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Assessing the Influence of Anthropogenic Causal Factors on Landslide Susceptibility in Bukit Antarabangsa, Selangor

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ABSTRACT

This study sought to assess the influence of causal factors related to anthropogenic activities on landslide occurrence in Bukit Antarabangsa, a township northeast of Kuala Lumpur in Ampang Jaya Municipal Council. Anthropogenic factors were chosen based on the township's rapid growth, numerous landslide records and intensity of hillside development. The study used a data-driven statistical model to identify factors most predictive of landslide occurrence based on an inventory of 20 landslides, and to evaluate the extent to which susceptibility was driven by factors related to urban development. A total of 17 factors were categorized into four clusters (geological, geomorphological, hydro-tographical and anthropogenic). Factor maps were classified to derive factor classes for each parameter. The dataset was then processed using a weight-of-evidence statistical model to determine the contrast value of each factor class. Contrast value (C) reflects the extent to which each factor class predicts landslide occurrence. The C-weighted factor maps were then combined to derive the landslide susceptibility index (LSI). The LSI enabled visualization of the spatial distribution of susceptibility based on a given combination of factors. Susceptibility maps were prepared for combinations containing only non-anthropogenic parameters and all landslide parameters. The study compared these combinations to determine the influence of anthropogenic factors on total LSI. Similar analyses were conducted to determine the effect of each anthropogenic factor on LSI. The results indicated that lineament density, distance to lineament and distance to road had a significant influence on landslide occurrence. A strong correlation with landslide occurrence was observed for land use/land cover, especially in high susceptibility zones, followed closely by the influence of one distance to road factor class. The results could be useful in planning infrastructure corridors in densely built-up landslide-prone areas.

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1. Introduction

Landslides are common in hilly and mountainous parts of Malaysia, and result in major losses of economic and environmental resources, including human fatalities (Akter et al., 2019). Landslide occurrence in Malaysia has been attributed to a number of factors, the most notable among these being design errors due to insufficient site-specific ground investigation (Kazmi et al., 2016). The prevalence of man-made causal factors ties in with Malaysia's rapid urbanization and development of highland and hilly terrain (Nor Diana et al., 2021), and points to a possible trend towards development beyond control of land use. Numerous studies on landslide risk focused on geological, geomorphological, hydro-topographical factors, although the hydrological effect of vegetation on rainfall-induced landslides has been rarely assessed (Gonzalez-Ollauri & Mickovski, 2017). Geographical Information Systems (GIS) are applied to landslide disaster preparedness primarily through geospatial mapping to determine an area's landslide susceptibility, hazard and risk, which enables planning authorities to carry out appropriate zonation for urban development based on landslide risk.

This study focuses on landslide susceptibility, which is typically the first stage of landslide hazard and risk analysis (Dikshit et al., 2020). Landslide susceptibility addresses the question of "where could landslides occur?", and can be seen as an estimation of the spatial probability of landslide occurrence at a given location (Hervás et al., 2007). To date, there have been a number of studies on landslide susceptibility in Peninsular Malaysia, the majority of which have focused on natural (i.e. geological, geomorphological, hydro-topographical) and, to some extent, anthropogenic factors. What remains less clear is the link between slope instability possibly attributed to anthropogenic causal factors related to urban development and landslide occurrence.

In Malaysia, numerous studies have been carried out on landslide mapping and risk zonation; however, few have focused on aspects such as causal factor analysis, sensitivity analysis and socio-economic characterization (Akter et al., 2019). This challenge has been observed despite a growing acknowledgment that landslide occurrence is being driven by natural as well as anthropogenic factors. Land urbanization has been linked to an increased likelihood of landslides, largely due to physical disturbances that result in reduced vegetation cover and cutting of natural slopes (Li et al., 2017). While urbanization on its own does not necessarily increase the likelihood of landslide occurrences, the pressure for more land can lead to building in areas that are susceptible to landslides (Klimeš & Novotný, 2011).

The area of study, Bukit Antarabangsa in Ampang Jaya Municipal Council (MPAJ), is one of the most landslide-prone regions in Malaysia, and recorded six landslide events in the period from 1993 to 2014 (Akter et al., 2019). The consequences of landslide occurrences in this area range from damage of roads and residential property to loss of life (Nor Diana et al., 2021). Bukit Antarabangsa is also a rapidly growing peri-urban area with considerable hillside development. Recent studies of this area have highlighted construction design errors and precipitation as main causal factors of landslide occurrence (Kazmi et al., 2017). However, the rapid urban development of the area, and subsequent increase in surface runoff could play a role in the area's proneness to slope failure (Majid et al., 2020). In Bukit Antarabangsa, improper planning and the continued development of hilly areas have been cited as contributing factors arising from human activity (Shafie et al., 2013). While the geology of the area remains fairly stable, the ongoing urban expansion has led to deforestation, which has in turn exacerbated weathering and erosion (Hassaballa et al., 2014)). The lithology of this area is characterized by extensive weathering which has turned granite into residual soil and fully weathered material that is prone to rapid loss of consistency when highly saturated (Chigira et al., 2011). The area is also typified by undulating topography with presence of streams and rivers, and a high population density (Izumi et al., 2019). Land use ranges from natural forest recreational areas to commercial and residential developments. The ongoing urbanization of this area has been attributed to deforestation which has in turn resulted in weathering and erosion that are a threat to slope stability (Hassaballa et al., 2014).

This research seeks to assess the influence of anthropogenic causal factors on landslide susceptibility in a landslide prone area using a data-driven geospatial method. It seeks to determine whether or not approaches that address housing and infrastructure development can provide a basis for sustainable, low-cost landslide risk reduction in urbanized areas.

2. Methodology

2.1 Description of Study Area

The choice of Bukit Antarabangsa as the area of study is owed largely to its rapid urbanization and prominence as one of the major hot spots of landslide occurrence in Malaysia. The township is situated in Klang Valley, which is an economic powerhouse in the region and as a result continues to experience rapid urban expansion in spite of landslide prevalence. The study covers a 1.15 square kilometer area in the township of Bukit Antarabangsa on the northeastern extent of Ampang Jaya Town Council. This specific area was selected for its high density of landslides. Bukit Antarabangsa is a hillside township located in Ulu Klang District, Selangor State, and is under the jurisdiction of Ampang Jaya Municipal Council. It is centered at geographic coordinates 3°12′00″ north latitude and 101°46′01″ north of Kuala Lumpur (Figure 1).

