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DAILY SUSPENDED SEDIMENT LOAD ESTIMATION USING MULTIVARIATE HYDROLOGICAL DATA

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ABSTRACT: Sediment rating curves (SRCs) have been applied to estimate daily-suspended sediment load (Q_s) worldwide because of its simplicity. In this method, current Q_s was estimated by a power function of a sole variable, a current daily water discharge at the same measurement station. However, many studies found that its accuracy is not very high. In this study, we developed a new approach to estimate Q_s using multivariate hydrological data at the same station and other upstream stations. Using correlation analysis, the additional variables were selected such as upstream water discharges, rainfall at the current or antecedent day. Therefore, spatial and temporal variability was simply considered in our new approach. Then, five methods, a multiple linear regression (MLR), a multiple nonlinear regression (SLR, QLR, and PLR) and an artificial neural network model (ANNs), were applied. The comparison between the SRC method and our new five methods were done using the Q_s data at three measurement stations in three basins of Thailand. The results showed that our new approach for all three-study areas (PLR, and ANNs) gave better results with the observed data than the traditional SRC method except MLR, SLR, and QLR. ANNs estimated Q_s with the highest accuracy at P1 (EI = 0.96) while PLR gave results similar ANNs at W4A. For Y14 the result of QLR (EI=0.94) better than ANNs Thus, the more complexity of the model structure and the consideration of the spatial and temporal variability can provide a higher accurate estimation of Q_s.

Keywords: Suspended sediment load, Artificial neural networks (ANNs), Sediment Rating Curve, Multiple Linear Regressions, and Multiple Non-Linear Regressions

1. INTRODUCTION

Sediment load data is useful for the design of reservoir storage. Before initiating any water resource projects, we must know water discharge and sediment load to estimate dead storage, useful storage, and a surcharge of a reservoir. However, it is difficult to measure sediment load daily. Thus, it is common to calculate sediment load using a relationship with water discharge or other hydrological data. Since sediment load is critical to indicate the lifespan of a reservoir, the underestimation of sediment load results in an insufficient volume of dead storage and, consequently, a rapid decrease of reservoir capacity while the overestimation will lead to higher construction and management costs. [1] Therefore, it is important to determine suspended sediment load accurately.

The measurement of suspended sediment load consumes more time and costs higher than other types of hydrological data. Thus, in Thailand, the suspended sediment load at one station is measured approximately 8-20 times per year. These data are used to estimate two parameters in the traditional sediment rating curve (SRC) equation in the form of the power function of water discharge at the same station. Although the SRC is very simple and depends on a sole variable, its accuracy is not high. Campbell and Bauder [2] studied 60 months of record from the Red River, Texas, USA, was found between rating curve derived load estimates and the measured values for seven sub-periods. The errors for the individual periods varied between -20 and +14.8% while the error for the total period was only +1.5 percent.

Many researchers have proposed other methods to estimate suspended sediment load instead of SRC. Jain [3] showed that the artificial neural networks (ANNs) method provided the results much better than SRC at Mississippi River, USA. Kumar et al. [4] studied suspended sediment load at the Kopili River basin, India. They used a machine learning approach to construct six models and found that the least square support vector regression (LS-SVR) and ANNs provided the best satisfactory. In their model, rainfall was included and gave better accuracy. Melesse et al. [5] predicted the suspended sediment load of three major rivers (Mississippi, Missouri, and the Rio Grande) in the USA using four models. From their results, ANNs again provided the highest accuracy for both daily and weekly simulations. In previous studies, water discharge and sediment load at the same station and rainfall were used as independent variables to build models to estimate suspended sediment load. However, there were no studies using hydrological data of upstream measurement stations to estimate suspended sediment load. In this study, we investigated the significance of upstream water discharge in estimating sediment load 3 study areas in northern Thailand. Five mathematical rainfall-runoff-sediment models were tested and their performances were discussed and compared with the traditional SRC.

