Multiple Linear Regression Model for Total Bed Material Load Prediction

S. K. Sinnakaudan; A. Ab Ghani; M. S. S. Ahmad; and N. A. Zakaria

Abstract: A new total bed material load equation that is applicable for rivers in Malaysia was developed using multiple linear regression analyses. A total of 346 hydraulic and sediment data were collected from nine natural and channelized rivers having diverse catchment characteristics in Malaysia. The governing parameters were carefully selected based on literature survey and field experiments, examined and grouped into five categories namely mobility, transport, sediment, shape, and flow resistance parameters. The most influential parameters from each group were selected by using all possible regression model method. The suitable model selection criteria namely the R-square, adjusted R-square, mean square error, and Mallow’s Cp statistics were employed. The accuracy of the derived model is determined using the discrepancy ratio, which is a ratio of the calculated values to the measured values. The best performing models that give the highest percentage of prediction from the validation data were chosen. In general, the newly derived model is best suited for rivers with uniform sediment size distribution with a $d_{50}$ value within the range of 0.37–4.0 mm and performs better than the commonly used Graf, Yang, and Ackers–White total bed material load equations.


CE Database subject headings: Sediment transport; Rivers; Regression models; Sediment load; Predictions; Bed materials.

Introduction

Reliable and quantitative estimates of the bed aggradation or degradation are very important in river engineering and water management projects as well as accurately predicting the water surface elevations during floods in estimating flood related damage. A number of sediment transport studies have been conducted in channels and flumes to develop analytical solutions for simplifying the governing equations describing complex phenomenon of the aggradation and degradation processes (Ab. Ghani 1993; Karim 1998; Molinas and Wu 2001; Sinnakaudan 2003). Researchers have separately treated the suspended load and the bed load calculation. However recent literature shows that total sediment load (or bed material load) equations are much preferred and researchers are now moving toward employing more complex analytical methods such as the artificial neural network (Nagy et al. 2002).

Good appraisals of available total sediment load equations and their performance were given by White et al. (1975), Brownlie (1981), Yang and Molinas (1982), Shen and Hung (1983), Raphelt (1990), Nakata (1990), Woo et al. (1993), and Nagy et al. (2002). Some of the available total bed material load equations are developed by Graf (1971), Ackers and White (1973), Van Rijn (1984a, b, c), and Karim (1998). The existing equations are mostly developed based on flume data in western countries including America and Western Europe. However not all of these equations are widely used or evaluated in other parts of the world. Several equations such as Ackers–White (1973) have been incorporated into current loose boundary models such as HEC-6 (USACE 1993) and the Graf (1971) equation is available in Fluvial-12 (Chang 1993) to simulate the sediment transporting capability of rivers.

Since the 1990s, few attempts have been made to evaluate the available equations for Malaysian conditions and are mostly cited in Ariffin et al. (2002) and Sinnakaudan et al. (2003). The Malaysian river data, against which these equations were checked, consists of field experiments in natural and channelized watercourses that were recently compiled by the Department of Irrigation and Drainage (DID) Malaysia (DID 2003). However, most of the developed equations rely heavily on flume data as well as river data (Brownlie 1981), which are not native to this region and have significant differences in hydraulic and sediment characteristics. The uncertainties of the usage of the existing equation for Malaysian river conditions are further proven by analysis of the discrepancy ratio, which is a ratio between predicted versus measured total bed material load values. Any equation is considered suitable if it falls within the acceptable range of 0.5–2.0. The performance test on Graf (1971) and Ackers and White (1973) as summarized in Table 1 indicates that these equations have a predictive power of less than 40%.
Most sediment transport equations have limitations of applicability that generally implies the range of data used for the equation’s calibration. For example, the Engelund–Hansen equation is applicable within the median sediment size range of less than 1.6 mm (Shen and Hung 1983) and the Yang, equation is 0.06–10 mm (Yang and Molinas 1982). The transport parameter ($\Phi$) in the Graf (1971) equation can be used for the range of $10^{-2} < \Phi < 10^1$ and the Ackers and Whites (1973) equation has been found unsuitable for fine sediments (Woo et al. 1993). These limitations are normally ignored by the equation testers.