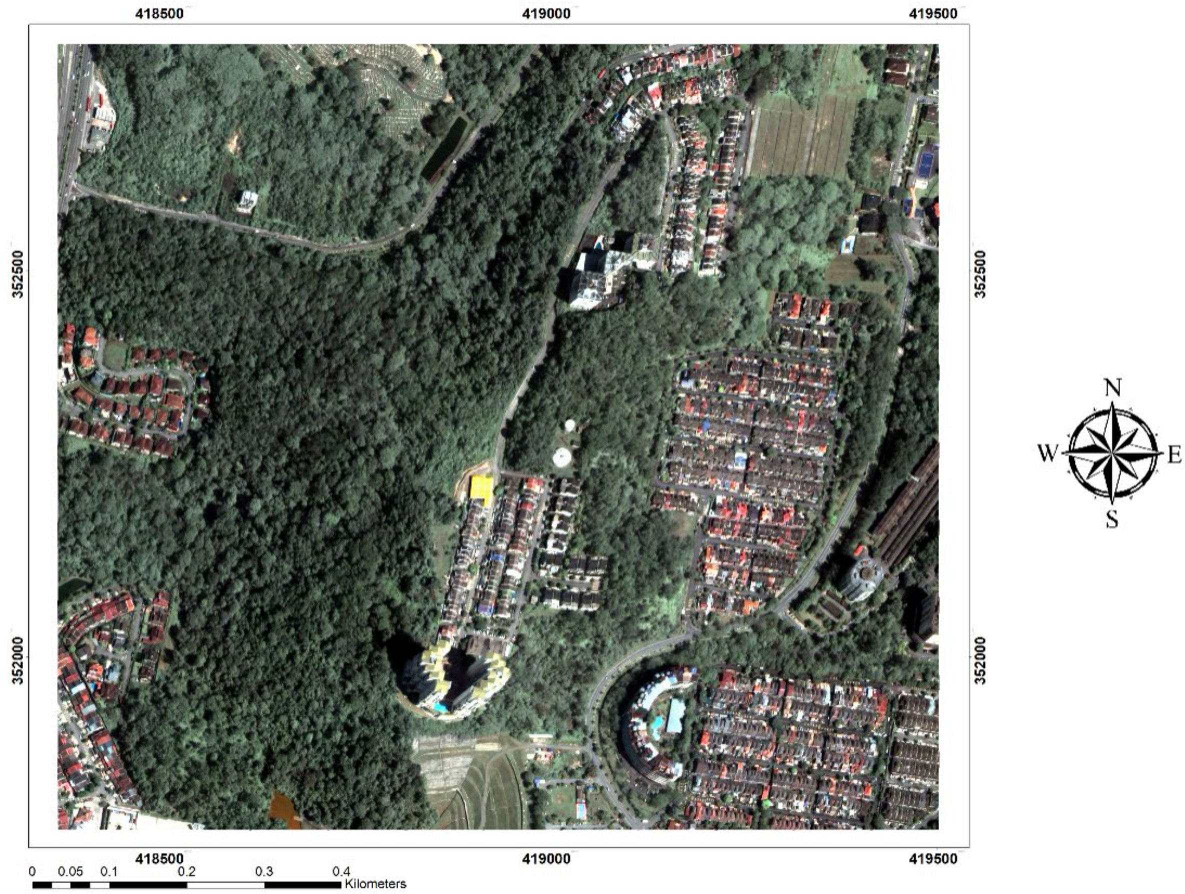


Figure 1 Study area in Bukit Antarabangsa (Ampang Jaya Municipal Council)

The township has witnessed a rapid increase in infrastructure development owing largely to its proximity to Kuala Lumpur (Hassaballa et al., 2014). Bukit Antarabangsa is a well-known landslide prone area and was selected for this reason. Recent significant events include December 1993, May 1999, November 2002 and December 2008. Several investigations conducted in the period following these incidents indicated that the landslide was the result of several factors such as loose soil from earth dumping during construction, a rise in ground water level due to extended rainfall in the months prior to the failure, sustained soil creep that expanded the existing cracks and created new tension cracks as well as heavily leaked active water pipe as a result of soil creep(Ismail et al., 2019). The 1993 landslide was responsible for the collapse of the Highland Tower condominium, which led to 48 fatalities. The occurrence of this landslide was partly attributed to presence of weathered granitic material which is porous, friable and inherits relict planes of weakness from the parent rock (Chigira et al., 2011). The 1999 landslide took place near Athenaeum Tower condominium. It did not result in any fatalities but cut off the access road to Bukit Antarabangsa and left many people trapped inside their homes. The failure was attributed to non-adherence to the minimum factor of safety requirements, inadequate slope drainage, weak material in the slope body, subsurface saturation by rainwater, vegetation removal due to dumping, and internal erosion of fill materials. The geologic setting of the study area is characterized by granitic rock, phyllite and schist, and limestone with minor intercalations of phyllite, with most landslides occurring on granitic rock formations (Lee et al., 2014). With a few exceptions in northern Europe and North America, granitic rocks in particular are known to be prone to weathering and thus are susceptible to landslide occurrence (Chigira et al., 2011).

2.2 Methods

This research was performed in the four major phases, namely selection of causal factors; data gathering and entry; data analysis; and model validation (Figure 2).

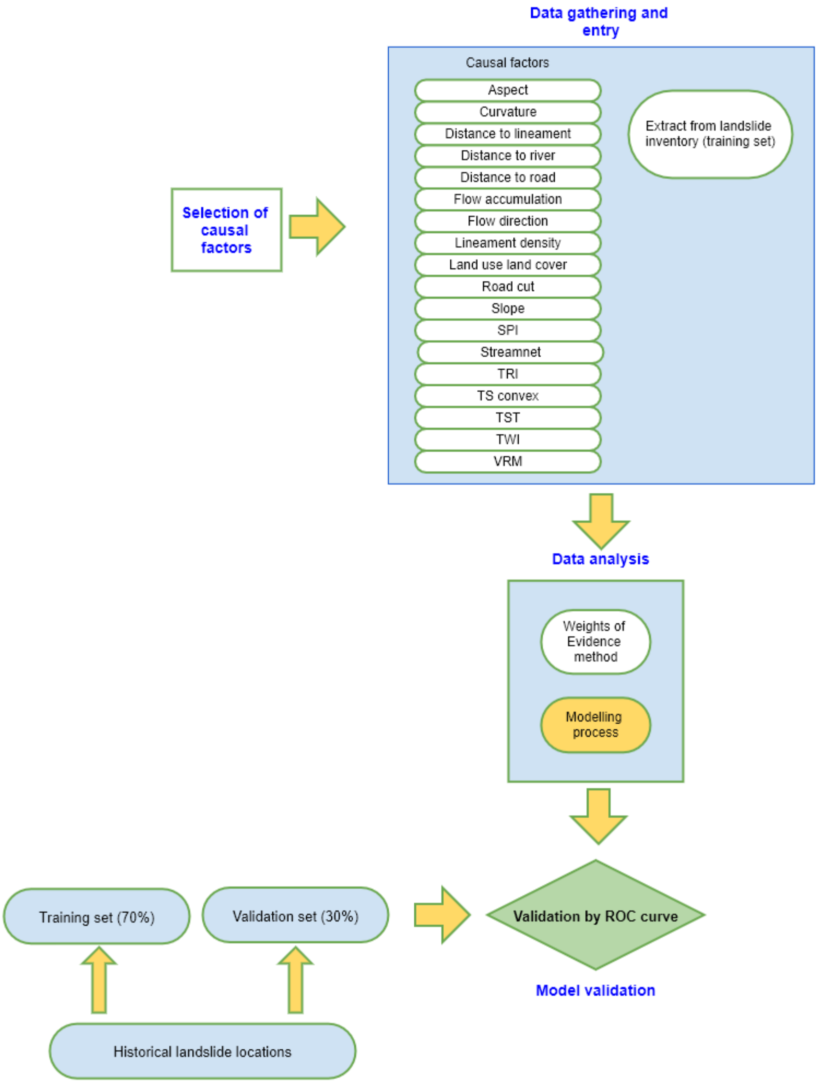


Figure 2 General method for the study

2.2.1 Selection of Causal Factors

The choice of factors was based on the review of guidelines and literature on the landslide mechanism and the causal factors specific to the area (Tian Huat et al., 2012); the selection also considers the availability of data. The study also considered Malaysian guidelines for prevention of slope failure related disasters (Raj, 2003) which highlight "rainfall, topography, drainage and vegetation cover" as four key factors related to the occurrence of slope failures. The landslide mechanism considered in this case is the shallow landslide and debris flows. It is worth noting that among the causal factors considered, only landslide conditioning factors are selected in line with recommendations for landslide susceptibility assessment. The thematic categories for landslide causal factors include geological; geomorphological; hydro-topographical; and anthropogenic factors. A description of these factors is presented in Table 1.

