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Suspended Sediment Load Prediction using Artificial Intelligence Techniques: Comparison between Artificial Neural Network (ANN), Adaptive Neuro-fuzzy Inference Systems (ANFIS), Group Method of Data Handling (GMDH), and Least Square Support Vector Machines (LS-SVM)

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Abstract:	Accurate prediction of suspended sediment (SS) concentration is a difficult task for water resources projects. In recent years, new methodologies such as artificial intelligence (AI) algorithms have been applied for sediment load estimation and these models have provided efficient results. The present study investigates the abilities of four distinct AI approaches for estimating monthly- SS load in Roodak station on Jajrood River, one of the longest waterways in the north of Iran, using the combinations of the present and antecedent monthly river flow data. This study aims to compare the predictive ability of artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), group method of data handling (GMDH), and least square support vector machines (LS-SVM) applied to predict the SS load. To develop the models, the monthly average river flow and the SS data for 50 years were obtained from Tehran regional water authority. Data were separated into three subsets (training, validation, and testing) and the SS concentration was predicted where the reliability of utilized approaches was assessed by statistical criterion including the correlation coefficient (R), mean absolute error (MAE) and root mean square error (RMSE). A comparison of the developed models revealed that the use of antecedent average river flow is able to enhance the prediction precision of suspended sediment concentration. The results indicate that the LS-SVM model generated superior results than the other models in terms of the mean error criteria, showing the ability of the model to reasonably predict the observed SS load values.
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Editor-In-Chief
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Dear Dr. Al-Amri,

Enclosed is a manuscript to be considered for publication in the Arabian Journal of Geosciences that Prof. Pradhan from University of Technology Sydney, Vadiati from Kharazmi University and Nadiri from University of Tabriz have collaborated in this research.

The manuscript entitled "Suspended Sediment Load Prediction using Artificial Intelligence Techniques: Comparison between Artificial Neural Network (ANN), Adaptive Neuro-fuzzy Inference Systems (ANFIS), Group Method of Data Handling (GMDH), and Least Square Support Vector Machines (LS-SVM)".

The manuscript is a comprehensive comparisons of models using ANN, ANFIS, GMDH, and LS-SVM for suspended sediment load prediction and to the best of our knowledge, this study is the first review to consider the application of GMDH to predict monthly river suspended sediment load. Moreover, the purpose of the present research is also to survey the precision and the accuracy of sediment load prediction in earth system science and sedimentology field and hopefully would be suitable for publication in the Arabian Journal of Geosciences

Sincerely,

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Suspended Sediment Load Prediction using Artificial Intelligence Techniques: Comparison between Artificial Neural Network (ANN), Adaptive Neuro-fuzzy Inference Systems (ANFIS), Group Method of Data Handling (GMDH), and Least Square Support Vector Machines (LS-SVM)

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Abstract

Accurate prediction of suspended sediment (SS) concentration is a difficult task for water resources projects. In recent years, new methodologies such as artificial intelligence (AI) algorithms have been applied for sediment load estimation and these models have provided efficient results. The present study investigates the abilities of four distinct AI approaches for estimating monthly- SS load in Roodak station on Jajrood River, one of the longest waterways in the north of Iran, using the combinations of the present and antecedent monthly river flow data. This study aims to compare the predictive ability of artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), group method of data handling (GMDH), and least square support vector machines (LS-SVM) applied to predict the SS load. To develop the models, the monthly average river flow and the SS data for 50 years were obtained from Tehran regional water authority. Data were separated into three subsets (training, validation, and testing) and the SS concentration was predicted where the reliability of utilized approaches was assessed by statistical criterion including the correlation coefficient (R), mean absolute error (MAE) and root mean square error (RMSE). A comparison of the developed models revealed that the use of antecedent average river flow is able to enhance the prediction precision of suspended sediment concentration. The results indicate that the LS-SVM model generated superior results than the other models in terms of the mean error criteria, showing the ability of the model to reasonably predict the observed SS load values.

Keywords: Data-driven methods, Fuzzy logic, Artificial intelligence, Jajrood River, Suspended sediment concentration.

1. Introduction

The use of water resources for drinking, bathing, industry and agriculture have led such waters to become widely compromised, and water quality degradation to become an issue of global concern (Vadiati et al. 2018). Anthropogenic impacts alongside various other ecological parameters can cause sediment release in riverine waters (Yang et al. 2015). Suspended sediment load (SSL) is a determining factor in some natural issues, such as designing the reservoirs, dams, and channels, protecting the aquatic territories, and watershed management (Partal and Cigizoglu 2008; Kisi and Zounemat-Kerman 2016). Sediment yield is also affected by several aspects such as watershed area, geology, vegetation, and the intensity and duration of precipitation (Heidarnejad et al. 2006; Zhu and Li 2014; Noori et al. 2016). Suspended sediment (SS) in water river can cause a degradation of the quality of drinking water, which is likely to impact agriculture activities (Ahn et al. 2017). Therefore, considering the importance of SSL in river systems and its ecological effects, the prediction of SSL is expected to be a valuable task for an extensive variety of engineering design problems (Nourani and Andalib 2015; Afan et al. 2016).

Generally speaking, a number of reviews have been performed in demonstrating the sediment transport processes. Precise prediction of the sediment content in the river is somewhat troublesome (Partal and Cigizoglu 2008). Some investigations have been carried out with the aim to decrease the complexities of the problem (Olyaie et al. 2015). In this regard, mathematical models including the conventional multiple linear regression (MLR), sediment rating curve (SRC), and autoregressive-based models have been extensively employed for SS prediction (Rajaee 2011). Cherif et al (2017) predicted the sediment yield in Northwest Algeria, Wadi El Hammam, at storm period during a 22-year period using SRC method. Also Hassanzadeh et al (2018) investigated the dam reservoir hydrography to optimize the correction coefficients of SRC in the

Karkheh dam, west Iran. In another research, the river channel morphology by Biswas et al. (2018) have studied to evaluate the sediment size alteration and flow behavior after the road bridge construction.

