**Indonesian Journal of Electrical Engineering and Computer Science**
Vol. 5, No. 1, January 2017, pp. 139 ~ 146
DOI: 10.11591/ijeecs.v5.i1.pp 139-146


# Spatial Modeling in Landslide Susceptibility

**Dwi Shanty A Gunadi[1], I Nengah Surati Jaya[2], BoediTjahjono[3]**
[1]Graduate School, Bogor Agricultural University, Masters of Science in Information Technology for Natural Resource Management, SEAMEO BIOTROP Campus, Bogor-Indonesia.
[2]Department of Forest Management, Faculty of Forestry, Bogor Agricultural University, Bogor 16680
[3]Department of Soil Science, Faculty of Agriculture, Bogor Agricultural University, Bogor 16680
Corresponding author, e-mail: shanty.g86@gmail.com*[1], ins-jaya@ipb.ac.id[2], boedi_tj@yahoo.com[3]

***Abstract***

*Landslide Susceptibility Mapping is one of the mitigation efforts to detect vulnerable areas for minimizing the risk of landslide disasters. This paper describes spatial model development for assessing landslide susceptibility by considering human and biophysical factors. The main objective of this research is to develop a spatial modeling of landslide susceptibility, particularly in several regencies of West Java Province. The data analysis includes data pre-processing, regression analysis, correlation analysis, score development, and weight determination using Principal Component Analysis (PCA). The study found that the most important factors that contributed to landslide susceptibility within the research area is the Landuse/Landcover, then followed by Slope, Distance to River, Soil Type, Annual Rainfall, Population Density, Geology Age, Climate Type, and Geomorphology. The first three highest factors occupied almost 53% of the total weight. The model successfully estimated the spatial distribution and degree of landslide susceptibility into 3 classes having overall accuracy of about 68%.*

**Keywords**: *Landslide Susceptibility, PCA, Spatial Modeling, West Java*



## 1. Introduction

As a country located within the ring of fire zone, Indonesia has been frequently affected by landslides. During the period 1981-2007 the annual landslide frequency have an average of 49 events per year [1]. Many landslides occur in mountainous regions. Mountainous regions have steep slopes which will cause materials from the surface to lose by gravity. In Central or South America, most landslides occur (or have the potential to occur) in mountainous regions of the Andes and steep slopes in volcanic regions [10]. Occurrence in mountainous regions is also happening in West Java. Based on landslide inventory data obtained from the Center of Volcanology and Geological Hazard Mitigation of Indonesia, since 1951 until 2003 the West Java Province suffered from landslides which were mainly in its mountainous area [6]. Total number of fatalities caused by landslide in Indonesia alone in the year 2007 was 465, which was the second highest number of fatalities next to China [9]. The impact in terms of loss of lives and damage to buildings, landslides in Indonesia produce significant damage to agricultural land and roads, with the subsequent economic disruption [7].

Landslide mechanism and evolution are closely related to the geological conditions and environmental factors, and are controlled not only by geological forces, lithologic structure, and other crustal internal factors; but also by topography, land cover, precipitation, changes in human activities, and environmental conditions [11]. Other triggering factors such as earthquake can induce the event of landslides which can be seen in 2009, where an earthquake that happened offshore of Tasikmalaya triggered rock avalanches and cracks in West Java. The cracks that were triggered by the earthquake enabled infiltration of precipitation which is high in West Java (exceeds 3000 mm/year) thus resulting the occurrence of landslides [12]. Landslides in Indonesia are mainly caused by topographic and morphology conditions, soil and deposit formation, geology structure, and rainfall intensity. But the characteristic of landslides occurrences in an area can differ from one another. Landslides in Java Island have a slow movement flow due to the characteristic of mostly clay stone and lime stone as for landslide in Sumatera Island are mostly fast debris flow because of the main influences of fault and steep slope [2]. Moreover, extensive land use as an impact from high human population has an important role to landslide occurrences [2].

