Predicting Suspended Sediment Loads and Missing Data for Gediz River, Turkey

Asli Ulke[1]; Gokmen Tayfur[2]; and Sevinc Ozkul[3]

Abstract: Prediction of suspended sediment load (SSL) is important for water resources quantity and quality studies. The SSL of a stream is generally determined by direct measurement of the suspended sediment concentration or by employing sediment rating curve method. Although direct measurement is the most reliable method, it is very expensive, time consuming, and, in many instances, problematic for inaccessible sections, especially during floods. On the other hand, measuring precipitation and flow discharge is relatively easier and hence, there are more rain and flow gauging stations than SSL gauging stations in Turkey. Furthermore, due to its cost, measurements of SSL are carried out in longer periods compared to precipitation and flow measurements. Although daily precipitation and flow measurements are available for most of the Turkish river basins, at best semimonthly measurements are available for SSL. As such, it is essential to predict SSL from precipitation and flow data and to fill the gap for the missing data records. This study employed artificial intelligence methods of artificial neural networks (ANN) and neurofuzzy inference system, the sediment rating curve method, multilinear regression, and multinonlinear regression methods for this purpose. The comparative analysis of the results showed that the artificial intelligence methods have superiority over the other methods for predicting semimonthly suspended sediment loads. The ANN using conjugate gradient optimization method showed the best performance among the proposed models. It also satisfactorily generated daily SSL data for the missing period record of Gediz River, Turkey.

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Introduction

The estimation of suspended sediment load is very important for water resources quantity and quality studies in the design and management of the water resources projects. Sediment load carried by rivers may lead to reduction in useful storage of a dam and congestion in water inlets (Nakato 1990). Furthermore, design of stable channels, estimation of aggradation and degradation at bridge piers, prediction of sand and gravel mining effects on riverbed, and determination of environmental impact assessment and dredging needs are affected by sediment load transport (Singh et al. 1998). Also, sediment either in suspension or on the river bed is a major pollutant and a carrier of nutrients, pesticides, and other chemicals. The real-time distribution of the sediment load and its forecast is necessary for controlling the pollution level in rivers and reservoirs (Lopez et al. 2001).

The suspended sediment load of a stream is generally determined by direct measurement of sediment concentrations or by the sediment transport equations. Direct measurement of suspended sediment is one of the most reliable methods. Yet, it is impractical and expensive to set up gauging stations at desired locations and collect data for a sufficiently long period of time. This may be the reason for having fewer operational sediment gauging stations on Turkish rivers. In general, before building a water structure such as a dam or a weir, the EIE (Electrical Works Authority) or the DSI (State Water Works) builds temporary gauging stations to measure sediment. Soon after the structure becomes operational, the gauging stations are either removed or not operated (EIE 2006).

Sediment transport equations can be grouped into three major groups—physically based, empirical, and regression-based. The physically based models require enormous data sets and parameter estimation (Ozturk et al. 2001; Tayfur 2003). Empirical models are not generic and are only applicable for the cases in which they have been developed (Yang 1996; Tayfur 2003). Regression-based models such as the sediment rating curve (SCR) method are simple and easily applicable ones (Jain 2001). The SRC relates suspended sediment concentration to flow rate through regression equation, which can be linear or nonlinear. In practice, SRC is generally preferred over other methods because ease of use and the availability of flow gauging stations. However, since it is a regression based, it has accuracy limitations. Specifically, SRC may have relatively low R^2 statistics and provide relatively poor load estimates for certain flow ranges and short-term load estimates (e.g., daily and weekly loads) (Crowder et al. 2007).

Researchers hence have looked for alternative approaches. In this last decade, the artificial neural networks (ANNs) (Cigizoglu 2002, 2004; Nagy et al. 2002; Tayfur and Guldal 2006; Raghuwanshi et al. 2006; Dogan et al. 2007; Alp and Cığızoğlu 2007),

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fuzzy logic (FL) (Tayfur et al. 2003), neurofuzzy [adaptive neurofuzzy- inference system (ANFIS)] (Kisi 2005), and genetic algorithms (Aytek and Kisi 2008) have been commonly employed for this purpose. The studies showed the superiority of the artificial intelligence methods over empirical equations (Nagy et al. 2002; Dogan et al. 2007), the SRC method (Cigizoglu 2002,2004; Kisi 2005; Aytek and Kisi 2008); the unit sediment graph method (Tayfur and Guldal 2006) and multilinear regression method (Raghuwanshi et al. 2006; Kisi 2005).

Most of the artificial intelligence method application studies predicted daily suspended sediment from daily flow data (Cigizoglu 2004; Kisi 2005; Alp and Cığızoğlu 2007), and daily precipitation data (Tayfur and Guldal 2006). However, as pointed out earlier, in Turkey, at best, one can find semimonthly measured suspended sediment (SS) data. It then becomes essential to predict semimonthly SS data using available daily flow and precipitation data. For this purpose, this study employs SRC, multiple linear regression (MLR), nonlinear multiple regression (NLMR), ANN, and ANFIS methods. The comparative study would shed a light on the performance of the models in predicting semimonthly SS data from daily flow and precipitation data for the Gediz River, located in the Western part of Turkey. Furthermore, this study would explore the capability of the models to fill the gap in SS data records for the Gediz River. That is the daily missing data of SS at the Gediz River would be generated by the proposed model.

Accurate estimation of suspended load is difficult because sediment concentration and flow rate vary significantly with time. The measurements of sediment concentration and flow rate respond rapidly to precipitation and snowmelt thus show very flashy trend. For example, Schilling (2000) presented details and patterns of flow rate and sediment load for water years 1996–1998 for Walnut Creek Watershed and observed that daily measures of these variables were very flashy. Therefore, working with low frequency sampling data, such as weekly, biweekly, or monthly, might lead to misleading results.

Accuracy of sediment load estimates is dependent upon sampling frequency resulting in better estimates but also higher associated cost. What is suggested is to do sampling frequently during high-flow seasons, but less frequently during low flows. In practice, the common frequency sampling is weekly, biweekly or monthly (Li et al. 2006). However, compared to daily measurements, these periodic measurements would result in an undersampled data set (Li et al. 2006). Schilling (2000) evaluated the effect of sediment sampling frequency on annual sediment loads and found that sampling weekly, biweekly, or monthly failed to adequately characterize sediment loads from the watershed.

Although higher sampling frequency (such as daily) results in better estimates, it is very costly. Hence, a balance between accuracy and cost is generally sought in practice (Li et al. 2006). One approach to obtain high-resolution sediment load values would be to sample sediment on a periodic basis (weekly, biweekly, or monthly) and then interpolate between measured values to generate daily data set (Li et al. 2006). Appropriate interpolation methodologies can be employed for this purpose. Li et al. (2006) employed the common geostatistical method of cokriging to estimate daily suspended sediment from weekly, biweekly, and monthly data. They showed that estimated daily sediment loads with cokriging using weekly measured data best matched the measured daily values. However, the cokriging method failed to predict daily values from biweekly and monthly samples (Li et al. 2006). This study, however, as it is presented later, employed ANN, which provided fairly good estimates of daily values from semimonthly data.

