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A comparative study of artificial intelligence models for predicting monthly river suspended sediment load

Khalil REZAEI ✉, **Meysam VADIATI**

Kharazmi University, Faculty of Earth Sciences, Applied Geology Department, No. 43, Mofatteh, 15719-14911, Tehran, Iran

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Abstract

When high precision modelling is required, for example, with the estimation of suspended sediment load (*SSL*), data-driven models are preferred over physically-based numerical models for their real-time, short-horizon prediction ability. The investigation of *SSL*, as an important index in engineering practices assessment, like design and operation of the hydraulic structures not only shows the hydrological behaviour of the river, but also illustrates the valuable information about the water quality deterioration, surface-groundwater interaction and land-use changes of the watershed. The following data-driven methods were compared in order to predict *SSL* at the Seyra gauging station on the Karaj River in Iran: Fuzzy logic (FL), two adaptive neuro-fuzzy inference systems (i.e., ANFIS-GP and ANFIS-FCM models), an artificial neural network (ANN), and least squares support vector machine (LSSVM). Monthly average river flow and *SSL* data for 50 years were obtained from the Tehran Regional Water Authority (TRWA). The data was first divided into training, validation and test sets and the *SSL* was then predicted using the ANN, FL, ANFIS, and LSSVM models. The reliability of the applied models was evaluated by the correlation coefficient (*R*), root mean square error (*RMSE*), and mean absolute error (*MAE*). The results showed that the ANFIS models outperformed the ANN, FL, and LSSVM models for predicting *SSL* using the given input and output data. Overall, the performances of the artificial intelligence models used in the present study were satisfactory in predicting the non-linear behaviour of the *SSL*.

Key words: *artificial intelligence, data-driven methods, Karaj dam, suspended sediment load, the Karaj River*

INTRODUCTION

Anthropogenic influences along with multiple environmental parameters can lead to sediment release resulting in a reduction in river water quality [REZAEI 2015]. Suspended sediment load (*SSL*) can be a critical factor for the management of water resources, especially in terms of designing reservoirs, dams, and channels, and protecting aquatic habitats [KISI, ZOUNEMAT-KERMAN 2016; VAFAKHAH 2013].

Suspended sediment load (*SSL*) can be a critical factor for the management of water resources, especially in terms of designing reservoirs, dams, and channels, and protecting aquatic habitats [KISI, ZOUNEMAT-KERMAN 2016; VAFAKHAH 2013]. The downhill movement of eroded soil into water bodies can result in reservoir sedimentation, bridge scour, and reduced channel capacity [NOORI *et al*. 2016]. Large amounts of sediment can also be carried via suspension or bed load by river and stream flows. When the flow rate slows due to streambed flattening or when entering a pond or lake, the suspended load (i.e., the total amount of sand, silt, and clay-sized particles) then settles [BUYUKYILDIZ, KUMCU 2017]. *SSL* is affected by various factors, such as watershed area, vegetation, geology, and precipitation intensity and duration [HEIDARNEJAD *et al*. 2006]. Anthropogenic influences along with multiple environmental parameters can lead to sediment release resulting in a reduction in river water quality [REZAEI 2015; VADIATI *et al*. 2013;].

In recent years, artificial intelligence (AI) methods have played a key role in the forecasting of hydrological phenomena and the estimation of suspended sediment (*SS*) volumes. Numerous data-driven models have been used for estimating and modelling sediment load [JHA, BOM-

BARDELLI 2011]. Black box data-driven models have been applied to problems related to water resources because of their relative robustness to solve nonlinear problems more simply and their ability to automatically calibrate the model parameters [KISI 2008; KISI, ZOUNEMAT-KERMANI 2016]. The applications of AI models to predict *SSL* are categorized in Table 1. In this table, we have discussed selected examples among tested approaches and applications published around the world on the basis of the type of applied models, input variables and time interval. In a research study in Bam city in southeast Iran, REZAEI *et al*. [2009] used feed-forward neural network and interpolation function models to predict the distribution of soil and subsurface sediments. Furthermore, *SSL* was assessed by JIE, YU [2011] using artificial neural network (ANN) and least squares support vector machine (LSSVM) models in the Kaoping River in southern Taiwan. Additionally, VAFAKHAH [2013] applied ANN, Adaptive Neuro Fuzzy Inference System (ANFIS), co-kriging, and ordinary kriging methods for *SS* prediction. HASSAN *et al*. [2015] used an ANN-based model for the estimation of weekly sediment and their results revealed that ANN was highly efficient at estimating sediment load values. GOYAL [2014] utilized wavelet regression and the M5 decision tree algorithm for sediment yield modelling and then compared them with ANN models. The applied methods (i.e., wavelet regression and M5 decision tree algorithm) were found to outperform the ANN model. Similarly, SHAMAEI, KAEDI [2016] evaluated a neuro-fuzzy and wavelet neuro-fuzzy approach alongside the conventional SRC for suspended sediment concentration prediction and found the hybrid model of wavelet and neuro-fuzzy performed best. Furthermore, NOURANI *et al*. [2016] presented a two-step modelling strategy for handling the spatiotemporal variation of *SSL*. SARI *et al*. [2017] explored the application of the ANN model to forecast SSC using turbidity and water level data related to 59 SSC values, collected from 2013 to 2015. KISI, YASEEN [2019] introduced a novel hybrid AI approach to predict SSC in the Eel River, California. Their results showed superiority of the proposed model over the other models. Based on Table 1, ANN was found to be the most frequently applied model.

Despite a notable increase in the number of hydrological studies using AI data-driven models in recent years, there is still a demand for a comprehensive comparisons of ANN, fuzzy logic (FL), ANFIS, and LSSVM models, for *SSL* prediction. This is due to a gap in the literature related to the assessment of: (1) the effects of monthly average river flow (*Q*) on the precision and accuracy of *SSL* prediction, (2) the effects of model structure and parameter on the results of applied models, and (3) the efficiency of ANN, FL, ANFIS and LSSVM as practical models for research applications. Therefore, the objective of this research is to compare the performance of widely accepted AI models (i.e., ANN, FL, ANFIS and LSSVM) for *SSL* prediction.

STUDY AREA AND METHODS

DATABASE

The paper considers *SSL* prediction using ANN, FL, ANFIS-GP, ASNFIS-FCM and LSSVM. Monthly average river flow and *SSL* data for 50 years was collected from Seyra gauging station on the Karaj River in order to illustrate the performance of the different AI models. The river flow and *SSL* data were monitored by Tehran Regional Water Authority on a monthly basis. Data from a 50-year period, April 1967 to March 2017, was used. The first 30 years were used for the training step, the next ten years for the validation step, and the final ten years were used for the test step.

