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NEURAL NETWORKS APPROACHES FOR MODELLING RIVER SUSPENDED SEDIMENT CONCENTRATION DUE TO TROPICAL STORMS

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ABSTRACT
Artificial neural networks are one of the advanced technologies employed in hydrology modelling. This paper investigates the potential of two algorithm networks, the feed forward backpropagation (BP) and generalized regression neural network (GRNN) in comparison with the classical regression for modelling the event-based suspended sediment concentration at Jiasian diversion weir in Southern Taiwan. For this study, the hourly time series data comprised of water discharge, turbidity and suspended sediment concentration during the storm events in the year of 2002 are taken into account in the models. The statistical performances comparison showed that both BP and GRNN are superior to the classical regression in the weir sediment modelling. Additionally, the turbidity was found to be a dominant input variable over the water discharge for suspended sediment concentration estimation. Statistically, both neural network models can be successfully applied for the event-based suspended sediment concentration modelling in the weir studied herein when few data are available.

KEYWORDS: event-based sediment, turbidity, water discharge, modelling, feed forward backpropagation, generalized regression neural network.

1. INTRODUCTION

The main objective of this study is to evaluate the potential of using artificial neural networks (ANNs) for modeling Jiasian diversion weir suspended sediment concentration due to tropical storms in Southern Taiwan. Recently, significant progresses in the fields of nonlinear complex system modelling have been made possible through the ANNs approaches. The ANN is a nonlinear mathematical structure capable to model any arbitrarily complex nonlinear process such as sediment load and water discharge relationship. The present study employed two algorithms, the feed forward backpropagation network (BP) and generalized regression neural network (GRNN) in comparison with the classical regression method.

In deed, estimates of suspended sediment load are essential for the river transportation research. According to Altunkaynak (2009), estimation of sediment load is required in practical studies for the planning, design, operation and maintenance of water resources structures. The sediments transportation monitoring requires a good sample technique which is very lengthy and costly (Pavanelli and Palgliarani, 2002). Therefore, it is important to develop a model that can predict accurately the suspended sediment concentration from continuous water data set. The sediment load process is a highly nonlinear and complex system. However, the classical regressions despite of their inability to represent successfully the nonlinear complex system have been widely used in sediment process to establish continuous relationship between water discharge, turbidity and suspended sediment (Lewis and Eads, 1996; Wang *et al*., 2006).

The emergence of ANN technology has given many promising results in the field of hydrology and water resources for solving the nonlinear system complexity problem (Sudheer *et al.,* 2003; Adeloye and Munari, 2006). The hydrological characteristics of the river such as the temporally and spatially changing of sediment concentrations, and the difficulties for their estimation encouraged the employment of the ANN models. In the river sediment loads modelling study during storm events of short duration, Rai and Mathur (2008) found the neural network as a suitable estimation tool in two catchments areas of United States of America. The availability of few data as well as the complex nonlinear process of sediments provided an impetus to investigate the potential of using the ANNs techniques for suspended sediment concentration modelling in the Jiasian diversion weir. The weir is built to supply water for civil and industrial use, nowadays; the demand for clean water has increased around the weir. The study compares the performance of BP, GRNN and classical regression in modelling the weir suspended sediment concentration estimation using continuous hourly water discharge and turbidity data collected during the storm events from July to October 2002. The data time scale of most of the papers is usually daily or monthly scaled. As well, few studies reported the use of ANN in event-based sediment concentration modelling (Agarwal *et al*., 2005; Raghuwanshi *et al.,* 2006; Rai and Mathur, 2008). This research has potentially an advantage to monitor the event-based suspended sediment concentration flux at short time step of storm events. The ANNs may overcome the low performance often met in the classical regression method and improve the accuracy of rivers suspended sediments concentration estimation. Sediment estimation is essential in Jiasian diversion weir to provide basic information on a wide range of problems related to the water quality monitoring, the operation systems and the river management.

2. STUDY AREA AND DATA NORMALIZATION

Jiasian diversion weir is located in Chishan River, Southern part of Taiwan at 22 57’ 30” North latitude and 120 12’ 0” East longitude (**Figure 1**). The Chishan River is a tributary of the Kaoping River which is one of the major rivers in Taiwan. The weir was built for supplying 0.3 million m^3 of water per day averagely for civil and industrial use. Also, the weir is a continuation of the Nanhua Reservoir which provides 0.8 millions m^3 of water per day. During the wet period, the surplus water of the Kaoping River is channeled into the Tsengwen Reservoir for allocation and storage. In this location, the average annual rainfall is 2794.4 mm with an abundance rainfall occurring in the wet season from May to October, conversely to the dry season from November to April. In the last fifty years, the total rainfall averages in dry and wet seasons were 235.9 and 2558.5 mm, respectively.

