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Analysis of Maximum-Rainfall-Infiltration-Induced Slope Stability Using the Transient Rainfall Infiltration and Grid-based Regional Slope-stability Model in Cililin, West Java, Indonesia

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Abstract - Landslide is one type of geological disasters that frequently occurs during the rainy season. Rainfall infiltration can cause soil saturation that increases the positive pore water pressure, disturbing the slope stability. Therefore, knowledge of future landslide-triggering rainfall is required for mitigation efforts and reducing the risk of landslide hazards. This paper presents slope-stability modeling in the Cililin area using the well-established infinite slope model called the transient rainfall infiltration and grid-based regional slope-stability (TRIGRS). The modeling used the rainfall data obtained from the statistical analysis of the maximum daily rainfall by using the Gumbel distribution. The present study applied six scenarios in the modeling. Scenario I is the initial condition without rainfall, showing the slope stability influenced by topography, slope, and soil characteristics. TRIGRS modeling involves rainfall infiltration in scenarios II, III, IV, V, and VI. The maximum rainfalls used in the modeling are 66, 76, 101, 120, and 132 mm/d, showing that rainfall infiltration affected the slope stability. The result indicates that rainfall triggered an increase and expansion of the area distributions critical to the slope stability.

Keywords: landslide, slope stability, rainfall-induced, TRIGRS model, Cililin

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Introduction

Background

Landslides are common geological disasters in Indonesia during the rainy season. Most landslides are caused by decreased shear strength properties of soil layers due to intensified rainfall or increased weathering. Landslides are commonly triggered by heavy rainfall; thus, rainfall is widely considered as the main temporal triggering factor in the landslide hazard assessments (Nagarajan *et al*., 2000; Fell *et al*., 2008; Tan *et al*., 2008; Park *et al*., 2013;). Infiltration of rainwater causes soil to saturate and subsequently increases positive pore water pressures in the soil, thus lowering the stability of hillslopes (Iverson, 2000; Tohari *et al*., 2013). Previous studies reports that landslides triggered by rainfall are mostly shallow landslides

(Salciarini *et al*., 2006; Tan *et al*., 2008; Kim *et al*., 2014; Cascini *et al*., 2015; Saadatkhah *et al*., 2015; Alvioli and Baum, 2016; Tang *et al*., 2017; Tran *et al*., 2017; Zhuang *et al*., 2017). Nevertheless, the occurrences of such shallow landslides still cause significant loss of lives and considerable economic losses (Dai *et al*., 2002; Highland and Bobrowsky, 2008; Kjekstad and Highland, 2009).

West Bandung District is one of the districts in West Java Province prone to landslide events during the rainy season. Figure 1 shows the annual landslide occurrences from 2005 to 2019 in the West Bandung District obtained from the Indonesian Disaster Information Data, National Disaster Management Agency. This figure shows that landslide occurrence increased during 2010, 2014, and 2019, indicating an increased landslide frequency every five years from 2005 to 2019. Of sixteen subregencies, the Cililin Subregency contributes to high landslide incidents in West Bandung District. Figure 2 shows the historical data of landslide incidents in the Cililin area from 2005 to 2019 recorded by the Centre for Volcanology and Geological Disaster Mitigation (PVMBG). This figure shows that high landslide incidents occurring in 2005, 2009, 2015, and

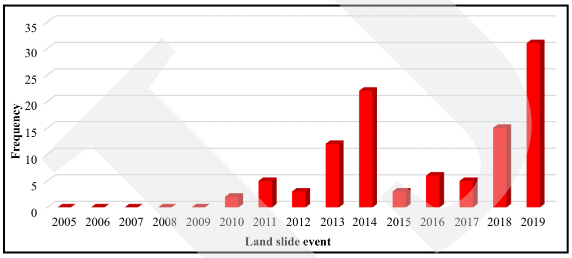

Figure 1. Histogram of landslide events in West Bandung Regency from 2005 to 2019.

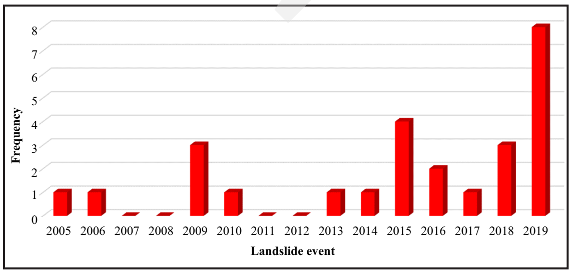

Figure 2. Histogram of landslide events from 2015 to 2019 in the Cililin area.

2019, imply the increasing trend of landslide incidents every four-five years. The most recent landslides in the Cililin subregency occurred in April 2019. Based on PVMBG (2019), the landslide disaster in this subregency was due to the high rainfall intensity and low soil strength. A rainfall of high intensity and long duration commonly occurs before the landslide event. As landslide disaster occurrences are prevalent in this subregency during the rainfall period, efforts to mitigate future landslide hazards are necessary. Any mitigation efforts require knowledge of the effect of rainfall intensity and other causative factors on the landslide susceptibility of the Cililin area.

Previous researchers have conducted different methods for landslide susceptibility modeling using the Geographic Information System (GIS). Statistical methods to create a landslide hazard zone map have been applied by researchers, such as Lee (2005), Lee and Sambath (2006), and Chauhan *et al.* (2010), using the logistic regression method. Hadji *et al.* (2017) and Zhao *et al.* (2017) used the analytic hierarchy process method for slope movement susceptibility. Wang *et al.* (2014) applied the weighted scoring method for the landslide susceptibility mapping. Lee and Pradhan (2006) and Kawagoe *et al.* (2010) evaluated a probabilistic model based on a multiple logistic regression analysis. Other studies also focused on landslide mechanisms based on deterministic methods to predict regional landslides. Montgomery and Dietrich (1994), Dietrich and Montgomery (1998), Pack *et al.* (1998), Wilcock *et al.* (2003), and Tran *et al.* (2017) studied a deterministic approach to determine landslide hazard analysis.

As far as the landslide mechanism is concerned, rainfall infiltration is a primary triggering factor for shallow landslides, because rainfall can increase pore water pressure. Accordingly, the physical-based models combined with hydrogeological models, such as the time-variant slope-stability (TiVaSS), Stability INdex MAPping (SINMAP), Shallow Landsliding Stability (SHALSTAB), GEOtop-factor of safety (FS), and transient rainfall infiltration and grid-based regional slope-stability (TRIGRS) models, were developed to predict shallow landslides triggered by precipitation infiltration. TiVaSS is a physical-based model that integrates the three-dimensional (3D) Richards equation subsurface flow model and a basic infinite slope-stability equation to assess rainfall-induced shallow landslides (Tran *et al*., 2017). The SINMAP implements the infinite slope-stability model that balances the destabilizing components of gravity and the restoring components of friction and cohesion components on a failure plane parallel to the ground surface with edge effects neglected (Pack *et al*., 1998). SHALSTAB is an approach that combines an infinite slope-stability model with a steady-state hydrology model for mapping the potential landslide areas (Montgomery and Dietrich, 1994). GEOtop-FS is the most complex physical-based model involving the combination of the two-dimensional (2D) surface flow with the 3D unsaturated subsurface flow for spatial and temporal prediction landslide assessment (Simoni *et al*., 2008). Finally, TRIGRS was developed based on a transient one-dimensional (1D) vertical infiltration model with simple infinite slope stability (Baum *et al*., 2002, 2008).