STUDY AREA

The Karaj River watershed (located between 52°2 and 51°32'E and between 35°52 and 36°11'N) has an estimated area of 850 km^2 and a boundary of 146 km along the southern slope of the Alborz mountain range. The highest and lowest points of the study area are 4200 and 1600 m, respectively. The Karaj River, one of the longest rivers in

Table 1. Past applications of artificial intelligence models to predict suspended sediment

References	Models				Input variables	Time interval
	ANN	FL	ANFIS	LSSVM		
KISI [2005]	✔		✔		Q_t, Q_{t-1}, SS_{t-1}	daily
ALP and CIGIZOGLU [2007]	✔				P_t, P_{t-1}, P_{t-2}, P_{t-3}, P_{t-4}, Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}	daily
KISI [2008]	✔				Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, SS_t, SS_{t-1}, SS_{t-2}, SS_{t-3}	daily
JIE and YU [2011]	✔			✔	Q_{t-3}, Q_{t-2}, Q_{t-1}, Q_t, Q_{t+1}, Q_{t+2}, Q_{t+3}	monthly
NOURANI *et al.* [2012]	✔				P_t, Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	daily
VAFAKHAH [2013]	✔		✔		P_t, P_{t-1}, P_{t-2}, P_{t-3}, Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}	daily
HASSAN *et al* [2015]	✔				Q_t, T_t, SS_t	weekly
ZOUNEMAT-KERMANI *et al.* [2016]	✔			✔	Q_t, SS_t	daily
NOURANI *et al.* [2016]	✔			✔	Q_{t-1}, Q_{t-12}, SS_{t-1}, SS_{t-2}, SS_{t-12}	monthly
KISI and ZOUNEMAT-KERMANI [2016]	✔		✔		Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	daily
BUYUKYILDIZ and KUMCU [2017]	✔		✔	✔	Q_t, Q_{t-1}, Q_{t-2}, SS_{t-1}, SS_{t-2}	daily
Current study	✔	✔	✔	✔	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	monthly

Explanations: ANN = artificial neural network; FL = fuzzy logic; ANFIS = adaptive neuro fuzzy inference system; SVM = support vector machines; SS = suspended sediment; *Q* = river flow; *P* = precipitation, *t* = time, *T* = temperature.
Source: own elaboration.

Iran, is roughly 66 km long and enters the Karaj Dam at the Seyra inlet station [HEIDARNEJAD *et al.* 2006]. The Karaj River that provides the drinking water for Tehran, capital city of Iran, was chosen to test the performance of the developed models. The main precipitation in the Karaj River basin falls from November to May. Based on the Köppen–Geiger climate classification system, the local climate is cold semi-arid. Snowmelt is a cause of peak flows in the summer. Monthly average stream flow and *SSL* data were collected at the Seyra gauging station on the Karaj River (station number: 41-101). The station is controlled by the Tehran Regional Water Authority (TRWA) and *SSL* is measured once or twice a month. Monthly average data for 50 years were obtained from the TRWA. The mean annual precipitation and temperature recorded at the station are 318 mm and 14.4°C, respectively. The station coordinates are described in Figure 1.

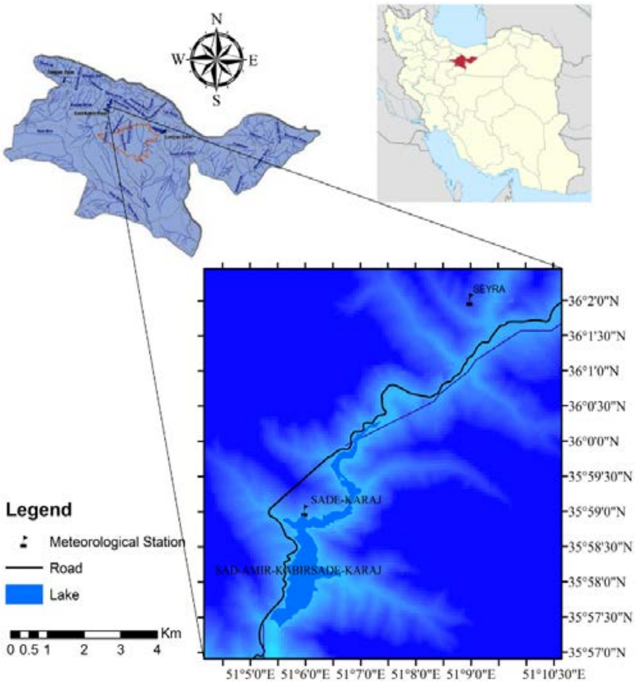

Fig. 1. The location of the Seyra gauging station on the Karaj River, Iran; source: own elaboration

ARTIFICIAL NEURAL NETWORKS (ANN)

ANN is a modelling approach used for non-linear problems that was originally inspired by the function of the human brain. It can handle multifaceted mapping among input and output data approximating non-linear functions. Since the physically or quasi-physically-based models need more data to delineate the hydrological behaviour of *SSL* in the river, and we cannot extract the mathematical relationship between the hydrological and physiographical characteristics of the watershed with *SSL*, then we could rely on ANN models that solve nonlinear problems based on the stream flow and *SSL* data. The multilayer perceptron (MLP) ANN, is the most frequently used class of neural networks and was, therefore, selected for the present study. In its simplest form, MLP consists of one input, one output, and one or more hidden layers [ANDERSON 1993]. One hidden layer has been found to be sufficient for solving complex nonlinear functions in hydrology. Finding the hidden node size is a key step. Among the numerous proposed methods for the recognition of the optimal number of neurons in the hidden layer, Eq. 1 was used to estimate the recommended upper limit of hidden nodes [MAIER, DANDY 2001]:

$$N^{H} = \min\left(\frac{2N^{1}+1;\, N^{TR}}{N^{1}+1}\right) \quad (1)$$

Where: N^H, N^1, and N^{TR} are the size of hidden nodes, input, and the training sample, respectively.

In the present study, the optimal size of hidden nodes was identified based on the widely used trial and error procedure. Tansigmoid and linear functions were selected as the transfer (i.e., activation) functions for the hidden and output nodes, respectively. It should be noted that the transfer function technically shows the ability of non-linear approximation of the ANN [KHALIL *et al.* 2015].

