



## **Geotechnical Study of Soil Landslides on the 22.7 km Road Section in Quelicai Sub-District, Baucau Regency and Ossu Sub-District, Viqueque Regency, Timor-Leste**

**Engracia Alves Mendes<sup>1\*</sup>, Amara Nugrahini<sup>2</sup>**

<sup>1,2</sup>Institut Teknologi Nasional Yogyakarta, Indonesia

Email: <sup>1\*</sup>4200221010@students.ac.id

### *Abstract*

*The Quelicai–Ossu road section in Timor-Leste, spanning 22.7 km, frequently experiences landslides that disrupt transport connectivity between Baucau and Viqueque districts. These slope failures are exacerbated by steep topography, intense rainfall, and lithological conditions dominated by cohesive clay soils prone to saturation. To address this issue, this study aims to identify and analyse the factors causing landslide vulnerability on the 22.7 km Quelicai–Ossu road section in Timor-Leste. The methods used included field surveys, laboratory testing, and analysis using the Analytical Hierarchy Process (AHP) method combined with GIS. The factors analysed included rainfall, slope gradient, lithology, elevation, drainage, soil type, land use, and road distance. The results of the study show that the study area is divided into three classes of landslide susceptibility: high (19%), moderate (67%), and low (14%). The main factors contributing to landslide susceptibility are rainfall (21%) and drainage (19%). In conclusion, areas with high vulnerability require mitigation measures such as geotechnical engineering to increase slope safety factors to above 1.5. This study provides technical recommendations to reduce landslide risk in the study area.*

**Keywords:** *Landslide Vulnerability, Analytical Hierarchy Process (AHP), GIS.*

## **1. INTRODUCTION**

Timor-Leste is located between the Indo-Australian Plate in the south and the Eurasian Plate in the north. This tectonic position has led to the formation of mountains with steep slopes, which often experience mass movements and subsidence. These phenomena are generally caused by various factors, including geological conditions, lithology, geological structure, geomorphology, climate, and human activity (Hidayat et al., 2023). In the study area, the lithology is dominated by highly cohesive clay soils, which tend to exacerbate the risk of landslides when saturated by rainfall (Bodos et al., 2024). Low-permeability soils such as clay can retain water, increase pore water pressure, and reduce friction, thereby increasing the likelihood of landslides. Landslides not only impact infrastructure but can also threaten the lives of people living in the surrounding area. Therefore, a thorough understanding of the contributing factors and geological conditions in this area is crucial.

One area that frequently experiences landslides is the Quelicai–Ossu road, which stretches 22.7 km and connects Baucau District and Viqueque District. This road passes through a hilly area with slopes varying from moderately steep to very steep, making it highly prone to landslides, especially during the heavy rainy season. According to local residents, landslides frequently occur at several points along this route, disrupting transport access between the two districts.

Previous research by Gerstner et al. (2023) showed that slope failures in critical areas are often influenced by geological structural conditions, such as layer discontinuities, foliation, joints and faults. However, in this study area, lithological factors are more dominant in influencing slope stability. The types of soil present, such as clay and fine-grained soil, can

increase susceptibility to landslides, especially when soil moisture conditions increase during the rainy season. In this case, weak soil lithology can increase susceptibility to landslides, especially in extreme weather conditions (Scaife, 2024).

Research on landslide vulnerability and stability has been widely conducted using GIS, risk modeling, laboratory analysis, and descriptive studies (Casagli & Tofani, 2025; Dikshit et al., 2020; Ehsan et al., 2025; Wang & Li, 2025). However, most of these studies still have limitations. GIS and multi-criteria-based mapping often only consider topographic, lithological, and rainfall factors without incorporating laboratory-derived soil mechanical properties (Fitra et al., 2025). Slope stability analyses are often localized and focused on single factors, while descriptive studies on landslide mechanisms and mitigation are rarely linked to quantitative and spatial data (Jiang et al., 2022; Zhang & Shen, 2024).

The Analytic Hierarchy Process (AHP) method has been widely and contemporarily used in disaster mitigation research to integrate various risk criteria, measure location vulnerability, and quantitatively prioritize mitigation strategies. For example, by combining AHP and GIS in multi-hazard risk assessments to map buildings based on their vulnerability to floods, landslides, and fires, resulting in risk-level maps as a basis for planning mitigation in affected areas (Gacu et al., 2025). Additionally, AHP has been used to evaluate flood vulnerability in watersheds through multi-criteria decision-making with a consistently valid pairwise comparison matrix to identify flood-prone zones as a tool for mitigation and strategic response (Sofi et al., 2024). A similar approach was employed by (Wijayanti et al., 2025) to map flood susceptibility in various urban and rural areas by weighting environmental factors such as slope, rainfall, land use, and geology, thereby producing more accurate risk zonation for location-based mitigation decisions. The integration of AHP in spatial multi-criteria evaluation allows for combining multiple risks, such as floods and landslides, into a single model to produce multi-hazard vulnerability maps that can be used by local governments in mitigation planning (Lyu & Yin, 2023). AHP applications also include its use in flood vulnerability mapping studies that consider physical and geomorphological variables through statistically validated AHP-weighted techniques, thereby enhancing the accuracy of disaster-prone area detection and providing a scientific basis for potential flood mitigation measures (Shekar & Mathew, 2023). Similarly, landslide vulnerability research combining AHP and GIS has been used to determine diverse landslide risk zones and support data-driven spatial mitigation strategies. Studies by (Widiastuti et al., 2025) and (Sofi et al., 2024) demonstrate AHP as an MCDM tool capable of unifying hazard, vulnerability, and exposure factors within a disaster mitigation decision-making framework. Consequently, the results serve as a practical reference for policymakers and disaster planners to establish scientifically data-oriented mitigation priorities.

