UNIVERSITI PUTRA MALAYSIA

MODELLING OF OPTIMIZED HYBRID DEBRIS FLOW USING AIRBORNE LASER SCANNING DATA IN MALAYSIA

USMAN SALIHU LAY

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By

USMAN SALIHU LAY

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

May 2019

DEDICATION

I dedicated this work to my late mother, Hajiya Fatima Lahmiyyu Ibrahim

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirements for the degree of Doctor of Philosophy

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Chairman : Associate Professor Zainuddin Bin MD Yusoff, PhD
Faculty : Engineering

Despite the well-reported havoc caused by debris flows in Malaysia especially mountain and foothill communities, it received little attention from researchers. It has therefore, become imperative to explore the nature of the disaster in the tropical Malaysia. The general objective of the study was the development of optimized hybrid debris flow models using airborne laser scanning data and Machine learning algorithms in Malaysia. The specific objectives are to identify the optimized geomorphological, topographic parameters derived from LiDAR data source for the tropical area; map the debris flow susceptible areas using the LiDAR data; and develop a hybrid RAMMS (Rapids Mass Movements) debris flow model for tropical countries. The quality of spatial data required and approaches adopted in acquiring the data is directly related to the level of analyses accuracy involve and pixel size. A high-resolution vertical accuracy (15 cm) airborne laser scanning data (LiDAR) discrete-return, echoes, and intensity was used to generate DEM; invariably used to derive the debris flow conditioning factors for the spatial prediction and modelling of debris flow. The topographic and geomorphological conditioning factors includes slope angle, slope aspect, total curvature, plane curvature, profile curvature, relative stream power index, topographic wetness index, stream catchment area, topographic roughness index, and topographic position index). Other determinants were velocity and rheological parameters data that is influencing debris flows run-out. In this study, an existing inventory data that depicts a number of debris flow locations was utilize for binary features selection with high-resolution airborne laser scanning data. The features were categorized into two *"debris flows present" (1)* and *"debris flow absent" (0).* Six hundred randomly selected sample points for each category was generated gives 640 sample points. The sample data of the area was randomly divided into a training dataset: 70 % (448) for training the models and 30% (192) for validation. Spearman Correlation was used to checked multi-collinearity effect on debris flow conditioning factors; evaluations factors of Information Value (IV), Crammer V were assessed.Wrapper feature subset selection technique was used,

different metaheuristic search algorithms (e.g. Cuckoo search), and evaluator or model inducing algorithms (e.g SVM) were utilized for feature subset selection, which further compared to select the optimal conditioning factors subset. At the initial stage, heuristic optimisation techniques were employed in identifying the global best latent SVM and MARS hyperparameter values selection used for debris flow prediction modelling. A susceptibility debris map is the combination of debris flow source area and run out model, this is achieved by emergent of revolutionary advancement in MLA, two optimized-data mining techniques (BFO-SVM and PSO-MARS) were amalgamated. The resultant susceptibility mapping and models strength were subjected to statistical accuracy evaluation metrics using Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC), Mean Asolute Error (MAE), Root Mean Square Error (RMSE), coefficient of determination (R^2) and Generalized Cross Validation (GCV) methods. To simulate debris flow run-out pattern, a friction resistance model (Voellmy model) RAMMS-dbf was modified by fusing erosion model; this improve the model results in reality. The model is capable of ameliorating decision-making process in planning and environmental risk- hazard mitigation and management. Results have shown that integrated Cuckoo search and induced SVM learning algorithm produced the best-selected feature subset with 99% coefficient of determination, lowest RMSE and MAE of 0.081 and 0.0132 respectively.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PEMODELAN SERPIHAN HIBRID YANG DIOPTIMUMKAN MENGGUNAKAN DATA PENGIMBAS LASER UDARA DI MALAYSIA

Oleh

USMAN SALIHU LAY

Mei 2019

Pengerusi : Profesor Madya Zainuddin Bin MD Yusoff, PhD
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Walaupun terdapat laporan berkenaan kekacauan yang berpunca daripada aliran serpihan di Malaysia terutama masyarakat digunung dan dikaki bukit, ia kurang menerima perhatian daripada penyelidik-penyelidik. Oleh itu, ia menjadi penting untuk meneroka sifat bencana di Malaysia tropika. Objektif umum bagi kajian ini adalah penciptaan model-model serpihan hibrid yang dioptimumkan dengan menggunakan data pengimbas laser udara dan algoritma-algorithma pembelajaran mesin di Malaysia. Objektif-objektif khusus adalah untuk mengenalpasti geomorfologi yang optimum, parameter-parameter topografi yang diolah daripada data LiDAR untuk kawasan tropika; memeta aliran serpihan dikawasan yang mudah terdedah dengan menggunakan data LiDAR; dan mencipta satu model hibrid RAMMS aliran serpihan untuk negara-negara tropika. Kualiti data spatial yang diperlukan dan pendekatan-pendekatan yang digunakan dalam memperoleh data adalah berkait secara langsung dengan ketepatan tahap analisis yang terlibat dan saiz pixel. Ketepatan menegak pulangan diskret data pengimbas laser udara beresolusi tinggi (15 cm), gema, dan keamatan telah digunakan untuk membuat DEM; selalunya digunakan untuk mendapatkan factor-faktor keadaan aliran debris untuk ramalan spatial dan aliran serpihan model. Faktor-faktor keadaan topografi dan geomorfologi termasuk sudut cerun, sudut aspek, jumlah kelengkungan, lengkungan satah, lengkungan profil, indeks kuasa aliran relatif, indeks kelembapan topografi, kawasan tadahan aliran, indeks kekasaran topografi dan indeks kedudukan topografi. Penentu-penentu yang lain adalah halaju dan data parameter reologi yang mempengaruhi jalan keluar aliran serpihan. Dalam kajian ini, data inventori sedia ada yang menggambarkan beberapa lokasi aliran serpihan telah digunakan untuk pemilihan ciri binary dengan data pengimbas laser udara beresolusi tinggi. Ciri-ciri tersebut telah dikategorikan kepada dua iaitu *"kehadiran aliran debris" (1)* dan *"ketiadaan aliran debris" (0)*. Enam ratus titik sampel dipilih secara rawak untuk setiap kategori dan sebanyak 640 titik sampel telah dijana. Data sampel bagi Kawasan tersebut telah dibahagikan secara rawak kepada dataset *training*: 70% (448) digunakan untuk