Currently, there is no sediment equation that would consistently predict the sediment discharge correctly for all ranges of sediment sizes and it is clearly apparent that there is no specific total bed material load sediment transport equation/s considering the morphological condition of Malaysia in particular and South East Asia in general. As such, there is a need for the development of a more reliable sediment transport equation that can cater to the Malaysian sediment transport mechanism. An initial attempt to develop sediment transport equations for Malaysian rivers was made by Ibrahim (2002) using 108 river data. Further development of the new sediment transport equations for Malaysian rivers is given herein utilizing a larger set of river data.

### Malaysian River Data

A reliable sediment and hydraulic database consisting of 346 data altogether was established based on recent studies (Ariffin et al. 2001, 2002; DID 2003). The bedload and suspended load were measured together with bed material samples. The 346 data sets were then shuffled and divided into two groups, whereby 181 of them were used for the analyses process (equation development), and the balance of 165 data were utilized for model validation. The data used for analyses and validation process are shown in Tables 2 and 3.

The wash load contribution (sediment size less than 0.0625 mm) to the total bed material load is considered very small and thus ignored. The uniformity of the sediment size was tested using the uniformity coefficient ($C_u$) equation given below (Julien 2002).

$$C_u = \frac{d_{50}}{d_{10}} < 3$$

If the $C_u$ values is less than 3, then the sediment sample can be considered as uniformly distributed. The results show that the Malaysian river data have a uniformity coefficient ($C_u$) ranging from 1.053 to 5.0 and an average uniformity coefficient value of 3.153. Thus it can be concluded that the sediment particles are nearly uniform for the study area and the use of $d_{50}$ is adequate for this study. It also assumed that the sediment transport functions being developed are suitable for rivers with uniform sediment size particle distribution.

### U.S. River Data

A total number of 968 available sediment and hydraulic databases from rivers in the United States (Brownlie 1981) were obtained to further validate the equation being developed in the present study. The available flow and sediment data from the Sacramento River which were collected by USGS at two standard USGS stations near Butte City (Station 11389000) and Colusa (Station 11389500) between the year 1977 and 1979 were obtained from the USGS online data base for sediment and auxiliary data at the web site (USGS 2003a,b). The measured sediment discharge only...
Table 4. Characteristic Parameters for Sediment Transport in Open Channels

<table>
<thead>
<tr>
<th>Parameter class</th>
<th>Dimensionless groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobility</td>
<td>$\Psi = \frac{(S_i - 1)d_{50}}{R S_0}$, $\frac{V}{\sqrt{g d_{50} (S_i - 1)}}$, $\frac{U_s}{V}$, $\frac{V S_0}{\omega_s}$</td>
</tr>
<tr>
<td>Transport</td>
<td>$C_v$, $\Phi = \frac{C_v V R}{\sqrt{g (S_i - 1) d_{50}^2}}$</td>
</tr>
<tr>
<td>Sediment</td>
<td>$D_{50} = d_{50} \left( \frac{g (S_i - 1)}{v^2} \right)^{1/3}$, $d_{50}/B$, $\frac{U_s}{\omega_s}$, $\frac{\omega_s d_{50}}{v}$</td>
</tr>
<tr>
<td>Conveyance shape</td>
<td>$B l y_0$</td>
</tr>
<tr>
<td>Flow resistance</td>
<td></td>
</tr>
</tbody>
</table>

represents suspended loads. The bed load discharge $T_b$ was then calculated using the Meyer–Peter–Muller equation as suggested by Vanoni (1975) and Nagy et al. (2002).

Evaluation of Governing Parameters for Sediment Transport

The most important task in developing new sediment transport equations is to find the most reliable parameters to be included in the equations. These parameters were used as a foundation to develop a new total bed material load equation that has a better prediction compared to the existing ones. There are two phenomena that make it difficult to derive the functional relationships between sediment transport and various independent variables. The first is the inherent variability of river flow and sediment transport data caused by the random components of storm events and analysis errors. Second, the large numbers of independent variables and parameters that may influence the mechanism of sediment transport process.

