Vol. 8, No. 1, January 2026: 139-149

Jambura Geoscience Review

p-ISSN 2623-0682 | e-ISSN 2656-0380

Department of Earth Science and Technology, Universitas Negeri Gorontalo

GIS-Based Landslide Susceptibility Mapping Using Weighted Overlay in Ogan Komering Ulu

Ilham Rahmat Juliansyah[1], Harnani[1], Dede Nurohim[1]

[1]*Geological Engineering Study Program, Sriwijaya University, Jl. Srijaya Negara, Palembang, South Sumatra, 30139, Indonesia*

ARTICLE INFO

Article history:
Received: 24 December 2025
Accepted: 26 January 2026
Published: 30 January 2026

Keywords:
Disaster mitigation; GIS; Landslide susceptibility; Ogan Komering Ulu; Weighted overlay

Corresponding author:
Harnani
Email: harnani@ft.unsri.ac.id

Read online:
Scan this QR code with your smart phone or mobile device to read online.

ABSTRACT

Landslides pose a major hazard in Ogan Komering Ulu Regency, South Sumatra, where rugged relief, high rainfall, and land-use change can reduce slope stability. This study develops a GIS-based landslide susceptibility map using the weighted overlay method to support disaster mitigation and spatial planning. Five conditioning factors—slope, rainfall, geology, soil type, and land use—were prepared as thematic layers from DEMNAS topography, CHIRPS rainfall estimates interpolated using Inverse Distance Weighting, geological shapefiles from Ina-Geoportal, soil information from the FAO–UNESCO Digital Soil Map of the World, and land-cover data from the Indonesian Base Map (RBI). Each factor was reclassified into susceptibility classes, assigned scores, and weighted according to its relative influence on landslide occurrence, then integrated through overlay analysis to produce a composite susceptibility index. The index was classified into low, moderate, and high susceptibility zones. The results indicate that moderate susceptibility dominates most of the study area, while high-susceptibility zones are concentrated in hilly to mountainous terrains with steep slopes and unfavorable geological and soil conditions. Model performance, evaluated using a landslide inventory and the Receiver Operating Characteristic curve, produced an Area Under the Curve value of 0.715, indicating moderate predictive accuracy. The susceptibility map provides actionable spatial information to prioritize monitoring and guide land-use management in Ogan Komering Ulu.

How to cite: Juliansyah, IR. (2026). GIS-Based Landslide Susceptibility Mapping Using Weighted Overlay in Ogan Komering Ulu. *Jambura Geoscience Review, 8*(1), 139-149. https://10.37905/jgeosrev.v8i1.36391

1. INTRODUCTION

Landslides are among the most recurrent geohazards in Indonesia and frequently disrupt settlements, transportation corridors, and productive land. In national planning and hazard-management contexts, landslides are defined as the downslope movement of soil and/or rock masses under gravity, commonly occurring through rotational or translational mechanisms (Peraturan Menteri Pekerjaan Umum Republik Indonesia Nomor 22/PRT/M/2007, 2007). As a form of erosion-related mass movement, landslide events are often characterized by rapid displacement of large material volumes within a relatively short time (Suripin, 2002). The occurrence of landslides generally reflects the interaction of multiple conditioning factors—such as rainfall intensity, geological characteristics, vegetation conditions, and topographic morphology—rather than a single controlling driver (Wang et al., 2017).

Ogan Komering Ulu (OKU) Regency, South Sumatra, is characterized by heterogeneous landforms ranging from plains to hilly and mountainous terrains, which generate substantial spatial variability in landslide potential. The combination of rugged relief and increasing human activities

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

places many parts of the regency at heightened risk of slope-related hazards. Demographic growth further amplifies this exposure, with the population reaching 387,348 residents in 2024 (Badan Pusat Statistik Kabupaten Ogan Komering Ulu, 2024). Empirical records also indicate that between 2018 and 2025, a total of 26 landslide events occurred in the region, with repeated impacts observed in Ulu Ogan, Muara Jaya, Semidang Aji, and Pengandonan Subdistricts, resulting in damage to houses, disruption of inter-village road networks, and agricultural losses (Badan Penanggulangan Bencana Daerah Ogan Komering Ulu [BPBD OKU], 2025). Beyond natural terrain conditions, land conversion for agriculture, settlement expansion, and road construction on sloping terrain has been shown to exacerbate slope instability and intensify landslide impacts (Faizana et al., 2015).

Landslide susceptibility mapping provides a practical basis for decision-making by identifying areas that are more likely to experience slope failure under comparable triggering conditions. Within this context, Geographic Information Systems (GIS) enable the integration, standardization, and analysis of multi-source spatial datasets relevant to landslide conditioning factors, thereby supporting the delineation of landslide-prone zones at the regional scale (Hardianto et al., 2020). Multi-criteria approaches—particularly scoring, weighting, and overlay—remain widely used because they are computationally efficient and transparent, while still allowing adaptation to local environmental settings (Erfani et al., 2023). In weighted overlay analysis, each thematic factor is reclassified into susceptibility classes, assigned scores, weighted according to relative influence, and combined into a composite index to generate susceptibility zonation (Wijaya et al., 2024; Rana et al., 2025).

