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GEOSTATISTICAL BASED SUSCEPTIBILITY MAPPING OF SOIL EROSION AND OPTIMIZATION OF ITS CAUSATIVE FACTORS: A CONCEPTUAL FRAMEWORK

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Abstract

Soil erosion hazard is the second biggest environmental challenges after population growth causing land degradation, desertification and water deterioration. Its impacts on watersheds include loss of soil nutrients, reduced reservoir capacity through siltation which may lead to flood risk, landslide, high water turbidity, etc. These problems become more pronounced in human altered mountainous areas through intensive agricultural activities, deforestation and increased urbanization among others. However, due to challenging nature of soil erosion management, there is great interest in assessing its spatial distribution and susceptibility levels. This study is thus intend to review the recent literatures and develop a novel framework for soil erosion susceptibility mapping using geostatistical based support vector machine (SVM), remote sensing and GIS techniques. The conceptual framework is to bridge the identified knowledge gaps in the area of causative factors' (CFs) selection. In this research, RUSLE model, field studies and the existing soil erosion maps for the study area will be integrated for the development of inventory map. Spatial data such as Landsat 8, digital soil and geological maps, digital elevation model and hydrological data shall be processed for the extraction of erosion CFs. GIS-based SVM techniques will be adopted for the establishment of spatial relationships between soil erosion and its CFs, and subsequently for the development of erosion susceptibility maps. The results of this study include evaluation of predictive capability of GIS-based SVM in soil erosion mapping and identification of the most influential CFs for erosion susceptibility assessment. This study will serve as a guide to watershed planners and to alleviate soil erosion challenges and its related hazards.

Keywords: Soil erosion, Causative factors, Susceptibility mapping, SVM, GIS.

Nomenclatures

A_s	Specific Catchment Area, m^2/m

Greek Symbols

β	Slope Gradient, deg.
ln	Napierian Logarithms

Abbreviations

ASCII	American Standard Code for Information Interchange
AUC	Area-Under-Curve
ANN	Artificial Neural Networks
P-Factor	Conservative Practice Factors
DT	Decision Trees
DEM	Digital Elevation Model
DD	Drainage Density, m/m^2
ETM+	Enhanced Thematic Mapper Plus
ENVI	Environment for Visualizing Images
FR	Frequency Ratio
GIS	Geographic Information System
LC	Land-Cover
C-Factor	Land Cover and Management Factor
LST	Land Surface Temperature, ^oC
LULC	Land-use/Land-cover
LS-Factor	Length-Slope Factor
LN	Linear Kernel Functions
LR	Logistic Regression
MUSLE	Modified Universal Soil Loss Equation, ton/ha/yr
NDVI	Normalized Difference Vegetation Index
PL	Polynomial Kernel Functions
PC	Profile Curvature
QGIS	Quantum Geographic Information System
RBF	Radial Basis Kernel Functions
R-Factor	Rainfall-Runoff Factor, MJ mm/ha/yr
RS	Remote Sensing Techniques
RUSLE	Revised Universal Soil Loss Equation, ton/ha/yr
SIG	Sigmoid Kernel Functions
SG	Slope Gradient, deg.
K-Factor	Soil Erodibility Factor
CFs	Soil Erosion Causative Factors
SMI	Soil Moisture Index
SI	Statistical Index
SPI	Stream Power Index
SLD	Structural Lineament Density
SVM	Support Vector Machine
SPOT	Systeme Pour 1’Observation de la Terre
TWI	Topographic Wetness Index

1. Introduction

Soil erosion is the most critical environmental challenges after population growth which is considered as the biggest [1]. It is a natural hazard that causes land degradation and desertification [2-4]. It has both on- and off-site effects with serious environmental and economic impacts [5]. Water induced erosion phenomenon is often caused by agricultural intensification, urbanization, indiscriminate deforestation, tectonic activities and climatic changes [6, 7] and thus threatens the sustainability of land and water resources. Soil erosion process involves interaction of different complex biophysical and anthropogenic factors which include soil properties, topography, climatic condition, land use and its management practices [8]. These factors vary both spatially and temporally from one location to another. Yves et al. [9] emphasized that there is no simple model that can consider all relevant factors, particularly in areas where human interference are predominant.