Ab. Ghani (1993) describes the fundamental parameters that govern the sediment transport processes in steady or gradually varied free surface flow in open channels consisting of the flow depth ($y_0$), hydraulic radius ($R$), mean flow velocity ($V$), shear stress ($\tau_0$), kinematic viscosity ($\nu$), density of water ($\rho$), sediment size ($d$), particle density ($\rho_p$), volumetric concentration of sediment ($C_s$), cross-section geometry ($B$ and $y_0$), bed roughness ($n$), friction factor with sediment ($\lambda_s$), bed slope ($S_0$), and acceleration due to gravity. Van Rijn (1984a,b,c) added a few more parameters such as particle fall velocity ($\omega_s$), diffusion of fluid momentum ($\epsilon$), the differences in the diffusion of a discrete sediment particle and the diffusion of a fluid particle ($\beta$ factor), and suspension parameter which expresses the influence of the upward turbulent fluid forces together with the downward gravitational forces ($Z$). A comprehensive analysis on total bed material load approaches and relevant variables used in the existing sediment concentration equations can be found in Nagy et al. (2002).

Based on previous studies, the most significant parameters controlling sediment transport can be grouped into five main categories (Table 4), which are the mobility parameters, the transport parameters, the sediment parameters, the channel shape parameters, and the flow resistance parameters. Some of these dynamic variables and parameters may be highly correlated with each other and each specific dimensionless parameter may represent more than one parameter class. Thus, choosing more than one parameter from the same class may not yield any significant changes to the prediction power of the model. This was taken into consideration when choosing variables for multiple linear regression analyses.

Total Bed Material Load Equation Development

A one to one relationship between total bed material load and governing parameters as highlighted in Table 4 was initially employed. This gave a general view of the most influential parameters by observing the perfect fit line. The general relation between total bed material load and the parameters can be described in the following equation:

$$T_b = f(R, y_0, V, y_0/d_{50}, R/d_{50}, B/y_0, U_s/V, V S_0/\omega_s)$$

Two other conditions that assume the transport parameter ($\Phi$) and concentration by volume ($C_v$) as dependent variables were also tested as depicted in the following equations:

$$\Phi = f(\Psi, R/d_{50}, y_0/d_{50}, D_{gr}, B/y_0, \lambda_s, U_s/V, V S_0/\omega_s)$$

$$C_v = f(B/l y_0, R/d_{50}, y_0/d_{50}, D_{gr}, B/y_0, \lambda_s, U_s/V, U_s/\omega_s, \omega_s d_{50}/u, V S_0/\omega_s)$$

Generally, all the parameters except $\lambda_s$ have a good correlation with the transport parameter ($\Phi$). The parameters $R/d_{50}$ and $V S_0/\omega_s$ which show good agreement with the transport parameter, were given special attention. Figs. 1 and 2 show the log-log plot between transport parameter versus $R/d_{50}$ and $V S_0/\omega_s$, respec-
tively. The aspect ratio parameter $B/y_0$ is only important for relatively small streams where the flow can be assumed as one dimensional. It does not have any impact on wide rivers since the flow is two or three dimensional. Thus, this parameter was ignored for equation development. However, all the parameters were chosen to test and establish the best-fit sediment transport equation. Sediment concentration by volume were chosen to test and establish the best-fit sediment transport equation. The selected analysis variables were changed to the form of logarithms of the original variables to minimize the percentage error. The first criterion is based on the coefficient of determination or $R^2$ that account for the number of variables in the model. While the addition of predictor variables will cause the mean square error MSE($p$) for a $p$ variable(s) equation. The model with minimum MSE($p$) is chosen. The third criterion is Mallow’s $C_p$ statistics. Mallow’s $C_p$ is used in multiple linear regression analysis as the criterion for choosing the best subset of predictor effects when a best subset regression analysis is being performed. This measure of the quality of fit for a model tends to be less dependent (than the $R$ square) on the number of effects in the model, and hence it tends to find the best subset that includes only the important predictors of the respective dependent variable. The best model is the one where the $C_p$ value is approximately equal to $p(C_p= p)$.

