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Research Article

Characteristics and factors affecting surface and shallow landslides in West Java, Indonesia

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Abstract

Bogor, Cianjur, and Sukabumi areas of West Java Province, Indonesia, are vulnerable landslide areas. This study analyzes the landslide characteristic and the factors affecting landslides. The analysis was carried out on 148 landslides from 415 of 2018-2020 landslides, which were selected purposively by considering the heterogeneity of soil, geology, slope classes, land use type, and accessibility of landslide locations. Landslide characteristics and factors affecting landslides were analyzed using frequency analysis and binary logistic regression. The results showed that the most dominant characteristics of surface and shallow landslides were the landslides characterized by slopes >45%, Quaternary geological period, Andisol soil type, agriculture land use type, the occurrence of rain, and absence of earthquake. The dominant factors affecting surface and shallow landslides are human activities in land use, soil properties, steep-very steep slopes, Inceptisol and Entisol soil orders, young rocks (Quaternary geological period), rainfall events, and high earthquake magnitude.

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Introduction

Landslides in Indonesia were the third most common disaster after floods and tornadoes. During the last five years, 2015 to 2020 occurred 1.154 landslides, or 22% of all disaster events, have caused >40 thousand fatalities, >2 thousand house damages, and >60 public facility damages, hitting health worship and education facilities. 36% of landslides occurred in West Java during that period and spread to Bogor, Cianjur, and Sukabumi areas (BNPB, 2020).

Investigation of the causes of the landslide has been carried out in various countries with different methods. Landslide investigations in the United States of America, Michigan, use a combination of physical, statistical, and hydrological models (Weidner et al., 2019); in Iran, use landslide positioning techniques, sample testing, and random sampling (Pourghasemi et al., 2019); in Algeria, China, Turkey, and Malaysia use geophysical methods (Su et al., 2016; Yalcinkaya et al., 2016; Nordiana et al., 2017; Mezerreg et al., 2019), in Italy and Poland use statistical methods and spatial mapping (Wistuba et al., 2018; Forte et al., 2019); while in Indonesia use self-potential methods, geological, geotechnical, and social investigations (Dwikorita et al., 2011; Santoso et al., 2019).

Investigations of landslide causes, using various methods and theories, indicated that, in general, landslides were caused by natural factors and human actions in land management. These natural factors and human influences were geology, geomorphology, geomorphometry, slope, human activities, earthquakes, rainfall (Chang et al., 2017; Ojala et al., 2017; Tanyas et al., 2018), hydrogeology, soil water content (Wistuba et al., 2018), vegetation (Ollauri and Mickovski 2017; Sidle and Ziegler, 2017), regional meteorology (Peruccacci et al., 2017), and previous avalanches (Samia et al., 2017). The factors that cause landslides differ in each location due to complex interactions among factors that affect slope stability (Ojala et al., 2017). Investigating landslide characteristics in a specific place becomes essential to determine the dominant factor causing landslides in that place.

This study objective was to analyze the landslide characteristics and factors affecting landslides in Bogor, Sukabumi, and Cianjur areas of West Java Province, Indonesia.

Materials and Methods

Study site

The study area covers Bogor Regency and City, Cianjur Regency, and Sukabumi Regency and City, West Java Province, Indonesia. In the study area, during the last three years (2018-2020), there have been at least 415 landslide events (Figure 1).

Landslide location

The landslide locations investigated were selected based on the landslide location characteristics, including rock type, soil type, slope steepness class, and land use type, by considering accessibility. The characteristics were analyzed from the distribution of landslide events during the 2018-2020 period on maps of soil type, rock type, slope class, and land use.

Data and tools

The data used to determine the characteristics of landslide locations were the 2018-2020 landslide locations from the BNPB Report (2020), soil types resulting from analysis of soil type maps at a scale of 1:50000 (BBSDLP, 2019) using the USDA classification system, rock types resulting from geological map analysis at the scale of 1:50000, slope steepness class resulting from analysis of DEMNAS data (National Digital Elevation Model) with a spatial resolution of 5 x 11.25 m, land cover types resulting from visual interpretation of SPOT 6 and 7 imagery with a spatial resolution of 1.5 x 1.5 m and verified through field inspections, three years earthquake latest data from USGS (United States Geological Survey) and BMKG (Meteorology, Climatology, and Geophysics Agency of Indonesia), and daily rainfall data for the 2018-2020 period (BMKG, 2019).

Landslide characteristics analysis

The landslide characteristics analysis included the landslide depth, land use type, lithology period type, soil type, occurrence and magnitude of the earthquake, rainfall occurrence, and landslide slope steepness (Table 1).

