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Assessment of Landslide Vulnerability in Urban Areas Using GIS and Remote Sensing: A Study in Ambon City

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ABSTRACT

Slope stability and land movements, commonly referred to as landslides, are natural hazards that involve the shifting of materials like soil, rock, and debris, primarily caused by the force of gravity. This research utilized both qualitative and quantitative approaches, focusing on spatial analysis by examining primary and secondary data derived from satellite imagery, observations, and pertinent institutions. Processing of the collected data using specialized software like Global Mapper 20, ArcGIS 10.8.1, and ER Mapper 8.1. The findings of this investigation disclosed that a significant portion of Ambon City, roughly 51.63% of its area, exhibited high susceptibility to landslides. Conversely, only about 16.26% of the total area demonstrated very low or low vulnerability. Similar trends were observed in urbanized regions, where the majority, around 39.01%, were classified as highly vulnerable (Z-4). In contrast, approximately 35.09% showed very low vulnerability (Z-1), and 11.89% depicted low vulnerability (Z-2). The study's findings clearly highlight a critical situation in Ambon City, where a substantial 89% of its territory, characterized by mountainous landscapes, is experiencing a markedly increased frequency of landslides. Given these concerning insights, it is absolutely essential for government authorities to engage in rigorous spatial planning. This should involve redirecting development efforts towards areas identified as safer, away from high-risk zones. Furthermore, the government must enforce and adhere to policies that not only mitigate landslide risks but also promote sustainable development, ensuring the long-term safety and resilience of Ambon City against such natural disasters.

INTRODUCTION

Landslides have garnered significant attention due to their status as one of the most prevalent natural disasters worldwide in terms of both human casualties and socio-economic devastation (Nefeslioglu et al., 2008; Shahabi et al., 2014; Benchelha et al., 2020). These events primarily stem from physiographic conditions and commonly manifest during rainy seasons (Moreover, rapid population growth (Lombardo et al., 2019), has exacerbated their impact, leading to thousands of deaths and substantial infrastructure damage annually across the globe (Juang et al., 2019). Landslides not only result in fatalities and structural destruction but also possess the potential to alter landscapes significantly. Regional topography, soil composition, vegetation, and land use significantly influence and hasten the occurrence of landslides (Lavan et al., 2021).

Yearly, landslides constitute a recurring natural phenomenon worldwide. For instance, these events claim around 200 lives annually in the Himalayan, resulting in economic losses surpassing the US $1 billion (Tran et al., 2021). Meanwhile, according to the National Geological Hazard Bulletin of China, between 2007 and 2016, an average of 762 individuals were reported dead or missing each year due to intense landslides

(He et al., 2020). In Indonesia, based on data from the National Disaster Management Agency (BNPB) from 2011 to 2015, there were 2,425 landslide incidents across provinces such as Central Java, West Java, East Java, West Sumatra, and East Kalimantan (BNPB, 2016).

Natural hazards refer to perilous natural occurrences within a specific time and space (Bhat et al., 2019). Among these, landslides represent hazardous events involving the movement of rock masses, debris, or soil down a slope under the influence of gravity (Varnes, 1978; Guzzetti et al., 2005; Benchelha et al., 2020). Often observed on hillsides (Ahmed et al., 2020). The initiation of slope movements results from intricate forces acting within the rock or soil mass on the slope (Cruden, 2018). wherein movement transpires when shear stress surpasses the material's strength, differing from soil erosion mechanisms (Devi, 2020). This concept of landslides encompasses the movement of material down a slope (Enigda & T, 2021).

In recent decades, advancements in remote sensing techniques and Geographic Information Systems (GIS) have significantly contributed to delineating areas prone to landslides, particularly in mountainous regions (Tewari & Misra, 2019). Additionally, GIS facilitates spatial data processing crucial for creating landslide hazard inventory and zoning maps (Van Westen, 1993; Singh, 2013; Uvaraj & Neelakantan, 2018).

Remote sensing involves capturing, measuring, and analysing images and digital representations of energy patterns emitted from sensor devices without direct contact, aiming to gather precise information about objects and the environment (Yadav et al., 2016). These systems are categorized into two groups based on technical solutions, with passive systems measuring existing radiation, such as solar radiation (Martensson, 2011). On the other hand, Geographic Information Systems (GIS) are utilized to collect, process, and integrate data and rapidly display outcomes in geographically referenced maps and reports (Sing et al., 2016).

Ambon, Indonesia, characterized by its physiography, predominantly comprises hilly to mountainous terrain, encompassing approximately 89% of the area with steep slopes, while only about 11% constitutes plains. This physiographic setup often triggers landslides, a natural geomorphological process inherent to mountainous landscapes (Wang & Li, 2017). However, the limited available land in Ambon City intensifies land conversion, particularly in hilly areas that typically serve as conservation zones.

Researchers have extensively investigated landslide occurrences in various locations using diverse analytical techniques and approaches. (Tran et al., 2021) conducted mapping of landslide vulnerability employing Naïve Bayes (NB), Multilayer Perceptron (MLP), and Alternating Decision Tree (ADT). (Lavan et al., 2021) Utilized Geographic Information Systems (GIS) to explore the correlation between rainfall runoff and landslides. (Tanizaki & Ayu, 2021) utilized remote sensing and GIS alongside the Analytical Hierarchy Process (AHP). (Enigda & Suryanarayana, 2021) assessed slope instability issues using the Main Ethiopian Rift (MER), while (Gong et al., 2021) devised a method to analyze landslide stability derived from rainfall and vegetation root systems.

The novelty in this research lies in the analytical approach that integrates GIS techniques with satellite imagery, topographical information, and other geospatial data to identify and classify landslide vulnerability in Ambon City. This study doesn't solely rely on a single landslide-causing factor. Still, it integrates several factors such as rainfall, slope inclination, soil type, and rock type to understand the risk level holistically. Furthermore, the analysis of patterns and distribution of landslide-prone areas is conducted by linking these factors with the development of built-up areas over time, providing a deeper understanding of the impact of urbanization on natural disaster vulnerability. The comprehensive integration of data and a multifactorial approach in this research strengthens the understanding of landslide vulnerability complexity, making it distinct and innovative compared to previous studies that tended to focus on only one or two factors.

RESEARCH METHODS

This research employed both qualitative and quantitative analytical methodologies with a spatial approach. The study encompassed interpretive and survey-based research methods, analysing primary and secondary data sourced from satellite imagery, on-site observations, and relevant agencies. A survey strategy was adopted, emphasizing observing and measuring variables essential for landslide analysis. The research was conducted from July to September 2022 in Ambon City (Figure 1), covering five administrative districts: Sirimau, Nusaniwe, South Leitimur, Ambon Bay, and Ambon Baguala Bay, for data collection and observation purposes.