The novelty of this study is mainly twofold: (1) predicting semimonthly SS data using daily measured flow rate and precipitation data and (2) generating daily SS data from semimonthly measured data.

Methods

Sediment Rating Curve

The standard form for SRC is (Julien 2002; EIE 2006)

$$\mathrm{SSL}_{(t)} = aQ_{(t)}^{b} \tag{1}$$

where $Q_{(t)}$=daily average flow (m^3/s); $\mathrm{SSL}_{(t)}$ is suspended sediment load (t/day); and a and b=constants, which depend on river characteristics.

Generally, the log transformation of SSL and flow data prior to the analysis is carried out. Comparisons of actual and predicted SSL, partially as a result of scatter about the regression line, as well as the conversion of results from log space to arithmetic space, indicate that rating curves can substantially underpredict the high, and overpredict the low actual loads (Walling and Webb 1988; Asselman 2000).

Multiple Linear Regression

Assuming that the dependent variable Y is affected by m independent variables $X_1, X_2, \ldots, X_m$ and a linear equation is selected for the relation among them, the regression equation of Y can be written as (Bayazıt and Oguz 1998)

$$y = b_0 + b_1x_1 + b_2x_2 + \ldots + b_mx_m \tag{2}$$

where y in this equation shows the expected value of the variable Y when the independent variables take the values $X_1=x_1$, $X_2=x_2, \ldots, X_m=x_m$.

The regression coefficients $b_0, b_1, b_2, \ldots, b_m$ are evaluated, in a manner similar to simple regression, by minimizing the sum of the error distances of observation points from the plane expressed by the regression equation (Bayazıt and Oguz 1998). In this study, the coefficients of the regressions were determined using the ordinary least square method.

SUMER (2006) and The Ministry of Environment and Forestry of Turkey (MOEF) (2007) investigated the impact of climate change on Gediz River basin. They carried out trend analysis for the observed monthly and annual flow, precipitation and temperature series. They could not come up with statistically meaningful trends. This implies that the data used in the current study might be stationary and therefore in MLR model, employing the ordinary least square method, would be sufficient.

Nonlinear Multiple Regression

Since the suspended sediment transported in the rivers is a nonlinear phenomenon, the multiple nonlinear regression models are also studied. A good empirical representation of the response that is inherently nonlinear in nature can be obtained through a polynomial model (Jain and Indurthy 2003). Hence, polynomial models are used for the nonlinear regression in this study. A multinonlinear regression equation can be expressed as (Jain and Indurthy 2003):

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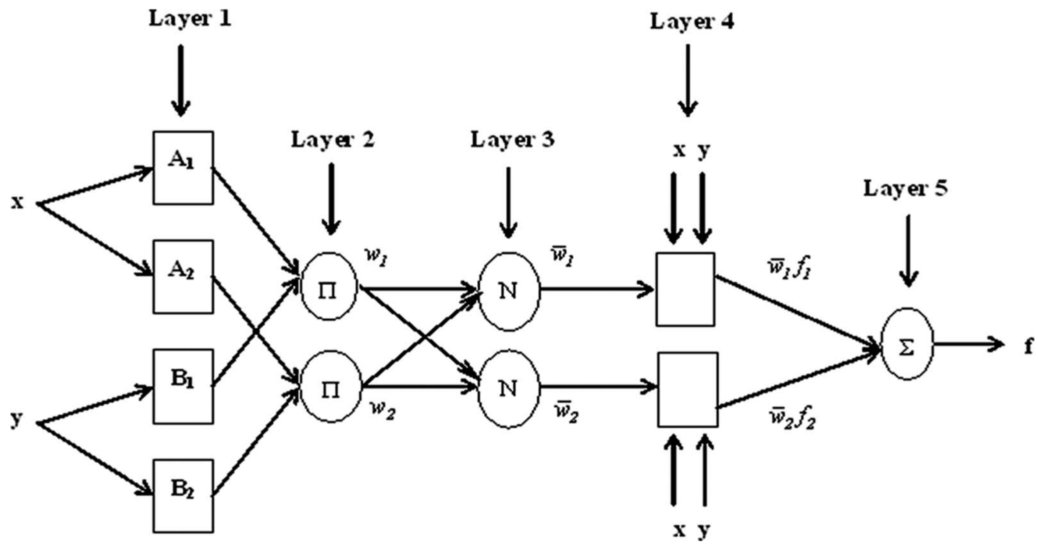

Fig. 1. ANFIS architecture

$$y = b_0 + b_1x_1 + b_2x_2 + b_{11}x_1^2 + b_{22}x_2^2 + \ldots \ldots \ldots \quad (3)$$

In this study, five different types of multinonlinear polynomial models were constructed.

Artificial Neural Network

The artificial neural network (ANN) is essentially a "black box" operation mapping input data onto output data using a particular set of nonlinear basis functions. Neurons, which are the basic units, are connected to each other by links known as synapses. Associated with each synapse, there is a weighting factor. Back propagation method is generally employed for training the feed-forward neural networks (FFNN) using a set of pairs of input and output values. Each neuron at input and inner layers receives input values, processes them and then passes the response to the next layer. The numbers of neurons in the input and the output layers are determined by the numbers of input and output variables, respectively. The most commonly used network is the three-layer feed-forward ANN (ASCE Task Committee 2000).

The ANN can have more than one hidden layer; however, theoretical works have shown that a single hidden layer is sufficient for an FFNN to approximate any complex nonlinear function (Cybenco 1989; Hornik et al. 1989). The detailed theoretical information about FFNN can be found in Haykin (1998) and ASCE Task Committee (2000).

In the present study, one-hidden-layer feed-forward artificial neural network is used. Levenberg–Marquardt and conjuge gradient optimization techniques are employed, since they are more powerful and faster than the conventional gradient descent technique (Hagan and Menhaj 1994; El-Bakyr 2003; Cigizoglu and Kisi 2005). The sigmoid function is used for the activation of the hidden and output neurons. Hence, before applying ANN, the input variables are scaled into the range of (0.1–0.9). Influence of scaling issue is discussed in elsewhere (Minns and Hall 1996).

Adaptive Neurofuzzy Inference System

Intelligent computing tools such as ANN and FL approaches are proven to be efficient when applied individually to a variety of problems. Recently there has been a growing interest in combining both these approaches, and as a result, neurofuzzy computing techniques have evolved. This approach has been tested and evaluated in the field of signal processing and related areas, but researchers have only begun evaluating the potential of neuro-fuzzy hybrid approach in hydrologic modeling studies.

There are only few neurofuzzy hydrological models in the literature. Jang (1993) was the first one who introduced an architecture and a learning procedure for the fuzzy inference system (FIS) that uses neural network learning algorithm for constructing set of fuzzy *if-then* rules with appropriate membership functions (MFs) from the specified input-output pairs. This procedure of developing a FIS using the framework of adaptive neural networks is called an ANFIS. There are two methods that ANFIS employs for updating MF parameters: (1) backpropagation for all parameters (a steepest descent method) and (2) hybrid method consisting of backpropagation for the parameters associated with the input membership and least-squares estimation for the parameters associated with the output MFs. As a result, training error decreases, at least locally, throughout the learning process. Therefore, the more the initial MFs resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise on the target system to be modeled may aid in setting up these initial MF parameters in the FIS structure.