melatih model-model dan 30% (192) untuk pengesahan. *Spearman Correlation* telah digunakan untuk menyemak kesan *muti-collinearity* ke atas factor keadaan aliran serpihan; penilaian-penilaian factor-faktor nilai informasi (IV), *Crammer V* telah dinilai. Teknik peimlihan ciri subset *Wrapper* telah digunakan, carian algoritma metaheuristic, yang berbeza (e.g. *Cuckoo search*), dan penilai atau model algoritma yang mendorong (e.g. SVM) telah digunakan untuk pemilihan ciri subset, dimana seterusnya telah dibandingkan untuk memilih subset faktor-faktor keadaan yang optimum. Pada peringkat awal, Teknik-teknik pengoptimuman heuristic telah dilaksanakan dalam mengenalpasti laten terbaik global SVM dan MARS pemilihan nilai parameter digunakan untuk pemodelan ramalan aliran serpihan. Peta serpihan kecenderungan adalah penggabungan kawasan sumber aliran serpihan dan model *"run out"*, kemunculan kemajuan revolusi dalam MLA telah mencapai: dua teknik perlombongan data yang optimum (BFO-SVM dan PSO-MARS) telah dicantumkan. Pemetaan kerentanan yang dihasilkan dan kekuatan model-model adalah tertakluk kepada metrik penilaian ketepatan statistik mmenggunakan lengkungan *Receiver Operating Characteristic* (ROC) dan *Area Under Curve* (AUC), *Mean Asolute Error* (MAE), *Root Mean Square Error* (RMSE), pekali penentuan (R^2) dan kaedah-kaedah *Generalized Cross Validation* (GCV). Untuk mensimulasi corak aliran serpihan *"run-out"*, sebuah model rintangan geseran (Voellmy model) RAMMS-dbf telah dimodifikasi dengan gabungan model hakisan; ini telah memperbaiki keputusan model yang nyata. Hasil kajian telah menunjukkan bahawa integrasi antara *Cuckoo search* dan algoritma pembelajaran SVM yang dihasilkan adalah subset ciri terpilih yang terbaik dengan 99% pekali penentuan, RMSE dan MAE terendah masing-masing sebanyak 0.081 dan 0.0132. Model tersebut berkebolehan uttuk memperbaiki proses membuat keputusan dalam perancangan dan mitigasi risiko dan pengurusan bahaya alam sekitar.

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Declaration by graduate student

I hereby confirm that:

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CHAPTER 1

INTRODUCTION

Movements in different forms of landslides descending down slope, and slope instability that acted upon the mass earth could transform landscapes and perhap causes rife damage, hurt and resulted to loss of human lives in a community. Debris flows are dangerous natural hazard in countries with mountainous terrain. There is no universal definition of debris flows because of its complexity in nature. Different definition of debris flows exists in the literature; the prominent criteria associated with debris flow definitions are fluids and solid sediments. Debris flow is one of the forms of rapid landslides with elongated dislodgements, and inundated speedy shape similar to the flow-fluid. An accepted dynamic term relating this rapid movement is ‘Complex flows’ (Hungr 1995). As one of the most hazardous and destructive phenomenon of very rapid landslides, its devastative potential virtually impossible to reduce via equilibrium of the cradle zones. Hence, logical risk evaluations are requisite in the runout prediction and modified for sustainable human habitat and development

A number of environmental hazards is at alarming rate globally, triggers by different agent factors rainfalls/precipitation; (Chen 2016), earthquake, tsunami, wildfire etc.). These factors have globally increase the occurrence and threat of landslides (debris flows, mud flow, avalanche, rock fall etc.) and flood hazards (Chen 2016). The major factor that contributes to landslides is the adverse climate conditions with its associated extreme elements especially the rainfall condition (Nadim et al., 2006; Pradhan et al. 2016); expected to rise annually in the tropical Malaysia; that called for the investigation and improveddebris-flow models that could yield conducive human shelters.

As the global population is increasing at exponential rate, human quest for shelter has led to directionally rapid developments towards encroaching into debris flow susceptible landscape. Reports have shown that, the most densely populated areas are found around the Ocean coasts and the mountaineous regions due to fundamental resources holdsin such areas. Hence, the need to proper understanding and evaluate the potential and occurrence of debris flow is very important. By so doing logically, protecting and conserving inherent values of the environment for now and future generation needs. Application of GIS spatial science modelling in geological engineering associated to mass movements (landslides and debris flow) are rightfully complex science and useful in addressing the event. It requires high levels of knowledge of the mechanisms and developments linked to slope instability (Hungr, 1995). Decision based capability should not ignored or substituted by scientific theories and empirically derived relationships. There is a considerable requisite for reliable techniques for predicting the dynamics, runout distance and accumulation areas of such event. In this regards, it is therefore of great public and private interest to identify debris flow hazardous area to reduce the risk through protection and mitigation measures. Machine learning approaches that is SVM (Vapnik 2005) and MARS (Friedman 1991; Friedman and Roosen 1995) and numerical simulation models that is RAMMS-df (Christen et al. 2012) provides useful tools for susceptibility mapping assessment and run-out by depiction of design events and prediction of future events.