This study presents a more thorough method that combines the Analytical Hierarchy Process (AHP) and GIS, using laboratory soil data like cohesion and friction angle. This approach allows for the determination of the critical weight of each landslide-causing factor, thereby yielding more accurate and field-representative vulnerability maps and bridging the gaps identified in previous studies.

To date, the road between Quelicai District and Ossu District has never been the subject of in-depth research on landslide potential. With the increasing frequency and intensity of landslides, there is an urgent need for systematic and comprehensive studies. Therefore, this study attempts to examine the problem of landslides in the area through a technical geological approach. This study will use various parameters such as soil type, cohesion, angle of repose, rainfall, slope gradient, geological factors (lithology), drainage, elevation, land use and roads.

Based on the above description, this study seeks to identify and analyse the factors causing landslide vulnerability on the 22.7 km Quelicai–Ossu road section in Timor-Leste. This research is expected to provide a better understanding of the factors that influence slope stability in the region and provide technical recommendations for landslide mitigation in the future.

## 2. RESEARCH METHODOLOGY

### 2.1. Data Collection

The data collection stage involved gathering both primary and secondary data. Primary data was obtained through field surveys for direct slope observation and soil sampling at landslide points using hand borers, test pits, CPT, and DCP for subsequent laboratory analysis. Secondary data, such as rainfall and soil type information, was acquired from relevant agencies. The research was structured into three substages: (a) geomorphological observation focusing on slope inclination and landforms, and (b) geological observation including lithological description.

### 2.2 Laboratory Testing Stage

Disturbed and undisturbed soil samples taken in the study area were collected and sent to the soil mechanics laboratory for testing at the Laboratório Ministério Obras Públicas Timor-Leste (MOPTL) and the Laboratório Teknik Sipil Universidade Nacional Timor Lorosae (UNTL).

The laboratory testing methods adopted for testing soil samples included: Moisture content (ASTM D2216); Specific gravity test (ASTM D853); Particle size analysis (ASTM C14.16); Atterberg limit test (ASTM D44.118); Submerged CBR test (ASTM D1883); and Direct shear test (ASTM D44.118).

### 2.3 Data Analysis Stage

The data analysis stage goes through several stages to achieve the research objectives, namely:

1. The first stage involves analysing data on slope inclination, rainfall, geological factors (lithology), soil type, land use, elevation, drainage and roads to produce a vulnerability map.
2. The soil sampling stage is intended to provide material to be used for laboratory analysis by the Timor-Leste Ministry of Public Works and UNTL. There are two types of soil and rock samples taken using different methods, namely disturbed samples and undisturbed samples.

Disturbed samples can be taken with soil sampling equipment using a pickaxe. Meanwhile, undisturbed samples can be taken with soil sampling equipment using a hand borer.

### 2.4 Sampling Method

Geotechnical sampling employed several field methods (Cavallaro, 2022): Cone Penetration Tests (CPT) to a depth of less than 10 m assessed soil characteristics, bearing capacity, and friction to locate hard strata. Hand boring to approximately 5 m collected disturbed and undisturbed samples to determine the water table and soil layering (Oteuil et al., 2022). Test pits (1x1x1.5 m) were excavated at eight locations for visual inspection and sampling. Additionally, Dynamic Cone Penetrometer (DCP) tests were conducted every 200 m to determine the subgrade's CBR value for pavement design, testing to a depth of 100 cm.

Field testing in this study employed CPT, DCP, and hand boring to obtain representative physical and mechanical soil parameters. CPT was performed to a depth of less than 10 meters using a Dutch-type static penetrometer with a capacity of approximately 2.5 tons. This test aimed to identify soil stratification, cone tip resistance (qc), and sleeve friction (fs) in order to determine soil layer characteristics and the depth

of the hard layer, which is generally assumed to correspond to a  $q_c$  value  $\geq 150$  kg/cm<sup>2</sup>. DCP was performed at intervals of approximately 200 meters per 1 km of the observation route, with testing depths up to 100 cm from the ground surface. This was done to obtain an estimated CBR (California Bearing Ratio) value of the soil, which is required for bearing capacity and slope stability analyses. Meanwhile, hand boring was carried out to a depth of approximately 5 meters using a standard diameter hand auger. The objectives were to collect disturbed and undisturbed soil samples, identify soil types per layer, and determine the groundwater table depth. All field testing procedures were conducted following standard field geotechnical practices and were correlated with ASTM-standard laboratory test results to ensure data consistency and reliability.

## **2.5 Analytical Hierarchy Process Analysis**

### **1. Criteria and Sub-Criteria:**

Determination of parameters to assess slope stability and create a vulnerability map of the study area, namely: geological factors, slope gradient, land use, soil type, rainfall, elevation, drainage, and roads.