A schematic representation of an ANFIS is shown in Fig. 1, where in Layer 1, A_1, A_2 and B_1, B_2 are the MFs for inputs x and y, respectively. Every node in this layer produces membership grades of an input parameter. The MFs can be Gaussian, generalized bell shaped, triangular, or trapezoidal shaped. Every node in Layer 2 is a fixed node whose output is the product of all incoming signals. Normalized firing strengths are computed in the nodes of Layer 3. Every node in Layer 4 is an adaptive node with a node function $O_{4,i}=\bar{w}_i f_i=\bar{w}_i(p_i x+q_i y+r_i)$ where $\bar{w}_i$ is the output of Layer 3 and $\{p_i,\ q_i,\ r_i\}$ is the parameter set of the node. The single node in Layer 5 is a fixed node, which computes the overall output as the summation of all incoming signals. The detailed theoretical information on ANFIS can be found in Jang (1993).

Triangular (trimf), generalized bell (gbellmf), and Gaussian (gaussmf) MFs and the hybrid learning algorithm, which combines the methods of gradient descent and the least squares, are employed in all ANFIS simulations in this study.

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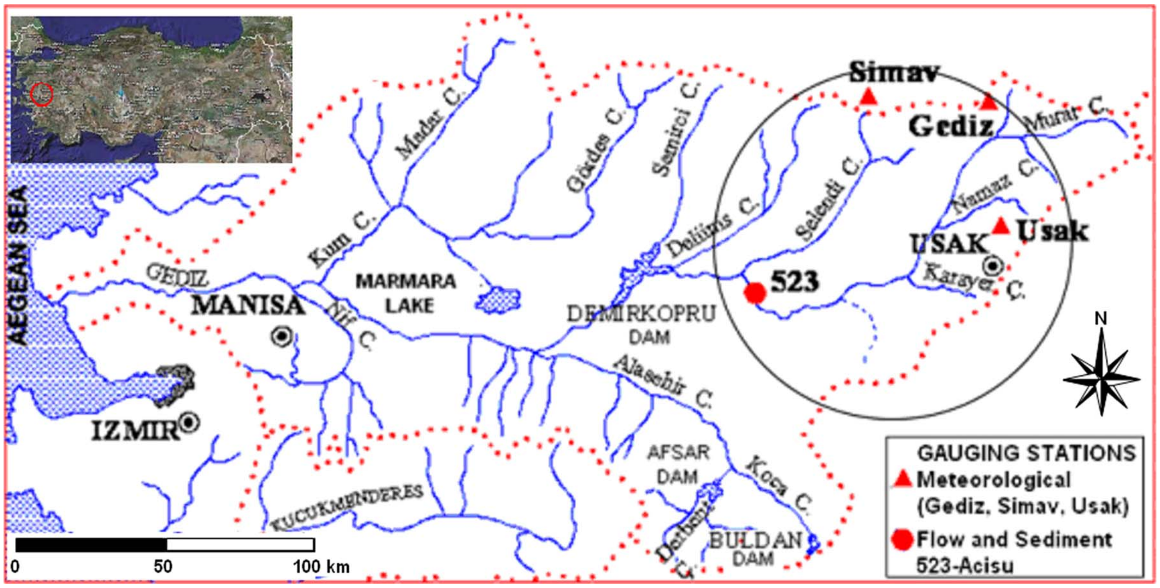

Fig. 2. Location of meteorological and sediment station on the Gediz catchment

Test Case and Data

Description of the Test Case

The Gediz River (Fig. 2) originates from Murat Mountain on the western part of the city of Kutahya. The three tributaries named Murat Creek, Namaz Creek, and Karayer Creek join and then merge into the Gediz River, which flows through the city of Usak and then enters the reservoir of Demirkopru Dam, with its estuary reaching the Aegean Sea. During its course the Gediz River travels a distance of 401 km and supplies water to an area of $17,500\ \text{km}^2$.

The hydrology of the Gediz Basin is typically Mediterranean. Precipitation falls between November and April, and peak river flows occur in February or March. Annual precipitation varies from 800 mm in higher inland areas to about 450 mm near the coast, with about 80% falling in the winter months. Under natural conditions there is a steady decline in stream discharge until May, when many of the smaller streams dry up. Summer flows are only present in the Gediz River and its largest tributaries. Net annual surface water availability in the Basin is estimated to be approximately 1,900 million m^3 per year. Since 1990, however, there has been a persistent decline in surface water flows into Demirkopru reservoir and water availability has only averaged about 940 million m^3 during this period. Demirkopru Dam is an important irrigation water supply for the region and it produces hydroelectrical energy during the irrigation season.

Due to conventional irrigation practices and degradation of land cover and river morphology, sediment concentrations in the Gediz River is very high. Sediment transportation and siltation is an important problem for not only Gediz Basin, but also most of the river basins in Turkey.

Data

Average daily flow and areally averaged total daily rainfall data are used as model input variables in estimation of semimonthly sediment loads by using soft computing and classical methods. Necessary hydrometeorological (rainfall and streamflow) data are collected by different agencies in Turkey. In contrast to meteorological observations and streamflow gaging, representative daily sediment sampling is done manually by using USDH-48, or USD-49 instruments once or twice a month at very few stations (e.g., only two in Gediz Basin). USDH-48 is used in shallow flow depths and placed into water directly by a person (EIE 2006). USD-49 is used in higher flow depths (but less than 4 or 5 m) and placed into water by a crane or a cable system (EIE 2006). A SRC is generally developed by EIE (2006) using monitored flow and suspended sediment concentrations. EIE (2006) use this curve to estimate SSL of ungauged neighboring subbasins.

The Demirkopru Dam, whose dead storage tends to fill earlier than planned, is chosen as the application area. 523-Acisu station, which is run by EIE, is the unique station having flow and sediment data in the upstream of the dam. Acisu station has a drainage area of $3,272\ \text{km}^2$. Although streamflow observations date back to 1969, sediment monitoring was initiated in 1971. The long term average flow and annual SSL are $9.97\ \text{m}^3/\text{s}$ and 247,969 t, respectively. The average distribution of suspended sediment is 62.3% sand and 37.7% silt.

The daily total rainfall has been measured by the Turkish State Meteorological Service (DMI). The rainfall data are prepared using the observations of three nearby meteorological stations named Uşak, Gediz, and Simav. The altitudes of the stations are 919, 825, and 809 m, respectively. The areal average daily rainfall data are computed using the Thiessen polygons method. The weights of rainfall stations are determined as 0.398 for Usak, 0.461 for Gediz, and 0.141 for Simav.

The locations of all stations are given in Fig. 2. Since the precipitation data record starts from 1975, this study is carried out with the data set covering a period of *Jan. 1, 1975–Aug. 1, 2005*, resulting in a total of 351 data points.