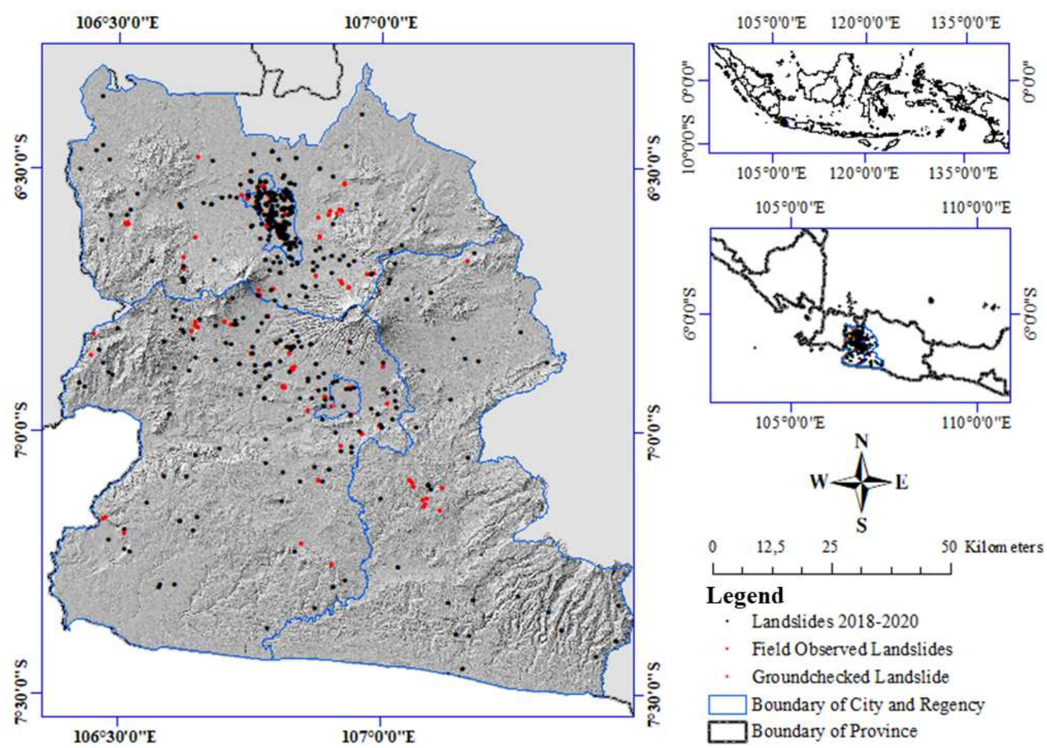


Figure 1. Research area.

Landslide depth was measured in the field and used to classify landslides into surface landslides and shallow landslides. The surface landslide was a landslide with a depth of <1.5 m, while the shallow landslide was a landslide with a depth of >1.5–10 m (Broms, 1975; Dou et al., 2015). Landslides with a depth of >10 m were classified as deep landslides. The measurement of landslide depth for one type of landslide is shown in Figure 2. Land-use types were analyzed from land use maps resulting from visual interpretation of SPOT 6 and 7 imagery validated in the field based on the land use type around the landslide location. In contrast, rock types and soil types were analyzed from the Soil Type Map, and Geological Map based on the landslide location due to landslide location coordinates in the field using GPS. The slope was measured using a clinometer and in some cases, using a roll-meter to measure the height and length of the landslide.

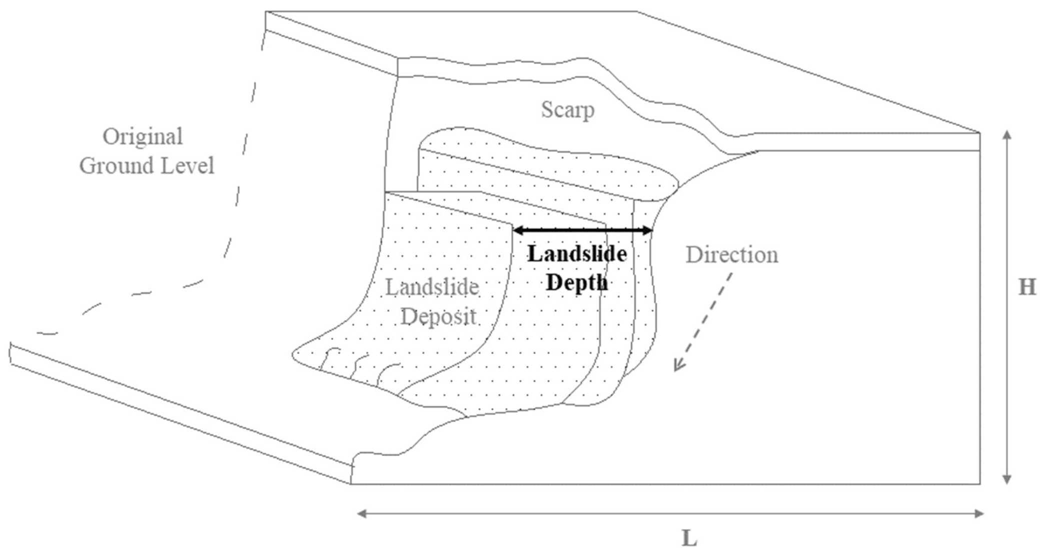


Figure 2. Measurement of landslide depth on the multiple rotational landslide type.

Analysis of factors affecting landslide

Factors affecting landslides were analyzed using two approaches, namely frequency analysis of landslide characteristics and binary-multivariate logistic regression. The frequency of landslide characteristics was analyzed based on the number of landslides with the six parameters' characteristics (Table 1). Meanwhile, binary-multivariate logistic regression is an analysis model to predict binary/dichotomous dependent variables based on a set of independent variables (Lee, 2004; Kalantar et al., 2017; Aditian et al., 2018). Binary dependent variables (Yj) used were surface landslides (Y=0) and shallow landslides (Y=1), and the independent variables (Xi) used were land cover, geological period, soil type, earthquake magnitude class, rainfall occurrence, and slope steepness. The types of data and the measurement scale of each independent variable (Xi) are presented in Table 1.