The second step is to divide the existing database into two groups. One is for equation development and the other for validation. There are few methods available such as holdout method, U-method, and bootstrap method (Hair et al. 1995; Sharma 1996). The method best suited the needs of the present research and was applied by splitting the database into two disjoint subsets. The first group, namely the analysis sample, is used to develop the multiple linear regression models. The second group, the holdout sample or validation sample, is used to test the regression models.

No definite guidelines have been established for dividing the sample for analysis and holdout groups (Hair et al. 1995; Sharma 1996). The divide range of 50% as suggested by Nagy et al. (2002) was favored in this research. However a slightly higher weight was given to the analysis group. Thus, the existing 346 data sets were shuffled using SPSSWIN software where 52% of them were used for the analyses process and the other 48% were used for validation.

**Multiple Linear Regression Analyses**

The selected analysis variables were changed to the form of logarithms of the original variables to minimize the percentage error. The multiple linear regression technique was applied to investigate the relationship between the dependent (response) variable and several independent (explanatory) variables. The fitting of all possible regression equation methods is preferred in this study since all the possible test cases formed must represent one variable from each category as listed in Table 4. A total number of 137 possible regression models were established and tested in this study.

Four criteria were used to select the best regression model. The first criterion is based on the coefficient of determination or $R$ square values. $R^2$ denotes the coefficient of determination for regression model with $p-1$ independent variables and an intercept term ($p$) which is less than or equal to the number of variables plus 1. The analysis adds variables to the model up to the point where any additional variable is not useful because it results in a small increase in $R^2$. The second criterion is to consider the mean significance of regression model

The analyses of variance (ANOVA) approach was used to test the statistical significance of the derived regression model. To test the hypothesis that the amount of variation explained by the regression model is more than the variation explained by the average, the $F$ ratio is used (Hair et al. 1995). The analyses items are further elaborated on as follows: The total sum of squares $SS_{YY}$ can be written as

$$SS_{YY} = SS_{k} + SS_{E}$$

Thus, the ANOVA table further can be arranged as shown in Table 5. The test hypothesis is

**null hypothesis**

$$H_0: \beta_1 = \beta_2 = \beta_i = 0$$

**alternative hypothesis**

$$H_1: \beta_i \neq 0 \text{ for at least one } i$$

The null hypothesis is rejected if $F_{i,k,p} > F_{0.05}$. An example of the model significance test for Eq. (6) is given in Table 5. From the $F$ distribution table with $F_{0.05}$, for $k=3$ (number of independent variables)

$$P = k + 1$$
64.24% of the variability in the validation data and has an acceptable range of 0.5–2.0. The values of discrepancy ratios were then averaged and the functions were recommended as the dependent variable versus the independent variables. The closer the value to unity and smaller the standard deviation, the better suited the model is accepted as significant.

**Suitability Analyses**

This step was necessary to give some idea about which variables might provide an insight into the relationships between selected parameters and total bed material load data. A discrepancy ratio was calculated for each measured sediment load by comparing the computed and measured sediment load as depicted in Eq. (9) (Yu and Woo 1994). The analysis was further extended by calculating the population mean (μ) or central value of the distribution and population standard deviation (σ) of the discrepancy ratio to show the variance of values from the mean discrepancy ratio values

\[ r = \frac{T_{\text{calculated}}}{T_{\text{measured}}} \]

where the acceptable range is 0.5–2.0. The values of discrepancy ratios were then averaged and the functions were recommended based on the mean of the discrepancy ratio. The closer the value to unity and smaller the standard deviation, the better suited the total sediment load equation is assumed for the current data set. The summary of the suitability analyses for the selected equations for analysis and validation data are given in Tables 6 and 7, respectively. Eq. (6) has the best performance where it shows 64.24% of the variability in the validation data and has an R-square value of 0.67. Eq. (6) can be rewritten in the form of Eq. (10) with the volumetric concentration \( C_v \) as the dependent variable

\[ C_v = 3.565 \times 10^{-4} \left( \frac{V_{50}}{\omega_v} \right)^{0.329} \left( R \frac{d_{50}}{S} \right)^{1.308} \left( \sqrt{\frac{S - 1}{d_{50}}} \right) \]

The predictive power of Eq. (10) is later improved by performing the outlier and fitted value tests.