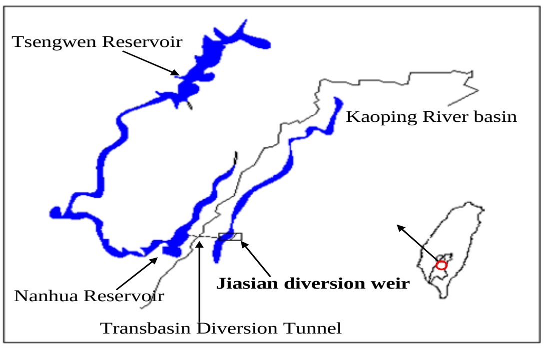

Figure 1. Sketch map of the investigation area.

The data sets were comprised of water discharge ($m^3\ s^{-1}$), turbidity (NTU) and sediment concentration (mg L^{-1}) collected from July 18, 2002 to October 10, 2002. Hourly data sampling were obtained during the storm events. The hourly sediment data have been collected because of the typical rainfall pattern and topography of the investigation area where most of the suspended sediment concentration is due to the typhoon storms. The water samples were analyzed by turbidimeter which applies a nephelometry technique that measures the level of light scattered by particles at right angles (90^{o}) to the incident light beam. The data sets had a total of 1309 patterns and were divided into two sets for the purpose of training (50%) and testing (50%) to reach the best generalization (SNNS, 1995). The training data sets are used to train the neural networks by minimizing the error of these data sets during the training. Then, the test sets are used for checking the overall performance of the trained networks. To prevent the effect of extreme values in the data sets and to match the sigmoid type of transfer function, which has a range of values between 0 and 1, the input and output data are normalized using the following transformation equation (Yeh, 1997).

$$Y_{norm} = \frac{Y_i - Y_{min}}{Y_{max} - Y_{min}} \quad (1)$$

Where, Y_{norm} is the normalized dimensionless variable; Y_i is the observed value of variable; Y_{min} and Y_{max} are the minimum and maximum values of the variables, respectively.

3. ARTIFICIAL NEURAL NETWORKS AND MODELS EVALUATION

The artificial neural network (ANN) is a massively parallel-distributed information processing system that has certain performance characteristics resembling to the biological arrangement of neurons in human brain (Kumar *et al*., 2008**)**. An ANN establishes a data-driven nonlinear relationship between inputs and outputs of a system. Thus, there have been numerous successful applications of artificial neural network in forecasting the future evolution of complex systems such as sediments flux from water flow data. The neural network typically consists of an input layer, an output layer and a layer of nonlinear processing elements, known as the hidden layer. The ANN has several algorithms used in forecasting and modelling processes. In this study, the feed forward backpropagation (BP) and generalized regression neural network (GRNN) algorithms were selected for modelling the suspended sediment concentration.

The most commonly used artificial neural network in hydrological predictions is the BP algorithm (Kerh and Ting, 2005). BP is a supervised learning technique used for training the neural networks. Basically, it is a gradient descent technique to minimize some error criteria. BP has been widely used in approximating a complicated nonlinear function. The BP network structure in this study possessed a three-layer learning network consisting of an input layer, a hidden layer and an output layer (**Figure 2)**. The variables X_1, X_2 and Y represent the turbidity (NTU), water discharge ($m^3\ s^{-1}$) and suspended sediment concentration ($mg\ L^{-1}$), respectively. The mathematical equation of each layer may be written as following:

$$Y_o = \Phi[\sum(W_{io}X_i - \theta_o)] \quad (2)$$

Where Y_o is the output of the neuron o, W_{io} is the weight increments between i and o, X_i is the input signal generated for neuron i, θ_o is the bias term associated with neuron o, and the nonlinear activation function Φ is assumed to be a sigmoid function as $\Phi(x) = 1/(1+e^{-x})$ for the continuous and differential process.

GRNN can be treated as a normalized radial basic function network in which there is a hidden unit centered at every training case. By definition, the regression of a dependent variable Y on an independent X estimates the most probable value for Y, given X and a training set. The regression method will produce the estimated value of Y with a minimized root mean square error. GRNN is a method for estimating the joint probability density function of X and Y, given only training set. Because the probability density function is derived from the data with no preconceptions about its form, the system is perfectly general. The success of the GRNN depends on the selection of the appropriate smoothing factors (α) (Wasserman, 1993). **Figure 3** shows a schematic diagram of generalized regression neural network architecture.