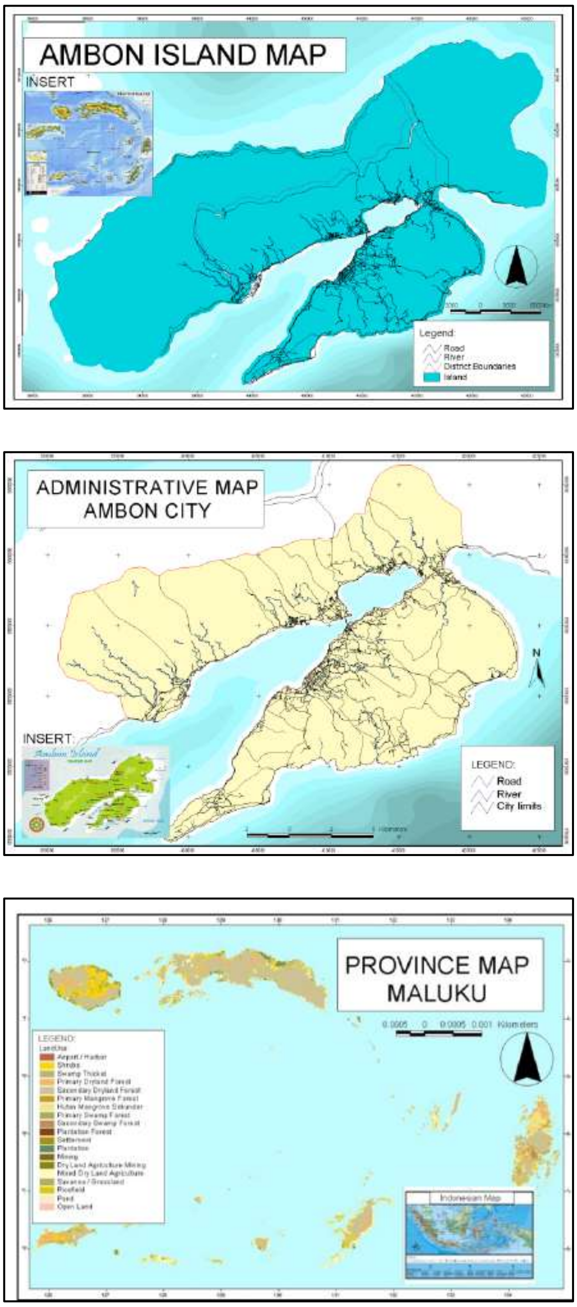

Figure 1. Research Location a. Ambon Island Map, b. Administrative Map Ambon City and c. Province Map Maluku (Source: Data Processing, 2023).

Table 1. Data Used in Research

No	Data	Source
		Secondary Data
1.	Landsat imagery	https://www.usgs.gov/landsat-missions/landsat-8
2.	SRTM imagery	https://www.earthdata.nasa.gov/sensors/srtm
3.	Slope maps	SRTM imagery processing
4.	Land Use Map	Landsat Satellites processing
5.	Soil maps	Faculty of Agriculture Unpatti (1985;
6.	Geological maps	Mining and Energy Office of Ambon City, 2022
7.	Rainfall maps	Ambon Pattimura Meteorological Station
8.	On-site observations	On-site surveys
9.	GPS data	GPS devices
10.	Digital photographs	Digital cameras

The materials utilized in this study comprised Landsat imagery, Shuttle Radar Topography Mission (SRTM) imagery for creating slope maps, soil maps, geological maps, and landform maps at a scale of 1:50,000, along with rainfall maps. These data were obtained from various sources including the Development Planning Agency at the Sub-National Level, Central Bureau of Statistics, and the Public Works Department. Research tools encompassed software applications such as Global Mapper 20, ER Mapper v. 8.1, ArcGIS 10.8.1, GPS devices, and digital cameras. The entire land area within Ambon City served as the research population, with land units selected for the research sample through an overlay approach. These land units were derived from overlaying land use maps, landforms, and slope data.

The analysis process involved aggregating variable values to generate class intervals of five, enabling the classification of landslide vulnerability levels. Data analysis encompassed several stages. The preparatory phase involved diverse methods of data processing, commencing with the analysis of land-use maps, soil types, landforms, and geology. Subsequently, SRTM image data processing was employed to construct slope maps, while Landsat images underwent various processes including image splicing, geometric correction, radiometric correction, and image sharpening before being interpreted and outlined on the screen.

The characteristics of the data analyzed in this study include Rain Intensity, Slope Gradient, Land Use, Soil Types, and Rock Types. Each variable has different classifications or category ranges to facilitate data grouping. For instance, Rain Intensity is divided into five classes based on millimeter ranges, while Slope Gradient is categorized into four distinct classes based on the percentage of slope inclination. Land Use, Soil Types, and Rock Types also possess specific class variations according to their respective types. This table serves as an important guide in organizing and classifying the data used in the research, allowing researchers to clearly understand the distribution and variations of each studied variable. The characteristics of this table can be seen in the following Table 2.

In the effort to determine the classes of land sliding, a guideline based on the level of "Harkat total" is utilized. This approach aids in categorizing data according to the intensity or level of the evaluated aspect. This procedure involves grading across five parameters, where the highest harkat amounts to 15 and the lowest amounts to 7. To establish four classes, a divisional interval of three is required. Thus, the classes of land sliding can be determined using a four-unit value interval, as depicted in Table 3.

The utilization of this guideline enables researchers or stakeholders to structure data more systematically and classify the intensity of land sliding in greater detail. By establishing class ranges based on the predetermined Harkat total parameter, this method facilitates a more accurate assessment of landslide risk in specific areas. These steps aid in depicting land conditions more clearly and support mitigation efforts or preventive measures that can be implemented to reduce the risk of land sliding impacts in a particular region.

Table 2. Characteristics of Research Data

No	Data Characteristics	Class	Score
1.	Rain Intensity		
	• 0 -13.6 mm	I	1
	• 13.6 - 20.7 mm	II	2
	• 20.7 - 27.7 mm	III	3
	• 27.7 - 34.8 mm	IV	4
	• >34.8 mm	V	5
2.	Slope		
	• Flat to sloping (0 – 8%)	I	1
	• Slightly tilted (8 – 15%)	II	2
	• Crooked (15 – 30%)	III	3
	• Very tilted (> 30%)	IV	4
3.	Land Use		
	• Forest	I	1
	• Plantation	II	2
	• A built area	III	3
	• Mixed garden	IV	4
	• Shrubs	V	5
4.	Soil Types		
	• Alluvial, Cambisol, Regosol, Gleysol	I	1
	• Cambisol, Latosol, Regosol	II	2
	• Latosol, Cambisol	III	3
	• Rendzina, Cambisol, Litosol	IV	4
5.	Rock Type		
	• Alluvial deposit, sandstone	I	1
	• Serpentine group, diabase, and gabbro	II	2
	• Granite unit, Limestone unit	III	3
	• Andesite group, dacite, breccia	IV	4
	• Loose materials	V	5

Source: (Yuniarta et al., 2015).

Table 3. Landslide Classes and Criteria

No.	Criteria	Total Dignity	Classes
1.	Very low	7 - 9	I
2.	Low	10 - 12	II
3.	Moderate	13 - 15	III
4.	Hight	16 - 18	IV

Source: Data Processing (2023)

Field observations were conducted during the implementation phase to validate the accuracy of image interpretation, ensuring alignment with the actual field conditions, and measuring parameters that couldn't be ascertained from the images. Surveys were conducted across the research area, particularly focusing on regions where land use density or weather factors, such as cloud cover, impeded precise image interpretation.

Validation was performed to assess interpretation accuracy by comparing the interpreted results from images with field-checked results. Activities were undertaken to enhance interpretation outcomes and mapping accuracy through sampling. Landsat satellite image data processing involved layer stacking, consolidating eleven different channels into a single dataset for easy analysis and comprehensive interpretation. Radiometric correction procedures were implemented to minimize errors resulting from the recording system and the passage of sunlight through objects to the recording camera. Radiometric accuracy denotes a system's capability to discern differences in electromagnetic energy, relying on the detector's signal-to-noise ratio and its capacity to convert continuous electromagnetic signals into digital ones. Higher sensor bit values correspond to increased levels of radiometric accuracy.

Radiometric correction employed in Landsat 8 images involves atmospheric reflectance correction, also known as Top of Atmosphere (ToA) correction. ToA correction serves the purpose of adjusting images by compensating for radiometric distortions arising from variations in the sun's position concerning Earth. This correction method accounts for the sun's differing positions during image acquisition times and across various locations. Its primary function involves transforming digital number values into reflectance values. The present study concentrates on evaluating Landsat-8 imagery's reflectance properties across diverse terrains, encompassing vegetation like forests and rice fields, open spaces such as barren land and settlements, and bodies of water. The application of ToA reflectance correction aims to convert digital values into reflectance values (Nugroho et al., 2017).

Radiometric correction serves to eliminate radiometric distortions present in images, which result from errors in recorded pixel intensity values. These distortions can emerge from multiple factors encountered during data collection, transmission, and recording processes. Notably, key factors contributing to radiometric distortions in Landsat images include detector malfunctions and scattering effects. The final phase of image pre-processing involves image cropping and delineating an area of interest (AOI). This step focuses the analysis on specific geospatial phenomena, enabling a concentrated discussion on relevant study areas.

