

LANDSLIDE SUSCEPTIBILITY MAPPING USING REMOTE SENSING DATA
AND GEOGRAPHIC INFORMATION SYSTEM-BASED ALGORITHMS

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DEDICATION

This thesis is dedicated to my lovely father and mother; Mr. Hassan Mohammadi and Mrs. Jamileh Ahmadnya, my beloved spouse; Sogand Amini, other member of my family, my helpful supervisors; Assoc. Prof. Dr. Baharin Bin Ahmad and Assist. Prof. Dr. Himan Shahabi.

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ABSTRACT

Whether they occur due to natural triggers or human activities, landslides lead to loss of life and damages to properties which impact infrastructures, road networks and buildings. Landslide Susceptibility Map (LSM) provides the policy and decision makers with some valuable information. This study aims to detect landslide locations by using Sentinel-1 data, the only freely available online Radar imagery, and to map areas prone to landslide using a novel algorithm of AB-ADTree in Cameron Highlands, Pahang, Malaysia. A total of 152 landslide locations were detected by using integration of Interferometry Synthetic Aperture RADAR (InSAR) technique, Google Earth (GE) images and extensive field survey. However, 80% of the data were employed for training the machine learning algorithms and the remaining 20% for validation purposes. Seventeen triggering and conditioning factors, namely slope, aspect, elevation, distance to road, distance to river, proximity to fault, road density, river density, Normalized Difference Vegetation Index (NDVI), rainfall, land cover, lithology, soil types, curvature, profile curvature, Stream Power Index (SPI) and Topographic Wetness Index (TWI), were extracted from satellite imageries, digital elevation model (DEM), geological and soil maps. These factors were utilized to generate landslide susceptibility maps using Logistic Regression (LR) model, Logistic Model Tree (LMT), Random Forest (RF), Alternating Decision Tree (ADTree), Adaptive Boosting (AdaBoost) and a novel hybrid model from ADTree and AdaBoost models, namely AB-ADTree model. The validation was based on area under the ROC curve (AUC) and statistical measurements of Positive Predictive Value (PPV), Negative Predictive Value (NPV), sensitivity, specificity, accuracy and Root Mean Square Error (RMSE). The results showed that AUC was 90%, 92%, 88%, 59%, 96% and 94% for LR, LMT, RF, ADTree, AdaBoost and AB-ADTree algorithms, respectively. Non-parametric evaluations of the Friedman and Wilcoxon were also applied to assess the models' performance: the findings revealed that ADTree is inferior to the other models used in this study. Using a handheld Global Positioning System (GPS), field study and validation were performed for almost 20% (30 locations) of the detected landslide locations and the results revealed that the landslide locations were correctly detected. In conclusion, this study can be applicable for hazard mitigation purposes and regional planning.

ABSTRAK

Sama ada tercetus secara semulajadi atau berlaku kerana aktiviti manusia, tanah runtuh membawa impak kepada kehilangan nyawa dan kerosakan besar kepada hartanah yang menjejaskan infrastruktur, jaringan jalanraya, bangunan, dan hartanah. Peta kecenderungan tanah runtuh (LSM) menyediakan pembuat polisi dan keputusan dengan beberapa informasi yang berharga. Kajian ini bertujuan untuk mengesan lokasi tanah runtuh dengan menggunakan data Sentinel-1 sebagai satu-satunya imej radar dalam talian secara percuma disamping untuk memetakan kawasan yang cenderung berlaku tanah runtuh menggunakan model AB-ADTree di Cameron Highlands, Pahang, Malaysia. Sejumlah 152 lokasi tanah runtuh dikesan menggunakan teknik integrasi RADAR bukaan interferometri (InSAR), imej Google Earth dan ukur lapangan yang menyeluruh. Walau bagaimanapun, 80% daripada data telah digunakan untuk melatih mesin algoritma dan baki 20% untuk tujuan pengesahan. Tujuh belas faktor pencetus dan penetap iaitu cerun, aspek, ketinggian, jarak ke jalan raya, jarak ke sungai, kehampiran ke gelinciran, kepadatan jalan, ketumpatan sungai, indeks normal tumbuh-tumbuhan (NDVI), taburan hujan, litupan bumi, litologi, jenis tanah, kelengkungan, kelengkungan profil, indeks kuasa aliran (SPI) dan indeks kelembapan (TWI) topografi diekstrak dari pada imej satelit, model ketinggian berdigit (DEM), peta geologi dan tanah. Faktor-faktor ini digunakan untuk menjana peta kecenderungan tanah runtuh menggunakan model regresi logistik (LR), model logistik pokok (LMT), hutan rawak (RF), pokok keputusan berselang (ADTree), meningkatkan penyesuaian (AdaBoost) dan model hibrid baru daripada model-model ADTree dan AdaBoost iaitu model AB-ADTree. Pengesahan adalah berdasarkan keluasan di bawah lengkung ROC (AUC) dan pengukuran statistik bagi nilai ramalan positif (PPV), nilai ramalan negatif (NPV), kepekaan, pengkhususan, ketepatan, dan ralat punca punca kuasa dua min (RMSE). Hasil kajian menunjukkan bahawa AUC adalah 90%, 92%, 88%, 59%, 96% dan 94% masing-masing bagi algoritma LR, LMT, RF, ADTree, AdaBoost dan AB-ADTree. Penilaian bukan parametrik Friedman dan Wilcoxon juga digunakan untuk menilai prestasi model, dimana hasil dapatan menunjukkan bahawa ADTree adalah lebih rendah daripada model lain yang digunakan dalam kajian ini. Dengan menggunakan sistem penentududukan sejagat (GPS) pegangan tangan, kajian lapangan dan pengesahan dilakukan kepada hampir 20% (30 lokasi) dari lokasi tanah runtuh yang dikesan dan hasil kajian menunjukkan lokasi-lokasi tanah runtuh telah dikesan dengan betul. Sebagai kesimpulan, kajian ini boleh digunakan bagi tujuan pengurangan malapetaka dan perancangan serantau.