1.1 Research Background

Debris flow is defined as a rapid mass movement of a mixture of water, organic matter and sediment of varying sizes, that generally occurs as bursts with a sediment concentration greater than 50% (Coussot and Meunier, 1997; Chambon and Laigle, 2013; Liebault et al., 2013). In another development, Spencer et al. (2009) defined debris flows as flows of sediments and water that verve down to a valley floor along traditional water paths or along slopes through new routes. In addition, Iverson (1997) mentioned that debris flows occur when masses of poorly sorted sediment, agitated and saturated with water, surge down slopes in response to gravitational attraction. This type of event develops after the rapid influx of large amounts of water on loose soils, particularly frequent in high-mountain regions. The phenomenon is a deriven gravitational force influence moving mass natural disaster which proceeds at an unprecedented rapid rate; that could occur anywhere whether in a valley or on mountain slope, destroying everything it passes through. The action may be sudden and cause residents in its path to suffer casualties and property loss, resulted to environmental degradations which gas become global issues that requires swift attention. Debris flow development constitute three phases or zones of metamorphosis that involves initiation (source areas), propagation (transport zone) reside around the transitional slope angle between 15º to 25º (Fannin and Wise 2001; Lay and Pradhan 2019) and finally deposition zones($\leq 9°$), "sometime referred to as runout region". At the end, the debris flow deposits are poorly selected and recognized on the ground because they make up typical banks and lobes.

A number of environmental hazards is at alarming rate globally, triggers by different agent factors (rainfalls/precipitation (Chen 2016), earthquake, tsunami, wildfire etc.). In addition, a number of factors such as heavy precipitation, lahar, earthquake, landslide and other anthropogenic activities (Hürlimann et al. 2015; Melzner et al. 2015; Xing et al. 2015; Nakatani et al. 2016; Xing et al. 2016) usually triggers debris flow. Exerts great force and flow at high velocity that results in extreme number of casualty and property damage along its path (Panek 2015). These factors have globally increase the occurrence and threat to landslides (debris flows, mud flow, avalanche, rock fall etc.) and flood hazards (Chen 2016). Malaysia is as well suffering from the effects of dynamics in climatic elements especially rainfall and temperature. Hence, it is a norm that rainfall initiated landslides, which further activated debris flow, and these sequences are cyclical problem in Malaysia. Landslides and Debris flow susceptibility and runout or propagation assessments are vital instruments for harnessing the natural hazards progression (early warning to mitigation) (Pradhan et al. 2016).

The unpredictable timing and magnitude of debris flows hamper some investigations, often-raised significance mitigating threat to man and his infrastructures. A number of tragic events related to debris flow fatalities, destructions resulted in loss of lives, and properties have been recorded at different scales. For instance, it was estimated that 200,000 people died in 1920 from an earthquake-induced loess flow in Kansu Province China (Lay and Pradhan 2019) In addition, 4000 people died after an earthquake-induced debris avalanche occurred at north peak of Nevados Huascaran, in Peru in 1962 (Lay and Pradhan 2019). In another development, Lari et al. (2011) reported a debris flow risk assessment at regional scale in an Alpine valley. The study observed the impact of debris flow over a period of three decades, particularly in the central Alpines, Northern Italy. It is reported that between 1983 and 2004, debris flow affected about 1000 sqkm with 31 casualties recorded and over 90,000 were people rendered homeless.

In the case of Malaysia, debris flow incidents are only investigated and reported when human lives and/or infrastructures are impacted. Based on the newspaper reports and literature survey, there was at least 15 cases of killer debris flow tragedies from 1994 to 2012 and at least 137 people were killed. Currently, research on debris flows in Malaysia is still very limited to post-disaster investigation within the scene of the event, despite the eventually cause heavy economic loses and human casualties by the catastrophes. In this regards, it is of great concerns to public and private to demarcate hazardous zone to decrease the risk through protection and mitigation measures.

As suggested by Stringer and Reed (2007) holistic and strategic approaches should be sets in the assesement of natural and man-made disaster driven factors, via scientific studies and the implementation apertinent techiques for an event analysis. The concept of geospatial techniques has become an accepted practice in risk management (Quan Lin et al., 2011) proposed as a potential tools for enhancing the amalgamtion of geospatial science, MLA and structured healthier human shelter for modelling debris-flow event. This has provided enabling tools to both public and private institutions to identify, map and predict hazards in anticipation to reduce their impact. In depth knowledge of areas prone to the danger of debris flow is required for emmergency preparedness and to mitigate the damaging consequences to lives, properties and other critical infrastructures (Quan Lin et al., 2014). There is urgent need to curtail the effects using GIS and remote sensing technology

Previously, conventional approach has been employed in the terrain information acquisition, such as ground field surveys, which is tedious, time consuming and cost effective but provides a precise data (Casas et al. 2012) for GIS analyses. Owing to the enormous damages experienced by the Government, development of appropriate debris flow modelling techniques become essential in formulating contending strategies. Remote sensing (RS) and geographic information system (GIS) techniques are capable of supporting debris flows management in Malaysia. They are source of quick geospatial data and analysis for geological, geomorphological and terrain studies.

