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Prediction of Sediment Yield Using the Algoritma Lavenberg-Marquardt

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Abstract. Erosion and sediment that occurs in the basin is very important to be studied scientifically. Forecasting of sediment yield in a basins area is important to used to evaluate the land-use/landcover change, soil erosion hazard, planning, water quality, water resources in river, and to determine the extent of the damage that occurred in the basins. The algoritmh lavenberg-marquardt can be used to forcest the total of sediment yield the basin area. Artificial neural networks using feedforward multilayer percePson with three learning algorithms namely Levenberg-Marquardt. The number of neurons of the hidden layer is three to sixteen, while in the output layer only one neuron because only one output target. The root mean square error (RMSE), mean absolute error (MAE), coefficient of determination (R²), and coefficient of efficiency (CE). The performance value in the training process, R², and CE (0.98 and 0.98). As well as for the testing process, R² and CE (0.98 and 0.97). Based on the performance statistics value, LM is very suitable and accurate for to forcesting by modeling the non-linear complex behavior of sediment yield responses to water discharge, intensity of rainfall, and water depth in the river.

Keywords: Sediment yield, Levenberg-Marquardt

1. Introduction

Sediment yield prediction can be used in various physical measurements of a land. Sediment yield prediction is an important parameter used in land use planning and land use change, land cover evaluation, soil erosion hazards, irrigation, reservoirs, dams, as well as water resources management and water quality [1]. Modeling applications to predict the amount of sediment in a watershed have been developed. These applications include Info Work Rs, QuantumGis (QGis), HEC-RAS, HEC-HMS, MODFLOW, regression method, and artificial intelligent such as artificial neural network [2]. Sediment yield forecasting using the LM algorithm has been widely carried out in the basin area with precise results [3]. One of the studies that has been carried out in the Jenderam Basin is to predict sediments yield with artificial neural networks. The study used a multilayer perceptron feedforward training algorithm using the Levenberg - Marquardt (LM) algorithm to predict the amount of sediment yield. The aim of this study to test the precision of the algorithm LM model in a small basin area.

The predictive measurement of sediment yield discharge can use artificial neural networks. The prophetical measuring of sediment yield will use artificial neural networks. The network could be an science system that has bound performance characteristics like biological neural networks in humans



[4]. Artificial neural networks are developed as generalizations of mathematical models of human knowledge or neural biology. supported the fundamental assumption that information processing happens in several straightforward parts referred to as neurons. Through the association link, the signal is shipped between neurons. every connection link has its own weight that is a typical neural net. every new generation multiplies the transmitted of signal by applying an activation perform to its internal input layer (the total of input signals weighed) to see the signal [5].

Artificial neural networks have characteristics consisting of connection patterns between neurons, connection selection strategies for training or learning, activation functions of association degrees. The connection pattern between neurons or full-connected layer neural network is divided into input layer, output layer, and hidden layer [6].

Full-Connected Layer (FCL) or Multilayer Perceptrons feedforward (MLP) can be methodologies for non-linear activation functions that consistently train full-connected layer. This method contains a reasonable mathematical basis for obtaining algorithms and coefficients in equations with quadratic values through the developed network model. On the other hand, the input, hidden, and output layers have interconnection weight values v and w between somatic cell layers [7]. The association pattern of the backpropagation artificial neural network can be seen in Figure 1. This study uses Multilayer Perceptrons feedforward (MLP) as a predictor of sediment yield. Through the multilayer neural examination method, the results of the MLP performance to force the sediment results support the number of neurons in the input, hidden, and output layers.