Among the various learning algorithms such as feed-forward back-propagation, RBF, gradient descent with momentum, and adaptive learning rate back propagation; Levenberg–Marquardt (LM), Bayesian regularization [ABRAHAM *et al.* 2003], the LM training algorithm was chosen as it is the most well-organized and powerful algorithm for training ANNs [KHALIL *et al.* 2015]. It can be calculated using the following equation:

$$y_i = f\left(\sum_{i=1}^{N} w_{ji} x_i + b_j\right) \quad (2)$$

Where: x_i and y_i are the i^{th} and j^{th} nodal value in the previous and present layers, respectively; b_j is the bias of the j^{th} node; w_{ji} is a weight connecting x_i and y_j; N_i is the number of nodes in the previous layer, and f is the activation function in the present layer. The general architecture of ANN is presented in Figure 2.

FUZZY LOGIC (FL)

Fuzzy set theory represents the uncertain information in mathematical form [ZADEH 1965] and is used for many purposes in the environmental sciences. A fuzzy set is defined as a membership function (MF) that assigns a domain of interest for the interval [0, 1]. An MF represents each fuzzy set, which has unclear boundaries and gradual transitions between the distinct sets, overcoming the inherent uncertainty [GRANDE *et al*. 2010]. This simple method can come up with a defined conclusion from ambiguous or imprecise information [KLIR, FOGER 1988]. Since FL is a promising tool to overcome the inherent uncertainty in different stages of measurement to the analysis of *SSL*, it is used in the present study to predict monthly river *SSL* in such a complex and uncertain environment. The membership functions may have different shapes including a Gaussian curve function (gussmf), triangular-shaped function (trimf), generalized bell function (gbellmf) and trapezoidal curve function (trapmf).

FL models are created using the Sugeno, Mamdani or Tsukamoto methods [MAMDANI, ASSILIAN 1975; VADIATI *et al*. 2019], all of which are commonly utilized in water resources studies. The main differences between these

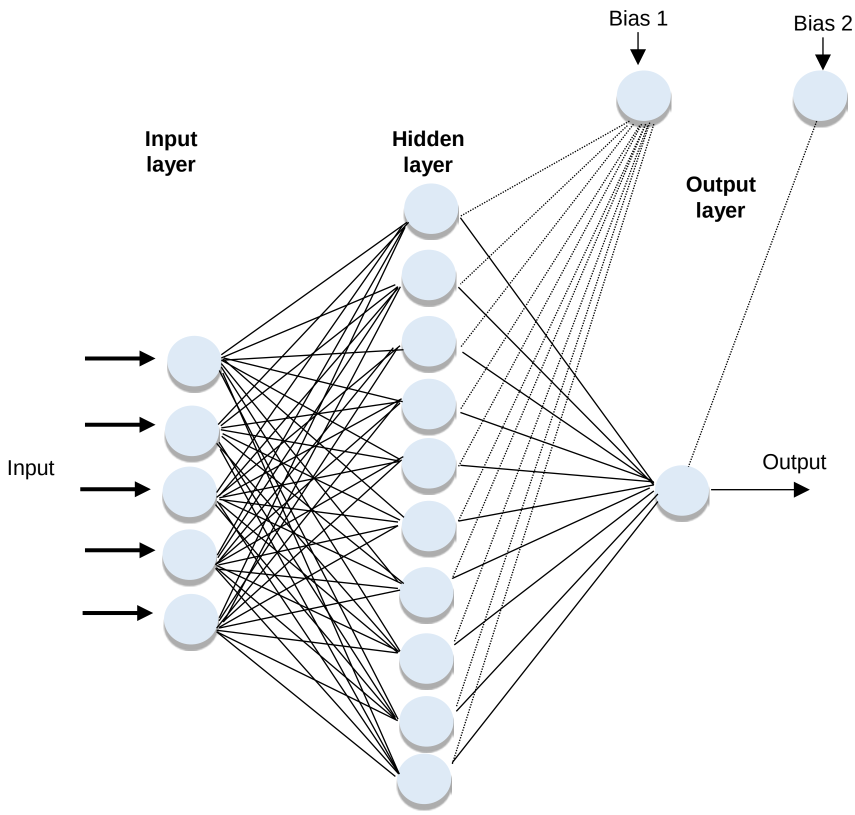

Fig. 2. The general structure of an artificial neural network (ANN); source: own elaboration

methods has to do with the aggregation and defuzzification processes used. In the case of this study, the Sugeno FL model was used for *SSL* prediction. Monthly average stream flow and *SSL* data were collected at Seyra gauging station on the Karaj River. Monthly average data for 50 years were obtained from the TRWA MATLAB Software [MathWorks 2014] was used to develop the FL model.

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

The data-driven model ANFIS incorporates the learning abilities of ANN and the reasoning capabilities of FIS. Any real continuous function can be approximated on a compact set with any grade of correctness [JANG *et al.* 1997]. ANFIS, as a feed-forward network that maps input variables on an output space, extracts fuzzy rules from certain input-output data [ABRAHAM *et al.* 2003]. Figure 3 represents the general architecture of ANFIS.

A standard ANFIS model should have a first layer supplying the input data and membership functions for subsequent layers and a second layer providing the product output. The third layer, the rule layer, matches the fuzzy rules and normalizes the weights. In the fourth layer, every node adapts with a node function, representing the contribution of the i^{th} rule in the total output. In the fifth layer, each node is fixed, indicating the total output as the incoming signal summation [JANG *et al.* 1997]. After that, the error signals spread backward. Premise parameter updating is done using a hybrid learning algorithm (i.e., the gradient descent and least-squares methods) introduced by JANG *et al.* [1997]. The Sugeno approach was used in the present study, to determine the values of the output variables. Several Sugeno models may be developed using subtractive clustering (SC), grid partitioning (GP), and fuzzy C-mean clustering (FCM) methods. In the case of this study, the most widely utilized strategies, GP and FCM, were used to generate an initial inference system. The ability of the ANFIS model is governed by the predefined interior ANFIS factors, including the step size and the number and shape of the MFs [EL-SHAFIE *et al.* 2007]. A propagation algorithm and its hybrid form with a least squares method are usually applied in FIS training to define the improved spreading of the MFs. The hybrid learning algorithm coding and ANFIS model used in this study were prepared using MATLAB Software [MathWorks 2014].

