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Anfis Based Reference Evapotranspiration (ET_0) Estimation Using Limited and Different Climate Parameters

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Abstract

This study aims to estimate the reference evapotranspiration (ET_0) with adaptive neuro-fuzzy inference system (ANFIS). The calculation of ET_0 requires climate data such as maximum and minimum temperature, wind speed, sunshine duration and humidity. Sometimes it may not be possible to access the climate data. In the study, ET_0 is estimated with ANFIS by using fewer input parameters. Moreover, it is proved that it is possible to calculate ET_0 via ANFIS by using some other climate parameters such as temperature-humidity-wind index (THW), air pressure, wind chill, which have no direct effect on the calculation of ET_0. In the study, five scenarios were created and evaluated with a statistical performance indicator. In Scenario 1, ET_0 was estimated using THW, air pressure and air density. The relationship between the ET_0 estimated by ANFIS and the calculated ET_0 was found to be 0.76 (R^2). In Scenario 2, THW, solar energy and solar radiation were used and R^2 was found to be 0.66. Scenario 3 used THW and wind chill, resulting in an R^2 of 0.43. In Scenario 4, THW and maximum temperature were used and R^2 was 0.87. In Scenario 5, THW and humidity were used and the R^2 with ET_0 was 0.84.

Research Article

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1. Introduction

In the effective use of irrigation water in plant cultivation, climate, soil, plant and water factors are evaluated together in the production process (Seydoşoğlu, 2018; Keten and Değirmenci, 2020; Özdoğan Çavdar et al., 2021). These factors can also be used to calculate reference evapotranspiration and crop evapotranspiration, which are very important for the irrigation schedule. Evapotranspiration is described as the loss of water to atmosphere through evaporation from the plant and soil surface. Estimating water potential plays an important role in water management and has a significant impact on plant production (Rajagopal et al., 2022). Precise estimation of reference evapotranspiration (ET_0) enables reliable management of scarce water resources. It is also one of the important stages in identify crop water consumption (Roy et al., 2022; Roy et al., 2021; Roy, 2021; Wu et al., 2021; Roy et al., 2020; Zeinolabedini Rezaabad et al., 2020). ET_0 is a dynamic, complex, unstable and non-linear hydrological process with important effect on efficient water resources planning and long-term management (Alam et al., 2024; Goyal et al., 2023; Lu et al., 2023). In addition, evapotranspiration is an important parameter used in hydrology and irrigation schedules. Reference evapotranspiration is particularly important. Estimating ET_0 changes is useful for analyzing the management of water resources (El-Kenawy et al., 2022).

Gupta et al. (2024) different soft computing models for ET_0 prediction were compared. Artificial neural network (ANN), wavelet-associated ANN (WANN), ANFIS and multiple nonlinear regression (MNLR) models were investigated. The Gamma test technique was used for the selection of appropriate climatic parameter. The results showed that the ANN-10 model was more successful in predicting ET_0 compared to the other models. Solar radiation was identified as the most sensitive input parameter, while actual vapor pressure was the least sensitive variable.

Kartal (2024) used an ANN model developed by the Levenberg-Marquardt method to predict monthly ET_0 values in Elazığ province. Data such as precipitation, relative humidity, wind speed, temperature and sunshine duration were used to predict ET. The results showed that the proposed model provided high accuracy (R values between 0.9898 and 0.9995) in Elazığ, Keban, Baskil and Ağın regions. Moreover, the MAPE values of the model were quite low and consistent with Hargreaves' method ($R^2 = 0.996$). These findings provide important information for water resources and agricultural irrigation management.

Qin et al. (2024) emphasizes the importance of ET_0 estimation for sustainable water resources management. Support vector regression, Bayesian linear regression, Ridge regression and Lasso regression models were used for ET_0 estimation. However, prediction errors occurred in these models due to data noise or overlearning. Hybrid models have been developed to reduce these errors and improve prediction accuracy. Before constructing the hybrid models, each model was weighted according to variance reciprocal and information entropy weighting methods. As a result, the information entropy-based hybrid model showed the best performance in the medium-term (1-30 days) ET_0 forecast in the Northern Plains of China.

