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Assessing the Impact of Wind Speed and Tree Cover on Slope Instability: A Case Study of Bukit Antarabangsa, Malaysia

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ABSTRACT

This study aimed to evaluate the influence of wind speed and vegetation as factors in slope instability using datasets from the Global Wind Atlas (GWA) and the Global Forest Change database. The GWA is a database of wind speed and power density data developed by the Technical University of Denmark and provides wind speed data at a relatively high spatial resolutions, allowing for microscale analysis of meteorological phenomena. The Global Forest Change database is a web-based visualization of global forest cover developed by the University of Maryland, United States. The study focused on the township of Bukit Antarabangsa, an elite metropolitan suburb of Kuala Lumpur, known as a hotspot for landslides. Slope failures in this area have been primarily attributed to intense and prolonged rainfall coupled with various human-induced factors, such as deforestation and urban development. However, the influence of wind on slope stability has not been extensively researched in this context. The study analyzed 16 environmental variables in a weight-of-evidence susceptibility model in order to map slope instability within the landslide hotspot, and to evaluate the relative influence of landslide explanatory factors. It found that while wind speed had a negligible influence on the landslide susceptibility index, tree cover was one of three most influential factors. The study also optimized the susceptibility model to a cluster of seven factors yielding an Area Under Curve value of 0.825. These factors included slope, distance to lineament, tree cover, SP, flow accumulation, land use land cover and terrain wetness index. This study therefore provides a simplified framework for selecting the optimal set of conditioning factors and highlights the significance of tree cover in regulating slope stability in this area.

Keywords: landslide susceptibility; wind influence; Global Wind Atlas; Bukit Antarabangsa; weights of evidence

INTRODUCTION

Landslides represent a considerable environmental threat in Malaysia, especially in metropolitan regions where accelerated urbanization and evolving land use practices can exacerbate slope instability (Lim, Jamaluddin, and Komoo 2019). Landslides occurring in Kuala Lumpur have been ascribed to a combination of anthropogenic and non-anthropogenic factors. Anthropogenic factors are characterized by disturbances related to rapid urban development, insufficient engineering design, and inadequate slope maintenance (Affandi et al. 2023). Spatially these factors are represented by indicators such as distance to roadways, slope modifications such as road cuts and land use land cover types, among others. Non-anthropogenic factors include landslide conditioning factors such as slope angle, lithological properties and discontinuities in underlying soil strata, as well as triggering factors such as prolonged and intense rainfall

(Kazmi et al. 2016). Vegetation cover may also play a role in regulating slope instability through root reinforcement and transferring wind- force to the soil resulting in tree throw or shallow landslide occurrences (Parra, Mohr, and Korup 2021). The role of vegetation cover in landslide occurrence around the Bukit Antarabangsa was investigated in a previous study (Hassaballa, Althuwaynee, and Pradhan 2014) which found that areas of high moisture content coincided with highly vegetated zones, indicating its potential influence on slope instability. However, effects of both wind speed and tree cover on landslide occurrence has not often been examined in the context of Peninsular Malaysia. Factors including the substantial mass of dense vegetation (for instance, arboreal structures) and the conveyance of drag forces induced by atmospheric currents may compromise the stability of slopes (Emadi-Tafti, Ataie-Ashtiani, and Hosseini 2021). Conversely it has been argued that land use changes, poor construction standards and an uptrend in deforestation are responsible for an increase in landslide occurrences in Peninsular Malaysia (Khor et al. 2023). Examining the wider context of the Hulu Kelang area, another study posited that vegetation influenced soil strength and rainfall interception which in turn improved slope stability (Jeong, Park, and Hwang 2018).

This paper aims to shed more light on the relationship between wind speed, tree cover and slope instability in the landslide hotspot of Bukit Antarabangsa, a densely populated upscale suburb of northeast Kuala Lumpur, Malaysia. Previous studies reveal that wind can influence landslides in several ways. Parra et al. (2021) report that the effect of wind load on woody vegetation can drive the destabilization of slopes alongside other secondary factors such as vegetation rooting and tree physiology, and that the effect of wind load could be enhanced by forest cover and terrain steepness. In the Bukit Antarabangsa area, forest comprises the second largest land use land cover category following housing (Lim, Jamaluddin, and Komoo 2019). In this case the researchers investigate the influence of wind speed and tree cover on landslide spatial distribution in the urbanized equatorial monsoon region of Bukit Antarabangsa, Malaysia. Previous research (Zhuang et al. 2022; Lin et al. 2025) explores the role of heavy rainfall and wind gusts linked to typhoon events in triggering landslides, noting additional factors including presence of forests and shallow soil thickness. These works point to a definitive link between wind gusts and landslide events through mechanical effects on trees. It is worth mentioning that this study did not address distinctions in vegetation types such as forests, grasslands, and shrubs, even though a large percentage of the study area is comprised of natural forest. The study was conducted in an urban equatorial setting known for its history of landslide occurrences. Bukit Antarabangsa, a neighborhood of the Ampang Jaya Municipal Council (MPAJ), is one of Malaysia's most landslide-prone areas, with 10 landslide occurrences documented between 1999 and 2020 (Akter et al. 2019; Diana et al. 2021).

