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Discussions

A new approach for modeling suspended sediment: Evolutionary fuzzy approach

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Abstract: This paper proposes the application of evolutionary fuzzy (EF) approach for prediction of daily suspended sediment concentration (SSC). The EF was improved by the combination of two methods, fuzzy logic and genetic algorithm. The accuracy of EF models is compared with those of the artificial neural network (ANN) and adaptive neuro-fuzzy inference system with fuzzy c-means clustering (ANFIS-FCM). The daily streamflow and suspended sediment data collected from two stations on the Eel River in California, United States are used in the study. Root mean square errors (RMSE), mean absolute errors (MAE) and determination coefficient criteria are used for evaluating the accuracy of the models. The EF is found to be superior to the ANN and ANFIS-FCM in SSC prediction. The relative RMSE and MAE differences between the optimal EF and ANN models were found to be 13-50% and 15-65% for the upstream and downstream stations, respectively. Comparison of the optimal EF, ANN and ANFIS-FCM models in estimating peak and total suspended sediments revealed that the EF model provided better accuracy than the ANN and ANFIS-FCM.

Keywords: Suspended sediment concentration; modelling; neural networks; fuzzy logic; genetic algorithm.

1. Introduction

The sediment transport in rivers is vital for pollution, channel navigability, reservoir filling, hydroelectric-equipment longevity and scientific interests. The assessment of the sediment amount being transported by a river has a vital importance in hydraulic engineering due to its importance in the design and management of water resources projects (Jain 2001; Kisi et al. 2006). The suspended sediment estimation is exceedingly difficult since it is closely related to flow and their relationship mechanism is highly non-linear and they have complicated interactions to each other (Sivakumar and Wallender 2005).

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Artificial neural networks (ANN) have been successfully applied in water resources in the last decades (Kisi and Shiri 2012; Kisi et al. 2012, 2013; Shiri et al. 2013). Recent investigations have reported that ANNs may offer a promising alternative for suspended sediment estimation (Jain 2001; Tayfur 2002; Kisi 2005; Cigizoglu & Kisi 2006, 2008, 2010; Dogan et al. 2007; Rai and Mathur 2008; Kisi et al. 2008, 2009; Cobaner et al. 2009; Jothiprakash and Garg 2009; Rajaee et al. 2009; Talebizadeh et al. 2010; Melesse et al. 2011; Mustafa et al. 2012; Kisi and Aytek 2013; Kitsikoudis et al. 2014). Jain (2001) compared single ANN approach with rating curve in establishing sediment-discharge relationship and found that the ANN model performed better than the rating curve. Tayfur (2002) used an ANN model for sheet sediment transport and compared with physically-based models, whose transport capacity was based on one of the dominant variables-flow velocity, shear stress, stream power, and unit stream power. He reported that the ANN performed as well as, in some cases better than, the physically-based models. Kisi (2005) used an ANN model for estimating suspended sediment and compared its results with sediment rating curve (SRC) and multiple linear regression (MLR). He used daily streamflow and suspended sediment data from two stations, Quebrada Blanca and Rio Valenciano, operated by the US Geological Survey. Comparison results indicated that the ANN model performs better than the regression and rating curve techniques in estimation of suspended sediment. Cigizoglu & Kisi (2006) proposed some methods to improve ANN accuracy in suspended sediment estimation. They used k-fold partitioning of the training data set and showed that similar or even superior sediment estimation performances can be obtained with quite limited data provided that the training data statistics of the subset are close to those of the testing data. Rai and Mathur (2008) developed a back propagation feed-forward ANN model for the computation of event-based temporal variation of sediment yield from the watersheds and compared with linear transfer function model. Based on the comparison, the ANN based model resulted better agreement than

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the linear transfer function model for the computation of runoff hydrographs and sedimentographs for both the watersheds (W-2 watershed of Treynor catchment and W7 of Goodwin Creek experimental watershed in USA). Kisi (2008) compared three different ANN training algorithms in suspended sediment estimation by using the flow and sediment data from the stations Quebrada Blanca and Rio Valenciano in USA. He indicated that the Levenberg–Marquardt and conjugate gradient algorithms performed better than the gradient descent in suspended sediment estimation. He also reported that the gradient descent algorithm took an unusually high number of iterations and time taken by the other two algorithms for training of the network. Jothiprakash and Garg (2009) used ANN model for estimating the volume of sediment retained in a reservoir and they found that the ANN model estimated the sediment volume with better accuracy and less effort as compared to conventional regression analysis. Rajaee et al. (2009) compared ANN with MLR and SRC models in daily simulation of suspended sediment concentration (SSC) using daily river discharge and SSC data from the Little Black River and Salt River stations in the USA. They indicated that the ANN model was more accurate than the MLR and SRC models in predicting SSC. Talebizadeh et al. (2010) made uncertainty analysis in sediment load estimation by using ANN and SWAT model. Melesse et al. (2011) used ANNs with an error back-propagation algorithm to predict the suspended sediment load from Mississippi, Missouri, and Rio Grande major rivers in USA. They evaluated different input combinations and compared the results with MLR, multiple nonlinear regression and autoregressive integrated moving average (ARIMA). Kisi and Aytek (2013) proposed explicit neural network (ENN) formulation for modeling daily suspended sediment-discharge relationship and compared with two different SRCs, MLR and nonlinear regression (NLR). They used daily streamflow and suspended sediment data from two stations on Tongue River in Montana, USA. The comparison results revealed that the ENN model performs better than the conventional SRC,

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MLR and NLR. Kitsikoudis et al. (2014) employed ANN and ANFIS for prediction of bed load transport rates in gravel-bed steep mountainous streams and rivers in Idaho (USA). They compared ANN and ANFIS results with those of the symbolic regression (SR) based on genetic programming (GP) and widely applied bed load formulas. The ANN and ANFIS models performed equally well, better than SR and bed load formulas. Mustafa et al. (2012) compared different ANN training algorithms (gradient descent, gradient descent with momentum, scaled conjugate gradient, and Levenberg-Marquardt) in prediction of the suspended sediment discharge of Pari River at Silibin in Peninsular Malaysia and they found that Levenberg-Marquardt (LM) was faster and more powerful than the other algorithms. In the present study, also, the LM is used for training ANN models.

Fuzzy logic has also been successfully employed for suspended sediment estimation during recent years (Tayfur et al. 2003; Kisi 2009; Lohani et al. 2007; Kisi et al. 2006, 2008, 2009; Mirbagheri et al. 2010; Wieprecht et al. 2013; Kitsikoudis et al. 2014; Roushangar 2014). Tayfur et al. (2003) applied fuzzy logic approach for modeling runoff-induced sediment transport from bale soil surfaces and obtained satisfactory results. They compared the fuzzy model with those of the physics-based models in predicting the mean sediment loads from experimental runs. The results indicated that the fuzzy model performed better than the physically-based model under very high rainfall intensities over different slopes and over very steep slopes under different rainfall intensities. Kisi et al. (2006) applied fuzzy logic approach to 5-year period of continuous streamflow and sediment concentration data of Quebrada Blanca Station operated by the United States Geological Survey. They indicated that fuzzy rule based models performs better than the SRC models in prediction of daily suspended sediment concentration. Lohani et al. (2007) used adaptive neuro-fuzzy inference system (ANFIS) for developing stage-discharge-sediment concentration relationships by using data from two gauging sites in the Narmada basin in India.

