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Spatial Pattern Analysis on Landslide Incidents in Kuala Lumpur, Malaysia

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ABSTRACT

Landslide occurrences increase alongside the urbanization rate in developing countries. Hence, the need to visualize the distribution pattern of increases is essential for the management of landslide cases, especially in Malaysia. Thus, a landslide monitoring system is proposed for landslide risk areas using computer-generated modelling to perform spatial distribution patterns, which is important for management and control. The purpose of this study is to evaluate the pattern of distribution and determine whether it is clustered or dispersed. A total of 145 landslide incidents were distributed in Kuala Lumpur. This paper will be focusing on one of the spatial pattern analyses, which is the spatial mean centre of the landslide incidents. It is found that the distribution pattern for landslide events is clustered. Meanwhile, the z-score is -4.091522 and there is a less than 1% likelihood. The nearest neighbor ratio is 0.82. Further studies to identify factors that contribute to landslide incidents in the urban Kuala Lumpur are required for landslides mitigation in the future.

Keywords: *Distribution, Landslides, Kuala Lumpur, Pattern analysis, Spatial mean centre*

Introduction

Landslide is one of the natural geohazards that occurs around the world and has caused enormous fatalities, injuries, and property loss (Oh *et al*., 2011; Petley, 2012; Mahmud *et al.,* 2013). More than 8,935 locations of landslide incidents were recorded worldwide in the past 10 years since 2010 where approximately 1,120 landslides happened in Southeast Asia until the year 2019 (NASA, 2020). One of the growing countries in SEA, Malaysia also went through landslide incidents over the past decades. There has been a dramatic increase in cases of landslides reported in Malaysia with a cumulative of 142 landslide incidents from the year 2010 until 2016 (USGS, 2021).

Having a tropical climate with constant hot and humid conditions all year round and an average rainfall above 2,000 mm annually, Malaysia has a high likelihood of soil movement. However, Malaysia experienced heavy rainfall during the northeast monsoon seasons from December to March compared to the southwest monsoon in April to November increasing the likelihood of mass movement (Saadatkhah *et al.,* 2014; Abd Majid and Rainis, 2019; Ab Rahman *et al*., 2020).

As one of the developing countries, landslide incidents in Malaysia are also triggered by anthropogenic factors such as land-use changes, quarries, road construction, traffic vibrations, and urbanization (Kyriou *et al.,* 2021). The urbanization process is often contributed to the rising trend of landslides in Malaysia. This geohazard is usually found in the form of slope failures on artificial slopes engineered by humans, especially slopes that involved reclamation activities in urban areas along highways and housing (Mahmud *et al*., 2013; Saadatkhah *et al*., 2014; Ab Rahman *et al.,* 2020; Nhu *et al.*, 2020; Abd Majid *et al*., 2018). Therefore, Selangor State has experienced the most landslides since the 1970s, as it is the most populated district in Malaysia, followed by the major city centre in this country, Federal Territory of Kuala Lumpur, as well as other fast-growing states such as Pahang, Penang, and Sabah (Sulaiman *et al*., 2019; Department of Statistic Malaysia, 2010).

Advance computing performance and the development of accessible geographical information system (GIS) platforms nowadays have further contributed to the extensive use of such reliable landslide forecasting targeted to the regional scale (Song *et al.,* 2020). There have been many studies on landslide hazard evaluation through GIS by using various analysis techniques. GIS provides information and tools to analyse the material behavior of the slope, estimate landslides risk, and to monitoring and mitigate the assessment of this geohazard (Simon *et al.,* 2017; Psomiadis *et al*., 2020).

Materials and Methods

Study Area

The Federal Territory of Kuala Lumpur is located in Klang Valley, which covers approximately 243.6 sq km surrounded by the Selangor State (Figure 1). The temperature in Kuala Lumpur is fairly constant at

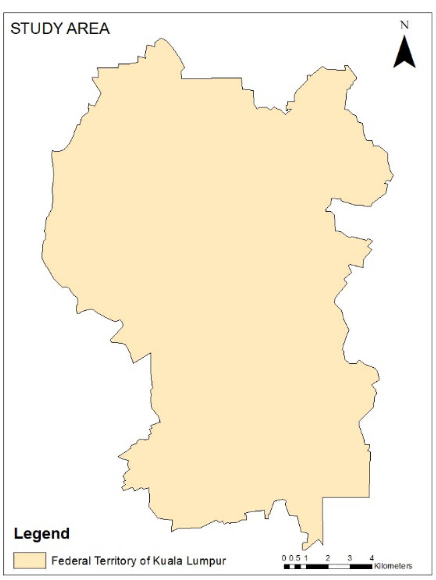

Fig. 1. Study's POI

22-33 °C throughout the year and the average annual precipitation is around 2,800mm (DID, 2020). With a population of 1.7 million as of 2015 and average population growth of 2% per year, rapid development in this capital city of Malaysia increases housing and infrastructures demand. This situation leads to land scarcity that urged the developers to take place at risky slopes within Kuala Lumpur. This development interrupted the stability of the high slope, disrupt the drainage flow, and vegetation unearthed, leaving the community with landslide risk (Mahmud *et al*., 2013).

