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Comparative Study among Bivariate Statistical Models in Landslide Susceptibility Map

Yukni Arifianti[1], Pamela[1], Fitriani Agustin[2], and Dicky Muslim[3]

[1]Center for Volcanology and Geological Hazard Mitigation, Geological Agency
Jln. Diponegoro No. 57 Bandung, Indonesia
[2]Geological Survey Institute, Geological Agency
Jln. Diponegoro No. 57 Bandung, Indonesia
[3]Faculty of Geological Engineering, Padjadjaran University
Jln. Raya Bandung-Sumedang Km.21 Jatinangor, Indonesia 45363

Corresponding author: yukni.arifianti@esdm.go.id, pamela@esdm.go.id, fitriani.agustin @esdm.go.id
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Abstract - The main purpose of this paper is to compare the performance of bivariate statistical models *i.e.* Frequency Ratio, Weight of Evidence, and Information Value for landslide susceptibility assessment. These models were applied in Cianjur Regency, West Java Province (Indonesia), in order to map the landslide susceptibility and to rate the importance of landslide causal factors. In the first stage, a landslide inventory map and the input layers of the landslide conditioning factors were prepared in the Geographic Information System (GIS) supported by field investigations and remote sensing data. The 298 landslides were randomly divided into two groups of modeling/training data (70%) and validation/test data sets (30%). The landslide conditioning factors considered for the studied area were slope angle, elevation, slope aspect, lithological unit, and land use. Subsequently, the thematic data layers of conditioning factors were integrated by frequency ratio (FR), weight of evidence (WofeE), and information value (IV). Model performance was tested with receiver operator characteristic analysis. The validation findings revealed that the three models showed promising results since the models gave good accuracy values. The success rates of FR, WofE, and IV models were 0.920, 0.926, and 0.930, while the prediction rates of the three models were 0.913, 0.912, and 0.895, respectively. However, the FR model was proved to be relatively superior in estimating landslide susceptibility throughout the studied area.

Keywords: frequency ratio, weight of evidence, information value, Cianjur

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Introduction

According to Landslide Inventory Database of Indonesia, from 2011 to 2015, almost 40% of landslides in Indonesia occur in West Java Province. Cianjur Regency with its prominent factors of landslide, highly weathered material (lithology), and the steep morphology is one of hotspots for landslide in West Java (Arifianti and Agustin, 2017). The accelerated population growth towards the landslide-prone areas caused the increasing of casualties by human-induced landslide hazard each year. A significant effort to reduce the number of losses was then carried out through landslide disaster mitigation. One of its activities is to conduct Landslide Susceptibility Assessment (LSA) as the basis of Landslide Susceptibility Map. LSA plays a significant part of landslide disaster mitigation, and has received more attention with the highest number of publications in international journals (Gokceoglu and Sezer, 2009).

Many studies have been carried out to assess landslide susceptibility, with increasing application of GIS using different models. Numerous methods have been used for landslide susceptibility assessment and mapping, which can be classified into two categories (i) qualitative and (ii) quantitative methods. Qualitative method is based on field observations and prior knowledge of experts in identifying judgment rules or assign weighted values for conditioning factor maps and which overlay them to produce a landslide susceptibility map, such as analytical hierarchy process (Ghosh, 2011; Kayastha *et al*. 2012; Mondal and Maiti, 2012). The quantitative method primarily refers to several statistical analyses, which can be categorized into bivariate statistical and multivariate analysis. This study was only using bivariate statistical analysis such as frequency ratio (Lee and Pradhan, 2006; Vijith and Madhu, 2007; Constantin *et al*. 2011; Mezughi *et al*. 2011; Regmi *et al*. 2014), information value model (Yin and Yan, 1988; Lin and Tung 2004; Sarkar *et al*. 2008; Conforti *et al*. 2011; Wang *et al*. 2014; Zhu *et al*. 2014), and weight of evidence model (Poli and Sterlacchini, 2007; Dahal *et al*. 2008; Sharma and Kumar, 2008; Kayastha *et al*. 2012; Chen and Li, 2014; Teerarungsigul *et al*. 2015). Geomatics by taking advantage of modern tools, such as Geographic Information System (GIS) and Remote Sensing (RS) provide a perfect opportunity for using, validating, and comparing different methods to produce a landslide susceptibility map (Vakhshoori and Zare, 2016). Some studies have applied and compared two or more methods to the same region (Pradhan and Lee, 2010a; Ercanoğlu and Temiz, 2011; Yalcin *et al*., 2011; Regmi *et al*., 2014; Vakhshoori and Zare, 2016; Akıncı *et al*. 2017; Chen *et al*. 2019).