### Analyses of Outliers and Influential Fitted Values

Outliers are observations that have large residual values and can be identified only with respect to a specific regression model. They may result from clerical errors or from initially accepting marginal or unacceptable data. A qualitative way of checking for outliers is applied by plotting one variable against another (the dependent variable under consideration versus the independent). Data that stand apart from the mass can be checked more closely as possible outliers. In identifying the extreme observations, studentized deleted residuals (SDR) test was used. Not all the outliers can be removed from the data sets to give a better prediction. The removal of the influential outliers may change the results of the regression model dramatically. Thus, a measure to determine whether case \( i \) is influential or not on the fitted value \( \hat{y}_i \) is tested using DFFITS.

A test case is considered as influential if the absolute value of DFFITS, exceeds 1 for small to medium size data and \( \sqrt{P/n} \) for large data sets. The procedures for the outlier test carried out for Eq. (10) are summarized as follows:

\[ t_{n-p-1}(P) = (n-p-1) \text{ degrees of freedom (DOF) } \]

For Eq. (10), with 181 analyses data and two independent variables

\[ p = 2 + 1 = 3 \]

\[ t_i(P) = (181 - 3 - 1) \text{DOF} = 177 \text{ DOF} \]

from the table of critical values for \( t \) distributions, 5% confidence interval, with 177 DOF then, \( t = 1.645 \). The obtained SDR for 181 data from SPSSWIN were compared with the \( t \) value. If the SDR values were greater than \( t \) values, then the sample is an outlier. A total number of nine outliers were identified from the data of Kulim, Langat, and Semenyi Rivers. The outliers were then checked to determine whether the case is influential or not by using the fitted value of DFFITS, as given in the following equation

The case is considered to be influential if it exceeds the value of

\[ \sqrt{\frac{p}{n}} = \sqrt{\frac{3}{181}} = 0.2575 \]

The nine identified outliers had a DFFITS, value less than 0.2575 and it was therefore concluded that it has no influence on the prediction model. The outliers were removed and the new form of Eq. (10) derived as

### Table 6. Summary of the Model Suitability and Performance Test for Analyses Data

<table>
<thead>
<tr>
<th>Equation number</th>
<th>Mean (μ)</th>
<th>Standard deviation (σ)</th>
<th>Discrepancy ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. (6) (present study)</td>
<td>1.249</td>
<td>0.934</td>
<td>66.85</td>
</tr>
<tr>
<td>Yang</td>
<td>15.007</td>
<td>30.489</td>
<td>35.91</td>
</tr>
<tr>
<td>Ackers and White (1973)</td>
<td>12.570</td>
<td>16.729</td>
<td>12.71</td>
</tr>
<tr>
<td>Graf (1971)</td>
<td>170.093</td>
<td>1,276.639</td>
<td>17.13</td>
</tr>
</tbody>
</table>

**n = 181**

\[ F_{0.05,3,179} = 2.605 \]

and

\[ F_0 = 118.816 > F_{0.05,3,179} \]

Therefore the null hypothesis is rejected and the model is accepted as significant.

### Table 7. Summary of Model Suitability and Performance Test for Validation Data

<table>
<thead>
<tr>
<th>Equation number</th>
<th>Mean (μ)</th>
<th>Standard deviation (σ)</th>
<th>Discrepancy ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eq. (6) (present study)</td>
<td>1.381</td>
<td>0.929</td>
<td>64.24</td>
</tr>
<tr>
<td>Yang</td>
<td>1.775</td>
<td>1.705</td>
<td>38.78</td>
</tr>
<tr>
<td>Ackers and White (1973)</td>
<td>26.689</td>
<td>14.008</td>
<td>0.00</td>
</tr>
<tr>
<td>Graf (1971)</td>
<td>156.298</td>
<td>984.369</td>
<td>10.91</td>
</tr>
</tbody>
</table>
Total bed material load is obtained by substituting Eq. (13) into the following equation:

\[
T_j = C_v^\ast \left( \frac{Q_s}{\rho_s} \right)^{0.293} \left( \frac{R}{d_{50}} \right)^{1.390} \sqrt{\frac{g(S_0 - 1)d_{50}^3}{VR}}
\]  

