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Review Article

A Review of Landslide Conditioning Factors in the Tropical Forests

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ABSTRACT

A variety of natural and human-induced factors can trigger landslides. A combination of these factors, with several key factor characteristics, may increase the risk of landslides. This paper reviews the comprehensive conditioning factors that contribute to landslide occurrence. Landslide occurrence varied with the conditioning factors and has been documented in response to the need to understand and mitigate the risks associated with these natural events. Twenty-six conditioning factors were identified in landslide occurrences from 16 articles reviewed using a systematic literature review with PRISMA guidelines. All 16 articles study landslides: Malaysia (66% of the article), Indonesia (13% of the article), Vietnam, Philippines and Brazil (7% of the article for each country) mostly applied the conditioning factors for landslides susceptibility map modeling. The discussion of this work focuses on the conditioning factor of landslides in tropical forests. This study is crucial in improving risk assessment and developing effective mitigation and management strategies. In addition, the information from this study can be used in future studies to develop and validate models that simulate landslide processes under different conditions and are essential for predicting potential landslide events and their impacts.

Keywords: Conditioning factor, landslide, risk, tropical forests, predisposing factor

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INTRODUCTION

A landslide is a geological occurrence involving soil movement in any downslope due to gravity force. Various landslides occur in terms of size and speed and can happen in various landscapes (Medwedeff et al., 2020). Landslides are a reoccurring problem, often involving natural and human-induced factors (Sezer et al., 2011). Justifying and comprehending the factors behind landslide occurrence is essential for risk assessment, public safety, environmental protection, infrastructure resilience, and informed decision-making at various levels. It enables a proactive approach to reducing landslide risks and enhancing disaster preparedness and response.

To date, distinctive disciplines of geotechnical engineering and earth sciences have been developed to investigate landslides' mechanics systematically and causes integrated with various machine learning algorithms (Reichenbach et al., 2018). The findings may provide insights into the development of more efficient and accurate landslide-predictive models that decision-makers and land-use managers can use to mitigate landslide hazards. They can also be instrumental in policy and decision-making regarding natural risk management.

Therefore, this review discusses the substantial steps in understanding the causes of landslides by systematically reviewing the conditioning factor contributing to landslides in tropical forests.

Concepts of Landslides and Conditioning Factors

Some key factors generally contributing to landslides are topography, hydrology, geology, soil and vegetation. Shirvani (2020) describes areas characterized by the factors mentioned above, also known as predisposing factors, as more susceptible to landslides. These factors set the stage for landslides by creating an elevated risk of slope failure. Predisposing factors often interact with triggering factors that can be (1) natural triggering factors such as heavy rainfall, earthquakes, and flood frequency or (2) anthropogenic factors such as forest fragmentation, forest loss, logging, and mining (Peduzzi, 2010; Shirvani, 2020). In tropical countries, where heavy rainfall and steep terrain are common (Forbes et al., 2012), several conditioning factors contribute to landslide occurrence, for example, rainfall intensity, topography, geological conditions, soil characteristics, land use, land cover change and forestry (LULUCF) and previous landslide history. Medwedeff et al. (2020) suggested that the contributing factors of landslides, i.e., topography, hydrology, geology, soil, and vegetation, require site-specific management for further investigate the physical controls on landslide size, thus dictating the degree to which landslides contribute to secondary hazards such as flooding and debris flows. Flood and debris flow following landslides may result from the intense and prolonged rainfall that saturated the soil, reducing its stability and triggering landslides (Canavesi et al., 2020; Diara et al., 2022; Lee, 2019; Soma & Kubota, 2018). The hilly terrain is prone to landslides and debris flows, mainly when rainwater infiltrates the soil (Li et al., 2016; Roback et al., 2018). In addition, in some areas, experiencing LULUCF will make the hillslope more susceptible to landslides since the stabilizing effect of the slope characterized by vegetation roots is removed (Diara et al., 2022; Soma & Kubota, 2018). The predisposing and triggering factors of landslides vary according to landscape.