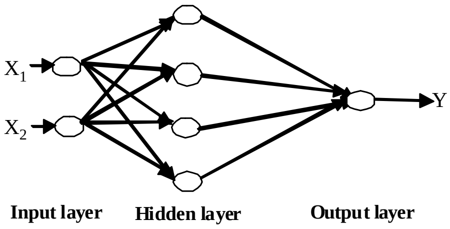

Figure 2. Schematic diagram of BP architecture

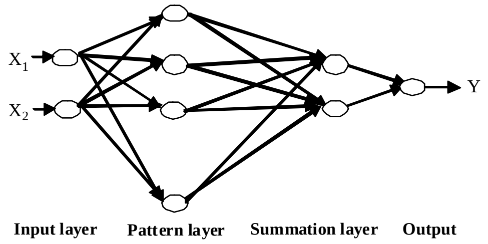

Figure 3. Schematic diagram of GRNN architecture

The classical model regressing sediment concentration to water discharge or turbidity variable has a power equation form and stemmed from the rating curve (Morehead *et al.,* 2003; Wang *et al.,* 2006). The sediment rating curve generally represents a functional relationship of the form:

$$Y_s = aX^b \tag{3}$$

Where Y_s represents the suspended sediment concentration, X is the turbidity or water discharge variable, and a and b are the constants.

The performances evaluation criteria were the root mean square errors (RMSE) and the coefficient of determination (r^2) expressed between estimated and observed suspended sediment concentration as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} d_i^2}{N}} \tag{4}$$

Where d_i is the difference between *i*th estimated and *i*th observed values of suspended sediment concentration and N is the number of observations. The coefficient of determination used to evaluate the performance of the models is defined as follows:

$$r^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y_i')^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{5}$$

Where y_i and y_i' are the *i*th observed (actual) and estimated values of y, and $\bar{y}$ is the mean of the observed values of y; and N is the number of observations.

4. COMPARISON OF ESTIMATION RESULTS

The feed forward back propagation (BP) algorithm is a commonly applied three layers network type consisting of an input layer, a hidden layer and an output layer. The determination of the number of nodes in a hidden layer providing the best training results was the initial process of the training procedure. The suspended sediment concentration estimation was carried out with the BP by considering the turbidity and water discharge as associate inputs of the network. Various hidden nodes numbers were tried for the BP algorithm. The configuration with 2 input nodes, 4 hidden nodes and unique output denoted as BP (2 4 1) provides the best performance during the training stage, i.e. highest r^2 (0.951). The final and most important step in this work of neural network is to test the configuration designed. The networks were tested using different input and output values that were not given for training previously. **Table 1** summarizes the networks performance during the training and testing stages. **Figure 4** shows the plots and scatters of estimated and observed sediment concentrations when the network used as inputs the turbidity and water discharge (**a, b**); turbidity (**c, d**), and water discharge (**e, f**).

During the testing period, BP (2 4 1) produced the closest values to the observed suspended sediment concentration by its highest r^2 (0.943) as shown in **Figures 4a** and **b**. In this configuration, the network has two inputs; hourly turbidity and water discharge for estimating the suspended sediment concentration. By using a single input variable, it has been observed that, the performance criteria of BP were higher for turbidity (RMSE=0.0334, r^2=0.938) than water discharge (RMSE=0.0525, r^2=0.846) during the testing period. In this configuration, the network has one input; two hidden nodes and unique output. **Figures 4 (c, d)** and **(e, f)** show the plots and scatters of estimated and observed sediment concentrations from turbidity and water discharge used as a single input variable, respectively. From these results of using a single input in the network, the turbidity seems to be a dominant variable over water discharge in Jiasian diversion weir suspended sediment concentration estimation.

Table 1. Performance of BP during the training and testing stages

Neural Network configuration	**Neural Network model input**	**Nodes in hidden layer**	**Training**	**Testing**	
			r^2	**RMSE**	**r^2**
BP (2 4 1)	Q, T	4	0.951	0.0336	0.943
BP (1 2 1)	T	2	0.924	0.0334	0.938
BP (1 2 1)	Q	2	0.879	0.0525	0.846

