International Journal of Environment, Agriculture and Biotechnology
Vol-9, Issue-6; Nov-Dec, 2024
Peer-Reviewed International Journal
Journal Home Page Available: https://ijeab.com/
Journal DOI: 10.22161/ijeab

Estimation of Ataturk Dam Evaporation Amount Using Fuzzy Logic Method

Ahmet Gül*, Fatih Üneş, Bestami Taşar

Department of Civil Engineering, Iskenderun Technical University, Türkiye
*Email: ahmetgul6300@gmail.com

Received: 14 Oct 2024; Received in revised form: 12 Nov 2024; Accepted: 18 Nov 2024; Available online: 24 Nov 2024

***Abstract*— *Accurate prediction of evaporation is important for various purposes such as dam structure design, operation, and the development and management of water resources. Determining water evaporation from the reservoir volume is an important parameter for reservoir operation studies, based on hydrological and meteorological data. In this study, daily average relative humidity, air temperature, wind speed, and sunshine duration parameters were used for evaporation estimation. In the study, daily evaporation estimation was performed using the methods of Multiple Linear Regression (MLR), Adaptive Neuro-Fuzzy Inference System (ANFIS) and Fuzzy Logic - Simple Membership Functions and Fuzzy Rule Generation Technique (Fuzzy -SMRGT). As the study area, the Atatürk Dam, located between the provinces of Adıyaman and Şanlıurfa, has been chosen. In the study, the model results were evaluated according to statistical criteria such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of Determination. When evaluating the model results, it was determined that the MLR, ANFIS and Fuzzy-SMRGT models yielded similar results in daily evaporation estimation and that the Fuzzy Logic (ANFIS and Fuzzy SMRGT) models were applicable.*

***Keywords*— Evaporation, Prediction, Regression, Fuzzy Logic, Modeling, ANFIS**

I. INTRODUCTION

Evaporation (E) estimation is important in water management and hydraulic designs. Evaporation is the process of converting the amount of water in liquid form into gas (vapor) form in nature. Evaporation is also one of the basic components of the hydrological cycle. Evaporation depends on factors such as solar energy, air temperature, wind, humidity and environmental conditions. Natural events are affected by many different variables and it is quite difficult to explain the nonlinear relationships between natural events and these variables.

Like all events in nature, since evaporation depends on many nonlinear variables and parameters and it is difficult to determine all of these parameters, it is difficult to estimate the amount of evaporation. Using classical methods, it is difficult to create a realistic hydrological model that accurately reflects its real dimensions due to the large number of affecting parameters and nonlinear structures. For this reason, efforts have been made to develop applicable practical methods to solve nonlinear problems and when the researches are examined, it is seen that the studies are still ongoing to determine the amount of evaporation that is realistic. These studies generally consist of experimental, numerical, statistical and recently artificial intelligence-based studies.

In recent years, many researchers have used artificial intelligence methods as an alternative to classical methods in hydrology and water resources studies[1-15] Tzimopoulos et al. [16] also tried to estimate evapotranspiration using the temperature parameter. Doğan et al. [17] studied evaporation estimation using data from 1990 to 2004 related to Lake Sapanca. Balve and Patel [18] tried to estimate evapotranspiration by entering the meteorological data of average temperature, relative humidity, wind speed and net radiation as parameters. For the predictions, models created by the Fuzzy Inference System of Fuzzy Logic method were used. Taşar et al. [19]

studied evaporation prediction by using wind speed, duration of sunshine and relative humidity data from the Massachusetts region of the United States from 2014 to 2017, employing classical methods and artificial neural network techniques. Kaya et al. [20] studied to estimate the amount of evaporation. They used M5-Tree and Turc methods to predict. Özel and Büyükyıldız [21] used ANN, epsilon-support vector regression (ε-SVR), and ANFIS techniques to predict the monthly evaporation amount of the Karaman meteorological station, which is located in Konya, Turkey. Petković et al. [22] investigated the effect of meteorological parameters on reference evapotranspiration using the ANFIS method. Yaseen et al. [23] used classification and regression trees, the cascade correlation neural network, gene expression programming, and the support vector machine (SVM) models for the prediction of evaporation. According to their model result, SVM has the best performance. Wu et al. [24] studied the Poyang Lake Basin of Southern China for monthly pan evaporation estimation. They used hybrid models (extreme learning machine) and improved M5 model tree and artificial neural network models.

