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Full Length Research Paper

Time-lagged recurrent network for forecasting episodic event suspended sediment load in typhoon prone area

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Forecasting suspended sediment load is crucial for river water quality continuous management. This paper investigates the accuracy of a time-lagged recurrent network (TLRN) for forecasting suspended sediment load (SSL) occurring episodically during the storm events in Kaoping River basin located in Southern Taiwan. For this study, two major stations of Kaoping River basin; Liukwei and Lao-Nung are taken into account where important data have been collected between years 1984 to 2005. The ability of TLRN in SSL estimation is assessed by using hydro-meteorological data such as rainfall, water level and discharge as input sets. The network accuracy was evaluated with the goodness-of-fit measures of normalized mean square error, mean absolute error and coefficient of correlation between estimated and observed data. The results showed that the TLRN has a good performance in SSL forecasting when using only water discharge variable as the network input for both stations. However, Liukwei station presented a better statistical performance than Lao-Nung. It was found that among the input variables considered in this study, water discharge is the most effective for sediment load forecasting in the two stations. Finally, TLRN can be successfully employed in Southern Taiwan for modeling river sedimentation if the other factors related to SSL are apprehended.

Key words: Neural network, performance, hydro-meteorological data, river sedimentation, water quality management.

INTRODUCTION

River water quality management has become increasingly complex in recent decades in Taiwan, with higher demands for clean water for domestic and industrial use. River water quality is troubled by the presence of the suspended sediment load transported by the runoff. The river water quality problem can be addressed through a continuous monitoring of the suspended load for providing at real time reliable information to users and managers (Argent et al., 2009). Sediment load estimates can contribute to improved monitoring design and water quality, decision-making, model application, and regulatory formulation (Harmel et al., 2009). Estimates of suspended sediments load are essential for the river transportation research and management. According to Leahy et al. (2008), river study is necessary for reliable study is necessary for reliable forecasting, but it is a difficult task due to the complexity and inherent non-linearity of its hydrological system. The sediments transportation monitoring required a good sample technique which is very lengthy and expensive (Pavanelli and Palgliarani, 2002). Therefore, it is necessary to develop a model that can predict accurately the suspended sediments load from continuous water data set.

The artificial neural network (ANN) is capable to model any arbitrarily complex nonlinear process that relates sediments load to continuous hydro-meteorological data. The artificial neural network is a massively parallel distributed information processing system based on concepts derived from research on the nature of human brains, and has many distinct advantages for data modeling (Zhu et al., 2007; Koutsoyiannis, 2007). The ANN is capable of storing the information gained by the process of learning, and of making it available for future use. The emergence

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of ANN technology has provided many promising results in the field of hydrology and water resources simulation (Kumar et al., 2002; Sudheer et al., 2003; Trajkovic et al., 2003; Adeloye and Munari, 2006; Kisi, 2007; Rai and Mathur, 2007). The hydrological characteristics of the river such as sediments concentration change temporally and spatially, therefore the difficulties for their estimation have encouraged the employment of the artificial neural models. Artificial neural network is as a worth technique in sediment modeling (Cigizoglu and Alp, 2006). It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. The artificial neural network models are primarily lumped, thus needing only cause-effect information of the system (Sahoo, 2006). According to Cigizoglu and Alp (2004), ANNs generally were found superior to conventional statistical techniques in suspended sediment estimation. In general, it has been demonstrated that the modeling of sediment, including load in a river is possible through the use of the ANN.

In recent years, several studies using neural network algorithms have been carried out by researchers in river water resources modeling. Among them exist the employments of generalized regression neural network for river sediment load (Kişi, 2006), feed forward back propagation network (Wang et al., 2008), adaptive neuro-fuzzy inference system for river flow forecasting (Firat, 2008), radial basic function for rainfall-runoff modeling (Cigizoglu et al., 2007). Another promising ANN type used with success for time series data modeling is the time-lagged recurrent networks (TLRNs). The TLRN is a very appropriate model for processing temporal (time-varying) information. Examples of temporal problems include time series prediction, system identification and temporal pattern recognition. The training algorithm used with TLRN is more advanced even than the standard back-propagation. The time-lagged recurrent network topology is found to be very suitable to deal with flood forecasting problem (Xue and Dibike, 2001). It has a fast convergence in time series data prediction than the back-propagation learning algorithm that can get trapped in local minimal (Hussain et al., 2008). The performance of TLRN over the standard back-propagation for time series data prediction is recently evidenced in Badjate and Dudul (2009), Kale and Dudul (2009) studies. According to Geqay and Liu (1997), the recurrent network filters noise successfully in small as well as large samples. In the past, Coulibaly and Evora (2007) indicated that a major feature of this architecture is that the nonlinear hidden layer receives the content of both the input time delays and the context units. Consequently, the TLRN has both static and adaptive memory that makes it suitable for complex sequential input learning. To the knowledge of authors, there is a very limited literature related to TLRN application for river suspended sediment load modeling. However, due to the river data serial structure, TLRN can provide real time sediment load information.