*Received August 29, 2016; Revised November 17, 2016; Accepted December 11, 2016*

Due to the high occurrences of landslides in Indonesia, and the high number of fatalities that can occur, there is a need of a mitigation method in Indonesia to prevent future landslide disasters. Various mitigations have been done such as stochastic analysis of rainfall effects [3], development of application vulnerability assessment considering social and economic aspects [8]. Mitigation regarding to landslide events in Indonesia have been stated in the law for regulation of the minister in Indonesia number 33 years 2006. The policy for the strategy for mitigation are 1) same perception in applying steps and procedures, 2) implementation is done with integration and coordination with all units and community, 3) preventive measures are prioritized to minimize disasters, and 4) raising awareness and powers through cooperation through all party with community empowerment and campaigns. One of the strategies of mitigation is to provide landslide susceptibility mapping.

Landslide susceptibility basically can be defined as the classification of volume (area), and spatial distribution of landslides which exists or potentially may occur in an area [4]. Spatial modeling approach that can model landslide susceptibility areas based on the nature of the landslide occurrences and the characteristic of the area is needed to generate an optimum landslide susceptibility map for any area. The development of this approach in spatial modeling for landslide susceptibility can be an input to enrich the modeling for landslide susceptibility in Indonesia which concludes the foundation of the main idea of this research.

The objective of this research is to develop a spatial model of landslide susceptibility that can model landslide susceptible areas and identify the significant driving forces of landslide mainly in area of West Java Province. The research area are 4 regencies within West Java Province which are; Cianjur Regency, West Bandung Regency, Bandung Regency, and GarutRegecy. This research have analyzed landslide susceptibility based on the biophysical factors, human factors, and triggering factors of landslides that were correlated with the landslide inventory data from Indonesian National Board for Disaster Management (BNPB) of the 109 landslide locations that have happened throughout the year 2011 – 2015 within the research area. The spatial modeling method used regression and Principal Component Analysis (PCA) to determine the factors and weight of the factors used in this analysis. The result of the method was compared using overall accuracy of the models with the landslide density of the research area.

## 2. Research Method

The study area covers four regencies in West Java Province, Indonesia, i.e. (1) Cianjur Regency, (2) West Bandung Regency, (3) Bandung Regency, (4) Garut Regency which (Figure 1). The research steps was divided into six processes, (1) Data Pre-Processing (2) Scoring Development (3) Correlation Analysis (4) Weight Determination (5) Susceptibility Class Development, and (6) Model Accuracy. Initially the model was developed by considering 11 factors consisting by biophysical and human factors namely landuse/landcover, slope, annual rainfall, climate type, geology age, soil type, geomorphology, and distance to fault, distance to river, population density, and farmer density.

The pre-processing includes a development of actual landslide density map that was derived from the 109 landslide events recorded from 2011-2015 by BNPB. This history events data was extracted into points from tabular data of past landslide events that have happened in Indonesia downloaded from the website of the Indonesian National Board for Disaster Management (BNPB). Actual landslide density was generated per 5 km$^2$ of the research area. This can be explained in Table 1.

Scoring and development was performed by analyzing the regression between the variable considered and the landslide ocurrency. It was examined that the score was obtained by applying several shape of trend i.e. linear, polynomial, and exponential. This scoring method was adopted from [5]. The equation and score is explained in Equation 1 and Table 2.

$$ScoreRout = \left[\frac{(ScoreEinput - ScoreEmin)}{(\mathrm{ScoreEmax} - \mathrm{ScoreEmin})} * (ScoreRmax - ScoreRmin)\right] + ScoreRmin \qquad (1)$$

Where:
Score Rout = Rescaled Score Score Emax=Maximum Expected Score
Score Einput = Estimated input score Score Rmax= Highest rescaled score

Score Emin = Minimum Expected Score Score Rmin= Lowest rescaled score

Regression also considered the relationship between the variable and the landslide occurrences based on $R^2$ of trend-line. The study considered all factors that have $R^2<45\%$ have low relationship to the landslide events. Distance to fault was chosen to be eliminated because of the low $R^2$ result.