(13)

Fig. 3. Comparison between measured and estimated total bed material load for Eq. (13)

The removal of outliers has resulted in an increase in the coefficient of determination \(R^2\) where Eq. (13) accounts for 71.51% of the variability in analyses data and 63.63% in the validation data. Figs. 3 and 4 show a comparison between measured and estimated total bed material load and validation of Eq. (13). Fig. 5 shows the derived sediment-rating curve using Eq. (13), which falls very closely to measured Malaysian River data. Table 8 shows the prediction results using Eq. (13) for rivers in the United States compared to the Ackers–White (1973) and Graf (1971) equations.

Fig. 4. Validation of Eq. (13)

Fig. 5. Sediment rating curve derived using Eq. (13)

Table 8. Performance Test with River Data from United States

<table>
<thead>
<tr>
<th>River (number of data)</th>
<th>Eq. (13) (present study)</th>
<th>Graf (1971)</th>
<th>Ackers and White (1973)</th>
<th>No. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sacramento River</td>
<td>20 72.41</td>
<td>23 79.31</td>
<td>0 0.00</td>
<td>2 6.90</td>
</tr>
<tr>
<td>Atchafalaya River (68)</td>
<td>23 33.82</td>
<td>3 4.41</td>
<td>12 17.65</td>
<td>13 19.12</td>
</tr>
<tr>
<td>Colorado River (100)</td>
<td>70 70.00</td>
<td>62 62.00</td>
<td>1 1.00</td>
<td>7 7.53</td>
</tr>
<tr>
<td>Mississippi River (165)</td>
<td>47 28.66</td>
<td>40 24.24</td>
<td>0 0.00</td>
<td>52 31.52</td>
</tr>
<tr>
<td>Middle Loup (38)</td>
<td>2 5.26</td>
<td>0 0.00</td>
<td>0 0.00</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Mountain Creek (100)</td>
<td>64 64.00</td>
<td>52 52.00</td>
<td>30 30.00</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Niobrara (40)</td>
<td>4 10.00</td>
<td>0 0.00</td>
<td>0 0.00</td>
<td>0 0.00</td>
</tr>
<tr>
<td>North Saskatchewan River (55)</td>
<td>12 21.82</td>
<td>21 38.18</td>
<td>5 9.09</td>
<td>7 12.73</td>
</tr>
<tr>
<td>Oak Creek (17)</td>
<td>1 5.88</td>
<td>0 0.00</td>
<td>0 0.00</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Red River (30)</td>
<td>8 26.67</td>
<td>9 30.00</td>
<td>0 0.00</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Rio Grande conveyance (8)</td>
<td>0 0.00</td>
<td>0 0.00</td>
<td>1 12.50</td>
<td>0 0.00</td>
</tr>
<tr>
<td>Rio Grande River (293)</td>
<td>11 3.75</td>
<td>117 39.93</td>
<td>0 0.00</td>
<td>82 27.99</td>
</tr>
<tr>
<td>Snake and Clearwater River (21)</td>
<td>0 0.00</td>
<td>6 28.57</td>
<td>0 21.00</td>
<td>7 33.33</td>
</tr>
<tr>
<td>Trinity River (4)</td>
<td>2 50.00</td>
<td>0 0.00</td>
<td>1 25.00</td>
<td>0 0.00</td>
</tr>
</tbody>
</table>
Based on the results of the present study, it may be concluded that Eq. (13) gives an overall better agreement with the measured data of Malaysian rivers than the others. Graf’s (1971) equation has a better prediction for overseas data as a total where the prediction percentage is 33.74 compared to Eq. (13) with a percentage of 26.85. However, Eq. (13) performs best for Atchafalaya River, Colorado River, Sacramento River, Trinity River, Mountain Creek, and relatively good for Mississippi River as summarized in Table 8. These rivers have the range of \(d_{50}\) within the predictive range of Eq. (13). Thus, the results clearly indicate that the range of sediment particle size \(d_{50}\) and physically justified parameters that were used in the model development play a prominent role in determining the model predictive capability. Records show that rivers in the United States have a relatively wider range of values for hydraulic parameters such as flow channel width, and velocity, as compared to Malaysian rivers (Brownlie 1981; DID 2003). Thus, it is expected that the model accuracy will improve dramatically if more data, which were measured during low and high flows, were incorporated into the existing hydraulic and sediment databases for rivers in Malaysia.