The initial radiance (L) in each spectral channel of the satellite image is measured in digital numbers (DN) recorded by the sensor. The equation for measuring the initial radiance in channel i is (Jensen, 2015):

$$\mathbf{L\_i = DN\_i * G\_i + B\_i \text{ .... } (1)}$$

Information:
L_i : Initial radiance in channel i
DN_i : Digital number value in channel i
G_i : Gain for channel i
B_i : Offset for channel i

This step involves radiometric correction to eliminate distortions caused by changes in sunlight and sensor characteristics. One commonly used method is the Top of Atmosphere (ToA) reflectance correction or atmospheric reflectance correction. The general equation to convert initial radiance to ToA reflectance values is (Jensen, 2015).

$$\mathbf{R\_i = (L\_i - L\_min) / (L\_max - L\_min) * (Q\_cal\_max - Q\_cal\_min) + Q\_cal\_min ...(2)}$$

Information
R_i : ToA reflectance value in channel i
L_i : Initial radiance in channel i
L_min : Minimum radiance in channel i
L_max : Maximum radiance in channel i
Q_cal_max : Maximum digital number value that the sensor in the channel can reach i
Q_cal_min : Minimum digital number value that the sensor in the channel can reach i

After radiometric correction, the image may undergo geometric correction to remove spatial and geometric distortions, which involves mapping the image to geographic coordinates or an appropriate projection. Equations and steps for geometric correction will vary depending on the method used.

The data gathered in this final stage is deemed suitable for analysis and serves as crucial material for comprehensive examination. The overall data compilation involves grouping and systematically analyzing data in a quantitative and deductive manner. Spatial analysis techniques were employed to discern spatial patterns within the collected datasets. The mapping process for each indicator was derived from the 2004 Puslittanak estimation model. Puslittanak, a research institution operating under the Indonesian Agency for Agricultural Research and Development, specializes in studying soil resilience and climatology in Indonesian agriculture. Utilizing this model, parameters are categorized based on their respective scores, which are then aggregated to ascertain geographical suitability. This process results in the assignment of five classes depicting landslide vulnerability levels: very low, low, moderate, high, and very high.

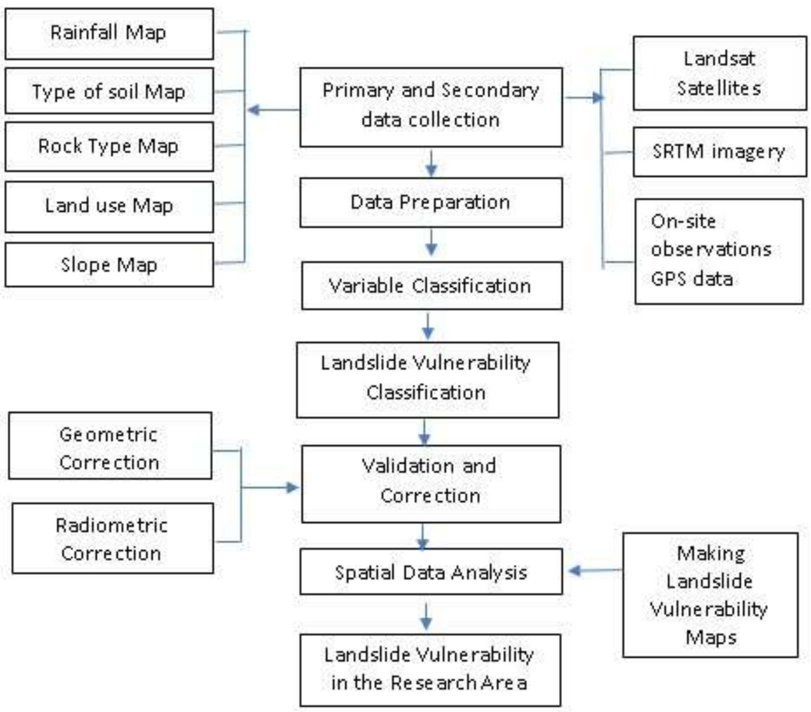

Figure 2. Research Flow Diagram

RESULTS AND DISCUSSION

Built-Up Area Development Analysis

An assessment was conducted to analyze the expansion and distribution of built-up areas in Ambon City from 2012 to 2021. This analysis involved utilizing land cover data from 2012, derived from Landsat 7 image classification, and land cover data from 2019 obtained from Landsat 8 image classification. The accuracy level of the Landsat 7 classification in 2012 was determined to be 92.51%, while the accuracy of the Landsat 8 classification in 2021 was found to be 91.08%. These accuracy levels fall within the coefficient range of 81-100% for Cohen's Kappa coefficient, as interpreted by (Altman, 1991), indicating an extremely high level of agreement suitable for analysis purposes.

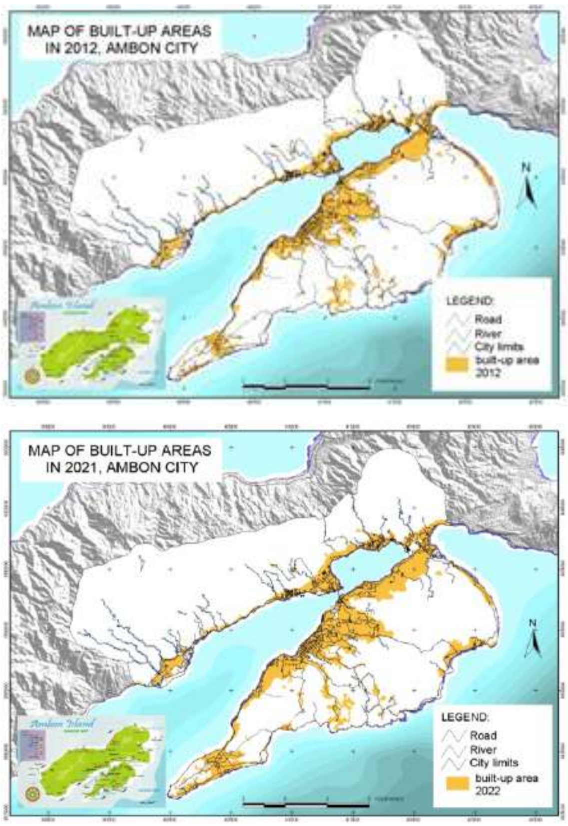

Figure 3. Map of Ambon City built area in 2012 (a) and 2022 (b)
(Source: Data Processing, 2023)

Table 4. Area of Ambon City Built-in 2012 and 2021

No	Land Use	Area (Ha
1.	The built-up area in 2012	4,527,424
2.	The built-up area in 2022	5,707,990

Source: Data Processing (2023)

2. Landslide Factor Analysis
Rainfall Factor

Rainfall plays a significant role in triggering landslides, particularly in regions like Indonesia characterized by a wet tropical climate where it stands as a primary determinant of the climate. It serves as an external factor outside the slope's body that can lead to landslides due to its intensity and subsequent flow in various locations (Handoko & Ikaputra, 2019) The assessment and calculation of rainfall intensity values are presented in Table 5.

Table 5. Rain Intensity Class Criteria

No	Class	Rain Intensity (mm)	Description	Score
1	I	0 -13.6	Very low	1
2	II	13.6 - 20.7	Low	2
3	III	20.7 - 27.7	Moderate	3
4	IV	27.7 - 34.8	High	4
5	V	>34.8	Very high	5

Source: Ambon Pattimura Meteorological Station, 2022

The study area's rainfall data is sourced from the Ambon Pattimura Meteorological

Station, revealing consistently high average annual rainfall over the past decade (2013-2022), averaging around 27,862 mm. This consistent high-intensity rainfall signifies the area's frequent exposure to substantial rainfall throughout the year. Table 2 outlines the criteria defining the classes of rainfall intensity, with the recorded range in Ambon City falling between 27.7 to 34.8 mm, indicating a classification of high rainfall intensity (class 3). Figure 2 illustrates the spatial distribution of rainfall across the study area.