Studied Area

The area under investigation is located in Cianjur Regency between 106°46’56”and 107° 29' 23” E latitudes and 6° 33’ 14” and 7° 26’ 49” S longitudes (WGS84 UTM 48 S), covering about 3,730 km^2 area (Figure 1). The altitude of the region ranges from 0 to 2,961 m above the mean sea level.

Based on its physiography, West Java Province is divided into four zones, viz; Jakarta Coastal Plain, Bogor, Bandung or Central Depression

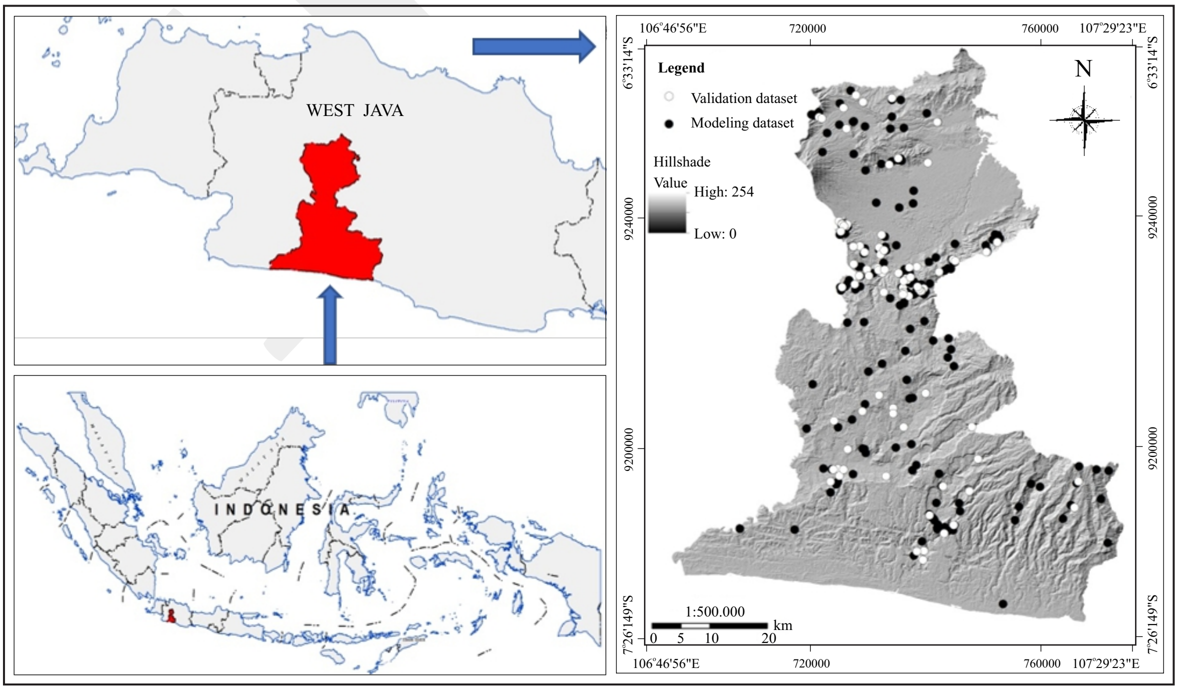

Figure 1. Location of the studied area in West Java Province and the location of landslides.

Zone, and West Java Southern Mountain Zone (Van Bemmelen, 1949). Cianjur area is situated in Bandung Zone with mainly morphological features of steep hills, and the predominant lithology is Quaternary volcanic products.

Methods and Materials

The landslide sampled as a homogen geo-referenced point (Poli and Sterlacchini, 2007; Neuhäuser *et al*., 2011; Ozdemir, 2011; Tien Bui *et al*., 2012; Xu *et al*., 2014). An approach called seed cell was used to indicate the occurrence or non-occurrence of landslides. Seed cell is a neighborhood analysis (spatial analysis tool) to select landslide pixels within a buffer zone along the crown and flanks. It is a method to describe a pre-failure conditions, the undestroyed morphological conditions before the landslides occurred (Süzen and Doyuran, 2004; Nefeslioglu *et al*., 2008; Bai *et al*., 2010; Dou *et al*., 2015; Hussin *et al*., 2015).

The total of 298 landslide points in Cianjur area were compiled and mapped into the landslide inventory map. The landslide points as the seed cells were used to build the models. The points were randomly divided into 196 points (70%) as a training dataset for building process model. The other 89 points (30%) as a test/validation dataset were not used in building process model, but were used for validation purposes.