Recently, the artificial intelligence (AI) methods have been used for forecasting the hydrological phenomena and estimation of suspended sediment volume (Kişi 2005; Nourani et al. 2012; Zounemat-Kermani et al. 2016; Talebi et al. 2017; Ahn et al. 2017). Various data-driven models have also been developed for estimating and modeling the sediment load as they can address nonlinear correlations between input and output dataset (Jha and Bombardelli 2011; Kisi and Zounemat-Kerman 2016). In this context, among the other models, artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), group method of data handling (GMDH), least square support vector machine (LS-SVM), and search optimization methods have been widely applied. In published literature, data-driven methods have been utilized extensively for estimating the SSL based on stream flow and sediment properties (Alp and Cigizoglu 2007; Melesse et al. 2011; Zheng et al. 2011; Mustafa et al. 2012; Ebtehaj and Bonakdari 2014; Nourani and Andalib 2015; Makarynskyy et al. 2015; Hassan et al. 2015; Chen and Chau 2016; Ouellet-Proulx et al. 2016; Ulke, et al. 2017; Buyukyildiz and Kumcu 2017;). However, only a few reviews the SSL simulation problems.

Doğan et al. (2007) found the superiority of artificial intelligence models including ANNs, NF, MLR, and SRC in time series prediction on the Little Black River gauging stations and Salt River. Misra et al. (2009) applied the SVM model for runoff and SSL prediction. These researchers stated that the SVM model was capable of providing significant improvements in training, calibration, and validation stages, which were distinct from the ANN model. Cobaner et al. (2009) applied the ANN and ANFIS model to deal with gauge SSL by utilizing hydro-meteorological datasets. Melesse et al. (2011) applied the ANN method to estimate the daily SSL. Senthil Kumar et al. (2011) made an attempt to predict the SSC by employing fuzzy logic (FL), ANN modelsand decision tree algorithms. Vafakhah (2013) applied the ANN, ANFIS, and two kriging methods for SS prediction. Azamathulla et al. (2013) have used GEP model to predict SSL three Malaysian rivers and compared the results with the ANFIS model. Kakaei Lafdani et al. (2013) investigated the ability of the ANN and the SVM methods to predict the SSL. These authors presented ANN and SVM methods using Gamma Test to select the ideal input combination. Kitsikoudis et al. (2014) applied the ANN methods to forecast sediment bed load in Idaho River in the USA by examining the capacity of several input data set. Hassan et al. (2015) applied an ANN-based method to predicti the SSL and uncovered the high accuracy of ANN in evaluating the sediment load values. Also, Olyaie et al. (2015) studied ANNs, ANFIS, and SRC models for SSL forecasting and found that the neuro-wavelet shows the best estimation among the selected methods. Chen and Chau (2016) employed an FF neural network model for the estimation of SSL by integrating the equation of fuzzy pattern recognition and the equation of ANNs. The results of their study revealed that the outcome is suitable for modeling the SSL. Shamaei and Kaedi (2016) examined the neuro-fuzzy model and the hybrid wavelet neuro-fuzzy alongside the conventional SRC in SSL forecasting and found that the wavelet neuro-fuzzy was the best model. Moreover, the study of Nourani et al. (2016) attempted to show a two-step modeling approach for dealing with the spatiotemporal variety of SSL. Riahi-Madvar and Seifi (2018) applied the ANN and ANFIS model to predict bed load transport using the different combination of input parameters.

Despite the prominent increase in the number of studies conducted on hydrological issues using AI data-driven models, there are still few comprehensive comparisons of models using ANN, ANFIS, GMDH, and LS-SVM for SS prediction in the literature. To the best of our knowledge, this study is the first review to consider the application of GMDH to predict monthly river SSL. Moreover, the purpose of the present research is also to survey the impact of the monthly average river flow (Q) on the precision and the accuracy of SSL prediction in the Jajrood River, Iran.

2. Material and methods

2.1. Artificial Neural Networks

ANN models have been broadly used in water resource research as a predicting approach. ANN, FF, and Back-Propagation networks are common models in water resource research. Three-layered FF Neural Networks produces a general framework that can represent the nonlinear mapping between input and output variables (Nourani and Andalib 2015). The multilayer perceptron (MLPs) ANN (Rumelhart and McClelland, 1986) is the frequently used type of neural networks (Cauchi et al. 2011; Khalil and Adamowski 2014. In its simplest form, the MLP model comprises of one input and output layer, and one or more hidden layers (ASCE 2000a,b). One hidden layer was found sufficient for solving the nonlinear models in hydrology research (Coulibaly and Anctil 1999). Finding the hidden node size is a key step that is typically done by the trial and error method. Among the various techniques proposed for the recognition of an ideal number of nodes in the hidden layer, Eq. 1 has been utilized in the present study to evaluate the recommended upper limit number of hidden nodes (Maier and Dandy 2001).

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

where N^H , N^1, and N^{TR} are the number of hidden nodes, input, and the training sample, respectively. However, in the present research, the number of hidden nodes was identified based upon the trial-and-error procedure. It has to be noted that the transfer function (also called as activation function) technically reveals the ability of non-linear approximation of the ANN (Shu and Ouarda 2007).Among different learning algorithms such as FF back-propagation, radial basis function (RBF), gradient descent with momentum, Levenberg-Marquardt (LM), and Bayesian regularization (ASCE 2000a,b), the LM training algorithm (Hagan and Menhaj 1994) has been chosen since it is a powerful algorithm for training the ANN models (Burney et al. 2004; Khalil et al. 2011) For more information, the interested readers are referred to Haykin (1999).

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS technique is able to provide potential advantages of both the ANN and the FL methods as unified predictive model. Basically, the ANFIS model covers the major problem in the design of fuzzy if-then rules, by efficiently employing the acquisition capacity of ANN for generating fuzzy rules and optimizing the parameters (Nayak et al. 2004; Olyaie et al. 2015). The ANFIS model, as an FF network that maps input variables on an output space, then extracts fuzzy if-then rules from the data set (Vadiati et al. 2016).

In its original form, the hybrid learning algorithm composed of the ANFIS model was introduced by Jang (1993). Sugeno approach, which is a specific type of ANFIS model, has been used in the present study (Sugeno 1985) for estimating the output variables. Several Sugeno models may be developed using the subtractive clustering (SC), grid partitioning (GP), and Fuzzy C-Mean Clustering (FCM) methods. In this work, the most broadly used methodologies, SC model, have been used to produce an initial inference system (El-Shafie et al. 2007).

The hybrid learning algorithmis usually applied in the FISs training to characterize the improved spreading of the membershp function (MF)s. The hybrid learning algorithm coding, which is a combination of the least-squares method and the gradient descent, and ANFIS model in this work were prepared in MATLAB Software (Mathworks 2014).