Since the parameters affecting the event are difficult and expensive to measure in the field, soft computing techniques such as Fuzzy-SMRGT, ANFIS are used today to reduce the need for large data sets. One of the models that can be developed to reduce the need for large data sets is the experience-based easily adjustable fuzzy rule generation approach (Fuzzy-SMRGT). One of the first applications of this approach was made by Toprak [25] using Fuzzy-SMRGT in modeling the relationship between open channel flow (natural or artificial) and its hydraulic and geometric properties.

In this study, the applicability and validity of artificial intelligence methods such as Simple Membership Functions and Fuzzy Rule Generation Technique (Fuzzy-SMRGT) and Adaptive Neuro-Fuzzy Inference System (ANFIS) as well as classical methods such as Multiple Linear Regression (MLR) in evaporation estimation were investigated.

II. MATERIAL and METHODS

2.1. Study Area

The Atatürk Dam is a dam located between the provinces of Adıyaman and Şanlıurfa, intended for energy and irrigation purposes. Within the GAP Project, the Karakaya Dam is located 51 km away from Adıyaman province and 24 km away from the Bozova district of Şanlıurfa province, situated on the Euphrates River, at an elevation of 180 km².With the dam's completion, the Atatürk Dam Lake, the third largest lake in Turkey, has been formed.

The height from the base is 169 meters. The minimum water level in terms of height above sea level is 513 meters, and the maximum water level reaches 542 meters. In Dam, the depth must be at least 133 meters for electricity generation. The length of the dam crest is 1644 meters, and its width is 15 meters. There are 6 spillway outlets, each controlled by radial gates measuring 16x17 meters. The maximum discharge is 16800m^3/s. The spatial and general appearance of the studied area and the dam is presented in Figure 1.

Fig. 1: The location of the work area and the dam view [26,27]

The data used in this study was obtained from the Şanlıurfa Regional Directorate of Meteorology. Parameters such as daily average relative humidity (%), daily average temperature (°C), daily average wind speed (m/s) and daily average sunshine duration (hours) were used in model studies to estimate evaporation. The statistical variations of all the parameters used are presented in Table 1. The daily variation of evaporation amounts related to the Atatürk Dam for the water years between 2004 and 2011 is shown in Figure 2.

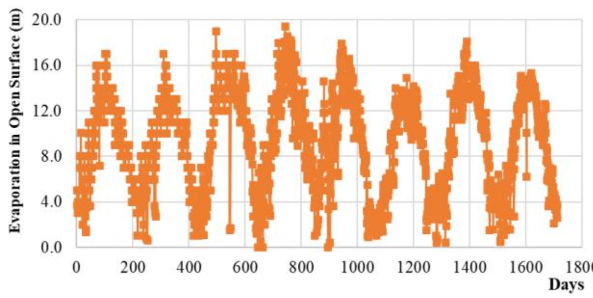

Fig. 2: Daily evaporation data change used in the study

Table 1. Statistical Changes for used data

Statistical Changes	Daily Average Relative Humidity (%)	Daily Average Temperature (°C)	Daily Average Wind Speed (m/s)	Daily Sunshine Duration (hours)	Daily Total Open Surface Evaporation (mm)
Average	42.97	23.95	1.16	10.41	9.27
Standard Error	0.34	0.16	0.03	0.08	0.10
Median	41	25	0.8	11.4	10
Mode	37.3	28	0.1	12.7	13
Standard Deviation	14.10	6.52	1.11	3.24	4.29
Sample Variance	198.84	42.55	1.24	10.47	18.42
Kurtosis	0.31	-0.75	1.35	1.70	-1.02
Skewness	0.67	-0.39	1.23	-1.48	-0.15
Range	80.40	31.80	6.90	14.10	19.40
Maximum	11.90	4.70	0.00	0.00	0.00
Minimum	92.30	36.50	6.90	14.10	19.40
Total	73560.10	40994.20	1982.00	17828.50	15874.80
Count	1712	1712	1712	1712	1712
Confidence Level (95.0%)	0.67	0.31	0.05	0.15	0.20

2.2 Methods

2.2.1. Multi Linear Regression (MLR)

A linear method for simulating the relationship between a scalar response and one or more explanatory variables is known as linear regression in statistics. Simple linear regression is used when there is only one explanatory variable; multiple linear regression is used when there are several variables. One method for simulating the relationship between a numerical dependent variable (y) and one or more independent variables (x) is called linear regression. The regression model is referred to as simple linear regression if there are only one independent variable. Multiple linear regression(MLR) is the term used when the model contains more than one explanatory independent variable. The dependent variable in linear regression needs to be numerical. The MLR equation is presented below in Equation 1.

$$y = A_0 + A_1 * X_1 + A_2 * X_2 \dots . + A_i * X_i + B \qquad (1)$$

In Equation 1, X_i (i = 1, …, n) represents the independent variables (inputs), y denotes the dependent variable (output), A indicates the regression coefficients, and B signifies the error.