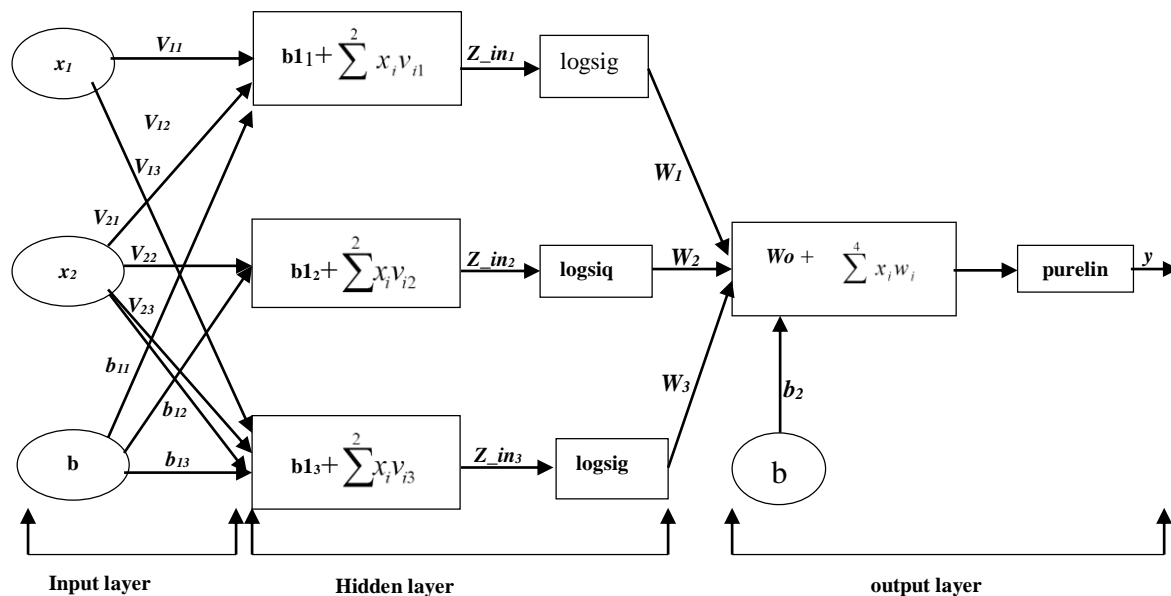


Figure 1. Flow diagram of multilayer perceptron feedforward network

2. Training algorithms

Multilayer FCL or MLP training on system artificial intelligent or artificial neural networks that are frequently used include for gradient descent with momentum, scalable gradient descent (GD), Levenberg-Marquardt and BFGS (quasi-newton). Each training has different characteristics. To forcest the amount of sediment yield in the Jenderam basin, this study uses the Lavenberg-Marquardt (LM) algorithm training. In mathematical formula the damped least squares, is also called the Levenberg Marquardt as part of the problem resolution to reduce numerical losses usually non-linear functions. The LM algorithm can be in the form of gauss Newton and GD method. The unit of luminous flux can also be described, even when the Gauss-Newton approach uses the thick region. Luminous flux units are generally used in curve fitting algorithms to solve common curve fitting problems. The Levenberg-Marquardt formula is intended to exploit the second by product approach without having to compute the

Wellington boot matrix. The luminous flux unit constructing algorithm for updating the weights uses the equation:

$$w_{t+1} = w_t - \Delta w_t \quad (1)$$

$$\Delta w_t = [J^T(w_t)J(w_t) + \mu I]^{-1} J^T(w_t)e(w_t) \quad (2)$$

where:

w_{t+1} the updating vector of the weights.

w_t the weight vector before updating.

I the represents the identity matrix

J the jacobian matrix containing the first derivative of the network error to its weight value.

μ the speed of learning

$e(w_t)$ the matrix error function that was evaluated in the previous iteration.

If the learning rate (μ) has a value zero (0), the result same if used the Newton's method, whereas if the learning rate is high, the result same with the gradient descent. The Newton's method is good because it is so fast and accurate. With this algorithm, it is expected to fast change the leaning rate to 0. After several tests, the algorithm of LM will systematically decrease the learning rate. The for to correct or increase in learning speed will be carried out when a (temporary) step is needed to reduce the performance of the function.

3. Selection of transfer function

The role of multilayer networks or neurons has an activation function and a transfer function. Full-connected layer or multilayer networks usually use logsig (or log-sig transfer function) in the hidden layer, while using linear transfer function for the output layer. The logsig function produces an output between zero and one because the net input of the neuron changes from negative to positive conservation [6]. The supply sigmoid transfer function is mostly used in non-linear information trained with feedforward. The supply sigmoid transfer operates in the hidden layer and the linear transfer function in the output layer is described as [8].