### **2. Assessment and Weighting:**

Conduct an assessment of each criterion with the involvement of experts or stakeholders, then use the AHP method to assign weights. The weighting of criteria using the AHP method was validated through a Consistency Ratio (CR) test to ensure the assessment's consistency level remained within acceptable limits ( $CR < 0.1$ ). The pairwise comparison weighting process was obtained via expert judgment, involving specialists in engineering geology, geotechnics, and landslide disaster management. This included academics and practitioners with experience in slope stability analysis and landslide vulnerability mapping. The involvement of these experts aims to maintain objectivity in assessing the importance level of each criterion, such as slope gradient, lithology, soil type, rainfall, land use, and other supporting factors. The assessment results from the experts were then processed quantitatively using the AHP method. Only comparison matrices that met the consistency threshold were used in subsequent analysis and integration with the Geographic Information System (GIS).

## **2.6 Vulnerability Map Creation**

Integration with GIS Enter the analysed data into GIS software to create a landslide vulnerability map. Use overlay techniques to visualise areas with different risks.

## **2.7 Verification and Validation**

Verify the vulnerability map results with field data and information from the local community.

## **2.8 Completion and Presentation Stage**

In the completion and presentation stage, data were analyzed, interpreted, and compiled into thematic maps which including slope, geology, soil type, rainfall, land use, road distance, elevation, and drainage density, and a comprehensive report. The final landslide vulnerability map for the study area was generated by applying AHP weighting in GIS to synthesize these map layers, supplemented by physical and mechanical analyses of soil samples, alongside a report detailing slope safety factor values.

## **2.9 Landslide Mitigation**

The alternative landslide mitigation measures described in the previous chapter can be selected according to each location, taking into account geological, topographical, land use, land ownership and local socio-cultural conditions.

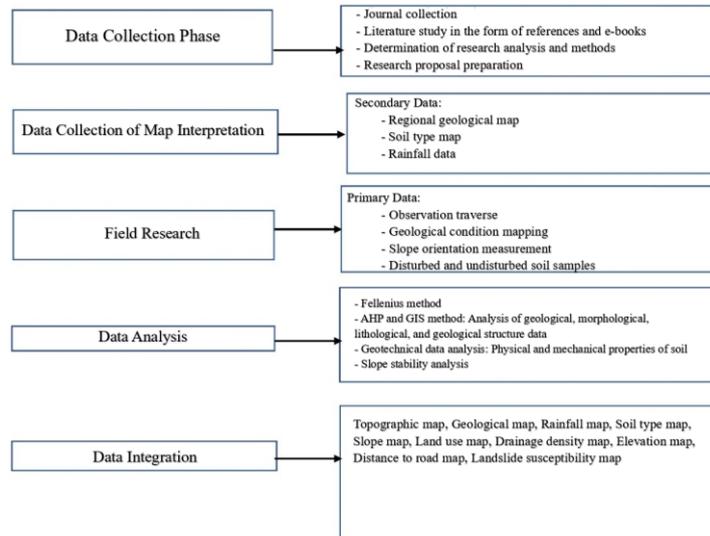


Figure 1. Research Methodology Flowchart

### 3. RESULTS AND DISCUSSION

#### 3.1. Analysis of Factors Affecting Slope Stability

##### 3.1.1. Parameters Affecting Slope Stability

##### 1. Slope gradient

In this study, slope gradients were divided into five classes based on the slope classification system developed by Irawan et al. (2024) for determining the risk of disasters, one of which is landslides.

Table 1. Slope Gradient Classes

Parameter	Classification	Class (O)	Area Size (m <sup>2</sup> )	Percentage (%)
Slope Gradient	Flat	0 – 2	0.162044	1%
	Slightly Sloping	2 – 4	1.245075	9%
	Sloping	4 - 8	3.412762	25%
	Slightly Steep	8 - 16	6.387396	48%
	Steep	16 - 35	2.223906	17%

Based on Table 1, slope gradient correlates with morphology, material, and landslide risk: flat areas (0°–2°) on fluvial plains have loose materials with minimal landslides; gentle slopes (2°–4°) rarely experience slow-moving landslides; somewhat prone slopes (4°–8°) occur in hilly areas; fairly steep slopes (8°–16°) have significant erosion and slow ground movement; and steep slopes (16°–35°) in structural hills face high erosion and rockfall risks, as illustrated in the slope gradient map (Figure 1).

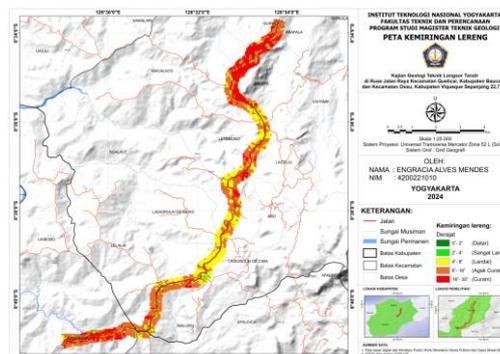


Figure 1. Slope Map of the Baucau-Viqueque Highway Research Area

## 2. Rainfall

Rainfall is one of the factors that triggers landslides. Based on the intensity of rainfall, the greater the intensity of rainfall, the greater the effect on landslides. In this study, the calculation of rainfall intensity produced a rainfall graph, and rainfall intensity was divided into three classes.

