Hydrological Processes

Application of Soft Compiting Techniques in River Flow Modeling in The Case of Euphrates-Tigres Basin

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Abstract

River stream estimation is a subject matter that needs constant research and development since it is all-important in the management of water resources, meeting the water demand, irrigation and agricultural activities, and providing distant signal in unwanted situations such as floods. Unfortunately, a universal technique has not been found yet although many techniques have been used for estimation and modelling. This has made it necessary to develop different techniques and/ or to make comparisons between techniques and to determine the most accurate method for the parameters used. In this study, using the 1981-2010 flow data of 14 stations located across Euphrates-Tigris basin, evaluations have been made through Adaptive-Network Based Fuzzy Inference Systems (ANFIS), Support Vector Regression (SVR-SVMR) techniques, and the newly used Gauss Process Regression (GPR), Extreme Learning Machine (ELM) and Emotional Neural Network (ENN) artificial intelligence techniques, and through rank analysis, it is aimed to find out which technique gives better results and to overcome some problems in traditional methods. Although all models work well, the sequence with regards to the comparison outcomes of the techniques obtained from rank analysis was observed to be ELM, GPR, ENN, SVM, ANFIS respectively. In addition, stream values were used in the whole

study, these values were examined within 3 different combinations and it was observed that the best result was found in the combination of [input]Q(t-3),Q(t-2),Q(t-1)/[output]Q(t).

Keywords: River Flow Modelling; ANFIS; SVM; GPR; ELM; ENN

1.INTRODUCTION

1.1 River Flow Modelling Background

Water, the main component of life, is an indispensable resource used to provide the energy required for living things to survive. For this reason, it is of great importance for living creatures. Stream modelling and estimation are required in cases such as efficient use of existing water resources, development of water structures, and the examination of the water source before the construction of water structures planned for different purposes. At the same time, the fact that there are many unknown factors in the occurrence of hydrological events, instabilities in the work field, irregularities in river systems and flow data have made it necessary for researchers to create models and make estimations for future. These estimations, which can be made through some mathematical methods, provide more successful results through artificial intelligence techniques and fuzzy logic methods, and thus, can be modelled within a shorter time. However, it was not possible to reduce these methods to a single one or to create a universal one that is superior to the others (Yaseen et al. 2019). Although a universal method does not exist for now, it is of great importance to create a method that can be used by hydrologists in a sound and reliable way and that will ensure the sustainable use of water resources. For this reason, most of the studies are aimed at making comparisons between methods and finding the best resul (Farmer et al. 2018).

1.1 Soft Computing Techniques Employment in The Field of Water Resources Engineering

The uses of artificial intelligence techniques are not limited to river stream modelling. Although ELM, ENN and GPR methods are newly used, there are many studies that have applied artificial intelligence techniques. For example, the methods used in many subjects and studies such as precipitation forecast (Akrami et al. 2014; Choubin et al. 2018; Li et al. 2018; Mokhtarzad et al. 2017), evapotranspiration forecast (Ferreira et al. 2019; Han et al. 2019; Tao et al. 2018), drought (Khan et al. 2020; Mokhtarzad et al. 2017; Zhang et al. 2020), air quality (Bhardwaj and Pruthi 2020; Ghasemi and Amanollah, 2019) soil moisture (Ji et al. 2019; Li et al. 2019), water level estimation (Deo and Şahin 2016; Hipni et al. 2013; Khan and Coulibaly 2006), water quality (Azad et al. 2019), evaporation (Mohamadi et al. 2020) have been developed or compared with different methods.

At the same time, these methods, used in different processes such as sediment transportation in open channels (Safari et al. 2019), and discharge coefficient in open channels (Azimi et al.

2017) which are of great importance for the development of hydraulic structures, have greatly contributed to the development of water resources engineering (see Appendix A).

1.2 River Flow Modelling Using Soft Computing Techniques

Although there are many methods that can be used for stream modelling, no universally used method considered to be superior to others has been found. This made it necessary to check those methods against each other, to compare them statistically and even to create new methods. In this context, there are many studies conducted using the ANFIS (He et al. 2014; Rezaeianzadeh et al. 2014; Zhou et al. 2019), ELM (Yaseen et al. 2016; Yaseen et al., 2019), ENN (Yaseen et al. 2020), SVM (He et al. 2014; Yaseen et al. 2016; Yaseen et al. 2019) and GPR (Sun et al. 2014) methods. Considering these studies and developments in model structures; ANFIS, a mixed learning model created by (Jang 1993), has been developed over time and has been used with new ANFIS methods such as ANFIS with grid partition (ANFIS-GP) and ANFIS with sub clustering (ANFIS-SC) (Sanikhani and Kisi 2012). (Khadangi et al. 2009) applied ANFIS and radial base function (RBF) methods for daily river stream modelling in their study and found that ANFIS provided a much better performance. The ELM structure, which was created to eliminate the need for iterative adjustment of latent neuron parameters in traditional models, was proposed by (Huang et al. 2006) and it was first used for river stream modelling by (Siqueira et al. 2014) for hydraulic power plants in Brazil, and they observed that the model was suitable for river stream studies. At the same time, the ELM structure was developed within time and different ELM structures were created for different studies. (Yaseen et al. 2019) used ELM and ANFIS to estimate river stream in their studies and observed that the improved ELM gave better results when compared to these techniques. In addition, in a study conducted in Iran, a semi-arid region, Generalized Regression Neural Network (GNRR), SVM, and ELM were compared and it was concluded that ELM gave better results (Yaseen et al. 2016). In another study (Adnan et al. 2019), in which ELM was used as Optimally Pruned ELM, ANFIS-PSO (particle swarm optimization), Multivariate Adaptive Regression Splines (MARS), and M5 model tree (M5Tree) techniques were compared by cross-validation and it was concluded that OP-ELM method could be used successfully in daily stream flow estimation. The ENN structure, which takes emotional parameters into account in addition to other models that simulate the brain structure in modelling studies, was developed by (Rumelhart 1986) , and was used in river stream modelling for the first time by (Yaseen et al. 2020) ENN was used in the study to create an hourly river stream model, it was compared with other well-structured machine learning methods, and it was found that ENN performed better.

In a study in which SVM, developed by (Rumelhart 1986), was used for river stream modelling, ELM was compared with Artificial Intelligence (AI), Genetic Programming (GP) and Support Vector Machine (SVM), and it was observed that ELM method gave faster and better results in river stream estimation than the other methods (Atiquzzaman and Kandasamy 2018). (Sun et al. 2014) studied the monthly estimation of GPR, compared GPR with autoregressive moving average with exogenous variables (ARMAX) and multilayer perceptron (MLP), used for more than four hundred stations in the USA, and concluded that GPR performed better.

1.3 Research Objectives

In this study, conducted for river stream estimation and modelling which is of great importance for water resources engineering, it is aimed to find the best results in the shortest time in river stream modelling by comparing widely used methods such as ANFIS and SVM with the rarely used ones such as ELM, GPR and ENN methods, to find the membership functions in traditional methods by trial and error, and to eliminate undesirable conditions such as the uncertainties in the interpretation of parameters, intense human intervention necessity in modelling, and slowspeed of learning. Rank analysis was performed in order to make an accurate evaluation between methods and to decide on the best model by taking all evaluation parameters into consideration, and it was aimed to find a reliable method for hydrology studies and river stream modelling by determining the best result with the aid of correlation coefficient (R), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE) performance indexes. At the same time, a comprehensive review of the artificial intelligence techniques used in this study is presented (See Appendix A).