Although ANNs offer advantages over mechanistic or conceptual hydrological models for river study, their applicability is limited by the fact that each ANN has to be specifically optimized and trained for a particular prediction problem and suitable input vectors selected. Kote and Jothiprakash (2008) employed successfully time-lagged recurrent networks for river level prediction. Time-lagged recurrent networks are known to be more powerful than feed forward multilayer neural networks and in nonlinear systems identification and control (Liu, 2001). TLRN is one of the most challenging works in water resources engineering. In this study, TLRN algorithm has been selected to carry out the suspended sediment load forecasting. The complex nonlinearity process of sediments flow provides an impetus for evaluating the accuracy of TLRN performance in Southern Taiwan. This could have potentially an advantage to monitor episodic rivers sediment flux at short time step during the storm events. However, in Taiwan, very few studies reported the use of ANN on river suspended sediment load modeling.

The main objective of this paper is to evaluate the accuracy of a TLRN model for forecasting suspended sediment load of Liukwei and Lao-Nung stations located at Kaoping River basin area in Southern Taiwan, where most of the water from the river is supplying for civil and industrial use. The activities in Southern Taiwan have been flourishing in recent years, the population has increased, and the demand for quality water and industrial water use increased around the Kaoping River basin. In this present study, the suitability of TLRN with time delay, laguarre memory structure is investigated for suspended sediment load forecasting by using the daily rainfall data, water level and discharge as input sets. Suspended sediment forecasting is essential to provide basic information on a wide range of problems related to the water quality monitoring, the operation systems and the river management.

Study area

Kaoping River basin is located in Southern part of Taiwan at 22° 57’ 30” North latitude and 120° 12’ 0” East longitude (Figure 1). Its two major stations selected for this study are the Liukwei and Lao-Nung. The Kaoping River basin is the largest and the most intensively used river basin in Taiwan. It is the Taiwan's second-longest river with its 171 km long and drains a catchment covering 3,257 km^2 of land that is roughly 9% of the island's total area. The island is well known as a typhoon prone area. Because of abundant rainfall during the summer season, the river accounts for as much as 12.7% of the total water on the island. But, the abundant river water has been contaminated by illegal dumping and sewage discharge from pig farms upstream. The pollution has left residents in Southern Taiwan short of water every year. According to Kao et al. (2003), the Kaoping River basin is heavily

