Weight of Evidence Method for Landslide Susceptibility Mapping in Sigi Biromaru, Central Sulawesi,

Imam A. Sadisun\textsuperscript{1,2,3}, Jevon A. Telaumbanua\textsuperscript{2}, Rendy D. Kartiko\textsuperscript{1,2}, Indra A. Dinata\textsuperscript{1}, Pamela\textsuperscript{4}

\textsuperscript{1} Applied Geology Research Group, Faculty of Earth Sciences and Technology, Institut Teknologi Bandung, Indonesia
\textsuperscript{2} Geological Engineering Study Program, Faculty of Earth Sciences and Technology, Institut Teknologi Bandung, Indonesia
\textsuperscript{3} Research Centre for Disaster Mitigation, Institut Teknologi Bandung, Indonesia
\textsuperscript{4} Centre of Volcanology and Geological Disaster Mitigation, Geological Agency, Bandung, Indonesia

*email: jev.albern@gmail.com

Abstract. Sigi Biromaru is an area prone to landslides. This study aims to apply the statistical method of Weight of Evidence (WoE) in landslide susceptibility mapping using Geographic Information Systems (GIS). The 265 landslides that occurred 2009-2019 were randomly divided into two groups, 70\% of the data were used as training dataset for susceptibility modelling and 30\% of the data were used as test data for validation of the susceptibility model. Twenty-one parameters were tested for their influence on landslides. Based on the Area Under Curve (AUC), parameters that significant controlling the landslides are slope gradient, elevation, aspect, flow direction, peak ground acceleration, clay content (<0.002 mm), land cover, terrain ruggedness index (TRI), river density, soil type, lineament density, lithology, rainfall and stream power index (SPI) respectively. The validation results show that the AUC success rate is 0.811 using the training dataset and AUC prediction rate is 0.756 using the test dataset. These results indicate that the WoE method produces a good landslide susceptibility map in the Sigi Biromaru area.

Keywords: Landslide susceptibility, Sigi Biromaru, weight of evidence, area under curve

1. Introduction
Indonesia has a high incidence of landslides. Landslide have claimed many lives and caused serious damage to local community. Sigi Biromaru is a mountainous area prone to landslides. It can bring damage and loss significantly to the surrounding community. To avoid casualties caused by landslides and guarantee the stable development of mountainous areas, it is critical to determine a control and prevention scheme for landslides in this area [1]. A susceptibility maps are beneficial to effectively mitigate the effects of landslide hazard.

Research area is located on medium - high landslide susceptibility zone. The available landslide susceptibility maps are still at provincial scale. A map of landslide susceptibility zones with a detailed scale: sub-catchment scale is required. In this study, a bivariate statistical method called the Weight of Evidence (WoE) was applied to determine landslide susceptibility map to evaluate landslide prone are in more detailed scale than provincial. Numerous research have applied the WoE method in landslide susceptibility mapping [1, 3-10, 14].
2. Location

The research area is located at Sigi Biromaru district, Sigi Regency, Central Sulawesi Province. It is located about 14.5 km at southeast Palu City. Topographically, slopes angles are in the range of 0-140%. Elevations ranges from 206 – 1852 m above sea level. The general trend is high northeast and low in the southeast. The annual rainfall ranges from 1642-2075 mm. The earthquake acceleration ranges from 0.19-0.35 gal. Geologically, this area composed by metamorphic complex, granite-granodiorite igneous rock and marine sediment.

3. Materials and Methods

A landslide inventory includes the locations of the past and recent landslides [2]. In the present study, the landslide inventory map was prepared based on the satellite images (Google Earth and Sentinel 2B) with remote sensing interpretation. A total of 265 landslide in Sigi Biromaru area were recorded into the landslide inventory map. These landslides were randomly selected 186 points (70%) as a training dataset used for building landslide susceptibility model and rest of them were selected 79 points (30%) as a test dataset used for validation of the model.

There are many causative factors that affect the landslide. A total 21 landslide conditioning factors were tested to determine their influence on the landslides. They are slope gradient, aspect, plan curvature, profile curvature, total curvature, elevation, flow direction, terrain ruggedness index (TRI), topographic wetness index (TWI), stream power index (SPI), distance to lineament, distance to river, lineament density, river density, lithology, soil, soil texture, clay content, peak ground acceleration (PGA) and land cover. Landslide inventory and causative factors map were converted into the raster with grid size of spatial resolution 8.3 x 8.3 m.