Landslides are often called major wasting events because they involve the rapid movement and displacement of significant amounts of Earth materials down a slope, such as rock, soil, and debris, especially in areas prone to landslides. These events result in the "wasting" or loss of material from the original location, and the substantial impact varies according to the landscape, environment, and human activities (Canavesi et al., 2020; Ibrahim et al., 2021; Nhu et al., 2020). The magnitude of the Landslide is the crucial factor in the wasting events. Medwedeff et al. (2020) highlight that cohesive strength and hillslope relief are correlated to landslide size and averaged to the distribution of hillslope in a landscape. The triggering factors in the landscape heightened the probability of landslide occurrence.

Recent advances in observation technology of remotely sensed imagery integrated with problem-solving algorithms and machine learning have facilitated landslide modeling and zonation susceptibility for hazard prediction and mitigation measures (Lee, 2019; Nsengiyumva & Valentino, 2020; Shirvani, 2020; Wang et al., 2021). In this work, however, we focus on identifying conditioning factors for landslide occurrence, and the application of modeling and algorithm-based assessment and monitoring for landslides is not included. The significance of this work is to provide decision-makers and land use managers with an understanding of the predisposing and triggering factors in areas prone to landslides and initial planning action for them to take action before modeling and algorithm can be made. Peduzzi (2010) discussed that decision-makers need to be convinced of the best management of natural resources in forest areas to protect human lives and their welfare from hazards. Thus, the lack of spatial vector and raster data due to high cost and availability and the lack of landslide-related experts in forestry-related agencies is one of the most significant aspects of this review work, which discusses the conditioning factors of landslides in forest areas where landslides are common (Hashim et al., 2017). Observing the conditioning factors without applying technology, modeling, and algorithms can further help related agencies take early preventive action by simply observing the surrounding conditions of the related factors.

MATERIALS AND METHODS

An illustrated four-fold framework for the SLR (Mohamed Shaffril et al., 2021) in Figure 1 is proposed for this review of conditioning factors for landslide occurrence. Keyword search is the first step in SLR in constructing a literature database. The search was conducted on the selected database in the Web of Science, Scopus, Science Direct, Google Scholars, and Google engine search using keywords and Boolean search criteria applied to the "title," "abstract," and "keywords" of the publications. The search content focuses on 'landslide,' 'conditioning factors,' 'tropical,' 'landslide mitigation,' and 'landslide susceptibility.' From the preliminary search of the title and the abstract, there is no limitation on literature and information type as long as the content is related to landslides. Since the study on landslides has systematically documented from 1900 with more than 30,000 results using the keywords mentioned above, this study has set the custom range search from 2010 to the present.

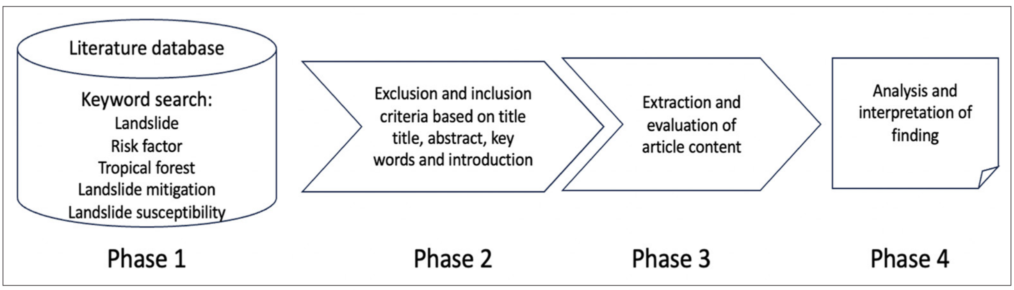

Figure 1. The Methodology for systematic literature review (SLR) search

A preferred reporting item for systematic reviews and meta-analyses (PRISMA) template (Page et al., 2021) is illustrated in Figure 2, which shows the 222 articles found from the identification using keyword search and excluded 196 articles since the articles not related to tropical forests. Next, all 24 remaining articles were screened based on indicators or criteria that lead to a landslide occurrence, which later excluded five articles. The remaining 19 articles were extracted by reading the eligibility of the articles that discussed the indicator or criteria of landslide occurrence. After the extraction, three articles were removed due to ineligibility. Finally, six articles from the analysis and interpretation of the findings are included as a literature database. A total of 26 factors are listed in Table 1 following the PRISMA guideline for identifying the conditioning factors, and these are the factors discussed in this review.