Statistical Analysis of Data

The statistical parameters [mean ($\bar{x}$), standard deviation (S_x), coefficient of variation (C_v), skewness coefficient (C_{sx}), overall maximum ($x_{\max}$), and minimum ($x_{\min}$)] of the whole data set are presented in Table 1. It is obvious from Table 1 that the SSL shows a skewed distribution with a high coefficient of variation.

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Table 1. Statistical Parameters of the Whole Data

Data set	Data type	$\bar{x}$	S_x	C_v	C_{sx}	x_{max}	x_{min}
Whole data	Precipitation, P (mm)	1.70	4.47	2.63	3.56	29.7	0
	Flow, Q (m^3/s)	10.47	17.57	1.68	5.18	195	0.03
	SSL (t/day)	2,026.8	9,102.7	4.49	6.92	98,409.2	0.14

The minimum and maximum values of the SSL change in a wide range. Hence, all of these statistics points to the complexity of modeling SSL behavior.

While determining the input variables for ANFIS and ANN, cross-correlations between the input and output variables were taken into account. The computed autocorrelations and cross-correlations are presented in Table 2. Since the correlations are weakening through the second lag, only one lag input scenario combinations are constructed. Since there is no consecutive measurement of daily SSL, the autocorrelations of SSL are not calculated and therefore the previous day's SSL values are not included in the input vector.

Table 2. Autocorrelations and Cross-Correlations of the Whole Data

	Autocorrelations		Cross-correlations		
	P-P	Q-Q	P-SSL	Q-SSL	P-Q
$r_{x,\,y,\,0}$	—	—	0.61	0.82	0.54
$r_{x,\,y,\,1}$	0.25	0.65	0.42	0.61	0.46
$r_{x,\,y,\,2}$	0.47	0.47	0.19	0.37	0.32

Data Sets and Scenarios

Two different training and testing data sets (Data Set 1 and Data Set 2) and their statistical parameters are summarized in Tables 3 and 4, respectively. The training data set is used to calibrate (train) the developed models. The testing data set is, on the other hand, used to validate (test) the models. The calibration (training) and validation (testing) of the models are given in the next section.

The purpose of employing two different training and testing data sets (Data Set 1 and Data Set 2) was to investigate the interpolation and extrapolation capability of the models for semi-monthly suspended sediment predictions. In the first scenario (Data Set 1), the peak value in the testing data set was smaller than that in the training data set (Table 3). As such, this scenario corresponds to testing the interpolation capability of the models. In the second scenario (Data Set 2), the peak value in the testing set was higher than that in the training set (Table 4), corresponding to investigation of the extrapolation capability of the models. Data Set 1 and Data Set 2, each consisting of 100 data points in the testing period, cover the periods *Mar. 13, 1979–Mar. 3, 1987* and *Jan. 5, 1975–Apr. 20, 1983,* respectively.

Table 3. Statistical Parameters of Data Set 1 (Sampling from Gediz River Station 523)

Data set	Data periods	Data type	$\bar{x}$	S_x	C_v	C_{sx}	x_{max}	x_{min}
Training	Jan. 5, 1975–Feb. 13, 1979	$P_{(t)}$	1.92	4.54	2.37	2.98	26.00	0
	Apr. 2, 1987–Aug. 1, 2005	$P_{(t-1)}$	2.68	7.21	2.69	4.21	52.64	0
		$Q_{(t)}$	9.74	18.46	1.89	5.73	195	0.03
		$Q_{(t-1)}$	10.89	25.37	2.33	6.32	261	0.121
		$SSL_{(t)}$	2,249.7	1,004.6	4.47	6.47	98,409.2	0.14
Testing	Mar. 13, 1979–Mar. 3, 1987	$P_{(t)}$	1.17	4.25	3.63	5.6	29.71	0
		$P_{(t-1)}$	1.43	3.64	2.55	3.63	20.20	0
		$Q_{(t)}$	12.28	15.01	1.22	2.73	90.6	0.252
		$Q_{(t-1)}$	13.88	18.39	1.32	3.0	118	0.33
		$SSL_{(t)}$	1,467.4	6,133.4	4.18	7.97	57,056.0	1.32

Table 4. Statistical Parameters of Data Set 2 (Sampling from Gediz River Station 523)

Data set	Data periods	Data type	$\bar{x}$	S_x	C_v	C_{sx}	x_{max}	x_{min}
Training	May 17, 1983–Aug. 1, 2005	$P_{(t)}$	1.69	4.36	2.58	3.46	26.8	0
		$P_{(t-1)}$	2.01	4.64	2.3	3.66	37.49	0
		$Q_{(t)}$	8.63	14.16	1.64	4.0	114	0.03
		$Q_{(t-1)}$	9.1	16.43	1.81	4.44	126	0.121
		$SSL_{(t)}$	1,390.2	6,847.8	4.93	7.45	71,694.7	0.14
Testing	Jan. 5, 1975–Apr. 20, 1983	$P_{(t)}$	1.72	4.75	2.76	3.87	29.71	0
		$P_{(t-1)}$	3.09	9.51	3.08	3.74	52.64	0
		$Q_{(t)}$	15.08	23.54	1.56	5.1	195	0.6
		$Q_{(t-1)}$	18.36	35.0	1.9	4.9	261	0.4
		$SSL_{(t)}$	3,624.8	13,073.5	3.61	5.38	98,409.2	1.09

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Table 5. Different Scenarios Employed Models

Simulations	Simulation numbers	Inputs
Simulation I	Sim I-1	$Q(t)$
	Sim I-2	$Q(t),\ Q(t-1)$
Simulation II	Sim II-1	$P(t),\ Q(t)$
	Sim II-2	$P(t),\ Q(t),\ Q(t-1)$
	Sim II-3	$P(t),\ P(t-1), Q(t),\ Q(t-1)$

Model Calibrations and Applications

Five different scenarios were composed according to input combinations. The simulation experiments are carried out in two categories: (1) simulating SSL using only flow data as input (Sim I) and (2) simulating SSL using both rainfall and flow data as input (Sim II) (see Table 5). From the table, $(t-1)$ denotes the previous day's input values and (t) denotes the current input values. The output is the SSL, which is measured once or twice a month in the Gediz River at Station 523. Estimating SSL using only rainfall data was found to be insufficient (Ulke et al. 2007a,b).

Different ANFIS and ANN architectures were tried and the appropriate structures were determined for two data sets. Different program codes, including neural networks and FL toolboxes, were written in MATLAB language for the all scenarios. The model results were compared by means of root-mean-square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2) statistics (Tayfur and Singh 2006).

ANN Model Training and Testing

For each data set, in the training and testing periods of the ANN model 250 and 100 data points were used, respectively. The numbers of hidden layer neurons were found using a simple trial-and-error method. The number of neurons used in the hidden layer varied from 2 to 10. For the training of ANN with CG (conjugate gradient) 500 epochs and with LM (Levenberg-Marquardt) 150 epochs were found to be sufficient.

