MULTI-LAYER PERCEPTRON MODEL FOR SOIL LOSS PREDICTION DUE TO FOREST LOGGING

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ABSTRACT

Geophysical conditions and levels of disturbances induced from forest activities have great impacts on hydrology. Clear-felling have the greatest impacts and is one of the major contributions to soil loss apart from construction of forest roads and timber harvesting. The ecological and economic forest values are largely dependent on the degree of erosion. Prediction of soil loss rate is therefore essential in order to preserve the above values. Multi-layer perception (MLP) model is proposed to predict soil loss due to forest logging in an experimental watershed comprising of three sub-catchments located in Bukit Tarek forest reserve in Malaysia. The measurement of soil loss was made in terms of sediment yield for the catchment under study. The proposed architecture uses back propagation networks with multiple hidden slabs of different activation function. The neuron architecture for each slab of the proposed models for sub-catchments 1, 2 and 3 in Bukit Tarek Watershed are 5:3:3:3:1. Five input variables namely the rainfall, length slope, soil erodibility, cropping management and conservation practice factors are used in this model. The proposed model had successfully predicted soil loss with great accuracy. This model has several advantages over other conventional methods for its simplicity and quick solution.

Keywords: *Multi-Layer Perception Model, Soil Loss*

1.0 INTRODUCTION

Soil loss estimate is very much required in the evaluation of different management practices, control techniques for forested catchments and for the purpose of watershed conservation. Soil loss that occur as a result of the construction of forest roads, timber harvesting, or fire would have detrimental effect on soil properties and structure. This is confirmed by [1] where soil erodibility is very much dependant on the surface cover and soil texture. A study carried out by [2] had found that the soil erodibility greater in areas between skid trails. [3] had confirmed the previous finding where soil erodibility is less affected in an undisturbed forest. [3] and [4] reported that soil loss from exposed areas or abandoned field would only decline over time if adequate foliage cover is provided. The above literature had provided useful information on the importance of the parameters namely vegetation cover, soil erodibilty, rainfall and length of slope to be considered in the establishment of soil loss model. The incorporation of the above parameters are supported by the Universal Soil Loss Equation (USLE).

[5] had carried out a study to evaluate the effect of land slope and vegetal cover to erosion and runoff. However, no clear criteria were given for the 13 events used in the calibration of their model. They had indicated that the runoff volumes were better simulated than erosion losses.

The most recent erosion model Reused Universal Soil Loss Equation (RUSLE) which was developed by [6] had incorporated the watershed geomorphology, soil type, land use, distribution and derivation of rainfall in their model. The use of small grids and the modeling computation had made possible the variation of variables in a watershed be included. However, the approach may be time consuming if it involves larger watershed.

The recent development was to advance towards a much simpler approach. Many had resorted to Artificial Neural Network (ANN) for various engineering applications such as hydrological rainfall runoff modeling, stream flow forecasting, groundwater modeling, water quality, water management policy, precipitation forecasting, hydrological time series and reservoir operations [7]. ANN model to predict soil erosion is indeed an alternative to the empirical models [8]. Nevertheless, the application of ANN in erosion studies has not been fully explored.

This study aims at establishing a soil loss multi-layer perception (MLP) model based on the Universal Soil Loss Equation (USLE) as an alternative to the conventional approach. Evaluation of Universal Soil Loss Equation (USLE) was made using data collected from the Bukit Tarek Experimental Watershed in Selangor. Comparative analysis had been carried out on the predicted values using USLE equation and the proposed model.

2.0 STUDY AREA

Figure 1 shows the experimental site of Bukit Tarek watershed. The watershed drains an area of about 80 hectares into the main river, Sungai Kerling. There are three sub-catchments within the watershed namely C1, C2 and C3. Sub-catchment C1 (33 hectares) acts as the control catchment. Sub-catchment C2 drains an area of approximately 34 hectares while the third sub-catchment C3 has an area of about 12.5 hectares which was established in October 1993. The watershed on the map is located at Latitude 3°31'30" North and Longitude 101°35'00" East. The catchment characteristics for sub-catchments C1 and C2 are shown in Table 1. The physiography of sub-catchment C3 is not available at the time of study. Weirs are located at the lowest contour level of the respective catchments of which all flows and eroded soils would be deposited. The catchment is drained by a third order stream that eventually flows into Sungai Jerneh, the tributary of the main river Sungai Kerling.

