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RESEARCH ARTICLE

Landslide Susceptibility Mapping Using Logistic Regression Methods in Bogor Regency

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Abstract

Landslides are a recurrent hazard in Bogor Regency, where steep volcanic terrain, high rainfall, varied lithology, land-use changes and active faults contribute to slope instability. This study presents the first regency-wide landslide susceptibility model using Logistic Regression supported by field validation. A dataset of 220 landslide occurrences from 2017 to 2022 and multiple geospatial factors including rainfall, slope, lithology, landcover, and NDVI was analyzed using a 70:30 train–test split to generate coefficient weights, probability surfaces and a binary susceptibility map derived from ROC-AUC thresholds. Landcover shows the strongest positive influence on landslide occurrence, whereas NDVI has the strongest negative effect, reflecting the stabilizing role of vegetation. Fault proximity exhibits near-zero influence, likely due to inactive structures or limited spatial resolution. The model achieved 82 percent accuracy with an AUC of 0.86. Susceptibility clustering near historical data suggests possible inventory bias. Improving model reliability will require more evenly distributed landslide data and UAV-based mapping to detect vegetation-covered past landslides.

Keywords: Landslide Susceptibility, Logistic Regression, Bogor Regency

1. Introduction

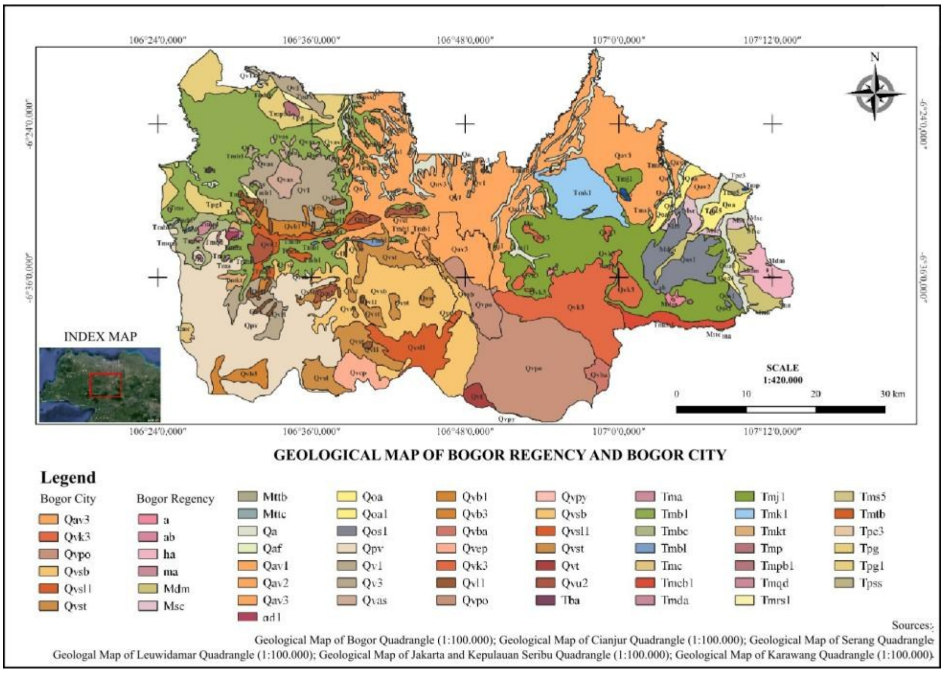
Landslides are a frequent disaster in Bogor Regency, with 176 landslide events recorded between January and October 2022 (Bogor Recency DMA, 2023). This phenomenon caused damage in infrastructures, logistic supply chains, and casualties. Multiple factors contribute to the high landslide risk in Bogor, including steep hilly topography, high rainfall, soil type, land use changes, and geological conditions with active faults that weaken soil structure (Highland & Bobrowsky, 2008; Sassa et al., 2009).

