



Research Article

© 2023 Murthy et al.  
This is an open access article licensed under the Creative Commons  
Attribution-NonCommercial 4.0 International License  
(<https://creativecommons.org/licenses/by-nc/4.0/>)

Received: 24 January 2023 / Accepted: 22 April 2023 / Published: 5 May 2023

## Geographical Information System (GIS)-Based Landslide Susceptibility Mapping in Malaysia: A Review of Past, Current and Future Trends

Tharshini Murthy<sup>1</sup>

Izham Mohamad Yusoff<sup>\*</sup>

Siti Hamsah Samsudin<sup>1</sup>

Taksiah A Majid<sup>2</sup>

Ismail Ahmad Abir<sup>3</sup>

Chan Huah Yong<sup>4</sup>

Mohd Ashraf Mohamad Ismail<sup>2</sup>

<sup>1</sup>School of Distance Education,  
Universiti Sains Malaysia,  
Penang, Malaysia

<sup>2</sup>School of Civil Engineering,  
Universiti Sains Malaysia,  
Penang, Malaysia

<sup>3</sup>School of Physics,  
Universiti Sains Malaysia,  
Penang, Malaysia

<sup>4</sup>School of Computer Sciences,  
Universiti Sains Malaysia,  
Penang, Malaysia

<sup>\*</sup>Corresponding Author

DOI: <https://doi.org/10.36941/ajis-2023-0069>

### Abstract

Landslides are very serious natural disasters that cause much damage and threaten human lives. Landslide susceptibility mapping studies are very common in landslide assessments. Geographic information systems (GISs) have been widely used in many fields, especially in landslide studies. This paper provides a review of GIS-based landslide susceptibility mapping in Malaysia from 2000 to 2022 and analyses the number of publications, study areas involved, parameters and models applied in this field over the past 22 years. The number of publications based on the topic shows an increasing trend, with an average of 2 articles published every year. This paper focused on Malaysia's territory only. The study areas involved in landslide susceptibility studies are Penang, Perak, Selangor, Sabah, Sarawak, Pahang, Kelantan and Kuala Lumpur. Pahang is the study area of the most articles (10), followed by Penang (8). Moreover, 21 parameters were identified, and the slope was the most used parameter (33 articles). Twenty-five models were used, and logistic regression was the most used model, followed by the frequency ratio, ANN and weighted overlay methods.

**Keywords:** Landslide susceptibility mapping, GIS, Malaysia, landslide hazard, landslide risk, landslide models

## 1. Introduction

Landslides are geological phenomena that include the flow of debris or dirt down a slope or a pile of rock (Ilyas A Huqqani et al., 2019; A.A. Ab Rahman et al., 2020). According to previous landslide studies, one of the world's most damaging environmental catastrophes is mass movement, debris, or dirt below the slope. Furthermore, the United States Geological Survey defines landslides as "the mass displacement of underlying rocks, debris, or soil" (USGS, 2019). Landslides are a kind of material loss that involves the movement of soil and rock under severe gravity pressure (A.A. Ab Rahman et al., 2020).

Landslide movement may be classified into numerous forms, including fall, topple, rotational sliding, translational sliding, lateral spreading, flow, and complicated. As a result, a landslide is viewed as a natural hazard and hazardous occurrence that causes property damage and injuries (Selamat et al., 2022; Siti et al., 2022). According to Siti Nursakinah Selamat et al. (2022), landslides are complicated natural catastrophes that incorporate a variety of conditioning elements, such as soil conditions, bedrock, topography, hydrology, and human activity.

In Malaysia, climate change has become a significant factor that triggers landslide incidents, especially in mountainous areas (Siti et al., 2022). Abd Majid et al., (2020) also supports this statement in their study. According to Abd Majid et al., (2020), landslides are common in this country, especially during the monsoon season, when rainfall may reach 700 mm per month. Heavy rainfall is a common source of landslides in Malaysia, notably during the summer monsoon, which occurs from the end of May to the end of September and from November to March.

However, Noradila Rusli and Nur Syahira (2018) mentioned that human activities that lead to drastic changes in land use and land cover have become an important factor that triggers most landslide incidents in Malaysia. Moreover, according to them, land clearance and human interference in the natural environment are inevitable in Malaysia owing to rising urbanization. These land clearance operations may hasten erosional processes and create a landslide in that risky location (Noradila Rusli & Nur Syahira, 2018).

Landslide incidents cause severe damage throughout the world every year; therefore, they are categorized as the most dangerous natural hazard. More than 55 000 people lost their lives because of landslide incidents from 2004 to 2016. Overall landslide damage throughout the world is estimated to be 20 billion US dollars annually (Sim et al., 2022). Selangor is the state in Malaysia that recorded the most landslide incidents until Dec 2021, with 55 cases, followed by Pahang, with 42 cases (Jason Loh & Amanda Yeo, 2022).

The collapse of Highland Tower a heart-breaking incident that happened in 1993, Kuala Lumpur, Malaysia. This incident claimed 48 innocents' lives. Human error became an important factor for this tragedy; people failed to perform soil testing before the construction of these apartments. Moreover, a significant element in the building's collapse was the collapse of retaining walls due to the failure to withstand strong rainfall, which resulted in a landslide. Two different types of design mistakes were made: failing to identify the site's peripheral conditions during the pre-design phase and performing an improper soil bearing test and preconstruction site visit. These mistakes were compounded by the failure to design a sufficient retaining wall to contain the site and the building that was built on it (Danish Kazmi et al., 2017). Table 1 shows landslide cases that occurred in Malaysia from 2010 to 2020.

**Table 1:** Landslide Cases in Malaysia

Num	Year	Location
1	2010	Ukay Perdana, Ampang, Selangor
2	2010	Taman Bukit Mulia, Ampang, Selangor
3	2011	Puncak Setiawangsa, Kuala Lumpur
4	2011	Jalan Semantan, Kuala Lumpur

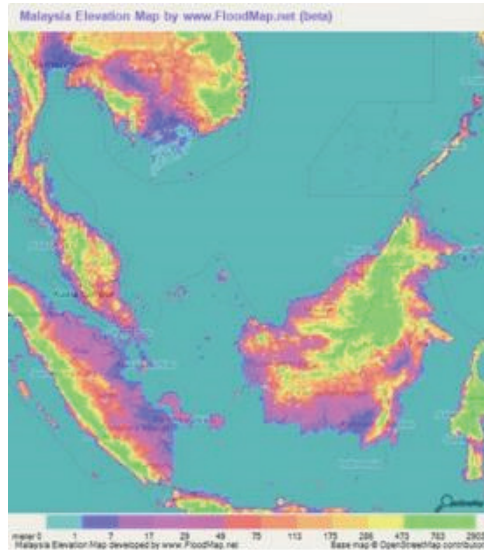
Num	Year	Location
5	2011	Pekan Batu 14 Hulu Langat, Selangor
6	2011	Kampung Tengah, Puchong, Selangor
7	2012	Taman Desa Sentosa, Hulu Langat, Selangor
8	2012	Taman Mulia Jaya, Ampang, Selangor
9	2013	Putra Heights, Subang Jaya, Selangor
10	2015	Kilometre 52.4 (Kuala Lumpur-Karak)
11	2016	Karak Highway
12	2016	Bau-Puncak Borneo (Sarawak)
13	2017	Tanjung Bungah, Penang Island
14	2018	Jalan Bukit Kukus, Georgetown, Penang Island
15	2019	Taman Batu Permai
16	2019	Jalan Lee Woon, Ampang, Selangor
17	2019	Genting Highland, Pahang
18	2020	Taman Kelab Ukey, Bukit Antarabangsa
19	2020	Taman Silibin Indah, Ipoh
20	2020	Sungai Pencala, Kuala Lumpur