TRIGRS is the most frequently used model among the above-mentioned physical-based models, because this physically based model considers variations in rainfall intensity to predict the shallow landslide susceptibility. Previous researchers applied the TRIGRS model for the landslide susceptibility mapping to estimate spatiotemporal changes in safety factor distribution triggered by rainfall (Baum *et al*., 2002, 2008, 2010; Godt *et al*., 2008; Kim *et al*., 2010; Park *et al*., 2013; Kim *et al*., 2014; Cascini *et al*., 2015; Saadatkhah *et al*., 2015; Sarah *et al*., 2015; Alvioli and Baum, 2016; Tang *et al*., 2017; Tran *et al*., 2017; Zhuang *et al*., 2017). Many important parameters are involved in the TRIGRS model, such as topographic factors, soil characteristics, and rainfall intensity data. The TRIGRS modeling results are presented in a spatial visualization application based on a GIS.

Although many previous studies have shown the capability of the TRIGRS programme to predict landslide occurrences, the program still has a limitation. The programme does not provide users with a post-processing tool for spatial visualization of a model result. Yunarto *et al*. (2016) developed the original TRIGRS model to TRIGRSMap to prepare the input grids and to visualize the landslide susceptibility modeling results. TRIGRSMap integrates the TRIGRS code with Microsoft Visual Basic as the computer programming language and MapInfo as the GIS software to facilitate the preparation of the input grid and visualization of the modeling result. Therefore, the modeling using TRIGRSMap is more user-friendly, efficient, and easy to use (Yunarto, 2016).

Knowledge of rainfall infiltration characteristics that trigger landslides is essential for establishing mitigation efforts for landslide hazard risk reduction. Dai (2002), Guzzetti (2008), Lateh *et al*. (2013), and Hong *et al*. (2018) studied that the relationship between landslide occurrence and rainfall characteristics formed the basis for the development of regional real-time landslide warning systems. The high rainfall intensity can add the load on the slopes as in increasing the pore water pressure, thus triggering landslides (Iverson, 2002; Huang and Lin, 2002). This paper presented spatial slope-stability modeling results from the TRIGRS model to assess the effect of the annual rainfall intensity on the landslide occurrence in the Cililin area, West Java, Indonesia. The main objectives of the present study are to (1) examine the effect of annual maximum rainfall intensity, (2) identify the factors controlling slope stability, and (3) determine the threshold of rainfall inducing a landslide in the studied area. The current study considered the annual maximum rainfall intensity to understand the maximum rainfall in the Cililin area predicted to trigger future landslides.

Researched Area

Cililin is one of sixteen subregencies in the West Bandung Regency, and this area is part of the Bandung Basin in the middle of the West Java Province, Indonesia (Figure 3). The Cililin Subregency covers an area of 77.79 km^2. Most of the studied areas are dam reservoirs, including Saguling. Geographical coordinates of the studied area are 107°23'34"-107°31'38" E and 07°03'05"-06°54'02" S. The morphology comprises flat to steep slopes with an altitude from 637.5 to 1987.5 m above mean sea level. The drainage pattern in this area is radial and subdendritic, controlled by its respective lithology (Figure 4).

Based on the regional geological maps (Figure 4) of Bandung Sheet (Silitonga, 1973), Cianjur Sheet (Sudjatmiko, 1972), and Sindang Barang and Bandarwaru Sheet (Koesmono *et al*., 1996), the lithology in the studied area, the oldest to the youngest formation, comprises tuffaceous breccia, lava, sandstone, conglomerate (Pb), andesite rock units (a), lake sedimentary units (Ql), and alluvium units (Qa).

Geologically, landslides in this area occur in various lithologic conditions, such as andesite and basaltic breccia units, lava, tuff sandstone, conglomerates (Pb) and tuffaceous clay, sandstone, gravel, and conglomerates (Ql). Soil types in the studied area are the result of weathering of volcanic rock and volcanic ash deposits. Soil types may cause geological engineering problems, for example, physical properties change and lack of strength and capacity. The selection of the studied area was based on the frequent landslide events occurring in the Cililin area. Therefore, it is important to understand the causative factors and to determine the susceptibility level. Lineaments in this area were obtained from the interpretation of the digital elevation model (DEM) shown in Figure 4. However, the structural geology in this area is not included as an input parameter in the modeling.

Methods

Input Parameters

The present study includes several stages for preparing data analysis, namely, field data