Weight of Evidence method is the main Bayesian probability system model in linear logic form and uses non-conditional and conditional probabilities [3]. An advantage of Bayesian probabilistic modelling is the possibility of incorporating uncertainty into the susceptibility model and to explicitly consider expert knowledge, which often exists for the investigated area [4]. WoE reveals the spatial association between dependent variable and independent variables [5]. Weights for each landslide predictive factor (B) are calculated based on the presence or absence of landslides (D) within the different classes of a conditioning factor [6]. The WoE is based on the calculation of importance of the presence of causative factors for the occurrence of landslides [1]. It if has a positive value (W+), presence of the factor is favourable for the occurrence of landslides (Eq.1) and if negative (W), it is not favourable (Eq.2). The difference between the two weights is known as the weight contrast (C, Eq.3), which provides a measure of the strength of correlation between the predictable variable and landslides [7]. The WoE formula is as follows:

\[
W^+ = \ln \left( \frac{P(B|A)}{P(B|\bar{A})} \right)
\]  \hspace{1cm} (1)

\[
W^- = \ln \left( \frac{P(\bar{B}|A)}{P(\bar{B}|\bar{A})} \right)
\]  \hspace{1cm} (2)

\[
C = w^+ - w^-
\]  \hspace{1cm} (3)

The WOE model processing steps can be summarized: (I) dividing the landslides data into two datasets, training set (70%) and test set (30%) (8,9,11); (II) dividing each causative factor into multiclass according to spatial distribution and character; (III) calculation of the weight of causative factors with landslides use WoE formula; (IV) verification of causative factors by comparing it with training dataset to get area under curve (AUC) value. AUC represents the how strong the causative factors affect the landslide. The causative factors with AUC value >0.6 is declared have dominant influence on landslide occurrences [10]; (V) addition causative factors weight map which has AUC > 0.6 to get landslide susceptibility map; (VI) validation of landslide susceptibility map using both of training and test dataset to get AUC value. The quantitative–qualitative relationship between AUC and prediction accuracy can be classified as follows: 0.9–1 as excellent, 0.8–0.9 as very good, 0.7–0.8 as good, 0.6–0.7 as average and 0.5–0.6 as poor [11].
4. Results and Discussion

Based on area under curve (AUC) value, fourteen causative factors were declared have dominant influence on landslides occurrences. The AUC value of each causative factors presented Table 1.

Table 1. AUC of 21 causative factors.

| No | Factor                                     | AUC  |
|----|--------------------------------------------|------|
| 1  | Slope Gradient                             | 0.721|
| 2  | Elevation                                  | 0.68 |
| 3  | Aspect                                     | 0.653|
| 4  | Flow Direction                              | 0.652|
| 5  | Peak Ground Acceleration (PGA)              | 0.652|
| 6  | Clay Content                               | 0.639|
| 7  | Land Cover                                 | 0.637|
| 8  | Terrain Ruggenedness Index (TRI)           | 0.616|
| 9  | River Density                              | 0.615|
| 10 | Soil                                       | 0.615|
| 11 | Lineament Density                          | 0.611|
| 12 | Lithology                                  | 0.61 |
| 13 | Rainfall                                   | 0.61 |
| 14 | Stream Power Index (SPI)                   | 0.601|
| 15 | Distance to River                          | 0.558|
| 16 | Topographic Wetness Index (TWI)            | 0.557|
| 17 | Total Curvature                            | 0.554|
| 18 | Distance to Lineament                      | 0.542|
| 19 | Profile Curvature                          | 0.534|
| 20 | Soil Texture                               | 0.509|
| 21 | Plan Curvature                             | 0.504|

Slope gradient, elevation, aspect, flow direction, PGA, clay content, land cover, TRI, river density, soil, lineament density, lithology, rainfall and SPI are then summed up to generate landslide susceptibility index. The landslide susceptibility index is reclassified into four landslide susceptibility zones based on landslide percentage in SNI 8291-2016 [12] (Figure 1). The zonation results are presented in Table 2. Visually, landslide susceptibility map is strongly influenced by slope gradient and lithology.

Table 2. Distribution of landslide susceptibility zonation based on SNI 8291-2016.

| Susceptibility | WoE Value From | Area | % Area | Landslide | % Landslides |
|----------------|---------------|------|--------|-----------|--------------|
| High           | 11430 - 821   | 338966 | 0.19 | 159       | 60           |
| Moderate       | 822 - 3291    | 503866 | 0.28 | 67        | 25           |
| Low            | -3292 - 5961  | 451740 | 0.25 | 26        | 10           |
| Very Low       | -5962 - 23352 | 498872 | 0.28 | 13        | 5            |

Final step is validation of landslide susceptibility map using training and test dataset to get AUC value. The purpose is to measure of the performance of a model [13]. The validation using training dataset is called success rate, used to reveal how well the model works with past landslides. The validation using test dataset is called prediction rate, used to show how well the model can predict unknown upcoming events. [13]. The calculation
shows that AUC of success rate of model is 0.811. This explains that model has very good quality for susceptibility modelling [11]. Meanwhile, the AUC of prediction rate is 0.756 (Figure 2). It explains that model has good quality in predicting the upcoming events. Overall, the model of landslide susceptibility map with Weights of Evidence method is acceptable.