Rainfall, a universal natural occurrence essential to various aspects of life, holds significant influence in Indonesia, especially in regions like Ambon City characterized by a tropical wet climate and frequent heavy rainfall. Intense rainfall often leads to increased surface water flow, resulting in substantial soil erosion and the potential displacement of soil material, subsequently compromising slope stability. According to (Arsyad et al., 2018), the precipitation amount on a slope tends to rise with altitude, rendering slopes devoid of vegetation or impermeable layers highly susceptible to landslides during heavy rains (Rienzi et al. 2013). The magnitude of rainfall directly impacts factors such as soil distribution strength, its carrying capacity, and vulnerability to damage (Hutapea, 2020). Studies by (Andriawan and Sarya, 2014) indicated that rainfall intensities exceeding 50 mm/h often trigger shallow landslides, while research by (Hidayat and Zahro, 2018) identified rainfall data as a catalyst for landslides in the Banjarnegara Region, particularly emphasizing that daily maximum rainfall of 56 mm could induce landslides. Furthermore, (Gemilang et al., 2017) noted that areas like the Bungus Hills, experiencing an average rainfall of over 200 mm, exhibit a notably high level of landslide hazard.

Slope Factor

Slope inclination is a critical factor contributing to landslides. It represents the ground surface's stability against gravitational forces (Fransiska et al., 2017). The determination and categorization of slope values are detailed in Table 6.

Table 6. Class and Slope Area

No	Class	Criteria			%	Score
		Slope Description	Slope (%)	Area (Ha)		
1.	I	Flat to sloping	0 – 8	5.087.65	15,80	1
2.	II	Slightly tilted	8 - 15	6,974.29	21.66	2
3.	III	Crooked	15 - 30	9,380,68	29.14	3
4.	IV	Very tilted	> 30	10,750,05	33.39	4
Total area				32,068,753	100.00	

Source: Data Processing (2023)

Table 6 illustrates that Ambon City exhibits diverse slopes, with the majority of the area comprising slopes very tilted than 30% and ranging between 15-30%, encompassing approximately 10,750.05 hectares. The terrain conditions in Ambon City, primarily consisting of slopes categorized as values 3 and 4 or with high percentage slopes (as depicted in Figure 2), pose a significant risk for potential landslides.

Slope inclination stands as a pivotal element influencing the occurrence of landslides, observed consistently across diverse global regions, including Indonesia, where the instability of steep or excessively steep slopes often leads to landslides (Fransiska et al., 2017). (Rompon and Almulqu, 2018) underscored the tendency for landslides to manifest more frequently in areas with elevated slope gradients. The slope factor contributes to diminishing the soil's shear strength, rendering it susceptible to collapse, as highlighted by (Akbar et al., 2022). Moreover, the inclination of the slope directly impacts the magnitude of landslides, evidenced by (Çellek, 2020) demonstrating an escalation in soil mass movement corresponding to an increase in slope, attributable to heightened gravitational thrust and shear stresses. (Nengsih, 2015) reinforced this notion, indicating that slope stability hinges upon the interplay between soil shear strength and shear stress, where soil collapse ensues when shear stress surpasses the soil's inherent strength.

Land Use Factor

The factor of land use encompasses the various human activities and natural elements covering the soil surface, such as vegetation and rock structures. As indicated by (Nugroho et al., 2017), different types of land use significantly influence the stability of slopes. Land use constitutes an external trigger that impacts the slope. Ambon City spans an area of 32,068,753 hectares, encompassing five primary land use types: forests, mixed gardens, shrublands, built-up areas, and plantations. Table 7 presents the classification of land use values in the area.

Table 7. Land Use Class and Area

No	Class	Land Use	Area (Ha)	%	Score
1.	I	Forest	7,875,105	24.46	1
2.	II	Plantation	6,132,103	19.05	2
3.	III	A built area	5,707,990	18.40	3
4.	IV	Mixed garden	10,832,291	33.65	4
5.	V	Shrubs	1,428,821	4.44	5
		Total area	32,068,753	100.00	

Source: Data Processing (2023)

Table 4 reveals that mixed garden land use, covering a total area of 10,832,291 hectares and classified with a value of 4, dominates the landscape of Ambon City. Built-up areas, spanning 5,923,844 hectares and classified with a value of 3, exhibit an evenly distributed presence throughout the city. Shrublands represent the smallest land use area, accounting for 1,428,821 hectares and classified with a value of 4, while plantations encompass the largest area, totaling 132,103 hectares and classified with a value of 2. The spatial distribution of land use signifies that mixed gardens, employing dryland farming techniques, predominantly occupy Ambon City. Shrublands, having the highest score among various land cover types in Ambon City (as depicted in Figure 2), significantly influence landslide occurrence frequencies.

Alterations in land use transitioning from natural conditions to agricultural, residential, or industrial purposes can bring about changes in soil and vegetation characteristics, leading to the uprooting of soil-bound roots, amplified erosion, and compromised slope stability. Poor land-use decisions, not in harmony with environmental requisites, can heighten the likelihood of landslides (Nugroho et al. 2017). According to Ritung et al (2007), regions characterized by steep slopes and specific land-use patterns, like moors and scrubs, often witness landslide occurrences. The potential degradation of slope stability contributes to increased landslides as land-use intensity escalates (Hasibuan and Rahayu 2017; Soewandita (2018). Mixed gardens are identified as high-risk areas for landslides, necessitating improved land management practices aligned with land conservation regulations. Suwarsito et al (2020) propose the strategic placement of perennial plants possessing deep root systems in sloping areas to mitigate the incidence of landslides.

Soil Type Factor

The soil type factor plays a crucial role in the occurrence of landslides. In Ambon City, the soil types are categorized into four units: 1) alluvial, cambisol, regosol, gleysol, 2) cambisol, latosol, regosol, 3) latosol, cambisol, and 4) rensina, cambisol, litosol. Table 8 presents the classification and values assigned to these soil types.

Table 8. Class and Area of Soil Types

No	Class	Soil Types	Area (Ha)	%	Score
1	I	Alluvial, Cambisol, Regosol, Gleysol	3,300,144	10.25	1
2	III	Cambisol, Latosol, Regosol	23,599,715	73.31	2
3	II	Latosol, Cambisol	1,969,064	6.12	3
4	IV	Rendzina, Cambisol, Litosol	3,323.746	10.32	4
		Total area	32,068,753	100.00	

Source: Faculty of Agriculture Unpatti (1985; Lasaiba, 2012)

Table 8 illustrates that the soil types prevalent in Ambon City predominantly comprise cambisol, latosol, and regosol soil units, collectively occupying an area of 23,599,715 hectares. However, the latosol and cambisol soil units only represent a small proportion, accounting for 6.12% of the total area or 1,699,064 hectares. Latosol soil type, in particular, while covering a relatively small land area, exhibits a widespread presence throughout Ambon City. The spatial distribution of this soil type is depicted in Figure 2.

Landslides tend to happen in specific soil types, especially following rainfall. The occurrence of landslides is notably influenced by the fine and smooth texture of the soil, particularly clay-based textures. As highlighted by (Harjadi & Paimin, 2013). soil textures classified as finer are more susceptible to shrinkage, instability, or movement. (Heradian and Arman, 2015), point out that clayey soils with high water content represent areas prone to landslides due to their lower resistivity values. (Soewandita, 2018) notes that thick soil layers with a porous structure, particularly found in sloped areas, exhibit high vulnerability to landslides. (Hadiyanto, 2011) highlighted the high sensitivity of cytosol and regosol soil types to water. Conversely, soil types such as alluvial, gleysol, planosol, laterite, and hydromorphone are less sensitive to water, resulting in a lower occurrence of landslides during the rainy season.

Rock Type Factor

Rock types in Ambon City encompass various categories such as sandstone, serpentine, diabase, gabbro groups, andesite groups, breccias, loose materials, granite units, limestone units, and alluvial deposits. Table 9 presents the classification and values assigned to these rock types in the area.