In Malaysia, especially in mountainous areas like Cameron Highlands, soil erosion has become serious environmental challenges in recent years due to extensive land-use for urban development, agricultural activities, deforestation among others [7, 10-14]. However, many of soil erosion impacts are currently been experienced in Cameron Highlands watershed as reported by many researchers [15, 16]. For instance, accelerated soil erosion resulted in water pollution [15], sedimentation of rivers and reservoirs that leads to flooding of downstream areas and reduced hydropower generation especially in Ringlet dam [16], low crop productivity due to loss of soil nutrients and extensive erosion that causes landslide in steep slopes terrains [17, 18]. As a result, there is great interest in determining the source, volume of soil loss, and producing accurate susceptibility maps of active erosion zones which help in hazards prevention and management [19, 20]. Evaluation techniques for land related hazards (such as landslide and soil erosion) are based on susceptibility mapping that classify land into zones of similar degree of hazards. Erosion susceptibility mapping indicates the relative probability of erosion occurrence at a certain location compared to other locations. The prediction of highly susceptible erosion locations is the most crucial part of erosion hazard prevention that allows the identification of locations and the best management practice required [20].

There have been increasing applications of Geographical Information Systems (GIS) and Remote Sensing (RS) techniques coupled with different qualitative and quantitative techniques for estimation of soil loss, assessing its spatial distribution and mapping of erosion susceptibility [21, 22]. Qualitative methods are subjective since the assessment is based on expert opinions and knowledge while quantitative approaches, such as statistical and probabilistic (deterministic) methods, are considered objective and accurate than qualitative owing to their data dependent nature [23]. Quantitative approaches are used for the analysis of numerical data in order to establish spatial relationships between causative factors (CFs) and landslide [17] as well as soil erosion. The main challenge in these methods is their dependence on data structure and sizes [24]. Both qualitative and quantitative methods implement spatial distribution of the past soil erosion to estimate the future trend taking into account interdependence of CFs [18]. It has been reported that accurate evaluation of soil erosion CFs is very crucial in the analysis and preparation of soil erosion susceptibility map. These CFs are often obtained from different sources such as topographical map, digital elevation model, digital soil maps, Landsat 8 or Landsat 7 ETM+ (Enhanced Thematic Mapper Plus) images, Systeme Pour 1'Observation de la Terre (SPOT) images and geological maps.

Generally, CFs for soil erosion are grouped into topographic, land-use, soil, geological and meteorological characteristics. Some of the frequently used CFs include slope, lithology, land-cover, aspect, soil thickness/slope, normalized difference vegetation index (NDVI), drainage density, topographic wetness index (TWI), elevation, etc. More so, many of these watershed factors are static factors that remain unchanged for long period of time. Although, there is no rule of thumb in the existing literature that specifies the number and type of CFs to be used for susceptibility analysis [25, 26]. This has generated issues of subjectivity on the selection of CFs and number to be selected to achieve accurate results. However, careful observation of existing literature indicated the absence of some multi-temporal factors as CFs which often changes over time. Thus, there is need to harness all the existing CFs and include multi-temporal factors, then optimize to identify the positive CFs to soil erosion. This study therefore intends to review previous studies and develop a framework for soil erosion susceptibility mapping with consideration of multi-temporal factors, and also to optimize the CFs, by adopting GIS, RS and Support Vector Machine (SVM) techniques. SVM as a quantitative technique is chosen for this study due to the fact that it is rarely used compare to other methods despite its high predictive ability as it has been proven by Tehrany et al. [26].