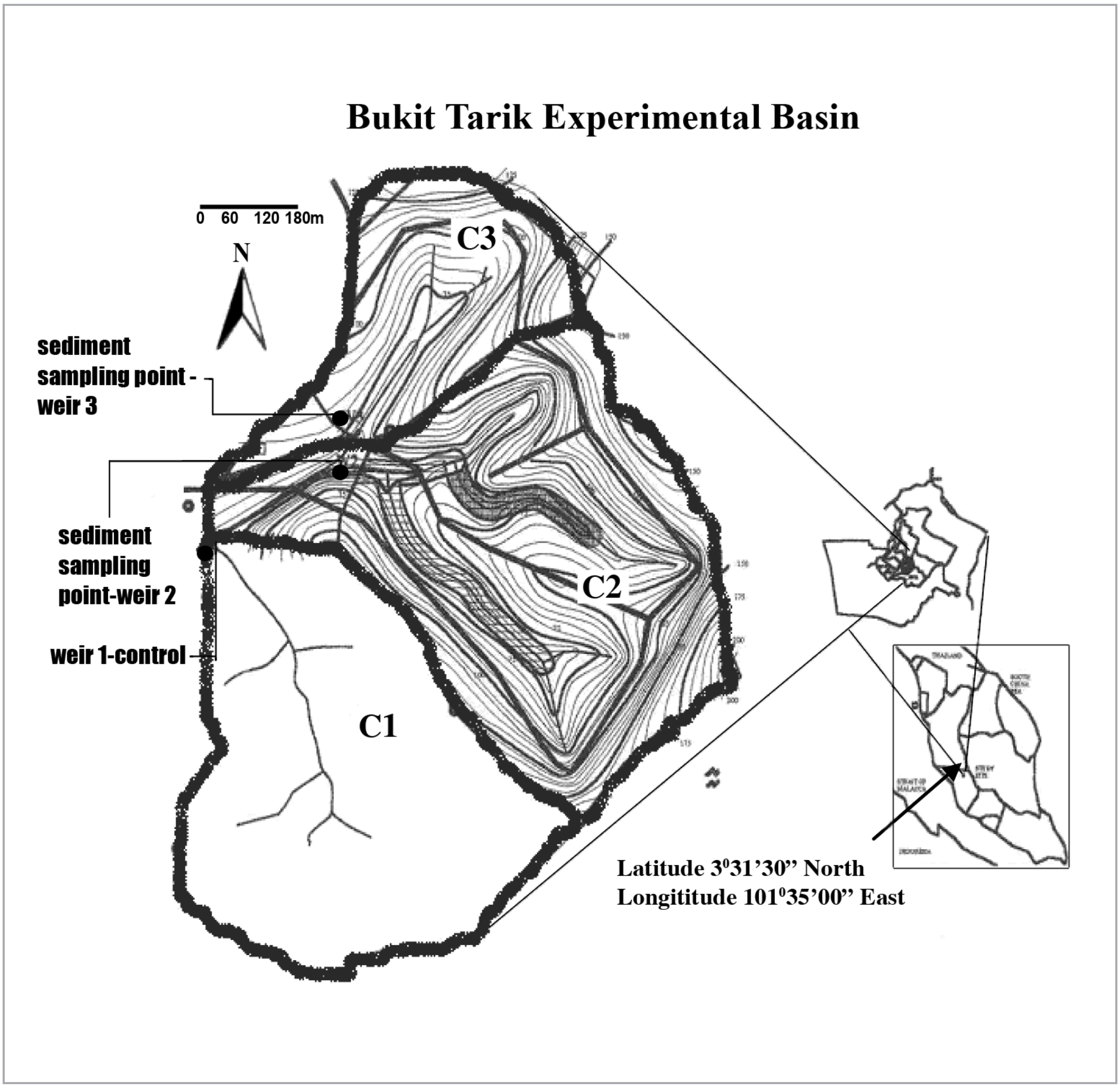

Figure 1: Bukit Tarek experimental basin [9]

Table 1: Equation and method used in determining the soil loss predictions of USLE

Characteristics	C1	C2	C3
Area (*ha*)	33	34	13
Elevation : Highest MSL Lowest MSL	 175 48	 213 53	 na na
Mean slope (%)	33	45	na
Drainage network (*m*)	1664	1660	na
Drainage density (km^2/km)	5.1	4.9	na
Length of overland flow (*m*)	130	122	na

3.0 SOIL LOSS ESTIMATION USING UNIVERSAL SOIL LOSS EQUATION (USLE)

USLE was used to estimate soil loss in forest areas. The equation is as follows,

$$A = R * K * LS * C * P$$

where A is the soil loss in tons/ha/yr ; R is the rainfall erosivity factor ; K is the soil erodibility factor ; LS is the topographic factor (slope length and steepness) ; C is the cropping management factor ; and P is the conservation practice factor.

The above equation was developed based on sediments derived from splash and sheet erosion (these are functions of soil and rainfall properties) which is specific for forest land. This equation does not consider gully or channel erosion [10]. According to [10], derivation of the USLE is specific for the forest land. Rainfall, soil erodibility, slope length, crop management and conservation practice are the four factors in this equation. Equation and method used in determining the soil loss predictors are given in Table 2.