Conditioning Factor for Landslide Occurrence in Tropical Forests

The literature database following PRISMA guidelines has reviewed 16 articles on landslide occurrence in tropical forests from the last 13 years. Twenty-six conditioning factors for landslide occurrence have been identified. The adaptation of these 26 factors varies since different landscapes have different conditioning factors, and the priority of the factors also varies (Ibrahim et al., 2021). The investigated articles covered five countries with tropics characterization: Malaysia (66% of the article), Indonesia (13% of the article), Vietnam, Philippines, and Brazil (7% of the article for each country). All the discussed

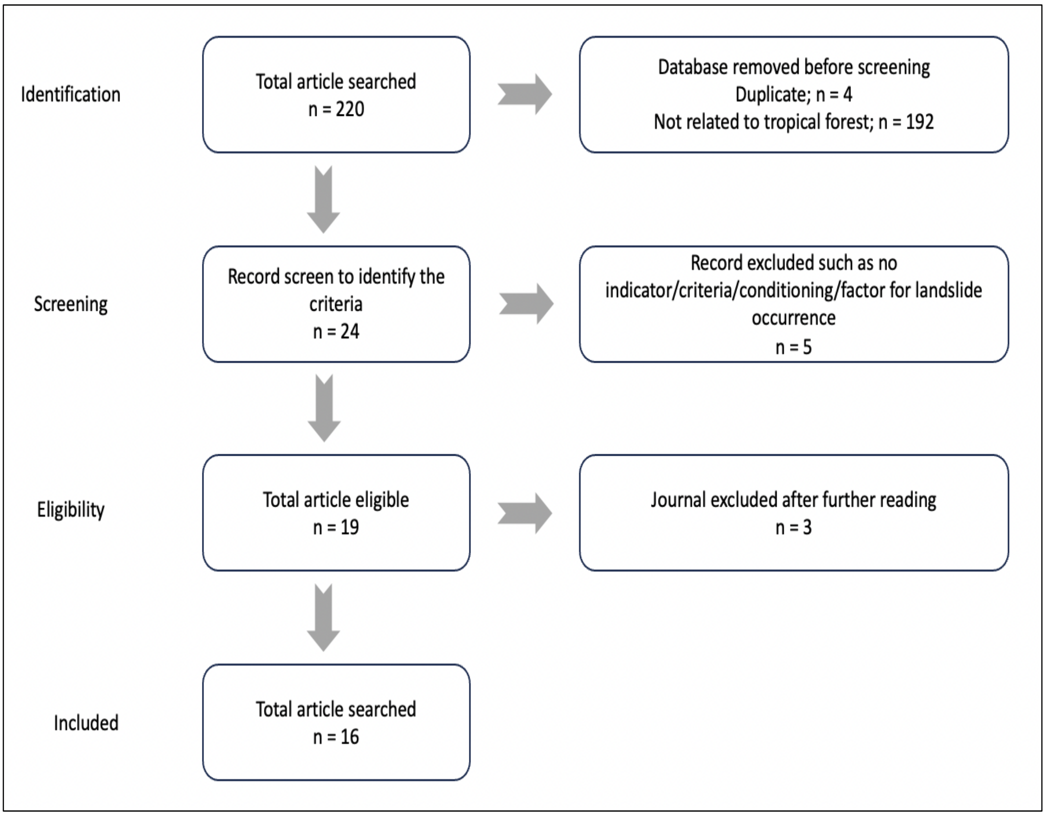

Figure 2. The literature database was developed based on PRISMA guidelines

Table 1
List of conditioning factors for landslide occurrence (Source: Author)

No.	Conditioning factor	Review from previous work*															
		A	B	C	D	E	H	I	J	K	L	M	N	O	P	Q	R
1	Rainfall						√	√		√	√	√	√	√		√	√
2	Slope	√	√		√	√	√	√	√	√	√	√	√	√	√	√	√
3	LULC	√	√	√	√	√	√	√	√		√	√		√	√	√	√
4	TWI	√							√				√			√	
5	Lithology	√	√		√	√	√	√	√	√	√	√	√			√	√
6	Distance to stream	√	√	√	√	√	√				√	√	√		√	√	√
7	Total Curvature	√				√	√				√		√			√	
8	Elevation	√	√	√		√			√	√	√		√			√	
9	SPI	√					√		√	√						√	
10	Soil		√	√	√	√	√	√	√	√		√		√	√	√	√
11	Aspect	√	√		√	√	√			√	√	√	√				√
12	NDVI		√	√	√	√	√					√			√	√	√

