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# Landslide Hazard Analysis Based on Geographic Information Systems in Sumedang Regency

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**Abstract:** Sumedang Regency has a hilly landscape, making it one of the 13 cities/regencies in West Java Province that are prone to landslides. A total of 80 landslide incidents were recorded from 2019 to 2023. These landslides resulted in 45 fatalities, 53 injuries, and damage to 317 infrastructure units. This situation indicates the importance of conducting an analysis of landslide hazard distribution. The landslide hazard distribution analysis is carried out using a weighting and scoring method on the parameters used, which include: slope gradient, rainfall, actual land cover, landform, lithology, and soil type. Based on these parameters, four landslide hazard classes were identified in Sumedang Regency: low, medium, high, and very high hazard classes. Proportions of these hazard are as follows: high hazard class (42.24%), medium hazard class (40.38%), low hazard class (13.90%), and very high hazard class (3.49%). The low hazard class is mainly found in the northern part of Sumedang Regency, the medium hazard class is widespread in sloping areas, and the high to very high hazard classes are primarily found in the Tampomas mountains and areas with hilly landforms. Slope gradient and rainfall are the factors that most influence landslide hazards, making it necessary to design appropriate mitigation.

**Keywords:** Hazard; Disaster; Landslide; Mitigation.

## Introduction

Indonesia's unique geographic position at the convergence of three tectonic plates—the Indo-Australian, Eurasian, and Pacific plates—makes it one of the most tectonically active regions in the world (Fauza et al., 2023). This tectonic activity results in frequent and intense geodynamic processes, including earthquakes, tsunamis, and landslides, that pose significant risks to human life and infrastructure. Coupled with Indonesia's wet tropical climate, driven by its equatorial location between two major oceans and continents, the country faces a heightened risk of natural disasters like floods, landslides, and erosion (Karimah et al., 2022a).

Landslides, in particular, are a common and destructive natural disaster in Indonesia, especially in regions with hilly or mountainous terrain. These landslides often occur during the rainy season and are exacerbated by factors such as steep slopes, loose soil, and high rainfall (Ba et al., 2017). The dynamic interaction of these factors destabilizes slopes, leading to the mass movement of soil, rock, and debris, which can cause catastrophic damage to both natural and built environments (Abbaszadeh Shahri et al., 2019).

Materials on the surface of landslides can be divided into three, namely rocks, soil, and debris. This classification is based on the size of the particles. The coarsest size and bound in the soil layer are called rock, coarse particles and 20-80% of the particles are larger than 2 mm are called debris, while particles that have a proportion of more than 80% with a size of 2 mm are called soil (Bianchini et al., 2018). The larger the particle

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size, the smaller the charge owned by the particles so that the binding power between particles will be lower, therefore a balanced proportion between particle sizes is very important in forming ideal physical properties in a type of soil (Rabby et al., 2020).

Landslides are triggered by a complex interplay of various natural and human-induced factors. Among the primary causes is high rainfall intensity, which saturates the soil, reduces its cohesion, and increases the likelihood of slope failure (Shafique, 2020). Steep slopes further exacerbate this risk, as gravity more easily pulls saturated soil and loose debris downhill. The presence of loose soil and weak rock formations, which lack the structural integrity to withstand added pressure from rainfall and other environmental stressors, also contributes significantly to landslide occurrences (Canavesi et al., 2020).

Human activities, such as inappropriate land use, can increase landslide susceptibility (Dwinanda et al., 2024). For instance, deforestation and the removal of vegetation for agriculture or urban development weaken the natural stability of slopes, reducing the land's ability to absorb and manage water runoff. This change in land cover can lead to accelerated erosion, stripping away the topsoil and further destabilizing the slope. The remnants of previous landslides can create weak zones that are more prone to reactivation, especially during periods of heavy rain (Nachappa et al., 2020).

Additionally, geological features such as discontinuity planes or unconformities—where layers of rock do not align or are separated by faults—serve as natural slip surfaces, making it easier for soil and rock to move. These factors, when combined, create conditions ripe for landslides, particularly in regions with a history of such events and where proactive land management and mitigation strategies are lacking (Palloan et al., 2023).

Despite extensive research on landslide causes, there is a critical need for more precise and localized hazard assessments, particularly in high-risk areas like Sumedang Regency in West Java. Sumedang's hilly and mountainous landscape makes it particularly susceptible to landslides, as evidenced by the 80 landslide incidents recorded between 2019 and 2023. Of these, 72% were directly linked to high rainfall intensity, resulting in significant loss of life and damage to infrastructure.

Spatial modeling of landslide hazards is a sophisticated process that leverages advanced geospatial technologies to analyze and interpret complex environmental data (Sharma et al., 2015). Key to this process is the use of specialized Geographic Information System (GIS) software, such as ArcGIS, QGIS, and ERDAS, which allows for the integration and analysis of diverse data types. These platforms enable the combination of vector and raster data, each serving distinct roles in spatial analysis (Sun et al., 2020).

