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Landslide Pattern Analysis in Penang Island using Average Nearest Neighbor (ANN) approach in Quantum GIS (QGIS)

Tharshini Murthy[1], Izham Mohamad Yusoff[1,2], Ismail Ahmad Abir[3], Siti Hamsah Samsudin[1]

[1]Geography Section, School of Distance Education, Universiti Sains Malaysia
[2]Transdisciplinary Research on Environmental Science, Occupational Safety and Health (TREES@USM) Section, School of Distance Education, Universiti Sains Malaysia
[3]Geophysics Section, School of Physics, Universiti Sains Malaysia

Correspondence: Izham Mohamad Yusoff (email: izham@usm.my)

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Abstract

Landslides, characterized by the sudden and often rapid movement of rock, soil, debris, or a combination of these materials down a slope or inclined surface, present a considerable danger to humans, animals and the environment. Their potential to cause widespread destruction and loss of life underscores the urgency of visually analyzing their distribution patterns, particularly in regions like Malaysia. To effectively manage and control landslip occurrences, this study proposes the establishment of a landslide monitoring system in high-risk areas, utilizing computer-generated models to evaluate geographical distribution patterns. This approach is vital for competent landslides management. The core objective of this research is to evaluate the spatial arrangement of the distribution pattern, discerning whether it manifests clustering or dispersion. The investigation focuses on 43 recorded landslide incidents spanning 12 years across Penang Island. The spatial mean center of landslip episodes assumes a central role in spatial pattern analysis. The findings reveal a clustered pattern in the study area, evident through an average nearest neighbor (ANN) ratio of less than 1, accompanied by a z-score of -2.196005. The nearest neighbor ratio stands at 0.82. Furthermore, the mean center for landslide incidents on Penang Island is situated at coordinates 100.272704 (longitude) and 5.389421 (latitude). Subsequently, nine landslide conditioning factors, identified through prior studies, were selected. These factors are employed to distribute landslide incidents on parameter layer maps, aiding in pinpointing high occurrence areas based on each parameter. Future studies should adopt a comprehensive perspective and attain a profound understanding of specific slope conditions in Penang Island, enabling the effective implementation of mitigation measures that align with the objectives of Sustainable Development Goals (SDG13 – Climate Action). This goal emphasizes the importance of fostering resilience and reducing disaster risks.

Keywords: Average Nearest Neighbor (ANN), landslides, landslide conditioning factor, Penang Island, spatial mean centre, spatial pattern analysis

Introduction

Due to the increasing frequency and severity of occurrences in the likes of landslides, especially in Penang Island, their study has become quite significant these days. These events are often mediated by climatic changes and human activities. In Malaysia, heavy rainfall, particularly during monsoon seasons, is a frequent landslide causative factor, warranting the need for more refined and predictive tools for the management and mitigation of hazards. GIS tools have come up as eminent instruments for landslide analysis, as these enable collection, storage, management and spatial analysis of remote sensing data for landslide occurrence pattern. Yet, as per ongoing research, one of the biggest challenges encountered while implementing GIS in landslide studies in Penang is the ability to define spatial distribution patterns in which landslides occur and identify risk areas. Combining machine learning with GIS has been shown to increase the predictive ability of landslide susceptibility models in Penang, bringing this subject to several recent contexts that include the application of ensemble classifiers and algorithms (Shirzadi et al., 2018; Wang et al., 2019; Chen et al., 2019).

One of the main challenges for GIS-based landslide studies in Penang is the inability to predict exact locations of occurrence. Landslide occurrence depends on natural as well as anthropogenic factors, including slope steepness, the type of soil, vegetation cover, land use changes and rainfall intensity. In Penang, human-induced modifications to slopes compound the problem by making it difficult to predict areas likely to experience landslide risk, especially in already urbanized hilly and mountainous regions. Even though the GIS tools represent some use for spatial information, integrating assessments from these factors poses an interpretation rather than representation challenge. This spatial variability of slope conditions against the backdrop of extreme weather patterns creates a difficulty once again of knowing how one can find at-risk zones without complicated models that can take into account this kind of dynamism. Recent studies have indicated the potential of machine learning approaches, such as random forests and support vector machines, in analyzing such complex interactions so that landslide susceptibility assessments can be improved in their accuracy (Wang et al., 2019; Zheng, 2023; Kuradusenge et al., 2020).

In addition, a very important issue concerns the use of specific GIS measures, such as the Average Nearest Neighbor (ANN) method, often employed to analyze spatial patterns of landslides. The ANN approach in QGIS determines the spatial arrangement of a set of events such as landslides-whether it is random, aggregated, or dispersed in distribution. Though this method provides valuable information on landslide spatial distribution, several challenges prohibit its application on Penang Island. One of the primary problems is that some high-resolution time-series data on landslides are required for optimal application of the ANN technique. The absence of complete historical landslide data in Penang makes it difficult to recreate patterns of spatial and temporal reliance and may produce over- or underestimates on clustering tendencies. Studies emphasize that machine learning models in conjunction with GIS can make use of existing datasets more efficiently to offset data deficiency (Elmahdy et al., 2014; Adnan et al., 2020).

Furthermore, ANN suffers from the problem of ignoring the effects of external conditioning factors, namely, rainfall, land-use change and soil stability, which greatly govern landslide occurrence. While ANN determines the spatial interrelation of landslide incidences, it does not address the environmental triggering factors that lead to their occurrence. In Penang Island, where diverse environmental factors play a significant role in the occurrence of landslides, an analysis solely based on ANN may not provide relevant insights about the risks involved. Thus, methods such as logistic regression or machine learning might have served well as supplementary tools to ANN analyses to include certain conditioning factors and ultimately improve the prediction accuracy of landslide risk assessments. Recent development in machine learning is promising in furthering the predictive reaches of landslide models through adding variables to ameliorate data-driven methods (Chen et al., 2017; Nocentini et al., 2023; Pham et al., 2016).

On the whole, the study's aims in adopting GIS-based analyses on landslide patterns existing on Penang Island arise from the intricate environmental variables resulting in landslide risk, the weaknesses in the ANN method of segregating spatial relationships while overlooking conditioning variables such as topology, rainfall, geology and soil type and the apparent lack of extensive landslides' records. Troubles with these issues will be dealt with through meticulous spatial analyses using the ANN method supplemented with conditioning factor analyses in QGIS so as to give a real picture of landslide patterns on Penang Island. This approach is aimed at improving this region's readiness for landslides and setting a direction for effective mitigation measures. Regional integration of machine learning techniques with GIS is important in upgrading the accuracy and reliability of the susceptibility assessment of landslides (Stanley et al., 2021, Luo et al., 2019, Chen et al., 2023).

The rest of this paper is organized as follows: the Literature Review section shall study the influential works on landslide occurrences, some regarding Southeast Asia and Malaysia, and some on the application of GIS tools in landslide risk assessment; Methodology will explicate the procedures for the analysis of spatial patterns of the landslides of Penang Island, which are concerned with the stages of data collection, GIS application and the ANN method. Results will feature the findings of the spatial analysis, presenting the trends and patterns, on how the landslides are distributed; the Discussion will juxtapose the results with some related research and discuss the implications of them in landslide risk management and mitigation programs. Conclusion will enumerate the significant findings and suggest directions for future works, while emphasizing adopting sustainable disaster risk reduction strategies that are in line with global development goals.

Literature review

Landslides are components of soil or rock masses that are propelled directly by gravity. They can range from individual pebbles sliding down a slope to entire mountainsides caving in (Beyene et al., 2023). According to WHO (2023), landslides are more common than any other geological occurrence and can happen anywhere around the world. They occur when massive amounts of dirt, rocks, or debris slide down a slope due to natural events or human activities. Mudslides and debris flows are examples of fast-moving landslides.

Between the years 1998 and 2017, an estimated 4.8 million people were affected by landslides and more than 18,000 lost their lives. It is anticipated that climate change and rising temperatures will lead to an increase in landslides, particularly in mountainous regions with snow and ice. As permafrost dissolves, stony terrain can become increasingly unstable, raising the likelihood of landslides (WHO, 2023). Furthermore, since 2010, approximately 8,935 landslide incidents have been recorded globally. Up until 2019, over 1,120 of these landslides have occurred in Southeast Asia (Majid et al., 2022).