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Comparison results revealed that the ANFIS model significantly improved the magnitude of prediction accuracy and could be successfully applied for sediment concentration prediction. Kisi et al. (2008) modeled daily suspended sediment estimation by ANFIS models and compared with radial basis neural network (RBNN), feed-forward neural network (FFNN), generalized regression neural network (GRNN), MLR and SRC. They used daily streamflow and suspended sediment data of four stations in the Black Sea region of Turkey. They reported that the ANFIS model, in general, gave better estimates than the other models. Kisi et al. (2009) investigated the accuracy of an ANFIS computing technique in monthly suspended sediment estimation. They used monthly streamflow and suspended sediment data from two stations, Kuylus and Salur Koprusu, in Kizilirmak Basin in Turkey. They obtained better estimates than the conventional SRC. Mirbagheri et al. (2010) used ANFIS method for SSC prediction by using daily data from the Rio Rosario gauging station, Puerto Rico, USA. They found that proposed ANFIS model was able to improve on the RMSE value of the SRC method by about 44.32%. Roushangar (2014) applied ANFIS method for modeling of total bed material load through developing the accuracy level of the predictions of traditional models. They used data of Qotur River (Northwestern Iran). The comparison results indicated that the ANFIS models performed better than the sediment transport formulas in modeling total bed material load transport rate. They also found that the models based on stream power approach (used by Bagnold and Engelund-Hansen) were more reliable than those based on shear stress approach (used by Laursen) in estimating sediment transport rate. It is apparent from the literature that no work has reported the use of fuzzy genetic approach for modeling SSC.

This study investigates the applicability of fuzzy genetic approach for predicting daily SSC. The evolutionary fuzzy (EF) models are compared with those of the ANN and ANFIS with fuzzy c-means clustering (ANFIS-FCM) models. To the best knowledge of the author, this is the first

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study that compares the accuracy of EF model with those of the ANN and ANFIS-FCM models in suspended sediment modeling.

2. Methods and materials

2.1. Fuzzy logic approach

Fuzzy logic is firstly introduced by Zadeh (1965) and used different scientific researches. The fuzzy concepts and algorithms can be found in many related textbooks (Kosko 1993; Ross 1995). The fuzzy logic (FL) theory has a mechanism for representing linguistic constructs such as “high”, “low”, “medium”, “few” etc. The FL has an inference system that enables human reasoning capabilities while the conventional binary set theory defines crisp events. The FL theory is based upon the notion of relative graded membership degree between 0 and 1.0. The fuzzy sets have ability to model indistinct or ambiguous data, often faced in real life (Sivanandam et al. 2007).

As seen from Figure 1, a typical fuzzy inference system is a rule-based system and composed of three conceptual components. These are; 1) a rule base comprising fuzzy IF-THEN linguistic rules relates the membership functions (MFs) of the input variables to the outputs’ MFs; 2) a database consisting membership functions used in fuzzy linguistic rules; 3) an inference mechanism that incorporate these rules to relate a set of outputs to a set of inputs and to obtain a reasonable output. In the fuzzification, input and/or output data are considered as having ambiguous characteristics and therefore, they are divided into subsets defined by linguistic terms (e.g., small, big) and membership degrees are determined. In the defuzzification, a crisp numerical value is computed from the fuzzy linguistic outputs obtained from the inference mechanism (Nayak et al. 2005). The part between IF and THEN is called antecedent, while the part after THEN is referred to consequent.

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Let assume that the input and output variables are partitioned into subsets with Gaussian fuzzy MFs. If there are three input variables comprising two membership functions in the antecedent part, there should be 2^3 rules in the fuzzy rule base. Increasing number of subsets may results in better accuracy. In this case, however, the rule base gets larger and its construction will be difficult to construct (Şen 1998). Assume that we have two inputs with two fuzzy subsets or MFs labeled as "weak" and "strong" and one output then there should be four rules as follows:

R_1: IF x_1 is weak and x_2 is weak THEN y_1

R_2: IF x_1 is weak and x_2 is strong THEN y_2

R_3: IF x_1 is high and x_2 is weak THEN y_3

R_4: IF x_1 is strong and x_2 is strong THEN y_4

where x_1 and x_2 are input1 and input2 and y_1, y_2, y_3 and y_4 are constant or linear equations.

In each fuzzy model used in the present study, membership degrees, w_n, for x_1 and x_2 are computed to be assigned to the corresponding output y_n for each triggered rule. Thus, a single weighted output, y, is computed by weighting average of the outputs obtained from four rules as:

$$y = \frac{\sum_{n=1}^{4} w_n \cdot y_n}{\sum_{n=1}^{4} w_n} \tag{1}$$

The output values, y, can be simply calculated from Eq. (1) for any input combination after setting up the rule base (Şen 1998).

2.2. Genetic algorithm

Holland (1975) explained in his book how to apply the principles of natural evolution to optimization problems and built the first genetic algorithms (GAs). In the last decades, GAs have been used as a powerful means for solving search and optimization problems (Sivanandam and

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Deepa, 2008). The main idea in GAs is to simulate the natural evolution mechanisms of chromosomes, including the rudimentary elements of natural genetics for example reproduction, crossover, and mutation.

Three core steps are included in a typical form of a GA (Preis and Ostfeld, 2008):

i. Generation of initial population: GA produces a set of strings (or population), with each string (chromosome) containing a set of parameter values to be optimized.
ii. Strings fitness calculation: GA assesses the fitness of each string (i.e., the objective function value).
iii. Production of new generation: The next generation is produced by performing selection, crossover and mutation. Selection is used to choose chromosomes from the recent population for reproduction with respect to fitness values.

One of the main reproduction operator employed is bit-string crossover (Figure 2). In this operator, two strings are used as parents and new individuals are generated by swapping a sub-sequence between the two strings. The other main operator is bit-flipping mutation (Figure 3). In this operator, a single bit in the string is flipped to constitute a new offspring string. All operators in GA are delimited to manipulate the string in a parallel manner to the structural interpretation of genes. For instance, two genes in the same location on two strings may be exchanged between parents, but not merged based on their values. Individuals are usually selected to be parents probabilistically with respect to their fitness values, and the offspring that are formed replace the parents (Sivanandam and Deepa, 2008).

GA is a powerful method with regard to search the optimum solution to complex problems such as the choice of the MFs where it is hard or almost impossible to test for optimality (Ahmed and Sarma, 2005).

The main differences between GAs and conventional optimization methods are:

- The parameter sets are coded in GAs, not the parameters.
- Local optimum is explored from a population in GAs, not a single point.
- The objective function information is used in GAs, not adjutant knowledge (e.g. derivatives).
- Probabilistic evolution rule is used in GAs, not deterministic rules (Goldberg, 1989).

The GA explores for the best potential solutions of a problem from existing solution sets. The problem is converted to binary form and the solutions are allowed to crossover and mate with a specified criterion to yield the optimal. The basics of the GA can be obtained from Wang (1991), Ahmed and Sarma (2005).

2.3. Evolutionary Fuzzy Approach

In this study, the EF was developed by the combination of two methods, fuzzy logic and genetic algorithm. The optimal parameters (e.g. antecedent and consequent parameters) of the fuzzy models were obtained by using genetic algorithms. Figure 4 demonstrates the flowchart of a fuzzy genetic model. Genetic algorithm optimization is done by minimizing the error (objective function) between model estimates and measured values. In this study, mean square error was used as objective function in genetic algorithm. The MSE can be expressed as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(yi_{observed} - yi_{model}\right)^2 \qquad (2)$$

where N is the number of training data. Here, the objective function given in Eq. 2 was minimized by adjusting the MF parameters of the input and outputs. The optimization of the MFs is a complex problem for the supervised learning scheme. Genetic algorithm, however, has a non-supervised learning scheme and can be successfully applied to solve this problem (Goldberg 1989, Ozger 2009).

