CIVIL & ENVIRONMENTAL ENGINEERING | RESEARCH ARTICLE

Quantitative analysis of soil erosion causative factors for susceptibility assessment in a complex watershed

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Abstract: Susceptibility analysis and mapping are prerequisites to sustainable land-use management and erosion prevention. Selection of appropriate erosion causative factors (CFs) is crucial in developing valid and accurate susceptibility models. However, existing literature lacks specific guidelines for its selection. As such, some important dynamic CFs are often not considered in several previous studies. Thus, this study quantitatively evaluates the impacts of the addition of dynamic CFs to frequently used non-redundant static CFs in erosion susceptibility mapping using remote sensing, geographic information system (GIS) and statistical technique. Revised universal soil loss equation (RUSLE) was used to quantify soil loss and CFs’ maps for Cameron Highlands were developed in the GIS environment. The watershed was delineated, and the corresponding CFs were evaluated for each sub-watershed. The frequently used

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PUBLIC INTEREST STATEMENT

In Cameron Highlands Malaysia, soil erosion is a serious environmental challenge due to extensive urban development, intensive agricultural activities, massive land clearing and indiscriminate deforestation. Some of the challenges currently experienced are deteriorating water quality, reservoir sedimentation, landslides, etc. Increasing human-environment interactions coupled with natural topography have increased the ecological disturbances. Sustainable management practices that will dampen these challenges include quantification of erosion, analysing its spatial distribution, identifying critical locations and evaluating its susceptibility. Susceptibility mapping measures the relative probability of erosion occurrence at a certain location compared to others under the influence of causative factors (CFs). Previous studies showed a lack of specific guidelines in selecting CFs for adequate susceptibility analysis. Thus, some crucial dynamic CFs are often not considered. This study quantitatively evaluates the impacts of the addition of dynamic CFs to frequently used non-redundant CFs for accurate susceptibility mapping using remote sensing, geographic information system and statistical techniques.
non-redundant CFs considered were lineament density, drainage density, soil erodibility, length-slope and normalized difference vegetation index. Hierarchical regression technique was adopted to evaluate the impacts of the addition of land surface temperature (LST), rainfall erosivity and soil moisture index (SMI). The results revealed that frequently used CFs accounted for 17.9% variation in soil loss. However, the successive inclusion of dynamic CFs such as LST, rainfall erosivity and SMI to the model further increased by 28.9%, 6.0% and 16.4%, respectively. This suggests that dynamic CFs, which often neglected in erosion susceptibility assessment could further increase modelling accuracy.

Subjects: Hydrology; Surface Hydrology; Environmental Health; Geomechanics; Georisk & Hazards; GIS, Remote Sensing & Cartography

Keywords: Soil erosion; susceptibility mapping; static and dynamic causative factors; hierarchical regression

1. Introduction
Soil erosion is an environmental problem that degrades land, threatens agricultural productivity and hydrologic systems in the watersheds. It is caused by extensive human-environment interactions through agricultural practices, urbanization, construction and deforestation (Ochoa et al., 2016; Panagos, Borrelli, & Meusburger, 2015). These activities impact on soil characteristics and reduce the land-cover that provides stability to the soil. Climate, topography, vegetation cover, land-use pattern and soil characteristics are biophysical factors aiding soil erosion processes. These make the processes uncertain and complex (Sun, Shao, Liu, & Zhai, 2014; Xu & Chen, 2005). The biophysical factors vary from one region to another, thus necessitate site-specific studies for sustainable erosion management (Brunner, Park, Ruecker, Dikau, & Vlek, 2004; Veih, 2000). Optimal watershed management to alleviate erosion challenges could be achieved when its magnitude, spatial distribution and susceptibility levels are adequately assessed (Rahman, Shi, & Chongfa, 2009; Vahabi & Nikkami, 2008). Researchers have developed several qualitative and quantitative (statistical) models for erosion assessment. Some of the available models are Universal Soil Loss Equation (USLE), its revised and modified versions, Erosion Productivity Impact Calculator (EPIC), European Soil Erosion Model (EUROSEM) and Water Erosion Prediction Project (WEPP). Many of the models are integrated with remote sensing and geographic information system (GIS) for easier and comprehensive analyses. Application of these techniques has increased due to their user-friendliness, low cost and availability of medium to high-resolution remote sensing data (Ali & Hagos, 2016; Meshesha, Tsunekawa, Tsubo, Ali, & Haregeweyn, 2014).