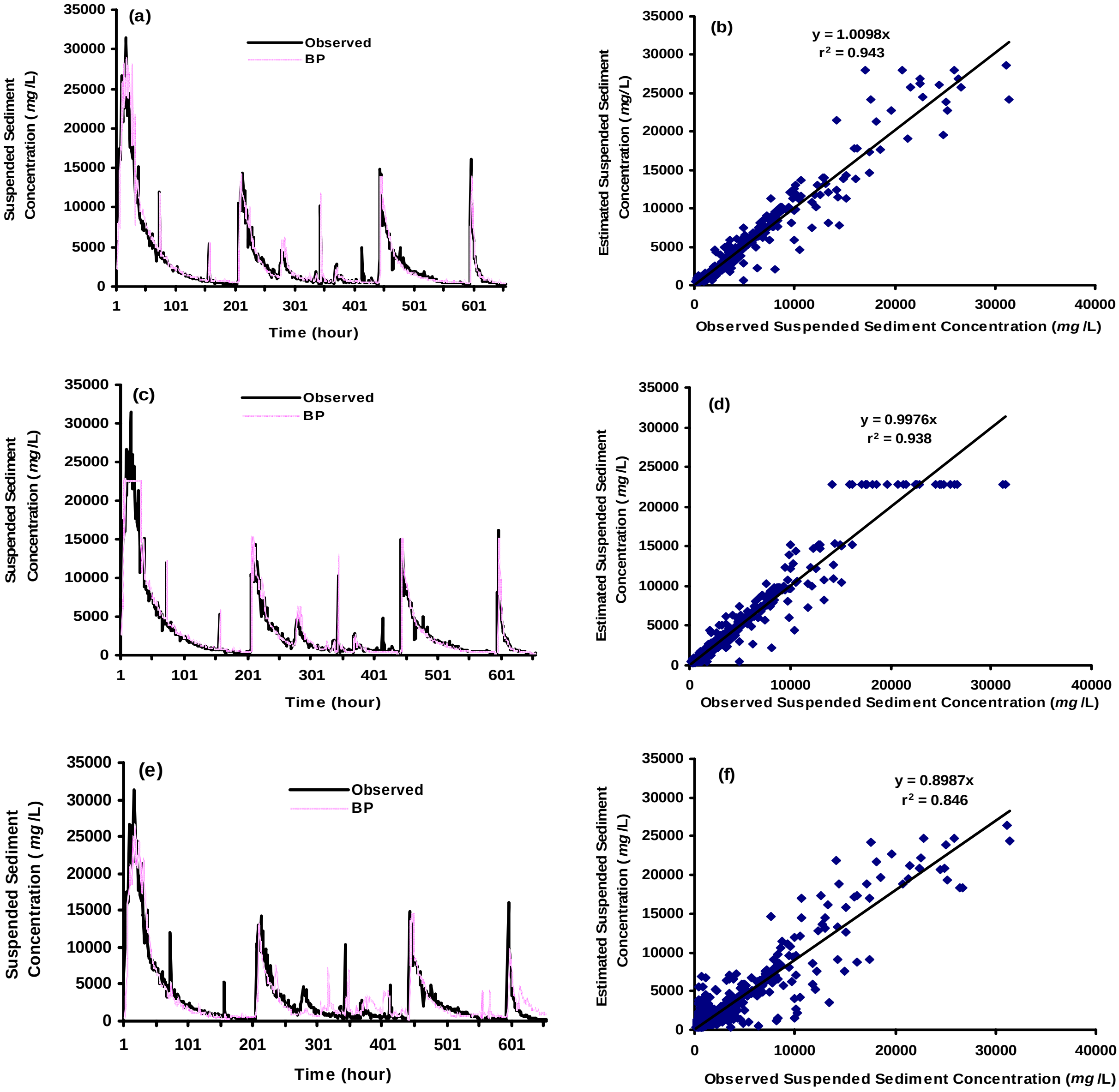

Figure 4. Suspended sediment concentration estimated by BP during the testing period using turbidity and water discharge (**a, b**), turbidity (**c, d**), and water discharge variables (**e, f**) as the networks inputs

In addition, the turbidity alone shows similar results with the BP (2 4 1) through the close values of their RMSE and coefficients of determination. Conversely, when water discharge alone is used in the network, the performance is poor. In both training and testing periods, the BP with two inputs (turbidity and water discharge) has an advantage of a good estimation of suspended sediment concentrations than using a single water discharge, which reduced the performance (r^2) of the network showed in **Table 1**. BP algorithm may not lead to good generalization properties for the network when the input data are limited (Sudheer *et al.*, 2003). It was observed in this study that, use of a single input with BP algorithm might decrease the performance of the estimation of the suspended sediment concentration. In general, from the results of this study, BP was found as a potential alternative estimation method which could be used for a better monitoring of sediments flux in the study site. Cigizoglu and Kisi (2006) reported that, BP network approach which is a nonlinear black-box model seems to be a useful alternative for modelling the complex suspended sediment series.

