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LANDSLIDE SUSCEPTIBILITY ANALYSIS IN KABANDUNGAN DISTRICT AND SALAK GEOTHERMAL FIELD, WEST JAVA

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Abstract. *Landslide hazards can be caused by several factors such as lithology, land cover, rainfall, slope, curvature, aspect, distance from river and road. In this study, a landslide susceptibility mapping was carried out using a Geographical Information System (GIS) in Kabandungan District and Salak Geothermal Field, West Java. The data used consisted of an inventory of points and landslide areas totalling 247 using a visual collection of Google Earth imagery. The Weight of Evidence (WoE) model is used to select parameters that cause landslides and to produce landslide vulnerability maps. The results of modeling indicate a positive relationship between selective factors for the occurrence of landslides, with Area Under Curve value of 0.89359; 0.76395; 0.75277; 0.73280 and 0.69093 respectively. Landslide susceptibility maps are made by adding up the WoE values for all the most influential parameters. Higher total WoE value is indicating a higher probability of landslide. Landslide susceptibility maps can be used as an effort to prevent potential hazards or mitigate landslides. In addition, this map can also be used furtherly for spatial planning and engineering activities.*

Keywords*: landslide susceptibility, causative factors, Kabandungan, Salak Geothermal Field, Weight of Evidence, Area Under Curve*

1. Introduction

Landslides have become geological phenomena that have resulted in significant losses, ranging from loss of human lives, property, ecosystems, and damage to infrastructure. West Java region is known as the region with the highest occurrences of landslides compared to other regions in Indonesia. Volcanic weathered material, steep contours, and high rainfall are some of the main components causing and triggering a landslide in West Java. From 2012 to 2019, 571 landslides have occurred in various regions in West Java (Center for Volcanology & Geological Disaster Mitigation, 2019).

Landslide incident is inseparable from the geological order and denudation process that continues to this day. In addition to natural factors, landslides can be affected by human activity changes in land use and construction activities in areas with slopes without regard to environmental aspects. Mitigation is an activity designed to reduce risk and potential disasters. Mitigation can take the form of structural and non-structural development in disaster-prone areas. Landslide susceptibility map is one of the spatial information that is useful as a support for structural and non-structural mitigation activities. The map is one of the important factors in assessing the feasibility of an area for development. The analysis is made by utilizing a landslide inventory map and causative map of landslides that originated from the Geospatial Information Agency (Geospatial Information Agency, 2019).

Landslide susceptibility identification is the most effective and economical way to provide basic data in spatial planning, land use, adaptation, and disaster mitigation (Zhou et al., 2016). Even though the time and location of landslide events are difficult to predict, but an evaluation of the potential of an area for landslides can be carried out. A large number of landslide analyses have been carried out and developed with various remote sensing-based methods and Geographic Information Systems (GIS) in various places (van Westen, 1993; Guzzetti, et al., 2005; Lee & Pradhan, 2006; Dahal, et al., 2008; Yilmaz, 2010; Yalcin, et al., 2011; Abrauw, 2017). In this case, the Weight of Evidence (WoE) method is widely used for mapping landslide susceptibility (Mărgărint et al., 2013; Heckmann et al., 2014). WoE method is based on information obtained from the relationship between the parameters of the landslide as a calculation parameter and the landslide event data, so that it can be predicted areas that are prone to landslides, taking into account the events before (prior) and after (posterior) (Barbieri & Cambuli, 2009). WoE method has advantages because it can assess the effect of different classes of each variable.

This study aims to visually present the level of vulnerability of an area to potential landslide hazards through mapping of landslide susceptibility zones. The researcher used and calculated different causative factors to produce landslide susceptibility maps (Neuhäuser et al., 2011). There are many parameters that need to be considered for analyzing landslides events. However, nothing, in general, explains the criteria for selecting parameters for making maps (Ayalew et al., 2005; in Che et al., 2011). In fact, each parameter in a different region will have a different effect on the occurrence of existing landslides. According to Ayalew et al. (2005); in Che et al. (2011), to determine the parameters that cause the formation of landslides using a statistical approach based on GIS, these parameters must meet the requirements including, can be operated, represent the whole area, not excessive and can be calculated. Pamela et al., (2018) use eight selective causative factors including slope degree, slope aspect, lithology, elevation, rainfall, distance to lineament, peak ground acceleration and flow direction.

The consideration based on area conditions in Aceh, Indonesia lie at earthquake-prone zone both active fault zone and source of the earthquake. No considerable earthquake zone is present in this research area, so the parameters used for evaluating landslide susceptibility are also quite different. Some parameters, such as peak ground acceleration and distance to lineament, are not used in this research. As a substitute for these factors, proximity to the road and land use become parameters that may considerably influence landslides events.