Statistical techniques have been adopted to evaluate and map the potential locations within the watershed that could experience soil erosion. This is required to mitigate erosion impacts and its related hazards. In achieving this, potential causative factors (CFs) i.e., watershed characteristics must be sufficiently evaluated (Rahman et al., 2009). Survey of the literature revealed that various erosion CFs and methods have been adopted in susceptibility analyses. Some of the methods employed in the previous works include logistic regression (Akgün & Türk, 2011; Conoscenti et al., 2014); analytical hierarchy process technique (Rahman et al., 2009); sensitivity analysis approaches (Mendicino, 1999); stochastic gradient treeboost (Angileri et al., 2016); weighting overlay (Dube et al., 2014; Magliulo, 2012; Mitasova, Hofierka, Zlocha, & Iverson, 1996); soft computing method (Gournellos, Evelopidou, & Vassilopoulos, 2004); fuzzy and artificial neural-network evaluation methods (He, 1999); bivariate method (Conforti, Acelli, Robustelli, & Scarciglia, 2011; Lucà, Conforti, & Robustelli, 2011; Magliulo, 2012). An in-depth evaluation of these studies and other related research showed that different numbers of potential CFs were considered that are static in nature. This category of CFs remains the same for a relatively long period of time despite changes in rainfall. However, some dynamic factors such as land surface
temperature (LST), rainfall erosivity and soil moisture index (SMI) are not considered due to data unavailability. Ali and Hagos (2016) highlighted that type and quality of factors considered in the analysis affect susceptibility results. Redundant CFs should be avoided (Ayalew & Yamagishi, 2005; Magliulo, 2012) as these would have double influence in the analysis thereby causing over-weighting of the model (Conforti et al., 2011). For instance, combined application of length-slope (LS), topographic wetness index (TWI), plan curvature and stream power index (SPI) together with slope angle could be regarded as redundant CFs. This is evident in the relationship between the aforementioned CFs and slope angle, although they are geomorphologically and hydrologically significant in soil erosion process (Magliulo, 2012). Remondo et al. (2003) emphasized that increasing the number of CFs does not necessarily increase the accuracy of susceptibility models as long as the factors are redundant. Conversely, Tehrany, Pradhan, Mansor, and Ahmad (2015) cited Donati and Turrini (2002) to have reported that researchers believed that the accuracy of susceptibility mapping increases with increase in the number of CFs. Addition of dynamic CFs to non-redundant static factors necessitate quantitative analysis to explain their behaviours in triggering erosion and to assess the potential improvement in the model’s accuracy. Hence, the objectives of this study are (i) to analyse the influence of CFs on the occurrence of soil erosion by considering heterogeneous nature of complex watershed (ii) to examine the impacts of the addition of dynamic CFs to frequently used non-redundant static CFs in erosion susceptibility mapping. Remote sensing, GIS and hierarchical regression techniques were explored to effectively evaluate the model performance by considering dynamic CFs which have suffered neglect in most reported susceptibility studies. Since the contributions of each factor are not uniform, hence there is a need to investigate their relative importance. The hierarchical regression technique was preferred to stepwise regression and partial least-square regression because it allows researchers to decide on what and when a particular variable (factor) can be selected in the analysis. Mountainous Cameron Highlands watershed was chosen for this study due to its complex nature and incessant occurrence of erosion. The output of the study would be useful in identifying and evaluating the impacts of erosion CFs necessary to be considered for erosion susceptibility mapping.

1.1. Description of the study area

Cameron Highlands (Figure 1) located in Pahang State, Malaysia was selected as the study area. It has a total area of approximately 175,978 acres representing about 2% of the State’s landmass area. Meteorological records indicated temperature range of 21–32°C (Sujaul, Sahid, Gasim, Rahim, & Toriman, 2015) and rainfall of 2,800 mm (Gasim et al., 2009), with the western foothill areas...
receiving higher precipitation compared to mountainous areas with peaks in the months of May and October (Aminuddin, Ghu lam, Abdullah, Zulkefi, & Salama, 2005). The monsoon system is very significant in controlling rainfall distribution. Northeast monsoon in Malaysia, falls between November and January resulting in high rainfall that can trigger erosion (Matori, Basith, & Harahap, 2011). Southwest monsoon periods fall between April and May with relatively low rainfall in West Malaysia compared to northwest monsoon period. However, the hottest and driest days occur in between the two monsoons (inter-monsoon) periods (Basith, 2011) which falls between June and October. The east coast of the Peninsular usually experiences heavy and continuous rainfall season during the northeast monsoon which is mainly caused by cold surges (Azemi et al., 2015). Cameron Highlands is characterized as a complex landscape having elevation ranges between 1000 m and 2031 m above mean sea level. Its terrain is predominantly steep with about 60% of the land areas steeper than 20°. Topographic nature of the area coupled with heavy rain makes it highly prone to erosion and landslides (Pradhan, 2010). In a report by World Wildlife Fund Malaysia (2002), 81% of the Cameron Highlands watershed has high erosion risk due to increased human activities and nature of the watershed. These have led to encroachment to hilly zones which have resulted in land degradation by soil erosion. The study area is one of Malaysia’s most important vegetable growing regions. The region has a cool temperature that often attracts local and international tourists. Cameron Highlands are deteriorating, and the region is becoming warmer due to extensive land-use changes (Lim, 2013). According to Mohd, Karim, Mokhtar, Gazim, and Abdullah (2010), about 2,000 ha of forest areas have been converted to agricultural lands. Market gardening, floriculture, mixed agriculture, tea and orchard constitute more than 11,000 ha. The list of activities contributing to soil loss and the amount contributed are reported by Mohd et al. (2010).