METHODOLOGY

Bukit Antarabangsa is a township in the Klang Valley, an economic region that continues to see significant urbanization despite the frequency of landslides. The study area covers 1.15 square kilometers in the Bukit Antarabangsa township, which is located in the northeastern part of Ampang Jaya Town Council. This particular area was chosen because of the high density of landslides. Bukit Antarabangsa is a hillside township in Ulu Klang District, Selangor State, administered by Ampang Jaya Municipal Council. The centre is located 3°12′00″ north latitude and 101°46′01″ north of Kuala Lumpur (see Figure 1). Bukit Antarabangsa's landscape is undulating, with tiny ravines and steep slopes (25°-40°) (Ismail, Taib, and Abas 2019). The area's land uses include a steep expanse of natural forest between 0 and 420 meters above sea level, as well as flat terrain at peat swamp forest, grassland, ex-mining, and scrub areas. The area's geology is almost completely made up of medium to coarse Kuala Lumpur granite (Lim, Jamaluddin, and Komoo 2019). With three lithological classes—schist, acid intrusive, and vein quartz—the areas' lithology is comparatively uniform (Jebur, Pradhan, and Tehrany 2014). Thick, deeply weathered soils are its defining feature, which may be related to the region's frequent precipitation and warm temperatures (Ismail, Taib, and Abas 2019). Local climate is classed as equatorial monsoon while rainfall distribution is characterized by two monsoon seasons, namely the Northeast Monsoon (NEM) that runs from November to March, and the Southwest Monsoon (SWM) that runs from May to September (M. L. Lee et al. 2014).

