Quantitative Estimation of Reservoir Sedimentation from Three Typhoon Events

Hong-Yuan Lee, M.ASCE[1]; Ying-Tien Lin[2]; and Yu-Jia Chiu[3]

Abstract: Study of soil erosion in the reservoir watershed, the main source of reservoir sedimentation that affects the reservoir's lifespan and capacity, is of vital importance for watershed management. Due mainly to the lack of data, empirical formulas are commonly used to estimate reservoir sedimentation. However, these estimations are far from accurate. Field measurements data of discharge and suspended sediment were collected during three typhoon events in Shihmen Reservoir watershed, Taiwan. Temporal variations of water surface elevation, discharge, and concentration of suspended sediment were measured. A numerical model, Hydrological Simulation Program Fortran (HSPF), developed by the USEPA was adopted to simulate the sediment yield. However, as calibration and verification data are not always available and the parameter-calibration process is complicated and tedious for novice users of the model, an artificial neural network (ANN) model was proposed. Significant amount of the synthetic data from the calibrated HSPF model were first generated to train the ANN model, which in turn was used to estimate the sediment yield. Comparisons of the sediment yield using both the HSPF and ANN model give correlation coefficients of 0.96 for training and 0.93 for validation. Without the complicated parameter calibration process, the ANN model was faster and easier to use than the HSPF model.

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CE Database subject headings: Sediment yield; Field investigations; Hydrologic models; Sediment concentration; Estimation; Reservoirs; Typhoons.

Introduction

Most rivers in Taiwan are short and steep. Rainfall of high intensity often generates large amounts of erosion from the watershed, which reduces the capacity and shortens the lifespan of reservoirs. Due to difficulty in data collection, empirical formulas (e.g., sediment rating curves) are commonly used to estimate sediment yield. However, these simplified relations between discharge and sediment yield cannot reflect temporal variations of sediment yield during storm events. Thus the estimations are far from accurate. For understanding temporal variations of sediment yield during storm events, it is necessary to collect time-series field data, including rainfall, discharge, and concentration of suspended sediment. Field data for three typhoon events were collected from Shihmen Reservoir watershed in this study. The locations of the Shihmen Reservoir and Yifong water level gauge are shown in Figs. 1 and 2, respectively. According to the field observations, at the same water surface elevation, the sediment yield on the rising stage of the discharge hydrograph was greater than that on the falling stage. The relationship between sediment yield and discharge is nonlinear. Hence using sediment rating curves to estimate sediment yield would generate significant errors (Jain 2001).

Two methods were used in this study to estimate the sediment yield in the watershed. A numerical model, Hydrological Simulation Program Fortran (HSPF) (Bicknel et al. 1996) developed by the USEPA was first adopted. The field data collected were used to calibrate and verify the model. However, as too many parameters had to be calibrated, the model was considered too complicated for the novice users. A numerical model constructed using the artificial neural network (ANN) concept was therefore proposed in this study. The established ANN model is able to simulate the relationship between precipitation, discharge, and sediment yield. Jain and Chalisgaonker (2000) showed that using the ANN model, the rating curve can be better represented.

Typhoons often strike Taiwan in summer. Due to high rainfall intensity, flow rates will increase rapidly in rivers during typhoon events. The increment can be of a factor of 100. Landslides and debris flows often occur and cause casualties. Due to the high winds, high water velocity, and suspended sediment concentration, automatic samplers were usually destroyed during typhoons. Hence it is very difficult to collect suspended sediment samples during typhoon events. Before this study, hydrographs of suspended sediment during typhoon events have never been measured in Taiwan. However, these data are crucial for numerical model calibration and verification. Regardless of all these difficulties, complete suspended sediment concentration hydrographs from three typhoon events were collected in this study. They were then used to calibrate and verify the HSPF model. To train the ANN model, a large amount of data sets are needed. Since complete field data from storm periods were not always available, synthetic data generated by the calibrated HSPF model were used

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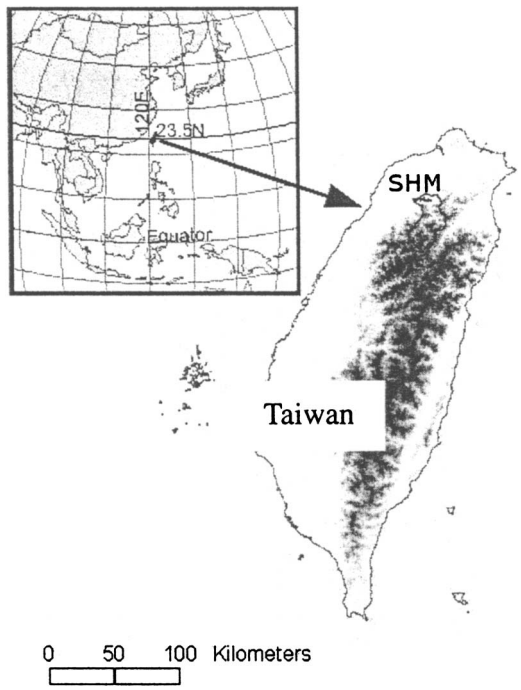

Fig. 1. Location of Shihmen Reservoir and watershed in Taiwan

to train the ANN model. The trained ANN model was then used to estimate the sediment yield from rainfall intensity and discharge. The flowchart of investigation is shown in Fig. 3.