Source: A.A. Ab Rahman et al., (2020)

Studies on landslides in Malaysia focus on a variety of connected issues and attempt to understand the circumstances that lead to landslides, giving viable mitigating measures to prevent further losses. One of the main and first stages of landslide analysis mentioned in many studies carried out in Asia is to generate a landslide inventory map and then find the causative factors. A landslide inventory map is also known as the landslide distribution, which is fundamental information that is the key knowledge needed to assess a landslide's magnitude and characteristics. According to Siti Nursakinah Selamat et al., (2022), a landslide inventory map is a crucial stage in every landslide investigation. The collection of reliable landslide inventories is essential in constructing accurate and efficient landslide vulnerability models. Furthermore, the most significant assessment criteria is landslide inventory, which comprises the fundamental information and landslide features required to generate landslide vulnerability, hazard, and risk maps. Thus, the utilization of precise inventory information may provide a solid prediction model and useful information that is widely regarded as a crucial component in disaster prevention and mitigation decision-making (Siti Norsakinah Selamat et al., 2022).

Therefore, most of the studies mentioned landslide inventory mapping as a first step of their research about landslides. These inventories could be generated using a variety of approaches (manual, semiautomated, and automatic) for a variety of objectives, including regional or local event recordkeeping and as the initial stage in susceptibility, vulnerability, and risk assessments (Dias et al., 2021). Moreover, the aim of the inventory and objectives of the study determine the technique, even though there are many techniques to create an inventory map. In Malaysia, most landslide inventory maps were created using satellite imagery and field surveys. Satellite imagery has been used in most studies because it offers high-resolution pictures, and the ability to show 3D ground surfaces has made it easier and more feasible to identify and map landslide distributions in the research region.

Therefore, this study aims to conduct an analysis and take into account four key factors, namely, the study area location, publication year, causes of landslides, and models used in landslide susceptibility mapping in Malaysia for the last twenty-two years (2000-2022). This paper is divided into four main phases: Phase 1: Introduction, Phase 2: Material and Methods, Phase 3: Results and Discussion, and Phase 4: Conclusion. There are four subphases for Phase 3: i. trend in published articles about landslide susceptibility mapping in Malaysia, ii. study area and number of landslide incidents mentioned in every article, iii. causative factors of landslides and their trends in Malaysia over the past 22 years, and iv. trends of models used to analyse landslide susceptibility mapping in Malaysia. The subphases of the Discussion section are discussed in detail in Phase 3.



**Figure 1:** Malaysia Elevation Map  
**Source:** Flood Map (2022)

## 2. Material and Methods

There are three main keywords used to identify landslide analysis: susceptibility, risk and hazard. The 'susceptibility' keyword can be defined as the probability of landslide incidents and is also related to landslide cause factors except earthquakes, human activity and rainfall. The risk level relies on both susceptibility and influencing variables. The existence of a target that is susceptible, such as persons or property, as well as the hazard word, determines the risk term. Precipitation and earthquake activity are two extremely significant influencing elements. Out of the three keywords, susceptibility has been included the most often in previous research.

In this paper, publications published during the previous 22 years (2000-2022) were utilized, specifically, the research location, number of articles, number of landslides, causes, and models, to assess the state and trends of GIS-based landslide susceptibility mapping in Malaysia. The keywords applied were "Malaysia", "GIS", "Susceptibility", "Hazard", "Risk", "Landslide" and states in Malaysia for the title, keywords, and abstract of the available publications. The analysis considered only papers written in Malay and English that applied a susceptibility analysis to landslides in Malaysian territory.

The number of articles published per year was calculated by categorizing the publications by year. This information was utilized to determine the annual patterns in GIS-based landslide susceptibility mapping investigations. Researchers and others also utilized the study area and number of landslides to develop new causes, use new models, and standardize and generalize findings in the future. Information on landslide causes and simulation models was also extracted from the articles to fulfil this review paper. Although there were not as many articles published about landslide susceptibility mapping using GIS in Malaysia as in other countries, each article provided valuable information about this natural disaster not only to the researcher but also to many authorities. Moreover, landslides are not as frequent as other natural disasters that occur in Malaysia, such as floods. Even though, in Web of Science

The articles were divided into three periods of 5 or 10 years based on the publication year and the number of articles: 2000-2010 (10 years), which included 10 articles; 2011-2016 (5 years), which included 14 articles; and 2017-Jun 2022 (5 years), which included 12 articles. This allowed for a clearer

identification of temporal trends. The data are utilized from each era to find the most frequent landslide causes and models and to identify patterns.

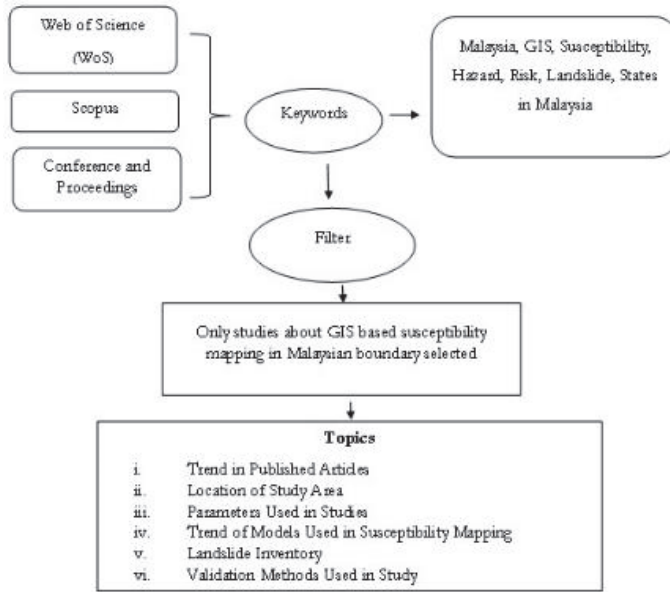


Figure 2: Systematic analysis based on three main phases: searching, filtering and categorization by topic.

### 3. Results and Discussion

Based on the articles search in the Web of Science (WoS) platform, 118 articles were collected. However, only 23 articles were related to the topic 'GIS-based Landslide Susceptibility Mapping in Malaysia' and pertained to Malaysian territory. Therefore, an additional 13 articles published in Scopus and Conference Proceedings regarding this topic were also utilized in this paper, and the total number of articles considered for further analysis was 36.

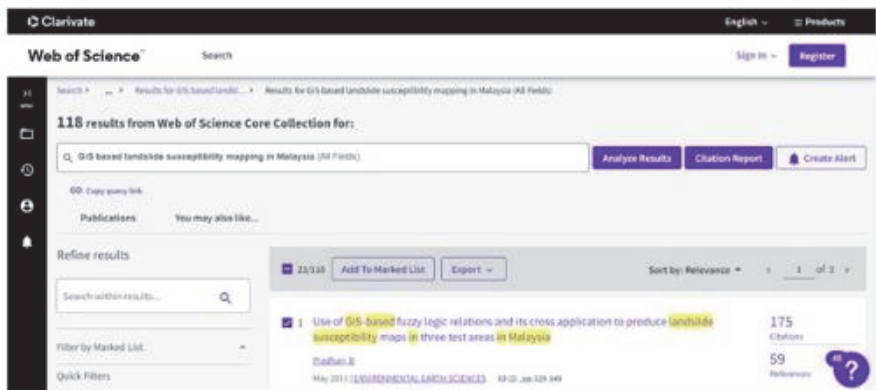


Figure 3: Print screen of article searching on related topic in WoS platform

### 3.1 Trend in Published Articles About Landslide Susceptibility Mapping in Malaysia

Articles about GIS-based landslide susceptibility mapping were selected for this review in a 22-year period in Malaysia, from 2000 to 2022. For the 22 years, an average of 2 articles were published every year related to landslide susceptibility mapping using GIS in Malaysia.