GRID PARTITION (GP)

Grid partition changes the input space into rectangular subspaces using a number of local fuzzy regions. Each linguistic variable can be divided by its values and represented by triangular/Gaussian MFs upon the input-output data. Consequently, grid partitions in feature space, resulting from fuzzy partitioning, are needed [HU 2007]. The least squares method was applied to calculate the fuzzy sets and parameters according to the partition and MF types. During the learning process, the fuzzy rules and functions were progressively trained [HU 2007]. The number of fuzzy rules is amplified as an exponential form by increasing the values of the input variables. For instance, if there are n input variables and m MFs for each rule, the total number of fuzzy rules equals $m \times n$. Applying the grid partition requires small input variables [SANIKHANI, KISI 2012].

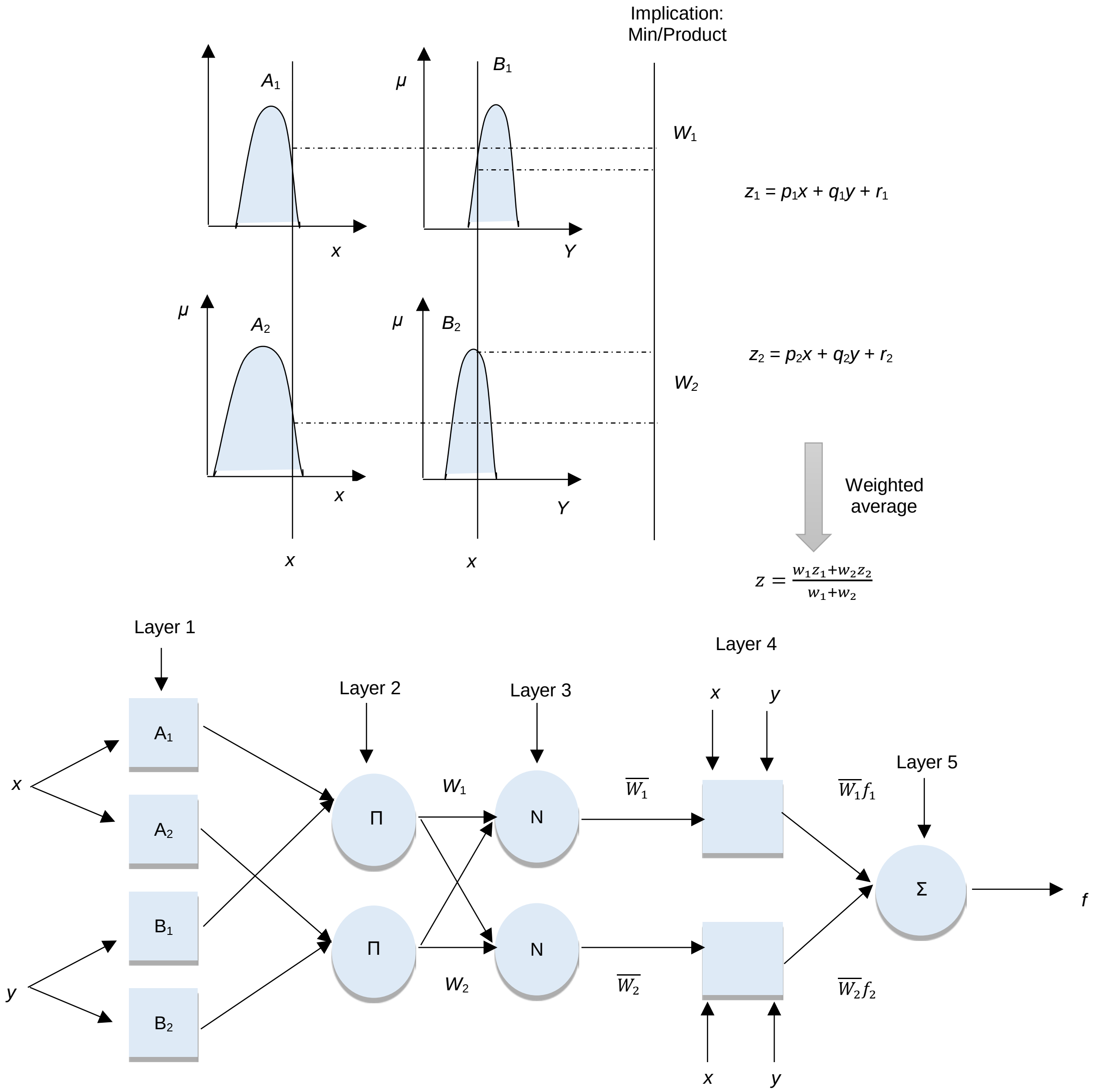

Fig. 3. The general structure of the adaptive neuro fuzzy inference system (ANFIS); source: own elaboration

FUZZY C-MEANS CLUSTERING

Clustering, as a training technique with several approaches, can be utilized for classifying data points into certain clusters. Fuzzy C-means clustering is a powerful technique introduced by JAIN and DUBESC [1988]. This technique categorizes the X data set into C groups and minimizes the errors regarding the weighted distance of each data point, X_i, toward all centroids of the C clusters. Afterward, the algorithm minimizes the objective function characterized as:

$$J_{FCM} = \sum_{c=1}^{c}\sum_{i=1}^{N} U_{ic}^{m}\|X_i - V_c\|^2 \quad (3)$$

Where: m ($m > 1$) is the fuzzifier exponent; N is the number of data points; and C, U_{ic}, X_i, and V are the number of clusters, the degree of belonging of the i^{th} data point to the c^{th} cluster, the input data, and the center of clusters, respectively. U_{ic} can be calculated using Equation (4) [BEZDEK *et al*. 1984].

$$U_{ic} = \frac{1}{\sum_{i=1}^{c}(d_{ic}^2/d_{ij}^2)^{1/(m-1)}} \quad (4)$$

After initializing the center vectors, centers are recalculated as:

$$v_c = \frac{\sum_{j=1}^{N} U_{jc}^{p} x_j}{\sum_{j=1}^{N} U_{jc}^{p}} \quad (5)$$

LEAST SQUARES SUPPORT VECTOR MACHINE

The support vector machine (SVM) model was developed based on statistical learning theory through the minimization of structural risk theory resulting in a reduction of both the experimental risk and the confidence interval in order to, ultimately, attain an ideal generalization ability

[RAGHAVENDRA, DEKA 2014]. LSSVM is a special type of SVM that was originally developed by CORTES and VAPNIK [1995] and can be used for the prediction of *SSL*. Using this method for training data we have: $\{(x_i + d_i)\}_i^N$ where. VAPNIK [2013] introduced the following optimization problem with an e-insensitivity loss function:

$$\text{minimize: } \frac{1}{2}\|\omega\|^2 + C\left(\sum_i^N(\xi_i + \xi_i^*)\right) \tag{6}$$

$$\text{subject to} \begin{cases} \omega_i * \emptyset(x_i) + b_i - d_i \le \epsilon + \xi_i^*, \quad i = 1,2,\dots,N \\ d_i - \omega_i * \emptyset(x_i) - b_i \le \epsilon + \xi_i, \quad i = 1,2,\dots,N \\ \xi_i, \xi_i^*, \quad i = 1,2,3,\dots,N \end{cases} \tag{7}$$

Where: x_i is the input vector, d_i is the desired value, and N is the total number of data patterns, ξ_i and ξ_i* are slack variables that penalize training errors by the loss function over the error tolerance ξ_i and C is a positive adjustment factor that regulates the degree of the experimental error in optimization problems.