2.METHODOLOGY

2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS, based on Takagi-SugenoKang inference system, was developed by (Jang 1993) to model nonlinear functions, determine nonlinear components in the control system, and predict the chaotic time series. The fuzzy logic inference system evaluated in ANFIS is transformed into adaptive networks and the most suitable condition is created through a learning algorithm. Neural adaptive learning techniques develop a model that “learns” the related system by using the data set selected for the fuzzy modelling. In other words, ANFIS uses the input/output data set and the backpropagation algorithm used in artificial neural networks alone or together with the least-squares method, and thus, by regulating the membership functions parameters, creates a fuzzy inference system (FIS). This regulation allows the fuzzy system to learn the relevant system with the help of the data that it has modelled. Namely, it customizes/adapts itself to the data will be modelled. The ANFIS structure, which has got the ability to update itself by using both the environmental information and the input and output data of the system, is as shown in Figure 1 (Jang and R. 1991).

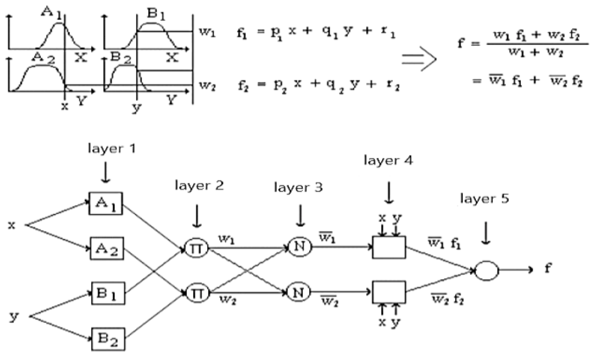

FIGURE 1 ANFIS Structure (Demuth 2000)

Information of the layers shown in Figure 1;

- The 1st layer is called the input layer. Input signals from each node in this layer are transferred to other layers. Output values for each i node are expressed as follows:

$O_{1,i} = \mu A_i(x) \quad i = 1,2 ....$ (1)

$O_{1,i} = \mu B_{i-2}(x) \quad i = 1,2 ....$ (2)

- The 2nd layer is called the blur layer. The output of each node here consists of membership degrees depending on the input values and the membership function used. The membership degrees obtained from the 2nd layer are shown as μ_{Ai} (x) and μ_{Bi} (y).

- The 3rd layer is the rule layer. Nodes are used to express the number and rules created according to Sugeno's fuzzy logic inference system. Output μi of each rule node is the product of membership degrees from layer 2.

- The 4th layer is the normalization layer.

- In layer 5, the weighted result values of a given rule in each node are calculated. The output value of the i. node in the 5th layer is as follows;

$y_i^5 = \overline{\mu_i}[p_i x_1 + q_i x_2 + r_i] \quad i = (1, n)$ (3)

(pi, qi, ri) variables here are the result parameters set of the i. rule.

- The 6th layer is the sum layer. This layer has only one node and is labelled as ∑. It is the output layer of the system (Demuth 2000).

While the biggest advantages of the ANFIS model can be regarded as its efficiency in mathematical analysis, success in adaptation and successful conclusion in numerical data, too much human intervention can be supposed as a disadvantage since training of ANFIS parameters takes quite a long time and the model has a structure with many rules.

2.2 Extreme Learning Machine (ELM)

ELM is a fully connected artificial neural network model developed by (Huanget al. 2006) and consists of an input layer, a hidden layer and an output layer. Unlike the commonly used gradient-based network structures, ELM, whose input weights and threshold values are randomly generated but output weights are analytically generated, creates an analytical equation of the model beyond finding the model weights, and thus, it prevents error clogging at a local point and removes the problem of learning process that takes a long time as in the other methods. In this way, it provides better performance compared to other methods and speeds up the model production process. At the same time, other learning algorithms sometimes have to apply procedures such as stopping the training process of the model earlier, adding regulation parameters, breaking weights or using validity sets as they may encounter undesirable situations such as improper learning rate, excessive learning and memorization, and stuck in local minimums, whereas ELM reaches the solution directly without any intermediate processing. In addition to all these advantages, the structure of the ELM method, which offers the possibility to use many activation functions which can be derivative, underivative or discrete, consists of the input layer where the data is read, the output layer where the classes are determined and the hidden layer where the intermediate operations are conducted, as shown in Figure 2.

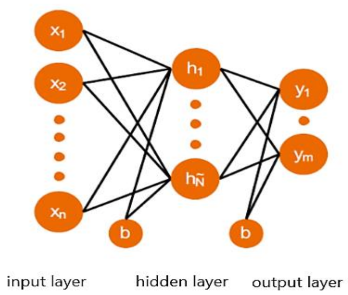

FIGURE 2 Algorithm of Extreme Learning Machine (Jin et al. 2020)

The ELM structure can calculate the output weight with the Moore-Penrose generalized inverse latent matrix without any need for iterative optimization. If L stands for the hidden node, β_j symbolizes the output neurons, and j_{th} is symbolized as the weight value connecting the hidden neurons, then the ELM structure can be expressed as;

$$\sum_{j=1}^{L} \beta_j h_j(x_i) = y_i, \qquad i = 1, \ldots, N, \tag{4}$$

Mapping the properties for J_{th} hidden node output $h_j(x_i)$; is

$$h_j(x_i) = \frac{1}{1+exp\left(-\left(w_j^T x_i + b_j\right)\right)} \tag{5}$$

w_j refers to the weight vector connecting input neurons used in this equation, $w_j = [w_{j1}, \ldots, w_{jD}]^T \in \mathbb{R}^D$ and J_{ht} hidden neuron, and b_j is expressed as expressed as trend (deviation) term. If equation 1 is to be expressed more simply;

$$H\beta = \mathrm{y},\ \beta = [\beta_1, \ldots, \beta_L]^T \in \mathbb{R}^L,\ \ y = [y_1, \ldots, y_N]^T \in \mathbb{R}^N \tag{6}$$

$$H(w_1, \ldots, w_L, b_1, \ldots, b_L, x_1, \ldots, x_N) = \begin{bmatrix} h_1(x_1) & \ldots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_N) & \ldots & h_L(x_N) \end{bmatrix} \in \mathbb{R}^{N*L} \tag{7}$$

H used in these equations denotes the hidden layer output matrix. ELM chooses the case with the minimum error and the lowest output weight among different traditional learning algorithms. Randomly initialized w_j hidden node parameters and bj is (j = 1; . . .; L) and the least squares solution of equation 3 is as follows;

$$\beta = H^{\dagger} \tag{8}$$

Here † Moore-Penrose denotes the generalized opposite. Decision function to be created to write $\hat{x}$, which is the new test example of ELM structure, can be expressed as (Jin et al. 2020);

$$\hat{y} = sign\ (h(\hat{x})\beta) \tag{9}$$

2.3 Emotional Neural Network Algorithm (EmNN)

This section describes the emotional neural network algorithm (EmNN). EmNN is based on the emotional back-propagation algorithm (EmBP- emotional back propagation), which is a modified version of the traditional back-propagation algorithm (BP-back propagation). As stated by (David and James 1987), the BP method is often preferred because of its simplicity of application and its rapid operation, especially when it has sufficient database. EmBP is described according to the information flow layers of the three-layer EmNN algorithm. Layers of the EmNN algorithm are called as follows:

i: input layer with neurons

h: hidden layer with neurons

j: output layer with neurons

(Fig. 3) shows the process for EmNN feed forward calculation (Khashman 2009);