Despite its operational advantages, a GIS-based weighted overlay product can be misleading if the selected factors, weighting rationale, and evaluation procedure are not methodologically defensible. A commonly adopted parameter framework in Indonesia integrates rainfall, slope, geology (lithology), soil type, and land cover as principal determinants of landslide susceptibility, providing a structured basis for factor selection and weighting (Pusat Penelitian Tanah dan Agroklimat [Puslittanak], 2004). To increase the credibility and usability of susceptibility zonation, the resulting map should also be supported by quantitative validation against landslide occurrence evidence. Receiver Operating Characteristic (ROC) analysis and the Area Under the Curve (AUC) are widely applied for this purpose because they summarize the discriminative ability of susceptibility models in distinguishing landslide-prone from less-prone locations (Budimir et al., 2015; Cantarino-Martí et al., 2018; Tien Bui et al., 2012). The interpretation of AUC values can be contextualized using established classification thresholds to communicate model performance transparently (Kurniawan & Setiawan, 2025).

Accordingly, this research aims to develop a GIS-based landslide susceptibility map using the weighted overlay method for Ogan Komering Ulu Regency by integrating five conditioning factors (rainfall, slope, geology, soil type, and land use/land cover) into a composite susceptibility index and validating the resulting zonation using ROC–AUC. The susceptibility map is intended to provide actionable spatial information for disaster mitigation and land-use management, including the prioritization of monitoring and risk-reduction interventions in OKU.

2. METHOD

2.1. Study Area

Ogan Komering Ulu (OKU) Regency, South Sumatra, was selected as the study area due to its diverse terrain conditions and recurring landslide impacts. The regency spans approximately 4,797.06 km² and administratively consists of 13 subdistricts and 157 villages, making susceptibility information useful for both district- and subdistrict-level planning (Bappeda Kabupaten Ogan Komering Ulu, 2021). The location and administrative context of the study area are shown in figure 1.

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

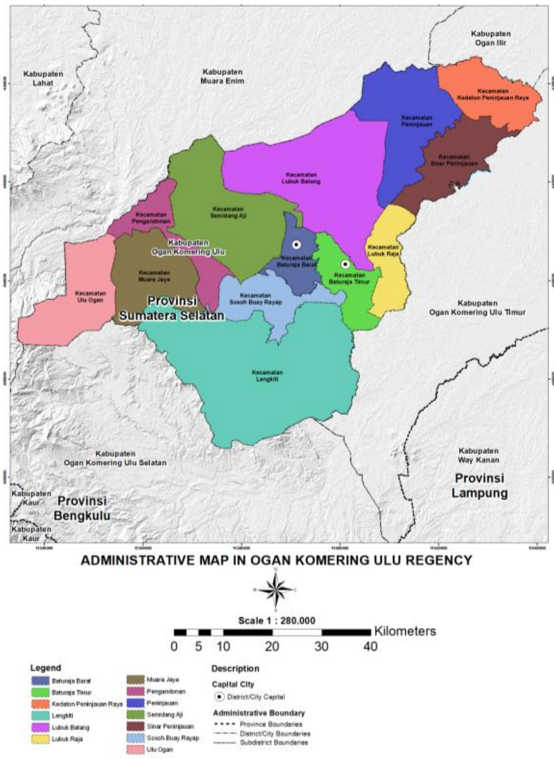

Figure 1. Administrative Map of Ogan Komering Ulu Regency

2.2. Research Design And Data Preparation

This research employed a GIS-based multi-criteria approach to construct a landslide susceptibility map by integrating multiple conditioning factors into a composite index. Indirect data collection was conducted by compiling secondary spatial datasets, standardizing them into comparable thematic layers, and processing them in a GIS environment. The overall workflow is summarized in figure 2.

Five conditioning factors were used: rainfall, slope, geology (lithology), land cover, and soil type. The selection of these factors follows an established Indonesian framework for landslide susceptibility assessment, which has been widely applied in regional-scale mapping (Puslittanak, 2004). All layers were converted to a consistent spatial reference, resolution, and extent before analysis, and each factor was reclassified into susceptibility classes to enable scoring and weighting.

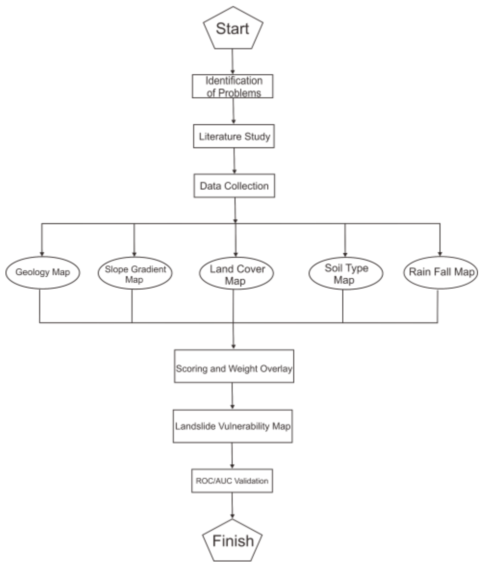

Figure 2. Research Flowchart

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

2.3. Scoring and weighting scheme

A scoring–weighting procedure was applied to quantify the relative contribution of each factor to landslide susceptibility. The scoring concept assigns ordinal numerical values to classes within a factor to represent increasing susceptibility levels, while the weighting step allocates relative importance among factors (Gunadi et al., 2015). The detailed scoring classes and factor weights used in this study are presented in Tabel 1. Skoring dan Pembobotan tiap tiap Parameter menurut (Puslittanak, 2004), which is adopted from the Puslittanak framework (Puslittanak, 2004).