2.2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) is used as an artificial neural network method based on fuzzy inference systems. The ANFIS model was developed by Jang starting in the early 1990s and is used for modeling nonlinear functions and predicting chaotic time series. ANFIS consists of nodes that are directly connected to each other, and each node represents a processing unit. ANFIS uses a hybrid learning algorithm because it employs both artificial neural networks and fuzzy logic inference methods. There are two approaches to fuzzy inference systems. These approaches are those of Mamdani and Sugeno. To apply the ANFIS, data sets with input and output are generally required. The ANFIS method finds the optimal values of membership functions of fuzzy sets by training the model based on the principle of error reduction. It also establishes fuzzy rules for FIS. The structure of the ANFIS is shown in Figure 3. Here; "X, Y" are independent inputs, "A1, A2, B1, B2" are input parameters, "∏ (pi)" represents the membership functions, "N" denotes the rules, and "wi" indicates the weights of the parameters, while ∑ represents the bias (summation function).

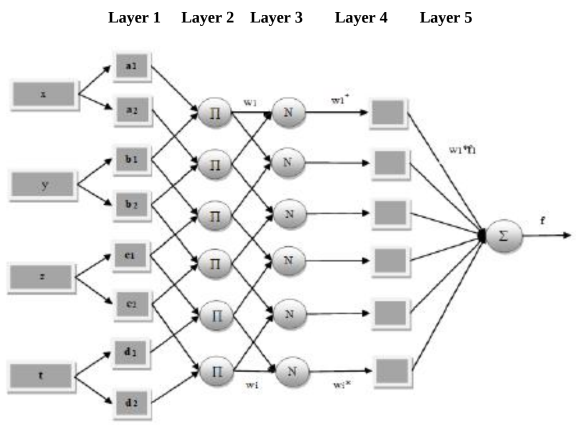

Fig.3: ANFIS model with four inputs and one output

The layers in Figure 3 represent the following:

Layer 1-) The degrees of membership of the variables and the selection of the membership function. In this study, the ANFIS model has at least two membership functions for each independent variable.

Layer 2-) All nodes in the second layer, represented by the symbol "∏", are fixed nodes. Fuzzy rules are a result of the product of the outputs of the first layer.

Layer 3-) In this layer, fixed nodes are represented by the symbol "N". ANFIS standardizes the values within the network structure. And as a result, these values are obtained.

Layer 4-) In this layer, all nodes are normalized nodes, and the weight values (w) coming from the third layer are multiplied by a first-degree polynomial equation. It is the layer output of "w1*f1".

Layer 5-) This layer contains a single fixed node. It shows the total result of all operations expressed as "Σ" [28].

2.2.3. Fuzzy Logic and Simple Membership Functions and Fuzzy Rules Generation Technique (Fuzzy SMRGT)

The components of a fuzzy logic system are the input, database, fuzzification unit, fuzzy inference mechanism, rule base, defuzzification unit, and output[29]. Below, the flowchart of the fuzzy logic system is shown in Figure 4.

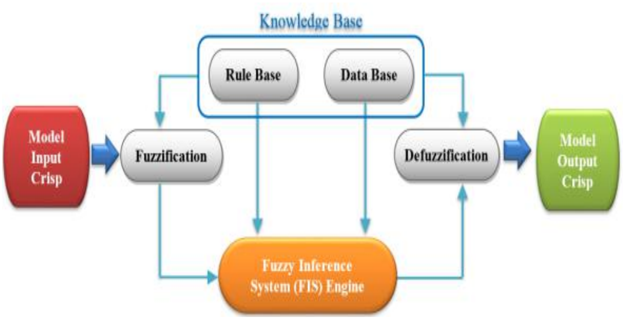

Fig.4: General Fuzzy Logic System[30]

Figure 4 shows the Input/Database of the General Fuzzy Logic System. This database contains the input variables that affect the event being studied and all related information. This information can be verbal or numerical. The unit where the necessary transformation process is carried out for the data coming from the input section to be used in the fuzzy inference mechanism is known as the fuzzification unit. This unit carries out personnel functions. However, the fuzzy rule base unit includes all the logical IF-THEN type rules that connect the input and output variables of the database. The fuzzy inference mechanism ensures that the system behaves as a single output by bringing together all the relationships established in parts between the input and output fuzzy sets within the fuzzy rule base. This method determines how the entire system will produce an output for given inputs by combining the inference of each rule. The fuzzy output values converted to a specific scale for the initial problem (values within the range of [0-1]) are known as the defuzzification unit. However, the output unit is used to solve the problem of the fuzzy logic system. This is obtained through the fuzzy output from the fuzzy inference mechanism and the defuzzification unit[31]