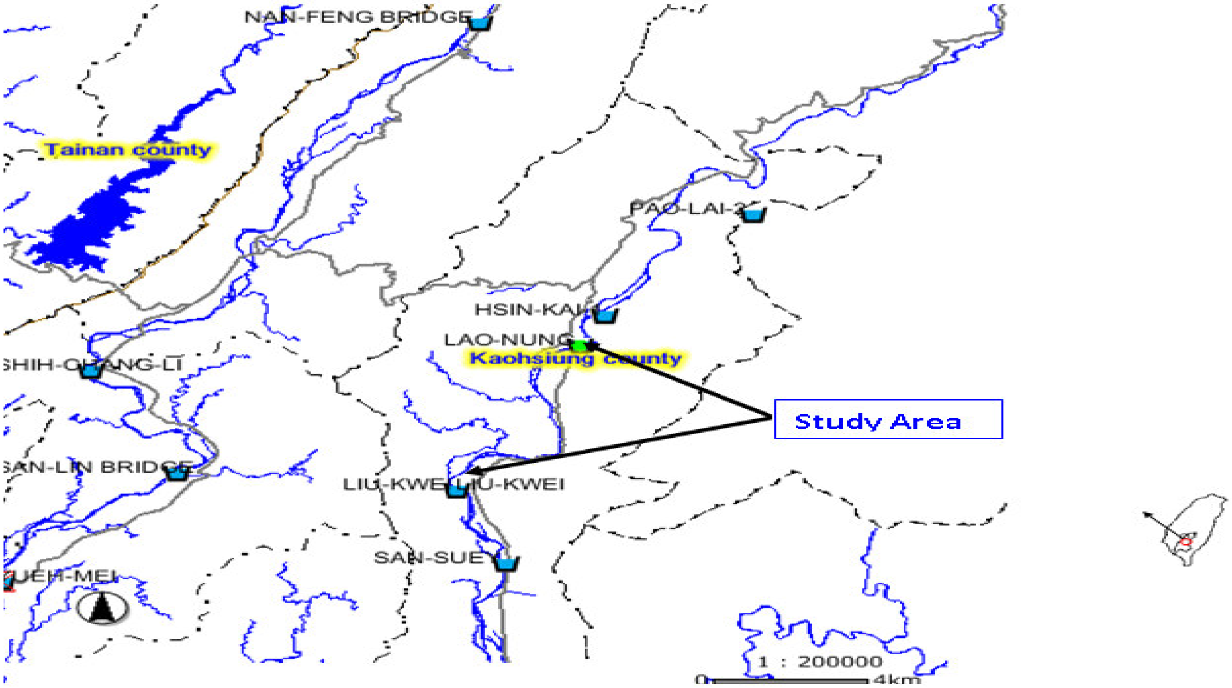

Figure 1. Sketch map of the investigation area.

polluted. Therefore, concern about the deteriorating condition of the river led the Government of Taiwan to amend the relevant legislation and strengthen the enforcement of the discharge regulations to effectively manage the river and control the pollution. Beside the industrial wastes exists the river sedimentation problem occurring during the storms events. The data for this study are continuously recorded, year to year, and the episodic loadings of suspended sediment occurrs during the storm events. The data sets collected between years 1984 to 2005 for this study were comprised of daily water level (mm), water discharge (m^3/sec), rainfall (mm) and suspended sediment load (MT/Day). In Kaoping area, the total cumulated of annual rainfall were around 3054 mm for the year 2005 with an abundance rainfall occurring in the wet season from May to October, conversely to the dry season from November to April.

Data processing

Daily hydro-meteorological data, which include water level (mm), water discharge (m^3/sec), rainfall (mm) and suspended sediment load (MT/Day), have been collected over a twenty five year period. The investigation area has a typical rainfall pattern and topography, and most of the sediment is due to the typhoon storms. The correlation procedure was carried out between hydrological input data and suspended sediments load in order to pre-screen the potential inputs variables in the sediment loads (Table 1). From results, rainfall and water discharge variables show relatively high relationships with the suspended sediment load in Liukwei and Lao-Nung stations. These two variables might have direct driving force of sediment production and transportation in the river. While, the water level (WL) variable is poorly correlated to the suspended sediment load. Therefore, in the beginning of our study, in order to determine the best configuration, water discharge (Q) which provided the highest correlation with the sediment load was considered as input of the neural network. To ensure an equal treatment for each variable in the model, the data are structured in seven different combinations of TLRN models. Table 2 illustrates the TLNR models and their input data structures.

The data set had a total of 647 patterns and was divided into three parts for the purpose of training (70%), cross validation (20%) and testing (10%) to reach the best generalization (SNNS, 1995). The training data set is used to train the neural network by minimizing the error of this data set during the training. The cross validation data are used to find the network performance by monitoring the training and guard against overtraining. Then, the test set is used for checking the overall performance of the trained network.

TIME-LAGGED RECURRENT NETWORK MODEL

Model theory

Multilayer perceptrons (MLPs) are the most commonly used ANN in hydrological predictions (Govindaraju and

Table 1. Correlation between hydrological variables and suspended sediment load for Liukwei and Lao-Nung stations.

	Water Level (mm)	Rainfall (mm)	Water discharge (m^3/sec)
Liukwei			
Suspended Sediment Load (MT/Day)	0.037 (.173)	0.325** (.000)	0.769** (.000)
Lao-Nung			
Suspended Sediment Load (MT/Day)	0.020 (.236)	0.254** (.000)	0.774** (.000)

** Correlation is significant at the 0.01 level (1-tailed).

Table 2. TLRN models inputs structures.

Neural network model	Input variable
TLRN1	Q
TLRN2	R
TLRN3	WL
TLRN4	Q, R
TLRN5	Q, WL
TLRN6	R, WL
TLRN7	Q, R, WL

NB:Q (water discharge); R (rainfall); WL (water level).