In the first ten years (2000–2010), 10 articles were published. The number of articles increased to 14 articles from 2011–2016. In the last five years, from 2017 to June 2022, 12 articles were published. As shown in Figure 2, the number of articles published each year shows an increasing trend from 2000 to 2022. The highest number of articles was published in 2010, 2011 and 2014, with 4 articles (11%). Therefore, it can be assumed that publication in landslide studies will continue to increase in the future. There are also years that do not record any publications on this topic: 2001, 2002, 2003, 2006 and 2017.

The first period of publications was from 2000 to 2010, and the publications were Omar & Jeber (2004); Saro Lee et al (2007); Saro Lee (2007); Pradhan et al. (2008); Simon et al (2009); Pradhan & Lee (2009); Pradhan et al (2009); Pradhan et al (2010); Pradhan (2010) and Mukhlisin et al (2010). The second period of publications was from 2011 to 2016, and the publications were Saadatkhah et al (2014) ; Shahabi & Hashim (2015) ; Mahmud et al (2013) ; Yusof & Pradhan (2014) ; Althuwaynee et al (2012) ; Oh & Pradhan (2011) ; Mezughi & Abulghasem (2016) ; Sezer et al (2011) ; Alkhasawneh, Ngah, Tay, Ashidi, et al (2014) ; Alkhasawneh, Ngah, Tay, & Isa (2014) ; Pradhan, Mansor, et al (2011) ; Pradhan, Sezer, et al. (2011) ; Roslee et al (2012) and Tay et al (2016). The rest of the publications in this study are from 2017 to 2022, and the publications were Daniel et al (2021) ; V.-H. Nhu et al (2020) ; V. Nhu, Mohammadi, Shahabi, Ahmad, Al-ansari, Shirzadi, Clague, et al (2020) ; Izzat et al. (2019) ; Bui et al. (2018) ; Fanos & Pradhan (2019) ; Udin et al. (2021) ; Ibrahim et al (2022) ; Selamat et al. (2022) and Bong et al. (2018).

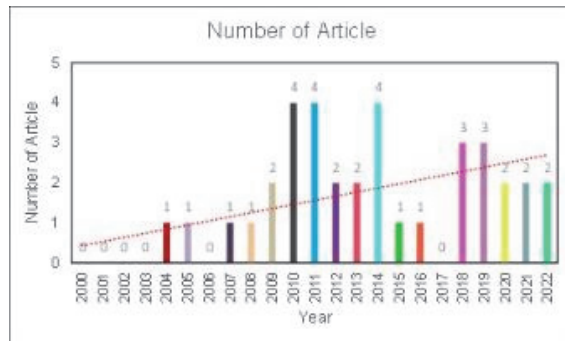


Figure 4: Number of articles published by year

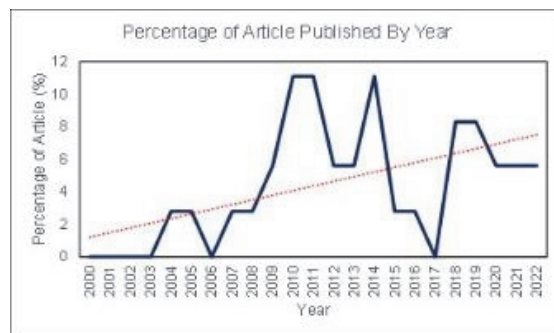


Figure 5: Percentage of articles published by year

The article for this review paper was selected from two languages, Malay language and English. The only article in Malay language was Simon et al (2009). The remaining 35 articles were published in English. This shows that researchers are more interested in publishing articles in English. Moreover, articles will reach more students and researchers around the world and be easy to understand by everyone worldwide if they are written in English. Therefore, researchers tend to publish their work in English rather than in Malay language.

According to Figure 6, there were 31 journals with two or more publications about landslide susceptibility mapping in Malaysia from 2000 to 2022: Advance in Space Research, Computers and Geosciences, Expert Systems with Applications, Disaster Prevention and Management, Earth Science, Environmental Earth Science, Forest, Geological Society of Malaysia, Geomatics, Natural Hazards and Risk, Geo-Spatial Information Science, Hindawi, IEEE Transactions on Geoscience and Remote Sensing, Indonesian Journal of Electrical Engineering and Computer Science, International Conference and Exhibition for Geospatial Technologies, International Journal of Engineering and Technology, International Journal of Engineering and Advanced Technology, International Journal of Environmental Research and Public Health, International Journal of Physical Sciences, International Journal of Remote Sensing, IOP Conference Series: Earth and Environmental Science, ITB Journal of Science, Journal of Advanced Science and Engineering Research, Journal of Applied Remote Sensing, Journal of Catena, Journal of Civil Engineering Research, Land, Landslides, Pertanika Journals Science and Technology, Remote Sensing, Scientific Reports and Sustainability, and IOP Conference Series: Earth and Environmental Science and Computers and Geosciences journals had two publications (6.66%). Other journals had only one publication on landslide susceptibility mapping in Malaysia, with a publication rate of 3.03%.

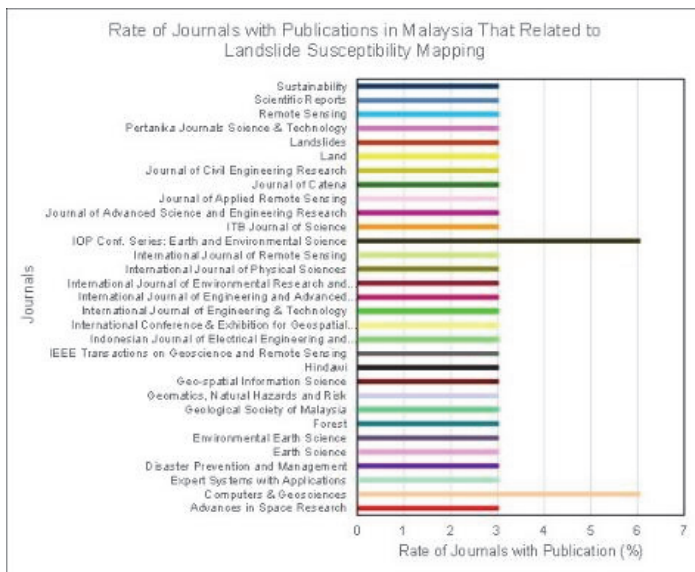


Figure 6: Percentage of journals with publications in landslide susceptibility mapping studies in Malaysia

### 3.2 Location of Study Area in The Articles

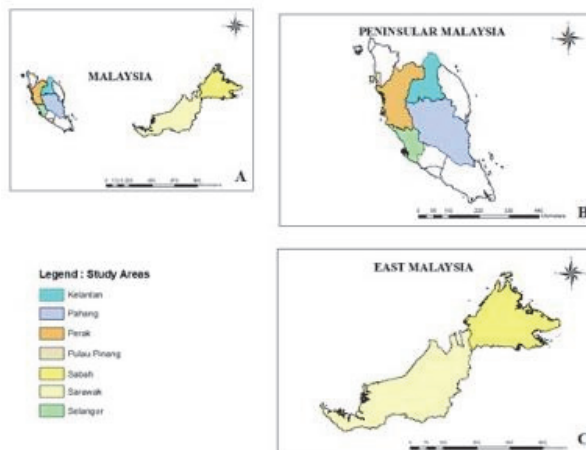
Malaysia is a country in Southeast Asia. Peninsular Malaysia and Borneo Island are its two archipelagos. Malaysia is a tropical country with a year-round warm and humid environment (Diana et al., 2021). Landslides occur rather frequently in Malaysia due to heavy rainfall, especially during annual monsoons, mainly known as the southwest monsoon from late May to September and the northeast monsoon from November to March (Tay et al., 2016).



