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ANALYSIS OF LANDSLIDE SUSCEPTIBILITY LEVEL USING SCORING METHOD IN THE NOTOHAMIDJOJO CAMPUS SATYA WACANA CHRISTIAN UNIVERSITY

ANALISIS TINGKAT KERAWANAN LONGSOR MENGGUNAKAN METODE SKORING DI KAMPUS NOTOHAMIDJOJO UNIVERSITAS KRISTEN SATYA WACANA

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ABSTRACT

Deforestation previously carried out for the construction of campus buildings in the Notohamidjojo campus was feared to cause soil erosion. The research's primary objectives is analyze the spatial distribution of landslide susceptibility levels. This research was conducted by utilizing GIS as the main analysis tool. The analysis method used to analyze the level of landslide susceptibility is the scoring method. The parameters of this study include slope steepness, land use, soil erodibility, and rainfall intensity. The results of this study indicate that more than 50% of the Notohamidjojo campus area is susceptible to landslides. The medium class has the largest distribution area on Notohamidjojo campus with an area of 5,77 ha or 46,50% of the total area. The very high class has the smallest distribution area with an area of 0,01 ha or 0,09% of the total area. The very low class has an area of 0,96 ha or 7,71% of the total area. The low class has an area of 4,48 ha or 36,10% of the total area. The high class has an area of 1,19 ha or 9,61% of the total area

Keywords : Deforestation; geographic information system; landslide; unmanned aerial vehicles

INTISARI

Deforestasi yang sebelumnya dilakukan guna pembangunan gedung-gedung di kampus Notohamidjojo dikhawatirkan dapat menyebabkan terjadinya erosi tanah. Tujuan utama dari penelitian ini adalah menganalisis distribusi spasial tingkat kerentanan longsor. Penelitian ini dilakukan dengan memanfaatkan SIG sebagai alat analisis utama. Metode analisis yang digunakan untuk menganalisis tingkat kerentanan longsor adalah metode skoring. Parameter penelitian ini meliputi kemiringan lereng, penggunaan lahan, erodibilitas tanah, dan intensitas curah hujan. Hasil dari penelitian ini menunjukkan bahwa lebih dari 50% wilayah kampus Notohamidjojo rentan terhadap longsor. Kelas sedang memiliki sebaran wilayah terluas di kampus Notohamidjojo dengan luas 5,77 ha atau 46,50% dari total luas wilayah. Kelas sangat tinggi memiliki luas sebaran terkecil dengan luas 0,01 ha atau 0,09% dari total luas wilayah. Kelas sangat rendah memiliki luas 0,96 ha atau 7,72% dari total area. Kelas rendah memiliki luas 4,48 ha atau 36,10% dari total area. Kelas tinggi memiliki luas 1,19 ha atau 9,61% dari total area.

Kata kunci: Deforestasi, sistem informasi geografis, tanah longsor, pesawat nirawak

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INTRODUCTION

Landslide is the downslope movement of debris, rocks, or earth material caused by gravity (Wubalem, 2022). In Indonesia, landslides represent a pervasive and recurrent geological hazard. Indonesia's unique geographical setting, characterized by mountainous regions, slope steepness, and a tropical climate, sets the stage for landslide occurrences. Landslides occur due to various elements such as steep terrain, heavy rainfall, soil or rock displacement, soil texture, land use, and the existence of surface formations (Saputra, Utami, & Agustina, 2022; Alsubal, Sapari, Harahap, & Al-Bared, 2019). In addition, human activities like underground mining can trigger landslides (Arca, Kutoğlu , & Becek, 2018).

The Notohamidjojo campus is in a hilly area with steep slopes. In 2022, there were two recorded landslides on Jalan. Dr. O. Notohamidjojo: first on October 2, 2022, and another on November 11, 2022 (Pejabat Pengelola Informasi dan Dokumentasi Salatiga, 2023). The topography of steep areas can increase the likelihood of landslides due to gravitational forces. Landscape geometry and topographic stress control the scale and frequency of large landslides, with steep slopes contributing to the potential for larger and more frequent landslides (Dente, Katz, Crouvi, & Mushkin, 2023; Prancevic, Lamb, McArdell, Rickli, & Kirchner, 2020). Excess topography and increased channel steepness are good predictors for landslide distribution, suggesting a causal relationship between the two (Chen, Liu, Chang, & Zhou, 2016).