Field Investigation

Yifong watershed of the Shihmen Reservoir was chosen to be the investigation site. The watershed area is 335.29 km^2. There is one streamflow gauging station and four rain gauges in the watershed. The location map of the watershed and corresponding gauging stations are shown in Fig. 2. Rainfall intensity and water level are recorded automatically every hour. Discharges and corresponding concentrations of suspended sediment are measured by the Shihmen Reservoir Authority twice a month. Based on these measurements, the rating curves of water level and flow discharge and sediment yield were obtained. The curves are shown in Fig. 4 and the corresponding regression equations are

$$Q = 62.77 \times (H - 684.5)^{2.141} \tag{1}$$

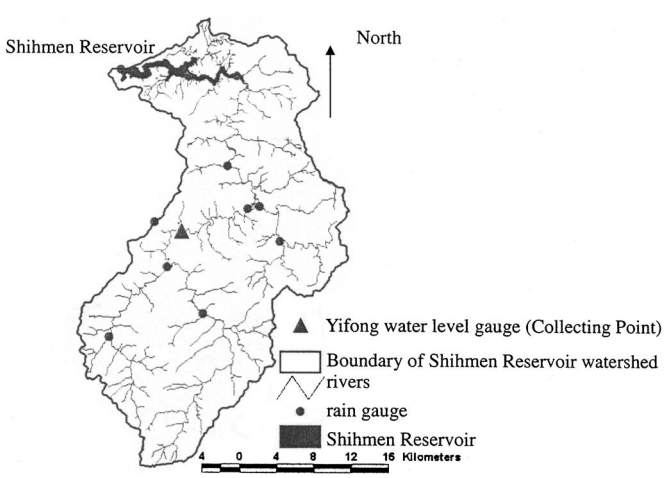

Fig. 2. Location map of Yifong water level gauge (collecting point) and Shihmen Reservoir

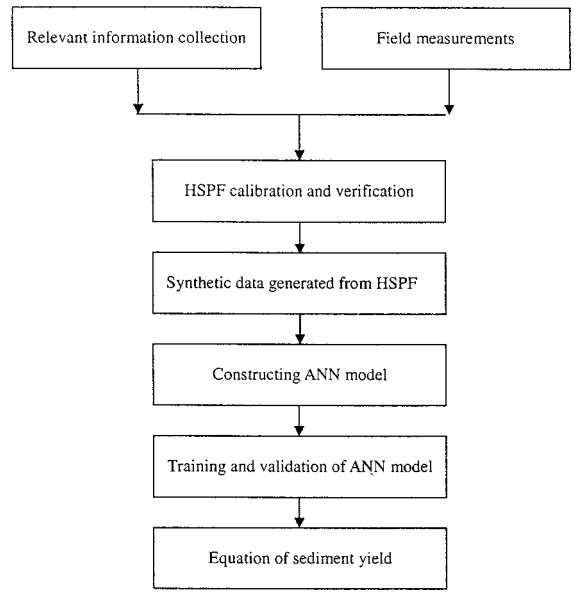

Fig. 3. Flowchart of investigation

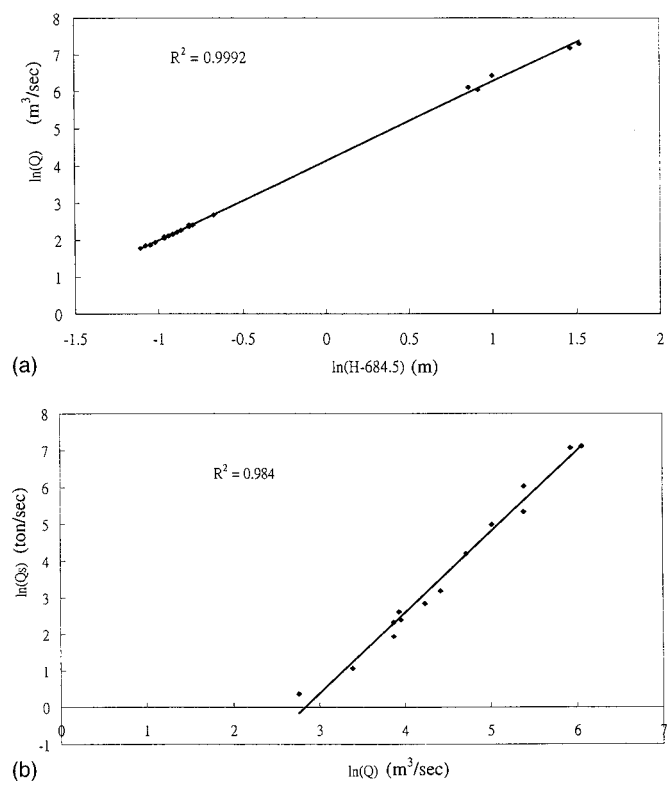

Fig. 4. (a) Water level versus discharge rating curve at Yifong station; (b) sediment yields versus flow discharge rating curve at Yifong station

Table 1. Important Hydraulic Characteristics of Three Typhoon Events

Item	Date		
	Typhoon Rammason (July 3–5, 2002)	Typhoon Nakri (July 10 and 11, 2002)	Typhoon Sinlaku (Sept. 5–7, 2002)
Average rainfall (mm)	578	72	259
Rainfall duration (h)	34	40	56
Maximum rainfall intensity (mm h^{-1})	50.4	11.5	19.0
Time that maximum rainfall intensity occurred (h)	20	18	9
Peak discharge ($m^3 s^{-1}$)	1,341	93	103
Time that peak discharge occurred (h)	27	27	42
Maximum suspended sediment concentration (ppm)	3,438	322	318
Maximum sediment yield (kg s^{-1})	4,611	28	29
Corresponding discharge at maximum sediment yield ($m^3 s^{-1}$)	1,341	86	93

$$Q_s = 1.98 \times 10^{-3} \times Q^{2.203} \quad (2)$$

where Q=flow discharge (m^3/s); H=water level (m); and Q_s=sediment yield (t/s). The rating curves are well-fitted, and correlation coefficients (R) are, respectively, 0.99 and 0.98.