2.2.1 Subtractive Clustering

Subtractive clustering (SC) method was developed by merging the ANFIS and the subtractive clustering algorithms (Sanikhani and Kisi 2012). The merit of the ANFIS-SC technique is its ability to remove the necessity to define a grid resolution. Basically, the procedure of SC process presents as follows:

Consider a collection of n data set $\{x1, x2, \ldots, xn\}$ in an M dimensional space, which have been standardized in every dimension. The potential of the data point xi to be cluster center is computed as:

$$P_i = \sum_{i=1}^{N} e^{-\alpha \left\| X_i - X_j \right\|^2} \quad (2)$$

where $\alpha = \frac{4}{r_a^2} \left\| X_i - X_j \right\|^2$ indicates the Euclidean distance and the positive constant $r_a$is is the radius indicating a neighborhood. If x_1^* is the situation of the primary cluster center and $P_1^*$is its potential, the following equation is representing the potential of each data point x_i:

$$P_i = P_i - P_1^* e^{-\beta \| X_i - X_1^* \|^2} \quad (3)$$

Where $\beta = \frac{4}{r_b^2}$ and $r_b$is a positive constant. Afterward, the potential of each data point is decreased based on its distance to the next cluster center. The effective radius is fundamental to specify the number of the clusters. Selecting a smaller radius causes an excessive number of smaller clusters and the need for more rules is inevitable and vice versa. As a result, choosing a proper effective radius and is a critical issue(Sanikhani and Kisi 2012).

2.3. Group Method of Data Handling (GMDH)

GMDH is an example of the self-organizing neural network methods. Self-organizing neural networks methods are successfully used in a broad range of science and engineering disciplines although their application in the field of hydrology is still in its infancy stage (Samsudin et al. 2010; Bayat et al. 2011; Garg 2014).

The GMDH was introduced by Ivakhnenko (1968) as a heuristic model used to obtain predictive models of complex systems. This model depends on the regression function and it derives the complex, high order polynomial models. Originally, the GMDH model was proposed as a method for dealing with higher order regression polynomials (Samsudin et al. 2010). The main function of GMDH is related to the principles used in the typical artificial neural networks where each layer comprises of the some nodes. In this paper, MATLAB ® software was used to generate the GMDH programs. Basic mathematical equations are provided below and more details on GMDH can be found in papers such as Farlow (1984) and Nariman-Zadeh et al. (2002). The relationships between the inputs and output data set can generally be stated using a complex polynomial Volterra series called the Kolmogorov-Gabor polynomial (Ivakhnenko 1995).

2.4. Least Square Support Vector Machine (LS-SVM)

Suykens and Vandewalle (1999) was introcuded the LS-SVM, which was derived from the traditional support vector machine (SVM) model, as an effective method to solve the non-linear classification problems (Kumar and Kar 2009). A learning theory, which operates through the minimization of structural risk, was applied to develop the SVM model that aims to reduce both experimental risk and the confidence interval, attaining a good generalization outcome (Raghavendra and Deka 2014) and as such, this method can ideally be used for the SSL prediction.

Several algorithms have been recommended to solve the optimization equation of the LS-SVM model (Shevade et al. 2000). It is noteworethy that the algorithms of conventional quadratic programming need enormous memory for the kernel matrix calculation while they can also have hitches in their application and may not be appropriate for complicated optimization problems.

The sequential minimal optimization (SMO) algorithm, introduced by Platt (1999) was employed in this study. The optimum number of C and γ (kernel width parameters) are determined by the trial and error. When γ is very large, the input patterns tend to look very alike, leading to the underfitting of the function. In contrast, when it is too small, the opposite event is likely to happen and over-fitting would be possible (Chang et al. 2005). The C factor assigns the weights of the model size (Basak et al. 2007). When C is too small, it is implied that the fitting of the data features was not successful, while an excessively large value of C is likely to overfit the input-target data (Lendasse et al. 2005). The LS-SVM model in the present study was executed by means of the codes available in the Library for Support Vector Machines (LIBSVM) software (Chang and Lin 2011).

3. Model Development

The monthly average river flow (Q in Lit/S) and SSC (in Mg/L) were combined in several ways to predict the SSC values in Jajrood River. Considering the SSC_t as the SSC at a time t, the Qs (i.e., Q_t, Q_{t-1} to Q_{t-3}) can be considered as the input data. Generally, the data used in data-driven models should be normalized equally to all obtained data throughout the training phase. Eq. 4 expresses a simple linear mapping formula for the data normalization (Nourani et al. 2013):

$$r_i = \frac{I_i - I_{min}}{I_{max} - I_{min}} \quad (4)$$

where I_i is the real value and I_{min} and I_{max} are the minimum and maximum of the values, respectively. Employing normalizing procedure and transferring data between [0, 1] expedites the training process of the models (Nourani and Fard 2012).

The present study examined different combinations of the Q and SSC as the model's inputs to evaluate the effectiveness of each of these input combinations on the SSL prediction accuracy using the ANN, ANFIS, GMDH, and LS-SVM models. The following combination of the present (Q_t) and antecedent monthly average river flow (Q_{t-1}, Q_{t-2}, Q_{t-3}) used for SSC prediction were selected based on the correlations among the inputs and the target (output):

(1) SSC = f (Q_t);

(3) SSC = f (Q_t, Q_{t-1});

(3) SSC = f (Q_t, Q_{t-1}, Q_{t-2});

(4) SSC = f (Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3});

In the present study, 50 years data were divided into the training, validation, and test data set assigned as the initial 30 years (April 1967-March 1997), the following 10 years (April 1997-March 2007), and the last 10 years (April 2007-March 2017), respectively. The basic statistics of data sets for the Roodak gauging station are given in Table 1.

It is notable that the high skewness coefficient has a remarkable adverse impact on the results of the model (Altun et al. 2007; Rajaee et al. 2010). Overall, Table 1 demonstrates satisfactory features between the training and testing sets, in respect to the values of statistical parameters.

