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EFFECTS OF SOIL ERODIBILITY ON RIVERBANK EROSION AND FAILURES

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ABSTRACT: Riverbank erosion is a natural process of removal of earthen materials from the bank surface. The process of riverbank erosion that is induced naturally results in the formation of landforms such as valleys, canyons, and productive floodplains. However, riverbank erosion can also be considered a hazard when the process occurs at an alarming rate causing loss of land. The extent of erosion depends on many factors. One of the main factors responsible for riverbank erosion is the soil erodibility which is the resistance of soil to erosion. The aim of this study is to quantify the riverbank erosion rates and the potential magnitude of riverbank erosion in order to generate an empirical predictive model to estimate riverbank erosion from physical and geomorphic variables for rivers susceptible to riverbank erosion. Several models were trained using the Regression Learner application in MATLAB software. Models that include soil erodibility parameters perform better than the models without the soil erodibility parameters. The model with the highest accuracy was found to be Model 2, with Root Mean Square Error (RMSE) of 3.70E-08 and coefficient of determination, R^2 of 0.55. The model produced in this study will be helpful to analyze and predict the effects of riverbank erosion and assist in the development of bank stabilization solution.

ABSTRAK: Hakisan tebing sungai adalah proses semula jadi terhadap penyingkiran bahan tanah dari permukaan tebing. Proses hakisan tebing sungai yang terjadi secara semula jadi ini mengakibatkan pembentukan bentuk muka bumi seperti lembah, ngarai dan dataran banjir yang produktif. Bagaimanapun, hakisan tebing sungai juga boleh dianggap sebagai ancaman apabila proses berlaku pada kadar membimbangkan sehingga menyebabkan kehilangan tanah. Tahap hakisan bergantung pada banyak faktor. Salah satu faktor utama yang menyebabkan hakisan tebing sungai adalah kebolehhakisan tanah iaitu ketahanan tanah terhadap hakisan. Kajian ini bertujuan untuk mengukur kadar hakisan tebing sungai, mengkaji potensi magnitud hakisan tebing sungai dan menghasilkan model ramalan empirik bagi menganggarkan hakisan tebing sungai daripada pembolehubah fizikal dan geomorfik bagi sungai yang terdedah kepada hakisan tebing sungai. Beberapa model telah dilatih menggunakan aplikasi *Regression Learner* dalam perisian MATLAB. Dapatan menunjukkan model yang mengandungi parameter kebolehhakisan tanah adalah lebih baik berbanding model tanpa parameter kebolehhakisan tanah. Model 2 didapati mempunyai ketepatan tertinggi dengan ralat punca min kuasa dua (RMSE) sebanyak 3.70E-08 dan pekali penentuan, R^2 sebanyak 0.55. Model dalam kajian ini dapat membantu dalam analisa berkaitan kesan hakisan tebing sungai dan penyelesaian kepada pembangunan kestabilan tebing.

KEYWORDS: *riverbank erosion; soil erodibility; erosion pin; Sungai Pusu*

1. INTRODUCTION

Riverbank erosion is a complex phenomenon which has garnered the attention of people all over the world. Riverbank erosion as defined by [1] is the removal of earth materials from the bank of a river. It is a geological process in which earthen materials from the bank of a river get detached and enter the receiving water body. Riverbank erosion can be a slow-paced process and can also occur at an alarming rate which leads to severe loss of bank material. It is an unpredictable hazard which has severe impacts on the land and people nearby.

Riverbank erosion studies are crucial to determine the rate of erosion due to fluvial entrainment and bank instability. In Malaysia, research conducted on riverbank erosion are limited due to the complexity of the fieldwork investigations which consist of measurement of riverbank erosion, soil properties and flow condition. Prediction of the magnitude of erosion using existing equations obtained from previous research that deals with rivers outside Malaysia may produce unfavorable results due to the difference in soil properties and river characteristics. Besides, most of the research conducted mostly focused on the surface erosion which utilizes the Universal Soil Loss Equation (USLE) method to determine the soil erodibility [2-4]. However, this method is not best suited for riverbank erosion investigation. In recent years, research conducted on riverbank erosion mostly utilizes remote sensing data to predict the riverbank erosion rate [5-7]. By using only remote sensing data, not all factors governing riverbank erosion will be included in the model development. Field riverbank measurements need to be conducted to properly investigate all the variables affecting riverbank erosion including flow parameters, riverbank geometry, and soil properties and characteristics to incorporate them into the riverbank erosion rate prediction.