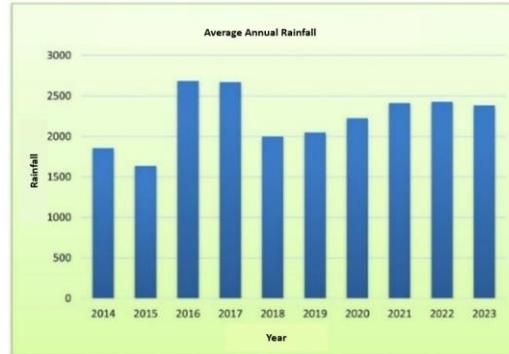


Figure 2. Rainfall graph for the research area of Baucau and Viqueque Highway

Table 2. Rainfall Classes

Parameter	Classification	Class (m <sup>2</sup> )	Area	Percentage (%)
Rainfall	Moderate	2005.34 - 2104.65	9.412867	70%
	Moderate	2104.65 - 2203.96	0.289342	2%
	Moderate	2203.96 - 2303.28	3.723517	28%

Based on the climate classification system according to Putri & Wibowo (2023), the study area is classified as having a temperate climate with a rainfall of 2000–3000 mm/year. Based on the table 2 above, rainfall is divided into three classes: class 2005.34–2104.65 mm/year in the Quelicai area, covering 70% of the total area; class 2104.65–2203.96 mm/year in the Ossu area, covering 28% of the total area, and 2203.96–2303.28 mm/year in the Nahareca area, covering 2% of the total area.

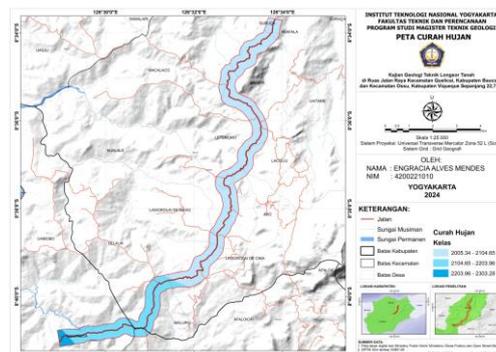


Figure 3. Rainfall Map of the Baucau-Viqueque Highway Research Area

## 3. Land Use

Land use is one of the factors that trigger landslides. In the study area, land use is divided into five classes.

Table 3. Land Use Classes

Parameters	Class	Area (m <sup>2</sup> )	Percentage (%)
Land Use	Water	0.119818	1%
	Rice fields	0.615175	5%
	Open areas	7.360093	55%
	Settlements	0.950803	7%
	Vegetation	4.479845	33%

Land use planning is a critical parameter because human activities, such as deforestation for settlements or slope cutting for roads which can alter water flow, raise the water table, and increase erosion, thereby triggering landslides. The study area is predominantly open land due to field clearance, which heightens landslide potential as the lack of deep-rooted vegetation fails to bind soil, especially when combined with moderate rainfall, steep slopes, and moderately resistant rocks, as illustrated in the land use map (see Figure 4).

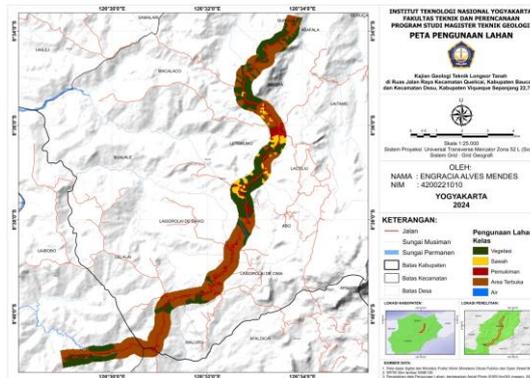


Figure 4. Land Use Map of the Baucau-Viqueque Highway Research Area

#### 4. Soil type

Soil type also contributes to erosion and landslide potential. Loose soil, for example, has a greater potential for landslides because water can easily penetrate the soil surface compared to compact soil such as clay or loamy soil. In the study area, soil types were divided into three (3) classes.

Table 4. Soil Type Classes

Parameters	Texture Class	Area Size	%
Soil Type	Sandy Clay	4.512216	34%
	Clay Loam	4.325877	32%
	Clay	4.587633	34%

The soil classification comprises three types (Pertiwi et al., 2025): sandy clay, which offers moderate drainage and cohesion but becomes unstable when saturated; silty clay, which has a balanced structure and water retention but softens significantly under heavy rainfall; and clay, which provides high cohesion but poor drainage, becoming heavy and weak when wet, leading to significant, dangerous slow-moving landslides, as shown in the soil type map (Figure 5).

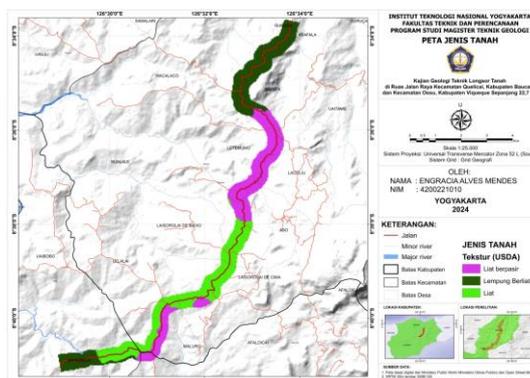


Figure 5. Soil Type Map of the Baucau-Viqueque Highway Research Area

## 5. Elevation

Elevation also has the potential to be vulnerable to ground movement when viewed from its height, i.e. the higher the elevation in a particular area, the greater the risk of ground movement.