Identification of landslide prone area in Bogor Regency becomes an important issue in mitigating future occurrence. Several methods has been utilised in modeling landslide prone area around the world, such as analytic hierarchy process (AHP; e.g., Myronidis et al., 2016; Pourghasemi et al., 2012; Saaty, 2008), weight of evidence (WoE; e.g., Batar & Watanabe, 2021; Mandal et al., 2023; Regmi et al., 2010), and logistic regression (Budimir et al., 2015; Lee, 2005; Yilmaz, 2009). AHP has limitations that it relies in assigning weighting factors for each parameter (Feizizadeh & Blaschke, 2013; Yalcin, 2008) and it does not consider past occurrences in the calculation (Akgun, 2012; Kavzoglu et al., 2014). Meanwhile, WoE has considered past occurrence but only consider relation between a pair of parameters (Regmi et al., 2010; Süzen & Doyuran, 2004). On the other hand, logistic regression provides multi-variable analysis which may better reflect the landslide phenomenon (Süzen & Doyuran, 2004). In this paper, the first result of regency-wide landslide prone area model produced from logistic regression analysis combined with fieldwork validation is presented to provide more information in mitigating future occurrence of landslide in the Bogor Regency area.

2. Geological Setting

According to Poedjoprajinto (2011), Bogor Regency has diverse geomorphological conditions. Generally, the region exhibits volcanic landforms that extend from the west to the east of the study area. In addition to volcanic landforms, the region includes various landscape origins such as denudational, fluvial volcanic, structural, denuded volcanic, and dissolution landscapes. The geomorphology of this area is dominated by steep slopes that significantly impact slope stability, thereby increasing landslide potential. This topographic condition makes the region susceptible to erosion and mass movement, especially during the rainy season, aligning with the physical characteristics of the area that indicate slope failure as a primary trigger for landslides in Bogor Regency (Highland & Bobrowsky, 2008).

The lithology in Bogor Regency comprises diverse volcanic and sedimentary rocks, including marl, sandstone, claystone, and limestone, originating from several geological units (**Figure 1**), such as the Bojongmanik, Klapanunggal, Jatiluhur, Cimapag, Rengganis, Parigi, Subang, Cihoe, Serpong, and Genteng Formations. According to Pulunggono and Martodjojo (1994 in Bachri, 2014), structural patterns in Bogor Regency are generally classified into three main orientations: the Meratus Pattern trending northeast-southwest (NE-SW), the Sunda Pattern trending north-south (N-S), and the Java Pattern trending west-east (W-E).



Sources:
Geological Map of Bogor Quadrangle (1:100.000); Geological Map of Cianjur Quadrangle (1:100.000); Geological Map of Serang Quadrangle
Geologal Map of Leuwidamar Quadrangle (1:100.000); Geological Map of Jakarta and Kepulauan Seribu Quadrangle (1:100.000); Geological Map of Karawang Quadrangle (1:100.000).

Fig 1. Geological map of Bogor Regency redigitised from several quadrangles (Achdan & Sudana, 1992; Effendi et al., 1998; Rusmana et al., 1991; Sudjatmiko, 1972, 1992; Turkandi et al., 1992).

Table 1. Specification of data used in this research.