Table 1 Overview of Landslide Causal Factors

Factor group	Causal Factor	Description
Geological	Distance to lineament	The term lineament included faults, fractures and escarpments (Getachew and Meten, 2021). It expresses the surface topography of underlying structural features and denote regions of faulting or fracturing (Sonker et al., 2021). As a general principle, the potential for slope failure increases with a corresponding decrease in the distance to lineaments.
	Lineament density	Lineament density is defined as the quotient of the total length of all recorded lineaments and the area under study (Edet et al., 1998). The lineament density of a given area is indicative of landslide susceptible zones (Sonker et al., 2021). A higher lineament density value typically correlates with a higher landslide susceptibility class.
Geomorphological	Slope	Terrain slope or slope gradient determines the spatial distribution and intensity of landslide occurrences, and is one of the more important factors that influence landslide susceptibility. An increase in the angle of a slope compounds slope instability, leading to an increased tendency for landslide occurrence (Sonker et al., 2021). Additionally, slope gradient 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).
	Aspect	Slope aspect has a considerable effect on slope characteristics such as vegetation cover, retention of moisture 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).
	Curvature	Curvature of a slope has an influence on surface runoff and therefore affects landslide occurrence (Nohani et al., 2019). The factor map for slope curvature is to be derived from a DEM, and classified into classes of negative and positive curvature.
	Stream power index (SPI)	Stream power index is a measure of the erosive power of a stream and is considered a key factor influencing slope stability (Regmi et al., 2014). The SPI value is determined by parameters of viscosity and steepness of terrain (Saadatkhah et al., 2015).
	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 et al., 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 & 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).
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 et al., 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).

Factor group	Causal Factor	Description
	Flow direction	Flow direction displays the direction of flow out for every terrain cell in a digital elevation model, and is considered an important characteristic of mass flow (Fan et al., 2019).
	Stream network	Stream network was subdivided into four categories (Class 1, Class 2, Class 3 and Class 4); however, this parameter was not used in the analytical model as it did not coincide with any landslide locations.
	Topographic wetness index (TWI)	Topographic wetness index reflects the tendency of water to accumulate at any point within a given catchment (a) in relation to the tendency for gravity to move the water downslope (β). It is calculated using the formula: $TWI = \ln\left(\frac{a}{\tan\beta}\right)$ (Regmi et al., 2014).
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 et al., 2003).
	Land use land cover	Land use 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). 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.
	Road cut	Road cuts expose joints and fractures that can make a slope unstable, and are often the sites of human induced instability (Regmi et al., 2014). The road cuts are to be represented as buffers around roads situated on steep slopes.

2.2.2 Data Gathering and Entry

The data gathering and data entry phase included data gathering, database design, and data manipulation. The data were gathered from the sources primarily comprising government agencies in Malaysia. These included the Mineral and Geoscience Department; Ampang Jaya Municipal Council; and the Public Works Department. The datasets with which the geodatabase was constructed included a set of 18 raster map files; landslide inventory shape file; boundary shape file for the study area; and 8 orthophoto raster files. The database was created in ESRI ArcGIS 10.8, initially with sub-folders for manipulated factor maps and landslide inventory-derived polygons. The database was built upon iteratively during subsequent phases to include the outputs of data manipulation such as resampled factor maps and reclassified factor maps.

Following the construction of the study geodatabase, pre-analysis data manipulation was carried out in order to ensure that -all factor maps and layers are projected to the same spatial reference and aligned with the study area boundary, and all input raster layers had the same cell size; all factor maps are reclassified using an appropriate classification method; extraction of training and validation datasets from the landslide inventory is performed. Resampling of factor maps to the 5m by 5m cell size was then carried out using a “bilinear” sampling method for continuous data such as slope, curvature and distance to river while a “nearest neighbor” method was used for categorical data such as land use land cover, aspect and flow direction. For the reclassification of factor maps, continuous data variables were reclassified using the “natural breaks (Jenks)” method, with the exception of highly skewed datasets namely flow accumulation and SPI. The natural breaks method was selected for its ability to minimize variance within groups of data, thus allowing for higher degree of homogeneity within the factor classes (Polykretis et al., 2015). For these exceptions, a “geometric interval” classification method was used in order to enable a more balanced distribution of factor classes across the study area.

The training dataset comprised 70% of landslide polygons in the study area, with 30% of polygons providing the validation dataset (Figure 3). 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.