Table 1. The statistical parameters of data set for the Roodak gauging station, Jajrood River, Iran

3.2. Efficiency Criteria

To evaluate the results of the developed model, statistical criteria including the correlation coefficient (R), mean absolute error (MAE), and RMSE were chosen:

$$R = \frac{\left(\sum_{i=1}^{N}(SS_{Oi} - \overline{SS_O})(SS_{Si} - \overline{SS_S})\right)^2}{\sum_{i=1}^{N}(SS_{Oi} - \overline{SS_O})^2 \sum_{i=1}^{N}(SS_{Si} - \overline{SS_S})^2} \quad (5)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|SS_{Si} - SS_{Oi}| \quad (6)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(SS_{Si} - SS_{Oi})^2}{N}} \quad (7)$$

where $SS_{Oi,}$ SS_{Si}, $\overline{SS_O}$, $\overline{S_S}$, and N are the observed suspended sediment of the ith data, predicted suspended sediment of the ith data, the mean of observed suspended sediment, the mean of estimated suspended sediment, and the number of observations, respectively. RMSE is a measure that is often used to find the difference between the values predicted and those that are observed. The RMSE is a measure of the goodness of fit that refers to a mean error in predicting the values. The ideal value for MAE and RMSE is zero. The higher values demonstrate higher quantities of error.

3.3. Study area

Jajrood River is situated in the Karaj-Latian basin, North East of Tehran Province, Iran. The climate in this region is moderate and annual precipitation ranges from 500 to 1100 mm. The average annual precipitation and temperature are about 711 mm and 26℃, respectively. Snowmelt in North mountains causes a noticeable increase in river flow (Razmkhah et al. 2010). The Fasham and Shemshak rivers form the Jajrood River in Fasham area (Mahjouri and Kerachian 2011). Finaly, the Jajrood River flows into the Latian dam reservoir, which is the main supplier of Tehran's domestic water for Tehran (Saeedi et al. 2011; Nikoo et al. 2011). Despite the notable increase in water quality assessment in Jajrood River due to its key role in supplying Tehran’s water, to best of our knowledge, there has been no comprehensive study on the SSL prediction in Jajrood River.

In the present work, the monthly average streamflow and SSC data were collected at the Roodak gauging station on Jajrood River (Station Number: 41-101), which was controlled by the Tehran Regional Water Authority (TRWA). Fig. 1, shows the the SSL data which were measured by TRWA once and often twice a month. Also, the monthly SSL and average river flow time series for Roodak gauging station on Jajrood River SSL are represented in Fig. 2.

Fig. 1 Map of the Jajrood River, Iran

Fig. 2 Time series of SSL and River discharge for Roodak gauging station on Jajrood River

4 Results and Discussions

4.1. Results of the ANN Model

Different input combinations for the ANN model (i.e., models denoted as one to four) were assessed in predicting the sediment concentration SSC in Jajrood River, through appropriate model steps. As shown in Table 2, which presented the results of the ANN model for all input combinations in different structures of the ANN model, the ANN model with combination 4 (with Q_t, Q_{t-1}, Q_{t-2}, and Q_{t-3} as its inputs) was the best model. The input combination 4 had the least RMSE and MAE while it had the highest R in the validation and test steps. Therefore, it it was evident that the best-fit model for SSL prediction for the current study. Moreover, the optimmim number of nodes in hidden layer was considered based on trial and error procedure, same as the earlier researches (Khalil et al. 2015). The number of nodes was changed from 1 to 10 until the model no longer showed a significant improvement in the training performance. This yielded the best architecture of ANN for model combination 4, recognized as 4-2-1, indicating 4 input, 2 hidden and 1 output nodes (Table 2). Fig. 3 presents the observed and the predicted SS values generated by the ANN model.

Table 2. Results of AI models SSL prediction for different input combination in monthly basisin the validation and test steps for the Roodak gauging station

Fig. 3 A comparison between observed and predicted SSL by ANN model for different input combination, the whole data set for the Roodak gauging station, Jajrood River, Iran

4.2. Results of the ANFIS Models

The ultimate architecture of the ANFIS methods were identified by a trial and error procedure. To create the fuzzy rules using the ANFIS-SC model, it is important to define the appropriate cluster radii (Sanikhani and Kisi 2010).

In the present study, the statistical criteria were applied to determine the optimal radius for every model structure. Based on Table 2, which the results of the different combinations of model are presented, ANFIS-GP models with combination 4 that uses Q_t, Q_{t-1}, and Q_{t-2} as inputs is the best model. Fig. 4 illustrates the observed and predicted SS values using the ANFIS, separately.

Fig. 4 A comparison between observed and predicted SSL by ANFIS-SC model for different input combinations for whole data set for the Roodak gauging station, Jajrood River, Iran

4.3. Results of the GMDH Model

To the best of the authors' knowledge, no research has been performed for prediction of the SSL using the GMDH approach. In a GMDH model, successive layers that have complex connections are formulated and built by means of second-order polynomial functions. In the structure of GMDH approach, computing regressions of the input and output variables are developed to bulid the primary layer and following layer. Afterthat, the best computing regressions are chosen for each the primary layer and following layer. Finally, the selection process halts when the stop criteria is found (Samsudin et al. 2010). The achievement and performance of GMDH models rely upon the choices of the number of input variables. We assessed the GMDH model with different combinations based on the SSC in Jajrood River. The results of GMDH model are presented in Table 2. Fig. 5 presents the observed and predicted SS values, using the GMDH model.

Fig. 5 A comparison between observed and predicted SSL by GMDH model for different input combination for the whole data set for the Roodak gauging station, Jajrood River, Iran

4.4. Results of LS-SVM Model

The LS-SVM model was evaluated using different combinations of datasets as the model's input. The performance results of different combinations the validation and test steps using LS-SVM model are provided in Table 2. These result showed that the LS-SVM model with the input combination 1 as the input had the best RMSE, MAE, and R results in the train and test period. Therefore, it was chosen as the best model for SS estimation. The RBF was recognized as a proper kernel function for this study. Different numbers of parameter C and kernel function parameter γ were determined for the LS-SVM based on the trial and error. The ideal number of C and γ for different combination are 20 and 0.5, respectively (Table. 2). Fig. 6 shows the observed and predicted SSL values using the LS-SVM model.

Fig. 6 A comparison between observed and predicted SSL by LS-SVM model for different input combination for the whole data set for the Roodak gauging station, Jajrood River, Iran

4.5. Comparison of the Results of Different Models

To attain a comprehensive assessment of the ANN, ANFIS-SC, GMDH, and LS-SVM methods, the combination 4 (Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}) was applied as the input to compare the performance of the ANN, ANFIS-SC, GMDH, and LS-SVM models. Comparing the AI models which are presented in Table 2, we see that the differences between the results of the ANN, ANFIS-SC, GMDH, and LS-SVM models were not significant. Moreover, it was also revealed that all models yielded appropriate results regarding to the MAE, RMSE, and R criteria. Overall, the performances of the ANN, ANFIS-SC, GMDH, and LS-SVM methods in the present study were satisfactory. Eventually, the results showed that the LS-SVM method had the best performance in predicting SSC for the used input and output data.