In this study, conditions considered as the primary factors were selected in the occurrence of a landslide in the studied area. There were the set of five landslide-related factors which were used and defined as conditioning factors. These conditioning factors are slope angle, slope aspect, elevation, lithological unit, and land use (Table 1). The factors were converted to raster maps of grid size of 15 x 15 m with a spatial resolution of 15 x 15 m. The relevant data and its analysis for this study were collected and processed in a GIS-environment using ArcGis 10.6 programmes.

In this study, Frequency Ratio, Weight of Evidence, and Information Value models were applied

Table 1. Details of Data Used in the Study

Category	Factors	Data Type	Scale/ resolution
Topographic map	Slope angle Slope aspect Elevation	Grid	15 x 15 m
Geological map	Lithology	Polygon	1 : 50.000
Land Use Map	Land Use	Polygon	1 : 50.000

on landslide susceptibility assessment to generate Landslide Susceptibility Maps (LSMs) of the studied area using the five landslide conditioning factors. All LSMs were classified into four landslide susceptibility zones based on the landslide distribution percentage of the total populated as very low (0% - 5%), low (5% - 10%), moderate (10% - 75%), and high (> 75%) (SNI, 2016).

Frequency Ratio (FR)

The FR is one of probability models which is based on observed spatial relationships between landslide distribution and each conditioning factor related to landslides (Pradhan and Lee, 2010a, 2010b; Choi *et al*., 2012; Mohammady *et al*., 2012; Park *et al*., 2013; Pardeshi *et al*., 2013). FR is the ratio of landslides (the probability of an occurrence and a nonoccurrence) in a desired class (given attributes) as a percentage of all landslides (%Ld) to the area of the class as a percentage of the entire map (%Cd):

$$FR_d = (\%L_d)/(\%C_d) \quad (1)$$

Where:
FR_d is the FR weight of the desired class.

The landslide susceptibility index (LSI) for each pixel or each factor ratio (Lee and Min 2001) is the summation of total overlapped pixels. It is formulated as:

$$\mathrm{LSI} = \sum_{d=1}^{n} FRd \quad (2)$$

Weight of Evidence (WofE)

The theory of evidence (Weight of Evidence) is a log-linear version on the theorem of Bayes used to calculate probability based on the concept of prior (P) and posterior probability (Agterberg *et al*., 1993; Elmoulat *et al*., 2015). This approach is based on the information obtained from the interrelation between landslide conditioning factors and the landslide distribution (Barbieri and Cambuli, 2009; Pardeshi *et al*., 2013). The landslide conditioning factors are the input parameters for the WofE approach and to provide the information which may control the occurrence of areas prone to landslides (Arifianti and Agustin, 2017). The WofE calculates the spatial relationship between the conditioning factors with the distribution of landslides (VM), in the form of positive (W+) and negative weights (W-). These positive and negative weights are calculated from the ratios of the natural logarithms (Bonham-Carter, 1994; Elmoulat *et al*., 2015), as below:

$$W^{+} = \ln \frac{P\{VP/VM\}}{P\{VP/\overline{VM}\}} \quad \text{.................................} \ (3)$$

$$W^{-} = \ln \frac{P\{\overline{VP}/VM\}}{P\{\overline{VP}/\overline{VM}\}} \quad \text{.................................} \ (4)$$

The contrast of the weight (C) is added to define how significant the overall spatial association between the landslide conditioning factors and the landslide distribution (Dahal *et al*., 2008, Neuhäuser *et al*., 2011). The contrast value is calculated as the difference of positive and negative weights (Ozdemir, 2011):

$$C = W^{+} - W^{-} \quad \text{...} \ (5)$$

Information Value Model (IVM)

The IVM is a statistical approach that has the advantage of assessing landslide susceptibility in an objective way. The IVM is used to calculate the weight for each class of factor layer by rationing landslide density of each class to the landslide density of the total area. In general, the landslides will occur in the future that has the same condition as the past landslides (Lee and Pradhan, 2006). The IVM model is used to evaluate the spatial relationship between the conditioning factor classes and the probability of landslide occurrence. The higher value of IVM corresponds to the stronger relationship between the probability of landslide occurrence and the conditioning factor class. The IV model can be calculated as follows (Yin and Yan, 1988; Zhu *et al*., 2004; Wang *et al*., 2014):

$$I_i = \log_2 \frac{S_i / A_i}{S / A} \quad \text{...} \ (6)$$

where:
S_i is the number of landslides containing factor class (i),
A_i is the area of factor class (i),
S is total number of landslides, and
A is the total area of the entire study.