Table 5. Elevation Classes

Parameters	Class	Area	Percentage (%)
Elevation	250 – 355	1.60759	12%
	355 – 460	2.058212	15%
	460 – 567	2.609454	20%
	567 – 669	4.913629	37%
	669 – 773	2.253849	16%

Elevation is divided into five classes, with landslide risk generally increasing with height: the lowest class (250–355 m) has flat to slightly hilly terrain and a lower risk; the 355–460 m class experiences steeper slopes and increased instability when saturated; the 460–567 m class has significantly higher potential due to steeper gradients and vulnerable soils; the 567–669 m class faces high risk from reduced cohesion on steep slopes; and the highest class (669–773 m) is very steep with high erosion and is highly susceptible to landslides, especially when soil is saturated.

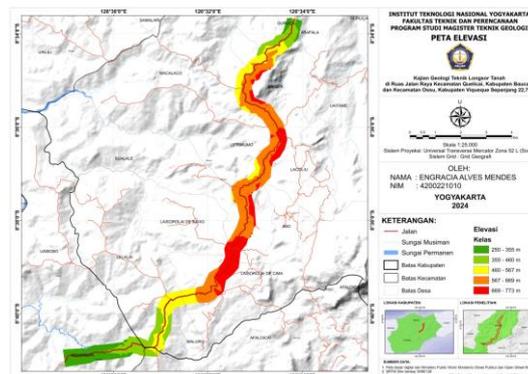


Figure 6. Elevation Map of the Baucau-Viqueque Highway Research Area

## 6. Drainage

Drainage is the continuous flow of water on the ground surface, usually in the form of rivers, small streams, or channels. Drainage can vary in size, depth, and flow velocity and plays an important role in ecosystems, water supply, and influences the shape of the ground surface through erosion and sedimentation processes.

Table 6. Drainage Density Class

Parameter	Class	Area Size (m <sup>2</sup> )	Percentage (%)
Drainage	0 - 70	5.596579	42%
	70 - 140	5.464021	41%
	140 - 210	1.868753	14%
	210 - 270	0.351762	3%
	270 - 347	0.153124	1%

Based on Table 6, drainage is classified into four flow classes. The smallest classes (0–70 and 70–140) dominate the area, comprising 42% and 41% respectively, indicating that small flows are most common. In contrast, the larger flow class (140–347) covers a much smaller area, demonstrating that significant drainage flows are far less frequent in the region, as shown in the drainage density map (Figure 7).

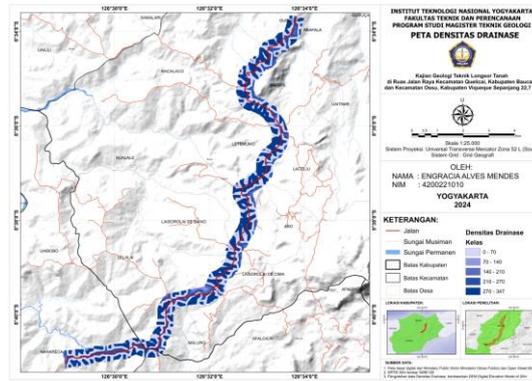


Figure 7. Drainage Density Map of the Study Area (Baucau-Viqueque Highway)

## 7. Road

Has a significant impact on soil stability and the risk of ground movement. Roads Understanding the interaction between roads and soil conditions is essential for safe and sustainable infrastructure planning. In the study area, roads are divided into three (3) classes.

Table 7. Road Distance Classes

Parameter	Class	Area Size (m <sup>2</sup> )	Percentage (%)
Road	0 - 120	6.045699	45%
	120 - 240	5.150313	38%
	240 - 360	2.23544	17%

The area distribution from Table 7 shows that the shortest road class (0–120 m) occupies the largest area at 45%, indicating that small local roads are predominant. In contrast, longer road classes (120–360 m) cover a significantly smaller area, suggesting that extended road networks are less common in the region.

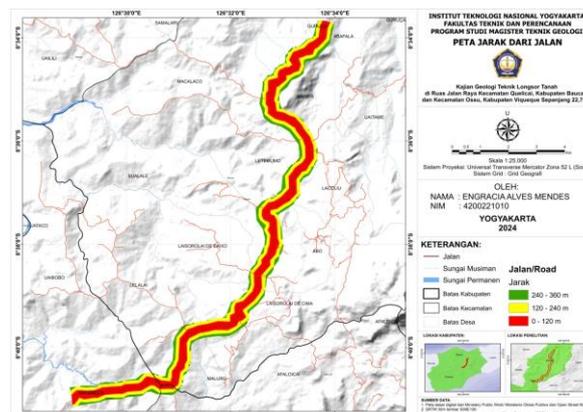


Figure 8. Distance Map from the Baucau-Viqueque Highway Research Area

### 3.2. Classification of Landslide Vulnerability Levels

Landslide vulnerability in the study area was determined by integrating key parameters which is slope gradient, rainfall, soil type, land use, lithology, elevation, drainage, and road distance through weighted overlay analysis in GIS (Seidualin et al., 2024). The Analytical Hierarchy Process (AHP) was applied to assign weights to these factors, which were then synthesized from their respective thematic maps to produce a final landslide vulnerability map. Following an adapted model from Khan et al. (2024), the resulting vulnerability is categorized into three classes: low, medium, and high.

