J. Mt. Sci. (2015) 12(3): 721-736 e-mail: jms@imde.ac.cn http://jms.imde.ac.cn
DOI: 10.1007/s11629-014-3416-3

# Landslide Susceptibility Mapping by Using Landslide Ratio-Based Logistic Regression: A Case Study in the Southern Taiwan

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**Citation:** Wu Chun-hung (2015) Landslide susceptibility mapping by using landslide ratio-based logistic regression: a case study in the Southern Taiwan. Journal of Mountain Science 12(3). DOI: 10.1007/s11629-014-3416-3



**Abstract:** The object of the research is to compare the model performance and explain the error source of original logistic regression landslide susceptibility model (abbreviated as or-LRLSM) and landslide ratio-based logistic regression landslide susceptibility model (abbreviated as lr-LRLSM) in the Chishan watershed with a serious landslide disaster after 2009 Typhoon Morakot. The landslide inventory induced by 2009 Typhoon Morakot in South Taiwan is the main research material, while the Chishan watershed is the research area. Six variables, including elevation, slope, aspect, geological formation, accumulated rainfall, and bank erosion, were included in the two models. The performance of lr-LRLSM is better than that of or-LRLSM. The Cox & Snell $R^2$, Nagelkerke $R^2$ value, and the area under the relative operating characteristic curve (abbreviated as AUC) of lr-LRLSM is larger than those of or-LRLSM, and the average correct ratio for the lr-LRLSM to predict landslide or non-landslide is larger than that of or-LRLSM by 5.0%. The increase of the average correct ratio (abbreviated as ACR) difference from or-LRLSM to lr-LRLSM shows in slope, revised accumulated rainfall, aspect, geological formation and bank erosion variables, and only light decreases in elevation variable. The error sources of continuous variables in building the or-LRLSM is the dissimilarity between the distribution of landslide ratio and production of coefficient and characteristic values, while those of categorical variables is due to low correlation of landslide ratio and the coefficient value of each parameter. Using the classification of landslide ratio as the database to build logistic regression landslide susceptibility model (abbreviated as LRLSM) can revise the errors. The comparison of or-LRLSM and lr-LRLSM in the Chishan watershed also shows that building the landslide susceptibility model (abbreviated as LSM) by using lr-LRLSM is practical and of better performance than that by using the or-LRLSM.

**Key words:** Logistic regression; Landslide susceptibility; Landslide ratio; Chishan watershed; Typhoon Morakot

## Introduction

Rainfall- or earthquake-induced landslide is the frequently occurred sediment-related disaster in Taiwan. The following decade after 1999 Chichi earthquake ($M_L$=7.3) is the decade with the most serious rainfall-triggered sediment-related disasters in the history of Taiwan. Several serious sediment-related disaster events occurred in this decade, including the disaster events induced by 2001 Typhoon Toraji (Wu and Chen 2009), 2004 Typhoon Mindulle, and 2009 Typhoon Morakot (Wu et al. 2011). The shaking effect due to the strong earthquake in 1999 and the following frequent and heavy rainfall events with high

**Received:** 16 December 2014
**Accepted:** 30 March 2015

rainfall intensity (Shiu et al. 2009) are the main reasons to turn the environment into high proneness to landslide or debris flow. The frequent sediment-related disaster events also make landslide modeling (Keijsersa et al. 2011) or landslide susceptibility assessment researches (Lee et al. 2008; Wu and Chen 2009) popular in Taiwan.

Logistic regression is also used in the landslide susceptibility assessment model for earthquake-triggered events or heavy-rainfall events in Taiwan or other countries (Chang et al. 2007; Lee et al. 2008; Lee and Fei 2014; Su et al. 2010; von Ruette et al. 2011). Most researches in building the LRLSM divide the landslide factors into continuous variable and categorical variable (Chang et al. 2007; Su et al. 2010; von Ruette et al. 2011; Lee and Fei 2014). Chang et al. (2007), for example, classifies eight variables, including elevation, slope, aspect, distance to fault line, distance to channel, distance to ridge line, the NDVI (normalized difference vegetation index), and the wetness index, into continuous category, and the other four variables, including surface shape, lithology, order of sub-basin and road buffer, into categorical category. The distribution of landslide susceptibility can be drawn by using the fitting equation of the independent variable (landslide or not) and dependent variables (the above-mentioned landslide factors) from the logistic regression analysis. Most researches in building the LRLSM have good prediction performance, i.e. ROC (relative operating characteristic; Pontius and Batchu 2003) or AUC ≧ 0.7 (Chang et al. 2007; von Ruette et al. 2011; Lee and Fei 2014). Furthermore, most researches proved that the performance of LRLSM in Taiwan is good, but few researches have built the LRLSM for the disaster induced by 2009 Typhoon Morakot which was an extreme rainfall event with the return period of over 200 years (Wu et al. 2011). That is the reason why the research adopts logistic regression method to build the LSM for the landslide disaster in the Chishan watershed, i.e. a watershed in Southwest Taiwan with the most serious landslide disaster after 2009 Typhoon Morakot.