Numerous natural disasters, including floods, earthquakes, landslides and heatwaves, occur annually in Southeast Asia, rendering it one of the world's most disaster-prone regions (He et al., 2021; Bandibas & Takarada, 2019; An et al., 2020). The Southeast Asian region is characterized by its mountainous terrain, distinguishing it from other geographical categories. Moreover, the most significant geological hazard in Southeast Asia is landslides, which can have catastrophic impacts on both lives and property (Hidayat et al., 2019; Aditian et al., 2018). This is due to the fact that 80% of Southeast Asia comprises mountains and hilly areas, and the region frequently experiences high temperatures and abundant rainfall. Consequently, landslides in Southeast Asia are often triggered by heavy rainfall and seismic activity (He et al., 2021).

Malaysia, a Southeast Asian country, frequently experiences landslides that are often triggered by prolonged heavy downpours. This susceptibility is due to Malaysia's substantial annual rainfall of approximately 3000 mm, largely attributed to its monsoonal seasons. This indicates that the nation is particularly prone to landslides, especially in mountainous and sloping areas (Muaz Abu Mansor Maturidi et al., 2020). According to a paper titled "National Slope Master Plan (2009-2023)," the earliest recorded landslide in Malaysia occurred in December 1919, resulting in the tragic loss of 12 lives. Another notable incident took place in the Ringlet Cameron Highlands in 1961. A total of 49 significant landslides have been documented, with 88% of them being attributed to human-induced slope alterations (Kazmi et al., 2016).

Selangor holds the unfortunate record for the highest number of landslide events in Malaysia, tallying at 55 as of December 2021, followed by Pahang with 42 (Murthy et al., 2023; Jason Loh & Amanda Yeo, 2022). Among the tragic incidents in Malaysian history, the collapse of Highland Towers in 1993 remains a heart-wrenching tragedy that struck Kuala Lumpur. This catastrophe claimed the lives of 48 innocent individuals. Adding to the grim list, the Batang Kali landslide in the preceding year, on December 16, 2022, stands as the deadliest landslide, claiming 31 lives, including 13 children (Fuad Nizam, 2023). Another notable occurrence transpired on November 28, 1998, in Paya Terubong, Penang, where a landslide buried and severely damaged 16 vehicles (Chigira et al., 2011).

The availability of easily accessible Geographical Information System (GIS) platforms in today's world has significantly contributed to the extensive utilization of precise landslip forecasting on a regional scale (Majid et al., 2022; Song et al., 2020). Furthermore, utilizing a GIS application can significantly improve the management of geographical data and provide enhanced processing capabilities (Saha et al., 2022; Merghadi et al., 2020). Numerous studies focused on assessing landslide risk through GIS have been conducted, employing various analytical methods. The Geographic Information System (GIS) provides both information and tools necessary for comprehending the behavior of slope materials, forecasting landslide risks, monitoring and mitigating this geohazard and more (Majid et al., 2022; Simon et al., 2017; Psomiadis et al., 2020).

Majid et al. (2022), employed GIS software, specifically Quantum GIS (QGIS), to analyze the spatial landslide patterns of Kuala Lumpur. They conducted an analysis and generated a spatial landslide pattern map for Kuala Lumpur using the Average Nearest Neighbor (ANN) method. Additionally, the researchers calculated the mean center to identify the average coordinates of the distribution of landslide incidents. Their findings revealed that the spatial landslide pattern in Kuala Lumpur exhibited a clustered arrangement, as evidenced by an ANN ratio below 1. The mean center was situated in the central area of Kuala Lumpur, precisely at coordinates 101.692018 (x-coordinate) and 3.135268 (y-coordinate) (Majid et al., 2022).

Then, Lin et al. (2010), conducted an analysis of the spatial pattern of landslides in Chenyulan, Taiwan, utilizing landscape metrics. They also employed logistic regression to determine the frequency of landslide occurrences. The results of the spatial pattern analysis revealed a correlation between the spatial landslide patterns and the quantity of landslides. For instance, the mean sizes of landslips in the 10 persistent low-occurrence landslides were greater compared to those of other landslides in the study area. Notably, in low-occurrence and persistent landslides, the overall patch shapes exhibited uneven characteristics, whereas the edge boundaries of recent landslides were extensive.

Method and study area

This study aims to analyze the spatial patterns of landslide incidents on Penang Island using QGIS. The spatial pattern of landslides will be assessed using the ANN method within QGIS. A total of 43 landslide incidents, collected from the updated Global Landslide Catalog NASA and from a previous study, are distributed across Penang Island. It is bordered by Kedah to the north and east, Perak to the south and the Malacca Strait to the west. Penang consists of the main island of Penang and a coastal strip on the mainland known as Province Wellesley (Huqqani et al., 2019). The island has a total size of around 300 km^2 (Yahaya et al., 2019). The island experiences a year-round tropical climate, characterized by consistent heat and humidity. The average annual temperature varies from 27 to 30 °C and the average annual relative humidity ranges from 70 to 90%. Additionally, the average annual rainfall totals between 267 and 624 cm (Akomolafe & Rosazlina, 2022). The Northeast monsoon season, the Southwest monsoon season, and the surrounding sea and wind systems all have an impact on Penang's climatic system (Tew et al., 2019).

As per the Department of Statistics Malaysia, Penang's economy is experiencing rapid growth. The region boasts a low unemployment rate and a high per capita income as a result. In 2016, Penang had the second-highest GDP per capita, following Kuala Lumpur (Tew et al., 2019; Ong & Tan, 2017) . Furthermore, the presence of the First Penang Bridge and the Georgetown-Seberang Perai Ferry service has spurred development in the northern neighboring area of Penang, while the Second Penang Bridge has done the same for the southern neighboring area. These robust road networks have significantly facilitated the movement of people between the mainland and the island. Conversely, the North-South Highway and the Butterworth-Kulim Highway linking Penang with neighboring regions in Kedah and Perak have enticed individuals to settle in these nearby areas while commuting to work daily. As the demand for housing and public infrastructure continues to grow, the development in these neighboring regions is poised to escalate rapidly (Samat & Mahamud, 2019). The rising demand for housing areas has resulted in construction on hillsides, subsequently contributing to an increase in landslide occurrences. (Zulkafli, Abd Majid et al., 2023b). Figure 1 refers to the selected study area, which refers to Penang Island.