The multiple logistic regression models being tested are presented in equations (1) and (2) (Hosmer and Lemeshow, 2000).

$$Y = ln\left(\frac{P(x)}{1-P(x)}\right) = \beta_0 + \sum_{l=1}^{k_j-1} \beta_{jl}x_{jl} + \beta_i x \quad (1)$$

$$P = \frac{e^Y}{1+e^Y} = \frac{e^{\beta_0+\sum_{l=1}^{k_j-1}\beta_{jl}x_{jl}+\beta_i x_i}}{1+e^{\beta_0+\sum_{l=1}^{k_j-1}\beta_{jl}x_{jl}+\beta_i x_i}} \quad (2)$$

Y is the dependent variable, where Y=0 (surface landslide) and Y =1 (shallow landslide). P is the probability of shallow landslides, while 1-P is the probability of surface landslides. The notation β_0 is a constant, and β_{jl} is the coefficient of the categorical independent variable "j", class "l", and x_{jl} is the categorical independent variable "j", class "l", j = 1, 2, …, 5, where 1: land cover, 2: geological period, 3: soil type, 4: earthquake magnitude, 5: rainfall. l_1: (1) Forest, (2) Agriculture, (3) Settlement, (4) Road, l_2: (1) Quaternary, (2) Neogene and Paleogene, l_3: (1) Inceptisol, (2) Alfisol, (3) Andisol, (4) Ultisol, (5) Entisol, l_4: (1) Earthquake absence, (2) Medium magnitude, (3) High magnitude, and l_5: (1) Rainfall absence, (2) Rainfall presence. β_i is the coefficient of the numerical independent variable "I". The notation χ_i is the numerical independent variable "i", i = 6, 6: the slope steepness, while e is a constant of 2.718.

Multiple logistic regression modelling uses three approaches, namely modelling using all independent variables (enter), backward elimination (Wald) (backward stepwise selection), and forward selection (Wald) (stepwise selection).

Table 1. Type, measurement scale, and description of independent variables.

Data Type	Independent Variables	Description	Code/Value	Measurement Scale
Categorical	x_1	Land Cover	$x_{1.1}$ = Forest $x_{1.2}$ = Agriculture $x_{1.3}$ = Settlement*) $x_{1.4}$ = Road	Dummy variable
	x_2	Geological Period	$x_{2.1}$ Quaternary $x_{2.2}$ = Neogene and Paleogene*)	Dummy variable
	x_3	Soil Type	$x_{3.1}$ = Inceptisols*) $x_{3.2}$ = Alfisols $x_{3.3}$ = Andisols $x_{3.4}$ = Ultisols $x_{3.5}$ = Entisols	Dummy variable
	x_4	Earthquake Magnitude	$x_{4.1}$ = Earthquake Absence*) $x_{4.2}$ = Medium Magnitude $x_{4.3}$ = High Magnitude	Dummy variable
	x_5	Rainfall	$x_{5.1}$ = Rainfall Absence*) $x_{5.2}$ = Rainfall Presence	Dummy variable
Numerical	x_6	Slope	-	Ratio

Note: *) = Reference variable.

The entry approach is modelling by entering all independent variables in one step. The backward elimination (Wald) (backward stepwise selection) approach is a model formulation that starts with a model that contains all independent variables (Full Model), and then proceeds to eliminate the independent variables in stages based on the statistical probability value of the Wald test. Elimination of independent variables is continued until the remaining independent variables in the model are independent variables that significantly affect the dependent variable (Sig <0.05). Meanwhile, in the forward selection (Wald) (stepwise selection) approach, the modelling begins with a model that does not contain the independent variables (Null Model), and then adds the independent variables to the model gradually based on the most significant independent variables. If the independent variables have no significant effect, the independent variables are excluded from the model based on the Wald statistical probability. The addition of independent variables continues until all independent variables are included in the model until a suitable model is obtained with independent variables that significantly affect the dependent variable (Sig <0.05).

The modelling process using backward elimination and forward selection approach also selected independent variables using the confounding test. The confounding test is a test to determine changes in the odds ratio value by excluding independent variables that have a low significance value (Sig >0.05) to determine which independent variables need to be removed from the model (change in odds ratio value <10%) or independent variables are confounding (change in odds ratio value >10%). Wald test is a test to determine the level of significance of an independent variable on the dependent variable. The level of significance is shown based on the p-value (Sig). If the value of Sig <0.05, it is stated that the independent variable has a significant effect. In addition, the value of Exp (β) from the Wald test is the value of the odds ratio, namely the effect of the independent variable relative to the dependent variable for shallow landslides (Y=1). The confidence interval (CI) for Exp (β) is 95%. The positive value of CI 95% means the increase of the independent variable can enhance the probability of the dependent variable and vice versa. The lower and upper boundaries are the prediction value range for the CI 95% (Hosmer and Lemeshow, 2000). The goodness of fit test of the model was tested using omnibus, Hosmer and Lemeshow (2000), overall percentage, coefficient of determination (-2 Log Likelihood, Cox and S, nell R square, and Negelkerke R Square), and Wald's test. The selection of the best model was based on Hosmer and Lemeshow (2000) using the results of the goodness of fittest. The best model in logistic regression is the model with the most significant log-likelihood value or the results of the goodness of fittest. The best model selection considering the goodness of fit test results and simplicity and practicality in use is also based on professional judgment.