The process involves the application of spatial analysis techniques, such as buffering, overlay, and interpolation, to assess how different environmental factors interact across a landscape (Ulfah et al., 2021). For instance, slope steepness derived from DEMs can be combined with rainfall data to identify critical zones where landslides are more likely to occur. Land use data can then be integrated to assess the potential impact on human settlements and infrastructure (Wang et al., 2019).

The outcome of this analysis is the creation of spatial-based landslide hazard maps, which are invaluable tools for disaster risk management and mitigation planning. These maps not only delineate high-risk areas but also provide insights into the underlying causes of landslides, allowing for more targeted interventions. By using geospatial-based software, planners and decision-makers can make informed choices about land use, infrastructure development, and emergency preparedness, ultimately reducing the vulnerability of communities to landslide hazards (Mahlianurrahman & Aprilia, 2024).

The study will utilize a combination of parameters—including slope steepness, rainfall, landform, geology, land use, and soil type—to generate a more accurate and actionable landslide hazard map for Sumedang Regency. This method represents a significant advancement in landslide hazard analysis, offering a sharper, more data-driven tool for disaster mitigation and planning.

## Method

Landslide Hazard Mapping is the process of identifying and mapping areas that are potentially prone to landslides, with the aim of minimizing the risks and impacts caused by landslide disasters (Diharja et al., 2022). This mapping is carried out through several stages of analysis that involve the collection and processing of both spatial and non-spatial data. The steps in the landslide hazard mapping model are explained in Figure 1.

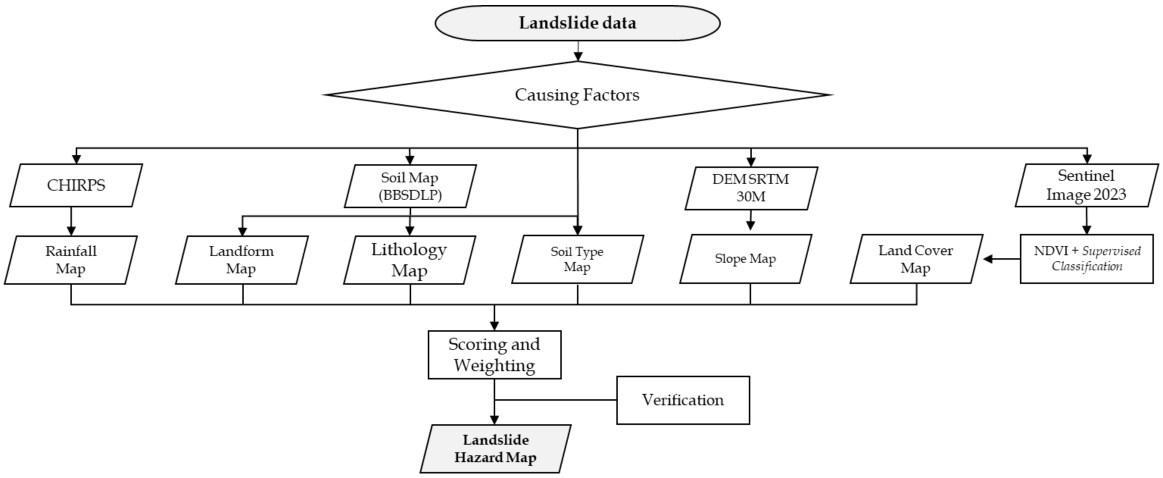


**Figure 1**. Landslide hazard model procedure

Landslide hazard analysis is conducted by weighting and scoring the parameters used, which include slope gradient, rainfall, landform, geology, current land use, and soil type (Asrizal et al., 2023). The weight of each parameter is determined from the factor analysis previously conducted. The weighting of each landslide triggering parameter refers to the formula used by as follow:

$$wj = \frac{n - rj + 1}{\sum(n - rj + 1)} \tag{1}$$

Equation information:
wj = normalized weight values
n = parameters amount (1,2,3,…..n)
rj = parameter sequence position

Based on the results of these weight calculations, the equation for creating a landslide hazard map (estimation model) is as follows:

$$H = 29 (S) + 24(R) + 19(LC) + 14(Lf) + 10(Lt) + 5(ST) \tag{2}$$

Equation information:
H = Landslide Hazard
S = Slopes
R = Rainfalls
LC = Land Covers
Lf = Landform
Lt = Lithology
ST = Soil Types

The results of the calculations using this formula are then classified into four hazard classes: low hazard, moderate hazard, high hazard, and very high hazard. Next, mapping of landslide hazard classes is carried out based on these four classes (Karimah et al., 2022b). Subsequently, the landslide hazard map will become the center point of this research. Classification is done using intervals calculated with the following formula:

$$\text{Class Intervals} = \frac{\text{Highest Value} - \text{Lowest Value}}{\text{Number of Class}} \tag{3}$$

Next, with field data in the form of the history of landslide events in each sub-district in Sumedang Regency, linear regression analysis can be used to test the accuracy of the landslide hazard map by comparing predictions from the hazard map with actual landslide occurrence data (Diharja et al., 2022). The regression is obtained based on the correlation results between landslide hazard classes and the landslide occurrence density values (density) according to the following linear regression equation.

$$Y = a + bX \tag{4}$$

Equation information:
Y = actual landslide event.
X = is the landslide danger value.
$a$ = is an interception.
$b$ = is the slope or slope of the regression line.