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LIST OF ACRONYM

AB-ADTree	-	Adaptive Boosting and Alternating Decision Tree
AdaBoost	-	Adaptive Boosting
ADTree	-	Alternating Decision Tree
AHP	-	Analytical Hierarchy Process
AIRSAR	-	Airborne Synthetic Aperture Radar
ALOS-	-	Advanced Land Observing Satellite Phase Array L-Band
PALSAR		Synthetic Aperture Radar
ANFIS	-	Adaptive Neuro-Fuzzy Interface System
ANFIS-FR	-	Adaptive Neuro Fuzzy Inference System Combined with the Frequency Ratio
ANN	-	Artificial Neural Network
ARM	-	Association Rule Mining
AUC	-	Area under the Curve
BN	-	Bayesian Network
CF	-	Certainty Factor
CNN	-	Convolutional Neural Network
DE	-	Differential Evolution
DEM	-	Digital Elevation Model
DInSAR	-	Differential Interferometry Synthetic Aperture RADAR
DT	-	Decision Tree
DTM	-	Digital Terrain Model
ENVI	-	Environment for Visualizing Images
ERTS	-	Earth Resource Technology Satellite
ESA	-	European Space Agency
ETM	-	Enhanced Thematic Mapper
ETM+	-	Enhanced Thematic Mapper Plus
EW	-	Extra Wide Swath
FA	-	Factor Analysis
FL	-	Fuzzy Logic
FLDA	-	Fisher's Linear Discriminant Analysis

FN	-	False Negative
FP	-	False Positive
FR	-	Frequency Ratio
GA	-	Genetic Algorithm
GAM	-	Generalized Additive Model
GCPs	-	Ground Control Points
GE	-	Google Earth
GIS	-	Geographic Information System
GPS	-	Geographic Positioning System
GRASS	-	Geographical Research Analysis Support System
GRD	-	Ground Range Detected
GWPC	-	Geographically Weighted Principal Component
IDW	-	Inverse Distance Weighted
InSAR	-	Interferometry Synthetic Aperture RADAR
IRS	-	Indian Remote Sensing
IW	-	Interferometry Wide Swath
KLR	-	Kernel Logistic Regression
LDA	-	Linear Discriminant Analysis
LFR	-	Likelihood Frequency Ratio
LIDAR	-	Light Detection and Ranging
LMT	-	Logistic Model Tree
LR	-	Logistic Regression
LSI	-	Landslide Susceptibility Index
LSM	-	Landslide Susceptibility Mapping
LST	-	Land Surface Temperature
MARSpline	-	Multivariate Adaptive Regression Spline
MCDA	-	Multi Criteria Decision Analysis
MCE	-	Multi-Criterion Evaluation
MD	-	Minimum Distance
ML	-	Maximum Likelihood
MLAs	-	Machine Learning Algorithms
MLR	-	Multiple Logistic Regression
MSI	-	Multi-Spectral Instrument

NASA	-	National Aeronautics and Space Administration
NB	-	Naïve Bayes
NDBI	-	Normalized Difference Built-up Index
NDVI	-	Normalized Difference Vegetation Index
NF	-	Neuro-Fuzzy
NIR	-	Near infrared
NOAA	-	National Oceanic and Atmospheric Administration
NPV	-	Negative Predictive Value
OLI	-	Operational Land Imager
OSM	-	Open Street Map
PCA	-	Principal Component Analysis
PFR	-	Probabilistic Frequency Ratio
PPV	-	Positive Predictive Value
PSO	-	Particle Swarm Optimization
RADAR	-	Radio detection and ranging
RF	-	Random Forest
RMSE	-	Root Mean Square Error
ROC	-	Receiver Operating Characteristics
ROIs	-	Region of Interests
RS	-	Remote Sensing
SAGA	-	System for Automated Geoscientific Analyses
SAM	-	Spectral Angle Mapper
SAR	-	Synthetic Aperture Radar
SDSS	-	Spatial Decision Support Systems
SEI	-	Site Exposure Index
SLC	-	Single Look Complex and Scan Line Corrector
SM	-	Strip-map
SMCE	-	Spatial Multi-Criteria Evaluation
SNAP	-	Sentinel Application Platform
SPI	-	Stream Power Index
SPOT	-	Satellite Probatoire d'Observation de la Terre
SPSS	-	Statistical Package for Social Sciences
SRR	-	Surface Relief Ratio