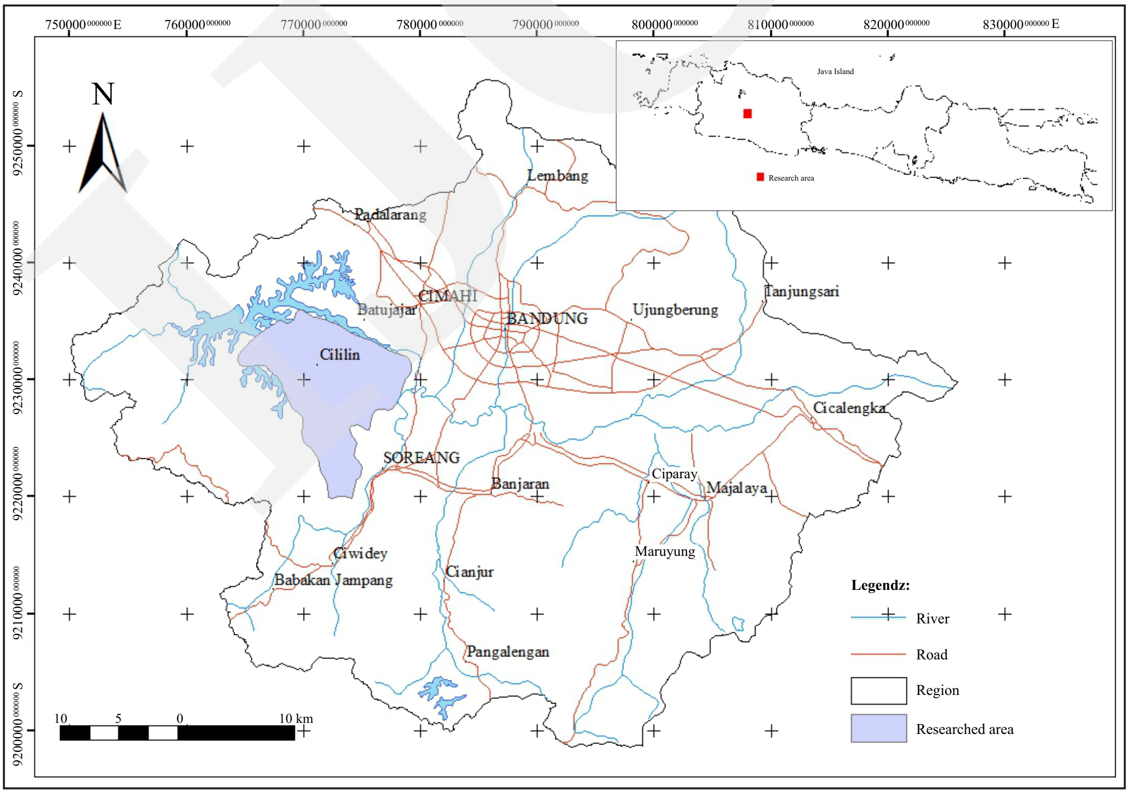

Figure 3. Location of the studied area.

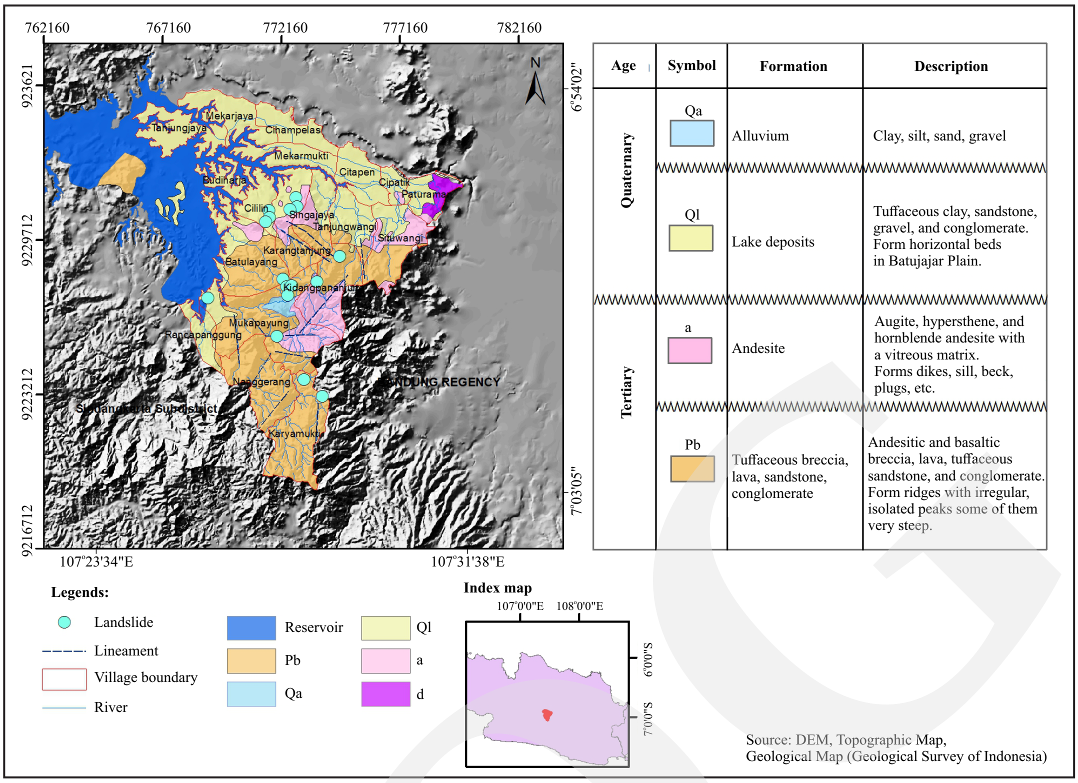

Figure 4. Geological map of the studied area in Cililin, West Java, Indonesia.

collection, landslide location mapping, laboratory samples testing, spatial data processing, and slope-stability modeling. GIS package was used to integrate the input data into the spatial slope-stability calculation at a pixel size of 10-m × 10-m grids. The TRIGRS is a model to determine the safety factor of slope stability affected by rainfall infiltration. The theoretical basis of the TRIGRS programme combines models for infiltration and subsurface flow of rainwater, routing of runoff, and slope stability to calculate the effects of storms on the regional slope stability.

The input data for modeling required a digital topographic map of the Cililin area of 1:25,000 scale to generate a DEM, slope, and flow direction. DEM and slope were used in the Topo index programme. The Topo index is a programme required for the runoff-routing calculations in slope-stability modeling. The input files for TRIGRS are slope, soil cohesion, friction angle, soil thickness, unit weight, permeability, porosity, depth of water table, diffusivity, hydraulic conductivity, infiltration rate, topographic index, and rainfall intensity. The rainfall intensity data used in modeling were the daily maximum rainfall intensity data for twenty-five years from 1986 to 2010. The data were obtained from Indonesia Power UP Saguling, Bandung Barat Regency. Parameters will be prepared in thematic maps with a 10-m × 10-m pixel using ArcGIS 9.1 application, then extracted to ASCII. The 10-m × 10-m pixel was intended to produce a more detailed resolution within the subdistrict.

Slope-Stability Model

The TRIGRS model developed by the United States Geological Survey (USGS) (Baum *et al.*, 2002) is a FORTRAN programing language designed for modeling safety factors for landslides by merging an infinite slope-stability calculation and an analytic, 1D solution for pore water pressure diffusion in a soil layer of finite depth in response to time-varying rainfall (Baum *et al.*, 2002, 2008). The TRIGRS model was developed by the USGS. This model is essential for landslide susceptibility mapping study and landslide hazard zoning for land-use planning on a regional scale. The modeling of slope stability calculates the FS using a consistently homogeneous slope-stability equation (Iverson, 2000), shown as:

$$\mathrm{FS} = \frac{\tan\varphi'}{\tan\theta} + \frac{c' - \psi(Z,t)\gamma_w \tan\varphi'}{\gamma_s Z \sin\theta\cos\theta} \quad \text{.................... (1)}$$

In Equation (1), φ' is the soil friction angle for effective stress, θ is the angle of the sliding plane, c' is the soil cohesion for effective stress, $\psi(Z,t)$ is the groundwater pressure head at time t and depth Z, γ_w is the unit weight of groundwater, and γ_s is the unit weight of soil. The ratio of resistive forces over driving forces on the slope is defined as the FS. If the FS value is <1.0, the slope area is unstable or prone to landslide.