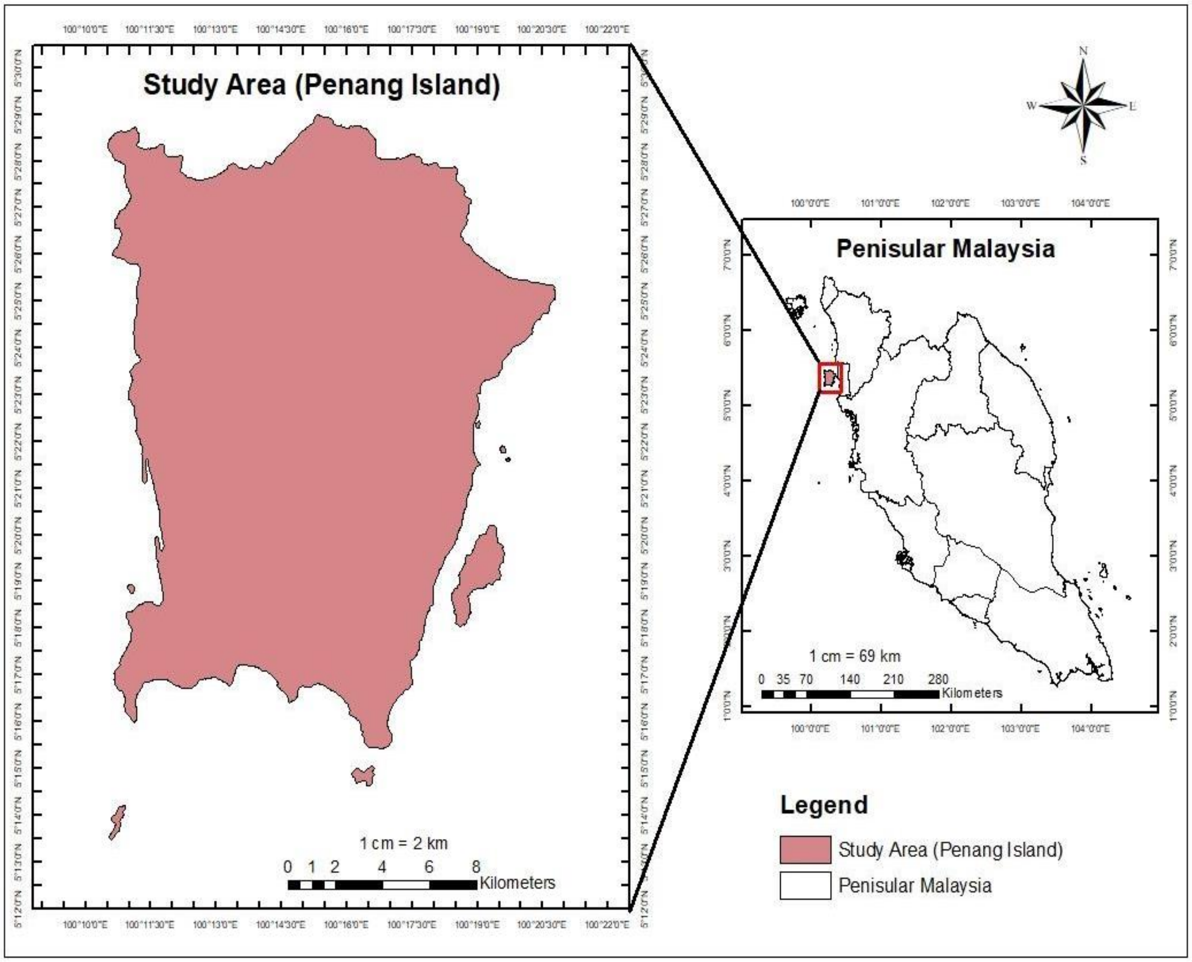

Figure 1. Study area, Penang Island

Data acquisition

The creation of landslide inventory maps is a fundamental element in various landslide research, as it holds a crucial role in understanding past occurrences and identifying their causes. Additionally, these maps are valuable for predicting areas susceptible to future landslides. (Zulkafli et al., 2023). Furthermore, these maps are also beneficial in identifying landslide patterns. As a result, a comprehensive landslide inventory map was generated, encompassing 43 landslide sites derived from the amalgamation of prior research findings and data from the Global Landslide Catalog (NASA). Landslide inventory maps were crafted to discern the landslide patterns present on Penang Island. The Average Nearest Neighbor (ANN) method was employed for identifying these patterns. Additionally, nine distinct landslide factors were chosen in accordance with earlier studies conducted on the island's terrain. These attributes were selected based on the examination of past landslide occurrences and their potential to contribute to the instability of slopes within the area (Ab Rahman et al., 2020). In addition, there are no specific guidelines for selecting characteristics of landslides (Zulkafli et al., 2023; Zhang et al., 2022). These factors include slope angle, slope aspect, distance to roads, distance to rivers, rainfall, land use, lithology, soil series and curvature.

Average Nearest Neighbor (ANN)

The ANN tool calculates the separation between the centroid locations of individual features and their nearest neighbors. These distances to the closest neighbors are then averaged. When analyzing the distribution of characteristics, if the calculated average distance is smaller than the average for an imaginary random distribution, the pattern is considered clustered. Conversely, if the average distance is greater, the characteristics are considered distributed. Furthermore, following the theory presented by Environmental Systems Research Institute (ESRI), a pattern is deemed clustered if the index (nearest neighbor ratio) is less than 1. Conversely, if the index surpasses 1, the prevailing trend is moving away from the central tendency (Majid et al., 2022; ESRI, 2023).

Spatial pattern analysis using the ANN method involves measuring the average distance from each point within the study area to its nearest point. This approach is used to characterize spatial distribution patterns. The real average distance is then compared to the anticipated average distance. This comparison generates an ANN ratio, which is essentially the ratio of observed to predicted values. If the ratio is less than 1, we can infer that the data exhibits a clustered pattern. Conversely, if the ratio exceeds 1, we can deduce that the data showcases a dispersed pattern (Majid et al., 2022; Choy et al., 2011). In this study, the ANN method was employed to analyze the spatial distribution pattern of landslides on Penang Island. The analysis using the ANN method was conducted within Quantum GIS (QGIS) through the process: Arctoolbox > Analyzing Patterns > Average Nearest Neighbor. Additionally, a spatial mean center, a statistical analysis tool, was calculated to explore the average x and y coordinates of all features within the research area. This method proves useful for comparing distribution properties and detecting any alterations in distribution. The spatial mean center coordinates were also computed using QGIS, specifically through the path: Geometry Tools > Centroids.

The ANN approach, when used in conjunction with QGIS, is the optimal selection for performing landslide pattern analysis owing to its amalgamation of straightforwardness, accuracy, and incorporation inside a resilient GIS framework (Titti et al., 2022). ANN offers a precise and quantitative assessment of spatial patterns, determining whether landslides are clustered, random, or distributed with statistical significance. This is essential for comprehending landslide behaviour and assessing hazards. QGIS improves this capacity by providing a user-friendly interface, a wide range of plugins, and smooth integration of spatial analytic tools, enabling thorough analysis from data preparation to visualisation (Titti et al., 2022). Compared to other intricate techniques or tools that may need specialised expertise or lack comprehensive assistance, using ANN with QGIS is easily accessible, adaptable to many sizes and extensively supported by a big community. Consequently, it is the most efficient and dependable choice for analysing landslide patterns.

Landslide conditioning factors

The present study collected data on various factors affecting landslide occurrences from multiple sources, as outlined in Table 1. As previously discussed, the locations of landslide incidents spanning a period of 12 years were sourced from the Global Landslide Catalog as well as earlier studies. QGIS was utilized to produce layered maps representing the nine influencing factors for landslides. To ensure consistency, all map layers in this study were projected using the Kertau Malaysian Rectified Skewed Orthomorphic (MRSO) coordinate system. The maps depicting soil series, lithology and rainfall were created by digitizing data from Zulkafli et al. (2023). Slope angle, slope aspect and curvature were obtained from a Digital Elevation Model (DEM) with a spatial resolution of 12.5m. Additionally, the land use map was sourced from the Department of Agriculture Malaysia, while the road network and river network data were obtained from Department of Survey and Mapping Malaysia (DSMM).

Table 1. Main data sources for landslide conditioning factors and ANN

Data	Source
Landslides	Previous Study, Global Landslide Catalog (NASA)
Soil series	Zulkafli, Abd Majid et al. (2023)
Lithology	Zulkafli, Abd Majid et al. (2023)
Land use	Department of Agriculture Malaysia
Road network	Department of Survey and Mapping Malaysia (DSMM)
River network	Department of Survey and Mapping Malaysia (DSMM)
Rainfall	Zulkafli, Abd Majid et al. (2023)
DEM	ASF Data Search Vertex (NASA)

Results and discussion

In this study, a total of 43 landslide incidents were identified and spread across Penang Island. The landslide inventory map was generated for the island area, encompassing these 43 landslide locations. These incidents were sourced from prior studies and the Global Landslide Catalog (NASA). It's worth noting that certain landslide incidents were situated in close proximity, leading to potential overlap and symbol concealment. Furthermore, the locations of these 43 landslide incidents were identified over the course of the past 12 years, forming the basis for constructing the landslide inventory.

The analysis of the spatial mean center was conducted in this study to identify the anticipated centers of occurrences. Within the study's framework, both the x and y attributes were appropriate for generating an average. This method is frequently employed to discern changes in distribution or establish connections between diverse types of feature distribution. A novel point feature class referred to as the mean center point was established to accurately depict the mean center for each feature. The mean values of X and Y incorporate attributes such as center, events, and dimension field mean, all of which are indicative of feature outcomes (Majid et al., 2022). Locations of landslide incidents are shown in Figure 2 along with their mean centers.