2. Methodology

2.1. Study Area

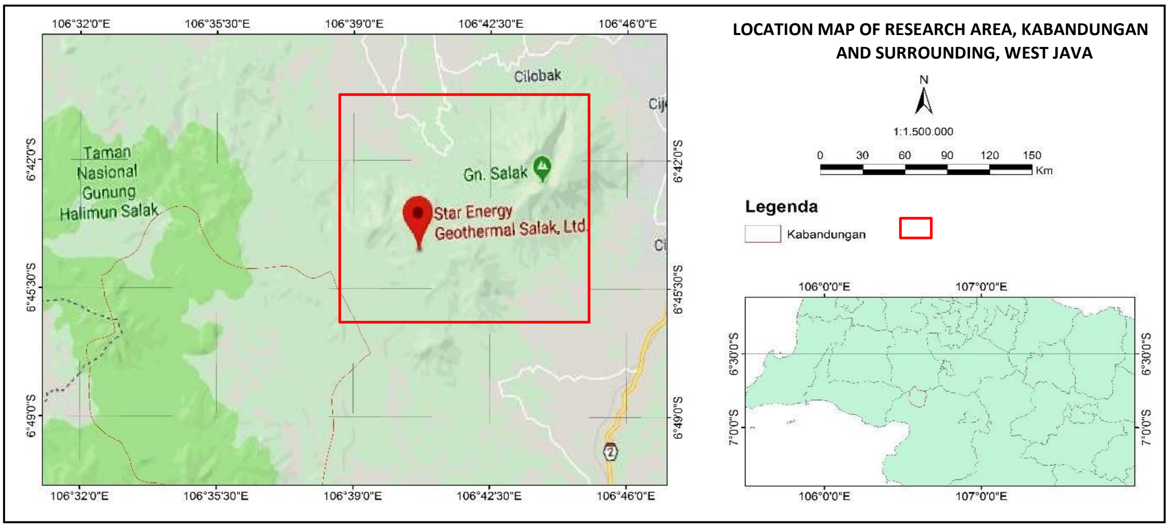

Figure 1. Study area (Google Maps, 2019)

In 2019, several regions in West Java experienced landslides. One of the areas is in Kabandungan District, Sukabumi Regency, West Java. Kabandungan District has records of landslide events that occurred in some villages, such as Cibeureum, Cianaga, and Cipeuteuy. Landslides take place in

February, April & May 2019. Kabandungan also borders Salak Geothermal Field. The field has a capacity of 377 MW (Directorate General of New and Renewable Energy and Energy Conservation, 2017). The research area is in Kabandungan and Parakan Salak District, Sukabumi Regency, West Java where located at 6°40'30" - 6°46'00" S and 106°38'30" - 106°45'00" E (Figure 1).

Figure 2 shows that research area composed of Older Volcanic Rocks including Unconsolidated Volcanic Rock (Qvu) that consists of breccias and lava flows, especially andesite; Volcanic Breccias (Qvb) that consists of andesite-basal breccias, local agglomerates, weathered; Volcanic Lava (Qvl) that consists of lava flow, in the Bogor area basalt with labradorite, pyroxene, and hornblende, in the Port of Ratu area, andesite and oligoclase-andesine and abundance of hornblende; Tuff (Qvt) that consists of pumiceous tuff; Gunung Pangrango Volcanics including Younger Deposits (Qvpy), andesitic lahar; Older Deposits (Qvpo), lahar and lava, andesitic basalt with oligoclase-andesine labradorite, olivine, pyroxene, and hornblende; Surficial Deposits including Alluvium Fans (Qav) that consist of mainly silt, sandstone, gravel and boulders from Quaternary volcanic rocks, redeposited as alluvial fans; Bogor Zone including Tuff and Breccia (Tmtb) that consist of pumiceous tuff, tuffaceous breccia (andesitic), tuff sandstone, tuffaceous clay with silicified wood and plant remains, sandstone is cross bedded; The Bojongmanik Formation (Tmb) consists of lithology which includes sandstones, pumice tuffs, marl with molluscs, limestone, claystone with bitumen clay and intercalation of lignite and fragment resins. The thickness of this formation is 550 m. Fossils in clay are planktonic indicating a Miocene age; Volcanic Rocks including Endut-Prabakti Lava (Qvep) that consists of andesite hornblende, containing oligoclase of andesine, hypersthene, and hornblende; Gunung Salak Volcanics including lava flow, basaltic andesite with pyroxene (augite) (Qvsl); lahar, tuffaceous breccia, and lapilli, basaltic andesite in composition, mostly strongly weathered (Qvsb); sandy pumiceous tuff. In the vicinity Cicurug, pumiceous tuff, locally called trass (Qvst).