In fuzzy modeling, the two most important aspects are the correct determination of fuzzy sets and the fuzzy rule base[32]. Although there are many methods developed for this purpose, the Fuzzy-SMRGT method, which allows for the simultaneous determination of both, is a relatively new method that was first presented by Toprak[25]. The method can only be used in conjunction with the "centroid" defuzzification method for determining both membership functions (triangular/trapezoidal) and fuzzy rules. According to the selected input and output data, fuzzy clusters and the most suitable cluster intervals have been obtained using the Fuzzy-SMRGT method. In the Fuzzy-SMRGT method, the maximum and minimum values for the dependent and independent variables are first determined. After that, the number and shape of the membership functions are determined. The parameters used to shape and structure the membership functions are calculated using the following equations. (Eq.3-11). The structure of the membership functions of the fuzzy SMRGT-based prediction model is represented in Figure 5. Fuzzy sets have been chosen as triangular. A total of 1712 data points from the years 2004-2011 were used at the station studied. In the study, 75% of all the data was used for training, and the remaining 25% was used for testing. The results/boundary values obtained from the equations for the Fuzzy-SMRGT prediction model for these data are shown in Table 2.

The unit width (UW), core value (Ci), and key values (Ki) of the fuzzy sets corresponding to each membership function created for the prediction model have been determined. To determine these values, it is first necessary to know the range of variation of fuzzy sets (XR). To determine the range of change, the lowest and highest values of the fuzzy sets specified in the second phase were used. The range of variation (XR) for each input and output parameter is seen in the formula. In the fuzzy model, since neighboring clusters overlap, an extended base width (EUW) is required. UW represents the unit width shown in Figure 5. nu shows the number of right triangles. The right triangle number is 8(2x3+2) and has been accepted as the determined core value (Ci).

$$X_R = X_{max} - X_{min} \tag{3}$$

$$UW = \frac{X_R}{n_U} \tag{4}$$

$$O = \frac{UW}{2} \tag{5}$$

$$EUW = \frac{X_R}{n_U} + O \tag{6}$$

$$K_1 = X_{min} + \frac{EUW}{3} \tag{7}$$

$$K_5 = X_{max} - \frac{EUW}{3} \tag{8}$$

$$Ci = \frac{X_R}{2} + X_{min} \tag{9}$$

$$C_{i-1} = \frac{Ci - X_{min}}{2} + X_{min} \tag{10}$$

$$C_{i+1} = X_{max} - \left(\frac{X_{max} - Ci}{2}\right) \tag{11}$$

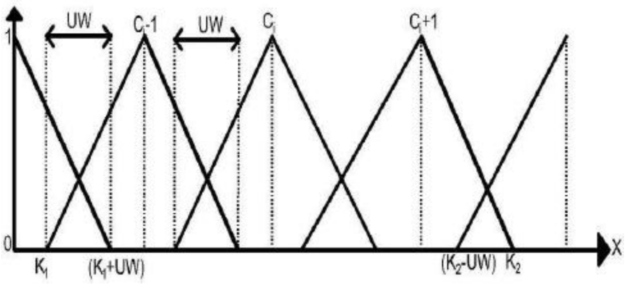

Fig. 5: Boundary parameters of the Fuzzy-SMRGT method with 5 membership functions[33]

Table 2. The Fuzzy-SMRGT boundary values of the 5 parameters obtained from this study

	Daily Average Relative Humidity (%)	Daily Average Temperature (°C)	Daily Average Wind Speed (m/s)	Daily Sunshine Duration (hours)	Daily Total Open Surface Evaporation (mm)
Max	91.00	36.10	6.90	14.10	18.10
Min	11.90	7.20	0.70	0.00	0.40
Xr	79.10	28.90	6.20	14.10	17.70
Ci	51.45	21.65	3.80	7.05	9.25
Ci-1	31.68	14.43	2.25	3.53	4.83
Ci+1	71.23	28.88	5.35	10.58	13.68
UW	9.89	3.61	0.78	1.76	2.21
O	4.94	1.81	0.39	0.88	1.11
EUW	14.83	5.42	1.16	2.64	3.32
K1	16.84	9.01	1.09	0.88	1.51
K5	86.06	34.29	6.51	13.22	16.99

III. ANALYSIS RESULTS AND DISCUSSION

In this study, 75% of the entire dataset (1284) was used for training, while the remaining 25% (428) was used as test data. The results of the MLR, ANFIS, and SMRGT models for test data have been evaluated using statistical parameters (RMSE, MAE, and R^2). For each model evaluation, the mean absolute error (MAE) (Equation 12), the square root of the mean of the squared errors (RMSE) (Equation 13), and the coefficient of determination (R2) have been used.