### 3.2.1. Analytical Hierarchy Process

The weighting of factors influencing landslide occurrence was carried out using AHP (Analytical Hierarchy Process) analysis (Liu et al., 2024). This analysis was conducted by grouping several parameters such as slope inclination, rainfall, soil type, land use, geological factors (lithology), elevation, drainage and road distance. The working principle of AHP is to simplify a complex problem into its parts and arrange them in a hierarchy or ranking. The initial input for the comparison matrix in this method is used by determining the score of each factor used. This scoring process is given based on the influence on landslides; the higher the score, the higher the influence of that factor on the landslide hazard. From the problems that exist in determining the factors that cause landslides in the study area, based on the level of importance of the parameters or criteria determined: The eight parameters that cause landslides are slope inclination, rainfall, soil type, land use, geological factors (lithology), elevation, drainage and road distance.

The Bobonaro Formation is a tectonic melange unit resulting from the collision (orogeny) of Timor Island. It is characterized by a mixture of scaly clay, silt, sandstone, and exotic rock fragments within a strongly deformed clay matrix. This intensive tectonic deformation process produces microstructures such as repeated shear fabric, aligned clay mineral orientation, and a high degree of internal fracturing. This condition explains why Bobonaro soils mechanically exhibit relatively low and highly variable cohesion and friction angles in direct shear test results, particularly in undisturbed samples from critical locations like STA 7+340 and STA 17+940.

Physically, the dominance of silt-clay fractions (up to >50% silt and approximately 10–19% clay) causes intergranular contacts to be dominated by weak electrostatic bonds rather than the mechanical interlocking typical of sand. When saturated, pore water quickly fills the spaces between particles and micro-shear planes, leading to a sharp decrease in effective stress. This is reflected in the very low cohesion values (even 0 kN/m<sup>2</sup>) and small friction angles (13–17°) at some stations, indicating soil behavior approaching residual conditions.

From a chemical-mineralogical perspective, the clay in the Bobonaro Formation generally contains active clay minerals (such as mixed smectite/illite) with high water adsorption capacity. Adsorbed water causes swelling and an increase in the distance between mineral sheets, further weakening interparticle bonds. The moderate to high Plasticity Index (PI) and activity >1 in some samples support the interpretation that this soil is sensitive to changes in water content.

Physically, the oriented structure of scaly clay forms natural slip planes. Under saturated conditions, pore water pressure increases and acts parallel to these planes, significantly reducing the shear force required to trigger landslides. This is why the Bobonaro Formation, although lithologically appearing massive, is the most dominant and landslide-prone unit in the study area (approximately 70% of the area), especially on gentle to moderately steep slopes with shallow groundwater tables.

Thus, the low shear strength of Bobonaro soil is not solely due to its grain composition but is a direct consequence of its geological formation history (tectonic-mélange), the microstructure of scaly clay, and the water-sensitive chemical properties of its clay minerals. This condition explains why increased water content from intense rainfall rapidly reduces slope stability and triggers ground movements along the research route. Based on these geological and geotechnical characteristics, the geological (lithology) factor is considered the dominant parameter in the pairwise comparison for the AHP method.

According to history and local residents, the parameter of geological factors (lithology) with a rainfall value of 2.00 indicates that geological factors (lithology) are considered twice as important as rainfall because geological conditions can affect soil stability more significantly than the amount of rainfall. The slope inclination parameter with elevation is given a value of 2.00, indicating that slope inclination is considered more important than elevation because slope inclination has a direct impact on landslide risk compared to height. The drainage parameter with soil type is given a value of 4.00 for drainage compared to soil type, indicating that the drainage system is far more important in the context of landslide risk than soil type, which has an influence but is not as strong as drainage (see Table 8).

### 1. Matrix Comparison

Table 8. Matrix Comparison

Criteria	Geological Factors (Lithology)	Rainfall	Slope Gradient	Elevation	Drainage	Land Use	Soil Type	Road Distance
Geological Factors (Lithology)	1.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Rainfall	0.50	1.00	3.00	2.00	3.00	2.00	3.00	4.00
Slope Gradient	0.50	0.50	1.00	2.00	2.00	2.00	1.00	3.00
Elevation	0.50	0.50	0.50	1.00	1.00	2.00	2.00	3.00
Drainage	0.50	0.33	0.50	1.00	1.00	4.00	5.00	5.00
Land Use	0.50	0.50	0.50	0.50	0.25	1.00	2.00	2.00
Soil Type	0.50	0.33	1.00	0.50	0.20	0.50	1.00	2.00
Roads	0.50	0.25	0.33	0.33	0.20	0.50	0.50	1.00
Number	4.50	5.42	8.83	9.33	9.65	14.00	16.50	22.00

### 2. Normalisation and Weight Calculation

Once the comparison matrix is complete, the next step is to normalise and calculate the weights:

a. Calculate the Total for Each Column:

Add up each column to obtain the total. This is important for the normalisation step.

b. Normalisation:

Divide each value in the column by the total for that column. This will give the percentage contribution of each criterion to the total.

c. Calculate the weight of each criterion

To obtain the weight of the criteria, add up the results of the normalised matrix calculation. Then divide the result by the number of criteria.