The unit stream power VS/\(\omega_0\) and relative roughness on the bed \(R/d_{50}\) variables have greater influence when predicting sediment load for rivers in Malaysia over the measured range of observed data. It is strongly recommended that the newly developed equations be appraised with river data from various parts of the world.

Conclusions

In general, the newly derived model is best suited for rivers with uniform sediment size distribution with a \(d_{50}\) value within the range of 0.37–4.0 mm and performs better than the commonly used Graf (1971), and Ackers–White (1973) total bed material load equations. The present study also indicates that employing local sediment transport data yielded a better equation that can accurately predict sediment transport in Malaysian rivers. The newly developed sediment transport equation in this study has been programmed into the SFlood model for flood risk analyses incorporating sediment transport (Sinnakaudan and Abu Bakar 2005).

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Notation

The following symbols are used in this paper:

\[
\begin{align*}
D_{50} & = \text{dimensionless grains size;} \\
\text{DFFITS} & = \text{influential fitted value;} \\
\text{DOF} & = \text{degree of freedom;} \\
\text{DOF} & = \text{median diameter of bed material;} \\
\text{\(r\)} & = \text{acceleration due to gravity (9.81);} \\
\text{MSE} & = \text{mean square error;} \\
\text{n} & = \text{size of data points;} \\
\text{MSE} & = \text{Manning's roughness coefficient;} \\
\text{\(p\)} & = \text{\(k+1\) (\(k\) is number of independent variables);} \\
\text{DOF} & = \text{total discharge (m}^3/\text{s);} \\
\text{DOF} & = \text{hydraulic radius (m);} \\
\text{DOF} & = \text{coefficient of determination;} \\
\text{DOF} & = \text{adjusted coefficient of determination;} \\
\text{DOF} & = \text{relative roughness on bed;} \\
\text{DOF} & = \text{discrepancy ratio;} \\
\text{DOF} & = \text{specific gravity of sediment (2.65);} \\
\text{DOF} & = \text{energy slope (m/m);} \\
\text{DOF} & = \text{sum of square error;} \\
\text{DOF} & = \text{sum of square residual;} \\
\text{DOF} & = \text{total sum of squares;} \\
\text{DOF} & = \text{total bed material load of sediment (kg/s);} \\
\text{DOF} & = \text{ratio of shear velocity and average velocity;} \\
\text{DOF} & = \text{ratio of shears velocity and fall velocity;} \\
\text{DOF} & = \text{average flow velocity (m/s);} \\
\text{DOF} & = \text{dimensionless unit stream power. Time rate of potential energy expenditure per unit weight in alluvial channel;} \\
\text{DOF} & = \text{flow depth (m);} \\
\text{DOF} & = \text{dimensionless flow depth (water depth ratio) and relative roughness on bed;} \\
\text{DOF} & = \text{suspension parameter;} \\
\text{DOF} & = \text{velocity-head coefficient;} \\
\text{DOF} & = \text{constant;} \\
\text{DOF} & = \text{diffusion coefficient;} \\
\text{DOF} & = \text{friction factor;} \\
\text{DOF} & = \text{friction factor with sediment;} \\
\text{DOF} & = \text{statistical mean;} \\
\text{DOF} & = \text{water density (t/s/m}^3\)); \\
\text{DOF} & = \text{sediment density (kg/m}^3\)); \\
\text{DOF} & = \text{statistical standard deviation;} \\
\text{DOF} & = \text{shear stress;} \\
\text{DOF} & = \text{kinematic viscosity;} \\
\text{DOF} & = \text{transport parameter;} \\
\text{DOF} & = \text{flow parameter;} \\
\text{DOF} & = \text{fall velocity of sediment particle (}d_{50}\text{)(m/s).} \\
\end{align*}
\]

References