2.4. Case Study

The daily streamflow and SSC data from two stations, upstream station near Dos Rios (station No: 11147000) and the downstream station at Scotia (station No: 11472150), on the Eel River in California were used in the present study. The stations are operated by the US Geological Survey (USGS). The drainage areas of the upstream and downstream stations respectively are 1368 km^2 and 8063 km^2. Daily data were downloaded from the web server of the USGS (http://webserver.cr.usgs.gov/sediment). In the both stations, the data from October 01, 1966 to September 30, 1971 were used for training, the data from October 01, 1971 to September 30, 1974 were used for validation and the data from October 01, 1974 to September 30, 1977 were used for models' testing. Streamflow and suspended sediment data of upstream and downstream stations are shown in Figures 5-6. In California rivers (e.g. Eel River), the geologic, climatic, physiographic, and land-use conditions are highly variable (Tramblay *et al.* 2010). An extraordinary flood was occurred on the Eel River near Scotia, California (downstream station, 11477000) in 1964. This is one of the most widespread and destructive floods in the history of the West Coast (Waananen *et al.* 1971). The Eel River is the most exceptional flood-producing river in the United States (O'Connor and Costa 2004). On December 23, 1964, the Eel River at Scotia, California, peaked up at a stage of 72 ft and a discharge, designated by a rating curve extension, of 752,000 ft^3/s. For measuring peak discharges above a threshold at this site, surface velocities measured by optical current meter are used. The Eel River is may be the only site in the US, where optical current meters are routinely used for high-flow discharge measurements (Costa and Jarrett 2008). Groundwater recharge, recreation, and industrial, agricultural and municipal water supply were supplied from the river (Brown and Ritter, 1971). The Eel River system is among the most dynamic in California due to the region's unsteady geology and the effect of

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major Pacific storms. The discharge is highly variable in this river; average flows in January and February are over 100 times greater than in August and September (USGS 2013). The Eel River also conveys the highest suspended sediment load of any river of its size in the United States, in part as a result of the frequent landslides in the region. Unlike most areas, suspended sediment discharge per unit area in the river increases with catchment size (Brown and Ritter, 1971; Janda and Nolan, 1979). As a result of ongoing uplift, main channels are generally more deeply incised than their tributaries, and so streamside landslides, which are major sources of sediment, are mainly plentiful along main channels. Parent material is mostly soft and friable, and therefore, bed particles quickly break down into smaller sizes (Knott, 1971). Accordingly, suspended-sediment load growths downstream at the expense of bedload (Brown and Ritter, 1971; Lisle 2013).

Statistical parameters of daily streamflow and SSC data are shown in Table 1 for the upstream and downstream stations. In this table, S_x, C_v, C_{sx}, x_{mean}, x_{max} and x_{min} are the standard deviation, variation coefficient, skewness coefficient, mean, maximum and minimum, respectively. From the table it is clear that the flow and SSC data have a considerably high skewed distribution (range 8.05-19.5 for the upstream station and range 7.11-14.5 for the downstream station). The validation and test data indicate much more skewed distribution than those of the training data for the both stations. The maximum-mean ratios (x_{max}/x_{mean}) for SSC series are also quite high especially for the validation and test data (244-154 and 135-156 for the upstream and downstream, respectively). It is evident from these statistics that the discharge-sediment phenomenon has a highly complex behavior.

3. Results and discussion

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Different EF models were tried in terms of number of membership functions and generations. The EF models were compared with ANN and ANFIS-FCM models. Three different program codes, including fuzzy logic, genetic algorithm and neural network toolboxes, were written in MATLAB language for the simulations of EF, ANN and ANFIS-FCM models.

Root mean square errors (RMSE), mean absolute errors (MAE) and determination coefficient (R^2) were used for evaluation of the applied models. The RMSE, MAE and R^2 statistics are expressed as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(SSCi_{observed} - SSCi_{predicted})^2} \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|SSCi_{observed} - SSCi_{predicted}\right| \tag{3}$$

$$R^2 = \left(\frac{\sum_{i=1}^{N}(SSCi_{observed} - \overline{SSC}_{observed})(SSCi_{predicted} - \overline{SSC}_{predicted})}{\sqrt{\sum_{i=1}^{N}\left(SSCi_{observed} - \overline{SSC}_{observed}\right)^2 \sum_{i=1}^{N}\left(SSCi_{predicted} - \overline{SSC}_{predicted}\right)^2}}\right)^2 \tag{4}$$

in which N is the number of data, SSC is the suspended sediment concentration, $\overline{SSC}$ is mean of the SSC.

Various input combinations including previous streamflows (Table 2) were tried to estimate suspended sediment concentrations of the upstream station. In this table, Qt and Qt-1 indicate the discharge at current and one previous days, respectively. Input combinations were determined according to the correlation analysis given in Table 2 and following the related literature (Jain, 2001; Kisi, 2005). For each input combination, optimum parameters of the EF, ANN and ANFIS-FCM models were obtained by minimizing the objective function (MSE error between calculated and observed SSC values) in validation period. The training and validation

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results of the EF, ANN and ANFIS-FCM models are shown in Table 3 for the upstream station. The computing times required for the applied models are also compared in this table. In this table, the EF(3,gauss,5000) model has the 3 Gaussian MFs for the inputs, Qt, Qt-1, Qt-2 and Qt-3 and 5000 generations. ANN(4,2,1) indicates an ANN model comprising 4 input, 2 hidden and 1 output nodes. ANFIS-FCM(5) model has 5 cluster or 5 Gaussian MFs for each input. In all ANN models, the logarithm sigmoid activation function commonly used in the literature was used for the hidden and output nodes. It is evident from Table 3 that the ANFIS-FCM models generally perform better than the EF and ANN models in the validation period. The ANFIS-FCM models require less computing time for calibration than the other models. The EF models has the most computing time in calibration (training). Table 5 compares the accuracy of the applied models in the test period. It is obvious from the table that all the EF models generally have better accuracy than the ANN and ANFIS-FCM models. The relative RMSE and MAE differences between the optimal EF (input combination iii) and ANN (input combination iv) models are 13% and 50%, respectively. Figure 7 illustrates the scatterplots of the optimal EF, ANN and ANFIS-FCM models in the test period for the upstream station. The R^2 value of ANN seems to be slightly higher than the EF model. However, the *a* and *b* fit line equation coefficients of the EF model (assume that the equation is $y=ax+b$) respectively closer to the 1 and 0 than those of the ANN model. Figure 8 demonstrates the log-scaled scatterplots of the optimal models in test period. The peak SSC estimates of the ANN model seem to be closer to the exact line than those of the EF and ANFIS-FCM. However, the EF and ANFIS-FCM models seem to be better the ANN model in low sediment estimation. It should be noted that the distribution of the EF and ANFIS-FCM models' estimates are similar to each other. Table 6 reports the comparison of the models' SSC peak-estimates. It is evident from the table that the EF model gives better estimates of peak SSC values than the ANN and ANFIS-FCM models. The ANFIS-FCM is the second best in estimating peak SSC. The EF and ANN models respectively estimated the observed total sediment load, 20,289,369 ton, as 30,308,073 ton and 31,820,879 ton with overestimations of 49.4% and 56.8% while the ANFIS-FCM model resulted in 9,514,219 ton with an underestimation of 53.1%. The EF model seems to be slightly better than the other models in estimating total sediment load.