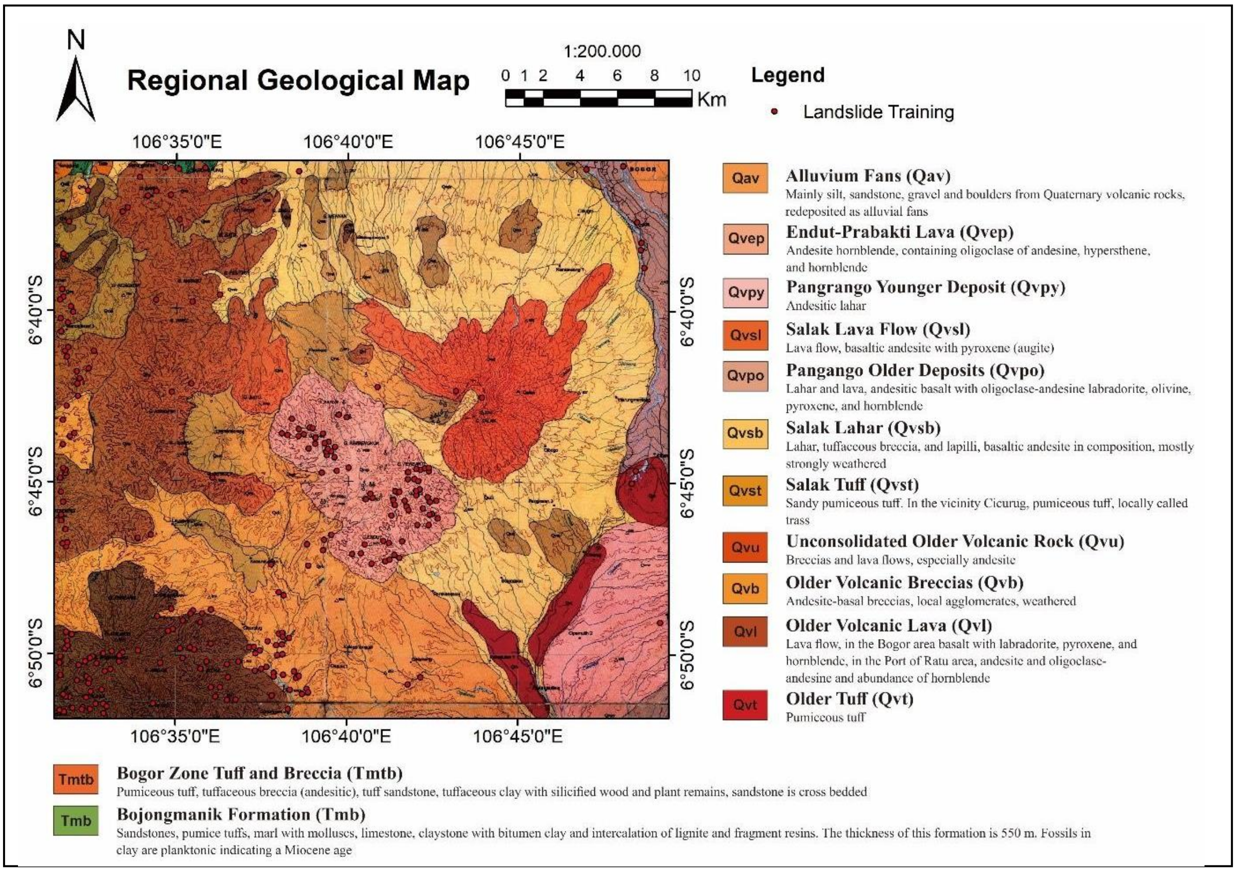

Figure 2. Geological map of research area (Effendi et al., 1998).

2.2. Causative Factors

Data on landslide events and causative factors are the main data needed in the analysis of landslide susceptibility maps. The inventory identified 247 landslide events from visual observation of Google Earth imagery. Information taken from the event data is the location coordinates (points) with an average area of events ± 15x15 m (225 m2). The number of landslides events is then used to test the validity of the parameters influencing the landslides, hereinafter referred to as landslide training.

The key to making susceptibility maps is assuming that current and previous landslides events will also occur in the future in similar areas (Che et al., 2011). In other words, the existing landslides inventory can be used to predict the susceptibility of an area in the future landslides. Eight parameters were chosen which are estimated to have an influence on the occurrence of landslides including rock type (lithology), land use, slope gradient, slope direction (aspect), slope curvature, distance from the river, distance from road and rainfall. Slope gradient, aspect, and curvature are obtained from a Digital Elevation Model (DEM) map with a resolution of 30 m (Geospatial Information Agency, 2019). The slope gradient is one of the main parameters of geomorphology, represent elevation points which influences on the slide susceptibility, since the driving force of the landslides, is the gravity (Torizin, 2011). The slope is typically considered to be one of the influential factors for landslide modeling because it controls the shear forces acting on hill slopes (Bui et al., 2011; Dou et al., 2009; Nolasco-Javier et al., 2015). Slope cuts can change the angle of slope and will reduce the resistance of the landslide. Slope direction or common mentioned as aspect, that relates to sunlight exposure and drying winds control the soil moisture were also considered an important factor in landslide studies (Magliulo et al., 2008).

Aspect, defined as the maximum slope of the terrain surface, played a fundamental role in slope stability due to variance in temperature, vegetation, and directional peak ground acceleration. For example, in the northern hemisphere, south-facing slopes were more open to sunshine and warm wind than north-facing ones (Zhou et al., 2016). Curvature shows the surface shape of an area, divided into three classes, namely positive curvature (convex), negative curvature (concave) and zero curvature (flat) (Kartiko, 2009). Differences in the level of curvature of an area can affect slope moisture, the ability to maintain slope saturation and the susceptibility of erosion to slope movement.

Lithology is considered one of the most influential factors in landslide susceptibility mapping because of its influence on the geo-mechanical characteristics of a terrain (Costanzo et al., 2012). Lithology represents different geological units or rock formation (Torizin, 2011). Each unit affects the stability of the slope differently in the level of vulnerability. Lithology plays an important influence in the case of landslides because rock units have certain characteristics such as compactness, composition, and structure. This situation then results in variations in resistance to slope movement (Carrara et al., 1991).