Infiltration Analysis

The infiltration models in TRIGRS use linearized solution of the Richards equation as described by Iverson (2000) and extensions by Baum *et al.* (2002). The solution by Iverson consists of steady-state infiltration and transient infiltration. The steady-state infiltration enables flow in an unequable direction depending on the steady infiltration rate and the slope angle. The transient infiltration considers 1D, vertical downward flow, a general time-varying sequence of surface fluxes of variable durations and intensities, and a zero-flux condition for times greater than the beginning at an infinitely deep basal boundary (Figure 5).

The following is the formula of the solution for transient pore water pressure in Equation as below:

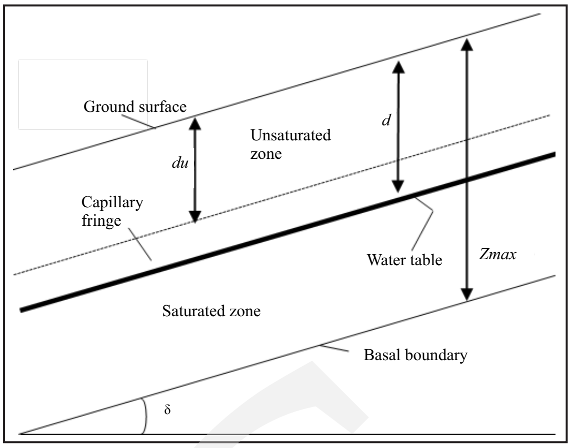

Figure 5. Conceptual diagram of the TRIGRS model.

In Equation (2), ψ is the groundwater pressure head at time t and depth Z; t is the time; $Z = z/\cos\delta$, where Z is the vertical coordinate direction (positive downward) and depth below the ground surface, z is the slope normal coordinate direction (also positive downward), and δ is the slope angle; d is the steady-state depth of the water table measured in the vertical direction; d_{LZ} is the depth of the impermeable basal boundary measured in the vertical direction; $\beta = \cos^2\delta - (I_{ZLT}/K_s)$, where K_s is the saturated hydraulic conductivity in the Z direction, and I_{ZLT} is the steady (initial) surface flux; I_{nZ} is the surface flux of a given intensity for the nth time interval; $D_1 = D_0/\cos^2\delta$, where D_0 is the saturated hydraulic diffusivity ($D_0 = K_s/S_s$, where K_s is the saturated hydraulic conductivity, and S_s is the specific storage); N is the total number of time intervals; $H(t - t_n)$ is the Heaviside step function; t_n is the time at the nth time interval in the rainfall infiltration sequence; and $erfc(\eta)$ is the complementary error function: $ierfc(\eta) = (1/\sqrt{\pi})\exp(-\eta^2) - \eta erfc(\eta)$, where m is the index

$$\psi(Z,t) = [Z-d]\beta + 2\sum_{n-1}^{N}\frac{I_{nz}}{K_k}H(t-t_n)^{\frac{1}{2}}\sum_{m=1}^{\infty}\left\{ierfc\left[\frac{(2m-1)d_{LZ}-Z}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]+ierfc\left[\frac{(2m-1)d_{LZ}+(d_{LZ}-Z)}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]\right\} \quad \text{... (2)}$$

$$-2\sum_{n-1}^{N}\frac{I_{nZ}}{K_z}H(t-t_n)[D_1(t-t_n)]^{\frac{1}{2}}\sum_{m=1}^{\infty}\left\{ierfc\left[\frac{(2m-1)d_{LZ}-(d_{LZ}-Z)}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]+ierfc\left[\frac{(2m-1)d_{LZ}-(d_{LZ}-Z)}{2[D_1(t-t_n)]^{\frac{1}{2}}}\right]\right\}$$

of infinite series displaying an odd term in the complementary error function.

Rainfall Intensity

The present study used the historical rainfall data f rom 1986 to 2010 obtained from the PT, Indonesia Power UP Saguling, Bandung Barat Regency. The data consist of the maximum daily rainfall intensity of the rainfall data from Cililin station, Saguling station, and Bandung station (Figure 6). The processing of rainfall data used the theoretical distribution functions for statistical analysis of maximum rainfall data.

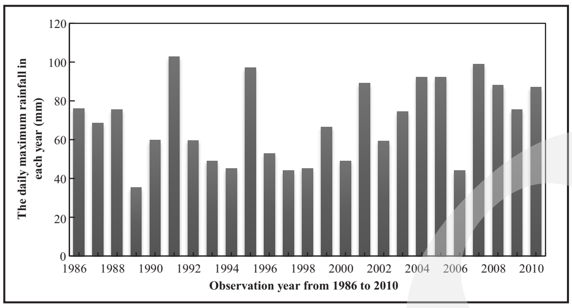

Figure 6. Graph of maximum rainfall intensity data for twenty-five years from 1986 to 2010.

The Generalized Extreme Value Distribution, Gumbel, and Log Pearson Type (LPT) III distributions are theoretical distribution functions commonly used in statistics. Gumbel and LPT III distributions are the two techniques of frequency analysis widely used to develop the relationship between rainfall intensity, storm duration, and rainfall return periods in an area (John and Brema, 2018). The return period is a hypothetical time when a certain amount of rain will be matched or exceeded (Cooley, 2013). Statistical analysis of maximum rainfall data used in the current study is the Gumbel distribution method. The Gumbel distribution is a distribution analysis method of data frequency to estimate extreme rainfall. This method is a distribution theory that is relatively simple, universal, and the result is the same as other ways (Cordeiro *et al*., 2012). These are some of the reasons for selecting the Gumbel method. The return periods of rainfall intensity data were required for modeling. TRIGRS modeling in the studied area used six rain data scenarios to determine the rainfall characteristic triggering a landslide. Scenario I in modeling did not involve any rainfall. Scenario II used the rainfall data of 2009. Scenarios III to VI in the modeling used the rainfall data generated from the Gumbel extreme probability distribution curve for return periods of 1.01, 2, 5, 10, 20, 2 5, and 50 years.

Results and Discussions

Topographic Process

The results of topographic processing comprising maps DEM, slope degree, and flow direction are presented in Figures 7-9. Figure 7 shows that the landslide locations in the studied area are dominated by a hilly topography with smooth to very coarse relief. Landslides occurred on hill slopes at various gradients of >25% (Figure 8). The southern studied area is dominated by a hilly area with a gentle-to-steep slope and borders with the Saguling Reservoir Dam. Based on Figure 9, most landslide events occured in the central part of the Cililin area with the flow direction to the north, southwest, and west.