Several algorithms have been recommended for solving the dual optimization problem related to the LSSVM [SHEVADE *et al*. 2000]. Conventional quadratic programming algorithms require enormous amounts of memory for the kernel matrix calculation and have hitches in their application that are not appropriate for complex problems. The sequential minimal optimization (SMO) algorithm, introduced by PLATT [1999], was employed in this study. It is an analytical solution of a subset, more details about SMO can be found in paper by PLATT [1999]. The optimal numbers of C and γ (i.e., kernel width parameters) are often determined via the trial and error approach. When the γ is very large, the input patterns tend to appear very similar, leading to the underfitting of the function. Contrarily, when γ is too small, overfitting may occur [CHANG *et al.* 2005]. The C factor trades off between training error and model complexity (i.e., the weights of model size) [BASAK *et al.* 2007]. When C is too small, it implies that the fitting did not succeed, while an excessively large C will overfit the data as well as the noise [LENDASSE *et al.* 2005]. All LSSVM processes in this study were performed using the present programming codes in the Library for Support Vector Machines (LIBSVM) software [CHANG, LIN 2011]. Figure 4 presents the common construction of an LSSVM.

MODEL DEVELOPMENT

The monthly average river flow, Q (m^3·s^{-1}), and *SSL* (Mg·day^{-1}) were combined in several ways for the prediction of *SSL* for the Karaj River, Iran. SSL_t, as the *SSL* at time t, and the Q (i.e., Q_t, $Q_{t\text{-}1}$ to $Q_{t\text{-}3}$) are the input data. Generally, the data used in data-driven models should be equally normalized in order to all obtained data throughout the training phase. Equation (8) expresses a simple linear mapping formula for data normalization [NOURANI *et al.* 2013]:

$$r_i = \frac{I_i - I_{\min}}{I_{\max} - I_{\min}} \tag{8}$$

Where: I_i is the real value; $I_{\max}$ and $I_{\min}$ are the maximum and minimum values, respectively.

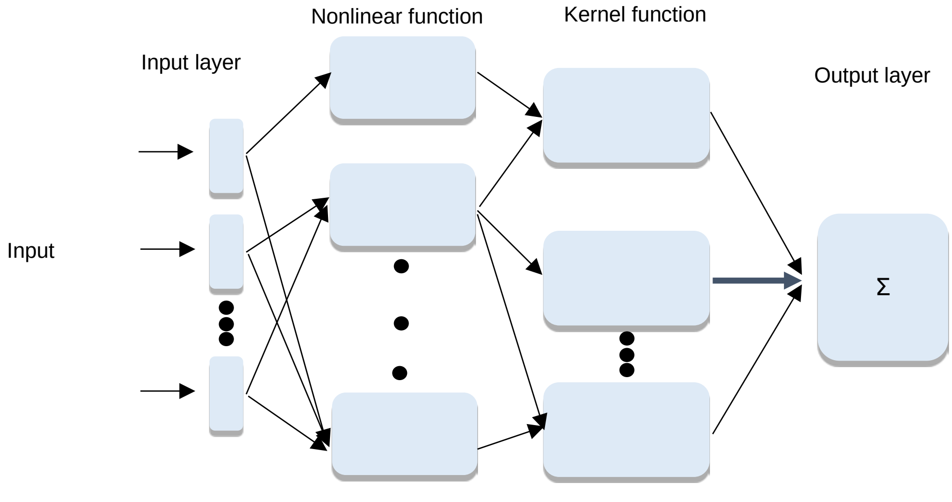

Fig. 4. The common construction of a least squares support vector machine (LSSVM); source: own elaboration

Table 2. The statistical parameters of the data set for the Seyra gauging station, the Karaj River, Iran

Data set	Data type	Mean	Standard deviation	Skewness	Max	Min	Max/Mean
Training	Q (m^3·s^{-1})	29.3	28.4	5.2	321	0.24	10.9
	SSL (Mg·day^{-1})	6 563	19 699	8.01	245 565	0.37	37.4
Validation	Q (m^3·s^{-1})	12.75	11.72	1.65	54.40	2.82	4.27
	SSL (Mg·day^{-1})	1 051	3 092	3.86	17 073	6.80	16.24
Test	Q (m^3·s^{-1})	18.67	20.67	2.03	102.19	0.52	5.47
	SSL (Mg·day^{-1})	1 917	6 689	5.59	49 578	2.50	25.86

Explanations: Q = monthly average river flow, *SSL* = suspended sediment load.
Source: own study.

Thus, the following combinations of the present (Q_t) and previous monthly average river flows ($Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$), for *SSL* prediction, were selected based on the correlations among the inputs and output:
(1) Q_t;
(2) Q_t, $Q_{t\text{-}1}$;
(3) Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$;
(4) Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$;

Table 2 shows the statistical factors of stream current and sediment data.

The Seyra gauging station on the Karaj River has high maximum-mean ratios (X_{max}/X_{mean}) of sediment data. In the training, validation and test steps, the X_{max}/X_{mean} data of the stations ranged from 0.37 to 245 565 Mg·day^{-1} for the training step, 6.8 to 17 073 Mg·day^{-1} for the validation step, and 2.5 to 49 578 Mg·day^{-1} for the test step.