Bidabadi et al. (2024) aims to predict ET_0 with incomplete meteorological data at Sirjan and Kerman synoptic stations in the arid regions of Iran. ANN, ANFIS and ANN with gray wolf optimization (ANN-GWO) models are tested with Penman-Monteith FAO-56 data. The ANFIS, ANN and ANN-GWO methods outperformed the Hargreaves method with more readily available data such as maximum and minimum temperature. ANFIS outperformed the other methods for all data combinations. The best results were obtained at Kerman and Sirjan using maximum and minimum temperature and ET_0 data of the neighboring station. As a result of this evaluation, the root mean square error (RMSE) was found to be 0.33 and 0.36.

Duhan et al. (2023) was conducted to develop and evaluate the performance of distinct machine learning (ML) models for ET_0 prediction. The models included Multiple linear regression (MLR), Least square-support vector machine (LS-SVM), ANNs and ANFIS. Using 50 years of meteorological data, ET_0 was predicted and the LS-SVM model showed the best performance (R^2 = 0.998). The ET estimated by LS-SVM was compared with MODIS satellite data and MODIS was found to overestimate ET. After applying the correction factor, the R^2 value of the satellite data was 0.74 and the RMSE value was 1.19 mm. It was stated that ML and satellite-based ET estimates would be useful for water budgeting at local and regional level to manage water scarcity.

Yan et al. (2023) proposed an innovative deep learning (DL) approach, HS-LSTM, for ET_0 prediction with limited daily climate data. The method was based on the Hargreaves-Samani (HS) model and Long short-term memory (LSTM) neural network, and ET_0 was predicted using only daily maximum and minimum air temperatures. The model outperformed traditional ML algorithms and other HS-based models in terms of accuracy. Tested in the Songliao Basin (Northeast China), the HS-LSTM method significantly reduced errors compared to other techniques. It was indicated that it can provide effective results for future ET_0 forecasts based only on air temperature data. This study presents a new strategy that provided more accurate ET_0 forecasts with limited meteorological data.

Zereg and Belouz (2024), investigated daily ET_0 prediction with limited measurement data using the Support vector regression (SVR) machine learning algorithm for ET_0 prediction. Ten years of data collected at the Dar-El-Beidha meteorological station in Algeria was used, and the Julian Day (J) is included as an input for the first time. Various SVR models were developed using data such as maximum, minimum and mean temperature, mean relative humidity, wind speed, sunshine duration. The results shown that SVR models were more successful in predicting ET_0 than traditional empirical equations, radial basis function neural networks (RBFNN) and ANFIS. SVR models performed in the range of RMSE 0.28-0.72 mm day^{-1}, R^2 0.86-0.98 and MAPE 7-19 %. These findings provided useful solutions for ET_0 estimation in data deficient regions.

Küçüktopcu et al. (2023) addressed the problem that machine learning (ML) models such as ANN, generalised neural regression networks (GRNN) and ANFIS may give inconsistent results in solving linear problems and proposed more accurate evapotranspiration (ET_0) prediction models by hybridising these models with ARIMA. The results of the models developed using daily ET_0 data collected between 2010-2020 in Samsun province reduced the root mean square error (RMSE) of the ARIMA-GRNN model by 48.38 %. It also showed that it reduced the ARIMA-ANFIS model by 8.56 % and the ARIMA-ANN model by 6.74 %. These hybrid models could provide more accurate forecasts for areas that need reliable ET_0 forecasts, such as agriculture and water management.

Adnan et al. (2021) proposed a hybrid heuristic algorithm (HA), an innovative technique in the field of machine learning, that improved the accuracy of ET_0 estimation, which was of great importance for regional water management, agricultural planning, and irrigation design. However, the new hybrid HA techniques, the Moth-Flame Optimisation Algorithm (MFO) and the Water Cycle Optimisation Algorithm (WCA), had rarely been applied for ET_0 estimation in previous literature.

Bakhtiari et al. (2022) utilized four data-aided methods (ANFIS, ANN, the M5 tree model), and support vector machine (SVM) for ET_0 prediction in the South Caspian region. The success of the models is check against the FAO-56 Penman-Monteith method using climate data such as solar radiation, average air temperature, average relative humidity and wind speed for the period 1991-2020. The results shown that the ANFIS model provides the highest accuracy, especially in the validation phase, and performs best when all climate variables were used. It was suggested that the ANFIS model was also effective with fewer climate variables when T-mean and R-s are used.