2. STUDY AREA

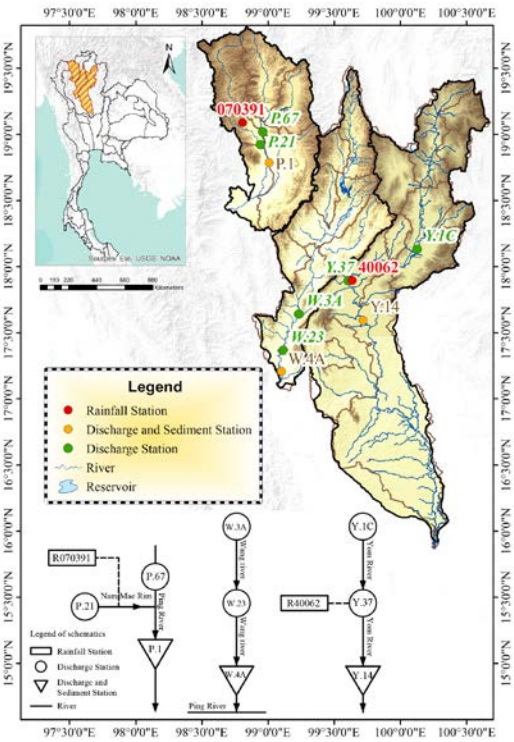

Fig. 1 Map and schematic of the study areas

Figure 1 shows a map of the whole study area. The total first area is about 6,350 km^2 which includes P1, P21, P67, and R070391. P1 is a discharge and suspended sediment station (Estimation station) located at 18^o 47' 09" N and 99^o 00' 29" E flow into the Ping Basin in Thailand. P21 and P67 are the discharge station located at 19^o 01' 11" N, 98^o 57' 42" E and 18^o 55' 29" N, 98^o 56' 34" E respectively. R070391 is a rainfall station located at 19^o 05' 09" N and 98^o 45 29" E.

The second area is about 10,493 km^2 which includes W4A, W23, and W3A. W4A is a discharge and suspended sediment station (Estimation station) located at 17^o 12' 22" N and 99^o 06' 08" E flow into the Ping River below. W23 and W3A are the discharge station located at 17^o 22' 01" N, 99^o 06' 55" E and 17^o 12' 22" N, 99^o 06' 08" E respectively.

The third area is about 12,100 km^2 which includes Y14, Y37, Y1C, and R40062. Y14 is a discharge and suspended sediment station (Estimation station) located at 17^o 35' 42" N and 99^o 43' 08" E flow into the Yom River in Thailand. Y37 and Y1C are the discharge station located at 17^o 53' 41" N, 99^o 36' 27" E and 18^o 07' 59" N, 100^o 07' 39" E respectively. R040062 is a rainfall station located at 17^o 53' 56" N and 99^o 36 24" E.

3. METHODOLOGY

3.1 Sediment Rating Curve

The maximum sediment concentration may not coincide with the flood peak and may either precede or lag behind the maximum water discharge. [6]

The Sediment rating curve is a non-linear relationship between the water discharge and suspended sediment load. [7] SRC is expressed as:

$$Q_s = aQ_w^b \tag{1}$$

where a and b are coefficients obtained by regression. Q_s is suspended sediment load (Tons/day) and Q_w is the discharge (m^3/s).

3.2 Input data selection

Model input for the estimation for the suspended sediment load at the 1st area are P1, P21, P67, and R070391, there are 371 data sets in the period 2000-2017. The 2nd area comprises W4A, W23, and W3A, there are 245 data sets in the period 2001-2017. The 3rd area consists of Y14, Y37, Y1C, and R40062, there are 302 data sets in the period 2000-2016.

The cross-correlation between the various input variables all three study areas are presented in Tables 1, 2 and 3. It indicated the output variable has a strong correlation with input variables as shown in equation (2), (3) and (4) respectively.

Table 1 Correlation matrix of the 1st area (P1)

	$Q_{P1,t}$	$Q_{P21,t}$	$Q_{P67,t}$	R_{t-2}	$S_{P1,t}$
$Q_{P1,t}$	1.00				
$Q_{P21,t}$	0.85	1.00			
$Q_{P67,t}$	0.97	0.80	1.00		
R_{t-2}	0.50	0.49	0.46	1.00	
$S_{P1,t}$	0.85	0.65	0.90	0.44	1.00

Note: $R_{t-2} = R_{070391,t-2}$

Table 2 Correlation matrix of the 2nd area (W4A)