Three complete field investigations were conducted during three typhoon events, namely, Typhoons Rammason (July 3–5, 2002), Nakri (July 10 and 11, 2002), and Sinlaku (Sept. 5–7, 2002). The precipitation data were obtained from the rain gauges. Discharges were estimated using the water level-discharge rating curve [Eq. (1)]. Concentrations of suspended sediment were collected and analyzed by our personnel, and corresponding sediment yield were then estimated. Important hydraulic characteristics of the typhoon events are given in Table 1. Findings from the field investigation are described below.

Precipitation and Discharge

Rainfall hyetographs and discharge hydrographs of the three typhoons are provided in Fig. 5. The rainfall hyetograph of Typhoon Rammason is more concentrated and the corresponding discharge hydrograph rises and drops very rapidly. Several peaks are observed in the rainfall hyetograph of Typhoon Sinlaku, and hence there exist four peaks in the corresponding discharge hydrograph.

Sediment Yield

Suspended sediment concentration samples were collected every 2 hours. The sediment yield was estimated accordingly. The maximum sediment yield and corresponding discharges of the three typhoon events are shown in Table 1. Among the three events, the rainfall intensity of Typhoon Rammason was the highest, and the corresponding duration was the shortest. Thus observed concentrations of the suspended sediment were extremely high, with maximum observed value at 3,438 ppm. Although the rainfall intensity and duration of Typhoon Nakri were lower and shorter than Typhoon Sinlaku, their maximum suspended sediment concentrations were about the same. The results show the complex nature of hydrological processes during storm events.

Dimensionless hydrographs of discharge and sediment yield were obtained by dividing by the corresponding maximum values, as shown in Fig. 6. The sediment yield increased rapidly during the initial stage of the corresponding discharge hydrograph. However, during the falling stage of the discharge hydrograph, the recession rate of the sediment yield is faster than that of the discharge. For Typhoon Sinlaku, due to the irregular rainfall dis-

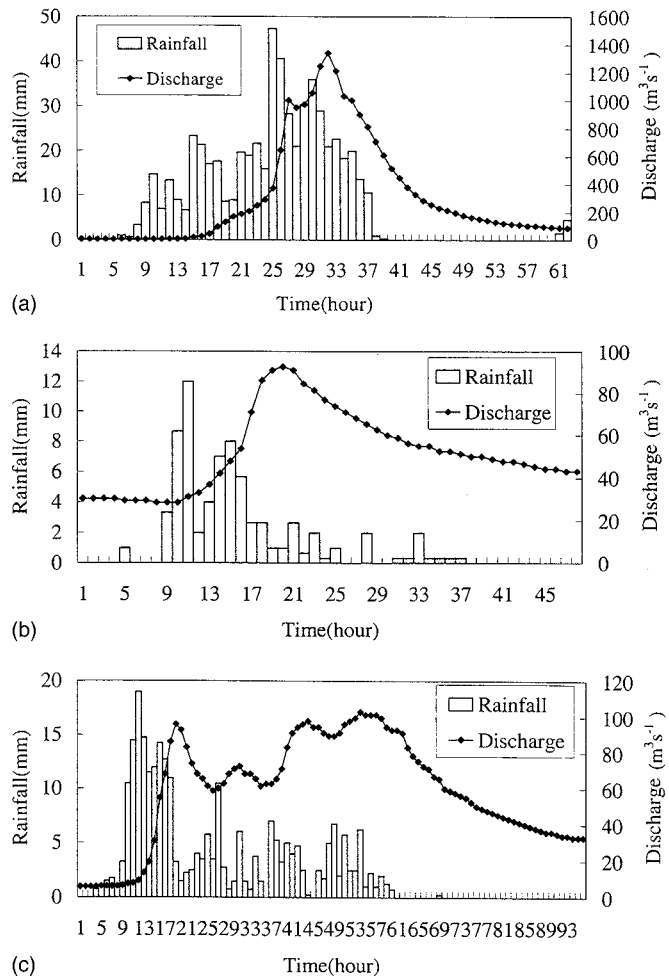

Fig. 5. (a) Rainfall hyetograph and corresponding discharge hydrographs of Typhoon Rammason; (b) rainfall hyetograph and corresponding discharge hydrographs of Typhoon Nakri; and (c) rainfall hyetograph and corresponding discharge hydrographs of Typhoon Sinlaku

tribution, multipeaks were obtained in the discharge and sediment yield hydrographs. The sediment yield was only half of the maximum value when the discharge reached its peak value. In all cases, under the same discharges, the sediment yield during the rising stage was greater than that of the falling stage. For example, in Fig. 6(b) dimensionless discharges were about the same value at the 10th and 17th hour, respectively, in rising and recession periods of discharge hydrographs. However, corresponding dimensionless sediment transport rate on the rising limb was 2.7 times greater than that in the recession period. Most sediment particles were eroded during the initial period, and the temporal variation of the sediment yield varied significantly during the storm events.

In summary, it is observed that soil was saturated in the initial phase of the precipitation, and when runoff occurred, the surface soil was eroded and corresponding sediment yield increased. After several hours, flow discharge and corresponding sediment yield reached their peak values. When the discharge started to decline, due to lack of sediment supply, the sediment yield declined abruptly.

It can be deduced from the analysis of field data that sediment yield obtained from discharge and sediment yield rating curves tends to generate significant discrepancies because of the nonlinear characteristic of the relationship. To accurately quantify temporal variations of sediment yield during these storm events, two numerical models were adopted. Details of the numerical models and their applications are described next.