1.2. Potential soil erosion causative factors

Human-environment interactions that bring about land-use changes subject watersheds to soil erosion (Castro, Sanchez-Azofeifa, & Rivard, 2003). The occurrence of soil erosion is driven by a number of watershed characteristics (i.e., erosion CFs). These include soil texture, permeability, antecedent moisture, rainfall intensity, land-use pattern, vegetation cover and slope as highlighted by Vahabi and Nikkami (2008). Sustainable land-use management to alleviate erosion risk necessitates the understanding of erosion mechanisms and interactions among the CFs (Ochoa et al., 2016). Thus, the impacts of watershed characteristics on soil erosion need to be studied for adequate analysis of susceptibility that is required for prevention strategies. This would enhance the understanding of the relationship of hydrologic systems with natural and agricultural landscapes (Chatterjee, Krishna, & Sharma, 2014). Studies have shown that a relatively large watershed exhibit varying levels of erosion susceptibility at different locations due to the uniqueness of some landscape units (known as sub-watersheds) (Chatterjee et al., 2014). In order to capture this uniqueness, analysis of erosion CFs is better done at the sub-watershed scale having different levels of human activities (Bakker et al., 2008). In many studies, watershed characteristics are classified broadly into topographical, lithological, land-cover characteristics (Prosdocimi, Cerdà, & Tarolli, 2016), climate and agriculture practices (Angileri et al., 2016). Some other studies classified them into erodibility and erosivity factors. The former is related to proneness of soil to erosion while the latter is related to the potentiality of running water and topography to initiate erosion. Erodibility factors are fragmented into land cover, weathering grades of the rocks, lineament density, soil texture, etc., while slope angle, profile curvature, stream power index, drainage density, sediment transport index and topographic wetness index represent the erosivity factors. Previous studies revealed that these factors interact with one another and result in degradation of watersheds. For instance, an increase in terrain slope angle decreases the infiltration rates and increases run-off volume. An increase in run-off volume favours initiation of soil erosion in the watershed (Ganasri & Ramesh, 2016). Also, the nature of the available soil, management practices together with rainfall rates and intensities within watersheds influence the actions of run-off on erosion (Brunner et al., 2004). Inherent soil texture, depth, organic matters and stoniness determines the erodibility level (Alaaddin, Recep, & Abdullah, 2008) while cohesiveness of soil is influenced by human activities (Pal, 2016). Slope aspect is another erosion CFs that expresses...
the degree of exposure of soil to sunlight and other climatic conditions (Pulice et al., 2009). Sultan, Wu, and Ahmed (2016) reported that topographic factors have a direct effect on the incoming solar radiation. This affects total heat energy received by the land surface and available soil moisture content which have been substantiated to influence erosion (Abdulkadir, Muhammad, Khamaruzaman, & Ahmad, 2018; Xue, Luo, Zhou, Sherry, & Jia, 2011). The magnitude of increase in run-off volume depends on the increase in antecedent soil moisture (Vahabi & Nikkami, 2008). In complex terrains, LST distribution is influenced by topography through the connection of different factors (Abdulkadir, Muhammad, Khamaruzaman, & Ahmad, 2017a; Mallick, 2014). Sun et al. (2014) observed that the correlation between rainfall erosivity depends upon land-use and land-cover conditions. Brunner et al. (2004) emphasized that soil properties are dynamic in nature which change with prevailing weather conditions, vegetation cover and land management practices. The complex interaction among these factors has hindered accurate erosion prediction or measurement (Vijith, Suma, Rekha, Shiju, & Rejith, 2012).

A vast literature on soil erosion susceptibility mapping considered majorly static CFs as earlier pointed out in the introductory section of this article. It was also observed that various researchers considered varying numbers and types of CFs without paying attention to its effect on the overall susceptibility model results (Abdulkadir, Muhammad, Khamaruzaman, & Ahmad, 2017b). For instance, Lucà et al. (2011) considered eight CFs which includes lithology, land-use, slope, aspect, TWI, SPI, LS-factor and curvature. Abdulkadir et al. (2017b) reported other researchers such as Akgün and Türk (2011) and Dube et al. (2014) to have considered seven CFs; Conoscenti, Di Maggio, and Rotigliano (2008) and Kachouri, Achour, Abida, and Bouaziz (2015) considered six CFs; Angileri et al. (2016) used 12 CFs; Vijith et al. (2012) and Shit, Pairo, Bhunia, and Maiti (2015) eight CFs; and Conoscenti et al. (2014) considered 27 CFs. The details of actual CFs used and methods adopted for the analysis could be found in their respective reports and some in the review prepared by Abdulkadir et al. (2017b). Careful examination of the above studies revealed that some redundant CFs which ought to be exempted according to Magliulo (2012), were implemented in the analysis. However, some crucial dynamic CFs such as LST, SMI and rainfall erosivity were not considered despite their roles in triggering erosion. These CFs are termed dynamic factors in the context of this study because they change during different rainfall cycle.