	$Q_{W4A,t}$	$Q_{W3A,t-1}$	$Q_{W23,t}$	$S_{W4A,t}$
$Q_{W4A,t}$	1.00			
$Q_{W3A,t-1}$	0.90	1.00		
$Q_{W23,t}$	0.94	0.97	1.00	
$S_{W4A,t}$	0.80	0.84	0.80	1.00

Table 3 Correlation matrix of the 3rd area (Y14)

	$Q_{Y14,t}$	$Q_{Y37,t}$	$Q_{Y1C,t-1}$	R_{t-2}	$S_{Y14,t}$
$Q_{Y14,t}$	1.00				
$Q_{Y37,t}$	0.97	1.00			
$Q_{Y1C,t-1}$	0.96	0.98	1.00		

R_{t-2}	0.48	0.46	0.42	1.00	
$S_{Y14,t}$	0.85	0.83	0.86	0.50	1.00

Note: $R_{t-2} = R_{40062,t-2}$

$$S_{P1,t} = f(Q_{P1,t}, Q_{P21,t}, Q_{P67,t}, R_{t-2}) \quad (2)$$

$$S_{W4A,t} = f(Q_{W4A,t}, Q_{W3A,t-1}, Q_{W23,t}) \quad (3)$$

$$S_{Y14,t} = f(Q_{Y14,t}, Q_{Y37,t}, Q_{Y1C,t-1}, R_{t-2}) \quad (4)$$

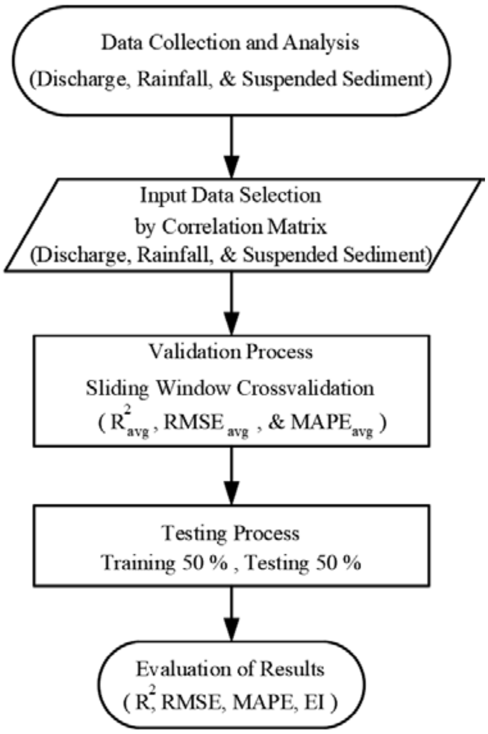

Fig. 2 Workflow for the whole process of investigation

3.3 Model Training and Testing

It is common for several studies to use 70% of the data for training and 30% for testing and validation of the model (The 70-30) [8]. Due to the limitations of the data collection, the suspended sediment load is observed at least 6 times a month on a random basis. This study focuses on developing models to estimate high value suspended sediment load to ensure that it can be used to estimate accurately.

High values of suspended sediment load do not occur often and do not occur throughout the whole data set. If we selected the 70-30, those high values would be missing for the test data set. Hence, we decided to use 50% of the date for training and 50% for testing.

3.4 Sliding Window Validation

This study has been validated for the reliability of data for all of the models by using window sliding validation. A model is trained using a training window and applied to the testing window to compute the performance for the first run. For the next run, the training window is slide to a new set of training records and the process is repeated until all the training windows are used. [9] In this study divided whole data were 2 set data (Initial 50% and Second window 50%) then sliding window 1 iteration per data set. This process repeated until the number of iteration equal to the total amount of whole data. The process of sliding window is shown in Fig. 3

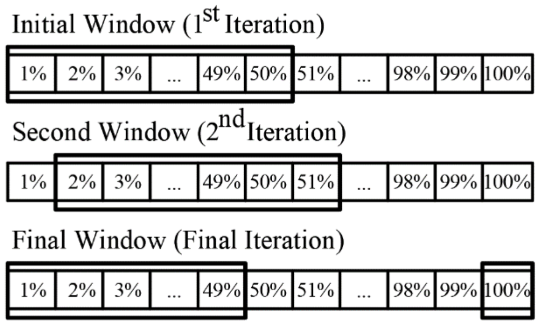

Fig. 3 Sliding window validation process

3.5 Performance Evaluation of Various Models

The data sets were divided into 2 groups, one for training and the other testing. Four indices are used to determine model performance which is the coefficient of determination (R^2), the root mean squares of errors (RMSE), the mean absolute percentage error (MAPE), Nash–Sutcliffe coefficient (EI).