Rao, 2000). Their main advantage is that they are easy to use, and able to approximate any input/output map. Time-lagged recurrent networks (TLRNs) are MLPs extended with short term memory structures and local recurrent connections. The input layer used the inputs delayed by multiple time points before presented to the network. Most real-world data contains information in its time structure that is how the data changes with time. Yet, most neural networks are purely static classifiers. TLRNs are the state of the art in nonlinear time series prediction. Basically, it is a gradient descent technique to minimize some error criteria. The network general architecture has three layers and the feedback connection from the hidden layer back to the input layer. Training of the TLRN was done with back-propagation through time with trajectory learning parameters. Back-propagation training involves information processing in two directions, the feed forward of the input information and the back-propagation of the error. The input information is processed in the neurons of the input layer and is passed down to the next layer through the links. Each neuron calculates its net input.

The gradients of the error function at time t is denoted by $E(t)$. Considering only the error at time t, output unit k's error signal is

$$\delta_k(t) = \frac{\partial E(t)}{\partial net_k(t)} \quad (1)$$

and some non-output j's back-propagated error signal at time $\tau < t$ is $\delta_j(\tau) = f'(net_j(\tau))\left(\sum_i w_{ij}\delta_i(\tau+1)\right)$, (2)

Where $net_i(\tau) = \sum_j w_{ij} a_j(\tau - 1)$ (3)

is unit i's current net input,

$$a_i(\tau) = f_i(net_i(\tau)) \quad d_i \quad (4)$$

is the activation of a non-input unit i with differentiable transfer function f_i, and w_{ij} is the weight on the connection from unit j to i. The corresponding contribution to w_{il}'s total weight update is $\eta\delta_j(\tau)a_l(\tau-1)$, where η is the learning rate, and l stands for an arbitrary unit connected to unit j.

The error path integral occurring at k at time step t is propagated back in time for $t-s$ time steps, to an arbitrary unit υ at time $s < t$. This scale the error by the following factor:

$$\frac{\partial\delta_\upsilon(s)}{\partial\delta_k(t)} = \begin{cases} f'(net_\upsilon(t-1))w_{k\upsilon} & t-s=1 \\ f'_\upsilon(net_\upsilon(s))\left(\sum_{l=1}^{n} \frac{\partial\delta_l(s+1)}{\partial\delta_k(t)} w_{l\upsilon}\right) & t-s>1 \end{cases} \quad (5)$$

For $s < \tau < t$ let l_τ denote the index of a generic non input unit in the replication of the network at time τ. Moreover, let $l_s = \upsilon$ and $l_t = k$.

Figure 2 shows a typical time-lagged recurrent network used in this study for the development of suspended sediment concentration estimation model.

Model parameters

Memory structures: There are several memory structures

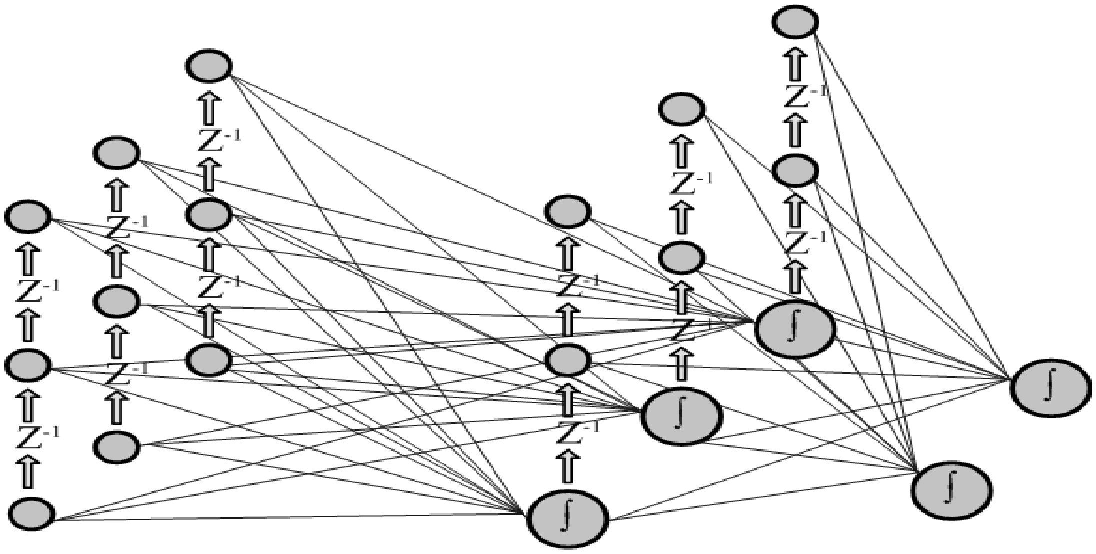

Figure 2. Time-lagged recurrent network structure.