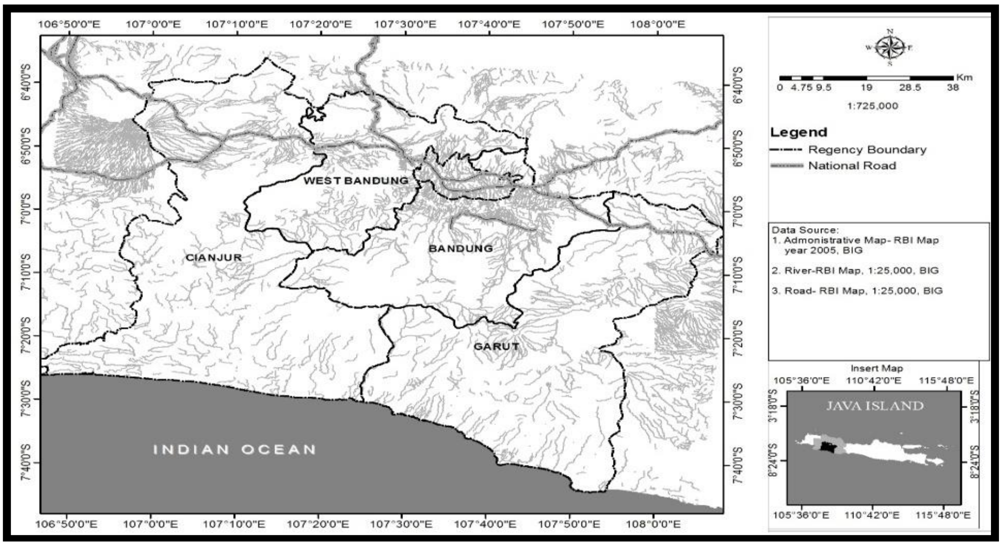


Figure 1. Research Area

To measure the independency among the independent variables of the model, correlation analysis was performed. Using the Pearson's Correlation, all factors that had significant correlation value >0.600 were considered. From this analysis, population density factor and farmer density factor had a correlation value >600. In order to prevent data redundancy, only one from those factors was chosen to be eliminated. Farmer density factor was chosen to be eliminated for this analysis resulting in 9 factors to be continued in this analysis in determining the landslide susceptibility for the research area.

In weight determination, this analysis used Principal Component Analysis (PCA). Research regarding the use of PCA in weight determination has been proposed in research such as [15]. Components used in determining the weight determination can also explain the total percent of variance of the data. The PCA process was done using statistic software SPSS. From the result of the PCA, principal components with explaining the component loadings were generated for the factors being analyzed this can be seen in Table 3. Weight determination was generated from the composite of multiplying the value of the component loadings to the percent of variance from each of the principal components (Equation 2).

$$W_i = \sqrt{\sum_{ij=1}^{n} V_{ij}^2 P_{ij}} \tag{2}$$

Where:

Wi = Weight of factor i

Vij = Component loading from principal component i to j

Pij = Percent of variance from principal component i to j

Susceptibility class development was then generated from the Landslide Susceptibility Index (LSI). Which represents the scores for the landslide susceptibility? LSI was generated by calculating the composite of the rescaled sub-factor scores multiplied by the weight of the representing factor. This equation is explained in Equation 3.

Table 1. Actual Landslide Density of research Area

| Landslide Density (LS/5 sq km) | Risk |
|---|---|
| 0 | Very Low |
| 0 - 0.025 | Low |
| 0.025 - 0.063 | Medium |
| 0.063 - 0.102 | High |
| ≥0.102 | Very High |