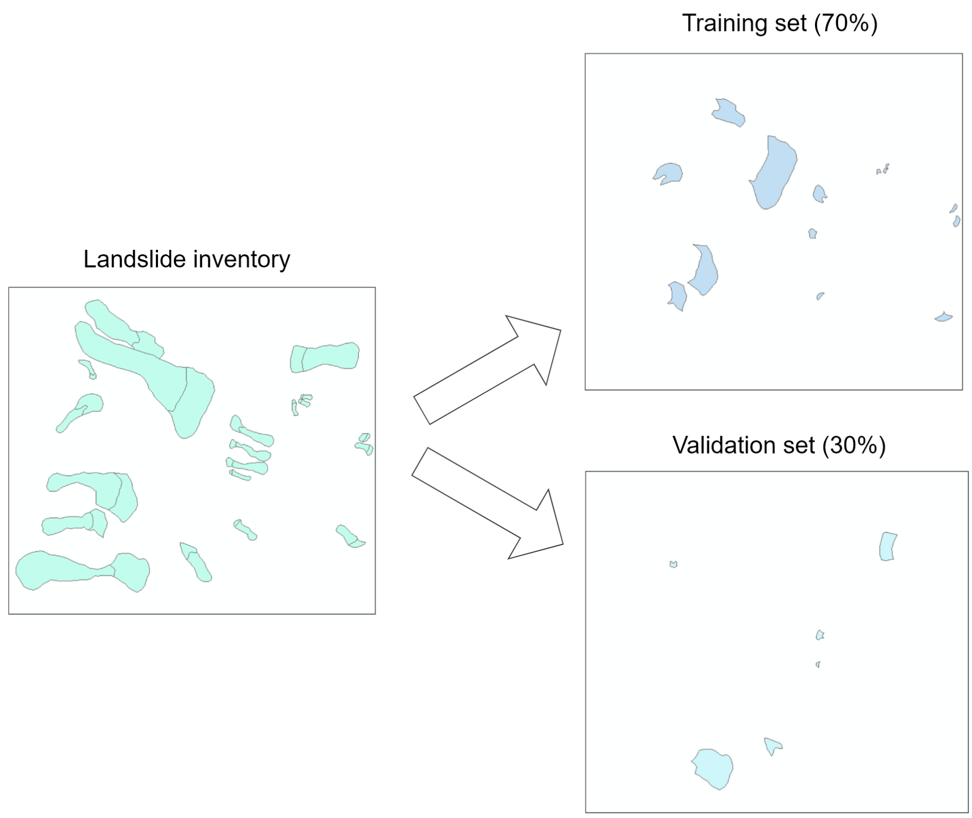
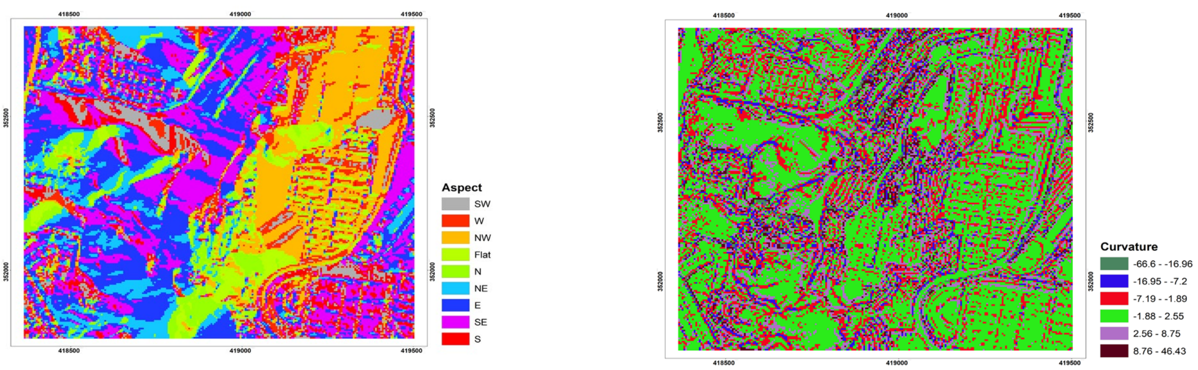
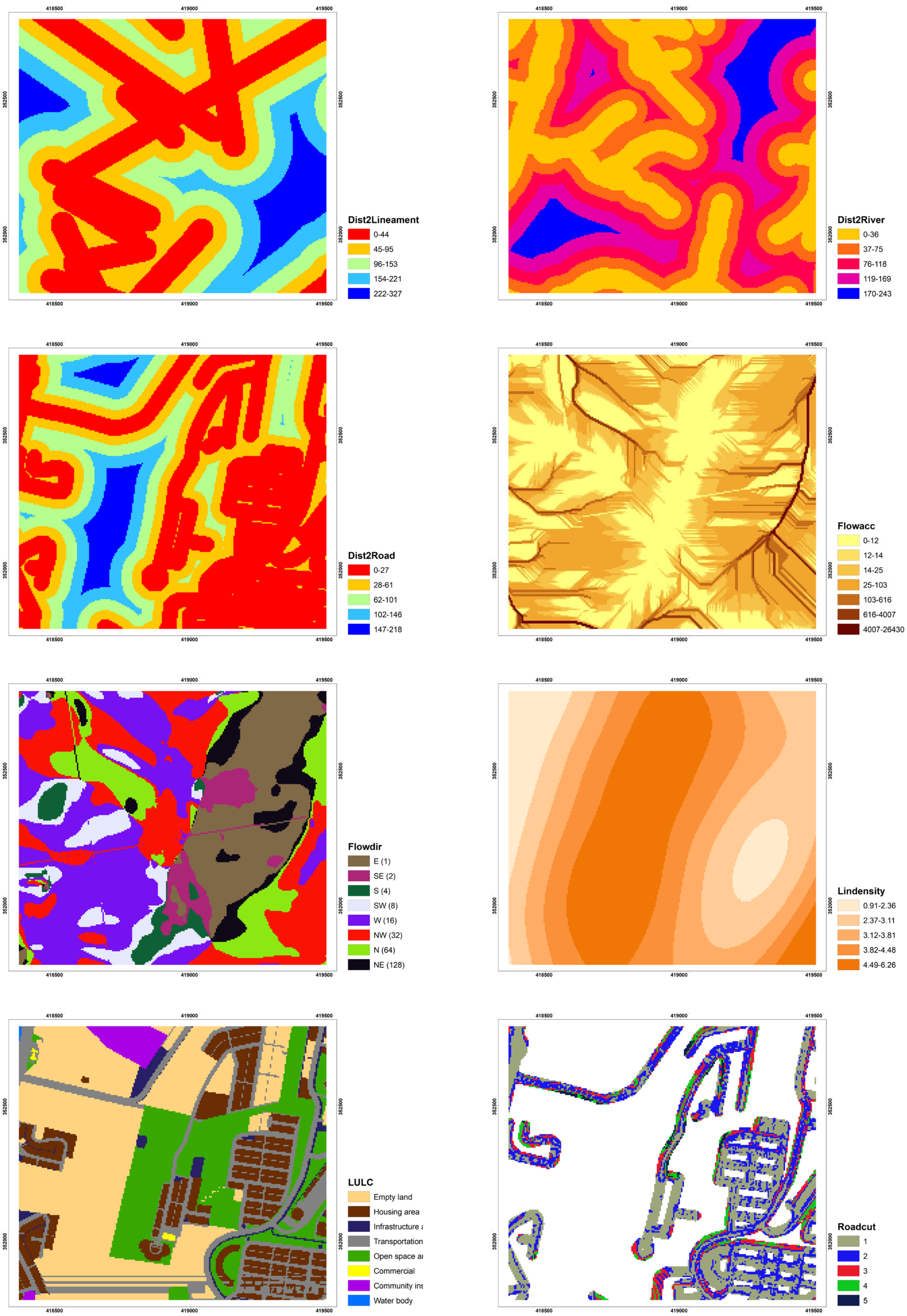


Figure 3 Results of extraction of training and validation sets

2.2.3 Data Analysis

A total of 18 causal factor maps were examined during the data analysis phase. One of these factors was subsequently left out of the analysis due to deficiencies in the data. This was the stream network dataset which was excluded because it did not coincide with any landslide locations in the training set which would have yielded null values. The 17 classified factor maps are presented in Figure 4.




Dist2Lineament
0-44
45-95
96-153
154-221
222-327
Dist2River
0-36
37-75
76-118
119-169
170-243
Dist2Road
0-27
28-61
62-101
102-146
147-218
Flowacc
0-12
12-14
14-25
25-103
103-616
616-4007
4007-26430
Flowdir
E (1)
SE (2)
S (4)
SW (8)
W (16)
NW (32)
N (64)
NE (128)
Lindensity
0.91-2.36
2.37-3.11
3.12-3.81
3.82-4.48
4.49-6.26
LULC
Empty land
Housing area
Infrastructure
Transportation
Open space a
Commercial
Community ins
Water body
Roadcut
1
2
3
4
5