at the input layer to choose from the TLRN parameters. We have applied Laguerre memory function to the data in order to search the best network structure that is the lowest value of statistical criteria. The equation (6) gives the Laguarre functions in which u is the memory resolution, and z^{-1} represents the delay operator.

$$L_i(z,u)=\sqrt{1-(1-u)^2}\,\frac{(z^{-1}-(1-u))^{i-1}}{(1-(1-u)z^{-1})^{i}} \tag{6}$$

Learning algorithms: The depth of the memory was setup to 10, which was later adapted by the network according to the Laguarre memory function. The learning rule for each layer in this study was the momentum setup to 0.7. For the activation function, tangsig transfer function which worked best was applied on the hidden layer and output layers. The number of nodes so-called processing elements in the hidden layers, the number of hidden layers and the epoch of learning were determined by trial-and-error method. The number of processing elements and the number of hidden layers are the two major factors to be determined. Since the study focus on a single variable forecasting, one output node which is the suspended sediment load is exclusively used in the output layer.

Performance measures

TLRN performances evaluation criteria were the normalized mean square error (NMSE), mean square error (MAE) and the square value of coefficient of correlation (r) between estimated and observed SSL.

These statistical criteria are given by the following equations:

$$NMSE=\frac{P\ N\ MSE}{\sum_{j=0}^{P}\frac{N\sum_{i=0}^{N}d_{ij}^{\ 2}-(\sum_{i=0}^{N}d_{ij})^{2}}{N}} \tag{7}$$

Where, P is the number of output processing elements, N is the number of observation in the data, d_{ij} is the desired output for the observed i at processing element j, and $MSE=\frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{ij}-y_{ij})^2}{NP}$ is the mean square error with y_{ij} representing the network output for the observed i at processing element j.

$$MAE=\frac{1}{N}\sum_{i=1}^{N}\left|y_i-d_i\right| \tag{8}$$

Where y_i and d_i represent the observed and estimated values for the *i*th values, respectively.

The coefficient of correlation has been used for further analysis to evaluate the performance of the models in SSL estimation. It is defined as follows:

$$r=\frac{\sum_{i=1}^{N}(y_i-\bar{y})(d_i-\bar{d})}{\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2\sum_{i=1}^{N}(d_i-\bar{d})^2}} \tag{9}$$

Where y_i and $\bar{y}$ are the observed and its average values; d_i and $\bar{d}$ are the estimated and its average values; N is the number of observations. Additionally, a linear regression $d = \alpha_1 y + \alpha_0$ is applied for evaluating the performance of models, where d is the dependent variable; y the independent variable; α_0 the intercept; and α_1 the slope.

DISCUSSION OF RESULTS

A time-lagged recurrent network (TLRN) was configured and trained to forecast the suspended sediment load by using the water discharge since its correlation with the suspended sediment was highly significant. The TLRN inferred time dependence through training features of the networks used to learn natural input-output relationships over time using feedback mechanisms. For setting up the best network configuration in this study, the water discharge is the independent variable used as input of the network. The suspended sediment load is used as the dependent variable for the network output. The determination of the number of the processing elements (PEs) in a hidden layer providing the best training results was the initial process of the training procedure. The numbers of PE in the hidden layer play a significant role in TLRN model performance. The hidden layers may be one or more depending on the data type and the model error statistics. Also, the numbers of nodes in the hidden layer play a significant role in ANN model performance (Sarangi and Bhattacharya, 2005). There are no fixed rules for developing an ANN model with predefined optimum number of PE, hidden layer and epoch parameters. Since no clear-cut guidelines are available (Vemuri, 1992), therefore, the trial-and-error method was decided. The normalized mean square error was chosen as the criterion for selection of optimal architecture. Various nodes have been tried in this study, and the optimum values were found with four and fives PEs for Liukwei and Lao-Nung, respectively. Figure 3 shows the optimum parameters reaching the best configuration of the network during the testing period for Liukwei (a, b, c) and Lao-Nung (d, e, f). The results also showed that only one hidden layer is enough for computing the sediment concentration in these two stations. The highest performances of the TLRN were found when learning the program at 2000 and 2500 epochs for Lao-Nung and Liukwei, respectively. The final and most important step in this work of neural networks is to test the program designed.