Landslides in Malaysia have always caused serious threats to settlements and structures that support transportation, natural resources, and tourism. They cause considerable damage to highways, waterways, properties, livestock, and pipelines. Although most of these landslides occurred on cut slopes or embankments alongside roads and highways in mountainous areas, landslides have occurred in other areas as well. A few landslides have occurred near high-rise apartments and in residential areas, causing death to humans (Muaz Abu Mansor Maturidi et al., 2020). Malaysia experienced 51 landslide disasters from 1998 to 2018 (V. Nhu, Mohammadi, Shahabi, Ahmad, Al-ansari, Shirzadi, Geertsema, et al., 2020).

According to Figure 7, there are seven states where study areas were selected for landslide susceptibility mapping from 2000 to 2022. They are Kelantan, Pahang, Perak, Penang, Sabah, Sarawak and Selangor. Pahang is the most highly elected state as a study area in 10 articles, followed by Penang with 8 publications. The Cameron Highlands was a hotspot location for the landslide susceptibility studies that were carried out in Pahang. There were few reasons mentioned by researchers for their studies in Cameron Highlands. According to Bui et al (2018), the Cameron Highlands record increasing trends in the occurrence of landslide incidents triggered by heavy rainfall and cause severe damage. Moreover, according to them, the lack of landslide inventory in Cameron Highlands leads to less effective landslide risk and hazard assessment. Therefore, they decided to carry out landslide susceptibility assessments in the Cameron Highlands and provide accurate information about landslide incidents. Izzat et al (2019) also mentioned that landslide susceptibility mapping is an important and main thing in landslide disaster management and mitigation processes. Landslide susceptibility mapping will provide valuable information about landslide incidents that occur in a place (Izzat et al., 2019). Therefore, the Cameron Highland has the highest selection as the study area in landslide studies. Penang was behind Pahang as the most selected study area. Most researchers choose Penang Island as a study area compared to the mainland because of the frequent occurrence of landslide incidents that cause property damage and threaten human lives (Alkhasawneh, Ngah, Tay, & Isa, 2014).

Only Pradhan (2010) used three locations, Penang, Cameron (Pahang) and Selangor, as study areas in his study. Furthermore, two landslide studies were carried out along highways. One study was carried out by Simon et al., (2009) along the East Coast Highway. In 2016, Mezughi & Abulghasem (2016) carried out a study along the east–west Highway. According to them, the reason behind the selection of the study area along highways is the frequent occurrence of landslide incidents and damage caused by them, especially the loss of many lives.



**Figure 7:** States involved in studying landslide susceptibility mapping in Malaysia. (A) Map of Malaysia; (B) State of study area in Peninsular Malaysia; (C) State of study area in East Malaysia.



**Table 2:** State, location of study area and year of publication

YEAR	STATE	LOCATION
2004	Pahang	Pos Slim-Cameron Highland
2005	Penang	Penang Island
2007	Selangor	Selangor
2008	Pahang	Cameron Highland
2009	Penang	Penang
2009	East Coast Highway	East Coast Highway
2010	Malaysia	Penang, Cameron, Selangor
2010	Pahang	Cameron Highland
2010	Selangor	Ulu Kelang
2010	Pahang	Cameron Highland
2011	Penang	Penang Island
2011	Selangor	Klang Valley
2011	Pahang	Cameron Highland
2011	Penang	Balik Pulau
2012	Sabah	Kota Kinabalu
2012	Kuala Lumpur	Kuala Lumpur
2013	Penang	Penang Island
2013	Kuala Lumpur	Kuala Lumpur
2014	Perak	Gua Tempurung, Jelapang
2014	Penang	Penang Island
2014	Penang	Penang Island
2014	Kuala Lumpur	Kuala Lumpur
2015	Pahang	Cameron Highland
2016	East-West Highway	East-West Highway
2018	Kuala Lumpur	Hulu Kelang
2018	Pahang	Cameron Highland
2018	Sarawak	Murum Reservoir Region
2019	Penang	Penang Island
2019	Pahang	Cameron Highland
2019	Perak	Kinta Valley
2020	Pahang	Cameron Highland
2020	Pahang	Cameron Highland
2021	Sarawak	Canada Hill
2021	Kelantan	Aring, Gua Musang
2022	Selangor	Langat River Basin
2022	Sarawak	Lawas

### 3.3 Causative Factor of Landslides and its Trends in Malaysia for the Past 22 Years

Twenty-one parameters were identified from the articles about landslide susceptibility mapping in Malaysia. These are slope, curvature, aspect, precipitation, elevation, altitude, surface roughness, lithology, distance from road, distance from lineament, distance from fault, soil type, stream power index (SPI), land use land cover (LULC), normalized difference vegetation index (NDVI), slope angle, slope gradient, elevation, topography, topographic witness index (TWI), drainage density, and distance from drainage. These parameters were divided and grouped into three periodic times, as shown in Figures 9, 10 and 11. Figure 8 shows the overall number of articles and their parameters for all three periods (2000-2022). Slope was the parameter used in 33 articles (13.1%), followed by precipitation (10%, 25 articles), curvature (9.6%, 24 articles), soil type (8.8%, 22 articles), aspect (8.4%, 21 articles) and lithology (7.6%, 19 articles).

For the first period (2000-2010), slope had the highest number of articles that selected it as a parameter, 13.2% (10 articles), followed by curvature, aspect and precipitation, which had the same number of publications, 8 articles each (10.5%). Figure 10 also shows that slope was the most highly elected parameter in the second period (2011-2016), with 11 articles (11.8%), followed by curvature (9.7%), soil type (9.7%), precipitation (8.6%) and lithology (7.5%). Slope (14.6%) remained the most

highly selected parameter for the third period (2017-2022), followed by elevation (11.0%) and precipitation (11.0%).

Bong et al., (2018) mentioned that these parameters are very important for landslide studies because they also provide information and details about the occurrence of landslide incidents. Moreover, these parameters also contribute to the probability of occurrence of landslide incidents (Selamat et al., 2022). Slope has become the most highly selected parameter in landslide studies in Malaysia because it can provide information about pore pressure, details about moisture contents and the hydrological process in the slope, which is very important for slope failure investigation (Selamat et al., 2022).