Same input combinations were used to estimate SSC values for downstream station. The training and validation results of the EF, ANN and ANFIS-FCM models are given in Table 4. The architectures of the EF, ANN and ANFIS-FCM models are also provided in the first column of this table. From the table, it is clear that the ANN models perform better than the EF and ANFIS-FCM in validation period. Here also ANFIS-FCM models require less computing time for calibration than the other models while the EF models has the most computing time in training. Comparison of Table 3 and 4 clearly reveals that the models' accuracies are better in upstream station than the downstream. The reason of this may be the fact that the downstream has much larger drainage area than the upstream and the SSC in downstream may be much more affected by perturbations (urbanization, land-use change, slope failures, forest fires, earthquakes, etc.). Table 5 compares the test accuracy of the models with respect to RMSE, MAE and R^2 values. Here, also the EF models perform better than the ANN and ANFIS-FCM models. The relative RMSE and MAE differences between the optimal EF (input combination iii) and ANN (input combination iv) models are 15% and 65%, respectively. The observed and estimated SSC values by the optimal EF, ANN and ANFIS-FCM models in the test period are shown in Figure 9 for the upstream station. It is evident from the fit line equations and R^2 values that the EF estimates are closer to the exact line than those of the ANN and ANFIS-FCM models. The log-scaled scatterplots of the optimal models are compared in Figure 10 for the test period. The EF model seems to have better accuracy in estimating average and low SSC values than the ANN and ANFIS-FCM models. The comparison of the optimal models' peak SSC estimates are made in Table 6 for the downstream station. The superior accuracy of the EF model to the ANN and ANFIS-FCM models is clearly seen from this table. The EF model estimated total sediment load as 6,252,171,710 ton instead of observed value of 5,051,074,055 ton, with an overestimation of 24% while the ANN and ANFIS-FCM models resulted in 6,422,653,088 ton and 6,464,368,673 ton with overestimations of 27% and 28%, respectively. The results indicate that all applied models generally provided overestimations for the peak and total SSC in both stations. The main reason of this may be the differences between training, validation and testing datasets. It is clear from Table 1 that the validation data set has much higher SSC values (661,000 ton for the upstream and 6,230,000 ton for the downstream) than those of the test data set (86,500 ton for the upstream 2,870,000 ton for the downstream) in both upstream and downstream stations. The significantly high streamflow and suspended sediment values are also clearly seen from Figures 5-6. It is clear from the figures that the high floods (e.g. 1590 m^3/s and 9170 m^3/s in 16 Jan 1974 for the upstream and downstream, respectively) occurred in validation period causes high SSC values (e.g. 661,000 mg/l and 6,230,000 mg/l in 16 Jan 1974 for the upstream and downstream, respectively). The great changeability of Eel River in space and time can be obviously seen from the figures. The optimal models were obtained according to their minimum MSE errors in the validation period. Therefore, the high SSC values in this period lead models to give overestimations in the test period. The difference between the validation and test data sets may be due to the fact that extreme SSCs in Californian Rivers show a great changeability in space and time, and are interrelated with some physiographic features at the station locality scale (Tramblay *et al.* 2010). O'Connor and Costa (2004) reported that the Eel River is the most exceptional flood-producing river in the United States.

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In overall, the EF models seem to be more adequate than the ANN and ANFIS-FCM for estimating SSC. The main disadvantage of the ANN is its black-box structure. The other disadvantage is it uses backpropagation (BP) methodology for adjusting the weights and it is very easy for the training process to get trapped in a local minimum (Kumar *et al*., 2002; Sudheer *et al*., 2003). By combining ANN and fuzzy (neuro-fuzzy), the individual strengths of each approach can be employed in a synergistic way for the building effective and powerful intelligent systems. Neuro-fuzzy (e.g., ANFIS) methods have the ability to get the benefits of both these fields in a single system. The drawback of fuzzy system design (getting a set of fuzzy if-then rules) is amended by ANFIS system where the learning ability of an ANN is used, automatic fuzzy if-then rules are generated and parameters are optimized (Jang, 1993; Nayak et al., 2004). The EF and ANFIS models use transparent, linguistic representation of a fuzzy system and provide set of rules on which the model is based. This provides further insight into the modeled process (Sayed *et al.*, 2003). In ANFIS, however, gradient descent algorithm is used for the determination of membership functions (MFs). The main disadvantage of this algorithm is that it uses BP methodology for amending the weights and it is very easy for the calibration process to get trapped in a local minimum (Kumar *et al*., 2002; Sudheer *et al*., 2003). The main advantage of EF compared to ANFIS is that it uses genetic algorithm. Genetic algorithm combines stochastic and directed search elements and they offer global optimum without being trapped in local optima (Mantoglou *et al.*, 2004; Karterakis *et al.*, 2007). The main disadvantage of the EF is that it requires long time for calibration.

6. Conclusions

In this paper, the applicability of fuzzy genetic approach for prediction of daily suspended sediment concentration was investigated. The EF models' accuracy is compared with those of the artificial neural networks and adaptive neuro-fuzzy inference system with fuzzy c-means clustering. The daily streamflow and SSC data from two stations on the Eel River in California were used in the applications. Various input combinations consisting previous streamflows were used as inputs to the EF, ANN and ANFIS-FCM models in order to estimate SSC of the upstream and downstream stations. For the both stations, the best EF and ANFIS-FCM models were obtained for the third input combination composed of current and two previous streamflow data while the ANN model gave the best accuracy for the inputs, Qt, Qt-1, Qt-2 and Qt-3 (fourth input combination). The comparison of the EF, ANN and ANFIS-FCM models showed that the EF models performed better than the ANN and ANFIS-FCM. The optimal EF, ANN and ANFIS-FCM models were also compared with each other in estimating peak and total suspended sediments and results indicated that the EF model generally provided better accuracy than the ANN and ANFIS-FCM. The results suggest that the EF can be successfully used for developing streamflow-sediment relationship in the rivers where the geologic, climatic, physiographic, and land-use conditions are highly variable.

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Figure Captions

Figure 1 A typical fuzzy inference system

Figure 2 Bit-string crossover of parents (i) and (ii) to form offspring (iii) and (iv)

Figure 3 Bit-flipping mutation of parents (ii) to form offspring (ii)

Figure 4 The flowchart of the fuzzy genetic model (Kisi and Tombul, 2013)

Figure 5 Streamflow and suspended sediment data of upstream station.

Figure 6 Streamflow and suspended sediment data of downstream station.

Figure 7 Scatterplots of the observed and estimated SSC by EF, ANN and ANFIS-FCM - Upstream station.

Figure 8 Scatterplots of the observed and estimated SSC by EF, ANN and ANFIS-FCM (logarithm scaled) - Upstream station.

Figure 9 Scatterplots of the observed and estimated SSC by EF, ANN and ANFIS-FCM - Downstream station.

Figure 10 Scatterplots of the observed and estimated SSC by EF, ANN and ANFIS-FCM (logarithm scaled) - Downstream station.

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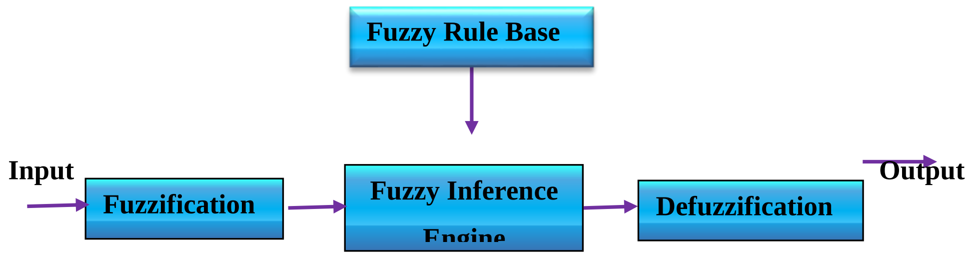

Figure 1

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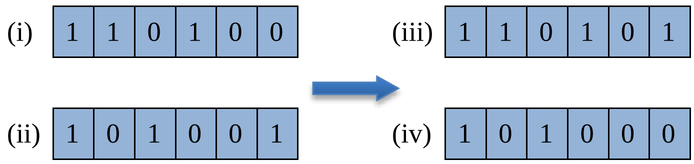