5. Conclusions

Past investigations on the prediction of SSL show that it is a critical issue considering the need for massive, point-by-point, and exact environmental data. Regarding the importance of SSL, as a complex phenomenon, the application of artificial intelligent data-driven models leads to a precise prediction of SSL. In this study, a comparison of different artificial intelligence methods such as ANN, ANFIS-SC, GMDH, and LS-SVM were used for prediction of SSL. For achieving this objective, Jajrood River station (Roodak station) in the Tehran Province, Iran was utilized to create different models investigated in this study. The input data set comprises the observed monthly Q and SSL. The optimum input combination for the models was perceived using the expert knowledge and the previous studies. The global statistics (R, MAE and RMSE) were chosen to evaluate the performances of different developed methods. The results shown that soft computing techniques were powerful tools to predict the SSL since all models generally showed low RMSE and MAE and a high R. Overall, the results of different models applied in this study showed that the LS-SVM has the better performance in terms of other models to predict the multifaceted non-linear behavior of the SSC. This study expected to guide the application of soft computing models in prediction of the SS alongside the rivers. Furthermore, as a plan for future reviews, alternating factors such as hydrological and meteorological parameters can be applied to model the SSL process.

6. References

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Figure

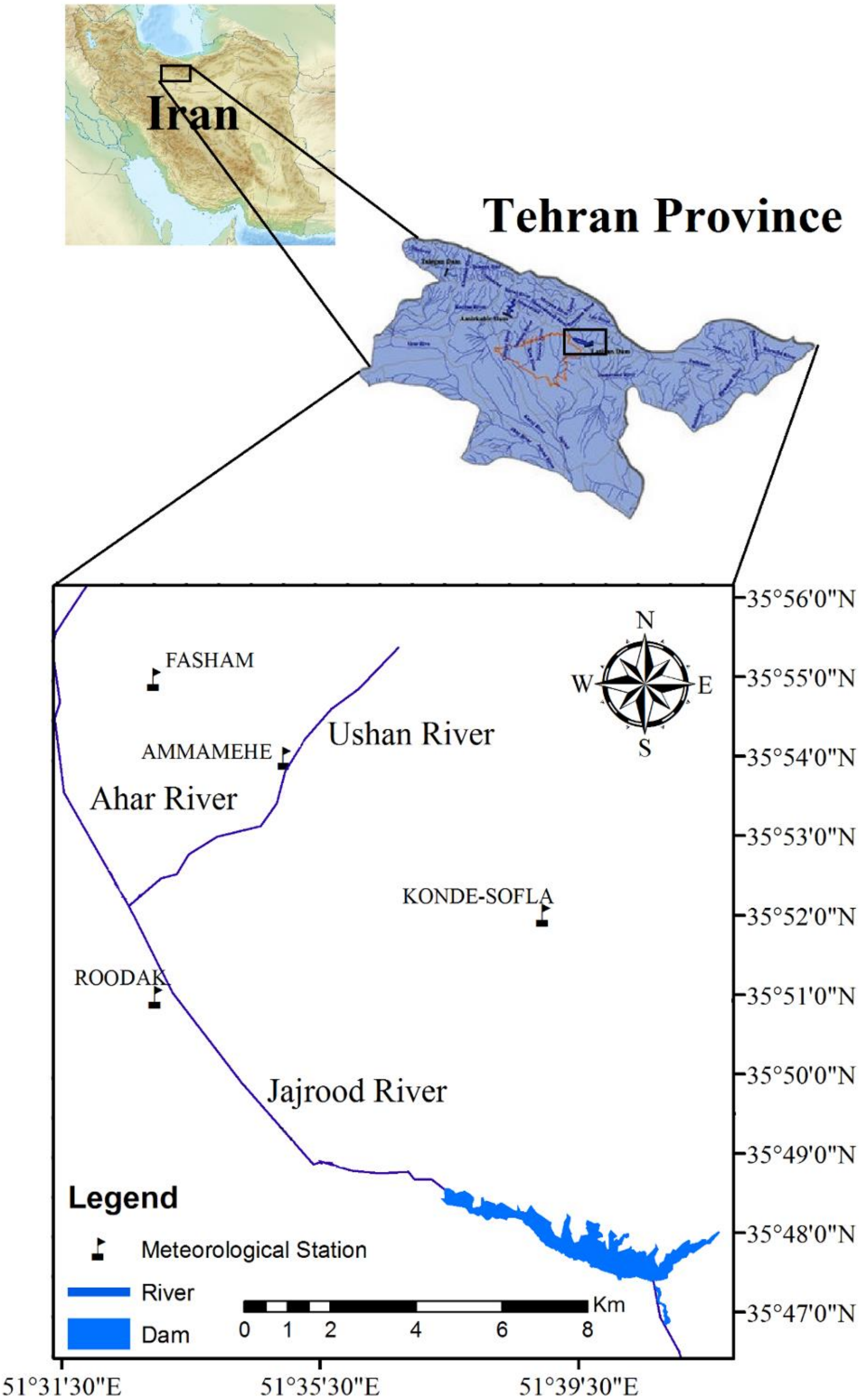

Fig. 1 Map of the Jajrood River, Iran

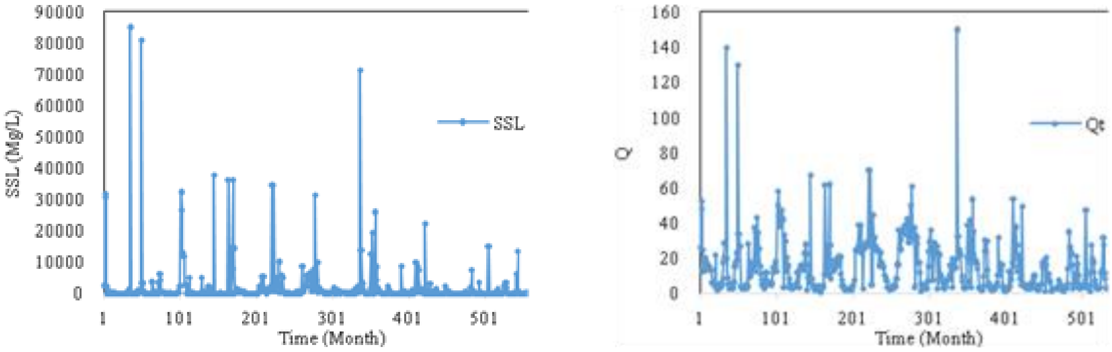

Fig. 2 Time series of SSL and River discharge for Roodak gauging station on Jajrood River