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \text{ with affixation } f'(x) = [1 + f(x)][1 - f(x)] \quad (3)$$

$$f(x) = x, \text{ with affixation } f'(x) = 1$$

x is the data input

4. Material and methods

4.1 Study area and source data

The source of data in this research is quantitative data which is measured directly in the field. These data include water dePsh data in rivers which were measured from January 2, 2012 to December 31, 2014. Measurement of changes in water dePsh data was carried out using the Omega-CPM instrument which was monitored every 10 minutes. Meanwhile, flow information and sediment yield samples were taken throughout the season and rainy season. during this study, the amount of sediment yield samples and flow rates from 2012 to 2014 was 1095. downfall data was measured employing a tree tipping-bucket pluviometer and also the data are stored Meanwhile, flow rate data and sediment yield samples were taken during the dry season and rainy season. during this study, the number of sediment yield samples and flow rates from 2012 to 2014 was 1095. downfall data was measured using a tree tipping-bucket rain gauge and the data will be stored within the hobo Event information Logger. in the hobo Event information Logger.

The location of this analysis was applied within the Jenderam Basin that is found in Selangor. Astronomically, this Basin is located between $101^{\circ} 40' 00''$ to $101^{\circ} 50' 00''$ East great circle and $020^{\circ} 45' 00''$ to $020^{\circ} 50' 00''$ South Latitude. The Jenderam Basin measures 20.51 km^2 . Characteristics of soil texture in the Jenderam Basin are fine sandy soil (low to moderate value), the soil is definitely scoured

once it rains especially on plowed slopes. Morphologically, the Jenderam basin is elongated with elongation magnitude relation is 0.44. the height of hydrograph runoff is characterised by fast ups and downs. the amount of drain frequencies is 8.93, whereas the stream order is 183. The analysis space consists of a series of soils classified as isohyperthermic, paleudult type, kaolinitic, fine clay.

4.2 Normalization of data

Normalization of information is completed to reduce data errors. normalisation of data to create the luminous flux unit algorithmic program on the neural network additional economical for every step of the method on the target network and input file [6]. The goal is to normalize the info to confirm diminution of errors throughout network coaching and quick convergence. [9]. The formula utilized in scaling/normalizing the data is as follows [10]:

$$X_n = \left(\frac{X_i - X_{min}}{X_{max} - X_{min}} \right) \tag{4}$$

X_n : the nomalized value

X_i : the original value

X_{max} : the maximum original value data

X_{min} : the manimum original value data

The processes of normalization step is important to applied to each input vector and therefore the target vector. The input and target data are normalized before being used for coaching and testing by reprocessing information from level zero to one. In order for the data to be coterminous with the limits of activation operations used in the neural network, the computer must be normalized [11].

4.3 The selection of input data, combination of input layer, and parameter statistical analyses

This study uses selection of input data, combination of input layers, and performant parameter statistical analysis. The selection of input data and the combination of input layers are very important in the proper development of neural networks [12]. Broadly speaking, multilayer neural network modeling classifies data for learning, validation, and testing. The first set is the set for the gradient scheme and network weights and biases. The second subset is the validation set. Errors throughout the coaching process, may be monitored on the validation set. The take a look at set error isn't used during training however is employed to check completely different models [6]. This study uses 2 subsets of data, namely 67% (January 1, 2012 until to December 31, 2013) to selected for data training and 33% for model data testing (January 2, 2014 until to December 31, 2015). The applied for training and testing subsets include minimum (Xmin), most (Xmax), mean (Xmean), skewness (Skn), standard deviation (SD), and constant of variation (CV).