2. Review of Literatures

Natural hazards are the elements of physical environmental which occurred in various forms such as hydrological (such as flood, drought, tsunami, desertification, etc.), geological (seismic, volcanic, landslide, soil erosion, etc.), atmospheric (hurricanes lightning, tornadoes, etc.) and wildfire hazards. These can potentially affect human beings due to their location, severity and frequency of occurrence [27]. Usually, human intervention within the prone zones of such hazards may lead to significant degree of severity and increased hazards frequency. Thus, there is need for accurate prediction of risk levels associated with these hazards which include risk quantification, vulnerability/susceptibility assessment and exposure patterns.

Susceptibility assessment has been recognized as a very vital tool in predicting how prone areas are to a particular hazard especially landslides, soil erosion and flooding. In an attempt to have good idea of susceptibility of these hazards in terms of volume or area, spatial distribution and potentiality of occurrence, qualitative and quantitative techniques have been adopted. The qualitative approach is subjective and less accurate while quantitative approach is objective and more accurate as earlier discussed. The quantitative approaches which could be bivariate or multivariate integrated with remote sensing and GIS techniques, relies on statistics or probabilistic analysis expressing the relationship between CFs and hazards in question [28]. A wide range of these qualitative and quantitative methods have been successfully applied to soil erosion susceptibility mapping by many researchers around the globe. Although, the most widely used quantitative technique is Universal Soil Loss Equation USLE and its revised versions. This revised USLE (RUSLE) [29] and modified USLE (MUSLE) [30] are empirical models popularly used in predicting average annual rate and, spatial and temporal distribution of erosion in watersheds under different conditions of cropping systems, management approaches and erosion control practices [31].

Literature survey revealed the existence of some bivariate (such as frequency ratio-FR, statistical index-SI and weight of evidence-WoE); multivariate (such as decision trees-DT, logistic regression-LR) and soft computing (support vector machines-SVM, artificial neural networks-ANN) methods that were used in landslide [32-37] and some were used in flood susceptibility mapping [26, 38-40]. These approaches estimate the probabilistic relationship between dependent (i.e., landslides, erosion, flood, etc.), and independent variables (i.e., causative factors) [24, 41]. Researchers have applied many of these techniques to analyze and develop soil erosion susceptibility maps for different localities [18, 20, 22, 42-48].

2.1. Soil erosion and its causative factors

Evaluation of hazards susceptibility requires definition and consideration of some vital causative factors responsible for its occurrence [49]. This is actually the starting point in susceptibility analysis using statistical techniques [46]. Massimo et al. [50] emphasised the need for the identification of triggering factor as one of the present knowledge gaps in soil erosion. The susceptibility of soil erosion in a watershed is controlled by spatial distribution of both erodibility and erosivity factors as CFs, which are respectively defined as the proneness of soils or rocks to be eroded and, the eroding power of running waters on slope terrains [18]. These CFs are generally grouped into topographical, lithological, land-cover characteristics [50, 51], climate and agriculture practices [45]. However, most of times, erodibility factors are broken down into fractional units like land-cover (LC), weathering grades of the rocks (WG), structural lineament density (SLD), soil texture, etc. and erosivity factors as follows: slope gradient (SG), profile curvature (PC), stream power index (SPI), drainage density (DD), topographic wetness index (TWI), etc. The erosive power of the runoff waters depends on topographic (steepness, slope length, curvature, etc.) and climatic attributes [18]. Most of these parameters are usually derived from different sources such as digital elevation model (DEM), digital soil map, Landsat 8 or 7 ETM+ images, SPOT images, geological map, etc. having different degrees of generalization and scales.