Landslide ratio, also named as frequency ratio (Yilmaz 2009), is the ratio of landslide area to total area in the specific area and an useful index to evaluate the seriousness of landslide disaster in Taiwan (Wu et al. 2011). Based on the experience from the past disasters in Taiwan, if a rainfall event causes the landslide ratio exceeding 1.0%, serious disaster events will occur in the watershed. Yilmaz (2009) proved that building the LRLSM based on landslide ratio is practicable. The object of the research is to build the LRLSM based on landslide ratio, compare the model performance and explain the error source of the lr-LRLSM with the or-LRLSM. Although most LRLSMs have good performance, can we promote the performance of LRLSM? The research analyzes in detail the error source of or-LRLSM and explains how the errors are revised in the lr-LRLSM. Furthermore, the research also analyzes in detail the error in each variable and each landslide classification area. The research adopted the landside inventory induced by 2009 Typhoon Morakot in the Chishan watershed in Southern Taiwan. The landslide disaster event in the Chishan watershed after 2009 Typhoon Morakot is the most serious event in the last decade (Wu et al. 2011). In the research, we also discuss the performance of or- and lr-LRLSMs in the high landslide ratio areas, i.e. serious disaster areas.

## 1 Study Area and Landslide Inventory

### 1.1 Study area

The Chishan watershed (Figure 1) is located in the upstream basin of the Kaoping river watershed in southwestern Taiwan. The main stream length and drainage area of the Chishan river is around 117 km and 819 km$^2$, respectively. The elevation of the Chishan watershed ranges from 26 m to 3,940 m with a mean value of 838 m, while the slope ranges from 0° to 79° with a mean value of 22.4°. The area with the elevation < 1000 m, 1000 m to 2000 m, and > 2000 m occupies around 64%, 19.4%, and 11.1% of the total watershed area, respectively. And the area with the slope < 20°, 20° to 50°, and > 50° occupies around 42.3%, 55%, and 2.4% of the total watershed area, respectively. The occupied percentage of each aspect, except flat aspect, in the Chishan watershed ranges from 8.6% (northeast aspect) to 15.5% (west aspect).

The climate of Chishan watershed belongs to tropical with the average annual temperature of 24.2°C. The average annual rainfall is around 4468 mm based on the rainfall records provided by the Jiaxian rainfall station (black circle in Figure 1a) with 58 years rainfall records. The monthly rainfall does not distribute uniformly in time. The average rainfall in the rainy season (from May to October) is around 3820 mm (85.5% of the average annual rainfall), while that in the dry season (from November to April) is only 648 mm. Most landslide

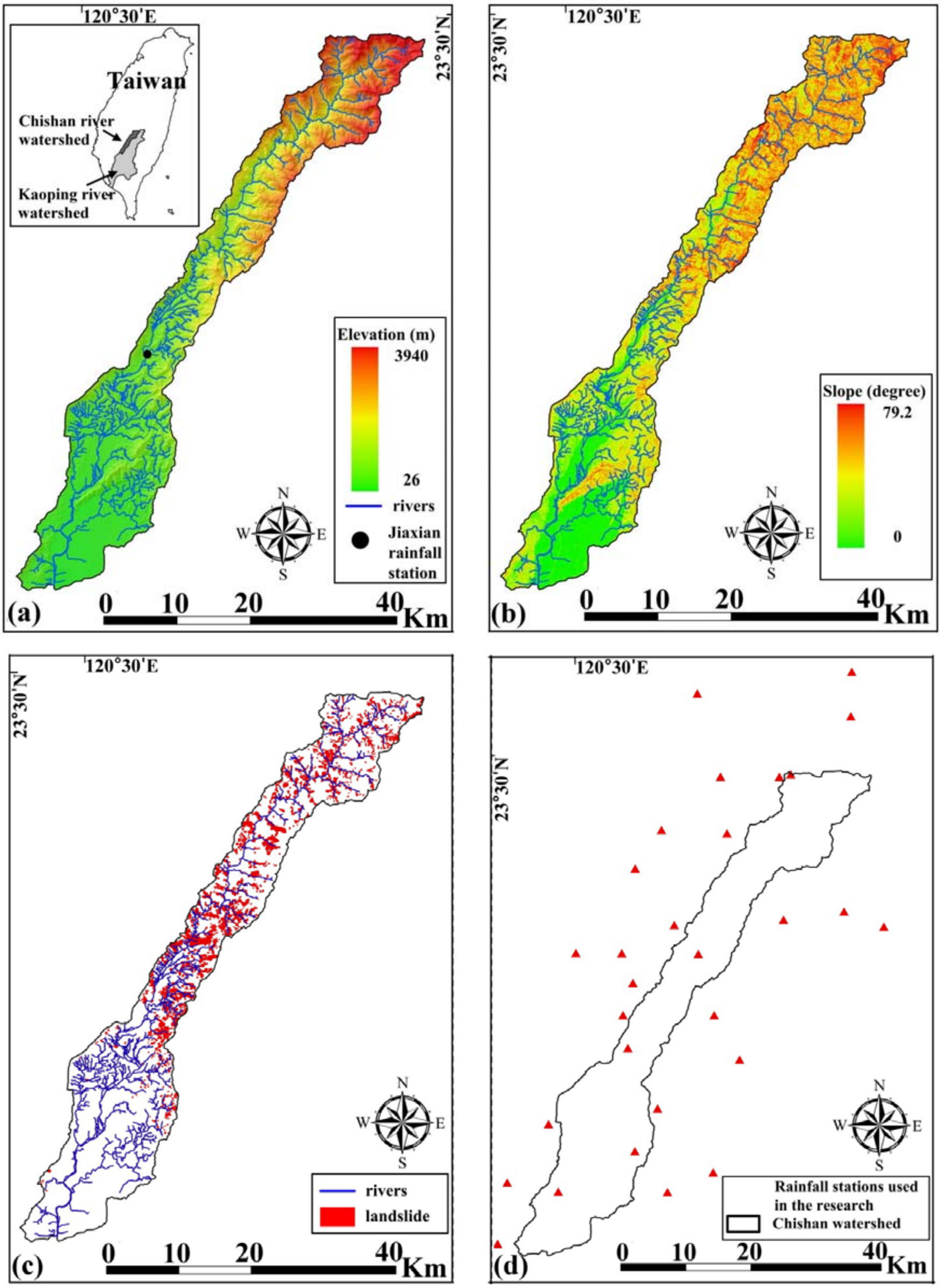


**Figure 1** The distribution of elevation (a), slope (b), landslide induced by 2009 Typhoon Morakot (c), and 30 rainfall stations used in the research (d), in the Chishan watershed (at different scale).

events were induced by typhoons or rainstorms with the accumulated rainfall > 1000 mm.