STI	-	Sediment Transport Index
SVM	-	Support Vector Machine
SWIR	-	Short-wavelength infrared
TIRS	-	Thermal Infrared Sensor
TM	-	Thematic Mapper
TN	-	True Negative
TOPS	-	Terrain Observation Progressive Scan
TP	-	True Positive
TRI	-	Topographic Roughness Index
TRMM	-	Tropical Rainfall Measuring Mission
TWI	-	Topographic Wetness Index
UTM	-	Universal Transverse Mercator
WEKA	-	Waikato Environment for Knowledge Analysis
WF	-	Weighting Factor
WLC	-	Weighted Linear Combination
WSP	-	Weighted Spatial Probability
WV		Wave

LIST OF SYMBOLS

hr	-	Hour
P	-	Probability
∞	-	Infinity
Σ	-	Summation sign
α	-	Alpha
$\sqrt{\quad}$	-	Radical sign
σ	-	Sigma
γ	-	Gamma

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Landslide includes various kind of slope movements, such as rock falls, slips, mud flows, debris flows, and etc. (Varnes, 1978; Cruden, 1991; Malamud et al., 2004; Shahabi et al., 2012a; Shahabi et al., 2012b; Hungr et al., 2014; Hermanns, 2016; Cruden, 2017; Sassa et al., 2018). However, it is a complex disaster, which triggered mainly by mining, earthquakes, heavy rainfall, volcanoes, snowmelt, and many more (Petley et al., 2005; Shahabi et al., 2012c; Shahabi et al., 2013; Hungr et al., 2014; Hermanns, 2016; Cruden, 2017; Mansor et al., 2018). Additionally, refer to the worldwide notification, landslide falls into the third type of natural disaster category (McClelland et al., 1997; Zillman, 1999; Mansor et al., 2004; Hungr et al., 2014; Lollino et al., 2016; Mărgărint & Niculiță, 2017; Turner, 2018).

Concern with the manmade actions or the natural conditions, landslides have produced multiple economic and human losses across the globe, which sometimes claimed up to 20000 lives and millions of dollars of damages to properties and human settlements (Schuster & Fleming, 1986; Guzzetti, 2000; Mansor et al., 2007; Hungr et al., 2014; Shahabi & Hashim, 2015; Lollino et al., 2016; Mărgărint & Niculiță, 2017; Turner, 2018). Table 1.1 shows statistics of the occurred destructive landslides in some landslide prone countries from the date 26 Oct 1954 until the date 9 January 2018.

Table 1.1: The distractive occurred landslides around the world (1954-2018) (Wikipedia, 2018a)

No.	Date	Place	Casualties
1	26 Oct 1954	Amalfi Coast, Italy	300
2	8 Jul 1958	Lituya Bay, Alaska, United States	22
3	10 Jan 1962	Ranrahirca, Peru	4,000 – 5,000
4	9 Oct 1963	Longarone, Italy	2,000
5	28 Mar 1965	El Cobre, Chile	200+
6	21 Oct 1966	Aberfan, Wales	144

7	18 Mar 1967	Caraguatatuba, Brazil	120
8	31 May 1970	Yungay, Peru	22,000+
9	18 Mar 1971	Chungar, Peru	400–600
10	Apr 1974	Junín Region, Peru	450
11	18 May 1980	Washington, United States	57
12	13 Nov 1985	Tolima Department, Colombia	23,000
13	28 Jul 1987	Valtellina, Lombardy, Italian Alps	29
14	30 Jul 1997	Thredbo, New South Wales, Australia	18
15	14–16 Dec 1999	Vargas, Venezuela	30,000
16	12 Jul 2000	Mumbai, India	78
17	9 Nov 2001	Amboori, Kerala, India	40
18	26 Mar 2004	Mount Bawakaraeng, Indonesia	32
19	10 Jan 2005	California, United States	10
20	17 Feb 2006	Southern Leyte, Philippines	1,126
21	11 Jun 2007	Chittagong, Bangladesh	123
22	6 Sep 2008	Cairo, Egypt	119
23	9 Aug 2009	Siaolin Village, Kaohsiung, Taiwan	439–600
24	4 Jan 2010	Attabad, Gilgit-Baltistan, Pakistan	20
25	20 Feb 2010	Madeira Island, Portugal	42
26	1 Mar 2010	Bududa District, Uganda	100-300
27	10 May 2010	Saint-Jude, Quebec	4
28	8 Aug 2010	Gansu, China	1,287
29	16 Jun 2013	Kedarnath, Uttarakhand, India	5,700
30	22 Mar 2014	Oso, Washington, United States	43
31	2 May 2014	Argo District, Afghanistan	350-500
32	30 Jul 2014	Pune district, Maharashtra, India	136
33	2 Aug 2014	Sindhupalchok District, Nepal	156+
34	20 Aug 2014	Hiroshima Prefecture, Japan	74
35	29 Oct 2014	Badulla District, Sri Lanka	16+
36	13 Dec 2014	Jemblung village, Java, Indonesia	93
37	23 Apr 2015	Badakhshan Province, Afghanistan	52
38	28 Apr 2015	Salvador, Bahia, Brazil	14
39	18 May 2015	Antioquia Department Colombia	83
40	1 October 2015	Guatemala Department, Guatemala	280
41	13 November 2015	Lidong Village, Zhejiang, China	38
42	2 April 2017	Mocoa, Colombia	329+
43	12 June 2017	Rangamati, Bangladesh	152
44	14 August 2017	Freetown, Sierra Leone	1,141+
45	9 January 2018	California, United States	20

