



SUPPORT VECTOR MACHINE FOR LANDSLIDE ACTIVITY IDENTIFICATION BASED ON VEGETATION ANOMALIES INDICATOR

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Abstract:

Landslide activity identification is critical for landslide inventory mapping. A detailed landslide inventory map is highly required for various purposes such as landslide susceptibility, hazard, and risk assessments. This paper proposes a novel approach based on vegetation anomalies indicator (VAI) and applying machine learning method namely support vector machine (SVM) to identify status of natural-terrain landslides. First, high resolution airborne LiDAR data and satellite imagery were used to derive landslide-related VAI, including tree height irregularities, canopy gap, density of different layer of vegetation, vegetation type, vegetation indices, root strength index (RSI), and distribution of water-loving trees. Then, SVM is utilized with different setting of parameter using grid search optimization. SVM Radial Basis Function (RBF) recorded the best optimal pair value with 0.062 and 0.092 misclassification rate for deep seated and shallow translational landslide, respectively. For landslide activity classification, SVM RBF recorded the best accuracy value for both deep seated and shallow translational landslides with 86.0 and 71.3, respectively. Overall, VAIs have great potential in tackling the landslide activity identification problem especially in tropical vegetated area.

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Landslide, Remote Sensing, Vegetation Anomalies, Machine Learning

Introduction

Landslide is a serious hazard to human life in many parts of the world (GEOHAZARDS, 2004; R L Schuster, 1996). These including effects on civilians, properties, environment, and infrastructures (Gaidzik et al., 2017; Kaur, Gupta, & Parkash, 2017; Mia, Sultana, & Paul, 2015; Robert L Schuster & Highland, 2003). Landslide can be characterized as the mass movement process on the natural and artificial slopes (Cruden, 1991; Gariano & Guzzetti, 2016). The slope-forming materials including rock soil may shift by falling, toppling, sliding, spreading, or flowing. According to the database from the Centre for Research on the Epidemiology of Disasters (CRED), the number of deaths reported from 2006 to 2015 due to landslide events is more than 9,000 lives (Sanderson & Sharma, 2016). Asia accounted for 77.4% of the total number of people killed by this disaster.

In Malaysia, landslides are still one of the natural disasters that frequently happened (Ahmad, Lateh, & Saleh, 2014; H. A. Rahman & Mapjabil, 2017). The tragedies have caused many fatalities and destroy the infrastructures such as buildings, roads, recreational parks, etc. Landslide damage and losses in Malaysia are partly related to the country's rapid urbanization and economic development. People keep expanding their economic activities into the highlands and steep terrain areas due to the lack of suitable low-lying locations. Cutting mountain sides and hilly areas to make way for high-rise buildings increases the risk of landslides (Jamaluddin, 2006). Furthermore, the regions with steep slopes are more likely to experience landslides especially when triggered by tectonic activities and the presence of active faults (Forbes, Broadhead, Brardinoni, Gray, & Stokes, 2013; Pirasteh, Li, & Chapman, 2018). In a wet tropical climate with heavy and prolonged rainfall throughout the year, the slope in Malaysia is generally sensitive to precipitation (Huat, Hossein, Afshin, Kazemian, & Keykha, 2011; Jamaluddin, 2006; Qasim, Harahap, & Syed Osman, 2013) as it weakens the ability of the soil which causing landslides.

The advancement of remote sensing technology has opened up a new perspective of landslide investigation with the capability of acquiring 3D information of the Earth's surface (Jaboyedoff et al., 2012; Scaioni, Longoni, Melillo, & Papini, 2014) and may speed up the process of landslide inventory maps production (N Casagli et al., 2016; Nicola Casagli et al., 2017; Guzzetti et al., 2012). Remote sensing technologies such as aerial photography, Interferometric Synthetic Aperture Radar (InSAR), and Light Detection and Ranging (LiDAR) represent a powerful tool for landslide investigation (Forbes et al., 2013; Guzzetti et al., 2012; Scaioni et al., 2014). Knowledge about landslide characteristics, for instance, their location, travel distance, date of occurrence, and state of activity can be reasonably obtained from remote sensing technology. This information is highly important for landslide hazard, susceptibility, vulnerability, and risk assessment.