The performance evaluation criteria model uses for measures standard statistical value: the root mean square error (RMSE), mean absolute error (MAE), efficiency coefficient (CE), and coefficient of determination (R2) as follows:

Means absolute error

$$MAE = \frac{1}{n} \sum_{i=1}^n (SSQ_{pi} - SSQ_{oi}) \tag{5}$$

Root mean sruare error

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (SSQ_{pi} - SSQ_{oi})^2}{n}} \tag{6}$$

Coefficient of determination

$$R^2 = \left[\frac{\sum_{i=1}^n (SSQ_{oi} - \bar{SSQ}_o) (SSQ_{pi} - \bar{SSQ}_p)}{\sqrt{\left(\sum_{i=1}^n SSQ_{oi} - \bar{SSQ}_o\right)^2} \sqrt{\left(\sum_{i=1}^n SSQ_{pi} - \bar{SSQ}_p\right)^2}} \right]^2 \tag{7}$$

Coefficient of efficiency

$$CE = 1 - \frac{\sum_{i=1}^n (SSQ_{oi} - SSQ_{pi})^2}{\sum_{i=1}^n (SSQ_{oi} - \bar{SSQ}_o)^2} \tag{8}$$

Each of the higher than formulas uses SSQoi and SSQpi information in their calculations. SSQoi data is that the determined average price, SSQpi data is the foreseen average value. Meanwhile, (n) is the range of observations made. usually the calculation of RMSE, MAE and, MSE is zero, whereas Ce and R² are one [13]. If the observed and predicted values are the same, then the error value are often zero and also the constant of determination value can be one.

Table 1. Structure model data input layer variable for MLP

Data set	Data Input	Unit	Total data	Variables for input layer	Model	Target
Training	1. Water depth	m.day ⁻¹	01 January 2012	1. Ps, Hs, Qs, Ps-1, Hs-1, Qs-1	MLP	SSQ
	2. Sediment yield	kg.day ⁻¹	- 31 December	2. Ps, Hs, Qs, Ps-1, Hs-1, Qs-1,		
	3. Rainfall	mm.day ⁻¹	2013	Ps-2, Hs-2, Qs-2, Ps-3, Hs-3,		
	4. Water discharge	m ³ .day ⁻¹		Qs-3 3. Ps, Hs, Qs 4. Ps, Hs, Qs, Ps-1, Hs-1, Qs-1,		
Testing	1. Water depth	m.day ⁻¹	2 January 2014	1. Ps, Hs, Qs, Ps-1, Hs-1, Qs-1	MLP	SSQ
	2. Sediment yield	kg.day ⁻¹	-31 Desember	2. Ps, Hs, Qs, Ps-1, Hs-1, Qs-		
	3. intensity rainfall	mm.day ⁻¹	2015	1, Ps-2, Hs-2, Qs-2, Ps-3, Hs-		
	4. water discharge	m ³ .day ⁻¹		3, Qs-3 3. Ps, Hs, Qs 4. Ps, Hs, Qs, Ps-1, Hs-1, Qs-1,		
				Ps-2, Hs-2, Qs-2		

Where:

- Qs : sediment yield kg/day
- Ps : intensity of rainfall mm/day
- Hs : the average of the water depth m/day
- Qs-1: water discharge at one the previous day
- Qs-2: water discharge at two the previous day
- Qs-3: water discharge at three the previous day
- Ps-1: intensity rainfall at one previous day
- Ps-2: intensity rainfall at two previous day
- Ps-3: intensity rainfall at three previous day
- Hs-1: the water depth at one the previous day
- Hs-2: the water depth at two the previous day
- Hs-3: the water depth at three the previous day

Table 2. The performance of statistics value for intensity rainfall, water depth, water discharge and sediment yield data.

Data set	Type of data	Minimum	Mean	Maximum	Skewness	SD	CV
Training	Water depth (m.day ⁻¹)	0.010	0.13	0.60	2.66	0.06	0.44
	Sediment yield (kg.day ⁻¹)	4.40	190.93	3,550.38	6.46	276.85	1.45
	Intensity rainfall (mm.day ⁻¹)	0.00	7.43	93.90	2.85	14.56	1.96
	Water discharge (m ³ .day ⁻¹)	1,707	30,902	1,2189,923	13.83	70,005	0.44
Testing	Water depth (mday ⁻¹)	0.03	0.09	0.65	3.29	0.06	2.30
	Sediment yield (kg.day ⁻¹)	0.50	87.83	4465.34	14.58	253.35	2.90
	(mm.day ⁻¹)	0.00	5.19	141.10	5.42	12.73	0.60
	Water discharge (m ³ .day ⁻¹)	1,703	30,952	1,218,992	13.84	69,990	2.30