Hadadi et al. (2022) evaluated the performance of models hybridised with ANFIS and two biomimetic optimisation algorithms (shuffled frog leaping algorithm-SFLA and grey wolf optimisation-GWO) for the prediction of monthly actual evapotranspiration (AET) in the Neishaboor basin (Iran) from 2001 to 2010. The models were tested using eight scenarios involving three groups of inputs: meteorological, remote sensing and hybrid-based predictors. The results showed that remotely sensed predictors, such as the Soil moisture deficit index (SWDI), significantly improved the accuracy and achieved the highest error reduction. The ANFIS models hybridised with SFLA and GWO algorithms achieved a 12 % and 14 % reduction in error rate, respectively. The performance of the models showed that the models indicated the highest accuracy in the first third.

Quej et al. (2022) evaluated the accuracy of three artificial intelligence (AI) models such as support vector machines (SVM), adaptive neuro-fuzzy inference system (ANFIS) and categorical boosting (CatBoost) for ET_0 prediction at five different locations in Mexico. The Penman-Monteith FAO-56 equation was used as a reference. Three different input combinations (temperature, precipitation, relative humidity) were tested. SVM models showed the best performance, outperforming ANFIS and CatBoost models. Relative humidity was found to improve model accuracy and temperature-based AI models performed better than the Hargreaves-Samani method. It is concluded that AI models can be an effective alternative to traditional methods.

Literature studies have also shown that accurate estimation of daily ET_0 is essential to improve real-time irrigation scheduling and decision-making for water resource allocation (Valipour et al., 2023; Sharafi et al., 2023). The aim of this study is to accurately predict ET_0 with a few input parameters using a machine learning based approach such as ANFIS. In order to achieve this objective, five scenarios with infrequently used meteorological data were developed and ANFIS was trained and then tested on these scenarios. In the proposed study, inputs such as THW, air pressure, air humidity, wind chill, which are not included in the reference evapotranspiration calculation formula and therefore do not directly affect the reference evapotranspiration, are used and the models are evaluated with five scenarios. A block diagram showing a summary of the proposed study is given in Figure 1.