Tables 6 and 7 show the simulation results for Data Set 1 and Data Set 2, respectively. As seen in these tables, both CG and LM give the best performance with lowest RMSE, MAE, and the highest R^2 for testing period for Data Set 1 in Simulation II-3 (Table 6) and for Data Set 2 in Simulation II-1 (Table 7). The results in the tables also show that inclusion of precipitation increases the accuracy.

ANFIS Model Calibration and Testing

Triangular (trimf), *Generalized bell (gbellmf)*, and *Gaussian (gaussmf)* functions were employed as MFs. The number of MFs was varied from 2 to 4. Employing more than four MFs resulted

Table 6. ANN Results for Data Set 1

		Levenberg-Marguardt				Conjugate gradient			
		R^2		RMSE	MAE	R^2		RMSE	MAE
Scenario	Model inputs	Train	Test	(t/day)	(t/day)	Train	Test	(t/day)	(t/day)
Sim I-1	$Q(t)$	0.85	0.80	2,847	1,193	0.81	0.71	3,346	1,265
Sim I-2	$Q(t),\ Q(t-1)$	0.97	0.76	5,967	1,456	0.90	0.71	4,937	1,169
Sim II-1	$P(t),\ Q(t)$	0.99	0.87	6,557	1,533	0.94	0.75	3,449	922
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.92	0.75	7,200	1,612	0.93	0.71	4,238	988
Sim II-3	$P(t),\ P(t-1), Q(t),\ Q(t-1)$	0.99	0.927	1,646	820	0.97	0.92	1,799	696

Table 7. ANN Results for Data Set 2

		Levenberg-Marguardt				Conjugate gradient			
		R^2		RMSE	MAE	R^2		RMSE	MAE
Scenario	Model inputs	Train	Test	(t/day)	(t/day)	Train	Test	(t/day)	(t/day)
Sim I-1	$Q(t)$	0.80	0.67	9,109	2,395	0.8	0.66	9,057	2,278
Sim I-2	$Q(t),\ Q(t-1)$	0.97	0.75	7,370	2,552	0.89	0.78	6,281	2,237
Sim II-1	$P(t),\ Q(t)$	0.91	0.87	4,731	1,614	0.90	0.89	4,384	1,332
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.93	0.71	7,097	2,451	0.85	0.84	5,346	1,668
Sim II-3	$P(t),\ P(t-1), Q(t),\ Q(t-1)$	0.99	0.65	7,928	2,488	0.91	0.70	7,139	2,356

Table 8. ANFIS Testing Period Results for Data Set 1

				R^2		RMSE	MAE
Scenario	Model inputs	MF	N	Train	Test	(t/day)	(t/day)
Sim I-1	$Q(t)$	gaussmf	4	0.76	0.70	3,706	1,420
Sim I-2	$Q(t),\ Q(t-1)$	Gauss 2 mf	3 3	0.87	0.72	4,637	1,260
Sim II-1	$P(t),\ Q(t)$	gaussmf	3 3	0.91	0.84	3,318	895
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	gaussmf	3 3 2	0.93	0.93	1,692	823
Sim II-3	$P(t),\ P(t-1), Q(t),\ Q(t-1)$	Gauss 2 mf	3 2 3 3	0.93	0.71	19,999	3,499

Note: MF=membership function type; N=number of membership functions.

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Table 9. ANFIS Testing Period Results for Data Set 2

Scenario	Model inputs	MF	N	R^2 Train	R^2 Test	RMSE (t/day)	MAE (t/day)
Sim I-1	$Q(t)$	gbellmf	4	0.60	0.87	7,291	2,140
Sim I-2	$Q(t),\ Q(t-1)$	gbellmf	2 2	0.63	0.84	7,124	2,239
Sim II-1	$P(t),\ Q(t)$	gbellmf	3 3	0.86	0.91	6,337	1,925
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	trimf	2 3 2	0.91	0.85	7,713	2,067
Sim II-3	$P(t),\ P(t-1),\ Q(t),\ Q(t-1)$	trimf	2 3 2 2	0.50	0.66	9,675	2,737

Note: MF=membership function type; N=number of membership functions.

in poor performance. The hybrid learning algorithm, which combines the methods of gradient descent and the least squares, was applied.

In Table 8, the ANFIS model results are presented for the Data Set 1. *Gaussian MF* (3 3 2) gives the best performance with the lowest RMSE, MAE, and the highest R^2 for the testing period in Simulation II-2 (Table 8). *Generalized bell* MF (3 3) gives the best performance for Data Set 2, with the lowest RMSE, MAE and the highest R^2 values in Simulation II-1 (Table 9). The results in Tables 8 and 9 also imply that inclusion of current precipitation in the input vector improves the model prediction performance.

SRC Model Calibration

The relationships between daily suspended sediment load and daily flow for Gediz River 523 Gauging Station for Data Set 1 and Data Set 2, respectively were obtained as

$$\mathrm{SSL} = 5.543Q^{1.642} \tag{4}$$

$$\mathrm{SSL} = 5.375Q^{1.562} \tag{5}$$

Note that the SRCs were obtained using the training data set. Tables 10 and 11 give the simulation results of SRCs for the calibration and testing periods.

Table 10. SRC Testing Period Results for Data Set 1

Scenario	Model inputs	R^2 Train	R^2 Test	RMSE (t/day)	MAE (t/day)
Sim I-1	$Q(t)$	0.78	0.59	5,280	1,047

Table 11. SRC Testing Period Results for Data Set 2

Scenario	Model inputs	R^2 Train	R^2 Test	RMSE (t/day)	MAE (t/day)
Sim I-1	$Q(t)$	0.77	0.81	11,510	3,035

MLR Model Calibration

The MLR models given in Tables 12 and 13 were constructed for all the simulations using the training data set. As seen in Tables 12 and 13, both for Data Set 1 and Data Set 2, Simulation II-2 gave better results than the other simulations. The MLR equation in Simulation II-2 was chosen for the testing period application.

NLMR Model Calibration

The NLMR models given in Tables 14 and 15 were constructed for all the simulations using the training data set. As seen in Tables 14 and 15, both for Data Set 1 and Data Set 2, Simulation II–3 gave better results than the other simulations. The NLMR equation in Simulation II-3 was chosen for the testing period application.

Note that SCR, MLR, and NLMR models presented above were developed in this study. We first constructed the models whose general forms were presented by Eqs. (1)–(3), respectively. Then, by the employment of the calibration data sets, we obtained the optimal values of the coefficients for each model. Eqs. (13) and (14) show the constructed models for the SCR method.