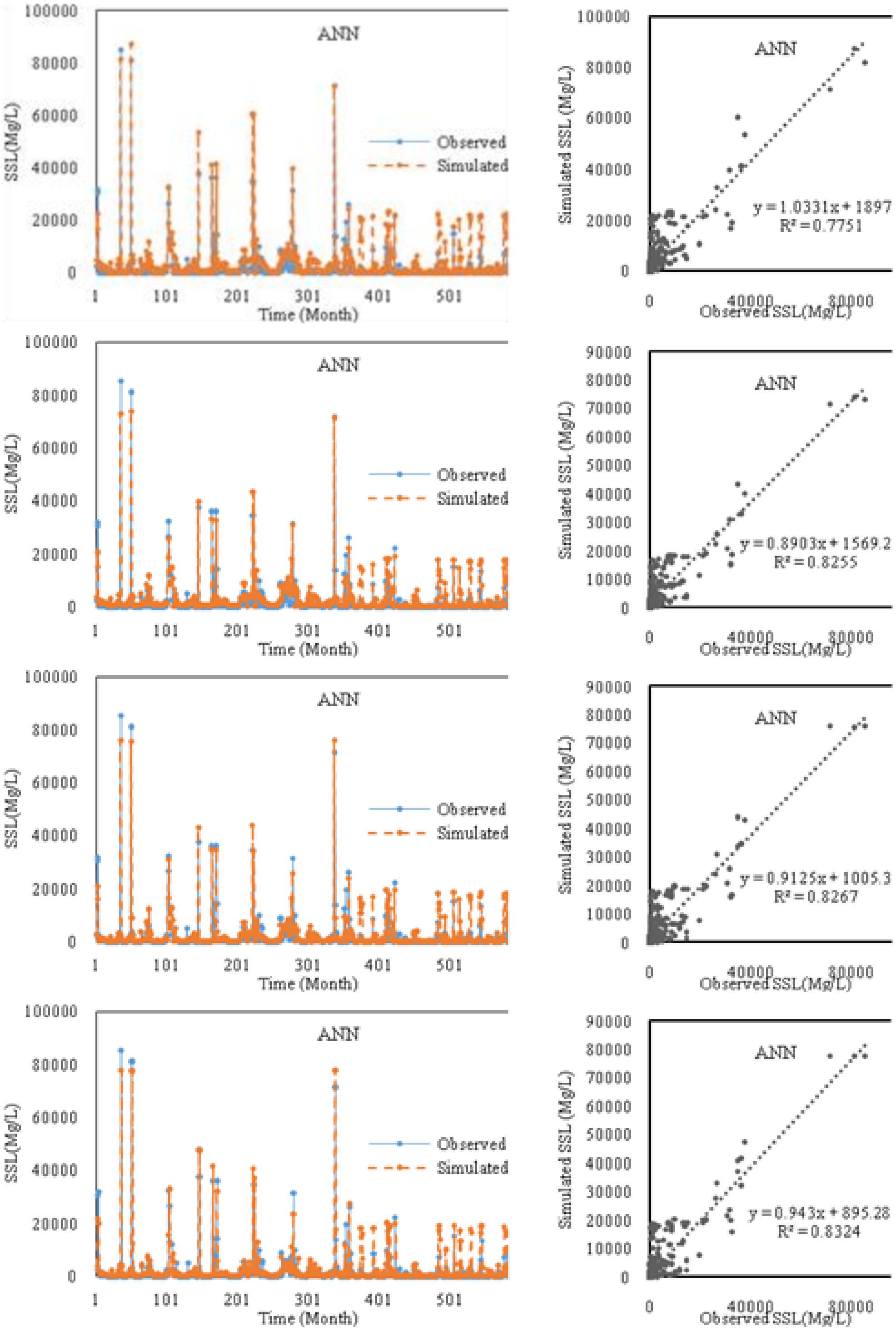

Fig. 3 A comparison between observed and predicted SSL by ANN model for different input combination, the whole data set for the Roodak gauging station, Jajrood River, Iran