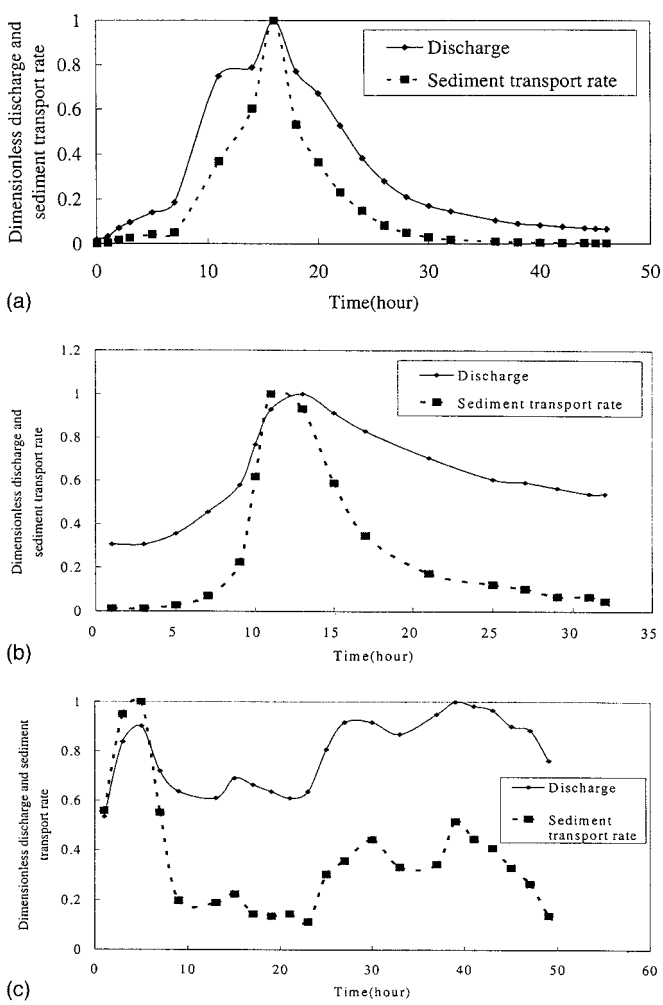

Fig. 6. (a) Dimensionless discharge and sediment transport rate hydrographs of Typhoon Rammason; (b) dimensionless discharge and sediment transport rate hydrographs of Typhoon Nakri; and (c) dimensionless discharge and sediment transport rate hydrographs of Typhoon Sinlaku

HSPF Model

The Hydrological Simulation Program Fortran (HSPF) is a river basin simulation model developed by the USEPA. It is a popular model for simulating rainfall-runoff, soil erosion, sediment transport, and nonpoint source pollutant transport behaviors in the watershed. The comprehensive hydrological model includes func-

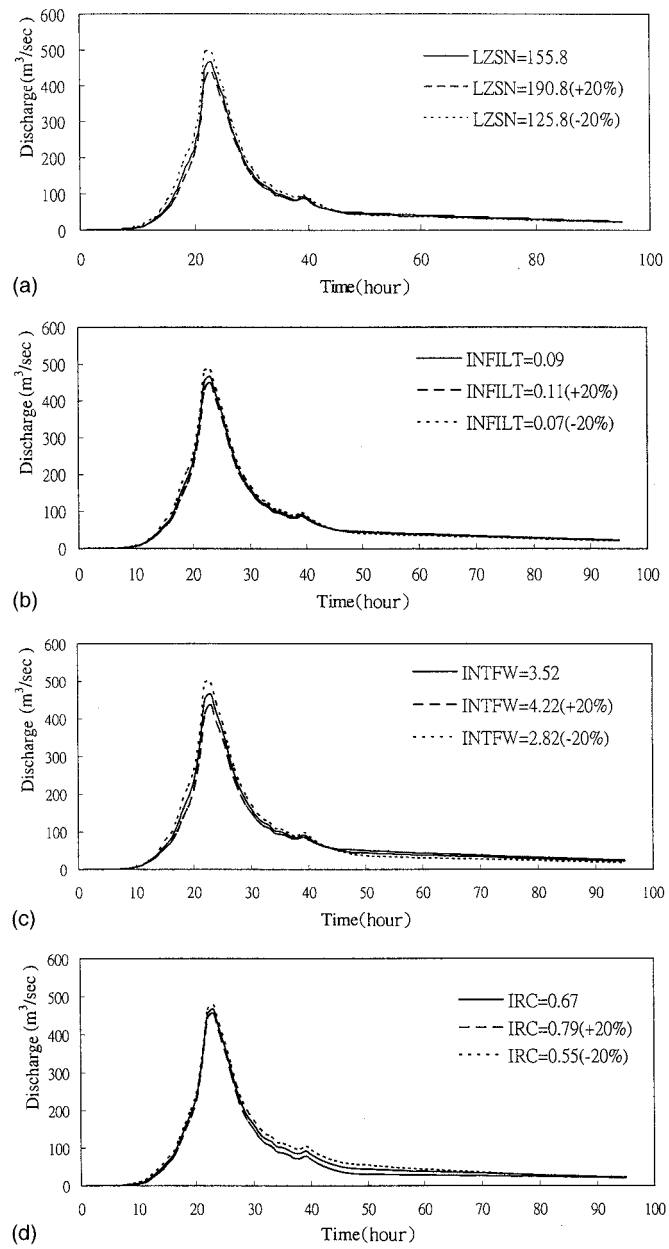

Fig. 7. (a) Sensitivity analysis of LZSN (HSPF); (b) sensitivity analysis of INFILT (HSPF); (c) sensitivity analysis of INTFW (HSPF); and (d) sensitivity analysis of IRC (HSPF)