Table 9. Broad Class of Rock Types

No		Rock Type	Area (Ha)	%	Score
1.	I	Alluvial deposit	4,402.08	13.67	1
2.	I	Sandstone	1,298.61	4.03	1
3.	II	Serpentine group, diabase, and gabbro	2,293.32	7.12	2
4.	III	Granite unit	2,099.98	6.52	3
5.	III	Limestone unit	1,924.40	5.98	3
6.	IV	Andesite group, dacite, breccia	5,684.05	17.66	4
7.	V	Loose materials	14,490,24	45.01	5
		Total area	32,068,753	100	

Source: Mining and Energy Office of Ambon City, 2022

The rock types in Ambon City exhibit diverse distributions, with loose material covering the most extensive area, spanning 10,960 hectares or 45.05% of the area. Additionally, the Andesite, Dacite, and Breccia groups collectively cover an area of 5,684.05 hectares. Conversely, sandstone represents the smallest area, covering only 1524.21 hectares or 4.73% of the total area. The prevalent distribution of loose material and the Andesite, Dacite, and Breccia groups signifies their significance as the most extensive rock types in

Ambon City, attributed to the Ambon volcanic deposits during the Pliocene era.

Ambon City exhibits geological structures primarily characterized by down (normal) faults and joint faults. The fault structures, evolving from northeast to southwest directions, intersect granite rock units, and clusters of serpentine, diabase, and gabbro units situated in the headlands of Seri Village and Hukurila Village. These findings align with Rahman (2010) suggesting that locations prone to landslides are associated with rock domes exposed to flow, and soil structures consisting of older Andesite and Andesite Breccia formations affected by numerous faults. Such rocks are prone to weathering into soil, rendering them susceptible to landslides when present on landslide-prone slopes (Putra et al. 2019). Volcanic sedimentary rocks and sedimentary rocks with sand-sized grains, along with compositions of gravel, sand, and clay, exhibit weaknesses. When subjected to weathering processes, these rocks swiftly transform into soil, posing vulnerability to landslides, particularly when situated on steep slopes (Darmawan et al. 2021).

3. Landslide Vulnerability Analysis

Regarding landslide vulnerability analysis, the determination of landslide hazard zoning in Ambon City was conducted by categorizing it into five risk classes: shallow, low, medium, high, and very high. This zoning was established based on the landslide hazard analysis design. By summing up (scoring) the factors present in each field unit, the level of vulnerability or likelihood of landslides can be calculated. Table 7 below illustrates five interval classes composed of the variables and their respective weights used in the analysis.

Table 7. Scoring and Area of Landslide Vulnerability

No	Vulnerability Class	Score	Area (ha)	Large (%)
1.	Very low	7 - 9	2.641.019	8.21
2.	Low	10 - 12	2,591,553	8.05
3.	Moderate	13 - 15	8,992,736	27.94
4.	Hight	16 - 18	16,619.011	51.63
5.	Very high	10 - 21	1,341,312	4.17
	Total area		32,185,631	100.00

Source: Data Processing (2023)

Table 7 delineates that a mere 2,641,019 hectares or 8.21% of Ambon City's total area is categorized as having a very low vulnerability to landslides, representing a minimal risk level (8%). Conversely, a significant high, totaling 16,619.011 hectares or 51.63% of the area, falls into the high vulnerability zone for landslides. Moreover, the middle range of the landslide vulnerability map demonstrates a vulnerability level ranging from medium to high, predominantly observed in the hilly and mountainous regions of Ambon City, especially in areas characterized by steep slopes. The spatial distribution of landslide vulnerability can be observed in Figure 3.

Moreover, the central zone depicted on the landslide vulnerability map tended to exhibit a vulnerability level ranging from moderate to high, particularly prevalent in the hilly and mountainous terrains of Ambon City, followed by regions characterized by steep slopes. This study draws parallels from research findings conducted in the Ponorogo Regency by (Yuniarta et al., 2015 & Naryanto et al., 2019), an area recognized for its predisposition to landslide occurrences owing to its predominant hill-based morphological features. A similar investigation conducted by (Fitrianingrum & Ruslanjari, 2012) in the Kulonprogo Regency, specifically the Menoreh Hills area, also highlighted geomorphological vulnerability to landslides, primarily attributed to high-intensity and rapid rainfall.

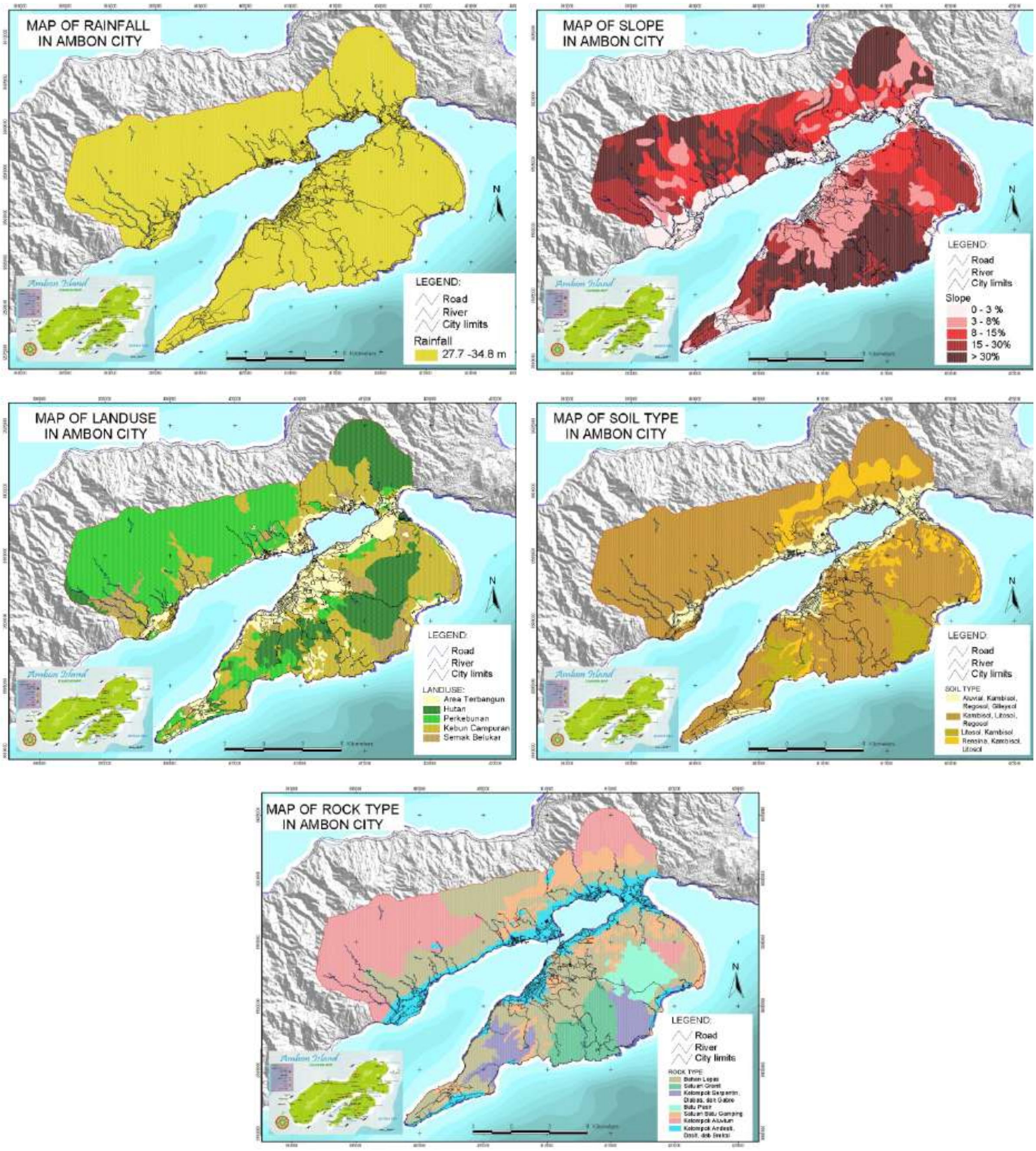

Figure 4. Rainfall Intensity Map, b) Slope Map, c) Land Use Map, d) Soil Type Maps, and e) Map of Rock Types

Figure 4 depicts the precise locations of landslides within the study area, causing substantial damage to several residential buildings. The Regional Disaster Management Agency (BPBD) in Ambon City reported that a total of 17 landslides resulted in damage to approximately 56 houses. These landslides occurred across four sub-districts: Teluk Ambon, Nusaniwe, Sirimau, and Baguala. In Nusaniwe District, landslides were observed in three locations: Kudamati, Benteng, and Amahusu. Sirimau District experienced landslides in Batu Gajah, Amantelu, Batu Meja, Waihoka, and Soya areas. In Teluk Ambon District, landslides took place in the Tawiri, Poka, and Tihu areas. The Baguala sub-districts affected by landslides include Negeri Lama, Lateri, Halong, and Passo.