Table 9. Matrix Normalisation

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	Priority Vector/ Weight Criteria	Weight (%)
C1	0.22	0.37	0.23	0.21	0.21	0.14	0.12	0.09	0.20	20%
C2	0.11	0.18	0.34	0.21	0.31	0.14	0.18	0.18	0.21	21%
C3	0.11	0.09	0.11	0.21	0.21	0.14	0.06	0.14	0.13	13%
C4	0.11	0.09	0.06	0.11	0.10	0.14	0.12	0.14	0.11	11%
C5	0.11	0.06	0.06	0.11	0.10	0.29	0.30	0.23	0.16	16%
C6	0.11	0.09	0.06	0.05	0.03	0.07	0.12	0.09	0.08	8%
C7	0.11	0.06	0.11	0.05	0.02	0.04	0.06	0.09	0.07	7%
C8	0.11	0.05	0.04	0.04	0.02	0.04	0.03	0.05	0.05	5%
								Total	1.00	100%

### 3. Consistency Analysis

After calculating the weights, it is important to evaluate the consistency of the comparisons made in the table below.

Table 10. Important Data for Consistency Ratio Checks

Criteria	Column Total (CT)	Priority Vector (PV)	CT * PV
C1	4.50	0.20	0.897
C2	5.42	0.21	1.129
C3	8.83	0.13	1.190
C4	9.33	0.11	1.016
C5	9.65	0.16	1.515
C6	14.00	0.08	1.090
C7	16.50	0.07	1.129
C8	22.00	0.05	0.998
Maximum Eigenvalue $\lambda$ of the comparison matrix			8.965

For the calculation of the Consistency Index (CI)

$$\begin{aligned}
 CI &= \frac{\lambda_{\max} - n}{n - 1} \\
 &= \frac{8,965 - 8}{8 - 1} \\
 CI &= 0,138
 \end{aligned}$$

Consistency Ratio (CR)

After determining the consistency index (CI), calculate:

$$CR = \frac{CI}{RI}$$

Where the RI value is taken from:

Table 11. Random Consistency Index

N	RI
1	0
2	0
3	0.58
4	0.9
5	1.12
6	1.24
7	1.32
8	1.41
9	1.45
10	1.49
14	1.57
15	1.59

$$\begin{aligned}
 CR &= \frac{CI}{RI} \\
 &= \frac{0,138}{1,41} \\
 CR &= 0,098
 \end{aligned}$$

After calculating the CR value, it shows that from the weight results, a value of 0.098 is obtained from  $CR \leq 0.1$ , so the above priorities are consistent. This is because it meets the AHP principle, where the consistency ratio must be less than 10% or 0.1. Therefore, it can be said that the calculation is consistent.

The results of the calculation of the landslide vulnerability parameters are: Geological Factors (Lithology) with a weight of 17%, rainfall with a weight of 21%, slope with a weight of 13%, elevation with a weight of 12%, drainage with a weight of 19%, land use with a weight of 8%, soil type with a weight of 7%, and roads with a weight of 4%. Based on the eight factors used in this study, each has parameters with different priorities. The most influential parameter is rainfall, which is the parameter with the greatest role in influencing landslides, with a weight of 21%.

Table 12. Parameter Weighting

No.	Criteria	Weight
1	Rainfall	21%
2	Drainage	19%
3	Geological Factors (Lithology)	17%
4	Slope Gradient	13%
5	Elevation	12%
6	Land Use	8%
7	Soil Type	7%
8	Road Distance	4%

### 3.2.2. Creating a Landslide Vulnerability Map

After calculating weights using the AHP method, each parameter attribute was assigned a score from 1 to 5 based on its influence on landslide causality, with a score of 5 indicating the most significant impact. This scoring and the subsequent weighting process were then executed within the ArcGIS 10.8 software.

#### 1. Scoring

##### a. Scoring of rainfall parameters

Table 13. Rainfall Parameter Scoring

Parameter	Classification	Class (mm)	Score
Average Rainfall	Moderate	2005.34 - 2104.65	4
	Moderate	2104.65 - 2203.96	3
	Moderate	- 2303.28	1

##### b. Assigning scores to Drainage parameters

Table 14. Drainage Parameter Scoring

Parameters	Class	Score
Drainage	0 - 70	5
	70 - 140	4
	140 - 210	3
	210 - 270	2
	- 347	1

##### c. Scoring of Geological Factors (Lithology) parameters

Table 15. Scoring of Geological Factors (Lithology)

Parameters	Formation (Lithology)	Score
Formation (Lithology)	Aituto Formation	4
	Cribas Formation	2
	Barique Formation	1
	Bobonaro sclay-clay	0