Name	Format	Source	Coordinate System	Data Specification
Landslide Location	Excel	Obtained from Regional Disaster Management Agency of Bogor Regency	Longitude/Latitude	Coordinate Points
Digital Elevation Model (DEM)	Raster	https://tanahair.indonesia.go.id/demnas/#/	Longitude/Latitude	8x8m Resolution
Landcover	Vector ESRI: Shapefile	https://www.indonesia-geospasial.com/	Longitude/Latitude	1:50.000
Landsat Image 8	GeoTIFF	https://earthexplorer.usgs.gov/	UTM Zone 48S	30m Resolution
Rainfall Intensity	Raster	https://data.chc.ucsb.edu/products/CHIRPS-2.0/indonesia_monthly/bils/	Unknown; processed to lon-lat at WGS84	0.05 Resolution
NDVI (Normalize Difference Vegetation Index)	GeoTIFF	Processing of Landsat 8 Imagery Data	UTM Zone 48S	1:25.000
Indonesian landform map (RBI)	Vector ESRI: Shapefile	https://www.indonesia-geospasial.com/2020/01/shp-rbi-provinsi-jawa-barat-perwilayah.html	Longitude / Latitude	1:25.000
Geologic Map of Bogor Regency Sheet	Raster	https://geologi.esdm.go.id/geomap/	Longitude / Latitude	1:100.000
Lithology	Vector ESRI: Shapefile	https://www.indonesia-geospasial.com/2020/03/download-data-shapefile-shp-geologi-se.html	Longitude / Latitude	1:25.000
Fault	Vector ESRI: Shapefile	https://geologi.esdm.go.id/geomap/	Longitude / Latitude	1:100.000
Proximity to Road	Vector ESRI: Shapefile	https://tanahair.indonesia.go.id/portal-web/	Longitude / Latitude	1:25.000
Proximity to River	Vector ESRI: Shapefile	https://tanahair.indonesia.go.id/portal-web/	Longitude / Latitude	1:25.000

Moreover, the geological structure of this region is characterized by the presence of active faults, such as the Cimandiri, Citarik, and Baribis Faults, which play a significant role in affecting slope stability. These faults reduce the resilience of slopes against gravitational forces, thereby increasing landslide risk, particularly in areas with lithologies prone to weathering and degradation (Keefer, 1984).

3. Data

The data used in this paper were divided into two categories: 220 past landslide occurrence data (2017-2022) and geospatial condition data of Bogor Regency (**Table 1**). The second category of data included rainfall, topography, geology, and vegetation cover. To connect the model with real geospatial condition of the area, field work data