Validation of Landslide Susceptibility Models

The validation of LSMs based on statistical methods reveals the reliability of the modelling processes. It is to compare the accuracy of different models and the choice of their parameter variables. The 'Area Under Curve' (AUC) of the 'Receiver Operating Characteristics' (ROC) method was performed for the validation. The success rate curve used the training dataset (70% of the whole set) to determine how well the resultant maps had classified the areas of existing landslides (Chung and Fabbri, 1999; Chen *et al*., 2017). The prediction rate curve using the validation dataset (30% of the whole set) can explain how well the models and conditioning factors predict the future landslides (Chung and Fabbri, 2003; Pradhan and Lee, 2010a). The model accuracy ratings are usually given as 0.9 - 1.0 = excellent, 0.8 - 0.9 = good, 0.7 - 0.8 = acceptable, 0.6 - 0.7 = poor, and 0.5 - 0.6 = failed (Yilmaz, 2009).

Results and Discussion

Spatial Relationship between Conditioning Factors and Landslides

The conditioning factors classified into several classes and weights were assigned to them for FR, WofE, and IV methods as shown in Figure 2. The spatial relationship between the conditioning factors and landslides is presented in Table 2.

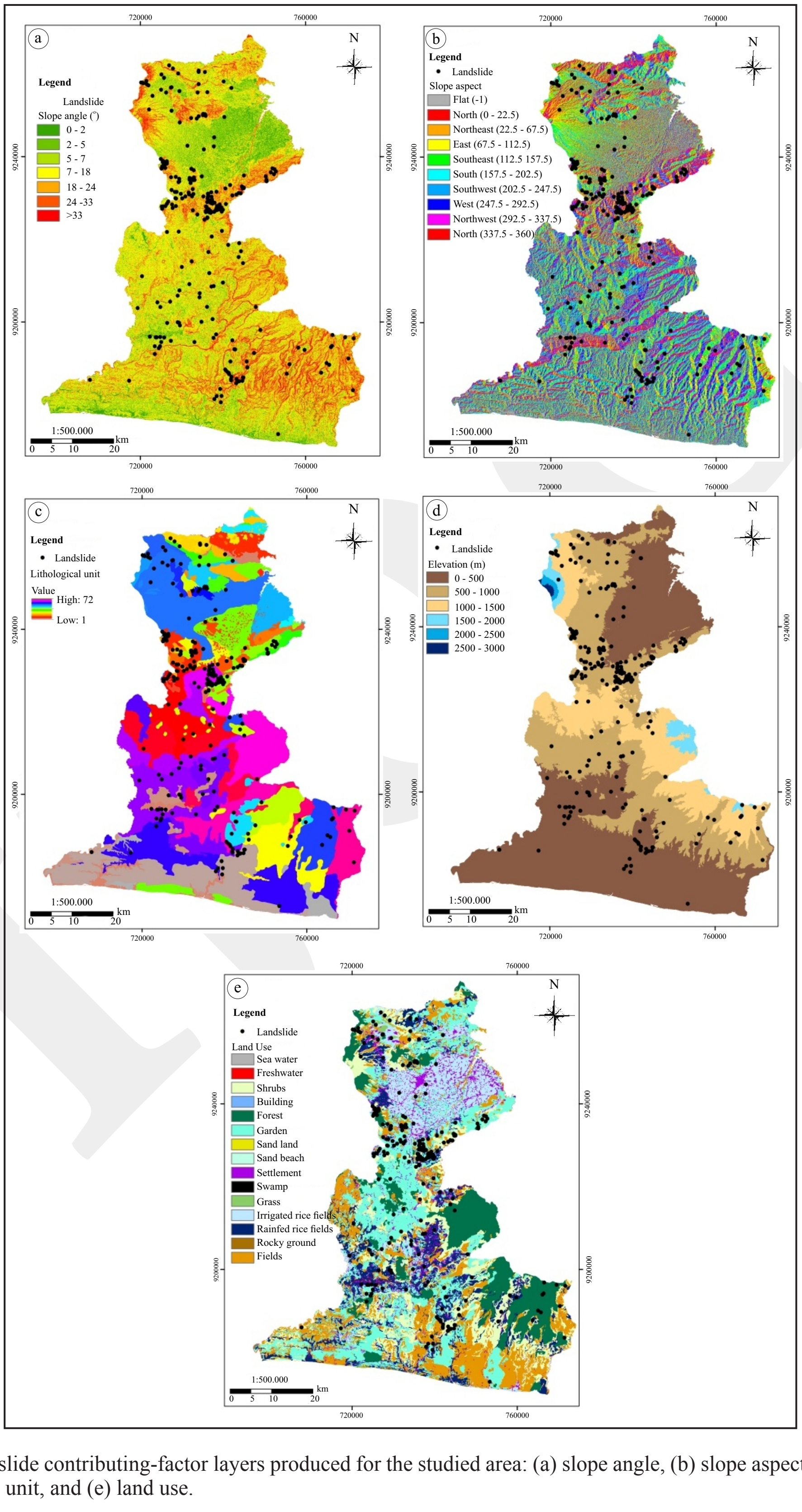

Figure 2. Landslide contributing-factor layers produced for the studied area: (a) slope angle, (b) slope aspect, (c) elevation, (d) lithological unit, and (e) land use.

Table 2. Spatial Relationship between Each Conditioning Factor and the Landslides for the FR, WofE, and IV Models

Conditioning Factor	Area Total (pixel)	Landslide points (n)	FR	WofE	IV
Slope angle (^{0})					
0 – 2	11225	4	309	-1207	-1174
2 – 5	19816	6	262	-1412	-1337
5 – 8	21774	20	796	-251	-227
8 – 18	61431	60	847	-243	-165
18 – 24	29537	45	1321	351	278
24 – 33	19021	39	1778	681	575
> 33	7184	22	2655	1055	976
Slope aspect					
Flat	4941	2	351	-1064	-1046
North	10996	19	1498	431	404
Northeast	18552	37	1729	632	547
East	19719	28	1231	231	208
Southeast	25710	31	1045	45	44
South	23396	10	370	-1086	-992
Southwest	19135	17	770	-295	-260