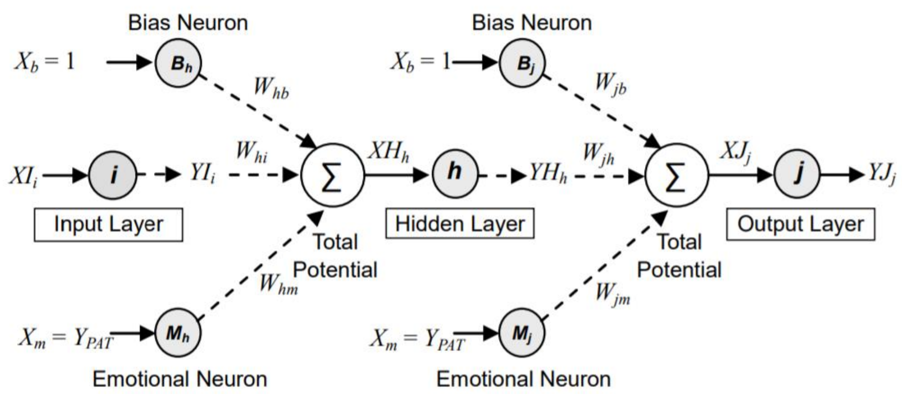

FIGURE 3 Process for EmNN feed forward calculation (Khashman 2009)

2.3.1 Feed forward calculations

Data processing from the input layer to the output layer in the neural network is as follows. Feed forward calculations are performed during the operation of a network.

Input layer with neurons (i);

Input layer neurons are unprocessed neurons. Thus, if Xl_i is defined as the input value of the input layer, and Yl_i as the output value of the input layer, the input values are equal to the output values.

$$Xl_i = Yl_i \tag{10}$$

Hidden layer with neurons (h);

Each neuron in the input layer is activated in the hidden layer. XH_h is defined as the input data of the hidden layer while YH_h is defined as its output data.

$$YH_H = \left\{\frac{1}{1+exp(-XH_h)}\right\} \tag{11}$$

On the other hand, in order to calculate theXH_h data, total potential output values TP_h of that neuron should be used. Since there are three different input groups, there are three different total potential values. The potential values are:

TP_{h_c} : conventional total potential value obtained by using the output values of the input layer and the conventional weight matrix

TP_{h_b}: hidden layer neurons and related weight

TP_{h_m}: hidden layer emotional neurons and related weights

$$TP_{hc} = \sum_{i=1}^{r} W_{hi}.Yl_i \tag{12}$$

$$TP_{hb} = W_{hb}.X_b \quad , \quad X_b = 1 \tag{13}$$

$$TP_{hm} = W_{hm}.X_m \tag{14}$$

The W_{hi} stands for the weight transferred by$h$ layer to i layer, W_{hb} stands for the weight provided by the h layer, W_{hm} stands for the weight transferred by h layer to the hidden layer emotional neuron m, X_m stands for the input values of the emotional neuron and,X_m value stands for the mean value. x_{max} and y_{max} are the maximum pixel numbers of the P (x, y) image in the directions of x and y (Khashman 2009) Thus;

$$X_m = Y_{PAT} = \sum_{x=1,y=1}^{x_{\max},y_{\max}} \frac{P(x,y)}{x_{\max}.y_{\max}} \tag{15}$$

$$XH_h = TP_{hc} + TP_{hb} + TP_{hm} \tag{16}$$

Output layer with neurons (j);

As in the hidden layer, each neuron needs to be activated in the output layer as well. If XJ_i and YJ_i are respectively defined as the input and output values of the neuron output layer (j), then;

$$XJ_i = TP_{jc} + TP_{jb} + TP_{jm} \tag{17}$$

$$YJ_i = \left\{\frac{1}{1+exp(-XJ_i)}\right\} \tag{18}$$

Provided that W_{jh} is the weight transferred from the hidden layer to the output layer, YH_h is the output value of the hidden layer, W_{jb} is the weight transferred from the hidden layer to B_j and X_b is the input value of the inclined neurons, W_{jm} is the emotional weight transferred from the hidden layer to M_j, and X_m is the input value of the emotional neuron, then;

$$TP_{jc} = \sum_{h=1}^{1} W_{jh}.YH_h \tag{19}$$

$$TP_{jb} = W_{jb}.X_b \tag{20}$$

$$TP_{jm} = W_{hm}.X_m \tag{21}$$

$$XJ_j = TP_{jc} + TP_{jb} + TP_{jm} \tag{22}$$

Emotional parameters;

Emotional parameters are used in conjunction with the current learning coefficient (η) and α momentum ratio. (μ) is defined as the anxiety coefficient and k is defined as the confidence coefficient, and it is observed how these two parameters act when learning each new task. Anxiety level decreases as confidence level increases. Both coefficients have normalized values between 0 and 1.

The level of anxiety depends on the mean value of the input pattern and the error indicator for each period. The average input value used here must always be positive because the pixel values are normalized to values between 0-1. At the same time, the error indication may provide negative feedback if an unstable condition exists there. In this case, the heuristic network will be unreliable and unstable, similar to traditional networks. Therefore, three imgateant parameters are arranged until a stable learning is found. These three parameters stand for the learning rate, momentum ratio and the count of hidden neurons. Therefore, as learning progresses, the anxiety rate decreases and the value of the confidence coefficient increases (Adnan et al. 2019).

The anxiety coefficient can be defined as follows:

$$\mu = Y_{AvPAT} + E \tag{23}$$

Y_{AvPAT} is defined as the mean value of the patterns presented in the EmNN algorithm.

If p represents the pattern index, N is the total number of patterns presented in a period, and E is the feedback error, then;

$$Y_{AvPAT=} \frac{\sum_{p=1}^{N_P} Y_{PAT}}{N} \tag{24}$$

$$E = \frac{\sum_{j=1}^{N_j} (T_{j-YJ_j})^2}{N_p.N_j} \tag{25}$$

k confidence coefficient;

$$k = \mu_0 - \mu_i \tag{26}$$

μ_0: value of anxiety coefficient at the end of the first iteration

μ_i : coefficient of anxiety at the end of subsequent iterations

2.4 Support Vector Machine (SVM)

SVM, an algorithm based on optimization, was designed by (Vapnik 1998) as a classification algorithm that minimizes the error. Later, the algorithm started to be used for regression purposes with the name of SVR. Since SVM depends on core functions, it is considered a nonparametric technique. SVM, created by including the maximum value in the structure, has become more efficient than other regression models. When the weight vector in the structure is expressed as w and the error value as ε, the minimization process is expressed based on the following equations;

$$\min 1/2\|w\|^2 \quad \text{denklemi } y_i - (w, x_i + b) \le \varepsilon \text{ ve } (w, x_i + b) - y_i \le \varepsilon \tag{27}$$

When x is a point on the hyperplane and b is called a bias, then the constraint equation is as follows;

$$f(x) = y_i(w, x_i + b) \tag{28}$$

If the model margin value is wanted to be calculated so as to keep all data in it, minimization is used. However, it is not possible to use all values in this way. In this case, slack variables are used (ξi, ξi*).

$$\min 1/2\|w\|^2 + C\sum_{i=1}^{N}(\xi i + \xi i^*) \quad (29)$$

Equation is formed depending on the $y_i - (w, x_i + b) \leq \varepsilon + \xi i$ ve $(w, x_i + b) - y_i \leq \varepsilon + \xi i$ equations. C>0 constant is used and values where equation f is greater than ± ε are tolerated as shown in Figure 4 (Burges 1998).