Soil Parameters

Soil engineering characteristics required for the modeling were obtained from laboratory analysis of soil samples collected according to the distribution of lithology units of the geological formations in the Cililin area. The soil engineering characteristics are presented in the form of thematic maps, including unit weight (γ_s), effective cohesion (c'), effective internal friction angle (φ'), and soil permeability (K_z) presented in Figures 10 and 11. The dominant soil type in the studied area is silty clay. Figures 10 and 11 show that landslide events are located in hilly areas where the soil is characterized by the higher unit weight and cohesion but lower effective internal friction angle and permeability than those of the surrounding area. Low permeability refers to the

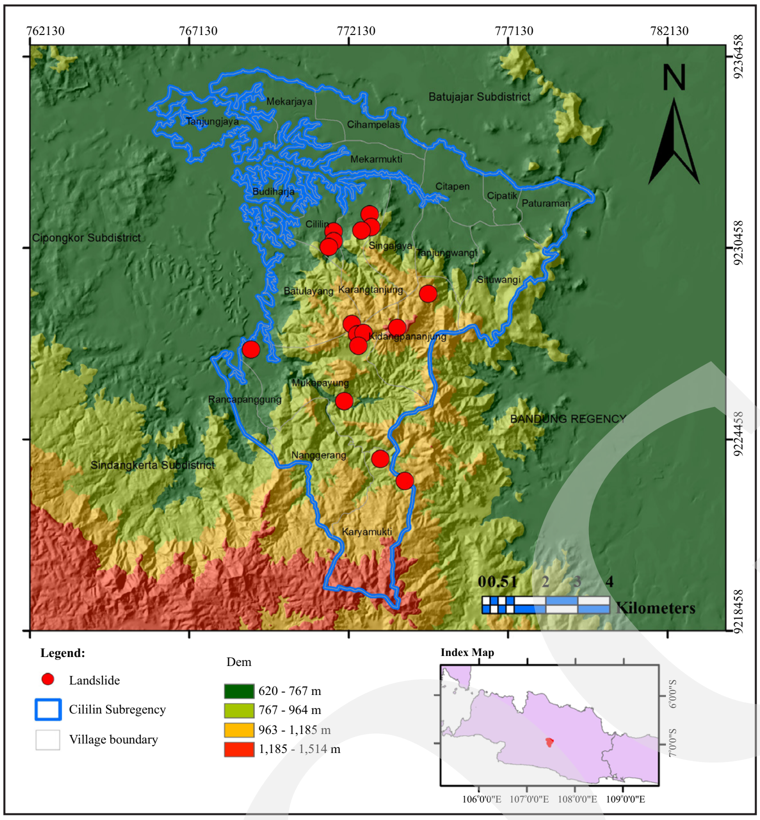

Figure 7. Digital elevation model of the studied area.

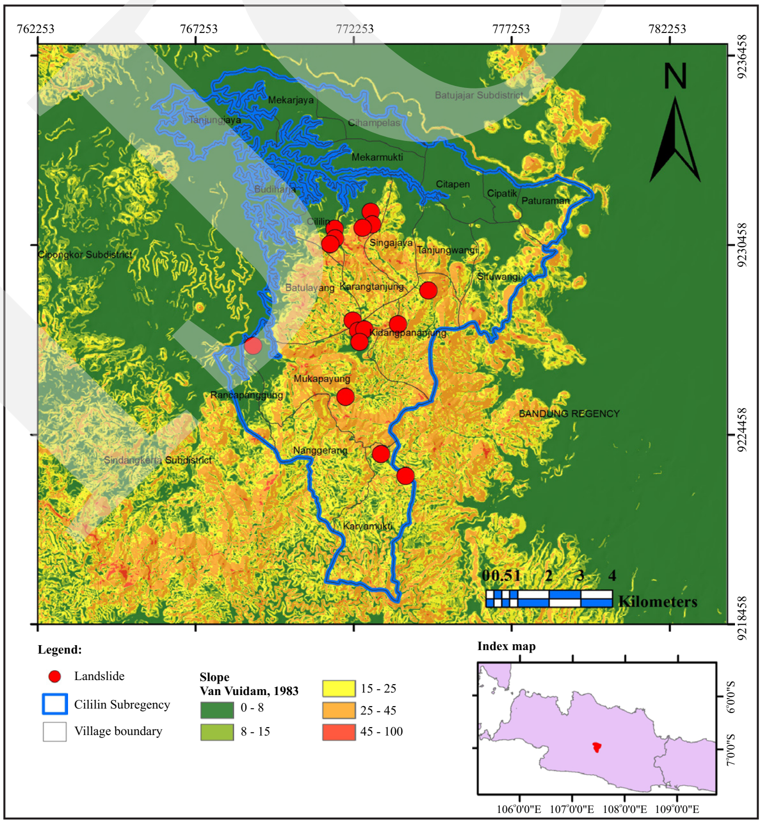

Figure 8. Slope map (in degree) of the studied area.

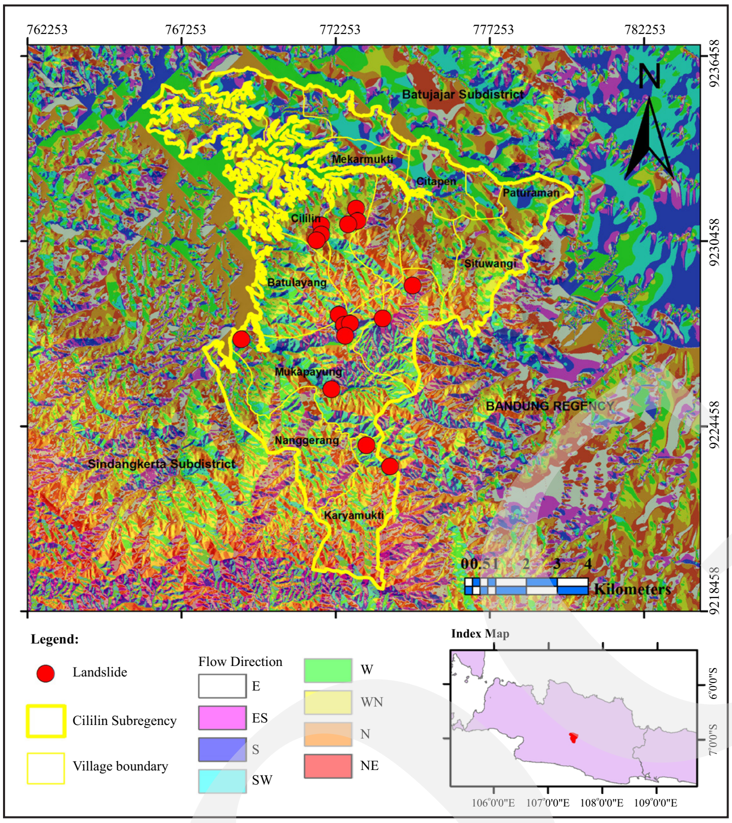

Figure 9. Map of flow direction in the Cililin area.