Deforestation previously carried out for the construction of campus buildings was feared to cause soil erosion. After all, several factors are interrelated. Deforestation reduces the capacity of the soil to absorb rainwater, resulting in increased surface flow and accelerated soil erosion (Lal, 2001; Campo-Bescós, Nasr, & Machín, 2009). The deforestation process results in a reduction of soil cohesion and a decrease in the shear strength of the soil profile, thereby heightening the susceptibility of slopes to landslides. The control that forest roots have on slope stability is lost, leading to an increase in landslide frequency (Manchado, Cánovas, Allen, & Stoffel, 2022). Deforestation can precipitate the depletion of the surface humus layer, traditionally a safeguard against soil erosion. The humus layer serves the dual purpose of shielding the soil and imparting density to its composition. The absence of this protective layer renders the soil more porous, heightening its susceptibility to erosion. The loose soil, due to the loss of the humus layer is more susceptible to erosion by rainwater, exacerbating the overall erosion magnitude (Mekuria & Aynekulu, 2013).

In the pursuit of identifying and mitigating landslide risks, the spatial analysis approach utilizes the Geographic Information System (GIS). GIS allows for the integration and analysis of various spatial data such as soil type, geology, rainfall, land use, and slope (Ganesh, Vincent, Pathan, & Benitez, 2023; Erfani, Naimullah, & Winardi, 2023). This integration helps in determining the level of landslide susceptibility by scoring and weighting different parameters and conducting overlay analysis (Agung, et al., 2023). In addition, GIS enables the creation of landslide susceptibility maps, which classify areas into different levels of susceptibility, ranging from very low to very high (Neupane, Paudyal, Devkota, & Dhungana, 2023).

This research endeavors to conduct a comprehensive analysis of landslide susceptibility, leveraging GIS as the primary analytical tool. The research primary objectives are analyzing the spatial distribution of landslide susceptibility level and crafting landslide susceptibility maps. These maps provide a visual representation of the areas prone to landslides, aiding in land use planning and the development of mitigation strategies. Additionally, GIS allows for the updating and real-time management of landslide databases, facilitating timely responses to potential landslide hazards. Through the investigation of landslide susceptibility factors and the utilization of GIS technology, this research aspires to make a substantial contribution to the understanding and management of landslide disaster risks. Furthermore, the outcomes of the landslide susceptibility analysis aim to offer guidance to policymakers in the development of more effective mitigation strategies, ultimately safeguarding communities and the environment from the potential perils associated with landslides.

METHODS

Research Area and Landslide Factors

The Notohamidjojo campus is located on Dr. O. Notohamidjojo Street, Salatiga, Central Java Province, with an area of about 12,41 ha. Several key factors are commonly considered to assess the factors contributing to the likelihood of landslide. The factors including: slope steepness, land use, erodibility, and rainfall intensity. Based on the data source, the factors of slope steepness, land use, and erodibility using primary data. Meanwhile, rainfall intensity factor using secondary data.