## Result and Discussion

*Analysis of Factors Causing Landslides*

The parameters used for landslide hazard analysis and mapping include: slope gradient, rainfall, landform, lithology, current land use, and soil type. Each factor will be analyzed based on its weight of influence on landslide disasters (Fadli et al., 2023). The explanation of each causative factor is as follows:

*Slopes*

Slope gradient is a crucial factor in the occurrence of landslides. The steepness of a terrain directly impacts soil stability and the likelihood of landslides. Areas with steep slopes have a significantly higher risk of landslides (Dharma et al., 2022). On such slopes, the force of gravity exerts a stronger pull on the soil mass, making the ground more prone to instability and eventual collapse. Steep slopes inherently have low soil stability, and any disturbance—such as soil loosening for agriculture or deforestation—can further reduce this stability, increasing the landslide hazard (Haribulan & Gosal, 2019). When coupled with high rainfall, steep slopes become even more vulnerable as rainwater quickly infiltrates the soil, leading to saturation. Waterlogged soil becomes heavier and less stable, significantly raising the risk of landslides (Gojali et al., 2020). The slope gradient classes are divided into 5 categories: 0%-8% (flat to gentle), 8%-15% (slightly steep), 15%-25% (steep), 25%-45% (very steep), and above 45% (extremely steep). The slope gradient conditions in Sumedang Regency area can be seen in Figure 2.

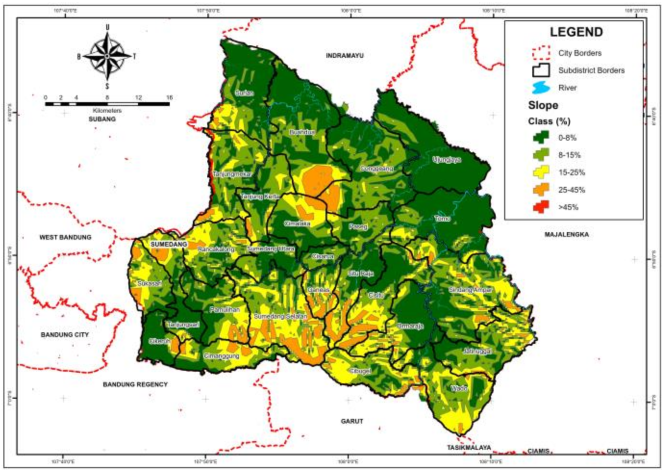


**Figure 2**. Slopes gradient class map

Based on Figure 2, it can be seen that slope classes potentially prone to landslides are steep (15-25%), very steep (25-45%), and steep (>45%). These are predominantly found in the upper slope areas of Mount Tampomas (in the districts of Cimalaka, Conggeang, and Buahdua) and hilly regions scattered in the southern, western, and southeastern parts of Sumedang regency. The slope and length of the slope are the two topographic elements that most influence landslides. Other elements that may influence are the configuration, uniformity and direction of the slope. The steeper the slope, the greater the possibility of land movement from the top to the bottom of the slope (Fathan Al-Hakim & Rizal, 2021).

From the distribution data of slope classes, the flat to gentle slope class dominates the area with 45.05%, while the very steep slope class covers only 0.01% of the area. Slope steepness is a crucial factor in triggering landslides (Febriarta & Wibowo, 2021). The inclination or steepness of an area directly influences soil stability and the potential for landslides. Regions with steep slopes have a higher potential for landslides. On steep slopes, gravitational forces exert a stronger pull on the soil mass downwards, leading to soil instability and eventual landslides. Steep slopes tend to have lower soil stability (Isneni et al., 2020).

**Table 1.** Slopes gradient class table

| Range | Class | Wide (ha) | Percent |
|---|---|---|---|
| 0-8% | Flat to gentle | 70,125.02 | 45.05% |
| 8-15% | Slightly steep | 45,553.35 | 29.26% |
| 15-25% | Steep | 29,427.60 | 18.90% |
| 25-45% | Very steep | 10,549.32 | 6.78% |
| >45% | Extremely steep | 9.95 | 0.01% |
| Total | | 155,665.24 | 100.00% |

*Rainfall*

Rainfall in a particular area is influenced by climate conditions, geographic position, and the convergence of air currents, rainfall is one of the influencing factors for landslides (Isneni et al., 2020). During periods of high rainfall, water infiltrates the soil through the process of infiltration. This infiltrated water increases the soil's moisture content, leading to saturation. Saturated soil becomes heavier. The addition of water increases the load on slopes, which can lead to soil instability, especially on steep slopes locations. When soil becomes saturated, the bonds between soil particles weaken. This reduces soil cohesion and shear strength, making it more vulnerable to movement or landslides (Pratiwi et al., 2022). The distribution of rainfall classes can be seen in Figure 3.