Currently, remotely sensed data collection approach, for topographic surface has been adopted in geosciences and engineering research. Precisely, in the recent past new frontiers and advancements in remote sensing technology. This development have produced a laser scanning technology (ALS, TLS, and MLS) or Light Detection And

Ranging (LiDAR). The ALS product contain a fine spatial resolution topography digital topographic model (DEM) that stimulated novel research approaches. Especially in mass movement, geomorphology, hydrogeology and engineering (Bhardwaj et al. 2016; Cerrillo-Cuenca 2016; Chen and Wang 2017; Frey et al. 2016; Goulden et al. 2016; Hergarten and Robl 2015; Lollino et al. 2015; Lopez et al. 2011; Neugirg et al. 2016; Pradhan et al. 2016; Pye and Blott 2016; Yamamoto et al., 2015). LiDAR DEM have advantages of high resolution, data in 3D, ability to penetrate through dense forest canopies and wider area coverage and all weather data capture; compare to other technologies, like photogrammetry, TLS and field surveys using global positioning systems (GPS) (Casas et al. 2012). Largely, these characteristics are what qualifies LiDAR data to be a source of topographic data, mostly used to generate the primary and secondary conditioning factors, serves in numerical hydrodynamic, landslides modelling, and natural hazard managements (Chen and Wang 2017; Gaidzik et al. 2017; García et al. 2016; Kim et al. 2016b; Lin et al. 2016; Lizarazo et al. 2017; Park et al. 2017), landslides (debris flow) susceptibility mapping (Bui et al. 2015; Wei Chen et al. 2018; Hong, Liu, Zhu, Shahabi, et al. 2017; Kalantar et al. 2018; Kim et al. 2016b, 2016a; Pham et al. 2015; Pradhan 2013; Pradhan and Lee 2010; Rickenmann 2016; Shirzadi et al. 2017) and upsurge the accuracy of hazard mapping (Bui et al. 2015; Pradhan 2013). There are abundance prospect to use LiDAR technology in mass movements' evaluation and modelling, which was used in this study.

To reduce the rate of the casualty and the advance effect of the debris flow a continuing number of work to predict the debris flow source in the area and its distribution pattern have been reported in literatures (Lay and Pradhan 2019). Despites the contribution made in modelling debris flow, there is need to improve the models for better and accurate result. Moreover, its became necessary to evaluate the extent, identify the debris flow initiation and occurrence in progression area, so as to harness, predict, and ease the unfavourable consequences in forward development (Termeh et al. 2018). Hence, the susceptibility model is a gauge to reach on this circumstance. Different data type, source from archive data, field survey data to remotely sensed data have been reported promising together with numerous analytical approaches in debris flow modelling.

Rapid development of machine learning algorithm (MLA) in different existing applications have exponentially increased in acceptability and adoption such as financial sectors (De Andrés et al. 2011), engineering, environmental and geological hazard mapping (Bhandari et al., 2015; Bui et al. 2015; Jin et al. 2018; Kalantar et al. 2018; Lay and Pradhan 2019; Liu et al. 2018; Pradhan 2013; Termeh et al. 2018; Pradhan, et al. 2016; Tien Bui, Tuan, et al. 2016). The approach is attributed to the problem of dimension in their learning algorithm ascend with the progress of feature variables (Liu et al. 2017). Various application problems of regression and classification requires distinctive and importance parameters/ features that depends on the provisional techniques and conditions of the events at hand. A common norms of the regression and classification encompasses judicial choice of relevant learning or training dataset in either continuous or categorical (regression and classification) formats respectively, generating accurate narration of the individual group models utilizing the accessible debris flow conditioning factors. Then evaluates the model prediction performance (Maldonado and Weber 2009; Panthong and Srivihok 2015). Researchers have reported a number of application that increases the efficiency and performances of debris flow prediction and classification models. In numerous applications, especially those involving prediction and mapping of mass movements often used large size of data; which could likely have some irrelevant feature or variables to the model. Abstraction of relevant information from these noisy datasets involves extensive exploration over the model space; run time complexity is introduce as a challenge with large volume and produce poor model accuracy. The problem can be handle via pre-processing feature size reduction approach, which is significance in model developments and improve the accuracy with associated downsizes overfitting for model generalizations

Expectedly, the essential feature contributes most with a peculiar robust in significant relationship with the subject on target (Liu et al. 2017).

In comparison, the excluded features are the redundancy variable that requires high processing or running time, invariably influence the model performance accuracy. Hence, it is imperative to remove the redundant, noisy and extraneous conditioning factorsthrough feature subset selection procedure, from the universal dataset of the training data. The issue is vital in MLA investigation, which impressively yielded a number of positive advantages; it lessens the modelling running time, eludes overfitting and increases simplification capacity (Liu et al. 2017; Liu and Zheng 2006; Maldonado and Weber 2009; Mason et al., 2018). Feature selection is a part of predictors data preparations before apply the principal classification or regression techniques, which involves feature reductions approaches. There are two categories of feature selection (Filter and wrapper) sometime embedded is consider as the third type; another data preparation is the feature extraction (feature transformation of normalization), detail explanation in the upcoming sections.