Table 2. Rescaled Score of Factors of Landslide

| Sub-factor | Score | Sub-factor | Score | Sub-factor | Score | Sub-factor | Score | Sub-factor | Score |
|---|---|---|---|---|---|---|---|---|---|
| Soil Type | | Population Density (person/km2) | | Rain (mm/Year) | | Distance to River (m) | | Geology Age | |
| Tropaquepts; Fluvaquents | 10.0 | 192.09 | 10.0 | 2082 | 10.0 | 250 | 100.0 | Pistosen-Holosen | 10.0 |
| Eutropepts; Tropaquepts | 15.3 | 252.22 | 13.7 | 2132 | 16.2 | 500 | 85.8 | Miosen | 18.6 |
| Dystrandepts; Tropudults; Eutropepts | 19.0 | 301.76 | 16.7 | 2201 | 24.9 | 750 | 72.9 | Holosen | 24.2 |
| Vitrandepts; Eutropepts | 21.5 | 404.34 | 23.0 | 2316 | 39.2 | 1000 | 61.1 | Miosen Tengah | 27.6 |
| Eutropepts; Tropudults; | 23.0 | 533.01 | 30.8 | 2436 | 54.2 | 1250 | 50.5 | Oligosen | 29.3 |
| Eutropepts; Rendolls | 23.9 | 616.62 | 35.9 | 2505 | 62.8 | 1500 | 41.1 | Plistosen | 30.3 |
| Paleudults; Eutropepts | 24.3 | 705.06 | 41.3 | 2601 | 74.8 | 1750 | 33.0 | PlistosenAtas | 31.3 |
| Dystropepts; Eutropepts; Tropudalfs; | 24.6 | 800.87 | 47.2 | 2610 | 75.9 | 2000 | 26.0 | Pliosen | 33.0 |
| Euntrandepts; Tropudults;Tropohumults | 25.1 | 935.09 | 55.4 | 2629 | 78.3 | 2250 | 20.2 | Kuarter | 36.1 |
| Dystropepts; Dystrandepts; Tropudults; | 26.0 | 977.91 | 58.0 | 2634 | 78.9 | 2500 | 15.6 | Plio-Plistosen | 41.5 |
| Dystropepts; Paleudults | 27.6 | 1048 | 62.2 | 2714 | 88.9 | 2750 | 12.2 | MioseAtas | 49.8 |
| Dystrandepts; Humitropepts; Hydrandepts | 30.2 | 1112.2 | 66.2 | 2737 | 91.8 | 3000 | 10.0 | Mio-Pliosen | 61.8 |
| Dystropepts; Humitropepts; Tropohumults | 34.1 | 1209.48 | 72.1 | 2739 | 92.0 | 4000 | 10.0 | OligosenAtas | 78.3 |
| Dystropepts; Tropudults; Troporthents | 39.5 | 1325.69 | 79.2 | 2751 | 93.5 | | | MiosenAtas | 100.0 |
| Eutrandepts; Troporthents | 46.8 | 1371.74 | 82.0 | 2766 | 95.4 | | | | |
| Eutropepts; Tropudults; Tropudalfs | 56.2 | 1389.2 | 83.1 | 2771 | 96.0 | | | | |
| Euntrandepts; Troperthents | 68.0 | 1447.3 | 86.6 | 2785 | 97.8 | | | | |
| Tropudults; Dystropepts | 82.5 | 1662.75 | 99.8 | 2800 | 99.6 | | | | |
| Tropudalfs; Paleudults; Dystropepts | 100.0 | >1662.75 | 100.0 | >2800 | 100.0 | | | | |
| Landuse | | Geomorphology | | Slope (%) | | Climate Type | | | |
| Urban | 10.0 | Alluvial Plains | 10.0 | 0-8% | 10 | A | 10 | | |
| Rice Field | 14.0 | Beaches | 24.3 | 8-15% | 32.5 | C | 100 | | |
| Non Timber Plantation | 20.0 | Fans and Lahars | 40.5 | 15-25% | 55 | | | | |
| Dry Land Agriculture | 28.1 | Plains | 58.5 | 25-40% | 77.5 | | | | |
| Shrub | 38.3 | Hills | 78.3 | >40% | 100 | | | | |
| Mixed Dry Land Agriculture | 50.6 | Mountains | 100.0 | | | | | | |
| Timber Plantation | 65.0 | | | | | | | | |
| Secondary Dry Land Forest | 81.5 | | | | | | | | |
| Bare Soil | 100.0 | | | | | | | | |

$$\mathrm{LSI} = \sum_{i=1}^{n} Score_i * W_i \quad (3)$$

Where:
LSI = Landslide Susceptibility Index
Scorei = Rescaled Score of sub-factor for factor i
Wi = Weight of Factor i

Overall accuracy analysis was done from the susceptibility classes to the actual landslide density. The susceptibility class was generated from a regression analysis between the LSI results to the actual landslide density. The overall accuracy will show which of the models show the most optimum consistency with the actual landslide density. A random 390 samples were generated from the actual landslide density for the overall accuracy analysis.