The geologic map of Chishan watershed (scale: 1: 50,000) is shown in Figure 2. The three geological formations with the largest occupied area in the Chishan watershed are the Changchihkeng formation (occupied 26.2% of the watershed area, and the lithology is alternations of sandstone and shale), the alluvium (occupied 17.8% of the watershed area, and the lithology is gravel, sand and clay), and the Nankang formation (occupied 17.8% of the watershed area, and the lithology is augillite or slate).

### 1.2 Serious landslide disaster after 2009 Typhoon Morakot

The Kaoping river watershed is a mountainous river watershed with high suspended sediment discharge of around $3.6 \times 10^7$ MT (ranks 11th in the world, Liu et al. 2002) and high sediment yield of around 5.9 kg/m$^2$/yr (around 2 times larger than that of global mountainous rivers, Milliman and Syvitski 1992; Hung and Hung 2003). Typhoon Morakot struck Taiwan during Aug. 6-10, 2009, and dumped over 2000 mm of rainfall (Figure 3, around 45% of the average annual rainfall) in the Kaoping river watershed in only 3 days (Aug. 8-10, 2009). The 2009 Typhoon Morakot induced a serious landslide disaster in the Kaoping river watershed, including the Chishan watershed. The return period of the rainfall records from Jiaxian Station during 2009 Typhoon Morakot is well over 200 year. The largest accumulated rainfall of Jiaxian rainfall station during 2009 Typhoon Morakot recorded as 1040 mm in 24 hrs, 1614 mm in 48hrs, and 1915 mm in 72 hrs (Wu et al. 2011). The research adopted the landslide inventory which was extracted from SPOT 5 images with the resolution of 2.5 m after 2009 Typhoon Morakot by Central Geological Survey (2009). The landslide inventory was extracted from SPOT image by using NDVI index, and additional field survey proceeded in some landslide-unrecognizable units. The main landslide types included in the landslide inventory are falls and slides, i.e. the most common rainfall-induced landslide types in Taiwan, based on the landslide classification suggested by Varnes (1978).

