INTRODUCTION

Landslide susceptibility is defined as a "quantitative or qualitative assessment of the classification, volume (or area), and spatial distribution of landslides which exist or potentially may occur in an area" (Fell et al., 2008). Using scientific analysis of landslides, we can assess and predict landslide susceptibility and decrease landslide damage through proper preparation (Lee et al., 2002).

Landslide susceptibility can be used to identify one or more landslide causes and triggers. The landslide causative factors are the reasons that a landslide occurred at that location and at that time. Several factors such as geomorphological, geological, hydrological and anthropogenic factors in addition to rainfall affect landslides occurrence. Geomorphology factors are elevation, slope, aspect, and curvature. Geology factors are lithology and structure (fault of lineament). Hydrology factors are river and density of the river. Human factor such as land use and road construction.

A few studies have evaluated land use change (LUC) contribution to landslide (Glade, 2003; García-
Ruiz et al., 2010; Mugagga et al., 2012). However, none of these researchers used LUC as a causative factor to build landslide susceptibility. Therefore, LUC will be used as a novel causative factor an anthropogenic factor. Land use change will not affect directly to landslide occurrence in one or two year but will be effect after a few years. For example, change the primary forest to farming area in steep slope, when the clear cutting the tree in primary forest to convert to farming area, in one or two year the stability slope still good, but after a few years when the roots were decay and make hole in soil, then the rainfall fill the hole. It is cause the slope unstable and landslide will occur. Kubota et al. (2007) point out that land with forest cover would reinforce the soil strength and stabilizes the slope due to its root system.

LUC is a process by which human activities transform the landscape. The latest intensification of land use changes has increased the level of susceptibility of landslides, especially in mountainous areas. LUC influences the occurrence of rainfall-induced landslides (Glade, 2003) and LUC can be related to landslide occurrence on a steep slope (Mugagga et al., 2012). LUC influences the occurrence of rainfall-induced landslides (Glade, 2003) and LUC can be related to landslide occurrence on a steep slope (Mugagga et al., 2012)

In South Sulawesi Indonesia, LUC has caused 31 landslide incidents from 2011 to 2015 triggered by the intensity of rainfall (BNPB Indonesia, 2016), especially in upper area of Ujung-Loe watershed. The topography is naturally very steep and mountainous (38.8 % slope class of >20 degrees) and has a very high level of instability, especially during the rainy season (Rainfall : 2,976 to 5,052 g mm/year with average annual rainfall 3,965 mm/year; Meteorology, Climatology, and Geophysical Agency Makassar, 2016). The main occupation of social community in that area is farming in the steep mountainous area. It is hard to avoid this agricultural practice because this has become people’s hereditary for practicing agriculture in the mountainous region. In Indonesia, where many upland areas can be found, land use/cover change due to farming activity commonly occurs (Rudiarto and Doppler, 2013).

The objectives of the study are to examine the effect of land use change in producing landslide susceptibility map to provide a comparative evaluation of the models.
2. STUDY AREA

Upper area of Ujung-Loe Watersheds is located in Bulukumba and Sinjai Regency, South Sulawesi Province, Indonesia. Landslide disasters occur almost every year, especially during the rainy season, which induces flash floods and debris flows in the upstream.

The upper area of Ujung-Loe Watersheds located at 119°55’42.34” E to 120°8’43.12” E and 5°18’19.07” S to 5°24’43.33” S with altitude 255-2, 860 meters above sea level with areas of 79.79 km² (Fig. 1).

South Sulawesi island climate is tropical with certain characteristics of the two seasons of the year: the rainy season and dry season. The northeast monsoon giving raises rainy season between November and July (March to July has the maximum precipitation), and the southwest monsoon causes the dry season from August to October. The annual rainfall data recorded at three stations, i.e., Apparang Hulu station, Malino station and Tanete/Bulo-bulo Station from 2010 to 2015. Rainfall recorded at Apparang Hulu station was 2,976 to 5,052 mm/year with average annual rainfall 3,965 mm/year; Rainfall recorded at Malino station was 3,271 to 5,346 mm/year with average annual rainfall 3,933 mm/year; and recorded at Tanete/bulo-bulo station was 2,237 to 5,711 mm/year with average annual rainfall 3,538 mm/year. The monthly rainfall is more than 400 mm in December and rises to 1,168 mm in July (Meteorological, Climatology, and Geophysical Agency Makassar, 2016).

Due to the increasing intensity of rainfall have been translated to numerous of landslides occurrence in this location. Such as Hasnawir and Kubota (2012) point out that increasing intensity of rainfall will lead to the possibility of landslides occurrence and especially in shallow landslides increased in line with the high-intensity rainfall in a short time.

3. MATERIAL AND METHOD

This research divided into three main stages, i.e., data preparation, data analysis and validation (Fig. 2).

3.1 Preparation of data

In preparation data, Management, collection, and selection must be accurate in establishing a spatial data landslide inventory and a causative factor. This preparation data using GIS tools with ArcGIS® 10.3. For the analysis of the frequency ratio (FR) and the certainty factor (CF) calculation is done by Microsoft Excel®, while for the logistic regression (LR) using the Statistical Package for Social Sciences (SPSS®) software.