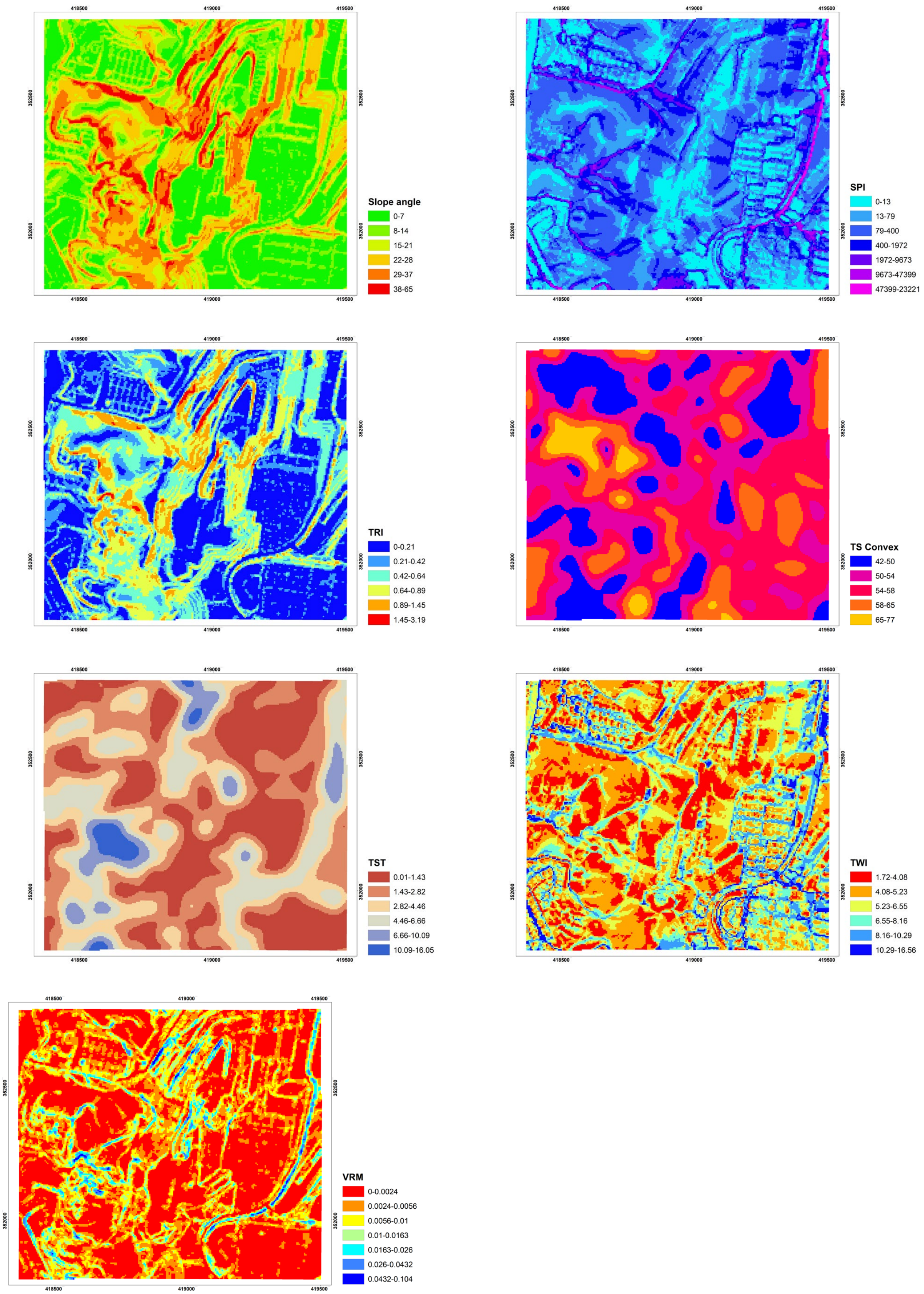


Figure 4 Causal factor maps used for the analysis

The weight of evidence method is based on Bayes theorem and concepts of prior and posterior probability. This approach aims to calculate the importance of each causal factor through a statistical technique, and to determine if a given set of causal factors could result in unstable slopes. It achieves this by assessing the spatial relationship between the areas affected by landslides, the known landslide locations, and the distribution of landslide related factors. The WoE method produces binary maps that aim to predict the presence or absence of the landslide event within each pixel. Each overlay of a given factor map layer and landslide inventory layer generates four possible combinations of landslide conditioning factors shown in Table 2.

Table 2 Possible combinations of a potential landslide conditioning factor. Note: Npix = number of pixels (Van Westen et al., 2003)

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

The study then assigned a weight to each factor class through a calculation of log-likelihood ratios (Equations 1 and 2) (Armas, 2012). The method allocates positive and negative weights to each factor class, for example the 0-7 degree slope class in a classified slope raster. A high positive weight indicates that a given factor class is highly predictive of landslide occurrence, while negative weights are less predictive of landslide concurrence (Getachew & Meten, 2021).

$$W^{+} = \ln\left(\frac{\frac{\text{Npix1}}{\text{Npix1+Npix2}}}{\frac{\text{Npix3}}{\text{Npix3 + Npix4}}}\right) \quad (1)$$

$$W^{-} = \ln\left(\frac{\frac{\text{Npix2}}{\text{Npix1+Npix2}}}{\frac{\text{Npix4}}{\text{Npix3 + Npix4}}}\right) \quad (2)$$

A self-developed tool was used to extract the Npix1 values using a cross-factor operation to determine the number of landslide pixels within each factor class (Figure 5).

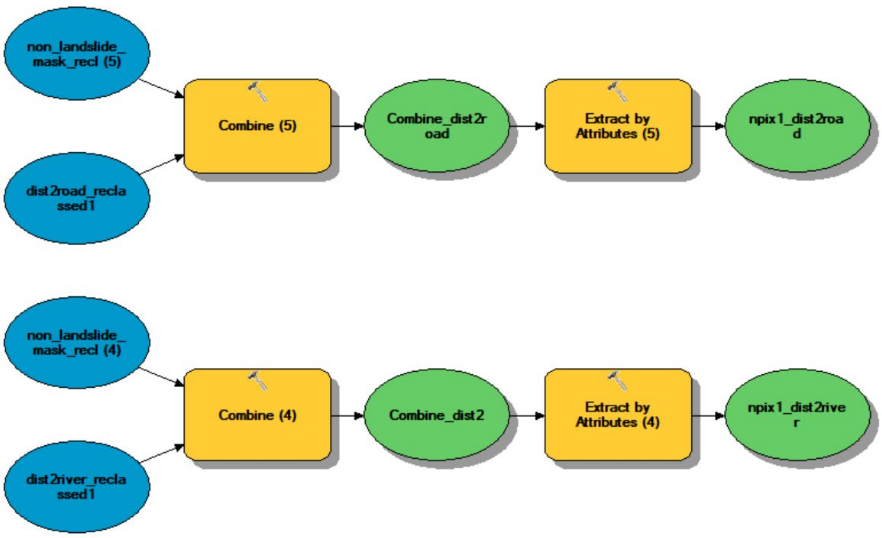


Figure 5 Model Builder tool for extraction of Npix1 grid cells

Once the values of Npix 1 were determined, the remaining values of Npix2, Npix3, and Npix4 were derived using the following formulas:

$$\text{Npix2} = \text{Nslide} - \text{Npix1} \quad (3)$$

$$\text{Npix3} = \text{Nclass} - \text{Npix1} \quad (4)$$

$$\text{Npix4} = \text{Nmap} - \text{Nslide} - \text{Nclass} + \text{Npix1} \quad (5)$$

From here, positive weight (W+) and negative weight (W-) values could be derived using Equations 1 and 2. A raster calculator operation was carried out to apply weight values to each factor class within the factor map layers. With the W+ and W- weighted layers, contrast value (C) layers (W+ - W-) were then derived for each factor map. Finally, all C-weighted maps were added up to generate the LSI map denoted by the equation:

$$\text{LSI} = \sum_{0}^{i} C_j \quad (6)$$

Where LSI is the landslide susceptibility index of the ith pixel and Ci is the contract value of the jth factor (Ilia & Tsangaratos, 2016). In order to create comparable LSI maps to enable assessment of the influence of anthropogenic factors, the final LSI values were categorized into five classes using a natural breaks classification method (Polykretis et al., 2015). The classes were ''Very low'', ''Low'', ''Moderate'', ''High'' and ''Very high''.

Following this classification, a set of LSI maps were prepared for different factor combinations including all 1) available factors; 2) and non-anthropogenic factors. Subsequently, map algebra subtraction operations were performed first to determine the influence of anthropogenic factors on the overall LSI (inclusive of all available factor maps), then through a raster operation, the difference that a single anthropogenic factor made to overall LSI.

A receiver operating characteristics curve was then drawn and the area under curve calculated. The ROC analysis is noted to be a robust method for validation of landslide susceptibility models (Polykretis et al., 2015). The validation was carried out with the remaining 30% of landslide polygons.

3. Results and Discussion

The data analysis performed a weight of evidence calculation, which determined positive and negative weights as well as contrast values for all factor classes. These values were the basis of the evaluation of factor significance. According to Getachew and Meten (2021), positive weight values between 0.1 and 0.5 are considered middle predictive, while values between 0.5 and 1 are deemed moderately predictive. Values between 1 and 2 are considered highly predictive of landslide occurrence. As such, the highest positive weight values were ranked in order to identify the most highly predictive factor classes, which might point to the most significant causal factors. These results are presented in Table 3.