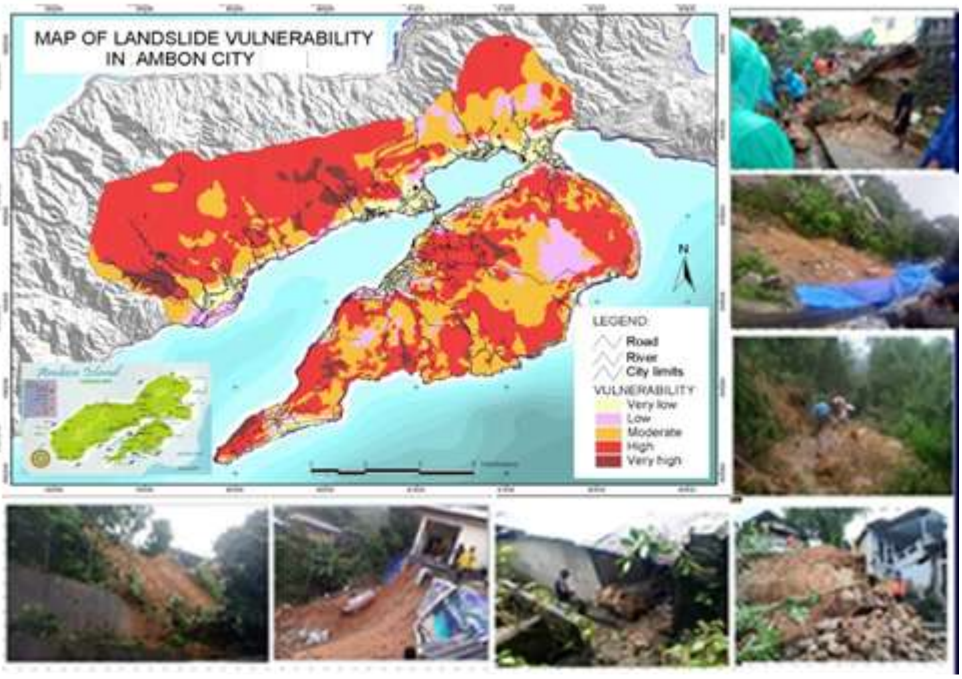

Figure 5. Map of Landslide Locations in Ambon City

Analysis of Built-up Land in Landslide Disaster Area

The study utilized the development data of built-up areas and conducted an analysis of landslide vulnerability in Ambon City. This information served as input for the analysis aiming to identify built-up areas situated within regions prone to landslides. The distribution of built-up areas within each class of landslide vulnerability was determined through an overlay process, specifically by overlaying the outcomes of the two analyses and conducting an intersect analysis. This method, known as Kawasan zoning, is detailed in the subsequent table.

Table 8. Area of Built-up Land in Landslide Disaster Area

Zone	Information	Area (Ha)	%
Z - 1	Built-up land on very low landslide hazard class	2,000,913	35.09
Z - 2	Built-up land on low landslide hazard class	678,094	11.89
Z - 3	Built-up land on moderate landslide vulnerability class	777,107	13.63
Z - 4	Built-up land on high landslide vulnerability class	2,224,549	39.01
Z - 5	Built-up Land on Very High Landslide Vulnerability Class	21,691	0.38
Total area		5,702,356	100.00

Source: Data Processing (2023)

The distribution and extent of built-up land within each class of landslide vulnerability in Ambon City are outlined in Figure 4 and detailed in Table 8. The largest areas among the zones are Z-1 and Z-4, covering 2,224,549 hectares (39.01%) and 2,000,913 hectares (35.09%), respectively, signifying the most extensive zoning classifications. Zones Z-2 and Z-3 encompass 678,094 hectares (11.89%) and 777,107 hectares (13.63%), respectively. On the other hand, Z-5 represents the smallest area, covering only 21,691 hectares (0.38%).

Zones Z-4 and Z-5 exhibit a high to very high vulnerability to landslides due to steep slopes ranging from 25% to greater than 40%, coupled with rock types prone to weathering and the prevalence of built-up land, which further amplifies slope instability. Additionally, these areas possess low soil retention capacity, rendering them highly susceptible to erosion. According to the Regulation of the Minister of Public Works No. 22 of 2007, constructing settlements is only recommended on slopes ranging from 0 to 15% (flat to slightly steep), designating zones Z-1, Z-2, and Z-3 as suitable and safe for built-up land use.

Development in areas like Z-4 and Z-5 with steep slopes requires specific criteria, including engineering measures like embankments to maintain slope stability. However, the extreme impacts of climate change could affect the resilience of these engineering interventions, possibly necessitating increased costs for handling such construction projects.

Most built-up areas within zones Z-4 and Z-5 have been established by communities highly susceptible to landslides, making relocation impractical. In the future, the government must proactively control the expansion of built-up land in these high-risk zones, focusing on policies and spatial planning. Development efforts should be directed towards areas with low to moderate landslide vulnerability, such as Z-1, Z-2, and Z-3 in Ambon City. Moreover, public education about the consequences of development activities leading to landslides is crucial, especially in high and very high vulnerability areas.

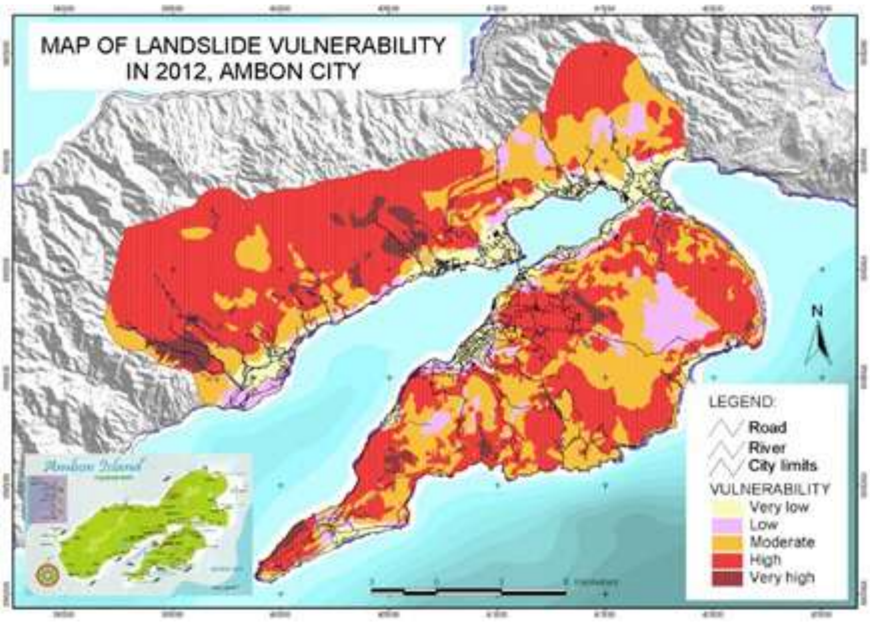

Figure 4. Map of Landslide Prone Areas of Land Zoning in Built-up Areas in Ambon City
Source: Data Processing (2023)

CONCLUSION

The research area's land units are categorized based on three primary factors: the steepness of the terrain, land use, and specific geological features. Landslides in this region were triggered by heavy rainfall, averaging between 27.7 to 34.8 meters, extensive steep to very steep slopes (constituting 62.53% of the area), predominant land use of mixed gardens and built-up areas (occupying 52.05% of the total area), and soil types like cambisol, latosol, regosol, alongside loose material rocks, covering approximately 73.31% and 45.01%, respectively.