Table 2: Catchment characteristics for sub-catchment C1 and C2 [6]

Soil loss predictors used in USLE	Equation / Method
Rainfall	R factor can be calculated using the equation proposed by Foster et al. [11] and Morgan [12] $E = 9.28$ $P = 8838.15$ Where E is annual erosivity and P is annual rainfall $R = (E*I_{30}) / (100*17.02)$
Soil Erodibility	K can be calculated by using Warrington *et. al*. [13]. The data requirements for estimating K factor are ***soil permeability, soil structure, % of organic matter, % of sand and % of silt and fine sand***. Soil series at Bukit Tarek Watershed is categorised as the Kuala Brang Soil Series and Bungor Soil Series, of which K factor for Kuala Brang Soil Series is 0.18 and Bungor Soil Series is 0.14. The above was taken from the soil survey result estimation for each grid in the (80m x 80m) plot was done using soil map.
Length Slope	LS factors was derived using the method proposed by Julien [14].
Cropping Management and Conservation Practice	C and P factors were calculated using the method Julien [15]. It was the modified version of the one proposed by Wischmeier and Smith [16].

The above equation was developed based on sediments derived from splash and sheet erosion (these are functions of soil and rainfall properties) which is specific for forest land. This equation does not consider gully or channel erosion [10]. According to [10], derivation of the USLE is specific for the forest land. Rainfall, soil erodibility, slope length, crop management and conservation practice are the four factors in this equation. Equation and method used in determining the soil loss predictors are given in Table 2.

In this study, a smaller grid size of 80m x 80m was used to estimate length of slope factor. Smaller grids would yield better accuracy in the estimates for rainfall, soil erodibility and vegetation covers. The factor values for every grid are used as data input for the model. Summary of the range of maximum and minimum soil loss estimates and statistical analysis for the respective catchments are given in Table 3.

Table 3: Summary of range of soil loss estimates and statistical analysis for the three catchments

	C1	C2	C1
Min (*t/ha/yr*)	0.3781	0.7824	8.5183
Max (*t/ha/yr*)	0.7194	2.1866	16.4071
Mean	0.5242	0.5242	11.9447
Median	0.5318	1.4267	12.2963
Std Deviation	0.1044	0.3508	2.4708
Variance	0.0109	0.1231	6.1048

This study had used USLE as the basis for computation of soil losses. Table 4 shows the range of values of soil loss predictors used in the analysis. The mean rainfall factors used in the analysis vary in the range from 852 to 872 mm. The mean soil erodibility factor is 0.16 for all sub-catchments and is categorised as Kuala Brang and Bungor Soil Series. Mean length of slope values are in the range of 9.0 to 15.5.

Mean of crop management and conservation practice factors are in the range of 0.001 to 0.003 and 0.12 to 0.3 respectively. The conservation practice factor depends on the type of activities in the watershed. There are substantial differences between the sub-catchments C2 and C3 as buffer zone has been established for sub-catchment C2. While in sub-catchment C3, no buffer zone is available. In assessing soil losses in forest areas, it is also necessary to account for the different forest treatment such as clear felling of trees, burning, re-planting and other activities. Due to the limitation of the current approach, the above may be difficult to incorporate.

Table 4: Range of values of soil loss predictors for sub-catchments C1, C2 and C3 used in the evaluation of USLE

Sub-Catchment	Soil loss predictors used in USLE	Values	
		Range	Mean
C1 (control catchment)	*R*	615.0 – 1170.4	852.8
	K	0.14 – 0.18	0.16
	LS	1.6 – 55.5	15.5
	C	0.0001 - 0.001	0.00055
	P	0.12	0.12
	A (tons/ha/year)	***0.38-0.72***	***0.52***
C2 (clear felling with residual trees left at the site - with buffer zone)	*R*	419.2 – 1171.7	804.3
	K	0.14 – 0.18	0.16
	LS	1.3 – 46.5	9.2
	C	0.003 – 0.009	0.006
	P	0.12	0.12
	A (tons/ha/year)	***0.78 – 2.19***	***1.50***
C3 (Clear felling but the residual trees were burnt - no buffer zone provided)	R	621.9 – 1197.9	872.3
	K	0.14 – 0.18	0.16
	LS	2.5 – 48.0	8.8
	C	0.003 – 0.009	0.006
	P	0.3	0.3
	A (tons/ha/year)	***8.52 – 16.41***	***11.94***

Note: *R factor can be calculated using the equation proposed by Foster et. al. [11] and Morgan [12]. The values for the K factor can be calculated using Warrington et. al. [13]. LS factors can be derived using the method proposed by Julien [14]. Cropping management factor, C and conservation practice factor, P can be using the method proposed by Julien [15] which the methods had modified after Wischemeier and Smith [16].*

4.0 PROPOSED MULTILAYER PERCEPTRON SOIL LOSS MODEL

The NeuroShell 2 developed by the Ward Systems Group Inc. is used in this study. The software is a window based system that runs under the Windows 95 operating system. The various steps involved in the development of the ANN Soil Erosion Model are discussed at length in this section. This section presents the development of the proposed model using Multilayer Perceptron Model network structure with back-propagation algorithm. Development of the proposed ANN soil loss model had undergone a series of processes such as variable selection, designation of neural network architecture, training, testing, production and validation phases.