Landslide leads to mass displacement of the earth materials. It happens in a variety of material, such as debris and rocks, which moves at different rates from one mm/year to tens of m/second (Varnes, 1978; Cruden, 1991; Hungr et al., 2014; Hermanns, 2016). However, topples, falls, flows, slides and spreads are various kind of movements (Malamud et al., 2004; Couture, 2011; Hungr et al., 2014; Mărgărint & Niculiță, 2017). Moreover, based on activity, landslide can be divided into variety of stages ranging from dormant to active (Varnes, 1978; Hungr et al., 2014; Hermanns, 2016; Sassa et al., 2018). Besides, it can be progressive, retrogressive and advancing, which moving along curved or flat surfaces (Cruden & Varnes, 1996; Hungr et al., 2001; Hungr et al., 2014; Cruden, 2017). Additionally, refer to the depth of occurrence

it can be shallow or deep seated (Binaghi et al., 1998; Gritzner et al., 2001; Gorsevski et al., 2003; Abella & Van Westen, 2008; Sassa et al., 2018).

One of the most common applications of satellite imageries is landslide inventory. In term of physical situation of the study area, the optical, multi-spectral and RADAR (Radio detection and ranging) systems should be acquired (Van Westen et al., 2008; Shahabi et al., 2012a; Yang et al., 2017; Tien Bui et al., 2018). In addition, identification and extraction of information related to landslide analysis from satellite imagery, can facilitate landslide risk analysis (McDermid & Franklin, 1995; Shahabi et al., 2012b; Pradhan et al., 2014; Tien Bui et al., 2018). It is also worth mentioning that, landslide susceptibility analysis is the best way to warn individuals, properties, populations, and environmentalists from the risks that may face with in near or remote future (Corominas et al., 2014; Shahabi & Hashim, 2015; Pradhan & Sameen, 2017).

Nowadays, due to a turning point in the commercial systems, application of Geographical Information System (GIS) for landslide susceptibility assessment has been increasingly raised (Bai et al., 2011; Bonham-Carter, 2014; Quattrochi et al., 2017; Tien Bui et al., 2018). Environmental modeling using Remote Sensing (RS) and GIS is an outstanding area of interest for many researchers across the globe (Lillesand et al., 2004; Lillesand et al., 2014). However, findings to date confirmed that these indispensable technologies play a great role in the sustainable management, risk assessment and global environmental changes (Lillesand et al., 2014; Maghsoudi et al., 2017; Quattrochi et al., 2017). Moreover, GIS is an applicable and useful tool for spatial analysis of multi-dimensional phenomenon like landslide (Carrara et al., 1991; Van Westen et al., 2006; Kainthura et al., 2015; Tien Bui et al., 2018).

GIS, is an effective space to analyze, assess and manages a huge amount of information at the same time (Carrara, 1983; Carrara et al., 1991; Ahmad & Samad, 2010; Ahmad et al., 2013; Leonardi et al., 2016; Hashim et al., 2017). Progresses in the GIS-based applications have made it easy to work on the spatial and geographical data (Kainthura et al., 2015). Using GIS, numerous methods for Landslide Susceptibility Mapping (LSM) have been suggested in the recent studies (Tien-Sze et al., 2013; Dou et al., 2015; Bui et al., 2016a; Tien Bui et al., 2018). Furthermore, it is

a powerful technology for integrating different types of data at once (Pradhan et al., 2014; Pradhan & Kim, 2016; Rawat et al., 2016; Quattrochi et al., 2017; Weng et al., 2018).

Integration of RS and GIS is an efficient technique for LSM (Shahabi, 2015; Youssef et al., 2016; Yang et al., 2017; Weng et al., 2018). Various algorithms have been applied to assess landslide prone areas using these two valuable techniques (Bulmer, 2002; Lee, 2013; Dahal, 2014; Youssef et al., 2015a; Youssef et al., 2015b). At the same time, RS technologies provide coverage of a large region at high frequency (Lillesand et al., 2014; Weng et al., 2018). However, they have been used to provide suitable landslide information to policy and decision makers during a disaster period (Metternicht et al., 2005; Zhao et al., 2017). Generally, RS is an applicable source of gaining information about the earth surface without any physical contact with (Lillesand et al., 2014; Yang et al., 2017; Weng et al., 2018).

Landslide inventory can be done through a number of approaches, ranging from manual image interpretation, field survey, historical reports, interferometry studies or even a combination of different techniques (Van Westen et al., 2008; Pradhan & Lee, 2009; Shahabi et al., 2012a; Shahabi et al., 2012b; Pradhan, 2013; Shirzadi et al., 2017; P. Chen et al., 2018). Images for deformation and change detection studies must be acquired before and after the events, such as landslide, earthquake, and volcanoes (Mickovski & Van Beek, 2006; Gad-el-Hak, 2008; Pradhan et al., 2010a; Shirzadi et al., 2017; Chen et al., 2018a; Chen et al., 2018b; Chen et al., 2018c).

Needless to say, the longer the wavelength, the more the backscatter will be, and the shorter the wavelength, the more the details will be (Curlander & McDonough, 1991; Attema et al., 2007; Jakowatz et al., 2012; Chan & Chu, 2016; Woodhouse, 2017; Villano et al., 2018). However, synthetic aperture RADAR systems, are valuable tools for detecting landslide locations in the tropical regions (Berens, 2006; Arikawa et al., 2010; Elhefhawy & Ismail, 2015; Barber et al., 2016; Woodhouse, 2017; Villano et al., 2018), such as Sentinel-1 satellite data in C-band with 5.7 cm wavelength. Furthermore, landslide detection depends greatly on variety of elements, including

vegetation coverage, physical situation of the study area, spatial resolution, technical characteristics of satellite images, and size of landslides. For example, for vegetated area Synthetic Aperture Radar (SAR) imagery is more applicable, because it can penetrate through vegetation and predict landslides ranging from small to big scales (Cheney & Borden, 2008; Amin, 2016; Barber et al., 2016; Stumpf et al., 2017).