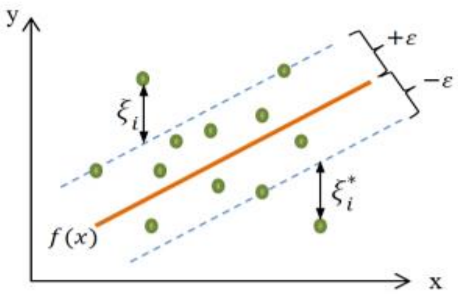

FIGURE 4 An example for SVM model structure (Chanklan 2018)

SVM, which is widely preferred due to its ease of application and compatibility with both linear and nonlinear data, also has disadvantages such as difficulties in interpreting model parameters and long duration of model training.

2.5 Gauss Process Regressıon (GPR)

GPR, a non-parametric model suitable for use in solving nonlinear regression problems, is based on the conversion of prior functions to posterior functions in Gaussian distribution (McDuff 2019). GP describes the probability distribution on functions and when M (x) refers to mean,

K(x,x') refers to covariance function, then the

$$f(x) \sim GP(m(x), K(x, x')) \quad (30)$$

equation is formed. In this equation m(x) and K(x,x') are expressed as follows;

$$m(x) = \mathbb{E}[f(x)] \quad (31)$$

$$K(x, x') = \mathbb{E}[(f(x) - m(x))((f(x') - m(x'))^T] \quad (32)$$

If θ_f indicates x- scaling (amplitude) and θ_t indicates y- scaling (length), then the covariance function is expressed with the equation below (Murphy 2012; Richardson 2017);

$$K = .\theta_f^2 \exp\left(-\frac{1}{\theta_t^2}\|x - x'\|^2\right) \quad (33)$$

The covariance matrix is as follows;

$$K = \kappa\big((x_1, \dots, x_n), (x_1, \dots, x_n)\big) = \begin{bmatrix} \kappa(x_1, x_1) & \kappa(x_1, x_2) & \dots & \kappa(x_1, x_n) \\ \kappa(x_2, x_1) & \kappa(x_2, x_2) & \dots & \kappa(x_2, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ \kappa(x_n, x_1) & \kappa(x_n, x_2) & \dots & \kappa(x_n, x_n) \end{bmatrix} \quad (34)$$

2.6 Model Development-Evaluation Criteria and Rank Analysis

Four different performance indices were used to evaluate the performance of the developed models. These indices, called R, RMSE, MSE and MAE, can be obtained with the help of the following equations;

$$R = \sqrt{1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y})^2}} \quad (35)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2} \quad (36)$$

$$MSE = RMSE^2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2 \quad (37)$$

$$MAE = \frac{1}{N} \sum_{j=1}^{N} \left| y_i - y_j \right| \quad (38)$$

y refers to the measured value, $\bar{y}$ refers to the average of measured values, and N refers to the total number of data. R value may have the best value of 1 and RMSE, MAE and MSE may have the best value of 0. Rank analysis is a method applied to determine the best performing model among the models by considering all evaluation criteria. This method, aiming to determine the performance evaluation score of the models and to find the model that gives the best result, is performed by assigning a rank to the models according to their proximity to the best value for each data set, and collecting and comparing the scores for all data sets. If R_i is represented as the rank value in the selected model of each data set and n is the number of models, the total rank value is determined by the equation that follows (Zhang et al. 2020).

$$Modal\ Total\ Rank = \sum_{i=1}^{n} R_i \quad (39)$$

3.STUDY AREA AND DATA

Euphrates-Tigris basin, growing out of Euphrates and Tigris rivers which break through the mountains in the east of Turkey and flow into the Persian Gulf, has 184,914 km^2 of precipitation, including 127,300 km^2 Euphrates Basin and 57,614 km^2 Tigris Basin. (Fig. 5). Examination of this basin, having the largest drainage area in Turkey and being consisted of the Euphrates River, the longest river in Western Asia, and the Tigris River, the second largest river in Western Asia, is of great importance since its average annual flow value is 52.94 km^3, its average annual output is 21.4 l sec / km^2 and its annual average energy generation potential is 54.7 GWh. At the same time, the Euphrates-Tigris basin is also all-important for the riparian countries.

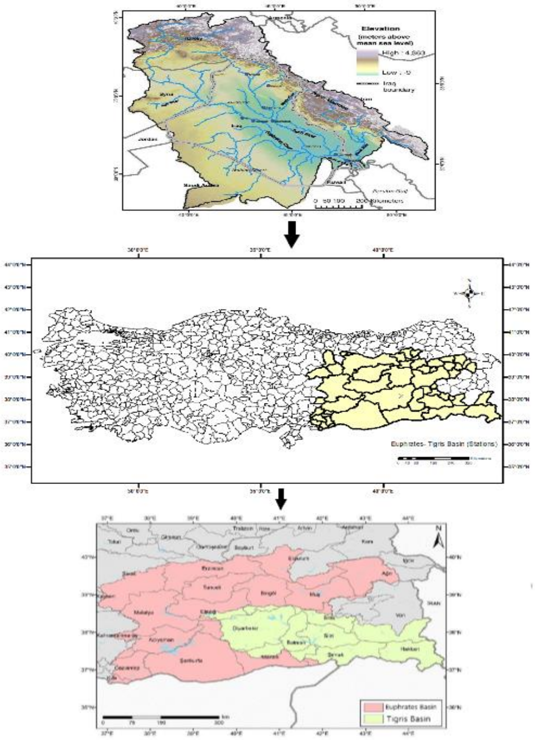

FIGURE 5 Euphrates-Tigris River Basin bordering on Turkey and riparian countries and the part of the basin in Turkey (examined in this study) (Chen 2011)

Euphrates-Tigris Basin, in addition to these important features, has the most complete daily stream data of all the basins in Turkey. Among the many stations 14 were selected to standardize global assessment and climate monitoring studies, and the stream data averages, standard deviation values, minimum and maximum values of those stations between 1981-2010 are shown in a table (DSI 2020) (Table 1) (Fig. 6).

