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Assessing ANFIS accuracy in estimation of suspended sediments

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Scientific paper - Preliminary report

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Assessing ANFIS accuracy in estimation of suspended sediments

Capabilities offered by an adaptive neuro-fuzzy inference system (ANFIS) in the estimation of daily sediment loads at four stations in the USA, are explored in the paper. For this purpose, models with various input combinations of data sets were constructed to enable identification of the best possible structure. The results show that the best ANFIS model exhibits better performance compared to the SRC model, in terms of the RMSE, MBE and R2 values. The results also indicate that the ANFIS model can be applied to facilitate modelling of nonlinear dynamics of complex systems.

Key words:
ANFIS, hysteresis, sediment concentration, sediment load

Prethodno priopćenje

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Procjena točnosti ANFIS-a u prognoziranju lebdećeg nanosa

U radu se istražuju mogućnosti koje pruža prilagodljivi sustav neizrazitog zaključivanja zasnovanog na neuronskoj mreži (ANFIS) u predviđanju dnevnih količina lebdećeg nanosa koje je obavljeno na četiri stanice u SAD-u. U tu su svrhu izrađeni modeli s različitim kombinacijama ulaznih podataka kao osnova za određivanje najbolje moguće strukture. Dobiveni rezultati pokazuju da se najbolji model ANFIS ponaša bolje od modela SRC s obzirom na dobivene vrijednosti RMSE, MBE i R2. Rezultati također pokazuju da se pomoću modela ANFIS može pojednostavniti modeliranje nelinearne dinamike složenih sustava.

Ključne riječi:
ANFIS, histereza, koncentracija nanosa, nanos

Vorherige Mitteilung

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Genauigkeitsabschätzung des ANFIS bei der Prognose von Schwebablagerungen

In dieser Arbeit werden die Möglichkeiten veränderlicher Systeme indirekter Schlussfolgerungen aufgrund neuronaler Netze (ANFIS) bei der Vorhersage täglicher Mengen von Schwebablagerungen untersucht, die an vier Stationen in den USA durchgeführt wurden. Dazu wurden vier Modelle mit verschiedenen Kombinationen von Eingangsparametern als Grundlage zur Ermittlung der optimalen Struktur erstellt. Die Resultate zeigen, dass sich in Bezug auf die gegebenen Werte RMSE, MBE und R2 das beste ANFIS Modell besser als das SRC Modell verhält. Außerdem geht aus den Resultaten hervor, dass sich aufgrund des ANFIS Modells die Modellierung komplexer nichtlinearer dynamischer Systeme vereinfachen lässt.

Schlüsselwörter:
ANFIS, Hysterese, Konzentration von Ablagerungen, Ablagerungen

1. Introduction

Knowledge of the quantity, quality and dynamics of sediments is essential for designing dams, sediment transport, prevention of pollution in lakes and rivers, fish habitats, watershed management, etc. Direct measurement of suspension load is most reliable, but it is expensive and cannot be conducted for as many streams as the measurement of water discharge [1]. On the other hand, most of the sediment transport equations are derived from detailed information about the flow and sediment characteristics. Traditionally, the influence of short-term dynamics of storm event on sediment loading is characterized by rating curves to predict the suspended sediment concentration (SSC) or suspended sediment load (SSL) according to stream discharge (Q) in a certain region [1-10]. A rating curve has the following form, according [11, 12, 3]:

$$Q_s = a \cdot Q^b \tag{1}$$

where Q_s is the SSL (ton/day) or (gr/l), Q (m^3/s) is the stream flow, and *a* and *b* are the rating coefficient and rating exponent, respectively. Due to high variability in water discharge and SSC values [13], this relationship is normally not homogenous in time, neither within nor between events, which causes a large scatter of SSC–discharge data pairs. On the other hand, the delivery of suspended sediments and water may result in hysteresis effects, i.e. different sediment concentrations for discharges of equivalent magnitude on the rising and falling limbs of a hydrograph [14-16].

Therefore, the SSC–discharge modelling is still a challenging task due to its nonlinear and hysteretic behaviour. According to [13], the form of the rating curve can be attributed to the dominant sediment source, dominant channel pattern and, to a certain extent, to the cross-section position within the river basin. Due to a large number of (unknown) parameters involved in this phenomenon, sophisticated computer modelling and simulation are required to predict the values accurately, and to enable finding nonlinear relations between variables. Recently, there has been a rise in interest about the use of soft computing methodologies, especially the artificial neural network (ANN) and the adaptive neuro fuzzy inference system (ANFIS), to model this phenomenon and enable finding nonlinear relations between variables.

In spite of suitable flexibility of ANN in modelling hydrologic time series, it may not be appropriate in situations when signal fluctuations are highly non-stationary and a physical hydrologic process operates under a large range of scales varying from one day to several decades. In such an uncertain situation, the Fuzzy Inference System (FIS) may be employed for estimating uncertainties in real situations. The ANN and FIS hybrid is one of the focal points of research, as it can make use of the advantages of both ANN and FIS and hence the acronym ANFIS.