2. Methodology

2.1. Soil erosion estimation and CFs

The revised universal soil loss equation (RUSLE) empirical model was used for the quantification of soil loss. This was achieved by parameterizing, classifying and combining erosion biophysical factors in Equation 1 to quantify soil loss in the watershed (Renard, Foster, & Weesies, 1997). The biophysical factors include rainfall erosivity, soil erodibility, slope length, cover and management, and supporting practices factors. The procedures for estimation of these factors and soil loss can be found in many studies (Farhan, Zregat, & Farhan, 2013; Ghosh, De, Bandyopadhyay, & Saha, 2013; Javed, Yasser, Shams Al-Deen, & Mohd, 2014; Kamaludin et al., 2013; Khosrokhani & Pradhan, 2014; Parveen & Kumar, 2012; Wolka, Tadesse, Garedew, & Yimer, 2015). The resulting soil loss map for the study area is presented in Figure 2(a). For the quantitative analysis of CFs, eight (8) prominent factors were selected after careful redundancy analysis of previously reported factors in the literature. The CFs include drainage density, lineament density, length-slope and soil erodibility as static factors, and LST, SMI and rainfall erosivity representing dynamic factors. These CFs were prepared using ArcGIS 10.2, ENVI 5.1 and Geomatica 2016. The drainage density and length-slope factor maps were derived from hydrologically corrected digital elevation model (DEM). The erosivity factor map was derived from synoptic weather stations within and around the study area using mathematical expression proposed by Wischmeier and Smith (1978). Rainfall data for computation of rainfall erosivity were obtained for each of the weather from the Malaysia Department of Irrigation and Drainage (DID). Erodibility map was derived from soil map obtained from a digital soil map of the world retrieved from U.S. Food and Agriculture Organization (FAO) archive. LST, SMI, NDVI and lineament density were derived from atmospherically corrected
Landsat 8 downloaded from U.S. Geological Survey's database for the area under consideration. The resulting maps for the CFs are presented in Figure 2(b-i).

\[ A = R \times K \times LS \times P \times C, \]  

(1)

where \( A \) = average annual soil loss (ton/ha/yr), \( R \) = rainfall erosivity factor (MJ mm/ha/yr), \( K \) = soil erodibility factor (ton ha/MJ/mm), \( LS \) = slope length factor, \( C \) = cover and management factor and \( P \) = supporting practices factor.

Cameron Highlands watershed was delineated into 64 distinct sub-watersheds to capture the heterogeneity nature of watershed responses to soil erosion. Then, the CFs' maps were extracted for each sub-watershed to explain their variability that is crucial to sustainable watershed management. For quantitative analysis, representative values for each sub-watershed were evaluated for both estimated soil loss and CFs. This was used to identify the roles of CFs, their criticality in soil erosion development and susceptibility assessment. Furthermore, the land-use composition was evaluated to understand the level of human-environment interactions in the watershed and the resulting map is presented in Figure 2(j).
2.2. Quantitative analysis using hierarchical regression

Multiple regression is a data-analytic technique for predicting the response (dependent) variable based on two or more predictor (independent) variables. It is used to evaluate the relative contribution of each predictor variable to the total variance in the model. Also, it can be applied to explain the variability in the response variable with the introduction of new predictor variables into the model which can be achieved using stepwise and hierarchical regression methods. Hierarchical regression (HR) allows researchers to determine the ordering pattern of variables contrary to a stepwise method where ordering is completely controlled by the modeling tool (Petrocelli, 2003). The advantages and disadvantages of these methods could be found in (Lewis, 2007). HR is often adopted to analyse the effect of a predictor or group of predictor variables in the model by controlling other variables. The variability in the results of the model is measured in terms of adjusted \( R^2 \) at each stage, thus accounting for the increment in variance after each variable (or group of variables) is introduced into the model (Petrocelli, 2003). Prior to application of HR model, it is recommended that some assumptions be checked and satisfied on the response and predictor variables (Antonakis & Dietz, 2011; Osborne & Waters, 2002; Pedhazur, 1997). The assumptions include (a) normality test on the response variable, (b) independence of the observations, (c) linearity checks among the predictor variables and, between predictor and response variables, (d) multicollinearity check among the predictor variables, (e) homoscedasticity test and (f) outlier test. The detailed descriptions of these assumptions could be found in the literature.

In this study, predictor variables (i.e., erosion CFs) are grouped into static and dynamic factors while the response variable is the actual soil loss. Based on the literature survey, frequently used non-redundant CFs considered in this analysis are drainage density, lineament density, length-slope, soil
erodibility and NDVI that constitute CFs in Block 1. Hierarchical regression was applied to evaluate the impact of the addition of other dynamic CFs such as LST, SMI and rainfall erosivity into erosion susceptibility analysis and mapping. After checking HR assumptions, the first model was performed with the frequently used non-redundant CFs as a set of predictor variables. The variance accounted for in this analysis for the set of CFs was evaluated. Block 2 was formed by the addition of LST to CFs in Block 1. Then, another analysis was carried out to evaluate the impact of LST on the model. Block 3 consisted of CFs in Block 2 with the inclusion of rainfall erosivity while Block 4 contained all CFs in Block 3 plus SMI. Analyses were performed to examine the contribution of each of dynamic CFs to the modelling results when combined with the other frequently used CFs.