The vulnerability of landslides in this area is notably high, encompassing approximately 51.63% of the total area. This high vulnerability is mainly concentrated in regions characterized by steep to very steep slopes in hilly terrains. An analysis of the built-up areas in regions susceptible to landslides, particularly zones Z-4 and Z-5, highlights slopes ranging from 25 to over 40%. These areas possess rock types highly susceptible to weathering, alongside land cover that exacerbates the slope's instability. Furthermore, their soil holding capacity is low, making them prone to erosion, intensifying the vulnerability to landslides.

REFERENCES LIST

Ahmed, K. A., Khan, S., Sultan, M., Bin Nisar, U., Mughal, M. R., & Qureshi, S. N. (2020). Landslides assessment using geophysical and passive radon exhalation detection techniques in Murree Hills, northern Pakistan: Implication for environmental hazard assessment. Journal of Earth System Science, 129(1). https://doi.org/10.1007/s12040-019-1327-y

Akbar, M. A., Utami, S. R., & Agustina, C. (2022). Simulasi Pengukuran Longsor Pada Kemiringan Lereng Dan Ketebalan Seresah Yang Berbeda. Jurnal Tanah Dan Sumberdaya Lahan, 9(2), 321–327. https://doi.org/https://doi.org/10.21776/ub.jtsl.2022.009.2.12

Andriawan, H. A., & Sarya, G. (2014). Intensitas Curah Hujan Memicu Tanah Longsor Dangkal di Desa Wonodadi Kulon. Jurnal Pengabdian LPPM. Surabaya: Fakultas Teknik UNTAG Surabaya, 1(1), 2014. https://doi.org/https://doi.org/10.30996/jpm17.v1i01.355

Arsyad, U., Barkey, R. A., Wahyuni, W., & Matandung, K. K. (2018). Karakteristik Tanah Longsor di Daerah Aliran Sungai Tangka. Jurnal Hutan Dan Masyarakat, 10(1), 203–214. https://doi.org/https://doi.org/10.24259/jhm.v0i0.3978

Banuzaki, A. S., & Ayu, A. K. (2021). Integrated Remote Sensing and GIS Analysis for Landslide Susceptibility Assessment along the Trenggalek–Ponorogo Road, East Java Province, Indonesia. Indonesian Association of Geologists Journal, 1(1), 39–48. https://doi.org/10.51835/iagij.2021.1.1.14

Benchelha, S., Chennaoui Aoudjehane, H., Hakdaoui, M., Hamdouni, R. E. L., Mansouri, H., Benchelha, T., Layelmam, M., & Alaoui, M. (2020). Landslide susceptibility mapping in the commune of Oudka, Taounate Province, North Morocco: A comparative analysis of logistic regression, multivariate adaptive regression spline, and artificial neural network models. Environmental and Engineering Geoscience, 66(1), 185–200. https://doi.org/10.2113/EEG-2243

Bhat, I. A., Shafiq, M. ul, Ahmed, P., & Kanth, T. A. (2019). Multi-criteria evaluation for landslide hazard zonation by integrating remote sensing, GIS and field data in North Kashmir Himalayas, J&K, India. Environmental Earth Sciences, 78(20), 1–15. https://doi.org/10.1007/s12665-019-8631-3

BNPB. (2016). Risiko Bencana Indonesia (Disasters Risk of Indonesia). International Journal of Disaster Risk Science, 22. https://doi.org/10.1007/s13753-018-0186-5

Çellek, S. (2020). Effect of the slope angle and its classification on landslide. Natural Hazards and Earth System Sciences Discussions, 1–23. https://doi.org/https://doi.org/10.5194/nhess-2020-87

Cruden, D. (2018). Landslide risk assessment. Routledge.

Darmawan, R. Y., Miswar, D., & Nugraheni, I. L. (2021). Analisis Daerah Rawan Longsor Di Kecamatan Limau Kabupaten Tanggamus. JPG (Jurnal Penelitian Geografi), 10(1), 34–42. http://jurnal.fkip.unila.ac.id/index.php/JPG/article/view/22624

Devi, S. (2020). Use of Remote Sensing and GIS in Landslide Hazard Analysis. International Journal of Science, Engineering and Technology Research (IJSETR), 9(1). https://d1wqtxts1xzle7.cloudfront.net/63158016/IJSETR

Enigda, E. A., & T, S. (2021). Landslide Evaluation In Parts of Tarmaber District (Debresina), Central Ethiopia;

An Expert Evaluation Approach. International Journal of Geoinformatics and Geological Science, 8(1), 15–26. https://doi.org/10.14445/23939206/ijggs-v8i1p103

Fitrianingrum, M. E., & Ruslanjari, D. (2012). Samigaluh Kabupaten Kulonprogo Yogyakarta. 2006, 181–190. https://doi.org/https://doi.org/10.17509/gea.v18i2.8481

Fransiska, L., Tjahjono, B., & Gandasasmita, K. (2017). Studi geomorfologi dan analisis bahaya longsor di Kabupaten Agam, Sumatera Barat. Buletin Tanah Dan Lahan, 1(1), 51–57. https://jurnal.ipb.ac.id/index.php/btanah/article/view/17691

Gemilang, W. A., Husrin, S., Wisha, U. J., & Kusumah, G. (2017). Kerentanan Pesisir Terhadap Bencana Tanah Longsor Di Bungus, Sumatera Barat Dan Sekitarnya Menggunakan Metode Storie. Jurnal Geosaintek, 3(1), 37–44. http://iptek.its.ac.id/index.php/geosaintek/article/view/2954

Gong, Q., Wang, J., Zhou, P., & Guo, M. (2021). A Regional Landslide Stability Analysis Method under the Combined Impact of Rainfall and Vegetation Roots in South China. Advances in Civil Engineering, 2021. https://doi.org/10.1155/2021/5512281

Gorsevski, P. V, Gessler, P. E., Foltz, R. B., & Elliot, W. J. (2006). Spatial prediction of landslide hazard using logistic regression and ROC analysis. Transactions in GIS, 10(3), 395–415. https://doi.org/https://doi.org/10.1111/j.1467-9671.2006.01004.x

Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., & Ardizzone, F. (2005). Probabilistic landslide hazard assessment at the basin scale. Geomorphology, 72(1), 272–299. https://doi.org/https://doi.org/10.1016/j.geomorph.2005.06.002

Hadiyanto. (2011). Pengaruh komposisi media organik terhadap pertumbuhan dan hasil tiga varietas jahe (Zingiber officinale Rosc.). http://repository.unej.ac.id/handle/123456789/23499

Handoko, J. P. S., & Ikaputra, I. (2019). Prinsip desain arsitektur bioklimatik pada iklim tropis. Langkau Betang: Jurnal Arsitektur, 6(2), 87–100. https://jurnal.untan.ac.id/index.php/lb/article/view/34791

Harjadi, B., & Paimin, P. (2013). Teknik identifikasi daerah yang berpotensi rawan longsor pada satuan wilayah daerah aliran sungai. Jurnal Penelitian Hutan Dan Konservasi Alam, 10(2), 163–174. https://doi.org/https://doi.org/10.20886/jphka.2013.10.2.163-174

Hasibuan, H. C., & Rahayu, S. (2017). Kesesuaian Lahan Permukiman pada Kawasan Rawan Bencana Tanah Longsor di Kabupaten Temanggung. Teknik PWK (Perencanaan Wilayah Kota), 6(4), 242–256. https://doi.org/https://doi.org/10.14710/tpwk.2017.18072

He, S., Wang, J., & Liu, S. (2020). Rainfall event-duration thresholds for landslide occurrences in China. Water (Switzerland), 12(2). https://doi.org/10.3390/w12020494

Heradian, E. A., & Arman, Y. (2015). Pendugaan Bidang Gelincir di Desa Aruk Kecamatan Sajingan Besar Kabupaten Sambas dengan Menggunakan Metode Tahanan Jenis. Prisma Fisika, III(2), 56–61. https://doi.org/ttp://dx.doi.org/10.26418/pf.v3i2.11878

Hidayat, R., & Zahro, A. A. (2018). Identifikasi Curah Hujan Pemicu Longsor di Daerah Aliran Sungai (DAS) Serayu Hulu-Banjarnegara. http://hdl.handle.net/11617/10336