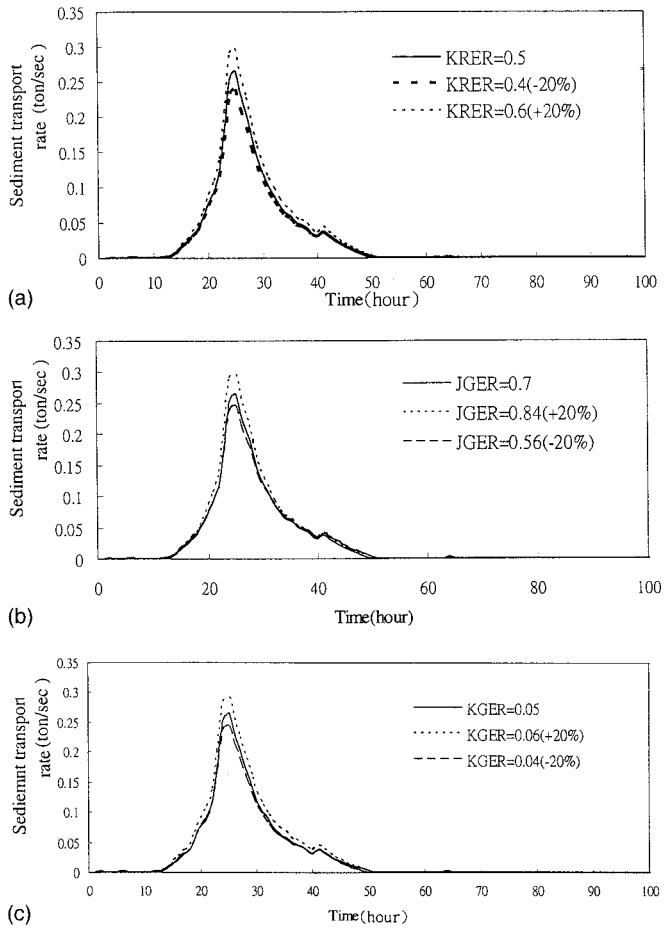

Fig. 8. (a) Sensitivity analysis of KRER (HSPF); (b) sensitivity analysis of JGER (HSPF); and (c) sensitivity analysis of KGER (HSPF)

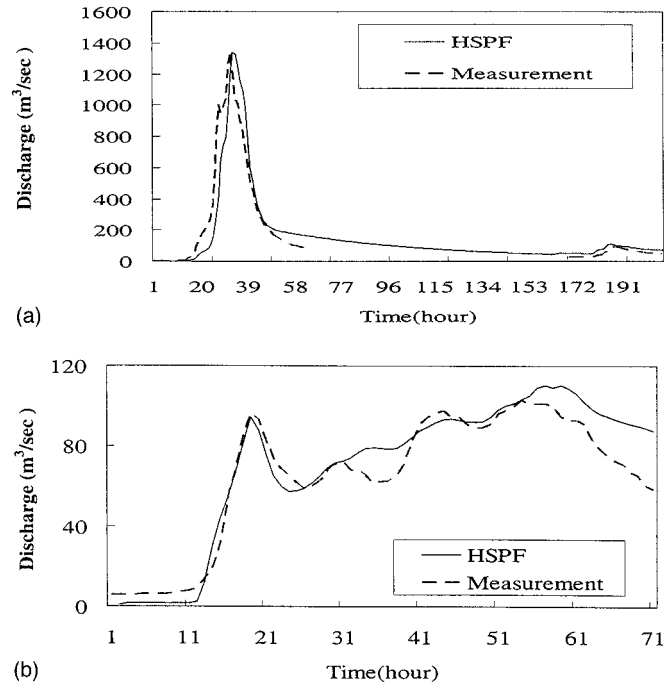

Fig. 9. (a) Simulation results of the discharge hydrograph (calibration); (b) simulation results of the discharge hydrograph (validation)

tions for simulation of runoff from various land covers and hydraulic simulation in dams and reservoirs (Donigian et al. 1983, 1984). HSPF has been used successfully in modeling the stream loading of sediment (Moore et al. 1988; Chew et al. 1991; Laroche et al. 1996). Using field data and relevant parameter information, including precipitation, discharge, concentration of suspended sediment, relevant geometric information, and event specific parameters, discharge hydrographs and temporal variation of sediment yield can be simulated. It is classified as a conceptual model and it has considerable complexity (Hydrocomp 1996).

Model Sensitivity Analysis

Input data of the HSPF model include rainfall, channel cross section, and relevant geological information. The rainfall data were obtained from four rain gauges. Channel cross sections were measured by the Shihmen Reservoir Authority. The output data are discharge and corresponding sediment yield hydrograph. The field data collected was used to calibrate and verify the HSPF model. Before application, sensitivity analysis was performed to identify the most sensitive parameters in HSPF.

Sensitive parameters for HSPF have been discussed in the literature (Donigian et al. 1984; Linsley et al. 1986; Al-Abed and Whiteley 2002). In our sensitivity analysis, all parameters in the model were adjusted ±20%. In the rainfall-runoff module, the

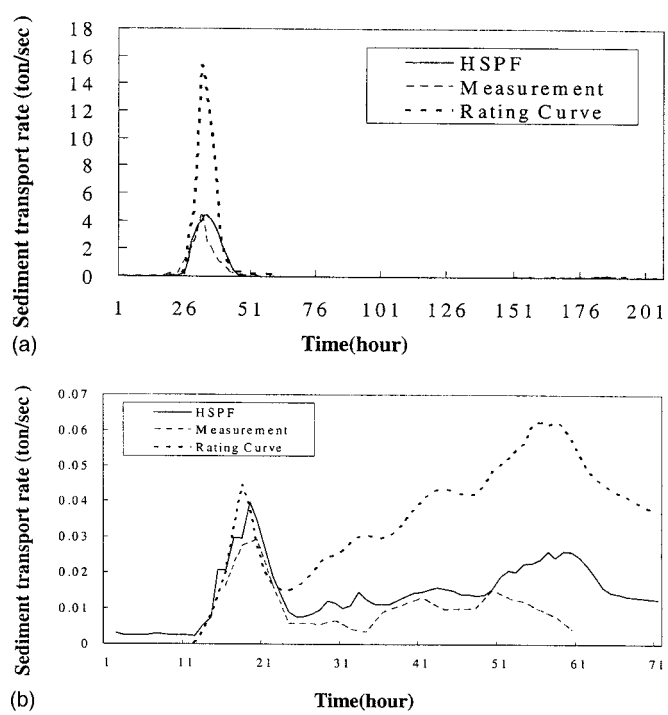

Fig. 10. (a) Simulation results of the sediment yield hydrograph (calibration); (b) simulation results of the sediment yield hydrograph (validation)