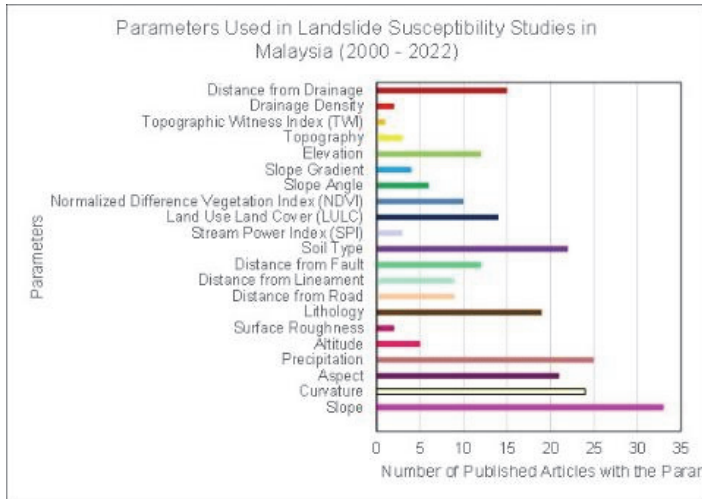


Figure 8: Parameters used in the published articles from 2000-2022

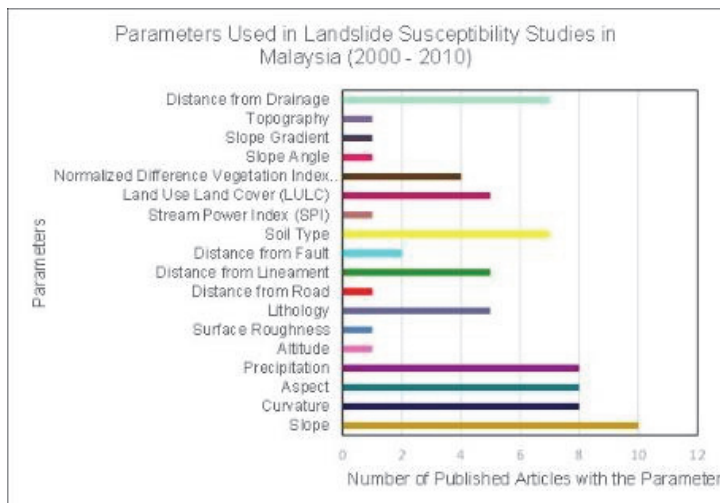


Figure 9: Parameters used in the published articles from 2000–2010.

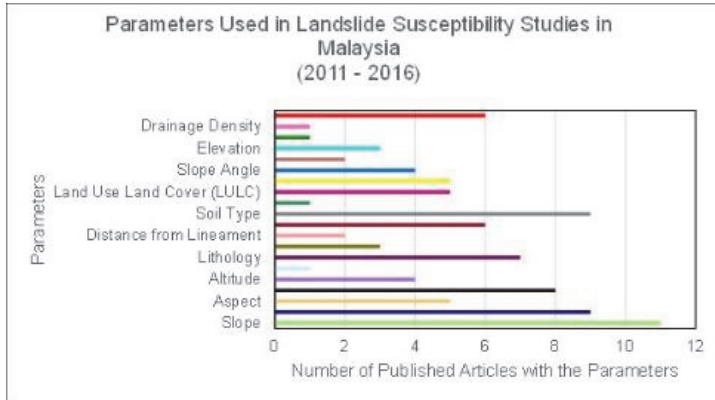


Figure 10: Parameters used in the published articles from 2011-2016

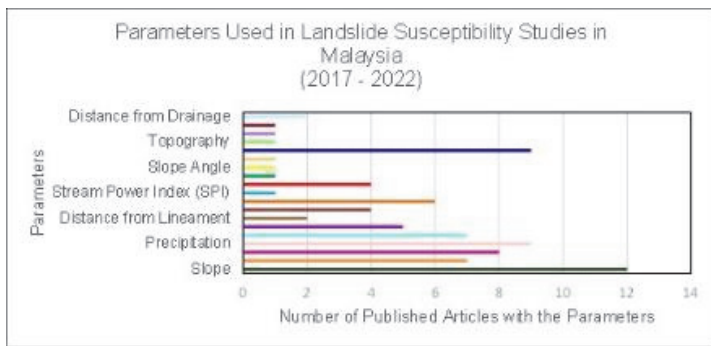


Figure 11: Parameters used in the published articles from 2017-2022

### 3.4 Trends of Models That Are Used to Analyse Landslide Susceptibility Mapping in Malaysia

There are a huge range of models and techniques used in GIS-based landslide susceptibility mapping. Saro Lee (2019) divided models into two categories. One is data, which can also be divided and simplified into 3 categories: machine learning, probabilistic and statistical models. The second model is knowledge-driven, which can be categorized as the weighted overlay and analytic hierarchy process (AHP). These two knowledge-driven models have been used widely in landslide studies (Saro Lee, 2019). Information value, evidential belief function, frequency ratio and weight of evidence are probabilistic models that are also used widely in landslide studies. Furthermore, logistic regression and statistical index are popular statistical models, and artificial neural networks, adaptive neuro fuzzy and random trees can be categorized as machine learning models (Saro Lee, 2019).

According to the article reviewed in this paper, 25 models were used in landslide susceptibility mapping in Malaysia from 2000-2022, with an average of 0.7 models per article. Logistic regression was the most commonly used model for the 22 years of landslide susceptibility mapping in Malaysia and was used in 7 articles (16.3%). The logistic regression model was most frequently used by Lee (2005), Lee et al (2007), Pradhan et al (2008), Pradhan (2010), Althuwaynee et al (2014), Mezughi & Abulghasem (2016), and V.-H. Nhu et al (2020). Logistic regression is very useful to predict the presence or absence of a feature or result based on the values of predictor variables. Logistic regression can be divided into two categories: binary logistic and multinomial logistic. Most researchers applied logistic regression in their study because it helps them to determine a suitable

model to explain the relationship between present and absence variables in landslide incidents, especially in regard to landslide susceptibility mapping (Pardeshi et al., 2013).

The frequency ratio, artificial neural network and weighted overlay method are the other models used frequently by researchers (9.3%), followed by using the AHP 3 times (7.0%). The frequency ratio is a bivariate statistical method that is used to identify the relationship between landslide distribution and the parameters that cause landslide incidents. Researchers have frequently used the frequency ratio because it helps them build a spatial correlation between landslide sites and explanatory variables for landslides. ANN is a model that is very useful in assessing landslide hazards. Furthermore, weighted overlay is a bivariate statistical model that assigns weight according to the relationship of landslide occurrence factors and their frequency (Pardeshi et al., 2013).

Other models are used 1 time only, which is equal to 2.4%. Frequency ratio was used by Saro Lee et al (2007), Pradhan, Mansor, et al (2011), Yusof & Pradhan (2014), Huqqani et al (2019) in their research. The weighted overlay was also used 4 times as much as the frequency ratio, by Mukhlisin et al (2010), Mahmud et al (2013), Bong et al (2018), and (Udin et al., 2021). ANNs were also used four times by Pradhan & Lee (2009), Pradhan, Youssef, et al (2010), Alkhasawneh, Ngah, Tay, & Isa, (2014) and Selamat et al (2022). Finally, the AHP was used by Shahabi & Hashim, (2015), Fanos & Pradhan (2019) and Ibrahim et al (2022).

**Table 3:** Models utilized in Articles (2000-2022)

Model	Amount of Articles in which the Model was Used	Rate of the Model being Used in Articles (%)
Logistic Regression	7	16.3
Frequency Ratio	4	9.3
Artificial Neural Network (ANN)	4	9.3
Weight of Evidence	1	2.3
Weighted Overlay Method (WOM)	4	9.8
Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	1	2.3
Neuro-Fuzzy	2	4.7
Evidential Belief Function	1	2.3
Factor Analysis Model (FAM)	1	2.3
Decision Tree	1	2.3
Chi-Squared Automatic Interaction Detection (CHAID)	1	2.3
Poisson Distribution	1	2.3
Analytic Hierarchy Process (AHP)	3	7.0
Weighted Linear Combination (WLC)	1	2.3
Spatial Multi-Criteria Evaluation (SMCE)	1	2.3
Support Vendor Machine	1	2.3
Index of Entropy	1	2.3
Information Value (IV)	1	2.3
AdaBoost (AB)	1	2.3
Alternating Decision Tree (ADTree)	1	2.3
Logistic Model Tree	1	2.3
Random Forest	1	2.3
Bivariate Statistical Model	1	2.3
Modified Information Value (MIV)	1	2.3
ETC	1	2.3

Table 4 shows the models used in articles for the first period from 2000 to 2010. There are 6 types of models used in the first period. They are logistic regression, frequency ratio, ANN, weight of evidence, weighted overlay method, etc. Logistic regression was used in 4 articles with a rate of usage of 40%, which was highest for the first period. These four publications are from S Lee (2005), Saro Lee et al (2007), Pradhan et al (2008), and Pradhan (2010).