The landslide susceptibility index (LSI) was calculated using a weighted linear combination:

$$LSI = (0.3 \times SCH) + (0.2 \times SS) + (0.2 \times SG) + (0.2 \times STL) + (0.1 \times SJT) \quad (1)$$

where SCH = rainfall score, SS = slope score, SG = geology score, STL = land-cover score, and SJT = soil-type score.

Table 1. Scoring and Weighting for Each Parameter

Parameter	Weight	Class/Category	Range / Description	Score (Level)
Rainfall	0.30 (30%)	Very Dry	< 1500 mm/year	1
		Dry	1500–2000 mm/year	2
		Moderate	2000–2500 mm/year	3
		Wet	2500–3000 mm/year	4
		Very Wet	> 3000 mm/year	5
Slope gradient	0.20 (20%)	Gentle	0–8%	1
		Slightly steep	8–15%	2
		Moderately steep	15–30%	3
		Steep	30–45%	4
		Very steep	> 45%	5
Geology (Rock type)	0.20 (20%)	Alluvial rock	Unconsolidated/alluvial deposits	1
		Sedimentary rock	Consolidated sedimentary formations	2
		Volcanic rock	Volcanic formations	3
Land use / Land cover	0.20 (20%)	Ponds/Reservoirs/Water bodies	Aquatic surfaces	1
		City/Urban area/Airport	Built-up areas	2
		Forest and plantation	Dense/perennial vegetation	3
		Shrubland	Shrubs/brush/grass	4
		Rice fields, agriculture	Annual crops/fields	5
Soil type	0.10 (10%)	Alluvial, Gelisol, Planosol, Hidromorf Kelabu, Laterik Air	Low susceptibility group	1
		Latosol		2
		Brown Forest Soil, Non-Calcic Brown, Mediteran		3
		Andosol, Laterik, Grumusol, Podsol, Podzolik		4
		Regosol, Litosol, Renzina	High susceptibility group	5

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

2.4. Weighted overlay analysis

Weighted overlay was used to integrate standardized thematic layers into a susceptibility surface. The method combines scored raster layers by multiplying each by its weight and summing results to produce a composite index, commonly used for regional susceptibility mapping (Erfani et al., 2023; Rana et al., 2025). Processing steps included: (1) reclassification of factors into scored classes, (2) application of factor weights, and (3) overlay summation to generate the LSI raster.

2.5. Susceptibility classification and area calculation

The resulting LSI raster was classified into three susceptibility levels (low, moderate, and high) to produce an interpretable zonation for planning and mitigation. Class thresholds were determined using an interval approach based on the index range divided by the number of classes, as commonly applied in Indonesian disaster risk mapping guidance (BNPB, 2012). The interval was computed as:

$$I = \frac{X_{max} - X_{min}}{k} \tag{2}$$

where $X_{\mathrm{max}}$and $X_{\mathrm{min}}$are the maximum and minimum LSI values, and $k = 3$represents the number of susceptibility classes. Area statistics for each class were then calculated in GIS and summarized by administrative unit for reporting.

2.6. Model validation (ROC–AUC)

Model validation assessed how well the susceptibility map distinguishes landslide-prone areas. Landslide occurrence points from the local inventory (2018–2025) were compared against non-landslide points (Badan Penanggulangan Bencana Daerah Ogan Komering Ulu [BPBD OKU], 2025). Receiver Operating Characteristic (ROC) analysis and Area Under the Curve (AUC) served as threshold-independent measures of predictive discrimination (Budimir et al., 2015; Cantarino-Martí et al., 2018; Tien Bui et al., 2012). AUC values were interpreted using an established classification scheme (Kurniawan & Setiawan, 2025).

3. RESULTS AND DISCUSSION

3.1. Conditioning Factors

Slope conditions control landslide susceptibility in OKU Regency. Steeper slopes increase shear stress, acting as a key predictor in susceptibility modelling (Wang et al., 2017; Setyanugraha et al., 2023). Slope gradients affect runoff and erosion, forming slip surfaces during rainfall (Amarasinghe et al., 2024; Zhang et al., 2024). The slope map from DEMNAS was reclassified into five classes following Puslittanak's scoring scheme. This standardization ensures comparability within a multi-criteria framework and reduces subjectivity (Puslittanak, 2004; Rana et al., 2025).