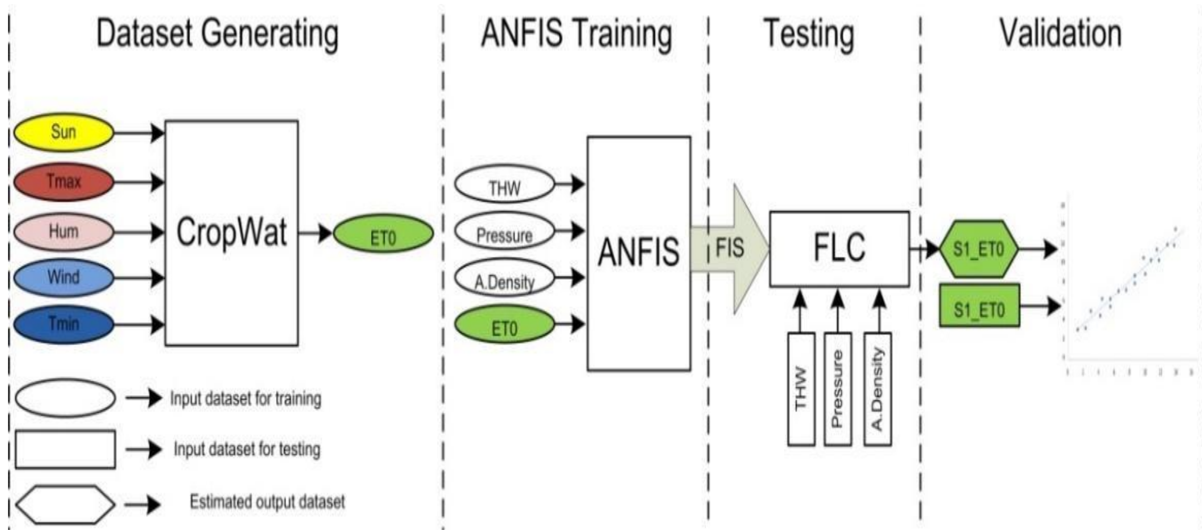

Figure 1. Summary block diagram describing the structure of the proposed work

2. Materials and Methods

2.1. Meteorological data of the studied area

This study was carried out in the fields of Eastern Mediterranean Gateway Agricultural Research Institute in Kahramanmaraş. Although Kahramanmaraş province is located in the Eastern Mediterranean Region, it has different climate characteristics due to its location at the transition point of many regions. Typical Mediterranean climate characteristics (cold and rainy winters, hot and dry summers) are observed in the region where the study was carried out. The altitude of the study area is 467 m above sea level. Meteorological data were obtained from the Davis Brand Vantage Pro-2 model climate station built in the field. The data were taken hourly from the climate station. The data were obtained from the climate station during July-August-September. In total, a data set was used consisting of 1912 rows. Out of this data set, 1612 rows were used for training and 300 rows were used for testing.

2.2. Evapotranspiration and traditional calculation methods

ET_0 is an important parameter used to characterise the water cycle of ecosystems (Zhu et al., 2024; Araghi et al., 2020). In other words, ET_0 is the amount of water lost per unit area under certain weather conditions in a given region. Since it has an important role in determining the water requirement of plants, it has a critical role in agriculture. Accurate estimation of reference evapotranspiration is important in scheduling agricultural irrigation, crop consumption and hydrological modelling (Katipoğlu, 2023). In addition, reference evapotranspiration is one of the main constituents of the hydrological cycle. Its estimation is of great importance in agricultural transactions of all crops, especially in irrigation (Aghelpour and Norooz-Valashedi, 2022). Suitable irrigation scheduling and agricultural water management essential a exact estimation of the crop water demand. In practice, ET_0 is first predicted and then used to calculate the evapotranspiration of each crop (Mehdizadeh et al., 2021). The evapotranspiration cycle can be explained by the block diagram was given in Figure 2.

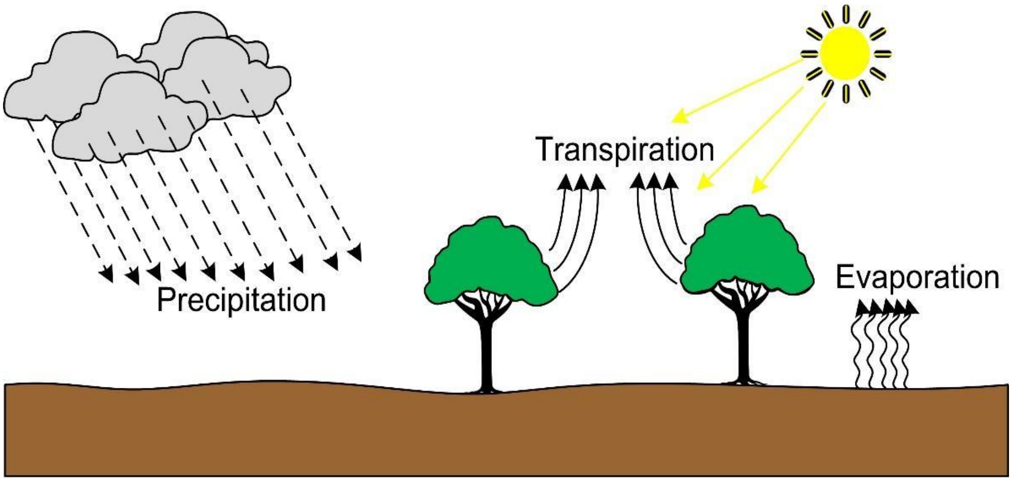

Figure 2. Block diagram explaining the occurrence of evapotranspiration

Many empirical methods have been developed to determine the reference evapotranspiration and many meteorological data are used in these methods. The most widely used of these is the Penman Monteith method (Allen et al., 1998). Using the Penman Monteith method, the reference evapotranspiration is calculated by Equation 1.

$$ET_o = \frac{0.408\Delta\,(R_n - G) + \frac{900}{T}\gamma u_2 \delta e}{\Delta + \gamma(1 + 0{,}34 u_2)} \qquad (1)$$

Where:

ET_o	:	Reference evapotranspiration (mm day^{-1})
Δ	:	Rate of change of saturation specific humidity with air temperature (Pa K^{-1})
R_n	:	Net irradiance (MJ m^{-2} day^{-1})
G	:	Ground heat flux (MJ m^{-2} day^{-1})
T	:	Air temperature (2m) (K)
u_2	:	Wind speed (2m) (m s^{-1})
δe	:	Vapor pressure deficit (kPa)
γ	:	Psychrometric constant ($\gamma \approx 66$ Pa K^{-1})

Based on the Penman Monteith method, ET_0 can also be determined by software such as Cropwat. In this study, the actual ET_0 value was calculated with Cropwat. In order to determine ET_0 with Cropwat, climate parameters such as maximum temperature and minimum temperature, wind speed, humidity and sunshine duration should be known. Nowadays, researches are being carried out to accurately estimate ET_0 with climate parameters other than the parameters required for the use of software such as Cropwat.