Table 2. Typhoon Events for Synthetic Data Generation

Typhoon name	Beginning	Ending	Category
Ellie	Aug. 16, 1991	Aug. 19, 1991	Training
Nat	Sept. 16, 1991	Sept. 25, 1991	Training
Mireille	Sept. 24, 1991	Sept. 26, 1991	Training
Polly	Aug. 26, 1992	Aug. 31, 1992	Training
Omar	Sept. 2, 1992	Sept. 5, 1992	Training
Tim	July 9, 1994	July 11, 1994	Training
Doug	Aug. 6, 1994	Aug. 8, 1994	Training
Deanna	June 5, 1995	June 9, 1994	Training
Ryan	Sept. 21, 1995	Sept. 23, 1995	Training
Yanni	Sept. 27, 1998	Sept. 29, 1998	Training
Kai-Tak	July 6, 2000	July 10, 2000	Training
Zeb	Oct. 14, 1998	Oct. 16, 1998	Validation

most sensitive parameters are lower zone nominal storage (LZSN), infiltration parameter (INFILT), interflow inflow parameter (INTFW), and interflow recession rate (IRC). In the soil erosion module, the most sensitive parameters are the coefficient in the soil detachment equation (KRER), the exponent in the matrix soil scour equation (simulates gully erosion, etc.) (JGER), and the coefficient in the matrix soil scour equation (simulates gully erosion, etc.) (KGER). Results of the sensitivity analysis are given in Figs. 7 and 8. From the results, we can know the relative influences of all sensitive parameters in the model. With the same adjustments for all parameters, the output data will change more when sensitive parameters are changed. When we calibrated the model, we would first choose the most sensitive parameters. This significantly improves the efficiency of the calibration step.

Model Calibration and Validation

The first two storm events (Typhoons Rammason and Nakri) were used to calibrate the HSPF model, and data from Typhoon Sinlaku were used for model validation. Model calibration and validation results are shown in Fig. 9. From Fig. 9, it can be seen that the HSPF model is able to simulate temporal variation of discharge accurately. The correlation coefficients for calibration and validation between observed and simulated results are 0.86 and 0.85, and root-mean-squared differences are 19.87 and 1.29, respectively.

Calibration and validation of sediment yield simulations are shown in Fig. 10. The corresponding values calculated by the discharge-sediment yield rating curve are also provided for comparison. For calibration cases, correlation coefficients and root-mean-squared differences between the calculated results using the rating curve and observed data are 0.70 and 0.57. The correlation coefficients and root-mean-squared differences between the simulated results using the HSPF model and observed data are 0.82 and 0.11. However, corresponding sediment yield correlation coefficients are only, respectively, 0.26 and 0.54, and the root-mean-squared differences are 0.004 and 0.001, for validation cases.

In the third storm event, the simulated results from HSPF are accurate during the initial period of the storm events and tend to overestimate the sediment yield after 24 h of continuous rainfall. The discrepancy between the measured and simulated sediment yield likely resulted from the irregular rainfall distribution. However, trends of temporal variation of sediment yield are similar. On the other hand, the results from the rating curve method are much higher than the other two, especially in the recession period of discharge hydrographs. Due to the simplified relation between discharge and sediment yield, the simulated sediment yield from the rating curve method increases as discharge increases. That method cannot reflect the temporal variations of sediment yield. Thus compared with the results from the rating curve method, the estimations from the HSPF model are more accurate.

There are a lot of parameters used to simulate hydrologic and hydraulic processes in a watershed in the HSPF model. A detailed description of HSPF can be found in Bicknell et al. (1996, 1997). Due to the tedious procedures in calibration and validation, only experienced engineers are able to tune the parameters and deal with the unpredictable sensitivity in each simulation. To provide practicing engineers with a simple yet reliable predictive tool, the artificial neural network concept is introduced to build a more user-friendly model.