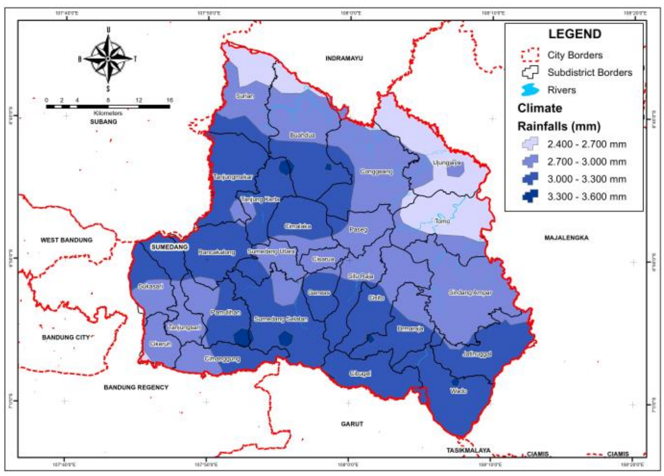


**Figure 3**. Rainfall class map

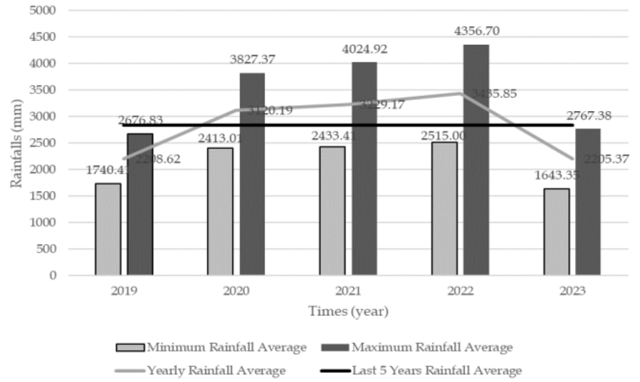

**Figure 4**. Rainfall class charts

High rainfall can cause surface runoff, which can erode soil and increase erosion. This erosion can remove the supporting soil layers that play a crucial role in maintaining slope stability (Ramadhan et al., 2021). As seen in Figure 4, the highest average rainfall was recorded from 2020 to 2022, ranging more than 3,000 mm/year. High rain intensity corelated with landslides frequency within 2020 to 2022.

**Table 2.** Rainfalls class table

| Rainfall Class | Wide (ha) | Percent |
|---|---|---|
| 2,400 – 2,700 mm | 17,000.25 | 10.92% |
| 2,700 – 3,000 mm | 61,461.36 | 39.48% |
| 3,000 – 3,300 mm | 75,735.47 | 48.65% |
| 3,300 – 3,600 mm | 1,468.15 | 0.94% |
| Total | 155,665.24 | 100.00% |

Based on Table 2, the distribution of rainfall in Sumedang Regency can be observed in terms of area. The most dominant rainfall range in Sumedang Regency is 3,000–3,300 mm/year covering an area of 75,735.47 hectares or 49%. Meanwhile, the smallest area is covered by rainfall ranging from 3,300 to 3,600 mm/year, which totals 1,468.15 hectares or 0.94% of the total area. This indicates that Sumedang Regency has a significant area with high rainfall intensity (>3,000 mm/year). High rainfall intensity can increase the load on slopes as a result of increased water content in the soil, which ultimately triggers landslides (Setyaningsih & Kurniasari, 2016).

*Land Cover*

The relationship between land cover and landslides is very close, as the type and condition of land cover can affect slope stability and the risk of landslides (Nugroho & Nugroho, 2020). Land cover is closely correlated with vegetation types and infrastructure development, especially buildings on the ground surface. Areas with steep to very steep slopes that have vegetation with strong root systems can stabilize slopes by binding soil particles and reducing surface erosion. Meanwhile, buildings and infrastructure on the ground surface can add weight to the soil and disrupt soil drainage systems, thereby increasing the risk of landslides (Rivai & Hanafi, 2021). Land cover spreads can be seen on Figure 4 .