2.3. Design of ANFIS model

In recent years, a lot of machine learning tools have been enhanced with the expect to replace traditional empirical models for ET_0 prediction that require difficult data collection and calibration (Chia et al., 2021). One of them is ANFIS, a hybrid machine learning technique involving artificial neural networks and fuzzy logic controller (Üneş et al., 2020). ANN is a powerful tool for modelling various complex and nonlinear systems. Moreover, their combination with fuzzy logic solves problems at a higher speed (Del Cerro et al., 2021). ANFIS represents a multilayer model that trains input parameters and output variables and provides the most efficient prediction matching between input and output (Alizamir et al., 2020). In other words, ANFIS learns all the relationships between the input parameters (P_1 and P_2) and the output variable and generates the function (f) of the desired output value. In addition, ANFIS has the ability to realise and detect the phenomenon without the need for mathematical management equations (Seifi ve Riahi, 2020). This can be expressed by Equation 2.

$$\begin{aligned}
&IF\ P_1\ is\ A_1\ and\ P_2\ is\ B_1\ then\ f = \rho_1 P_1 + q_1 P_2 + r_1 \\
&IF\ P_1\ is\ A_2\ and\ P_2\ is\ B_2\ then\ f = \rho_2 P_1 + q_1 P_2 + r_2 \\
&. \\
&. \\
&. \\
&IF\ P_1\ is\ A_n\ and\ P_2\ is\ B_n\ then\ f = \rho_n P_1 + q_n P_1 + r_n
\end{aligned} \tag{2}$$

In all these aspects, ANFIS is defined as an approach that includes machine learning and fuzzy logic methods used in solving non-linear and complex engineering problems. The block diagram of the ANFIS model to be used in the proposed study is given in Figure 3.

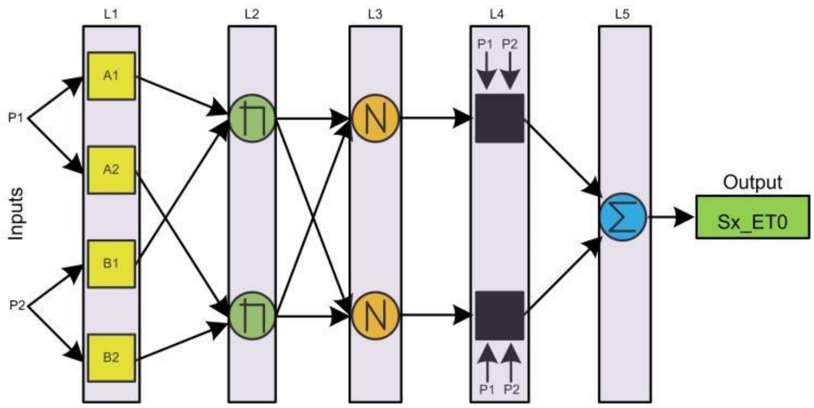

Figure 3. Block diagram of the ANFIS model to be used in the proposed study

The actual ET_0 value was calculated with Cropwat software. For this purpose, maximum temperature, minimum temperature, humidity, sunshine duration and wind speed dataset were used as input. The ANFIS model was trained with the actual ET_0 data obtained. The ANFIS model was run with the untrained test dataset and estimated ET_0 values were obtained. Finally, the actual ET_0 and estimated ET_0 were compared on scatter plots.

3. Results and Discussion

In this section, the results of the proposed study are discussed. Accordingly, within the scope of the study, 5 different scenarios were created by combining climate parameters that are not directly effective in ET_0 calculation. For each scenario, a data set consisting of 1612 rows was created to be used in training. The training of ANFIS was carried out over these datasets. The test data set consists of 300 rows for each scenario. The scenarios, the input parameters used in these scenarios and the RMSE values in ANFIS training are given in Table 1.