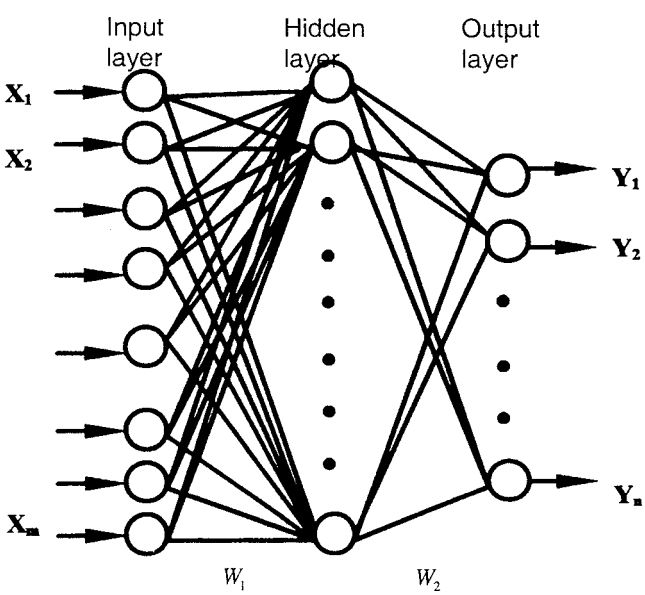

Fig. 11. Network structure of the ANN model

Artificial Neural Network Model

Introduction

ANN is a model developed by imitating human mind and brain activity. Constructing a network with simple artificial neurons, it is able to simulate the learning behavior by operating these neurons. Provided enough training data sets, the ANN has been demonstrated to be a powerful tool to relate highly nonlinear responses or functions. With its self-learning nature, an ANN can automatically adjust weighting parameters when additional data sets are available. It was concluded that the ANN model was the most efficient black-box model tested for calibration periods (Sajikumar and Thandaveswara 1999). Hence it is easy to modify the model and to increase simulation accuracy without elaborate parameter-tuning processes. Thirumalaiah and Deo (1998) used an ANN model for river stage simulation. Jain et al. (1999) used an ANN model for flow discharge and reservoir operation simulation. To evaluate applications of ANN models, an ASCE Task Committee on Application of Artificial Neural Networks in Hy-

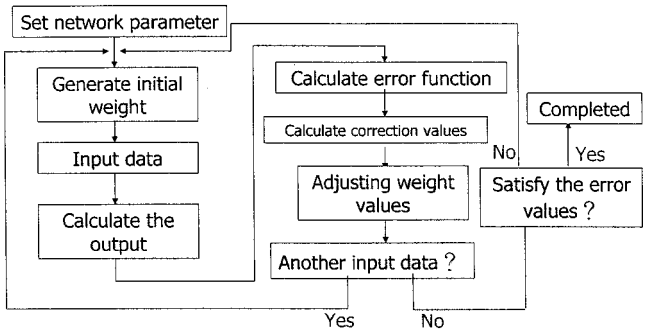

Fig. 12. Flowchart of back-propagation network process

drology (ASCE 2000a,b) was established to review the concepts and corresponding applications. It was concluded that ANN models can perform as well as existing models.

Methodology

The most commonly used ANN scheme, the back propagation network (BPN) (Rumelhart and McClelland 1986), was adopted in the study. The basic principle of BPN is to use the concept of the gradient steepest descent method to minimize the error function. For practical reasons, BPN with only one hidden layer was chosen to construct the model.

Although many factors are involved in sediment transport, the rainfall intensity and discharge are the most relevant parameters. Generally, the concentration of suspended sediment increases as the flow discharge increases. The discharge information is set to be an input parameter of the ANN model. Since soil erosion and hence sediment supply are affected by the rainfall intensity, the precipitation information is also an important parameter. Theoretically, given enough data, it is possible to build an ANN model to simulate the concentration of the suspended sediment using the precipitation and discharge information provided. However, concentration of suspended sediment is extremely high in storm periods during which time data collection is difficult and dangerous. Complete data sets from storm periods are not always available for ANN model training. One approach is to generate data sets that preserve the corresponding characteristics of rainfall intensity, discharge, and concentration of the suspended sediment. In this study, synthetic data were generated from the calibrated and verified HSPF model to construct and train the ANN model. With the well-verified ANN model, users can easily estimate the concentration of the suspended sediment and discharge from only rainfall intensity input.

Application

A total of 12 typhoons affected the watershed between 1991 and 2000 (Table 2) and are used to train and verify the ANN model. The first 11 events were fed to the validated HSPF model to generate synthetic data for ANN model training, and the 12th event was used to validate the model's predictive capability. The ANN model consists of three layers, namely, input layer, hidden layer, and output layer, with rainfall intensity and discharge sets as the input parameters [X's] and sediment yield as an output parameter [Y] (Fig. 11).

A transfer function is used to modulate the input data. In this

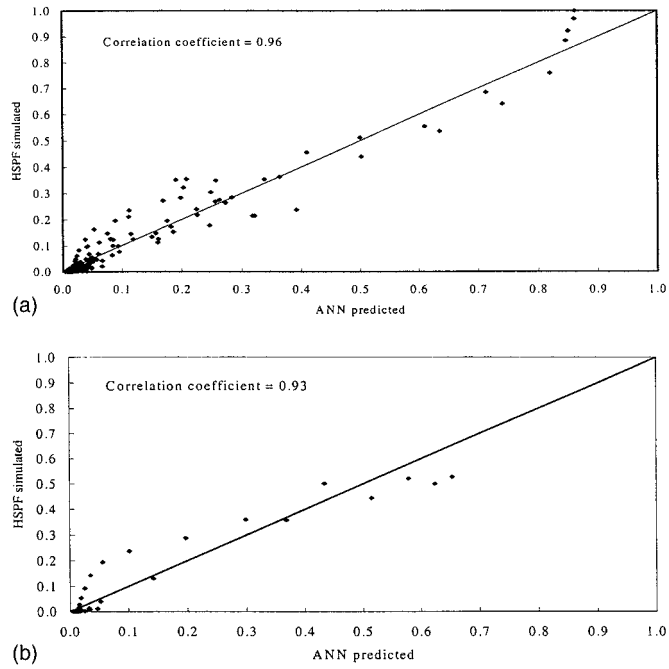

Fig. 13. Comparisons of the simulation results using both ANN and HSPF models

study, a unipolar sigmoid function ranging from 0 to 1 is used as the transfer function because of good convergence of this function. It is expressed as

$$a(f) = \frac{1}{1 + e^{-f}} \tag{3}$$

Due to the unipolar sigmoid function chosen, input and output data should be transferred to the map to the same value region [0,1] with the transfer function. Thus input and output data are normalized by dividing by their maximum values. There are several combinations of input data of rainfall intensity and discharge used to estimate sediment yield. According to estimate results from Hsu et al. (2003), the optimal input and output parameters are denoted as

Input data: $R_t, R_{t-1}, R_{t-2}, R_{t-3}, R_{t-4}, Q_t$

Output data: Qs_t

where R_t, Q_t, and Qs_t=rainfall intensity, discharge, and sediment yield at time t; and R_{t-n} indicates the rainfall intensity at the nth time step before time t.