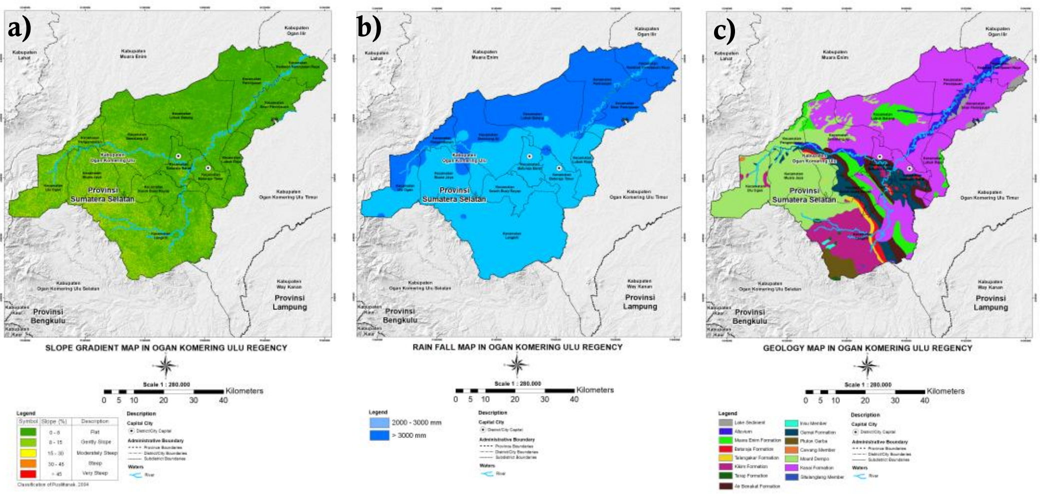

Figure 3. a) Slope Gradient Map, b) Rainfall Map, c) Geological Map Location

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

Rainfall acts as the primary hydrometeorological trigger that can transform potentially unstable slopes into active landslides. High rainfall intensity and/or long rainfall duration may increase soil moisture, raise pore-water pressure, reduce effective stress, and ultimately lower shear strength—mechanisms widely documented in rainfall-induced landslides in tropical regions (Amarasinghe et al., 2024; Wang et al., 2017). From a monitoring perspective, the reliability of spatial rainfall representation also matters because uncertainty in areal rainfall estimation can propagate into susceptibility results (Ribeiro et al., 2021).

In this study, rainfall distribution was generated from CHIRPS data and interpolated using IDW to produce a spatially continuous rainfall surface. The rainfall layer was then reclassified according to the Puslittanak criteria to match the scoring system used for the weighted overlay integration (Puslittanak, 2004; Rana et al., 2025). The mapped pattern indicates that much of the study area falls into high to very high rainfall classes (2500–3000 mm to >3000 mm), which is consistent with higher susceptibility expectations during the wet season (Amarasinghe et al., 2024).

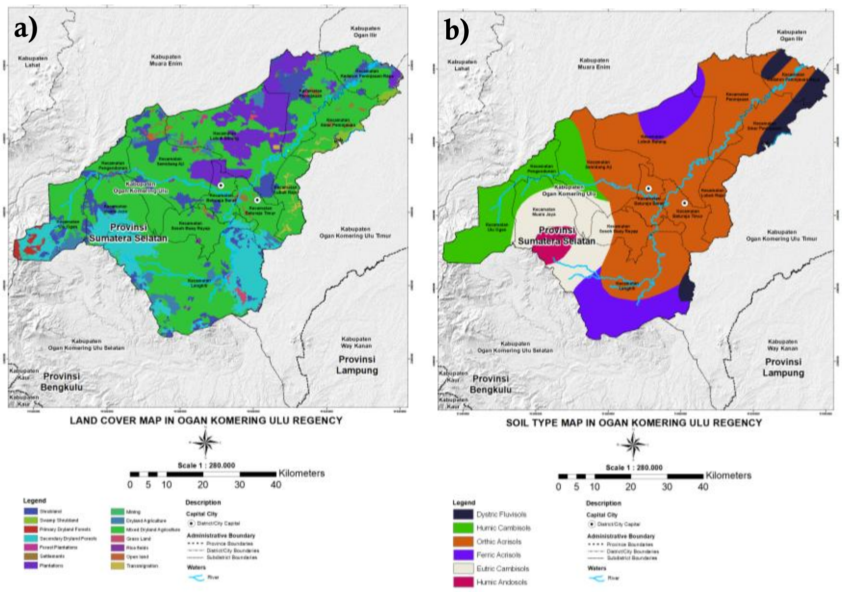

Figure 4. a) Land Cover Map, b) Soil Type Map

Land cover influences slope hydrology, erosion processes, and near-surface soil reinforcement. Vegetation canopy interception, root reinforcement, and improved infiltration capacity can reduce landslide probability in many contexts, whereas land conversion often increases runoff, accelerates erosion, and weakens shallow slope stability (Hanifudin et al., 2024; Faizana et al., 2015). These effects become more critical when conversion occurs on sloping terrain and is coupled with infrastructure expansion (Faizana et al., 2015).

The land cover map shows a mix of plantations, rice fields, forests, shrubs, swamps, settlements, mining areas, bare land, and grassland, with dominance of mixed dryland agriculture and secondary dryland forest. Areas dominated by mixed dryland agriculture typically have less dense vegetation and shallower root systems, which can reduce hydrological buffering and promote slope degradation relative to forested zones (Hanifudin et al., 2024). This pattern supports the higher scoring assigned to disturbed/built-up land cover categories in landslide susceptibility mapping (Puslittanak, 2004; Wijaya et al., 2024).