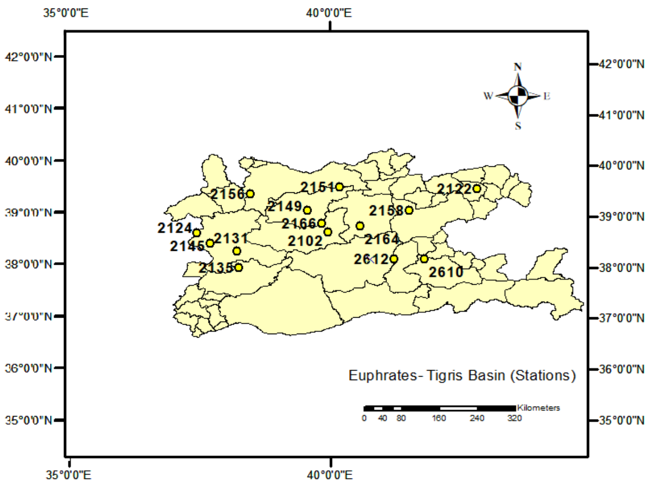

FIGURE 6 Selected stream observation stations in the Euphrates-Tigris Basin

TABLE 1 Selected stream stations in the Euphrates-Tigris Basin.

Station number	Name	Longitute-latitute	Mean (flow) (m^3/sn)	Max (flow) (m^3/s)	Min (flow) (m^3/s)	Standart deviation (flow)
2102	Murat Rıver - Palu	(39° 56' 22" E - 38° 41' 49" N)	179,23	997	12,1	207,606
2122	Murat Rıver- Tutak	(42° 46' 49" E - 39° 32' 19" N)	47,48	821	1,97	73,041
2124	Tohma Bourn - Yazıkoy	(37° 26' 33" E - 38° 40' 21" N)	6,605	59,8	0,425	3,855
2131	Bey Stream - Kılayık	(38° 12' 36" E - 38° 19' 21" N)	1,343	38,8	0,11	1,894
2135	Bulam Stream - Fatopasa	(38° 14' 13" E - 37° 59' 38" N)	3,624	27,3	0,844	2,438
2145	Tohma Bourn - Hısarcık	(37° 41' 08" E - 38° 28' 32" N)	20,019	251	5,53	13,285
2149	Munzur Bourn - Mıskısag	(39° 32' 35" E - 39° 06' 29" N)	24,714	274	5,53	23,045
2151	Fırat Rıver - Demirkapı (Sansa)	(40° 10' 05" E - 39° 34' 41" N)	58,863	712	4,07	74,378
2156	Karasu - Asagıkagdarıc	(38° 26' 55" E - 39° 25' 57" N)	150,9272	980	54,8	116,844
2158	Bingöl Stream - Abdurrahman paşa Brıdge	(41° 29' 14" E - 39° 06' 30" N)	18,4965	338	1,3	29,181
2164	Goynuk Stream - Çayagzı	(40° 33' 17" E - 38° 48' 06" N)	32,497	630	0,45	56,143
2166	Perı Bourn - Logmar	(39° 48' 50" E - 38° 51' 31" N)	76,742	967	0,55	96,458
2610	Bıtlıs Stream - Baykan	(41° 46' 57" E - 38° 09' 41" N)	17,969	420	1,95	24,602
2612	Batman stream - Malabadı Brıdge	(41° 12' 16" E - 38° 09' 16" N)	112,848	990	0,015	150,300

3.FINDINGS

In this study conducted with the data of 14 stations in the Euphrates-Tigris Basin, daily stream data were divided into two as 70% train and 30% test. At the same time, it was aimed to find the best result in the shortest time by examining the stream data in 3 different input combinations. The first of these input combinations uses the stream data from a month ago (Q(t-1)) as input, and includes the current stream data as output (Q(t)), the second combination comprises Q(t-2)+Q(t-1) input data and Q(t) output data, and the third combination contains Q(t-3),Q(t-2), Q(t-1) input data and Q(t) output data. Modelling results of station 2102 made through these combinations are given in Table 2. As can be seen in the table, according to the results of R, RMSE, MSE and MAE, rank analysis was performed both between models and between data set combinations, and it was observed that ELM model gave the best results for station 2102, while the best result among data set combinations was found to be input Q(t-2)+Q(t-1)/ output Q(t) combination. At the same time, the outputs of ELM, ANFIS, ENN, SVM and GPR techniques are given in Figure 7.

TABLE 2 Model Results of Murat River- Palu (2102) station

			TRAIN								TEST									
		TRIAL NO	RMSE	*RANK*	MSE	*RANK*	R	*RANK*	MAE	*RANK*	RMSE	*RANK*	MSE	*RANK*	R	*RANK*	MAE	*RANK*	*TOTAL RANK*	
Evaluation According To The Method	ELM	Q(t-1)-Q(t)	62,03	4	3.847,50	4	0,9873	4	0,12	5	53,09	3	2.819,06	3	0,9815	4	0,70	4	31	
		Q(t-2)+Q(t-1)-Q(t)	56,36	4	3.176,19	4	0,9898	4	0,23	5	46,02	4	2.118,20	4	0,9847	4	1,56	3	32	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	67,35	2	4.535,52	2	0,9884	2	0,28	5	49,82	4	2.481,69	4	0,9820	3	2,17	4	26	89
	ANFIS	Q(t-1)-Q(t)	63,02	3	3.970,92	3	0,9873	3	0,94	3	53,07	4	2.816,83	4	0,9814	3	0,27	5	28	
		Q(t-2)+Q(t-1)-Q(t)	76,59	1	5.866,19	1	0,9822	1	3,27	3	60,50	1	3.660,17	1	0,9741	1	5,29	2	11	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	100,60	1	10.120,12	1	0,9746	1	3,31	3	75,10	1	5.639,93	1	0,9629	1	6,89	3	12	51
	SVM	Q(t-1)-Q(t)	66,04	1	4.361,10	1	0,9798	1	22,75	2	50,58	5	2.558,79	5	0,9814	2	2,16	2	19	
		Q(t-2)+Q(t-1)-Q(t)	61,65	2	3.800,50	2	0,9849	3	19,60	2	45,68	5	2.086,61	5	0,9846	3	1,00	5	27	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	62,90	3	3.956,00	3	0,9849	3	28,96	1	47,15	5	2.223,45	5	0,9845	4	8,44	2	26	72
	GPR	Q(t-1)-Q(t)	50,10	5	2.509,90	5	0,9899	5	0,45	4	54,33	1	2.951,49	1	0,9804	1	0,85	3	25	
		Q(t-2)+Q(t-1)-Q(t)	6,93	5	1,48	5	0,9897	5	1,94	4	55,42	2	3.071,47	2	0,9831	2	1,45	4	29	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	1,27	5	1,60	5	0,9953	5	0,48	4	57,63	2	3.320,83	2	0,9790	2	1,22	5	30	84
	ENN	Q(t-1)-Q(t)	65,82	2	4.332,70	2	0,9824	2	23,27	1	54,12	2	2.928,30	2	0,9840	5	21,98	1	17	
		Q(t-2)+Q(t-1)-Q(t)	61,14	3	3.738,20	3	0,9849	2	20,75	1	50,04	3	2.503,70	3	0,9864	5	20,31	1	21	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	61,02	4	3.723,00	4	0,9849	4	20,69	2	49,82	3	2.481,80	3	0,9865	5	20,10	1	26	64
Evaluation by Data Combination	ELM	Q(t-1)-Q(t)	62,03	2	3.847,50	2	0,9873	1	0,12	3	53,09	1	2.819,06	1	0,9815	1	0,70	3	14	
		Q(t-2)+Q(t-1)-Q(t)	56,36	3	3.176,19	3	0,9898	3	0,23	2	46,02	3	2.118,20	3	0,9847	3	1,56	2	22	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	67,35	1	4.535,52	1	0,9884	2	0,28	1	49,82	2	2.481,69	2	0,9820	2	2,17	1	12	
	ANFIS	Q(t-1)-Q(t)	63,02	3	3.970,92	3	0,9873	3	0,94	3	53,07	3	2.816,83	3	0,9814	3	0,27	3	24	
		Q(t-2)+Q(t-1)-Q(t)	76,59	2	5.866,19	2	0,9822	2	3,27	2	60,50	2	3.660,17	2	0,9741	2	5,29	2	16	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	100,60	1	10.120,12	1	0,9746	1	3,31	1	75,10	1	5.639,93	1	0,9629	1	6,89	1	8	
	SVM	Q(t-1)-Q(t)	66,04	1	4.361,10	1	0,9798	1	22,75	2	50,58	1	2.558,79	1	0,9814	1	2,16	2	10	
		Q(t-2)+Q(t-1)-Q(t)	61,65	3	3.800,50	3	0,9849	3	19,60	3	45,68	3	2.086,61	3	0,9846	3	1,00	3	24	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	62,90	2	3.956,00	2	0,9849	2	28,96	1	47,15	2	2.223,45	2	0,9845	2	8,44	1	14	
	GPR	Q(t-1)-Q(t)	50,10	1	2.509,90	1	0,9899	1	0,45	3	54,33	3	2.951,49	3	0,9804	2	0,85	3	17	
		Q(t-2)+Q(t-1)-Q(t)	6,93	2	1,48	3	0,9897	3	1,94	1	55,42	2	3.071,47	2	0,9831	3	1,45	1	17	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	1,27	3	1,60	2	0,9953	2	0,48	2	57,63	1	3.320,83	1	0,9790	1	1,22	2	14	
	ENN	Q(t-1)-Q(t)	65,82	1	4.332,70	1	0,9824	1	23,27	1	54,12	1	2.928,30	1	0,9840	1	21,98	1	8	
		Q(t-2)+Q(t-1)-Q(t)	61,14	2	3.738,20	2	0,9849	2	20,75	2	50,04	2	2.503,70	2	0,9864	2	20,31	2	16	
		Q(t-3),Q(t-2), Q(t-1)-Q(t)	61,02	3	3.723,00	3	0,9849	3	20,69	3	49,82	3	2.481,80	3	0,9865	3	20,10	3	24	
		Q(t-1)-Q(t)			73,00		Q(t-2)+Q(t-1)-Q(t)		95,00		Q(t-3),Q(t-2), Q(t-1)-Q(t)						72			