During the preprocessing stage, the data were grouped into three distinct sets called training, testing, production or validation sets. Design and test options were chosen for the designation of neural network architecture specifically for training and testing phases. The training set would be the largest set used by neural network to learn patterns present in the data. The testing set is used to evaluate the generalisation ability of the supposedly trained data set. Test set extraction was used to separate a test data set from the training data. A final check on the performance of the trained network was made through the production set of the trained model.

The soil loss predictors (*R, K, LS, C* and *P*) in each grid size serve as inputs in the proposed model. All data had undergone rigorous screening before they were used for model development and model testing. The robustness of the proposed model can be confirmed through the production phase. In this phase, the targets (measured soil loss value) were removed. There were only the input parameters that were being fed into the model. The performance of the trained network is measured from the discrepancy ratio. Predicted soil erosion values given by the model are solely based on the selected architecture, momentum and the learning rate parameters of the trained network. The ratio of the predicted soil loss values (calculated using the trained network) to measured soil loss values were then determined. Predictions are deemed accurate if the values lie between the discrepancy ratios of 0.5 to 2.0. About 80% and 20 % of data were used in the training and testing phases, respectively.

The selected architecture for the proposed network is error-back propagation algorithm with multiple hidden slabs of different activation function. Back propagation network was chosen because of their ability to generalise well on a wide variety of problems. According to [8], back-propagation network is a supervised type of network that uses both inputs and outputs in training the model. However, training may be slower than other paradigms (architecture) depending upon the number of pattern. Degree of accuracy will increase by creating a separate network for each output.

The hidden layers in a ward network function act as feature detectors. Selection of ward networks is based on the suitability of the input data. Different activation functions for the different hidden layers of each slab detect different features of pattern processes through the network. The output layer will consists of different views of data that combines two feature sets that may lead to better estimates.

The detail design of neural network architectures for sub-catchments C1, C2 and C3 are illustrated in Figure 2. Number of neurons refer to the parameter predictors (*R, K, LS, C* and *P*) that are used to estimate the amount of soil loss. The neuron are then distributed to the system network for computation of soil loss in the system. In back-propagation, the network computes the mean (average) squared error between the actual and predicted values for all outputs over all patterns. The way it works is that the network first computes the squared error for each output in a pattern, totals them, and then computes the mean of the total for each pattern. The network then computes the mean of that number over all patterns in the training set. According to [17], a learning rate is used to increase the chance of avoiding the training process being trapped in a local minimum instead of global minimum.

Calibration interval refer to the specific number of events or test set patterns that are propagated through the network before the average error for the test set is computed. This is imperative in the testing phase. Calibration finds the optimum network for the data in the test set (which means that the network is able to generalise well and give good results on new data). Calibration does this by computing the mean squared error between actual and predicted for all outputs over all patterns. Calibration computes the squared error for each output in a pattern totals them and then computes the mean of that number over all patterns in the test set.

To design a neural network that gives the best estimate for soil loss when compared against the measured soil loss would involve several trial runs with different options for the momentum and learning rate parameters. The model development involved training of the input data to get the best model that can accurately predict soil loss.