West	19963	15	651	-478	-428
Northwest	18320	20	946	-67	-54
North	9256	17	1592	491	465
Elevation (m)					
0-500	83104	47	490	-1224	-712
500-1000	54708	121	1918	1098	651
1000-1500	28107	26	802	-378	-220
1500-2000	3396	2	510	-798	-671
2000-2500	451	0	0	-5407	-17975
2500-3000	222	0	0	-5406	-18684
Lithology					
Limestone member	2458	0	0	-5302	-16279
Black sandstone, tuffaceous sandstone, siltstone	16049	7	378	-1030	-972
Claystone, siltstone, sandstone, tuffaceous sandstone, tuff	3093	1	280	-1276	-1271
Loose materials, blocks, boulder, gravel from sand, clay	3519	1	246	-1405	-1400
Andesite basalt intrusive	257	2	6749	1916	1909
Limestone	308	0	0	-5289	-18356
Andesite lava	239	0	0	-5289	-18610
Hornblende andesite Intrusive	93	2	18651	2947	2925
Breccia, tuffaceous sandstone, calcareous sandstone	227	2	7641	2041	2033
Old volcanic deposits: Breccia, lava	4098	22	4655	1628	1538
Mount Gede Volcanic Slide; basalt	1194	1	726	-323	-319
Andesite lava	1200	3	2168	777	773
Old volcanic lava deposit	594	6	8760	2198	2170
tuffaceous breccia, lava, sandstone, conglomerate	934	1	928	-77	-74
Lava, Beser sand	130	0	0	-5288	-19219
Breccia, lava, Beser sand	74	0	0	-5288	-19782
Old volcanic deposits: breccia, lava	436	3	5967	1796	1786
Alluvial fan: breccia, lava, lahar	1043	0	0	-5294	-17137
Old volcanic lava deposit	402	1	2157	766	768
Intrusive: vitrophyre, porphyry, dolerite	603	0	0	-5291	-17685
Sandstone	728	1	1191	171	175
Claystone	872	2	1989	687	687
Pyroclastic, lahar	339	0	0	-5290	-18260
Breccia andesite, Tuffaceous breccia	208	0	0	-5289	-18749
Brownish sandstone, Tuffaceous sandstone, andesite	7118	1	121	-2111	-2105
Pyroxene andesite	556	1	1559	441	444
Lahar deposits; breccia, tuf andesite	557	2	3114	1138	1135
Alluvial fan: breccia, lava, lahar	184	1	4713	1550	1550
Old Volcanic Sediment of Pasir Menteng: Clay, marl, quartz sandstone	1208	12	8615	2209	2153
Alluvial fan: breccia, lava, lahar	5003	1	173	-1757	-1752
pyroclastic, lahar	790	1	1097	89	93
Breccia	523	0	0	-5291	-17827
Quartz sandstone	983	5	4411	1500	1484
Breccia, Mount Manengge lava	719	1	1206	183	187
Quater limestone	1580	0	0	-5297	-16721

Table 2. continued...