Figure 2

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Figure 3

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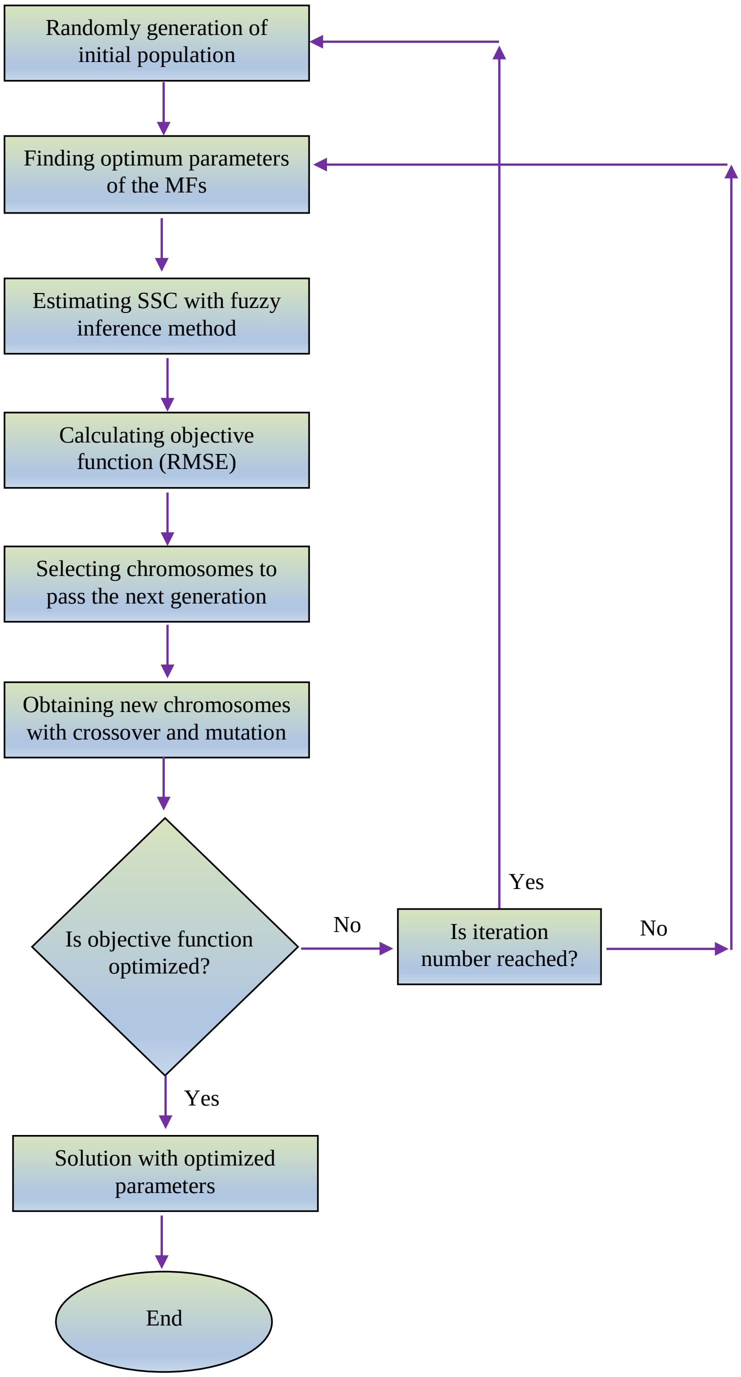

Figure 4

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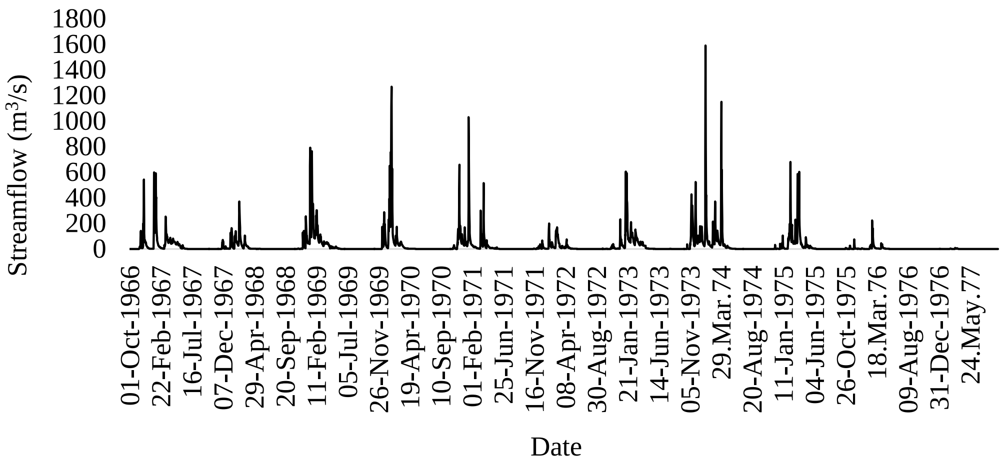