The statistical criteria used in the equations below are given. The comparisons of model performance based on the analysis results are shown in Table 3.

$$\mathbf{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\mathbf{Ei}_{\mathbf{measured}} - \mathbf{Ei}_{\mathbf{predicted}}\right| \quad (12)$$

$$\mathbf{RMSE} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N}\mathbf{Ei}_{\mathbf{measured}} - \mathbf{Ei}_{\mathbf{predicted}}\right)^{2}} \quad (13)$$

Here, E represents the evaporation, and N represents the number of data used.

Table 3. Error amount and correlation changes of the models

Model	Model Inputs	MAE (mm)	RMSE (mm)	R^2
MLR	RH, AT, WS, SD	1.61	3.95	0.86
ANFIS	RH, AT, WS, SD	1.49	3.39	0.87
Fuzzy-SMRGT	RH, AT, WS, SD	1.51	3.47	0.87

In Table 3, relative humidity (RH), air temperature (AT), wind speed (WS), and sunshine duration (SD) were used in the models to estimate evaporation (E).

3.1. MLR Results

In the method of MLR, daily average relative humidity (%), daily average temperature (°C), daily average wind speed (m/s), and daily average sunshine duration (hours) data have been used for the estimation of evaporation (mm). The distribution graph of the results for the test data in the MLR method is shown in Figure 6, while the scatter plot is presented in Figure 7.

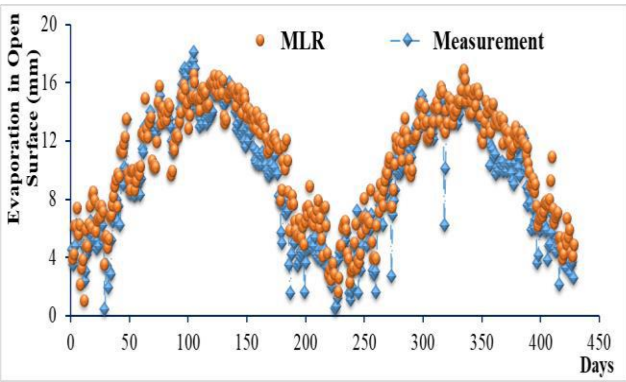

Fig.6: Distribution graph of MLR and Measurement values for the test phase

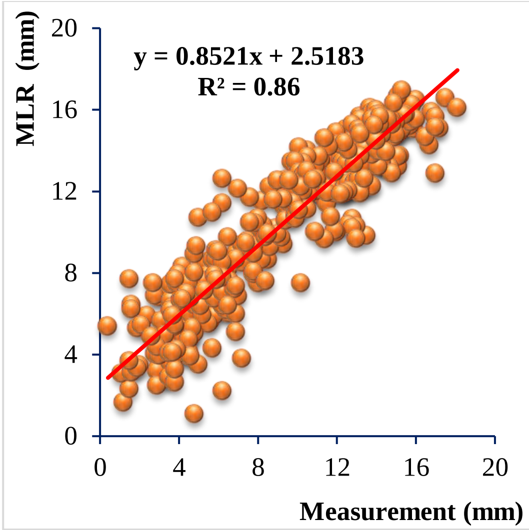

Fig.7: Scatter plot of MLR and Measurement values for the test phase

According to the scatter plot (Figure 7) and Table 1, the coefficient of determination $R^2 = 0.86$. The MLR model has the lowest determination value when examined in the testing phase. The MLR model has shown that some high evaporation amounts provided lower predictions than the actual evaporation values.

3.2. ANFIS Results

In the ANFIS model (similar to the MLR method), the inputs used to predict Evaporation (mm) include daily average relative humidity (%), daily average temperature (°C), daily average wind speed (m/s), and daily average sunshine duration (hours). The results of the ANFIS method on the test data are shown below in the distribution (Figure 8) and scatter plot (Figure 9).