Several studies about the application of ANFIS in the prediction of sediment have been conducted so far. The proof of concept for the application of ANFIS has been investigated in a number of research papers, and it was established that it performs comparatively well with respect to conventional sediment rating curve models, and that it takes into account the non-linear complex phenomenon [17-19]. Kisi and Shiri [20] compared the Genetic Programming (GP) technique with the ANFIS, ANN and SVM (Support Vector Machine) models for estimating the daily SSL at two stations in the Cumberland River in the U.S. The comparison results indicate that the GP is superior to the ANFIS, ANN and SVM models. Kisi [21] modelled the SSC using the ANFIS and ANN methods and found that the ANFIS model is superior to the ANN. Another study [22] highlights the advantage of ANFIS over ANN and SRC (sediment rating curve) models in the monthly suspended sediment prediction at Kuylus and Salur Koprusu stations in Kizilirmak Basin in Turkey. Aytek and Kisi [23] applied GP to suspended sediment transport, and found that it performs better than the conventional rating curve and multi-linear regression techniques. Rajaee et al. [24] applied the ANFIS, SRC, and ANN to estimate daily SSC, and they showed that the ANFIS works better compared to the others, and that it can satisfactorily simulate hysteresis phenomena. Yang et al. [25] examined the total sediment transport prediction using the ANN model. The average flow velocity, water surface slopes, average flow depth, and median particle diameter, were used to train the ANN. In another study, Rajaee [26] investigated the combined use of the ANN and Wavelet (WANN) for daily SSL prediction in rivers. Results showed that the WANN model simulated the hysteresis event better than other models. Furthermore, the ANN model simulated hysteresis in only one event, while the SRC model was unable to simulate the hysteresis phenomenon. Jain [27] presented a SVR (support vector regression) application to model the river discharge and sediment concentration rating relations, and compared the results with those derived from the ANN model. It was established that the SVR approach is better when compared to the ANN.

The reviewed literature shows that, despite many investigations on the discharge-sediment relationship using intelligent techniques, most efforts have been focused on the development of optimum ANFIS model parameters in order to estimate the suspended sediment, and then to verify the model efficiently with regard to peak SSL or hysteresis. The aim of this research was to characterize the effect of different input data on the SSL estimation accuracy. In particular, we explored the best combination of input data for the estimation of hysteretic behaviour and sediment load peaks using appropriate ANFIS structures at four stream-gauging stations in the USA.

2. Data and method

2.1. ANFIS

ANFIS is a multi-layer adaptive network-based fuzzy inference system [29]. An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a function with fixed or adjustable parameters. Learning or training phase of a neural network is a process aimed at determining parameter values to sufficiently fit the training data. The basic learning rule is the well-known back-propagation method that seeks to minimize some measures of error, usually sum of squared differences between network's outputs and desired outputs [30]. The benefit of the ANFIS architecture comes from combining the fuzzy decision-making capability and the ANN learning capability to represent the dynamics of a non-linear system. ANFIS can be constructed as a five layer MLP network illustrated in Figure 1, with the following five layer operations:

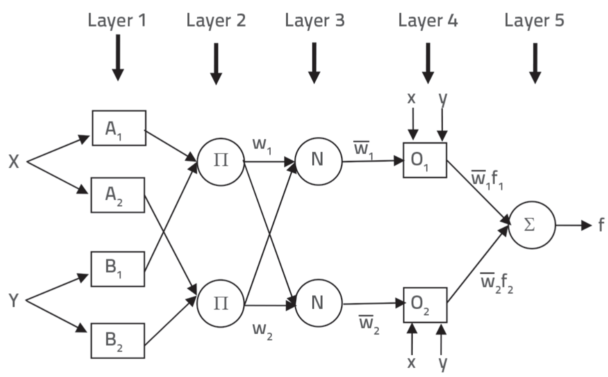

Figure 1. A typical ANFIS structure

Layer (1): X and Y are two typical input values fed at two input nodes, which will then transform these values to membership functions.

$$O_i^1 = \mu_{Ai}(x) \quad i = 1, 2$$
$$O_i^1 = \mu_{Bi-2}(y) \quad i = 3, 4 \qquad (2)$$

where X (or Y) is input and μ_{A_i} (ili $\mu_{B_{i-2}}$) is the fuzzy set associated with this node.

Layer (2): Every node in this layer multiplies the incoming signals. The output O^2_i of the node *i* can be computed as:

$$O_i^2 = W_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y)\, i = 1, 2 \qquad (3)$$

Layer (3): Such products or firing strengths are then averaged:

$$O_i^3 = \overline{w}_i = \frac{w_1}{w_1 + w_2}\, i = 1, 2 \qquad (4)$$

Layer (4): The node *i* in this layer calculates the contribution of i^{th} rule in the model output function, which is defined based on the first-order method as [31]:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i X + q_i Y + r_i)\, i = 1, 2 \qquad (5)$$

where $\overline{w}$ is the output of layer 3 and p_i, q_i, r_i are the parameter sets.

Layer (5): The single node of this layer calculates the weighted global output of the system as follows:

$$O_i^5 = \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (6)$$

Additional details about the ANFIS and hybrid algorithm can be found in [32].