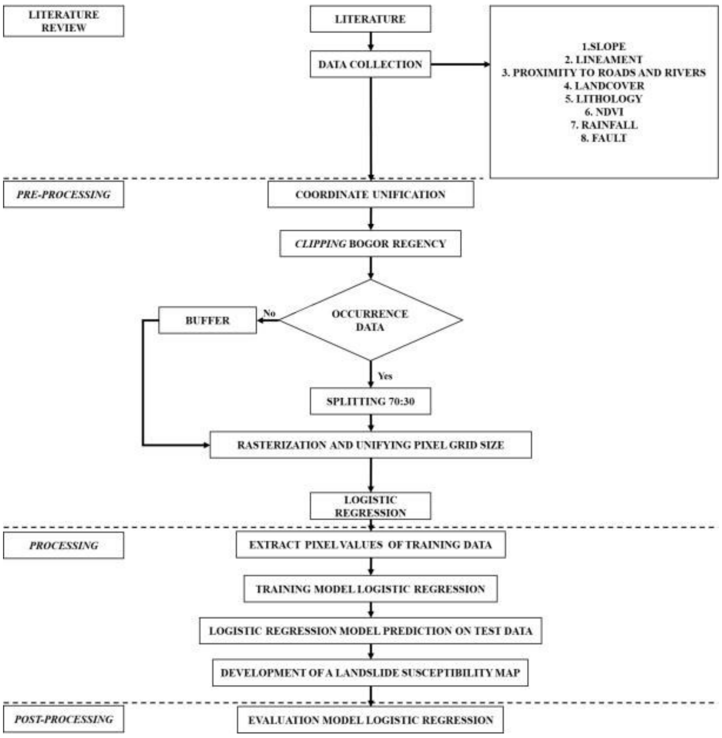


Fig 2. Research workflow of logistic regression modeling

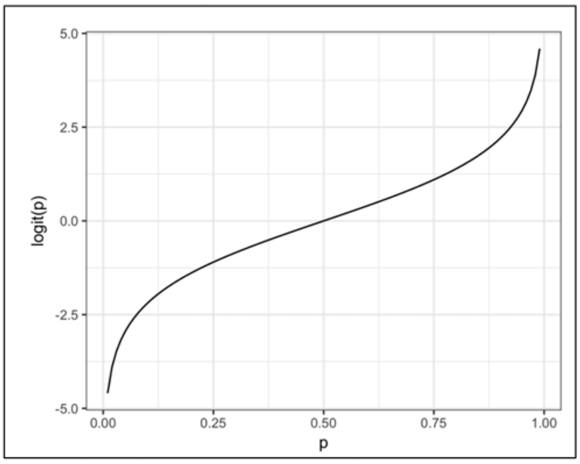


Fig 3. S-curve logit function (Bruce et al., 2020)

including location, topography, land cover, surface geology, and landslide information were collected in May 2023.

4. Method

The logistic regression employed in this study follows procedure as can be seen in **Figure 2**. The initial step involved extracting pixel values from each variable associated with landslide occurrences, followed by separating the data into two parts: Y and X. Here, Y represents the target or dependent variable, while X serves as the predictor or independent data. Then, data splitting of 30%:70% was conducted. The first 30% of the total dataset is isolated as test data, while the remaining 70% is used as training data to train the model. This proportion was shown to produce good predictive model by previous authors (Felicísimo et al., 2013; Hong et al., 2018; Tien Bui et al., 2012). The trained logistic regression model is then applied to the test data to predict landslide occurrences within the study area. The process of creating a landslide susceptibility map involves several stages, including calculating variable coefficients, Z values, probabilities, and classifying areas into two categories: landslide and non-landslide.

According to Bruce et al. (2020), in logistic regression, the dependent variable has only two possible outcomes, corresponding to the logistic response function and the logit function, both within a 0 to 1 scale, such as present/absent, success/failure, or occurrence/non-occurrence. Dai and Lee (2002) explain that logistic regression predictions yield a probability scale between 0 and 1. When sufficient predictor variables are included in logistic regression, the predicted probability of the dependent variable will follow an S-shaped curve **Figure 3**.

The calculation of Z-values and event probabilities follows the formulation by Dai and Lee (2002). The probability of an event occurring, here referring to a landslides, is expressed using the logistic function:

$$\Pr(\text{Event}) = \frac{1}{1+e^{-Z}} \quad (1)$$

where Pr(Event) represents the probability of an event occurring, in this case, a landslide. Since Z ranges from $-\infty$ to $+\infty$, the resulting probability will span from 0 to 1, adhering to an S-shaped curve Dai and Lee (2002). The Z-value is computed as a linear combination of multiple independent variables and is expressed as:

$$Z = B_0 + B_1X_1 + B_2X_2 + \cdots + B_nX_n \quad (2)$$

where B_i $(i = 0, 1, \dots, n)$ are coefficients derived from the sample data, n is the number of independent variables, and X_i $(i = 1, 2, \dots, n)$ are the independent variables corresponding to landslide-related physical parameters Dai and Lee (2002). The predictive results are subsequently transformed into a susceptibility map, identifying areas according to their landslide vulnerability levels. Model validation is conducted using evaluation metrics such as the confusion matrix, precision, recall, F1-score, and accuracy, providing a comprehensive assessment of the logistic regression model's effectiveness in identifying landslide-prone regions.

In addition to mathematical-based validation, field observation was also conducted. The observation was carried to observe real condition that might not be cover by the input data due to spatial resolution, temporal resolution, or specific physical mechanism.

5. Result

Based on the LR calculation, variable with the highest positive value is landcover (1.152950) while the most negative is NDVI (-8.583039) (**Table 2**). Positive value of landcover variable imply that this variable contributes positively on landslide occurrence in the area (Lee, 2005; Lee & Sambath, 2006). In contrast, the highly negative value of NDVI means that high value of NDVI causes lower occurrence of landslide in the area. The value really close to zero such as fault (-0.000035) shows that it practically not contribute to the landslide occurrence in the area.