This was followed by ANN with two publication (20%), Pradhan & Lee (2009) and Pradhan,

Youssef, et al (2010). The frequency ratio was used 1 times (10%), by Saro Lee et al (2007). The weight of evidence was used 1 time (10%), by Pradhan, Oh, et al (2010), and the weighted overlay method was also used one time, by Mukhlisin et al (2010).

**Table 4:** Models used in articles for the first period (2000-2010)

Model	Amount of Articles in which the Model was Used	Rate of Model being Used in Articles (%)
Logistic Regression	4	40
Frequency Ratio	1	10
Artificial Neural Network (ANN)	2	20
Weight of Evidence	1	10
Weighted Overlay Method (WOM)	1	10
ETC	1	10

Table 5 shows the models used in articles for the second period from 2011 to 2016. In this period, the number of models used was higher than that in the first period (2000-2010). Fourteen models were used from 2011 to 2016. They are ANFIS, frequency ratio, neuro fuzzy, evidential belief function, FAM, ANN, weighted overlay method, decision tree, logistic regression, CHAID, Poisson distribution, AHP, weighted linear combination and SMCE. Logistic regression and frequency ratio were used in 2 articles with a rate of usage of 12.5% each. For the second period (2011-2016), logistic regression was used by Althuwaynee et al (2014) and Mezughi & Abulghasem (2016). The frequency ratio was used two times, by Pradhan, Mansor, et al (2011) and Yusof & Pradhan (2014). Moreover, neuro-fuzzy was also used two times in this period, by Pradhan, Sezer, et al (2011) and Sezer et al (2011). Furthermore, three models (AHP, weighted linear combination and spatial multicriteria evaluation) were used together in a study by Shahabi & Hashim (2015).

The rest of the model from Table 5 is used 1 time with a rate of 5.9%. ANFIS was applied in the study by Oh & Pradhan (2011), evidential belief function by Althuwaynee et al (2012), factor analysis model (FAM) by Roslee et al (2012), ANN by Alkhasawneh, Ngah, Tay, & Isa, (2014), weighted overlay method by Mahmud et al (2013), decision tree by Alkhasawneh, Ngah, Tay, Ashidi, et al (2014), chi-squared automatic interaction (CHAID) by Althuwaynee et al (2014), and Poisson distribution by Tay et al (2014).

**Table 5:** Models used in articles for the first period (2011-2016)

Model	Amount of Articles in which the Model was Used	Rate of the Model being Used in Articles (%)
Adaptive Neuro-Fuzzy Inference Systems (ANFIS)	1	5.9
Frequency ratio	2	11.8
Neuro-Fuzzy	2	11.8
Evidential Belief Function	1	5.9
Factor Analysis Model (FAM)	1	5.9
Artificial Neural Network (ANN)	1	5.9
Weighted Overlay Method (WOM)	1	5.9
Decision Tree	1	5.9
Logistic Regression	2	11.8
Chi-Squared Automatic Interaction detection (CHAID)	1	5.9
Poisson Distribution	1	5.9
Analytic Hierarchy Process (AHP)	1	5.9
Weighted Linear Combination (WLC)	1	5.9
Spatial Multi-Criteria Evaluation (SMCE)	1	5.9

Table 6 shows the models used in articles for the third period from 2017 to 2022. In this period, the number of models used was the same as that in the previous period (2011 to 2016) but more than that in the first period (2000-2010). Fourteen models were used from 2017 until 2022. They are support vendor machine, index of entropy, weighted overlay method, AHP, frequency ratio, information value, modified information value, AdaBoost (AB), alternating decision tree (ADTree), logistic regression, logistic model tree, random forest, bivariate statistical, and artificial neural network (ANN).

There were changes in the most commonly used parameters for this period: Logistic regression was used only 1 time, a rate of 6.3%, but the AHP and weighted overlay method were used two times, a rate of 12.5%, becoming the most commonly used parameters. Moreover, there are studies that used more than one parameter in this period. Logistic regression, random forest, and logistic model tree were used together for the study carried out in the Cameron Highland by V. Nhu, Mohammadi, Shahabi, Ahmad, Al-ansari, Shirzadi, Geertsema, et al (2020). The frequency ratio, information value and modified information value were also used together in a study carried out on Penang Island by Huqqani et al (2019). V. Nhu, Mohammadi, Shahabi, Ahmad, Al-ansari, Shirzadi, Clague, et al (2020) also applied two models, AdaBoost (AB) and Alternating Decision Tree (ADTree), in their study carried out in the Cameron Highland.

**Table 6:** Models used in articles for the third period (2017-2022)

Model	Amount of Articles in which the Model was Used	Rate of the Model being Used in Articles (%)
Support Vendor Machine	1	6.3
Index of Entropy	1	6.3
Weighted Overlay Method (WOM)	2	12.5
Analytic Hierarchy Process (AHP)	2	12.5
Frequency Ratio	1	6.3
Information value (IV)	1	6.3
Modified Information Value (MIV)	1	6.3
AdaBoost (AB)	1	6.3
Alternating Decision Tree (ADTree)	1	6.3
Logistic Regression	1	6.3
Logistic Model Tree	1	6.3
Random Forest	1	6.3

#### 4. Conclusion

The analysis and review of papers on landslide susceptibility in Malaysia from 2000 to 2022 enables us to understand the factors, input data and methods commonly used in Malaysia for landslide studies. The results have shown the trends in landslide susceptibility mapping published during the selected periods, the parameters that have been used, and the models and study areas that are involved. All of these have been discussed in detail in this paper.

The landslide susceptibility mapping was focused on Malaysia's territory only, which involves all of the states, but there are states that are not listed as study areas because they are not studied in the published articles. The study areas involved in landslide susceptibility studies are Penang, Perak, Selangor, Sabah, Sarawak, Pahang, Kelantan and Kuala Lumpur.

The number of published articles on this topic also shows an increasing trend from 2000 to 2022. Most of the publications are published in English rather than in Malay language. Only one publication was identified that was published in Malay language. Moreover, the highest number of publications was recorded in 2010, 2011 and 2014, with 4 Twenty-one parameters have been identified that have been used in landslide susceptibility mapping in Malaysia for the last 22 years. Slope was the parameter used in most of the publications, followed by precipitation, curvature and aspect.

Moreover, these parameters are also divided into three categories and have been discussed in detail in the discussion section. Models used in landslide susceptibility studies in Malaysia were also identified. Twenty-five models were used, and logistic regression was the most commonly used model, followed by the frequency ratio, ANN and weighted overlay method. However, the trend of the logistic regression model shows a decreasing trendline where it is used most in the first and second periods, and for the third period, the weighted overlay method and AHP become the most commonly used models.

This review lacks landslide susceptibility studies in Malaysia; only 31 articles can be identified. Moreover, landslides are dangerous disasters that cause much damage and threaten human lives. Therefore, in the future, it is recommended to conduct more landslide susceptibility studies in Malaysia and provide more details about landslides.

## 5. Acknowledgement

This study was funded by Ministry of Higher Education Malaysia for Long Term Research Project with Project Code: LRGS/1/2016/UTM/01/1/3 Intelligent Green Energy Landslide Real-Time Alerting System in The Tropics and research grant number 203/PJJAUH/6776003 LandGIS – An Eco Smart GIS Based Real-Time Data Model For Landslide Spatial Visualization.