3.1.1 Landslide inventory

Inventory of landslides can include field surveys and interpretation of remote sensing images based on spectral characteristics, shape, contrast and morphological expression (Kanungo et al., 2006). This study used landslide events during 2012-2016 to quantitatively evaluate the influences of land use change and landslide occurrences during 2004-2011. Landslides from 2012 to 2016 were collected by using air photography from Google Earth Pro® and ground survey (Fig. 1 and Fig. 3). To identify landslides occurrence by year, we delineated image according to year, started from 2012 until 2016. 188 landslides were identified, covering area of 43.65 hectares (0.44 km²). Most of the landslides are of the shallow type with minimum and maximum landslide area of 137 m² and 15,600 m² respectively. The study area was limited to the upper area of Ujung-Loe Watersheds. Fig. 1 shows the location of all landslide data that were divided into two groups, i.e., landslide for training 2,873 pixels (70%) and a landslide for validation 1,230 pixels (30%). The selection data of training and validation data was using ARG GIS tool by randomly selection.

3.1.2 Landslide causative factors

In landslide susceptibility map, the most important assumption that the incidence of landslides that will occur in the same condition is affected by the cause of the landslides that have occurred. There are no strict guidelines for the selection of causal factors for use in logistic regression analysis and assurance factor analysis, and have been widely used by many studies (Ayalew and Yamagishi, 2005; Dou et al., 2015). Also, the determination of landslide causative factors is heavily reliant on data availability. Therefore, we chose causative factors based on the general knowledge found in previous studies (Rasyid et al., 2016) and data availability in the target area. So according to past research and data availability, we use eleven (11) causative factor i.e., elevation, slope, aspect, curvature, lithology, distance from fault, distance to river, drainage density, precipitation, distance from the road, and land use change (LUC) (Fig. 4).

Causative factor, i.e., elevation, slope, aspect, curvature, were extracted from digital contour data with an interval of 12.5 meters. Digital contour data was derived from RBI (Indonesia Terrain) map with a scale of 1:25,000 from Badan Informasi Geospasial (Geospatial Information Agency). In this study, we used six class of slope i.e. 0-10°, 10-20°, 20-30°, 30-40°, 40-50°, and above 50°, which considered and represented in the form of slope thematic data layer. Likewise, the aspect map plays a significant role in slope stability assessment (Chauhan et al., 2010). Aspect was divided into nine classes.
namely, flat, north, northeast, east, southeast, south, southwest, west, and northwest. Profile curvature was classified into three categories: concave, convex, and flat. The value of the arch represents topographic morphology. In the case of profile curvature, it is generally associated with inundation conditions after heavy rains. Curvature slope profiles contain more water and hold water from high rainfall for longer periods (Lee and Lee, 2006).

The geology data consists of lithology and fault lines. It is related to the strength of the material, because lithologic composition and structure vary for different types of rocks (Kanungo et al., 2006), and resistance to the driving force depends on the strength of rocks. Faults are structural features, which describes the zones/areas of weakness, fractures, and among lineament going higher susceptibility to landslides. It has been observed that the probability increased of landslide occurrence in a location close to faults, and not only affect the surface structure of the material but also contributes to the permeability and cause slope instability (Rasyid et al., 2016). For this purpose, the distance to faults used to analyze the incidence of landslides occurrence. The distance to fault is done by buffering the map of faults.

Distance to river and landslide occurrence in the hilly area have strong association due to erosion process. closer to the river, the soil conditions will be more humid and with soil moisture soil fertility will be high so that the soil bonds are not strong so it will easily occur erosion and landslides, especially during the rainy season. The distance from the river was calculated by buffering the map of river in ARC GIS 10.3. River layer derived from a topographic map of scale 1:25,000. The classification of distance to river starts from 0 to 100 m and ends with >500 m. Similarly, distance from the river, distance from the road also derived from the topographic map by interval 500 m in nine class, and the class starts from 0 to 500 meter and ends with >4000 meters. Moreover, drainage
density calculated by using Arc Toolbox kernel density in \( \text{km/km}^2 \). The class of drainage density classify in five class and start from 0 to 1 \( \text{km/km}^2 \) and ends with >4 \( \text{km/km}^2 \).

In addition to topographic and geological factors, land use change is a key element/factor responsible for landslide events. The incidence of landslides is inversely proportional to the density of vegetation. This research used land use change (LUC) factor as identification of vegetation density. Change in land use to the critical slope triggered a series of shallow and profound landslides (Mugagga et al., 2012). The LUC map derived from overlaid land use 2004 and land use 2011. Land use data was derived from interpretation Landsat 5 TM (date recorded September, 21th 2004) and Landsat 7 ETM+ (date recorded October, 11th 2011) images, each with a 30 m resolution, collected from United States Geological Survey (USGS). The unsupervised classification method is applied to classify land use. The unsupervised classification consists of three steps: 1) Create an N spectral class map using the self-organizing iterative data analysis algorithm; 2) development of land use map (LU) with the aid of reference data; and 3) the accuracy of all LU assessments will validate with reference maps using independent data (Lang et al., 2008). This method is applied to classify land use into seven classes i.e. open area, paddy field, farming area, scrub, savanna, secondary forest and primary forest. LU validated by using ground control points method in the same year of Landsat images, and Google Earth Pro\textsuperscript{®} imagery map was used to measure the accuracy. Accuracy assessment was using random sampling. Overall accuracy values of LU 2004 and LU 2011 were 86% and 90% respectively. Kappa values of 0.83, 0.88 were achieved for the unsupervised classified maps of LU 2004 and LU 2011, respectively. Moreover, LUC built by classifying again LU 2004 and 2011 in four classes i.e. One (open area, paddy field), two (Farming area and Shrub, Savana), three (secondary forest) and fourth (primary forest). Then, overlay each other using ArcGIS\textsuperscript{®} 10.3 and founded 13 classes as a class of LUC. i.e., 1-1 (no change of open area and paddy field), 1-2 (change from open area and paddy field to farming area and scrub, savanna), 2-1 (change from farming area and scrub, savanna to open area and paddy field), 2-2 (no change on farming area and scrub, savanna), 3-1 (change from farming area and scrub, savanna to secondary forest), 3-2 (change from secondary forest to open area and paddy field), 3-3 (no change of secondary forest), 3-4 (change from secondary forest to have similar density of primary forest), 4-1 (change from primary forest to open area and paddy field), 4-2, 4-3 (change from primary forest to secondary forest), and 4-4 (no change on primary forest). LUC in pixel 30 x 30-meter resampled to pixel 10 x 10 meter.