Lithology affects the strength and permeability associated with the slope of the gradient. The lithology map is obtained from Effendi et al. (1998) in the TIFF image format. Digitization needs to be done to obtain lithological boundaries in polygon format. Rainfall becomes one of the parameters in landslides occurrence because it raises the pore water pressure in a slope, causing the slope resisting force to decrease.

Land use map and road obtained from BIG polygon type. The occurrence of landslides is a natural phenomenon that will occur whether there is human activity or not. However, land use due to human activities can accelerate and have a large role in the formation of landslides events, such as land use and development in sloped areas that do not follow the rules of environmental sustainability.

Distance from road or proximity to the road is estimated to have a significant effect due to the construction of the road usually carried out the process of excavation and addition of material on the slopes in several places. This condition can trigger the occurrence of landslides. Distance from river parameter means the closer distance to the river is estimated to have a significant effect on the lower slope, which can cause landslide (Che et al., 2011). Rainfall becomes one of the parameters in landslides occurrence because it raises the pore water pressure in a slope, causing the slope resisting force to decrease. All maps were converted to raster by using the functions in ArcGIS and have a projection system of UTM Zone 48S. Each parameter data must have the same coverage, resolution, and number of pixels.

2.3. Weight of Evidence (WoE)

Weight of Evidence (WoE) is included in the bivariate statistical method, which is a method based on the Bayes probability framework that is displayed in a series of GIS environments (Mezughi et al., 2011). WoE model is a quantitative technique that is driven by data, using some combinations of data to produce maps of weighted data, both continuous and categorized based on prior (initial) and posterior (after) probabilities (Bonham-Carter, 1994; van Westen et al., 2003; Poli & Sterlacchini, 2007). WoE method allows for the incorporation of uncertainties in the susceptibility model (type, quality, and calculation of each data) and explicitly considers expert knowledge into the process (Chung et al., 2003). WoE calculates the relationship between selective causative factor classes with the distribution of landslides in the form of positive (W+) and negative weights (W-). Apart from the calculation of W+ and W-, the contrast of weight (C') is added to define how significant the overall spatial association between a selective causative factor and landslide distribution.

$$(W+)_i \ = Ln(\frac{\left(\frac{Ls_{F_i}}{\sum_{a=0}^{n} Ls_{F_a}}\right)}{\left(\frac{A_i - Ls_{F_i}}{\sum_{a=0}^{n} A_a - \sum_{a=0}^{n} Ls_{F_a}}\right)}) \tag{1}$$

$$(W-)_i \ = Ln(\frac{\left(\frac{\sum_{a=0}^{n} Ls_{F_a} - Ls_{F_i}}{\sum_{a=0}^{n} Ls_{F_a}}\right)}{\left(\frac{\sum_{a=0}^{n} A_a - A_i - \sum_{a=0}^{n} Ls_{F_a} + Ls_{F_i}}{\sum_{a=0}^{n} A_a - \sum_{a=0}^{n} Ls_{F_a}}\right)}) \tag{2}$$

$$C_i = (W+)_i - (W-)_i \tag{3}$$

$$WoE_i = (W+)_i + \sum_{a=0}^{n}(W-)_a - (W-)_i \tag{4}$$

with,

$W+_i$ = Positive probability of landslide for i-class
Ls_{Fi} = Corrected landslide events for i-class
A_i = Area, number of pixels of i-class
C_i = Constant for simplifying the equation
WoE_i = Weight of Evidence for i-class

$$AUC_i = \frac{(\%Ls_{i-1} + \%Ls_i) * (\%A_i - \%A_{i-1})}{2} \tag{5}$$

$$AUC_{kum\,i} = \sum_{a=0}^{i} AUC_a \tag{6}$$

with,

AUC_i = Area Under Curve for i-class
AUC_{kum} = Accumulation of AUC
Ls_i = Number of occurrences of landslides for i-class
A_i = Area, number of pixels of i-class

3. Results and Discussion

All of these parameters have their class values (Figure 3). The following explanation of the eight parameters selected is as follows. Slope angle values in the research area ranged from 0°-89° and were divided into 20 classes with intervals magnification of 4.5°. Aspect shows the direction of slope divided into ten sections with class intervals of 45° to north, northeast, east, southeast, south, southwest, west, northwest, flat, and north. Rainfall divided into nine classes, per 120 mm/month interval.

The lithology condition in research area composed of 13 rock type group as refer to Effendi et al. (1998) including Unconsolidated Volcanic Rock (Qvu); Volcanic Breccias (Qvb); Volcanic Lava (Qvl); Tuff (Qvt); Younger Deposits (Qvpy); Older Deposits (Qvpo); Alluvium Fans (Qav); Tuff and Breccia (Tmtb); Bojongmanik Formation (Tmb); Endut-Prabakti Lava (Qvep); lava flow, basaltic andesite with pyroxene (augite) (Qvsl); lahar, tuffaceous breccia, and lapilli, basaltic andesite in composition, mostly strongly weathered (Qvsb); sandy pumiceous tuff. In the vicinity of Cicurug, pumiceous tuff, locally called trass (Qvst). Distance from the road is made into nine classes with 50 m class interval, and for distance >400 m is made into one class with the assumption that there is no influence from the existence of the road (Che et al., 2011). Distance from the river is divided into seven classes at intervals of 50 m per class, with pixels having a distance from the river >300 m made into a single class assuming the influence of the river can be ignored (Che et al., 2011). Curvature map divided into three classes that consist of positive curvature (convex), negative curvature (concave) and zero curvature (flat). Meanwhile, land use in the research area consists of 11 groups including primary dryland forest, secondary dryland forest, industrial forest, plantation, settlement, dryland farming, bush- mixed farmland, rice fields, shrubs, bare land, and water body.