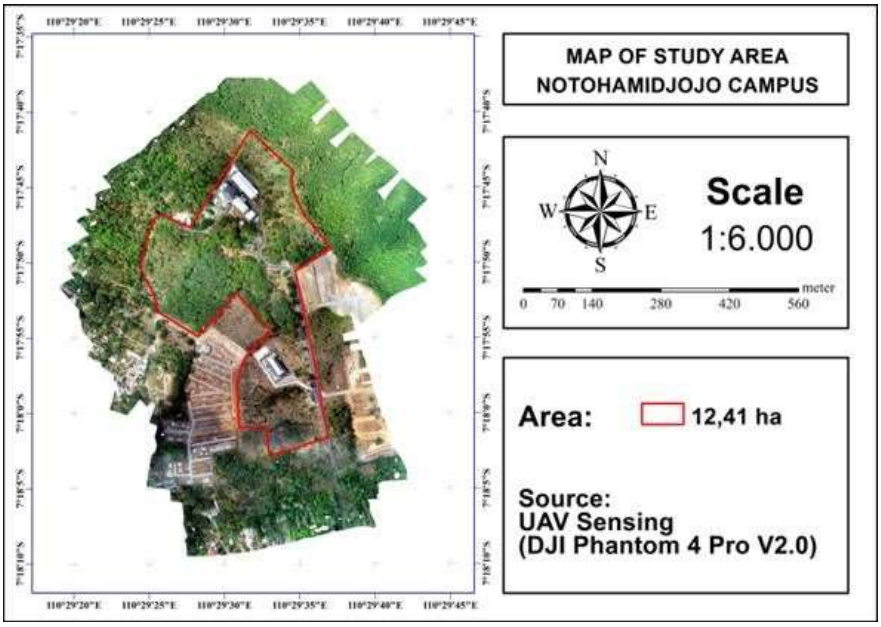

Figure 1. Map of research area: The Notohamidjojo campus (UAV sensing: 13 October 2023)

Research Workflow

The entire research workflow is shown in Figure 2. UAV imagery analysis for slope assessment and land use identification can be effectively conducted using Agisoft Metashape and ArcGIS. The collected imagery is processed using Agisoft Metashape software to create a Digital Elevation Model (DEM) of the terrain and Orthomosaic imagery development.

ArcGIS software is employed to calculate the slope angle of the terrain based on the DEM data, enabling the identification of areas with varying degrees of steepness. The results of the slope analysis are visualized on maps, aiding in understanding the topographic variations and potential slope hazards in the study area. Supervised classification using orthomosaic data in ArcGIS is a valuable method for land use analysis. The process involves training data to classify different land cover classes. In addition, manual digitization was carried out to determine the building class. This was conducted to obtain more accurate results because the class training sample was similar to other classes.

Inverse Distance Weighting (IDW) is a usual GIS technique for evaluating soil characteristics and rainfall intensity. IDW interpolation determines cell values based on a weighted mixture of sample points. The weight is a function of the inverse distance. The interpolated surface should be a location dependent variable. Nearby data will have the most effect on the interpolation, and the surface will be more detailed.