Perfect coefficient of variation (R) = 1, perfect root-mean-squared error (RMSE) = 0, perfect mean absolute error (MAE) = 0, perfect MSE = 0.

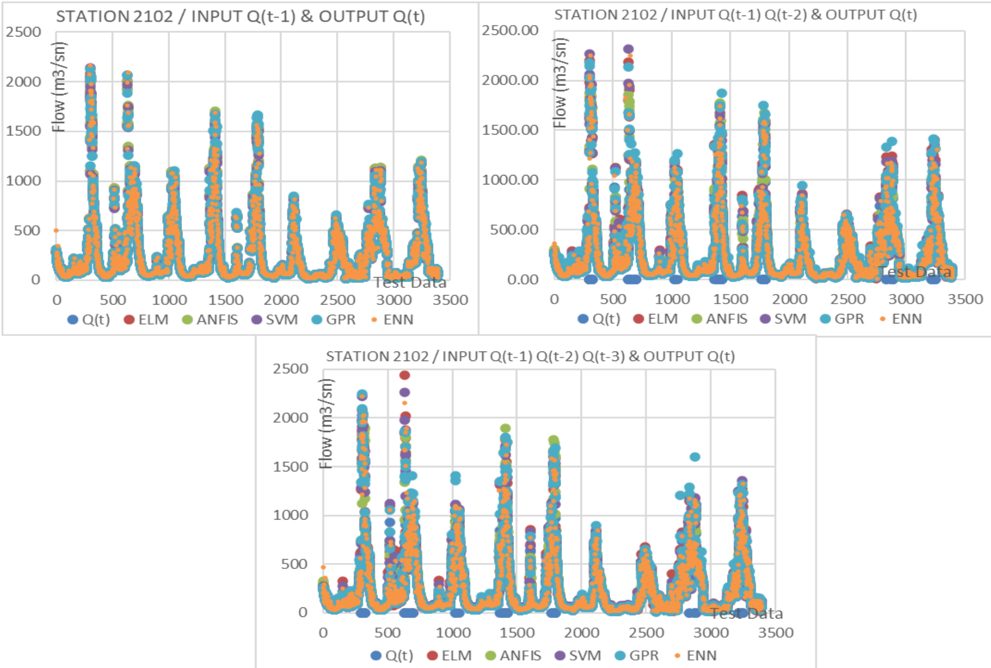

FIGURE 7 ELM, ANFIS, SVM, GPR and ENN outputs of the station 2102

The results shown in Figure 8 (a, b, c, d) were obtained when evaluations for all stations were carried in this way.

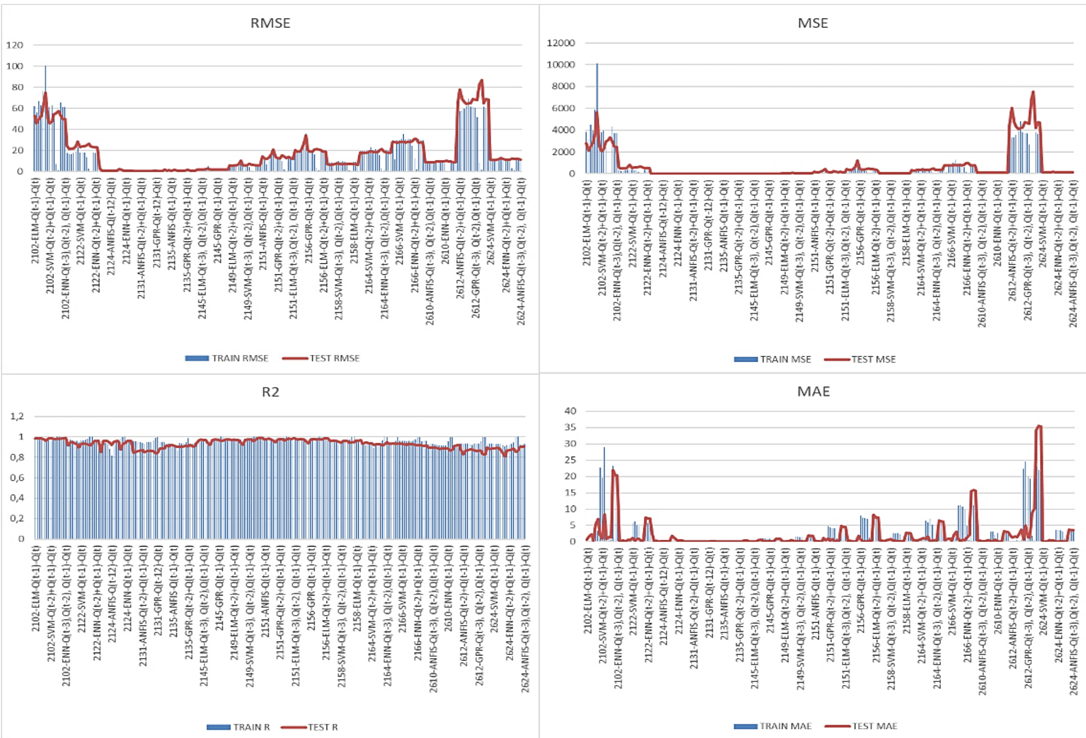

FIGURE 8 Evaluation results for 14 stations (a) RMSE values (b) R^2 values (c) MSE values (d) MAE values

In addition, rank values of all stations are given in Table 3, out of five points for five methods and out of three points for three data combinations.