Landslide describes as the dependent variable, and causative factor i.e. elevation, slope, curvature, distance to river, drainage density, lithology, distance to faults, precipitation, LUC and distance to roads describe as the independent variable. Independent variables and the dependent variable was used as a input for analysis landslide susceptibility map with pixel resolution of 10 m \( \times \) 10m. We can see the causative factor map in Fig. 4.
3.2 Data Analysis

Three analyses methods were conducted to produce landslide susceptibility map, i.e., frequency ratio (FR), certainty factor (CF) and logistic regression.

3.2.1 Frequency Ratio

The relationship between the area of the landslide and the causes can be inferred from the relationship between the area where the landslide and non-landslide area with considering the causative factors. Frequency ratios for each causative factor type or range were calculated by dividing the landslide occurrence ratio by the area ratio. If the ratio is bigger than 1.0, the relationship between the landslide and the causative factor is higher, and, if the relationship is less than 1, the relationship between the landslide and each causative factor is low (Lee and Lee, 2006). A ratio value in each class shows the level of relationship the frequency ratio value calculated by the following Eq. 1.

\[
FR = \frac{P_{\text{xcL}(ij)}}{\sum \text{Pixel}(ij)}
\]

Where, \(P_{\text{xcL}(ij)}\) number of pixel with landslide within class i of j parameter, \(\text{Pixel}(ij)\) Number of pixel in class i of j parameter, \(\sum \text{Pixel}\) total pixel of j parameter, and \(\sum \text{Pix}\) total pixel of the area.

3.2.2 Certainty factor

The certainty factor (CF) is a rule-based expert system method developed by (Shortliffe and Buchanan, 1975). The CF values range between \([-1,1]\), where \(-1\) indicates a measure of belief and disbelief and can be calculated using the following function as Eq. 3.

Here, higher CF value indicates higher relationship with landslide occurrences.

\[
\text{CF} = \begin{cases} 
PPa - PPs \quad \text{if} \ PPa \geq PPs \\
PPa(1 - PPs) \quad \text{if} \ PPa < PPs 
\end{cases}
\]

Where; \(PPa\) is the probability of landslides in class and \(PPs\) is the prior probability of a total number of landslides in the study area.

3.2.3 Logistic regression

A simple introduction to logistic regression available in (Chau and Chan, 2005) which defines the probability occurrence of landslides divided by the probability of non-occurrence of landslides. It is useful to predict the presence or absence of a characteristic or outcome based on values of a set of predictor variables. Generally, in the logistic regression, spatial prediction is modeled by the independent variables and the dependent variable (Shirzadi et al., 2012). It is useful when the variable is a binary or dichotomous.

Variables can be continuous, or discrete, or a combination of the two types and they do not always have a normal distribution. The probability of regression can be understood as the probability of a state dependent variables. They are restricted to fall within a range of values from 0 to 1 (Xu et al., 2013) with zero shows probability of 0% landslide occurrences, and one showed a 100% probability (Dai et al., 2004). The logistic regression based on logistic function \(\frac{1}{1+exp^{-z}}\) expressed by the following Eq. 4.

\[
P = \frac{1}{1+exp^{-z}}
\]

Where \(P\) is the probability of landslide occurrence that estimated values vary from 0 to 1. Variable \(Z\) is landslide causative factors and assumed as a linear combination of the causative factors \(x_i (i=1,2,\cdots n)\).

Fixing the sample size to create an equation in logistic regression analysis can be done using an equal number of landslide data and no landslide data to reduce bias in the sampling process. The constant and coefficient of independent variables provided by logistic regression analysis using SPSS (Rasyid et al., 2016).