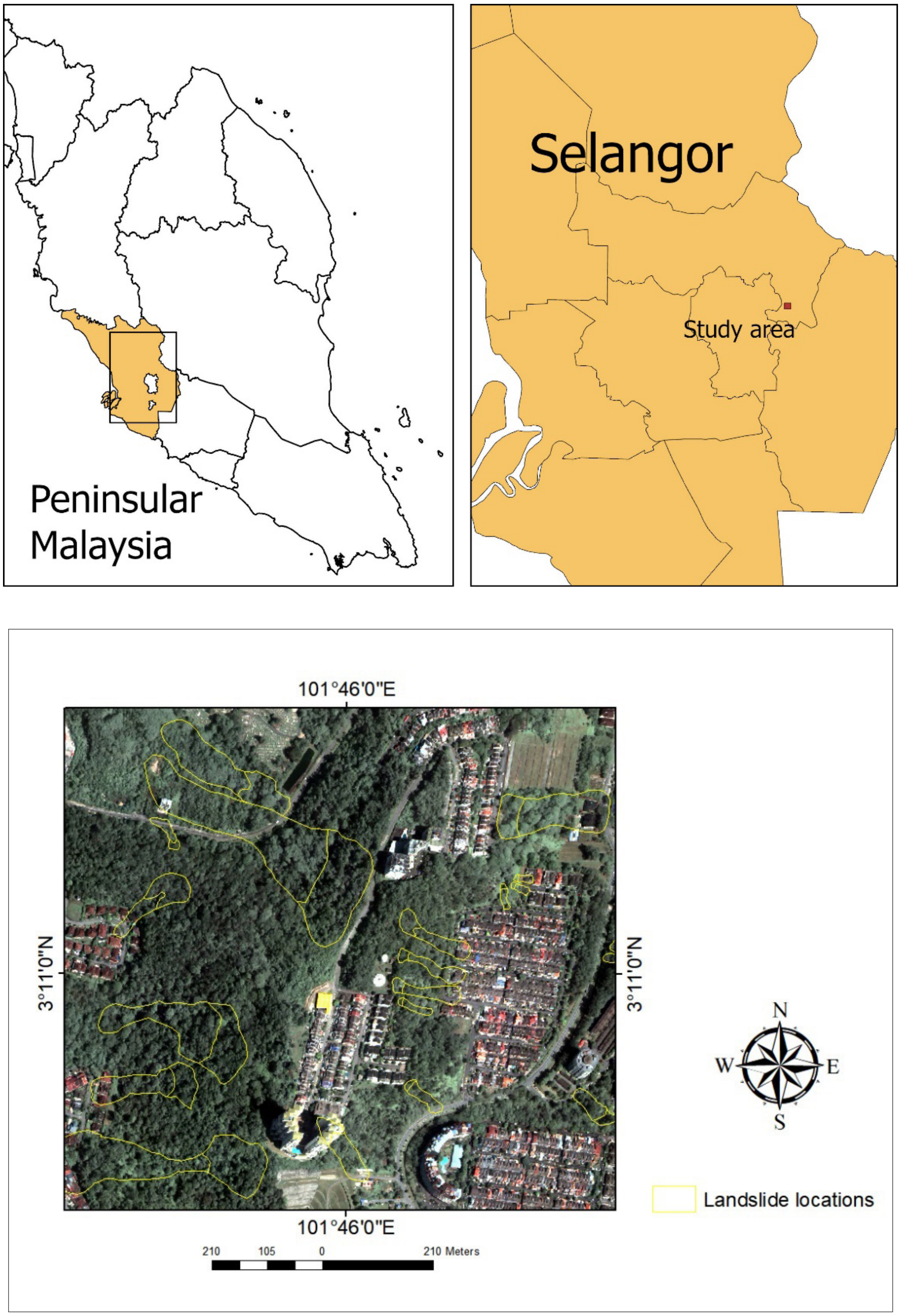

FIGURE 1. Study area

Landslide susceptibility is described as the possibility of a landslide occurring in a specific location, taking into consideration the local environmental conditions (Nicu 2018). The concept of susceptibility explicitly excludes any consideration of the timing or probability of landslide occurrence, and therefore overlooks triggering factors. Another important distinction between susceptibility and hazard is the emphasis on spatial distribution rather than temporal distribution in the case of hazard (van Westen, van Asch, and Soeters 2005). The four main stages of the landslide susceptibility assessment were selection of causal factors; data gathering and entry; data analysis; and model validation. Physically based and statistical slope stability models are typically used in contemporary approaches to susceptibility assessment, with machine learning models becoming more popular in recent years (Park and Lee 2021). The landslide locations were sourced from local government agencies including the Mineral and Geoscience Department; Ampang Jaya Municipal Council; and the Public Works Department. Twenty raster map files, a landslide inventory shape file, a boundary shape file for the study region, and eight orthophoto raster files were among the datasets used to build the geodatabase. ESRI ArcGIS 10.8 was used to develop the database, which at first contained subfolders for landslide inventory-derived polygons and transformed factor maps. To estimate landslide susceptibility, several factor categories were considered, including geological, geomorphologic, hydrological, anthropogenic, and climatic categories. The choice of factors was based on availability of data and a review of literature from the study area (Calcaterra et al. 2022; Jebur, Pradhan, and Tehrany 2014). It should be noted that, in accordance with definition of landslide susceptibility mapping, only landslide conditioning factors were chosen from among the cause components taken into consideration (Raj and Thimmaiah 2019). An overview of the landslide explanatory variables used in this study is presented in Table 1.

TABLE 1. Explanatory variables

Factor group	Causal factor	Description
Geological	Distance to lineament	The term lineament denotes features such as faults, fractures and shear zones which may be identified from satellite imagery (Sema, Guru, and Veerappan 2017). It is generally understood that the presence of lineaments significantly influences the stability of rock masses thereby increasing potential for slope failure (Yusof et al. 2011).
Geomorphological	Slope	A steeper slope angle typically correlates with a higher probability of landslide occurrence (Sonker, Tripathi, and Singh 2021). Slope angle has an influence on the concentration of moisture and the level of pore pressure at the local scale, as well as hydraulic continuity at larger scales (Getachew and Meten 2021). Slope angle is also one of the more important landslide conditioning factors in the Kuala Lumpur landscape (Althuwaynee, Pradhan, and Ahmad 2015).
	Aspect	Slope aspect is a conditioning factor that can have a considerable effect on slope properties such as vegetation cover, moisture retention, and soil strength (Khan et al. 2019). It determines the level of exposure of terrain to elements such as sunlight, wind and rain, which in turn determines the degree of weathering and soil moisture content (Getachew and Meten 2021). However, Capitani et al. [(2013)] posited that the influence of this factor is constrained by landslide type and lithology.
	Curvature	Curvature is defined as the relationship between the earth's ground shape and the resulting runoff (Selamat et al. 2022). The curvature of a slope has an influence on surface runoff and therefore affects landslide occurrence (Nohani et al. 2019). The greater the positive or negative value, the higher the probability of landslide occurrence (S. Lee and Talib 2005). A DEM is used to generate the curvature factor map.
	Terrain roughness index (TRI)	The terrain roughness index, also known as terrain ruggedness index, denotes the degree of elevation difference between adjacent grid cells in a DEM (Riley, DeGloria, and Elliot 1999). It is a measure of the general heterogeneity of a given area and reflects the degree of surface erosion and variability (Shirvani 2020).
	Terrain surface texture (TST)	Terrain surface texture defines the variability in regularity and intensity of pits and peaks within a given radius (Furze et al. 2021). It is defined specifically as the number of pits and peaks within a radius of ten cells (Iwahashi and Pike 2007).
	Vector ruggedness measure (VRM)	Vector ruggedness measure provides a quantification of a given area's ruggedness by way of slope and aspect (Furze et al. 2021). VRM is also a proxy of terrain roughness (Lombardo et al. 2021).