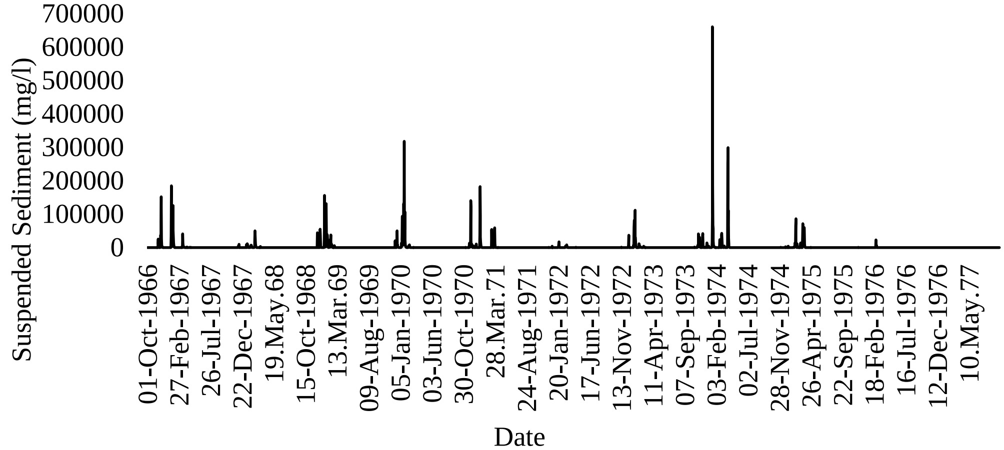

Figure 5

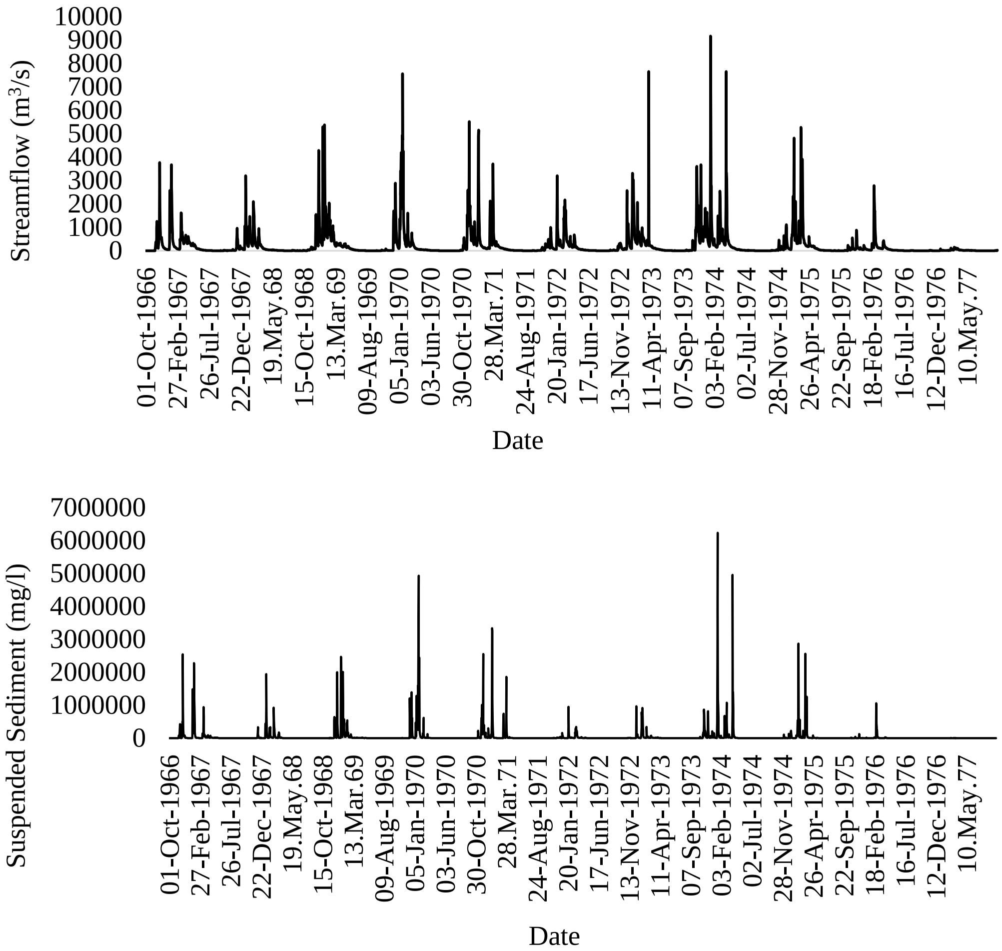
Streamflow (m3/s)
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
01-Oct-1966
27-Feb-1967
26-Jul-1967
22-Dec-1967
19.May.68
15-Oct-1968
13.Mar.69
09-Aug-1969
05-Jan-1970
03-Jun-1970
30-Oct-1970
28.Mar.71
24-Aug-1971
20-Jan-1972
17-Jun-1972
13-Nov-1972
11-Apr-1973
07-Sep-1973
03-Feb-1974
02-Jul-1974
28-Nov-1974
26-Apr-1975
22-Sep-1975
18-Feb-1976
16-Jul-1976
12-Dec-1976
10.May.77
Date
Suspended Sediment (mg/l)
7000000
6000000
5000000
4000000
3000000
2000000
1000000
0
Date

Figure 6

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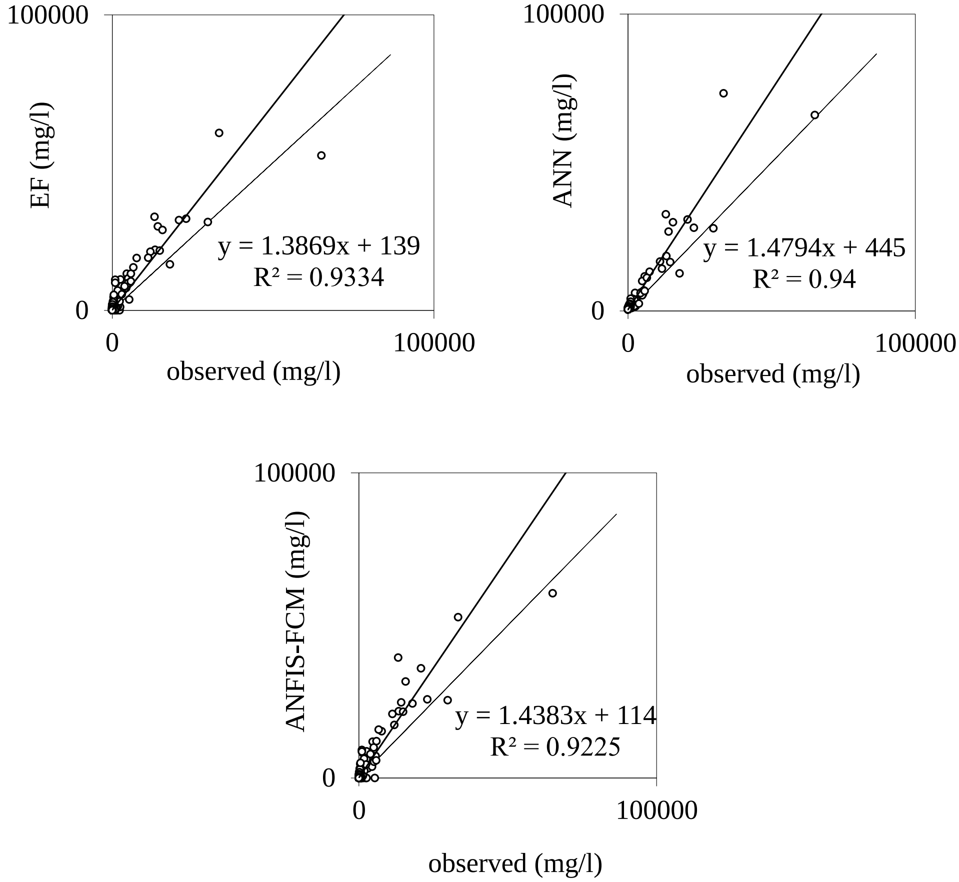

Figure 7

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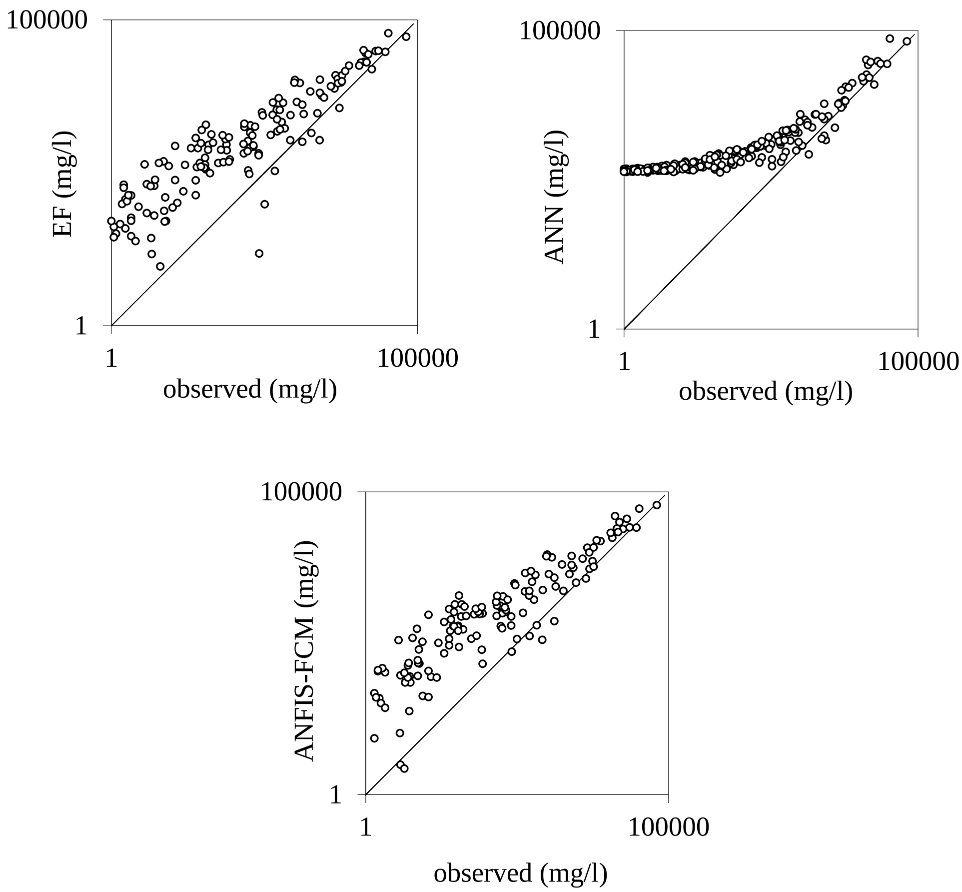