1.2 Statement of Problem

Landslide is a highly destructive phenomenon especially when it occurs next to the human settlements and infrastructures. Every year many people loss their properties and even their lives because of this natural disaster, which has significant impact on the local and global economy as well (Mansor et al., 2004; Mansor et al., 2007; Thiery et al., 2007; Pradhan & Buchroithner, 2010; Shahabi, 2015; Pradhan & Kim, 2016; Abdulwahid & Pradhan, 2017; Chen et al., 2018a). With remarkable impacts on residential areas, topographic relief, landslide trigger a major natural hazard in many mountainous areas (Shahabi & Hashim, 2015; Calvello et al., 2016; Chen et al., 2017b; Stumpf et al., 2017). However, real time monitoring of landslides is defined as a complicated process (Shahabi et al., 2012a; Tay et al., 2014; Bhatta & Thangadurai, 2016; Tien Bui et al., 2018). But, these phenomenon are very hazardous motions, which sometimes move tons of materials that threaten human life in landslide prone areas (Chen et al., 2017c; Mikoš et al., 2017; Chen et al., 2018a). Since, only 25% of Malaysia is mountains, therefore Malaysia cannot be defined as a mountainous territory, however the slope failures are a common disaster in the most parts of the country (Othman et al., 2012). Landslide in Malaysia is not a new phenomenon and vary from small scale to large scale (Murakmi et al., 2014).

Cameron Highlands has experienced millions of dollars of damages to economic activities and settlements caused by landslides (Nichol & Wong, 2005; Nichol et al., 2006; Abdulwahid & Pradhan, 2017). Because of landslides, the total economic losses in the study area have been estimated at about US \$1 billion between the years 1973 to the year 2007 (Nichol et al., 2006). However, because of the cloudy and rainy weather conditions, which are dominated in the region almost whole year

and also the dense vegetation coverage, landslide inventory and susceptibility mapping by far is difficult in the study area. But, using RADAR imagery technique these problems can be addressed to a great extent (Cheney & Borden, 2008; Jakowatz et al., 2012; Amin, 2016; Hong et al., 2017a; Hong et al., 2017b; Pham & Prakash, 2018). SAR technique can easily penetrate into the trees and vegetation coverage, not blocked by the clouds, and work day and nights (Pettinato et al., 2013; Elhefhawy & Ismail, 2015; Hashim et al., 2017; Zhu et al., 2018). It is worth mentioning that, C-band satellite imageries with shorter wavelength (5.7 cm) rather than L-band (24 cm) cannot penetrate through thick trunk and branches of trees, but are able to penetrate into the thin vegetation (Jebur et al., 2014a; Hashim et al., 2017). Additionally, the C-band imagery has a wavelength similar to size of the small-scale vegetation, such as crop structure, foliage, and canopies, therefore SAR images at C-band are dependent on the variation of these features (Berens, 2006).

In order to save human lives and also to avoid negative effects on the regional and national economies, detecting the areas with high risks is vital in landslide warning systems (Pradhan & Kim, 2016; Chen et al., 2017d). Landslide susceptibility models, can support and boost the spatial planning and decisions focused on mitigating landslide hazards (Mansor et al., 2007; Goetz et al., 2015; Nicu, 2017; Sharma & Mahajan, 2018). Inevitably, landslide is one of the current natural hazard problems in most Malaysian regions and also is a significant obstacle to progress in many parts of the country. According to Star report (2008), in the years 2006, 2008 and 2009, the heavy rainfall have triggered thee destructive landslides in many parts of Peninsular Malaysia, which cost millions of dollars of damages to properties and claimed many lives (Biswajeet & Saro, 2007; Pradhan & Lee, 2009; Sezer et al., 2011). Besides, the landslide-induced damages have been regularly experienced, because of the little consideration about these problems in the slope management and the land cover planning (Song et al., 2012; Elmahdy et al., 2016; Behnia & Blais-Stevens, 2018). In addition, landslide in Malaysia is mostly triggered by rainfalls, which result in failure of the rock surfaces along joint, cleavage and fracture (Pradhan & Lee, 2010).

According to the United Nations Economic and Social Commission for Asia and the Pacific (UNESCAP) alongside flood, storms and extreme temperature,

landslide is one of the top four disasters, which result in losses and fatalities in many parts of the globe (Kalimuthu et al., 2015; Pradhan & Kim, 2016; Pham et al., 2017). Unlike the other aforementioned disasters, which are mainly caused by the natural factors, landslide also can be controlled by human activities (Kalimuthu et al., 2015; Mansor et al., 2018). In November 2014, landslide in Cameron Highlands caused damages to 20 houses, 20 vehicles and also 5 people lose their life, at the same time a similar event occurred in the year 2013, which claimed 4 lives and over 100 houses were completely demolished (Samy et al., 2014; Hong et al., 2015b; Chan & Chu, 2016).