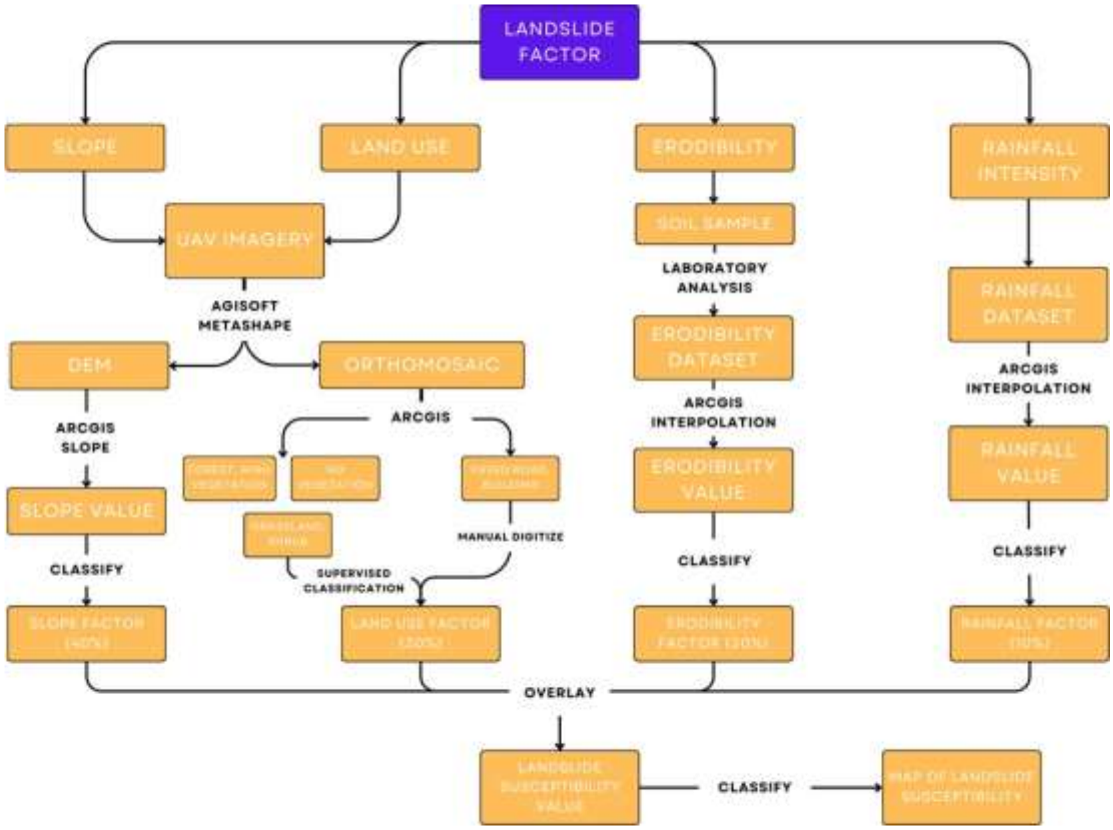

Figure 2. The research workflow

Aerial Imagery Analysis

Unmanned aerial vehicles (UAVs) are being used for land use and slope mapping. UAVs are equipped with high-quality cameras that can capture images essential for mapping outputs such as Digital Elevation Models (DEM) and Digital Orthophotos (Zolkepli, et al., 2023). The Aerial imagery obtained through remote sensing using UAV type DJI Phantom 4 Pro V2.0 and will be used to analyze slope steepness and land use. UAVs provide a quick, reliable, precise, cost-effective, and easily operable method for gathering data for slope mapping. (Rau, Jhan, Lo, & Lin, 2012). Overall, the use of UAVs for land use and slope mapping has proven to be effective and efficient in geotechnical engineering applications.

Table 1. Classification of slope steepness and land use

Code	Slope steepness		Land use
	Class	Value (%)	Class
1	Flat	< 8	Forest, high vegetation
2	Small slope	8 – 15	Grassland, shrub
3	Moderate slope	15 – 25	Agriculture, rice field
4	Steep	25 – 45	Paved road, building
5	Very steep	> 45	No vegetation

Source: (Kusumo & Nursari, 2016; Sunardi, Anggraini, Alfiandy, & Ilahi, 2022).

Soil Erodibility Factor Analysis

Soil erodibility determined in the soil laboratory. A total of 12 samples were collected to determine primary soil particles (silt, sand, and clay), organic matter content, soil permeability, and soil structure. The soil erodibility determined by using the Wishmeier, Johnson and Cross (1971) equation:

To determine the spatial distribution of the erodibility factor, the values of the erodibility factor are analyzed using ArcGIS software. Spatial analysis for the erodibility factor using the Inverse Distance Weighting (IDW) method. After obtaining the area distribution of the erodibility factor, these values are reclassified according to the Arsyad (2010).

$$K = \frac{1{,}292[2{,}1 \times M^{1{,}14}(10^{-4})(12 - OM) + 3.25(S - 2) + 2.5(P - 3)]}{100}$$

K = Erodibility factor
M = Soil particle percentages [(% verry fine sand + % silk) (100 - % clay)
OM = Organic matter content
S = Soil structure code
P = Permeability code

The soil structure and permeability code classified according to Arsyad (2010).

Table 2. Classification of soil structure and permeability

Code	Soil structure		Permeability	
	Diameter size (mm)	Class	Value (cm/h)	Class
1	< 1	Very fine granular	> 12,5	Rapid
2	1 – 2	Fine granular	6,25 – 12,5	Medium to rapid
3	2 – 10	Coarse granular	2 – 6,25	Medium
4	(blocky, platy, massive)	Blocky, solid plates	0,5 – 2	Medium to slow
5	–	–	0,125 - 0,5	Slow
6	–	–	< 0,125	Very slow

Source: (Arsyad, 2010)

To determine the spatial distribution of the erodibility factor, the values of the erodibility factor are analyzed using ArcGIS software. Spatial analysis for the erodibility factor using the Inverse Distance Weighting (IDW) method. After obtaining the area distribution of the erodibility factor, these values are reclassified according to the Arsyad (2010).