Topographical factors, such as slope gradient, slope aspect, curvature of the hillslopes, slope length, altitude, TWI and the SPI derived from DEM are often considered for susceptibility studies owing to their roles in triggering erosion. Soil erosion caused by water is directly related to slope morphological factors of the watershed [52]. SPI describes the erosive power of flowing water by assuming that the discharge is proportional to the specific catchment area and to the slope [53]. It is also an indicative of the potential energy available to entrain sediment [54]. Furthermore, TWI indicates the amount of water accumulation at a point in watershed and trend of water to flow downslope by gravity [55]. Dube et al. [56] explained that TWI is a function of both slope and the upstream contributing area per unit width orthogonal to the flow direction. TWI and SPI can be calculated respectively from the empirical models in Eqs. 1 and 2. According to Imeson and Lavee [57], slope aspect influences the susceptibility of soil to erosion. This expresses the stability of soil aggregates and its exposure to sunlight and other numerous climatic conditions and thus controls the occurrence of gully erosion

[58]. The length-slope factor (LS) is another topographical factor that expresses the steepness of slope and the length of slope. This can be calculated in GIS environment using an empirical equations described by Moore and Burch [59].

$$TWI = \ln\left(\frac{As}{\tan\beta}\right) \tag{1}$$

$$SPI = As * \tan\beta \tag{2}$$

where *As* = specific catchment area (m2/m), β = slope gradient in deg.

Erodibility of soils in watersheds is influenced by its physical, chemical, mineralogical and morphological features of soil, which are the products of specific processes of soil formation [46]. Some factors such as rock hardness, infiltration and permeability, drainage density, etc are used to describe erodibility factors in erosion susceptibility analysis [60]. The weathering conditions of rocks representing the role of lithology and drainage density were reported to be considered as CFs in erosion processes [61]. Moreover, land-use plays crucial roles on geomorphological stability of slope to erosion while land-cover such as vegetation or plant residue provides protection to soil by intercepting raindrops, increase rate of infiltration, decrease runoff speed and transporting capacity of water flow [20]. Literature survey highlighted that various researchers adopted different CFs for their studies depending on their understanding of its effects on soil erosion and availability of such data. This shows varying and inconsistences in selection of CFs.

Table 1 presents the summary of some authors with varying number of CFs and methods adopted for their studies. For instance, Angileri et al. [45] considered twelve (12) CFs and grouped them into discrete variables consisting of four factors and eight continuous variables as listed in Table 1. The outcome of geospatial analysis of these factors identified elevation, aspect, landform and land-use as the most significant variables in rill-interrill erosion modelling, while plan and profile curvatures, SPI and TWI were the most significant variables for gully erosion prediction. In a similar study by Conoscenti et al. [42], they considered twenty-seven (27) CFs by further broken down the factors. These factors are describing the variability of lithology, land-use, topography and road position and their potential impacts on erosion processes, while the dependent variable was given by presence or absence of gullies.

Analysis of Remondo et al. [62] highlighted that increasing the number of CFs does not necessarily increase the accuracy of the model as long as the factors are not positive CFs. In addition to this, Magliulo [46] reported that several authors including Ayalew et al. [63] to have stated that all the selected CFs should be non-redundant factors, i.e., should not have double consequences in the analysis. Magliulo [46] further argued that combined usage of slope angle, length-slope (LS) factor, plan curvature and SPI could be regarded as redundant CFs because all these parameters are dependent on slope angle though they have geomorphological and hydrological significances. The same also applicable to both slope aspect and TWI as they are slope angle dependent. In order to do away from overweighting of the results of susceptibility assessment validation procedure, therefore CFs that have relational linkage should be avoided [46, 64]. It was agreed that all the aforementioned CFs have one way or the other influenced the formation of soil and initiation of soil erosion as many of them are hydrologically and morphologically significant.