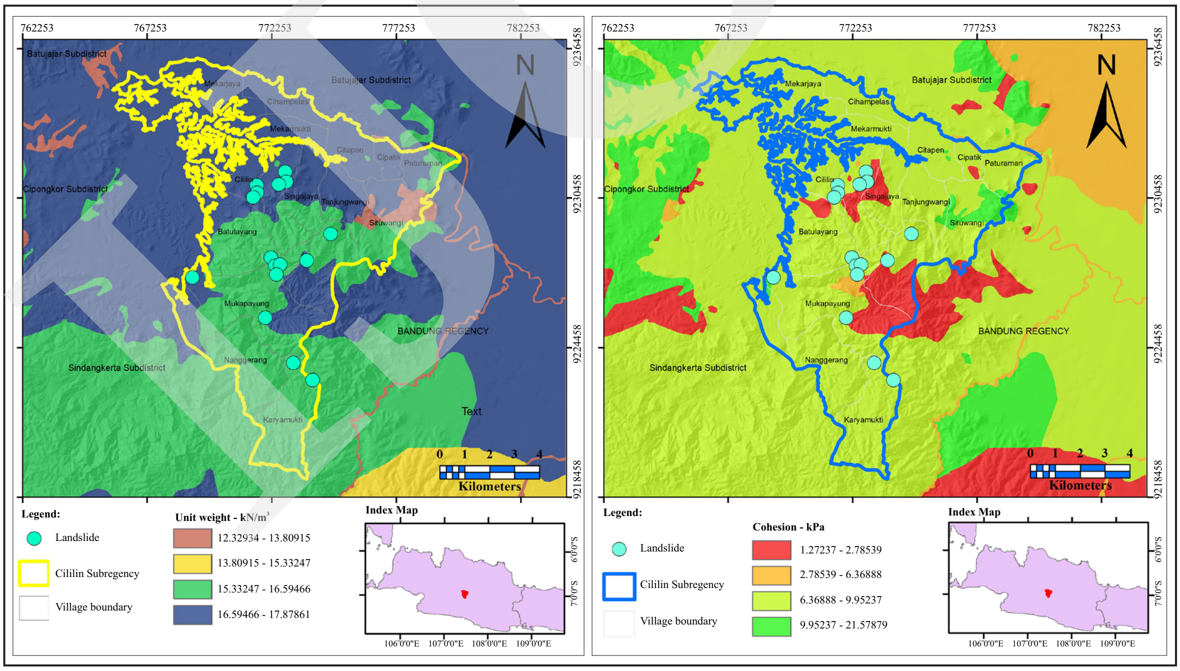

Figure 10. Raster maps of (a) unit weight and (b) effective cohesion.

rock or soil ability of the rock or soil to pass the water at a very slow flow rate. Therefore, the slower the soil permeability, the more water will be retained in the soil, and the more saturated the soil will be. The water-saturated soils have the potential to develop when the rains become more

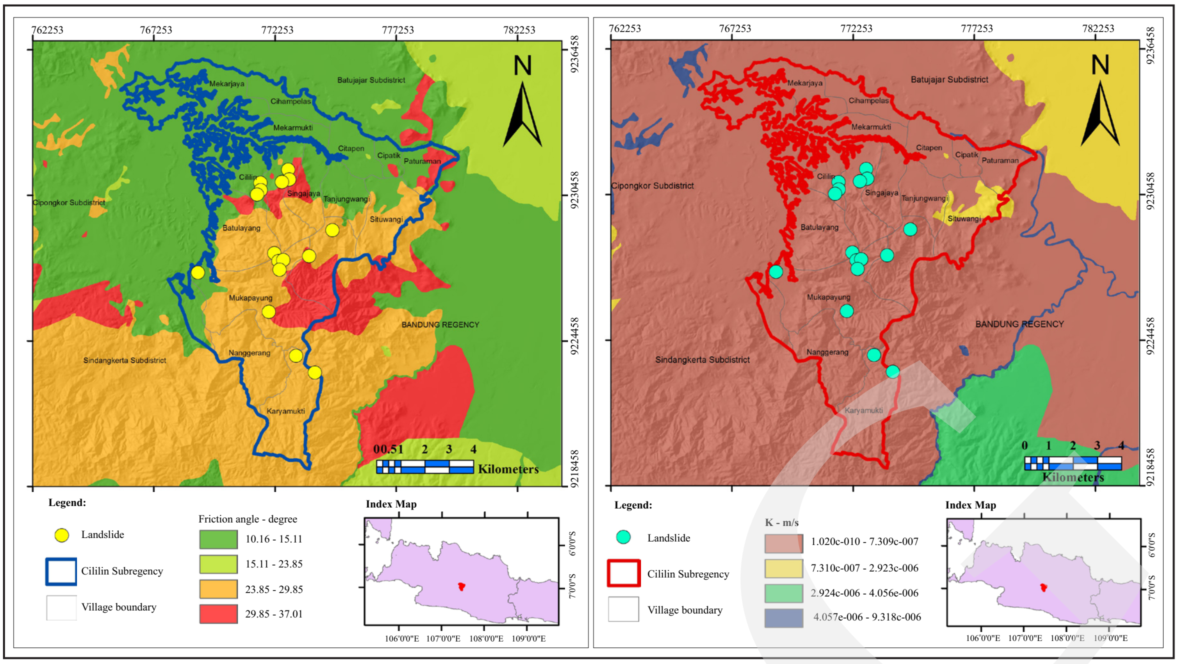

Figure 11. Raster maps of (c) effective internal friction angle and (d) soil permeability.

intense and more prolonged. Full saturation in soils may develop during heavier and longer rainfall. This saturation helps increase the pore water pressure and consequently results in a decreased shear strength of soils, thus triggering landslides.

Rainfall Intensity of the Gumbel Method

The maximum daily rainfall intensity data in the Cililin area from 1986 to 2010 have been statistically analyzed based on the Gumbel extreme distribution theory (Figure 12). The probability and rainfall distribution curve graph shows the amount of rainfall intensity at each return period. The present study used six different scenarios of maximum daily rainfall intensity to perform rainfall-induced shallow landslide modeling using TRIGRS (Table 1). Scenario I used the initial condition without involving rainfall influence for modeling (t = 0). Scenario II used the data of rainfall intensity in 2009 that amounted to 76 mm/d. Finally, scenarios III to VI used the return periods from the probability distribution curve and rainfall distribution curve based on the Gumbel extreme distribution. The present study evaluated each return period of 2, 10, 25, and 50 years with a rainfall intensity of 66, 101, 120, and 132 mm/d, respectively, for the slope-stability modeling.