EFFICIENCY CRITERIA

To evaluate the performance of the prepared model, statistical criteria including the mean absolute error (*MAE*), the root mean square error (*RMSE*), and correlation coefficient (*R*) were used as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|SS_{Si} - SS_{Oi}| \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(SS_{Si}-SS_{Oi})^2}{N}} \tag{10}$$

$$R = \frac{(\sum_{i=1}^{N}(SS_{Oi}-\overline{SS_O})(SS_{Si}-\overline{SS_S}))^2}{\sum_{i=1}^{N}(SS_{Oi}-\overline{SS_O})^2\sum_{i=1}^{N}(SS_{Si}-\overline{SS_S})^2} \tag{11}$$

Where: SS_{Oi}, SS_{Si}, $\overline{SS_O}$, $\overline{S_S}$, and N are the observed suspended sediment load (*SSL*) of the i^{th} data, simulated *SSL* of the i^{th} data, the mean of observed *SSL*, the mean of estimated *SSL*, and the number of observations, respectively.

RESULTS AND DISCUSSION

ARTIFICIAL NEURAL NETWORK (ANN) MODEL

Different input combinations for the ANN model (i.e., one to four) were evaluated based on the *SSL* in the Karaj River, Iran, in training, validation and test data sets. The results of several combinations are presented in Table 3. The ANN model using combination 2 (i.e., Q_t and $Q_{t\text{-}1}$) as the input had the lowest *RMSE* and *MAE* and the highest *R* in the validation and test steps. It was therefore selected as the best-fit model for *SSL* prediction for the present study. The number of neurons in the hidden layer was determined based on trial and error, as in previous studies [KHALIL *et al*. 2015]. The number of nodes was changed from 1 to 10 until the model no longer showed significant performance improvements. For instance, the best architecture of ANN for combination 4, was recognized as 4-2-1, indicating 4 input, 2 hidden, and 1 output nodes (Tab. 3). Figure 5 presents the observed and simulated *SSL* values using the prepared ANN for the four input combinations.

FUZZY LOGIC (FL) MODEL

The FL model was also evaluated based on the *SSL* of the Karaj River using different input combinations. The performance results are shown in Table 4.

The parameter radius used in FL model development was chosen from 0.2 to 0.9, resulting in the outcomes given in Table 4. Since combination 1 showed the best *RMSE*, *MAE*, and *R* in both the training and test sets, it was selected as the best-fit model. The parameter radius for combination 1 was selected as 0.5 (Tab. 4). Figure 6 presents the observed and simulated *SSL* values, using the FL model.

Table 3. The performance results of the different input combinations for artificial neural network in the validation and test steps and using data from the Seyra gauging station, the Karaj River, Iran

Input combination	Structure	Validation			Test		
		RMSE (Mg·day^{-1})	*R*	*MAE*	*RMSE* (Mg·day^{-1})	*R*	*MAE*
Q_t	(1,1,1)	3 321.3	0.64	1 786.2	8 526.9	0.63	4 201.8
Q_t, $Q_{t\text{-}1}$	(2,2,1)	3 210.1	0.65	1 671.3	8 202.4	0.64	3 900.3
Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$	(3,2,1)	3 632.5	0.61	1 856.3	9 266.8	0.60	4 429.0
Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$	(4,2,1)	3 487.1	0.63	1 973.5	7 820.5	0.70	4 061.5

Explanations: Q = river flow, *RMSE* = the root mean square error, *R* = correlation coefficient, *MAE* = mean absolute error.
Source: own study.

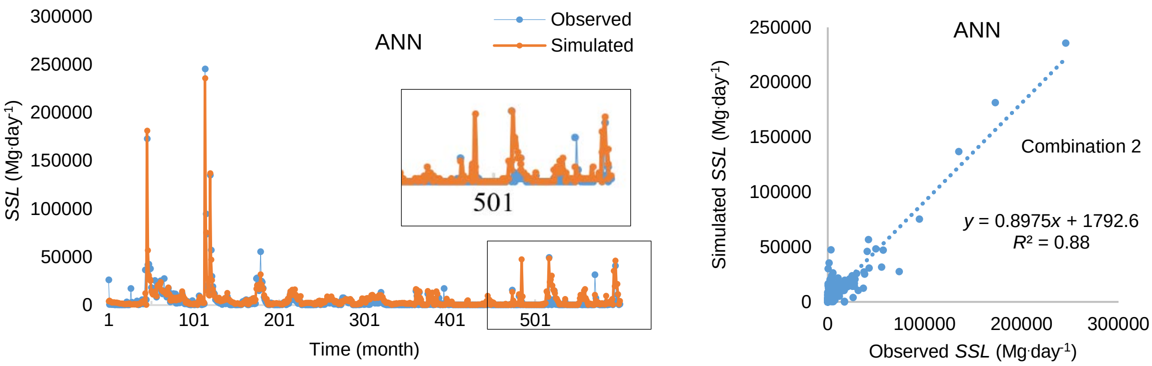

Fig. 5. The observed and simulated suspended sediment load for combination 2 using the artificial neural network (ANN) model and data from the Seyra gauging station, the Karaj River, Iran; source: own study

Table 4. The performance results of the different input combinations using the fuzzy logic model in the validation and test steps and data from the Seyra gauging station, the Karaj River, Iran

Input combination	Radius	Validation			Test		
		RMSE (Mg·day^{-1})	*R*	*MAE*	*RMSE* (Mg·day^{-1})	*R*	*MAE*
Q_t	0.5	6 672.5	0.67	2 349.0	9 070.6	0.63	7 147.3
Q_t, $Q_{t\text{-}1}$	0.5	9 486.5	0.63	7 027.1	9 004.6	0.64	6 865.5
Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$	0.5	9 223.7	0.63	6 648.6	9 517.3	0.62	6 875.2
Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$	0.5	9 073.8	0.65	6 475.8	9 368.6	0.64	6 673.3

Explanations as in Tab. 3.
Source: own study.

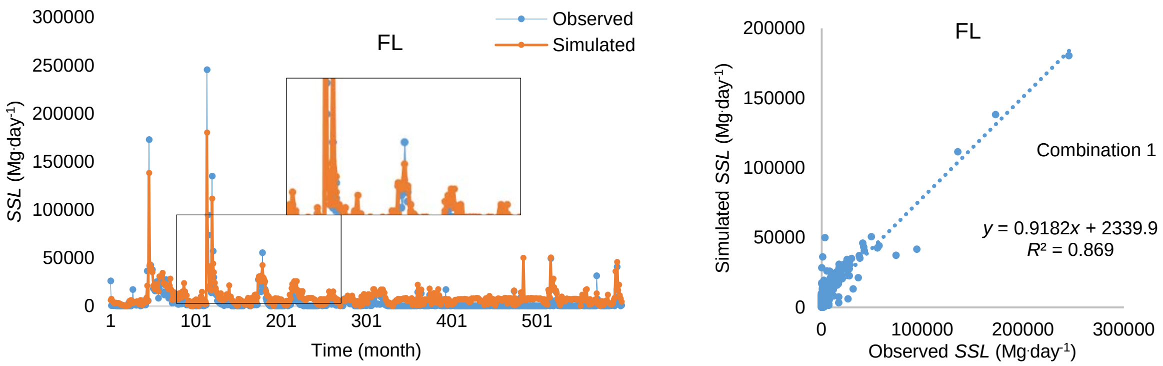

Fig. 6. Observed and simulated suspended sediment load for combination 1 using the fuzzy logic (FL) model and data from the Seyra gauging station, the Karaj River, Iran; source: own study

ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS) MODEL

The ANFIS model removes the expert presence of a fuzzy expert system while retaining the advantages. The performance results of the different input combinations of both ANFIS models (i.e., ANFIS-GP and ANFIS-FCM) are presented in Table 5. Looking at the table it becomes evident that for both ANFIS models combination 4 (Q_t to $Q_{t\text{-}3}$) provided the best results when used as the input. The commonly used method for building the ANFIS model was also applied in the present work to construct the neuro-fuzzy models. Various membership functions (MFs) were used for the ANFIS architecture and different numbers of MFs were tested in order to select the optimum model. Sugeno's fuzzy approach was used to establish the output values from the input data of the FIS architecture. Adjusting the type and the number of MFs is an important process to obtain an optimal fuzzy system. The nature of data and the subject to be solved along with the expert knowledge delineate the best MFs. Therefore, in the present study, the trial and error approach and expert knowledge at the same time were utilized to determine the type and the number of MFs for ANFIS models. In the interest of minimizing the time and calculation volume, modelers should avoid using a large number of MFs [SHIRI, KISI 2011]. Among the different possible types of MFs, the gussmf was found to give the best output results. For instance, using input combination 4, the ANFIS model had 2 gussmf MFs for the inputs. Figure 7 illustrate the observed and forecasted *SSL* values using the ANFIS-GP and ANFIS-FCM models.

LEAST SQUARES SUPPORT VECTOR MACHINE (LSSVM) MODEL

The LSSVM model was evaluated using different combinations of datasets as inputs and the performance

Table 5. Performance results of the different input combinations using adaptive neuro-fuzzy inference system – grid partition (ANFIS--GP) and adaptive neuro-fuzzy inference system – fuzzy C-mean clustering (ANFIS-FCM) in the validation and test steps and data from the Seyra gauging station, the Karaj River, Iran

ANFIS type	Input combination	Structure	Validation			Test		
			RMSE (Mg·day^{-1})	*R*	*MAE*	*RMSE* (Mg·day^{-1})	*R*	*MAE*
ANFIS-GP	Q_t	(2, Gaussmf)	9 794.2	0.70	3 098.8	6 290.9	0.68	3 210.8
	Q_t, $Q_{t\text{-}1}$	(2, Gaussmf)	8 351.3	0.68	3 173.9	5 059.0	0.73	2 387.1
	Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$	(2, Gaussmf)	7 347.6	0.68	2 819.7	6 211.9	0.66	3 823.5
	Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$	(2, Gaussmf)	5 193.8	0.69	2 171.5	5 368.0	0.70	2 221.9
ANFIS-FCM	Q_t	(2, Gaussmf)	9 794.2	0.70	3 098.8	6 762.4	0.53	2 420.7
	Q_t, $Q_{t\text{-}1}$	(2, Gaussmf)	7 536.0	0.69	2 852.4	5 950.5	0.69	2 473.1
	Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$	(2, Gaussmf)	7 306.7	0.71	2 986.2	5 973.3	0.71	2 806.3
	Q_t, $Q_{t\text{-}1}$, $Q_{t\text{-}2}$, $Q_{t\text{-}3}$	(2, Gaussmf)	7 227.5	0.71	3 255.5	7 227.5	0.71	3 255.5

Explanations as in Tab. 3.
Source: own study.

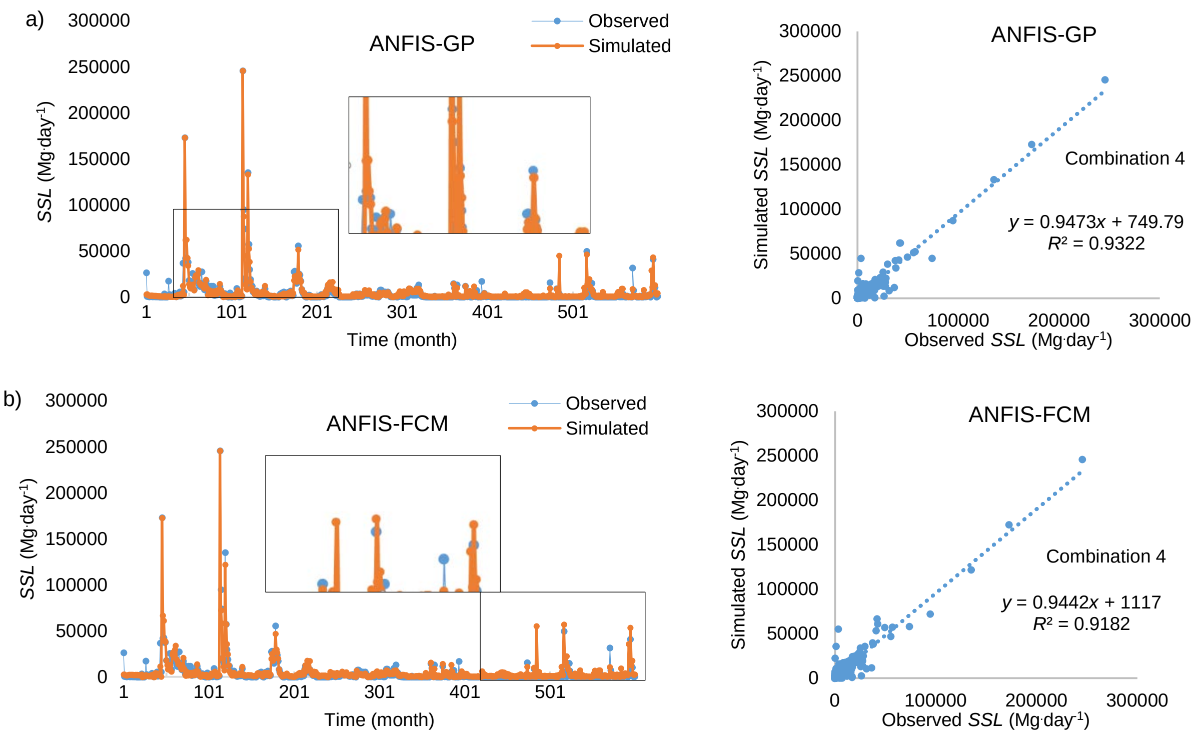

Fig. 7. Observed and simulated suspended sediment load for combination 4 using the two adaptive neuro-fuzzy inference systems models and data from the Seyra gauging station, the Karaj River, Iran: a) ANFIS-GP, b) ANFIS-FCM; source: own study