Table 1. Summary of authors with varying number of CFs and methods

Paper ID	Nature of hazard	CFs considered	Geostatistical methods
[20]	Gully erosion	7-factors: WG, SG, PC, SPI, LC, DD and SLD	Logistic regression
[18]	Sheet & rill-interrill erosion and gully	6-factors: bedrock lithology, soil use, soil texture, plan curvature, stream power index and slope-length factor	Multivariate
[43]	Gully	12-factors: slope, aspect, plan curvature, profile curvature, general curvature tangential curvature; SPI, TWI, slope length factor; lithology, soil texture, land-use	Bayes' theorem
[45]	Rill-interrill and gully erosion	12-factors: outcropping lithology, land-use, slope aspect and landform classification, length-slope factor, the topographic wetness index, the stream power index, plan and profile curvatures, elevation, distance to the river and slope angle	Stochastic Gradient Treeboost
[46]	Gully and, sheet and/or rill erosion	4-factors: Lithology, land-use, slope angle and slope aspect	Weighting values (Wi),
[47]	Gully erosion	9-factors: lithology, dynamic and slope inclination, land-use, aspect, plan curvature, stream power index, topographical wetness index and length-slope	Weighting values
[42]	Gully	27 factors describing the variability of lithology, land-use, topography and road position	Logistic regression
[56]	Gully	7-factors: Land-cover, soil type, distance from river, distance from road, Sediment Transport Index, Stream Power Index and Wetness Index	Weight of evidence
[21]	Soil erosion	8-factors: Land-use/Land-cover, NDVI, landform, drainage density, drainage frequency, lineament frequency, slope and relative relief	Weighted index Overlay

Several researchers have been using all sort of CFs depending on their understanding and availability of their usage in existing literatures. Until today, no standing guidelines or procedures have been proposed on the ways and manners for the selection of CFs [63, 65]. However, studies have shown that several CFs considered, as mentioned above, are static factors which often remain the same through the months of the year while multi-temporal factors such as precipitation, soil moisture and land surface temperature are dynamic. These multi-temporal factors are very important CFs whose impacts on soil erosion susceptibility assessment have not been investigated. In spite of their significance, they often neglected due to insufficient number of meteorological stations in the watershed under consideration [20]. Soil moisture as one of the multi-temporal CFs has been substantiated by Jamali [66] to influence soil erosion process. As earlier mentioned, precipitation levels dictate the erosive power of runoff generation which increases its aggressiveness to cause erosion [67].

Land surface temperature (LST) is another crucial erosion triggering factor. KCCC [68] pointed out that frozen soil is highly resistant to erosion while rapid thawing caused by warm rains can lead to serious erosion. Regions of warmer climates usually have thinner organic cover on the soil that may result in erosion. Soil moisture is often affected by temperature through evaporation and transpiration processes and thereby speeds up the runoff rate. Furthermore, as important as runoff factor in water induced erosion, it is often not considered in several soil erosion susceptibility studies. Although, precipitation that generated this runoff may be homogenous over a small watershed area and not considered in the analysis as pointed out by [18, 20] but this often changed during different periods of year. The spatial and temporal distribution of this precipitation may indeed reduce the accuracy of the susceptibility mapping since different land-use units in the watershed have different level of exposure. According to Lee et al. [65], some land-use/land-cover (LULC) types yielded more runoff compare to areas with dense vegetation. Thus, these knowledge gaps have to be investigated by assessing the impact of multi-temporal (dynamic) factors on the accuracy of soil erosion susceptibility mapping.

3. Conceptual Framework: Field Survey and Data Analysis

The literature survey revealed that a significant number of researchers focused in developing new soil erosion models and applying it for its assessment (of soil loss), quantifying its volume while some others focused on identification of prone areas. This present study therefore focuses on susceptibility assessment of soil erosion using quantitative, GIS and RS techniques. It has been established that studies of soil erosion within watersheds involve the interaction of complex biophysical factors such as climate, land-cover, land-use, topography and soil. These parameters always vary in both space and time. Thus, case-specific studies are often required to understand its behaviours. This study is proposed to be conducted on Cameron Highlands watershed in Pahang State of Malaysia due to increased rate of urbanization and agricultural activities that have exposed the area to massive soil erosion. The spatial data of the study area such as digital elevation model, Landsat 7 ETM+ or Landsat 8 images, SPOT images, geological map, soil erosion map and climatic data will be obtained from appropriate agencies. The satellite data will be processed to have specific coordinate system for the area under consideration. The analogue maps of the required spatial data will be geometrically and topographically corrected using Quantum GIS (QGIS) while the Landsat 8 and

SPOT images will be processed for atmospheric corrections using Geomatica software to remove the haze and cloud cover if present.