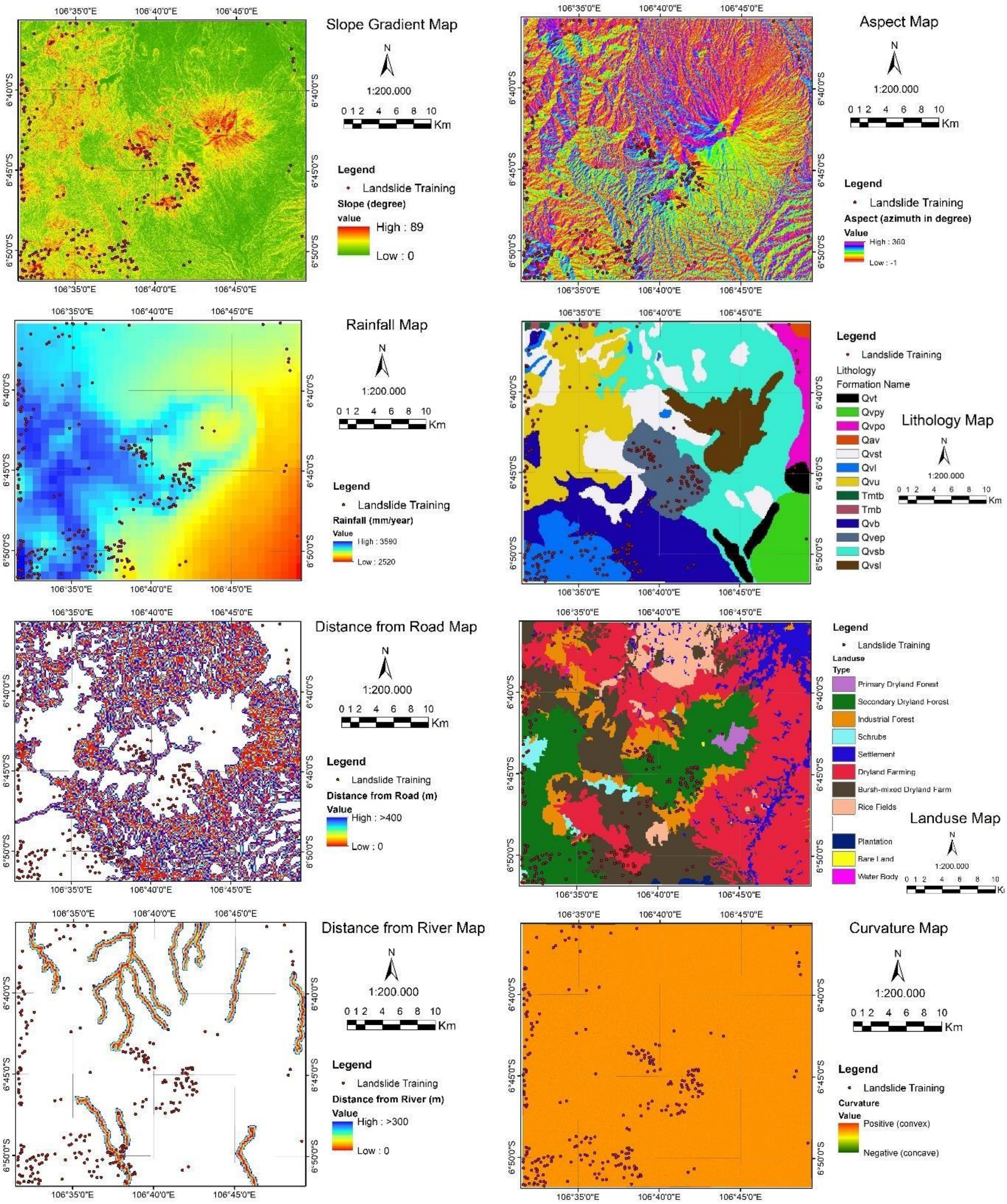

Figure 3. Causative factor induced landslide: aspect, slope, rainfall, lithology, distance from road, distance from river, curvature and land use

By WoE calculation in Table 1, it can be found some positive relationship between each of the parameters and landslide events. The strongest positive relation between landslides and lithology can be found in volcanic breccia and lava. Volcanic breccia (Qvb) consist of breccia and andesitic-basaltic, volcanic lava (Qvl) consist of a lava flow, basaltic with labradorite, pyroxene, and hornblende. The weighting of the slope gradient classes showed that the slope gradient of 32 - 36° is the highest susceptible to landslides.