Table 3. Component Loadings

| | Component Loadings | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Geomorphology | 0.76 | 0.18 | -0.34 | 0.24 | -0.1 | 0.06 | 0.11 | -0.04 | 0.44 |
| Landuse | 0.7 | 0.33 | 0.07 | 0.17 | 0.1 | 0.55 | -0.09 | -0.08 | -0.2 |
| soil | 0.68 | 0.24 | 0.29 | -0.2 | -0.39 | -0.12 | 0.42 | 0.02 | -0.14 |
| Slope | 0.64 | 0.32 | -0.18 | 0.42 | 0.09 | -0.44 | -0.18 | 0.04 | -0.19 |
| Population density | -0.63 | 0.57 | -0.16 | 0.09 | -0.15 | 0.12 | 0.02 | 0.46 | 0 |
| Geology age | 0.62 | 0.05 | 0.58 | -0.29 | -0.07 | -0.05 | -0.36 | 0.18 | 0.16 |
| Rainfall | 0.62 | -0.49 | -0.07 | -0.04 | 0.47 | 0.03 | 0.21 | 0.33 | -0.03 |
| Distance to River | -0.33 | 0.61 | 0.44 | 0.03 | 0.51 | -0.09 | 0.17 | -0.11 | 0.12 |
| Climate Type | -0.24 | -0.39 | 0.56 | 0.67 | -0.16 | 0.05 | 0.07 | 0.06 | 0.04 |

**3. Results and Discussion**

From the weight determination process, a set of weights from examining various set of principal components was generated to find out the most accurate weight composition that could explain the magnitude load of each factors to assess the landslide occurrences by applying the Equation 2, the composition of each PC set is summarized in Table 4. Based on the total cumulative variance for each set of the PC, we found that PC 1-7, PC1 -8, and PC 1-9 explain more than 90% of the total variance.

Based on each PC set examined, then the study classified the landslide susceptibility into five classes starting from very low to very high landslide susceptibility as summarized in Table 5. The performance of each set was expressed by the overall accuracy. The study show that the accuracy of each PC set is shown in the bottom row of Table 5.

The overall accuracy result determines the best PC set to become the weight of the model. Based on the overall accuracy, LSI generated by the weight determination of the composite of components PC 1 until PC 8 (PC1-8) showed the most accurate among all of the other set of components. This can also be seen in Table 5 where PC 1-8 showed the highest at 27.95% overall accuracy than other set of components for classifying five susceptibility classes. In detailed version, the accuracy assessment for PC 1-8 is provided in Table 6.

Table 4. Weight of Factors Based on Set of Principal Components

| | Principal Component Set | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Factor | PC 1 | PC 1-2 | PC 1-3 | PC 1-4 | PC 1-5 | PC 1-6 | PC 1-7 | PC 1-8 | PC 1-9 |
| Climate | -0.085 | 0.079 | 0.115 | 0.144 | 0.109 | 0.069 | 0.066 | 0.066 | 0.062 |
| Geology age | 0.219 | 0.089 | 0.122 | 0.12 | 0.083 | 0.054 | 0.068 | 0.068 | 0.071 |
| Geomorphology | 0.269 | 0.113 | 0.111 | 0.108 | 0.08 | 0.054 | 0.054 | 0.054 | 0.094 |
| Landuse/Landcover | 0.249 | 0.117 | 0.099 | 0.094 | 0.071 | 0.241 | 0.232 | 0.231 | 0.22 |
| Population density | -0.225 | 0.138 | 0.12 | 0.111 | 0.089 | 0.073 | 0.071 | 0.073 | 0.069 |
| Rain | 0.219 | 0.126 | 0.107 | 0.098 | 0.167 | 0.1 | 0.099 | 0.1 | 0.094 |
| Dist. to river | -0.118 | 0.122 | 0.127 | 0.116 | 0.182 | 0.115 | 0.112 | 0.112 | 0.107 |
| Slope | 0.229 | 0.11 | 0.097 | 0.109 | 0.078 | 0.195 | 0.189 | 0.188 | 0.18 |
| Soil | 0.242 | 0.107 | 0.102 | 0.099 | 0.141 | 0.098 | 0.108 | 0.107 | 0.103 |
| Cumulative Variance (%) | 36.25 | 51.69 | 64.05 | 73.36 | 81.24 | 87.28 | 92.12 | 96.3 | 100 |