2.2. Data and statistical analysis

Four river gauging stations operated by the US Geological Survey (USGS) provided time series data of discharge and sediment load that were used in this research. These stations are: 1100000 (Merrimack river at Lowell, New Hampshire), 1491000 (Choptankriver near Greensboro, Maryland), 1570500 (Susquehanna river at Harrisburg, Pennsylvania), and 1573000 (Swatara Creek at Harper Tavern, Pennsylvania),

Table 1. River monitoring stations and characteristics of their drainage areas

Hydrological station	Station ID	Station description	Latitude	Longitude	Drainage area [km²]	Date of the data day/month/year
Station 1	1100000	Merrimack river at lowell	42°38'45"	71°17'56"	12005	25/05/1967 - 28/09/1972
Station 2	1491000	Choptank Near Greensboro	38°59'50"	75°47'10"	292.67	02/10/1980 - 30/09/1989
Station 3	1570500	Susquehanna river at harrisburg	40°15'17"	76°53'11"	62419	01/01/1976 - 30/09/1979
Station 4	1573000	Swatara creek at Harper Tavern	40°24'09"	76°34'39"	872.83	08/05/1959 - 30/09/1960 01/10/1976 - 31/12/1978

Table 2. Statistical characteristics of the observed flow (m^3/s) and SSL (ton/day)

	Station ID	Data type	x_{min}	x_{mean}	x_{max}	*Sx*	Csx
Train	1	Flow	9.54	220.09	1210	216.90	0.98
		Sediment	1.80	579.02	24500	1912.76	3.30
	2	Flow	0.07	3.39	65.7	5.17	1.52
		Sediment	0.02	5.04	351	19.35	3.84
	3	Flow	138	1203.78	11600	1313.61	1.09
		Sediment	57	8348.11	287000	26372.36	3.16
	4	Flow	0.93	19.42	306	29.81	1.54
		Sediment	0	232.50	18100	1108.65	4.77
Test	1	Flow	12.5	208.66	1210	219.22	1.05
		Sediment	7	595.02	26300	2025.60	3.40
	2	Flow	0.12	3.59	63,1	5.41	1.51
		Sediment	0.02	6.08	406	25.22	4.15
	3	Flow	136	1165.11	9800	1284.24	1.10
		Sediment	66	6911.12	135000	17442.14	2.52
	4	Flow	1.36	17.86	228	26.84	1.50
		Sediment	0	174.71	7440	714.81	4.09

and are herein referred to as the Station 1, Station 2, Station 3, and Station 4, respectively. The gauging stations, geographic coordinates, and operation periods, are presented in Table 1. Table 2 summarizes statistical characteristics of the observed discharge and SSL in training and testing sets, namely the minimum (x_{min}), maximum (x_{max}), mean (x_{mean}), standard deviation (*Sx*,), and coefficient of variation (Csx). The difference between the SSL and discharge data is identifiable. According to Table 2 C_{sx} for SSL data is almost three times higher than the discharge data.

2.3. Evaluation criteria

The performance of the models was evaluated using quantitative statistical metrics including the root mean square errors (RMSE), mean absolute errors (MAE), and coefficient of determination (R^2) statistics. R^2 is a statistic that will give some information about the goodness of fit of a model. In regression, the R^2 coefficient of determination is a statistical measure of how well the regression line approximates measured data. Moreover, the R^2 tends to reflect the proportion of the total variance in the observed data that can be explained by the model [33]. Different types of information about predictive capabilities of the model are measured through RMSE and MAE and also its variant in form of mean bias error (MBE) that includes the sign of deviation. The RMSE sizes the goodness of fit as related to high discharge coefficient values, whereas the MBE measures a more balanced perspective of the goodness of fit at moderate discharge coefficients [34]:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(A_i - B_i)^2}{n}} \tag{7}$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n} A_i - B_i}{n} \tag{8}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(A_i - \bar{A}\right)\left(B_i - \bar{B}\right)}{\sqrt{\sum_{i=1}^{n}\left(A_i - \bar{A}\right)^2}\sqrt{\sum_{i=1}^{n}\left(B_i - \bar{B}\right)^2}} \tag{9}$$

where n is the number of data set, A_i and B_i are the observed and estimated values, respectively, $\bar{A}$ and $\bar{B}$ are mean values of observed and estimated values, respectively.

2.4. Development of ANFIS model

Literature reviews on ANFIS show no specific rules for the subdivision of test and train data. However, from the overall input/output data, 75 % are normally used for the training procedure and the rest 25 % for model testing. The test and train data were chosen randomly in this research. One of the most important steps in the development of a satisfactory estimation model is the selection of input variables, which determines the structure of the ANFIS model, and affects the weighted coefficient and the results of the model [35]. Different combinations of antecedent values of daily river flows and daily SSL or SSC were used for constructing an appropriate input

Table 3. Summary of final architecture of ANFIS models

Model input	Station ID	Input MF	Output MF	Number of input MF	Number of fuzzy rules
Q_t	1	[a]Gauss2	Linear	3	3
	2	[b]Tri	Linear	4	4
	3	[c]Gbell	Constant	4	4
	4	[d]psig	Linear	3	3
Q_t, T	1	[e]Pi	Constant	3 3	9
	2	Gauss2	Constant	4 4	13
	3	Gbell	Constant	3 3	8
	4	Gbell	linear	4 4	15
Q_t, Q_{t-1}	1	Pi	Constant	2 2	4
	2	Gauss2	Linear	2 2	4
	3	Gbell	Constant	4 4	16
	4	[f]tarp	Constant	3 3	9
Q_t, Q_{t-1}, T	1	Tri	Linear	3 3 3	23
	2	Gauss	Constant	3 3 3	22
	3	Gbell	Constant	3 3 3	8
	4	Gbell	Constant	3 3 3	12
Q_t, Q_{t-1}, SSL_{t-1}	1	Tri	Constant	3 3 3	16
	2	Gbell	Constant	3 3 3	27
	3	Tri	Constant	3 3 3	15
	4	Gauss2	Constant	3 3 3	23