Figure 1. Landslide susceptibility map of Sigi Biromaru area using Weight of Evidence.
Figure 2. Validation of landslide susceptibility map.

5. Conclusion

There are 14 causative factors that used to make landslide susceptibility mapping. The dominant parameter is slope gradient followed by elevation, slope aspect, flow direction, PGA, clay content, land cover, TRI, river density, soil, lineament density, lithology, rainfall and SPI.

All parameters in summed up to generate landslide susceptibility map. After that, the landslide susceptibility is divided into 4 susceptibility zones according to landslide percentage, they are high, medium, low, very low. Validation is needed to know how well of the performance of the model with past landslides and predicting the upcoming events. Based of area under curve (AUC) value, the landslide susceptibility map using Weight of Evidence (WoE) method is good and acceptable because the AUC values exceed the recommended limit. Finally, this model can be used as important consideration for planners, decision makers and engineers.

6. References

[1] Chen, W., Sun, Z., Han, J. 2019 Landslide susceptibility modelling using integrated ensemble weights of evidence with logistic regression and random forest models Machine Learning Techniques Applied to Geoscience Information System and Remote Sensing MDPI 142-167

[2] Mandal, S., Mandal, K. 2018 Bivariate Statistical Index for Landslide Susceptibility Mapping in The Rorachu River Basin of Eastern Sikkim Himalaya, India Spatial Information Research 26 59-75

[3] Dahal, R.K., Hasegawa, S.; Nonomura, A., Yamanaka, M. Masada, T., Nishino, K. 2008 GIS based weights-of-evidence modelling of rainfall-induced landslides in small catchments for landslide susceptibility mapping Environ. Geol. 54 311–324

[4] Chung, C.F., Fabbri, A.G. 1999 Probabilistic prediction models for landslide hazard mapping Photogram Eng. Remote Sens 65 1389–1399

[5] Arabameri, A., Roy, J., Saha, S., Blaschke, T., Ghorbanzadeh, O., Bui, T.D. 2019 Application of probabilistic and machine learning models for groundwater potentially mapping in Damghan sedimentary plain, Iran Remotes Sens. 11 3015

[6] Kayastha, P., Dhital, M. R., De Smidt. F. 2012 Landslide susceptibility mapping using the weight of evidence method in the tinau watershed, Nepal; Nat. Hazards 6 479–498

[7] Weights of evidence method for landslide susceptibility mapping; Prahova Subcarpathians, Romania Nat. Hazards 60 937–950

[8] Torizin, J. 2011 Bivariate statistical methods for landslide susceptibility analysis using ArcGIS. Hannover Project of Technical Cooperation ‘Mitigation of Georisks’, BGR-Report: BGR, unpublished.

[9] Zhou S., Wang W., Chen G., Liu B., Fang L. 2016 A combined weight of evidence and logistic regression method for susceptibility mapping of earthquake-induced landslides: a case study of the April 20, 2013 Lushan Earthquake, China China: Acta Geologica Sinica.

[10] Geological Agency of Indonesia, German Federal Institute for Geosciences and Natural Resources (BGR) 2015 Technical guide: landslides susceptibility analysis with bivariate statistical method using ArcGIS 10.x
[11] Pourghasemi, H.R., Moradi, H.R., Aghda, F.S.M. 2013 Landslide susceptibility mapping by binary logistic regression, analytical hierarchy process, and statistical index models and assessment of their performances *Natural Hazard* 69 749-779

[12] Indonesia National Standard (SNI) 8291 2016 *Preparation and assessment of landslide susceptibility zonation* National Standard Bureau (BSN)

[13] Chung, C. F. dan Fabbri, A. 2003 Validation of spatial prediction models for landslide hazard mapping. Springer. *Natural Hazards* 30 451-472

[14] Wang, Q., Li, Y., Wu, Y., Pei, Y., Xing, M., dan Yang, D. 2016 A comparative study on the landslide susceptibility mapping using evidential belief function and weights of evidence models *Journal of Earth System Science* 125