The degree of riverbank erosion is dependent on various factors. Soil erodibility is one of the factors that plays a significant role in determining the rate of riverbank erosion. Soil erodibility is the soil's resistance to erosion based on the physical characteristics of each soil [8]. It is one of the major factors that govern the rate of riverbank erosion. The physical properties of soil that influence erodibility are aggregate size, particle size distribution, bulk density, water content, and temperature [9]. The erodibility of soil also varies with soil structure, stability, shear strength, aggregates, soil depth, soil organic matter, bulk density and chemical constituents [10]. In general, soil with high erodibility factor may be eroded much more easily compared to soil with low erodibility factor. Low erodibility soil has higher resistance to both detachment and transport process.

The aim of this study is to quantify the rates of riverbank erosion and generate a model to estimate riverbank erosion from physical and geomorphic variables for rivers susceptible to riverbank erosion. In this study, ascertaining the effects of soil erodibility to riverbank erosion and failures by comparing the riverbank erosion prediction model, which incorporates soil erodibility parameters, with models that exclude the soil erodibility parameters is attempted.

2. STUDY AREA AND METHODOLOGY

The study area is Sungai Pusu which has a total length of approximately 4.1 kilometers and flows through the International Islamic University Malaysia (Gombak campus) before it joins Sungai Gombak. Sungai Pusu is currently classified as a Class IV River, which is regarded as the worst river water quality condition according to Malaysian water quality standards [11]. Riverbank erosion is also prominent at several sections of the river. Figure 1 shows the flow path of Sungai Pusu and the selected fieldwork sites. A total of four sections of the riverbank were selected where it is deemed suitable and accessible for field measurements and data collection. Table 1 shows the geographical coordinates of all the selected bank sections of Sungai Pusu.

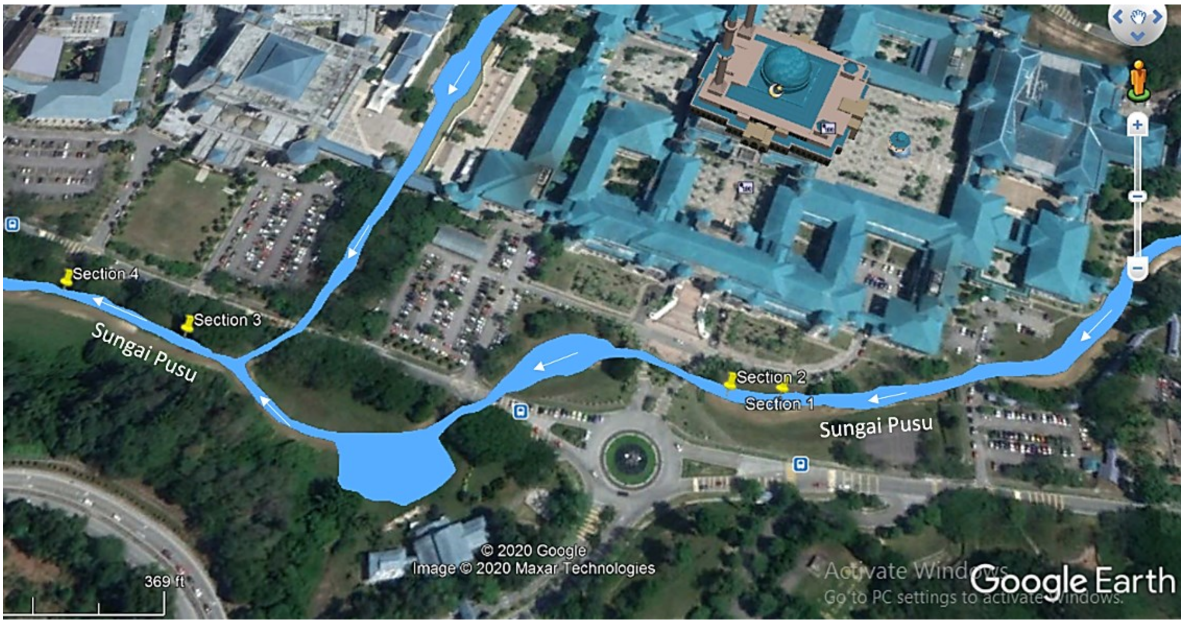

Fig. 1: Sungai Pusu flowing through the International Islamic University Malaysia, Gombak campus.

Table 1: Coordinate of sections

Section no.	Coordinate
1	3°15'01"N 101°43'52"E
2	3°15'00"N 101°43'55"E
3	3°14'59"N 101°44'05"E
4	3°14'59"N 101°44'07"E

Figure 2 shows the riverbank of the selected sections of Sungai Pusu. Riverbank erosion features were observed at a few stretches of the river. Distinct signs of sedimentation were also discovered along the riverbank. The length of each section is approximately 10 to 15 meters.