Table 3. Classification of soil erodibility

Code	Soil erodibility value	Class
1	0,00 – 0,10	Very low
2	0,11 – 0,21	Low
3	0,22 – 0,32	Medium
4	0,33 – 0,44	Medium to high
5	0,45 – 0,55	High
6	0,56 – 0,64	Very high

Source: (Arsyad, 2010).

Rainfall Intensity Factor Analysis

The analysis of rainfall intensity utilizes secondary data from the Badan Pusat Statistik (BPS) Kota Salatiga (2023). The dataset covers the last 10 years, from 2013 to 2022. Afterward, the data reclassified according to the Erfani, Naimullah, & Winardi (2023).

Table 4. Classification of soil erodibility

Code	Rainfall intensity value (mm/y)	Class
1	< 1500	Extremely dry
2	1501 – 2000	Dry
3	2001 – 2500	Normal
4	2501 – 3000	Wet
5	> 3000	Extremely wet

Source: (Erfani, Naimullah, & Winardi, 2023)

Overlay Analysis

Overlay analysis is a process of analyzing spatial layers with different attributes to understand the spatial integration among these datasets. The result is a new map that combines attributes and features from the original data layers. The primary objective of overlay analysis is to reveal patterns, relationships, or spatial connections between different layers of data.

In this research using the scoring method, which uses the intersect tools in ArcGIS software. The spatial data layers such as boundary maps, slope steepness, rainfall intensity, soil erodibility, and land use, which had already been classified into code classes of each factor, are combined to generate a landslide susceptibility distribution map and its classification. Before the overlay analysis, each factor was assigned a weight that reflected its impact level on the landslide distribution. This is done to assign each factor's impact level on the landslide distribution, affecting the overlay results. The percentage weighting for each factor was determined based on its impact level on the landslide distribution, according to Purba, Subiyanto, & Sasmito (2014).

Table 5. Weights of landslide susceptibility factors

Factor	Weight (%)
Slope steepness	40
Land use	30
Soil erodibility	20
Rainfall intensity	10

Source: (Purba, Subiyanto, & Sasmito, 2014)

To classify the level of landslide susceptibility, it is necessary to calculate the minimum and maximum scores of each variable, including slope steepness (a), land use (b), soil erodibility (c), and rainfall intensity (d).

$$Score = (a \times Weight_a) + (b \times Weight_b) + (c \times Weight_c) + (d \times Weight_d)$$

The minimum and maximum scores are obtained by multiplying the factor code with the factor weight.

Table 6. Minimum-maximum scores of landslide susceptibility

Factor	Weight (%)	$Code_{min}$	$Code_{max}$	$Score_{min}$	$Score_{max}$
Slope steepness	40	1	5	0,4	2,0
Land use	30	1	5	0,3	1,5
Soil erodibility	20	1	6	0,2	1,2
Rainfall intensity	10	1	5	0,1	0,5
Total score				**1**	**5,2**

To determine the classification of landslide susceptibility level using the interval method. In this research, the landslide susceptibility level is divided into 5 classes (Purba, Subiyanto, & Sasmito, 2014).

$$Interval = \frac{(Score\ max - Score\ min)}{5}$$

Table 7. Landslide susceptibility classification

Code	Class	Score
1	Very low	1,00 – 1,84
2	Low	1,85 – 2,68
3	Medium	2,69 – 3,52
4	High	3,53 – 4,36
5	Very high	4,37 – 5,20

Source: (Purba, Subiyanto, & Sasmito, 2014)

RESULTS AND DISCUSSION

The slope steepness of the Notohamidjojo campus is divided into 5 classes as seen in Figure 3. The 5 classes include <8% (flat), 8% - 15% (small slope), 15% - 25% (moderate slope), 25% - 45% (steep), and >45% (very steep). The slope steepness class of 25% - 45% (steep) has the largest distribution area on Notohamidjojo campus with an area of 3,59 ha or 28,90% of the total area. Slope steepness class of <8% (flat) has the smallest distribution area with an area of 1,22 ha or 9,81% of the total area. The slope steepness class of 8% - 15% (small slope) has an area of 2,39 ha or 19,23% of the total area. The slope steepness class of 15% - 25% (moderate slope) has an area of 3,17 ha or 25,55% of the total area. The slope steepness class of >45% (cery steep) has an area of 2,05 ha or 16,50% of the total area.