## References

- A.A. Ab Rahman, N. Abd Majid, & S.N. Selamat. (2020). A comprehensive deriving the factors of landslide happened in Malaysia. *International Journal on Emerging Technologies*, 11(5), 310–314. [https://www.researchtrend.net/ijet/pdf/46 A Comprehensive Deriving the Factors of Landslide Happened in Malaysia-3209-A.A.pdf](https://www.researchtrend.net/ijet/pdf/46%20A%20Comprehensive%20Deriving%20the%20Factors%20of%20Landslide%20Happened%20in%20Malaysia-3209-A.A.pdf)
- Alkhasawneh, M. S., Ngah, U. K., Tay, L. T., Ashidi, N., Isa, M., & Al-batah, M. S. (2014). *Modeling and Testing Landslide Hazard Using Decision Tree*. 2014.
- Alkhasawneh, M. S., Ngah, U. K., Tay, L. T., & Isa, N. A. M. (2014). Determination of importance for comprehensive topographic factors on landslide hazard mapping using artificial neural network. *Environmental Earth Sciences*, 72(3), 787–799. <https://doi.org/10.1007/s12665-013-3003-x>
- Althuwaynee, O. F., Pradhan, B., & Ahmad, N. (2014). Landslide susceptibility mapping using decision-tree based CHi-squared automatic interaction detection (CHAID) and Logistic regression (LR) integration. *IOP Conference Series: Earth and Environmental Science*, 20(1). <https://doi.org/10.1088/1755-1315/20/1/012032>
- Althuwaynee, O. F., Pradhan, B., & Lee, S. (2012). Application of an evidential belief function model in landslide susceptibility mapping. *Computers and Geosciences*, 44, 120–135. <https://doi.org/10.1016/j.cageo.2012.03.003>
- Bong, Y. S., Zulkifly, M. H., Sati, I., & Harahap, H. (2018). *GIS Analysis & Landslide Susceptibility Mapping (LSM) in Murum Reservoir Region, Sarawak*. 7, 456–459.
- Bui, D. T., Shahabi, H., Shirzadi, A., Chapi, K., Alizadeh, M., Chen, W., Mohammadi, A., Ahmad, baharin Bin, Panahi, M., Hong, H., & Tian, Y. (2018). Landslide Detection and Susceptibility Mapping by AIRSAR Data Using Support Vector Machine and Index of Entropy Models in Cameron. *Remote Sensing*, 10(1527), 1–32. <https://doi.org/10.3390/rs10101527>
- Daniel, M. T., Ng, T. F., Abdul Kadir, M. F., & Pereira, J. J. (2021). Landslide Susceptibility Modeling Using a Hybrid Bivariate Statistical and Expert Consultation Approach in Canada Hill, Sarawak, Malaysia. *Frontiers in Earth Science*, 9(March), 1–15. <https://doi.org/10.3389/feart.2021.616225>
- Diana, M. I. N., Muhamad, N., Taha, M. R., Osman, A., & Alam, M. M. (2021). Social vulnerability assessment for landslide hazards in Malaysia: A systematic review study. *Land*, 10(3), 1–19. <https://doi.org/10.3390/land10030315>
- Dias, H. C., Holbling, D., & Grohmann, C. H. (2021). Landslide Susceptibility Mapping In Brazil: A Review. *Geosciences (Switzerland)*, 11(10), 1–15. <https://doi.org/10.3390/geosciences1100425>
- Fanos, A. M., & Pradhan, B. (2019). A novel rockfall hazard assessment using laser scanning data and 3D modelling in GIS. *Catena*, 172(March 2018), 435–450. <https://doi.org/10.1016/j.catena.2018.09.012>
- Huqqani, I. A., Tay, L. T., & Saleh, J. M. (2019). Analysis of landslide hazard mapping of Penang island Malaysia using bivariate statistical methods. *Indonesian Journal of Electrical Engineering and Computer Science*, 16(2), 781–786. <https://doi.org/10.11591/ijeecs.v16.i2.pp781-786>



- Ibrahim, M. ., Z.Mustaffa, Balogun, A. ., Indra, S. H. H., & Ain, A. N. (2022). Landslide's analysis and Hazard mapping based on Analytic Hierarchy Process ( AHP ) using GIS , in Lawas , Sabah-Sarawak Landslide ' s analysis and Hazard mapping based on Analytic Hierarchy Process ( AHP ) using GIS , in. *IOP Conference Series: Earth and Environmental Science*, 1–10. <https://doi.org/10.1088/1755-1315/1064/1/012031>
- Izzat, M., Hanafiah, M., Solemon, B., Omar, R., Roslan, R., Wahab, A., Nor, I., Baharuddin, Z., & Gunasagaran, V. (2019). *Landslide Susceptibility Assessment for Cameron Highlands using Analytical Hierarchy Process*. 1, 3494–3499. <https://doi.org/10.35940/ijeat.A2673.109119>
- Jason Loh, & Amanda Yeo. (2022, January 17). Thoughts BERNAMA - - Stop Illegal Logging Once and For All to Minimise the Occurrence of Landslides and Floods. *Bernama*. <https://www.bernama.com/en/thoughts/news.php?id=2044001>
- Kazmi, D., Qasim, S., Harahap, I. S. H., & Baharom, S. (2017). Landslide of Highland Towers 1993: a case study of Malaysia. *Innovative Infrastructure Solutions*, 2(1), 1–9. <https://doi.org/10.1007/s41062-017-0069-4>
- Lee, S. (2005). Application of logistic regression model and its validation for landslide susceptibility mapping using GIS and remote sensing data. *International Journal of Remote Sensing*, 26(7), 1477–1491. <https://doi.org/10.1080/0143116041233131012>
- Lee, Saro. (2019). *Current and Future Status of GIS-based Landslide Susceptibility Mapping : A Literature Review*. 35(1), 179–193.
- Lee, Saro, Resources, M., & Pradhan, B. (2007). *Landslide hazard mapping at Selangor , Malaysia using frequency ratio and logistic regression models* *June 2014*. <https://doi.org/10.1007/s10346-006-0047-y>
- Mahmud, A. R., Awad, A., & Billa, R. (2013). Landslide susceptibility mapping using averaged weightage score and GIS: A case study at Kuala Lumpur. *Pertanika Journal of Science and Technology*, 21(2), 473–486.
- Majid, N. A., Taha, M. R., & Selamat, S. N. (2020). Historical landslide events in Malaysia 1993-2019. *Indian Journal of Science and Technology*, 13(33), 3387–3399. <https://doi.org/10.17485/ijst/v13i33.884>
- Mezughi, T. H., & Abulghasem, Y. A. (2016). *GIS-based logistic regression model for landslide susceptibility mapping : a case study along the E-W highway , Malaysia*. December, 6–8.
- Muaz Abu Mansor Maturidi, A., Kasim, N., Abu Taib, K., Nur Aifa Binti Wan Azahar, W., & Husain Husain, N. M. (2020). Rainfall-Induced Landslides in Cameron Highland Area, Malaysia. *IOP Conference Series: Materials Science and Engineering*, 917(1). <https://doi.org/10.1088/1757-899X/917/1/012019>
- Mukhlisin, M., Idris, I., Salazar, A. S., & Nizam, K. (2010). GIS Based Landslide Hazard Mapping Prediction in Ulu Klang, Malaysia. *ITB Journal of Science*, 42(2), 163–178.
- Nhu, V.-H., Mohammadi, A., Shahabi, H., Ahmad, B. Bin, Al-Ansari, N., Shirzadi, A., Geertsema, M., Kress, V. R., Karimzadeh, S., Kamran, K. V., Chen, W., & Nguyen, H. (2020). Landslide Detection and Susceptibility Modeling on Cameron Highlands (Malaysia) : a Comparison between Random Forest, Logistic Regression and Logistic Model Tree Algorithms. *Forest*, 11(830), 1–28.
- Nhu, V., Mohammadi, A., Shahabi, H., Ahmad, B. Bin, Al-ansari, N., Shirzadi, A., Clague, J. J., & Jaafari, A. (2020). *Landslide Susceptibility Mapping Using Machine Learning Algorithms and Remote Sensing Data in a Tropical Environment*.
- Nhu, V., Mohammadi, A., Shahabi, H., Ahmad, B. Bin, Al-ansari, N., Shirzadi, A., Geertsema, M., & Kress, V. R. (2020). *Landslide Detection and Susceptibility Modeling on Cameron Highlands ( Malaysia ) : A Comparison between Random Forest , Logistic Regression and Logistic Model Tree Algorithms*.
- Oh, H. J., & Pradhan, B. (2011). Application of a neuro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area. *Computers and Geosciences*, 37(9), 1264–1276. <https://doi.org/10.1016/j.cageo.2010.10.012>
- Pardeshi, S. D., Autade, S. E., & Pardeshi, S. S. (2013). Landslide hazard assessment: Recent trends and techniques. *SpringerPlus*, 2(1). <https://doi.org/10.1186/2193-1801-2-523>
- Pradhan, B. (2010). Remote sensing and GIS-based landslide hazard analysis and cross-validation using multivariate logistic regression model on three test areas in Malaysia. *Advances in Space Research*, 45(10), 1244–1256. <https://doi.org/10.1016/j.asr.2010.01.006>
- Pradhan, B., & Lee, S. (2009). *Landslide risk analysis using artificial neural network model focussing on different training sites*. 4(1), 1–15.
- Pradhan, B., Lee, S., Mansor, S., & Buchroithner, M. (2008). *Utilization of optical remote sensing data and geographic information system tools for regional landslide hazard analysis by using binomial logistic regression model*. October 2008. <https://doi.org/10.1117/1.3026536>
- Pradhan, B., Lee, S., & Resources, M. (2009). *Regional landslide susceptibility analysis using back-propagation neural Regional landslide susceptibility analysis using back-propagation neural network model at Cameron. March*. <https://doi.org/10.1007/s10346-009-0183-2>