The generalized regression neural network (GRNN) performance analysis was carried out by trying different smoothing parameters in order to obtain the best criteria. Similarly to BP (2 4 1), the network structure GRNN (2, 0.01, 1) with 2 inputs, smoothing parameter 0.01 and 1 output gave the highest r^2 (0.979) during the training stage (**Table 2**). However for the testing stage given in **Table 2**, GRNN (1, 0.01, 1) with only turbidity data as input provided the best performance (RMSE=0.0367, r^2=0.931). **Figure 5** shows the plots and scatters of estimated and observed suspended sediment concentration during the testing period with the GRNN networks using turbidity and water discharge (**a, b**); turbidity (**b, c**), and water discharge (**e, f**). Although BP gave slightly a better performance than GRNN, statistically, both estimation methods produce similar good results. Therefore, the performances criteria obtained with GRNN and BP configuration suggest these two methods for suspended sediment concentration estimation in the Jiasian diversion weir. Further observations of GRNN show similar results with BP for turbidity (RMSE=0.0367, r^2=0.931) which was found as a dominant parameter over water discharge (RMSE=0.0553, r^2=0.836) for suspended sediment concentration estimation. According to Zhu *et al.* (2007), other factors which are not included in the network inputs could explain this poor relationship between sediment and water discharge. It has been documented at least by Zhou *et al.* (2004) and Lu (2005) that the human activity related to land surface disturbance increase the suspended sediment flux. Study done by Sahoo *et al.* (2006) on the catchments hydrological processes data analysis revealed that, the water quality parameters are mostly affected by weather forces and land use of the catchments. The human activity could increase the suspended flux independently to the water discharge. This could explain the poor relationship between water discharge and suspended sediment concentrations recorded at the weir.

For the classical regression, the data selected for training were used to build up the models, and then the testing data were used to evaluate their performances. **Figures 6** showed the classical models by regressing suspended sediment concentration to the turbidity (**a**) and water discharge (**b**) variables, respectively. The coefficient of regression of the model obtained from the turbidity variable (r^2=0.898) is better than water discharge (r^2=0.609).

Table 2. Performance of GRNN during the training and testing stages

Neural Network configuration	Neural Network model input	Training	Testing	
		r^2	RMSE	r^2
GRNN (2, 0.01, 1)	Q, T	0.979	0.0388	0.925
GRNN (1, 0.01, 1)	T	0.930	0.0367	0.931
GRNN (1, 0.01, 1)	Q	0.894	0.0553	0.836

The performances evaluation showed clearly in **Figures 7 (a, b)** and **(c, d)** that the classical model using turbidity (r^2=0.891) and water discharge (r^2=0.547) variables performs poor than the artificial neural networks. The classical model cannot estimate the nonlinear suspended sediment flux with high accuracy, due to their simple structure and mathematical methods. Jain (2001) and Sarangi and Bhattacharya (2005) in their comparative studies concluded that the ANNs provided high accuracy than the classical model in sediment modelling. Kisi (2004) also demonstrated the evidence of ANN ability in daily River suspended sediment concentration modelling. According to Brikundavyi *et al.* (2002), the performance of the BP was found to be superior to conventional statistical and stochastic methods in continuous flow series forecasting. The superiority of artificial neural networks over a conventional method in the reviewed prediction study can be attributed to their capability to capture the nonlinear dynamics and generalize the structure of the whole data set (Celikoglu and Cigizoglu, 2007).

Obviously, using the artificial neural networks for modelling sediment estimation is more reliable than the classical method in the weir studied herein.

