib.}$	0.99	23.5	0.59	79.0	Fair
			MK_{Calib}	1.10	25.5	0.57	75.3	Fair
			FPM	1.14	27.0	0.57	72.4	Fair
			HR	0.83	19.6	-0.06	85.4	Good
			PT	1.10	25.6	-0.75	75.2	Fair
			MK	1.31	30.9	-0.89	63.6	Poor
Shahrbabak	N	D	$ANFIS_{FPM}$	1.44	34.0	0.72	55.9	Poor
			$ANFIS_{HR}$	1.20	28.5	0.73	69.2	Fair
			$ANFIS_{PT\ or\ MK}$	1.16	27.5	0.79	71.2	Fair
			$HR_{Calib.}$	1.17	27.7	0.72	70.8	Fair
			$PT_{Calib.}$	1.14	27.1	0.77	72.1	Fair
			MK_{Calib}	1.30	30.5	0.79	64.6	Poor
			FPM	1.42	33.6	0.74	77.0	Poor
			HR	0.83	19.6	0.00	85.5	Good
			PT	1.32	31.2	-0.97	62.9	Poor
			MK	1.43	33.9	-0.95	56.2	Poor

N: near; F: Far; S: similar; D: dissimilar

Table 6 (Continued).

Stations	N/F	S/D	Models	RMSE (mm.day^{-1})	NRMSE (%)	MBE (mm.day^{-1})	NSE (%)	Rating
Yasouj	N	D	$ANFIS_{FPM}$	0.89	21.2	-0.38	82.9	Fair
			$ANFIS_{HR}$	0.87	20.2	-0.34	83.7	Fair
			$ANFIS_{PT\ or\ MK}$	0.89	21.0	-0.29	83.2	Fair
			$HR_{Calib.}$	0.98	23.3	-0.41	79.4	Fair
			$PT_{Calib.}$	0.85	20.2	-0.35	84.5	Fair
			MK_{Calib}	1.00	23.9	-0.39	78.3	Fair
			FPM	0.87	20.7	-0.39	83.8	Fair
			HR	0.94	22.2	-0.12	81.3	Fair
			PT	1.24	29.5	-0.93	66.9	Fair
			MK	1.44	34.2	-1.00	55.4	Poor
Zarghan	N	S	$ANFIS_{FPM}$	0.93	22.0	-0.42	81.6	Fair
			$ANFIS_{HR}$	0.84	20.0	-0.36	84.8	Fair
			$ANFIS_{PT\ or\ MK}$	0.85	20.2	-0.37	84.5	Fair
			$HR_{Calib.}$	1.38	32.7	-1.05	59.4	Poor

$PT_{Calib.}$	0.83	19.6	-0.35	85.4	Good
MK_{Calib}	0.96	22.8	-0.45	80.2	Fair
FPM	0.89	21.1	-0.44	83.1	Fair
HR	0.93	22.1	0.33	81.4	Fair
PT	1.05	24.9	-0.68	76.3	Fair
MK	1.37	32.4	-0.91	60.0	Poor

N: near; F: Far; S: similar; D: dissimilar

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