In recent past, various approaches from the conventional statistics to modern data mining algorithm techniques were implemented in investigation of mass movements. In this regards, a lot of classification and regression models exist, which can be categorized into four (Yu et al. 2011; Zhang et al., 2013), in order of chronological paradigm shift: (i). statistic- discriminant analysis, logistic regression decision tree. (ii) Artificial intelligent (AI), decision making approach-AHP, Fuzzy system and Support Vector Machine (SVM), MARS; (iii) Hybrid, Combine and ensemble (HCE) relates fuzzy system and ANN, rough set and SVM (Vapnik, 1995), hybrid/or SVM, adaptive neuro-fuzzy inference system (ANFI), neuro-Fuzzy, case-based reasoning and SVM, NNS. The MLA approaches proved efficient positive results in different geo-hazard applications landslides (mudflow, debris flow, and avalanches), earthquakes, rock falls, and erosion.

In this study, SVM and MARS were considered to predict the debris flow susceptibility. Friedman (1991) developed MARS for prediction using continuous explanatory variables and a set of independent variable. Like the universal characteristics of MLA, MARS is a nonparametric and nonlinear approach; this approach is capable of determine the number of basis function and the relationship that exist amongst the individual input variable automatically. The model is more flexible than a linear regression models, it is simple to understand and interpret than NN or RF; for detail explanation see section 2.1. Meanwhile SVR is a novel technique of MLA developed by Vapnik (1995) by means of optimization approaches base on statistical learning theory (Chen et al., 2009). It defines high dimension spaces utilizing the subset of the training points “support vector and requires small sample data. However, the problem of premature optimization is present here. These models can be applied to a problem of classification and regression.

Recently, more researcher are combined MLA with metaheuristic algorithm (MA) to achieve optimal model performances; PSO-GA, ACO (Termeh et al. 2018), SVR and PSO (Bui et al. 2015; Samui and Kothari 2012; Tien Bui et al. 2016; Wu and Law 2011; Yesilnacar and Topal 2005), PSO-ANFI (Chen et al., 2017; Shahnazar et al., 2017), GA and PSO for optimal distribution generated location and size in distribution system (Moradi and Abedini 2012). In addition, MLA can be combine with the statistical approaches Olden et al., (2008) and accomplished promising results with limited datasets (Rahmati et al., 2017). This accord to this study, which has some scarce auxiliary dataset (rainfall, soil and landform datasets). Inview of this, the traditional statistical approaches were actually substituted by more effective AI specifically machine learning algorithm (MLA). According to Termeh et al. (2018) the former method’s underline assumptions are rigid and data demanded to execute the model, are linear in nature and unstable with continuous data sets. Similarly, other reported some difficulties associated to the traditional statistical approaches, which includes the under-fitting or over-fitting, network architecture resolute, limited minima and consumes lengthy training time (Chen et al., 2009). The simply alternative way to handle the aforementioned shortfall possibly through the adoption of MLAs, that has not known accentuated assumption(s), capable of handling a complex nonlinear phenomena with an accurate results (Hamadeh et al., 2014; Kalantari and Abdollahifard 2016; Rahmati et al., 2017).

To mitigate a deris-flow hazard, there is need to discern accurately debris flow runnout distance,release volume. The debris flow is termed complex flows (Hungr, 1995) that rapidly moves to flow plain. The distance covered by this phenomenon at the last stratification is defined as runout (Federico and Cesali 2015; Han et al. 2015; Li et al. 2016). It is necessarily to assessment the runout distance and pattern due to its significant in debris flow hazard and risk assessment. Some importance propagation or runout modelling factors are factors (velocity, flow rheology, sediment entrainmens) are capable to improves the disaster model outcome. And provide means to delineate the susceptible zones , ascertain the effect of the hazard. These input data provide considerable factors in urban planning guard procedure. A digital terrain model (DTM) representation is an essential data source for parameterizing environmental models such as debris flow because terrain configuration largely influences surface flow processes and quality of the model output. Based on fluid theory, flow model is categorised into: Newtonian and non-Newtonian model (Iverson, 1995), exist in either single two. Some models require detailed data on rheological (Scheidl et al., 2013), topography, hydrological and geomorphological, which are obtainable at a site normally a vulnerable passage of a debris flows (Armento et al. 2008).

A number of literatures related to modelling debris flows and it trajectory exists, but quantitative assessment with better accuracy of prediction, simulation using artificial intelligence and logistic regression methods have been prove reliable in a similar natural hazard studies (Iverson, 2014). Different debris flow models are attested to it require input data of parameters some are directly derive while others are indirectly; depending on the model assumptions and application stage. Run out model approaches for predicting kinematic effect are clustered into three Chen and Lee (2004) includes physical scale approaches, empirical approaches, and dynamic modelling. Further segregated into specific sub models applies in debris flow.

Various debris-flow models analyses (run-out models and trajectory) exist in the literatures. This include one-dimensional Dynamic Analysis (DAN-W) developed by Hungr (1995); two-dimensional model FLO-2D (O'Brien et al., 1993); FLO-R, TopRunDF, TopFlowDF (Rickenmann and Scheidl, 2010); DAN-2D, DAN3D and RAMMS-df. While FLO-2D and RAMMS are dynamical models based on physical model approaches, TopRunDF is based on a semi-empirical approach combined with stochastic elements. TopFlowDF (Han et al., 2016) combines a simple physical approach with the flow algorithm implemented in TopRunDF (Rickenmann and Scheidl, 2010). Besides these modelling approaches; simulation, artificial intelligent and logit regression methods have become more attractive and demanding in natural disaster assessment due to their high prediction capabilities and accuracy. Among these, no model is superior to the other in reality; but, combination of two or more can be considered to produce better result in a particular application.