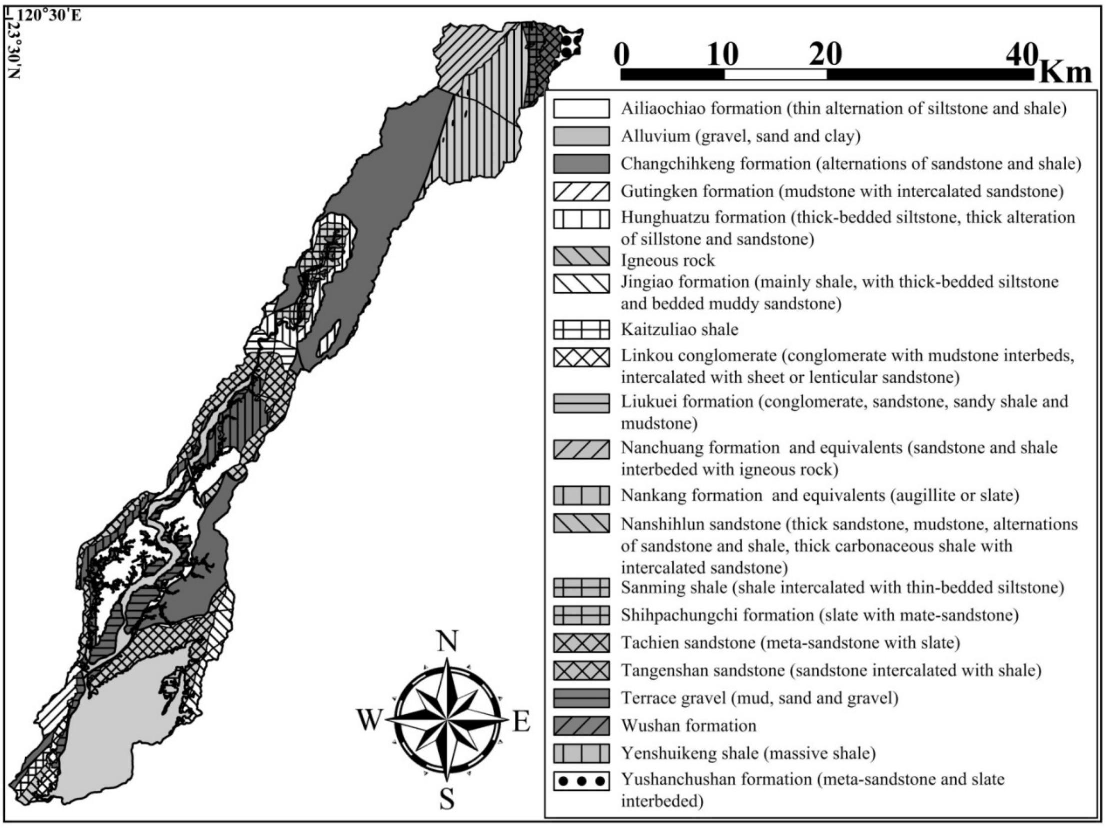


**Figure 2** The distribution of geological formation in the Chishan watershed.

A small portion of landslide cases (< 1% of the count of total landslide cases) in the landslide inventory which maybe belonged to "flows" landslide types were not deleted by the research because these cases usually occurred along the rivers or torrents and were hard to be recognized as flows or bank-erosion falls. Finally, 2061 landslide cases with a total landslide area of 33.9 km² (Figure 1c and Table 1) were induced by the heavy rainfall during 2009 Typhoon Morakot in the Chishan watershed. The landslide ratio in Kaoping river watershed, for example, is 5.5% and over 500 deaths were claimed in this watershed. The landslide ratio (4.1%) after 2009 Typhoon Morakot in the Chishan watershed also hit a historical record high.

## 2 Methods

### 2.1 Logistic regression

Good model performances (Chang et al. 2007; Lee et al. 2008; von Ruette et al. 2011) coupled with a strong reliability even when multiple replicates are modelled (Felicisimo et al. 2013; Lombardo et al. 2014) represent the primary reasons supporting the widespread use of logistic regression in assessing landslide susceptibility. In the first step in building the LRLSM, the research area is classified into numerous squared mapping units marked as a function of landslide presence or absence. All the selected variables are classified into continuous and categorical variables by using the logistic regression. The characteristic value of

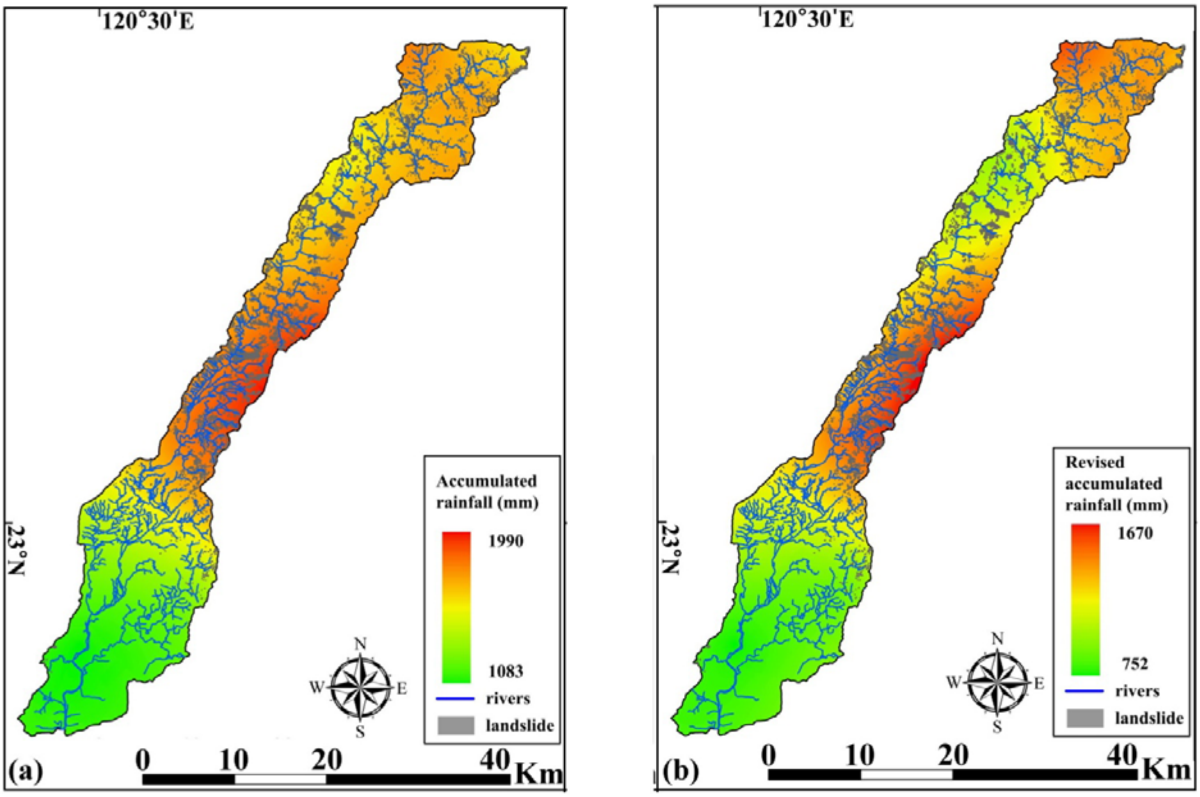


**Figure 3** The distribution of accumulated rainfall (a) and $R_{re}$ (b) during 2009 Typhoon Morakot in the Chishan watershed.

