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 infrastuktur, 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 algorithma 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 diekstak 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-PALSAR	-	Advanced Land Observing Satellite Phase Array L-Band 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
$\surd$	-	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 & Niculiţă, 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 & Niculiţă, 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 & Niculiţă, 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 loses 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 km^2 (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 km^2 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.

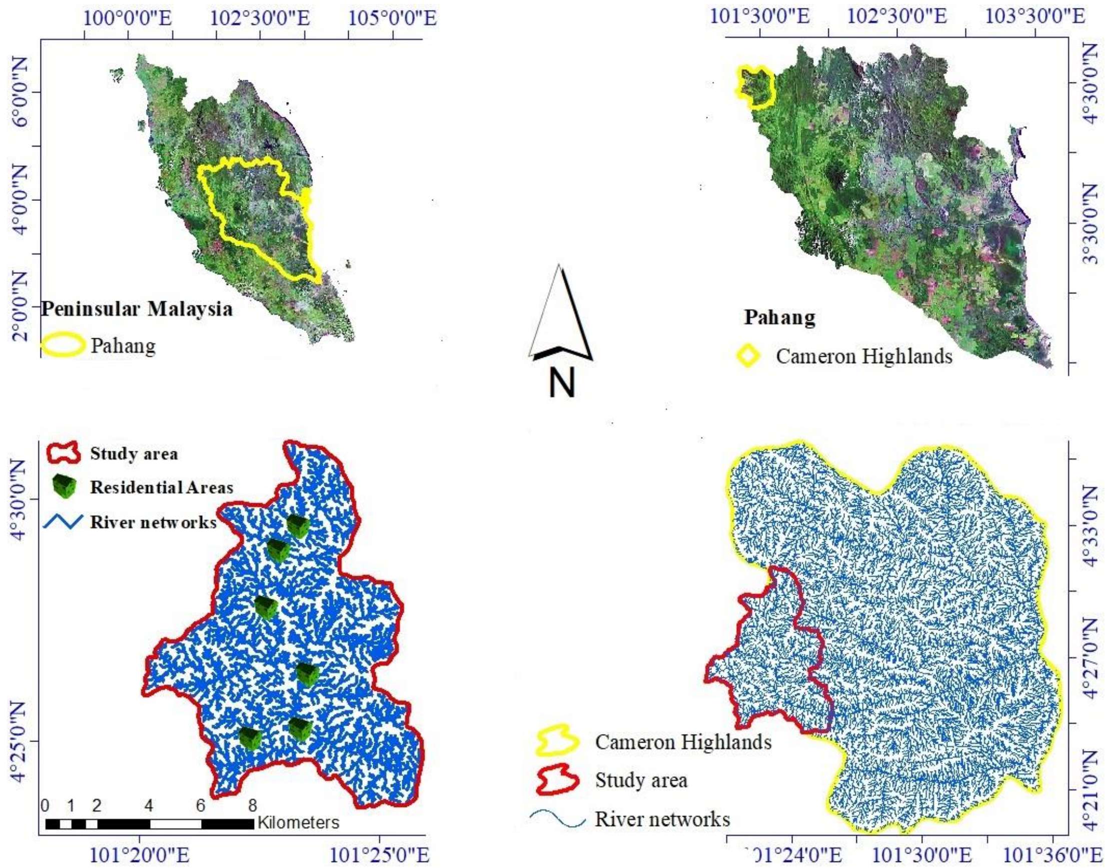

Figure 1.1: The geographical position of the study area

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.

REFERENCES

Abdullah, F., Shamsulaman, K., Isa, S. M., & Sina, I. (2008). Beetle fauna at Cameron Highlands Montane Forest. Paper presented at the Seminar Scientific Montane Expedition of Cameron Highland.

Abdulwahid, W. M., & Pradhan, B. (2017). Landslide vulnerability and risk assessment for multi-hazard scenarios using airborne laser scanning data (LiDAR). Landslides, 14(3), 1057-1076.

Abedi, R., Bonyad, A. E., Moridani, A. Y., & Shahbahrami, A. (2018). Evaluation of IRS and Landsat 8 OLI imagery data for estimation forest attributes using k nearest neighbour non-parametric method. International Journal of Image and Data Fusion, 1-15.

Abella, E. A. C., & Van Westen, C. J. (2008). Qualitative landslide susceptibility assessment by multicriteria analysis: a case study from San Antonio del Sur, Guantánamo, Cuba. Geomorphology, 94(3), 453-466.

Aghanabati, A. (2004). Geology of Iran: Geological survey of Iran.

Ahmad, A., & Samad, A. M. (2010). Aerial mapping using high resolution digital camera and unmanned aerial vehicle for Geographical Information System. Paper presented at the Signal Processing and Its Applications (CSPA), 2010 6th International Colloquium on.

Ahmad, A., Tahar, K. N., Udin, W. S., Hashim, K. A., Darwin, N., Hafis, M., Room, M., Hamid, N. F. A., Azhar, N. A. M., & Azmi, S. M. (2013). Digital aerial imagery of unmanned aerial vehicle for various applications. Paper presented at the Control System, Computing and Engineering (ICCSCE), 2013 IEEE International Conference on.

Akgun, A., Dag, S., & Bulut, F. (2008). Landslide susceptibility mapping for a landslide-prone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models. Environmental Geology, 54(6), 1127-1143.

Akgün, A., & Bulut, F. (2007). GIS-based landslide susceptibility for Arsin-Yomra (Trabzon, North Turkey) region. Environmental Geology, 51(8), 1377-1387.

Alqurashi, A. F., & Kumar, L. (2014). Land use and land cover change detection in the Saudi Arabian desert cities of Makkah and Al-Taif using satellite data. Advances in Remote Sensing, 3(03), 106.

Althuwaynee, O. F., Pradhan, B., & Ahmad, N. (2015). Estimation of rainfall threshold and its use in landslide hazard mapping of Kuala Lumpur metropolitan and surrounding areas. Landslides, 12(5), 861-875.

Amin, M. G. (2016). Through-the-wall radar imaging: CRC press.

Amit, S. N. K. B., Shiraishi, S., Inoshita, T., & Aoki, Y. (2016). Analysis of satellite images for disaster detection. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International.

Anderson, E. R., Griffin, R. E., & Irwin, D. E. (2017). Implications of Different Digital Elevation Models and Preprocessing Techniques to Delineate Debris Flow Inundation Hazard Zones in El Salvador. Natural Hazard Uncertainty Assessment, 167-177.

Ardhuin, F., Stopa, J., Chapron, B., Collard, F., Smith, M., Thomson, J., Doble, M., Blomquist, B., Persson, O., & Collins III, C. O. (2017). Measuring ocean waves in sea ice using SAR imagery: A quasi-deterministic approach evaluated with Sentinel-1 and in situ data. Remote Sensing of Environment, 189, 211-222.

Arikawa, Y., Osawa, Y., Hatooka, Y., Suzuki, S., & Kankaku, Y. (2010). Development status of Japanese advanced land observing satellite-2. Paper presented at the Proc. of SPIE Vol.

Aslan, G., Cakir, Z., Ergintav, S., Lassarre, C., & Renard, F. (2018). Identification of secular ground motions in Istanbul by long term time-resolved InSAR analysis (1992-2017). Paper presented at the EGU General Assembly Conference Abstracts.

Attema, E., Bargellini, P., Edwards, P., Levrini, G., Lokas, S., Moeller, L., Rosich-Tell, B., Secchi, P., Torres, R., & Davidson, M. (2007). Sentinel-1-the radar mission for GMES operational land and sea services. ESA bulletin, 131, 10-17.

Ayalew, L., Yamagishi, H., & Ugawa, N. (2004). Landslide susceptibility mapping using GIS-based weighted linear combination, the case in Tsugawa area of Agano River, Niigata Prefecture, Japan. Landslides, 1(1), 73-81.

Ayalew, L., & Yamagishi, H. (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. Geomorphology, 65(1), 15-31.

Bai, S., Lü, G., Wang, J., Zhou, P., & Ding, L. (2011). GIS-based rare events logistic regression for landslide-susceptibility mapping of Lianyungang, China. Environmental Earth Sciences, 62(1), 139-149.

Ballard, T., & Willington, R. (1975). Slope instability in relation to timber harvesting in the Chilliwack Provincial Forest. The forestry chronicle, 51(2), 59-63.

Barac, A., Kellner, K., & De Klerk, N. (2004). Land user participation in developing a computerised decision support system for combating desertification. Environmental monitoring and assessment, 99(1), 223-231.

Barber, M., Lopez-Martinez, C., & Grings, F. (2016). Assessment of L-Band SAR polarimetry for soil and crop monitoring. Paper presented at the EUSAR 2016: 11th European Conference on Synthetic Aperture Radar, Proceedings of.

Barrow, C., Clifton, J., Chan, N., & Tan, Y. (2005). Sustainable development in the Cameron highlands, Malaysia. Malaysian Journal of Environmental Management, 6, 41-57.

Beguería, S. (2006). Validation and evaluation of predictive models in hazard assessment and risk management. Natural hazards, 37(3), 315-329.

Behnia, P., & Blais-Stevens, A. (2018). Landslide susceptibility modelling using the quantitative random forest method along the northern portion of the Yukon Alaska Highway Corridor, Canada. Natural hazards, 90(3), 1407-1426.

Bennett, N. D., Croke, B. F., Guariso, G., Guillaume, J. H., Hamilton, S. H., Jakeman, A. J., Marsili-Libelli, S., Newham, L. T., Norton, J. P., & Perrin, C. (2013). Characterising performance of environmental models. Environmental Modelling & Software, 40, 1-20.

Berens, P. (2006). Introduction to synthetic aperture radar (SAR). Retrieved from

Bhatta, N. P., & Thangadurai, N. (2016). Detection and prediction of calamitous landslide in precipitous hills. Paper presented at the Advanced Communication Control and Computing Technologies (ICACCCT), 2016 International Conference on.

Bignel, F., & Snelling, G. (1977). The geochronology of the main range Batholith: Cameron Highlands road and Gunong Bujang Melaka. Overseas Geol Miner Resour, 47, 3-35.

Binaghi, E., Luzi, L., Madella, P., Pergalani, F., & Rampini, A. (1998). Slope instability zonation: a comparison between certainty factor and fuzzy Dempster–Shafer approaches. Natural hazards, 17(1), 77-97.

Biswajeet, P., & Saro, L. (2007). Utilization of optical remote sensing data and GIS tools for regional landslide hazard analysis using an artificial neural network model. Earth Science Frontiers, 14(6), 143-151.

Bonham-Carter, G. F. (2014). Geographic information systems for geoscientists: modelling with GIS (Vol. 13): Elsevier.

Brardinoni, F., Slaymaker, O., & Hassan, M. A. (2003). Landslide inventory in a rugged forested watershed: a comparison between air-photo and field survey data. Geomorphology, 54(3), 179-196.

Brardinoni, F., & Church, M. (2004). Representing the landslide magnitude–frequency relation: Capilano River basin, British Columbia. Earth surface processes and landforms, 29(1), 115-124.