1.2 Problem Statement

Investigations show that debris flow is often caused by extreme rainfall intensity (Allen et al., 2015; Martha et al., 2015). In the early month of December 2015, heavy rain wreaks havoc in most parts of Malaysia, especially in Selangor, Sugai Siput and Sepang; triggered flash flood, landslide and debris flow that renders major roads impassable for more than 1,000 villagers (Straits Time, 2015). More socioeconomic and infrastructural facilities have been damaged by debris flow in recent past. To overcome these menance a number of innovative techniques have been investigated and provided, often on flood and landslide susceptibility assessment (Hsu et al., 2011, 2012; Lugeri et al., 2010; Markus et al., 2010; Pandey et al., 2010; Pradhan et al., 2012). However, relevance research to on debris-flows events (initiation, susceptibility and runout) modelling have not received the much needed attention from the scientific community (Blijenberg 2007). The few studies on the debris flow in Malaysia (Pradhan et al. 2017; Lay and Pradhan 2019) used the laser scanning technology to predict the debris flow initiation or source area and assessed the areas susceptible to debris flow in Pahang area; but non of these research deliberated on the appropriate (optimal) feature subset selection that is best fitted as model input conditioning factor for the area.

Meanwhile, (Chen et al. 2017; Fong et al., 2015; Termeh et al. 2018; Wang and Niu 2017) pointed that a large number of features influences model output accuracy due to the existent of redundant and irrelevant conditioning factors, which may negatively affects the model performance. In addition, data dimensionality has been considered to be the main hinderance in quality of several machine learning and data mining processes and resultant accuracy. High dimensional datatsets for learning training a classification or regression model could intoduce overfitting in the modelling procedures, which diminishes the simplification of the trained model and produced poor model's output. Features selection is an important pre-processing step that aim to eliminate noisy variables from further analyses, this procedure enhance the the model performance accuracy and reduces the model's runing time. Picking the best model value from a subset feature selection and the best approach process in hazard forecasting problems are always serious issue not easy to tackle (Bui et al. 2018). SVM-RBF and MARS have two hyper-parameters or control factors (kernel function and panel parameters) capable to influence the models complex structures, performance selection and there is need to optimize the values in order to produce a high accuracy result.

In any case, source areas of potential debris flows was mapped out, and a step towards that is a susceptibility map of debris flows generated for a given geographic locations. Such a map help to estimate real debris flow hazard, in an assumed realistic debris-flow scenario. Part of such a scenario is not only recognition of a source area but also estimation of a debris-flow magnitude. In many cases such magnitudes can only be empirically determined on the basis of historical data available in the region. Why the need for estimating a debris-flow magnitude? This is in a way needed to estimate realistic run-outs and delineate safe areas from endangered ones.

Regarding debris flow suscepceptibility mapping, some empirical model such a conventional statistical approach (multivariate, regression) and machine learning algorithms (ANN, SVM RF, MARS etc.) have been used to identify the initiation zone and predicting the susceptibilty behaviour of debris flows in different regions (Pradhan et al. 2017; Chen et al. 2015; Lay and Pradhan 2019; Luna et al. 2012; Magirl et al., 2010; Rahmati et al. 2017; Road et al. 2013; Takahashi, 2007). Researcher have reported the challenges associated to the traditional statistical model, which include under or over-fittings, resolute model architecteral network, limited minima that takes long processing learning time (Chen et al., 2009; Wu et al. 2013; Xing et al. 2016). The simple alternative way to handle the aforementioned shortfall is through the adoption of MLAs, that has not known accentuated assumption(s), capable of handling a complex nonlinear phenomena with an accurate results (Hamadeh et al., 2014; Kalantari and Abdollahifard 2016; Rahmati et al. 2017). In addition, MLA can be combined with the statistical approaches (Olden et al., 2008) and accomplished promising results with a limited data (Rahmati et al. 2017). Meanwhile integration of MLA and metaheuristics approach in hyperparameter selection have been proved promising (Agarwalla and Mukhopadhyay 2018; Al-Yaseen et al., 2017; Azeez et al., 2018; Chen 2003; Hernández-Ocaña et al., 2016; Jin and Xu 2011; Li and Sun 2011; Mafarja and Mirjalili 2017; Mafarja and Mirjalili 2018; Mahi et al., 2018; Mason et al., 2018; Nakariyakul 2018; Nobile et al. 2018; Panja et al. 2018; Singh and Sundar 2018; Tien Bui et al., 2016; Yousefi and Loo 2018). In contrast, this novelty approach results proved better accuracy performances than using single tradition methods and ML approach. For instant PSO-SVM, PSO-ABC.

Thought, they suggested further research should be carried out on universal multi-objectives approach in feature selection. Despite the plentiful state-of-the-art, hybrid optimization algorithms using remote sensing data and geographic information system modelling approaches, yet it is not given proper attention, although little research have been done in relation to debris flow susceptibility mapping. Thus, to tackle this contest, two different hybrids MA (PSO and BFO) connected with MLA (SVM and MARS) were selected to identify the optimal or global best model parameter's values that were extremely significance in the construction of MLAs and choose the best modelling algorithm procedure suitable in critical prediction of debris flow. Thought, improving the model input features/parameters and optimized approaches controls MLA factor (kernel and penalty) have created uncertainties. Subsequently, conditioning factorsredundancy in mass wasting modelling, obviously reported to have the tendency of influencing modelling output accuracy and increases the processing running time. Even a fraction of a percentage rise in debris flow model accuracy result is substantially triumph (West 2000). Two different hybrids MA (PSO and BFO) connected with MLA (SVM and MARS) were modelled to identify the optimal or global best model parameters value that were extremely significance in the construction of MLAs and choose the best modelling algorithm procedure suitable in critical prediction of debris flow.