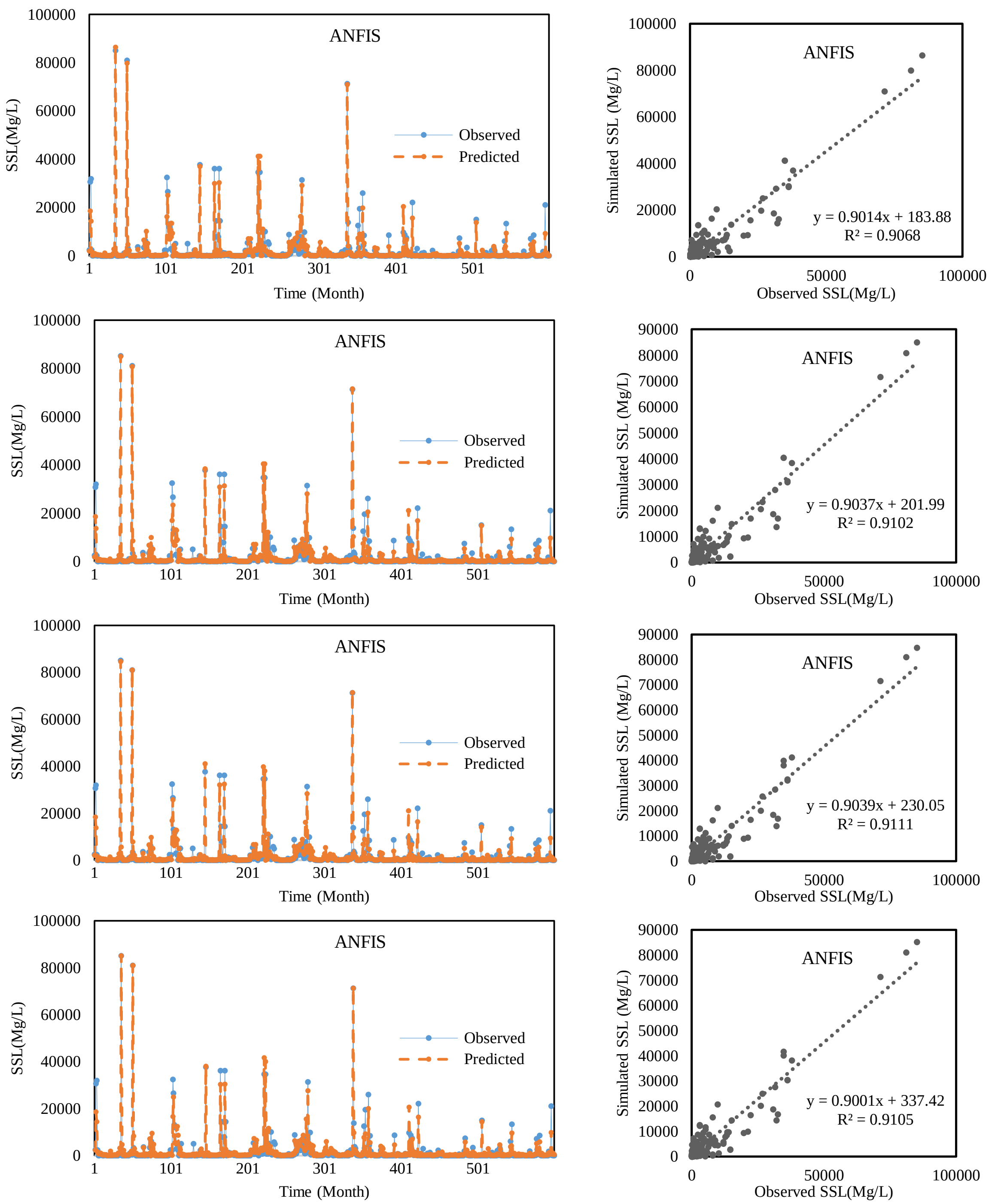

Fig. 4 A comparison between observed and predicted SSL by ANFIS-SC model for different input combinations for whole data set for the Roodak gauging station, Jajrood River, Iran

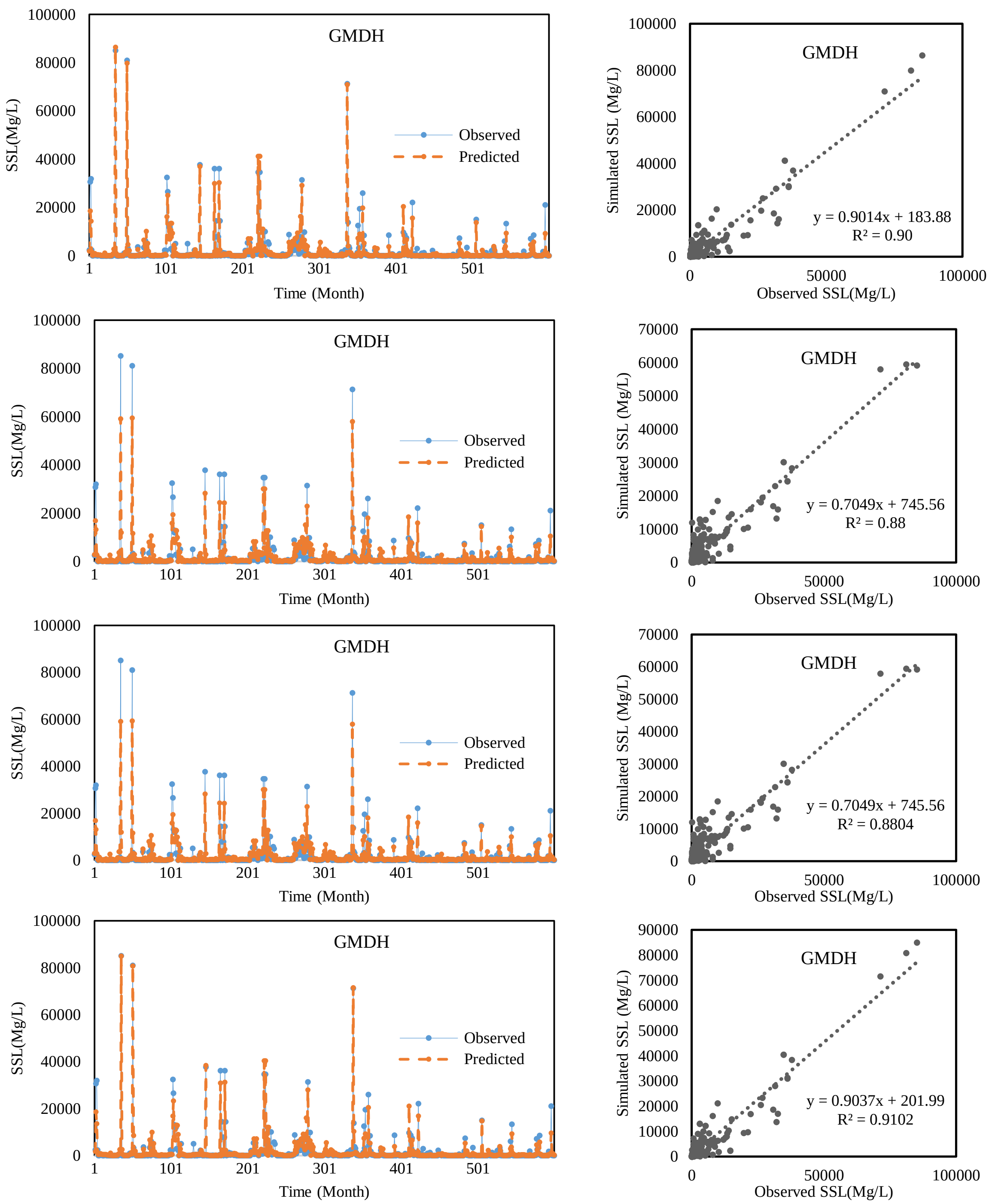

Fig. 5 A comparison between observed and predicted SSL by GMDH model for different input combination for the whole data set for the Roodak gauging station, Jajrood River, Iran