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Factor group	Causal factor	Description
Hydro-topographic	Distance to river	This is sometimes referred to as distance to streams. Rivers and streams could influence landslide occurrence by wearing the slope base or saturating the lower horizons of hill slopes (Mousavi et al. 2011). This factor is intended to test the assumption that landslides occur more frequently along streams (Van Westen, Rengers, and Soeters 2003).
	Flow accumulation	Flow accumulation is a quantification of the land area that channels surface water to zones where surface water may accumulate (Dahal et al. 2008).
	Stream power index (SPI)	The stream power index is a measure of a stream's erosive power and is thought to be a key factor influencing landslide occurrence (Ageenko et al. 2022). The SPI value is influenced by viscosity and terrain steepness parameters (Saadatkhah, Kassim, and Lee 2014).
	Tree cover	Tree cover in this case was operationally characterized as the proportion of canopy occlusion for vegetation exceeding 5 meters in height, as delineated from temporal sequences of Landsat imagery with a spatial resolution of 30 meters (Parra, Mohr, and Korup 2021).
Climatic	Wind speed	Wind is a common cause of disturbance in forested areas and while wind speed is the primary driver, rooting and tree physiology are also significant (Parra, Mohr, and Korup 2021). The effect of wind is possibly enhanced by the presence of forest cover and terrain steepness. Wind also indirectly influences processes of water infiltration and rainfall spatial pattern. The study used mean wind speed (m/s) from the Global Wind Atlas (GWA) at 10m height. Developed by the Technical University of Denmark, the GWA visualizes modelled wind speed and mean power density at a 250m "microscale" resolution (DTU Wind, n.d.). The low resolution of wind speed data at 250 meters introduces a degree of uncertainty, as values within each grid cell are aggregated into a single parameter with limited detail. Interpolating this dataset would not reduce uncertainty, as the technique lacks precision when averaging grid estimates with detailed empirical records. Nevertheless, interpolation is conducted to ensure a consistent set of raster layers for the study.
Anthropogenic	Distance to road	Road networks have a major role in influencing landslide concurrence (Mousavi et al. 2011). Construction of roads along slopes results in a decrease of the slope base, and road ditch infiltration can contribute to an increase in soil moisture. This factor map is widely used as a test of whether or not landslides occur frequently along roads, and accounts for anthropogenic activities such as poorly designed cut-slopes and roadside drainage (Van Westen, Rengers, and Soeters 2003).
	Land use and land cover (LULC)	Land use and land cover has a significant influence on slope stability as it influences characteristics such as infiltration, runoff production, runoff production and mechanical reinforcement of soil by vegetation (Moresi et al. 2020; Polykretis, Ferentinou, and Chalkias 2015; Zhuo et al. 2019). The LULC map is to be classified into classes such as green area, water bodies, developing area and built-up area following selection of an appropriate classification scheme.

The study used a data-driven weight-of-evidence model to quantify the influence of 20 landslide causal factors on landslide susceptibility. The model was implemented in a GIS environment using spatial layers sourced from local and national authorities in Malaysia as well as global wind speed (https://globalwindatlas.info/api/gis/country/MYS/wind-speed/10) and tree cover (https://earthenginepartners.appspot.com/science-2013-global-forest) datasets. An overview of the analytical workflow is presented in Figure 2. Wind speed and tree cover data were interpolated and resampled to enable visualization and analysis at a large scale (Figure 3).