Soil properties control infiltration behaviour, water retention, and shear strength parameters that directly affect slope stability. Fine-textured soils and soils with weaker structure may become rapidly saturated during high rainfall, increasing pore-water pressure and reducing shear strength (Amarasinghe et al., 2024; Suripin, 2002). In susceptibility mapping, soil type is therefore treated as a key conditioning factor alongside slope and rainfall (Puslittanak, 2004; Wang et al., 2017).

Six soil types were identified, with Orthic Acrisols as the dominant unit. The dominance of Acrisols can be important because such soils are often acidic with relatively low organic matter and may present unfavourable structural stability under intensive rainfall conditions. In comparison, unconsolidated or highly porous soil units can also raise susceptibility due to higher infiltration and

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

rapid saturation processes (Suripin, 2002; Amarasinghe et al., 2024). These soil-related considerations align with the rationale of assigning soil scores within the Puslittanak framework for landslide susceptibility mapping (Puslittanak, 2004).

3.2. Weighted Overlay Integration

The modelling stage integrates multiple conditioning factors into a single susceptibility surface. Weighted overlay is widely used in GIS-based multi-criteria decision analysis because it enables standardized integration of layers with different units and spatial structures through scoring, weighting, and map algebra (Wijaya et al., 2024; Rana et al., 2025). Methodologically, this approach is suitable when a study aims to produce an interpretable susceptibility zonation that can be communicated to planning stakeholders (Erfani et al., 2023).

In this study, each parameter class was scored using Puslittanak's scheme and then combined through weighted overlay in ArcGIS. Using a recognized scoring–weighting reference improves transparency and reduces arbitrary judgement compared with ad-hoc weighting, although the results remain sensitive to the chosen weights and the underlying data quality (Puslittanak, 2004; Rana et al., 2025).

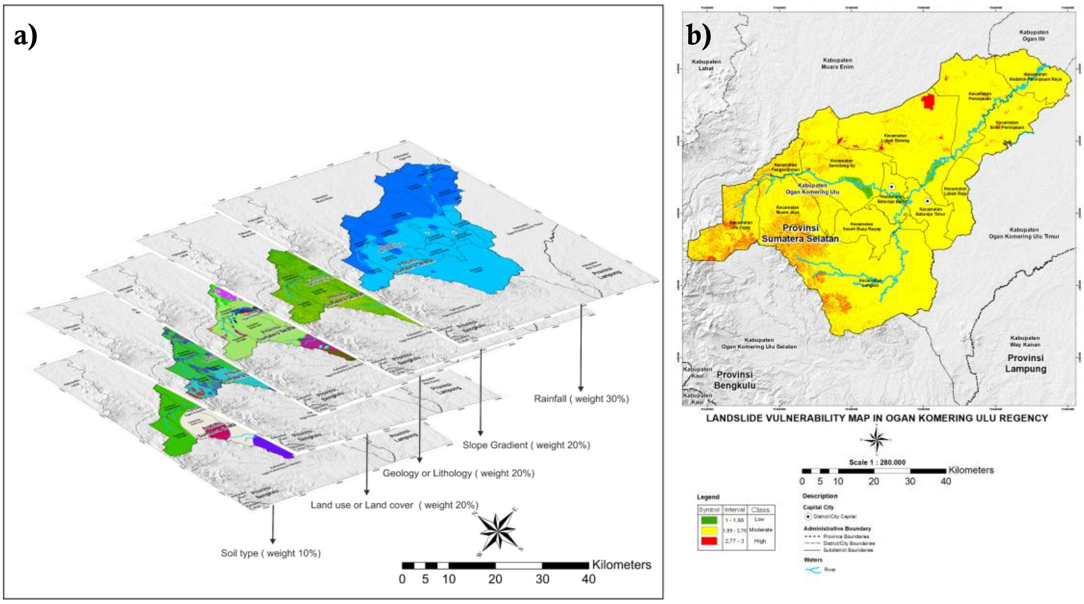

Figure 4. a) Weighted Overlay Modeling for Each Parameter, b) Landslide Vulnerability Zone Map in OKU Regency Research

The susceptibility map needs to be classified into practical categories for decision-making. The classification into three levels (low, moderate, high) follows BNPB guidance commonly used in Indonesian disaster risk assessment contexts, supporting consistency with planning and mitigation frameworks (BNPB, 2012). Categorization also improves interpretability for non-technical audiences while still preserving the multi-layer logic of the GIS model (Erfani et al., 2023).

Table 2. Classification of Landslide Disaster Risk in OKU

Interval	Class
1 – 1,88	Low
1,89 – 2,76	Moderate
2,77 - 3	High

The resulting susceptibility zonation highlights the spatial dominance of moderate susceptibility across OKU Regency. Areas classified as moderate typically correspond to hilly zones with moderately steep to steep slopes, high rainfall exposure, and increasingly disturbed vegetation cover—conditions frequently associated with elevated susceptibility in GIS-based studies (Wijaya et al., 2024; Wang et al., 2017). Meanwhile, high-susceptibility zones concentrate in steeper mountainous sectors where multiple unfavourable factors co-occur (e.g., steep slope + intense

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

rainfall + weaker lithology/soil), reflecting the multi-factor interaction emphasized in landslide literature (Amarasinghe et al., 2024; Yuniarta et al., 2015).