Results and Discussion

Landslide characteristics

The number of selected landslides from 415 landslides for the 2018-2020 period was 148 landslides. The characteristics of 148 landslides are presented in Figure 3, which shows six landslide characteristics that occur in more than two landslide events.

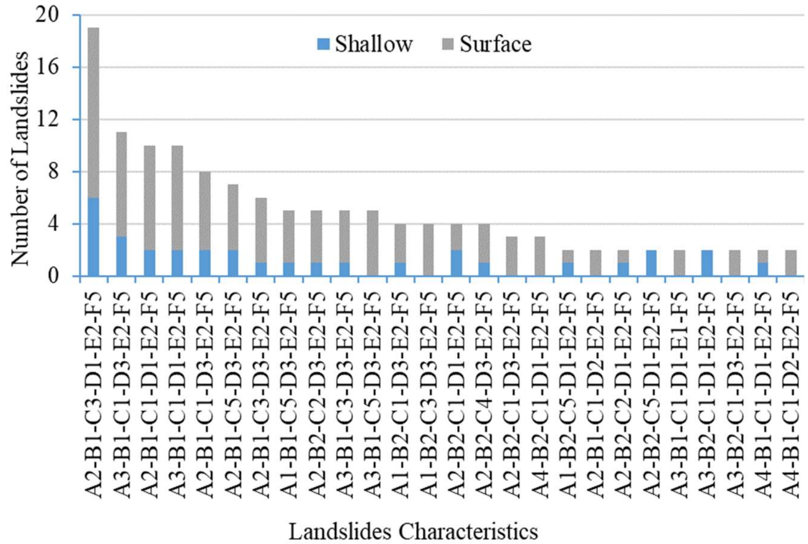


Figure 3. Characteristics of shallow-surface landslides ≥two events.

Notes:

A	:	Land Use/Cover; (A1) Disturbed Forest; (A2) Agriculture; (A3) Settlement; (A4) Road
B	:	Geological Period; (B1) Quaternary and (B2) Neogene and Paleogene
C	:	Soil Type; (C1) Inceptisols; (C2) Alfisols, (C3) Andisols, (C4) Ultisols, (C5) Entisols
D	:	Earthquake; (D1) Absent; (D2) Moderate magnitude; (D3) High magnitude
E	:	Rainfall; (E1) Absent; (E2) Present
F	:	Slope steepness class; (F1) <8%; (F2) 8–15%; (F3) 15–25%; (F4) 25–40%; (F5) >40%

The distribution of 6 parameters individually in 148 landslides, both surface and shallow landslides, is presented in Figure 4. Illustrations of shallow-surface landslides are presented in Figure 5. Based on the data in Figure 3, most (70%) of the landslides were surface landslides, and the others (30%) were shallow landslides, and landslides occurred in 43 combinations of six landslide characteristic parameters. However, most (19 out of 148 landslides) occurred in locations with slope characteristics >40% (F5), agricultural land use (A2), Quaternary geological period (B1), Andisols soil type (C3), absence earthquake (D1), and when rain occurred (E2). Of 19 landslides, 13 were surface landslides, and 6 were shallow landslides.

Figures 3 and 4 show that landslides, both surface and shallow landslides, all occurred on land use that was affected by human activities in various forms, namely disturbed forest (A1), agriculture (A2) and settlement (A3) land, and road construction (A4), as well as where rain occurred (E2), and mainly occurs on land with a slope >45% (F5), Quaternary geological period (B1), and Inceptisols soil type (C1). Landslides also occurred with no earthquake (D1) and an earthquake with a high magnitude (D3). Landslides in Bogor, Cianjur, and Sukabumi generally (50%) occur when a high magnitude earthquake occurs, but many (46%) occur when there is no earthquake (Figure 4). However, when viewed from the interaction of parameters of landslide characteristics, landslides mainly occur when there is no earthquake (Figure 3). Statistically, high magnitude earthquakes significantly affect shallow landslides, and the effect is 3.3 times greater than earthquake absence. A high magnitude earthquake is very logical to have a significant effect on both shallow and surface landslides. According to Ojala et al. (2017), the greater the magnitude of the earthquake, the greater the opportunity to reduce the shear strength of the soil so that it triggers deeper landslides (shallow landslides). The surface recovery of post-seismic landslides probably affecter the active landslides trend and debris flow (Chen et al., 2021). Earthquake vibrations affect slope stability. However, that does not mean that without an earthquake, there will be no landslides because landslides can occur due to the character of the land that is vulnerable to landslides and can be triggered by other factors, namely rainfall and human activities that reduce slope stability. Rain is the main trigger factor for landslides in the study area. 95% of the occurrences of shallow-surface landslides in the field occur with rainfall presence. The dominant types of slope movements are surface and shallow landslides that mostly endanger settlements, roads, structures, and cutting slopes (Figure 4 and Figure 5). Moreover, the land use system will be triggered by the precipitation and changes in groundwater levels (Arbanas et al., 2016).