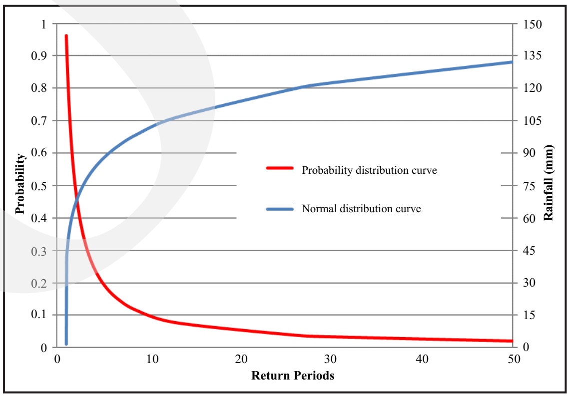

Figure 12. Distribution curves of probability and rainfall based on the Gumbel method.

Table 1. Period of Maximum Rainfall Intensity by The Gumbel Method

Return period (t)	Gumbel (mm/d)
1.01	31
2	66
5	87
10	101
20	115
25	120
50	132

Slope-Stability Modeling

In this paper, the regional landslide susceptibility maps in the Cililin area, West Java, Indonesia were established based on the spatial safety factors obtained using the TRIGRS model. In Figure 13a, the spatial distributions of the safety factor of the initial condition modeling result without involving the rainfall show that the unstable areas with FS <1.0 are located in the steep hill area at an elevation of 800-900 m above sea level. The unstable areas include Batulayang, Cililin, and Mukapayung Villages. Thus, it indicates that the slope stability is affected by gradient slope in the hilly regions of the Cililin area.

The following results of the slope stability using the TRIGRS model for rainfall-induced landslides are shown in Figures 13-15. The results of Scenario I show that only 6.16% of the Cililin area are unstable slopes (Figure 13a). The interpretative results show that the soil character in the Cililin area is mostly stable to landslides, whereas the unstable area is steep to very steep slopes. Figure 13b illustrates the result of Scenario II, which shows the 16% increase in the distribution of areas with unstable slopes from the initial state. In contrast, the results in Scenario III-VI show an average increase of 16% in the distribution of areas with unstable slopes from the initial state (Figures 14a, b, and 15a, b. The results show no significant differences in the increase in the unstable areas for scenarios II-IV, because the areas have reached the maximum limit of saturation. Therefore, it is interpreted that the slope stability in the Cililin area is influenced by rainfall infiltration. As mentioned above, this area has a poor permeability that allows the rainwater to pass through the slope surface at a very slow rate, causing near the slope surface to reach a saturated condition. The saturation in the slope has influenced the increase of pore water pressure and decrease of the shear strength of the rock and soil, thus decreasing the slope stability.

Table 2 shows the spatial distribution of safety factors in the Cililin area, covering 78% for stable areas and 22% for unstable areas. The results indicate an increased number of landslide susceptible areas. Nevertheless, as the rainfall intensity is >66 mm/d, the increase of unstable areas is not significant (Figure 16). Therefore, it is interpreted that the rainfall intensity >66 mm/d would be the threshold for slope stability.

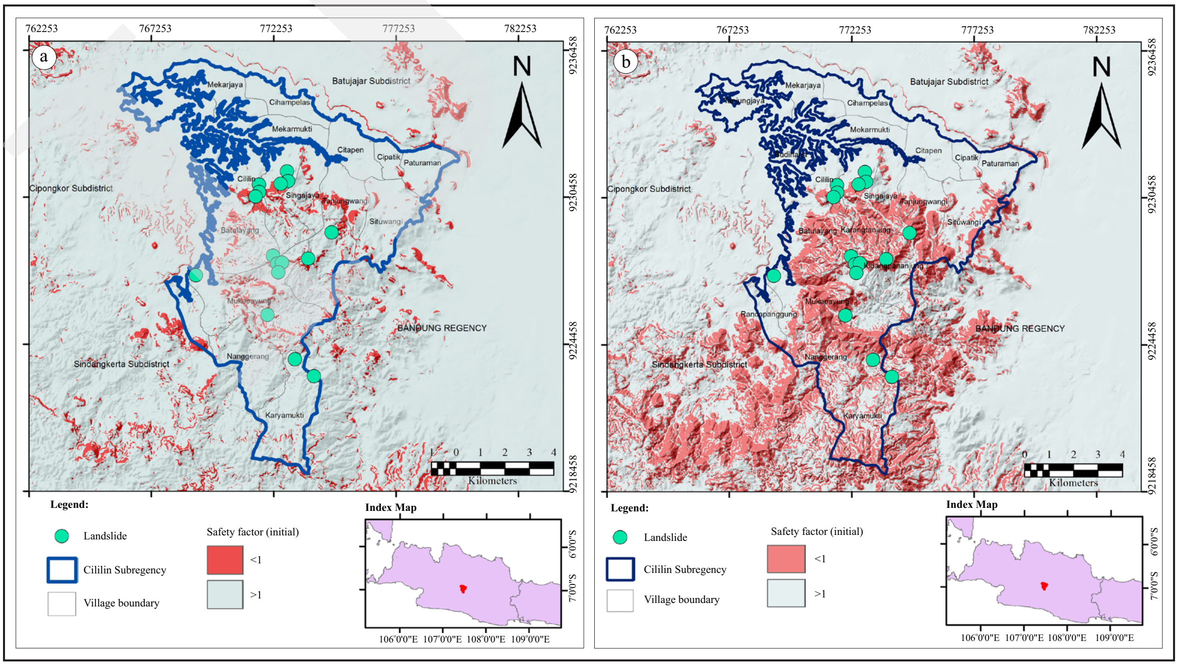

Figure 13. Safety factor maps at (a) the initial condition $t = 0$; and (b) rainfall $t = 2009$ with an intensity of 76 mm/d.