Nowadays, the best and fast method for hazard studies, including mass movement, is to use remotely sensed data, by which a lot of data can be mapped and used for hazard studies. However, many researches have pointed out that ancillary data, such as soil and vegetation index (McKean et al., 1991), geological information (Shahabi et al., 2012a), topographic data (McKean & Roering, 2004), rainfall data (Samy et al., 2014), and textural information (Shih & Schowengerdt, 1983), increase the accuracy of geomorphic mapping. As a matter of fact, Normalized Difference Vegetation Index (NDVI), aspect, elevation, slope, land cover, distance to road, proximity to river, lithology, distance to fault, rainfall, soil types, Stream Power Index (SPI), Sediment Transport Index (STI), Topographic Wetness Index (TWI), landform, Topographic Roughness Index (TRI), and many more, are factors affecting landslide and must be considered in landslide susceptibility assessments (Pham et al., 2016; Tien Bui et al., 2016; Chen et al., 2017d; Tien Bui et al., 2018).

The most common way of getting information about landslide is inventory mapping using satellite imagery, aerial photographs, field investigation, historical reports, and etc. (Rib & Liang, 1978; Mollard & Janes, 1984; Sezer et al., 2011; Nefeslioglu et al., 2012; Shahabi et al., 2013; Hong et al., 2015a; Vasu & Lee, 2016; Hemasinghe et al., 2018). Even if these methods are useful for landslide inventory, but they have some certain disadvantages. Remote sensing data are either expensive or unavailable for many areas through-out the world (Brardinoni et al., 2003; Brardinoni & Church, 2004; Wang et al., 2009; Marjanović et al., 2011; Trigila et al., 2015; Quraishi et al., 2017; Soma & Kubota, 2018). Moreover, using old images are less

accurate and also do not cover new events. Unavailability of data on a special date of the landslide event makes it hard to detect and assess landslides exactly (Van Westen et al., 2006). Furthermore, for the regions, which are located in the vegetated and tropical areas, SAR image is an effective and applicable tool to detect the occurred deformations.

Despite a considerable advancement in our knowledge related to the instability mechanisms (Corominas et al., 2014), decreasing the impact of landslide is still an unsolved problem for many policy and decision makers worldwide. However, with a precise landslide inventory model, the exact places of occurred landslides can be detected. Detection of landslide locations and their scar extent is often a challenging and time consuming issue (Lin et al., 2016; Lee et al., 2017). In Cameron Highlands, natural hazards, such as landslides, flash floods and mass movements fall under the top great social concerns (Pradhan & Lee, 2010; Tien Bui et al., 2018).

Because of the land clearing for housing, hotels, and plantation the study area is undergoing rapid development and changing, which resulted in erosion and landslide (Pradhan & Lee, 2010; Matori et al., 2012; Mohammadi et al., 2018b; Tien Bui et al., 2018). The study area is one of the tourist attractive places and plantation fields in Malaysia, where landslide prevention is highly essential for the economy of Malaysia. However, this is a great issue that need to be addressed to a great extent. In this study a few old methods, such as Logistic Regression (LR), Logistic Model Tree (LMT), Random Forest (RF) and two recently introduced models of Alternating Decision Tree (ADTree) and Adaptive Boosting (AdaBoost) learning ensemble technique as well as a novel hybrid artificial intelligence approach based on AdaBoost and ADTree algorithms namely; “AB-ADTree” were employed to map susceptible areas to landslides in the study area. In this study, for the first time Sentinel-1 satellite imagery, as the only RADAR imagery online for free was used for the application of landslide inventory and creation of Digital Elevation Model (DEM) in Cameron Highlands. Besides, in this study for the first time Google Earth images were applied for landslide detection in the study area. A new model of AB-ADTree for landslide susceptibility, is another issue that this study solved, because the previous models used in the study area were overused and old.

1.3 Objectives of Study

The aim of the study is to detect landslide locations and also to map areas prone to landslides in a part of Cameron Highlands, Pahang, Malaysia. The objectives of this work are listed as follows:

- I. To create a 10 meter cell size DEM (from which many layers can be extracted) using Interferometry Synthetic Aperture RADAR (InSAR) technique and Sentinel-1 imagery as the only RADAR imagery available online for free.
- II. To apply a novel combination method of Sentinel-1 and Landsat-8 satellite imageries and also combination of different algorithms of Maximum Likelihood (ML), Minimum Distance (MD), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Spectral Angle Mapper (SAM) by using Decision Tree (DT) model, for generating land cover map of the study area as one of the important layers for application of landslide susceptibility mapping in the study area.
- III. To detect historical landslides using integration of InSAR technique, Google Earth (GE) images (for first time in the study area), and extensive field investigation.
- IV. To generate landslide susceptibility maps using Machine Learning Algorithms (MLAs) of LR, LMT, RF classifier, ADTree, AdaBoost, and a novel hybrid artificial intelligence approach based on AdaBoost and ADTree models namely; “AB-ADTree” model.

1.4 Research Questions

Concern with the objectives of the study, in order to see whether the researcher have achieved the objectives or not, the following questions should be answered:

- I. Is Sentinel-1 satellite image appropriate for extracting DEM for the vegetated areas like Cameron Highlands?
- II. Is combination model of Landsat-8 and Sentinel-1 satellite imageries as well as the combination of different algorithms (ML, MD, SVM, SAM, and ANN models), can help to extract all land covers of the study area precisely?
- III. With regard to the tropical and the highly vegetated situation of Cameron Highlands, is the C-band imagery of Sentinel-1 can detect historical landslides?
- IV. Are LSM methods, including a novel hybrid model of AB-ADTree, can precisely map the landslide-prone areas in Cameron Highlands?