3.6 Multiple Linear Regression (MLR)

Multiple linear regressions (MLR) analysis was performed on the same data set to estimate sediment load and compare the results with output from the SRC model. The MLR equation is defined as:

$$\boldsymbol{Y = a + bX_1 + cX_2 + dX_3 + eX_4} \quad (5)$$

where a, b, c, d and e are the regression coefficients.

3.7 Multiple Non-linear Regression (MNLR)

Various forms of non-linear equations are used for regression to compare the ability to estimate the suspended sediment load. This study uses three forms of multiple non-linear equations i.e., Squared linear regression (SLR), Quadratic linear regression (QLR), and Power linear regression (PLR).

Table 4 Results of Sliding window validation 50-50 of MLR, SLR, QLR, PLR, and ANNs 371 Days

Input Variables	Model	R^2_{avg}	RMSE $_{avg}$	MAPE $_{avg}$
$S_{P1,t} = f(Q_{P1,t}, Q_{P21,t}, Q_{P67,t}, R_{t-2})$	MLR	0.81	3003	165
	SLR	0.94	1960	217
	QLR	0.89	2518	189
	PLR	0.91	3958	80
	ANNs	0.87	1765	402
$S_{P1,t} = f(Q_{P1,t}, Q_{P21,t}, Q_{P67,t})$	MLR	0.78	3227	1427
	SLR	0.94	2013	204
	QLR	0.90	2624	207
	PLR	0.89	4280	80
	ANNs	0.88	1657	438

Table 5 Results of SRC, MLR, SLR, QLR, PLR, and ANNs during testing period 185 Days (50% of all Data)

Input Variables	Model	R^2	RMSE	MAPE	EI
$S_{P1,t} = f(Q_{P1,t})$	SRC	0.89	1980	150	0.71
$S_{P1,t} = f(Q_{P1,t}, Q_{P21,t}, Q_{P67,t})$	MLR	0.70	2493	3107	0.54
	SLR	0.96	800	588	0.95
	QLR	0.95	866	192	0.94
	PLR	0.91	1553	138	0.82
	ANNs	0.96	769	207	0.96

Table 6 Results of Sliding window validation 50-50 of MLR, SLR, QLR, PLR, and ANNs 245 Days

Input Variables	Model	R^2_{avg}	RMSE $_{avg}$	MAPE $_{avg}$
$S_{W4A,t} = f(Q_{W4A,t}, Q_{W3A,t-1}, Q_{W23,t})$	MLR	0.73	3640	4259
	SLR	0.76	3063	2427
	QLR	0.76	3430	2454
	PLR	0.75	3346	130
	ANNs	0.84	1969	3200

Table 7 Results of SRC, MLR, SLR, QLR, PLR, and ANNs during testing period 122 Days (50% of all Data)

Input Variables	Model	R^2	RMSE	MAPE	EI
$S_{W4A,t} = f(Q_{W4A,t})$	SRC	0.76	2641	205	0.73
$S_{W4A,t} = f(Q_{W4A,t}, Q_{W3A,t-1}, Q_{W23,t})$	MLR	0.69	3751	2840	0.46
	SLR	0.73	4589	1389	0.19
	QLR	0.75	4250	501	0.30
	PLR	0.84	2392	151	0.78
	ANNs	0.81	2382	326	0.78

3.7.1 Squared linear regression (SLR)

The SLR equation can be written as

$$Y = a + bX_1^2 + cX_2^2 + dX_3^2 + eX_4^2 \quad (6)$$

where a, b, c, d and e are the regression coefficients.