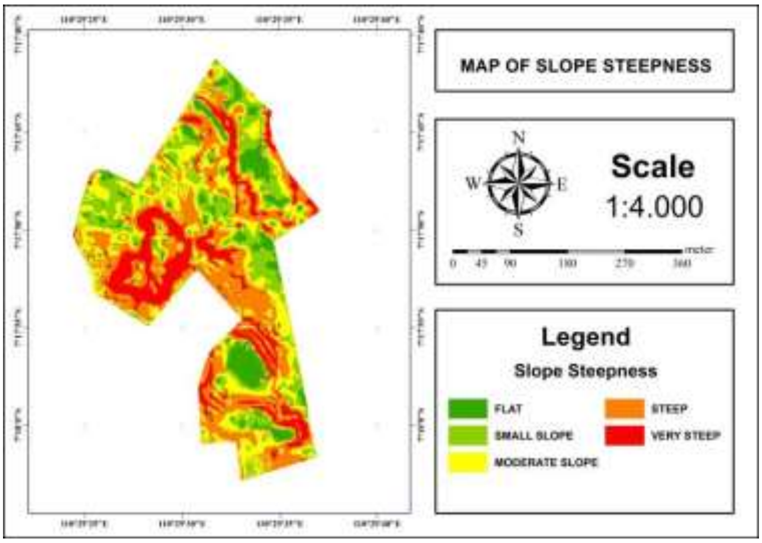

Figure 3. Map of slope steepness

The land use of Notohamidjojo campus is divided into 4 classes as seen in Figure 4. The 4 classes include forest, grassland and shrub, paved road and building, and no vegetation area. The forest area has the largest distribution area on Notohamidjojo campus with an area of 4,42 ha or 35,64% of the total area. No vegetation area has the smallest distribution area with an area of 1,94 ha or 15,66% of the total area. The grassland and shrub area has an area of 3,81 ha or 30,68% of the total area. The paved road and building area has an area of 2,24 ha or 18,03% of the total area.

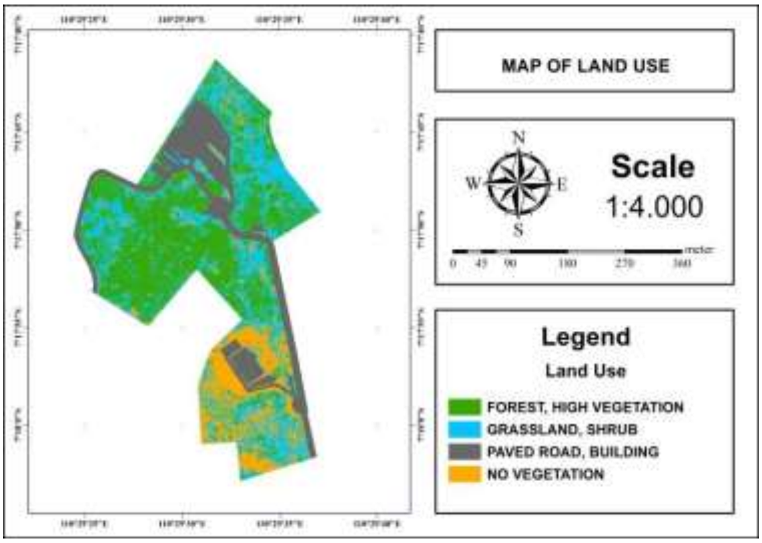

Figure 4. Map of land use

The soil erodibility of Notohamidjojo campus is divided into 2 classes as seen in Figure 5. The 2 classes include low soil erodibility (0,11 – 0,21) and medium soil erodibility (0,22 – 0,32). The low soil erodibility area has the largest distribution area on Notohamidjojo campus with an area of 9,63 ha or 77,64% of the total area. Medium soil erodibility area has the smallest distribution area with an area of 2,77 ha or 22,36% of the total area.