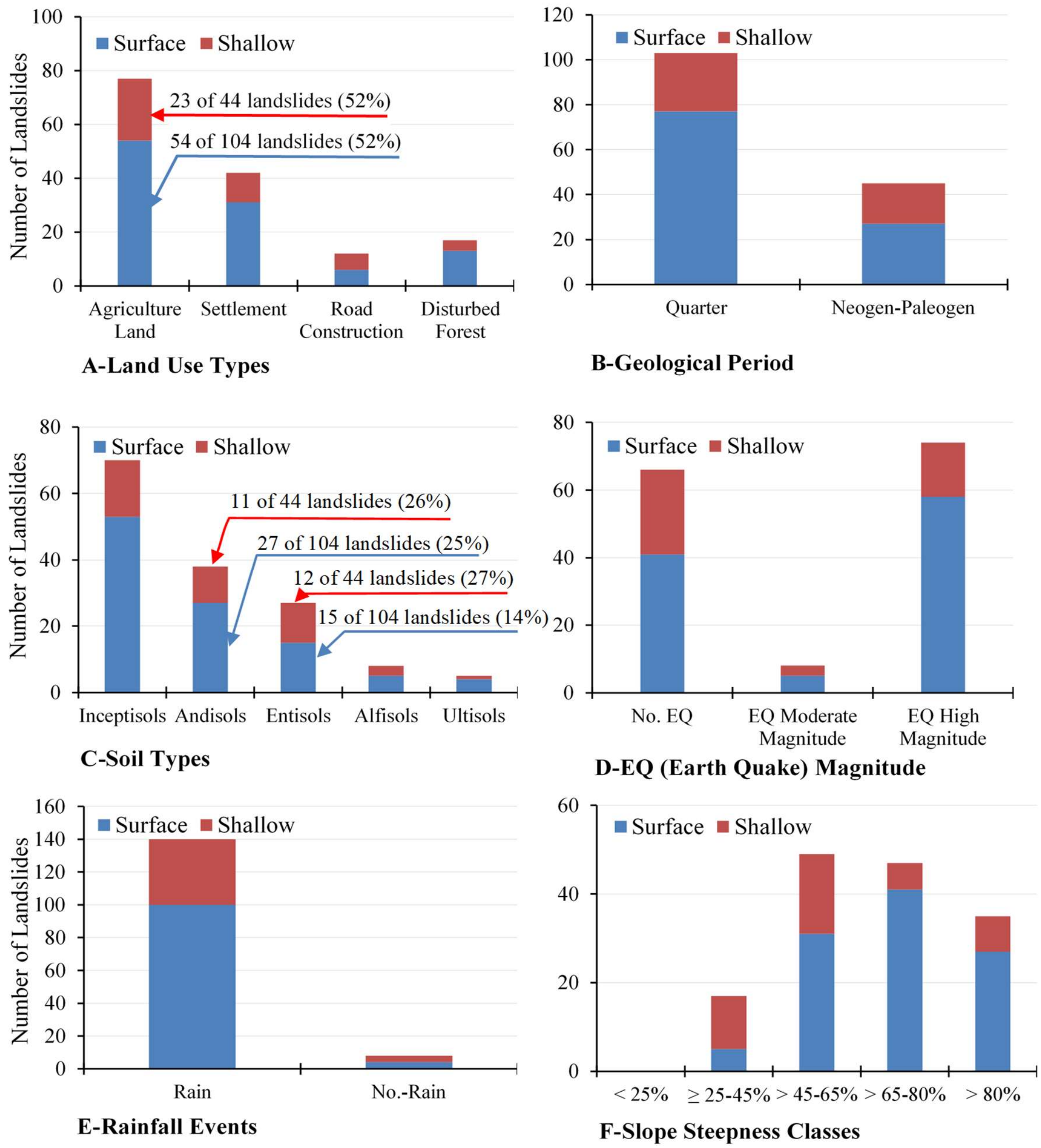
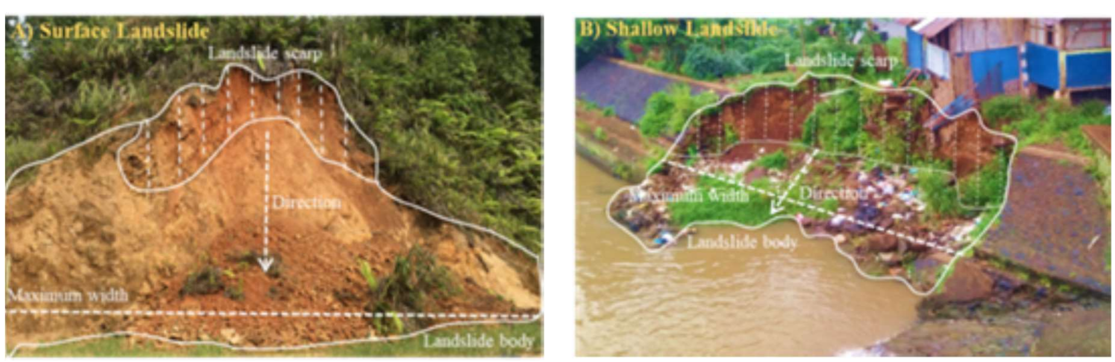


Figure 4. Distribution of 6 parameters (A–F) individually in 148 landslides.