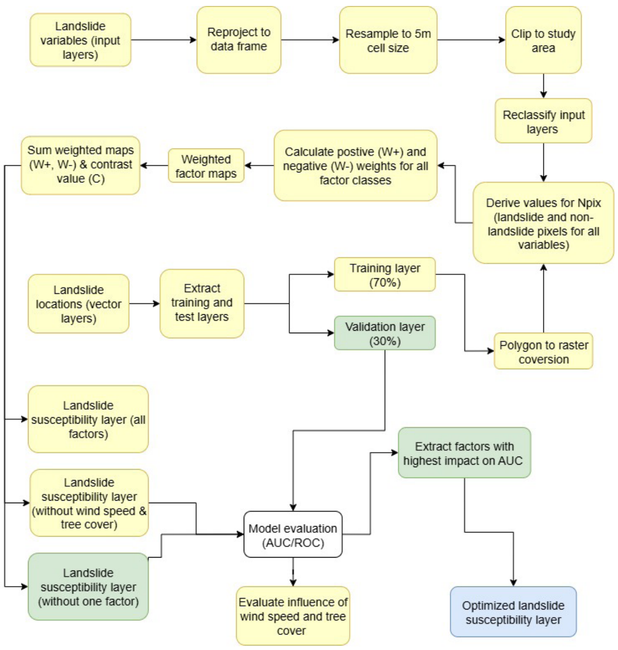

FIGURE 2. Data processing workflow

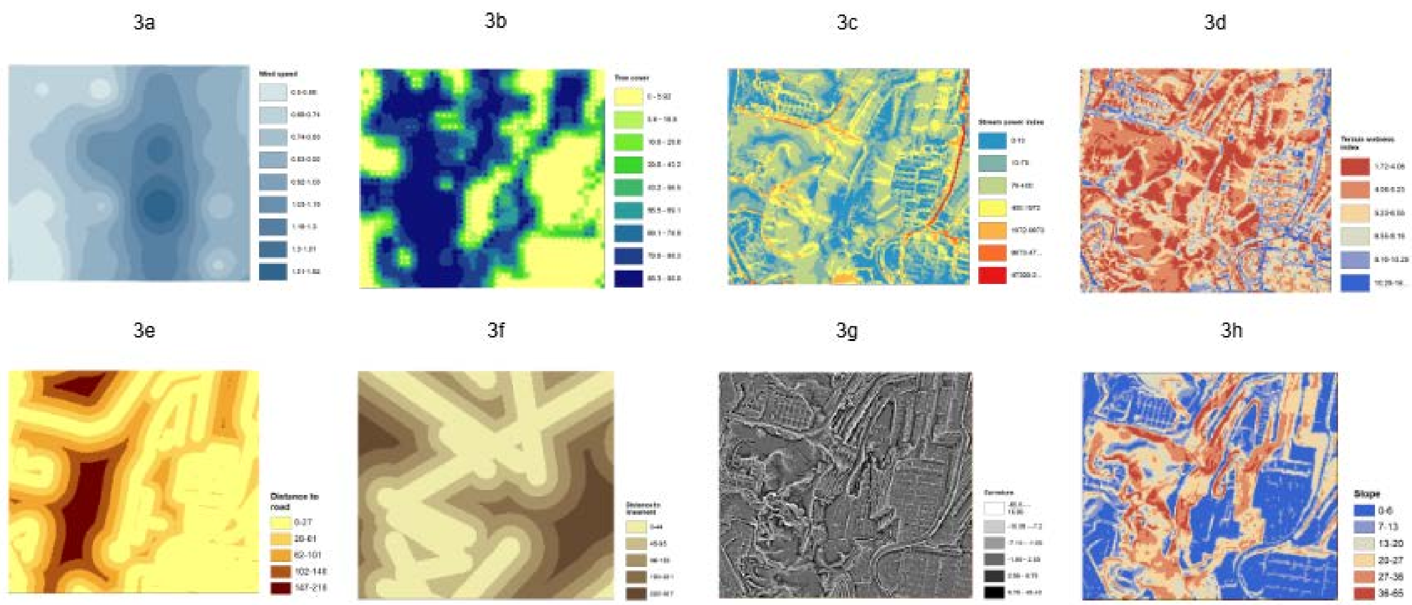

FIGURE 3. Some of the input variables used to build the landslide susceptibility model: 3a) wind speed; 3b) tree cover; 3c) stream power index; 3d) terrain wetness index; 3e) distance to road; 3f) distance to lineament; 3g) curvature; and 3h) slope angle

Following the establishment of the study geodatabase, preliminary data manipulation was executed to guarantee that all factor maps and layers are projected within a uniform spatial reference and aligned with the delineation of the study area, while ensuring that all input raster layers possess an identical cell size; all factor maps are subsequently reclassified utilizing an appropriate classification methodology; the extraction of training and validation datasets from the landslide inventory is conducted. The resampling of factor maps to a cell size of 5m by 5m was subsequently conducted employing a "bilinear" interpolation technique for continuous variables, including slope, curvature, and distance to river, whereas a "nearest neighbour" approach was utilized for categorical variables, such as land use land cover, aspect, and flow direction. For the purpose of reclassifying factor maps, continuous data variables underwent reclassification employing the "natural breaks (Jenks)" methodology, with the notable exception of datasets exhibiting significant skewness, specifically flow accumulation and SPI. The natural breaks technique was chosen due to its efficacy in reducing variance among data groups, thereby facilitating a greater level of homogeneity within the categorical factors (Polykretis, Ferentinou, and Chalkias 2015). A "geometric interval" classification was employed to address these anomalies, facilitating a more uniform allocation of factor categories across the research area. Wind speed and tree cover datasets were subjected to interpolation and resampling techniques to enhance visualization and analysis on a broader scale.

The training dataset comprised 70% of landslide polygons in the study area, with 30% of polygons providing the validation dataset. Prior to extraction of the training and validation datasets, an operation was executed to extract zones of landslide initiation that were used for the analytical model.

During the data analysis stage, 16 causal factor layers were used as inputs. Due to limitations in the data, one of these variables was later excluded from the analysis. The stream network layer was eliminated because it did not overlap with any landslide locations in the training set that would have produced null values. Figure 4 displays the factor maps that were selected and classified.

The Weight of Evidence (WoE) model generates binary raster maps aimed at forecasting the occurrence or non-occurrence of potential landslides at the pixel level. The intersection of a particular factor layer with the landslide inventory layer yields four distinct combinations, as shown in Table 2.

TABLE 2. Possible combinations of a potential landslide conditioning factor and a landslide inventory map (Goyes-Peñafiel and Hernandez-Rojas 2021)

Bi : Potential landslide conditioning factor			
		(Present)	(Absent)
S: Landslides	Present	Npix1	Npix2
	Absent	Npix3	Npix4