Picking the best model parameter's value from a feature subset selection and the best approach process in hazard forecasting problems always poses serious issues that are not easy to tackle (Bui et al. 2018). Considerably, SVM-RBF had two hyper-parameters or control factors (kernel function and panel parameters) believed to influence the model complexity performance selection in term of prediction accuracy and there is need to optimize the values in order to produce a higher accurate results. MARS is also, influence by limits of basis function and number of interaction. However, researchers have established empirical, statistical and semi analytical procedures to understand the debris modelling (source areas, susceptibility to runout and propagations) (Chen et al. 2011; Dai et al. 2008), this explainthat most of the traditional approaches are inappropriate, complex while others are obsolescence. The MLA and meta-heuristic approach are very suitable on a complex system which allowed the evaluation,prediction of debris-flow source and the model performances using some derived topographics and geomorphological elements derived from the laser scanning data (LiDAR) DEMEven though, several MLA and optimization algorithms have been utilized in landslides related assessments globally, but in debris flow susceptibility modelling not until now the hybridazation of the approaches have not been adopted for debris flow mapping.

The occurrence of debris flows have been recorded for more than a century in the European Alps, accounting for the risk to settlements and other human infrastructure, which has led to the loss of life, building damage and traffic disruptions. One of the difficulties in the quantitative hazard assessment of debris flows is estimating the run-out behaviour, which includes the run-out distance and the related hazard intensities like the height and velocity of a debris flow. In addition, as reported in the literature, process of entrainment of material during the run-out can be 10–50 times in volume, with respect to the initially mobilized mass triggered at the source area. The entrainment process is evidently an important factor that can further determine the magnitude and intensity of debris flows. Research on numerical modelling of debris flow entrainment is still on-going and involves some difficulties. This is partly due to our lack of knowledge of the actual process of the uptake and incorporation of material and due the effect of entrainment on the final behaviour of a debris flow. Therefore, it is important to model the effects of this key erosional process on the formation of run-outs and related intensities. This study analysed a debris flow event with high entrainment rates that occurred in 2015 at the Ringlet catchment in the Cameron Highlands (Pahang). The historic event was back-analyzed using the Voellmy rheology and an entrainment model imbedded in the RAMMS 2-D numerical modeling software. A sensitivity analysis of the rheological and entrainment parameters was carried out and the effects of modeling with entrainment on the debris flow run-out, height and velocity were assessed.

Investigation on debris flow runout modelling are being carried out to predict prone or hotspot zones of the event (Han et al., 2016; Hergarten and Robl 2015; Schraml et al. 2015; Schneider et al. 2014; Scheidl et al. 2013; Bühler et al. 2011 and Christen et al. 2010). However, selection of adequate runout prediction models, is mainly based on their accessibility and on the requirements of local hazard assessments (Scheidl and Rickenmann 2011). Entrainment is a significant variable in determining the release volume from the source area through channel propagation to depositional runout model. Number of researcher adopted numerical model in debris flow exploration without emphase on erosion or entrainment process, this could be the reasons for outrageous results. In this research, a numerical runout prediction method have been improve to accuratelly estimate the debris flows runout distance and volume using RAMMS-df (Christen, Kowalski, and Bartelt 2010). Furthermore, 2D runout predictions for debris-flow events are presented, applying a dynamic numerical simulation model (RAMMS) incapsulation with erosion approach. Application of this model in debris flow disaster zone mapping could be used for hazard mitigation and adaption of the mass movements (landslides, debris flow and avalanche) to man and his environs. In additon, the modelling is capable to give an accurate estimation of runout velocity and distance, that is useful for developmet planning and decision making process.

Other approaches used to study runout model include, dynamic models (DAN3D), numberical and physical model. Indivual approach has required input parameters for the simulation models on different dimentional spaces (2D or 3D). The data source extended from archived data, remotely sensed data to field observation; more detail has been explained in Chapter two of this thesis.

However, the idea of developing concern neither BFO -SVM nor PSO - MARS have been employed to predict area susceptible to debris flow in a complex rugged environment. The fragile areas like the Cameron Highlands, there exist evidence debris-flow disaster accelerated by number of environmental factors, which necessitate to be thoroughly investigated for the purpose of decisionmaking process.

1.3 Research Motivation

Generally, only very few publications are available on debris flow assessment or modelling in Malaysia. Research focus on debris flow modelling is new in the realm of academics and engineering. The Malaysian disaster management agency focused attention to flooding and landslide. After the devastating 2015 flooding, landslide and debris flow events caused by heavy monsoon rainfall, the disaster management has become more proactive on slope instability studies and other earth movement hazards into its development planning. To assess disasters around the mountainous area especially the rugged terrain of Cameron Highlands requires information on the surface terrain and the state of the slope instability. Past is key to the future; to assess potential debris flow in the areas, inventories is necessary.

Experts reached a decision that in developing a specific debris flow model, considering and identifying the appropriates debris flow conditioning factorsare fundamentals (Blais-Stevens and Behnia 2016; Dashwood 2017; Horton et al. 2013; Kappes et al. 2011; Lancaster et al. 2012; Lay and Pradhan 2019; Lin et al. 2013; Magirl et al., 2010; Mathias and Jakob 2005; Sodnik et al. 2013). In the past, various researchers set model features subset base on the user-define discreet, which could introduce redundancy in the conditioning factors. An organized criterion considered to minimize feature selections and the costs implications in data acquisition, has inspired this exploration as to what extent does the Airborne laser scanning technology (ALS)/or LiDAR derived conditioning factors (topographic and geomorphomertric factors) only are adequate to produce actual debris flow susceptibility mapping.