For aspects, landslide events have many points in a southeast direction. In parameter of proximity to the river, strong positive relationships can be found at 300 m away from the main river. In another side, at 300-400 m distance from the road, it has high susceptibility to landslides. The relation between landslides and rainfall has positive relation for 328-337 mm/month precipitation. Type of secondary dry forest becomes the highest susceptibility to landslides in the land-use factors. Last, the strongest positive relation between landslides and curvature can be found in positive or convex class.

Table 1. WoE and AUC value for landslide causative parameters

WoE value	Area (pixel)	Cum. area	Cum. area (%)	Landslide number	Cum. landslide number	Cum. Landslide number (%)	AUC value
Slope							
3167	144522	144522	0.01019	48	48	0.19512	0.00099
2909	45595	190117	0.01340	14	62	0.25203	0.00072
2447	377050	567167	0.03998	59	121	0.49187	0.00989
2117	13846	581013	0.04096	2	123	0.50000	0.00048
1615	699275	1280288	0.09025	51	174	0.70732	0.02976
459	1070334	2350622	0.16571	28	202	0.82114	0.05766
-345	1508450	3859072	0.27204	19	221	0.89837	0.09142
-1384	2079345	5938417	0.41863	10	231	0.93902	0.13467
-1803	2703160	8641577	0.60919	9	240	0.97561	0.18242
-2683	2255498	10897075	0.76819	3	243	0.98780	0.15609
-4086	3252270	14149345	0.99745	1	244	0.99187	0.22694
-5508	10797	14160142	0.99821	2	246	1.00000	0.00076
-5510	25330	14185472	1.00000	0	246	1.00000	0.00179
						AUC total	0.89359
Aspect							
1421	181799	144522	0.06141	61	61	0.24797	0.00761
1197	148425	292947	0.12448	43	104	0.42276	0.02115
903	170143	463090	0.19678	38	142	0.57724	0.03615
346	213221	676311	0.28739	29	171	0.69512	0.05764
145	140452	816763	0.34707	16	187	0.76016	0.04343
57	200276	1017039	0.43217	21	208	0.84553	0.06832
-39	104632	1121671	0.47663	10	218	0.88618	0.03850
-44	157408	1279079	0.54352	15	233	0.94715	0.06131
-2436	962918	2241997	0.95269	13	246	1.00000	0.39836
-5487	74049	2316046	0.98416	0	246	1.00000	0.03147
							0.76395
Rainfall							
1147	3279	3279	0.04713	22	22	0.08980	0.00212
663	5268	8547	0.12285	39	61	0.24898	0.01283
573	5068	13615	0.19569	40	101	0.41224	0.02408
444	1091	14706	0.21137	49	150	0.61224	0.00803
55	9353	24059	0.34580	38	188	0.76735	0.09273
-374	4616	28675	0.41215	19	207	0.84490	0.05348
-511	7343	36018	0.51769	10	217	0.88571	0.09133

Table 1. (Continued)

WoE value	Area (pixel)	Cum. area	Cum. area (%)	Landslide number	Cum. landslide number	Cum. Landslide number (%)	AUC value
-544	9534	45552	0.65472	22	239	0.97551	0.12752
-788	8923	54475	0.78297	1	240	0.97959	0.12537
-1813	6807	61282	0.88080	3	243	0.99184	0.09644
-2259	6019	67301	0.96732	2	245	1.00000	0.08616
-5567	2274	69575	1.00000	0	245	1.00000	0.03268
							0.75277
Lithology							
5036	143	143	0.00209	3	3	0.01224	0.00001
2102	101	244	0.00356	0	3	0.01224	0.00002
1514	4943	5187	0.07567	66	69	0.28163	0.01060
719	10195	15382	0.22440	46	115	0.46939	0.05585
156	10861	26243	0.38285	46	161	0.65714	0.08925
109	239	26482	0.38634	1	162	0.66122	0.00230
-450	2070	28552	0.41654	5	167	0.68163	0.02028
-1194	1740	30292	0.44192	2	169	0.68980	0.01741
-1464	4424	34716	0.50646	67	236	0.96327	0.05334
-2656	3770	38486	0.56146	1	237	0.96735	0.05309
-2843	8521	47007	0.68577	2	239	0.97551	0.12076
-3631	17017	64024	0.93403	4	243	0.99184	0.24420
-5626	4522	68546	1.00000	2	245	1.00000	0.06570
							0.73281
Distance from road							
1015	29886	29886	0.43645	196	196	0.80000	0.17458
-1358	5599	35485	0.51822	10	206	0.84082	0.06708
-1444	7764	43249	0.63160	13	219	0.89388	0.09834
-1757	10907	54156	0.79089	14	233	0.95102	0.14693
-2247	14319	68475	1.00000	12	245	1.00000	0.20399
							0.69093
Landuse							
2210	213	213	0.00433	7	7	0.03167	0.00007
827	14080	14293	0.29049	119	126	0.57014	0.08611
702	5767	20060	0.40770	43	169	0.76471	0.07823
-663	526	20586	0.41839	1	170	0.76923	0.00820
-671	24379	44965	0.91387	46	216	0.97738	0.43270
-1136	4238	49203	1.00000	5	221	1.00000	0.08516
							0.69046
Distance from river							
1184	1011	1011	0.01520	8	8	0.04145	0.00031
540	942	1953	0.02936	4	12	0.06218	0.00073
180	1006	2959	0.04448	3	15	0.07772	0.00106
-36	60426	63385	0.95276	172	187	0.96891	0.47532
-54	1269	64654	0.97183	3	190	0.98446	0.01863
-124	908	65562	0.98548	2	192	0.99482	0.01351
-879	966	66528	1.00000	1	193	1.00000	0.01448
							0.52404
Curvature							
145	697933	144522	0.09707	127	127	0.51626	0.02506
-45	714476	858998	0.57694	118	245	0.99593	0.36283
-2583	76466	935464	0.62830	1	246	1.00000	0.05125
							0.43914