Conditioning Factor	Area Total (pixel)	Landslide points (n)	FR	WofE	IV
Sandstone, siltstone	1399	8	4959	1631	1601
Mount Manengge lava	18	0	0	-5288	-21196
Breccia, lava, lahar	3881	2	446	-816	-805
Breccia, lava, Beser sand	468	0	0	-5290	-17938
loose material, clay, sand, boulder, gravel and the mix	1151	3	2260	819	815
Breccia, lava, lahar	319	0	0	-5290	-18321
Marl, quartz sandstone	1178	0	0	-5295	-17015
Loose material, clay, sand, gravel, blocks	2659	3	978	-25	-21
Basalt	9	0	0	-5288	-21889
Pyroclastic, lahar	1500	6	3469	1261	1243
Cirata Lake	8	0	0	-5288	-22007
Breccia, lava, lahar	3423	0	0	-5308	-15948
Mount Pangrango Volcanic deposits	135	0	0	-5288	-19181
Breccia, lava	357	0	0	-5290	-18209
Mount Gede lava	290	0	0	-5289	-18417
Mount Gede pyroclastic deposits	14567	10	595	-556	-518
Breccia, Mount Limo lava	1356	5	3197	1175	1162
Claystone and silstone	603	3	4314	1470	1462
Mount Patuha breccia	5715	3	455	-803	-786
Breccia, Mount Balukbuk lava	723	1	1199	178	181
Breccia, lava, pyroclastic, lahar	494	2	3511	1258	1255
Andesite breccia, tuffaceous sandstone, tuff, lapilli, conglomerate	13756	3	189	-1717	-1665
Old terrace deposits	1541	0	0	-5297	-16746
Brownish sandstone, Tuffaceous sandstone, andesite	5918	7	1025	22	25
Claystone	8243	12	1262	242	233
Andesite breccia	5325	4	651	-441	-428
Claystone Beser Formation	500	0	0	-5291	-17872
Old volcanic sediment of Pasir Menteng: breccia, lava, tuff, conglomerate	1853	21	9828	2389	2285
Sandstone	972	0	0	-5293	-17207
Mount Kendeng lahar and lava	7254	0	0	-5331	-15197
Breccia, lava, lahar	4924	5	880	-133	-127
Breccia, lava, lahar	4932	5	879	-135	-128
Mount Patuha lava	1218	2	1424	351	353
Black sandstone	789	0	0	-5292	-17416
Breccia, lava, lahar	2305	0	0	-5301	-16344
Tuffaceous breccia, crystal tuff	6717	2	258	-1374	-1353
Pyroxene andesite	5169	9	1510	423	412
Land Use					
Sea water	16	0	-5298	0	-21314
Freshwater	879	0	-5303	0	-17308
Shrubs	24350	53	780	1887	635
Building	46	0	-5298	0	-20258
Forest	23426	22	-247	814	-205
Garden/agriculture land	44747	51	-29	988	-11
Sand land	3	0	-5298	0	-22988
Sand beach	2	0	-5298	0	-23393
Settlement	9986	14	194	1215	195
Swamp	13	0	-5298	0	-21522
Grass	653	1	270	1328	283
Irrigated rice fields	14456	8	-790	479	-734
Rain-fed rice fields	18052	25	192	1201	183
Rocky ground	10	0	-5298	0	-21784
Fields	33349	22	-667	572	-558

The spatial relationship between landslide occurrence and its conditioning factors using the three models indicates a relative similar susceptibility of each class. The most susceptible classes of the slope angle are 7° - 18°, 18° - 24°, and 24° - 33°. The models show that the landslide probability increases with the slope angle. This defined as a strong correlation between the slope angle and the landslide occurrence.

In the case of slope aspect and elevation factors, the models depicted the highest susceptible classes is the northeast facing slope with the elevation of 500 - 1,000 m a.s.l. The frequency of landslides is relatively lower on the south direction, with the exception in the flat areas. This means the two factors have less correlation with the landslide occurrence and elevation than the slope angle.

The result from lithology factor indicates that the most susceptible classes were (1) breccia, lava, tuff, and conglomerate from old volcanic sediments of Pasir Menteng, (2) clay, marl, and quartz sandstone from Rajamandala Formation, (3) breccia and lava from old volcanic deposits, and (4) old volcanic lava deposits. These four lithological units are most prone to landslides in the studied area. The land use factor has an approximately similar susceptibility on the three models. It shows the highest susceptible is in the vicinity of settlement, shrubs, rain-fed rice fields, agricultural areas, and forestry region.