A significant amount of erosion can be seen at the riverbank from the figure above. Based on field observation, it is evident that several parts of the river have considerable amount of erosion which could eventually lead to problems in the future. Additionally, distinct signs of sedimentation were observed along the river network. High concentration of sediments in the river have also caused floods, the worst of which was recorded specifically in 2014 at the International Islamic University Malaysia, Gombak campus [12].

2.1 Field Measurement

Field measurements were carried out to obtain the data needed to investigate riverbank erosion. The process included measurement of the erosion rate, soil erodibility, riverbank cross-section and bank geometry, river flow velocity and collection of soil samples. The cross-section and riverbank geometry were established through measurement and surveys. The data that were measured in the field includes river width, depth, riverbank angle, and riverbank height. Flow velocities were measured using a current meter each time the measurement of erosion pins was taken.

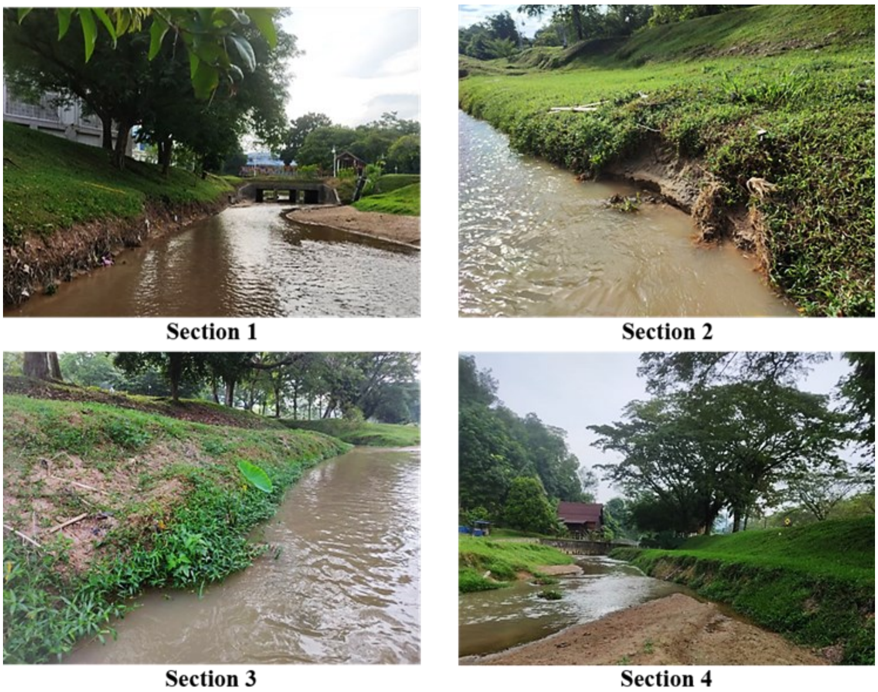

Fig. 2: Selected sections of Sungai Pusu.

2.2 Erosion Pins Method

The method that was used for measurement of the riverbank erosion rate was the erosion pin method. Numerous publications have emphasized the advantages of employing erosion pins. Erosion pins are an economical way to quantify erosion and deposition rates of soil [13]. This method can easily be employed without having to use any special equipment and the erosion pins themselves are relatively low cost. Erosion pins have high sensitivity where small changes in bank retreat can be measured using erosion pins. Figure 3 shows the erosion pins installed at the riverbank of Sungai Pusu.

Fig. 3: Erosion pins installed at the site.

Erosion pins were installed at the left and right bank for all the selected sections of the river. The ideal length of the pin is between 0.30 to 0.50 meters [14]. Erosion pins with a length of 60 cm were used in a recent study that was conducted to estimate rates of riverbank erosion for Sungai Bernam [15]. In this study, mild steel rods that were 60 cm long and 6 mm in diameter were utilized. The pin diameter in this study was selected to be as small as possible to avoid material disturbance and minimize public visibility. Selection of the pin length depends on the expected rate of erosion, the frequency of site visits, and pin resetting. The pins were inserted horizontally into the bank leaving out only 10 cm from the total length of the pin. The end of the pins were labeled with numbers to ease the pin measurement process. A total of 140 pins were installed at the site. Figure 4 shows the schematic diagram of the erosion pins arrangement.