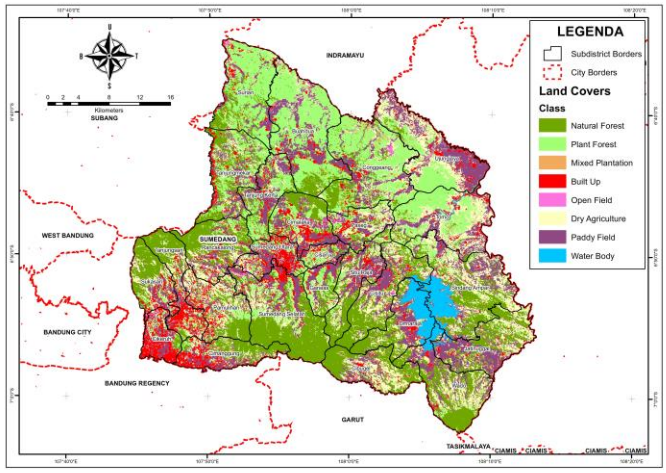

**Figure 4**. Land covers map

Based on Figure 4, natural forests are distributed in the southern and western regions of Sumedang Regency. Meanwhile, the northern and northeastern parts predominantly have plantation forests. Generally, forested areas feature hilly and mountainous terrain, with land cover on slopes and hill ridges focusing on agricultural fields such as dryland farming, terraced paddy fields, and mixed gardens. Settlements are commonly found on some slopes and at the foot of hills.

**Table 3.** Land covers table

| Land Covers | Wide (ha) | Percent |
|---|---|---|
| Dryland agriculture | 30,796.53 | 19.78% |
| Paddy field | 33,265.93 | 21.37% |
| Plantation forest | 33,031.98 | 21.22% |
| Built-up area | 11,542.72 | 7.42% |
| Open area | 824.29 | 0.53% |
| Mixed garden | 2,121.63 | 1.36% |
| Nature forest | 40,189.67 | 25.82% |
| Water body | 3,892.48 | 2.50% |
| Total | 155,665.24 | 100.00% |

Based on the table 3, natural forests cover the largest area at 40,189.67 hectares (25.82%), followed by rice fields at 33,265.93 hectares (21.37%), plantation forests at 33,031.98 hectares (21.22%), and dryland farming at 30,796.53 hectares (19.78%). Open land and mixed gardens have the smallest areas, each comprising 0.53% of the total area. Land cover plays a crucial role in mitigating and increasing the risk of landslides. Wise land use practices and effective vegetation management can reduce landslide hazards by enhancing slope stability and reducing soil erosion. Reforestation, the use of deep-rooted plants, and appropriate terracing designs are some steps that can be taken to mitigate landslide hazards (Julianto et al., 2020).

*Landform*

Landforms are physical features of the Earth's surface created by various geological processes, such as erosion, sedimentation, and tectonic activities. Landforms include different types of Earth's surface features, such as mountains, valleys, plains, and others. They reflect the geological history and natural processes occurring in a region (Raharjo, 2013). The study related to landform formation is called geochronology. The distribution of landforms can be seen in Table Figure 5.

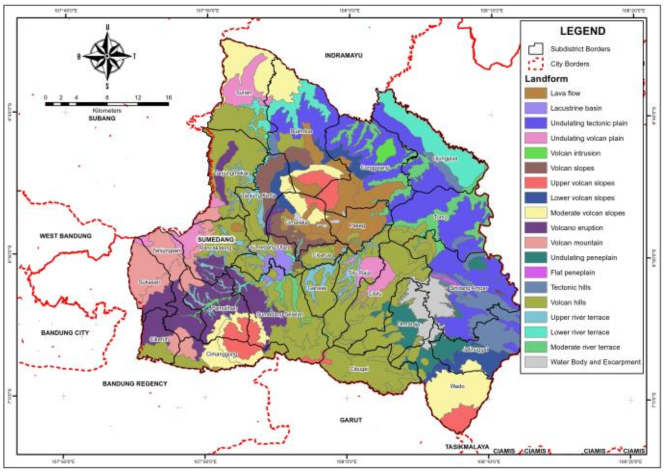

**Figure 5**. Landform distribution map

Based on the map of landform distribution, areas with steep to very steep topography host volcanic hill, volcanic mountain, and volcanic slope (upper and middle) landforms. Landforms formed by volcanic activity dominate the landscape of Sumedang Regency, followed by those shaped by tectonic activity and hydrological processes. Volcanic hills are landforms created by volcanic activity. They are formed from materials ejected by volcanic eruptions, such as lava, volcanic ash, and pyroclastic rocks. These materials accumulate around the crater or volcanic fissures, forming hills that often have steep slopes. Volcanic hills are typically located in areas prone to volcanic hazards such as eruptions, lava flows, and landslides.

