Using Artificial Neural Network to Predict Suspended Sediment Concentration with Hydrology and Hydrodynamics Data: Case Study on Managawa River Basin, Japan

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Abstract

Artificial neural network (ANN) is used to estimate the hourly suspended sediment concentration in the upstream of Managawa dam, Fukui prefecture, Japan. The sediment yield from upstream of the river was dropped in to the river then the sediment will be transported to deposit into dam. The serious area of sediment erosion of Managawa river basin is monitored by suspended sediment gauge. The hourly suspended sediment concentration was related to the rainfall, temperature, water discharge and the absolute of discharge changing. This artificial neural network (ANN) was calibrated and validated by using the recently suspended sediment concentration data from December 2006 to March 2007. Choosing an appropriate neural network structure and providing field data to that network for training purpose are address by using a constructive back propagation algorithm. Without the previous step of suspended sediment data as input the outputs from network were fairly good agreement with observed data. However, it is demonstrated that the artificial neural network (ANN) is capable of modeling the hourly suspended sediment concentration with good accuracy when proper variables, their previous time step on the suspended sediment concentration and the absolute of discharge changing are used as inputs of network.

Keywords: Artificial neural network, Suspended sediment concentration, Managawa river basin

1. Introduction

Suspended sediment in river is an important parameter for reservoir management and it is an index for the status of soil erosion and ecological environment of a catchment. Mathematical models are widely used in studying soil erosion and sediment transportation which many empirical models and physical models have been developed to model the suspended sediment flux of a catchment. Artificial Neural Network (ANN) is a type of empirical model. It is derived from the researches on the nature of the human brain (Muller et al., 1995). Hydrologic applications of Artificial Neural Network (ANN) include the modeling of daily rainfall-runoff-sediment yield process, snow-rainfall process, assessment of stream's ecological and hydrological responses to climate change, rainfall-runoff forecasting, ground water quality prediction and ground water remediation. Artificial Neural Network (ANN) can be applied to predict the monthly, weekly and daily suspended sediment in the catchment by relating it to average rainfall, temperature, rainfall intensity and water discharge (Yun-Mei Zhu, 2007). This study is an attempt to predict an hourly suspended sediment concentration on the river by using back propagation artificial neural network.

2. Study area

Managawa Dam constructed during 1965-1977 in Fukui prefecture, Japan is located at latitude 35º 55' 50" N and longitude 136º 32' 31" E. Managawa Dam is a concrete arch dam with 127.5 m height, 357 m width and 115 MCM capacity designed for irrigation, water supply and power generation where Managawa river is a tributary of Kuzurui river. Catchment area above the dam is about 223.7 km^2 that the mean elevation is 830 m above mean sea level and land slope is about 0.45. The sediment depositing volume in Managawa dam until year 2004 is about 2.8 MCM. There are Kumokawa Dam and Sasougawa Dam, situated on up stream of Managawa Dam located on heavy rainfall area as the average annual rainfall is 2,391 mm. The area is covered by forest where accounts for 94% area of total watershed. The major soil types in the study area are sandstone, mudstone and conglomerate (Managawa Dam office, 2005). Sediment yield and turbidity are the serious problems for reservoir management therefore the monitoring of sediment flow into this reservoir is necessary. The suspended sediment gauge is settled on Okumotani River which it is an upstream branch of Managawa River. Okumotani catchment as shown in Figure 1 is about 8.01 km^2, the average slope is 0.49 and the annual sediment yield calculated by Modified Universal Soil Loss Equation (MUSLE) is about 3,307 m^3 resulted by Chadin and Tetsuya (2007).