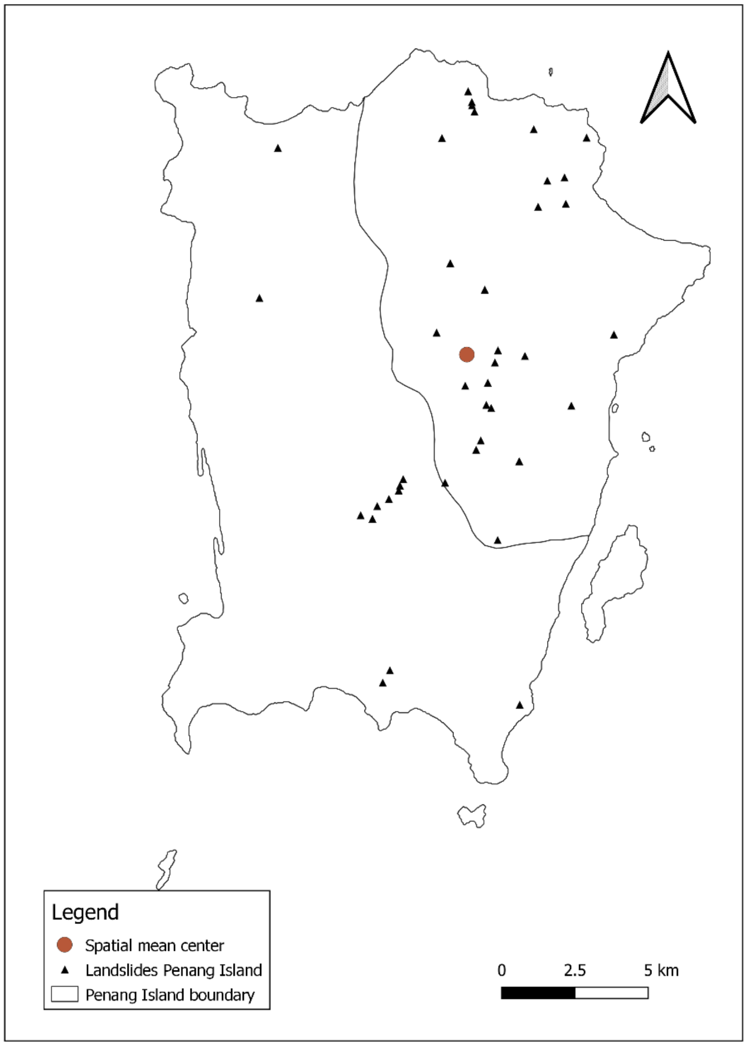

Figure 2. Landslide Incidents and spatial mean center of landslides in Penang Island

The mean center for landslide incidents in Penang Island located at the coordinate 100.272704 (longitude), 5.389421 (latitude). According to Majid et al. (2022), spatial statistical distribution and pattern analysis constitute vital components in discerning the geographical distribution of slope failure incidents across the research area. These methodologies play a pivotal role in determining the dispersion and spatial arrangements of landslides. Consequently, a pattern distribution analysis was conducted utilizing the ANN method to enhance the findings. The outcome of this analysis revealed that the prevailing pattern within the studied region is clustered. This is indicated by an average nearest neighbor ratio of less than 1, accompanied by a z-score of -2.196005. It provides further evidence that the clustering pattern is statistically significant, usually at a confidence level of 95% or greater, due to the z-score's divergence from 0. The calculated nearest neighbor ratio stands at 0.82. Additionally, it's noteworthy that the majority of landslide incidents are more prone to occur in proximity to the middle of the island. This mostly due to the presence of rugged hills that raise substantial concerns. The geographical features of this region, distinguished by steep inclines and high elevation, render it more prone to landslides, particularly during periods of intense precipitation. The inherent topography of the centre region of the island, along with possible anthropogenic actions such as deforestation or development, intensifies the precariousness of these inclines, resulting in a greater incidence of landslides. These can be proved by statement mentioned by Husainy et al. (2023) in his publication, where the geographical relief and soil-rock characteristics of Penang Island, which is mostly composed of granitic rocks, rainfall and characterised by huge mountainous hills in the middle section, are significant factors contributing to many landslide incidents.

This observation signifies the existence of a variable that impacts the documented landslide occurrence rate on Penang Island. Extensive research has highlighted various factors that act as triggers for landslide incidents on the island. These factors include slope angle, aspect, rainfall, lithology, land use, curvature, soil composition, distance to roads and distance to rivers. Zulkafli et al. (2023), conducted a study centered around spatial analysis, aiming to investigate the discrepancies in factors contributing to landslides on Penang Island. Their analysis incorporated these nine factors. Consequently, this paper also adopts the selection of these same nine landslide conditioning factors. This choice was informed by a thorough review of the existing literature from previous studies.