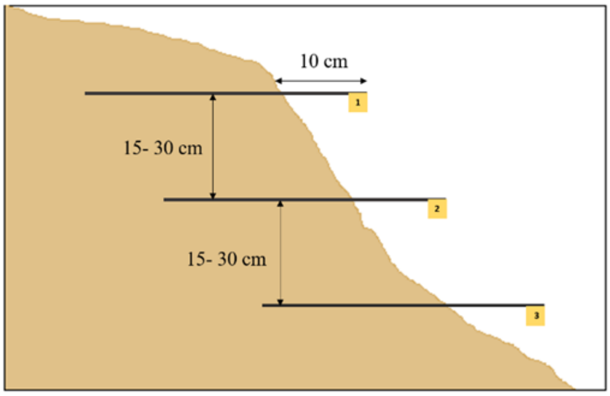

Fig. 4: Schematic diagram of the erosion pins arrangement.

The pins were arranged in a grid pattern along the river sections, spaced evenly at one-meter intervals and vertically at intervals of between 15 and 30 cm, depending on the height of the bank. Each site consisted of 10 to 15 plots with 3 pins installed at each plot. As erosion proceeds, more and more of rod will be exposed.

2.3 Soil Sampling

A total of 10 soil samples were collected from the selected bank sections of Sungai Pusu using a hand auger. The number of soil samples to be collected depends on the variation of soil at the site. Based on previous study, a total of 10 to 13 samples is considered sufficient to study the soil properties of the river [16-19]. The soil samples collected were sent to the laboratory to conduct soil testing. In this study, sieve analysis, a hydrometer test, an Atterberg limits test, and a bulk density test were conducted to determine mean particle diameter, d_{50}, the percentage of silt, sand, and clay in the soil composition, plasticity index, bulk density, and soil porosity.

2.4 Soil Erodibility Coefficient Determination

The soil erodibility coefficients were computed using the equation by [20]. The equation shows the correlation between critical shear stress and clay-silt fraction.

$$\tau_c = 0.1 + 0.1779\ (SC\%) + 0.0028\ (SC\%)^2 - 2.343\times10^{-5}\ (SC\%)^3 \quad (1)$$

Where τ_c is the critical shear stress and SC% is the combined percentage of clay and silt. After calculating the critical shear stress, the soil erodibility coefficient was determined using the empirical correlation found by [21].

$$k_d = 0.2\ \tau_c^{-0.5} \quad (2)$$

Where k_d is the soil erodibility coefficient (cm^3/N-s).

2.5 Dimensional Analysis

Dimensional analysis was performed to determine the relationship between variables that influence riverbank erosion rate and reduce the number of variables for subsequent analysis. The variables involved in quantifying the riverbank erosion were grouped into five categories namely bank geometry, hydraulic characteristic, soil characteristics and properties and others. Table 2 shows the selected variables used in the dimensional analysis and the categories.

Table 2: Selected variables for dimensional analysis

Categories	Variables	Symbol	Units	Fundamental quantities
Riverbank erosion rate	Erosion rates	ξ	m/s	LT^{-1}
Hydraulic characteristics	Near bank velocity	u_b	m/s	LT^{-1}
	Fall velocity	ω	m/s	LT^{-1}
	Water depth	D	m	L
Bank geometry	Bank height	h_b	m	L
	Bank angle	β	-	-
	Bankfull width	B	m	L
Soil characteristics and properties	Mean particle density	d_{50}	m	L
	Porosity	P	-	-
	Plasticity index	PI	-	-
	Critical shear stress	τ_c	N/m^2	$ML^{-1}T^{-2}$
	Erodibility coefficient	k_d	$m^3/N\text{-}s$	
	Particle density	ρ_s	kg/m^3	ML^{-3}
Others	Water density	ρ_w	kg/m^3	ML^{-3}

Functional relationships addressing riverbank erosion rates were established using Buckingham's Pi Theorem. There were fourteen (14) variables and three fundamental dimensions selected in the relationship. As the number of variables, n is 14, and the number of fundamental dimensions, m is 3, the number of dimensionless groups will be 11. The selection of repeating variables to be used in the dimensional analysis was based on the guidelines from previous study [22] which are as follows; (1) The repeating variables must not be able to form a dimensionless group by themselves; (2) The repeating variables must represent all the fundamental quantities in the study which are M, L and T; (3) The repeating variables should not have the same dimensions or dimensions that differ by only an exponent ; (4) Whenever possible, simple variables should be selected over complex variables. Table 3 shows the different sets of repeating variables selected in this study.