Table 12. MLR Models for Data Set 1

Scenario	Model inputs	Train R^2	MLR equations
Sim I-1	$Q(t)$	0.73	$\mathrm{SSL}=466.1Q_{(t)}-2{,}291.57$
Sim I-2	$Q(t),\ Q(t-1)$	0.768	$\mathrm{SSL}=649.51Q_{(t)}-152.69Q_{(t-1)}-2{,}415$
Sim II-1	$P(t),\ Q(t)$	0.759	$\mathrm{SSL}=416.18P_{(t)}+413.79Q_{(t)}-2{,}578$
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.78	$\mathrm{SSL}=302.97P_{(t)}+578.3Q_{(t)}-125.11Q_{(t-1)}-2{,}602.6$
Sim II-3	$P(t),\ P(t-1),\ Q(t),\ Q(t-1)$	0.76	$\mathrm{SSL}=208.14P_{(t)}+49.84P_{(t-1)}+584.14Q_{(t)}-136.03Q_{(t-1)}-2{,}637.96$

Table 13. MLR Models for Data Set 2

Scenario	Model inputs	Train R^2	MLR equations
Sim I-1	$Q(t)$	0.51	$\mathrm{SSL}=346.21Q_{(t)}-1{,}596.84$
Sim I-2	$Q(t),\ Q(t-1)$	0.60	$\mathrm{SSL}=562.75Q_{(t)}-224.74Q_{(t-1)}-1{,}419.97$
Sim II-1	$P(t),\ Q(t)$	0.55	$\mathrm{SSL}=345.66P_{(t)}+295.63Q_{(t)}-1{,}745.82$
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.61	$\mathrm{SSL}=136.09P_{(t)}+518.69Q_{(t)}-199.68Q_{(t-1)}-1{,}498.35$
Sim II-3	$P(t),\ P(t-1),\ Q(t),\ Q(t-1)$	0.60	$\mathrm{SSL}=111.61P_{(t)}+131.47P_{(t-1)}+515.38Q_{(t)}-217.49Q_{(t-1)}-1{,}531$

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Table 14. NLMR models for All Scenarios for Data Set 1

Scenario	Model inputs	Train R^2	NLMR equations
Sim I-1	$Q(t)$	0.75	$\mathrm{SSL}=331.185Q_{(t)}+1.085Q_{(t)}^2-1,448.42$
Sim I-2	$Q(t),\ Q(t-1)$	0.83	$\mathrm{SSL}=953.41Q_{(t)}-581.02Q_{(t-1)}-2.22Q_{(t)}^2+2.32Q_{(t-1)}^2-1,518.98$
Sim II-1	$P(t),\ Q(t)$	0.79	$\mathrm{SSL}=38.13P_{(t)}+269.89Q_{(t)}+25.0P_{(t)}^2+1.051Q_{(t)}^2-1,515.4$
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.84	$\mathrm{SSL}=-66.2P_{(t)}+847.46Q_{(t)}-502.76Q_{(t-1)}+14.85P_{(t)}^2-1.80Q_{(t)}^2+1.99Q_{(t-1)}^2-1,498.14$
Sim II-3	$P(t),\ P(t-1),\ Q(t),\ Q(t-1)$	0.845	$\mathrm{SSL}=-141.24P_{(t)}-70.95P_{(t-1)}+855.84Q_{(t)}-535.90Q_{(t-1)}+18.39P_{(t)}^2-6.06P_{(t-1)}^2-1.55Q_{(t)}^2+1.90Q_{(t-1)}^2-1,364.70$

Tables 12 and 13 present the developed MLR models and Tables 14 and 15 summarize the calibrated NLMR models for Data Set 1 and Data Set 2, respectively.

Discussion of Results

The performance of the developed models for testing periods for Data Set 1 and for Data Set 2 is compared in Tables 16 and 17, and in Figs. 3 and 4, respectively. The fit line equations are given for significance level of 5% in Tables 16 and 17. For Data Set 1, ANFIS and ANN estimates closely follow the observed values (Fig. 3). It can be seen from the hydrograph that the models were able capture the peak values and the trend of SSL. The fit line equations and R^2 values for each model in Fig. 3 is given in Table 16. The estimates of the ANFIS and ANN models are closer to the exact fit line ($y=x$ line) than those of MLR, NLMR, and SRC (Table 16). The ANN_LM model estimated the observed peak suspended sediment load as *55,293 t/day* while ANN_CG estimated this peak to be *54,666 t/day* and the ANFIS model estimated this peak as *48,393 t/day*. The ANN models were rather close to the observed value *57,056 t/day*. Though the R^2 in these ANN models are nearly equal (Table 16), the fit line equation of ANN_CG (Table 16) (assuming that the equation is $y=a_0x+a_1$) suggests the plausibility of this model since its $a_0=0.996$ is closer to the 1 and its intercept is closer to zero with $a_1=73.5$. MLR, NLMR, and SRC have lower performance than the soft computing methods (Table 16, Fig. 3). The results produced by MLR and NLMR are more reasonable than those by SRC. The cumulative error of the ANFIS, ANN_LM, MLR, NLMR, ANN_CG, and SRC are, 18%, 7%, 85%, and 57% higher and 5%, 61% percent lower than the observed total value, respectively (Table 15). In other words, ANN produced lowest error around 6%, followed by

Table 15. NLMR Models for All Scenarios for Data Set 2

Scenario	Model inputs	Train R^2	NLMR equations
Sim I-1	$Q(t)$	0.58	$\mathrm{SSL}=80.23Q_{(t)}+3.63Q_{(t)}^2-300.11$
Sim I-2	$Q(t),\ Q(t-1)$	0.68	$\mathrm{SSL}=653.72Q_{(t)}-579.05Q_{(t-1)}-0.45Q_{(t)}^2+3.44Q_{(t-1)}^2-68.5$
Sim II-1	$P(t),\ Q(t)$	0.63	$\mathrm{SSL}=485.39P_{(t)}+4.92Q_{(T)}-6.18P_{(T)}^2+3.93Q_{(T)}^2-418.78$
Sim II-2	$P(t),\ Q(t),\ Q(t-1)$	0.69	$\mathrm{SSL}=363.75P_{(t)}+550.55Q_{(t)}-518.34Q_{(t-1)}-10.65P_{(t)}^2+0.204Q_{(t)}^2+3.14Q_{(t-1)}^2-187.13$
Sim II-3	$P(t),\ P(t-1),\ Q(t),\ Q(t-1)$	0.70	$\mathrm{SSL}=292.55P_{(t)}-154.85P_{(t-1)}+610.53Q_{(t)}-537.41Q_{(t-1)}-4.37P_{(t)}^2+11.64P_{(t-1)}^2-0.88Q_{(t)}^2+3.20Q_{(t-1)}^2-247.89$

Table 16. Comparison of the Models in Terms of MSE, MAE, R^2, and Cumulative Error in Test Period for Data Set 1

Models	R^2	RMSE (t/day)	MAE (t/day)	Cumulative error	Fit line equations
ANFIS	0.926	1,692	823	+18	$y=0.895x+430.5$
ANN_CG	0.919	1,799	696	−5	$y=0.996x-73.5$
ANN_LM	0.927	1,646	820	+7	$y=0.910x+228.1$
SRC	0.59	5,280	1,047	−61	$y=0.158x+335.0$
MLR	0.59	5,444	3,285	+85	$y=1.0124x+1633.5$
NLMR	0.56	5,408	2,682	+57	$y=0.9919x+851.1$

Note: The fit line equations are given for $\alpha=0.05$ significance level.