Comparison and Validation

Landslide susceptibility maps were constructed from bivariate statistical analysis using the FR, WofE, and IV models. The LSMs obtained from three models were divided into four zones using the quantile method in ArcGis: very low, low, moderate, and high (Figure 3).

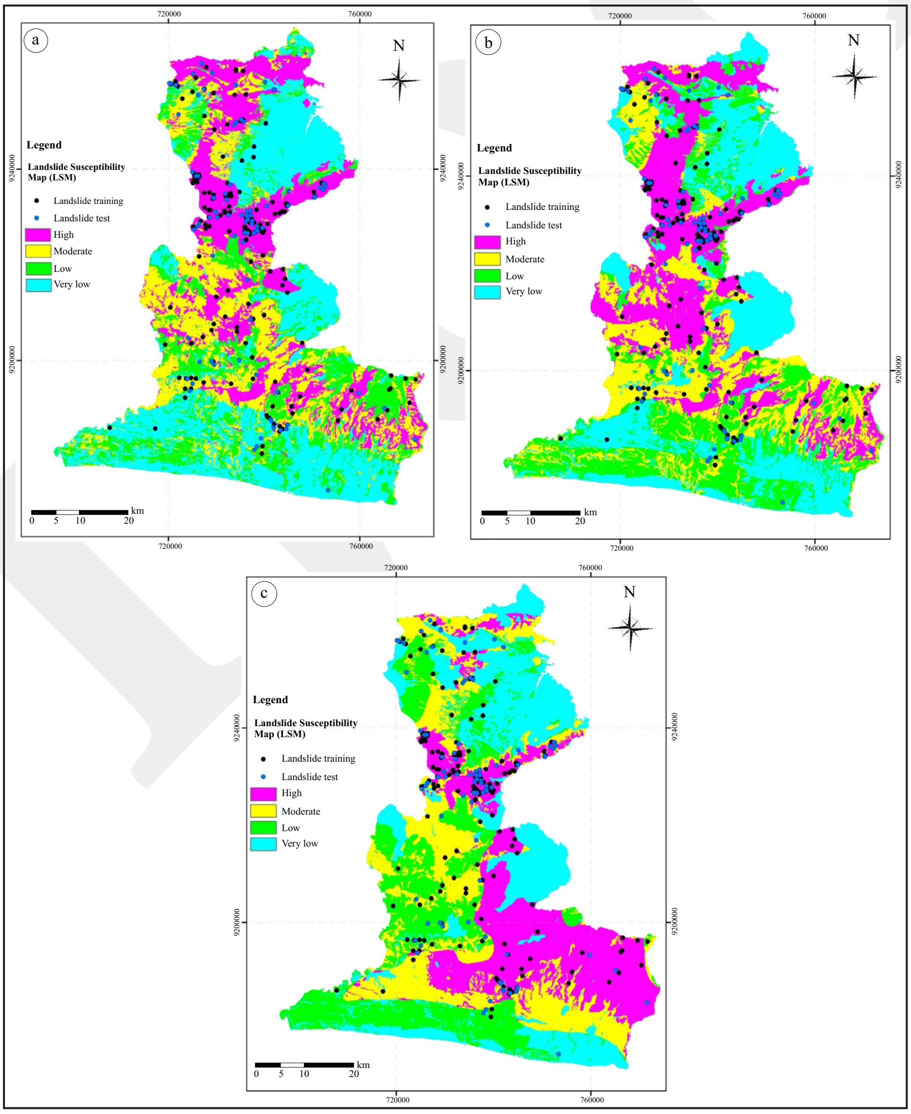

Figure 3. Landslide susceptibility map derived from the models of: (a) FR, (b) WofE, (c) IV.

The areas and the seed cells in the very low, low, moderate, and high in LSM of each models are shown in Table 3. Most of the landslides in the whole studied area with the FR, WofE, and IV models have 85.17 %, 84.69%, and 83.73 % seed cells respectively occuring in areas with susceptibility zones of moderate to high. The three models produced acceptable results as it shows the majority of the seed cells which are in moderate to high susceptibility zones.

Table 3. Densities of Landslides among the Classified Susceptibility Zones of the Three Models

	Zones	Area %	Seed %
FR	Very Low	31.53	8.61
	Low	21.65	6.22
	Moderate	23.06	12.44
	High	23.77	72.73
WofE	Very Low	32.99	8.61
	Low	20.88	6.7
	Moderate	22.46	16.27
	High	23.66	68.42
IV	Very Low	24.91	6.22
	Low	25.07	10.05
	Moderate	24.97	22.49
	High	25.06	61.24

Finally, the AUC of the ROC method was applied in order to reveal which model is more accurate in this study. The AUC was obtained for both the training dataset and the validation dataset (Figure 4). The AUCs value of success rates based on training dataset are 0.92 for the FR model, 0.926 for the WofE model, and 0.93 for the IV. The AUCs value of the prediction rate based on the validation dataset for the FR, WofE, and the IV models are 0.913, 0.912, and 0.895, respectively.