Brehaut, L., & Danby, R. K. (2018). Inconsistent relationships between annual tree ring-widths and satellite-measured NDVI in a mountainous subarctic environment. Ecological Indicators, 91, 698-711.

Breiman, L. (2001). Random forests. Machine learning, 45(1), 5-32.

Bryant, R., Moran, M. S., McElroy, S. A., Holifield, C., Thome, K. J., Miura, T., & Biggar, S. F. (2003). Data continuity of Earth Observing 1 (EO-1) Advanced Land I satellite imager (ALI) and Landsat TM and ETM+. IEEE transactions on geoscience and remote sensing, 41(6), 1204-1214.

Bui, D. T., Ho, T.-C., Pradhan, B., Pham, B.-T., Nhu, V.-H., & Revhaug, I. (2016a). GIS-based modeling of rainfall-induced landslides using data mining-based functional trees classifier with AdaBoost, Bagging, and MultiBoost ensemble frameworks. Environmental Earth Sciences, 75(14), 1101.

Bui, D. T., Tuan, T. A., Klempe, H., Pradhan, B., & Revhaug, I. (2016b). Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree. Landslides, 13(2), 361-378.

Bulmer, M. (2002). Studies of Landslides using Remote Sensing Data CEOS Landslide Hazard Team Report. 6p.

Bürgmann, R., Rosen, P. A., & Fielding, E. J. (2000). Synthetic aperture radar interferometry to measure Earth's surface topography and its deformation. Annual review of earth and planetary sciences, 28(1), 169-209.

Calvello, M., Papa, M. N., Pratschke, J., & Crescenzo, M. N. (2016). Landslide risk perception: a case study in Southern Italy. Landslides, 13(2), 349-360.

Campbell, A. (1966). Measurement of movement of an earthflow. Soil Water, 2(3), 23-24.

Campbell, D., & Church, M. (2003). Reconnaissance sediment budgets for Lynn Valley, British Columbia: Holocene and contemporary time scales. Canadian Journal of Earth Sciences, 40(5), 701-713.

Canuti, P., Casagli, N., Ermini, L., Fanti, R., & Farina, P. (2004). Landslide activity as a geoindicator in Italy: significance and new perspectives from remote sensing. Environmental Geology, 45(7), 907-919.

Carrara, A. (1983). Multivariate models for landslide hazard evaluation. Mathematical geology, 15(3), 403-426.

Carrara, A., Cardinali, M., Detti, R., Guzzetti, F., Pasqui, V., & Reichenbach, P. (1991). GIS techniques and statistical models in evaluating landslide hazard. Earth surface processes and landforms, 16(5), 427-445.

Casagli, N., Cigna, F., Bianchini, S., Hölbling, D., Füreder, P., Righini, G., Del Conte, S., Friedl, B., Schneiderbauer, S., & Iasio, C. (2016). Landslide mapping and monitoring by using radar and optical remote sensing: examples from the EC-FP7 project SAFER. Remote sensing applications: society and environment, 4, 92-108.

Cevik, E., & Topal, T. (2003). GIS-based landslide susceptibility mapping for a problematic segment of the natural gas pipeline, Hendek (Turkey). Environmental Geology, 44(8), 949-962.

Chan, Y.-K., & Chu, C.-Y. (2016). Ground based synthetic aperture radar for land deformation monitoring: Preliminary result. Paper presented at the Progress in Electromagnetic Research Symposium (PIERS).

Chang, K.-T. (2006). Introduction to geographic information systems: McGraw-Hill Higher Education Boston.

Chang, K.-T., Wan, S., & Lei, T.-C. (2010). Development of a spatial decision support system for monitoring earthquake-induced landslides based on aerial photographs and the finite element method. International Journal of Applied Earth Observation and Geoinformation, 12(6), 448-456.

Chatterjee, S., & Hadi, A. S. (2015). Regression analysis by example: John Wiley & Sons.

Chauhan, S., Sharma, M., Arora, M., & Gupta, N. (2010). Landslide susceptibility zonation through ratings derived from artificial neural network. International Journal of Applied Earth Observation and Geoinformation, 12(5), 340-350.

Chen, Ge, Y., & Jia, Y. (2017a). Integrating object boundary in super-resolution land-cover mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(1), 219-230.

Chen, Panahi, M., & Pourghasemi, H. R. (2017b). Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. Catena, 157, 310-324.

Chen, Pourghasemi, H. R., Kornejady, A., & Zhang, N. (2017c). Landslide spatial modeling: introducing new ensembles of ANN, MaxEnt, and SVM machine learning techniques. Geoderma, 305, 314-327.

Chen, Xie, X., Wang, J., Pradhan, B., Hong, H., Bui, D. T., Duan, Z., & Ma, J. (2017d). A comparative study of logistic model tree, random forest, and classification and regression tree models for spatial prediction of landslide susceptibility. Catena, 151, 147-160.

Chen, Peng, J., Hong, H., Shahabi, H., Pradhan, B., Liu, J., Zhu, A.-X., Pei, X., & Duan, Z. (2018a). Landslide susceptibility modelling using GIS-based machine learning techniques for Chongren County, Jiangxi Province, China. Science of the Total Environment, 626, 1121-1135.

Chen, Pourghasemi, H. R., & Naghibi, S. A. (2018b). A comparative study of landslide susceptibility maps produced using support vector machine with different kernel functions and entropy data mining models in China. Bulletin of Engineering Geology and the Environment, 77(2), 647-664.

Chen, Yan, X., Zhao, Z., Hong, H., Bui, D. T., & Pradhan, B. (2018c). Spatial prediction of landslide susceptibility using data mining-based kernel logistic regression, naive Bayes and RBFNetwork models for the Long County area (China). Bulletin of Engineering Geology and the Environment, 1-20.

Chen, P., Lu, N., Formetta, G., Godt, J. W., & Wayllace, A. (2018). Tropical Storm-Induced Landslide Potential Using Combined Field Monitoring and Numerical Modeling. Journal of Geotechnical and Geoenvironmental Engineering, 144(11), 05018002.

Cheney, M., & Borden, B. (2008). Imaging moving targets from scattered waves. Inverse problems, 24(3), 035005.

Chipman, J. W., Kiefer, R. W., & Lillesand, T. M. (2004). Remote sensing and image interpretation. New York.

Choi, J., Oh, H.-J., Lee, H.-J., Lee, C., & Lee, S. (2012). Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS. Engineering geology, 124, 12-23.

Chow, W., Zakaria, M., Ferdaus, A., & Nurzaidi, A. (2003). Geological terrain mapping. JMG unpublished report, JMG. SWP. GS, 1-42.

Choy, F., & Hamzah, F. (2001). Cameron Highlands hydroelectric scheme: Landuse change—impacts and issues. Hydropower in the new millennium, 215-221.

Churchill, R. R. (1982). Aspect-induced differences in hillslope processes. Earth surface processes and landforms, 7(2), 171-182.

Ciabatta, L., Camici, S., Brocca, L., Ponziani, F., Stelluti, M., Berni, N., & Moramarco, T. (2016). Assessing the impact of climate-change scenarios on landslide occurrence in Umbria Region, Italy. Journal of Hydrology, 541, 285-295.

Claverie, M., Vermote, E. F., Franch, B., & Masek, J. G. (2015). Evaluation of the Landsat-5 TM and Landsat-7 ETM+ surface reflectance products. Remote Sensing of Environment, 169, 390-403.

Cleary, P. W., & Sawley, M. L. (2002). DEM modelling of industrial granular flows: 3D case studies and the effect of particle shape on hopper discharge. Applied Mathematical Modelling, 26(2), 89-111.

Conforti, M., Muto, F., Rago, V., & Critelli, S. (2014a). Landslide inventory map of north-eastern Calabria (South Italy). Journal of maps, 10(1), 90-102.

Conforti, M., Pascale, S., Robustelli, G., & Sdao, F. (2014b). Evaluation of prediction capability of the artificial neural networks for mapping landslide susceptibility in the Turbolo River catchment (northern Calabria, Italy). Catena, 113, 236-250.

Corominas, J., Van Westen, C., Frattini, P., Cascini, L., Malet, J.-P., Fotopoulou, S., Catani, F., Van Den Eeckhaut, M., Mavrouli, O., & Agliardi, F. (2014). Recommendations for the quantitative analysis of landslide risk. Bulletin of Engineering Geology and the Environment, 73(2), 209-263.

Couture, R. (2011). Introduction–National Technical Guidelines and Best Practices on Landslides. Geological Survey of Canada, Open File, 6765(6).

Cracknell, M. J., & Reading, A. M. (2014). Geological mapping using remote sensing data: A comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. Computers & Geosciences, 63, 22-33.

Criminisi, A., & Shotton, J. (2013). Decision forests for computer vision and medical image analysis: Springer Science & Business Media.

Cruden, D. (2017). Landslide risk assessment: Routledge.

Cruden, D. M. (1991). A simple definition of a landslide. Bulletin of Engineering Geology and the Environment, 43(1), 27-29.

Cruden, D. M., & Varnes, D. J. (1996). Landslides: investigation and mitigation. Chapter 3-Landslide types and processes. Transportation research board special report(247).

Curlander, J. C., & McDonough, R. N. (1991). Synthetic aperture radar: John Wiley & Sons New York, NY, USA.

Dahal, R. K. (2014). Regional-scale landslide activity and landslide susceptibility zonation in the Nepal Himalaya. Environmental Earth Sciences, 71(12), 5145-5164.

Dai, F., Lee, C., Li, J., & Xu, Z. (2001). Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong. Environmental Geology, 40(3), 381-391.

Das, I., Sahoo, S., van Westen, C., Stein, A., & Hack, R. (2010). Landslide susceptibility assessment using logistic regression and its comparison with a rock mass classification system, along a road section in the northern Himalayas (India). Geomorphology, 114(4), 627-637.

De la Rosa, D., Mayol, F., Díaz-Pereira, E., Fernandez, M., & de la Rosa Jr, D. (2004). A land evaluation decision support system (MicroLEIS DSS) for agricultural soil protection: With special reference to the Mediterranean region. Environmental Modelling & Software, 19(10), 929-942.

Demir, G. (2018). Landslide susceptibility mapping by using statistical analysis in the North Anatolian Fault Zone (NAFZ) on the northern part of Suşehri Town, Turkey. Natural hazards, 92(1), 133-154.

Devkota, K. C., Regmi, A. D., Pourghasemi, H. R., Yoshida, K., Pradhan, B., Ryu, I. C., Dhital, M. R., & Althuwaynee, O. F. (2013). Landslide susceptibility mapping using certainty factor, index of entropy and logistic regression models in GIS and their comparison at Mugling–Narayanghat road section in Nepal Himalaya. Natural hazards, 65(1), 135-165.

Dietrich, W. E., Reiss, R., Hsu, M. L., & Montgomery, D. R. (1995). A process-based model for colluvial soil depth and shallow landsliding using digital elevation data. Hydrological processes, 9(3-4), 383-400.