5. Result and discussion

5.1. Multilayer perceptron feedforward

The results of the multilayer perceptron (MLP) feedforward performance victimisation the Levenberg-Marquardt (LM) rule using daily knowledge may be seen in Table 3. The results of the comparison between sediment yield and also the discovered and foreseen rate of flow are then premeditated and might be seen in Figure 2. The comparison is predicated on structure data that has been inputted with coaching and testing records for 2 years and one year, respectively, using the LM algorithm. The quantity of nodes (neurons) within the input layer is six (Ps, Hs, Qs, Ps-1, Hs-1, Qs-1), nine (Ps, Hs, Qs, Ps-1, Hs-1, Qs-1, Ps-2, Hs-2, Qs-2), three (Ps, Hs, Qs), nine (Ps, Hs, Qs, Ps-1, Hs-1, Qs-1, Ps-2, Hs-2, Qs-2), and twelve (Ps, Hs, Qs, Ps-1, Hs-1, Qs-1, Ps-2, Hs-2, Qs-2, Ps-3, Hs-3, Qs-3) consecutive. Meanwhile, the amount of nerve cells within the hidden layer is decided by the trial and error method. there's just one output neuron as a result of there is only one target output that is sediment yield from the artificial neural network model.

Table 3. The statistical value using algorithm LM

No	ANN model inputs	Lavenberg-Marquard (LM)								
		Structure	Training				Testing			
			RMSE	MAE	CE	R ²	RMSE	MAE	CE	R ²
1	Ps, Hs, Qs, Ps-1, Hs-1, Qs-1	6:10:1	3.40	0.60	0.99	0.99	18.96	13.90	0.99	0.99
2	Ps, Hs, Qs, Ps-1, Hs-1, Qs-1, Ps-2, Hs-2, Qs-2, Ps-3, Hs-3, Qs-3	12:12:1	3.36	0.70	0.99	0.99	25.63	24.72	0.98	0.99
3	Ps, Hs, Qs	3:7:1	3.40	0.57	0.99	0.99	21.44	15.99	0.99	0.99
4	Ps, Hs, Qs, Ps-1, Hs-1, Qs-1, Ps-2, Hs-2, Qs-2	9:10:1	3.54	0.86	0.99	0.99	25.94	18.66	0.97	0.99