Table 5. Criteria of Landslide Susceptibility Class Based on EachPrincipal Component Set

| Susceptibility Class | PC 1-2 | PC 1-3 | PC 1-4 | PC 1-5 | PC 1-6 | PC 1-7 | PC 1-8 | PC 1-9 |
|---|---|---|---|---|---|---|---|---|
| Very Low | 0-20 | 0-21 | 0-20 | 0-25 | 0-20 | 0-20 | 0-21 | 0-20 |
| Low | 20-27 | 21-33 | 20-32 | 25-34 | 20-28 | 20-27 | 21-35 | 20-29 |
| Moderate | 27-34 | 33-43 | 32-42 | 34-42 | 28-41 | 27-41 | 35-47 | 29-47 |
| High | 34-54 | 43-53 | 42-53 | 42-51 | 41-54 | 41-54 | 47-61 | 47-56 |
| Very High | 54-100 | 53-100 | 53-100 | 51-100 | 54-100 | 54-100 | 61-100 | 56-100 |
| Accuracy 3 Class (%) | 67.17 | 65.38 | 58.97 | 56.92 | 60.51 | 59.74 | 68.2 | 63.58 |
| Accuracy 5 Class (%) | 23.84 | 19.74 | 14.61 | 16.66 | 12.05 | 10 | 27.94 | 13.33 |

Table 6. Overall Accuracy for Five Class Landslide Susceptibility Using PC 1-8

| | 5 Class Landslide Susceptibility | | | | | Total |
|---|---|---|---|---|---|---|
| Class | Very Low | Low | Moderate | High | Very High | |
| Very Low | 0 | 22 | 7 | 1 | 0 | 30 |
| Low | 10 | 12 | 3 | 5 | 0 | 30 |
| Moderate | 0 | 18 | 55 | 17 | 0 | 90 |
| High | 0 | 20 | 42 | 28 | 0 | 90 |
| Very High | 0 | 0 | 0 | 136 | 14 | 150 |
| Total | 10 | 72 | 107 | 187 | 14 | 390 |
| Overall Accuracy | 27.95% | | | | | |
| Kappa Accuracy | 9.49% | | | | | |

As mentioned above, the most accurate PC set is PC 1-8. From the weight found for PC 1-8 that is explained in Table 4, the study noted that the largest weight has been contributed by Landuse/landcover factor followed by slope, distance to river, soil type, annual rainfall, population density, geology age, climate type, and geomorphology. Landuse/landcover as the most significant factor to the events of the landslides in the area might be caused by landuse change within the area that can cause instability. This study is in line with research done by [13] where the susceptibility had been affected strongly due to the increase of bare soil. The other following factors which were slope, followed by distance to river, soil type, and rainfall might be caused by the slope gradient and the condition of slope as the initiation factor of the instability of slope. This can be proven by research done by [14] which shows the research in slope failures that was induced by heavy rainfall. Based on research [14], the seepage and rainfall tests on model slopes indicate that slope failure always occurred when the soil moisture content within a certain region near the toe of slope became nearly fully saturated, even if other parts of the sliding mass were still only partially saturated.

By applying the weight of PC 1-8, using the five class as described in Table 6, the study notes that there were some confusion particularly in susceptibility classes of low to moderate and high to very high resulting the accuracy to be lower than 60% at five classes. To increase the accuracy, then the study merge the five classes into only three classes as tabulated in Table 7 which are very low, low/moderate, and high/very high.