[a] Membership function based on a combination of two Gaussian functions, [b] Triangular membership function
[c] Generalized bell-shaped membership function, [d] Product of two sigmoid membership functions
[e] π shape membership function, [f] Trapezoidal membership function , MF - membership function

structure. Generally, two types of time series models can be developed: univariate and multivariate. Consequently, ANFIS was designed to model univariate and multivariate time series in which the univariate time series models used current and past discharge data alone, while the multivariate time series models used discharge data along with sediment load data. Therefore, five different ANFIS models were established to estimate SSL (SSC) for four downstream stations in the river system with the corresponding input vectors as follow:

(1) Q_t
(2) Q_t, T
(3) Q_t, Q_{t-1}
(4) Q_t, Q_{t-1}, T
(5) Q_t, Q_{t-1}, SSL_{t-1} or (SSC_{t-1})

Where Q_t is the flow at the t-th day, Q_{t-1} is the flow at the t-1st day, SSL_{t-1} or SSC_{t-1} the suspended sediment load and concentration at the t-1st day, and T stands for centralized time for dates.

A program code including fuzzy toolbox was written in the MATLAB software for ANFIS simulation. Different ANFIS architectures were checked using this code, and an appropriate model structure was obtained. For all models, the training was performed using an optimum hybrid method. This method is a combination of backpropagation and least squares methods that are used to train the network so as to minimize the error between the ANFIS output and desired response (SSL or SSC). Various types of input membership functions (triangular, trapezoidal, Gaussian and Gumbel membership functions) were tried for each ANFIS model. The training stage was carried out using the trial and error procedure by utilizing various estimator structures to determine an optimum set of fuzzy rules. The summary of optimum values is given in Table 3. It can be seen quite clearly that the best entry functions in different stations and in different entry models were not the same and that, in most models, the constant membership function performed better than the linear one. Three or four membership functions for ANFIS models were considered sufficient for SSL modelling.

3. Results and discussion

Statistical values of the best input combination of the training and test sets for ANFIS models at each station are presented in Table 4. The R^2 values for the ANFIS training model ranged from 0.80 to 0.87 for the four stations for input M1 model when only the current day flow was used for SSL predictions. Similarly, the R^2 ranged from 0.87 to 0.94 when the current day flow and centralized time for dates derived from the aforementioned analyses were used for the input M2 model at the training stage. The greatest R^2 were obtained at Gauging Station 4, and the values from 0.87 to 0.94 were obtained for M1 and M2 models on the training data set. When antecedent flow was also used in the input matrix, the range of R^2 values increased for all four gauging stations as in the M3 model and M4 model where R^2 ranged from 0.90-0.94 and 0.94-0.96, respectively. In M4 model, higher MBE and RMSE values indicate higher error, which shows poorer agreement of the modelled and observed values. Of the five ANFIS models, M5 model performed slightly better than the others in three stations out of four stations, and it resulted in the highest coefficients of determination (0.92-0.96). In addition, the RMSE and MBE values of M5 model for the station data set are lower than those of other models. The M5 model offered the lowest MBE values compared to other models in all stations. In Table 4, the best input combination at the training stage, in all stations except for Station 1, are sorted from lowest to highest as M1 model to M5 model; while the highest R^2 were obtained in Station 1 by M4 model. Comparison of input parameters revealed that the parameter T was almost non-effective at Station 4 while in other stations this parameter improved the results in the second and fourth combination, and had the most accurate estimation.

During the testing phase, all developed models were used to conduct a SSL (SSC) forecast using an independent training dataset. As can be seen quite clearly in Table 4, unlike the results obtained at the training stage, the M2 model generally had better results compared to M3 model at the test stage at all stations, except at Station 4. In addition, the best model defined at the training phase (M5 model) consistently outperformed the others during testing stages at all stations except at Station 1. Also, the parameter T improved the accuracy of predictions at the training stage for all stations, except for Station 4. This might be due to the fact that there was a 16-year gap between the data collected at this gauging Station, and that there was an extreme increase in T parameter values in the second part of data compared to the first part. The ANFIS technique could not adequately simulate these alterations, and so this parameter was not allowed to influence the values predicted at this station. Wang and Linker [36] used non-linear regression to show that parameter T could represent the effect of long-term changes on sediment load, but ANFIS was not capable

Table 4.Performance of SRC and ANFIS models simulating SSL at various gauging stations (RMSE and MBE= ton/day)