Table 1. Input parameters and RMSE values of the scenarios

Scenario	Input parameters for ET_0 estimation	ANFIS minimal training RMSE
S1	THW, Air Pressure, Air Density	2.954612
S2	THW, Solar Energy, Solar Radiation	2.379339
S3	THW, Wind Chill	2.638500
S4	THW, Max. Temperature	1.844835
S5	THW, Output Humidity	2.067438

According to Table 1, in Scenario 1, ET_0 was estimated using THW, air pressure and air density as input parameters. The relationship between the ET_0 estimated by ANFIS and the actually calculated ET_0 was found as 0.76 (R^2). In Scenario 2, THW, solar energy and solar radiation were used as input parameters. The R^2 between predicted and actual ET_0 was found to be 0.66. In Scenario 3, THW and whind chill parameters were used. As a result, R^2 was 0.43. In Scenario 4, THW and maximum temperature were used as input and R^2 was 0.87. Finally, in Scenario 5, the input parameters are THW and humidity. The R^2 of the prediction made with these two inputs with the actual ET_0 was found to be 0.84. The scatter plots of the estimated ET_0 value obtained as a result of ANFIS against the actual ET_0 value of the scenarios are given in Figure 4.

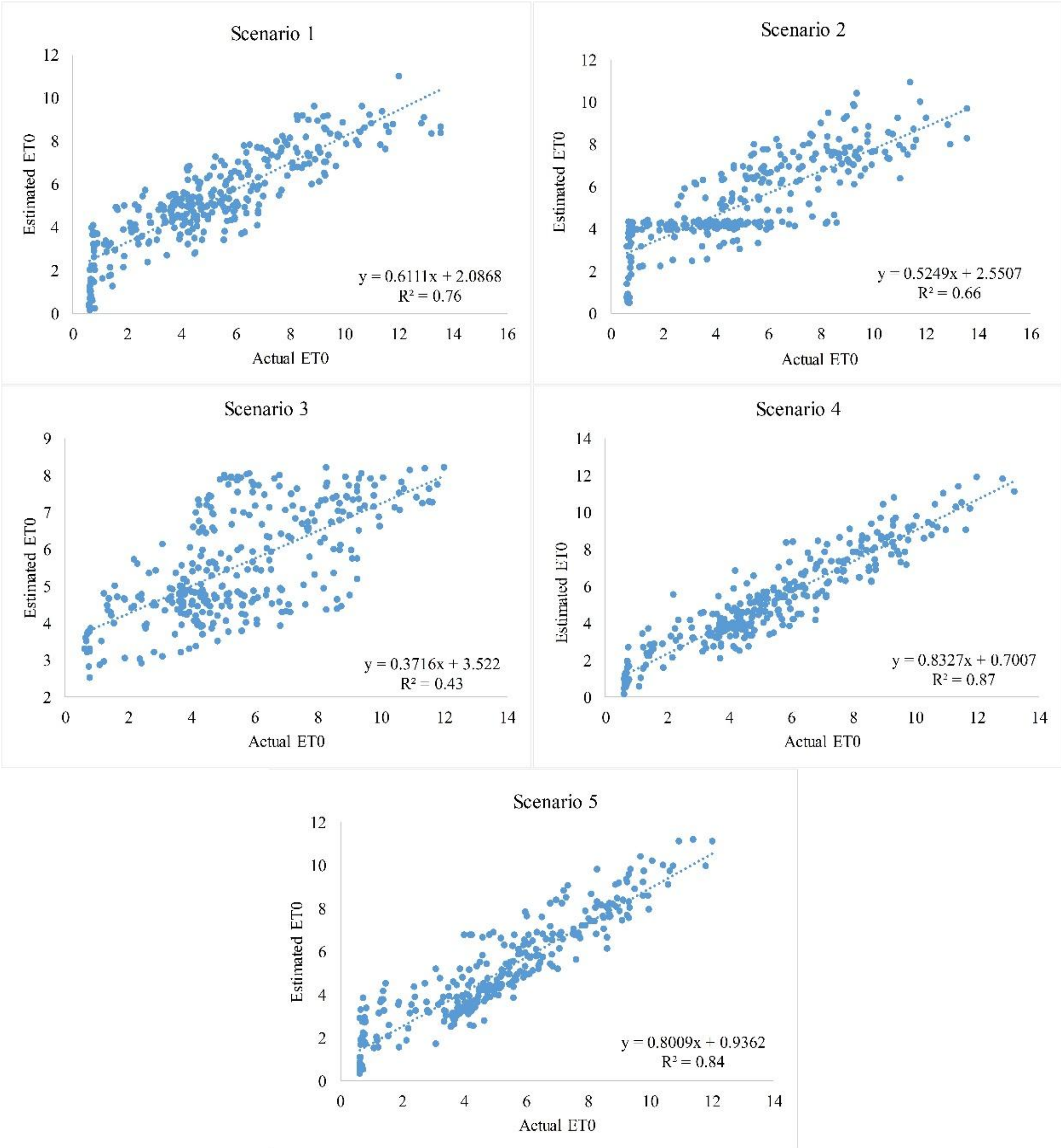

Figure 4. Scatter plots of actual and predicted ET_0 values for five scenarios

When the graphs given in Figure 4 are analysed, it is understood that Scenario 4 has the highest R^2 of actual ET_0 and ET_0 estimated by ANFIS among all scenarios. In addition, the scenario with the lowest ANFIS minimal training RMSE value is the scenario 4. Three input parameters were used in Scenarios 1 and 2. In Scenarios 3, 4 and 5, two input parameters were used. Özel and Büyükyıldız (2019) used average temperature, maximum temperature, minimum temperature, wind speed, relative humidity, monthly total precipitation, vapour pressure and atmospheric pressure as input to ANFIS to predict monthly evaporation in Karaman. When they used eight sets of climate data as input in their study, they found R^2 to be 0.82. Among these data, when they used only average and maximum temperature as input, they obtained R^2 as 0.72. Ladlani et al. (2014) used six different climate data such as average temperature, maximum temperature, minimum temperature, wind speed, relative humidity, sunshine duration as input to ANFIS by classifying them with various scenarios to predict daily ET_0 in Algeria. They found the highest R^2 as 0.83 in the scenario where all six inputs were used. Terzi et al. (2006), they used climate parameters such as air