3. Results and discussion

3.1. Descriptive statistics of soil erosion and CFs
Cameron Highlands was delineated into 64 sub-watersheds to understand the heterogeneity nature of the complex landscape. Soil loss (response variable) and corresponding CFs values (predictor variables) were evaluated for each sub-watershed. This was done to analyse the relative importance of erosion CFs on the occurrence of soil erosion in a complex watershed. The sample size of 64 was found satisfactory for HR analysis as recommended by (Knofczynski & Mundfrom, 2008). Table 1 shows that soil loss in the watershed varied significantly from 0.04 to 2.93 ton/ha/yr with an average value of 0.762 ton/ha/yr. This was due to increased human-environment interactions through increasing agricultural practices and massive land clearing for the developmental projects. Previous studies have shown that land-cover provides protection to land surface against erosion. Characteristics of the 64 sub-watersheds showed a wide range of variations. The sub-watersheds size (area) ranged from 6.12 to 45.54 ha. The land-use composition was evaluated to understand the extent of human activities in the watershed. Land-use composition showed that forest was dominated occupying about 69.5% of the watershed area. This is followed by agriculture which occupied about 22.3% of the water. Urban land usage was about 8.1% whereas water occupied only 0.051% of the total watershed area. The agriculture and forest land-use areas varied significantly from 0.07% to 91.03% and 0% to 99.03%, respectively, for sub-watersheds. The coefficient of variation (CV) for soil erosion was observed to be 88.2%, while agricultural land-use was highest with a value of about 91.1%. Furthermore, LST and rainfall erosivity had their CV below 10%. The detailed descriptive statistics for the variables involved in the analysis are depicted in Table 1.

3.2. Evaluation of the influence of erosion CFs on soil loss
A hierarchical regression model was applied to evaluate the influence of each of erosion CFs on soil loss in Cameron Highlands watershed. As earlier discussed in Section 3.2, the application of HR requires the satisfaction of some critical assumptions to establish a valid relationship between soil erosion and its CFs. One of which is that the response variable must be drawn from the normally distributed population. A preliminary analysis of soil loss showed that the data are positively skewed with a statistic value of 1.052 and standard skewness error of 0.299. The Shapiro-Wilk test was performed to evaluate the skewness of data distribution and kurtosis to check the shape of the distribution (Stevens, 2012). Shapiro-Wilk sig. (p) value was observed to less than \( \alpha \)-value (level of significance for the statistics, \( \alpha < 0.001 \)). Thus, the data is statistically significant and it is not normally distributed (Zar, 1999). To overcome this violation, soil loss data for sub-watersheds were normalized using Napierian logarithm transformation. Shapiro-Wilk sig. (p) value greater 0.001 obtained for the transformed soil loss showed that it is normally distributed. This satisfies one of the basic requirements of parametric analysis. During the analysis of HR model, linearity test was observed using scatter-plot matrix and residual plot of standardized residuals against predicted values. Any form of systematic pattern or clustering of the residuals plot indicates a violation of the linearity assumption (Stevens, 2012). Random scatter pattern of residual plot about the horizontal line observed for this study (Figure 3) satisfied the assumption (Field, 2013). Furthermore, the assumption of independent error test as required for HR was checked using Durbin-Watson statistic. The Durbin-Watson statistic was estimated to be 2.282 (Table 2) which fell between 1.5 and 2.5 as recommended by Field (2013). Thus, the data was not auto-correlated and the assumption was not violated. The variables were checked for outliers as any significant outliers in the analysis could increase the model errors. This was achieved by observing the standardized residual value which is
Table 1. Descriptive statistic of Cameron Highlands watershed

| Category   | Variables       | Units       | Average | Standard deviation | Coefficients of variation | Minimum | Maximum |
|------------|-----------------|-------------|---------|--------------------|---------------------------|---------|---------|
| Response   | Erosion         | ton/ha/yr   | 0.762   | 0.672              | 0.882                     | 0.04    | 2.93    |
| Dynamic CFs| SMI             | None        | 0.086   | 0.026              | 0.297                     | 0.02    | 0.13    |
|            | NDVI            | None        | 0.510   | 0.063              | 0.123                     | 0.26    | 0.61    |
|            | LST             | None        | 23.680  | 0.779              | 0.033                     | 22.30   | 26.26   |
| Static CFs | Erosivity       | MJ mm/ha/yr | 2288.441| 99.250             | 0.043                     | 2104.32 | 2529.56 |
|            | Length-Slope    | None        | 3.015   | 0.537              | 0.178                     | 1.82    | 4.56    |
|            | Drainage density| km/km²      | 8383.859| 5263.121           | 0.628                     | 673.97  | 21236.37|
|            | Lineament Density| None  | 0.243   | 0.076              | 0.312                     | 0.11    | 0.39    |
|            | Erodibility (K) | ton ha/MJ/mm| 0.017   | 0.140              | 0.001                     | 0.014   | 0.020   |
| % Land-use | Agriculture     | %           | 22.304  | 20.315             | 0.911                     | 0.07    | 91.30   |
|            | Forest          | %           | 69.514  | 26.268             | 0.378                     | 0.00    | 99.03   |
|            | Urban           | %           | 8.131   | 8.994              | 1.106                     | 0.00    | 34.62   |
|            | Water           | %           | 0.051   | 0.344              | 6.704                     | 0.00    | 2.74    |
expected to fall within ±3.3 to satisfy outlier assumption (Tabachnick & Fidell, 2007). With standardized residual value ranged between −2.554 and 1.728, hence, there was no evidence of outlier. “The assumption of homoscedasticity is referred to as equal variance of errors across all levels of the predictor variables (Osborne & Waters, 2002)” This was validated by inspecting residual plot and was found satisfactory.