Table 1 *(Continue)*

No.	Conditioning factor	Review from previous work*															
		A	B	C	D	E	H	I	J	K	L	M	N	O	P	Q	R
13	Distance to road	√	√			√	√				√	√	√		√	√	√
14	TRI	√															
15	Forest status													√			
16	Road density															√	
17	River density										√					√	
18	Profile Curvature	√	√						√	√						√	
19	Plan Curvature		√	√	√				√	√					√		
20	Distance to fault	√	√	√		√	√					√			√	√	√
21	Fault density				√						√						
22	Sediment transport index (STI)									√							
23	Landform						√	√									
24	Slope gradient								√								
25	Slope curvature								√								
26	Flow accumulation								√								

*A: Al-Najjar et al. (2019); B: Javier and Kumar (2019); C: Sezer et al. (2011); D: Pradhan et al. (2010); E: Pradhan and Lee (2010); F: Althuwaynee et al. (2012); G: Diara et al. (2022); H: Canavesi et al. (2020); I: Ibrahim et al. (2021); J: Soma and Kubota (2018); K: Hashim et al. (2017); L: Selamat et al. (2022); M: Arfadly et al. (2023); N: Pradhan (2011); O: Nhu et al. (2020); P: Shahabi and Hashim (2015)

articles adopt the conditioning factors to model the landslide occurrence with a landslide susceptibility map (LSM). The conditioning factors reported in this review can also be found in all areas of the globe and may not represent tropical areas because tropical regions vary widely in topography. Factors such as altitude, proximity to the equator, prevailing winds, and geological history all influence the landscape of a particular tropical area. The conditioning factors reviewed and reported in this work can accurately predict the occurrence of landslides when the areas share the same characteristics as those reported in the 26 reviewed works (Gonzalez et al., 2024).

The most common conditioning factor for landslide occurrence is slope (100%), followed by land use and land cover (LULC) and soil (94%) and lithology (88%). The other factors that can be related to landslide occurrence are distance to stream (75%), aspect (69%), distance to road and distance to fault (63%), elevation, rainfall and normalised different vegetation index (NDVI) (56%). These 11 conditioning factors are prevalent in tropical forests as predisposing factors, and two of them, LULC (94%) and rainfall

(56%), are the triggering factors. Literature also records total curvature, stream power index (SPI), plan curvature, profile curvature, terrain wetness index (TWI), altitude, river density, fault density, landform, terrain ruggedness index (TRI), forest status, road density, sediment transport index (STI), slope gradient, slope curvature and flow accumulation as conditioning factors of landslides in tropical forests. Even though these 16 factors are not the common conditioning factors of landslides as used by selected researchers cited in Table 1, the availability of this information will help the decision-makers increase the accuracy of landslides prediction.

LULC, distance to stream, elevation, distance to river, distance to fault, and rainfall are straightforward conditioning factors that decision-makers or the public can observe to determine the occurrence of potential landslides. However, soil, lithology, aspect, and NDVI require experts to initially analyze the characteristics that contribute to landslides. Suppose the decision makers or the public are well-known in the areas. In that case, the information on soil and lithology can be understood through information usually available from geological agencies (Pradhan et al., 2010; Sezer et al., 2011). Meanwhile, for aspect and NDVI, the data can be obtained from satellite imagery and require image processing. The primary purpose of this NDVI is to differentiate vegetation density (Sezer et al., 2011; Nhu et al., 2020). If aspects and NDVI are unavailable, changes or unusual events identified from the triggering factor of rainfall will help decision-makers or the public predict the potential of landslide occurrence when those six conditioning factors (slope, LULC, distance to stream, elevation, distance to river, and distance to fault) exist in those particular areas.