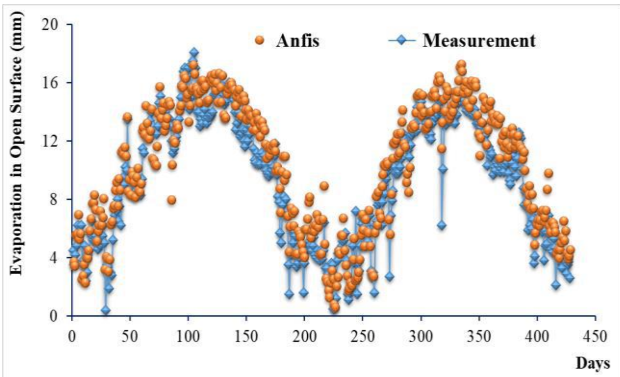

Fig. 8: Distribution graph of ANFIS and Measurement values for the test phase

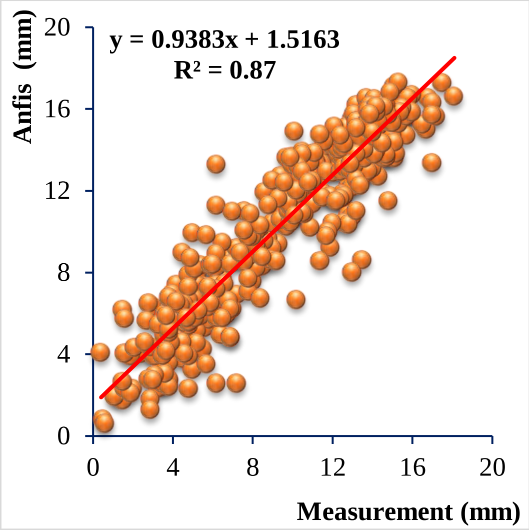

Fig. 9: Scatter plot of Anfis and Measurement values for the test phase

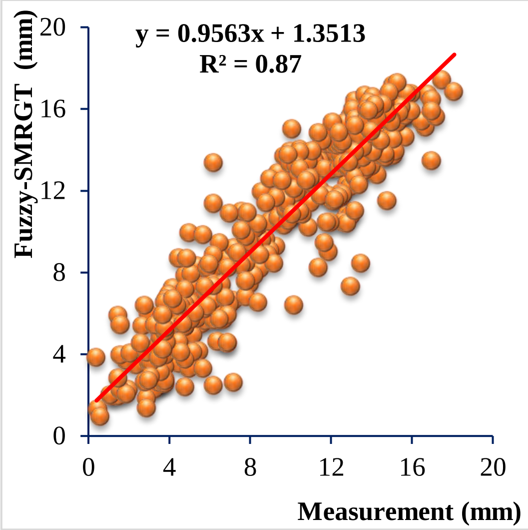

Fig.11: Scatter plot of Fuzzy-SMRGT and Measurement values for the test phase

As shown in Figures 8 and 9, there is a correlation between the actual measurement values of evaporation (mm) and the prediction results of the ANFIS model. The ANFIS method, which has a determination coefficient, R^2 = 0.87, has provided slightly more accurate results in evaporation prediction compared to the classical method of MLR.

3.3. Fuzzy-SMRGT Results

In the Fuzzy-SMRGT method, similar to the MLR and ANFIS methods, the amount of Evaporation (mm) has been estimated using data on daily average relative humidity (%), daily average temperature (°C), daily average wind speed (m/s), and daily average sunshine duration (hours). The results obtained using the test data of the Fuzzy-SMRGT model are shown below as a distribution (Figure 10) and scatter plot (Figure 11).

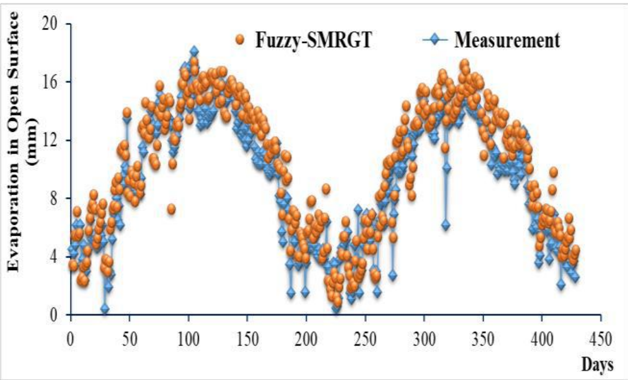

Fig. 10: Distribution graph of Fuzzy-SMRGT and Measurement values for the test phase

As shown in Figures 10 and 11, there is a correlation between the actual measurement values of evaporation (mm) and the prediction results of the Fuzzy-SMRGT method. The coefficient of determination R^2 = 0.87 observed in the Fuzzy-SMRGT method has yielded results that are more accurate than the classical method of MLR, which is almost the same as the ANFIS method, in predicting evaporation.