Landslide activity is one of the important elements highlighted in the landslide inventory database (Del Ventisette, Righini, Moretti, & Casagli, 2014; Guzzetti et al., 2012). In general, the evaluation process for future displacement rates is very important to know by estimating their current state of activity due to progressively growing landslides and their cycles when they enter the process. There are also various methods of identifying a landslide's state of activity such as field investigation, multi-temporal landslide inventory maps, remote sensing technique, etc. For the last decade, the method of detecting landslides under forested areas also has been dependent on the geological, geomorphological feature, and drainage pattern of the area (Glenn, Streutker, Chadwick, Thackray, & Dorsch, 2006; Hutchinson, 1994; McKean & Roering, 2004). Unfortunately, previous studies have shown that landslide mapping in a vegetated area is very challenging. The hilly and inaccessible area complicates the actual landslide boundary identification. The covering effect of dense vegetation (Jaboyedoff et al., 2012; Mezaal, Pradhan, Shafri, & Yusoff, 2017; Pirasteh & Li, 2016; Salleh et al., 2018; Van Den Eeckhaut, Kerle, Hervás, & Supper, 2013), its widespread distribution in an undulating area (Brardinoni, Slaymaker, & Hassan, 2003; Korup, 2005; McKean & Roering, 2004; Tien Bui et al., 2018), and rapid vegetation growth (Brardinoni et al., 2003; Mezaal, Pradhan, Sameen, Mohd Shafri, & Yusoff, 2017; Mezaal, Pradhan, Shafri, et al., 2017; Musinguzi & Asiimwe, 2014; Pradhan, Jebur, Shafri, & Tehrani, 2015; Guruh Samodra, Bhandary, & Yatabe, 2017; G Samodra, Chen, Sartohadi, & Kasama, 2018) will remove the landslide signature and complicates the determination of landslide boundary and state of activity.

Therefore, this study aims in classifying landslide activity based on different landslide types and depths with Vegetation Anomalies Indicators (VAIs) as a predictor along a tectonically active region, Kundasang. VAI maps used in the modelling process can be derived from both LiDAR and satellite image data as they gave us a new understanding of how vegetation characteristics differed from one landslide type, depth, and activity.

Methodology

Landslide Inventory Map

Getting ready landslide inventory maps is critical for landslide studies. In general, a landslide inventory map provides basic information such as location of mass movements and the date of occurrences. It also contains a collection of polygon shapes, types, lengths, widths, areas, locations, and other information related to landslides (Pirasteh & Li, 2016). Landslide inventory maps also portray spatial and temporal distribution of landslide patterns, type of movement, type of displaced material (earth, debris or rock), rate of movement etc. With such valuable information, landslide inventory data can be integrated in GIS environment. This implementation enables us to increase the level of understanding of landslide phenomena across regions and through space and time. Moreover, landslide inventory map represented as fundamental element in a framework for accessing landslide susceptibility, hazard, and risk.

In this study, the landslide inventory map was delineated based on three derived datasets namely topographic openness, hillshade, and colour composite. High resolution of digital terrain model (DTM) and orthophoto with 7 cm spatial resolution were used in delineating the

landslide inventory. Orthophoto has also been used to see if any recent activity has taken place. Active landslide is identified with the clear evidence of failure and it has almost no vegetation coverage. Meanwhile, a dormant landslide is an inactive landslide which can be reactivated by its original causes or other causes. The scarp and body of the failure are still visible in the hillshade, but if the location is densely vegetated and does not show recent activity. A relict landslide is an inactive landslide which has been protected from its original causes by remedial measures. The scarp and body of the failure through LiDAR hillshade are not obvious, while the orthophoto shows that the area is densely vegetated or has been mitigated by retaining wall. Sustainable tourism as defined by The World Tourism Organization (UNWTO) is tourism that takes full account of current and future economic, social and environmental impacts...

(TNR, 12, single spacing, justify)

Parameterization of Vegetation Anomalies Indicator

In this study, seven groups of VAIs were used in landslide activity classification i.e., tree height irregularities, canopy gap, different layers of vegetation, vegetation type distribution, vegetation indices, root strength index, and distribution of water-loving trees. The distribution of tree height significantly reflects the quality and quantity of tree stand and its future growth. Trees in landslide areas have relatively low height, small crown, and more irregularities (Razak et al., 2013). Tree height irregularities were calculated using the standard deviation of tree height within a selected area size (i.e., a grid of 20 m). This calculation was applied to the LiDAR-derived CHM of the study area. High standard deviation indicates highly irregular tree height in a specific area. For canopy gap, a strong relationship can be found between landslide and forest canopy gaps (Moos, 2014). The presence of landslides under the forested area is believed to be detectable by measuring the gaps in the area.