Table 3 summarizes in the two stations the models performances during the testing stage. The models performances are ranged in the study areas from 0.0213 to 0.9442, 0.2088 to 14.9343 MT/Day and 0.6501 to 8.8593 MT/Day for r2, NMSE and MAE, respectively. In this study, the highest r^2 obtained during the testing stage were 0.8010 and 0.9442 for Lao-Nung and Liukwei, respectively. Cobaner et al. (2009) by using four different neural network algorithms in Mad River and Arcata/Eureka station in California found during the testing stage the highest r^2 at 0.880. Note that the r^2 term provides information for linear dependence between observation and corresponding estimates values. According to Kisi et al. (2009), it is not always expected that the coefficient of correlation is in agreement with performance criteria such as root mean square error, and an r value equal to 1 does not guarantee that a model captures the behavior of the investigated time series. Therefore, they suggested in suspended sediment estimation study the root mean square error as the main performance criterion when selecting the best model.

Hence, in this study the normalized mean square error is employed as the main criterion for the model determination. The TLRN1 model with only water discharge (Q) variable provides the highest performances for Liukwei (r^2 = 0.9442, NMSE = 0.2088 MT/Day, MAE = 0.6501 MT/Day) and Lao-Nung (r^2 = 0.8010, NMSE = 0.4938 MT/Day, MAE = 1.0020 MT/Day). Based upon the normalized mean square error criteria, the poorest performances were obtained with the model of TLRN6 in both stations with the highest NMSE, 3.4689 and 14.9343 MT/Day for Liukwei and Lao-Nung, respectively. However, the highest MAE value belongs to TLRN7 in Liukwei station. For time series suspended sediment estimation, a mean square error criterion is the best statistical criteria for selecting the models since the high correlation does not reflect always the model performances (Cobaner et al., 2009). It can be observed in both stations that the TLRN1 whose input is only water discharge variable has the best accuracy among the seven inputs combinations from the NMSE, MAE and r^2 viewpoints. From these results, water discharge is found as a dominant input variable over water level and rainfall data in the observed condition. Water discharge seems to be the most effective variable among the data considered in this study for Kaoping River basin sedimentation.

Figures 4a and b show the plots of suspended sediment predicted with the model TLRN1 during the testing period for Liukwei and Lao-Nung, respectively. From Figure 4, it can be clearly seen particularly for Liukwei station that, the time-lagged recurrent networks can be potentially used for suspended sediment load forecasting when only water discharge variable is available. According to Weigend and Gershenfeld (1994), recurrent networks store information about past values in the network itself; therefore it can be potentially used for forecasting. From the results of this study, neural network can be a potential estimation method which could be used for a better understanding of sediments flux. Cigizoglu and Kisi (2006) reported on the nonlinearity of the neural network so-called black box model which seems to be a useful alternative for modeling the complex suspended sediment series. The predictive accuracy of the neural network model was found to be better for modeling sedi-