The WoE algorithm gives each factor class positive and negative weights inside the reclassified raster layer. A factor class's capacity to forecast landslide occurrence is shown by a high positive weight, while its incapacity to do so is indicated by a low positive weight (Getachew and Meten 2021). A custom modelling workflow was used to derive Npix1 values using a cross-factor operation to determine the number of landslide pixels within each factor class. Equations 1 and 2 could then be applied to determine positive weight (W+) and negative weight (W-) values. Weight values were applied to each factor class within the factor map layers using a map algebra operation. For each factor map, contrast value (C) layers (W+ - W-) were then obtained using the W+ and W-weighted layers. Finally, the LSI map represented by the following equation was created by adding up all of the C-weighted maps:

$$LSI = \sum_{0}^{i} C_j \tag{1}$$

where Cj is the contract value of the jth factor and LSI is the ith pixel's landslide susceptibility index (Ilia and Tsangaratos 2016). Using a natural breaks categorization approach, the final LSI values were divided into five classes in order to produce comparable LSI maps that would allow evaluation of the factor class influences. A series of LSI maps were created for various factor combinations after this classification, including all selected landslide conditioning factors and a set of LSI outputs that exclude one of the factors to illustrate the relative importance of landslide explanatory variables. This aimed to identify which factors made a significant variation to the analysis. A receiver operating characteristic (ROC) curve was subsequently generated, and the area beneath this curve was computed. The ROC analysis is seen as a dependable approach for verifying models related to landslide susceptibility (Polykretis, Ferentinou, and Chalkias 2015). The remaining 30% of landslide polygons were used for the validation. A further stage in optimizing landslide explanatory factors involved gradually removing the least significant (lowest AUC value) component from the validation input to identify an optimal combination of factors.

RESULTS AND DISCUSSION

The analytical assessment conducted a weight of evidence computation, which ascertained both positive and negative weights alongside contrast values for every category of factors. Contrast values indicate the predictive capability of a given factor class on slope stability at known landslide locations. Weight values ranging from 0.1 to 0.5 are classified as possessing an intermediate level of predictive capability, whereas values from 0.5 to 1 are regarded as exhibiting a moderate degree of predictive power (Getachew and Meten 2021). Values in the range of 1 and 2 are thought to be highly predictive of landslides occurrences. The most highly predictive factor classes were thus determined by ranking the highest positive weight values. The landslide susceptibility map for the complete set of factors shows indicates high susceptibility values in northwest and southwest quadrants of the study area (Figure 4).

An image differencing task (Figure 5) found that the inclusion of the tree cover layer had an extensive effect on LSI and increased the areal extent of the model's highest and lowest susceptibility classes by 2% and lowest 6.69% respectively, with an overall increase of 4.79%.