(a) Surface landslide **(b) Shallow landslide**

Figure 5. Surface landslide (a) and shallow landslide (b) in the study area.

Shallow landslides are due to human activities that increase soil moisture near the surface, such as construction, poor and insufficient sewage systems, and the obstruction of springs, which together result in a decrease in shear strength of slope materials at shallow depths (Tebbens, 2019). Surface landslides dominate the groundwater basin, while shallow landslides dominate the non-groundwater basin (Fata et al., 2022).

Dominant factors causing shallow-surface landslide

The results of binary-multivariate logistic regression analysis using data from field investigations of 148 landslides resulted in a model of the relationship between shallow-surface landslides (Y0,1) with the factors affecting landslides as presented in equations (3)-(4), (3)-(5), and (3)-(6). Equation (3)-(4) is the model generated from the analysis using the enter approach (Model-1), and Equation (3)-(5) is the model resulting from the analysis using the backward elimination (Wald) approach (Model -2), while equation (3)-(6) is the model of the analysis using the forward selection (Wald) approach (Model-3).The constants and coefficients of the independent variables in equations (4), (5), and (6), and the results of the test of the effect of the independent variables on the dependent variable, namely Wald, Sig, and Exp (β) for each model are presented in Tables 3, 4, and 5.

$$P = \frac{e^Y}{1+e^Y} \tag{3}$$

$$\begin{aligned} \mathrm{Y} = {} & \beta_0 + \beta_{1.1}x_{1.1} + \beta_{1.2}x_{1.2} + \beta_{1.4}x_{1.4} + \beta_{2.1}x_{2.1} + \beta_{3.2}x_{3.2} + \beta_{3.3}x_{3.3} + \beta_{3.4}x_{3.4} \\ & + \beta_{3.5}x_{3.5} + \beta_{4.2}x_{4.2} + \beta_{4.3}x_{4.3} + \beta_{5.2}x_{5.2} + \beta_6 x_6 \end{aligned} \tag{4}$$

$$\mathrm{Y} = \beta_0 + \beta_{2.1}x_{2.1} + \beta_{3.5}x_{3.5} + \beta_{4.3}x_{4.3} + \beta_6 x_6 \tag{5}$$

$$\mathrm{Y} = \beta_0 + \beta_{2.1}x_{2.1} + \beta_{3.5}x_{3.5} + \beta_{4.3}x_{4.3} + \beta_6 x_6 \tag{6}$$

Results of recapitulation of the goodness of fit test using the model accuracy test, model suitability test (Hosmer and Lemeshow), simultaneous test (Omnibus test), and coefficient of determination test (R^2 and log-likelihood) are presented in (Table 5).

The number of selected landslides from 415 landslides for the 2018-2020 period was 148 landslides. The characteristics of 148 landslides are presented in Figure 3, which shows six landslide characteristics that occur in more than two landslide events. The distribution of 6 parameters individually in 148 landslides, both surface and shallow landslides, is presented in Figure 4. Illustrations of shallow-surface landslides are presented in Figure 5.

Table 2. Regression coefficient value, odd ratio, Wald value, and p-value (α) (Sig) of the entry approach.

Independent Variables	Symbol	β	S.E	Wald	df	Sig	Exp(β)	95% CI for	
								Lower	Upper
Forest	$x_{1.1}$	1.299	0.877	2.195	1	0.138	3.665	0.657	20.432
Agriculture	$x_{1.2}$	0.244	0.515	0.224	1	0.636	1.276	0.465	3.505
Settlement*)	$x_{1.3}$								
Road	$x_{1.4}$	-0.195	0.854	0.052	1	0.819	0.823	0.154	4.390
Quaternary	$x_{2.1}$	1.232	0.544	5.132	1	0.023	3.429	1.181	9.956
Neogene and Paleogene*)	$x_{2.2}$								
Inceptisol*)	$x_{3.1}$								
Alfisols	$x_{3.2}$	0.199	0.998	0.040	1	0.842	1.220	0.173	8.629
Andisols	$x_{3.3}$	-0.299	0.564	0.282	1	0.595	0.741	0.246	2.237
Ultisols	$x_{3.4}$	0.242	1.345	0.032	1	0.857	1.274	0.091	17.790
Entisols	$x_{3.5}$	-1.530	0.615	6.196	1	0.013	0.216	0.065	0.722
Earthquake Absence*)	$x_{4.1}$								
Medium Earthquake Magnitude	$x_{4.2}$	-0.606	0.952	0.406	1	0.524	0.546	0.084	3.522
High Earthquake Magnitude	$x_{4.3}$	0.916	0.479	3.659	1	0.056	2.500	0.978	6.391
Rainfall Absence*)	$x_{5.1}$								
Rainfall Presence	$x_{5.2}$	0.959	0.929	1.065	1	0.302	2.609	0.422	16.119
Slope	x_6	-0.057	0.015	15.276	1	0.000	0.944	0.917	0.972
Constant		3.717	2.693	1.905	1	0.168	41.126		

Note: *) = Reference variable.