Table 3: Repeating variables

No	Repeating variables
1	u_b, ρ_w, h_b
2	u_b, ρ_w, d_{50}
3	u_b, ρ_w, D

There is a total of three sets of repeating variables which yield three sets of functional relationship between the parameters. In order to form the dimensionless groups or also called as π-term, each non-repeating variable is multiplied to repeating variables that are raised to an exponent. Typically, it takes the form of $x_i x_1^a x_2^b x_3^c$, where a, b, and c are determined through calculations to make the combination dimensionless. The example of calculation for the π-term is as follows;

For repeating variables: u_b, d_{50}, ρ_w

$$\pi 1 = \xi\, u_b\, a1\ \rho_w\, b1\ d_{50}\, c1$$

$$= M^0 L^0 T^0$$

Substitute the dimensions,

$$M^0 L^0 T^0 = (LT^{-1})^{a1}(ML^{-3})^{b1}(L)^{c1}$$

$$a^1 = -1$$

$$b^1 = 0$$

$$c^1 = 0$$

$$\pi_1 = \frac{\xi}{u_b}$$

The calculations were then repeated for the other π-terms. The functional relationship derived from the dimensional analysis were presented in the result and discussion section.

2.6 Regression Learner

Different models were trained using the Regression Learner app in the MATLAB software to develop a model to estimate rates of riverbank erosion. Regression Learner is an app that can interactively train and validate regression models to predict data. There are many model type options such as linear regression, regression tree, Gaussian process regression, support vector machines, ensembles of regression tree and neural network regression models. Using the parallel pool, these multiple models can be trained at a time and be compared side to side to validate the errors. The best model with the lowest Root Mean Square Error (RMSE) and the highest R-squared value were selected.

3. RESULTS AND DISCUSSION

Dimensional analysis was utilized to identify significant dimensionless numbers for the riverbank erosion process. The potential variables governing the riverbank erosion process were grouped into five categories: riverbank erosion rate, bank geometry, hydraulic characteristics and soil characteristics and properties. The parameters for hydraulic characteristic include near-bank velocity, u_b, fall velocity, ω, and water depth, D. The parameters for bank geometry consist of bank height, hb, bank angle, β, and bankfull width, B. The parameters for soil characteristics and properties include mean particle diameter, d_{50}, particle specific gravity, porosity, p, plasticity index, PI, critical shear stress, τ_c and erodibility coefficient, k_d. The Buckingham π theorem is applied to obtain all sets of dimensionless parameters from the selected variables. The riverbank erosion rate, ξ serves as the dependent variable. The dimensional analysis performed in this study yields several functional relationships using different sets of repeating variables.

Table 4 shows the sets of repeating variables and the respective functional relationships for the dimensional analysis performed using all 14 variables from all parameter categories. Table 5 shows the established functional relationship by performing dimensional analysis using the variables from the hydraulic characteristic and bank geometry categories only. Two sets of repeating variables were selected which results in two sets of functional relationship. This step was conducted in order to determine the significance of soil parameters in the riverbank erosion prediction. In order to do so, the training result for models which include soil parameters and models that exclude soil parameters will be compared.

Different regression models were trained using the Regression Learner application available in MATLAB software. A total of 220 data from field observations were used in the model development. The data were split into training and testing data by a ratio of 70:30. After running the data through several different models, models that showed best fit were extracted and compared. The process was then repeated for the other equations. The model's accuracy was measured using the R-squared (R^2) and Root Mean Squared Error (RMSE) value. RMSE is the standard deviation of residuals or prediction error. It is used to measure the average magnitude of error in the predicted value. The RMSE value is measured in the same unit as the independent variables or the predictor. Generally, the lower the value of RMSE, the better is the model performance. Meanwhile, R^2, also known as coefficient of determination, gives an indication of the model fits. High R^2 value indicates that the model has good fits for the dataset. Table 6 shows the training results for the trained regression models for Eqs. 3 - 5.