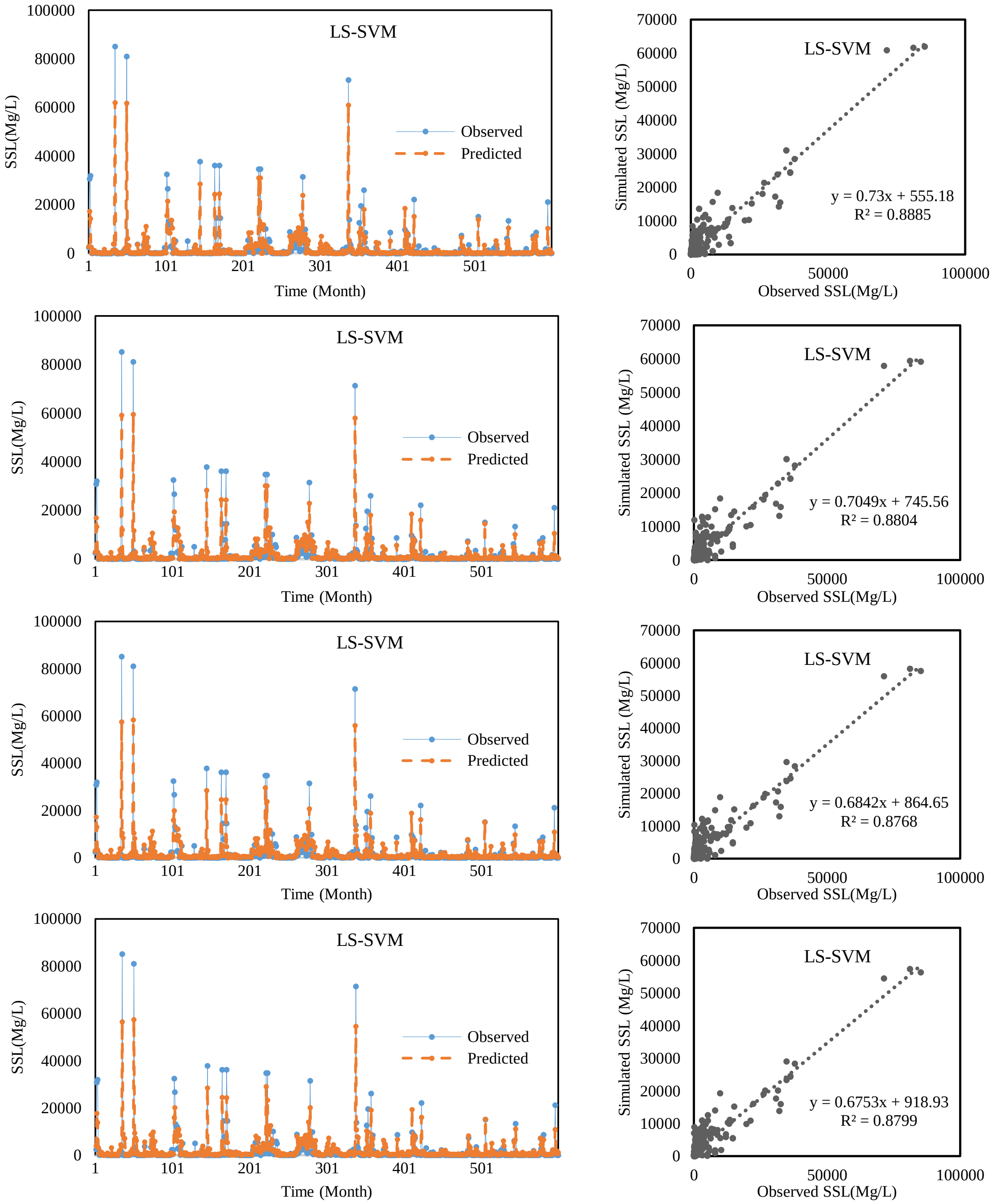

Fig. 6 A comparison between observed and predicted SSL by LS-SVM model for different input combination for the whole data set for the Roodak gauging station, Jajrood River, Iran

Table 1. The statistical parameters of data set for the Roodak gauging station, Jajrood River, Iran

Data Set	Data Type	Xmean	Xstdev	Xske	Xmax	Xmin	Xmax/Xmean
Training	Q (Lit/S)	17.3	17.8	3.2	150	0.36	8.65
	SS (Mg/L)	2809	9265	5.90	85162	1.49	30.3
Validation	Q (Lit/S)	9.15	9.9	2.15	53.99	1.18	5.90
	SS (Mg/L)	743	2543	6.16	22173	1.07	29.8
Test	Q (Lit/S)	10.64	10.2	1.54	47.53	1.3	4.47
	SS (Mg/L)	932	2936	4.77	21148	1.2	22.6

Table 2. Results of AI models SSL prediction for different input combination in monthly basisin the validation and test steps for the Roodak gauging station

AI Models	Input Combinations	Structure (ANN) Radius (ANFIS)	Validation			Test		
			RMSE(Mg/L)	R	MAE	RMSE(Mg/L)	R	MAE
ANN	Q_t	(1,1,1)	4724	0.70	2054	6334	0.64	3119
	Q_t, Q_{t-1}	(2,2,1)	3295	0.75	1581	4403	0.71	2302
	Q_t, Q_{t-1}, Q_{t-2}	(3,2,1)	3348	0.75	1445	4519	0.71	2181
	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	(4,2,1)	3198	0.76	1222	4768	0.70	2220
ANFIS	Q_t	(0.45)	2523	0.95	1091	1234	0.90	456
	Q_t, Q_{t-1}	(0.5)	2479	0.96	1097	1204	0.92	466
	Q_t, Q_{t-1}, Q_{t-2}	(0.5)	2463	0.96	1100	1203	0.92	501
	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	(0.6)	2494	0.95	1198	1206	0.91	578
GMDH	Q_t		2984	0.94	1311	1347	0.91	628
	Q_t, Q_{t-1}		3164	0.94	1489	1338	0.90	745
	Q_t, Q_{t-1}, Q_{t-2}		3284	0.93	1498	1390	0.89	781
	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}		3302	0.94	1595	1454	0.87	812
LS-SVM	Q_t	10, 0.5	3036	0.94	1320	1321	0.91	587
	Q_t, Q_{t-1}	10, 0.5	3215	0.94	1480	1312	0.90	696
	Q_t, Q_{t-1}, Q_{t-2}	10, 0.5	3335	0.93	1582	1363	0.89	730
	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}	10, 0.5	3353	0.94	1599	1425	0.87	759