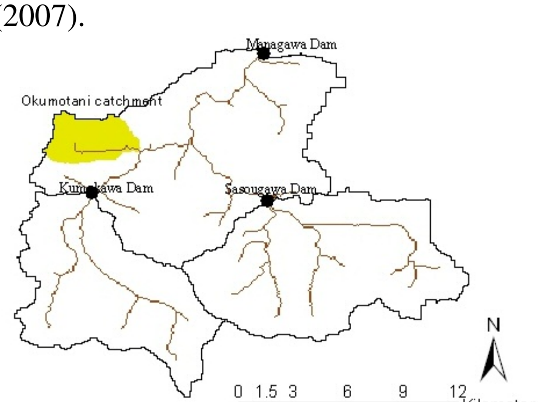

Figure 1. Okumotani catchment

3. Methodology

3.1 Artificial Neural Network (ANN) with back propagation process

Artificial Neural Network (ANN) can be categorized into feed forward and recurrent networks according to the direction of the information flow processing. In the current study, a multilayer perception with logistic sigmoid function as the transfer function and back propagation algorithm as the training algorithm is used. It consists of an input layer, a hidden layer and an output layer. Neurons on the input layers represent the casual variables at different time steps. The neuron on the output layer is suspended sediment concentration. The number of neurons on the hidden layer is decided by trial and error method. Each neuron on the hidden layer is connected with all neurons in the adjacent layers. During the training, the input information is processed in the neurons of the input layer and is passed down to the hidden layer through the connections. Each neuron calculates its net input as the weighted sum of all inputs and performs a logistic sigmoid transformation to it before passing to the next layer. When the information processes reach the last layer, the final output is produced and an error indicating the difference between the predicted and observed outputs is computed. This error is back propagated through the network to each neuron, and the connection weights are adjusted correspondingly. The training process is stopped until the error is smaller than a specified value or when the error starts to rise after reaching a minimum. The performances of the models were evaluated with two statistical parameters, root mean square error (RMSE) and coefficient of determination (R^2).

3.2 Data collection and data analysis

However suspended sediment concentration at Okumotani station has been measured once twenty minutes since December 2006, this study applies an hourly suspended sediment concentration data for training the network. The climate, hydrologic and hydraulic data in this catchment indicate a relationship among rainfall, temperature, water discharge and sediment load during the considered period that hourly data at the study area are available. The suspended sediment concentration data for training the network is during the heavy rainfall events on March 2007 and for testing this network is during the heavy rainfall events on December 2006 and February 2007. The coefficients between climatic, hydrologic and hydraulic variables; Rainfall (R), Temperature (T), Discharge (Q), Absolute of $(Q_t-Q_{t-2})/2$, Wind Speed, Solar, Snow, and suspended sediment concentration are given in Table 1.

Table 1. Correlation coefficients of the input data with suspended sediment

time	R	T	Q	$\lvert Q_t-Q_{t-2}\rvert/2$	Wind	Solar	Snow	SS
t	0.322	0.250	0.580	0.434	-0.002	-0.006	0.011	1.000
t-1	0.371	0.259	0.558	-	-	-	-	0.660
t-2	0.383	0.257	0.535	-	-	-	-	0.645

4. Results

The root mean square error (RMSE) and coefficient of determination (R^2) values of all case during calibration and verification periods are given in Table 2. The performance of network is depended on the inputs and network structure. The networks, in case of rainfall and temperature are inputs, show relatively poor performance as case 1, 2 and 3. The coefficient of determination (R^2) of case 1, 2 and 3 during verification period are 0.261, 0.231 and 0.285 respectively. In case of applying weather as inputs, the performance of networks is also poor performance as case 4 and 5. For improving performance of network, it is necessary to add discharge data as input to network that in case 7 the inputs are rainfall, temperature and discharge because this is mainly due to the close relationship between suspended sediment concentration and water discharge. The coefficient of determination (R^2) of case 7 is 0.635 and root mean square error (RMSE) is about 24.79 % that this network is good performance for forecast suspended sediment concentration on this catchment. Thus the best network for forecasting suspended sediment concentration when the climate, hydrologic and hydraulic data are available is network case 7 which inputs are rainfall, temperature, water discharge and their previous time step data. If the suspended sediment data in previous time step is one of input of network, the results from this network will be more closely with observed data. The performances of networks from case 11 to 18 are good that the coefficients of determination (R^2) are more than 57 % and root mean square error (RMSE) is less than 22 %. The correlation coefficient of the absolute of $(Q_t\text{-}Q_{t-2})/2$ and suspended sediment concentration is also high therefore this study try to apply the absolute of $(Q_t\text{-}Q_{t-2})/2$ to be one of inputs for increasing the performance of network. The performances of network case 15 and 16 are more than case 13 and 14 in sequence and the performances of network case 17 and 18 are also more than case 11 and 12 in sequence. If the absolute of $(Q_t\text{-}Q_{t-2})/2$ is added to be one of inputs of network, the performance of that network will increase.