- Pradhan, B., Mansor, S., Pirasteh, S., & Manfred, F. (2011). *Landslide hazard and risk analyses at a landslide prone catchment area using statistical based geospatial model*. 1161. <https://doi.org/10.1080/01431161.2010.484433>
- Pradhan, B., Oh, H.-J., & Buchroithner, M. (2010). Weights-of-evidence model applied to landslide susceptibility mapping in a tropical hilly area. *Geomatics, Natural Hazards and Risk*, 1(3), 199–223. <https://doi.org/10.1080/19475705.2010.498151>
- Pradhan, B., Sezer, E. A., Gokceoglu, C., & Buchroithner, M. F. (2011). Landslide Susceptibility Mapping by Neuro-Fuzzy Approach in a Landslide-Prone Area. 4164 *IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING*, 48(June 2014), 4164–4177. <https://doi.org/10.1109/TGRS.2010.2050328>
- Pradhan, B., Youssef, A., & Varathrajoo, R. (2010). Approaches for delineating landslide hazard areas using different training sites in an advanced artificial neural network model Approaches for Delineating Landslide Hazard Areas Using Different Training Sites in an Advanced Artificial Neural Network Model. *Geo-Spatial Information Science*, 5020(2), 93–102. <https://doi.org/10.1007/s11806-010-0236-7>
- Roslee, R., Jamaluddin, T. A., & Talip, M. A. (2012). Landslide Susceptibility Mapping (LSM) at Kota Kinabalu, Sabah, Malaysia using Factor Analysis Model (FAM). *Journal of Advanced Science and Engineering Research*, 2(June 2015), 80–103. <https://www.sign-ific-ance.co.uk/dsr/index.php/JASER/article/view/134>
- Rusli, N., & Syahira, N. (2018). *Analysis of Landslide Prediction As Related To Landuse Changes Analysis of Landslide Prediction As Related To* (Vol. 1, Issue August).
- Saadatkah, N., Kassim, A., & Lee, L. M. (2014). Qualitative and quantitative landslide susceptibility assessments in Hulu Kelang area, Malaysia. *Electronic Journal of Geotechnical Engineering*, 19 C(January), 545–563.
- Selamat, S. N., Majid, N. A., Taha, M. R., & Osman, A. (2022). Landslide Susceptibility Model Using Artificial Neural Network (ANN) Approach in Langat River Basin, Selangor, Malaysia. *Land*, 11(6), 833. <https://doi.org/10.3390/land11060833>
- Sezer, E. A., Pradhan, B., & Gokceoglu, C. (2011). Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia. *Expert Systems with Applications*, 38(7), 8208–8219. <https://doi.org/10.1016/j.eswa.2010.12.167>
- Shahabi, H., & Hashim, M. (2015). *Landslide susceptibility mapping using GIS-based statistical models and Remote sensing data in tropical environment*. <https://doi.org/10.1038/srep09899>
- Sim, K. Ben, Lee, M. L., & Wong, S. Y. (2022). A review of landslide acceptable risk and tolerable risk. In *Geoenvironmental Disasters* (Vol. 9, Issue 1). <https://doi.org/10.1186/s40677-022-00205-6>
- Simon, N., Akhir, J. M., Napiah, A., & Kee, T. H. (2009). Pemetaan potensi bencana tanah runtuh menggunakan faktor penilaian bencana tanah runtuh dengan pendekatan GIS. *Bulletin of the Geological Society of Malaysia*, 55, 47–53.
- Siti, C., Koh, N., Lee, P., Abu Bakar, R., Aziz, S., & Raihan Taha, M. (2022). Pengurusan risiko bencana tanah runtuh di Semenanjung Malaysia (Disaster risk management of landslides in Peninsular Malaysia). *Bulletin of the Geological Society of Malaysia*, 73(May), 23–33. <https://doi.org/10.7186/bgsm73202203>
- Tay, L. T., Alkhasawneh, M. S., & Lateh, H. (2016). *Landslide Hazard Mapping of Penang Island Using Poisson Distribution with Dominant Factors*. January 2014. <https://doi.org/10.5923/c.jce.201402.12>
- Tay, L. T., Alkhasawneh, M. S., Lateh, H., Hossain, K., & Kamil, A. A. (2014). Landslide Hazard Mapping of Penang Island Using Poisson Distribution with Dominant Factors. *Journal of Civil Engineering Research*, 2014(3A), 72–77. <https://doi.org/10.5923/c.jce.201402.12>
- Udin, W. S., Yahaya, N. N., & Shariffuddin, S. I. M. (2021). Landslide Susceptibility Assessment Using Geographic Information System in Aring, Gua Musang, Kelantan. *IOP Conference Series: Earth and Environmental Science*, 842(012008), 0–5.
- USGS. (2019). *What is a landslide and what causes one?* | U.S. Geological Survey. USGS Science for a Changing World. <https://www.usgs.gov/faqs/what-landslide-and-what-causes-one>
- Yusof, N. M., & Pradhan, B. (2014). Landslide susceptibility mapping along PLUS expressways in Malaysia using probabilistic based model in GIS. *IOP Conference Series: Earth and Environmental Science*, 20(1). <https://doi.org/10.1088/1755-1315/20/1/012031>