Table 3. Regression coefficient value, odd ratio, Wald value, and p-value (α) (Sig) of backward elimination (Wald) (backward stepwise selection) approach.

Independent Variables	Symbol	β	S.E	Wald	df	Sig	Exp(β)	95% CI for	
								Lower	Upper
Quaternary	$x_{2.1}$	0.938	0.440	4.554	1	0.033	2.555	1.080	6.049
Entisol	$x_{3.5}$	-1.211	0.542	4.992	1	0.025	0.298	0.103	0.862
High Earthquake Magnitude	$x_{4.3}$	1.205	0.437	7.621	1	0.006	3.338	1.418	7.853
Slope	x_6	-0.055	0.014	16.190	1	0.000	0.946	0.921	0.972
Constant		2.818	0.997	7.911	1	0.005	16.751		

Table 4. Regression coefficient value, odd ratio, Wald value, and p-value (α) (Sig) of forward selection (Wald) (stepwise selection) approach.

Independent Variables	Symbol	β	S.E	Wald	df	Sig	Exp(β)	95% CI for	
								Lower	Upper
Quaternary	$x_{2.1}$	0.938	0.440	4.554	1	0.033	2.555	1.080	6.049
Entisol	$x_{3.5}$	-1.211	0.542	4.992	1	0.025	0.298	0.103	0.862
High Earthquake Magnitude	$x_{4.3}$	1.205	0.437	7.621	1	0.006	3.338	1.418	7.853
Slope	x_6	-0.055	0.014	16.190	1	0.000	0.946	0.921	0.972
Constant		2.818	0.997	7.911	1	0.005	16.751		

Table 5. The results of the model accuracy-test value, model suitability test, simultaneous test, and coefficient of determination test.

Description	Approach		Explanation
	Enter	Backward elimination and Forward selection (Wald)	
Model accuracy test	77%	77.7%	The model uses an enter, backward elimination, and forward selection approach and accurately predicts 77% of shallow-surface landslides.
Goodness of fit (Hosmer and Lemeshow)	0.135 > 0.05	0.097 > 0.05	Enter, backward elimination and forward selection models are acceptable.
Simultaneous Test (Omnibus test)	0 < 0.05	0 < 0.05	The addition of independent variables can significantly affect the model (model fit).
R-square (Nagelkerke)	0.322	0.283	Based on the coefficient of determination (R-square) test, the ability of the independent variable to explain the dependent variable (shallow landslide) is <35% or the level of suitability between the independent variable and the dependent variable is low.
R-square (Cox and Snell)	0.227	0.199	
-2 log likelihood	142.106 < 177.39	147.214 < 177.39	The model of the relationship between the independent variables in explaining the dependent variable (shallow landslides) is suitable (fit) with the data being used.

Based on the model accuracy, the Goodness of Fit (Hosmer and Lemeshow) and Omnibus test results (Table 5), it is indicated that the three models (equations 3-4, 3-5, and 3-6) are suitable models to be used to explain the relationship between independent and dependent variables. However, from the relationship between independent and dependent variables based on parameters that explain the strength of the relationship between independent and dependent variables (R^2-Nagelkerke, R^2-Cox and Snell, and -2 log-likelihood) (Table 5), it is indicated that the relationship between the independent and weak dependent variable, is low.

The best models based on the log-likelihood value are the Backward elimination and Forward selection-Wald models. However, in terms of the coefficient of determination (R^2), Model-1, as the result of the entering approach, shows a higher R^2 value than that of the elimination-selection approach (Models 2 and 3). In this case, Hosmer and Lemeshow (2000) do not recommend using the R^2 value in choosing the best logistic regression model because R^2 is affected by the number of independent variables used. Model-2 and Model-3 both have the same simplicity as the model. However, the forward selection approach (Model-3) is better than the backward elimination approach (Hosmer and Lemeshow, 2000). Hence, the model resulting from the forward selection approach (Model-3, Table 4) is chosen to explain the factors that affect the surface-shallow landslide.

Based on Model-3 (equations 3 and 6, Table 4), the factors that significantly affected shallow landslides are Quaternary geological period, Entisol soil type, high earthquake magnitude, and slope with Sig <0.05. The effect of the Quaternary geological period was 2.6 times greater than those of the Neogene and Paleogene geological periods (reference variables). The effect of Entisol soil type on shallow landslides was very small (Exp $(\beta)_{Entisol}$ <1) relative to Inceptisol soil type. The high earthquake magnitude is more influential than earthquake absence; the effect on shallow landslides was three times greater than earthquake absence. The slope steepness in Model-3 is a numerical independent variable (not categorical). The value of the slope steepness shows that with each increase in the slope steepness, the probability of affecting shallow landslides increases by 109%.

The results of the logistic regression analysis showed that the land use factors categorized into the disturbed forest (A1), agriculture (A2), settlement (A3), and road (A4) did not significantly affect shallow landslides. The result is possible because the number of landslide samples observed was not balanced between the number of surfaces and shallow landslides. Statistically, it had no significant effect. However, based on landslide characteristics and the frequency analysis in the 148 landslides analyzed (Figures 3 and 4), it can be shown that the agricultural land use category (A2), both together with other parameters (Figure 3), or individually (Figure 4), is a dominant factor in every landslide event, both surface and shallow landslides, namely 52% vs 52% (percentage relative to the number of each type of landslide).