Based on Table 4, the landform that dominates Sumedang Regency is volcanic hills, covering 40,058.67 hectares (26%), while the smallest area is occupied by flat peneplain landform, covering 162.3 hectares (0.10%). Mountainous and hills landform are naturally became potential factor that affect landslides because of it slopes (Raharjo & Haryono, 2020)

**Table 4.** Landform distribution table

| Landform | Wide (ha) | Percent |
|---|---|---|
| Upper river terrace | 3,898.27 | 2.50% |
| Middle river terrace | 7,158.28 | 4.60% |
| Lower river terrace | 7,698.29 | 4.95% |
| Lacustrine basin | 1,039.12 | 0.67% |
| Flat peneplain | 162.29 | 0.10% |
| Wavy peneplain | 4,278.13 | 2.75% |
| Undulating tectonic terrain | 20,789.84 | 13.36% |
| Tectonic hills | 6,138.53 | 3.94% |
| Upper volcanic slopes | 5,054.37 | 3.25% |
| Middle volcanic slope | 13,257.46 | 8.52% |
| Lower volcanic slopes | 4,430.34 | 2.85% |
| Vulcan foot | 3,916.82 | 2.52% |
| Lava flow | 8,539.16 | 5.49% |
| Volcanic canyon | 11,702.17 | 7.52% |
| Undulating volcanic plain | 5,477.89 | 3.52% |
| Volcanic hills | 40,058.67 | 25.73% |
| Volcano mountains | 7,525.38 | 4.83% |
| Volcanic intrusion | 649.38 | 0.42% |
| Escarpment | 294.46 | 0.19% |
| Water body | 3,596.39 | 2.31% |
| Total | 155,665.24 | 100.00% |

*Lithology*

Lithology, which refers to the types and characteristics of rocks that make up the Earth's surface, has a significant relationship with the occurrence of landslides. Rocks with high porosity allow water to infiltrate more easily, increasing weight and reducing soil particle cohesion, thereby triggering landslides. Less compact and easily weathered rocks tend to be more prone to landslides. Hard and compact rocks are usually more resistant to landslides (Raharja, 2023). Based on the distribution of parent rock materials, there are four main types of parent rocks found in Sumedang Regency: alluvium, andesite, claystone, and colluvium. The distribution of these parent materials can be seen in Figure 6.

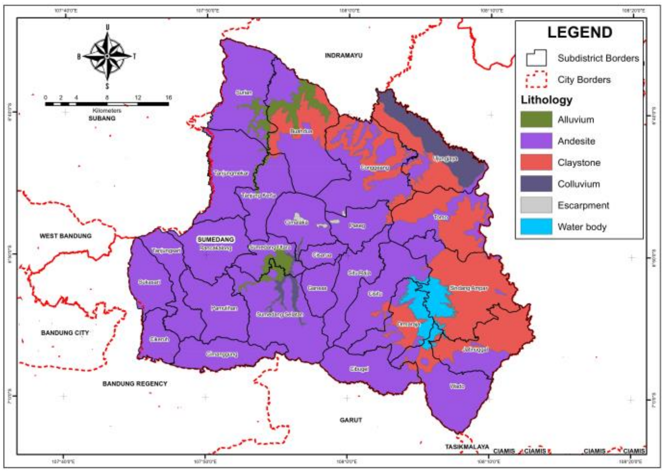


**Figure 6**. Lithology distribution map

Based on Figure 6, it can be seen that the distribution of andesite parent material dominates Sumedang Regency, except for parts of the north, northeast, east, and southeast regions. Andesite parent material is often found in volcanic areas with hilly or mountainous topography and steep slopes. This steep topography naturally increases the risk of landslide disasters, especially if the slopes are covered by thick and loose weathered andesite soil.

**Table 5.** Lithology distribution table

| Lithology | Wide (ha) | Percent |
|---|---|---|
| Andesite | 110,888.07 | 71.23% |
| Claystone | 31,418.80 | 20.18% |
| Colluvium | 5,352.68 | 3.44% |
| Alluvium | 4,114.83 | 2.64% |
| Water body | 3,596.39 | 2.31% |
| Escarpment | 294.46 | 0.19% |
| Total | 155,665.24 | 100.00% |

Based on Table 5, andesite is the parent material with the widest distribution, covering 110,888.07 hectares (71.23%). Meanwhile, colluvium and alluvium occupy the smallest lithological areas, each accounting for 3.44% and 2.64% of the total area. Andesite is a type of volcanic rock that generally has high strength and durability. However, when andesite undergoes weathering, its strength can significantly decrease. Weathering produces loose and porous soil, which is more prone to landslides. Andesite often has cracks and fissures formed by the rapid cooling process after volcanic eruptions. These cracks can allow water to seep deeper into the soil, increasing soil saturation and decreasing soil cohesion, which can trigger landslides (Asyari et al., 2023). By understanding the characteristics of parent materials and how they affect slope stability, appropriate preventive and mitigation measures can be implemented to reduce landslide hazards in vulnerable areas.

*Soil Type*

The relationship between soil type and landslides is very close, as the physical properties of soil can significantly influence slope stability. Soil with a high clay content has a large water-holding capacity but can become very plastic and slippery when saturated, increasing the risk of landslides. Sandy soil has low particle cohesion and is easily eroded, but it also has good drainage, making it less likely to become saturated. Clay soil can absorb and retain water well, but when saturated, its stability can decrease, leading to landslides (Safriani et al., 2024).

The physical characteristics of soil can be categorized based on soil type, with 15 subgroups that can be simplified into six orders: inceptisols, alfisols, ultisols, andisols, entisols, and vertisols. The distribution of soil types by area in Sumedang Regency can be seen in Figure 7.