3.4 Validation and verification

During the modeling predictions, the most important and critical component is to carry out the validation of the results of prediction (Chung and Fabbri, 2003). Data for validation were selected randomly on each part of landslide occurrence with not include in training dataset. To illustrate the procedure, a small portion of the landslide-prone areas selected as the data for validation. Size, area, depth of landslides and distribution significantly varies from place to place. Also, we used the ROC curve to plot predicted probabilities to estimate the model’s accuracy. For validating the landslide susceptibility map, Area under curve (AUC) used as a measure of overall fit and comparison of modeled predictions. The model with higher AUC is considered to be the best. If the area under the AUC is close to 1, the result of the test is excellent. On the other hand, if the model does not predict well, then this value will be close to 0.5. The area determines the success rate AUC of the training data set, and predictable level calculated from the AUC of the validation dataset. ROC curves are used to evaluate the predictive accuracy of the model selected in the statistical approach of dichotomous, such as logistic regression (Gorsevski et al., 2006), and AUC Obtained from the ROC plot statistics most preferred types and influence rating (Akgun et al., 2012). Predicted probabilities generated by logistic regression can be seen as an indicator continuously to compare
| Factor                        | Class | Pixel Class | \% Class | Landslide | % Landslide | Frequency Ratio | PPA     | PPA   | CF   |
|------------------------------|-------|-------------|----------|-----------|-------------|----------------|---------|-------|------|
| Elevation (meter)            |       |             |          |           |             |                |         |       |      |
| 0                            | 10    | 277391      | 34.88    | 233       | 8.11        | 0.23           | 0.00083997 |       |      |      |
| 10–20                        | 20    | 193490      | 24.33    | 504       | 17.54       | 0.72           | 0.000064786 |       |      |      |
| 20–30                        | 30    | 142736      | 17.95    | 519       | 18.06       | 1.01           | 0.000536388 |       |      |      |
| 30–40                        | 40    | 119495      | 14.46    | 613       | 21.34       | 1.48           | 0.000532568 |       |      |      |
| 40–50                        | 50    | 57695       | 7.14     | 819       | 28.51       | 3.99           | 0.001442083 |       |      |      |
| >50                          |       | 9864        | 1.24     | 185       | 6.44        | 5.19           | 0.018760775 |       |      |      |
| Slope (degree)               |       |             |          |           |             |                |         |       |      |
| Carvarature                  | Concave | 335269      | 42.16    | 1,614     | 56.18       | 1.33           | 0.000481404 |       |      |      |
| Convex                       | Flat   | 100826      | 12.68    | 156       | 5.50        | 0.43           | 0.000156703 |       |      |      |
| Aspect                       |       | 359132      | 38.22    | 382       | 13.18       | 0.82           | 0.000365725 |       |      |      |
| Lithology                    | QVb    | 159381      | 24.62    | 0         | 0.00        | 0.00           | 0         |       |      |
| Qv                           | QV     | 562441      | 70.73    | 2,826     | 98.36       | 1.39           | 0.000524527 |       |      |      |
| QvQb                         | QvQv   | 36986      | 5.65     | 47        | 1.64        | 0.35           | 0.000127317 |       |      |      |
| Distance to Faults (meter)   |       |             |          |           |             |                |         |       |      |
| 0–250                        |       | 228372      | 28.20    | 913       | 31.78       | 1.11           | 0.003997663 |       |      |      |
| 2500–5000                    |       | 123498      | 15.53    | 1,333     | 46.40       | 2.99           | 0.010796979 |       |      |      |
| 5000–7500                    |       | 106243      | 13.36    | 472       | 16.43       | 1.23           | 0.004442644 |       |      |      |
| 7500+                        |       | 92127      | 11.58    | 155       | 5.40        | 0.47           | 0.001682464 |       |      |      |
| Drainage Density (km²/m³)    |       |             |          |           |             |                |         |       |      |
| 0–1                          |       | 147677      | 18.57    | 698       | 24.30       | 1.31           | 0.003826666 |       |      |      |
| 1–2                          |       | 228100      | 28.88    | 635       | 22.10       | 0.77           | 0.000278367 |       |      |      |
| 2–3                          |       | 252005      | 31.69    | 829       | 28.85       | 0.91           | 0.001328617 |       |      |      |
| 3–4                          |       | 121675      | 15.30    | 512       | 17.82       | 1.16           | 0.004078964 |       |      |      |
| 4+                           |       | 61765      | 7.86     | 199       | 6.93        | 1.20           | 0.003434792 |       |      |      |
| Precipitation (mm m³/year)   |       | 186406      | 23.44    | 0         | 0.00        | 0.00           | 0         |       |      |
| 3538                         |       | 61646      | 8.77     | 84        | 2.93        | 0.38           | 0.000590709 |       |      |
| 3953                         |       | 547175     | 68.81    | 2,789     | 97.08       | 1.41           | 0.000362619 |       |      |
| 3695                         |       |             |          |           |             |                |         |       |      |
| LUC                          | 1–2   | 167966      | 21.12    | 608       | 21.16       | 1.00           | 0.00361978 |       |      |      |
| 1–2                          |       | 44883      | 5.64     | 276       | 9.61        | 1.70           | 0.000614932 |       |      |      |
| 2–1                          |       | 127015      | 15.97    | 154       | 4.66        | 0.29           | 0.001054994 |       |      |      |
| 2–3                          |       | 140425      | 17.66    | 215       | 7.48        | 0.42           | 0.001531066 |       |      |      |
| 3–1                          |       | 3971       | 0.50     | 0         | 0.07        | 0.14           | 0.000503651 |       |      |      |
| 3–2                          |       | 24542      | 3.09     | 157       | 5.46        | 1.77           | 0.006379179 |       |      |      |
| 3–3                          |       | 88061      | 11.07    | 513       | 17.86       | 1.61           | 0.005825507 |       |      |      |
| 3–4                          |       | 30715      | 3.86     | 158       | 5.50        | 1.42           | 0.001540466 |       |      |      |
| 3–5                          |       | 4602       | 0.58     | 26        | 0.90        | 1.56           | 0.006497181 |       |      |      |
| 4–1                          |       | 954        | 0.12     | 30        | 1.04        | 8.70           | 0.031446541 |       |      |      |
| 4–2                          |       | 19912      | 2.50     | 177       | 5.67        | 2.16           | 0.003888912 |       |      |      |
| 4–3                          |       | 55800      | 7.02     | 180       | 6.27        | 0.89           | 0.003225806 |       |      |      |
| 4–4                          |       | 86381      | 10.86    | 397       | 13.82       | 1.27           | 0.004595918 |       |      |      |