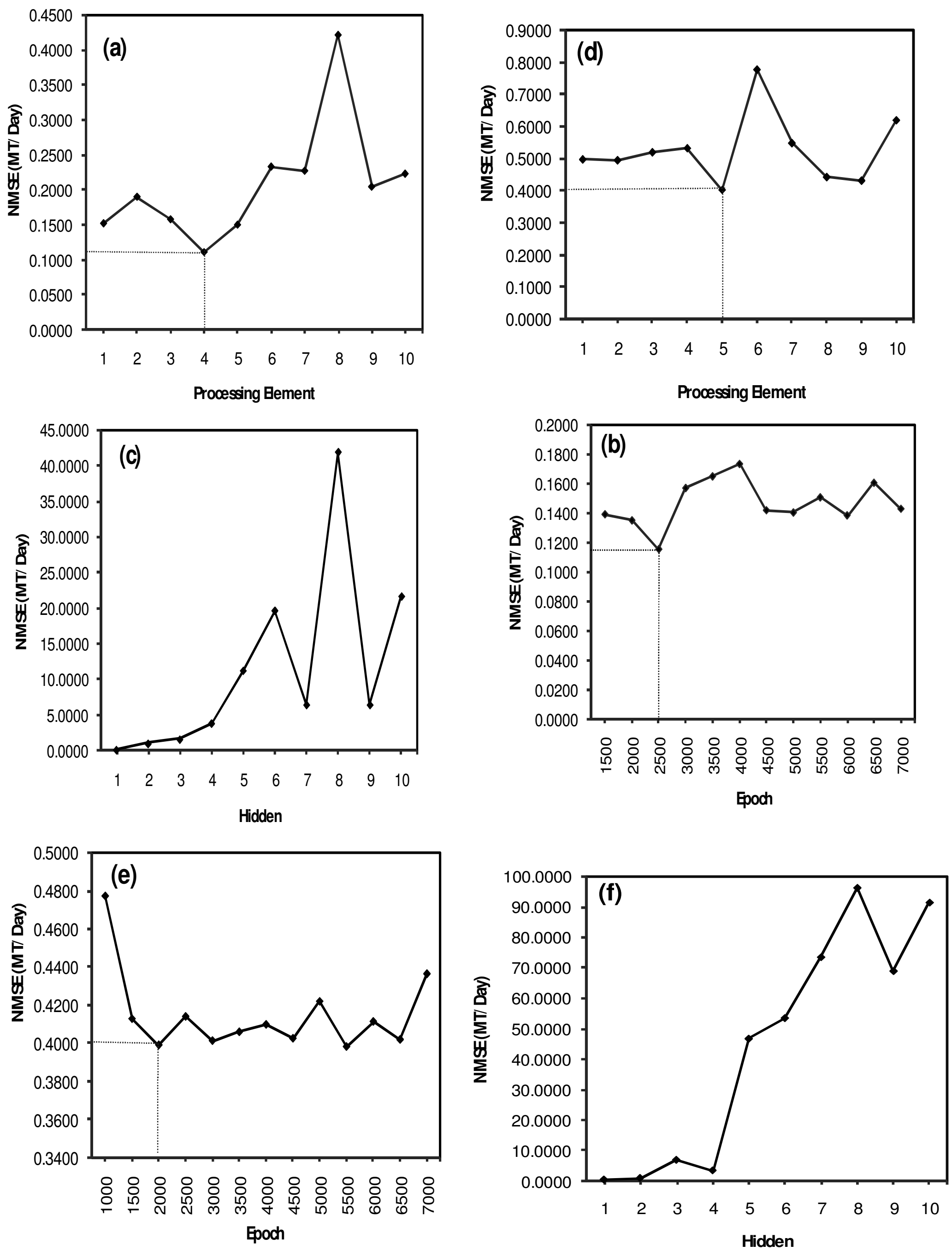

Figure 3. TLRN performances statistic under the variation of the network parameters (processing element, epoch, hidden layer) for Liukwei (a, b, c) and Lao-Nung (d, e, f) during the testing process.

transport (Bhattacharya, 2005). The good performance of neural network for river suspended sediment prediction study can be attributed to their capability to capture the non-linear dynamics and generalize the structure of the whole data set (Celikoglu and Cigizoglu, 2007). Previous report (Kisi, 2004) demonstrated from the daily suspended sediment concentration simulation that, the modeling of sediment concentration in a river is possible through the use of neural network. In a recent study done by Kisi et al. (2009), the advantages of using the artificial neural network are their flexibility and ability to model non-linear relationships. So, this technique could be suggested for sediments forecasting in Kaoping River basin. The results from combining the inputs variables which are represented by TLRN4, TLRN5, TLRN6 and TLRN7 showed significant decreasing of the models per-

Table 3. Time-lagged recurrent network models performance statistics summary during the testing stage.

Location	Model	Input structure	$\propto_1$	$\propto_0$	r_2	NMSE	MAE
	TLRN1	Q	1.1974	25253	0.9442	0.2088	0.6501
	TLRN2	R	0.6802	123898	0.5246	0.5852	1.4906
	TLRN3	WL	0.1601	291864	0.0213	2.2157	3.3673
Liukwei	TLRN4	Q R	0.9062	13532	0.7628	0.2644	0.8283
	TRLN5	Q WL	0.7135	219440	0.1687	2.8475	2.7146
	TRLN6	R WL	0.3812	265526	0.0497	3.4689	3.4072
	TRLN7	Q,R, WL	0.4971	323886	0.0869	3.3837	3.6011
	TLRN1	Q	0.325	74699	0.8010	0.4938	1.0020
	TLRN2	R	0.249	16877	0.0500	1.9024	1.8818
	TLRN3	WL	0.936	77496	0.2500	9.6026	7.8147
Lao-Nung	TLRN4	Q, R	0.6070	16099	0.2367	1.5568	1.8719
	TLRN5	Q, WL	0.5150	16877	0.4746	0.6480	1.7657
	TLRN6	R, WL	0.6340	87978	0.0598	14.9343	8.8593
	TLRN7	Q, R, WL	0.4880	16054	0.4065	0.7983	1.7987