The result for the success rate and prediction rate curve shows that all the three models exhibit a similar performance. The models are found to have an excellent fit to the data with a slight difference where the IV model is the best one with the model accuracy of 93%, followed by WofE with 92.6%, and FR with 92%. It means the IV model produced the most accurate landslide susceptibility map in the studied area. In contrast, the model with the highest prediction ability is FR model with the prediction accuracy of 91.3%, followed by WofE with 91.2%, and IV model with 89.5%. It means the FR model showed the best accuracy in predicting the landslide susceptibility of the studied area.

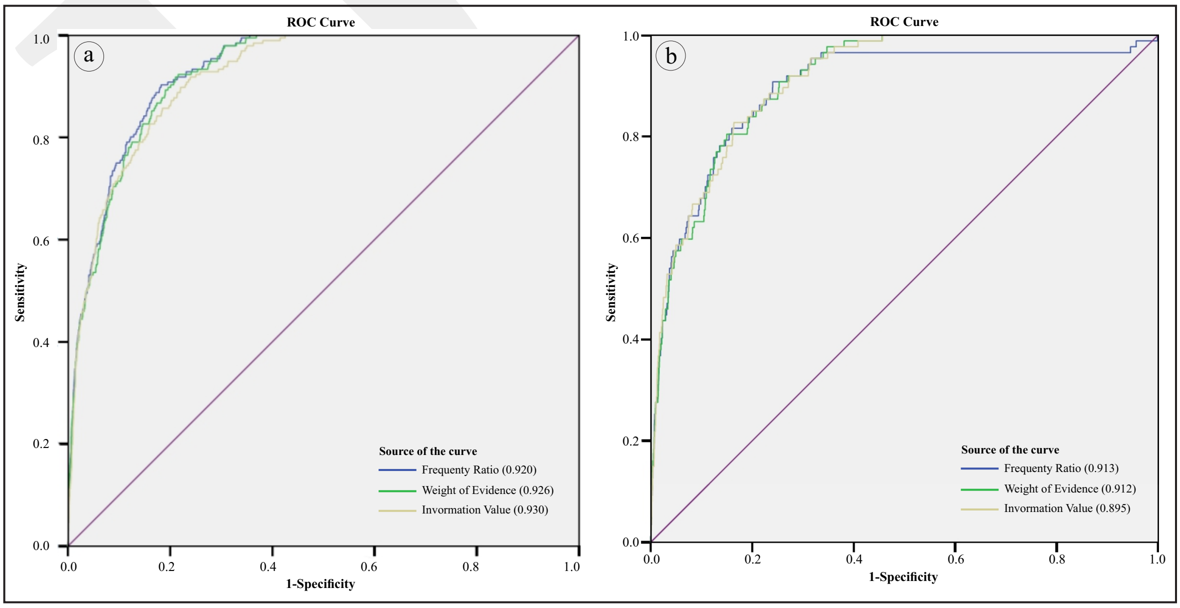

Figure 4. Success rate curve (a) and prediction rate curve (b) for different models by ROC curve.

Conclusions

It is observed in Table 3, that the moderate to high susceptible zones of the LSMs produced by the FR, WofE, and IV model cover 46.83%, 46.12%, and 50.03% of the studied area, respectively. These covered areas are the most landslide-prone regions that should be considered in a susceptibility management. Preferably in the vicinity of settlement, shrubs, rain-fed rice fields, agricultural, and forestry area, with a slope angle between 18° - 33° and the elevation of 500 - 1,000 m a.s.l.

Although this bivariate statistical models, using the term "favourability values" by Chung *et al*. (1995) were applied in the conditioning factors (*e.g*., slope units, litholigical units, etc.) for better values to the expert's opinion, the selection of the models and the landslide related factors was based on a consideration within expert's scientific knowledge. This knowledge-base component was applied for finding the relevance, availability, and scale of data for the studied area.

According to the result given, the success rates and prediction rates of the three models are above 89% (Figure 4). The result reveals that the landslide susceptibility map of each model in this study has succesfully achieved a high degree of reliability. The LSMs of the models will provide spatial-based decision making for the of goverment Cianjur Regency and other associated authorities and agencies.

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