Dikau, R., Brunsden, D., Schrott, L., & Ibsen, M. (1996). Landslide recognition (Prepoznavanje zemeljskih udorov). In: Wiley, England.

Dimri, S., Lakhera, R., & Sati, S. (2007). Fuzzy-based method for landslide hazard assessment in active seismic zone of Himalaya. Landslides, 4(2), 101.

Ding, Q., Chen, W., & Hong, H. (2017). Application of frequency ratio, weights of evidence and evidential belief function models in landslide susceptibility mapping. Geocarto International, 32(6), 619-639.

Dou, J., Bui, D. T., Yunus, A. P., Jia, K., Song, X., Revhaug, I., Xia, H., & Zhu, Z. (2015). Optimization of causative factors for landslide susceptibility evaluation using remote sensing and GIS data in parts of Niigata, Japan. PloS one, 10(7), e0133262.

Dragan, M., Feoli, E., Fernetti, M., & Zerihun, W. (2003). Application of a spatial decision support system (SDSS) to reduce soil erosion in northern Ethiopia. Environmental Modelling & Software, 18(10), 861-868.

Duman, T. Y., Can, T., Gokceoglu, C., Nefeslioglu, H. A., & Sonmez, H. (2006). Application of logistic regression for landslide susceptibility zoning of Cekmece Area, Istanbul, Turkey. Environmental Geology, 51(2), 241-256.

Eisenbeiß, H. (2009). UAV photogrammetry. ETH Zurich,

El Khattabi, J., & Carlier, E. (2004). Tectonic and hydrodynamic control of landslides in the northern area of the Central Rif, Morocco. Engineering geology, 71(3), 255-264.

Elhefhawy, M., & Ismail, W. (2015). Study of short-range synthetic aperture radar system. Paper presented at the Open Systems (ICOS), 2015 IEEE Confernece on.

Elhefnawy, M., & Ismail, W. (2015). Fundamentals of Synthetic Aperture Radar Systems.

Elmahdy, S. I., Marghany, M. M., & Mohamed, M. M. (2016). Application of a weighted spatial probability model in GIS to analyse landslides in Penang Island, Malaysia. Geomatics, Natural Hazards and Risk, 7(1), 345-359.

Ercanoglu, M. (2005). Landslide susceptibility assessment of SE Bartin (West Black Sea region, Turkey) by artificial neural networks. Natural Hazards and Earth System Sciences, 5(6), 979-992.

Ercanoglu, M., Kasmer, O., & Temiz, N. (2008). Adaptation and comparison of expert opinion to analytical hierarchy process for landslide susceptibility mapping. Bulletin of Engineering Geology and the Environment, 67(4), 565-578.

Erener, A., Mutlu, A., & Düzgün, H. S. (2016). A comparative study for landslide susceptibility mapping using GIS-based multi-criteria decision analysis (MCDA), logistic regression (LR) and association rule mining (ARM). Engineering geology, 203, 45-55.

ESA. (2018a). SENTINEL-1 SAR User Guide Introduction Retrieved from https://sentinel.esa.int/web/sentinel/user-guides/sentinel-1-sar

ESA. (2018b). Sentinel-2 User Handbook. Retrieved from https://sentinel.esa.int/web/sentinel/user-guides/sentinel-2-msi/document-library/-/asset_publisher/Wk0TKajiISaR/content/sentinel-2-user-handbook

Falaschi, F., Giacomelli, F., Federici, P., Puccinelli, A., Avanzi, G. A., Pochini, A., & Ribolini, A. (2009). Logistic regression versus artificial neural networks: landslide susceptibility evaluation in a sample area of the Serchio River valley, Italy. Natural hazards, 50(3), 551-569.

Fawcett, T. (2006). An introduction to ROC analysis. Pattern recognition letters, 27(8), 861-874.

Florentino, A., Charapaqui, S., De La Jara, C., & Milla, M. (2016). Implementation of a ground based synthetic aperture radar (GB-SAR) for landslide monitoring: system description and preliminary results. Paper presented at the Electronics, Electrical Engineering and Computing (INTERCON), 2016 IEEE XXIII International Congress on.

Francisca, L. (2008). Feature Selection for Hybrid Neuro-Logistic Regression Applied to Classification of Remote Sensed Data. Paper presented at the Eighth International Conference on Hybrid Intelligent Systems.

Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. Journal of computer and system sciences, 55(1), 119-139.

Freund, Y., & Mason, L. (1999). The alternating decision tree learning algorithm. Paper presented at the icml.

Friedman, J., Hastie, T., & Tibshirani, R. (2000). Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). The annals of statistics, 28(2), 337-407.

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. Journal of the american statistical association, 32(200), 675-701.

Gad-el-Hak, M. (2008). Large-scale disasters: prediction, control, and mitigation: Cambridge University Press.

Galve, J. M., Sánchez, J. M., Coll, C., & Villodre, J. (2018). A New Single-Band Pixel-by-Pixel Atmospheric Correction Method to Improve the Accuracy in Remote Sensing Estimates of LST. Application to Landsat 7-ETM+. Remote Sensing, 10(6), 826.

Gao, J. (1993). Identification of topographic settings conducive to landsliding from DEM in Nelson County, Virginia, USA. Earth surface processes and landforms, 18(7), 579-591.

García-Llamas, P., Geijzendorffer, I. R., García-Nieto, A. P., Calvo, L., Suárez-Seoane, S., & Cramer, W. (2018). Impact of land cover change on ecosystem service supply in mountain systems: a case study in the Cantabrian Mountains (NW of Spain). Regional Environmental Change, 1-14.

Geudtner, D., Torres, R., Snoeij, P., Davidson, M., & Rommen, B. (2014). Sentinel-1 system capabilities and applications. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2014 IEEE International.

Ghosh, S., van Westen, C. J., Carranza, E. J. M., Jetten, V. G., Cardinali, M., Rossi, M., & Guzzetti, F. (2012). Generating event-based landslide maps in a data-scarce Himalayan environment for estimating temporal and magnitude probabilities. Engineering geology, 128, 49-62.

Glade, T. (2001). Landslide hazard assessment and historical landslide data-an inseparable couple? Advances in Natural and Technological Hazards Research, 17, 153-168.

Goetz, J., Brenning, A., Petschko, H., & Leopold, P. (2015). Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. Computers & Geosciences, 81, 1-11.

Gomez, H., & Kavzoglu, T. (2005). Assessment of shallow landslide susceptibility using artificial neural networks in Jabonosa River Basin, Venezuela. Engineering geology, 78(1), 11-27.

Gorsevski, P. V., Gessler, P. E., & Jankowski, P. (2003). Integrating a fuzzy k-means classification and a Bayesian approach for spatial prediction of landslide hazard. Journal of geographical systems, 5(3), 223-251.

Gorsevski, P. V., & Jankowski, P. (2010). An optimized solution of multi-criteria evaluation analysis of landslide susceptibility using fuzzy sets and Kalman filter. Computers & Geosciences, 36(8), 1005-1020.

Griffiths, P., van der Linden, S., Kuemmerle, T., & Hostert, P. (2013). A pixel-based Landsat compositing algorithm for large area land cover mapping. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6(5), 2088-2101.

Gritzner, M. L., Marcus, W. A., Aspinall, R., & Custer, S. G. (2001). Assessing landslide potential using GIS, soil wetness modeling and topographic attributes, Payette River, Idaho. Geomorphology, 37(1), 149-165.

Gruber, A., Wessel, B., Huber, M., & Roth, A. (2012). Operational TanDEM-X DEM calibration and first validation results. ISPRS Journal of Photogrammetry and Remote Sensing, 73, 39-49.

Gu, B., & Sheng, V. S. (2017). A Robust Regularization Path Algorithm for $\nu $-Support Vector Classification. IEEE transactions on neural networks and learning systems, 28(5), 1241-1248.

Guthrie, R., & Evans, S. (2004). Magnitude and frequency of landslides triggered by a storm event, Loughborough Inlet, British Columbia. Natural Hazards and Earth System Science, 4(3), 475-483.

Guzzetti, F. (2000). Landslide fatalities and the evaluation of landslide risk in Italy. Engineering geology, 58(2), 89-107.

Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., & Ardizzone, F. (2005). Landslide hazard assessment in the Staffora basin, northern Italian Apennines. Geomorphology, 72, 272-299.

Guzzetti, F., Mondini, A. C., Cardinali, M., Fiorucci, F., Santangelo, M., & Chang, K.-T. (2012). Landslide inventory maps: New tools for an old problem. Earth-Science Reviews, 112(1), 42-66.

Hand, D. J. (2009). Measuring classifier performance: a coherent alternative to the area under the ROC curve. Machine learning, 77(1), 103-123.

Hanssen, R. F. (2001). Radar interferometry: data interpretation and error analysis (Vol. 2): Springer Science & Business Media.

Hardenbicker, U., & Grunert, J. (2001). Temporal occurrence of mass movements in the Bonn area. zeitschrift fur geomorphologie supplementband, 13-24.

Harp, E. L., Keefer, D. K., Sato, H. P., & Yagi, H. (2011). Landslide inventories: the essential part of seismic landslide hazard analyses. Engineering geology, 122(1), 9-21.

Hart, R. P. (1984). Verbal style and the presidency: A computer-based analysis: Academic Pr.

Hashim, M., Pour, A., & Misbari, S. (2017). Mapping land slide occurrence zones using Remote Sensing and GIS techniques in Kelantan state, Malaysia. Paper presented at the Journal of Physics: Conference Series.

He, S., Pan, P., Dai, L., Wang, H., & Liu, J. (2012). Application of kernel-based Fisher discriminant analysis to map landslide susceptibility in the Qinggan River delta, Three Gorges, China. Geomorphology, 171, 30-41.

Hemasinghe, H., Rangali, R., Deshapriya, N., & Samarakoon, L. (2018). Landslide susceptibility mapping using logistic regression model (a case study in Badulla District, Sri Lanka). Procedia Engineering, 212, 1046-1053.

Henriques, C., Zêzere, J. L., & Marques, F. (2015). The role of the lithological setting on the landslide pattern and distribution. Engineering geology, 189, 17-31.

Hermanns, R. L. (2016). Landslide. Encyclopedia of Engineering Geology, 1-3.

Highland, L. (2004). Landslide types and processes (2327-6932). Retrieved from

Hong, H., Pradhan, B., Xu, C., & Bui, D. T. (2015a). Spatial prediction of landslide hazard at the Yihuang area (China) using two-class kernel logistic regression, alternating decision tree and support vector machines. Catena, 133, 266-281.

Hong, H., Xu, C., & Bui, D. T. (2015b). Landslide Susceptibility Assessment at the Xiushui Area (China) Using Frequency Ratio Model. Procedia Earth and Planetary Science, 15, 513-517.

Hong, H., Chen, W., Xu, C., Youssef, A. M., Pradhan, B., & Tien Bui, D. (2017a). Rainfall-induced landslide susceptibility assessment at the Chongren area (China) using frequency ratio, certainty factor, and index of entropy. Geocarto International, 32(2), 139-154.