Analizirani modeli				Station							
				Train				Test			
Model	Inputs	Vrsta	Statistički pokazatelji	1	2	3	4	1	2	3	4
M1	Q_t	SRC	R^2	0,84	0.83	0.78	0.73	0.80	0.80	0.80	0.72
			RMSE	774	8.0	8465	580	923	11.9	6850	413
			MBE	-91.7	0.5	368	42	-84.2	-0.1	1679	60
		ANFIS	R^2	0.87	0.85	0.80	0.88	0.88	0.84	0.80	0.73
			RMSE	693	7.4	11714	387	723	10.8	10158	454
			MBE	0.0	0.0	120	0	-29.1	-0.7	793	21
M2	Q_t,T	ANFIS	R^2	0.94	0.91	0.87	0.91	0.90	0.91	0.83	0.72
			RMSE	477	5.8	9503	337	641	9.5	7287	430
			MBE	0.3	0.0	284	3	-10.8	-1.1	-10	5
M3	Q_t,Q_{t-1}	ANFIS	R^2	0.90	0.92	0.90	0.94	0.86	0.84	0.83	0.83
			RMSE	616	5.4	8198	267	750	10.1	8133	315
			MBE	0.0	0.8	81	8	-23.5	-0.1	170	11
M4	Q_t,Q_{t-1},T	ANFIS	R^2	0.96	0.94	0.94	0.94	0.87	0.85	0.85	0.79
			RMSE	401	4.8	6217	271	739	9.9	6945	349
			MBE	-0.6	0.0	2494	12	-35.8	-0.2	2807	-10
M5	Q_t,Q_{t-1},SSL_{t-1}	ANFIS	R^2	0.92	0.96	0.95	0.95	0.86	0.95	0.94	0.91
			RMSE	548	3.6	5796	244	764	6.9	4746	223
			MBE	0.0	0.3	0	9	-16.8	0.2	1	2

R2 - the coefficient of determination, RMSE - root mean square error, MBE - mean bias error