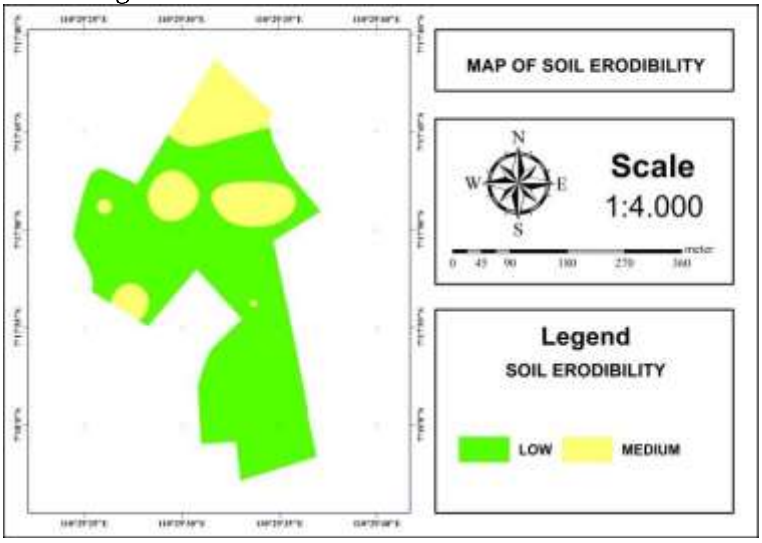

Figure 5. Map of soil erodibility

The average rainfall intensity in the Notohamidjojo campus area is 2429 mm/year which is categorized as a normal class of 5 rainfall intensity class categories. These results are determined based on the average rainfall intensity over the last 10 years (2013 - 2022).

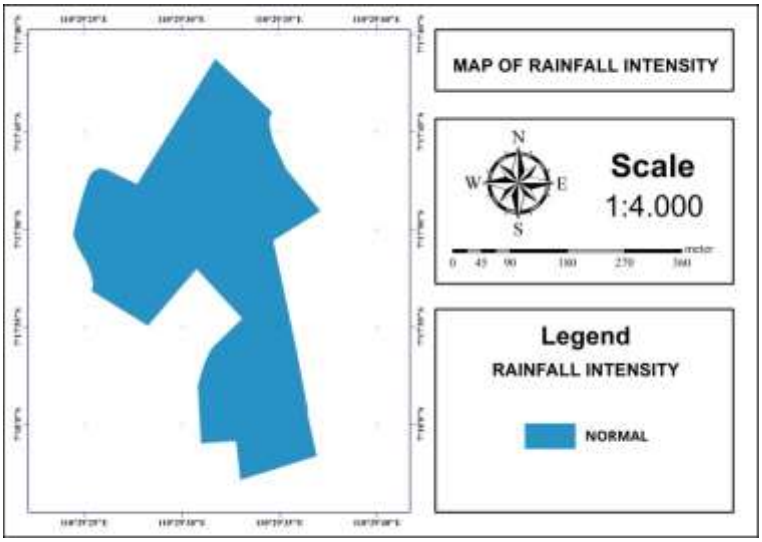

Figure 6. Map of rainfall intensity

The landslide susceptibility level of the Notohamidjojo campus is divided into 5 classes as seen in Figure 7. The medium class has the largest distribution area on Notohamidjojo campus with an area of 5,77 ha or 46,50% of the total area. The very high class has the smallest distribution area with an area of 0,01 ha or 0,09% of the total area. The very low class has an area of 0,96 ha or 7,71% of the total area. The low class has an area of 4,48 ha or 36,10% of the total area. The high class has an area of 1,19 ha or 9,61% of the total area.