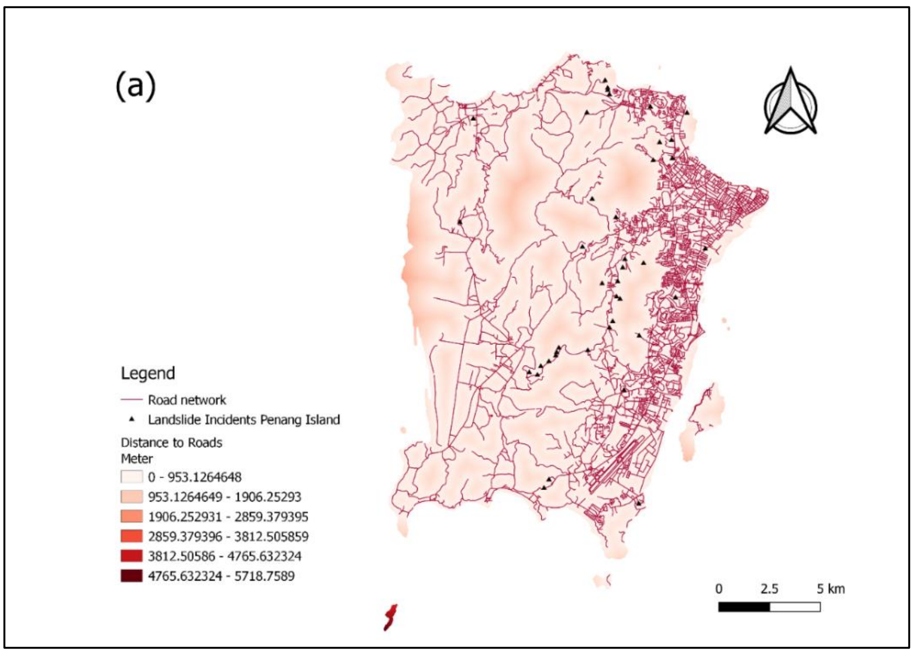

Figure 3a. Road network covering Penang Island

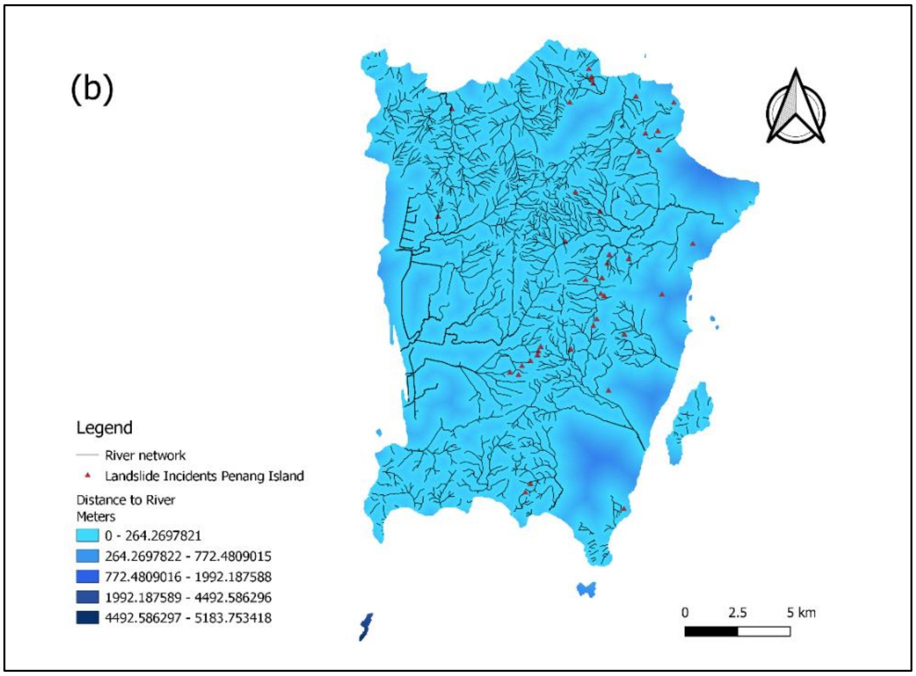

Figure 3b. River network covering Penang Island

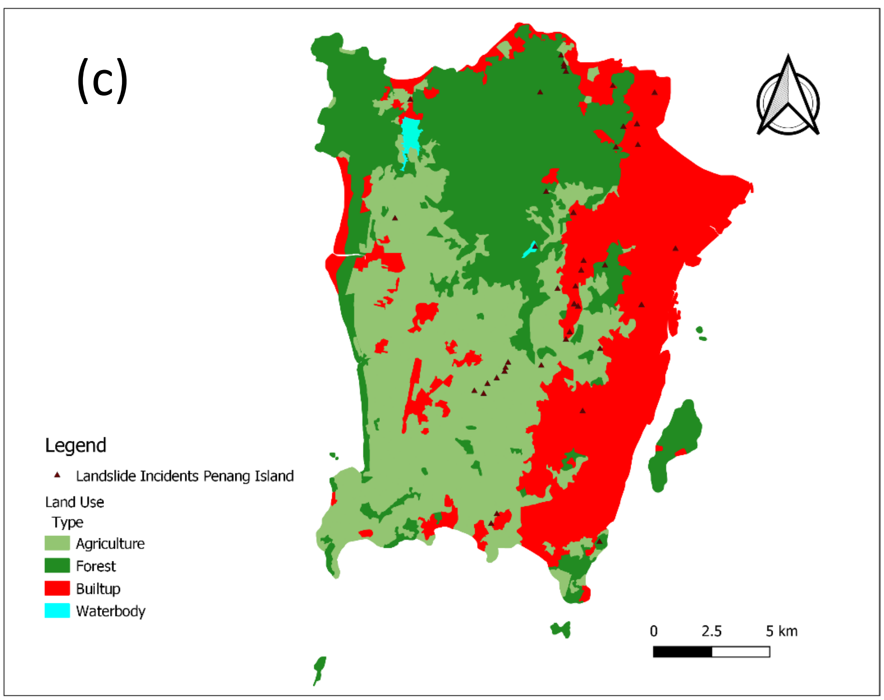

Figure 3c. Land use type covering Penang Island

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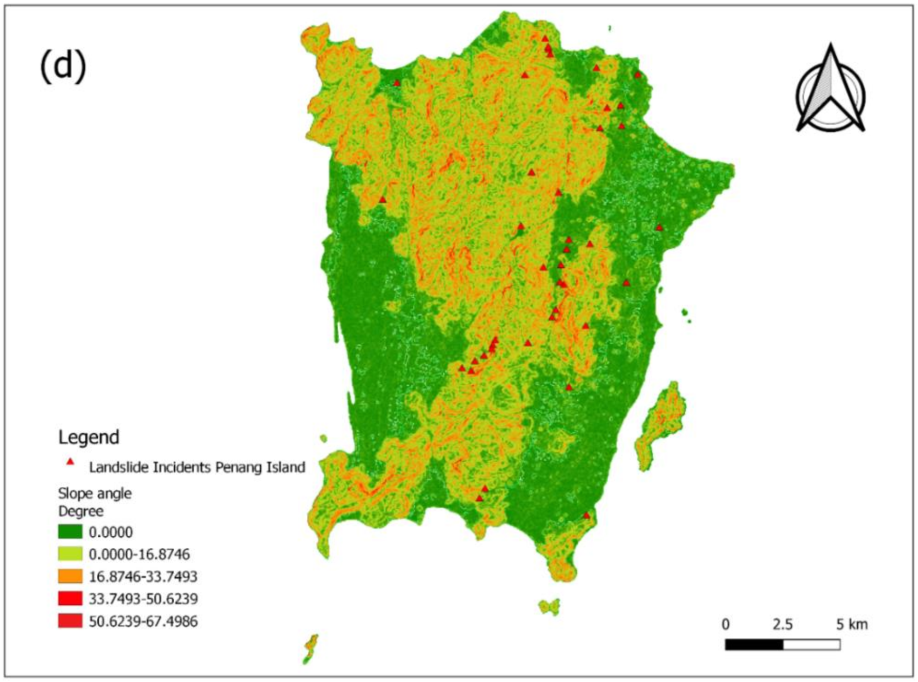