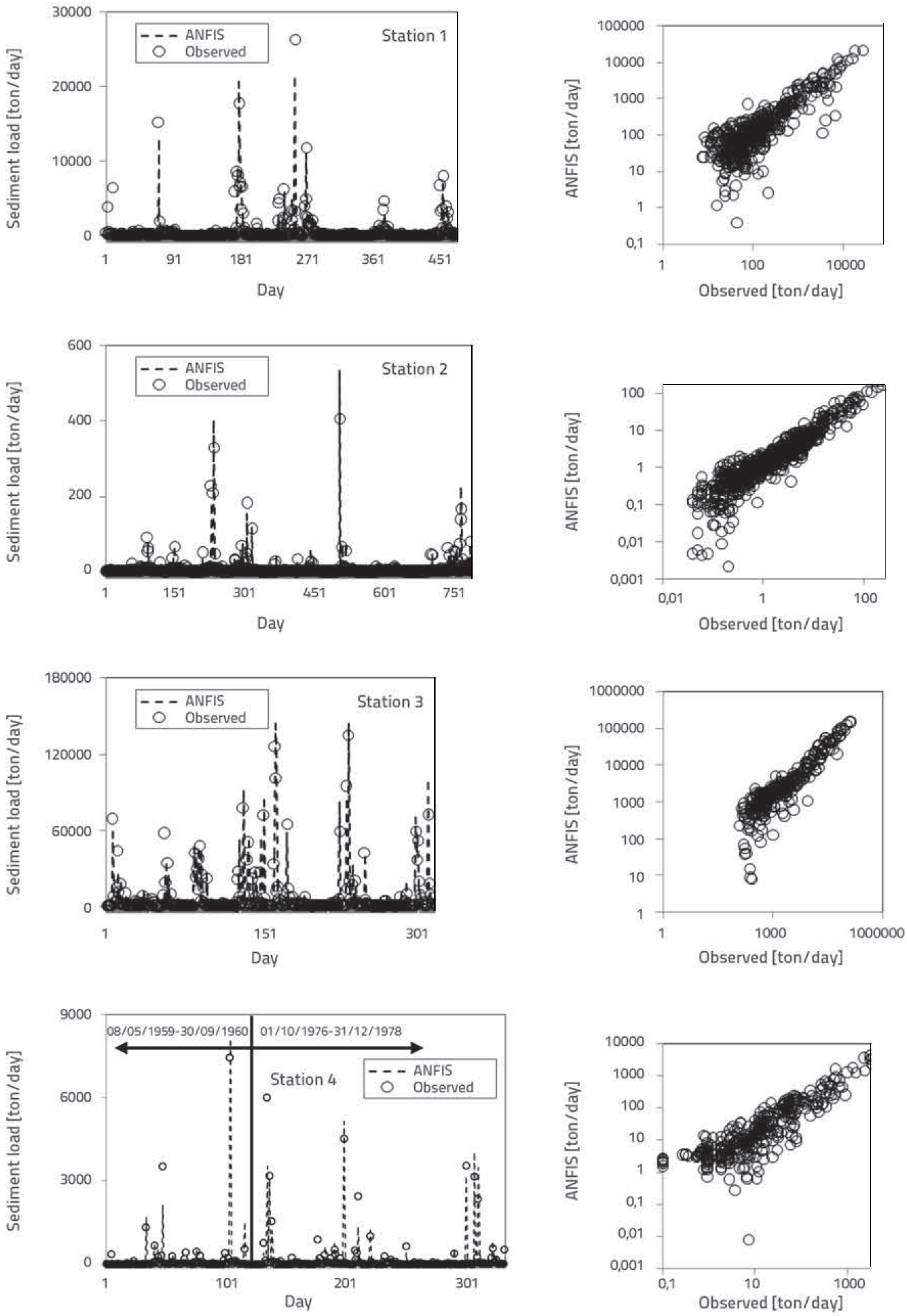

Figure 2. SSL estimation using M5 model at test period for four stations

of conducting reliable simulations using this parameter when there was a long gap between the data. The parameter T does not require data measurements and is determined by time, and so it is easily computable and may increase the estimated sediment concentration accuracy. The use of this parameter leads to a preferable simulation. In the third model, imposing Q_{t-1} to Q_t decreased errors in the results. The decreased error value percentages for stations 1 to 4 were 12 %, 37 %, 43 %, and 45 %, respectively, at the training stage, and -4 %, 7 %, 25 %, and 44 %, respectively, at the test stage. However, the testing error was slightly higher at Station 1. With the inclusion of SSL_{t-1} parameter in the M5 model, the error decreased conspicuously, so that the decreased error percentages for Stations 2 to 4 were 50 %, 41 %, and 9 %, respectively, at the training stage, and 46 %, 71 %, and 41 %, respectively, at the test stage. At Station 1, the error value decreased by 12 % at the training stage, but it slightly increased at the test stage. In general, it was clear that the M4 model was more accurate than the M3 model at all stations, and the accuracy of the M2 model was higher compared to the M1 model. The comparison between the regression model and the first model (Q_t) showed that the regression model clearly outperformed the ANFIS model at the training and test stages for Station 3, and at the test stage for Station 4. It can be said that at other stations the ANFIS yielded better results than the regression model. As a result, the ANFIS model, which has the current day flow, antecedent flow, and the antecedent SSL (SSC) as inputs, was selected as the best fit model for SSL (SSC) predictions. The temporal variations of the observed and predicted SSL are shown in Figure 2 using the M5 model for testing period at each station. Moreover, the SSL predictions are plotted against the observed SSL results for each station. It can be seen from scatterplots that the M5 model predictions are slightly closer to the exact fit line at Stations 2 and 3, compared to Stations 4 and 1, especially for high values. These plots, when combined with results shown in Table 4, indicate that the model performance for the full range of SSL data evaluated in this study was superior for the M5 model, as confirmed by greater R^2 and lower RMSE and MBE values compared to those determined for other ANFIS models and the SRC model. .

3.1. Peak SSL estimation error

To study the accuracy of results produced by different ANFIS models for the peak SSL prediction, the sediment peaks observed at the test stage were compared with predicted values for all stations. The goodness of fit statistics of maximum SSL losses during testing are presented in Table 5 for various model approaches. It is evident from Table 5 that each model produces different results at different stations. For instance, the M1 model, which consists of Q_t for the Station 1 data set had the worst performance compared to other ANFIS models, and its results at Station 2 were almost the same as those of the M2 model, while at Station 3 it performed even worse compared to the regression model. Better results were obtained when parameter T was also used to determine Q_t in the input matrix (M2 model), and the range of error values dramatically decreased by 5 to 77 % for all four gauging stations.

By adding T into the input combination, the inputs being Q_t, Q_{t-1}, the SSL estimation slightly improved the model performance at Station 3. However, it failed to preserve its performance at other stations. Overall, this implies that parameter T could affect models to improve the accuracy of prediction without discharge antecedent (Q_{t-1}) in the input because, otherwise, the inclusion of T as input increases the training time with no increase in model performance.

The overall results confirmed that the model 5, which included flow (Q_t), antecedent flow (Q_{t-1}), and sediment load at the t-1st day (SSL_{t-1}), obtained the highest values of R^2. The lowest RMSE and MBE values outperformed the other combinations for simulating the sediment load corresponding to the maximum discharge at all stations except at Station 1. M2, M3 and M4 models outperformed the M5 model at Station 1.

The peak SSL depends on many factors, and the model that uses only the same day flow (Q_t) as input was unable to compute high SSLs with reasonable accuracy, as evidenced by high RMSE and MBE values (Table 5). For example, considering the magnitude of SSL prediction at Station 1, it was clear that SSL corresponding to almost equivalent Q values are mostly 2.5 times different in magnitude (Q = 1120, 1150; SSL = 10300, 24500, respectively). This fact can be seen at other stations as well. The M5 model that used SSL in the t-1st day (SSL_{t-1}) inputs is able to provide a significant accurate estimate of extreme SSL alterations. There is, thus, a definite advantage in choosing SSL_{t-1} as input for SSL_t predictions. As shown in Table 5, the models tended to slightly underestimate excessive SSL at Station 2, except for the M5 model. The values were overestimated in almost all models for Station 3, while the values were overestimated in the M1 and M3 models at Station 4. The obtained SRC model results clearly show that the peak SSL could only be accurately estimated at Station 2 as indicated by greater R^2, but it failed to preserve its performance at other stations. The R^2 for the M1 model (Q_t) ranged from 0.23 to 0.7, whereas the peak SSL at Station 3 was predicted fairly well by M1 model with an R^2 of 0.23, which was almost as small as the value obtained using the SRC model. However, the M1 model had relatively acceptable results at other stations with R^2 higher than 0.41. It can be concluded that the ANFIS model with the same input values as those for the SRC model will increase the accuracy of the results.