By using the coefficient, landslide susceptibility map was calculated. The result map was then classified into two classes: 0 (non-landslide) and 1 (landslide) based on threshold obtained from ROC AUC curve graph (**Figure 4** and **Figure 5**) and the confusion matrix (**Table 3**).In terms of precision, recall, and F1-score for the 0 classification (non-landslide occurrence), the model achieved a value of 0.67, indicating that approximately 67% of predictions classified as non-landslide were accurate. For the 1 classification (landslide occurrence), precision, recall, and F1-score values reached 0.88, reflecting the model's high accuracy in identifying landslide-prone areas. Additionally, the logistic regression landslide susceptibility validation map achieved an accuracy of 82%. Furthermore, the ROC AUC calculation, shown in **Figure 6**, yielded a value of 0.86. With an AUC of 0.86, the model demonstrates a strong ability to distinguish between landslide-prone areas and non-landslide areas.

Table 2. Coefficients of variables supporting landslides occurrence.

No.	Variable	Coefficient
1	Slope	0.006995
2	Lineament	-0.011155
3	Proximity to roads	0.002613
4	Proximity to rivers	0.014117
5	Landcover	1.152950
6	Lithology	0.229499
7	NDVI	-8.583039
8	Rainfall intensity	0.011194
9	Fault	-0.000035

Table 3. Model performance.

Prediction	Precision	Recall	F1-score
0 (non-landslides)	0.67	0.67	0.67
1 (landslides)	0.88	0.88	0.88