3.3. Susceptibility Zonation

Quantifying the area of each susceptibility class provides an operational basis for prioritization. ArcGIS Tabulate Area outputs are commonly used to summarize class coverage and support district-level planning comparisons (Gunadi et al., 2015). This step bridges the susceptibility map with administrative management needs and supports targeted mitigation decisions (BNPB, 2012).

Table 3. Landslide Disaster Vulnerability Area in OKU Regency (Data Processing Results)

Subdistrict	Low	Moderate	High	Total Area
Sosoh Buay Rayap	0	17226.09	51.75	17277.84
Pengandonan	0	14416.92	1138.59	15555.51
Peninjauan	14.31	31714.92	432.63	32161.86
Baturaja Barat	81.27	10120.68	1.44	10203.39
Baturaja Timur	3.69	13888.17	7.83	13899.69
Ulu Ogan	0	21694.41	4340.43	26034.84
Semidang Aji	1431.99	39409.83	1120.77	41962.59
Lubuk Batang	820.53	53522.28	2433.78	56776.59
Lengkiti	0	79691.94	5529.96	85221.9
Sinar Peninjauan	12.06	20366.58	256.86	20635.5
Lubuk Raja	0	14153.58	9.36	14162.94
Muara Jaya	0	22737.69	2152.26	24889.95
Kedaton Peninjauan Raya	0	18437.22	151.38	18588.6
Ogan Komering Ulu Regency	2363.85	357380.31	17627.04	377371.2

The mapped distribution indicates that moderate susceptibility dominates the study area, while high susceptibility occurs in fewer but critical clusters. The total susceptibility area is reported as 377,821.20 ha, with low susceptibility 2,363.85 ha, moderate 357,830.31 ha, and high 17,627.04 ha. This pattern is consistent with multi-criteria zonations where broad hilly–upland regions form a moderate class, and high class emerges where slope–rainfall–geology conditions compound (Wijaya et al., 2024; Rana et al., 2025).

High susceptibility is identified in several subdistricts (including Ulu Ogan, Muara Jaya, Lengkiti, Lubuk Batang, Semidang Aji, Pengandonan, and Sosoh Buay Rayap). This spatial signal is meaningful because repeated landslide impacts have been historically reported in key affected areas of OKU Regency, indicating that susceptibility outputs align with empirical hazard occurrence patterns (BPBD OKU, 2025).

3.4. Area Statistics And Implications

The susceptibility pattern reflects interactions rather than any single parameter acting alone. Landslide occurrence is typically controlled by combined effects of steep terrain, rainfall triggers, material weakness (soil/lithology), and land cover disturbance (Wang et al., 2017; Amarasinghe et al., 2024). In OKU, the dominance of moderate susceptibility can be interpreted as a landscape-scale condition where at least two major drivers (e.g., rainfall and slope) are present across broad areas, while high susceptibility emerges where several drivers co-locate (Yuniarta et al., 2015; Hanifudin et al., 2024).

Human land conversion can intensify these combined effects. Expansion of agriculture, settlements, and roads on slopes may increase instability by altering runoff pathways and weakening slope materials, thereby elevating susceptibility particularly within hilly belts (Faizana et al., 2015; Hanifudin et al., 2024).

The weighted overlay method provides a practical framework for susceptibility mapping to enable planning-ready zonation. Similar GIS scoring–overlay approaches have proven effective across Indonesian settings for regional-scale screening (Erfani et al., 2023; Wijaya et al., 2024). However, this semi-empirical approach is sensitive to weight assignments and class thresholds, as alternative weighting strategies (e.g., FAHP) or data-driven models may yield different

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

susceptibility patterns (Budimir et al., 2015; Kurniawan & Setiawan, 2025). Input data resolution and modelling choices can introduce spatial uncertainty affecting susceptibility boundaries, making sensitivity checks valuable where data permits (Ribeiro et al., 2021; Rana et al., 2025).

3.5. Validation

Model validation is essential to assess whether the susceptibility map has acceptable discriminatory power. ROC–AUC is widely used to evaluate landslide susceptibility models because it measures how well predicted susceptibility separates observed landslide locations from non-landslide locations across thresholds (Tien Bui et al., 2012; Budimir et al., 2015). In addition, ROC-based interpretation provides a standardized basis for comparing mapping outputs across studies and regions (Cantarino-Martí et al., 2018).

Interpreting AUC values requires a clear classification reference. The AUC classification used here follows the published threshold categories shown in the manuscript, supporting consistent interpretation of whether the model performance is weak, acceptable, good, or excellent (Kurniawan & Setiawan, 2025).

Table 4. AUC value classification

Value Range	Classification
> 0,90	Very Good
0,80 – 0,90	Good
0,70 – 0,80	Fair
0,60 – 0,70	Poor
0,50 – 0,60	Very Poor

The validation results indicate an acceptable predictive performance for regional-scale susceptibility mapping. The ROC curve yields AUC = 0.715, which corresponds to a "fair/adequate" discrimination level based on the cited AUC classification framework. In practical terms, performance above 0.7 is commonly considered acceptable for susceptibility screening maps intended for planning support, especially when using heuristic multi-criteria overlay methods (Tien Bui et al., 2012; Budimir et al., 2015; Wijaya et al., 2024).