3.7.2 Quadratic linear regression (QLR)

The QLR equation can be written as

$$Y = a_1 + a_2X_1 + a_3X_2 + a_4X_3 + b_1X_1^2 + b_2X_2^2 + b_3X_3^2 + b_4X_4^2 \quad (7)$$

Table 8 Results of Sliding window validation 50-50 of MLR, SLR, QLR, PLR, and ANNs 371 Days

Input Variables	Model	R^2 avg	RMSE avg	MAPE avg
$S_{Y14,t} = f(Q_{Y14,t}, Q_{Y37,t}, Q_{Y1C,t-1}, R_{t-2})$	MLR	0.75	7,987	18,552
	SLR	0.85	7,770	3,894
	QLR	0.83	9,178	4,450
	PLR	0.87	5,372	117
	ANNs	0.85	5,190	9,349
$S_{Y14,t} = f(Q_{Y14,t}, Q_{Y37,t}, Q_{Y1C,t-1})$	MLR	0.75	8,200	17,779
	SLR	0.83	7,870	4,162
	QLR	0.82	9,229	5,061
	PLR	0.86	6,228	119
	ANNs	0.89	4,772	7,782

Table 9 Results of SRC, MLR, SLR, QLR, PLR, and ANNs during testing period 185 Days (50% of all Data)

Input Variables	Model	R^2	RMSE	MAPE	EI
$S_{Y14,t} = f(Q_{Y14,t})$	SRC	0.94	5962	111	0.66
$S_{Y14,t} = f(Q_{Y14,t}, Q_{Y37,t}, Q_{Y1C,t-1})$	MLR	0.75	8730	16,336	0.26
	SLR	0.98	5927	8,694	0.66
	QLR	0.96	10073	13,013	0.02
	PLR	0.96	2411	205	0.94
	ANNs	0.97	4451	2,899	0.81

where $a_1, a_2, a_3, a_4, b_1, b_2, b_3$ and b_4 are the regression coefficients.

3.7.3 Power linear regression (PLR)

The PLR equation can be written as

$$Y = aX_1^{\,b}X_2^{\,c}X_3^{\,d}X_4^{e} \tag{8}$$

where a, b, c, d and e are the regression coefficients.

3.8 Artificial Neural Networks (ANNs) Overview

The Artificial neural networks consist of three layers of the node: the Input layer, the hidden layer, and the output layer. The data from the input layer was calculated and passed through the transform function from the hidden layer to the output layer. The principal learning process of the model is changing the weight value of each connection to adjust the results of the model to be as close to the true value as possible by the back-propagation method.[10]

The theory of ANNs has been described in several papers; this study is described here as briefly. The numbers of the hidden layer were found using the trial and error method. The subsampling of all the data for training and validation was conducted using the function 'divide block' of MATLAB.

4. RESULT AND DISCUSSIONS

From this study, we found that the suspended sediment load varies from a few tons per day to approximately 40,000 tons per day. RMSE might not be a good indicator of model accuracy therefore, we have 2 consider. MAPE has the main indicator of model accuracy.

We examined the importance of upstream water discharge in estimating sediment load three study areas in northern Thailand which include P1, W4A, and Y14. Five mathematical rainfall-runoff-sediment models were tested and their performances were discussed and compared with the traditional SRC. It was found that the MLR, SLR, and the QLR were not to estimate the suspended sediment load for three study areas. Thus, we only compared the traditional method (SRC) with the appropriate models (PLR and ANNs) of this study as shown in Fig. 4, Fig. 5, and Fig. 6. The result of three study areas below in detail:

4.1 Ping Basin (P1 Station)

The results of the sliding window validation were shown in Table 4. The SLR model performed better than other models (R^2 avg = 0.94, RMSE avg = 1960, MAPE avg = 217) but other models provided satisfactory model performance as well.

The rainfall data has been removed from the testing data because it provided correlation with suspended sediment lowest (0.44) as shown in Table 1. Also, we have compared estimation performance on all models with and without the rainfall data and the estimation performance is indifference. Therefore, the input data remained only the discharge data ($Q_{P1,t}$, $Q_{P21,t}$, $Q_{P67,t}$). All performance indices, except for the MAPE, are indifferent whether the model contains rainfall data as a predictor variable or not (as shown in table 2). In addition, the process of the sliding window validation verified that the selected data in this study can be used to further divide the training period and the testing period.