TABLE 3 Rank value table for the 14 stations

	TOTAL RANK (Evaluation According To The Method)														
STATION	Q(t-1)-Q(t)					Q(t-2)+Q(t-1)-Q(t)					Q(t-3),Q(t-2), Q(t-1)-Q(t)				
	ELM	ANFIS	SVM	GPR	ENN	ELM	ANFIS	SVM	GPR	ENN	ELM	ANFIS	SVM	GPR	ENN
2102	31	28	19	25	17	32	11	27	29	21	26	12	26	30	26
2122	27	31	16	25	21	34	14	20	27	25	34	14	20	28	24
2124	19	31	23	26	21	33	16	26	22	23	26	16	25	23	30
2131	25	30	17	28	20	26	23	22	26	23	30	15	21	26	28
2135	24	24	21	30	21	30	21	20	27	22	25	15	27	23	30
2145	28	26	18	25	23	29	12	26	28	25	27	12	26	28	27
2149	30	24	18	29	19	33	12	21	28	26	31	12	21	31	25
2151	24	31	18	25	22	34	12	22	27	25	35	13	19	30	23
2156	30	21	18	25	26	32	14	22	27	25	33	11	23	28	25
2158	26	29	20	26	19	35	20	17	26	22	34	11	21	28	26
2164	31	29	16	26	18	35	22	14	26	23	33	11	21	31	24
2166	25	29	24	26	16	36	24	18	25	17	34	15	24	26	21
2610	32	28	17	25	18	34	24	14	26	22	33	13	19	29	26
2612	24	26	23	25	22	27	24	23	24	22	26	26	22	24	22
TOTAL	***376***	***387***	***268***	***366***	***283***	***450***	***249***	***292***	***368***	***321***	***427***	***196***	***315***	***385***	***357***
COMBINATION TOTAL	***1680***					***1680***					***1680***				
	TOTAL ELM	**1253**		**TOTAL ANFIS**	**832**		**TOTAL SVM**	**875**		**TOTAL GPR**	**1119**	**TOTAL ENN**			**961**
STATION	TOTAL RANK (Evaluation by Data Combination)														
	Q(t-1)-Q(t)					Q(t-2)+Q(t-1)-Q(t)					Q(t-3),Q(t-2), Q(t-1)-Q(t)				TOTAL
2102	73					95					72				***240***
2122	66					83					91				***240***
2124	64					86					90				***240***
2131	75					87					78				***240***
2135	72					79					89				***240***
2145	68					87					85				***240***
2149	63					89					88				***240***
2151	61					75					104				***240***
2156	66					81					93				***240***
2158	67					82					91				***240***
2164	72					72					96				***240***
2166	83					73					84				***240***
2610	67					75					98				***240***
2612	69					81					90				***240***
COMBINATION TOTAL	***966***					***1145***					***1249***				***3360***

Taking the 14 stations selected for the Euphrates-Tigris basin into consider, it is seen that the model performance ranking appears to be ELM, GPR, ENN, SVM, ANFIS, which proves the eligibility of ELM, GPR and ENN techniques, which are rarely used for river stream. At the same time, this result shows that the problems and uncertainties in commonly used ANFIS and SVM models are solved in ELM, GPR and ENN models. Moreover, it is seen that the best data set combination is the one that takes the stream data from 1, 2 and/or 3 days ago as input and the current stream data as output.

3.RESULT

In this study, five different artificial intelligence techniques were used for daily river stream estimation and it was aimed to find the best technique. In this context, river stream estimations were made using ANFIS, ELM, ENN, SVM, GPR techniques and daily stream data from the climate reference periods between 1981-2010. Rank analysis was applied to decide the best model and it was observed that the method with the highest rank value was ELM. In addition, the performance ranking was observed to be ELM, GPR, ENN, SVM, and ANFIS respectively. These results show that ELM, GPR and ENN give much better results when compared with traditional artificial intelligence techniques such as ANFIS and SVM. This shows that these techniques are also reliable models for river stream modelling, and the problems seen in traditional methods can be solved, and these models can be applied more quickly. When the evaluation was made on the basis of the data combination, it was observed that the best combination was the one created with Q(t-3), Q(t-2), Q(T-1) inputs and Q(t) output. In this way, more than one data set type was examined and it was found that the results given by the models for different input numbers were consistent.

APPENDIX A Applicability of ANFIS, ELM, ENN, SVM and GPR approaches and streamflow forecasting, and hydrologic engineering fields.

Hydrological Processes	Scholars & Case study location	Time scale	Predictive models	Unique aspects or salient features
Precipitation Forecast	(Akrami et al. 2014)/ Malaysia	Monthly	connecting the wavelet decomposition method to ANFIS, ANFIS, ANN	It was recommended to make precipitation prediction by connecting the wavelet decomposition method to ANFIS and artificial neural networks. As a result of the study, it was seen that ANFIS based on wavelet decomposition performed better than ANN and ANFIS.
	(Mokhtarzad et al. 2017) /Tehran	Monthly	YSA, SVM, ANFIS (ın addıition to SPI)	In this study in which YSA, SVM and ANFIS techniques were compared for precipitation prediction, the input parameter was used as temperature, humidity and precipitation while the output parameter was SPI. In addition to the high accuracy of all models, SVM was found to provide the best performance.
	(Choubin et al. 2018)/ Iran	Time Series	Classification and regression trees (CART), ARIMA, ANFIS	CART, ARIMA and ANFIS were used for precipitation estimation and these methods were compared. It was seen that the CART method gave better results.
	(Li et al. 2018) / China	Monthly	variational mode decomposition (VMD), ELM, back propagation (BP) and Elman	In the study, ELM and VMD were used to make estimations through precipitation time series. Then, a comparison was made with the hybrid models BP and Elman neural network. It was observed that ELM gave better results than the others.
Evapotranspiration	(Ferreira et al. 2019) / Brazil	Daily	SVM, K-means, Cluster	SVM was used for evapotranspiration estimation. In addition, k-means and