Table 17. Comparison of the Models in Terms of MSE, MAE, R^2, and Cumulative Error in Test Period for Data Set 2

Models	R^2	RMSE (t/day)	MAE (t/day)	Cumulative error	Fit line equations
ANFIS	0.91	6,337	1,925	−33	$y=0.557x+376.72$
ANN_CG	0.89	4,384	1,332	−22	$y=0.847x-248.4$
ANN_LM	0.87	4,731	1,614	−22	$y=0.913x-489.11$
SRC	0.81	11,510	3,035	−82	$y=0.148x+111.36$
MLR	0.75	7,535	3,426	−20	$y=0.499x+1086.6$
NLMR	0.72	10,125	3,368	+22	$y=1.198x+88.52$

Note: The fit line equations are given for $\alpha=$ 0.05 significance level.

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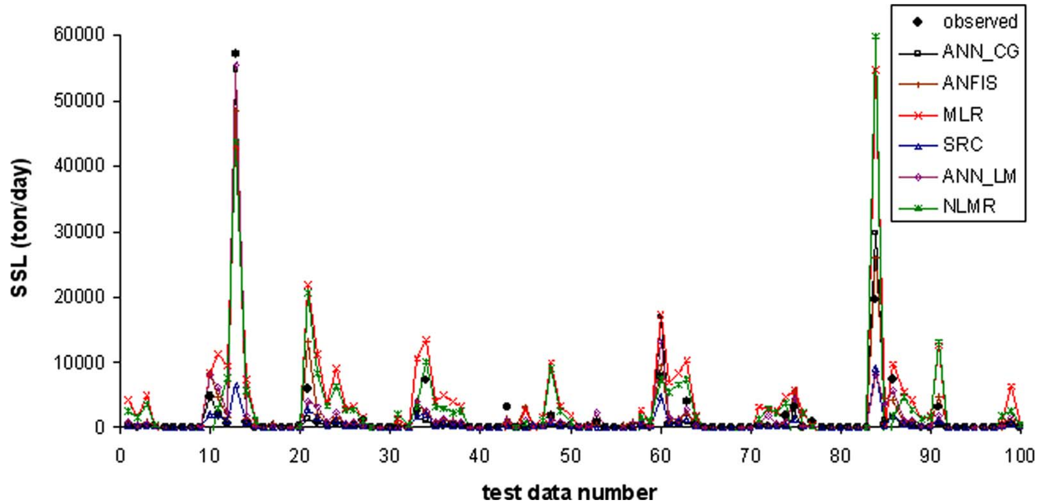

Fig. 3. Comparison of all methods for Data Set 1

ANFIS around (20%). Others produced higher cumulative errors more than 60% (Table 16).

In Data Set 2, ANFIS could not capture the peak values of SSL and the trend of the sedimentograph (Fig. 4). The ANN_LM model estimated the observed peak SSL as *109,787 t/day*, while ANN_CG estimated this peak to be *99,897 t/day* and the ANFIS model estimated this peak as *52,827 t/day*. The ANN models were rather close to the observed value *98,409 t/day*. Although both of the ANN models performed satisfactorily, from the viewpoint of capturing the peak and the fit line equation, ANN_CG produced more plausible results. NLMR had a better performance than the other conventional methods but it overestimated the peak as *170,000 t/day*. Especially, by SRC model, the estimated values are nearly *1/10* of the observed values (Fig. 4). The underestimations of the peaks are obviously seen for ANFIS, MLR, and SRC (Fig. 4). The cumulative error of the NLMR is 22% higher and ANN_LM, ANN_CG, ANFIS, MLR, SRC are, 22, 22, 33, 20, and 82% percent lower than the observed total value, respectively (Table 17). ANN had overall about 22% cumulative error for Data Set 2. This is about 4 times higher than that for Data Set 1. This is an expected performance since ANNs, as shown by Tayfur et al. (2007), are not good extrapolators.

Above results imply that, although ANN_CG and ANN_LM satisfactorily predicted the observed peak value, all the models, especially SCR, in general, performed poorly for Data Set 2, which corresponds to the investigation of the extrapolation capability of the models. On the other hand, artificial intelligence methods, especially ANN_CG and ANN_LM, performed satisfactorily for Data Set 1, which corresponds to the investigation of the interpolation capability of the models. Since, overall, ANN_CG performed better than all the other models, it is recommended, in this study, to be employed for predicting semimonthly SSL from daily measured flow rate and precipitation data.

Predicting Missing Data

The analysis of the results above proved that the ANN_CG model produced slightly better results than ANN_LM and ANFIS and it outperformed SRC, MLR, NLMR. Hence, for the missing data predictions for Gediz River, we employ only the ANN_CG. For this purpose, we applied the trained ANN_CG network model to the data, which cover the period Mar. 13, 1979–Apr. 2, 1985. In

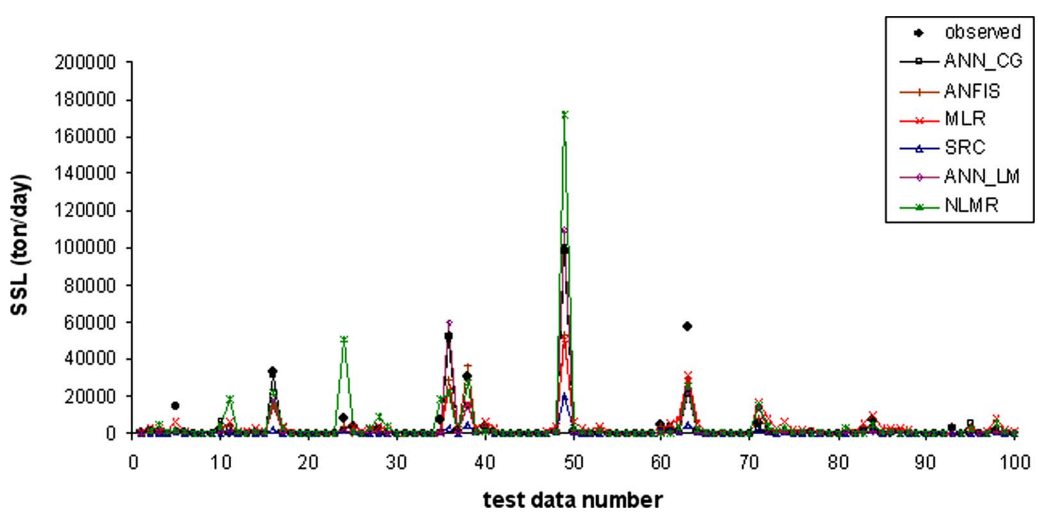

Fig. 4. Comparison of all methods for Data Set 2

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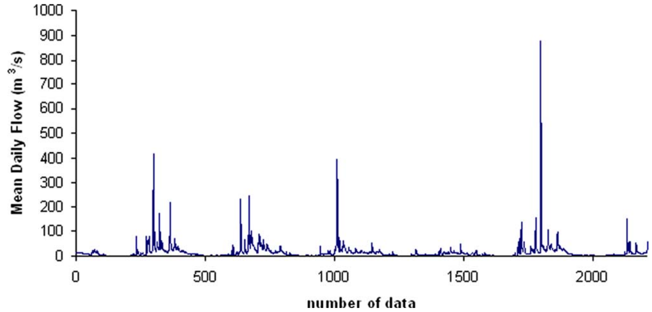