Table 5. ROC Validation Data (Data Processing Results)

Class	Amount	
	Positive	Negative
High	15	19
Moderate	9	84
Low	2	21
Total	26	124

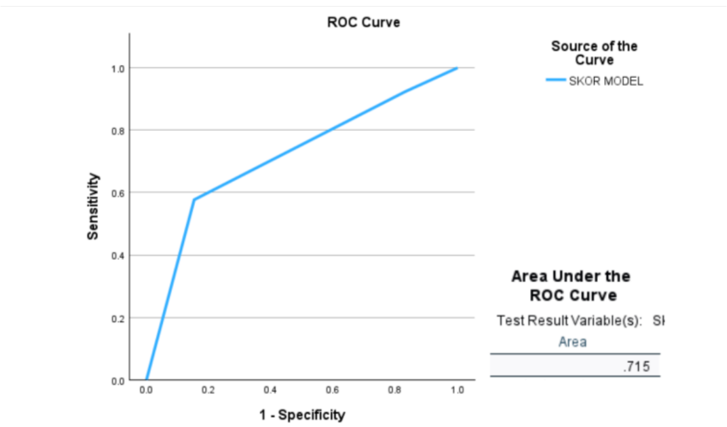

Figure 10. ROC and AUC Graphic

4. CONCLUSIONS

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

This study produced a GIS-based landslide susceptibility map for Ogan Komering Ulu (OKU) Regency using a weighted overlay approach that integrates five conditioning factors—rainfall, slope, geology, soil type, and land use/land cover. The susceptibility zonation indicates that the regency is dominated by the moderate susceptibility class, while high susceptibility zones occur more locally and are primarily associated with areas where steep slopes coincide with high rainfall exposure and less favourable geological–soil conditions, often compounded by reduced protective land cover.

Area statistics show a total mapped extent of 377,821.20 ha, comprising 2,363.85 ha of low susceptibility, 357,830.31 ha of moderate susceptibility, and 17,627.04 ha of high susceptibility. These outputs provide practical spatial information to prioritize monitoring and mitigation, particularly in subdistricts where high susceptibility clusters are present and where slope disturbance from land-use change may intensify hazard impacts.

Model validation using ROC analysis yielded an AUC value of 0.715, indicating moderate predictive accuracy and supporting the use of the resulting map for regional-scale screening and planning purposes. Future improvements may be achieved by expanding the landslide inventory, refining factor weights through local calibration, and incorporating additional conditioning variables or alternative modelling approaches to enhance predictive performance.

5. REFERENCES

Amarasinghe, M. P., Kulathilaka, S. A. S., Robert, D. J., Zhou, A., & Jayathissa, H. A. G. (2024). Risk assessment and management of rainfall-induced landslides in tropical regions: A review. *Natural Hazards, 120*(3), 2179–2231. https://doi.org/10.1007/s11069-023-06277-3

Badan Nasional Penanggulangan Bencana. (2012). Peraturan Kepala Badan Nasional Penanggulangan Bencana Nomor 02 Tahun 2012 tentang Pedoman Umum Pengkajian Risiko Bencana. BNPB.

Badan Penanggulangan Bencana Daerah Kabupaten Ogan Komering Ulu. (2025). Data kejadian bencana di Kabupaten Ogan Komering Ulu tahun 2018–2025 [Data set]. BPBD Kabupaten OKU.

Badan Perencanaan Pembangunan Daerah Kabupaten Ogan Komering Ulu. (2021). Rencana tata ruang wilayah Kabupaten Ogan Komering Ulu tahun 2021–2041. Bappeda Kabupaten OKU.

Badan Pusat Statistik Kabupaten Ogan Komering Ulu. (2024). Kabupaten Ogan Komering Ulu dalam angka 2024. BPS Kabupaten OKU.

Budimir, M. E. A., Atkinson, P. M., & Lewis, H. G. (2015). A systematic review of landslide probability mapping using logistic regression. *Landslides, 12*(3), 419–436. https://doi.org/10.1007/s10346-014-0550-5

Cantarino-Martí, I., Carrión Carmona, M. Á., Goerlich-Gisbert, F., & Martínez Ibáñez, V. (2018). A ROC analysis-based classification method for landslide susceptibility maps. *Landslides, 16*, 265–282. https://doi.org/10.1007/s10346-018-1063-4

Erfani, S., Naimullah, M., & Winardi, D. (2023). SIG metode skoring dan overlay untuk pemetaan tingkat kerawanan longsor di Kabupaten Lebak, Banten. *Jurnal Fisika Flux: Jurnal Ilmiah Fisika FMIPA Universitas Lambung Mangkurat, 20*(1), 61–79. https://doi.org/10.20527/flux.v20i1.15057

Faizana, F., Nugraha, A. L., & Yuwono, B. D. (2015). Pemetaan Risiko Bencana Tanah Longsor Kota Semarang. Jurnal Geodesi Undip, 4(1), 223-234. https://doi.org/10.14710/jgundip.2015.7669

Gunadi, B. J. A., Nugraha, A. L., & Suprayogi, A. (2015). Aplikasi Pemetaan Multi Risiko Bencana Di Kabupaten Banyumas Menggunakan Open Source Software Gis. *Jurnal Geodesi Undip, 4*(4), 287-296. https://doi.org/10.14710/jgundip.2015.9955

Hanifudin, F., Nugraha, A. L., & Firdaus, H. S. (2024). Analisis Pengaruh Perubahan Tutupan Lahan Terhadap Ancaman Bencana Longsor Dengan Menggunakan Sistem Informasi Geografis (Studi Kasus: Kabupaten Kebumen). *Jurnal Geosains dan Teknologi, 7*(1), 36-46. https://doi.org/10.14710/jgt.7.1.2024.36-46

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.