temperature, water temperature, relative humidity, solar radiation, wind speed and air pressure as inputs to predict the evaporation of Lake Eğirdir (Isparta, Turkey) using ANFIS. They obtained coefficient of determination of 0.98, RMSE of 0.24, and average performance error of 4.6 %, which are consistent with the evaporation values calculated by Penman method. The results of our proposed study and the results obtained by other researchers in the literature were generally consistent with each other. Cobaner (2011) compared three empirical models (CIMIS Penman, Hargraves and Ritchie) with an artificial neural network based approach using the ANFIS model. As a result, they concluded that the ANFIS model provides high accuracy with less computation. (Kisi et al., 2014) compared ANFIS models with empirical models (Valiantzas equations, Turc, Hargreaves and Ritchie) and their calibrated versions. The comparison results show that the three- and four-input ANFIS models outperform the respective empirical equations in modeling ET 0, while the calibrated two-parameter Ritchie and Valiantzas equations outperform the two-input ANFIS models. (Seifi et al., 2020) gamma test was used to select the best input vectors and the ET_0 predictions of the LSSVM-GT model with different kernels (RBF, linear, polynomial) were compared with ANN-GT, ANFIS-GT and empirical equations. Gamma test showed that the most important climate variables are minimum and maximum air temperature and wind speed. The LSSVM model outperformed ANFIS and ANN models when the same meteorological inputs were used. Moreover, LSSVM, ANFIS and ANN models outperformed empirical equations such as Blaney-Criddle and Hargreaves-Samani.

4. Conclusions

The results obtained from the study and the results of the researchers show that even with a limited number of input parameters, it is possible to estimate ET_0 with a high accuracy with ANFIS. In addition, it is possible to obtain a high accuracy ET_0 value with ANFIS even with parameters that are calculated empirically (equation-based) and not included in the ET_0 calculation. The study and the ANFIS-based ET_0 estimation studies in the literature have shown that average, maximum and minimum temperature have an important role in ET_0 estimation. It has been observed that the number of parameters and data of the dataset provided as input parameters to ANFIS significantly increases the accuracy of the prediction value obtained as a result of ANFIS.

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