Hong, H., Ilia, I., Tsangaratos, P., Chen, W., & Xu, C. (2017b). A hybrid fuzzy weight of evidence method in landslide susceptibility analysis on the Wuyuan area, China. Geomorphology, 290, 1-16.

Hong, H., Liu, J., Bui, D. T., Pradhan, B., Acharya, T. D., Pham, B. T., Zhu, A.-X., Chen, W., & Ahmad, B. B. (2018). Landslide susceptibility mapping using J48 Decision Tree with AdaBoost, Bagging and Rotation Forest ensembles in the Guangchang area (China). Catena, 163, 399-413.

Horton, R. E. (1933). The role of infiltration in the hydrologic cycle. Eos, Transactions American Geophysical Union, 14(1), 446-460.

Humagain, K., Portillo-Quintero, C., Cox, R. D., & Cain, J. W. (2017). Mapping Tree Density in Forests of the Southwestern USA Using Landsat 8 Data. Forests, 8(8), 287.

Hungr, O., Evans, S., Bovis, M., & Hutchinson, J. (2001). A review of the classification of landslides of the flow type. Environmental & Engineering Geoscience, 7(3), 221-238.

Hungr, O., Leroueil, S., & Picarelli, L. (2014). The Varnes classification of landslide types, an update. Landslides, 11(2), 167-194.

Hutchinson, J. (1995). Keynote paper: landslide hazard assessment. Landslides. Balkema, Rotterdam, 1805-1841.

Hutchison, C. S., Tan, D. N. K., Universiti, M., & Geological Society of, M. (2009). Geology of Peninsular Malaysia.

Ibetsberger, H. J. (1996). The Tsergo Ri landslide: an uncommon area of high morphological activity in the Langthang valley, Nepal. Tectonophysics, 260(1-3), 85-93.

Ilanloo, M. (2011). A comparative study of fuzzy logic approach for landslide susceptibility mapping using GIS: An experience of Karaj dam basin in Iran. Procedia-Social and Behavioral Sciences, 19, 668-676.

Ilia, I., & Tsangaratos, P. (2016). Applying weight of evidence method and sensitivity analysis to produce a landslide susceptibility map. Landslides, 13(2), 379-397.

Irish, R. R., Barker, J. L., Goward, S. N., & Arvidson, T. (2006). Characterization of the Landsat-7 ETM+ automated cloud-cover assessment (ACCA) algorithm. Photogrammetric engineering & remote sensing, 72(10), 1179-1188.

Islam, M. B., Becker, M., Bargiel, D., Ahmed, K. R., Duzak, P., & Emana, N.-G. (2017). Sentinel-2 Satellite Imagery based Population Estimation Strategies at FabSpace 2.0 Lab Darmstadt.

Jaada, M. (2009). Landslides Hazard Analysis Using Frequency Ratio Model. Universiti Putra Malaysia, Serdang, 77.

Jadda, M., Shafri, H. Z., & Mansor, S. B. (2011). PFR model and GiT for landslide susceptibility mapping: a case study from Central Alborz, Iran. Natural hazards, 57(2), 395-412.

Jakowatz, C. V., Wahl, D. E., Eichel, P. H., Ghiglia, D. C., & Thompson, P. A. (2012). Spotlight-Mode Synthetic Aperture Radar: A Signal Processing Approach: A Signal Processing Approach: Springer Science & Business Media.

Jebur, M. N., Pradhan, B., & Tehrany, M. S. (2014a). Detection of vertical slope movement in highly vegetated tropical area of Gunung pass landslide, Malaysia, using L-band InSAR technique. Geosciences Journal, 18(1), 61-68.

Jebur, M. N., Pradhan, B., & Tehrany, M. S. (2014b). Optimization of landslide conditioning factors using very high-resolution airborne laser scanning (LiDAR) data at catchment scale. Remote Sensing of Environment, 152, 150-165.

Jebur, M. N., Pradhan, B., & Tehrany, M. S. (2015). Using ALOS PALSAR derived high-resolution DInSAR to detect slow-moving landslides in tropical forest: Cameron Highlands, Malaysia. Geomatics, Natural Hazards and Risk, 6(8), 741-759.

Jensen, J. R., & Lulla, K. (1987). Introductory digital image processing: a remote sensing perspective.

Julian, M., & Anthony, E. (1996). Aspects of landslide activity in the Mercantour Massif and the French Riviera, southeastern France. Geomorphology, 15(3-4), 275-289.

Kainthura, P., Singh, V., & Gupta, S. (2015). Gis based model for monitoring and predition of landslide susceptibility. Paper presented at the Next Generation Computing Technologies (NGCT), 2015 1st International Conference on.

Kalimuthu, H., Tan, W. N., Lim, S. L., & Fauzi, M. F. A. (2015). Assessing frequency ratio method for landslide susceptibility mapping in Cameron Highlands, Malaysia. Paper presented at the Research and Development (SCOReD), 2015 IEEE Student Conference on.

Kamp, U., Growley, B. J., Khattak, G. A., & Owen, L. A. (2008). GIS-based landslide susceptibility mapping for the 2005 Kashmir earthquake region. Geomorphology, 101(4), 631-642.

Kanevski, M., Parkin, R., Pozdnukhov, A., Timonin, V., Maignan, M., Demyanov, V., & Canu, S. (2004). Environmental data mining and modeling based on machine learning algorithms and geostatistics. Environmental Modelling & Software, 19(9), 845-855.

Kawabata, D., & Bandibas, J. (2009). Landslide susceptibility mapping using geological data, a DEM from ASTER images and an Artificial Neural Network (ANN). Geomorphology, 113(1), 97-109.

Kayastha, P., Dhital, M. R., & De Smedt, F. (2013). Application of the analytical hierarchy process (AHP) for landslide susceptibility mapping: a case study from the Tinau watershed, west Nepal. Computers & Geosciences, 52, 398-408.

Klees, R., & Massonnet, D. (1998). Deformation measurements using SAR interferometry: potential and limitations. Geologie en Mijnbouw, 77(2), 161-176.

Kononenko, I., & Bratko, I. (1991). Information-based evaluation criterion for classifier's performance. Machine learning, 6(1), 67-80.

Korhonen, L., Packalen, P., & Rautiainen, M. (2017). Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index. Remote Sensing of Environment, 195, 259-274.

Kornejady, A., Heidari, K., & Nakhavali, M. (2015). Assessment of landslide susceptibility, semi-quantitative risk and management in the Ilam dam basin, Ilam, Iran. Environmental Resources Research, 3(1), 85-109.

Krähenbuhl, R. (1991). Magmatism, tin mineralization and tectonics of the Main Range, Malaysian Peninsula: consequences for the plate tectonic model of

Southeast Asia based on Rb–Sr, K–Ar and fission track data. Bulletin of the Geological Society of Malaysia, 29, 1-100.

Krejčí, O., Baroň, I., Bıl, M., Hubatka, F., Jurová, Z., & Kirchner, K. (2002). Slope movements in the Flysch Carpathians of Eastern Czech Republic triggered by extreme rainfalls in 1997: a case study. Physics and Chemistry of the Earth, Parts A/B/C, 27(36), 1567-1576.

Kuhnert, P. M., Martin, T. G., & Griffiths, S. P. (2010). A guide to eliciting and using expert knowledge in Bayesian ecological models. Ecology letters, 13(7), 900-914.

Kumar, D., Thakur, M., Dubey, C. S., & Shukla, D. P. (2017). Landslide susceptibility mapping & prediction using support vector machine for Mandakini River Basin, Garhwal Himalaya, India. Geomorphology, 295, 115-125.

Kumaran, S., & Ainuddin, A. (2006). Forests, water and climate of Cameron Highlands: School of Humanities, Universiti Sains Malaysia.

Kuri, M., Bhattacharya, A., Arora, M. K., & Sharma, M. L. (2016). Time series insar techniques to estimate deformation in a landslide-prone area in Haridwar region, India. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International.

Lang, A., Moya, J., Corominas, J., Schrott, L., & Dikau, R. (1999). Classic and new dating methods for assessing the temporal occurrence of mass movements. Geomorphology, 30(1), 33-52.

Laurin, G. V., Liesenberg, V., Chen, Q., Guerriero, L., Del Frate, F., Bartolini, A., Coomes, D., Wilebore, B., Lindsell, J., & Valentini, R. (2013). Optical and SAR sensor synergies for forest and land cover mapping in a tropical site in West Africa. International Journal of Applied Earth Observation and Geoinformation, 21, 7-16.

Lee, C. (2009). Palaeozoic stratigraphy. Geology of Peninsular Malaysia, 55-86.

Lee, S., Choi, J., & Min, K. (2002). Landslide susceptibility analysis and verification using the Bayesian probability model. Environmental Geology, 43(1), 120-131.

Lee, S., & Lee, M.-J. (2006). Detecting landslide location using KOMPSAT 1 and its application to landslide-susceptibility mapping at the Gangneung area, Korea. Advances in Space Research, 38(10), 2261-2271.

Lee, S. (2013). Landslide detection and susceptibility mapping in the Sagimakri area, Korea using KOMPSAT-1 and weight of evidence technique. Environmental Earth Sciences, 70(7), 3197-3215.

Lee, S., Lee, M.-J., & Jung, H.-S. (2017). Data mining approaches for landslide susceptibility mapping in Umyeonsan, Seoul, South Korea. Applied Sciences, 7(7), 683.

Leick, A., Rapoport, L., & Tatarnikov, D. (2015). GPS satellite surveying: John Wiley & Sons.

Leite, L. R., Carvalho, L. M. T. d., & Silva, F. M. d. (2017). Change Detection in Forests and Savannas Using Statistical Analysis Based on Geographical Objects. Boletim de Ciências Geodésicas, 23(2), 284-295.

Leonardi, G., Palamara, R., & Cirianni, F. (2016). Landslide Susceptibility Mapping Using a Fuzzy Approach. Procedia Engineering, 161, 380-387.

Levin, N. (2016). Human factors explain the majority of MODIS-derived trends in vegetation cover in Israel: a densely populated country in the eastern Mediterranean. Regional Environmental Change, 16(4), 1197-1211.

Lillesand, T., Kiefer, R. W., & Chipman, J. (2014). Remote sensing and image interpretation: John Wiley & Sons.

Lillesand, T. M., Kiefer, R. W., & Chipman, J. (2004). Remote Sensing and Image Interpretation. New York: JohnWiley and Sons. In: Inc.

Lin, Y., Xia, K., Jiang, X., Bai, J., & Wu, P. (2016). Landslide susceptibility mapping based on particle swarm optimization of multiple kernel relevance vector machines: case of a low hill area in Sichuan Province, China. ISPRS International Journal of Geo-Information, 5(10), 191.

Liu, G., Guo, H., Yue, H., Perski, Z., Yan, S., Song, R., Fan, J., & Ruan, Z. (2016). Modified four-pass differential SAR interferometry for estimating mountain glacier surface velocity fields. Remote Sensing Letters, 7(1), 1-10.