The vegetation density layer at a certain height from the ground was measured using the density of high points (DHP) method (M. Rahman & Gorte, 2009). This method utilised point clouds obtained from the airborne LiDAR data and the density of the reflected laser pulses above a certain height from the ground. The vegetation layers were then classified into four classes i.e., low vegetation, young woody vegetation, matured woody vegetation, and old forest. The process started by deriving normalized point clouds and were then categorized based on height classification scheme and the vegetation density of each layer class was calculated within a 1 m search radius with a final resolution of 0.25 m. For vegetation type distribution, four classes of vegetation type were produced such as grass, secondary forest, primary forest, and agriculture. These indicators were mapped from satellite imagery and LiDAR-derived CHM.

Vegetation indices can be defined as the form of band ratios related to vegetation (Mwaniki, Agutu, Mbaka, Ngigi, & Waithaka, 2015). Six indices were used in this study, namely Normalized Difference Vegetation Index (NDVI), Difference Vegetation Index (DVI), Soil Adjusted Vegetation Index (SAVI), Optimized Soil Adjusted Vegetation Index (OSAVI), Green Difference Vegetation Index (GDVI), and Green Normalized Difference Vegetation Index (GNDVI). These vegetation indices were extracted from the Pleiades satellite images. Each index was derived based on the combination of visible light bands and Near Infrared (NIR). Root strength is one of the factors of soil reinforcement (Abdi, 2018). Increasing the strength will increase the soil reinforcement (Stokes, 2002). Changing the tree root strength

affects slope stability (Capilleri, Motta, & Raciti, 2016). Root strength index (RSI) was derived based on the estimated tree height and tree density (Iwahashi, Okatani, Nakano, Koarai, & Otoi, 2014). The estimated tree height was obtained from the airborne LiDAR data, while tree density was defined as the number of trees in a 30 m grid.

Water-loving trees, also known as hydrophytes, are usually found in wetlands of all sorts, either in or on the water, or where soils are flooded or saturated long enough to establish anaerobic conditions in the root zone (Cronk & Fennessy, 2016). Distribution of water-loving trees indicates the high presence of active landslides (Johnson, Swanston, & McGee, 2000). In this study, the distribution of water-loving trees was produced by combining the aerial photographs, satellite imagery, CHM, and topographic wetness index (TWI) datasets, which were derived from the high resolution DTM over the study area. Water loving trees were characterised by their lower height value, i.e., 1 m to 3 m (Chatwin & Howes, 1991). The vegetated pixel area was classified automatically from satellite imagery. The height value of vegetation pixel was extracted from the CHM dataset and the pixel value of 1 m to 3 m was used for estimation of water loving trees. The presence of low vegetation and high TWI value for certain area indicates a high density of water-loving trees.

Support Vector Machine (SVM)

SVM was initially developed to find a hyperplane that separates two classes optimally (i.e., landslides with a specific activity class and other landslides with activity class) by maximising the margins of class boundaries for linearly separable cases (Abe, 2005). The optimum hyperplane was derived from support vectors with the closest values to the classification margin. The classification of new data can be performed once the decision surface is acquired. However, classification with linear function is very challenging. In this case, a non-linear approach can be performed by using kernel function (i.e., linear, polynomial, radial basis function, and sigmoid).

In the SVM modeling approach, several parameters needed to be configured such as kernel function, regularisation parameter (C), gamma (γ), and degree of polynomial (d). Different kernel type requires different parameters. Parameter C is able to monitor any overfitting activity of the model while parameter γ controls the degree of non-linearity of the model. In this study, three SVM kernel functions were used namely Linear, Polynomial, and Radial Basis Function (RBF). The selection of parameter value is specified based on grid search optimization process.