Table 4: Repeating variables and its functional relationship (Eqs. 3 - 5)

Equation No.	Repeating Variables	Functional Relationship
3	u_b, ρ_w, h_b	$\frac{\xi}{u_b} = f\left(\frac{B}{h_b}, \frac{D}{h_b}, \frac{d_{50}}{h_b}, \beta, \frac{\tau_c}{\rho_w u_b^2}, p, PI, \frac{\omega}{u_b}, \frac{\rho_s}{\rho_w}, \frac{g h_b}{u_b^2}, u_b \rho_w k_d\right)$
4	u_b, ρ_w, d_{50}	$\frac{\xi}{u_b} = f\left(\frac{B}{d_{50}}, \frac{D}{d_{50}}, \frac{h_b}{d_{50}}, \beta, \frac{\tau_c}{\rho_w u_b^2}, p, PI, \frac{\omega}{u_b}, \frac{\rho_s}{\rho_w}, \frac{g d_{50}}{u_b^2}, u_b \rho_w k_d\right)$
5	u_b, ρ_w, D	$\frac{\xi}{u_b} = f\left(\frac{B}{D}, \frac{d_{50}}{D}, \frac{h_b}{D}, \beta, \frac{\tau_c}{\rho_w u_b^2}, p, PI, \frac{\omega}{u_b}, \frac{\rho_s}{\rho_w}, \frac{g D}{u_b^2}, u_b \rho_w k_d\right)$

Table 5: Repeating variables and its functional relationship (Eqs. 6 and 7)

Equation No.	Repeating Variables	Functional Relationship
6	u_b, ρ_w, h_b	$\frac{\xi}{u_b} = f\left(\frac{B}{h_b}, \frac{D}{h_b}, \beta, \frac{\rho_s}{\rho_w}, \frac{g h_b}{u_b^2}\right)$
7	u_b, ρ_w, D	$\frac{\xi}{u_b} = f\left(\frac{B}{D}, \frac{h_b}{D}, \beta, \frac{\rho_s}{\rho_w}, \frac{g D}{u_b^2},\right)$

Table 6: Training results for Eqs. 3 - 5

Functional Relationship	Model No.	Model Type	Equation Type	RMSE	R-squared
Functional Relationship 1 (3)	1	Stepwise Linear Regression	Stepwise Linear	4.27E-08	0.43
	2	Ensemble	Boosted tree	3.70E-08	0.55
	3	Ensemble	Bagged tree	4.13E-08	0.47
Functional Relationship 2 (4)	4	Linear Regression	Linear	4.71E-08	0.31
	5	Stepwise Linear Regression	Stepwise linear	4.21E-08	0.45
	6	Ensemble	Boosted tree	4.60E-08	0.34
Functional Relationship 3 (5)	7	Linear Regression	Linear	4.83E-08	0.28
	8	Stepwise Linear Regression	Stepwise Linear	4.66E-08	0.33
	9	Ensemble	Boosted tree	4.87E-08	0.28

Among the models trained, Model 2 which showed the lowest RMSE value and highest R-squared value were selected as the best model. The RMSE and R-squared values are respectively 3.70E-08 and 0.55.

Table 7 shows the training results for the trained model using equation 6 and equation 7. Model 15 was selected as the best models among the other six models as it has the lowest RMSE value and the highest R^2 value. The RMSE and R^2 value are 4.63E-08 and 0.33 respectively.

Table 8 shows the comparison of training results for the selected models for the functional relationship that includes parameters from the soil characteristics and the equation that exclude the variables from that particular category. Both models have the same model type which is the Ensemble boosting model. Ensemble Boosting is a well-known ensemble learning approach used to improve the performance and accuracy of machine learning systems. The fundamental idea behind the boosting technique is the sequential addition of additional models to the ensemble. Weak learners are efficiently boosted to strong learners in this ensemble [23]. Most of the weak models do not perform well on their own mostly because they contain high bias. The final strong model is created by combining all of the weak learners by weighted majority voting [24,25].

Table 7: Training results for Eqs. 6 and 7

Functional Relationship	Model No.	Model Type	Equation Type	RMSE	R-squared
Functional Relationship 1 (6)	10	Linear Regression	Linear	5.16E-08	0.16
	11	Ensemble	Bagged tree	4.88E-08	0.25
	12	Ensemble	Boosted tree	4.86E-08	0.26
Functional Relationship 2 (7)	13	Linear Regression	Linear	5.11E-08	0.18
	14	Ensemble	Bagged tree	4.89E-08	0.25
	15	Ensemble	Boosted tree	4.63E-08	0.33

Table 8: Comparison of training results for Model 2 and Model 15

Model	Functional Relationship	Model Type	Equation Type	RMSE	R-squared
2	$\frac{\xi}{u_b} = \mathrm{f}\left(\frac{B}{h_b}, \frac{D}{h_b}, \frac{d_{50}}{h_b}, \beta, \frac{\tau_c}{\rho_w u_b^2}, \mathrm{p}, \mathrm{PI}, \frac{\omega}{u_b}, \frac{\rho_s}{\rho_w}, \frac{g h_b}{u_b^2}, u_b \rho_w k_d\right)$	Ensemble	Boosted tree	3.70E-08	0.55
15	$\frac{\xi}{u_b} = \mathrm{f}\left(\frac{B}{D}, \frac{h_b}{D}, \beta, \frac{\rho_s}{\rho_w}, \frac{gD}{u_b^2},\right)$	Ensemble	Boosted tree	4.63E-08	0.33

It can be seen from the result that models which include soil characteristic and properties perform better compared to the models which include only hydraulic characteristic and bank geometry parameters. The R-squared value for Model 2 was significantly higher compared to Model 15. The RMSE value of Model 2 is also lower compared to Model 15 which signifies that the error in predicted value is also smaller.