**Table 1** **The characteristic of landslide inventory after 2009 Typhoon Morakot in the Chishan watershed.**

| | Watershed | Landslide in the watershed |
|---|---|---|
| Area (km²) | 818.2 | 33.9 |
| Mean elevation (m) | 838.2 | 1121.9 |
| Mean slope (degree) | 22.4 | 31.9 |
| Mean accumulated rainfall during 2009 Typhoon Morakot (mm) | 1527.5 | 1731.8 |

each variable is recorded in each mapping unit. The elevation (continuous variable in this research) characteristic value of a mapping unit located at the elevation of 1,150 m, for example, is 1,150, while the aspect (categorical variable in this research) characteristic value of a mapping unit located in the north slope is 2, the assigned number in the aspect variable with flat starts at 1 and northwest ends at 9. The database in building the LRLSM includes the coordinate column, landslide or non-landslide column, and the characteristic values columns of all variables. The logit equation for the landslide susceptibility is written as the following form:

$$\mathrm{logit(y)} = \mathrm{a} + b_1 x_1 + b_2 \mathrm{x}_2 + \cdots \quad (1)$$

where y is the linear predictor for landslide, $x_n$ is the characteristic value of continuous or categorical variables, a is a constant, and $b_n$ is the $n$-th regresion coefficient. The product of characteristic value ($x_n$) and coefficient ($b_n$) of each variable is named as the weighted values of each variable. And the landslide susceptibility $P$ can be written as the following form:

$$\mathrm{P} = \frac{\exp\,(\mathrm{logit(y)})}{1 + \exp\,(\mathrm{logit(y)})} = \frac{\exp(\mathrm{a}+\mathrm{b}_1\mathrm{x}_1+\mathrm{b}_2\mathrm{x}_2+\cdots)}{1+\exp(\mathrm{a}+\mathrm{b}_1\mathrm{x}_1+\mathrm{b}_2\mathrm{x}_2+\cdots)} \quad (2)$$

## 2.2 Dependant variables

The research adopted the 20 m grid, which is re-sampled from 5 m grid DEM, as the mapping unit in building the LRLSM. The LRLSM in the research was developed with 6 variables, including elevation, slope, aspect, geological formation, accumulated rainfall and bank erosion. Figure 1, Figure 3, Table 1 and Table 2 show the relationship between each variable and landslide inventory after 2009 Typhoon Morakot.

Three topographic variables, including elevation, slope, and aspect, are common used variables in the LSM. The data source of the three topographic variables is the 5 m × 5 m DEM. The 5 m grid DEM used in the research was produced from Light Detection and Ranging (abbreviated as LiDAR) scanning data in 2004 to 2006 by Ministry of Interior, Taiwan, and the error of 5 m grid DEM is 0.5 m n flat ground and 0.8 m in mountain area.

We can find the landslide-prone area in each variable from Table 2. The highest landslide-prone area, i.e. the high landslide ratio area, in elevation variable is the elevation at 500 m to 1250 m and greater than 3000 m. The total area of the elevation at 500 m to 1250 m and greater than 3000 m occupy 20.7% of the total watershed area, but the total landslide area in the two areas occupy 55.1% of the total landslide area in the Chishan watershed. The meaning of elevation variable in the research is to show the influence of man-made development and vegetation distribution to landslide. In Taiwan, the area with low elevation (< 500 m in Table 2) is usually of high man-made development density and low vegetation density, but it is still of low landslide ratio (Table 2) because of the mild slope. On the contrary, the area with high elevation (>1500 m in Table 2) is usually of the steep slope, but it is of decreasing landslide ratio (Table 2) because of low man-made development density and high vegetation density. The research considers that the reason why the area with medium elevation (500-1500 m in Table 2) is of the highest landslide ratio in whole watershed area should be the outcome of medium man-made development density, vegetation density and medium slope.

The highest landslide-prone area in slope variable is the slope at 20° to 50° and greater than 60°. Furthermore, the total areas with the slope at 20° to 50° and greater than 60° occupy around 55.7% of the total watershed area, but the landslide area in the two areas occupy around 85.3% of the total landslide area in the Chishan watershed. As the Typhoon Moarkot struck Taiwan in 2009, Typhoon Morakot also enhanced the Southwest Monsoon and brought heavy rainfall. The areas with northeast, east, and southeast aspects have higher landslide ratio, especially the northeast aspect, while the areas with south, southwest, west, and northwest aspects have lower landslide ratio.

The data source of geological formation variable is the basin geological map, and 20 geological formations are in the Chishan watershed. The Changchihkeng formation (the lithology is alternations of sandstone and shale), alluvium (the lithology is gravel, sand and clay), Tangenshan sandstone (the lithology is sandstone intercalated with shale), Nankang formation (the lithology is augillite or slate), and Terrace gravel (the lithology

**Table 2 The occupied percentage, landslide ratio and the landslide ratio-based classification of six variables based on the landslide inventory after 2009 Typhoon Morakot in the Chishan watershed.**

| Variables | OP(%) | LR(%) | LRC | Variables | OP(%) | LR(%) | LRC |
|---|---|---|---|---|---|---|---|
| **Elevation (m)** | | | | 1500~1750 | 6.5 | 5.5 | 3 |
| <250 | 34.9 | 0.1 | 1 | 1750~2000 | 6.5 | 3.4 | 2 |
| 250~500 | 14.9 | 3.1 | 2 | 2000~2250 | 4.9 | 2.4 | 2 |
| 500~750 | 7.8 | 10.3 | 6 | 2250~2500 | 2.9 | 1.4 | 1 |
| 750~1000 | 6.3 | 11.1 | 6 | 2500~2750 | 1.7 | 1.1 | 1 |
| 1000~1250 | 5.6 | 12.2 | 6 | 2750~3000 | 0.6 | 1.7 | 1 |
| 1250~1500 | 6.4 | 9.4 | 5 | >3000 | 1.0 | 10.2 | 6 |
| **Slope (degree)** | | | | 30~40 | 22.8 | 7.5 | 4 |
| <10 | 27.4 | 0.4 | 1 | 40~50 | 10.6 | 6.3 | 4 |
| 10~20 | 14.9 | 2.7 | 2 | 50~60 | 2.1 | 4.9 | 3 |
| 20~30 | 22.0 | 5.1 | 3 | >60 | 0.3 | 10.5 | 6 |
| **Aspect** | | | | Southeast | 12.9 | 4.1 | 3 |
| Flat | 0.1 | 0.0 | 1 | South | 13.7 | 3.6 | 2 |
| North | 10.3 | 4.7 | 3 | Southwest | 14.5 | 3.7 | 2 |
| Northeast | 8.6 | 6.3 | 4 | West | 15.5 | 3.6 | 2 |
| East | 10.6 | 4.8 | 3 | Northwest | 13.9 | 3.6 | 2 |
| **$R_{re}$ (mm)** | | | | 1200~1500 | 40.2 | 5.9 | 3 |
| <900 | 23.9 | 0.1 | 1 | 1500~1800 | 5.8 | 11.0 | 6 |
| 900~1200 | 30.2 | 3.7 | 2 | | | | |
| **Distance to river (m)** | | | | 500~1000 | 42.6 | 3.8 | 2 |
| <500 | 35.2 | 4.5 | 3 | >1000 | 22.2 | 0.5 | 1 |