*Total pixel area 795,227 **Landslide Training 2,873

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with a binary response variable observed. In this study, the validation process further demonstrates the level of accuracy of landslide susceptibility map is to calculate the ratio of the data for validation of landslides that falls into each class of vulnerability. It was generally assumed that most of the landslides for validation must occur on a high-class to a higher susceptibility (H + VH).

4. RESULTS AND DISCUSSION

4.1 Frequency ratio

Table 1 indicates a correlation between landslide occurrence and each class of presence and absence landslides inventories between each class of landslide causative factors. In the case of the relationship between landslide occurrence and LUC, LUC from Primary forest to open area and paddy field (4 – 1) has the highest probability of landslide occurrence with frequency ratio 8.70. Moreover, LUC from Primary forest to Farming area, savanna, scrub (4 – 2) with frequency ratio 2.46. It is happening because the vegetation has the effect to the stability of the slope. Land with forest by the root system would reinforce the soil strength and stabilizes the slope (Kubota et al., 2007), and forest clearance seems to have manifested primarily through increased rates of landslide activity (Glade, 2003). Then, in slope class, slope above 20° has a ratio of >1 which indicates a high probability of landslide occurrence. For slope below 20° has a ratio of <1, which indicates a very low probability of landslide occurrence.

In class of elevation 1000 to 2000 meters (m) show the highest correlation with landslide with landslide occurrences. In the class of curvature, the values represent the topographic morphology. A convex indicates a positive value, concave showed negative, and the value of zero indicates a flat surface. In line with frequency ratio values of both concave (1.33) has a probability of landslide occurrence higher than concave (0.85) and flat (0.43). In the case of the class aspect, north, northwest, south and northeast-facing slopes, the frequency ratio >1, which shows a high rate of probability of the occurrence of landslides.

In the case of lithology classes, only Qlv has a ratio of >1 among the three lithology classes, which indicates a high probability of landslide occurrence. Quarter lompoabattang volcanic (Qlv) is one of the volcanic and sediment formation in South Sulawesi area. In this case, the distance of the fault, rivers, and roads, the ratio of the distance/proximity is used to understand the degree of influence on the landslide. Distance from the errors below 7500 m has a ratio >1. It shows that as the distance from the fault decrease, the probability of landslide occurrence increases. Also in the distance from the river below 100 m has frequency ratio >1. In the case of the distance from the road above 500 m has a ratio of >1. In the event of distance from roads, the landslide densities are higher for distance classes far away.

In precipitation class, class precipitation 4.528 mm/year has a ratio >1, which indicates a high probability of landslide occurrence. Moreover, indicated more precipitation would induce more landslide occurrence such as Aditian and Kubota (2017) increasing rainfall rate; it is possible to become unstable and prone to landslide disaster.

To create an index susceptibility to landslides, all maps causative factor in the form of raster maps of the value FR then summed by using Eq. 5.

$$LSI = FR_1 + FR_2 + ... + FR_n$$

Where FR 1, FR 2, FR 3····FRn is the frequency ratio raster maps of landslide causative factors. The index value of frequency ratio falls in the range of 3.34 to 29.66. The higher LSI value showed a higher susceptibility to landslides and if the LSI lower showed lower susceptibility.

4.2 Certainty Factor

Table 1 indicates a correlation between landslide occurrence and each class of presence and absence landslides inventories between each class of landslide causative factors. In the case of the relationship between landslide occurrence and LUC, LUC from Primary forest to open area and paddy field (4 – 1) has the highest belief of probability of landslide occurrence with certainty factor (CF) 0.888. Moreover, LUC from primary forest to Farming area, savanna, scrub (4 – 2) with CF value 0.596. It also same with FR is happening because the vegetation has the effect to the stability of the slope. Then in slope class, slope class above 50°, 40° – 50°, 30° – 40° and class 20° – 30° has a CF value 0.810, 0.752, 0.325 and 0.006 respectively, which indicates a great belief of probability of landslide occurrence. For slope below 20° has a CF value <1, which indicates a very low probability of landslide occurrence.

In Elevation class, Elevation between 1000 to 2000 meters (m) stated belief to the likelihood of landslide occurrence. In curvature class, only concave has a conviction of probability of landslide occurrence with CF value 0.250. In the case of aspect class, the north, northwest, south and northeast facing slopes, CF value is >0, which indicates belief to the probability of landslide occurrence.

In the case of lithology classes, only Qlv has a ratio of >0 among the three lithology classes, which indicates a belief of probability of landslide occurrence.
In the case of the distance from the fault, rivers, and roads used to understand the ratio of the distance/proximity to the level of influence on the landslide. Distance from fault below 7500 m has a ratio of >0. It shows that as the distance from the fault decreases, there is a belief of probability of landslide occurrence increases. Also in the distance from the river below 100 m has CF value >0. In the case of the distance from the road above 500 m has a CF value >1. In the event of distance from roads, the landslide densities are higher for distance classes far away, and its meaning distance to the road is not to effect to the landslide in this case. In precipitation class, only in class precipitation 4528 mm/year has a CF >0, which indicates a belief of probability of landslide occurrence. This increasing rainfall rate, it is possible for many forest slopes to become unstable and prone to landslide disaster shortly (Aditian and Kubota, 2017).