Table 2. Performances of Artificial Neural Networks

Inputs	Case	Time	Network	Calibration		Verification	
				R^2	RMSE %	R^2	RMSE %
R,T	1	t	2,16,1	0.350	24.20	0.262	36.12
	2	t, t-1	4,8,1	0.440	22.43	0.231	45.25
	3	t,t-1,t-2	6,6,1	0.410	23.08	0.285	38.71
R,T,W	4	t	5,10,1	0.368	23.83	0.238	40.01
	5	t,t-1	7,14,1	0.518	20.82	0.328	65.24
R,T,Q	6	t	3,6,1	0.477	21.68	0.423	27.85
	7	t,t-1	6,6,1	0.549	21.14	0.635	24.79
R,Q	8	t	2,4,1	0.435	22.53	0.316	28.83
	9	t,t-1	4,4,1	0.427	22.69	0.767	25.20
	10	t,t-1,t-2	6,12,1	0.521	20.75	0.525	30.29
R,Q,SS	11	t	3,6,1	0.665	17.37	0.570	21.20
	12	t,t-1	6,18,1	0.821	12.68	0.674	21.44
Q,SS	13	t	2,4,1	0.599	18.97	0.599	19.41
	14	t,t-1	4,4,1	0.631	35.45	0.728	17.58
Q,D,SS	15	t	3,6,1	0.673	17.15	0.730	16.29
	16	t,t-1	5,5,1	0.641	17.95	0.695	17.08
R,Q,D,SS	17	t	4,4,1	0.616	18.57	0.615	19.11
	18	t,t-1	7,7,1	0.698	16.49	0.683	18.34

W is weathers data: wind, solar and snow.
D is absolute of $(Q_t\text{-}Q_{t-2})/2$.
For SS at time t, it means SS_{t-1} and for SS at time t-1, it means SS_{t-2}.

According to their performances, network case 14, 15 and 18 could be selected as the networks that can be used for suspended sediment prediction. The suspended sediment concentration of them are plotted in Figure 2 and the scatter plots of the observed and computed suspended sediment concentration by the three networks for verification and calibration of case 18 are shown in Figure 3. From Figure 2 (c), it shows that peak and time to peak of computed line and observed line by verification period are almost the same therefore the network case 18 is the best for suspended sediment prediction.