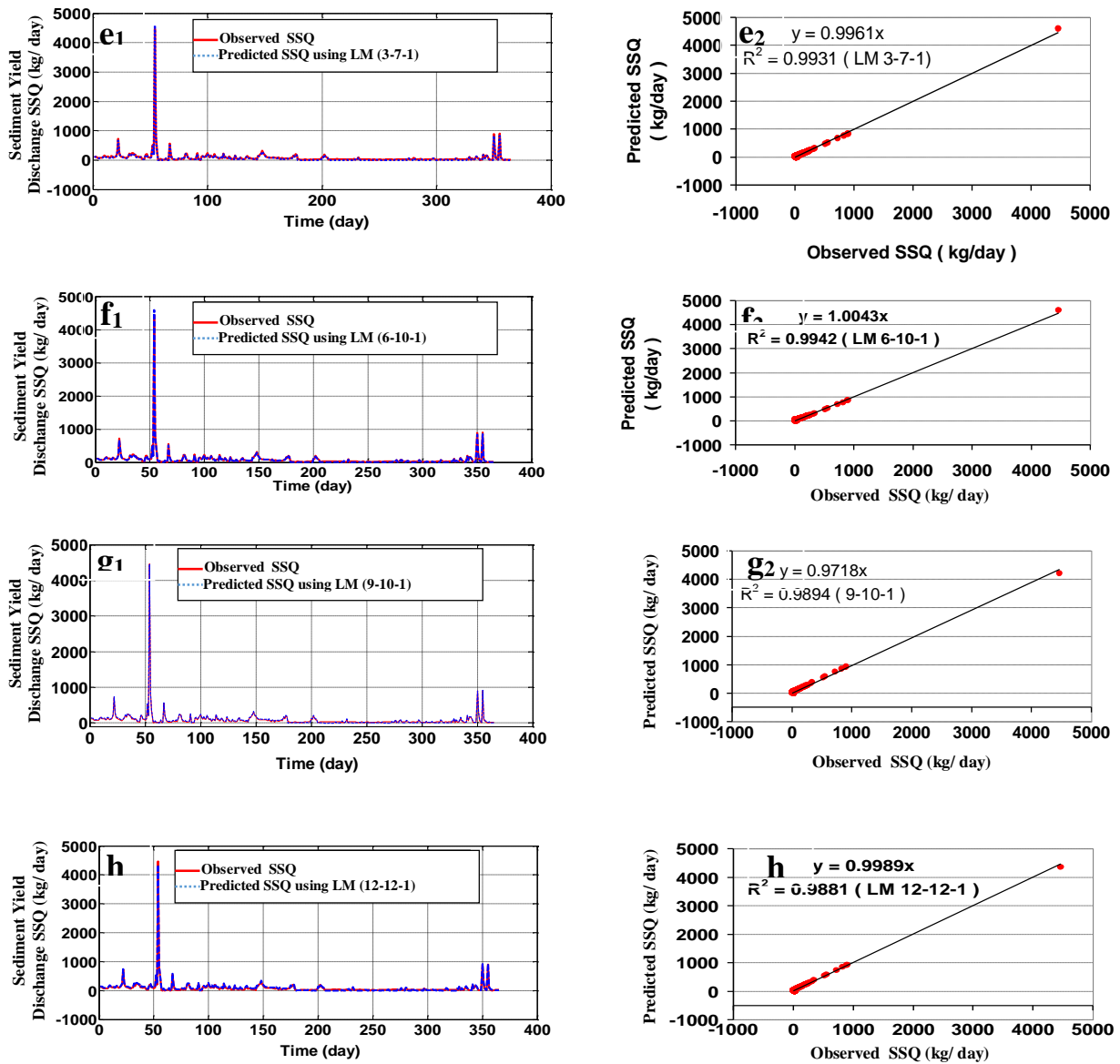


Figure 2. The data observed and predicted sediment yield using LM algorithm

The results of LM performance to predict sediment yields based on the number of neurons in the hidden layer, input layer, and output layers (Table 3). The best value performance statistics for the CE, RMSE, R2, and MAE are in Structure data set 6-10-1. The structure consists of 6 neurons in the input layer, 10 neurons in the hidden layer, and 1 neuron in the output layer during the training and testing process. The lowest performance values in the MAE and RMSE testing processes were 13.91 and 18.95, while the highest R2 and CE were 0.99 respectively when using the LM model structure data (3-7-1, 9-10-1, and 12-12-24-1). The test results were obtained with the model data structure of LM 6-10-1 where the observed sediment results were almost the same or had low differences with the entire range of test data. The MAE on data structure LM 3-7-1 and LM 6-10-1 is negative value, where the number of predictions is value smaller than the number of observations. While the MAE on structure data LM 9-10-1 and 12-12-1 is positive, meaning that the total prediction is higher than the observed one. Thus,

these results very the accuracy and reliability of the Lavenberg-Marquardt (LM) algorithm which is recommended for predicting sediment yields in the Jenderam Basin.

6. Conclusions

The results of this study indicate the accuracy and dependableness of the Levenberg-Marquardt performance accustomed predict the sediment yield within the Jenderam basins. The test results were obtained with the LM 6-10-1 model where the observed sediment yield was almost the same or had a low difference with the entire range of test data. MAE on LM structure data 3-7-1 and LM structure data 6-10-1 has a negative value where the number of predictions is smaller than the number of observations. While the MAE on LM structure data 9-10-1 and 12-12-1 is positive, meaning that the total prediction is higher than the observed. Thus, these results show the accuracy the Lavenberg-Marquardt (LM) algorithm rules which are usually recommended for predicting sediment yield discharge in the Jenderam Basin. This shows that the luminious flux unit is appropriate for forecasting use the modeling non-linear response behavior of advanced sediment yields to intensity of rainfall, water depth of river, and water discharge river.

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