results for the validation and test steps are presented in Table 6. It was concluded that the LSSVM model with combination 1 as the input had the best *RMSE*, *MAE*, and *R* results for the training and test periods. Therefore, it was chosen as the best model for *SSL* estimation. The radial basis function (RBF) was recognized as a proper kernel function for this study. Different values for parameter *C* and the kernel function parameter γ were determined for the LSSVM based on the trial and error method. The optimal values of *C* and γ for different combinations were 20 and 0.5, respectively (Tab. 6). Figure 8 presents the observed and predicted *SSL* values using the LSSVM model.

Table 6. Performance results of the different input combinations using the least squares support vector machine model in the validation and test steps; data are from the Seyra gauging station, the Karaj River, Iran

Input combination	Parameter *C*, γ	Validation			Test		
		RMSE (Mg·day^{-1})	*R*	*MAE*	*RMSE* (Mg·day^{-1})	*R*	*MAE*
Q_t	20, 0.5	5 175.2	0.69	2 113.7	5 641.3	0.69	2 074.8
Q_t, Q_{t-1}	20, 0.5	6 288.9	0.65	2 839.9	5 151.8	0.66	2 215.9
Q_t, Q_{t-1}, Q_{t-2}	20, 0.5	6 273.1	0.65	3 119.7	5 171.0	0.66	2 594.6
Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	20, 0.5	6 380.6	0.64	3 276.7	5 272.2	0.65	2 754.3

Explanations: *C* = kernel width parameter, γ = kernel width parameter, the others as in Tab. 3. Source: own results.

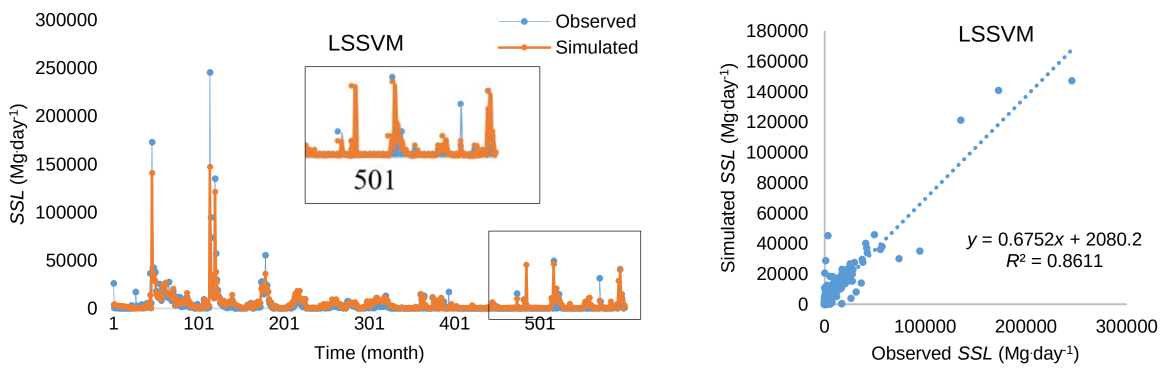

Fig. 8. Observed and simulated suspended sediment load for combination 1 using the least squares support vector machine (LSSVM) model and data are from the Seyra gauging station, the Karaj River, Iran; source: own study

COMPARISON OF RESULTS FROM THE DIFFERENT MODELS

To obtain a comprehensive evaluation of the ANN, FL, ANFIS-GP, ANFIS-FCM and LSSVM models, the different combination (1 to 4) for the developed models were compared on the basis of river flows (Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}). Although the results showed that all AI models could predict *SSL* appropriately, ANN results better for combination 2 rather than other input combinations. The results of combination 1 were better than other input parameters for FL and LSSVM models. Also, results showed that both ANFIS models could predict *SSL* for combination 4 (Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}) appropriately, but for other combination, the performance of the models was not satisfactory. The optimal architecture for ANN has 2 hidden layers and the parameter radius was 0.5 for FL. Also, For ANFIS model the two gussmf MFs for the inputs give the best output results. The best values of C and γ for LSSVM were 20 and 0.5 for all combination. Therefore, the comparative analysis of the optimum input combinations and models structure were checked at the same time using the given input and output data.

From the results of AI models (Tabs. 3–6), it is evident that the statistical indices of each model used in the present study were satisfactory. Based on the values of NSE criterion, the overall results of *SSL* prediction using the ANFIS models were better than the other models. A comparison of the *RMSE* and *R* values among the models showed that both ANFIS models had the best performance. However, the results showed that the ANFIS models outperformed the other models for predicting *SSL* using the given input and output data. The outcomes of the present study are consistent with those of KISI and ZOUNEMATKERMANI [2016] who compared ANFIS-FCM and ANN models. Moreover, it was observed that all models provided good results based on *MAE*, *RMSE*, and *R* criteria. Overall, the performances of the ANN, FL, ANFIS-GP, ANFIS-FCM, and LSSVM models used in the present study were satisfactory.

CONCLUSIONS

Accurate and reliable suspended sediment load (*SSL*) prediction in rivers is a significant issue in watershed management due to its effects on designing and monitoring of hydraulic structures This study explored the potential usage of artificial intelligence techniques (i.e., ANN, FL, ANFIS-GP, ANFIS-FCM and LSSVM) in predicting river *SSL* based on present and previous monthly average river flows (Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}). The Seyra gauging station on the Karaj River, Iran was selected to test data-driven models based on the monthly data from the 50-year period. Using four antecedent combination inputs, containing Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, the present study tried to generate the best-fit model. The models' performances were assessed by global statistics: *R*, *RMSE*, and *MAE*. All models generally showed low *RMSE* and *MAE* and high *R* and results were satisfactory. Overall, the results of various models applied in this study showed that the LSSVM had the best performance in forecasting the multifaceted, non-linear behaviour of the *SSL*. This study could be used as a guide for using artificial intelligence methods in estimating the *SSL* in rivers in the future.

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