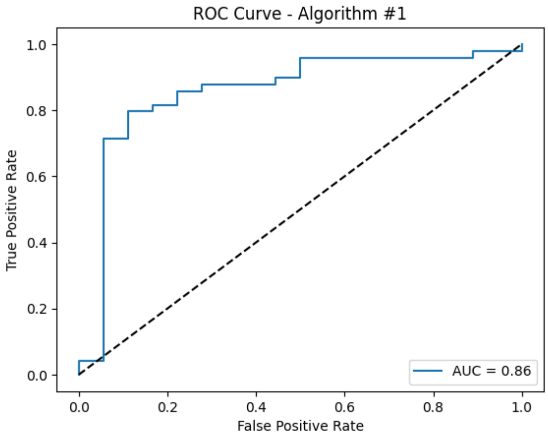


Fig 4. ROC AUC graphs of the model

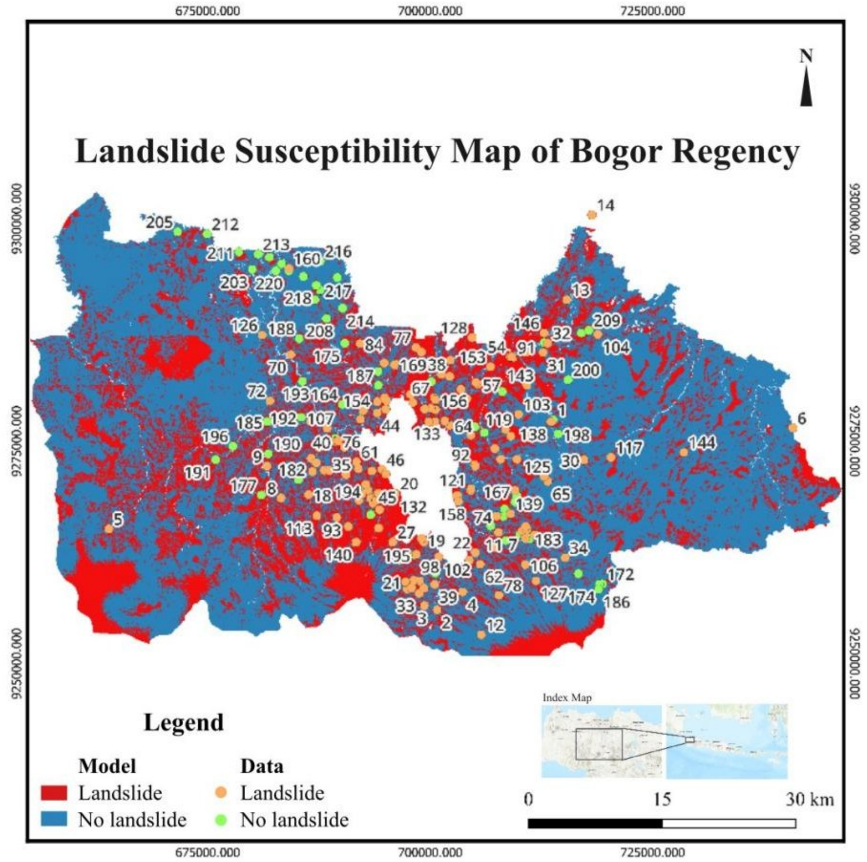


Fig 5. Landslide susceptibility map produced from logistic regression with validation data.

Fig 6. Condition of observation sites; (a) landslide-predicted area with landslide occurrence; (b) landslide-predicted area with no landslide; (c) non-landslide-predicted area with no landslide.

Field observation in several areas with predicted value of 1 shows location with already occurred landslide and location with no sign of landslide inducing properties (**Figure 6**). Observation on the area with predicted value of 0 shows no sign of landslide.

6. Discussion

From the coefficient calculation. It can be seen that the two most opposing contributors to landslide occurrence in the area are landcover (positive) and NDVI (negative). The change of landcover type in a particular area, especially into more open types such as farmland or housing, has been reported to correlate positively with landslide occurrence (Pacheco Quevedo et al., 2023; Reichenbach et al., 2018). In case of the study area, most reported landslide occurred in landcover of housing and farmland. Meanwhile, NDVI shows very negative. The negative value of NDVI might arise because vegetation may reduce soil erodibility and maintain overall soil strength (Schwarz et al., 2010; Stokes et al., 2009). However, slope only shows low positive coefficient (0.006995) which is fairly unusual in previously reported case (Lee, 2005). For near-zero coefficient of fault, it may be caused by inactivity of the fault as input data. The other possibility is that spatial resolution of input fault data may not account for smaller faults that might contribute to the landslide.

From the susceptibility map, it can be seen that areas with predicted landslides (red at **Figure 5**) are mostly located at the center and west part of Bogor Regency. This distribution is in line with the coefficient resulted from the calculation. However, upon field observation, some areas that were predicted to have high susceptibility showed no local characteristics that may induce landslide (**Figure 6**). It might be caused by land modification after input data creation, implying currently safer than prediction. For the areas with non-landslides, they may still have risk of other type of ground movement, such as creeping that might not be able to be modeled in the same way as landslide (Huang et al., 2023; Hungr et al., 2014).

It also needs to be noted that concentration of the susceptible area lies near the historical data. To the east, most of the areas are not susceptible even though they lie on mountainous terrain which counter intuitive. It might be caused by reporting bias that the historical landslide occurrence only covers events relatively near to area with human habitation. This shifted the model towards area with more data (Stanley & Kirschbaum, 2017; Steger et al., 2017). Even though relatively high calculated accuracy and precision, re-modeling using more evenly distributed data is still needed to produce more reliable landslide susceptibility maps. To account for remote areas, employment of unmanned aerial vehicles (UAV) with visual and topographic mapping ability might help to identify vegetation covered past landslides.

7. Conclusion

Based on the findings and discussion, several points can be concluded:

1. The Logistic Regression (LR) method demonstrates high accuracy in predicting landslide-prone areas in Bogor Regency, with an accuracy rate of 82% and a predictive precision of 88%.
2. The model might still not account for local geospatial conditions below input data resolution and other styles of ground movement, such as creeping.
3. Better models need to be produced by employing more evenly distributed data.

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