Figure 8

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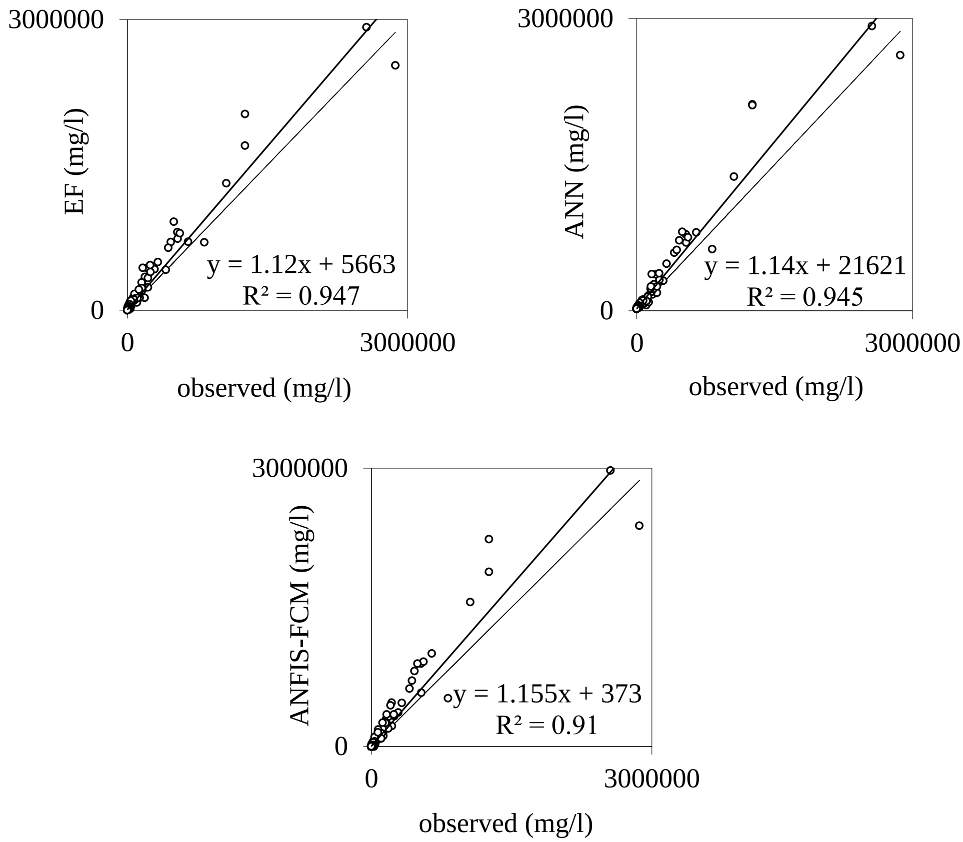

Figure 9

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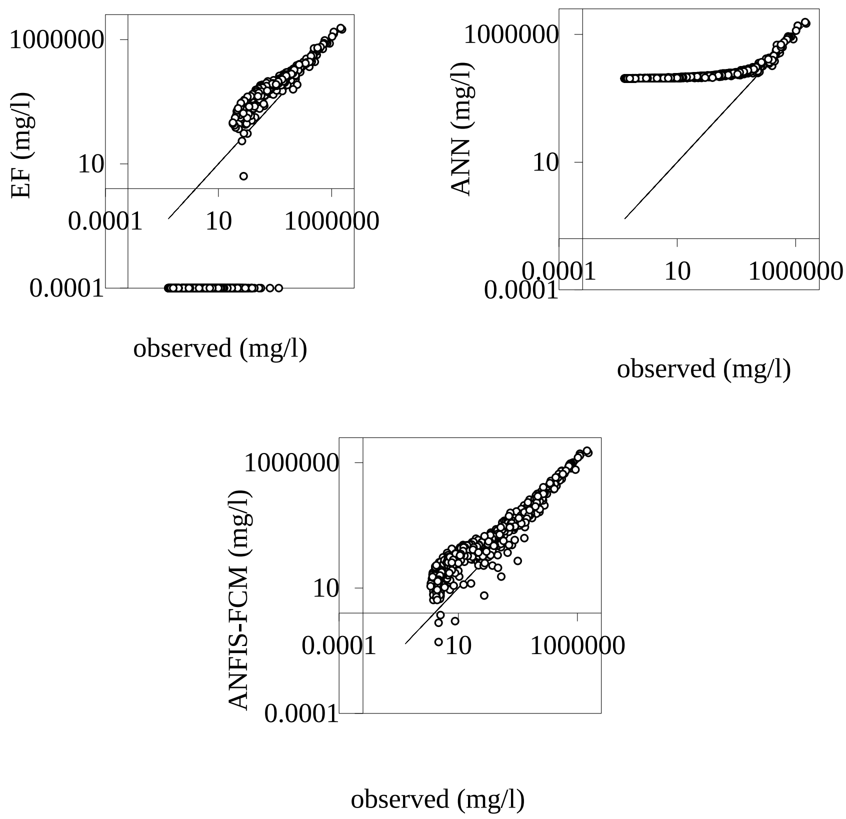

Figure 10

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TABLES

Table 1. The daily statistical parameters of data set for the stations.

Data set	Station	Basin area (km^2)	Data type	x_{mean}	S_x	C_v (S_x/x_{mean})	C_{sx}	x_{max}	x_{min}	$\frac{x_{max}}{x_{mean}}$
Training	Upstream (11472150)	1368	Flow (m^3 s^{-1})	32.7	92.8	2.83	6.31	1270	0.05	38.8
			Sediment (mg l^{-1})	2790	17076	6.12	10.8	318000	0	114
	Downstream (11477000)	8063	Flow (m^3 s^{-1})	266	625	2.35	5.01	7560	2.07	28.4
			Sediment (mg l^{-1})	60966	288396	4.73	8.50	4930000	0.23	80.9
Validation	Upstream (11472150)	1368	Flow (m^3 s^{-1})	33.3	95.5	2.86	8.02	1590	0.08	47.7
			Sediment (mg l^{-1})	2706	25108	9.28	19.5	661000	0	244
	Downstream (11477000)	8063	Flow (m^3 s^{-1})	296	693	2.34	6.32	9170	2.32	31.0
			Sediment (mg l^{-1})	46210	303083	6.55	14.4	6230000	0	135
Test	Upstream (11472150)	1368	Flow (m^3 s^{-1})	12.1	49.1	4.05	8.05	680	0	56.1
			Sediment (mg l^{-1})	561	4780	8.52	13.1	86500	0	154
	Downstream (11477000)	8063	Flow (m^3 s^{-1})	131	408	3.12	7.11	5270	0.71	40.3
			Sediment (mg l^{-1})	18432	143023	7.76	14.5	2870000	0.06	156

Table 2. The cross-corelations between disharge and SSC in the upstream and downstream stations.