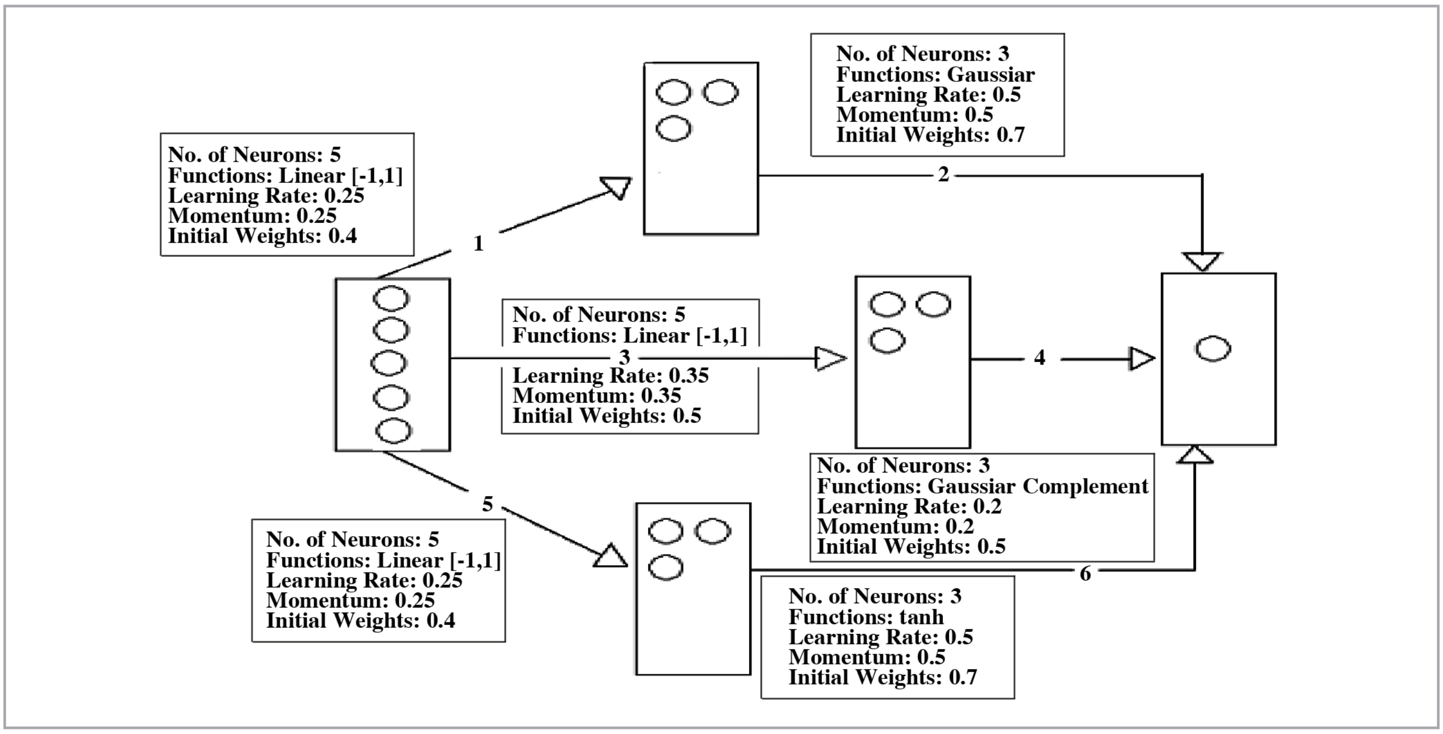

Figure 2: Neural network architecture design for sub-catchments C1, C2 and C3 of Bukit Tarek Watershed

All catchment possesses specific design for the neural network architecture. Training of the model stops once the best prediction is achieved. This is based on the training graphics and trial output processor. More often in training a network, its performance will continue to improve (measured relative to the training data) albeit at an ever decreasing pace. However, when performance is measured relative to a set of test patterns (not used for training) the performance will usually stop improving after a while, and often will start to degrade. Since the test patterns provide a more accurate assessment of the generalised performance of the network, it is best to cease training when performance is optimum relative to the testing set. The training time used for all sub-catchments is 5 minutes and the calibration interval is set at 300.

5.0 RESULTS AND ANALYSIS

Three hidden slabs with different activation function were chosen as the neural network architectural design for all sub-catchments in Bukit Tarek Watershed. The proposed architecture consists of an input layer with three hidden slabs and one output layer. The designed architecture for all sub-catchments consists of 5 neurons in the input layer, 3 neurons in each of the three hidden slabs and 1 output neuron (predicted value) in the output layer. The neural network architecture Bukit Tarek Watershed catchments can be summarised as 5:3:3:3:1. The momentum, learning rate parameters and the functions used for both architectures differ from one layer to the other. Total grid for 16 years analysis for sub-catchment C1 and C2 are 992 and 1728, respectively. The total grid for sub-catchment C3 is 1428 for 12 years grid analysis.

The performance of the model in training and testing phases are as shown in Figures 3, 4 and 5 for sub-catchments C1 , C2 and C3 ; respectively. The soil loss ANN prediction is given in *t/ha/yr*. In the production phase only 10% of the total grid data was used to predict soil loss without the presence of the measured values. This is to test the reliability and the robustness of the model to estimate soil loss.