The results of SRC, MLR, SLR, QLR, PLR, and ANNs during the testing period are shown in Table 5. The result from SRC has derived from the relationship between the discharge (m^3/s) and suspended sediment load (Tons/day) at station P1 only by using the data in 2000-2005, 2007-2010 (186 data sets) for the training period, the equation was $Q_s = 2.0259Q_w^{1.4856}$ to be used in the testing period. Although the SRC provides good results (R^2 = 0.89, RMSE = 1980, MAPE = 150, EI = 0.71), it can be seen that SRC was unable to estimate the high sediment at all peaks suspended sediment load and also it underestimates low values suspended sediment load.

The MLR provided the regression coefficients a_0 (constant), a_1, a_2, a_3, and a_4 during the training period were found to be -1971.25, -49.29, -75.74 and 138.72, respectively. It was found that the MLR model performs poorly on the estimation of the suspended sediment load. The performance indices of the MLR were R^2 = 0.70, RMSE = 2493, MAPE = 3107, EI = 0.54 respectively.

The performance of the SLR model was also evaluated and presented in Table 5. It provided a highly of EI = 0.95 because it can capture almost every peak of suspended sediment load but it provided too high estimation for the low suspended sediments Moreover, it was shown that the SLR is unable to estimate the low suspended sediments. The estimates for the low sediments are found to be around 400 tons/day. It was shown that the SLR cannot estimate for the low suspended sediments.

The QLR model was found to be relatively accurate. During the testing period, the values of R^2, RMSE, MAPE, and EI were found to be 0.95, 866, 192 and 0.94, respectively.

The PLR model provided a similar level of accuracy to the SRC. In a comparison of both models, the SRC generated suspended sediment from only one variable (discharge at P1) but the PLR model consists of 3 variables (discharge at P1, P21, and P67). The values of R^2, RMSE, MAPE, and EI of the PLR model were found 0.91, 1553,138, and 0.82 respectively.

The ANNs model presented in Fig. 4(c). It can be observed that the model converges well and tends to capture almost all the peaks. The values of RMSE, MAPE of the ANNs model were found 769 and 207 respectively, compared with the RMSE, MAPE of the QLR model (866 and 193) it was found that the ANNs model provides an accurate prediction on the high value of suspended sediment load. The errors are less than those obtained from the QLR.

4.2 Wang Basin (W4A Station)

The performance indices of the models by using window sliding validation are shown in Table 6. The ANNs model provides the best performance than other models (R^2_{avg} = 0.84, RMSE $_{avg}$ = 1969, MAPE $_{avg}$ = 3,200) but other models provided similar performance as well.

The results of SRC, MLR, SLR, QLR, PLR, and ANNs during the testing period are shown in Table 7. The result from SRC has determined from the relationship between the discharge (m^3/s) and suspended sediment load (Tons/day) at station W4A only by using the data in 2001-2014 (123 data sets) for the training period, the equation was $Q_s = 1.3628Q_w^{1.5388}$ to be used in the testing period. The SRC provides R^2 = 0.89, RMSE = 1980, MAPE = 150, EI = 0.71. From Fig. 5(a), it can be seen that SRC was unable to estimate the high sediment every peak suspended sediment load and it underestimates low values suspended sediment load. It gave a similar result to the P1 station.

The MLR gave the regression coefficients a_0 (constant), a_1, a_2, and a_3 during the training period were found to be -908.80, 52.67, 94.73, and -100.87 respectively. It was found that the MLR model unable to estimate the suspended sediment load. (R^2 = 0.76, RMSE = 2641, MAPE = 205, EI = 0.73).

The performance of the SLR and the QLR model was shown in Table 7. It provided the lowest of EI = 0.19 and 0.30 respectively. Both models gave not much difference.

The PLR model and the ANNs models provide an accurate estimation of the high value of suspended sediment load as shown in Fig. 4(b) and Fig. 4(c). Both tend to capture almost all the peaks of suspended sediment load but the PLR provides the performance indices better than ANNs.

4.3 Yom Basin (Y14 Station)

The results of the sliding window validation were shown in Table 8. The PLR model performed better than other models (R^2_{avg} = 0.87, RMSE $_{avg}$ = 5,372 MAPE $_{avg}$ = 117).