	Qt	Qt-1	Qt-2	Qt-3	Qt-4	Qt-5
Upstream St	0.884	0.545	0.353	0.353	0.310	0.275
Downstream St	0.873	0.524	0.358	0.358	0.317	0.259

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Table 3. The traning and validation performances of the EF, ANN and ANFIS-FCM models in suspended sediment prediction – Upstream station

Models	Inputs	Training time (sec)	Training RMSE (mg/l)	MAE (mg/l)	R^2	Validation RMSE (mg/l)	MAE (mg/l)	R^2
EF(2,gauss,10000)	i) Qt	1047	5482	1378	0.898	9704	1604	0.912
EF(2,gauss,1000)	ii) Qt, Qt-1	144	4876	1190	0.919	9783	1415	0.908
EF(3,gauss,5000)	iii) Qt, Qt-1, Qt-2	2442	4579	983	0.928	9973	1259	0.908
EF(3,gauss,5000)	iv) Qt, Qt-1, Qt-2, Qt-3	5211	4436	1095	0.933	12232	1610	0.816
ANN(1,1,1)	i) Qt	6.96	6175	2242	0.874	13097	2389	0.818
ANN(2,2,1)	ii) Qt, Qt-1	7.64	4177	1149	0.941	11836	1568	0.824
ANN(3,2,1)	iii) Qt, Qt-1, Qt-2	7.78	4176	1152	0.941	11837	1567	0.838
ANN(4,2,1)	iv) Qt, Qt-1, Qt-2, Qt-3	7.92	4162	1173	0.941	11826	1593	0.841
ANFIS-FCM(8)	i) Qt	0.75	4703	943	0.924	20784	1602	0.315
ANFIS-FCM(7)	ii) Qt, Qt-1	0.31	3966	930	0.946	6390	1012	0.948
ANFIS-FCM(5)	iii) Qt, Qt-1, Qt-2	1.14	4379	1016	0.934	9032	1248	0.912
ANFIS-FCM(5)	iv) Qt, Qt-1, Qt-2, Qt-3	3.58	4319	1258	0.937	8524	1580	0.923

Table 4. The traning and validation performances of the EF, ANN and ANFIS-FCM models in suspended sediment prediction – Downstream station

Models	Inputs	Training time (sec)	Training RMSE (mg/l)	Training MAE (mg/l)	Training R^2	Validation RMSE (mg/l)	Validation MAE (mg/l)	Validation R^2
EF(2,gauss,20000)	i) Qt	2211	85898	23182	0.912	164866	32127	0.777
EF(5,gauss,1000)	ii) Qt, Qt-1	327	63122	16028	0.952	168184	31977	0.698
EF(2,gauss,50000)	iii) Qt, Qt-1, Qt-2	10354	75041	19719	0.932	214455	40579	0.610
EF(4,gauss,5000)	iv) Qt, Qt-1, Qt-2, Qt-3	8768	72437	19282	0.937	182543	34471	0.701
ANN(1,2,1)	i) Qt	7.56	93265	36014	0.898	160822	43381	0.734
ANN(2,2,1)	ii) Qt, Qt-1	7.74	75190	25994	0.933	139047	37361	0.823
ANN(3,1,1)	iii) Qt, Qt-1, Qt-2	7.46	89231	34060	0.907	168271	44889	0.708
ANN(4,1,1)	iv) Qt, Qt-1, Qt-2, Qt-3	8.68	89035	34651	0.907	167950	45222	0.709
ANFIS-FCM(2)	i) Qt	0.45	87038	24817	0.909	157874	34597	0.773
ANFIS-FCM(8)	ii) Qt, Qt-1	0.35	73337	16598	0.935	177645	26975	0.751
ANFIS-FCM(8)	iii) Qt, Qt-1, Qt-2	1.53	80011	17997	0.923	202776	29772	0.712
ANFIS-FCM(3)	iv) Qt, Qt-1, Qt-2, Qt-3	0.88	78597	20174	0.926	176095	34031	0.731

Table 5. The test performances of the optimal EF, ANN and ANFIS-FCM models in suspended sediment prediction

Models	Inputs	RMSE (mg/l)	MAE (mg/l)	R^2
Upstream station				
EF(2,gauss,10000)	i) Qt	2588	503	0.892
EF(2,gauss,1000)	ii) Qt, Qt-1	2654	445	0.931
EF(3,gauss,5000)	iii) Qt, Qt-1, Qt-2	2583	413	0.933
EF(3,gauss,5000)	iv) Qt, Qt-1, Qt-2, Qt-3	2685	476	0.928
ANN(1,1,1)	i) Qt	3206	1583	0.875
ANN(2,2,1)	ii) Qt, Qt-1	2999	708	0.941
ANN(3,2,1)	iii) Qt, Qt-1, Qt-2	2989	709	0.941
ANN(4,2,1)	iv) Qt, Qt-1, Qt-2, Qt-3	2962	736	0.943
ANFIS-FCM(8)	i) Qt	3172	449	0.904
ANFIS-FCM(7)	ii) Qt, Qt-1	3065	401	0.926
ANFIS-FCM(5)	iii) Qt, Qt-1, Qt-2	2912	416	0.922
ANFIS-FCM(5)	iv) Qt, Qt-1, Qt-2, Qt-3	3022	499	0.935
Downstream station				
EF(2,gauss,20000)	i) Qt	47773	10285	0.929
EF(5,gauss,1000)	ii) Qt, Qt-1	44593	8414	0.939
EF(2,gauss,50000)	iii) Qt, Qt-1, Qt-2	42714	9032	0.947
EF(4,gauss,5000)	iv) Qt, Qt-1, Qt-2, Qt-3	45493	10149	0.948
ANN(1,2,1)	i) Qt	53083	25489	0.927
ANN(2,2,1)	ii) Qt, Qt-1	52215	18227	0.907
ANN(3,1,1)	iii) Qt, Qt-1, Qt-2	50986	24917	0.944
ANN(4,1,1)	iv) Qt, Qt-1, Qt-2, Qt-3	50491	25444	0.945
ANFIS-FCM(2)	i) Qt	50499	10994	0.921
ANFIS-FCM(8)	ii) Qt, Qt-1	54149	8591	0.919
ANFIS-FCM(8)	iii) Qt, Qt-1, Qt-2	45569	1498	0.940
ANFIS-FCM(3)	iv) Qt, Qt-1, Qt-2, Qt-3	51721	11229	0.937

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Table 6. The comparison of EF, ANN and ANFIS-FCM peak-estimates for the test period-Upstream station.

Day	Peaks > 15000 (mg/l)	EF (mg/l)	ANN (mg/l)	ANFIS-FCM (mg/l)	Relative Error		
					EF (%)	ANN (%)	ANFIS-FCM (%)
135	65100	52375	65890	60511	-19.5	1.2	-7.0
136	86500	121380	124244	108905	40.3	43.6	25.9
137	18000	15494	12534	24360	-13.9	-30.4	35.3
168	29800	29905	27751	25478	0.4	-6.9	-14.5
169	71300	101871	116166	120171	42.9	62.9	68.5
170	33300	60004	73166	52681	80.2	120	58.2
172	20800	30555	30703	35895	46.9	47.6	72.6
175	15700	27199	29803	31601	73.2	89.8	101
176	59800	108508	116646	120463	81.5	95.1	101
514	23000	30997	27956	25787	34.8	21.5	12.1
		Total (Absolute) =			**434**	**519**	**497**

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Table 7. The comparison of EF, ANN and ANFIS-FCM peak-estimates for the test period-Downstream station.

Day	Peaks > 500000 (mg/l)	EF (mg/l)	ANN (mg/l)	ANFIS-FCM (mg/l)	Relative Error		
					EF (%)	ANN (%)	ANFIS-FCM (%)
132	538000	737820	700519	579618	37.1	30.2	7.7
133	535000	806291	783917	892406	50.7	46.5	66.8
135	822000	702169	631613	520127	-14.6	-23.2	-36.7
136	2870000	2526702	2624083	2381486	-12.0	-8.6	-17.0
137	649000	705882	802897	1004263	8.8	23.7	54.7
143	560000	793386	752534	915272	41.7	34.4	63.4
169	2560000	2920197	2922853	2976379	14.1	14.2	16.3
170	1260000	1699105	2116979	2235129	34.8	68.0	77.4
				Total (Absolute) =	**298**	**346**	**436**