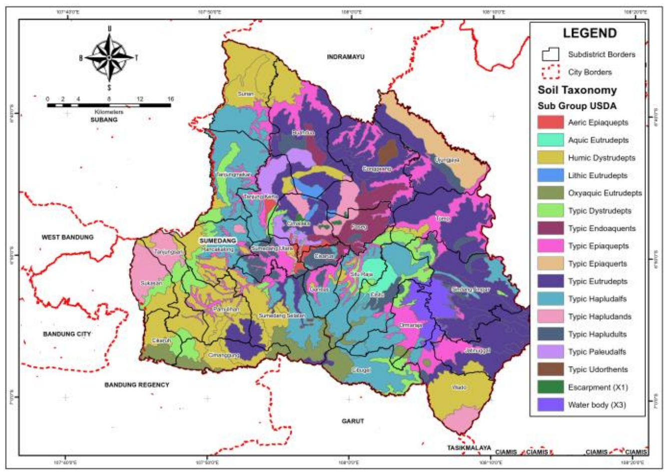


**Figure 7**. Soil types map

Based on the soil type distribution map, soils of the orders inceptisols, alfisols, and ultisols are the most widely distributed across nearly all areas with slopes that have the potential for landslide disasters.

**Table 6.** Soil types table

| Soil Type | Wide (ha) | Percent |
|---|---|---|
| Typic Epiaquepts | 18,401.21 | 11.82% |
| Typic Eutrudepts | 35,538.71 | 22.83% |
| Typic Epiaquerts | 4,622.58 | 2.97% |
| Typic Hapludalfs | 25,353.90 | 16.29% |
| Typic Hapludults | 6,020.18 | 3.87% |
| Typic Hapludands | 7,397.19 | 4.75% |
| Humic Dystrudepts | 27,466.09 | 17.64% |

| Soil Type | Wide (ha) | Percent |
|---|---|---|
| Aeric Epiaquepts | 1,031.27 | 0.66% |
| Typic Paleudalfs | 2,885.55 | 1.85% |
| Typic Endoaquents | 4,592.26 | 2.95% |
| Lithic Eutrudepts | 895.55 | 0.58% |
| Typic Dystrudepts | 9,464.34 | 6.08% |
| Aquic Eutrudepts | 1,731.81 | 1.11% |
| Oxyaquic Eutrudepts | 5,724.37 | 3.68% |
| Typic Udorthents | 649.38 | 0.42% |
| Escarpment | 294.46 | 0.19% |
| Water Body | 3,596.39 | 2.31% |
| Total | 155,665.24 | 100.00% |

Based on the table 6, soils of the typic eutrudepts subgroup have the widest distribution, covering 35,538.71 hectares (22.83%). It can also be interpreted that several inceptisols orders have a fairly wide distribution, each covering more than 10%, such as typic epiaquepts (11.82%), typic eutrudepts (22.83%), and humic dystrudepts (17.64%). Inceptisols are still in the early stages of soil development and can have various textures, from sand to clay. When found on steep slopes, inceptisols with poorly developed structure and poor drainage can increase vulnerability to landslides.

Soils of the typic hapludalfs subgroup (alfisols order) also cover more than 10% of the area, specifically 25,353.90 hectares (16.29%). Alfisols are generally found in areas with temperate to tropical climates. These soils are known for their argillic horizons, which contain clay accumulation, and are often found in forested or grassland areas. The relationship with landslide occurrence can be understood by examining some of their characteristics and physical properties that affect slope stability. Physical properties determine soil drainage; poorly drained soils tend to retain water, increasing pore water pressure, which can reduce soil shear strength and increase the risk of landslides (Lasaiba et al., 2024).

*Landslide Hazard Analysis*

Landslide hazards represent a significant threat in many regions, particularly those characterized by steep terrain, unstable geological formations, and high rainfall. Landslides occur when the equilibrium of a slope is disrupted, causing soil, rock, and debris to move downhill under the force of gravity. These events can be triggered by natural factors such as intense rainfall, earthquakes, volcanic activity, or human activities like deforestation, mining, and construction, which disturb the natural stability of the land (Purnamasari et al., 2024).

The creation of a landslide hazard map is carried out using overlay techniques, which include slope maps, rainfall maps, landform maps, lithology maps, present land use maps, and soil type maps. The overlay is done by incorporating the weighting of factor analysis results, and then scoring is performed based on the calculated weights. The total landslide hazard parameter scores are then classified to produce a landslide hazard class map, as shown in Figure 8.