The performance of the selected trained model was assessed using the predicted vs actual response plot, residual plot and the performance of test set. The predicted vs actual response plot is a visual representation of the actual and predicted values. Fig. 5 shows the predicted vs true graph for Model 2.

The model that performed well should have the predicted values scattered near the diagonal line. To obtain a perfect regression model, all the points must be on the line. The error of the prediction is equal to the vertical distance from the line to any given point. The vertical distance from the line to any point is the error of the prediction for that point. The residual plots are presented in Fig. 6 which shows the error functions of the model.

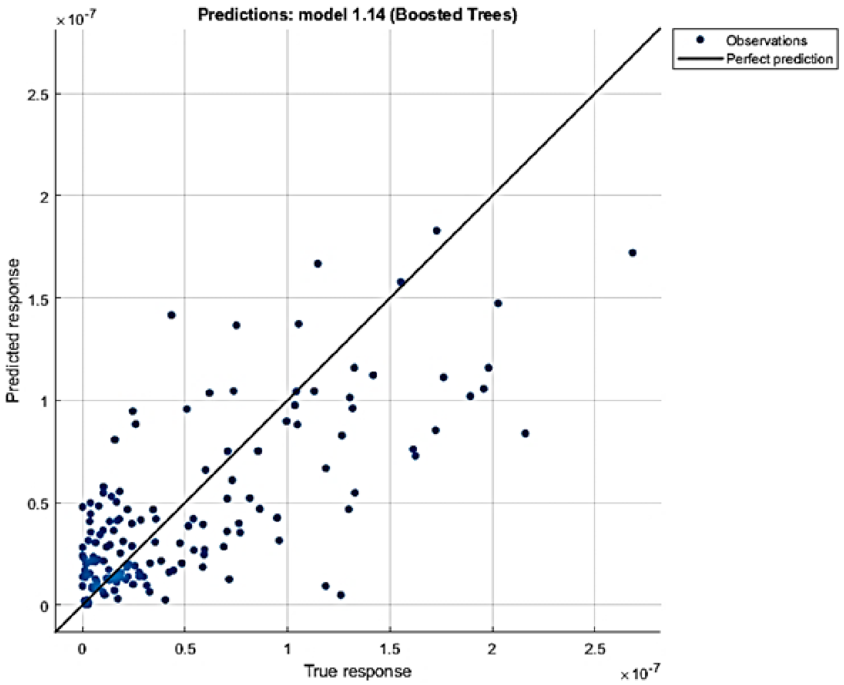

Fig. 5: Predicted vs True Graph for Model 2.