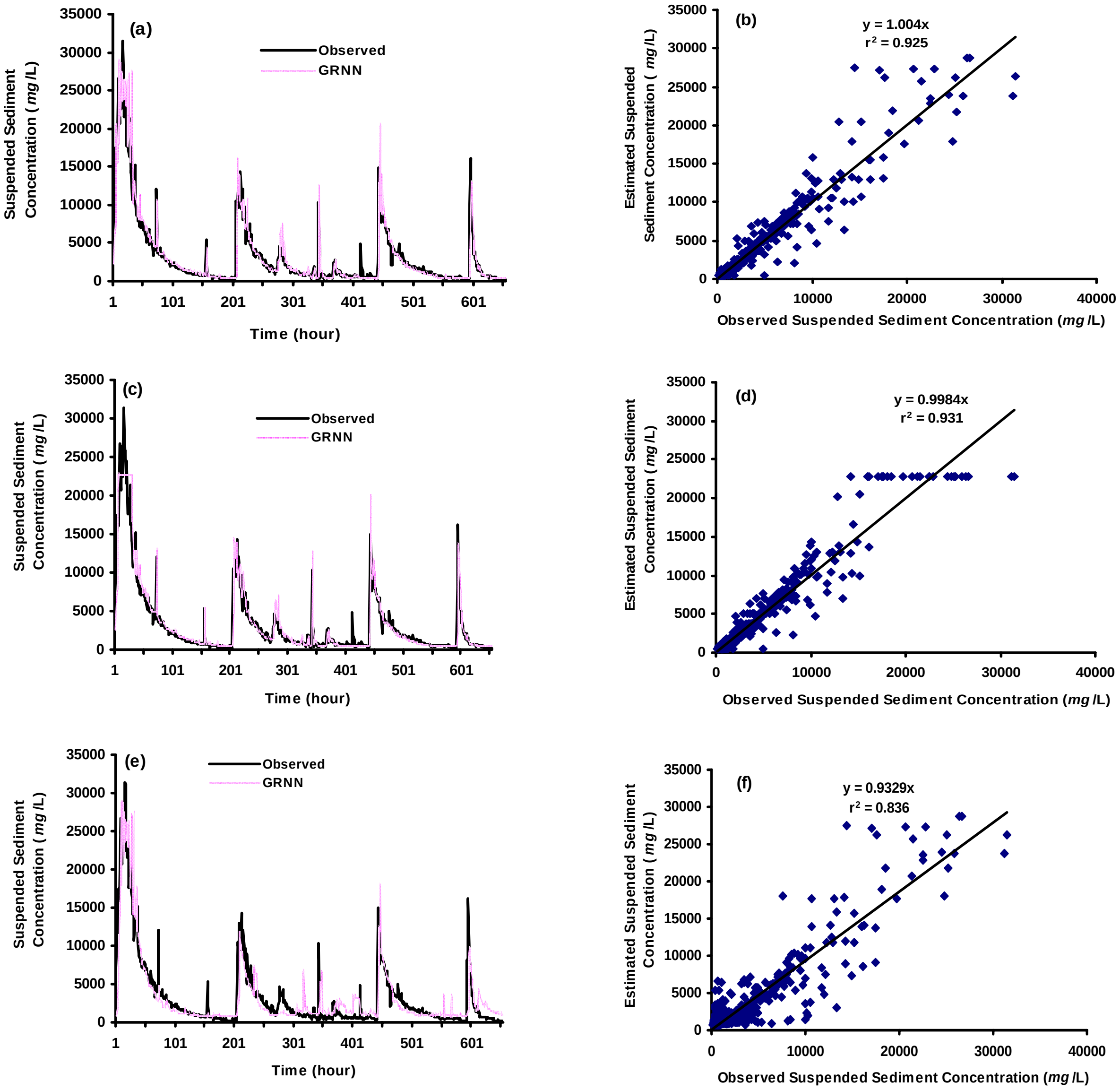

Figure 5. Suspended sediment concentration estimated by GRNN during the testing period using turbidity and water discharge (**a, b**); turbidity (**c, d**) and water discharge (**e, f**) as the networks inputs

5. CONCLUSIONS

The suspended sediment concentration modelling in Jiasian diversion weir is necessary for a continuous monitoring of the weir water quality, which demand has recently increased. In this study, the artificial neural networks methodologies were applied to estimate the weir hourly event-based suspended sediment concentration due to tropical storm by using the turbidity and water discharge as input variables. From the results of this study, the BP configuration established shows the highest statistical performance in the sediment estimation when the turbidity and water discharge data were used as associated input variables in the network. While, the GRNN showed its highest performance in the suspended sediment concentration estimation with the turbidity data used as a single input variable of the neural network. It was found in all models that the turbidity seems to be a dominant input variable over water discharge for the suspended sediment concentration estimation in the Jiasian diversion weir.

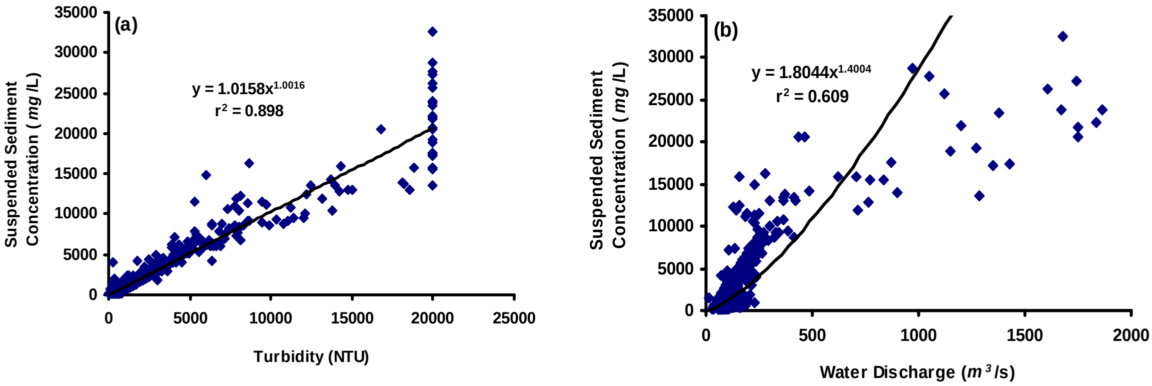

Figure 6. Classical models determined by regressing suspended sediment concentration versus turbidity **(a)** and water discharge **(b)** using the rating curve equation with the data selected for the training period