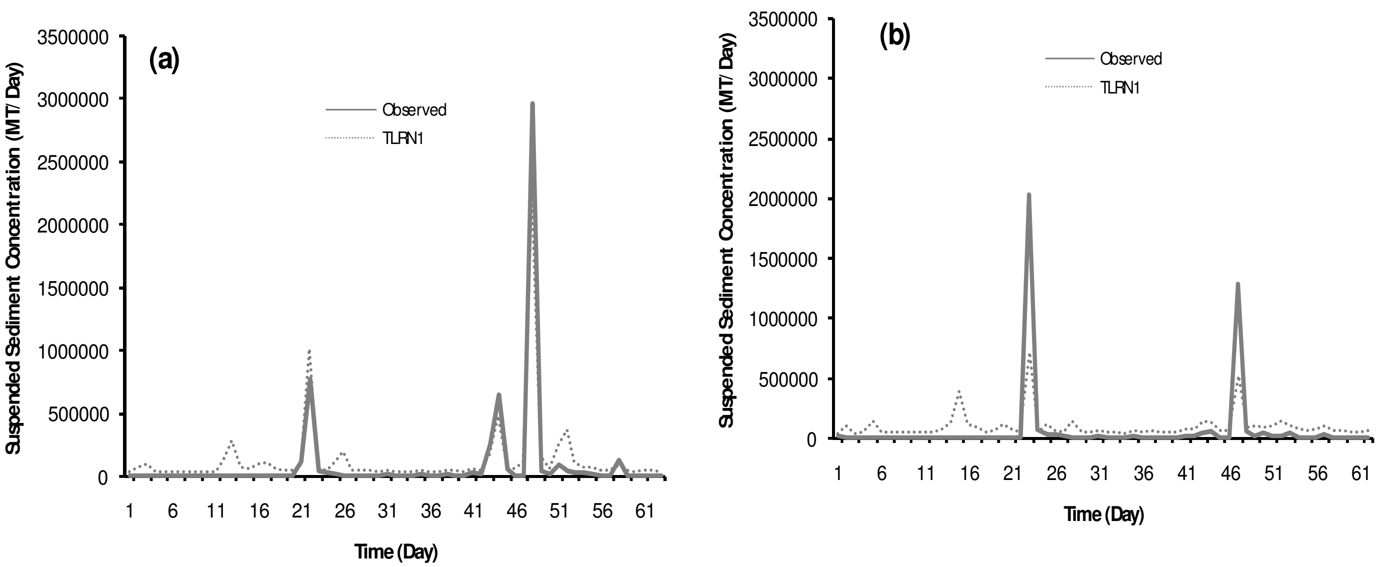

Figure 4. Suspended sediment load estimated by TLRN1 using water discharge variable during the testing stages for Luikwei (a) and Lao-Nung (b) stations.

performances. The variables such as rainfall and water level variables are less effective as evidenced by the performances of TLRN2 and TLRN3 models in comparison with TLRN1 which used water discharge. In general, it was observed that the performance of TLRN models for Liukwei is significantly higher than Lao-Nung. Even using the most effective water discharge variable, TLRN1 predicts better in Liukwei than Lao-Nung. This implied that some key variables causing the suspended

Other factors involved in the sediment loads but not included in the network input could explain the performance of TLRN for Lao-Nung station. Studies done by Zhou et al. (2004) and Lu (2005) denoted that human activity related to land surface disturbance increase the suspended sediment flux. Data analysis of hydrological processes of the watershed reveals that the water quality parameters are mostly affected by weather forces and land use of the watershed (Sahoo, 2006). Human activity could increase the suspended flux independently to the water discharge. More input variables need to be explored for modeling with high accuracy the suspended sediment load in Kaoping River basin. Finally, time-lagged recurrent network algorithm can be considered for hydrological modeling studies in Southern Taiwan where reliable estimates models are not available.

Conclusion

Time-lagged recurrent network was applied to forecast daily suspended sediment load in Kaoping River basin by using the data of rainfall, water level and water discharge as input variables. From the results of this study, it was observed that water discharge is the most effective variable for event suspended sediment loads forecasting in Kaoping River basin. TLRN is capable to forecast successfully the episodic event suspended sediment load using only water discharge in both stations. However, the statistical performances were found to be high in Liukwei than Lao-Nung station. Additionally, the water discharge is seen as the most dominant among the variables considered for the suspended sediment loads forecasting. The results of Lao-Nung station indicate that it must be some key variables that have caused the suspended sediment loads such as land use due to human activity which are missing in the neural network model. Therefore, additional information about the land uses information which are not taken into account in this study are extremely required to be into the model for Lao-Nung station. Human activity related to land surface disturbance could probably increase the suspended sediment flux independently to the water discharge. Time-lagged recurrent network can be successfully employed in Southern Taiwan for providing real time information related to rivers sedimentation problem if the factors causing the sediment loads are apprehended.

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