Hardianto, A., Winardi, D., Rusdiana, D. D., Putri, A. C. E., Ananda, F., Devitasari, Djarwoatmodjo, F. S., Yustika, F., & Gustav, F. (2020). Pemanfaatan informasi spasial berbasis SIG untuk pemetaan tingkat kerawanan longsor di Kabupaten Bandung Barat, Jawa Barat. *Jurnal Geosains dan Remote Sensing, 1*(1), 23–31. https://doi.org/10.23960/jgrs.2020.v1i1.16

Setiawan, B., & Kurniawan, D. (2025). Analisis Zona Rawan Bencana Tanah Longsor Menggunakan Pendekatan Fuzzy Analytical Hierarchy Proses (FAHP). Studi Kasus Daerah Barangin dan Sekitarnya, Kota Sawahlunto, Sumatera Barat. *Jurnal Pendidikan, Sains, Geologi, Dan Geofisika (GeoScienceEd Journal), 6*(4), 1976–1986. https://doi.org/10.29303/goescienceed.v6i4.1191.

Kementerian Pekerjaan Umum Republik Indonesia. (2007). Peraturan Menteri Pekerjaan Umum Republik Indonesia Nomor 22/PRT/M/2007 tentang Pedoman Penataan Ruang Kawasan Rawan Bencana Longsor.

Pusat Penelitian Tanah dan Agroklimat. (2004). Laporan akhir pengkajian potensi bencana kekeringan, banjir, dan longsor di kawasan satuan wilayah sungai Citarum–Ciliwung Jawa Barat bagian barat berbasis sistem informasi geografis. Puslittanak.

Ribeiro, A. S., Almeida, M. C., Cox, M. G., Sousa, J. A., Martins, L., Loureiro, D., Brito, R., Silva, M., & Soares, A. C. (2021). Role of measurement uncertainty in the comparison of average areal rainfall methods. *Metrologia, 58*(4). https://doi.org/10.1088/1681-7575/ac0d49

Setyanugraha, T., Romdania, Y., & Herison, A. (2023). Pemetaan kemiringan lereng menggunakan software geographic information system pada Sub DAS Way Pubian. *Jurnal Rekayasa Sipil dan Desain (JRSDD), 11*(2), 351–362. https://doi.org/10.23960/jrsdd.v11i2.3274

Suripin. (2002). Pelestarian sumber daya tanah dan air.

Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., & Dick, O. B. (2012). Landslide susceptibility assessment in the Hoa Binh Province of Vietnam: A comparison of the Levenberg–Marquardt and Bayesian regularized neural networks. *Geomorphology, 171–172*, 12–29. https://doi.org/10.1016/j.geomorph.2012.04.023

Rana, H., Mushtaq, T., & Anburaj, R. (2025). Impact of geofactors on landslide susceptibility using weighted overlay method: An integrated GIS and field-based analysis on NH-07, Chamoli, Uttarakhand. *Geosystems and Geoenvironment*, *4*(4), 100420. https://doi.org/10.1016/J.GEOGEO.2025.100420

Wang, F., Xu, P., Wang, C., Wang, N., & Jiang, N. (2017). Application of a GIS-Based Slope Unit Method for Landslide Susceptibility Mapping along the Longzi River, Southeastern Tibetan Plateau, China. *ISPRS International Journal of Geo-Information*, *6*(6), 172. https://doi.org/10.3390/ijgi6060172

Wijaya, A. H., Fajriyanto, T. C. N., & Rahmadi, E. (2024). Pemetaan daerah bahaya tanah longsor di Kecamatan Balik Bukit Kabupaten Lampung Barat dengan metode weighted overlay. *Journal of Plano Studies, 1*(2), 62–71. https://doi.org/10.36982/jops.v1i2.4904

Yuniarta, H., Saido, A. P., & Purwana, Y. M. (2015). KERAWANAN BENCANA TANAH LONGSOR KABUPATEN PONOROGO. *Matriks Teknik Sipil*, *3*(1). https://doi.org/10.20961/MATEKSI.V3I1.37327

Zhang, Q., Cao, S., Du, Y., Du, M., Zhao, Y., & Nie, Y. (2024). Based on the improved SCGM(1,1)c and WIV rainfall landslide susceptible area prediction model. *Geomatics, Natural Hazards and Risk, 15*(1). https://doi.org/10.1080/19475705.2024.2399667

Copyright © 2026 The Authors. Published by Department of Earth Science and Technology, Universitas Negeri Gorontalo
This work is licensed under a Creative Commons Attribution (CC-BY) 4.0 International License.