Figure 3d. Delineated slope angle covering Penang Island

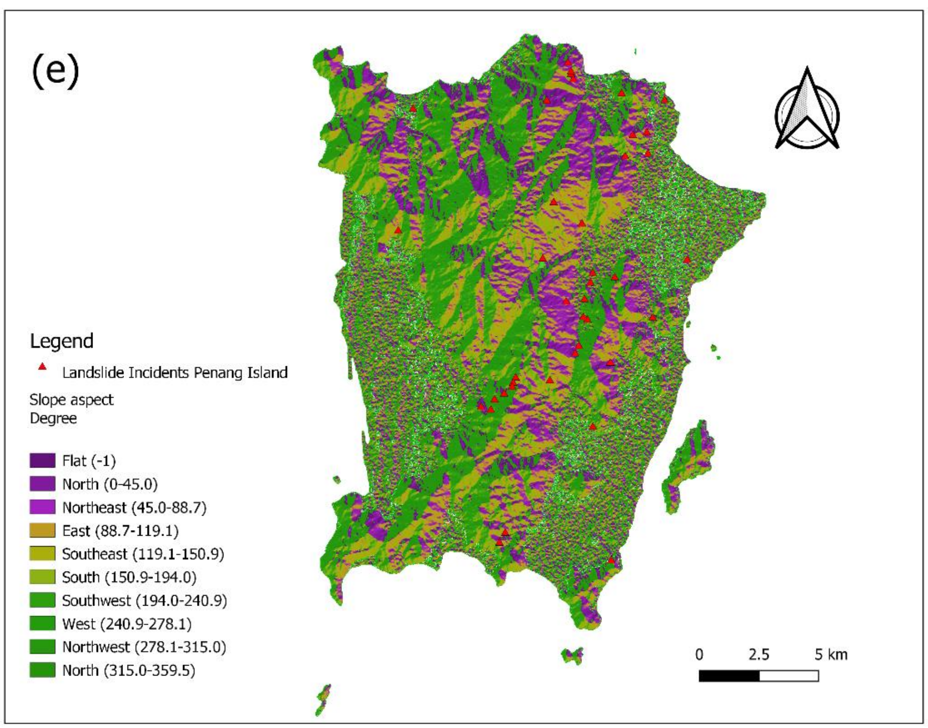

Figure 3e. Delineated slope aspects covering Penang Island

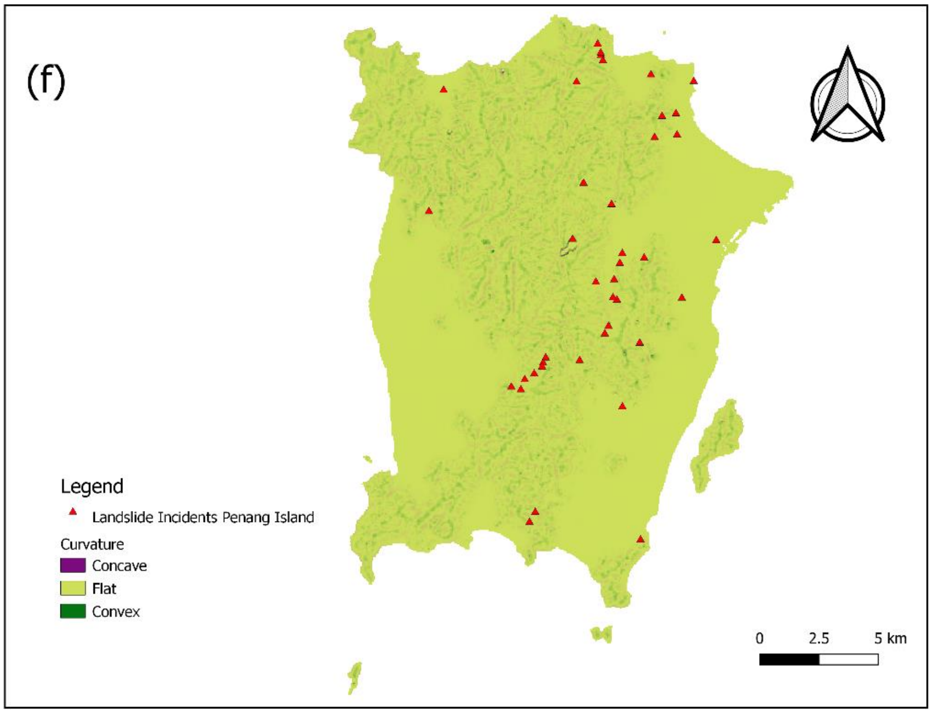

Figure 3f. Derived curvature of Penang Island

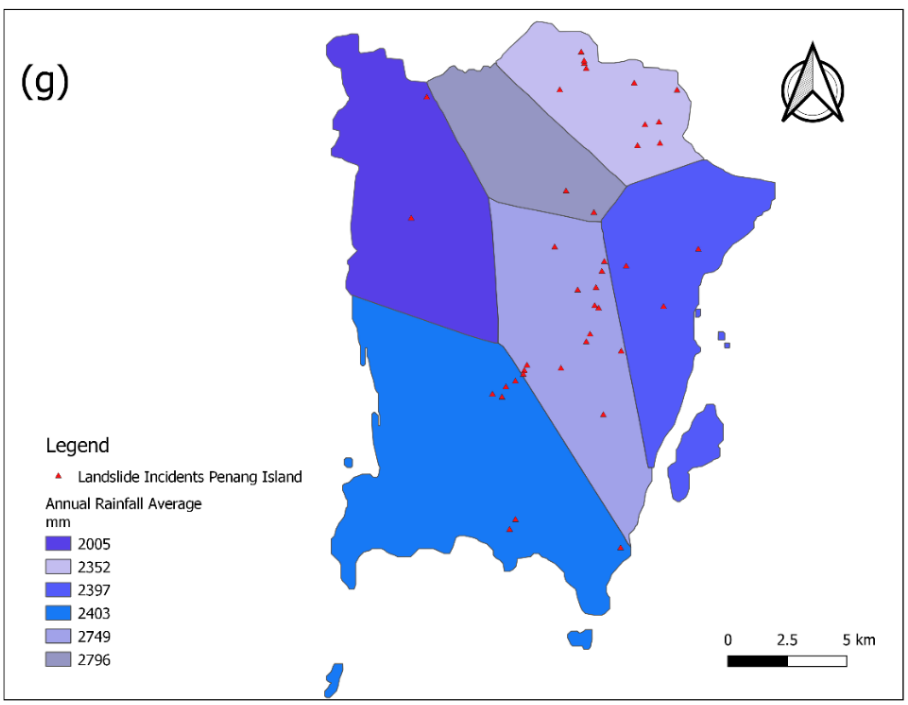

Figure 3g. Annual rainfall average coverage covering Penang Island

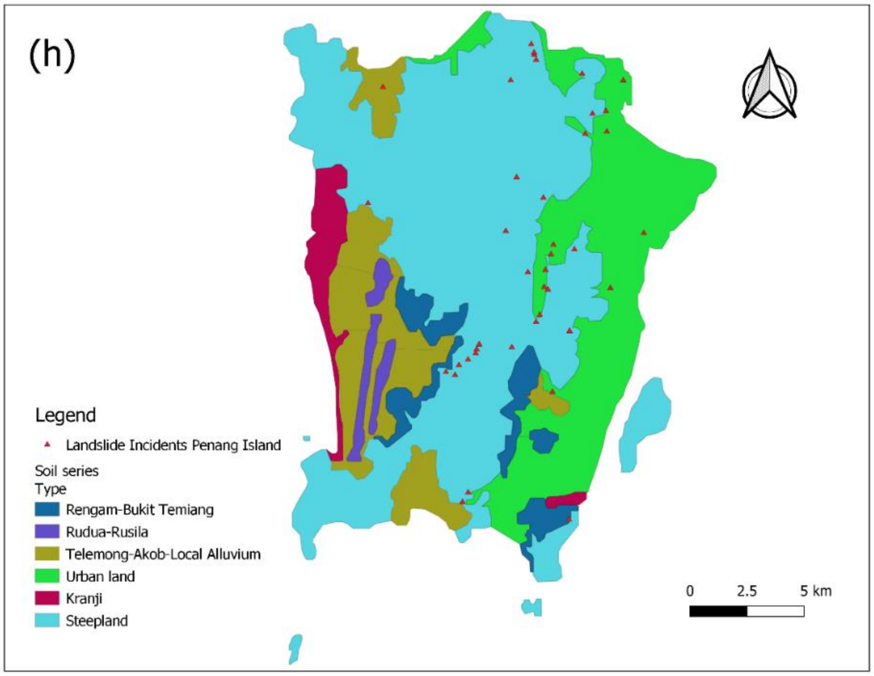

Figure 3h. Soil series covering Penang Island

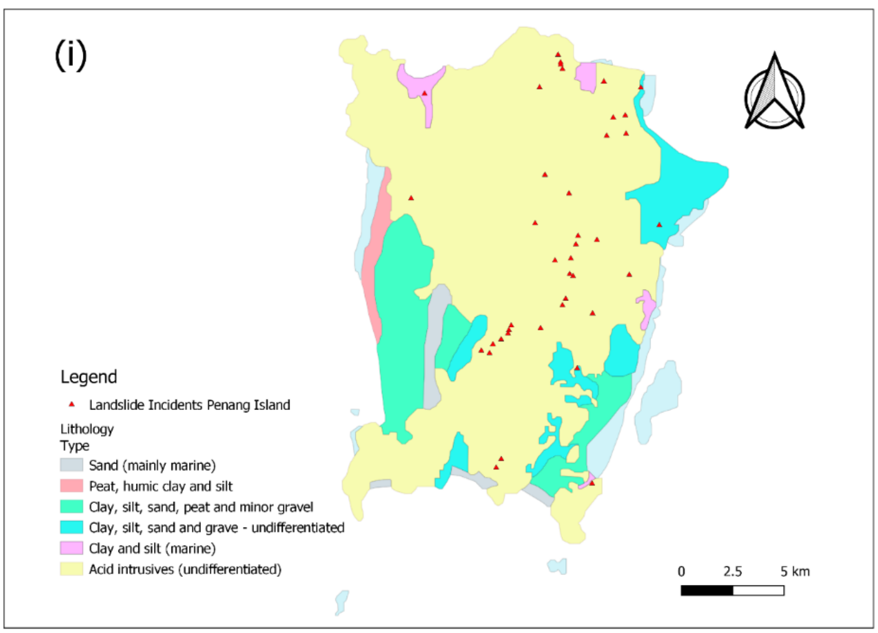

Figure 3i. Soil lithology covering Penang Island

Figure 3a-i depicts landslide distribution on landslide conditioning factors: (a) distance to roads, (b) distance to rivers, (c) land use, (d) slope angle, (e) slope aspect, (f) curvature, (g) annual rainfall average, (h) soil series and (i) lithology. Penang Island has gained renown for its rapid development encompassing buildings, roads and apartments. As depicted in Figure 3(a), the estimated values for the distance to roads in Penang Island reveal that a majority of landslide incidents occurred in areas with a low concentration of road networks. The bulk of the road network is situated on the eastern side of the island, where the slope steepness is less than 15°. This pattern suggests that road networks are not major contributors to slope failure.