Table 7. Overall Accuracy for 3 Class Landslide Susceptibility

| | 3 Class Landslide Susceptibility | | | Total |
|---|---|---|---|---|
| Class | Very Low | Low/Moderate | High/Very High | |
| Very Low | 0 | 29 | 1 | 30 |
| Low/Moderate | 10 | 88 | 22 | 120 |
| High/Very High | 0 | 62 | 178 | 240 |
| Total | 10 | 179 | 201 | 390 |
| Overall Accuracy | 68.20% | | | |
| Kappa Accuracy | 41.08% | | | |

The study noted that by merging the five class of landslide susceptibility into three class, overall accuracy increased to 68.2% as displayed in Table 7. By overlaying the spatial model of landslide susceptibility with the actual landslide density, the study then define that the very low class of the model was at LSI score range of 0-21, followed by low/moderate class at 21-47, and high/very high class at 47-100 as displayed in Table 8. Visualization of the applied LSI score of PC 1-8 in three susceptibility class is displayed in Figure 2.

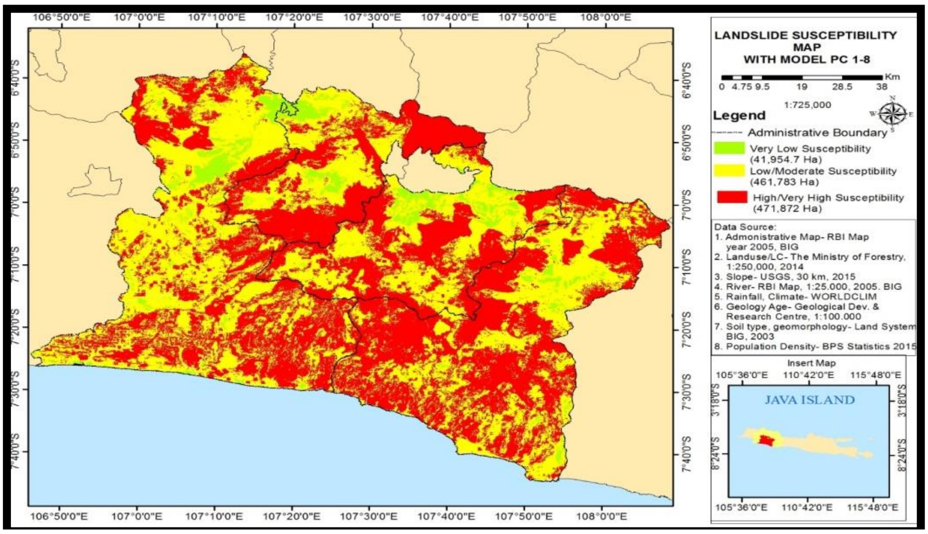


Figure 2. Landslide Susceptibility Map With 3 Class of Susceptibility

Table 8. Score of Landslide Susceptibility Class for Model PC 1-8

| PC 1-8 Model 3 Susceptibility Class | | Actual Landslide Density |
|---|---|---|
| Landslide Susceptibility Class | Score | Landslide Event / 5x5 km2 |
| Very Low | 0 - 21 | 0 |
| Low/Moderate | 21 - 47 | 0 - 0..063 |
| High/Very High | 47 - 100 | > 0.063 |

## 4. Conclusion

From the foregoing discussion, the study concluded that best model for assessing landslide susceptibility was the model developed by considering nine factors i.e. landuse/landcover, slope, distance to river, soil type, rainfall, population density, geology age, climate type, and geomorphology having weight 0.231, 0.188, 0.111, 0.107, 0.100, 0.073, 0.068, 0.066, and 0.054 respectively. It was also concluded that the model might asses the landslide into 3 classes of susceptibility from very low, low/moderate, and high/very high with overall accuracy of 68.2%. Since the landslide characteristic might vary from place to place, the study suggests that model may only be applied to assess areas having relating similar characteristic with the study area.

## References


[1] Christanto N, Hadmoko DS, Westen CJ, Lavigne F, Sartohadi J, Setiawan MA. Characteristic and Behavior of Rainfall Induced Landslides in Java Island, Indonesia: an Overview. Geophysical Research Abstracts 11. 2008.