1.5 Significance of Study

Because of the topographical, climatic, and human conditions, the earthflows and mudflows are most existing types of slope failures in Cameron Highlands, Malaysia (Nichol & Wong, 2005; Nichol et al., 2006; Shahabi & Hashim, 2015; Tien Bui et al., 2018). Needless to say that the earthquakes are the major triggering factor in the occurrences of landslides, but according to Pradhan and Lee (2010), Malaysia is not a seismically active region, and landslides in Malaysia are mainly induced by the heavy rainfalls.

The study area is mainly covered by the vegetation and florification rather than the dense forest (Mohammadi et al., 2019), therefore a C-band SAR satellite image, such as Sentinel-1, RADARSat-2, and ERS-2 are able to penetrate into the vegetation coverage and detect the landslide locations. With regard to this fact that most of SAR imageries are costly even for a few km² (Curlander & McDonough, 1991; Eisenbeiß, 2009; Robinson, 2018), therefore in this study the historical landslides were detected by the C-band Sentinel-1 satellite imageries supported by GE images and intensive field investigation. It is worth mentioning that Sentinel-1 is the only RADAR imagery online for free and it is the first time that this data is used for identifying the historical landslide in the study area.

Despite providing transparent calculation and also reasonable accuracy, the previous methods of LSMs have been overused and out of date. Therefore, it is highly necessary to explore new methods. In recent years, various MLAs have been developed, which are also known as advanced automatic inductive approaches (Cracknell & Reading, 2014). Even though application of these new MLAs has been examined for geoscience studies, including groundwater quant potential (Naghibi et al., 2017) and land subsidence (Pradhan et al., 2014), their application rarely used for landslide susceptibility studies. More recent years, machine learning ensembles and the hybrid methods have proven to be better than conventional methods in landslide studies (Hong et al., 2017a; Chen et al., 2018a). However, exploration of ADTree and AdaBoost methods for the application of LSM has seldom been carried out before and the combination of these two algorithms is a novel attempt for LSM in this study.

In this study 17 conditioning factors, including NDVI, proximity to roads, distance to river, proximity to faults, road density, river density, curvature, profile curvature, aspect, slope, elevation, land cover, rainfall, soil types, lithology, SPI, and TWI, were selected based on the other studies and applied for the application of landslide susceptibility assessment, which were extracted from different sources of DEM, satellite imageries, geological and soil maps. Overall, this study is significant in a number of ways:

- I. Applying a novel hybrid artificial intelligence approach based on AdaBoost and ADTree models namely; the “AB-ADTree” model.
- II. Integration of InSAR technique (Using Sentinel-1 data), GE image and extensive field investigation for landslide inventory.
- III. Using a novel combination model of Landsat-8 and Sentinel-1 imageries to extract the land covers of the study area.
- IV. Extracting a DEM (With 10 meter cell size) using Sentinel-1 satellite imagery.
- V. Extraction, digitization and preparation of all the 17 intrinsic and extrinsic parameters used in the study by the researcher.

The findings can be useful and highly applicable for decision and policy makers in order to mitigate landslide occurrence and managing the effected regions. In addition, this work can assist the locals to know about landslide-prone areas and also to know that to what extend their physical environment is stable.

1.6 Scope of Study

Due to the frequent occurrences of landslides, a part of Cameron Highlands surrounded by longitudes 101° 20' 00''E to 101° 27' 10''E and latitudes 4° 23' 30'' N to 4° 31' 10'' N (Geographic, WGS 84) was selected as the study area for the application of landslide susceptibility assessments. It is worth mentioning that the study area was extracted based on the first stream order of Ringlet River (Figure 1.1). The study area is undergoing rapid development of land clearing for housing, hotels, and plantation, which result in erosion and landslide (Pradhan et al., 2010b; Matori et al., 2012; Mohammadi et al., 2018b; Tien Bui et al., 2018; Mohammadi et al., 2019). Cameron Highlands is a unique district in Pahang State, Malaysia, where covers an area of 81.249 km² and is located in the south western part of Cameron Highlands. Brinchang, Sungai Bertam, Tanah Rata, Habu, Taman Ringlet and Sungai Khazanah are the residential areas in the study area, therefore, this study can be helpful to the people to know that to what extend their environment is stable.