Area under curve (AUC) of success rate of slope degree, slope aspect, rainfall, lithology, distance from road, distance from river, curvature and land use are 0,89359; 0,76395; 0,75277; 0,73280; 0,69093; 0,52404; 0,43914 and 0,23467, respectively, shown in Table 1 and Figure 4. AUC value close to 1; the better quality of the model is (Arifianti & Agustin, 2017). It should be noted that not all classes in each parameter can display their AUC value. This is related to the WoE value of the class that meets the criteria with the landslide training data. The AUC value, which is intended to assess the influence of the parameters of the landslide event is the accumulation of the AUC value of each class that meets the criteria for a parameter.

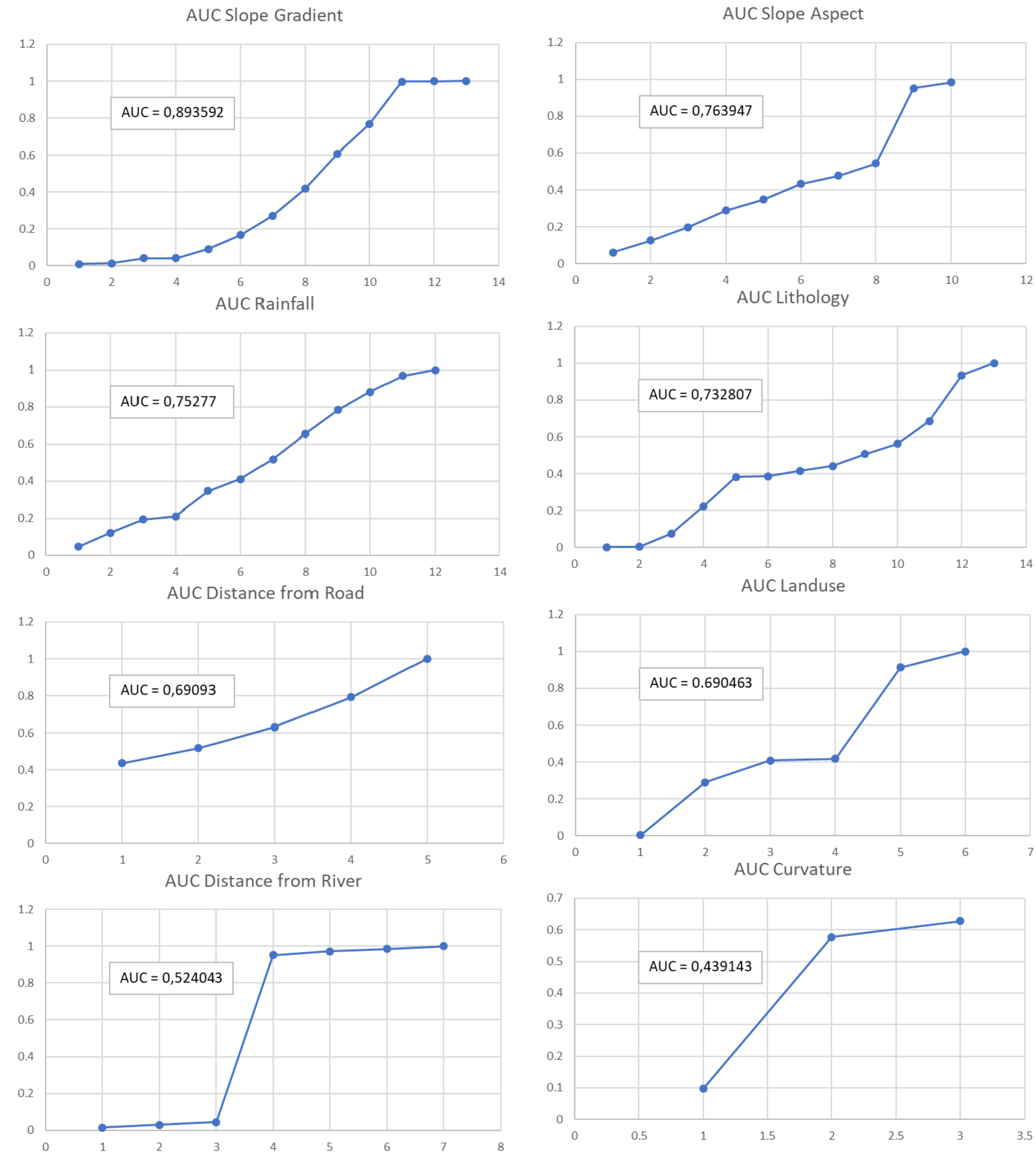

Figure 4. Area Under Curve (AUC) value for slope, aspect, rainfall, lithology, distance from the road, distance from the road, curvature and land use. The X-axis represents the total area in %, and Y-axis represents the landslide area in %