3.2. Hysteresis phenomenon

The behaviour of suspended sediments, and changes in SSC response to rainfall–runoff events, are not only a function of energy conditions but are also related to variations in channel supply and depletion. These changes in sediment availability result in the so-called hysteresis effects [6]. As stated above, due to hysteresis, the sediment concentration of two identical discharges were

Table 5. Comparative statistical analysis of peak SSL at testing phase

Hydrological station	Statistical indicators	SRC Model	ANFIS Model				
			M1	M2	M3	M4	M5
Station 1	R^2	0.36	0.42	0.97	0.52	0.31	0.35
	RMSE	7050	5083	1784	4425	5360	5365
	MBE	-2650	-1739	-141	-985	-1249	-1522
Station 2	R^2	0,58	0.70	0.84	0.67	0.68	0.93
	RMSE	70	62	55	59	59	40
	MBE	-21	-19	-28	-4	-1	11
Station 3	R^2	0.30	0.23	0.68	0.89	0.63	0.98
	RMSE	70183	75061	34763	65167	38361	23705
	MBE	43889	63279	13603	63551	11470	11287
Station 4	R^2	0.27	0.41	0.51	0.42	0.55	0.70
	RMSE	2062	2357	2190	1637	1783	1112
	MBE	-186	85	-382	168	-393	-133

higher in the rising limb than in the falling limb of the hydrograph. The concentration of sediment loads can be compared when the discharge at two sides of the hydrograph is the same.

In order to examine the accuracy at which the ANFIS models can simulate the hysteresis behaviour, the models were used at the testing stage for sediment load simulation at each station. At stations 1 to 4 there were two, three, two and one identical discharge(s), respectively, at two sides of the hydrograph. The discharges selected at two limbs of the hydrograph, and the corresponding SSC, are presented for four stations in Figure 3. These discharges, along with the given sediment loads, were used to investigate the hysteresis phenomenon.

In Figure 3, the (*) sign indicates the SSC with reasonable estimation (i.e. the significant interval is in % 10 levels), and the (ⁱ) sign shows that the predicted SSC on the falling limb of the hydrograph is less than that on the rising limb, and that it differs from the observed values. According to Figure 3, it can be observed that in the regression model the estimated SSC are the same for both the ascending and falling limbs in an equal discharge because the SSC increases as a result of increase in discharge caused by the power law relation between them [37]. As expected, the M1 model that used Q_t as its only input could not simulate such a phenomenon at all stations because, as observed in the regression model, the discharge was the only input parameter. Thus the model was unable to accurately simulate hydrograph conditions, and distinguish whether the given discharge was on the ascending or descending limb of the hydrograph. Considering the M2 model, the use of T as an additional input did not improve the prediction accuracy in any of the four gauging stations because the use of this parameter alone in ANFIS does not enable determination of the ascending and falling limbs of the hydrograph. The regression model and M2 model tend to predict a much higher SSC rate for a similar flow discharge. Therefore, the results of these two models indicate that Q_t and T could not be used alone to correct hysteresis using the ANFIS model. However, using Q_{t-1} as an additional input led to a more accurate prediction of hysteresis phenomenon. Therefore, there is an apparent advantage in choosing Q_{t-1} as an input for SSC prediction. The results also revealed that the M3 model can accurately simulate hysteresis behaviour at all stations except at Station 1 (Figure 3). However, in some cases the accuracy declined dramatically as the estimated sediment of the falling limb is mostly larger than for equivalent SSC on the rising limb. As a comparison, Figure 3 shows the accuracy of 62.5 % (i.e. 5 out of 8 events) for SCS prediction using the M3 model. It can be concluded that the trained M3 model performs well when compared to the M1 and M2 models.

It can be concluded that inclusion of the previous day discharge (Q_{t-1}) had a significant influence on the simulation of hysteresis in the ANFIS model because it enabled prediction of discharge on the ascending or falling limb, and presented an appropriate estimation. The M4 model, which utilized (Q_t, Q_{t-1}, T) performed more accurately in some events but, in comparison with the M3 model, its performance decreased in most of the events. It therefore did not improve the simulation process. Considering the M5 model, which includes SSC_{t-1} as an additional input to the M4 model, its performance shown in Figure 3 is reasonably appropriate, with a poor low value related to Station 1, and is comparable to that of M3 model, although the M5 model performance is slightly better as, out of 8 high flow events analysed, 6 showed a good matching.