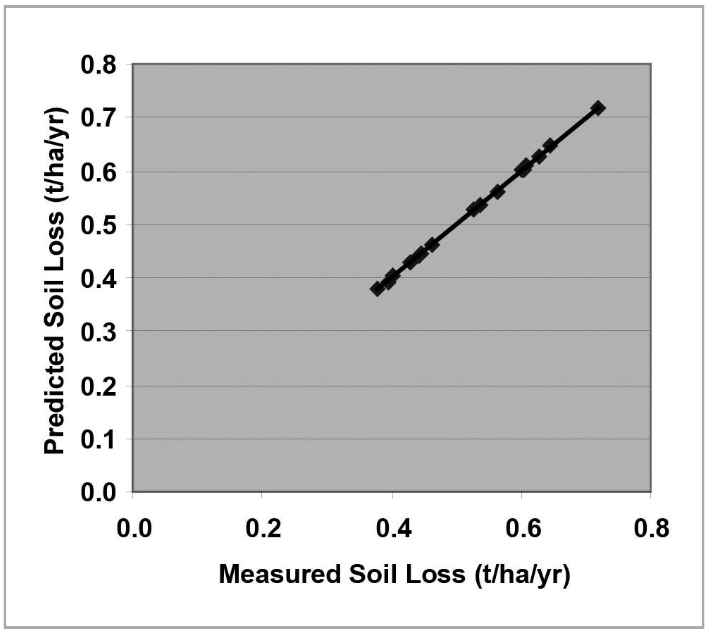

Figure 3: Predicted versus measured values for sub-catchment C1

All graphs show very good fit between the ANN predicted and measured soil loss using USLE. Results of the analysis had indicated perfect prediction of soil loss using the proposed model and the significance of the USLE parameters as soil loss predictors.

The values of soil loss and statistical interpretation outputs for sub-catchments C1, C2 and C3 are given in Tables 5, 6 and 7. From analysis and results confirmation, soil loss prediction using Artificial Neural Network Model showed very good prediction with *R, K, LS, C* and *P* as predictors. The proposed neural network architecture for Bukit Tarek Watershed catchment is 5:3:3:3:1.