Fig. 5. ANN-predicted 2213 missing data for the period Mar. 13, 1979–Apr. 2, 1985

this period, there are 2,213 daily measured hydrometeorological data but only semimonthly or monthly measured 75 number of SSL data. That means there is about 2,138 SSL missing data record, corresponding to 6-year period. The purpose here is to generate these missing SSL data using hydrometeorological information for Gediz River. For this purpose, the same network inputs $(P_t, P_{t-1}, Q_t, Q_{t-1})$ were employed in the input vector to produce the missing SSL values. There were 2,213 daily SSL data (of which 2,138 are missing) generated by the developed ANN model as shown in Fig. 5. Figs. 6 and 7 show the measured precipitation and flow discharge data for the same period of Mar. 13, 1979–Apr. 2, 1985. As seen, in those figures, the model was able to capture the trend of SSL data, compatible with the precipitation and discharge data. That is, during the periods of high precipitation and flows, the model generated high SSL values. During drought periods, it produced low values. The cumulative SSL produced for the missing data for this period of 6 years found

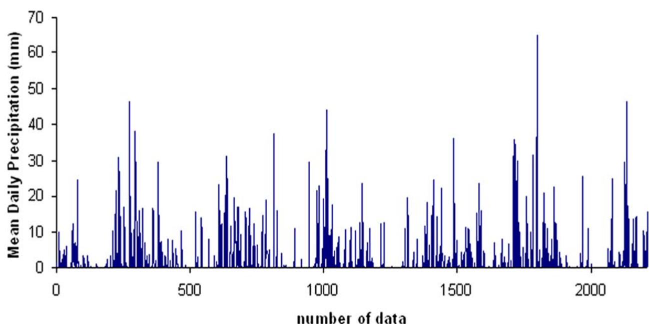

Fig. 6. Measured precipitation data in the period Mar. 13, 1979–Apr. 2, 1985

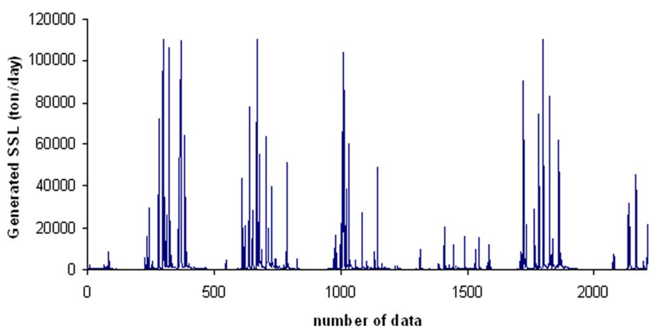

Fig. 7. Measured flow discharge data in the period Mar. 13, 1979–Apr. 2, 1985

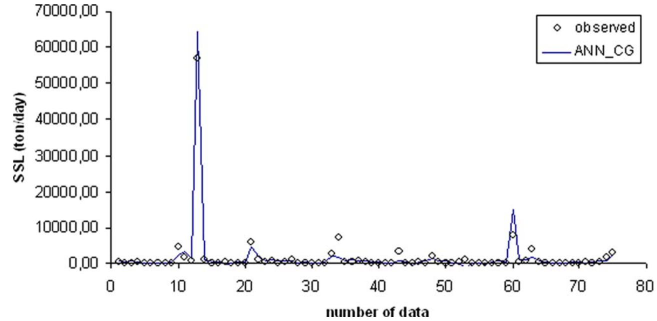

Fig. 8. Comparison of predicted missing 75 SSL data against the measured data

to be about $\Sigma SSL_{missing} = 5,65 \times 10^6$ t, about 0.94×10^6 t/year. This is in agreement with the estimates of DSI, which designed 88.4×10^6 m^3 volume for the dead storage volume of Demirkopru reservoir, receiving sediment loads from rivers Gediz, Selendi, Demirci, and Deliinis (Fig. 2) (Baytas and Ozkul 2000). The estimated dead storage volume by DSI, assuming that sediment density is 2.5 t/m^3, corresponds to about 221×10^6 t sediment load accumulation in 100 years of life expectancy of the dam. That means, the DSI-annual estimate was 2.2×10^6 t, of which about 48% (1.05×10^6 t/year) is carried by Gediz river (Baytas and Ozkul 2000). Hence, DSI estimated that Gediz river may be carrying about 1.05×10^6 t/year sediment into Demirkopru Dam reservoir. ANN estimated this value as 0.94×10^6 t/year, about 10% less than that of DSI. These results show the comparability of the estimates. To further illustrate the plausibility of the results, Fig. 8 shows the comparison of the produced missing data against the 75 (out of 2,213) SSL data measured during this period (Mar. 13, 1979–Apr. 2, 1985). As seen in Fig. 8, the model was satisfactorily able to capture measured values, including the maximum value, which may be one of the main concerns. The computed R^2 value for Fig. 8 is 0.97. These results are encouraging in the sense that ANN trained with few semimonthly data can be employed for filling the daily missing SSL data records which is one of the main concerns of the hydrologists.

Summary and Conclusions

This study developed artificial intelligence (ANN, ANFIS) and regression based (SCR, MLR, NLMR) models to predict semimonthly suspended sediment loads from daily measured flow discharge and precipitation data. The models were trained (calibrated) and tested (validated) employing the data from Gediz River, located in the western part of Turkey. The interpolation and extrapolation capability of the models were investigated by employing two different data sets. The artificial intelligence methods turned out to be very good interpolators and outperformed the regression-based models. Although ANN models lack extrapolation capability, they showed better performance than the others.

One of the main contributions of this study is that it developed models which can do predictions for SSL measured less frequently (semimonthly or monthly) in Turkey. Other contribution is that the ANN model can successfully generate daily SSL data which is one of the main concerns for the hydrologists and hydraulic engineers who design reservoir dead storage volume, and river navigation, and water quality pollution in water bodies. Working with daily data provides better estimation of sediment loads coming into reservoirs (Li et al. 2006). This is important for better monitoring of the dead storage volume. The real time distribution of the sediment load and its forecast is also necessary for controlling the pollution level in rivers and reservoirs (Lopez et al. 2001). Daily sediment is related with water quality parameters, this, in turn, affects the decision on water intake level in drinking water reservoirs.

Although daily sampling frequency may result in better estimates, it is very costly. Therefore, a balance between accuracy and cost is generally sought in practice by sampling sediment on a periodic basis (biweekly or monthly) and then interpolating between measured values to generate daily data set. This is exactly what is done in this study.

The following conclusions were also drawn from this study.

1. Inclusion of precipitation, along with flow rate data in the input vector improves the SSL predictions by the developed models.
2. ANN_CG model outperformed the other proposed models.
3. All the proposed models gave better results for Data Set 1 than Data Set 2. This is expected since the peak values in the test period are much higher than those in the training period in the Data Set 2. This reaffirms the lack of ANN capability for extrapolation.

ANN model trained with few semimonthly data can be used to fill gaps in missing daily SSL data records.

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