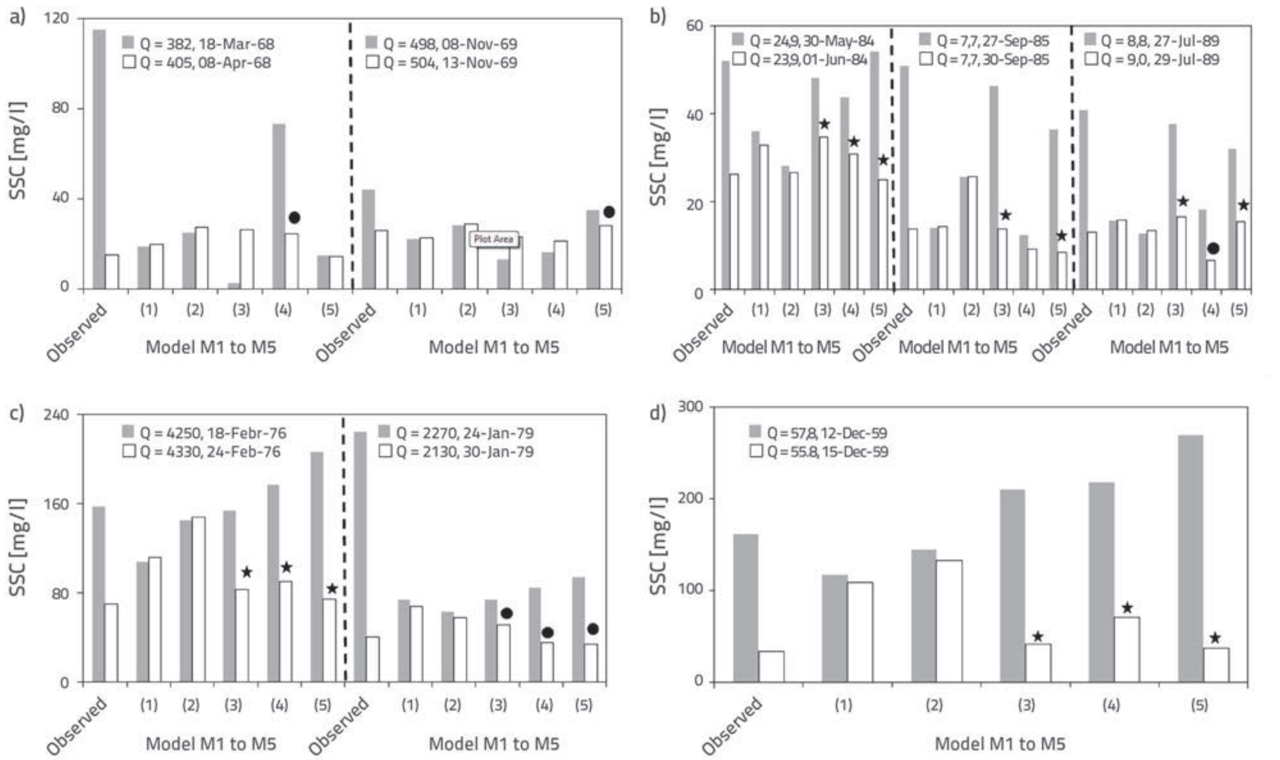

Figure 3. Comparison of observed and simulated sediment concentrations for ANFIS models: a) Station 1, b) Station 2, c) Station 3, d) Station 4

4. Conclusion

In the present study, the ANFIS and SRC models were developed and a comprehensive comparison of the observed SSL was carried out using different statistical criteria. In addition, the observed and simulated SSL in different high flow events were compared. To this aim, four sediment/river flow gauging stations, namely the Merrimack River at Lowell, Choptank near Greensboro, Susquehanna River at Harrisburg, and Swatara Creek at Harper Tavern, operated by the USGS, were employed to develop various models. After trying different structures in terms of membership function type and number, an optimum ANFIS model was obtained. ANFIS models with different parameter settings were then built. Three standard statistical performance evaluation measures were adopted to evaluate the performance of various models developed. The ANFIS estimates were compared with the SRC model.

A small R^2 value for all four gauging stations indicated that the discharge in the t-th day alone (M1 model) can not be used to accurately predict the SSL using the ANFIS model, and that the SRC was superior to the M1 Model at the testing and trying phases. Among five different combinations for the ANFIS model, the parameter T and the antecedent discharge (Q_{t-1}) increased the SSL estimation accuracy. Based on the results, it can additionally be concluded that the most important factor at the test stage was the introduction of the most recent SSL antecedent (SSL_{t-1}), so that it can improve the ANFIS simulation. The best ANFIS combination (M5 model) significantly improved model performance with respect to the regression model. The M5 model simulated the SSL satisfactorily and with reasonable accuracy. The R^2 values for the M5 Model ranged from 0.92 -0.96 for the training data set, and from 0.86-0.95 for the testing data set, while the greatest R^2 was obtained at the Gauging Station 2. In the next step, in order to utilize the responses of ANFIS models for predicting the peak sediment load data sets, they were compared at the test stage with the predicted values at all stations. At three out of four stations, the RMSE and MBE values of the M1 model were higher than the corresponding values from other models, but the significant improvement in the prediction accuracy occurred when the parameter T was also used together with Q_t in the input matrix. However, the inclusion of the T parameter in the inputs of Q_t, Q_{t-1} reduced the model performance. We found that the use of the T parameter contributed to the maximum SSC prediction accuracy, when it did not contain discharge antecedent (Q_{t-1}) in the input. On the other hand, when the previous day discharge and SSL were considered as inputs, the best result corresponded to the combination Q_t, Q_{t-1}, SSL_{t-1} without the effect of T on model improvement. According to the results, M5 Model which included Q_t, Q_{t-1} and SSL_{t-1} was selected as the best fit for predictions at stations 2, 3, and 4.

An additional analysis was conducted to determine the ability of the studied models to handle hysteresis behaviour. Our tests showed that the estimated SSC are the same for both the ascending and falling hydrograph limbs in an equal discharge in the regression model, which was due to the use of a power law relation between the sediment load and discharge. Also, the results obtained through M1 and M3 models indicated that Q_t and T alone did not accurately predict the SSC using the ANFIS model. The M2 Model presented a more accurate simulation of hysteresis behaviour. Therefore, the variable Q_{t-1} was identified as the most effective factor in the hysteresis behaviour analysis. In brief, significant improvements in the simulation of hysteresis could be obtained by including in the model the hysteresis effect of sediment concentration within single events, including Q_t and Q_{t-1}.

Finally, visual observations based on graphical comparison between the observed and predicted values, and the qualitative assessment of the models, indicated that the M5 model is superior to other ANFIS models and SRC approximations in almost all evaluated sediment observations, taking into account the daily SSL, peak SSL, and hysteresis.

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