According to the validation results of AUC evaluation, the slope gradient has the highest factor controlling the landslide in this area, followed by aspects, rainfall, and lithology in sequence. Overall, the AUC of the effective factors in the study area showed how good the quality between the causative factors and landslides distribution data. WoE modeling, which was applied to the five selective causative factors, were then resulting in a total WoE of landslide susceptibility (Figure 5). Results of the WoE values that have been added are given a gradation of green-red, where red has a high WoE value, which indicates a high tendency for landslides.

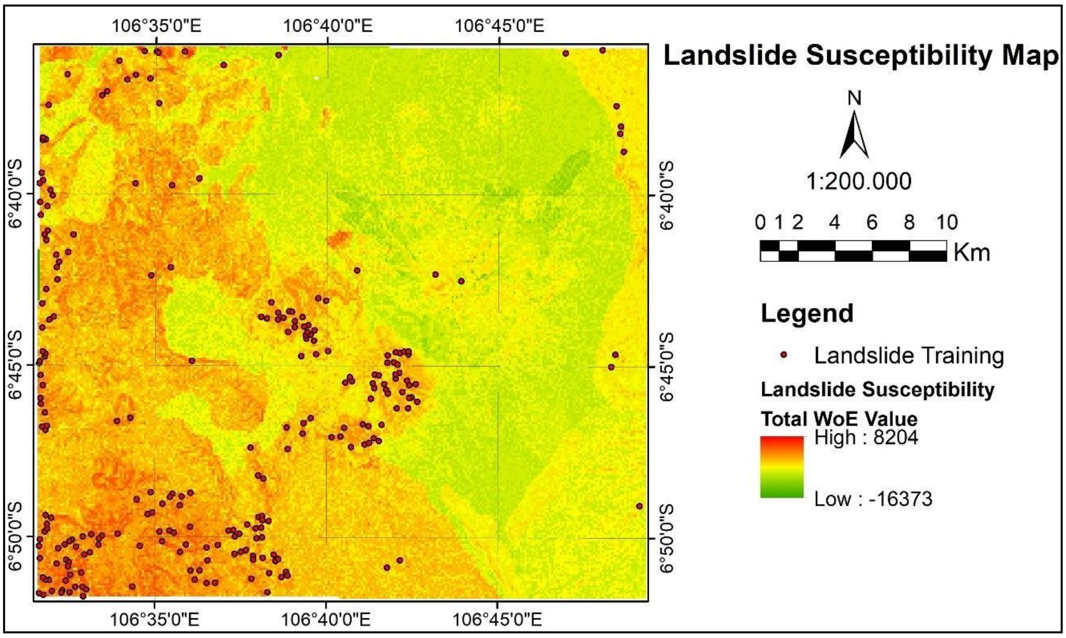

Figure 5. Landslide susceptibility map in the research area that represented by total WoE value.

Comparison with related research in a different geological background, Pamela et al., (2018) in the research area of Takengon, Aceh concluded that the slope gradient is also the most dominant causative factor that affects the stability of a slope. Other parameters that most influenced landslides in their research area are aspects, peak ground acceleration, and elevation. This result differs slightly where there are differences in influence on rainfall and lithology factors after the slope gradient. This is understandable because conditions are different in tectonic setting background. Research area where located in the Salak region, West Java is an area that has high rainfall.

Precipitation becomes the dominant parameter in its effect on the landslide. Meanwhile, in Aceh, peak ground acceleration plays an important role in landslides. Arifianti et al., (2016) states that Aceh has earthquake-induced landslides occurred in Takengon, Central Aceh district. Takengon is located at Sumatra Island, an active fault zone, the source of active earthquakes. The effects of slope movements of earthquakes in Sumatra were associated with numerous landslide disasters. It can be considerably stated that topographic related factor that is slope gradient and aspect are two factors most contributing to landslides. The lithology parameter in these two research areas does not play a big role compared to the two previous factors. This may lead to the conclusion that each area had different local conditions compared to other locations. The difference in local conditions that will affect the incidence of landslides is caused by any factor.

4. Conclusion

The parameters affect landslides events in research area consisted of five parameters that are slope, aspect, rainfall, lithology, and distance from the road. This is indicated by the AUC value, which meets the criteria. These parameters will be different and adjust to the local conditions of each area. It might be possible to consider that the slope can be a factor that most often influences the occurrence of landslides. Landslide susceptibility maps are made by combining the weighting of the five parameters in the form of a WoE total value map. The greater value of WoE, the possibility of landslides will be higher. Current landslide susceptibility maps can be used for the prevention and mitigation of initial landslide hazards and appropriate planning for land use and infrastructure development. Due to the dynamic nature of rainfall, rapid urbanization, deforestation, and anthropogenic activities, landslide susceptibility map presented can change. Therefore, maps must be verified and modified on time by adding other landslide conditioning factors in the analysis.

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