HR analysis was performed using four sets of model Blocks. Block 1 of the model comprised non-redundant erosion CFs that have been used by many researchers. The factors are lineament density, drainage density, LS-factor, erodibility factor and NDVI. They are mainly non-static CFs except for the NDVI which is dynamic in nature. Block 2 consisted of the above-mentioned CFs in Block 1 with the addition of LST, while Block 3 comprised of all CFs in Blocks 1, LST and erosivity factors. Lastly, Block 4 of the model consisted of CFs in Block 1, LST, erosivity and SMI. In the analysis of variation (ANOVA), F-ratio was evaluated to assess the improvement of the model by the addition of dynamic CFs. F-ratio represents the ratio of improvement in the model prediction to residual errors present in the model. The ANOVA results in Table 3 showed that values of F-ratio for all the models in each Block were greater than 1.0. This shows improvement in the model fitting was much greater than the inaccuracy (errors) within the model. The model for Block 1 was statistically insignificant as p > 0.001 (Zar, 1999) with an F-ratio value of 3.207. Block 1 had relatively low F-ratio value compared to other Blocks. Sequential addition of other dynamic CFs to Blocks 2, 3 and 4 increased the significance level of the models for each Block (as p < 0.001). This suggests that further improvement could be achieved with the introduction of some other relevant factors into the model.

Table 4 shows model parameters suggesting the nature of the existing relationship between CFs and soil loss. Block 1 showed that NDVI and drainage density had a negative relationship with soil loss while lineament density and LS-factor had a positive relationship. The negative relationship indicates a lower chance of triggering soil loss in the watershed. Land-use composition with 69.5% forest indicated that watershed has higher NDVI that provide protections to land surface against erosion (Bakker et al., 2008; Kavzoglu, Sahin, & Colkesen, 2015; Rahman et al., 2009). Similarly, activeness of drainage density to cause erosion could be dampened by the abundance of vegetation and land management practice (i.e., higher NDVI). Hence, these CFs have negative relationships with the occurrence of soil erosion. Slope steepness increases run-off velocity (Lucà et al., 2011; Valentin, Poesen, & Li, 2005) and presence of fractured and weathered terrain coupled with heavy rainfall in the study area favoured soil erosion (Barrow, Clifton, Chan, & Tan, 2005). Thus, topographic nature of Cameron Highlands with higher LS-factor and presence lineament positively influenced the occurrence of soil erosion which concurred with the findings of Lucà et al. (2011), Kachouri et al. (2015) and many other researchers. Rainfall erosivity had a positive relationship...
with the occurrence of erosion as it measures the aggressiveness of rainfall to induce erosion (Lal, 2001). The study area is characterized by heavy rainfall (Gasim et al., 2009) that increases the tendency of triggering soil erosion (Barrow et al., 2005). It was observed that drainage density had the lowest contributions to the formation of soil erosion in Cameron Highlands. The beta ($\beta$) values with corresponding standard errors were examined to explain whether the achieved $\beta$-value differ significantly from zero. The t-test values associated with $\beta$-value of lineament density was significant (Sig. <0.05) in Block 1, hence it majorly contributed to soil loss (Table 4). Blocks 2, 3 and 4 in Table 4 indicated that lineament density, LS-factor, rainfall erosivity, SMI and NDVI were statistically significant (Sig. <0.05) in triggering erosion in the study area. Summary of the model in Table 2 shows the variability in soil loss occurrence that can be accounted for by all the CFs in the model Blocks. This was evaluated by analysing the changes in residual $R^2$ values for each Block in the model. Multiple correlation coefficients (R) between CFs and soil loss are as shown in Column 2 of Table 2 with Block 1 having the lowest value of 0.423. This could be attributed to insufficient erosion CFs considered for the analysis. Introduction of other dynamic CFs showed substantial increment in the correlation coefficients. This indicates that LST, rainfall erosivity and SMI have significant contributions to the model. The $R^2$ values in Column 6 (Table 2) indicated how much variability in the response variable (i.e., soil loss) is accounted for by the predictors (i.e., CFs). Analysis of Block 1 results showed that its CFs account for 17.9% of the variation in soil loss. Addition of LST to Block 2, rainfall erosivity to Block 3 and SMI to Block 4 further increased the variations by 28.9%, 6.0% and 16.4%, respectively (see Table 2, Column 6). This indicates that consideration of dynamic CFs in erosion susceptibility assessment could increase modelling accuracy. Pearson correlation method was used to examine the relationships within the CFs considered.

### Table 2. Summary of the model

| Block | R    | $R^2$ | Adjusted $R^2$ | Std. Error of the Estimate | $R^2$ Change | Sig. F Change | Durbin-Watson |
|-------|------|-------|----------------|---------------------------|--------------|---------------|---------------|
| 1     | 0.423$^a$ | 0.179 | 0.123 | 1.02054 | 0.179 | 0.019 | |
| 2     | 0.684$^b$ | 0.468 | 0.422 | 0.82843 | 0.289 | 0.000 | |
| 3     | 0.727$^c$ | 0.528 | 0.479 | 0.78681 | 0.060 | 0.009 | |
| 4     | 0.832$^d$ | 0.692 | 0.654 | 0.64123 | 0.164 | 0.000 | 2.282 |

$a$ CFs: LinDen, DranDen, LSfactor, K-factor, NDVI; $b$ CFs: LinDen, DranDen, LSfactor, K-factor, NDVI, LST; $c$ CFs: LinDen, DranDen, LSfactor, K-factor, NDVI, LST, Erosivity; $d$ CFs: LinDen, DranDen, LSfactor, K-factor, NDVI, LST, Erosivity, SMI.