Result Validation

Our classification scheme included three classes: active, dormant, and relict. We used of accuracy and kappa index to check and compare the performance of the algorithm in ability to classify the landslide state of activity. Overall accuracy (OA) (1) and Kappa index (2) can be computed based on the following equations as described by Ghayour et al. (2021):

$$\text{Overall Accuracy} = \frac{\text{Total number of correct samples}}{\text{Total number of samples (\%)}} \quad (1)$$

$$Kappa = \frac{\epsilon_1 - \epsilon_2}{1 - \epsilon_2}; \epsilon_1 = \frac{\sum_{i=1}^n D_{ii}}{N}; \epsilon_2 = \frac{\sum_{i=1}^n D_{i+} D_{+i}}{N^2} \quad (2)$$

Where D_{ii} is the number of observations in row i and column i of the confusion matrix, n is the number of rows in the error matrix, N is total number of counts in the confusion matrix, x_{i+} is the marginal total of row i , and x_{+i} is the marginal total of column i .

Main Results

Grid Search Optimization

According to the Table 1 (a) and Table 1 (b), two sets of support vector machine (SVM) optimal pair value were derived from grid search optimization process. Overall, SVM RBF produced the lowest misclassification rate value for both landslide depth i.e. deep seated, translational and shallow, translational. These optimal parameter pair values were used for landslide activity classification process.

Table 1: Optimal Pair Value of SVM Parameters for (a) Deep Seated Translational, and (b) Shallow, Translational

Deep Seated, Translational				
Kernel Function	Optimal Pair Value			Misclassification Rate
	Cost	Gamma	Degree	
Linear	32	0.031	NA	0.104
Polynomial	32	0.063	3	0.122
RBF	8	0.125	NA	0.062

(a)

Shallow, Translational				
Kernel Function	Optimal Pair Value			Misclassification Rate
	Cost	Gamma	Degree	
Linear	16	0.125	NA	0.425
Polynomial	1	0.1	3	0.304
RBF	32	0.0625	NA	0.092

(b)

Landslide Activity Classification

The classification process was conducted using the optimal parameter value as discussed in the previous section. The generated classified maps were evaluated using overall accuracy and kappa index value. According to Table 2, SVM RBF outperformed other methods with 86.0% and 0.769 of OA and kappa values, respectively. For shallow translational landslide, SVM RBF yielded the highest OA (71.3%) and kappa (0.563) values. Based on the results, SVM RBF would be considered as the best method for both landslide depth.

Table 2: Accuracy Assessment of Landslide Activity Classification for Deep-Seated and Shallow Translational Landslides

Assessment	Linear			Polynomial			RBF		
	Active	Dormant	Relict	Active	Dormant	Relict	Active	Dormant	Relict
Deep-seated, Translational									
PA (%)	55.5	81.5	80.6	54.7	81.8	80.4	81.4	88.8	85.6
UA (%)	78.2	72.1	73.1	78.1	72.0	73.7	88.0	85.4	84.8
OA (%)		73.7			73.6			86.0	
Kappa		0.560			0.557			0.769	
Shallow, Translational									
PA (%)	20.4	53.0	81.4	20.5	50.5	81.8	59.2	70.9	80.7
UA (%)	51.8	54.9	54.5	49.7	54.9	53.8	72.8	72.6	69.3
OA (%)		54.4			53.7			71.3	
Kappa		0.294			0.284			0.563	

*PA = Producer's Accuracy, UA = User's Accuracy, OA = Overall Accuracy

The analysis of the classification results for each activity class is carried out by measuring the producer's accuracy (PA) and user's accuracy (UA). For deep-seated translational landslide, all the methods recorded satisfactory results of PA and UA. The PA values ranged from 54.7% – 88.0%, 81.5% – 88.8%, and 80.4% – 85.6% for active, dormant, and relict, respectively while, UA values ranged from 78.1% – 88.0% (active), 72.0% – 85.4% (dormant), and 73.1% – 84.8% (relict). For shallow translational landslide, the PA values ranged from 20.4% – 59.2%, 50.5% – 70.9%, and 80.7% – 81.8% for active, dormant, and relict, respectively while, UA values ranged from 49.7% – 72.8% (active), 54.9% – 72.6% (dormant), and 53.8% – 69.3% (relict) which can be categorised as moderate results. Overall, it can be summarized that SVM with RBF kernel function outperformed other kernel types.

Conclusion

This study has provided a landslide activity classification by utilizing vegetation anomalies as the indicators. In order to accomplish this purpose, seven group of VAIs were employed in the analysis. Support Vector Machine with optimal parameter pair value were implemented in order to classify landslide activity. The results revealed that VAIs could be used for landslide activity identification with SVM RBF yielded the best accuracy value. Specifically, the generated map could help the local authorities and decision makers to identify the area subject to damage by future landslides and choose appropriate locations for the implementation of developments.

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