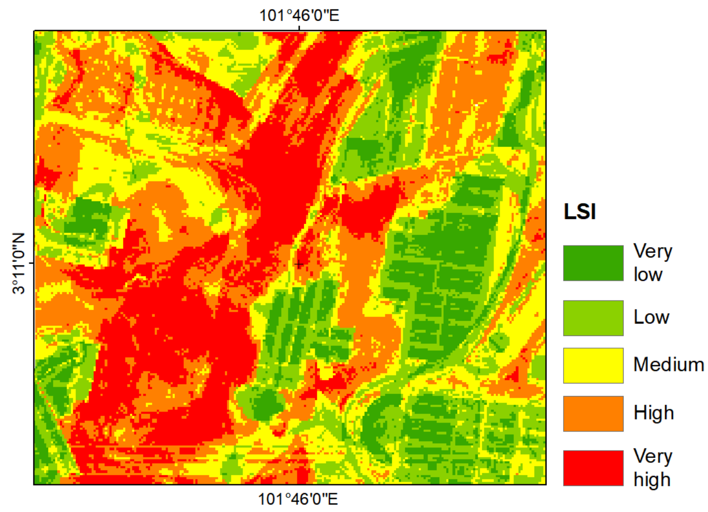

FIGURE 4. LSI map from susceptibility model including all sixteen factors

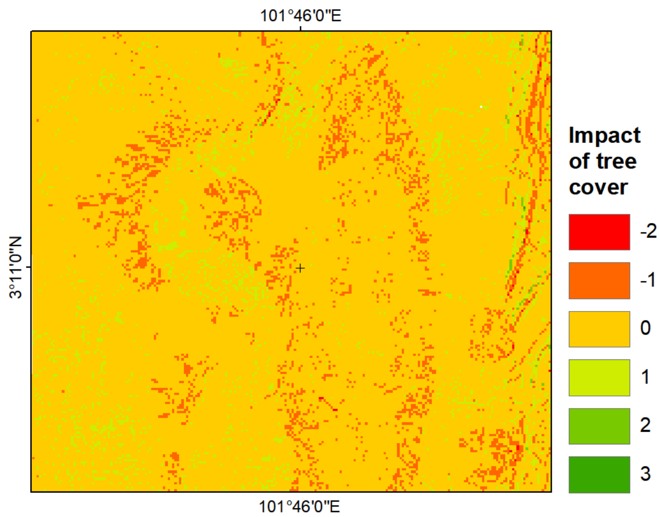

FIGURE 5. Incremental effect of tree cover variable on LSI

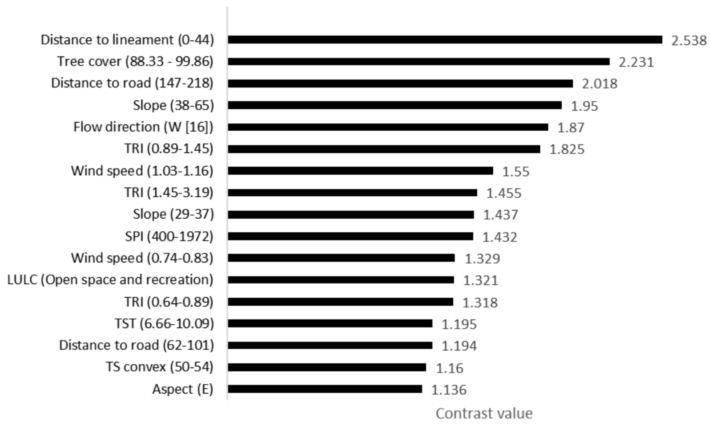

FIGURE 6. Highest weighted landslide factor classes by contrast value

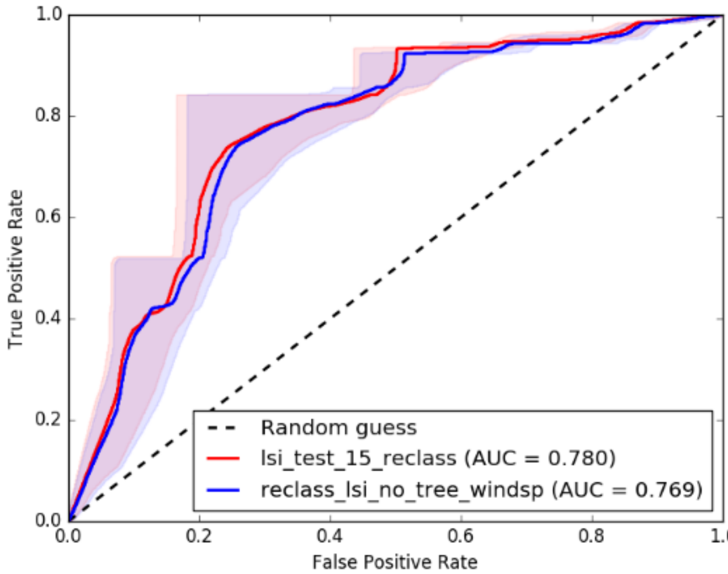

FIGURE 7. Validation result for susceptibility model containing all 16 factors (AUC= 0.78) and susceptibility model with tree cover and wind speed excluded (AUC= 0.769)

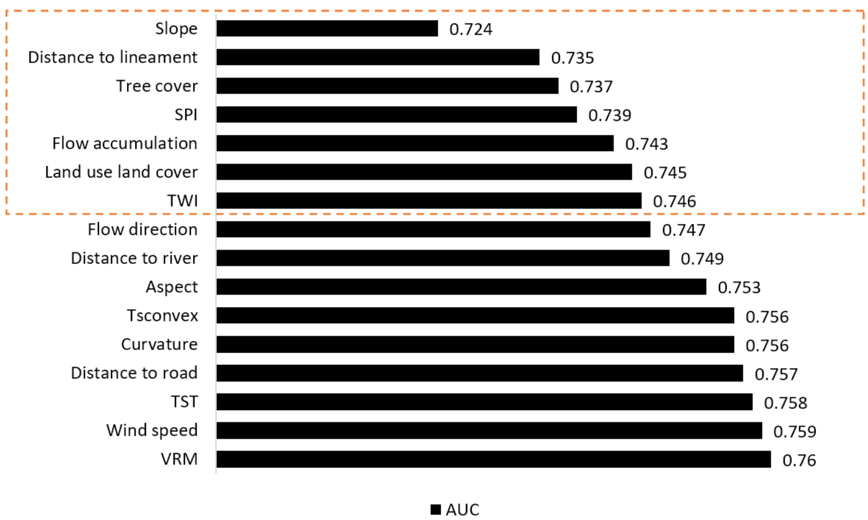

FIGURE 8. relative importance of landslide conditioning factors by contribution to AUC (lower value indicates higher influence on AUC)

The computation of contrast values indicates that areas characterized by steep slopes, proximity to geological lineaments and dense tree cover were more prone to landslide occurrences (Figure 6). The analysis also indicates that tree cover plays a more significant role than wind speed in predicting landslide occurrence. During model validation, the complete set of factors achieved an area under curve (AUC) value of 0.779. The inclusion of tree cover and wind speed yielded a marginal increase in model accuracy (Figure 7).

Subsequent computations of AUC values showed: a) the relative influence of each landslide conditioning factor on the validation result when only one spatial layer is eliminated from the LSI map (Figure 8), and b) the validation result when the lowest-ranked variable is successively removed from the LSI map (Figure 9). The results indicate that the AUC value peaks at 0.825 with a set of factors that include slope, distance to lineament, tree cover, stream power index, flow accumulation, land use land cover and terrain wetness index.

Figure 10 shows a visual comparison of the original (left) and optimized (right) LSI map.