### Table 3. Analysis of variance (ANOVA)

| Block | Item | Sum of squares | df | Mean square | F     | Sig. |
|-------|------|----------------|----|-------------|-------|------|
| 1     | Regression | 13.362 | 4 | 3.341 | 3.207 | .019$^a$ |
|       | Residual   | 61.448 | 59 | 1.041 | | |
|       | Total      | 74.811 | 63 | | | |
| 2     | Regression | 35.006 | 5 | 7.001 | 10.201 | .000$^b$ |
|       | Residual   | 39.805 | 58 | 0.686 | | |
|       | Total      | 74.811 | 63 | | | |
| 3     | Regression | 39.523 | 6 | 6.587 | 10.641 | .000$^c$ |
|       | Residual   | 35.287 | 57 | 0.619 | | |
|       | Total      | 74.811 | 63 | | | |
| 4     | Regression | 51.785 | 7 | 7.398 | 17.992 | .000$^d$ |
|       | Residual   | 23.026 | 56 | 0.411 | | |
|       | Total      | 74.811 | 63 | | | |

$a$, $b$, $c$ and $d$ define the significance of CFs in each model Block, df = degree of freedom.
Table 4. Model parameters for each block

| Block | Unstandardized coefficients | Standardized coefficients | t    | Sig.  | Collinearity Statistics |
|-------|-----------------------------|---------------------------|------|-------|-------------------------|
|       | CFs | Beta (B) | Std. Error | Beta (B) | Tolerance | VIF |
| 1     | (Constant) | -1.615 | 1.654 | -0.977 | 0.333 |
|       | NDVI | -3.116 | 2.275 | -0.179 | -1.370 | 0.176 | 0.811 | 1.233 |
|       | K-factor | 0.051 | 0.028 | 0.025 | 0.212 | 0.024 | 0.654 | 1.110 |
|       | LSfactor | 0.453 | 0.260 | 0.223 | 1.741 | 0.087 | 0.847 | 1.181 |
|       | DranDen | -1.05e-06 | 0.000 | -0.051 | -0.416 | 0.679 | 0.93 | 1.076 |
|       | LinDen | 4.839 | 1.955 | 0.337 | 2.475 | 0.016 | 0.753 | 1.328 |
| 2     | (Constant) | -20.77 | 3.666 | -5.666 | 0.000 | |
|       | NDVI | -1.252 | 1.876 | -0.072 | -0.668 | 0.507 | 0.786 | 1.273 |
|       | K-factor | 0.045 | 0.015 | 0.012 | 0.122 | 0.222 | 0.542 | 1.041 |
|       | LSfactor | 0.425 | 0.211 | 0.209 | 2.010 | 0.049 | 0.846 | 1.182 |
|       | DranDen | -5.65e-07 | 0.000 | -0.027 | -0.275 | 0.785 | 0.928 | 1.078 |
|       | LinDen | 5.122 | 1.588 | 0.356 | 3.226 | 0.002 | 0.752 | 1.329 |
|       | LST | 0.768 | 0.137 | 0.549 | 5.616 | 0.000 | 0.961 | 1.041 |
| 3     | (Constant) | -34.665 | 6.211 | -5.581 | 0.000 | |
|       | NDVI | -2.716 | 2.309 | 0.156 | 1.176 | 0.244 | 0.468 | 2.138 |
|       | K-factor | 0.051 | 0.101 | 0.025 | 0.231 | 0.102 | 0.264 | 1.140 |
|       | LSfactor | 0.437 | 0.201 | 0.215 | 2.175 | 0.034 | 0.846 | 1.182 |
|       | DranDen | -4.13e-07 | 0.000 | -0.020 | -0.211 | 0.833 | 0.927 | 1.079 |
|       | LinDen | 5.549 | 1.516 | 0.386 | 3.660 | 0.001 | 0.744 | 1.344 |
|       | LST | 0.909 | 0.140 | 0.650 | 6.494 | 0.000 | 0.827 | 1.209 |
|       | Erosivity | 0.004 | 0.001 | 0.333 | 2.701 | 0.009 | 0.544 | 1.839 |
| 4     | (Constant) | -98.222 | 12.692 | -7.739 | 0.000 | |
|       | NDVI | -6.387 | 1.998 | 0.368 | 3.196 | 0.002 | 0.415 | 2.410 |

(Continued)
| Block       | Unstandardized coefficients | Standardized coefficients | t     | Sig.  | Collinearity Statistics |
|------------|------------------------------|----------------------------|-------|-------|-------------------------|
| K-factor   | 0.364                        | 0.084                      | 0.042 | 0.412 | 0.047                   | 0.254 | 1.200                  |
| LSfactor   | 0.566                        | 0.165                      | 0.279 | 3.425 | 0.001                   | 0.828 | 1.207                  |
| DranDen    | 2.14e-06                     | 0.000                      | 0.103 | 1.288 | 0.203                   | 0.854 | 1.171                  |
| LinDen     | 2.468                        | 1.358                      | 0.172 | 1.817 | 0.075                   | 0.616 | 1.624                  |
| LST        | 3.455                        | 0.480                      | 2.470 | 7.198 | 0.000                   | 0.047 | 1.417                  |
| Erosivity  | 0.001                        | 0.001                      | 0.113 | 1.042 | 0.302                   | 0.468 | 2.135                  |
| SMI        | 82.184                       | 15.05                      | 1.929 | 5.461 | 0.000                   | 0.044 | 2.694                  |