Landslide susceptibility index created by combined pairwise layer according to the integration rules (Pourghasemi et al., 2013). The combination of CF values of two thematic layers 'Z' is expressed by the following equation as given by Binaghi et al. (1998) as Eq. 6.

$$z = \begin{cases} 
CF_1 + CF_2 & \text{if } CF_1, CF_2 \geq 0 \\
1 - \min \left( \frac{CF_1, CF_2}{C_{fes-a}} \right) & \text{if } 0 < CF_1, CF_2 < 1 \\
1 - \min \left( \frac{CF_1, CF_2}{C_{fes-a}} \right) & \text{if } CF_1, CF_2, \text{opposite signs} \geq 0 
\end{cases}$$

(6)

The certainty factor values are computed by overlaying each thematic layer with the landslide map and calculate the landslide frequencies. Each thematic layer is reclassified according to the certainty factor value calculated and is combined pairwise to generate the landslide susceptibility map using the integration rule of Eq. 6. Table 2 illustrates the integration using a parallel combination.

### 4.3 Logistic regression

Hence, this study proposes ten iterations (Table 3). Ten interations for logistic regression analysis will obtain the best result and sense of fairness with equal data between the landslide and non-landslide data such as Rasyid et. Al. (2016). Logistic regression method was conducted to compute the landslide occurrence probability, and if values are closer to one, landslides are more likely to occur. Land use change as a new causative factor for value was the distance to the river with 2.837 that shows the distance to the river has the highest effect on landslide occurrence. Moreover, the lowest value was the distance to the road with -0.148, that indicates this causative factor is not influential in landslide occurrences. Moreover, according to likelihood ratio test LR indicates Slope was the highest affected to landslide occurrence with chi-square value 417.299 and LUC on 5th place from eleven causative factor, after distance to river, distance to faults and aspect with value 85.065 (Table 4).

### 4.4 Validation

Table 5 shows results of AUC curve for both success rate and predictive rate for each test. In general, the AUC of ROC curves representing excellent, good, and missing values tests were plotted on the graph. The classify the accuracy of a diagnostic test i.e.

### Table 2

| No | CF\(_e\) | CF\(_s\) | CF\(_{es}\) | CF\(_a\) | C\(_{fes-a}\) |
|----|--------|--------|-----------|--------|-----------|
| 1  | 0.660  | 0.320  | 0.728     | 0.110  | 0.758     |
| 2  | 0.220  | -0.280 | -0.077    | -0.440 | -0.483    |
| 3  | 0.340  | -0.280 | 0.083     | 0.110  | 0.184     |
| 4  | -0.100 | -0.770 | -0.793    | 0.110  | -0.767    |
| 5  | 0.220  | 0.750  | 0.805     | -0.660 | 0.426     |
| 6  | 0.220  | 0.010  | 0.228     | -0.440 | -0.275    |

CF\(_e\): Certainty factor value for elevation; CF\(_s\): Certainty factor value for slope; CF\(_{es}\): Combined certainty factor value of elevation and slope after integration for the various combination; CF\(_a\): Combined certainty factor value combination of elevation-slope and aspect after integration for the various combination.

### Table 3

| Number | Test | Elevation | Slope | Aspect | Curvature | Lithology | Distance to Faults | Distance to Drainage Density | Distance to River | Precipitation | Distance to Road | LUC | Constant |
|--------|-----|-----------|-------|--------|-----------|-----------|-------------------|-----------------------------|-----------------|--------------|----------------|-----|----------|
| 1      | 0.261 | 0.593     | 0.571 | 0.429  | 1.453     | 0.469     | 0.977             | 2.84                        | 0.597           | 0.168        | 0.378          | -9.97 |
| 2      | 0.248 | 0.574     | 0.576 | 0.408  | 1.37      | 0.457     | 0.653             | 2.989                       | 0.839           | -0.164       | 0.57           | -10.175 |
| 3      | 0.195 | 0.503     | 0.525 | 0.503  | 1.439     | 0.573     | 0.862             | 3.05                        | 0.749           | -0.162       | 0.661          | -10.661 |
| 4      | 0.401 | 0.554     | 0.526 | 0.445  | 1.219     | 0.489     | 0.794             | 2.632                       | 0.722           | -0.187       | 0.623          | -9.825 |
| 5      | 0.351 | 0.561     | 0.498 | 0.634  | 1.535     | 0.483     | 0.901             | 2.624                       | 0.638           | -0.183       | 0.441          | -10.126 |
| 6      | 0.22  | 0.617     | 0.513 | 0.554  | 1.374     | 0.491     | 0.786             | 2.92                        | 0.708           | -0.143       | 0.596          | -10.275 |
| 7      | 0.332 | 0.548     | 0.501 | 0.449  | 1.184     | 0.52      | 1.031             | 2.837                       | 0.754           | -0.148       | 0.589          | -10.175 |
| 8      | 0.314 | 0.538     | 0.507 | 0.473  | 1.167     | 0.546     | 0.684             | 2.647                       | 0.801           | -0.185       | 0.479          | -9.561 |
| 9      | 0.383 | 0.572     | 0.568 | 0.379  | 1.235     | 0.5       | 0.733             | 2.738                       | 0.644           | -0.201       | 0.539          | -9.674 |
| 10     | 0.312 | 0.545     | 0.478 | 0.539  | 1.212     | 0.484     | 0.97              | 2.775                       | 0.76            | -0.083       | 0.502          | -10.088 |
the value ranges from 0.50 to 0.60 (fail), 0.60-0.70 (poor), 0.70-0.80 (fair), 0.80-0.90 (good), and 0.90-1.00 (excellent) (Rasyid et al., 2016). The results show that the entire test of FR, CF and LR methods fall into the good category because the value ranges from 0.828 to 0.857 in success rate and 0.827 to 0.856 in predictive rate. Moreover, success rate and predictive rate value for all method were a closeness with interval 0.01 that indicates all the method more reliable to a predictive landslide in the future. The closeness of success rate and predictive rate values show how the method helps in landslide prediction in the future (Meten et al., 2015).