| Category (geological formation) | OP(%) | LR(%) | LRC |
|---|---|---|---|
| Alluvium | 17.8 | 0.1 | 1 |
| Ailiaochiao formation | 7.6 | 1.5 | 1 |
| Changchihkeng formation | 26.2 | 6.6 | 4 |
| Gutingken formation | 1.3 | 0.5 | 1 |
| Hunghuatzu formation | 2.9 | 10.5 | 6 |
| Igneous rock | 0.0 | 5.3 | 3 |
| Kaitzuliao shale | 0.6 | 0.0 | 1 |
| Linkou conglomerate | 0.9 | 0.0 | 1 |
| Liukuei formation | 0.4 | 0.0 | 1 |
| Nanchuang formation and equivalents | 3.6 | 2.3 | 2 |
| Nankang formation and equivalents | 10.8 | 4.2 | 3 |
| Nanshihlun sandstone | 0.5 | 0.0 | 1 |
| Sanming shale | 2.3 | 5.3 | 3 |
| Shihpachungchi formation | 1.1 | 4.2 | 3 |
| Tachien sandstone | 1.3 | 3.1 | 2 |
| Tangenshan sandstone | 10.5 | 8.1 | 5 |
| Terrace gravel | 5.9 | 0.9 | 1 |
| Wushan formation | 0.5 | 0.0 | 1 |
| Yenshuikeng shale | 4.9 | 4.5 | 3 |
| Yushanchushan formation | 0.7 | 13.0 | 6 |

**Notes:** The OP means the occupied percentage, i.e. the ratio of the area in the specific area and the total watershed area. The LR means landslide ratio, while the LRC means landslide ratio-based classification.

is mud, sand and gravel) are the five formations which occupies more than 5.0% of the total watershed area. But the yushanchushan formation (the lithology is meta-sandstone and slate interbeded), Hunghuatzu Formation (the lithology is thick-bedded siltstone, thick alteration of sillstone and sandstone), Changchihkeng formation (the lithology is alternations of sandstone and shale), Igneous rock (the lithology is igneous rock), and Sanming shale (the lithology is shale intercalated with thin-bedded siltstone) are the five formations of the landslide ratio greater than 5.0% in the Chishan watershed.

The research uses the rainfall records from 30 rainfall stations in the Chishan watershed or in the neighborhood of Chishan watershed during 2009 Typhoon Morakot (from 20:30 on Aug. 5 to 5:30 on Aug. 10, 2009) to draw the accumulated rainfall distribution (Figure 3) by using co-universal Kriging module in ArcGIS software. According to the rainfall record of Jiaxian station, there is no rainfall in 3 days before the starting point of 2009 Typhoon Morakot (20:30 on Aug. 5, 2009). The accumulated rainfall in the Chishan watershed during 2009 Typhoon Morakot ranges from 1083 mm to 1990 mm with an average rainfall of 1529 mm. The accumulated rainfall during 2009 Typhoon Morakot is apparently over-estimated to trigger the landslide, because the rainfall threshold value for debris flow warning in the Chishan watershed is only 350 mm (Soil and Water Conservation, 2014), i.e. 22.9% of the mean accumulated rainfall during 2009 Typhoon Morakot. Pietro (2004) showed that most landslide cases were triggered before the appearance of the largest rainfall intensity in the rainfall events. The research followed the suggestion from Pietro (2004) and assumed that the landslide cases in the Chishan watershed were triggered before the time when the largest rainfall intensity occurred during 2009 Typhoon Morakot (abbreviated as $T_{maxi}$) and uses the accumulated rainfall from the starting time to Tmaxi instead of the accumulated rainfall. The accumulated rainfall from the starting time to Tmaxi during 2009 Typhoon Morakot is named as revised accumulated rainfall (abbreviated as $R_{re}$) in the research. The $R_{re}$ ranges from 752 mm to 1670 mm with an average rainfall of 1152 mm. The reduction from the accumulated rainfall to $R_{re}$ during 2009 Typhoon Morakot is around 226 mm to 331 mm. Because the $R_{re}$ is still 3.3 times larger than the rainfall threshold value for debris flow warning, the assumption that the landslide cases in the Chishan watershed were triggered before the Tmaxi should be acceptable and reasonable. According to the previous analysis result (Table 2), the occupied percentage of $R_{re}$ < 900 mm, 900 mm to 1200 mm, and > 1200 mm in the Chishan watershed is 23.9%, 30.2%, 40.2%, and 5.8%, respectively, while the landslide ratio in the above-mentioned four classification area is 0.1%, 3.7%, 5.9%, and 11.0%. As the $R_{re}$ increases, the landslide ratio also increases.