Note: DranDen = Drainage density, LinDen = Lineament density, K-factor = Soil erodibility.
Table 5. Pearson correlation matrix for the selected erosion CFs

| CFs          | Soil loss  | NDVI    | K-factor | LS-factor | DranDen | LinDen | LST    | Erosivity |
|--------------|------------|---------|----------|-----------|---------|--------|--------|-----------|
| Soil loss    | 1.000      |         |          |           |         |        |        |           |
| NDVI         | -0.383     | 1.000   |          |           |         |        |        |           |
| K-factor     | 0.012      | 0.001   | 1.000    |           |         |        |        |           |
| LS-factor    | 0.061      | 0.167   | 0.001    | 1.000     |         |        |        |           |
| DranDen      | -0.082     | 0.230   | 0.017    | 0.155     | 1.000   |        |        |           |
| LinDen       | 0.327      | -0.385  | -0.001   | -0.014    | -0.017  | 1.000  |        |           |
| LST          | 0.576      | -0.188  | 0.010    | 0.003     | -0.081  | 0.003  | 1.000  |           |
| Erosivity    | 0.073      | -0.060  | 0.014    | -0.043    | -0.113  | 0.015  | 0.159  | 1.000     |
| SMI          | -0.368     | -0.065  | 0.001    | -0.113    | 0.043   | 0.378  | 0.934  | 0.378     |

Note: *Transformed soil loss values, DranDen = Drainage density, LinDen = Lineament density.
in the analysis. The correlation matrix generated is as shown in Table 5. It was observed that all CFs have moderate correlations with one another.

4. Conclusion
Susceptibility assessment measures the relative probability of occurrence of soil erosion in a location based on the relationships between its past and a set of causative factors. This approach is very vital to sustainable land-use management and erosion prevention. Hence, adequate selection of critical CFs is required to achieve accurate susceptibility results. The present study investigated the effects of CFs on the occurrence of water-induced soil erosion using remote sensing, GIS and statistical techniques. The watershed with 69.5% forest and 22.3% agricultural land-use had its soil loss varied significantly from 0.04 to 2.93 ton/ha/yr. Previous studies on erosion susceptibility assessment devoid of some crucial CFs termed dynamic CFs in the context of this study. In order to address this issue, the watershed area under consideration was delineated into 64 sub-watersheds to capture its heterogeneity nature. A hierarchical regression model was adopted to assess the impacts of some dynamic CFs on frequently used static CFs in erosion susceptibility. CFs in Block 1 composed of lineament density, drainage density, erodibility, LS-factor and NDVI after due consideration for redundancy. These factors constitute the frequently used erosion CFs in many previous studies. Dynamic factors (such as LST, rainfall erosivity and SMI) were sequentially introduced into the existing model of Block 1 to form Blocks 2, 3 and 4. The results of the study indicated that modelling with CFs in Block 1 accounted for 17.9% of the variation in soil loss. However, the addition of LST (in Block 2), rainfall erosivity (in Block 3) and SMI (in Block 4) to the existing model further increased the variation by 28.9%, 6.0% and 16.4%, respectively. This suggests that the introduction of dynamic CFs into erosion susceptibility assessment could increase the modelling accuracy. Frequently used non-redundant CFs in Block 1 showed that NDVI and drainage density had negative relationships with soil loss while lineament density and LS-factor had a positive relationship. The analysis also showed that LST, rainfall erosivity and SMI had positive relationships with soil loss. The negative and positive relationships, respectively, indicate a weaker and stronger relationship of CFs to the occurrence of soil erosion. The study revealed that both static and dynamic CFs considered were statistically significant except drainage density that had the lowest contributions to the development of soil erosion. This study provides a framework to evaluate the impacts of dynamic CFs that could improve erosion susceptibility mapping accuracy if included in the analysis. It is recommended that further studies should be carried out on the watershed to implement the results of this study to produce erosion susceptibility map.

Acknowledgements
This research was supported by Universiti Teknologi PETRONAS, Malaysia [0153AA-G04]. The authors would like to acknowledge the Malaysian Department of Irrigation and Drainage for the provision of useful data for the accomplishment of this research.

Funding
This work was supported by the Universiti Teknologi PETRONAS, Malaysia [0153AA-G04].

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Citation information
Cite this article as: Quantitative analysis of soil erosion causative factors for susceptibility assessment in a complex watershed, Taofeq Sholagberu Abdulkadir, Raza UI Mustafa Muhammad, Khamaruzaman Wan Yusof, Mustafa Hashim Ahmad, Saheed Adeniyi Aremu, Adel Gohari & Abdurrasheed S Abdurrasheed, Cogent Engineering (2019), 6: 1594506.
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