Average Nearest Neighbor (ANN)

According to theory, if the index (nearest neighbor ratio) is less than 1, the pattern displayed is clustered. Meanwhile, if the index is bigger than 1, the trend direction is toward the dispersed distribution (Environmental Systems Research Institute, 2020). Spatial distribution pattern mapping was conducted by pattern analysis using average nearest neighbor (ANN) analysis that measures the average distance from each point in the study area to its nearest point. The average distance is compared to the expected average distance. In doing so, an ANN ratio is created, which, in simple terms, is the ratio of observed/expected. If the ratio is less than 1, we can say that the data exhibits a clustered pattern, whereas a value greater than 1 indicates a dispersed pattern in our data (Choy *et al.*, 2011).

Statistical Analysis

Statistical analysis is used to identify and confirm spatial patterns, such as the centre of a group of features, the directional trend, and whether features form clusters. Statistical functions analyse the underlying data and measures that can be used to confirm the existence and strength of the pattern (Choy *et al.,* 2011). Thus, the statistical analyse in this study will help to provide answers for linking the distribution pattern of landslide incidents with its possible factors mapping of landslide events distribution trend identifies relationship with specific physical characteristics.

The spatial mean centre is the main pattern analysis used in this study to analyse the average coordinates x and y of all features in the study area. It is useful to detect any changes in distribution or to compare features of distribution. This analysis shows leaning centred phenomena, especially, to visualize the mean of landslide incidents reported in the study area. If the mean of *x* and *y* show the value of the mean centre, it means that the dimensional field was included as the product of features.

Mean centreis calculated as below:

$$\bar{X} = \frac{\sum_{i=1}^{n} x_i}{n} \quad .. (1)$$

$$\bar{Y} = \frac{\sum_{i=1}^{n} y_i}{n} \quad .. (2)$$

where *xi* and *yi* are coordinates for *i,* and n is the total number of the features.
where x_i and y_i are coordinates for *i*, and *n* is the total number of the features.
The weighted mean is as below:

$$\bar{X}w = \frac{\sum_{i=1}^{n} W_i x_i}{\sum_{i=1}^{n} W_i} \quad .. (3)$$

$$\bar{Y}w = \frac{\sum_{i=1}^{n} W_i y_i}{\sum_{i=1}^{n} W_i} \quad .. (4)$$

where wi is the weigh on characteristic i.

Method to calculate center for three dimensions is the z attribute for every feature:

$$\bar{Z} = \frac{\sum_{i}^{n} = Zi}{n} \quad .. (5)$$

$$\bar{Z}w = \frac{\sum_{i=1}^{n} W_i z_i}{\sum_{i=1}^{n} W_i} \quad .. (6)$$

Results and Discussion

From this study, it is found that a total of 145 landslide incidents were distributed in Kuala Lumpur. Spatial mean centre analysis to observe where incidents are to be centred. All of the x and y features fitted as an average in the study area. It is often utilized to distinguish distribution changes or to relate feature distribution kinds. A new point feature class was created as the mean centre point to represent the mean centre of every feature. The mean of X and Y stand for the value of centre, events, and dimension field mean included as the outcome of features. Figure 2 shows the location of landslide incidents with its mean centre. The spatial mean centre is located in the middle of this study site. The mean centre for all landslides in Kuala Lumpur is located at x-coordinate 101.692018 and y-coordinate 3.135268.

Spatial statistical distribution and pattern analysis play important roles to figure the distribution of landslide incidents geographically in the study area as the distribution and spatial pattern are derived from certain techniques. Pattern distribution analysis was conducted to enhance the finding results, and it was found that the clustered pattern is dominant in this study area with an average nearest neighbor ratio of less than 1. This shows that there is a factor affecting the frequency of landslides reported in Kuala Lumpur. Above all, this study also shows that spatial modeling should take into account landslide trigger factor analysis for further studies. It is observed by many research that landslide incidents in Kuala Lumpur are triggered by different factors such as prolonged rainfall, construction, geology profile, and elevation (Sulaiman *et al.,* 2019). Future urbanization, social and environmental vulnerabilities have contributed to the risk of future landslide risk. If unprecedented population growth and rapid urbanization continue as projected, there will be gradual increases in the severity, frequency, geographical distribution, and magnitude of landslide incidents in the future.

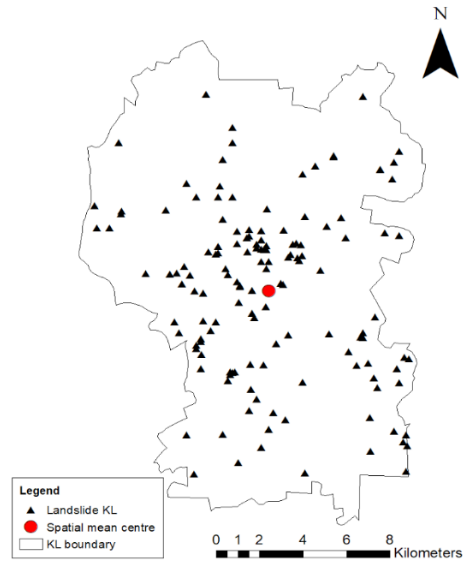

Fig. 2. The spatial mean center of landslide incidents in Kuala Lumpur.

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Conflict of Interest

The authors declare no conflict of interest

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