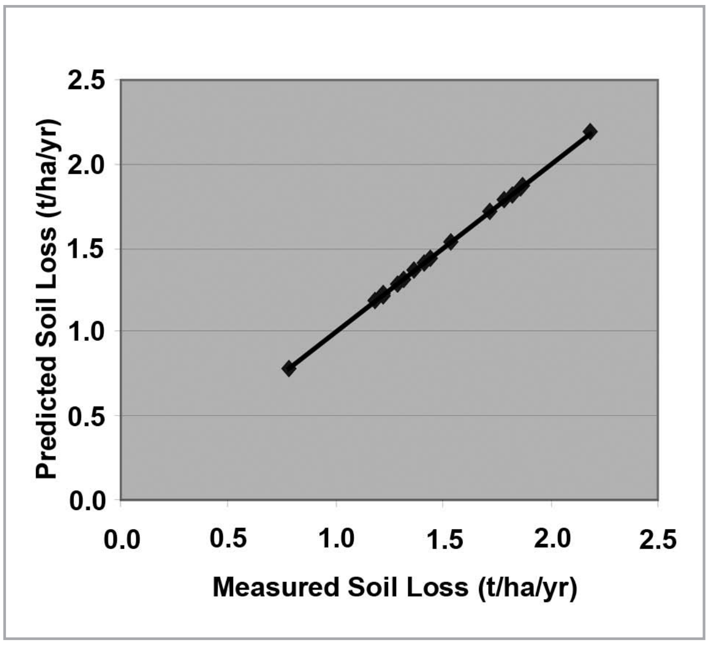

Figure 4: Predicted versus measurd values for sub-catchment C2

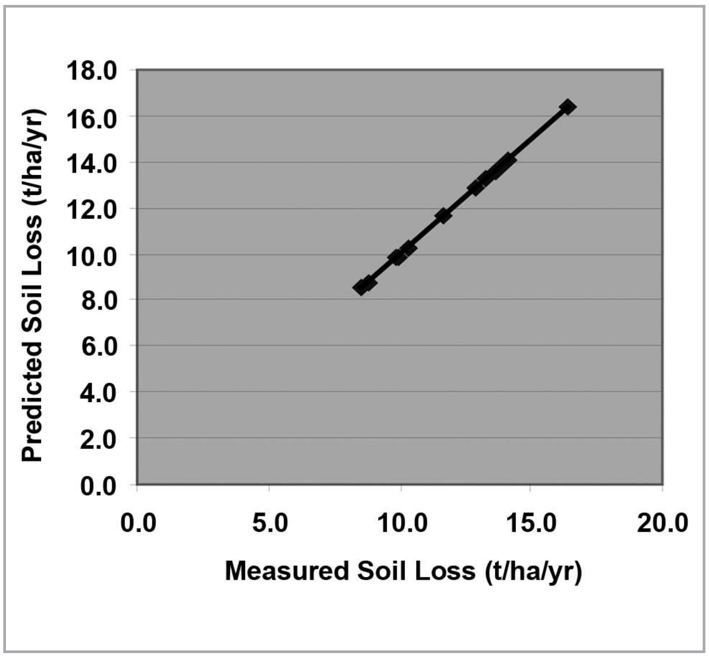

Figure 5: Predicted versus measured soil loss in sub-catchment C3

Table 5: Summary of statistical analysis for sub-catchment C1

	USLE (*t/ha/yr*)	Proposed model (*t/ha/yr*)
1989	0.4273	0.4273
1990	0.4030	0.4028
1991	0.6462	0.6460
1992	0.4626	0.4623
1993	0.6092	0.6092
1994	0.4454	0.4456
1995	0.6021	0.6015
1996	0.5625	0.5624
1997	0.3938	0.3936
1998	0.3781	0.3779
1999	0.6027	0.6020
2000	0.6272	0.6268
2001	0.4436	0.4433
2002	0.5358	0.5359
2003	0.7194	0.7190
2004	0.5279	0.5279
Mean	0.5242	0.5240
Min	0.3781	0.3779
Max	0.7194	0.7190
Median	0.5318	0.5319
Std. Deviation	0.1044	0.1043
Variance	0.0109	0.0109

Table 6: Summary of statistical analysis for sub-catchment C2

	USLE (*t/ha/yr*)	Proposed model (*t/ha/yr*)
1989	1.3178	1.3172
1990	1.2234	1.2229
1991	1.8725	1.8716
1992	1.4387	1.4380
1993	1.8204	1.8193
1994	1.2887	1.2883
1995	1.7827	1.7816
1996	1.7173	1.7166
1997	1.1872	1.1866
1998	0.7824	0.7819
1999	1.4147	1.4136
2000	1.8604	1.8592
2001	1.3667	1.3661
2002	1.5377	1.5370
2003	2.1866	2.1859
2004	1.2188	1.2182
Mean	1.5010	1.5002
Min	0.7824	0.7819
Max	2.1866	2.1859
Median	1.4267	1.4258
Std. Deviation	0.3508	0.3507
Variance	0.1231	0.1230

Figures 6, 7 and 8 show the graphs of ANN prediction versus USLE estimates in the production phases for sub-catchments C1, C2 and C3; respectively. The graphs show very good fit between the values predicted using ANN model and USLE equation. The model yields 100% accuracy in the production phase for sub- catchments C1 and C2 using a total of 160 grids. For sub-catchments C3, the model showed 95% accuracy with a total of 480 grids in the production phase. The statistical interpretation for sub-catchments C1, C2 and C3 are given in Table 8.

Table 7: Summary of statistical analysis for sub-catchment C3

	USLE (t/ha/yr)	Proposed model (t/ha/yr)
1993	13.2882	13.2485
1994	10.2964	10.2968
1995	13.9269	13.9192
1996	12.9138	12.9187
1997	8.5183	8.5398
1998	8.8154	8.7885
1999	14.1228	14.1123
2000	13.6353	13.6017
2001	9.8138	9.8250
2002	11.6787	11.6443
2003	16.4071	16.3854
2004	9.9191	9.8500
Mean	11.9447	11.9275
Min	8.5183	8.5398
Max	16.4071	16.3854
Median	12.2963	12.2815
Std. Deviation	2.4708	2.4670
Variance	6.1048	6.0863

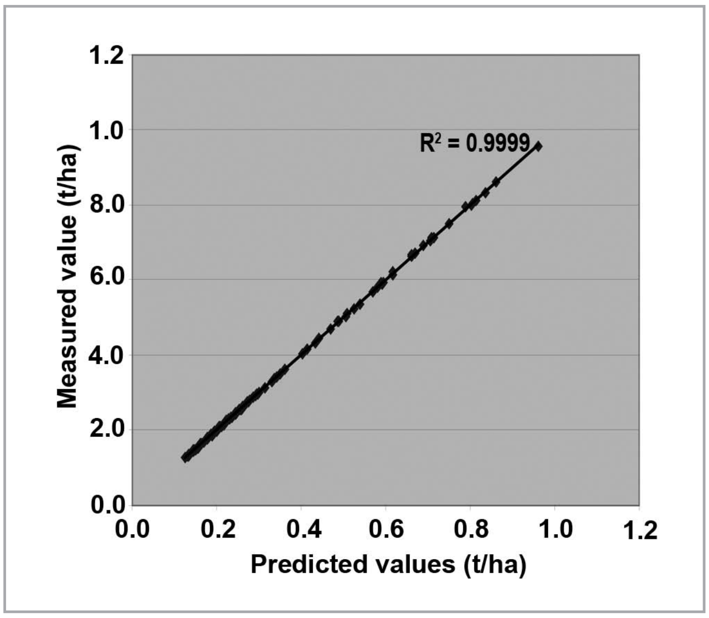

Figure 6: Graph of ANN predicted versus measured values in the production phase for sub-catchment C1