The land-use categories at the landslide location are entirely in the category of human activities induced lands, namely land that has changed due to human activities. The agriculture category includes land use in rice fields, dryland farms, mixed plantations, plantations, and bush, which have changed due to slope cutting, making trails, drainage channels, and terraces for agricultural and plantation activities. In addition to changing the initial slope steepness, these activities also change the soil characteristic, decreasing slope stability. The category of the disturbed forest is natural and plantation forest that is used as an ecotourism location where there are footpaths and the main access road at the top of the slope that changes the initial form of the slopes and soil properties, especially in the crest of the access road location, as well as on the new toe of the slope resulting from the path construction, as well as drainage from the access road which is concentrated at specific points.

The Quaternary geological period was found in 103 landslides (70%), 77 landslides were surface, and 26 shallow landslides (Figure 4). Statistically, the logistic regression analysis results showed that Quaternary rocks had a significant effect on shallow landslides. The effect is 2.6 times greater than that of Neogen-Paleogene rocks. The Quaternary geological period is the youngest geological period composed of gravel, clay, sand, sandy loam, and alluvial materials (Göktürkler et al., 2008). Young geological rocks are still unstable because hard rocks have not yet formed, so the potential for landslides is highest. However, the old geological period can also have potential shallow landslides due to weathering, cracks, or rock fractures (Hardiyatmo, 2012).

Inceptisols soil type was found in 70 landslides (49%), 55 of which were surface landslides. Inceptisols were much more common than Andisols (38 landslides) and Entisols (27 landslides). However, statistically, Entisol soil type significantly affected shallow landslides, while Andisol soil type had no significant effect. It is probably due to the larger proportion of Entisol soil types in shallow landslides than that of Andisol soil types (Figure 4C). The value of Exp $(\beta)_{Entisols}$ <1 indicates that Entisol soil type's effect on shallow landslides is smaller than that of Inceptisols soil type. Inceptisols and Entisols are soils with lithic contact at 40–50 cm depth from the soil surface and are quickly saturated by water. Inceptisols are saturated with water at a depth of 100 cm for most of the year, while Entisols are highly water-saturated at more than 25 cm from the soil surface for more than 21 hours per day (BBSDLP, 2016). Saturated soils experience increased pore water pressure faster than unsaturated soils (Bordoni et al., 2016).

Meanwhile, Andisols soil types are mineral soils with organic matter content exceeding the organic carbon limit (BBSDLP 2016). Andisol soil has a loose surface layer with a thickness of ±1 m, is porous, has a low density, and has an aggregation structure that is relatively weak (Arabia et al., 2015). The stability of the Andisols soil aggregates is good, and the permeability is high, so this soil is relatively resistant to erosion by water, except for the types of Andisols that experience intensive hydration and intensive drying. Even though the Andisol soil type has relatively better properties against landslides as compared to the Entisol soil type, if it interacts with other parameters that are vulnerable to landslides (steep-very steep slopes, human activities that reduce land stability, high-intensity rainfall), it was potential to exhibit landslides as shown by the data in Figure 3. The slope steepness significantly affects the probability of shallow landslides (Table 4). Based on the value of Exp(β), the higher the slope, the higher the probability of shallow landslides, 0.946. The frequency analysis results showed that all shallow landslides occurred at slopes >45% (Figures 3 and 4). The slope of the surface landslide was steeper because artificial slopes dominated it. The slope level affects the type and size of the landslide (Reichenbach et al., 2018).

Based on the characteristics of 148 landslides in the Bogor, Sukabumi, and Cianjur areas, as well as the results of logistic regression analysis, it can be demonstrated that landslide occurrence, both surface and shallow landslides, are the result of complex parameter interactions, both between physical land parameters (slope steepness, geological period type, soil type) and triggering parameters (land use, rainfall, earthquake), making it difficult to determine the dominant factors.

However, based on the parameter characteristic, logistic regression analysis, and the landslide frequency, the parameters that have a relatively dominant role in landslide occurrence especially shallow landslides, are the land physical characteristics that are vulnerable to landslides, namely steep-very steep slopes, young geological rocks (Quaternary), Entisols and Inceptisols soil type, and the triggering parameters such as high magnitude earthquake, rainfall, and human activities in land use.

Conclusion

The characteristics of landslides in the Bogor, Sukabumi, and Cianjur areas vary. There are at least 43 landslide characteristics. The most dominant character of landslides (surface and shallow landslides) is characterized by slopes >45%, Quaternary geological period, Andisol soil type, land use in the form of agriculture, the occurrence of rain, and absence of triggering an earthquake. Although there is no earthquake in an area, landslides occur when the physical properties of the land are vulnerable to landslides (slopes are steep-very steep, and the rock is young). Some factors that act as a trigger are rainfall occurrence and human activities that change the slope steepness and soil properties that reduce the stability of the land.

The dominant factors influencing surface and shallow landslides are human activities in land use that change the initial shape of the slope steepness, soil properties, steep-very steep slopes, Inceptisol and Entisol soil types, and young rocks (Quaternary geological period), rainfall events, and high earthquake magnitude.

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