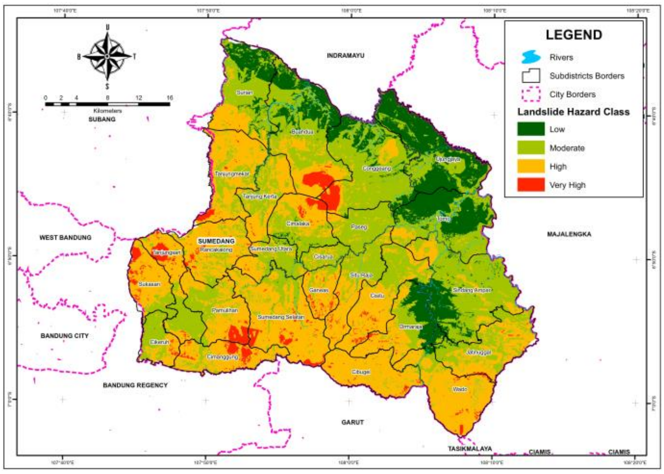


**Figure 8**. Landslide hazard map

**Table 7.** Landslide hazard table

| Hazard Class | Interval | Wide (ha) | Percent |
|---|---|---|---|
| Low | > 178 | 21,634.87 | 13.90% |
| Moderate | 178 - 250 | 62,852.80 | 40.38% |
| High | 250 - 322 | 65,746.37 | 42.24% |
| Very High | > 322 | 5,431.20 | 3.49% |
| Total | | 155,665.24 | 100.00% |

Based on Table 7, it can be seen that, with this model, Sumedang Regency has varying landslide hazard classes, ranging from low to very high. The high landslide hazard class dominates Sumedang Regency, covering an area of 65,746.37 hectares or 42.24% of the total area of Sumedang Regency. This is followed by the medium landslide hazard class with 62,852.80 hectares or 40.38%, the low landslide hazard class with 21,634.87 hectares or 13.90%, and the very high landslide hazard class with 5,431.20 hectares or 3.49%. According to Figure 8, areas with low landslide hazards are located in the northern part of Sumedang Regency.

The impact of landslides can be devastating, leading to loss of life, destruction of infrastructure, and disruption of communities. The economic costs associated with landslides include not only immediate damages but also long-term consequences such as the loss of arable land, increased erosion, and the need for costly mitigation measures (Prabandari & Manessa, 2024). By understanding the underlying factors that contribute to landslides, scientists and planners can assess the vulnerability of specific areas. This information is critical for developing effective land-use policies, designing resilient infrastructure, and implementing early warning systems that can save lives and reduce property damage (Maruddani et al., 2024).

*Landslide Hazard Map Accuracy Test*

The verification parameters for the landslide hazard map are used to assess the map's accuracy by using landslide occurrence data combined with the landslide hazard map to calculate the R square ($R^2$) value of the relationship. Verification is done by plotting landslide hazard classes with density. The results of the verification of the existing landslide hazard map are presented in Table 8 and Figure 9.

**Table 8.** Hazard density map

| Hazard Class | Wide (ha) (L) | Landslide Point (n) | Density (n/L) x 10000 |
|---|---|---|---|
| Low | 21,634.87 | 0 | 0.00 |
| Moderate | 62,852.80 | 4 | 0.64 |
| High | 65,746.37 | 11 | 1.67 |
| Very High | 5,431.20 | 3 | 5.52 |

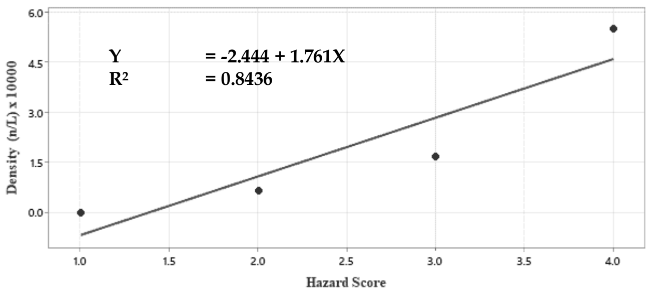


**Figure 9**. Linear regression of hazard model verification

Based on the results of verifying the landslide hazard map with actual landslide points using a linear model, an R square of 0.8436 was obtained. With this R square value, the landslide hazard map resulting from the study is considered quite good. The regression value indicates how well the hazard values from the landslide hazard class map explain the variability in actual landslide occurrences (Husdi & Dalai, 2023). Therefore, landslide hazard can be used as a reference for considering spatial planning improvements and mitigations.

## Conclusion

The landslide hazard distribution analysis is carried out using a weighting and scoring method on the parameters used, which include: slope gradient, rainfall, actual land cover, landform, lithology, and soil type. Based on these parameters, four landslide hazard classes were identified in Sumedang Regency: low, medium, high, and very high hazard classes. Proportions of these hazard are as follows: high hazard class (42.24%), medium hazard class (40.38%), low hazard class (13.90%), and very high hazard class (3.49%). The low hazard class is mainly found in the northern part of Sumedang Regency, the medium hazard class is widespread in sloping areas, and the high to very high hazard classes are primarily found in the Tampomas mountains and areas with hilly landforms. Slope gradient and rainfall are the factors that most influence landslide hazards, making it necessary to design appropriate mitigation.

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