Liu, J.-K., & Shih, P. T. (2013). Topographic correction of wind-driven rainfall for landslide analysis in Central Taiwan with validation from aerial and satellite optical images. Remote Sensing, 5(6), 2571-2589.

Lohnes, R., & Handy, R. (1968). Slope angles in friable loess. The Journal of Geology, 76(3), 247-258.

Lollino, P., Cotecchia, F., Elia, G., Mitaritonna, G., & Santaloia, F. (2016). Interpretation of landslide mechanisms based on numerical modelling: two case-histories. European Journal of Environmental and Civil Engineering, 20(9), 1032-1053.

Louis, J., Charantonis, A., & Berthelot, B. (2010). Coud Detection for Sentinel-2. Paper presented at the ESA Living Planet Symposium.

Luo, Q., Zhou, G., & Perissin, D. (2017). Monitoring of Subsidence along Jingjin Inter-City Railway with High-Resolution TerraSAR-X MT-InSAR Analysis. Remote Sensing, 9(7), 717.

Luo, S., Sarabandi, K., Tong, L., & Pierce, L. (2016). Landslide prediction using soil moisture estimation derived from polarimetric Radarsat-2 data and SRTM. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International.

Maghsoudi, M., Navidfar, A., & Mohammadi, A. (2017). The sand dunes migration patterns in Mesr Erg region using satellite imagery analysis and wind data. Natural Environment Change, 3(1), 33-43.

Makoundi, C., Zaw, K., Large, R. R., Meffre, S., Lai, C.-K., & Hoe, T. G. (2014). Geology, geochemistry and metallogenesis of the Selinsing gold deposit, central Malaysia. Gondwana Research, 26(1), 241-261.

Malamud, B. D., Turcotte, D. L., Guzzetti, F., & Reichenbach, P. (2004). Landslide inventories and their statistical properties. Earth surface processes and landforms, 29(6), 687-711.

Mansor, S., Abu Shariah, M., Billa, L., Setiawan, I., & Jabar, F. (2004). Spatial technology for natural risk management. Disaster Prevention and Management: An International Journal, 13(5), 364-373.

Mansor, S., Pradhan, B., Daud, M., Jamaludin, N., & Khuzaimah, Z. (2007). Landslide susceptibility analysis using an artificial neural network model. Paper presented at the Remote Sensing for Environmental Monitoring, GIS Applications, and Geology VII.

Mansor, S., Saadatkhah, N., Khuzaimah, Z., Asmat, A., Adnan, N. A., & Adam, S. N. (2018). Regional modelling of rainfall-induced runoff using hydrological model by incorporating plant cover effects: case study in Kelantan, Malaysia. Natural hazards, 93, 739-764.

Marchesini, I., Santangelo, M., Fiorucci, F., Cardinali, M., Rossi, M., Bucci, F., & Guzzetti, F. (2018). TXT-tool 1.039-1.2 Bedding Attitude Information Through the Interpretation of Stereoscopic Aerial Photographs and GIS

Modeling. In Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools (pp. 175-186): Springer.

Mărgărint, M. C., & Niculiţă, M. (2017). Landslide type and pattern in Moldavian Plateau, NE Romania. In Landform Dynamics and Evolution in Romania (pp. 271-304): Springer.

Marjanović, M., Kovačević, M., Bajat, B., & Voženílek, V. (2011). Landslide susceptibility assessment using SVM machine learning algorithm. Engineering geology, 123(3), 225-234.

Markham, B. L., Storey, J. C., Williams, D. L., & Irons, J. R. (2004). Landsat sensor performance: history and current status. IEEE transactions on geoscience and remote sensing, 42(12), 2691-2694.

Massonnet, D., & Feigl, K. L. (1998). Radar interferometry and its application to changes in the Earth's surface. Reviews of geophysics, 36(4), 441-500.

Mather, P. M., & Koch, M. (2011). Computer processing of remotely-sensed images: an introduction: John Wiley & Sons.

Matori, A. N., & Basith, A. (2012). Evaluation of landslide causative factors towards efficient landslide susceptibility modelling in the Cameron Highlands, Malaysia. Monitoring, Simulation, Prevention and Remediation of Dense and Debris Flows IV, 4, 207.

Matori, A. N., Basith, A., & Harahap, I. S. H. (2012). Study of regional monsoonal effects on landslide hazard zonation in Cameron Highlands, Malaysia. Arabian Journal of Geosciences, 5(5), 1069-1084.

McClelland, D., Foltz, R., Wilson, W., Cundy, T., Heinemann, R., Saurbier, J., & Schuster, R. (1997). Assessment of the 1995 & 1996 floods and landslides on the Clearwater National Forest. Part I: Landslide assessment. Missoula, MT: USDA Forest Service, Region, 1, 52.

McDermid, G., & Franklin, S. (1995). Remote sensing and geomorphometric discrimination of slope processes. zeitschrift fur geomorphologie supplementband, 165-185.

McKean, J., Buechel, S., & Gaydos, L. (1991). Remote sensing and landslide hazard assessment. Photogrammetric engineering and remote sensing, 57(9), 1185-1193.

McKean, J., & Roering, J. (2004). Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry. Geomorphology, 57(3), 331-351.

Megahed, Y., Cabral, P., Silva, J., & Caetano, M. (2015). Land cover mapping analysis and urban growth modelling using remote sensing techniques in greater Cairo region—Egypt. ISPRS International Journal of Geo-Information, 4(3), 1750-1769.

Melchiorre, C., Castellanos Abella, E., & Matteucci, M. (2007). Analysis of sensitivity in artificial neural network models: application in landslide susceptibility zonation, Guantánamo province, Cuba: poster+ abstract.

Metternicht, G., Hurni, L., & Gogu, R. (2005). Remote sensing of landslides: An analysis of the potential contribution to geo-spatial systems for hazard assessment in mountainous environments. Remote Sensing of Environment, 98(2), 284-303.

Miao, T., & Wang, M. (2015). Susceptibility Analysis of Earthquake-Induced Landslide Using Random Forest Method.

Micheletti, N., Foresti, L., Robert, S., Leuenberger, M., Pedrazzini, A., Jaboyedoff, M., & Kanevski, M. (2014). Machine learning feature selection methods for landslide susceptibility mapping. Mathematical Geosciences, 46(1), 33-57.

Mickovski, S., & Van Beek, L. (2006). A decision support system for the evaluation of eco-engineering strategies for slope protection. Geotechnical & Geological Engineering, 24(3), 483-498.

Mikoš, M., Vilímek, V., Yin, Y., & Sassa, K. (2017). Advancing Culture of Living with Landslides: Vol. 5 Landslides in Different Environments: Springer.

Miliaresis, G. C. (2001). Geomorphometric mapping of Zagros Ranges at regional scale. Computers & Geosciences, 27(7), 775-786.

Miller, S., Brewer, T., & Harris, N. (2009). Rainfall thresholding and susceptibility assessment of rainfall-induced landslides: application to landslide management in St Thomas, Jamaica. Bulletin of Engineering Geology and the Environment, 68(4), 539.

Mingers, J. (1989). An empirical comparison of selection measures for decision-tree induction. Machine learning, 3(4), 319-342.

Mohammadi, A., Bin Ahmad, B., & Shahabi, H. (2018a). Extracting Digital Elevation Model (DEM) from Sentinel-1 Satellite Imagery: Case Study a Part of

Cameron Highlands, Pahang, Malaysia International Journal of Management and Applied Science, 4(9), 109-114.

Mohammadi, A., Shahabi, H., & Bin Ahmad, B. (2018b). Integration of InSAR technique, Google Earth images, and extensive field survey for landslide inventory in a part of Cameron Highlands, Pahang, Malaysia applied ecology and environmental research, 16(6), 8075-8091.

Mohammadi, A., Shahabi, H., & Bin Ahmad, B. (2019). Land-cover Change Detection in a Part of Cameron Highlands, Malaysia Using ETM+ Satellite Imagery and Support Vector Machine (SVM) Algorithm EnvironmentAsia, 12(2).

Mollaee, S., Pirasteh, S., Ramli, M. F., & Rizvi, S. M. (2013). Identifying effecting factors and landslide mapping of cameron highland Malaysia. Paper presented at the Geo-Information Technologies for Natural Disaster Management (GiT4NDM), 2013 Fifth International Conference on.

Mollard, J., & Janes, J. (1984). Air Photo Interpretation of the Canadian Landscape: Energy. Mines and Resources Canada.

Montgomery, D. C., Peck, E. A., & Vining, G. G. (2012). Introduction to linear regression analysis (Vol. 821): John Wiley & Sons.

Montgomery, D. R., Wright, R. H., & Booth, T. (1991). Debris flow hazard mitigation for colluvium-filled swales. Bull Assoc Eng Geol, 28(3), 303-323.

Montgomery, D. R., & Dietrich, W. E. (1994). A physically based model for the topographic control on shallow landsliding. Water resources research, 30(4), 1153-1171.

Moore, W. K. (2004). Malaysia: A Pictorial History: Archipelago Press.

Moreira, A. (2013). Synthetic aperture radar (SAR): principles and applications.

Moreiras, S. M. (2005). Landslide susceptibility zonation in the Rio Mendoza valley, Argentina. Geomorphology, 66(1), 345-357.

Mukherjee, S., Joshi, P., Mukherjee, S., Ghosh, A., Garg, R., & Mukhopadhyay, A. (2013). Evaluation of vertical accuracy of open source Digital Elevation Model (DEM). International Journal of Applied Earth Observation and Geoinformation, 21, 205-217.

Murakmi, S., Nishigaya, T., Tien, T. L., Sakai, N., Lateh, H. H., & Azizat, N. (2014). Development of historical landslide database in Peninsular Malaysia. Paper presented at the Telecommunication Technologies (ISTT), 2014 IEEE 2nd International Symposium on.

Murck, B. W., & Skinner, B. J. (1999). Geology today: understanding our planet (Vol. 1): Wiley.

Nagarajan, R., Roy, A., Kumar, R. V., Mukherjee, A., & Khire, M. (2000). Landslide hazard susceptibility mapping based on terrain and climatic factors for tropical monsoon regions. Bulletin of Engineering Geology and the Environment, 58(4), 275-287.

Naghibi, S. A., Moghaddam, D. D., Kalantar, B., Pradhan, B., & Kisi, O. (2017). A comparative assessment of GIS-based data mining models and a novel ensemble model in groundwater well potential mapping. Journal of Hydrology, 548, 471-483.

NASA. (2018). Landsat 7 Science Data Users Handbook. Retrieved from https://landsat.gsfc.nasa.gov/landsat-7-science-data-users-handbook/

Navarro-Sanchez, V. D., Lopez-Sanchez, J. M., & Vicente-Guijalba, F. (2010). A contribution of polarimetry to satellite differential SAR interferometry: Increasing the number of pixel candidates. IEEE Geoscience and Remote Sensing Letters, 7(2), 276-280.

Nefeslioglu, H. A., Duman, T. Y., & Durmaz, S. (2008). Landslide susceptibility mapping for a part of tectonic Kelkit Valley (Eastern Black Sea region of Turkey). Geomorphology, 94(3-4), 401-418.