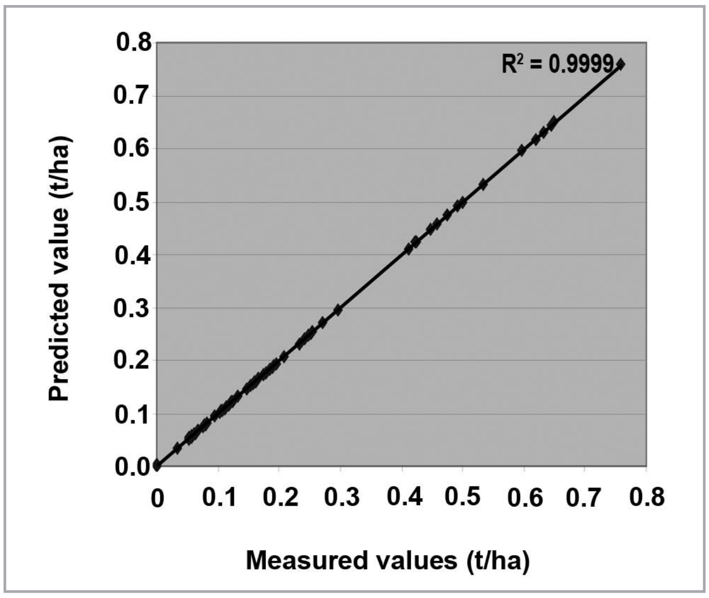

Figure 7: Graph of ANN predicted versus measured values in the production phase for sub-catchment C2

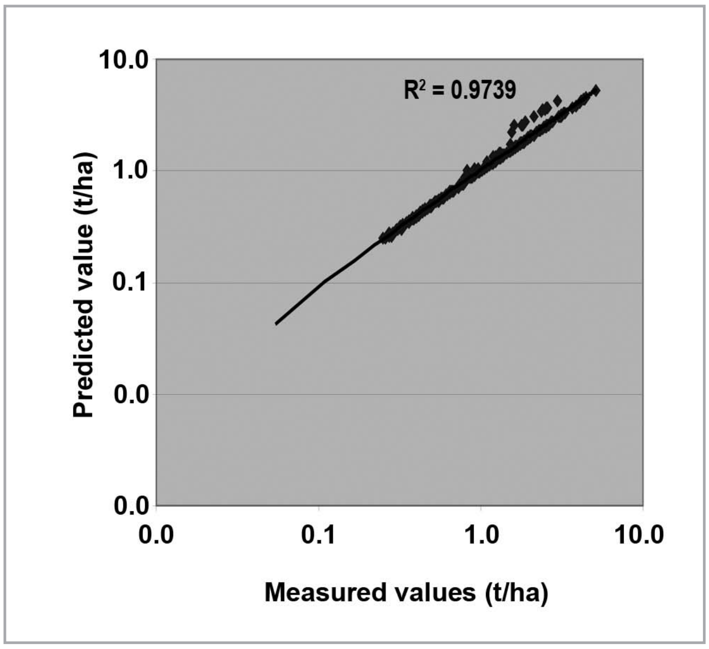

Figure 8: Graph of ANN predicted versus measured values in the production phase for sub-catchment C3

6.0 CONCLUSION

A soil loss multi layer perceptron model has been successfully developed and proposed for the experimental watershed of Bukit Tarek, Malaysia using back-propagation algorithm. The neuron architecture for each slab of the proposed model for sub-catchments 1, 2 and 3 in Bukit Tarek Watershed are 5:3:3:3:1. The derived model is applicable only for use in catchment where forest logging activity is evident.

An improved and a more reliable soil loss model of short processing time would be an advantage for the preservation of the environment. This development would be useful in strategising the appropriate conservation measure and should benefit the relevant agency in institutionalising the guidelines for soil conservation practice.

Table 8: Summary of analysis for sub-catchments C1, C2 and C3 in the production phase

	Sub-catchment C1		Sub-catchment C2		Sub-catchment C3	
	USLE (t/ha)	*Proposed Model (t/ha)*	*USLE (t/ha)*	*Proposed Model (t/ha)*	*USLE (t/ha)*	*Proposed Model (t/ha)*
Mean	0.2977	0.2984	0.1457	0.1457	1.0751	1.0968
Min	0.1263	0.1258	0.0000	0.0015	0.0000	0.0012
Max	0.9602	0.9578	0.7586	0.7586	5.1723	5.2017
Median	0.2255	0.2265	0.0952	0.0948	1.0640	1.0663
Std. Deviation	0.1879	0.1879	0.1536	0.1530	0.8237	0.8618
Variance	0.0353	0.0353	0.0236	0.0234	0.6784	0.7426

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