Malaysia has experienced heavy and continuous rainfall that leads to floods and landslides (Pradhan et al., 2010a) with debris flow. In extreme rainfall conditions, the soil layers become oversaturated, and steep slopes lose stability and collapse almost simultaneously, as Komoo (2022) stressed following debris flow landslides that happened at the end of 2021 in Malaysia. He added that additional factors include geological factors (soil and rock type, basin shape and rock structure) and non-geological factors (forest clearance in steep areas; slope cuts to build infrastructure, including roads; and land clearing for agriculture). Soma and Kubota (2018) and Javier and Kumar (2019) also found that areas covered with sparse vegetation have a higher probability of landslide occurrence, affecting slope stability. Gonzalez et al. (2024) highlighted that when rainwater reaches the soil surface and is absorbed into the soil, soil moisture increases, triggering landslides in tropical areas (Aristizabal et al., 2017; Lee et al., 2014; Mansor et al., 2018; Maturidi et al., 2021; Saadatkhah et al., 2016).

Each conditioning factor the researchers selected has varied justification depending on their landscape characteristics. Slope directly influences the soil strength and Landslide (Park & Kim, 2019). Aspects related to meteorological and morphological characteristics represent the horizontal direction of mountain/hill slope faces (Youssef et al., 2015). Lithology can be indicative of soil characteristics. These characteristics can be diverse and may influence erosion, ground stability and slide occurrence (Kalantar et al., 2018; Mancini et al., 2010). Elevation can influence landslide predictions; an area with high elevation has a higher probability of elevation when other conditioning factors and triggering factors exist (Kalantar et al., 2018; Sezer et al., 2011). Plan and profile curvatures are the descending flow acceleration (erosion/deposition rate) and the flow velocity variation of a slope, respectively (Kalantar et al., 2018). Additional information on cross-sectional curvature helps assess the curvature across a slope, identifying concave features like channels by intersecting with the slope's normal plan and being perpendicular to its aspect direction.

In contrast, longitudinal curvature calculates curvature along the slope's downward direction by intersecting with the average slope plan and aspect direction (Alkhasawneh et al., 2013; Ehsani & Malekian, 2012). The distance to the fault is considered because landslides are more likely to occur near faults and rivers due to factors like erosion and unstable ground, including distance to streams and roads (Jebur et al., 2015; Kalantar et al., 2018). LULUCF can have different events of landslides. Forest areas cleared, for example, harvesting activity coupled with heavy rainfall can cause large landslides (Hashim et al., 2018) and forests characterized by high slopes are evidenced to have widespread landslides due to unstable landforms (Canvensi et al., 2020). Areas with sparse vegetation may reduce the soil strength since fewer trees absorb the soil moisture, and soil strength is reduced due to fewer roots holding the soil, thus increasing the potential of soil erosion and landslides (Nhu et al., 2020). NDVI information used as the conditioning factor can also help predict landslide occurrence, as NDVI provides information on vegetation densities (Soma & Kubota, 2018).

Identifying the conditioning factors for landslide susceptibility modeling is beneficial because it allows for a more accurate and effective landslide risk assessment. The precision of the prediction model of landslides, for example, LSM, needs prioritizing the conditioning factors (Hashim et al., 2018; Norizah, 2022), which may lead to better predictions and more targeted mitigation efforts. This prioritization helps allocate resources efficiently, enhances hazard mapping, and ultimately aids in reducing the impact of landslides on communities and the environment.

CONCLUSION

In conclusion, conditioning factors play an important role in determining the susceptibility of tropical forests to landslides. These factors encompass a wide range of geological, topographical, climatic, and environmental characteristics that collectively influence the likelihood of landslides occurring in these regions. Understanding these conditioning factors is vital before landslide susceptibility modeling and predictions can be made. Although this SLR focuses on tropical forests, the accuracy of landslide susceptibility modeling that will be developed using conditioning factors reviewed in this work will depend on the similarity of area characteristics. The relationship of how each conditioning factor influences one another is also crucial in ensuring the accuracy of landslide susceptibility modeling. For example, rainfall patterns can affect soil saturation, influencing slope stability. In addition, prioritizing which conditioning factors influence landslide occurrence most is very important to accurately develop the landslide susceptibility models, and this involves decision-making on multiple conditioning factors. Understanding the Methodology or algorithms for multi-criteria decision-making analysis (MCDA) can create robust landslide susceptibility models that provide valuable insights into areas at high risk of landslides. Therefore, understanding the conditioning factors allows for implementing targeted mitigation efforts. It enables authorities and stakeholders to focus their resources and interventions on areas with the highest landslide susceptibility, reducing the potential for disaster and safeguarding human communities and the natural environment. In addition, this, in turn, aids in land-use planning, infrastructure development, and disaster preparedness.

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