Nefeslioglu, H. A., San, B., Gokceoglu, C., & Duman, T. (2012). An assessment on the use of Terra ASTER L3A data in landslide susceptibility mapping. International Journal of Applied Earth Observation and Geoinformation, 14(1), 40-60.

Neuhäuser, B., & Terhorst, B. (2007). Landslide susceptibility assessment using "weights-of-evidence" applied to a study area at the Jurassic escarpment (SW-Germany). Geomorphology, 86(1), 12-24.

Nichol, J., & Wong, M. (2005). Satellite remote sensing for detailed landslide inventories using change detection and image fusion. international Journal of Remote sensing, 26(9), 1913-1926.

Nichol, J. E., Shaker, A., & Wong, M.-S. (2006). Application of high-resolution stereo satellite images to detailed landslide hazard assessment. Geomorphology, 76(1), 68-75.

Nichol, S. L., Hungr, O., & Evans, S. (2002). Large-scale brittle and ductile toppling of rock slopes. Canadian Geotechnical Journal, 39(4), 773-788.

Nicu, I. C. (2017). Frequency ratio and GIS-based evaluation of landslide susceptibility applied to cultural heritage assessment. Journal of Cultural Heritage, 28, 172-176.

Nobile, A., Dille, A., Monsieurs, E., Basimike, J., Bibentyo, T. M., d'Oreye, N., Kervyn, F., & Dewitte, O. (2018). Multi-Temporal DInSAR to Characterise Landslide Ground Deformations in a Tropical Urban Environment: Focus on Bukavu (DR Congo). Remote Sensing, 10(4), 626.

Norušis, M. J. (2006). SPSS 14.0 guide to data analysis: Prentice Hall Upper Saddle River, NJ.

Ohlmacher, G. C., & Davis, J. C. (2003). Using multiple logistic regression and GIS technology to predict landslide hazard in northeast Kansas, USA. Engineering geology, 69(3-4), 331-343.

Othman, A. N., Naim, W. M., & Noraini, S. (2012). GIS based multi-criteria decision making for landslide hazard zonation. Procedia-Social and Behavioral Sciences, 35, 595-602.

P O'Neill, M., & Mark, D. M. (1987). On the frequency distribution of land slope. Earth surface processes and landforms, 12(2), 127-136.

Pachauri, A., & Pant, M. (1992). Landslide hazard mapping based on geological attributes. Engineering geology, 32(1-2), 81-100.

Park, S. H. (2011). Simple Linear Regression. In International Encyclopedia of Statistical Science (pp. 1327-1328): Springer.

Patterson, T. C. (2007). Google Earth as a (not just) geography education tool. Journal of Geography, 106(4), 145-152.

Pearson, K. (1895). Note on regression and inheritance in the case of two parents. Proceedings of the Royal Society of London, 58, 240-242.

Peduto, D., Nicodemo, G., Maccabiani, J., & Ferlisi, S. (2017). Multi-scale analysis of settlement-induced building damage using damage surveys and DInSAR data: A case study in The Netherlands. Engineering geology, 218, 117-133.

Peng, L. C., Leman, M. S., Nasib, B., & Karim, R. (2004). Stratigraphic lexicon of Malaysia: Geological Society of Malaysia.

Pepe, A., Yang, Y., Manzo, M., & Lanari, R. (2015). Improved EMCF-SBAS processing chain based on advanced techniques for the noise-filtering and selection of small baseline multi-look DInSAR interferograms. IEEE transactions on geoscience and remote sensing, 53(8), 4394-4417.

Petley, D., Dunning, S., & Rosser, N. (2005). The analysis of global landslide risk through the creation of a database of worldwide landslide fatalities. Landslide risk management. Balkema, Amsterdam, 367-374.

Pettinato, S., Santi, E., Paloscia, S., Pampaloni, P., & Fontanelli, G. (2013). The Intercomparison of X-Band SAR Images from COSMO-SkyMed and TerraSAR-X Satellites: Case Studies. Remote Sensing, 5(6), 2928-2942.

Pham, B. T., Tien Bui, D., Indra, P., & Dholakia, M. (2015). Landslide susceptibility assessment at a part of Uttarakhand Himalaya, India using GIS–based statistical approach of frequency ratio method. Int J Eng Res Technol, 4(11), 338-344.

Pham, B. T., Pradhan, B., Bui, D. T., Prakash, I., & Dholakia, M. (2016). A comparative study of different machine learning methods for landslide susceptibility assessment: a case study of Uttarakhand area (India). Environmental Modelling & Software, 84, 240-250.

Pham, B. T., Bui, D. T., Prakash, I., & Dholakia, M. (2017). Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. Catena, 149, 52-63.

Pham, B. T., & Prakash, I. (2018). Machine Learning Methods of Kernel Logistic Regression and Classification and Regression Trees for Landslide Susceptibility Assessment at Part of Himalayan Area, India. Indian Journal of Science and Technology, 11(12).

Pietraszek, T. (2007). On the use of ROC analysis for the optimization of abstaining classifiers. Machine learning, 68(2), 137-169.

Pike, R. J. (2000). Geomorphometry-diversity in quantitative surface analysis. Progress in Physical Geography, 24(1), 1-20.

Pleskachevsky, A., Jacobsen, S., Tings, B., Schwarz, E., & Krause, D. (2018). Sea State Retrieval from Sentinel-1 Imagery as Support of Maritime Situation Awareness. Paper presented at the EUSAR 2018; 12th European Conference on Synthetic Aperture Radar.

Polykretis, C., Ferentinou, M., & Chalkias, C. (2015). A comparative study of landslide susceptibility mapping using landslide susceptibility index and artificial neural networks in the Krios River and Krathis River catchments (northern Peloponnesus, Greece). Bulletin of Engineering Geology and the Environment, 74(1), 27-45.

Potere, D. (2008). Horizontal positional accuracy of Google Earth's high-resolution imagery archive. Sensors, 8(12), 7973-7981.

Pour, A. B., & Hashim, M. (2014). Structural geology mapping using PALSAR data in the Bau gold mining district, Sarawak, Malaysia. Advances in Space Research, 54(4), 644-654.

Pour, A. B., & Hashim, M. (2016). PALSAR-2 remote sensing data for detection of hazards zones of geological origin in Kelantan river basin, Peninsular Malaysia. Paper presented at the Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International.

Pradhan, A., & Kim, Y. (2016). Evaluation of a combined spatial multi-criteria evaluation model and deterministic model for landslide susceptibility mapping. Catena, 140, 125-139.

Pradhan, B., Singh, R., & Buchroithner, M. (2006). Estimation of stress and its use in evaluation of landslide prone regions using remote sensing data. Advances in Space Research, 37(4), 698-709.

Pradhan, B., & Lee, S. (2009). Landslide risk analysis using artificial neural network model focussing on different training sites. International Journal of Physical Sciences, 4(1), 1-15.

Pradhan, B., & Buchroithner, M. F. (2010). Comparison and validation of landslide susceptibility maps using an artificial neural network model for three test areas in Malaysia. Environmental & Engineering Geoscience, 16(2), 107-126.

Pradhan, B., & Lee, S. (2010). Regional landslide susceptibility analysis using back-propagation neural network model at Cameron Highland, Malaysia. Landslides, 7(1), 13-30.

Pradhan, B., Lee, S., & Buchroithner, M. F. (2010a). A GIS-based back-propagation neural network model and its cross-application and validation for landslide susceptibility analyses. Computers, Environment and Urban Systems, 34(3), 216-235.

Pradhan, B., Sezer, E. A., Gokceoglu, C., & Buchroithner, M. F. (2010b). Landslide susceptibility mapping by neuro-fuzzy approach in a landslide-prone area (Cameron Highlands, Malaysia). IEEE transactions on geoscience and remote sensing, 48(12), 4164-4177.

Pradhan, B. (2011). Use of GIS-based fuzzy logic relations and its cross application to produce landslide susceptibility maps in three test areas in Malaysia. Environmental Earth Sciences, 63(2), 329-349.

Pradhan, B., Mansor, S., & Pirasteh, S. (2011). Landslide Susceptibility Mapping: an Assessment of the Use of an Advanced Neural Network Model with Five Different Training Strategies. In Artificial Neural Networks-Application: InTech.

Pradhan, B. (2013). A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. Computers & Geosciences, 51, 350-365.

Pradhan, B., Abokharima, M. H., Jebur, M. N., & Tehrany, M. S. (2014). Land subsidence susceptibility mapping at Kinta Valley (Malaysia) using the evidential belief function model in GIS. Natural hazards, 73(2), 1019-1042.

Pradhan, B., & Sameen, M. I. (2017). Landslide susceptibility modeling: optimization and factor effect analysis. In Laser Scanning Applications in Landslide Assessment (pp. 115-132): Springer.

Qi, Z., Tian, Y., & Shi, Y. (2013). Robust twin support vector machine for pattern classification. Pattern Recognition, 46(1), 305-316.

Quattrochi, D. A., Wentz, E., Lam, N. S.-N., & Emerson, C. W. (2017). Integrating Scale in Remote Sensing and GIS: CRC Press.

Quraishi, I., Hasnat, A., & Choudhury, J. P. (2017). Selection of optimal pixel resolution for landslide susceptibility analysis within the Bukit Antarabangsa, Kuala Lumpur, by using image processing and multivariate statistical tools. EURASIP Journal on Image and Video Processing, 2017(1), 21.

Rahmati, O., Samani, A. N., Mahdavi, M., Pourghasemi, H. R., & Zeinivand, H. (2015). Groundwater potential mapping at Kurdistan region of Iran using analytic hierarchy process and GIS. Arabian Journal of Geosciences, 8(9), 7059-7071.

Ramli, M., Petley, D., Murphy, W., & Inkpen, R. (2002). Integration of high resolution thematic mapper and digital elevation model for landslide mapping. Paper presented at the Proceedings of the Regional Symposium on Environmental and Natural Resources, Kuala Lumpur.

Rasul, M., Islam, M. S., Yunus, R. B. M., Mokhtar, M. B., Alam, L., & Yahaya, F. (2017). Spatial and Temporal Variation of Water Quality in the Bertam

Catchment, Cameron Highlands, Malaysia. Water Environment Research, 89(12), 2088-2102.

Rawat, M., Joshi, V., & Sundriyal, Y. (2016). Slope stability analysis in a part of East Sikkim, using Remote Sensing & GIS. Paper presented at the Next Generation Computing Technologies (NGCT), 2016 2nd International Conference on.

Razak, K. A., Santangelo, M., Van Westen, C. J., Straatsma, M. W., & de Jong, S. M. (2013). Generating an optimal DTM from airborne laser scanning data for landslide mapping in a tropical forest environment. Geomorphology, 190, 112-125.

Rebentrost, P., Mohseni, M., & Lloyd, S. (2014). Quantum support vector machine for big data classification. Physical review letters, 113(13), 130503.