Turning to Figure 3(b), the distances to rivers are illustrated. Given its geographical isolation as an island surrounded by the sea, Penang boasts a series of rivers that, despite their relatively limited length and size, hold significant importance in supporting early human settlements on the island. Penang Island is home to two notable rivers named Sungai Pinang, with one winding along the eastern shore and the other coursing around the western coast. Additionally, two rivers referred to as Sungai Dua, or "second river," exist one on the island and another on the mainland. As Figure 3(b) indicates, a considerable portion of landslide locations are situated in proximity to stream areas, with distances to rivers ranging from 0.0000 to 1295.9362 meters. This can be attributed to the natural variability in water flow density, which leads to the formation of distinct erosion patterns, consequently heightening the susceptibility of slope angles (Zulkafli et al., 2023; Mahmud et al., 2013).

In Figure 3(c), it is evident that the majority of slope failure incidents occurred in built-up areas. The prevalence of these occurrences can be attributed to increased development in regions susceptible to landslides. This development is a direct consequence of escalating requirements and demands (Selamat et al., 2023). Furthermore, as highlighted by Zulkafli et al. (2023), the occurrence of landslide incidents in built-up areas on Penang Island underscores how the persistent and unsustainable activities of human beings have substantially increased the stress on the land. This heightened stress has led to a greater vulnerability to slope instability and subsequently, a rise in the frequency of landslides. Additionally, Figure 3(d) displays the slope angle map, revealing that a majority of landslides occurred on slopes exceeding 16.8746°. Moving to Figure 3(e), the slope aspect map indicates that landslides occurred predominantly on slopes exceeding 45°. Penang Island's topography, featuring steep terrain at elevations surpassing 60 meters, encompasses over half of its land area. Consequently, the island is marked by a notable susceptibility to landslides, with nearly 50 percent of its land considered at risk. As the slope inclination increases, the shear stress experienced by soil and other unconsolidated materials intensifies (Zulkafli et al., 2023b). The landslide distribution map based on the curvature layer is depicted in Figure 3(f). The impact of curvature also holds significance in the occurrence of landslides. This study has identified that slope failures primarily took place on convex slopes.

The map illustrating the average annual rainfall, presented in Figure 3(g), highlights that a majority of landslides are situated in regions receiving an annual rainfall of around 2749 mm. This observation further underscores that rainfall is a triggering factor for slope failures on Penang Island. The instances of landslides are often attributed to the conjunction of heavy precipitation and human-induced activities (Zulkafli et al., 2023; Mahmud et al., 2013; Nuriah Abd Majid et al., 2020; Nuriah Abd Majid et al., 2022; Selamat et al., 2022). Construction activities, particularly in urban areas like Pulau Pinang, have demonstrated indirect adverse effects on the environment. The combination of significant precipitation and human actions results in slope instability, necessitating the implementation of comprehensive management strategies (Abd Majid & Rainis, 2019). Additionally, as pointed out by Pradhan and Lee (2010) slope stability is notably influenced by precipitation and subsequent water infiltration into the ground.

Rainfall triggers changes in soil moisture levels, which in turn lead to shifts in interstitial pore water pressure, seepage pressure, soil weight and a reduction in cohesiveness. The presence of substantial debris within the soil mass initiates the process of sliding. Notably, the recent increase in landslide occurrences could be attributed to the accelerated pace of construction and land clearance activities in mountainous regions.

Figure 3(h) provides an overview of the soil series on Penang Island, which is categorized into six distinct classes: Rengam-Bukit Temiang, Rudua-Rusila, Telemong-Akob-Local Alluvium, Urban land, Kranji and Steepland. Notably, approximately 70% of Penang Island is characterized by steepland soil series. This soil series is predominantly composed of weathered granitic rocks, which cover the central region of the island. The Rengam series is defined by sandy clay with a texture ranging from fine to medium coarse. This series is primarily found in igneous and high-grade metamorphic rock formations. On the other hand, the Telemong-Akob-Local Alluvium series is comprised of fine to medium grained loamy material (Pradhan & Lee, 2010). The soil series landslide distribution map distinctly illustrates that most slope failure incidents occur in the steep land areas, while only a few occur in urban land. Moving to Figure 3(i), the lithology map portrays that most landslide incidents take place in areas characterized by acid intrusive. Acid intrusive rocks are defined by a high proportion of silicate minerals, often linked with granitic or granodioritic compositions. These types of rocks are prone to weathering due to their mineral composition. The degradation of minerals can lead to the formation of weak zones and reduce the cohesion of rock materials, rendering them more susceptible to sliding.

Indeed, the study has identified and discussed the nine factors that influence landslides on Penang Island, as previously documented in other studies. As elucidated by the research conducted by Zulkafli et al. (2023), the occurrence of landslides on Penang Island is notably influenced by slope angle and aspect when compared to other factors. Given the island's topography, approximately 50% of its land is susceptible to landslides. Consequently, the necessity for slope cutting arises as an inevitable requirement in urbanization endeavors. Furthermore, an increased slope inclination can result in heightened gravitational force acting on materials, leading to an augmented vulnerability to landslides (Zulkafli et al., 2023b).

ANN influences for landslide causative factors

The application of the ANN method in the QGIS environment is essential for gaining insights into the spatial distribution of landslides and for assessing whether these incidents manifest aggregated, random, or dispersed patterns. While explaining based on the conditioning factors, ANN provided significant support in revealing the clustering tendencies of landslides incidents that occurred on Penang Island, following the analysis of its conditioning factors. The distance analysis performed in relation to elements such as distance to roads, rivers, land use, slope angle and other environmental variables helps ANN compute how landslide events are spatially related.

One of the critical roles of the ANN method is the detection of patterns based on distance to crucial infrastructures like roads and riverbanks. The mapping results in Figure 3(a) indicate that most landslide incidents occurred in locations with little road networks; therefore, road construction is not a significant contributor to slope failures, because landslide incidents are situated in the opposite proximity of river systems, as displayed in Figure 3(b), where many landslides occurred more closely to river systems. These landslide-river relationships can be characterized through natural erosion processes, in conjunction with water influence on the stability of the slope, thereby increasing the susceptibility of any slope to failure.

Also, the ANN approach is an analysis that points to the relationship between human activity and the occurrence of landslides. Figure 3(c) shows that many landslides occurred in built-up areas, considerably in rapidly urbanized regions. The clustering of landslides in these areas indicates the influence of human-induced stress on the environment, whereby slope cuttings and additional superimposed load via the path of urbanization exacerbate slope instability. The ANN establishes that urbanization aggravates the problems of landslide concentration, particularly in areas that have undergone more anthropogenic pressure. Regarding topographical influences, the ANN method provides evidence that angle and slope contributed greatly. As shown in Figures 3(d) and 3(e), most landslides occurred on steep zones with angles higher than 16.87° and slopes greater than 45°.

Landslides clustering in areas makes slope steepness indicative of gravitational action or acceleration of shear stress to soil stability. Because of the ANN analysis, those steep terrain features were termed the three-dimensional hotspots of landslides on Penang Island, rendering them areas of amenable inspection for risk. Besides the ANN method, other factors that prove highly effective as conditioning parameters--soil series and lithology--can also be used to test the spatial distribution of landslides. Indeed, Figures 3(h) and 3(i) show that landslides occurred primarily in areas characterized by the presence of steep soils and acid intrusive rocks. These geological formations have the greatest susceptibility to weathering and reduced cohesion, which contribute to the likelihood of slope failure. The zoning of landslides in such particular soil and lithology zones highlights the ability of ANN to identify and analyze areas of higher geological vulnerability.