As the MAE, RMSE and R^2 results in Table 2 show, the estimation results obtained using ANFIS and Fuzzy Logic methods are seen to be slightly more successful than the results obtained from the classical method MLR in estimating evaporation amounts.

IV. CONCLUSION

In this study, daily evaporation amount was estimated using 'daily relative humidity, air temperature, wind speed and sunshine duration' for the Atatürk Dam located between Adıyaman and Şanlıurfa provinces between 2004-2011. For daily evaporation estimation, Fuzzy-SMRGT, ANFIS and MLR models were used and the models were compared with each other according to statistical criteria. From a total of 1712 daily data, 1284 were used for training and 428 for testing in the estimation models. The measured evaporation values were compared with the estimation output of the model.

To evaluate the performance of Fuzzy-SMRGT, ANFIS and MLR models, coefficients of determination (R2), RMSE and MAE were calculated. It was determined that the Fuzzy-SMRGT model performed better than the MLR model and had results close to the traditional ANFIS model.

It is thought that the Fuzzy-SMRGT method can be an alternative to classical methods for hydrology science and can be used for regions with different climatic conditions.

ACKNOWLEDGEMENTS

The data used in this study was obtained from the Şanlıurfa Regional Directorate of Meteorology. The authors express their gratitude to the mentioned institution.

REFERENCES

[1] Hipni, A., El-shafie, A., Najah, A., Karim, O. A., Hussain, A., & Mukhlisin, M. (2013). Daily forecasting of dam water levels: comparing a support vector machine (SVM) model with adaptive neuro fuzzy inference system (ANFIS). Water resources management, 27, 3803-3823.

[2] Ünes, F., Yildirim, S., Cigizoglu, H.K., & Coskun, H. (2013). Estimation of dam reservoir volume fluctuations using artificial neural network and support vector regression. Journal of Engineering Research, 1(3), 53-74.

[3] He, Z., Wen, X., Liu, H., & Du, J. (2014). A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region. Journal of Hydrology, 509, 379-386.

[4] Demirci, M., Üneş, F., & Aköz, M.S. (2015). Prediction of cross-shore sandbar volumes using neural network approach. Journal of Marine Science and Technology 20(1), 171-179.

[5] Mirzavand, M., Khoshnevisan, B., Shamshirband, S., Kisi, O., Ahmad, R., & Akib, S. (2015). Evaluating groundwater level fluctuation by support vector regression and neuro-fuzzy methods: a comparative study. Natural Hazards, 1(1), 1-15.

[6] Üneş, F., Demirci, M., & Kişi, Ö. (2015). Prediction of millers ferry dam reservoir level in usa using artificial neural network. Periodica Polytechnica Civil Engineering, 59(3), 309–318.

[7] Demirci, M., Unes, F., & Akoz, M. S. (2016). Determination of nearshore sandbar crest depth using neural network approach. International Journal of Advanced Engineering Research and Science, 3(12).

[8] Tezel, G., & Buyukyildiz, M. (2016). Monthly .evaporation forecasting using artificial neural networks and support vector machines. Theoretical and applied climatology, 124, 69-80.

[9] Taşar, B., Üneş, F., Demirci, M., & Kaya, Y. Z. (2018). Yapay Sinir Ağları Yöntemi Kullanılarak Buharlaşma Mİktarı Tahmini. DÜMF Mühendislik Dergisi, 543-551(in Turkish).

[10] Yin, Z., Feng, Q., Yang, L., Deo, R. C., Wen, X., Si, J., & Xiao, S. (2017). Future projection with an extreme-learning machine and support vector regression of reference evapotranspiration in a mountainous inland watershed in north-west China. Water, 9(11), 880.

[11] Üneş, F., Doğan, S., Taşar, B., Kaya, Y. Z., & Demirci, M. (2018). The Evaluation and Comparison of Daily Reference Evapotranspiration with ANN and Empirical Methods. Naural and Engineering Sciences 3(3), 54-64.

[12] Meshram, S. G., Singh, V. P., Kisi, O., Karimi, V., & Meshram, C. (2020). Application of artificial neural networks, support vector machine and multiple model-ANN to sediment yield prediction. Water Resources Management, 34(15), 4561-4575.

[13] Niu, W. J., & Feng, Z. K. (2021). Evaluating the performances of several artificial intelligence methods in forecasting daily streamflow time series for sustainable water resources management. Sustainable Cities and Society, 64, 102562.

[14] Yilmaz, M., Tosunoğlu, F., Kaplan, N. H., Üneş, F., & Hanay, Y. S. (2022). Predicting monthly streamflow using artificial neural networks and wavelet neural networks models. Modeling Earth Systems and Environment, 8(4), 5547-5563.