Table 3 Highest ranked factor classes by contrast value

Causal factor	Factor class	W+	W-	C
Lineament density	4.49-6.26	1.152	-1.415	2.567
Distance to lineament	0-44	0.991	-1.547	2.538
Distance to road	147-218	1.741	-0.277	2.018
	62-101	0.892	-0.302	1.194
Road density	12.44-19.01	0.684	-0.515	1.199
	19.01-28.47	0.7152	-0.3571	1.072
Slope	38-65	1.752	-0.198	1.950
	29-37	1.096	-0.341	1.437
TRI	0.89-1.45	1.566	-0.259	1.825
	1.45-3.19	1.437	-0.018	1.455
	0.64-0.89	0.953	-0.365	1.318
Flow direction	W (16)	0.995	-0.875	1.870
Land use/land cover	Open space and recreation	0.895	-0.426	1.321
TST	6.66-10.09	1.091	-0.104	1.195
Aspect	East	0.790	-0.346	1.136

The results indicate strong positive correlations (W+) in factor classes for distance to road, lineament density, slope, TRI, and TST factors. Moderate to highly predictive anthropogenic factor classes included LULC classes (infrastructure and utilities and open space and recreation); distance to road (147-218m); road density; and distance to multi-storey buildings (81-157m).
Medium to moderately predictive classes for non-anthropogenic factors included the east, northeast and southeast-facing slope classes for aspect; negative (-66.6 - -16.96 and -16.95 - -7.2) and positive (8.76 - 46.43) curvature classes (0.6843- 0.7092); 0m-44m distance to lineament (0.9906); 37m-75m distance to river (0.5757); flow accumulation (12-14 and 14-25); (SW) flow direction (0.9946); 50-54 TS convex (0.6704); 1.72-4.08 TWI (0.5278); and four of six VRM classes (0.4332-0.9719).
Highly predictive classes for non-anthropogenic factors included highest (4.49-6.26) lineament density (1.1517); highest (29°-37°, 38°-65°) slope classes (1.0956 and 1.7522); 400-1972 SPI (1.1032); highest TRI values (1.5663 and 1.4372); 6.66-10.09 terrain surface texture (1.0914).

3.1 Output for All Causal Factors

The main output of the model was a set of susceptibility maps representing different factor combinations from which the influence of anthropogenic factors may be assessed. The main outputs included 1) a susceptibility map classified from the LSI of all landslide causal factors (Figure 6); and 2) a susceptibility map classified from the LSI of non-anthropogenic factors (Figure 7). The results indicate that overall, susceptibility within the study area is high and the highest susceptibility class correlates significantly with the high lineament density and TRI.

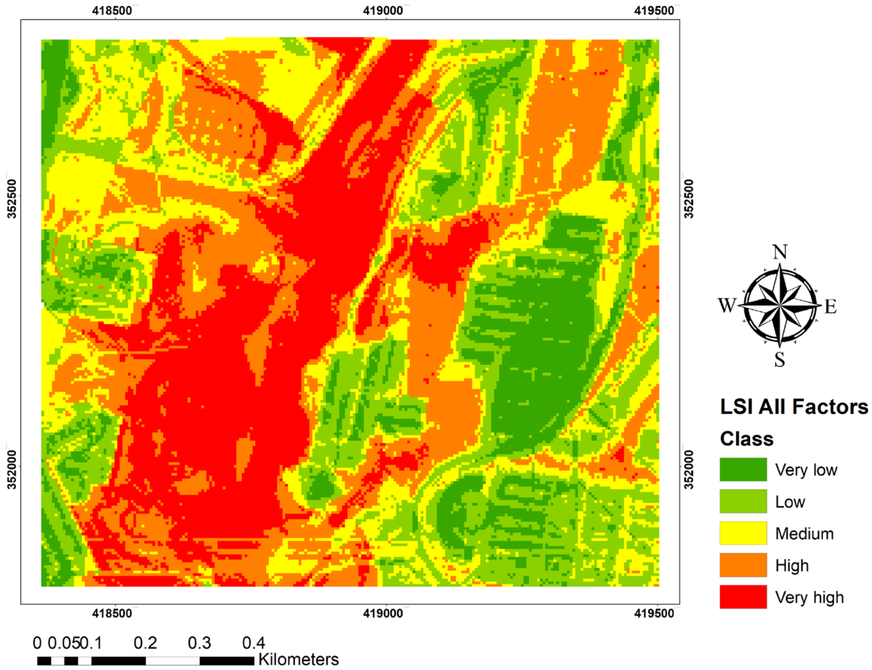


Figure 6 Susceptibility map derived from LSI of all landslide causal factors

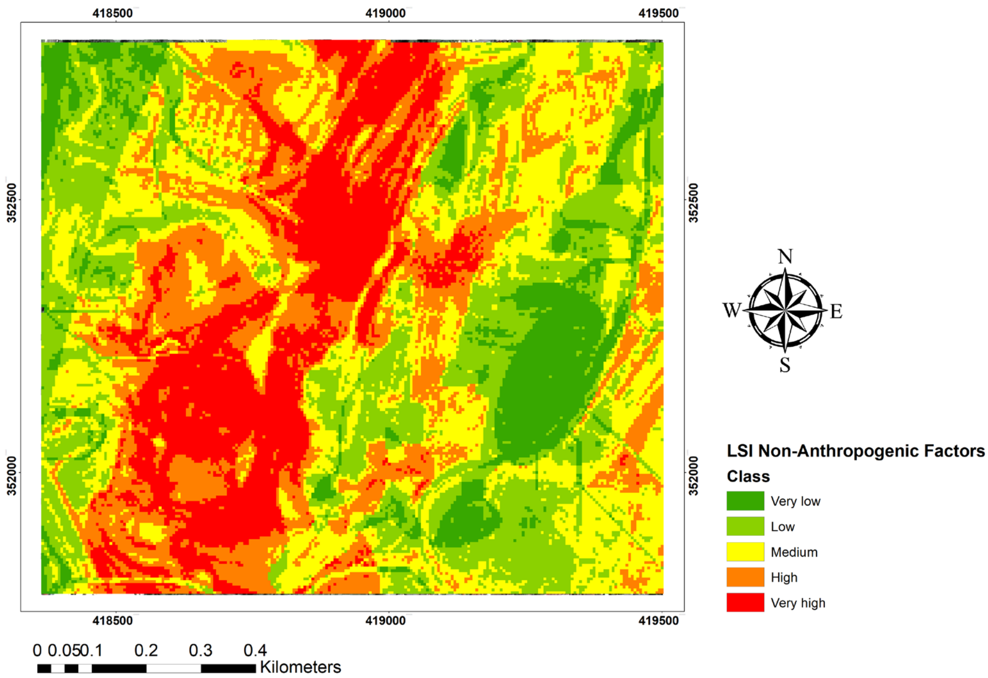


Figure 7 Susceptibility map derived from LSI of non-anthropogenic landslide causal factors

3.2 Influence of Anthropogenic Factors

A separate raster layer was processed to help visualize the incremental change in susceptibility when anthropogenic factors are added to the non-anthropogenic dataset. The results show the areas where anthropogenic factors had the highest influence on susceptibility (Figure 8). These areas were situated in the "High" to "Medium" susceptibility classes in the eastern and western peripheries of the study area, but were outside the "Very high" susceptibility class in the central to southwestern zone. Overall, the difference in susceptibility class value for any given pixel ranges from -2 to 2. The zones with "High" to "Medium" susceptibility lie closer to residential developments on the eastern and western peripheries of the study area. It was observed that while the addition of anthropogenic factors did not affect "Very high" susceptibility areas, it did alter considerably the extent of the "High" susceptibility areas. However, the most significant increases in LSI were noted to occur within areas that overlay with the highest weighted LULC and distance to road classes indicating further that these were the most important anthropogenic factors in the overall dataset.