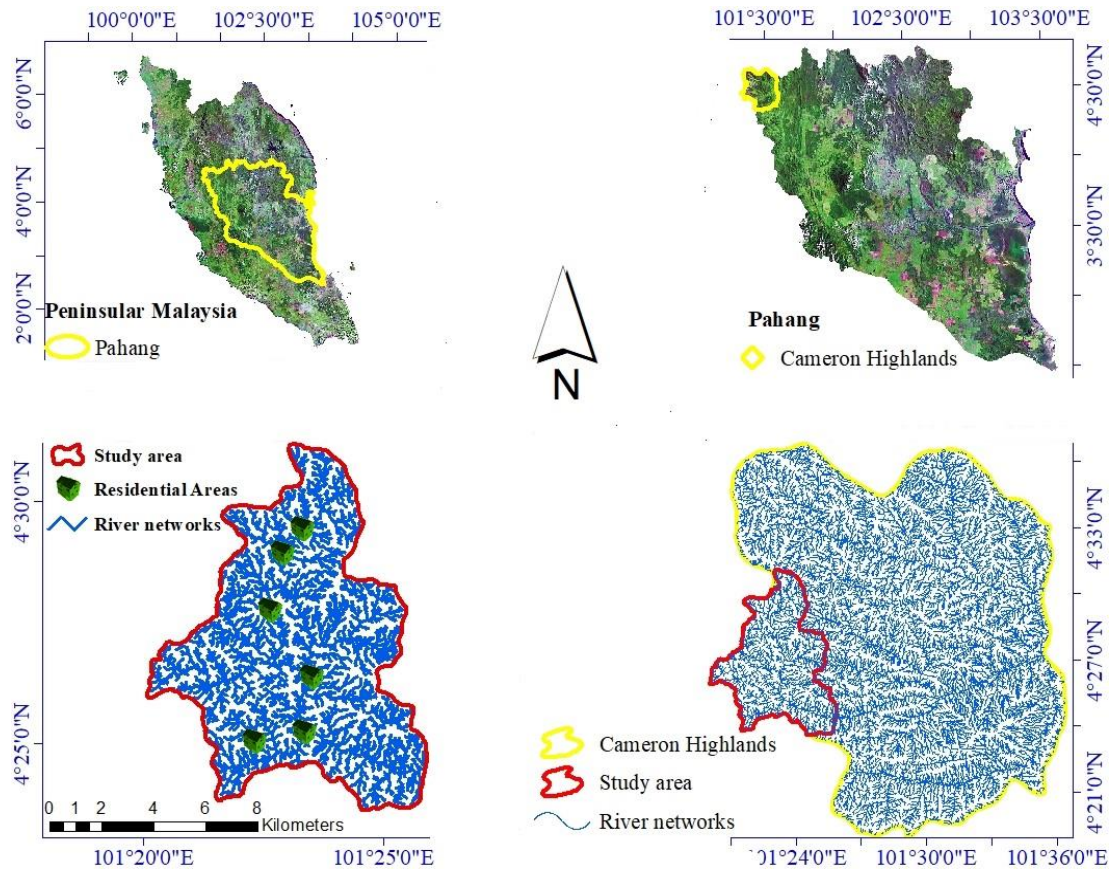


Figure 1.1: The geographical position of the study area

1.6.1 Factors Used for LSMs

There are many parameters that can be used for LSM. In this study, 17 conditioning parameters, which include slope, aspect, elevation, distance to road, distance to river, proximity to fault, road density, river density, NDVI, rainfall, land cover, lithology, soil types, curvature, profile curvature, SPI and TWI were utilized for generating the LSMs.

1.6.2 Models and Techniques

Integration of InSAR technique, GE and extensive field survey were used for the application of landslide inventory. A set of the MLAs, including LR, LMT, RF, ADTree, AdaBoost learning ensemble technique, and a novel hybrid artificial

intelligence approach based on AdaBoost and ADTree models namely; “AB-ADTree” model were employed for LSM in this study. Like the landslide inventory InSAR technique was also used for creating a 10-m DEM. Land covers of the study area were extracted by using different algorithms of ML, MD, ANN, SVM, and SAM. Needless to say that there is always differences among different models, but the models used for land cover extraction can be used for LSMs as well.

1.6.3 Software

Sentinel Application Platform (SNAP), ArcGIS and SNAPHU software were employed for landslide inventory and creating the DEM. Statistical Package for the Social Sciences (SPSS), Waikato Environment for Knowledge Analysis (WEKA) and ArcGIS software were applied for generating LSMs. ArcGIS, SNAP and Environment for Visualizing Images (ENVI) software were utilized for producing maps of land cover of the study area. System for Automated Geoscientific Analyses (SAGA) software was applied for generating TWI and SPI layers in this study.

1.6.4 Satellite Imageries

There are several satellite imageries were used in this study. Sentinel-1 satellite imagery with the product type of Single Look Complex (SLC) and the sensor mode of Interferometry Wide Swath (IW) was applied for the application of landslide inventory and generating the DEM of the study area. While the product type of Ground Range Detected (GRD) and the sensor mode of IW was employed for the combination with Landsat-8 imagery for extracting the land covers of the study area. Landsat-7 was downloaded for generating the Land covers of the study area as well. Sentinel-2 satellite data was acquired for extracting NDVI map of the study area.

1.7 Overview of the Thesis

The structure of this thesis has been divided into five chapters. The description of each chapter is described as follows:

Chapter 1 is about introduction of the study. The general idea of the study, the problem statement, the objectives, the research questions, the significance of study and the scope of the study have been presented in this chapter.

Chapter 2 describes the previous studies on landslide detection and susceptibility mapping. The concepts, satellite imageries, models and theories have been included in this chapter as well.

Chapter 3 is associated with the research methodology of the study. The research methodology of generating the layers, landslide inventory, DEM and LSMs, supported by the flowcharts, tables and figures have been explained in this chapter.

Chapter 4 points out the result and analysis of this study. The findings of this study, including the accuracy assessment of each result, supported by figures and tables have been discussed in this chapter.

Chapter 5 is about conclusion and recommendations of the study. The summary of the study is presented in this chapter.

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