The bank erosion-induced landslide is important in landslide disasters in Taiwan (Chen et al. 2014). The research created a 1000 m river buffer, which divides the study area into the area within 1000 m of river and outside the river buffer area, in building the or-LRLSM. And in building the lr-LRLSM, the research creates a double 500 m river buffer, which divides the research area into the area within 500 m of river, the area within 500 m to 1000 m of river, and outside the river buffer area. The area within 500 m of river, the area within 500 m to 1000 m of river, and outside the river buffer area occupies around 35.2%, 42.6%, and 5.8% of the Chishan watershed, but the landslide ratio in the above-mentioned three classifications is 4.5%, 3.8%, and 0.5%, respectively. The data shows the clear bank-erosion effect on landsliding in the Chishan watershed.

### 2.3 Development of the original and landslide ratio-based LRLSM

The analysis in the research was raster-based with the basic grid of 20 m × 20 m. The research area was partitioned into approximately 1,600,000 squared mapping units (Carrara et al. 1995; Guzzetti et al. 1999) in the following analyses. In the first step, the research marked each grid as landslide grid (marked as 1) or non-landslide grid (marked as 0) based on the landslide inventory after 2009 Typhoon Morakot. All of the landslide area in the Chishan watershed, which is around 33.9 km$^2$, had been divided into 84,743 mapping units marked as 1. The object of the research is the comparison of the or- and lr-LRLSMs. In building the or-LRLSM, the 6 variables were divided as continuous variables, including elevation, slope, and $R_{re}$, and categorical variables, including aspect, geological formation and bank erosion. In building the lr-LRLSM, all variables were classified based on the landslide ratio of each category. The landslide ratio in each category ranges from 0.0% to 13.0% (Yushanchushan formation in geological formation variable), so the research classified the research area under six classifications based on landslide ratio. The number of landslide ratio classification (abbreviated as LRC) in a specific category is marked as 1, 2, 3, 4, 5, and 6 if the landslide ratio in a specific category is < 2.0%, 2.0% to 4.0%, 4.0% to 6.0%, 6.0% to 8.0%, 8.0% to 10.0%, and > 10.0%. The difference of lanslide ratio in each LRC group is 2.0% just for convenience in the following analysis.

Because the count of mapping unit in the Chishan watershed was too much to calculate by using commercial software (SPSS), the research took random sampling instead of the whole mapping units. Using equal proportions of landslide unit and non-landslide unit in logistic regression analysis is recommended (Dai ad Lee 2002). The count of landslide grid in the Chishan watershed based on the landslide inventory after 2009 Typhoon Morakot is 84,743. The research took all landslide units and 84,743 non-landslide units into the logistic regression analysis. But the count of non-landslide units used in the research only occupies 5.6% of whole non-landslide units in the Chishan watershed after 2009 Typhoon Morakot, the research does 10 times random sampling and choose the random sampling groups with the best Cox and Snell $R^2$ value and Nagelerker $R^2$ value to avoid the possible error from the random sampling processes. The research does random sampling by using the random sampling module in ArcGIS software.

### 2.4 Performance assessment of LRLSM

The logistic regression result with the Cox & Snell $R^2$ value and Nagelkerker $R^2$ value > 0.15 indicates the result is acceptable. Because 84,743 non-landslide units only occupied around 6% of all non-landslide grids, the research does 10 times random sampling and select the random sampling groups with the best Cox and Snell $R^2$ value and Nagelerker $R^2$ value to avoid the possible error from the random sampling processes. This is the training process in building the model.

The research assessed the performance of the two models by using the AUC and error matrix. The AUC value can explain the ability of the model to classify the cases of landslide and non-landslide (Pontius and Batchu 2003), and should be greater than 0.7 to represent the analysis result of random sampling acceptable (Hosmer and Lemeshow 2000). The prediction results in the analysis of error matrix will be assessed by using 4 indexes, including predicted landslide correct ratio (abbreviated as PLCR), predicted non-landslide correct ratio (abbreviated as PNLCR), predicted landslide wrong ratio (abbreviated as PLWR), and predicted non-landslide wrong ratio (abbreviated as PNLWR). The PLCR (PNLCR) means the ratio of the predicted (not) landslide area in the actual (not) landslide area, while the PLWR (PNLWR) means the ratio of the predicted (not) landslide area in the actual non-landslide (actual landslide) area. The research names the average of PLCR and PNLCR as the ACR, and uses ACR to assess the model performance. The analysis of error matrix is useful to understand the error sources of the model.

## 3 Results

### 3.1 Performance of the original and landslide ratio-based LRLSM

In building the or- and lr-LRLSMs, the research selected the random sampling group with the best Cox & Snell $R^2$ and Nagelkerke $R^2$ values as the database for the following analysis. The or-LRLSM is significant at the 1% level with Cox & Snell $R^2$ = 0.190 and Nagelkerke $R^2$ = 0.253, while the lr-LRLSM is also significant at the 1% level with Cox & Snell $R^2$ = 0.196 and Nagelkerke $R^2$ = 0.260. The Cox & Snell $R^2$ and Nagelkerker $R^2$ value in both of or- and lr-LRLSMs are greater than 0.15, and this also means the results from two LRLSMs are acceptable. Although the Cox & Snell $R^2$ value and Nagelkerke $R^2$ value for lr-LRLSM is slightly larger than those for the or-LRLSM, this also means that the fitting result of logistic regression for lr-LRLSM is better than that for the or-LRLSM. The AUC of or-LRLSM in the Chishan watershed is 0.72, while that of lr-LRLSM is 0.77. Both of the AUCs of or- and lr-LRLSM exceed 0.7 and this means the two models have good differential ability to recognise unstable conditions throughout the watershed.