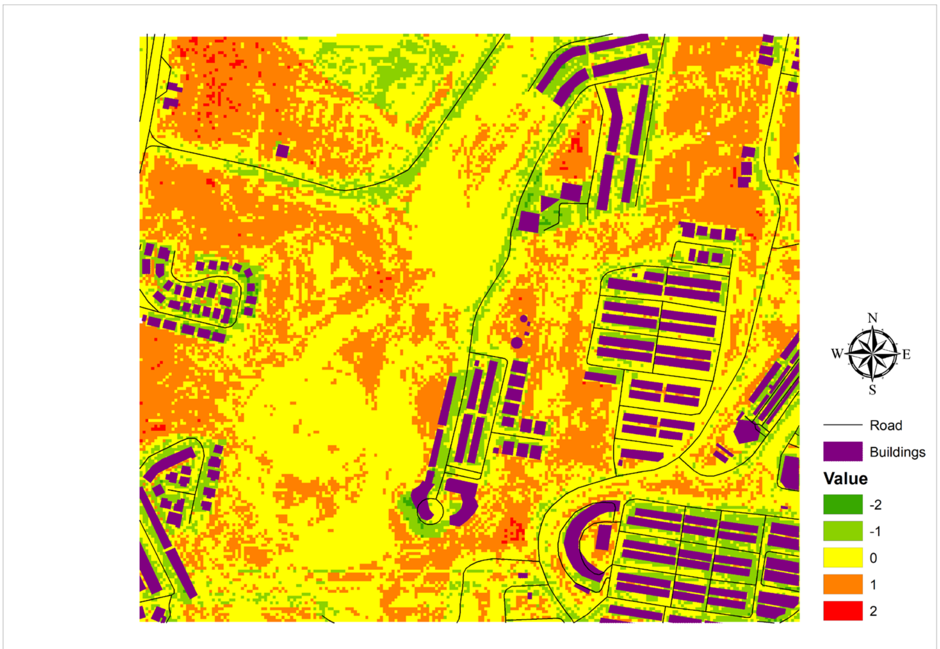


Figure 8 Illustrating the incremental change in LSI when anthropogenic factor layers are added to the dataset

3.3 Influence of a Single Anthropogenic Factor

In this step, a subtraction was carried out to determine the susceptibility values for a single anthropogenic factor, which is distance to road. This was intended to highlight the incremental effect that a single anthropogenic factor can have on susceptibility. The results of this analysis are presented in Figure 9. They indicate that the addition of distance to road to total LSI had a marginal effect across the study area with susceptibility values increasing or lowering by only one class. The spatial extent of these shifts in susceptibility class was also small relative to other anthropogenic causal factors. In relation to the highest weighted causal factors, the values indicate a close spatial association with distance to road, TRI and distance to lineament causal factors.

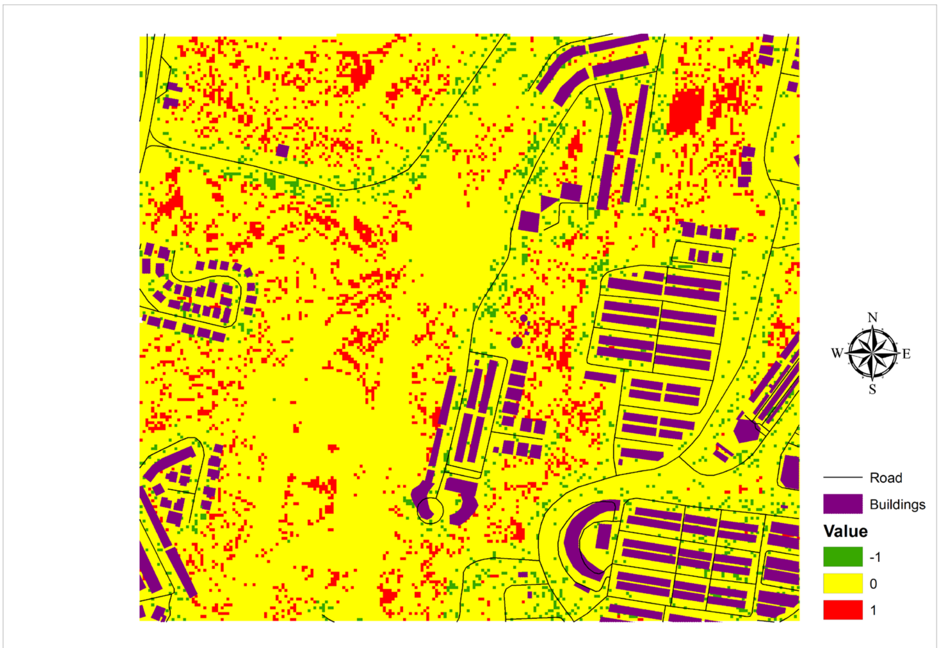


Figure 9 Incremental change in susceptibility class following addition of the distance to road layer

A similar function was executed for land use land cover. Both distance to road and land use land cover registered a change in susceptibility value ranging from -1 to 1. In the case of land use land cover, a similar pattern was observed wherein increase in susceptibility class due to addition of the single factor occurred in the "Medium" and "High" susceptibility classes. These zones were also located closer to residential developments (Figure 10). In relation to the highest observed factor classes, these areas showed a spatial association with LULC and distance to lineament layers.

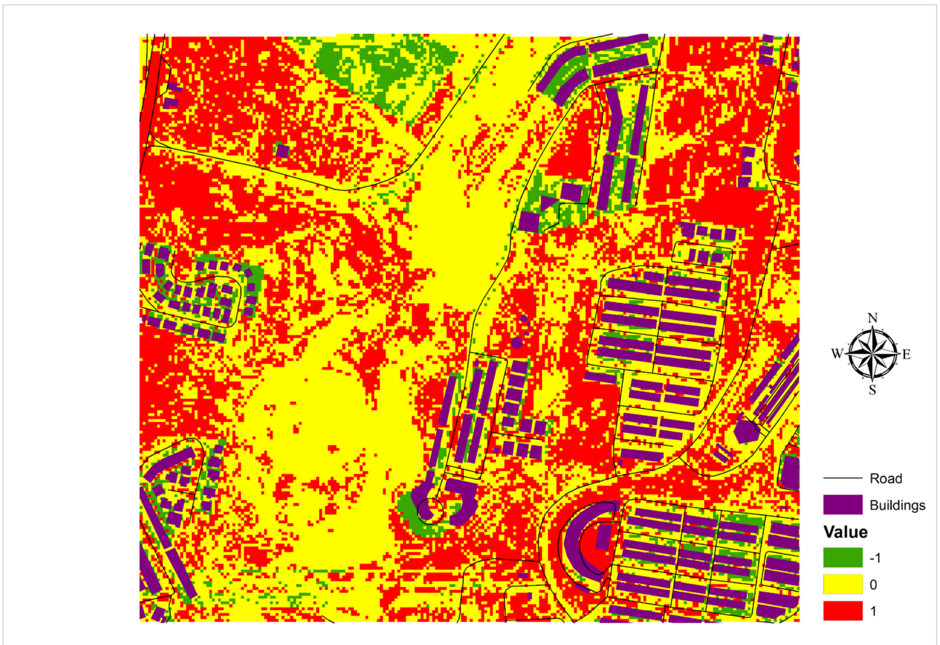


Figure 10 Incremental change in susceptibility class due to addition of land use land cover

The road cut layer registered similar results in terms of the range of susceptibility class differences, although the extent of the changes, specifically "High" and "Medium" susceptibility areas was noticeably larger than distance to road but smaller than LULC (Figure 11). The incremental effect for the road cut layer showed a close spatial association with highest weighted classes for distance to road and distance to lineament as well as LULC. These results appear to confirm the importance of land use as a significant factor in the morphology of slopes (Armas, 2012