We have tried to remove the rain from the model similar to P1 station because it provided a correlation with suspended sediment lowest (0.50)

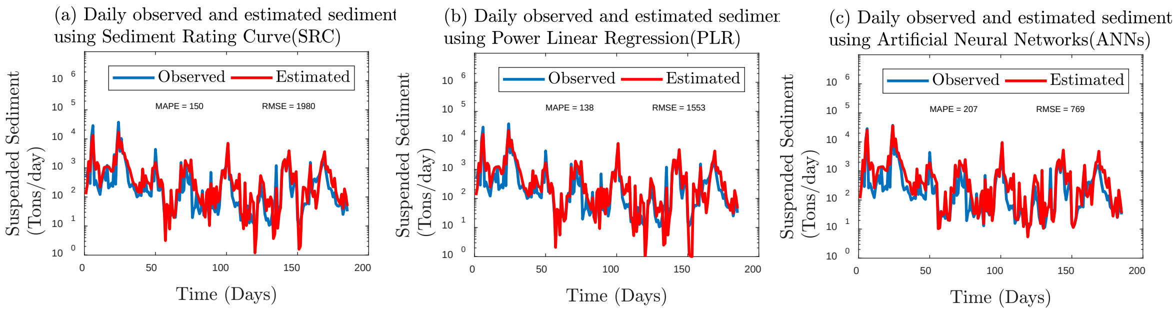

Fig. 4 Estimation results of various model of the 1st area (a) The SRC, (b) The power (PLR), (c) The ANNs.

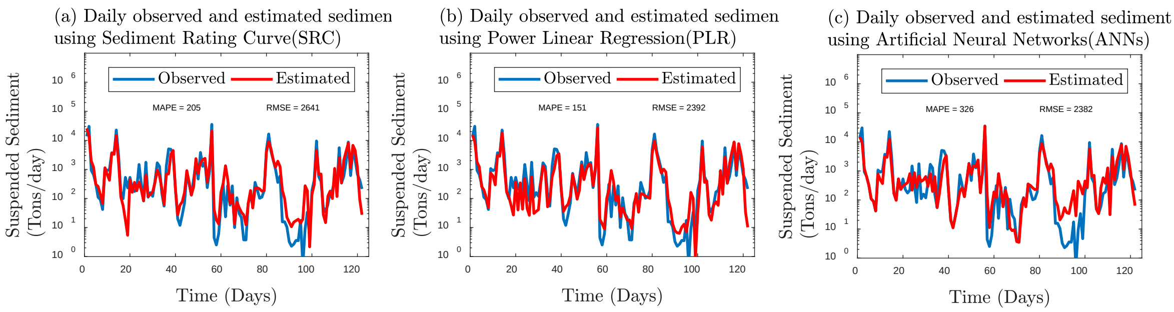

Fig. 5 Estimation results of various model of the 2nd area (a) The SRC, (b) The power (PLR), (c) The ANNs.

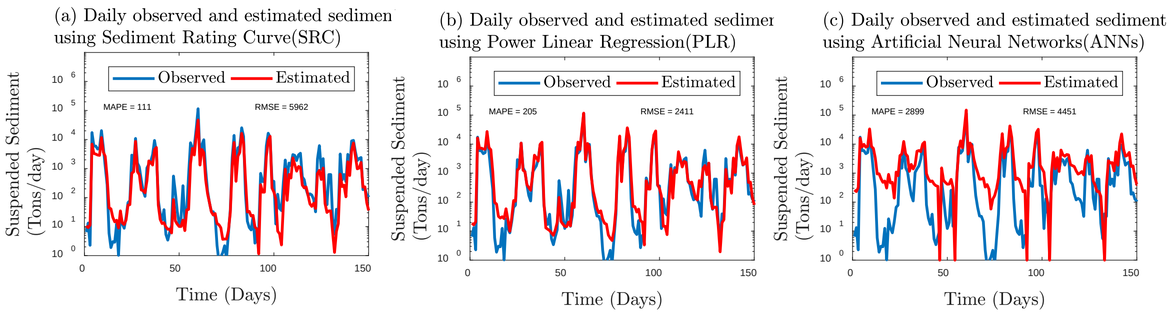

Fig. 6 Estimation results of various model of the 3rd area (a) The SRC, (b) The power (PLR), (c) The ANNs.

as shown in Table 3. It was found that the performance indices of the PLR indifference.