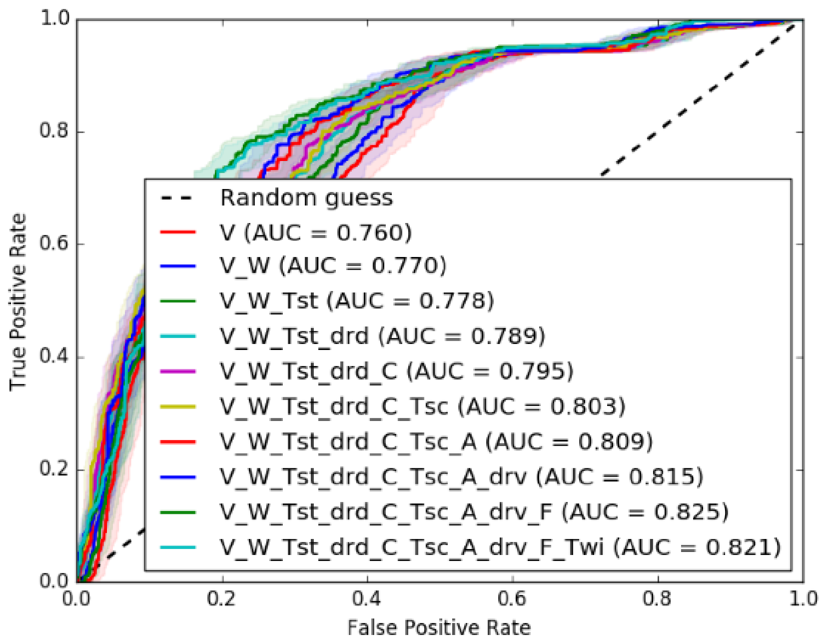

FIGURE 9. Validation results following successive removal of lowest ranked landslide factor

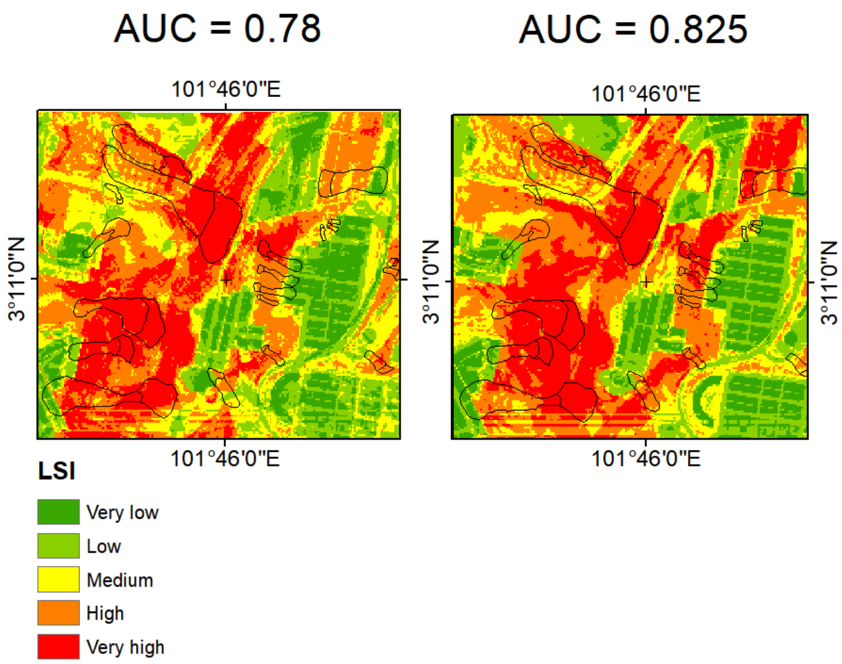

FIGURE 10. Initial LSI (left) and optimized LSI (right) maps

The results reiterate the significance of geological, geomorphologic and hydrologic factors such as slope angle and distance to lineaments in controlling slope stability in the study area. The susceptibility model showed higher accuracy with the inclusion of wind speed and tree cover (Figure 7). More intriguingly, the examination revealed that tree cover exerted a more significant influence on model accuracy than did wind speed (Figure 8). The low wind speed score could be explained by the fact that the input data was based on global scale simulations rather than empirical observations and may not provide an accurate depiction of local conditions. The distance to road layer showed a high correlation with landslide occurrences, although it proved to have a negligible influence on model accuracy, indicating a potential redundancy with other variables. The influence of tree cover on landslide locations and the susceptibility model highlights its importance in driving susceptibility; however, the exact mechanism is yet to be established as the present study uses a data-driven approach.

CONCLUSION

This study aimed to establish the influence of wind speed and tree cover on landslide susceptibility in Bukit Antarabangsa using an inventory of twenty landslide locations and sixteen environmental factors. The study found that while the wind speed variable had a negligible influence on the susceptibility model, tree cover appeared to have a significant influence on landslide initiation and model accuracy. The poor performance of wind speed data could be attributed to the fact that it was based on a global modelled dataset that was downscaled for microscale study. The study however could not establish the exact mechanism by which tree cover regulates slope stability as the analysis relied on a data-driven approach. Future research may investigate integrating soil moisture and other hydrological variables which could shed more light on the correlation between vegetation and slope stability in this area. The study also does not categorize the different types of tree cover which could shed light on the relative influence of various tree species on slope stability. Future investigations could also benefit from an up-to-date, high-resolution tree cover dataset that matches the observation period of other environmental factors in the model.

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DECLARATION OF COMPETING INTEREST

None.

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