Lastly, the effect of rainfall is one of the major influences on landslide occurrences in Penang Island, as illustrated in Figure 3(g). The ANN method reveals clusters of landslides in areas with high annual rainfall providing that intense rainfall serves as a very critical triggering factor of slope failures. The spatial extent of clustering of landslides in areas of about 2749 mm down to anthropogenic activities such as constructions brings forth the complex interplay of landslide risk determinants- human works therein. Thus, the ANN method in QGIS stands out as an able tool to analyze the spatial distribution of landslides on Penang Island, pinpoint significant clusters of landslides vis-a-vis essential environmental-as well as anthropogenic-factors like proximity to the rivers, steep slopes, urbanization, soil types, lithology and rainfall. This information will be of utmost importance for understanding the spatial pattern of landslides as they contribute towards risk management strategies that are aimed at reducing landslide hazards on Penang Island.

Significance of QGIS for landslide incident analysis

The use of QGIS for the assessment of landslide occurrences on Penang Island as illustrated by the results above is of paramount importance and also offers an aesthetically pleasing novelty in methodology and sophistication of insights. Being an open-source GIS platform, QGIS has a great number of spatial analysis tools at its disposal, foremost among which is the handy Average Nearest Neighbor method; this tool is fundamental in understanding landslide patterns holistically and accurately. Some of the aspects of the importance and novelty of QGIS are discussed in this section, weaving relations to the results already shown.

a. Comprehensive spatial analysis with multi-layered data integration

QGIS provided an ideal for mapping landslides in conjunction with these considerations, as illustrated in Figure 3(a-i). The novelty lies in the power of QGIS to effortlessly handle multiple complex spatial data and present an integrated view of how these factors jointly trigger landslide occurrence. For instance, there are results where landslides will, on the one hand, occur near rivers,

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as noted in Figure 3b; on the other hand, they won't, as shown in Figure 3a. These two points accentuate the power of QGIS to layer this data for detailed exploration.

b. Enhanced visualization and mapping capabilities

The graphical presentations of QGIS create very detailed maps as presented in Figures 3(a-i) to present the spatial relations between landslides and several environmental features. This brings forward new information for interaction: making for the clearer introduction of patterns, landslides appear to cluster in the greater built-up aspects and steep slopes as presented in Figures 3(c) and 3(d). QGIS offers novelty in its ability to produce maps of very high resolutions showing spatial distribution but also stacking additional factors upon one another, thereby providing immediate visual insights into risk areas. The visual aspect is an important feature for decision-makers and urban planners who would need an order of what really happened so they can work on something pertaining to mitigation strategies.

c. Average Nearest Neighbor

In the application of the ANN method in QGIS to understand the landslide spatial pattern-whether they are clustered, random, or dispersed-gives relevance to the analysis. The outcome shows, in fact, that ANN did highlight clusters with regard to slope angels, built-up areas and distance to rivers. Another novelty lies in QGIS making this analysis very simple by executing the ANN aids in its demarcation of landslide-prone zones on a quantitative basis. This approach transforms QGIS from the mapping tool it once was into a spatial analytics platform which can shine a light on the underlying spatial processes, thus helping in more accurate predictions of future risks.

d. QGIS is obviously an open-source tool!

One crucial novelty and advantage of QGIS boils down to its monopoly as an open-source tool, any advanced spatial analysis software within users' reach, including researchers, government agencies and urban planners, comes with none of the cost implications of proprietary software. This situation proves crucial, as it ensures that the analyses being proposed are pursued in regions like Penang, where finances for environmental management are scarce possibilities. With ample powers in the analyses to a level, cost-effectiveness is observed on the part of QGIS in terms of sophisticated analyses of this manner that rely on spatial data to put forward insights in a somewhat more affordable milieu. People's technology is of broad application and a level of scalability to spread to other regions with landslide risks.

e. From data-driven Risk Management Decision Support

QGIS offers tremendous insights into the spatial pattern analysis concerning environmental and atherogenic triggers into such areas, thus serving as a basis of evidence for decision support. In the analyses, landslide causative factors like annual rainfall (Figure 3g) and soil type (Figure 3h) correlated directly with landslide incidents, thereby enabling a deeper understanding of where and why landslides occur. The novelty presented is not confined only to the site of occurrence of landslides; rather, it considers the conditioning factors around the landslides together with predicting those landslides, providing a basis for informed risk management decisions through

QGIS. This predictive ability from QGIS, then makes it possible to develop and implement effective landslide mitigation plans and urban planning in areas like Penang Island, where such hazards are most prone.

f. Customize and extend the analytical methods

QGIS provides flexibility to customize and extend analysis capability, with the availability of several plugins and tools. For example, the availability of advanced geospatial plugins allowed for more in-depth mean centers and analysis of spatial relationships in this study to enable a deeper understanding of landslide distribution in Penang Island. The capacity of calculating such spatial statistics within QGIS without the need for any external software is one of the innovative moves that helped in streamlining the workflow that should have otherwise delayed an extensive geospatial analysis. The outcome of the analysis, which shows clustered spatial arrangements of landslides within certain regions, has consequently benefited from this flexibility, allowing the experimentation with variants of methods and parameters to fine-tune analysis.

g. Capability of handling substantial data and complicated models

To analyze 43 landslide incidences over a 12-year period on Penang Island, large spatial datasets were handled and contributions from QGIS in support of managing large geospatial data were vital. QGIS, too extends its capability of using complicated models that need a combination of several environmental layers like those comprising curvature, lithology and rainfall, which follows its logical applicability to any large-scale study. This reliable process including the handling and processing of complex datasets is a major improvement not only in literary practice but also for environmental and disaster management application.

Conclusion

A landslide inventory map is a crucial tool for understanding past slope failure incidents and identifying their underlying causes. In this study, a landslide inventory map was constructed for the island area, encompassing 43 landslide locations. These incidents were sourced from prior studies and the Global Landslide Catalog (NASA), spanning a 12-year period. The aim of this study was to analyze the pattern of landslide incidents on Penang Island using the ANN method. The findings indicated a clustered pattern in the studied region, supported by an average nearest neighbor ratio of less than 1 and a z-score of -2.196005. The mean center for landslide incidents on Penang Island was identified at coordinates 100.272704 (longitude) and 5.389421 (latitude). Furthermore, a considerable number of landslide incidents occurred closer to the island's central region.

This observation implies the presence of a factor influencing the rate of landslide occurrences documented on Penang Island. As a result, nine landslide factors were selected based on previous studies. These factors include slope angle, aspect, rainfall, lithology, land use, curvature, soil, distance to road and distance to river. These nine factors were transformed into maps using QGIS, with layered landslide incident data added to identify regions with a higher concentration of landslide occurrences based on each factor. Each individual landslide factor exhibited a specific area where most of the landslide incidents occurred.

GIS use for landslide analysis on Penang Island signify a significant progression toward spatial analysis since it enables an understanding of landslide occurrences in relation to environmental and anthropogenic factors. Using Average Nearest Neighbor (ANN) with QGIS emerges as a powerful identification mechanism for spatial patterns, showing that landslide incidents cluster in areas of steep slopes, adjoining rivers and that have been urbanized. The multiple layer assessment done using QGIS offers a comprehensive evaluation of landslide risk assessment, based on results from road networks, rainfall, soil series and lithology layered assessment. The findings reflect the critical nature of contributing factors such as angle of slope, human development and environmental triggers such as rainfall towards landslide occurrences, and on providing data-driven insights to facilitate risk mitigation and disaster preparedness.

Its significance and novelty lie in QGIS being an accessible open-source tool capable of performing elaborate spatial analysis and visualization on large datasets. Its suitability towards adoption of different and more advanced spatial techniques such as ANN is well met within the context of geospatial debates, that can demonstrate complex geospatial data such as this. More in-depth analytical capabilities, coupled with clarity of representation, are reason enough for QGIS to advocate and guide an all-round deliberation amongst planners and policymakers for conferring remedial solutions to landslide risks. The paper brings forth the utility of QGIS as an emergency planning and disaster management tool in regions characterized by rapid urban development and ecological exigencies. Of worthy note is that the analysis of factors such as rainfall, soil properties and land use types along with the individual cumulative effects arising there from mandates effective land use planning in managing slippage risk on Penang Island.

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