The results of SRC, MLR, SLR, QLR, PLR, and ANNs during the testing period are shown in Table 9. The result from SRC has received from the relationship between the discharge (m3/s) and suspended sediment load (Tons/day) at station P1 only by using the data in 2001-2006 (151 data sets) for the training period, the equation was Qs = 0.1724Qw1.7298 to be used in the testing period. From Fig. 6(a), it can be seen that SRC was unable to estimate the high sediment every peak suspended sediment load and it underestimates low values suspended sediment load. It gave a similar result to the P1 station and Y14.

The MLR provided the regression coefficients a_0 (constant), a_1, a_2, and a_3 during the training period were found to be -2913.13, 99.28, 102.89, and 97.76 respectively. It gave MAPE = 16,336 higher than other models.

The performance of the SLR model was shown in Table 9. It provided R^2 = 0.98, RMSE = 5927, MAPE = 8694, EI = 0.66 respectively.

The QLR model gave the performance indices worse than the others model (EI = 0.02).

The PLR model and the ANNs models provide an accurate estimation of the high value of suspended sediment load as shown in Fig. 6(b) and Fig. 6(c). Both tend to capture almost all the peaks of suspended sediment load but the PLR provides the error less than ANNs.

5. CONCLUSIONS

According to our investigations, we firstly found that rain data has very little impact on the estimation of the suspended sediments. Therefore, we decided to take the rain data out for the testing process. From the testing results, The ANNs model, the SLR model, the QLR model, and the PLR model provided better estimation results than using sediment rating curves (SRC; the traditional method), given the input data from nearby stations together.

However, it was found that the MLR model is poorly model for this estimation as most of the estimates are negative approximately 80% for three study areas. The SLR model estimates well on high values of suspended sediment but provides too high estimation for the low suspended sediments. Although the SLR model can estimate suspended sediment as accurate as of the ANNs, it has the highest errors in the low suspended sediment compared to other models except for W4A.

The QLR model provides good performance indices only for P1 station.

The PLR model and the ANNs models provide an accurate estimation of the high value of the suspended sediment load model accurately for three study areas and also it can estimate low values suspended sediment.

The results of this study show that mathematical models such as Multi-linear regression, Multi non-linear regression, and ANNs can be used on multivariate Hydrological data to estimate the suspended sediment load.

6. ACKNOWLEDGMENTS

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7. REFERENCES

[1] Alp, M. and Cigizoglu, H.K., Suspended sediment load simulation by two artificial neural network methods using hydrometeorological data. Environmental Modelling & Software, 22(1), 2007, pp.2-13.

[2] Campbell, F.B. and Bauder, H.A., A rating‐curve method for determining silt‐discharge of streams. Eos, Transactions American Geophysical Union, 21(2), 1940, pp.603-607.

[3] Jain, S.K., Development of integrated sediment rating curves using ANNs. Journal of hydraulic engineering, 127(1), 2001, pp.30-37.

[4] Kumar, D., Pandey, A., Sharma, N. and Flügel, W.A., Daily suspended sediment simulation using machine learning approach. Catena, 138, 2016, pp.77-90.

[5] Melesse, A.M., Ahmad, S., McClain, M.E., Wang, X. and Lim, Y.H., Suspended sediment load prediction of river systems: An artificial neural network approach. Agricultural Water Management, 98(5), 2011, pp.855-866.

[6] Walling, D.E., Limitations of the rating curve technique for estimating suspended sediment loads, with particular reference to British rivers. In Erosion and solid matter transport in inland waters, IAHS Publication, 122, 1977, pp. 34-48.

[7] Malik, A., Kumar, A. and Piri, J., Daily suspended sediment concentration simulation using hydrological data of Pranhita River Basin, India. Computers and Electronics in Agriculture, 138, 2017, pp.20-28.

[8] Shahin, M.A., Maier, H.R. and Jaksa, M.B., Data division for developing neural networks applied to geotechnical engineering. Journal of Computing in Civil Engineering, 18(2), 2004, pp.105-114.

[9] Kotu, V. and Deshpande, B., Data Science: Concepts and Practice, 2nd ed., Morgan Kaufmann, 2019, pp 439-443.

[10] Riad, S., Mania, J., Bouchaou, L. and Najjar, Y., Rainfall-runoff model usingan artificial neural network approach. Mathematical and Computer Modelling, 40(7-8), 2004, pp.839-846.