In the BPN algorithm, the network parameters (including learning rate, learning cycle, and error threshold) must be prede-

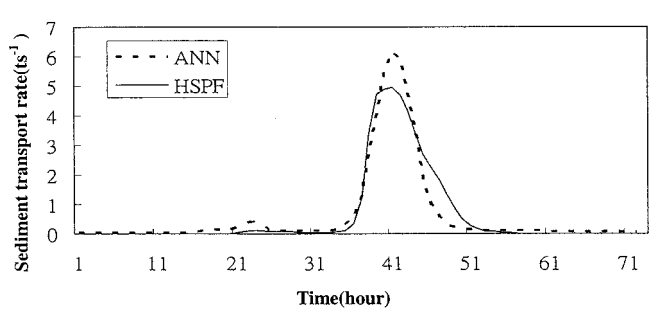

Fig. 14. Simulation results of the sediment transport rate using ANN and HSPF models

termined. The initial weights are given as random variables, and input-output pairs can then be fed to the BPN. The error function E could be shown as

$$E = \frac{1}{2}\sum_{i=1}^{n} (d_i - y_i)^2 \tag{4}$$

where d_i=desired (observed) value at the ith output element; and y_i=estimated value at the ith output element. If errors between observed and estimated values exceeded the threshold value, the weights should be adjusted. The training work is completed when the errors are within the threshold value. The final weights are then determined. This process is shown in Fig. 12.

The simulation results are provided in Figs. 13 and 14. Correlation coefficients between the ANN and HSPF models are 0.96 for the training and 0.93 for the validation (Fig. 13). Comparisons of simulation results from both ANN and HSPF models are shown in Fig. 14. The simulated results from both models are similar. The ANN model is proved to be an acceptable alternative to estimate sediment yield of the watershed area. From the ANN simulation results, an equation for sediment yield estimation is obtained, which is

$$\text{sediment yield} = \text{sigmoid}\left\{[W_2] \times \begin{bmatrix} 1 \\ \text{sigmoid}([W_1] \times [X]) \end{bmatrix}\right\} \tag{5}$$

where sigmoid=$a(f)=1/1+e^{-f}$; $[X]=[1\ R_t\ R_{t-1}\ R_{t-2}\ R_{t-3}\ R_{t-4}\ Q_t]$=input vector; $[W_1]$ the weight matrix between the input and hidden layers is

$$\begin{bmatrix} -0.50 & 0.01 & 0.24 & -0.43 & 0.10 & -0.51 & -0.21 & -0.79 & -0.25 & -1.38 & -0.83 & -4.64 \\ -0.73 & -0.06 & 0.03 & -0.19 & 0.26 & -0.24 & 0.09 & -0.65 & -0.38 & -0.81 & -0.79 & -3.34 \\ -0.59 & -0.40 & -0.52 & -0.20 & -0.09 & -0.18 & 0.01 & 0.39 & -0.32 & 0.50 & -0.09 & -3.27 \\ -0.17 & -0.23 & -0.33 & -0.37 & 0.00 & -0.18 & 0.05 & -0.09 & -0.12 & -0.27 & -0.26 & -1.91 \\ -0.44 & -0.15 & -0.30 & -0.21 & 0.07 & -0.18 & 0.05 & 0.00 & -0.18 & -0.30 & -0.48 & -2.31 \\ -0.52 & -0.02 & 0.20 & -0.14 & 0.36 & -0.72 & -0.21 & -0.79 & -0.36 & -1.23 & -0.95 & -4.56 \\ 0.00 & 0.79 & -0.28 & 0.47 & 0.01 & 0.43 & -0.43 & 0.90 & -0.74 & 1.18 & -0.44 & -3.09 \end{bmatrix} [W_2],$$

the weight matrix between the hidden and output layers is

$$[W_2] = [2.55 \quad -3.45 \quad -2.51 \quad -3.35 \quad -1.90 \quad -2.09 \quad -3.36 \quad -3.62]$$

Given the input vector $[X]$, this equation now can be used to estimate sediment yield from the Yifong watershed with easier and faster procedures.

Conclusions

Field data from three typhoon events were collected and analyzed in this study. The analysis of the data shows the relationship between temporal variations of rainfall intensity, discharge, and corresponding sediment yield are highly nonlinear. The sediment yield in the rising period of discharge hydrograph is larger than that in the recession period. To more accurately estimate sediment yield during storm events, two methods were used in this study. The HSPF model was found to be able to accurately estimate the sediment yield from the Yifong watershed, but the use of such a model requires tedious calibration and verification procedures. Using synthetic data generated from the calibrated HSPF model, an ANN model is established. In the validation case for Typhoon Sinlaku, the total sediments in tons from the observed data, from the rating curve method, and from the HSPF and the ANN models are 1,784, 5,868, 2,794, and 2,904 t, respectively. The results show that total sediment yields are overestimated in the rating curve method. The HSPF and ANN models are more accurate than the rating curve method. The ANN model was shown to be able to calculate the watershed sediment yield with good accuracy. Comparisons of the sediment yield using both the HSPF and ANN models give correlation coefficients of 0.96 for training and 0.93 for validation. The ANN model was proved to be an acceptable alternative for estimation of sediment yield of the watershed.

Only experienced modelers are able to tune the parameters in the HSPF model. Hence the application of the HSPF model is rather inconvenient from the novice user's point of view. On the other hand, with its self-learning nature, ANN could adjust the weighting parameters automatically when additional data sets are available. Thus it is easy to modify the model and reach additional precision without an elaborate parameter-tuning process. It is concluded that the ANN model is a faster and generally more accurate tool for practicing engineers in the future.

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