Hutapea, S. (2020). Biophysical Characteristics of Deli River Watershed to Know Potential Flooding in Medan City, Indonesia. Journal of Rangeland Science, 10(3), 316–327. https://journals.iau.ir/article_672809_3011c0a146017c54e0985dcbe2141186.pdf

Jensen, J. R. (2015). Introductory Digital

Image Processing: A Remote Sensing Perspective. Pearson Education. https://books.google.co.id/books?id=ahXPswEACAAJ

Juang, C. S., Stanley, T. A., & Kirschbaum, D. B. (2019). Using citizen science to expand the global map of landslides: Introducing the cooperative open online landslide repository (COOLR). PLoS ONE, 14(7), 1–28. https://doi.org/10.1371/journal.pone.0218657

Lasaiba, M. A. (2012). Perubahan penggunaan lahan di kota Ambon tahun 2002-2009. Disertasi. http://etd.repository.ugm.ac.id/penelitian/detail/54572

Lavan Kumar, Sushanth, Manikanta, M. Z. R. (2021). IRJET- Application of GIS in Investigating the Influence of Rainfall-Runoff on Landslides. International Research Journal of Engineering and Technology (IRJET), 8(6), 3646–3653. https://www.irjet.net/archives/V8/i6/IRJET-V8I6661.pdf

Lombardo, L., Opitz, T., & Huser, R. (2019). Numerical Recipes for Landslide Spatial Prediction Using R-INLA. In Spatial Modeling in GIS and R for Earth and Environmental Sciences. Elsevier Inc. https://doi.org/10.1016/b978-0-12-815226-3.00003-x

Martensson, U. (2011). Introduction to Remote Sensing and Geographical Information Systems. Department of Physical Geography and Ecosystems Sciences, 55.

Naryanto, H. S., Soewandita, H., Ganesha, D., Prawiradisastra, F., & Kristijono, A. (2019). Analisis Penyebab Kejadian dan Evaluasi Bencana Tanah Longsor di Desa Banaran, Kecamatan Pulung, Kabupaten Ponorogo, Provinsi Jawa Timur Tanggal 1 April 2017. Jurnal Ilmu Lingkungan, 17(2), 272. https://doi.org/10.14710/jil.17.2.272-282

Nefeslioglu, H. A., Gokceoglu, C., & Sonmez, H. (2008). An assessment on the use of logistic regression and artificial neural networks with different sampling strategies for the preparation of landslide susceptibility maps. Engineering Geology, 97(3–4), 171–191. https://doi.org/https://doi.org/10.1016/j.enggeo.2008.01.004

Nengsih, S. (2015). Pengaruh Kadar Air Terhadap Kestabilan Lereng (Kampus Politeknik Negeri Padang). Jurnal Ilmiah Rekayasa Sipil, 12(2), 36–45. https://core.ac.uk/download/pdf/268097274.pdf

Nugroho, A. S., Aji, A., & Indrayati, A. (2017). Perubahan Penggunaan Lahan Sawah Menjadi Non Sawah dan Pengaruhnya terhadap Keberlanjutan Sawah Lestari di Kabupaten Klaten. Geo-Image, 6(2), 139–146. https://doi.org/https://doi.org/10.29244/jpsl.8.2.258-263

Putra, R., Edial, H., & Prarikeslan, W. (2019). Studi Karakteristik Lahan Terhadap Longsor Di Kelurahan Balai Gadang Kecamatan Koto Tangah Kota Padang. Buana, 3(2), 29–34. https://doi.org/https://doi.org/10.24036/student.v3i2.417

Rahman, A. (2010). Penggunaan Sistim Informasi Geografis untuk Pemetaan Kerawanan Longsor di Kabupaten Purworejo. Sumber, 5(2500), 5.

Rienzi, E. A., Fox, J. F., Grove, J. H., & Matocha, C. J. (2013). Interrill erosion in soils with different land uses: The kinetic energy wetting effect on temporal particle size distribution. Catena, 107, 130–138. https://doi.org/https://doi.org/10.1016/j.catena.2013.02.007

Ritung, S., Wahyunto, A. F., & Hidayat, H. (2007). Panduan evaluasi kesesuaian lahan dengan contoh peta arahan penggunaan lahan Kabupaten Aceh Barat. Balai Penelitian Tanah Dan World Agroforestry Centre (ICRAF), Bogor, Indonesia, 45. https://www.worldagroforestry.org/publication/panduan-evaluasi-kesesuaian-lahan

Rompon, M. S., & Almulqu, A. (2018). Identifikasi Dan Pemetaan Daerah Bencana Rawan Longsor Di

Kecamatan Amarasi Barat Dengan Menggunakan Arc View Gis. Partner, 23(2), 810–821.

Shahabi, H., Keihanfard, S., Ahmad, B. Bin, & Amiri, M. J. T. (2014). Evaluating Boolean, AHP and WLC methods for the selection of waste landfill sites using GIS and satellite images. Environmental Earth Sciences, 71(9), 4221–4233. https://doi.org/https://doi.org/10.1007/s12665-013-2816-y

Singh, J. P. (2013). Predictive Validity Performance Indicators in Violence Risk Assessment: A Methodological Primer. Behavioral Sciences \& the Law, 31(1), 8–22. https://doi.org/https://doi.org/10.1002/bsl.2052

Soewandita, H. (2018). Analisis Kawasan Rawan Longsor Dan Keterkaitannya Terhadap Kualitas Tanah Dan Penggunaan Lahan (Kasus Di Kawasan Agribisnis Juhut Kabupaten Pandeglang). Jurnal Alami : Jurnal Teknologi Reduksi Risiko Bencana, 2(1), 27. https://doi.org/10.29122/alami.v2i1.2826

Suwarsito, S., Afan, I., & Suwarno, S. (2020). Analisis Hubungan Kerawanan Longsor Lahan dengan Penggunaan Lahan di Sub-Das Kali Arus Kabupaten Banyumas. Sainteks, 16(2), 129–135. https://doi.org/10.30595/st.v16i2.7130

Tewari, N. K., & Misra, A. K. (2019). Landslide vulnerability assessment in Gangotri valley glacier Himalaya through GIS and remote sensing techniques. Applied Water Science, 9(4), 1–10. https://doi.org/10.1007/s13201-019-0992-y

Tran, T. H., Dam, N. D., Jalal, F. E., Al-Ansari, N., Ho, L. S., Phong, T. Van, Iqbal, M., Le, H. Van, Nguyen, H. B. T., Prakash, I., & Pham, B. T. (2021). GIS-Based Soft Computing Models for Landslide Susceptibility Mapping: A Case Study of Pithoragarh District, Uttarakhand State, India. Mathematical Problems in Engineering, 2021. https://doi.org/10.1155/2021/9914650

Uvaraj, S., & Neelakantan, R. (2018). Fuzzy logic approach for landslide hazard zonation mapping using GIS: a case study of Nilgiris. Modeling Earth Systems and Environment, 4(2), 685–698. https://doi.org/10.1007/s40808-018-0447-8

Van Westen, C. J. (1993). Remote sensing and geographic information systems for geologic hazard mitigation. ITC Journal, 393–395. ttps://www.researchgate.net/profile/Cj-Westen/publication/209805617

Varnes, D. J. (1978). Slope movement types and processes. Special Report, 176, 11–33. https://www.researchgate.net/profile/Ahmad

Wang, Q., & Li, W. (2017). A GIS-based comparative evaluation of analytical hierarchy process and frequency ratio models for landslide susceptibility mapping A GIS-based comparative evaluation of analytical. Physical Geography, 3646(March), 0. https://doi.org/10.1080/02723646.2017.1294522

Yadav, K. K., Gupta, N., & Kumar, V. (2016). 2016 National Conference. American String Teacher, 66(1), 53–60. https://doi.org/10.1177/000313131606600112

Yuniarta, H., Saido, A. P., & Muslih Purwana, Y. (2015). Kerawanan Bencana Tanah Longsor Kabupaten Ponorogo. Jurnal Matrik Teknik Sipil, 3(1), 194–201. https://doi.org/https://doi.org/10.20961/mateksi.v3i1.37327