[15] Samantaray, S., & Sahoo, A. (2024). Prediction of flow discharge in Mahanadi River Basin, India, based on novel hybrid SVM approaches. Environment, Development and Sustainability, 26(7), 18699-18723.

[16] Tzimopoulos, C., Mpallas, L., & Papaevangelou, G. (2007). Estimation of Evapotranspiration Using Fuzzy Rules and Comparison with the Blaney-Criddle Method. International Symposium of European Water Resources Association

[17] Dogan, E., Isik, S., & Sandalci, M. (2007). Estimation of daily evaporation using artificial neural networks. Tek Dergi 18 (2), 4119–4131.

[18] Balve, P. N., & Patel, J. N. (2016). Prediction of evapotranspiration using Fuzzy logic. Journal of Agrometeorology, 18(2), 311–314.

[19] Taşar, B., Kaya, Y. Z., Varçin, H., Üneş, F., & Demirci, M. (2017). Forecasting of suspended sediment in rivers using artificial neural networks approach. International Journal of Advanced Engineering Research and Science, 4(12), 237333.

[20] Kaya, Y. Z., Mamak, M., & Unes, F. (2016). Evapotranspiration prediction using M5T data mining method. International Journal of Advanced Engineering Research and Science, 3(12), 236973.

[21] Özel, A., & Büyükyıldız, M. (2019). Aylık Buharlaşma Tahmininde Yapay Zeka Yöntemlerinin Kullanılabilirliği. Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi, 8(1), 244-254(in Turkish).

[22] Petković, B., Petković, D., Kuzman, B., Milovančević, M., Wakil, K., Ho, L. S., & Jermsittiparsert, K. (2020). Neuro-fuzzy estimation of reference crop evapotranspiration by neuro fuzzy logic based on weather conditions. Computers and Electronics in Agriculture, 173. https://doi.org/10.1016/j.compag.2020.105358

[23] Yaseen, Z. M., Al-Juboori, A. M., Beyaztas, U., Al-Ansari, N., Chau, K. W., Qi, C., ... & Shahid, S. (2020). Prediction of evaporation in arid and semi-arid regions: A comparative study using different machine learning models. Engineering applications of computational fluid mechanics, 14(1), 70-89.

[24] Wu, L., Huang, G., Fan, J., Ma, X., Zhou, H., & Zeng, W. (2020). Hybrid extreme learning machine with meta-heuristic algorithms for monthly pan evaporation prediction. Computers and electronics in agriculture, 168, 105115.

[25] Toprak, Z. F. (2009). Flow discharge modeling in open canals using a new fuzzy modeling technique (SMRGT). CLEAN–Soil, Air, Water, 37(9), 742-752.
[26] Google Earth, www.earth.google.com
[27] Anonymous, https://www.balikligol.com/gundem/ataturk-barajinda-doluluk-orani-yuzde-94u-asti-h67618.html
[28] Kocabaş, H., Üneş, F., Taşar, B., & Cansız, Ö. F. (2023). Türkiye Karayollarındaki Karbondioksit Emisyonunun Yapay Zekâ Yöntemleri ile Tahmini. Türkiye Teknoloji ve Uygulamalı Bilimler Dergisi, 4(2), 82-101(in Turkish).
[29] Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neuro-fuzzy and soft computing-a computational approach to learning and machine intelligence [Book Review]. IEEE Transactions on automatic control, 42(10), 1482-1484.
[30] Üneş, F., Demirci, M., Zelenakova, M., Çalışıcı, M., Taşar, B., Vranay, F., & Kaya, Y. Z. (2020). River flow estimation using artificial intelligence and fuzzy techniques. Water, 12(9), 2427.
[31] Uygunoğlu T., Ünal O. Seyitömer uçucu külünün betonun basınç dayanımına etkisi üzerine bulanık mantık yaklaşımı. Yapı Teknolojileri Elektronik Dergisi 2005; 1(1): 13-20 (in Turkish).
[32] Dayan, F., Demirci, M., Üneş, F., Taşar, B. (2021). Nehirlerdeki Katı Madde Miktarının Bulanık Smgrt Yöntemi İle Tahmini. Kahramanmaraş Sütçü İmam Üniversitesi Mühendislik Bilimleri Dergisi, 24(4), 294-307(in Turkish). https://doi.org/10.17780/ksujes.912425
[33] Er, E. E., Üneş F., & Taşar, B. Estimating Dam Reservoir Level Change of Istanbul Alibey Dam with The Fuzzy-SMRGT Method. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 5(Özel Sayı), 80-95.