In this study, LR method conducts one more validation to choose the best statistical model for creating landslide susceptibility map and the best equation in logistic regression approach from the ten tests. The sum of FR value and equation of the LR models were used to create landslide susceptibility map (LSM). Moreover, for CF by using Eq.(6) to create landslide susceptibility map (LSM). All LSM class creates by reclassifying LSI of the models using natural breaks method and overlaid landslide data validation on LSM will describe another level of accuracy beside AUC curve. The natural breaks method or Jenks optimization method has been used widely especially by planners, and it is designed to determine the best arrangement of values into different classes. This approach maximizes the variance between classes and reduces the variance within classes. The five classes include very low, low, moderate, high and very high describing the level of landslide susceptibility (proneness) in the study area. The level of accuracy of the landslide susceptibility map was verified by overlying with the landslide data for validation. Table 5 shows the results of overlaid landslide data for validation on LSM. LR method 7th iterations ratio (0.857) in AUC success rate were better than the ratio of FR (0.828) and CF (0.831), which shows that LR model is better of a model of identifying landslide. In predictive rate, LR method 7th iterations ratio was also better than the ratio of FR (0.827) and CF (0.830), which shows that LR model is better to predict of landslide occurrence. On the other hand, validation with the percentage of landslide fall into L5M class high and very high, CF model (85.28%) was better than the percentage of FR (81.46%) and LR model (82.1%). The curve of the

| Causative Factor               | Likelihood Ratio Tests | Chi-Square |
|-------------------------------|------------------------|------------|
| Slope                         | 417.229                |            |
| Distance to River             | 291.508                |            |
| Distance to Faults            | 164.011                |            |
| Aspect                        | 128.522                |            |
| LUC                           | 85.065                 |            |
| Lithology                     | 53.832                 |            |
| Drainage Density              | 35.265                 |            |
| Precipitation                 | 27.894                 |            |
| Elevation                     | 22.557                 |            |
| Curvature                     | 13.895                 |            |
| Distance to Road              | 7.405                  |            |

Tabel 5 landslide had value 0.589 (7th iteration) that indicates have the effect of landslide occurrence. The highest AUC of ROC curve of success and predictive rate of landslide validation on landslide susceptibility map using FR, CF and LR Method

| Method          | FR  | CF  | LR  |
|-----------------|-----|-----|-----|
|                 | 1   | 2   | 3   |
|                 | 4   | 5   | 6   |
|                 | 7   | 8   | 9   |
|                 | 10  |     |     |
| AUC Success rate| 0.828| 0.831| 0.857|
|                 | 0.857| 0.857| 0.856|
|                 | 0.856| 0.857| 0.857|
|                 | 0.857| 0.857| 0.857|
|                 | 0.857| 0.857| 0.857|
|                 | 0.857| 0.857| 0.857|
| AUC Predictive rate| 0.827| 0.83| 0.855|
|                 | 0.856| 0.856| 0.856|
|                 | 0.856| 0.855| 0.856|
|                 | 0.856| 0.855| 0.855|
|                 | 0.856| 0.855| 0.856|
|                 | 0.856| 0.855| 0.856|
| H+VII (%)       | 81.46| 82.5| 81.63|
|                 | 82.03| 80.98| 72.85|
|                 | 81.87| 80.73| 82.11|
|                 | 80.65| 80.57| 79.59|

Table 6 The Characteristic of susceptibility classes on landslide susceptibility map using FR, CF, and LR method

| Class Number | Reclassified index value | Susceptibility class | Number of pixels | % area covered | Number of landslide validation pixel | % area of landslide validation covered |
|--------------|--------------------------|----------------------|------------------|---------------|-------------------------------------|---------------------------------------|
| Frequency Ratio |                          |                      |                  |               |                                     |                                       |
| 1            | 3.34 - 7.16              | Very Low             | 177234           | 22.29         | 0                                    | 0.60                                  |
| 2            | 7.16 - 19.36             | Low                  | 143392           | 18.03         | 8                                    | 0.65                                  |
| 3            | 10.36 - 13.04            | Moderate             | 201593           | 25.35         | 220                                  | 17.89                                 |
| 4            | 13.04 - 16.14            | High                 | 188458           | 23.70         | 428                                  | 34.80                                 |
| 5            | 16.14 - 29.66            | Very High            | 84550            | 10.63         | 574                                  | 46.67                                 |
| Certainty Factor |                      |                      |                  |               |                                     |                                       |
| 1            | -1 - 0.7647              | Very Low             | 369510           | 46.47         | 31                                   | 2.52                                  |
| 2            | -0.7647 - -0.2785        | Low                  | 75038            | 9.44          | 70                                   | 5.69                                  |
| 3            | -0.2785 - -0.2626        | Moderate             | 48592            | 6.11          | 80                                   | 6.50                                  |
| 4            | 0.2626 - 0.7096          | High                 | 80360            | 10.11         | 148                                  | 12.03                                 |
| 5            | 0.7096 - 0.9997          | Very High            | 221727           | 27.88         | 901                                  | 73.25                                 |