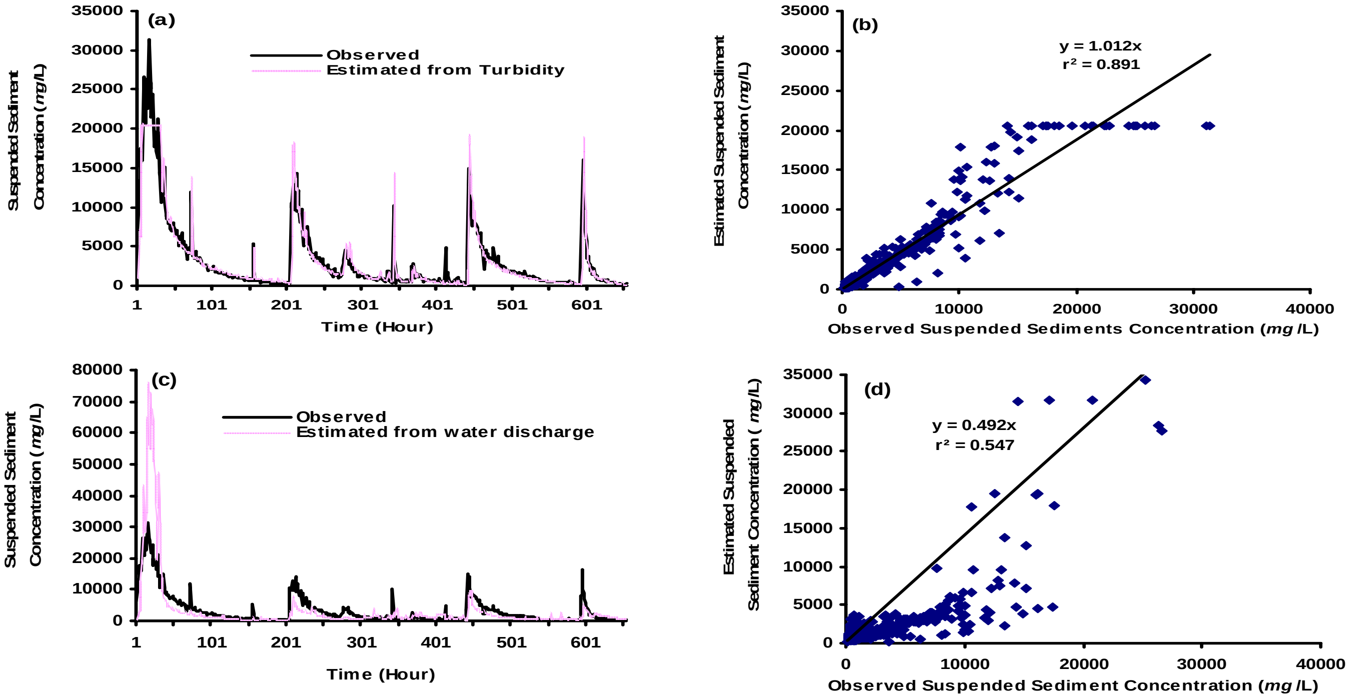

Figure 7. Comparison of the suspended sediment concentration estimated by the classical regression models using turbidity **(a, b)** and water discharge **(c, d)** during the testing period in the Jiasian diversion weir

The poor estimation of the sediment from the water discharge could be explained probably by others factors such as human activity related to the land surface disturbance which could increase the sediment flux independently to the water discharge. The models performances evaluation showed both BP and GRNN statistically superior to the classical regression regardless of the input sets. Therefore, both BP and GRNN configurations can be suggested as potential tools for modelling the event-based suspended sediment concentration in the Jiasian diversion weir when few data are available. Obviously, artificial neural networks are more reliable than the conventional regression method to monitor continuously the weir water quality.

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REFERENCES

Adeloye A.J. and Munari A.D., (2006), Artificial neural network based generalized storage–yield-reliability models using the Levenberg-Marquardt algorithm, *Journal of Hydrology*, **326**(1-4), 215-230.