Reddy, G. O., Kumar, N., Sahu, N., & Singh, S. (2018). Evaluation of automatic drainage extraction thresholds using ASTER GDEM and Cartosat-1 DEM: A case study from basaltic terrain of Central India. The Egyptian Journal of Remote Sensing and Space Science, 21(1), 95-104.

Regmi, N. R., Giardino, J. R., & Vitek, J. D. (2010). Assessing susceptibility to landslides: using models to understand observed changes in slopes. Geomorphology, 122(1), 25-38.

Rib, H. T., & Liang, T. (1978). Recognition and identification. Transportation research board special report(176).

Richter, R., Wang, X., Bachmann, M., & Schläpfer, D. (2011). Correction of cirrus effects in Sentinel-2 type of imagery. international Journal of Remote sensing, 32(10), 2931-2941.

Robinson, I. (2018). Applications of Remotely Sensed Image Data to Marine Modeling. In Modeling marine systems (pp. 141-180): CRC Press.

Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. Ore Geology Reviews, 71, 804-818.

Romer, C., & Ferentinou, M. (2016). Shallow landslide susceptibility assessment in a semiarid environment—a quaternary catchment of KwaZulu-Natal, South Africa. Engineering geology, 201, 29-44.

Roslee, R., Simon, N., Tongkul, F., Norhisham, M. N., & Taharin, M. R. (2017). Landslide Susceptibility Analysis (LSA) using Deterministic Model (Infinite Slope)(DESSISM) in the Kota Kinabalu Area, Sabah, Malaysia.

Rowbotham, D. N., & Dudycha, D. (1998). GIS modelling of slope stability in Phewa Tal watershed, Nepal. Geomorphology, 26(1), 151-170.

Roy, D. P., Kovalskyy, V., Zhang, H., Vermote, E. F., Yan, L., Kumar, S., & Egorov, A. (2016). Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. Remote Sensing of Environment, 185, 57-70.

Sabokbar, H. F., Roodposhti, M. S., & Tazik, E. (2014). Landslide susceptibility mapping using geographically-weighted principal component analysis. Geomorphology, 226, 15-24.

Safaei, M., Omar, H., Huat, B. K., & Yousof, Z. B. (2012). Relationship between Lithology Factor and landslide occurrence based on Information Value (IV) and Frequency Ratio (FR) approaches—Case study in North of Iran. Electronic Journal of Geotechnical Engineering, 17.

Salas-Romero, S., Malehmir, A., Snowball, I., Lougheed, B. C., & Hellqvist, M. (2016). Identifying landslide preconditions in Swedish quick clays—Insights from integration of surface geophysical, core sample-and downhole property measurements. Landslides, 13(5), 905-923.

Samy, I. E., Marghany, M. M., & Mohamed, M. M. (2014). Landslide modelling and analysis using remote sensing and GIS: A case study of Cameron highland, Malaysia. Journal of Geomatics, 8(2).

Santini, M., Grimaldi, S., Nardi, F., Petroselli, A., & Rulli, M. C. (2009). Pre-processing algorithms and landslide modelling on remotely sensed DEMs. Geomorphology, 113(1), 110-125.

Sassa, K., Tiwari, B., Liu, K.-F., McSaveney, M., Strom, A., & Setiawan, H. (2018). Landslide Dynamics: ISDR-ICL Landslide Interactive Teaching Tools: Volume 2: Testing, Risk Management and Country Practices: Springer.

Schuster, R. L., & Fleming, R. W. (1986). Economic losses and fatalities due to landslides. Bull Assoc Eng Geol, 23(1), 11-28.

Sezer, E. A., Pradhan, B., & Gokceoglu, C. (2011). Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia. Expert Systems with Applications, 38(7), 8208-8219.

Shahabi, H., Ahmad, B. B., & Khezri, S. (2012a). Application of satellite remote sensing for detailed landslide inventories using frequency ratio model and GIS. Int J Comput Sci, 9, 108-117.

Shahabi, H., Ahmad, B. B., Mokhtari, M. H., & Zadeh, M. A. (2012b). Detection of urban irregular development and green space destruction using normalized difference vegetation index (NDVI), principal component analysis (PCA) and post classification methods: A case study of Saqqez city. International Journal of Physical Sciences, 7(17), 2587-2595.

Shahabi, H., Khezri, S., Ahmad, B., & Allahverdiasl, H. (2012c). Application of satellite images and comparative study of analytical hierarchy process and frequency ratio methods to landslide susceptibility mapping in central Zab basin, NW Iran. International Journal of Advances in Engineering & Technology, 4(2), 103.

Shahabi, H., Ahmad, B., & Khezri, S. (2013). Evaluation and comparison of bivariate and multivariate statistical methods for landslide susceptibility mapping (case study: Zab basin). Arabian Journal of Geosciences, 6(10), 3885-3907.

Shahabi, H. (2015). Landslide Susceptibility Mapping in Central Zab Basing Using Satellite Data. Universiti Teknologi Malaysia,

Shahabi, H., & Hashim, M. (2015). Landslide susceptibility mapping using GIS-based statistical models and Remote sensing data in tropical environment. Scientific reports, 5, 9899.

Sharma, S., & Mahajan, A. (2018). A comparative assessment of information value, frequency ratio and analytical hierarchy process models for landslide susceptibility mapping of a Himalayan watershed, India. Bulletin of Engineering Geology and the Environment, 1-18.

Shih, E. H., & Schowengerdt, R. A. (1983). Classification of arid geomorphic surfaces using Landsat spectral and textural features. Photogrammetric engineering and remote sensing.

Shimokawa, E., Jitousono, T., & Takano, S. (1989). Periodicity of shallow landslide on Shirasu (Ito pyroclastic flow deposits) steep slopes and prediction of potential landslide sites. Transactions, Japanese Geomorphological Union, 10(4), 267-284.

Shirzadi, A., Bui, D. T., Pham, B. T., Solaimani, K., Chapi, K., Kavian, A., Shahabi, H., & Revhaug, I. (2017). Shallow landslide susceptibility assessment using a novel hybrid intelligence approach. Environmental Earth Sciences, 76(2), 60.

Sidle, R. C., Pearce, A. J., & O'Loughlin, C. L. (1985). Hillslope stability and land use: American geophysical union.

Sidle, R. C., & Chigira, M. (2004). Landslides and debris flows strike Kyushu, Japan. Eos, Transactions American Geophysical Union, 85(15), 145-151.

Sidle, R. C., & Ochiai, H. (2006). Landslides: processes, prediction, and land use (Vol. 18): American Geophysical Union.

Singhroy, V., Mattar, K., & Gray, A. (1998). Landslide characterisation in Canada using interferometric SAR and combined SAR and TM images. Advances in Space Research, 21(3), 465-476.

Skempton, A., & DeLory, F. (1984). Stability of natural slopes in London clay. In Selected Papers on Soil Mechanics (pp. 70-73): Thomas Telford Publishing.

Skoković, D., Sobrino, J. A., & Jiménez-Muñoz, J. C. (2017). Vicarious calibration of the landsat 7 thermal infrared band and lst algorithm validation of the etm+ instrument using three global atmospheric profiles. IEEE transactions on geoscience and remote sensing, 55(3), 1804-1811.

Smith, R. (2006). Introduction to interpreting digital RADAR images. MicroImages Tutorials, Learning Geospatial Analysis, 2001 www. microimages. com.

Soeters, R., & van Westen, C. J. (1996). Landslides: Investigation and mitigation. Chapter 8-Slope instability recognition, analysis, and zonation. Transportation research board special report(247).

Soma, A. S., & Kubota, T. (2018). Landslide susceptibility map using certainty factor for hazard mitigation in mountainous areas of Ujung-loe watershed in South Sulawesi. Forest and Society, 2(1), 79-91.

Song, K.-Y., Oh, H.-J., Choi, J., Park, I., Lee, C., & Lee, S. (2012). Prediction of landslides using ASTER imagery and data mining models. Advances in Space Research, 49(5), 978-993.

Sönmez, İ., Erdi, E., Tekeli, A. E., Demir, F., & Arslan, M. (2011). Foogle: fire monitoring tool for EUMETSAT's active fire product over Turkey using Google Earth. Geomatics, Natural Hazards and Risk, 2(1), 1-13.

Spackman, K. A. (1989). Signal detection theory: Valuable tools for evaluating inductive learning. Paper presented at the Proceedings of the sixth international workshop on Machine learning.

Stanley, T., & Kirschbaum, D. B. (2017). A heuristic approach to global landslide susceptibility mapping. Natural hazards, 87(1), 145-164.

Starkel, L. (1976). The role of extreme (catastrophic) meteorological events in contemporary evolution of slopes. Geomorphology and climate, 203-246.

Stehman, S. V. (1997). Selecting and interpreting measures of thematic classification accuracy. Remote Sensing of Environment, 62(1), 77-89.

Steinwart, I., & Christmann, A. (2008). Support vector machines: Springer Science & Business Media.

Stigler, S. M. (1989). Francis Galton's account of the invention of correlation. Statistical Science, 73-79.

Stopa, J. E., & Mouche, A. (2017). Significant wave heights from Sentinel-1 SAR: Validation and applications. Journal of Geophysical Research: Oceans, 122(3), 1827-1848.

Stumpf, A., Malet, J.-P., & Delacourt, C. (2017). Correlation of satellite image time-series for the detection and monitoring of slow-moving landslides. Remote Sensing of Environment, 189, 40-55.

Sukopp, H. (1998). Urban ecology—scientific and practical aspects: Springer.

Sumner, M., Frank, E., & Hall, M. (2005). Speeding up logistic model tree induction. Paper presented at the European Conference on Principles of Data Mining and Knowledge Discovery.

Suzana, R., Wardah, T., & Hamid, A. (2011). Radar hydrology: New Z/R relationships for Klang River Basin Malaysia based on rainfall classification. World Academy of Science, Engineering and Technology, 59.

Swanston, D., & Dyrness, C. (1973). Managing steep land. I. Stability of steep land. Journal of forestry.

Tay, L. T., Alkhasawneh, M. S., Ngah, U. K., & Lateh, H. (2014). Landslide hazard mapping of Penang Island using dominant factors. Paper presented at the Telecommunication Technologies (ISTT), 2014 IEEE 2nd International Symposium on.

Thenkabail, P. S., & Lyon, J. G. (2016). Hyperspectral remote sensing of vegetation: CRC Press.

Thiery, Y., Malet, J.-P., Sterlacchini, S., Puissant, A., & Maquaire, O. (2007). Landslide susceptibility assessment by bivariate methods at large scales: application to a complex mountainous environment. Geomorphology, 92(1), 38-59.

Thome, K. (2001). Absolute radiometric calibration of Landsat 7 ETM+ using the reflectance-based method. Remote Sensing of Environment, 78(1-2), 27-38.

Thomson, S. (1971). Analysis of a failed slope. Canadian Geotechnical Journal, 8(4), 596-599.

Tien-Sze, L., Voon-Chet, K., Yee-Kit, C., Lateh, H., & Sumantyo, J. T. S. (2013). Development of a ground-based Synthetic Aperture Radar for land deformation monitoring. Paper presented at the Synthetic Aperture Radar (APSAR), 2013 Asia-Pacific Conference on.