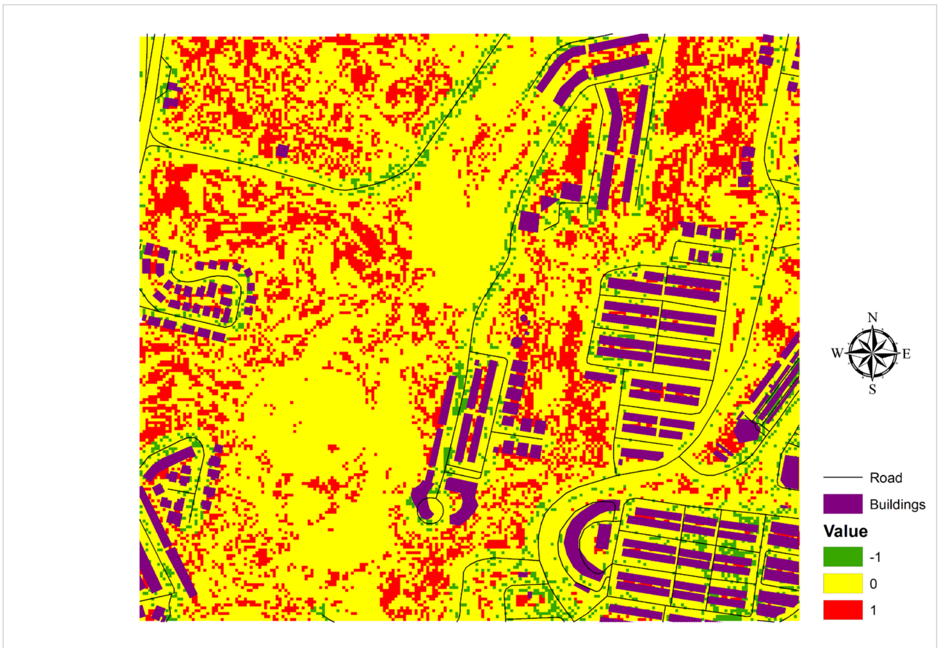


Figure 11 Incremental change in susceptibility class due to addition of road cut

3.4 *Validation of the Susceptibility Model*

The results indicated an AUC of 78.57% for all causal factors and 78.67% for non-anthropogenic factors, which was considered a good accuracy level (El Khouli et al., 2009) (Figure 12). The anthropogenic factors however, yielded an AUC of 57% which was a low level of accuracy by comparison.

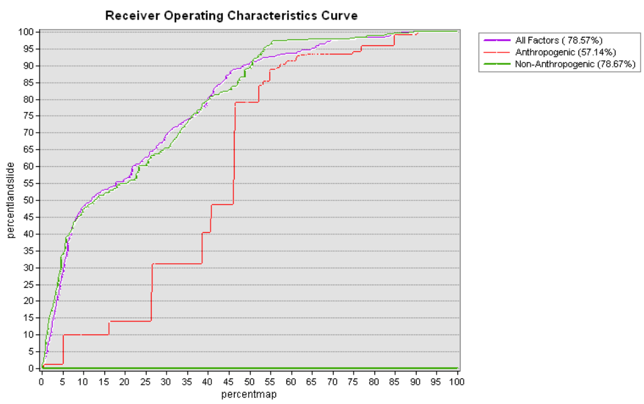


Figure 12 ROC curve for all landslide causal factors, anthropogenic factors and non-anthropogenic factors

4. Conclusion and Recommendations

The results indicate that while anthropogenic factors contribute considerably to landslide susceptibility, their influence on the cumulative LSI value is comparably less prominent than that of non-anthropogenic factors, specifically geological and geomorphological factors. Additionally, among anthropogenic causal factors, land use/land cover and distance to road have the biggest influence in landslide susceptibility. Specifically, zones in the open space and recreational area factor class show a strong spatial association with steeper slope classes (29°-65°) and higher TRI values. This might indicate that areas inherently prone to slope failure due to higher slope angles are also less built-up. These forested slopes constitute the zones of highest susceptibility ("High" and "Very high") in the LSI map. A possible reason for high susceptibility within these zones - as put forward in a study by Hassaballa et al. (2014) - is that areas covered by forest carry more moisture, and thus are more prone to soil saturation. Conversely, impervious surfaces that characterise built-up areas show low soil moisture content. Distance to road classes 62m-101m and 147m-218m were also noted to have a strong correlation with landslide locations. The analysis also found that although distance to road factor classes had the highest contrast value among the anthropogenic factors, the incremental effect of land use land cover on LSI was more widespread across the study area, and followed respectively by road cut and distance to road. The results indicate further that anthropogenic factors have a relatively lesser influence on the "Very High" susceptibility classes (undeveloped forested slopes that constitute 17.75% of the study area) but are more influential in the built-up areas. The anthropogenic factors had a significant effect on the spatial extent of areas in the "High" susceptibility class (22.1% of the study area). The most significant increases in LSI were noted to occur within areas that overlay with the highest weighted land use/land cover and distance to road classes indicating further that these were the most important anthropogenic factors in the overall dataset. An examination of the influence of each anthropogenic factor showed that land use/land cover had the largest incremental effect on landslide susceptibility across the study area, thus underpinning its significance in the morphology of slopes (Armas, 2012).

The limitations of the research relate primarily to the constraints of the model, and the number of anthropogenic factors used for the study. The limitations of the model are that first, it considers only the spatial distribution of landslide occurrence, thereby omitting information about the historicity of terrain units in relation to multiple landslide events (Corominas et al., 2013). Studies on the spatial-temporal distribution of landslides are one way to remedy this issue, and have been highlighted as a knowledge gap and opportunity for new research (Akter et al., 2019). Owing to constraints in the availability of data, this study excluded an in-depth look into other environmental factors such as vegetation and soil characteristics, which also bear significantly on slope stability. Specifically, vegetation cover has a strong influence on soil moisture, saturation and ultimately ground water level, all of which have an impact on slope stability, and are particularly relevant in the context of a rapidly developing urban landscape. Similarly, lithological characteristics were left out of the analysis due to the lack of spatial variance within the study area (only one lithological unit). This, however, limited the consideration of weathering and associated processes as a conditioning factor of landslide occurrence.

The study sheds light on the influence of anthropogenic landslide conditioning factors at larger scales within densely populated hillside settlements. It indicates that while the overall influence of human-related factors is peripheral in comparison to geological and geomorphological factors, the effect of infrastructure, particularly roads, is significant. Additionally, the study further highlights the significance of infrastructure development activities particularly road development on slope stability, and reinforces the principle that any activities or processes affecting the natural morphology of slopes will increase an area's proneness to landsliding. The study also indicates that anthropogenic factors could indirectly affect landslide susceptibility in the neighborhood of built-up urban spaces. It indicates that where impervious surfaces in built-up areas surround steep forested slopes, increases in soil moisture from the accumulation of runoff could increase landslide susceptibility on such slopes. Anthropogenic causal factors are also observed to have a more extensive effect on landslide susceptibility in built up areas, particularly land use land cover.

This study recommends that future research conducts a more in-depth analysis of anthropogenic factors, with a specific emphasis on non-conventional factors, for example building characteristics such as building type. Similarly, conventional factors such as roads may be expanded upon to include a classification of roads by attributes like pavement type, width and drainage among others.
Subsequent studies may also investigate the influence of these and other anthropogenic factors using a spatial-temporal approach in order to investigate links between the temporal distribution of landslide incidents and anthropogenic pressures. On the other hand, the spatial approach may be enhanced by a consideration of landslide activity attributes, which is to say, a similar spatial approach may divide the landslide inventory data into several input datasets categorized as dormant, active or potentially reactivated landslides. Further works should also consider different susceptibility scenarios based on landslide type, as these are driven by a unique set of causal factors (Van Westen et al., 2003).

The present study is important in the context of infrastructural development in the Kuala Lumpur peri-urban areas as it highlights the importance of road corridors and their influence on slope stability within landslide-prone regions. It also emphasizes the need for better approaches to protect steep, potentially unstable slopes from surface runoff.

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