Agarwal A., Singh R.D., Mishra S.K and Bhunya P.K., (2005), ANN-based sediment yield models for Vamsadhara river basin (India), *Water SA,* **31**(1), 95-100.

Altunkaynak A., (2009), Sediment load prediction by genetic algorithms. *Advances in Engineering Software,* **40**(9), 928-934.

Brikundavyi S., Labib R., Trung H.T. and Rousselle J., (2002), Performance of neural networks in daily streamflow forecasting, *Journal of Hydrologic Engineering,* **7**(5), 392-398.

Celikoglu H.B. and Cigizoglu H.K., (2007), Public transportation trip flow modeling with generalized regression neural networks, *Advances in Engineering Software*, 38, 71-79.

Cigizoglu H.K. and Kisi O.Z., (2006), Methods to improve the neural network performance in suspended sediment estimation, *Journal of Hydrology*, 317, 221-238.

Jain S.K., (2001), Development of integrated sediment rating curves using ANNs, *Journal of Hydraulic Engineering*, 127, 30-37.

Kisi Ö., (2004), Multi-layer perceptions with Levenberg–Marquardt training algorithm for suspended sediment concentration prediction and estimation, *Hydrological Sciences Journal*, 49, 1025-1040.

Kerh T. and Ting S.B., (2005), Neural network estimation of ground peak acceleration at stations along Taiwan high-speed rail system, *Engineering Applications of Artificial Intelligence*, 18, 857-866.

Kumar M., Bandyopadhyay A., Raghuwanshi N.S. and Singh R., (2008), Comparative study of conventional and artificial neural network-based ETo estimation models, *Irrigation Science*, 26, 531-545.

Lewis J. and Eads R., (1996), Turbidity-controlled suspended sediment sampling, *Management council net-worker*, **6**(4), 1-3.

Lu X.X., (2005), Spatial variability and temporal changes of water discharge and sediment flux in the lower Jinsha tributary: impact of environmental changes, *River Research and Applications*, 21, 229-243.

Morehead M.D., Syvitski J.P., Hutton E.W.H. and Peckham S.D., (2003), Modeling the temporal variability in the flux of sediment from ungauged river basins, *Global and Planetary Change,* 39, 95-110.

Pavanelli D. and Palgliarani A., (2002), Monitoring water flow, turbidity and suspended sediment load, from an Apennine catchment basin, Italy, *Biosystems Engineering*, **83**(4), 463-468.

Raghuwanshi N.S., Singh R. and Reddy L.S., (2006), Runoff and sediment yield modeling using artificial neural networks: Upper Siwane River, India, *Journal of Hydrologic Engineering*, **11**(1), 71-79.

Rai R.K. and Mathur B.S. (2008), Event-based sediment yield modeling using artificial neural network. *Water Resources Management*, **22**(4), 423-441.

Sahoo G.B., Ray C. and De-Carlo E.H., (2006), Use of neural network to predict flash flood and attendant water qualities of a mountainous stream on Oahu, Hawaii, *Journal of Hydrology*, **327**, 525-538.

Sarangi A. and Bhattacharya A.K., (2005), Comparison of artificial neural network and regression models for sediment loss prediction from Banha watershed in India, *Agricultural Water Management*, **78**, 195-208.

SNNS., (1995), User manual, version 4.1, Rep. No. 6/95, Institute for Parallel and Distributed High Performance Systems, Univ. of Stuttgart, Stuttgart, Germany.

Sudheer K.P., Gosain A.K. and Ramasastri K.S., (2003), Estimating actual evapotranspiration from limited climatic data, using neural computing technique, *Journal of Irrıgation and. Drainage . Engineering,* **129**(3), 214-218.

Wang Y.M., Juaug S.C. Lai C.C. and Kerh T., (2006), Estimation of suspended sediment discharge for a storm. *Journal of University of Science and Technology Beijing*, **28**(2), 152-156.

Wasserman P.D., (1993), Advanced Methods in Neural Computing, Van Nostrand Reinhold, New York, USA, 155-161.

Yeh Y.C., (1997), Applied neural networks, *Rulin Publishing Co, Taiwan*.

Zhou Y., Lu X.X., Huang Y. and Zhu Y.M., (2004), Anthropogenic impact on the sediment flux in the dry-hot valleys of Southwest China – an example of the Longchuan River, *Journal of Mountain Science*, **1**, 239-249.

Zhu Y.M., Lu X.X. and Zhou Y., (2007), Suspended sediment flux modeling with artificial neural network: An example of the Longchuanjiang River in the Upper Yangtze Catchment, China, *Geomorphology*, **84**, 111-125.