The GIS techniques using ArcGIS, Geomatica and ENVI (Environment for Visualizing Images) software will be adopted for the evaluation and extraction of required soil erosion biophysical factors from satellite and topographic data for the computation of soil loss and development of soil erosion map using the most popular empirical model called Revised Universal Soil Loss Equation (RUSLE) model. The said factors are: rainfall-runoff-R, terrain (slope-length)-LS, erodibility-K, land-cover and management-C, and conservative practice-P factors for the spatial assessment of soil erosion. Thus, soil erosion (inventory) map shall be developed by integrating both the developed map and the existing soil map of the study area. Field studies (ground truthing) will be conducted to inspect the spatial distribution of soil erosion within the watershed to compliment the results from the model. This is required to update the existing soil erosion map in order to generate reliable inventory map that will serve as basis for susceptibility assessment of the area under consideration.

Also, the digital satellite data will be processed in GIS environment to extract and prepare maps for the soil erosion CFs for susceptibility analysis. The training and test points during model development will be selected by considering the inventory map and thematic CFs maps for use in susceptibility mapping using Support Vector Machine (SVM) techniques as quantitative approach. SVM model is similar to neural networks model. It performs classification by constructing N-dimensional hyper planes that optimally separates the data into two sets [69]. The CFs in ASCII format would be input into SVM learning algorithms modeller for training using four different Kernel functions (such as LN-Linear, PL-Polynomial, SIG-sigmoid, RBF-Radial Basis Function) to examine the efficacy of each in classification and select the best fit function as indicated in the methodological framework in Fig. 1. The advantages and disadvantages of each can be found in the literature.

Extensive surveys of the past studies on soil erosion susceptibility mapping have been conducted to identify the current trends and the existing gaps in this research area. It was understood that various quantitative and qualitative approaches have been applied with a number of CFs considered by various researchers. Similar studies have been devoid of some critical CFs owing to its homogeneity in a small watershed or unavailability of the data. However, this study will have a rare opportunity of including runoff layer derived from precipitation records which often neglected in several studies. Moreover, conditions of soil moisture and LST (multi-temporal factors) are not always considered in many studies due to its unavailability. However, the advancement in remote sensing techniques for data acquisition has eased these challenges. These data, LST and soil moisture index (SMI) can now be extracted from Landsat 8 or 7 ETM+ images for a particular period of time. More so, performance of some soft computing techniques like SVM learning algorithms have not been tested on soil erosion susceptibility despite its high prediction capability as confirmed in flood susceptibility assessments [38] and very few studies on landslide assessments. The proposed methodological framework to be adopted for this study is as shown Fig.1. The CFs such as land-use/land-cover, NDVI, LST and SMI shall be derived from Landsat 8 or 7 ETM+ images; lineament and bed lithology from geological map; soil type from soil map; runoff layer from climatic data; and slope gradient, drainage density, curvature, aspect, SPI, TWI and distance to river from digital topographic map or DEM. For all the CFs to be used in this study, certainty function approach shall be adopted to optimize the CFs in order to identify the most influential ones for soil erosion development in the watershed under consideration.