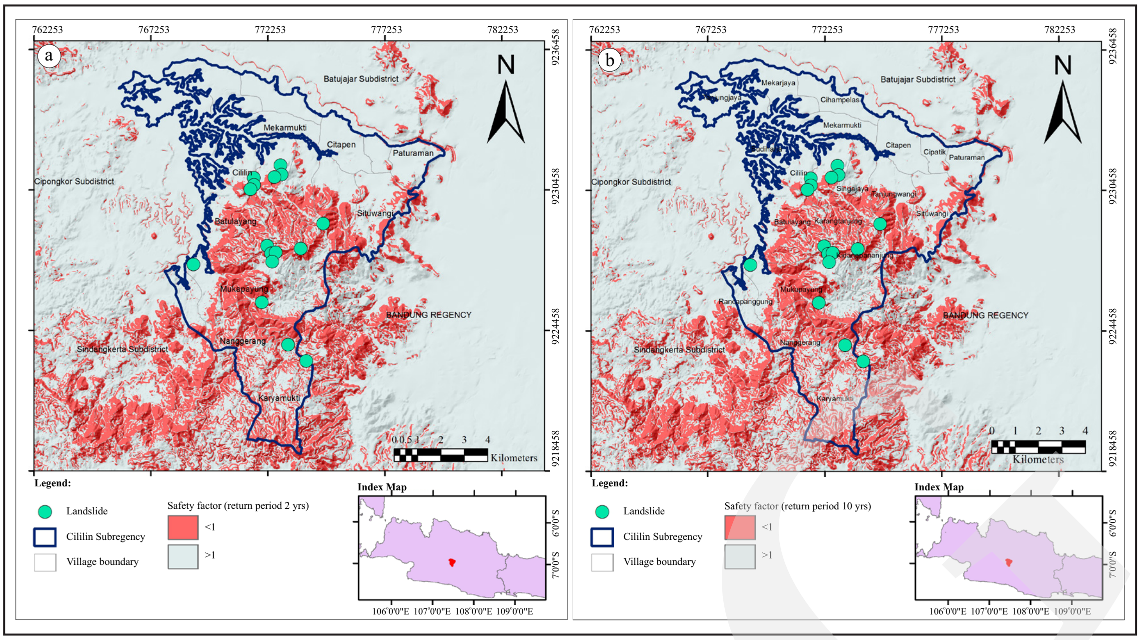

Figure 14. Safety factor maps of the slope to rainfall intensity of (a) 66 and (b) 101 mm/d.

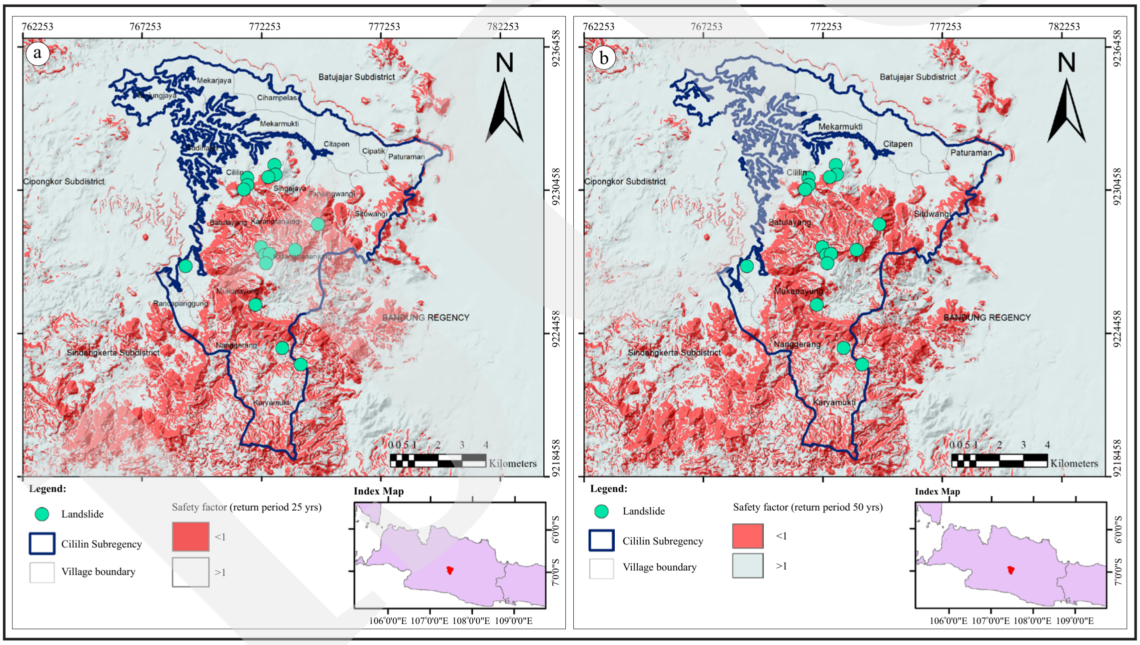

Figure 15. Safety factor maps of the slope to rainfall intensity of (a) 120 and (b) 132 mm/d.

Table 2. Area Spatial Distribution of Safety Factor in The Cililin Area (in m^2)

Factor of Safety	Unit	*t*=0	*t*=2009	*t*=2 RP	*t*=10 RP	*t*=25	*t*=50
Unstable (FS <1)	m^2	213,778	767,699	767,678	767,747	767,769	767,769
Stable (FS > 1)	m^2	3,257,337	2,703,416	2,703,437	2,703,368	2,703,346	2,703,346

The histogram graph in Figure 17 shows that the low slope stability in the studied area is mainly located in areas made up of volcanic rock. Based on Figures 12-14, the unstable areas

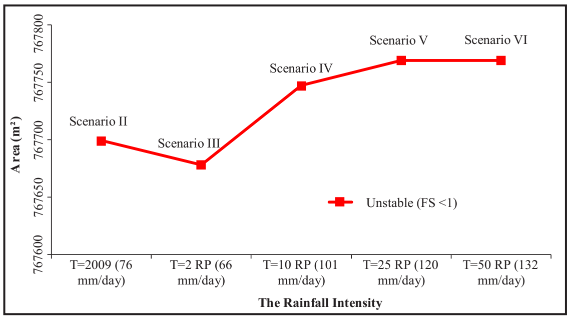

Figure 16. Area spatial distribution of unstable area.

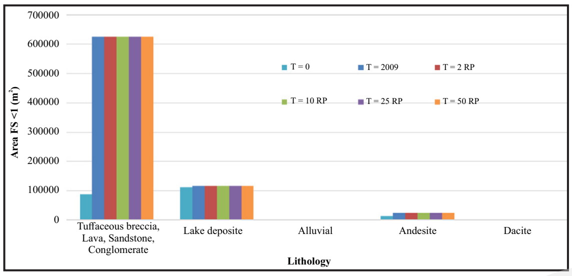

Figure 17. Histogram of the area distribution of unstable slopes (factor of safety < 1).

include Batulayang and Cililin Villages occupying an area of 622,500 m^2. The other landslides in the Cililin area occured in the lithology units of tuffaceous clay, sandstone, gravel, and conglomerates in Mukapayung, Batulayang, and Karangtanjung Villages covering an area of 115,896 m^2. Referring to Figures 10-12, the unstable slope areas are made up of soils with high unit weight and cohesion but a low friction angle and permeability. Thus, the modeling shows that the geological condition of the study area is also a controlling factor of the landslide susceptibility of the area.

Conclusions

The results of slope-stability modeling using TRIGRS show that the slope gradient is the main controlling factor of slope stability in the Cililin area. The unstable hillslope areas are concentrated in steep to very steep slopes made up of volcanic soils.

The modeling results also indicate that the rainfall infiltration would reduce the safety factor of soil slopes of low permeability. An increased rainfall rate would increase the unstable areas with a safety factor <1.0 compared with the initial condition.

The TRIGRS modeling shows an increase in unstable areas due to the increased rainfall rates as depicted by the increase of areas with an FS of <1.0 compared with the initial condition. Based on the current study, a rainfall intensity of >66 mm/d would be the rainfall threshold inducing landslides in the studied area.

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