				clustering method were used to group the meteorology stations. In this way, the performance of the models increased.
	(Tao et al. 2018)/Burkina Faso	Daily	ANFIS, ANFIS-FA	ANFIS-FA, a new hybrid intelligent ANFIS model, was proposed for evapotranspiration prediction. The model was created with a large number of meteorological inputs and it provided good performance .
	(Han et al. 2019)/ China	Monhly	XGBoots, multivariate adaptive regression splines (MARS), GPR	In this study in which evapotranspiration was estimated by comparing XGBoost, MARS and GPR techniques, it was concluded that the MARS model was superior.
Drought	(Khan et al. 2020)/ Pakistan	Time series	SVM, k-Nearest Neighbour (KNN) and Standardized Precipitation Evaporation Index (SPEI)	In this study, the first drought prediction for Pakistan, SVM and KNN were used, and SPEI was used for drought calculations.
	(Zhang et al. 2020)/ China	Yearly	autoregressive integrated moving average (ARIMA), wavelet neural network (WNN), SVM	Drought analysis was carried using SPEI drought index, and drought prediction modelling was performed with ARIMA, WNN and SVM. It was seen that ARIMA model gave better results.
	(Mokhtarzad et al. 2017)/Khorasan	3 monthly	artificial neural network (ANN), SVM, ANFIS, SPI	Drought analysis was performed by comparing ANN, SVM and ANFIS models, it was observed that the SVM model gave better results.
Air Quality	(Ghasemi and Amanollahi 2019)/ Kermanshah	Daily	ANFIS, forward selection (FS)	In this study, in which air quality was examined through ANFIS, FS and ANFIS models were developed and it was found to be a suitable method for air quality examinations.
	(Bhardwaj and Pruthi 2020)/ India	Time series	particle swarm optimization	In order to analyse an air pollutant, PSO and GA were used together with the ANFIS model, and as a result of

			(PSO) and genetic algorithm (GA)	this integration, it was seen that the model providing the best performance was ANFIS-PSO.
Soil Moisture	(Li et al. 2019)/ China	Time series	GPR	The results of the study, in which GPR was used for soil moisture and temperature estimation, show that GPR is better in predicting soil moisture.
	(Ji et al. 2019)/Hulan	Time series	stochastic weight particle swarm optimization algorithm (RandWPSO), ELM	In this study, ELM and RandWPSO models were used to measure soil moisture quality and to test the usability of ELM. The accuracy level of ELM was found quite high.
Water Level Estimation	(Hipni et al. 2013)/ Malaysia	Daily	SVM, V-fold cross-validation and the time lag	SVM was used to estimate the daily dam water level, SVM was used together with V-fold cross-validation and the time lag to find the best result. The best result (R; amount of precipitation, L; water level) was achieved in combination of R(t-2) L(t-2).
	(Deo and Şahin 2016)/ Eastern Queensland	Monthly	ANN, ELM	In the study in which water level estimation was performed using ANN and ELM models, it was concluded that ELM was superior in water level prediction.
	(Khan and Coulibaly 2006)/ North America	3-12 monthly	SVM, multilayer perceptron (MLP), seasonal autoregressive model (SAR)	In the study in which long-term estimation of lake water levels was made using SVM, SVM was compared with common artificial neural networks MLP and SAR, and it was seen that SVM gave better results.
Water Quality	(Azad et al. 2019)/ The Zayandehrood Basin	Time series	evolutionary algorithm(EA), ANN , ANFIS, ANFIS-PSO	In the study investigating the water quality using ANFIS, ANN and EA, those models were compared with ANFIS-PSO and it was seen that ANFIS-PSO gave better results.

Evaporation	(Mohamadi et al. 2020)/Mianeh and Yazd	Monthly	Shark algorithm (SA), d frefy algorithms (FFA),multilayer perceptron (MLP) radial basis function (RBF), ANFIS	ANFIS, RBF, MLP, RBF-SA, MLP-SA, RBF-FFA, MLP-FFA models were used for monthly evaporation estimation. It was observed that the ANFIS model gave better results when developed.
Sediment Transportation	(Safari et al. 2019)	Time series	Gene Expression Programming (GEP), ELM, Generalized Structure Group Method of Data Handling (GS-GMDH) ,Fuzzy c-means(FCM), FCM-ANFIS	In the study investigating sediment transport in open channels through GEP, ELM, GS-GMDH, FCM-ANFIS models, it was observed that GS-GMDH model gave better results.
Discharge Coefficient	(Azimi et al. 2017)	Time series	ELM	Genetic Algorithm (GA) - Least Square Estimator (GL) and adaptively developed ANFIS were used as R(ANFIS) and R-ANFIS(GL) for river stream modelling. It was seen that the R-ANFIS (GL) model gave better results.
River Stream Estimation	(Zhou et al. 2019)/ China	Time series	R-ANFIS, R-ANFIS(GL)	Genetic Algorithm (GA) - Least Square Estimator (GL) ve uyarlanabilir şekilde geliştirilmiş ANFIS; R(ANFIS) ve R-ANFIS(GL) şeklinde nehir akımı modellemesi için kullanılmıştır. Çalışmada R-ANFIS(GL) modelinin daha iyi sonuç verdiği görülmüştür.
	(He et al. 2014)/ China	Monthly	ANN, ANFIS, SVM	ANN, ANFIS and SVM were used in the study in which three different data-based models were used for river stream estimation. It was observed that SVM provided better performance than other methods and it was stated that these methods could be

			used in regions with complex topography.
(Rezaeianzadeh et al. 2014)/ Iran	Daily	multiple linear regression (MLR) ,multiple nonlinear regression (MNLR), ANN, ANFIS	NN, ANFIS, MLR and MNLR were used to estimate the maximum daily stream. In this study in which precipitation and stream data were used in different combinations for simulations, it was stated that the MNLR model was superior.
(Yaseen et al. 2019)/ Malaysia	Daily	EELM, ELM, SVM	In the study in which the ELM model was developed and compared with SVM in the form of EELM, it was seen that the developed ELM model has much superior features.
(Yaseen et al. 2016)/ Malaysia	Daily	ELM, SVR, single-layer feedforward neural network (SLFN)	In the study in which ELM, SVR (SVM) and SLFN models were used, ELM was suggested for river stream modelling and it was found that ELM was superior to other models.
(Adnan et al. 2019)	Daily	ELM-ANFISPSO, multivariate adaptive regression splines(MARS), M5 model tree (M5Tree)	In the study in which ELM was developed and used as OP-ELM, ANFIS PSO, MARS and M5Tree models were compared with OP-ELM and it was stated that OP-ELM was superior to other methods.
(Yaseen et al. 2020)/ Australia	Hourly	ENN, MARS, RVM, MPMR	In the study in which ENN, Multivariate adaptive regression splines (MARS), Minimax Probability Machine Regression (MPMR), Relevance Vector Machine (RVM) methods were applied for hourly river stream modelling, ENN was proposed for the first time for river stream and it was found to be superior to other models.

(Sun et al. 2014)/ ABD	Daily	GPR	In the study in which river stream estimations were made by using GPR for MOPEX basins, it was concluded that GPR performed well when long-term stream data were used.

DATA AVAILABILITY

The data used in the study Turkey's State Hydraulic Works Electrical Power Resources Survey and Development Administration current supplied by the General Directorate of the annual observations were obtained. Current observation annuals can be accessed at https://www.dsi.gov.tr/Sayfa/Detay/744. At the same time, MATLAB R2020a program was used for the techniques used. While MATLAB Toolbox is used for ANFIS, SVM, GPR techniques, MATLAB codes obtained from the web address http://www.ntu.edu.sg/home/egbhuang/ for ELM technique while developing the ENN technique at https://www.researchgate.net The code was developed with reference to the broadcast at the web address / publication / 269399412.

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