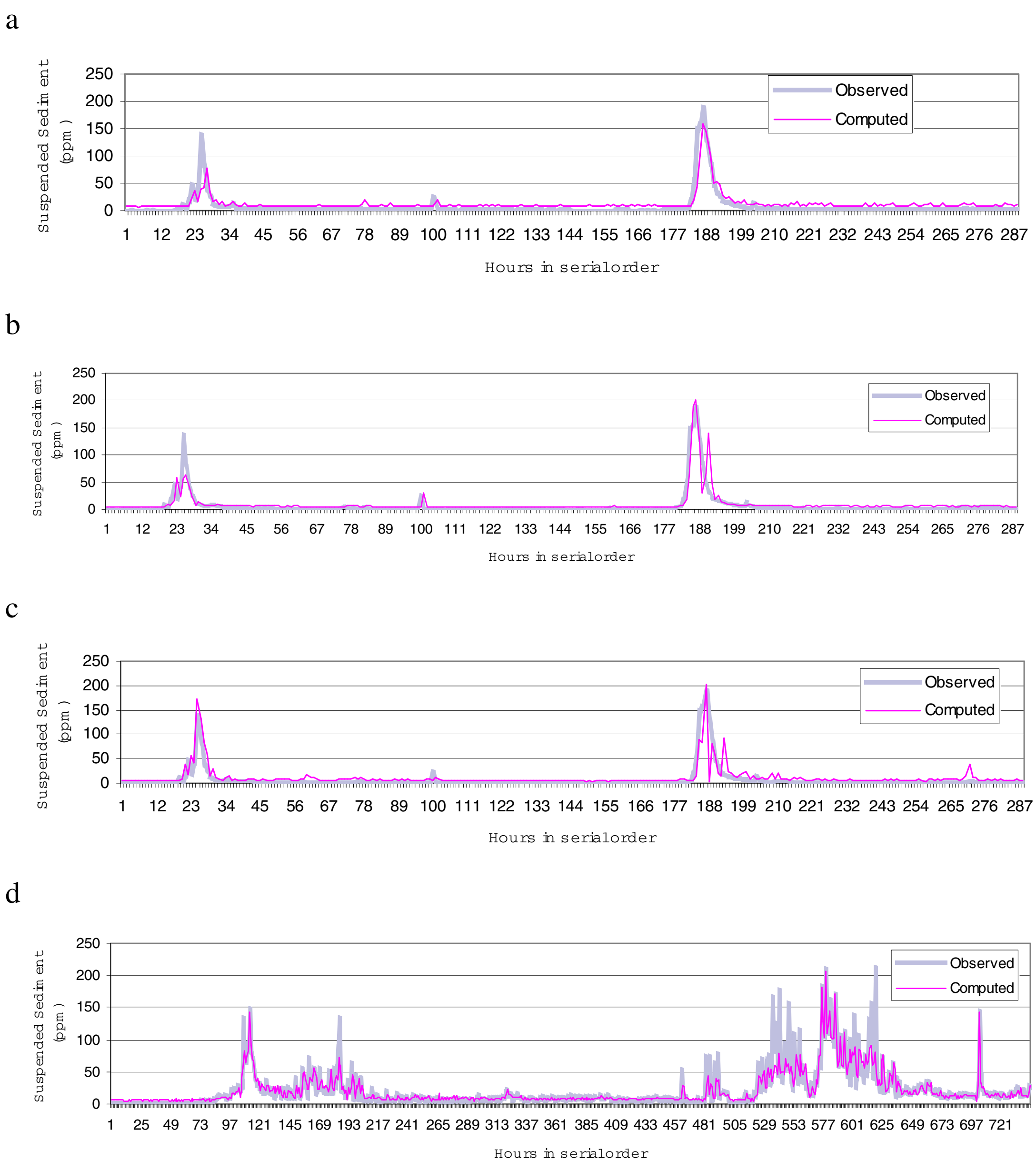

Figure 2. Comparisons between the observed and computed suspended sediment concentration: (a) Verification case 14, (b) Verification case 15, (c) Verification case 18 and (d) Calibration case 18

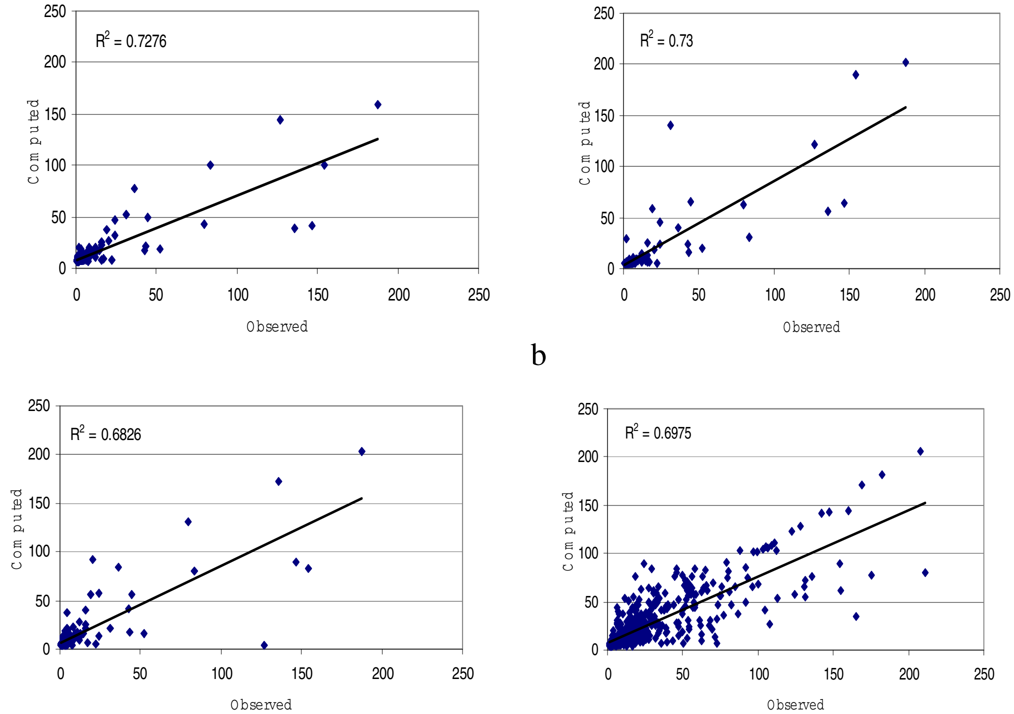

Figure 3. Scatter plots of observed and computed suspended sediment: (a) Verification case 14, (b) Verification case 15, (c) Verification case 18 and (d) Calibration case 18

5. Discussion and conclusion

Artificial neural network (ANN) was applied to predict the hourly suspended sediment concentration in Okumotani catchment, by relating rainfall, temperature, water discharge, absolute of $(Q_t\text{-}Q_{t-2})/2$ and previous time step of suspended sediment concentration. It is demonstrated that the artificial neural network (ANN) is capable of modeling the hourly suspended sediment concentration with good accuracy when proper inputs variables, the absolute of $(Q_t\text{-}Q_{t-2})/2$ and their lag affect on suspended sediment concentration. This model can be used for real time prediction when the previous time step data of suspended sediment concentration are known. In order to improve and confirm this model for upstream of Managawa dam, the seasonal effect should be considered and the duration of training and testing the network should be extended.

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