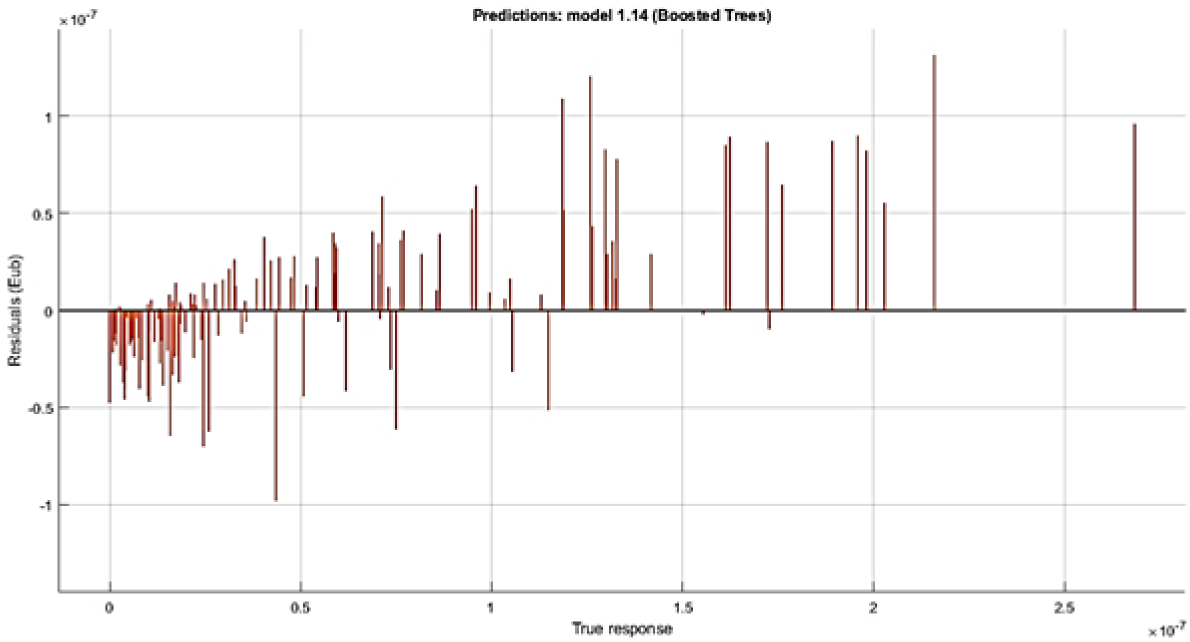

Fig. 6: Residual Plots of Model 2.

The graph explains how far away the predicted values are compared to the true values. The horizontal line at the position y=0 represents the True values scales. The further the points from the line, the less accurate the predicted values. Based on Fig. 5 and Fig. 6, it can be seen that the model gives better prediction for lower values of riverbank erosion. One of the possible reasons is that the higher value of erosion rate is the bank erosion that is caused by bank failures which occurs only when there is a storm event. In order to improve the models, it might be better to separate the data for grain by grain erosion and bank failure and train the models separately. However, in this study, there is not enough data for the model to be trained separately and thus all the riverbank erosion rates are combined and trained in a single model.

The model was also validated using test set to assess the performance. A total number of 66 data were used for model verification. The comparison between the training and testing results is shown in Table 9.

Table 9: Comparison of training and testing result

	Root Mean Square Error (RMSE)	Coefficient of Determination, R^2
Training data	3.70E-08	0.55
Testing data	3.88E-08	0.51

There should be a good agreement between the training and testing results. It is normal for the training accuracy to be slightly higher than testing accuracy. From the table, it can be seen that the R^2 value for training and testing model does not differ greatly. Table 10 shows the model performance of published studies on riverbank erosion prediction for rivers in Malaysia.

Table 10: Model performance of published studies on riverbank erosion prediction for rivers in Malaysia

Source	Method of Data Collections	Model Type	Model Performance
Saadon et al. [26]	Field measurement and erosion pins	Non-linear Multiple Regression	Coefficient of determination, $R^2 = 0.422$
Saadon et al. [27]	Field measurement and erosion pins	NARX-QR Factorization Model	Coefficient of determination, $R^2 = 0.740$

The result from this research was compared with results with published studies with similar methods of data collections and variables selected for model training. The table suggests that the model performance obtained from this study falls within the range of R^2 value obtained by previous study which uses similar methodology in terms of data collections. It is quite challenging to produce a riverbank erosion rate predictive model with high accuracy using the field measurement method as there are some limitations to it such as loss of erosion pins that could lead to missing data. Models that are generated using remote sensing data usually yield higher accuracy. However, field measurement is better suited for small rivers such as Sungai Pusu as the data from remote sensing will not be as accurate due to geometric distortion. This kind of error greatly affects the results obtained for small rivers.

4. CONCLUSION

In conclusion, the aims of the study have been achieved. This research was carried out to quantify the riverbank erosion rates at Sungai Pusu, through field measurement and to generate a model that incorporates soil erodibility parameters to estimate riverbank erosion for a river that is susceptible to erosion.

It can be seen from the result that Model 2, which incorporates parameters from the soil characteristics and properties category performed better compared to the Model 15 which excluded the soil characteristics and properties variables. Model 2 has a significantly higher R^2 value and lower RMSE value. Model 2 was selected as the best model with RMSE of 3.70E-08 and R^2 value of 0.55. The model produced will be helpful to predict the riverbank erosion for river susceptible to bank erosion.

Future improvement of this research can be made to further refine the results obtain from the research. This study mostly focused on soil physical properties such as mean particle diameter, soil composition, porosity, plasticity index, specific gravity, critical shear stress, and soil erodibility coefficient. Other soil parameters such as soil organic matter, infiltration capacity, stability and chemical constituents can be studied further to develop a more accurate predictive model to estimate bank erosion rate using soil properties.

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