Based on these results, more than 50% of the Notohamidjojo campus area is susceptible to landslides. The area with high landslide susceptibility is centered on the southern area of the campus as can be seen in Figure 7. This is because the area is dominated by areas with steep slopes and no vegetation areas. The most influential factor of landslide susceptibility level using the scoring method is the topography factor, including elevation and slope aspect (Suni, Mappatoba, & Basoka, 2023). Steeper slopes have a significant effect on landslide susceptibility. The frequency ratio model applied in the Nilgiris district of Tamil Nadu, India, showed that steeper slopes have a greater probability of landslides, with a predicting rate of 8.25% (Yuvaraj & Dolui, 2023). In California and Switzerland, field observations and measurements of soil landslides indicated that steeper hillslopes typically have thinner soils, which inhibit landslides due to enhanced cohesion and boundary stresses (Cha, Gang, & Kim, 2022). The Kuranji watershed in Padang, Indonesia, also demonstrated that smaller slopes and heights result in more stable slopes, while larger slopes are more unstable (Lamb, McArdell, Rickli, & Kirchner, 2020). These findings suggest that the relationship between slope steepness and landslide susceptibility is complex, with factors such as soil thickness and stability playing a role.

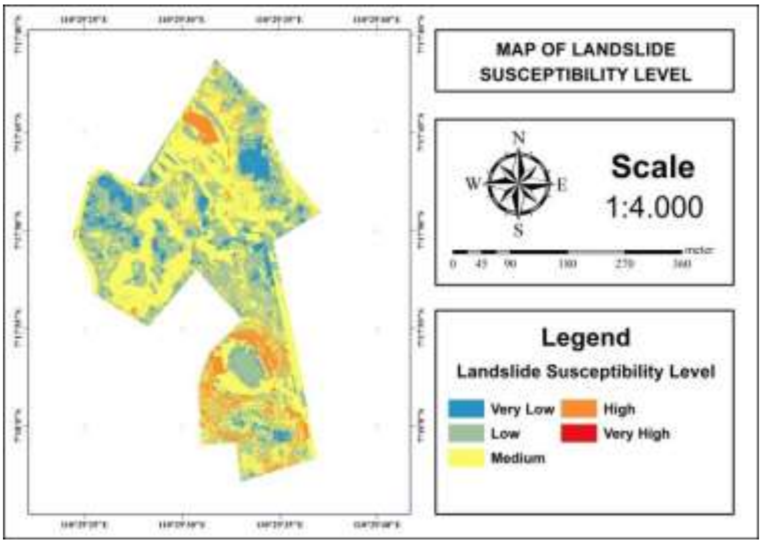

Figure 7. Map of landslide susceptibility level

Additionally, land use also has a significant impact on landslide susceptibility. Changes in land use and land cover (LULC) can increase the risk of landslides, especially in areas with steep slopes, weak soils, or concentrated water flow (Jurchescu, *et al.*, 2023). Deforestation and expansion of infrastructure are some of the main factors contributing to landslide risk (Quevedo, *et al.*, 2023). The forests play a crucial role in preventing shallow landslides by reinforcing and drying soils (Behera & Sahoo, 2023). Conversely, transitions from forests to other land uses can increase landslide occurrence (Dandridge, Stanley, Kirschbaum, Amatya, & Lakshmi, 2022). The land conversion to forest has been found to have a positive correlation with landslide activity (Manchado, Cánovas, Allen, & Stoffel, 2022).

CONCLUSION

Based on these results, more than 50% of the Notohamidjojo campus area is susceptible to landslides. The medium class has the largest distribution area on Notohamidjojo campus with an area of 5,77 ha or 46,50% of the total area. The very high class has the smallest distribution area with an area of 0,01 ha or 0,09% of the total area. The very low class has an area of 0,96 ha or 7,71% of the total area. The low class has an area of 4,48 ha or 36,10% of the total area. The high class has an area of 1,19 ha or 9,61% of the total area. The area with high landslide susceptibility is centered on the southern area of the campus. This is because the area is dominated by areas with steep slopes and no vegetation areas.

The main thing that can be done to minimize the risk of landslides is to conserve land into forest areas. Especially in the southern campus area, which is dominated by no vegetation areas. Land conservation plays a crucial role in reducing landslide risk. Excessive soil water content, steep slopes, weak soils, and topography that concentrates water are the main factors contributing to landslide risk. Trees and forests are essential in preventing shallow landslides by reinforcing and drying soils, as well as obstructing smaller slides and rock falls.

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