##### d. Assigning scores to slope parameters

Table 16. Slope Gradient Parameter Scoring

Parameter	Classification	Class (O)	Score
Slope Gradient	Flat	0 - 2	0
	Slightly Sloping	2 - 4	1
	Sloping	4 - 8	2
	Slightly Steep	8 - 16	3
	Steep	- 35	5

e. Assigning scores to the Elevation parameter

Table 17. Elevation Parameter Scoring

Parameters	Class	Score
Elevation	250 - 355	1
	355 - 460	2
	460 - 567	3
	567 - 669	4
	- 773	5

f. Scoring of Land Use parameters

Table 18. Land Use Parameter Scoring

Parameters	Class	Score
Land Use	Water	2
	Rice fields	3
	Open areas	5
	Settlements	1
	Vegetation	4

g. Scoring of Soil Type parameters

Table 19. Soil Type Parameter Scoring

Parameters	Texture Class	Score
Soil Type	Sandy Clay	1
	Clay Loam	2
	Clay	3

h. Assigning scores to the Road Distance parameter

Table 20. Road Distance Parameter Scoring

Parameter	Class	Score
Road	0 - 120	3
	120 - 240	2
	240 - 360	0

## 2. Weighting

Weighting is the assignment of weights to each parameter that influences the occurrence of landslides. Weighting here is based on calculations using the AHP (Analytical Hierarchy Process) method.

Table 21. Parameter Weights for Determining Landslide Vulnerability Maps

Criteria	Weight
Geological Factors (Lithology)	17%
Rainfall	21%
Slope Gradient	13%
Elevation	12%
Drainage	19%
Land Use	8%
Soil Type	7%

The analysed data can then be classified according to its level by analysing it using the overlay technique in ARCGIS 10.8 to produce a map.

Table 22. Landslide Vulnerability Overlay Results

No.	Class	Area (km)	%
1	Low vulnerability	1.82	14
2	Medium	9.00	67
3	High	2.61	19

### 3. Analysis Results

The overlay analysis produced three landslide vulnerability classes: a low class covering 1.82 km<sup>2</sup> (14%), a moderate class covering 9 km<sup>2</sup> (67%), and a high class covering 2.61 km<sup>2</sup> (19%). The high-vulnerability areas, indicated in maroon, have slope safety factors below 1.2, are unstable, and are prone to landslides when triggered. The dominant moderate class, marked in yellow, has safety factors between 1.07 and 1.18, where ground movement occurs less frequently. The stable low-vulnerability class, in light green, has a safety factor of 1.67 and rarely experiences landslides without significant disturbance.

Based on the landslide vulnerability map (Figure 9), the study area is classified into three hazard levels. The low-potential (stable) class experiences rare landslides that require specific triggers. The moderate-potential class, found in hilly areas with high rainfall and vulnerable land cover, experiences fairly common landslides. The high-potential (unstable) class, located on steep to very steep slopes with intense rainfall, is highly prone to frequent landslides.

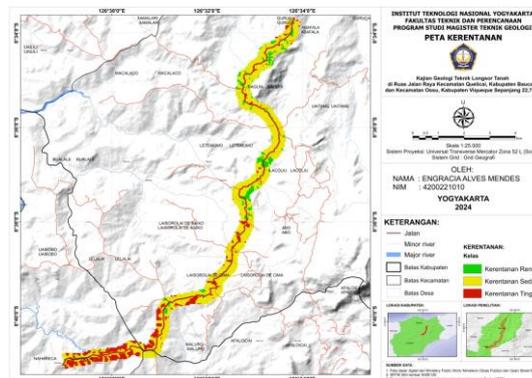


Figure 9. Landslide Vulnerability Map of the Study Area

### 4. CONCLUSION

Based on the results of the analysis of the data and the discussion above, the following conclusions can be drawn:

1. The engineering geological conditions in the study area consist of four geological formations, namely the Aituto Formation, Cribas Formation, Barique Formation, and Bobonaro scaly clay Formation. The Bobonaro scaly clay Formation has the most significant influence on landslide occurrence. Laboratory analysis shows the mechanical characteristics of the soil, including density, specific gravity, moisture content, Atterberg limits, and CBR values. CBR values at several points, such as STA 7+340 (2.487%), STA 10+080 (4.247%), and STA 10+880 (1.833%), indicate the vulnerability of the soil to landslides. The moisture content ranged from 16.12% to 18.71%, with a decrease to 13.48% at STA 17+940.
2. The results of the slope stability analysis showed that the slope angle varied between 20 and more than 35 degrees. Using the Fellenius method, most slopes have a safety factor that is vulnerable to landslides. For example, STA 7+340 (0.967) and STA 10+880 (1.18) indicate a risk of landslides, while STA 10+080 (1.67) is considered safe but still at risk during high rainfall. This analysis provides an initial overview, but does not fully represent the entire slope conditions.
4. Analysis using the AHP and GIS methods produced a landslide vulnerability map with three classifications: highly vulnerable (19%), moderately vulnerable (67%), and not vulnerable (14%).

5. Areas with high vulnerability levels require slope engineering to reduce the risk of landslides. The recommended safety factor is 1.87 or more than 1.5. Applicable engineering methods include geometric techniques, the use of geotextiles, and various types of slope retaining walls, which are adapted to environmental conditions and local community needs.
6. For areas with FS < 1.2, it is recommended to construct a retaining wall 2–3 m high with lateral drainage, or to use soil nailing with a pin spacing of 1.5 m according to the characteristics of the local clay soil. For areas with FS 1.2–1.5, slope reinforcement can consist of a short retaining wall and erosion-resistant vegetation. Further, areas with FS >1.5 require routine monitoring and maintenance.

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