[2] Djamal H. Landslide Disaster Occurred from 1990-2002 in Indonesia. *International Congress: INTERPRAEVENT 2002 in the Pacific Rim MATSUMOTO/JAPAN* 2002; Congress Publication. 2002; 2: 619-628.

[3] Faris F, Wang F. Stochastic Analysis of Rainfall Effect on Earthquake Induced Shallow Landslide of Tandikat, West Sumatra, Indonesia. *Geo-environmental Disasters*. 2014; 1: 12. DOI: 10.1186/s40677-014-0012-3.

[4] Fell R, Corominas J, Bonnard C, Cascini L, Leroi E, Savage W.Z. Guidelines for Landslide Susceptibility Hazard and Risk Zoning for Land Use Planning. *Eng. Geo 2008*. 2008; 102: 85-98.

[5] Jaya INS, Purnama ES, Arianti I, Boonyanuphap J. Forest Fire Risk Assessment Model and Post-Fire Evaluation Using Remote Sensing and GIS: A Case Study in Riau, West Kalimantan and East Kalimantan Provinces, Indonesia. *The Forest restoration and rehabilitating Training Course and Workshop in the Viiki Tropical Resources Institute (VITRI) of the University of Helsinki, Finland*. 2007.

[6] Kartiko RD, Brahmantyo B, Sadisun LA. Slope and Lithological Controls on Landslide Distribution in West Java, Indonesia. *Proceedings of International Symposium on Geotechnical Hazards. Prevention, Mitigation, and Engineering Response.* 2006; ISBN: 979-8636-13-9.

[7] Kuncoro A, Resosudarmo BP. Survey of Recent Developments. *Bulletin of Indonesian Economic Studies*. 2006; 42(1): 7-3.

[8] Park Y, Pradhan A, Kim U, Kim Y, Kim S. Development and Application of Urban Landslide Vulnerability Assessment Methodology Reflecting Social and Economic Variables. *Hindawi Publishing Corporation* 2016; Advances in Meteorology. Vol 2016. Article ID: 4572498. http://dx.doi.org/10.1155/2016/4572498.

[9] Petley D. The Global Occurrence of fatal Landslides in 2007. *Geophysical Research Abstracts* 2008; Vol. 10, EGU2008-A-10487. SRef-ID: 1607-79621/gra/EGU2008-A-10487. EGU General Assembly 2008. © Author(s) 2008.

[10] Preti F, Letterio T. Shallow Landslide Susceptibility Assessment in a Data-Poor Region of Guatemala (Comitancillo Municipality). *Journal of Agricultural Engineering*. 2015; XLVI: 450.

[11] Shan W, Hu Z, Guo Y, Zhang C, Wang C, Jiang H, Liu Y, Xiao J. The Impact of Climate Change on Landslide in Southern of High-Latitude Permafrost Regions of China. *Frontiers in Science* 2015; DOI: 10.3389/feart.2015.00007. 2015; 3(7).

[12] Yamada M, Wang G, Mukai K. The Classification and Features of Earthquake-Induced Landslides in the World. *Earthquake-Induced Landslides* 2013; DOI: 10.1007/978-3-642-32238-9_13, © Springer-Verlag. Berlin Heidelberg.

[13] Reichenbach P, Busca C, Mondini A C, Rossi M. The Influence of Land Use Change on Landslide Susceptibility Zonation: The Briga Catchment Test Site (Messina, Italy). *Environmental Management* 2014; 54:1372–1384. DOI 10.1007/s00267-014-0357-0, Springer.

[14] Orense Rolando P. Slope Failures Triggered by Heavy Rainfall. Phillipine Engineering Journal 2004; *PEJ*. 2004; 25(2): 73–90.

[15] Behestizadeh H, Rezaie A, Rezaie A, Ghandi A. Principal component analysis and determination of the selection criteria in bread wheat (TriticumaestivumL.) genotypes. *International Journal of Agriculture and Crop Sciences* 2013; Intl J Agri Crop Sci. 2013; 5(18): 2024-2027.