Logistic Regression

| Class Number | Reclassified index value | Susceptibility class | Number of pixels | % area covered | Number of landslide validation pixel | % area of landslide validation covered |
|--------------|--------------------------|----------------------|------------------|---------------|-------------------------------------|---------------------------------------|
| 1            | 0.0011 - 0.1186          | Very Low             | 282841           | 35.57         | 4                                    | 0.33                                  |
| 2            | 0.1186 - 0.3026          | Low                  | 163178           | 20.52         | 43                                   | 3.50                                  |
| 3            | 0.3026 - 0.5063          | Moderate             | 138129           | 17.37         | 173                                  | 14.07                                 |
| 4            | 0.5063 - 0.7216          | High                 | 114794           | 14.44         | 336                                  | 27.32                                 |
| 5            | 0.7216 - 0.9997          | Very High            | 96285            | 12.11         | 674                                  | 54.80                                 |
model and validation proves that the susceptibility model is acceptable and the model could be applied to predict the potential landslides in future. As an interesting point to be noticed in Table 6, the seventh tests for LR have a good result in AUC curve, which is 0.857 in success rate and 0.856 in predictive rate.

**Fig. 5** shows the landslide susceptibility map using FR, CF and LR method 7th iterations. The LSM by LR model was obtained using the coefficient values of landslide causative factors as in the equation below:

\[
Z = -10.175 + 0.332 \text{Elevation} + 0.548 \text{Slope} + 0.501 \text{Aspect} + 0.449 \text{Curvature} + 1.184 \text{Lithology} + 0.52 \text{faults} + 1.031 \text{Drainage density} + 2.837 \text{Distance to River} + 0.734 \text{Precipitation} - 0.148 \text{Distance to Roads} + 0.589 \text{LUC}
\]

The ranges of the index value of each model in five classes were established using natural breaks method. Can et al. (2005) and Bai et al. (2010) stated two important guidance for validating landslide susceptibility map i.e. 1) the high to very high class should cover only small areas and 2) landslide data validation should lie in high or very high classes.
Table 5 shows the characteristics of susceptibility class for FR, CF and LR models. It indicates that the ratio of high to very high susceptibility class covers a small area. The ratio generated by dividing the number of pixels in each class on LSM to the total number of pixels. Furthermore, the ratio of landslide data for validation that fall on the LSM has high value on high to very high class compared to very low to low class. The ratio calculated by dividing the number of a landslide for validation pixels, which lies on each susceptibility class to the total number of a landslide for validation pixels. This method is similar to FR, and CF model or the density method. In general, the procedure of creating landslide susceptibility map begins with the use of data of landslide occurrence as the dependent variable and landslide causative factors as the independent variable. Logically, landslide data covers a small area and occasionally in the form of scattered areas in the entire study area. The accuracy of the predicted future landslide that laid on the LSM should have a lower ratio in the class of low to very low class and higher in the high to very high class (Rasyid et al., 2016). Fig. 6 shows, the ratio of the area with the classification of low to very low grade in LSM from FR, CF, and LR models have a total average of more than 40% of the total area, and the data validation landslide that fell on the class shows the ratio below 10%. Also, the proportion of the area with the classification of high to very high grade in landslide susceptibility map from FR, CF, and LR model has a total average of more than 40% of the total area, and the data validation landslide that fell on the class shows the ratio of 80%. The highest values were 85, 38% in the CF model. It indicates that the CF are better than others for validation by LSM with the landslide at high and very high-class.

5. CONCLUSIONS

In conclusion, by using land use change (LUC) as a novel causative factor to produce landslide susceptibility map, LUC is influential in the creation of LSM. It can be inferred from the results of FR and CF, LUC has the highest value on both at LUC from primary forest to open area and paddy field. However, in logistic regression method, LUC has on 5th place from eleven causative factor, according to likelihood ratio test with chi-square value 85.065 after Slope, distance to river, distance to faults and aspect. This research comparatively evaluates the performance of Frequency Ratio (FR), Certainty Factor (CF) and Logistic Regression (LR) models as well. Two step of validation were carried out in this study. First, performances of each landslide model were tested using AUC curve for success and predictive rate, which is more than 82% with the highest at LR Model. In the second, the ratio of landslides falling on high to a very high class of susceptibility was obtained, which indicates the level of accuracy of the model. In the CF model have highest accuracy with 85.28% landslides fall in the range of high to very high class while in LR and FR model, it is 82.11% and 81.46%. By the two-step of validation that LR shows highest accuracy in step 1 and CF show the highest in step 2. Moreover, it is better that we combine the usage of LR for causative factor optimization and CF for making susceptibility map.

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