The requisite of exploring the recent data tools (LiDAR) for debris flow modelling than the classical remotely sensed data source in the rough terrain area; developing a methodology for debris flow runout modelling; establishing approach on debris flow susceptibility analysis; instituting optimal parameter for debris flow modelling and evaluations. In the absent of specific readily available debris flow inventory data, the historical record in landslide inventory data of the same study area was used, which is sourced from the work of (Pradhan et al., 2010). Because debris flow is a form of landslides categories (Hungr 1995), this research centres on the utilization of archived data of the past landslide inventory to quantitatively analyse as training and validation dataset for the debris flow susceptibility and run out modelling.

1.4 Research Questions

Some of the most interesting questions that are yet to be answered, but will be addressed in this study include:

i. Which of the LiDAR derived geomorphological and hydrogeological datasets best contributes to accurate modeling of debris flow initiation zones and run out?
ii. Are there specific parameters for debris flow prediction in tropical region?
iii. What impact does DEM resolution has on the accuracy of the resulting model?

iv. Are the existing models effective for debris flow prediction?.

1.5 Research Aim and Objectives

The aim of this study is to developed a debris flow model for the tropical Malaysia. This was achieved using the following specific objectives:

i. To identify optimal LiDAR derived geomorphological and topographic parameters for debris flow modeling;
ii. To detect effective debris flow initiation zones using the LiDAR DEM data; and map debris flow susceptible area using the optimised parameters; and
iii. To develop a hybrid runout model for tropical countries.

1.6 Scope and Limitations

This study centre around the Cameron Highland, which had always been the focused by researchers because of the frequent occurance of landslides and debris flow that usually accompany by heavy rainfall every year. While the hazards of the resultant mass movement of debris transported downhill has been largely not given the necessary attentions. Other forms of landslides do occur in the area include soil creep, rock fall, Mud and other transported materials flow longer distances (run-out) outside the release area and the devastating impact along its course is controlled by the nature of the topographical and morphological settings, velocity and density of the transported material.

However, it is almost impossible to totally eschew or avert the debris flow incidence due to its intricacy. Improving and adopting rightful prediction analytical process and using relevance variables (dataset) in predicting the past debris flow susceptible in the region can give alert on the onset of the hazard and even reimburse the situation Termeh et al. (2018) in the future effect for developmental plan in different debris flow prone zones. In this research, the size of the area that are prone or possibly encroach by the debris flows were ascertained by geomorphometric and topographic stability of the terrain. Understanding of debris flow behaviour from initiation to deposition is crucial to be able to predict potential debris flow activities for the development of hazard zonation mapping to protect life and infrastructure.

Meanwhile, this research was carried out in twofold sections, firstly investigated and optimization of the conditioning factors, which adopted hybrid (wrapper and filter) feature subset selection approaches as earlier discussed.Secondly, the study evaluated and optimized hyperparameter values of (SVM and MARS) models, the selected optimal values were integrated in predicting areas susceptible to debris flow. Worthy mentioning that both sections adopted metaheuristic nature inspiring optimization algorithms.

A main limitation to this study is the accessibility of spatio-temporal higher resolution LiDAR data. One of the contraints is the availability of climate data, especially rainfall data, Rainfall data has not being considered in this study despite it significant contribution in modelling geologicalhazards; due to the size of this study. Hence, rainfall data is exempted from the modelling because is considerably uniform over the area (Pradhan 2012). Unlike land use and climate variables which change rapidly over short time, lithology and soil properties are not considered as part of the conditioning factorsin this study because they are assumed to be constant over a longer time scale (Keijsers et al. 2011). Adding these parameters to the model has demostrated a tendency of negativelly influence in the accuracy of the debris flow prediction models. Furthermost, the existing data are suited for models at regional scale.

1.7 Thesis organization

This thesis is structured into five chapters as brifly described below;

Chapter 1 introduces the bacground of the study, explained the basis for embacking on the research, then research problems formulation followed by the enthusiasm in the study, research questions and aim and objectives.

Chapter 2 is literature review describing landslide in general, debris flow, and debris flow assessment using landslide susceptibility information and debris flow modelling.

Chapter 3 describes the study area physical condition and explains the materials used in the research as well as the method used to collect and process the materials.

Chapter 4 is result and discussion of the study including landslide assessment, debris flow modelling and debris flow assessment. Chapter Chapter 6 is final conclusion which states the objective achievement and the recommendation for the study area itself as well as the future studies.

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LIST OF PUBLICATIONS

Journal articles

Lay, U. S., Pradhan, B., Yusoff, Z. Bin, & Bin, A. F. (**Accepted, 2019**). Data Mining and Statistical Based Approach in Debris Flow Susceptibility Modelling Using Laser Scanning Data. *Remote Sensing (MDPI)*, 1-30. (**MDPI, Q1, IF = 3.03**)

Lay, U. S., Pradhan, B., Yusoff, MD. Z., Abdullah, A. F. & M. Shattri (**Submitted**). A Novel Hybrid Bfoa/Pso_Optimized SVM-Based Model for Predicting Tropical Debris Flow Using Lidar Data. *Remote Sensing of the Environment* (**Elsevier – SCOPUS Index – Q1, IF = 8.157**).

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