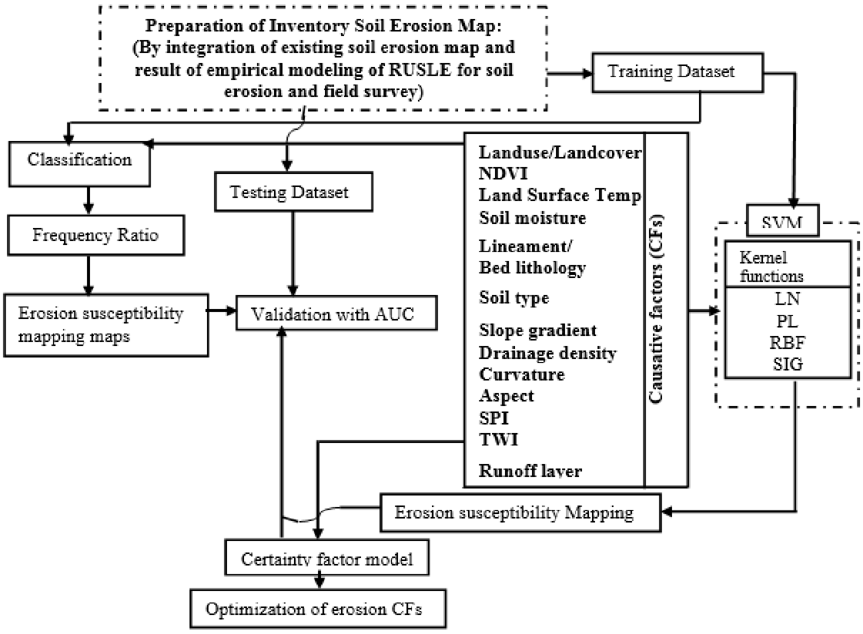

Fig. 1. **Conceptual methodological framework for the study.**

4. Model Validation

The performance and predictive capability of erosion mapping methods are usually assessed by validation of the resulting maps. The validation of developed soil erosion susceptibility maps with independent parameters is often required although obtaining spatial validation data is a complicated issue [66]. In this study, one of the most popular geostatistical approaches preferably frequency ratio (FR) method for susceptibility assessment will be adopted to validate the reliability of results obtained from SVM approach. FR is defined in the literature as the ratio of probability of occurrence to non-occurrence of specific attributes such as landslide, erosion, etc., in a particular location [25]. This method is selected for usage owing to its simplicity in application as compare to others like logistic regression and neural networks [70].

Moreover, the model validation method known as Area-Under-Curve (AUC) technique shall also be adopted to measure the prediction accuracy of the model. Literatures have revealed that AUC is the most popular method used for susceptibility model validation [25, 34, 49, 70, 71]. AUC values often range between 0 and 1 in which its proximity to 1 indicates a stronger prediction accuracy of the model. The developed susceptibility model will then be tested in another area of similar environmental and climatic conditions within Malaysia or any other similar region.

5. Conclusion

Soil erosion phenomenon causes land degradation, desertification and water deterioration with enormous economic and social impacts. Some of its impacts on watersheds include loss of soil nutrients leading to low crop yield, sedimentation of hydropower reservoirs leading to reduced power generation and flood risk, landslide, high water turbidity, etc. The focus of this paper was to review the recent literatures in the area of soil erosion susceptibility assessment in order to understand the trend and identify areas that require improvements. The findings revealed inconsistencies in the selection of CFs and missing of some multi-temporal CFs that are very crucial to soil erosion processes. This paper provides a novel conceptual framework to bridge these gaps which might consequently improve the accuracy of soil erosion susceptibility mapping. The results of the study shall include: evaluation of spatial distribution of soil erosion in the watershed; evaluation of all soil erosion CFs; delineation of study area to different soil erosion probability zones. Furthermore, the results shall examine the predictive capability of GIS-based SVM in soil erosion mapping; establishment of spatial relationship between CFs and soil erosion occurrence; identification of most influential CFs for soil erosion susceptibility mapping; and development of soil erosion susceptibility/risk maps for the watershed. The results will ensure sustainable use of land resources and will serve as a guide to watershed managers in preventing and alleviating soil erosion occurrence and the hazards related to it.

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