Tien Bui, D., Pham, B. T., Nguyen, Q. P., & Hoang, N.-D. (2016). Spatial prediction of rainfall-induced shallow landslides using hybrid integration approach of Least-Squares Support Vector Machines and differential evolution optimization: a case study in Central Vietnam. International Journal of Digital Earth, 9(11), 1077-1097.

Tien Bui, D., Shahabi, H., Shirzadi, A., Chapi, K., Alizadeh, M., Chen, W., Mohammadi, A., Ahmad, B., Panahi, M., & Hong, H. (2018). Landslide detection and susceptibility mapping by AIRSAR data using support vector machine and index of entropy models in Cameron Highlands, Malaysia. Remote Sensing, 10(10), 1527.

Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., & Brown, M. (2012). GMES Sentinel-1 mission. Remote Sensing of Environment, 120, 9-24.

Trigila, A., Iadanza, C., Esposito, C., & Scarascia-Mugnozza, G. (2015). Comparison of logistic regression and random forests techniques for shallow landslide susceptibility assessment in Giampilieri (NE Sicily, Italy). Geomorphology, 249, 119-136.

Tsukamoto, Y., Ohta, T., & Noguchi, H. (1982). Hydrological and geomorphological studies of debris slides on forested hillslopes in Japan. International Association of Hydrological Sciences Publication, 137, 89-98.

Turner, A. K. (2018). Social and environmental impacts of landslides. Innovative Infrastructure Solutions, 3(1), 70.

Uchida, T., Kosugi, K. i., & Mizuyama, T. (2001). Effects of pipeflow on hydrological process and its relation to landslide: a review of pipeflow studies in forested headwater catchments. Hydrological processes, 15(11), 2151-2174.

Umar, Z., Pradhan, B., Ahmad, A., Jebur, M. N., & Tehrany, M. S. (2014). Earthquake induced landslide susceptibility mapping using an integrated ensemble frequency ratio and logistic regression models in West Sumatera Province, Indonesia. Catena, 118, 124-135.

USGS. (2016). Landslide Types and Processes. Retrieved from https://pubs.usgs.gov/fs/2004/3072/fs-2004-3072.html

USGS. (2018). Landsat 8 Data Users Handbook. Retrieved from https://landsat.usgs.gov/landsat-8-data-users-handbook

Van Den Eeckhaut, M., Vanwalleghem, T., Poesen, J., Govers, G., Verstraeten, G., & Vandekerckhove, L. (2006). Prediction of landslide susceptibility using rare events logistic regression: a case-study in the Flemish Ardennes (Belgium). Geomorphology, 76(3-4), 392-410.

Van Westen, C. (1994). GIS in landslide hazard zonation: a review, with examples from the Andes of Colombia. In Mountain environments & geographic information systems: Taylor & Francis.

Van Westen, C., Rengers, N., & Soeters, R. (2003). Use of geomorphological information in indirect landslide susceptibility assessment. Natural hazards, 30(3), 399-419.

Van Westen, C., Van Asch, T. W., & Soeters, R. (2006). Landslide hazard and risk zonation—why is it still so difficult? Bulletin of Engineering Geology and the Environment, 65(2), 167-184.

Van Westen, C. J., Castellanos, E., & Kuriakose, S. L. (2008). Spatial data for landslide susceptibility, hazard, and vulnerability assessment: an overview. Engineering geology, 102(3), 112-131.

Vanderlooy, S., & Hüllermeier, E. (2008). A critical analysis of variants of the AUC. Machine learning, 72(3), 247-262.

Varnes, D. J. (1978). Slope movement types and processes. Special report, 176, 11-33.

Varnes, D. J. (1984). Landslide hazard zonation: a review of principles and practice.

Vasu, N. N., & Lee, S.-R. (2016). A hybrid feature selection algorithm integrating an extreme learning machine for landslide susceptibility modeling of Mt. Woomyeon, South Korea. Geomorphology, 263, 50-70.

Villano, M., Krieger, G., Papathanassiou, K. P., & Moreira, A. (2018). Monitoring dynamic processes on the earth's surface using synthetic aperture radar. Paper presented at the 2018 IEEE International Conference on Environmental Engineering (EE).

Wachal, D. J., & Hudak, P. F. (2000). Mapping landslide susceptibility in Travis County, Texas, USA. GeoJournal, 51(3), 245-253.

Wakatsuki, T., Tanaka, Y., & Matsukura, Y. (2005). Soil slips on weathering-limited slopes underlain by coarse-grained granite or fine-grained gneiss near Seoul, Republic of Korea. Catena, 60(2), 181-203.

Wang, L.-J., Guo, M., Sawada, K., Lin, J., & Zhang, J. (2015). Landslide susceptibility mapping in Mizunami City, Japan: a comparison between logistic regression, bivariate statistical analysis and multivariate adaptive regression spline models. Catena, 135, 271-282.

Wang, W.-D., Xie, C.-M., & Du, X.-G. (2009). Landslides susceptibility mapping in Guizhou province based on fuzzy theory. Mining Science and Technology (China), 19(3), 399-404.

Weisberg, S. (2005a). Simple linear regression. Applied Linear Regression, Third Edition, 19-46.

Weisberg, S. (2005b). Applied linear regression (Vol. 528): John Wiley & Sons.

Weng, Q., Quattrochi, D., & Gamba, P. E. (2018). Urban remote sensing: CRC press.

Wikipedia. (2018a). List of landslides. Retrieved from https://en.wikipedia.org/wiki/List_of_landslides

Wikipedia. (2018b). Cameron Highlands District. Retrieved from https://en.wikipedia.org/wiki/Cameron_Highlands_District

Wise, S. (2007). Effect of differing DEM creation methods on the results from a hydrological model. Computers & Geosciences, 33(10), 1351-1365.

Woodhouse, I. H. (2017). Introduction to microwave remote sensing: CRC press.

Wu, C.-H., & Chen, S.-C. (2009). Determining landslide susceptibility in Central Taiwan from rainfall and six site factors using the analytical hierarchy process method. Geomorphology, 112(3), 190-204.

Wu, X., Ren, F., & Niu, R. (2014). Landslide susceptibility assessment using object mapping units, decision tree, and support vector machine models in the Three Gorges of China. Environmental Earth Sciences, 71(11), 4725-4738.

Xiao, R., & He, X. (2013). Real-time landslide monitoring of Pubugou hydropower resettlement zone using continuous GPS. Natural hazards, 69(3), 1647-1660.

Xing, A., Wang, G., Yin, Y., Jiang, Y., Wang, G., Yang, S., Dai, D., Zhu, Y., & Dai, J. (2014). Dynamic analysis and field investigation of a fluidized landslide in Guanling, Guizhou, China. Engineering geology, 181, 1-14.

Xu, C. (2015). Preparation of earthquake-triggered landslide inventory maps using remote sensing and GIS technologies: Principles and case studies. Geoscience Frontiers, 6(6), 825-836.

Yagüe-Martínez, N., Prats-Iraola, P., Gonzalez, F. R., Brcic, R., Shau, R., Geudtner, D., Eineder, M., & Bamler, R. (2016). Interferometric processing of Sentinel-1 TOPS data. IEEE transactions on geoscience and remote sensing, 54(4), 2220-2234.

Yalcin, A., & Bulut, F. (2007). Landslide susceptibility mapping using GIS and digital photogrammetric techniques: a case study from Ardesen (NE-Turkey). Natural hazards, 41(1), 201-226.

Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): comparisons of results and confirmations. Catena, 72(1), 1-12.

Yalcin, A., Reis, S., Aydinoglu, A., & Yomralioglu, T. (2011). A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. Catena, 85(3), 274-287.

Yang, K., Pan, A., Yang, Y., Zhang, S., Ong, S. H., & Tang, H. (2017). Remote sensing image registration using multiple image features. Remote Sensing, 9(6), 581.

Yeap, E. (1993). Tin and gold mineralizations in Peninsular Malaysia and their relationships to the tectonic development. Journal of Southeast Asian Earth Sciences, 8(1-4), 329-348.

Yesilnacar, E., & Topal, T. (2005). Landslide susceptibility mapping: a comparison of logistic regression and neural networks methods in a medium scale study, Hendek region (Turkey). Engineering geology, 79(3), 251-266.

Yokota, S., & Iwamatsu, A. (2000). Weathering distribution in a steep slope of soft pyroclastic rocks as an indicator of slope instability. Engineering geology, 55(1), 57-68.

Youssef, A. M., Al-Kathery, M., & Pradhan, B. (2015a). Landslide susceptibility mapping at Al-Hasher area, Jizan (Saudi Arabia) using GIS-based frequency ratio and index of entropy models. Geosciences Journal, 19(1), 113-134.

Youssef, A. M., Pradhan, B., Jebur, M. N., & El-Harbi, H. M. (2015b). Landslide susceptibility mapping using ensemble bivariate and multivariate statistical models in Fayfa area, Saudi Arabia. Environmental Earth Sciences, 73(7), 3745-3761.

Youssef, A. M., Pourghasemi, H. R., El-Haddad, B. A., & Dhahry, B. K. (2016). Landslide susceptibility maps using different probabilistic and bivariate statistical models and comparison of their performance at Wadi Itwad Basin, Asir Region, Saudi Arabia. Bulletin of Engineering Geology and the Environment, 75(1), 63-87.

Zakaria, M., & Chow, W. (2003). Geological terrain mapping in Cameron Highlands district, Pahang. Paper presented at the Proceeding of Annual Geological Conference.

Zha, Y., Gao, J., & Ni, S. (2003). Use of normalized difference built-up index in automatically mapping urban areas from TM imagery. international Journal of Remote sensing, 24(3), 583-594.

Zhang, G., Cai, Y., Zheng, Z., Zhen, J., Liu, Y., & Huang, K. (2016). Integration of the statistical index method and the analytic hierarchy process technique for the assessment of landslide susceptibility in Huizhou, China. Catena, 142, 233-244.

Zhang, H. K., Roy, D. P., Yan, L., Li, Z., Huang, H., Vermote, E., Skakun, S., & Roger, J.-C. (2018). Characterization of Sentinel-2A and Landsat-8 top of atmosphere, surface, and nadir BRDF adjusted reflectance and NDVI differences. Remote Sensing of Environment.

Zhao, W., Li, A., Nan, X., Zhang, Z., & Lei, G. (2017). Postearthquake Landslides Mapping From Landsat-8 Data for the 2015 Nepal Earthquake Using a Pixel-Based Change Detection Method. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(5), 1758-1768.

Zhu, A.-X., Miao, Y., Wang, R., Zhu, T., Deng, Y., Liu, J., Yang, L., Qin, C.-Z., & Hong, H. (2018). A comparative study of an expert knowledge-based model and two data-driven models for landslide susceptibility mapping. Catena, 166, 317-327.

Zillman, J. (1999). The physical impact of disaster. Natural Disaster Management. Leicester: Tudor Rose Holdings Ltd.