### 3.2 Comparison of original and landslide ratio-based LRLSMs

The coefficients for each variable in the or- and lr-LRLSMs are shown in Table 3 and Table 4. The landslide susceptibility maps by using the or- and lr-LRLSMs are shown as Figure 4. The mean value of landslide susceptibility in the Chishan watershed by using the or-LRLSM is 0.40, while that by using lr-LRLSM is 0.34.

Equally classification of landslide susceptibility value is often seen in the LSM researches, like 4 portions in Ozdemir and Altural (2013), 5 portions in Yilmaz (2009) and Wang et al. (2013). The research follows the process in Ozdemir and Altural (2013) to classify the landslide susceptibility into four classifications, including low landside susceptibility as $P \leqq 0.25$, middle landside susceptibility as $0.25 < P \leqq 0.5$, middle-high landside susceptibility as $0.5 < P \leqq 0.75$, and high landside susceptibility as $P > 0.75$. The landslide susceptibility zoning by using the or- and lr-LRLSMs are shown in Figure 4 and Table 5. The occupied percentage of low (high) landslide susceptibility area in the Chishan watershed decreases from 53.1% (23.6%) in the or-LRLSM to 42.0% (7.9%) in the lr-LRLSM, while that of middle (middle-high) landslide susceptibility area in the Chishan watershed increases from 11.8% (29.5%) in the or-LRLSM to 29.4% (20.7%) in the lr-LRLSM.

The unit with the landslide susceptibility value > 0.5 have been reclassified as a predicted landslide unit, while that with the landslide susceptibility value ≦ 0.5 will be classified as a predicted non-landslide unit. The study also uses the error matrix to assess the model performance (Table 5). The ACR of lr-LRLSM (73.3%) is better than that of or-LRLSM (68.3%). Two main reasons

**Table 3** The coefficients in the or-LRLSM based on the landslide inventory after 2009 Typhoon Morakot in the Chishan watershed.

| Variables | Coe* | Variables | Coe* |
|---|---|---|---|
| Elevation (m) | -0.001 | $R_{re}$ (mm) | 0.003 |
| Slope (degree) | 0.015 | Bank Erosion | 0.408 |
| Aspect | | Southeast | 18.545 |
| Flat | --- | South | 18.231 |
| North | 18.290 | Southwest | 18.092 |
| Northeast | 18.751 | West | 18.042 |
| East | 18.721 | Northwest | 17.990 |
| Geological formations | | Nankang formation and equivalents | -0.305 |
| Alluvium | -2.745 | Nanshihlun sandstone | -20.916 |
| Ailiaochiao formation | -0.989 | Sanming shale | -0.779 |
| Changchihkeng formation | 0.220 | Shihpachungchi formation | --- |
| Gutingken formation | -0.563 | Tachien sandstone | 0.304 |
| Hunghuatzu formation | -0.212 | Tangenshan sandstone | 0.147 |
| Igneous rock | -0.205 | terrace gravel | -1.206 |
| Kaitzuliao shale | -21.000 | Wushan formation | -20.984 |
| Linkou conglomerate | -21.024 | Yenshuikeng shale | -0.360 |
| Liukuei formation | -21.311 | Yushanchushan formation | 2.887 |
| Nanchuang formation and equivalents | -1.057 | | |
| Constant | -21.510 | | |

**Notes:** *Coe stands for coefficient.

**Table 4** The coefficients in the lr-LRLSM based on the landslide inventory after 2009 Typhoon Morakot in the Chishan watershed.

| Variables | Landslide ratio-based classifications | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Elevation | --- | 1.132 | 1.255 | --- | 1.700 | 1.950 |
| Slope | --- | 0.659 | 0.864 | 0.963 | --- | 1.457 |
| $R_{re}$ | --- | 1.733 | 2.067 | --- | --- | 2.160 |
| Aspect | --- | 16.954 | 17.237 | 17.476 | --- | --- |
| Geological Formations | --- | -0.893 | -0.545 | -0.155 | 0.741 | 1.110 |
| Bank Erosion | --- | 0.086 | 0.519 | --- | --- | --- |
| Constant | -21.513 | | | | | |

**Table 5** The susceptibility classifications and performance comparison of two models in the Chishan watershed by using the error matrix.

| | or-LRLSM | lr-LRLSM |
|---|---|---|
| Mean value of landslide susceptibility | 0.40 | 0.34 |
| PLCR (%) | 72.4 | 73.2 |
| PNLCR (%) | 64.3 | 73.3 |
| ACR(%) | 68.3 | 73.3 |
| PLWR (%) | 27.6 | 26.8 |
| PNLWR (%) | 35.7 | 26.7 |
| AWR(%) | 31.7 | 26.7 |
| Landslide susceptibility zoning | | |
| Low (km²/%) | 435.0 / 53.1 | 343.7 / 42.0 |
| Middle (km²/%) | 96.2 / 11.8 | 240.1 / 29.4 |
| Middle-high (km²/%) | 94.1 / 11.5 | 169.7 / 20.7 |
| High (km²/%) | 192.9 / 23.6 | 64.7 / 7.9 |

**Notes:** The or-LRLSM means the original logistic regression landslide susceptibility model, while the lr-LRLSM means the landslide ratio-based logistic regression landslide susceptibility model.

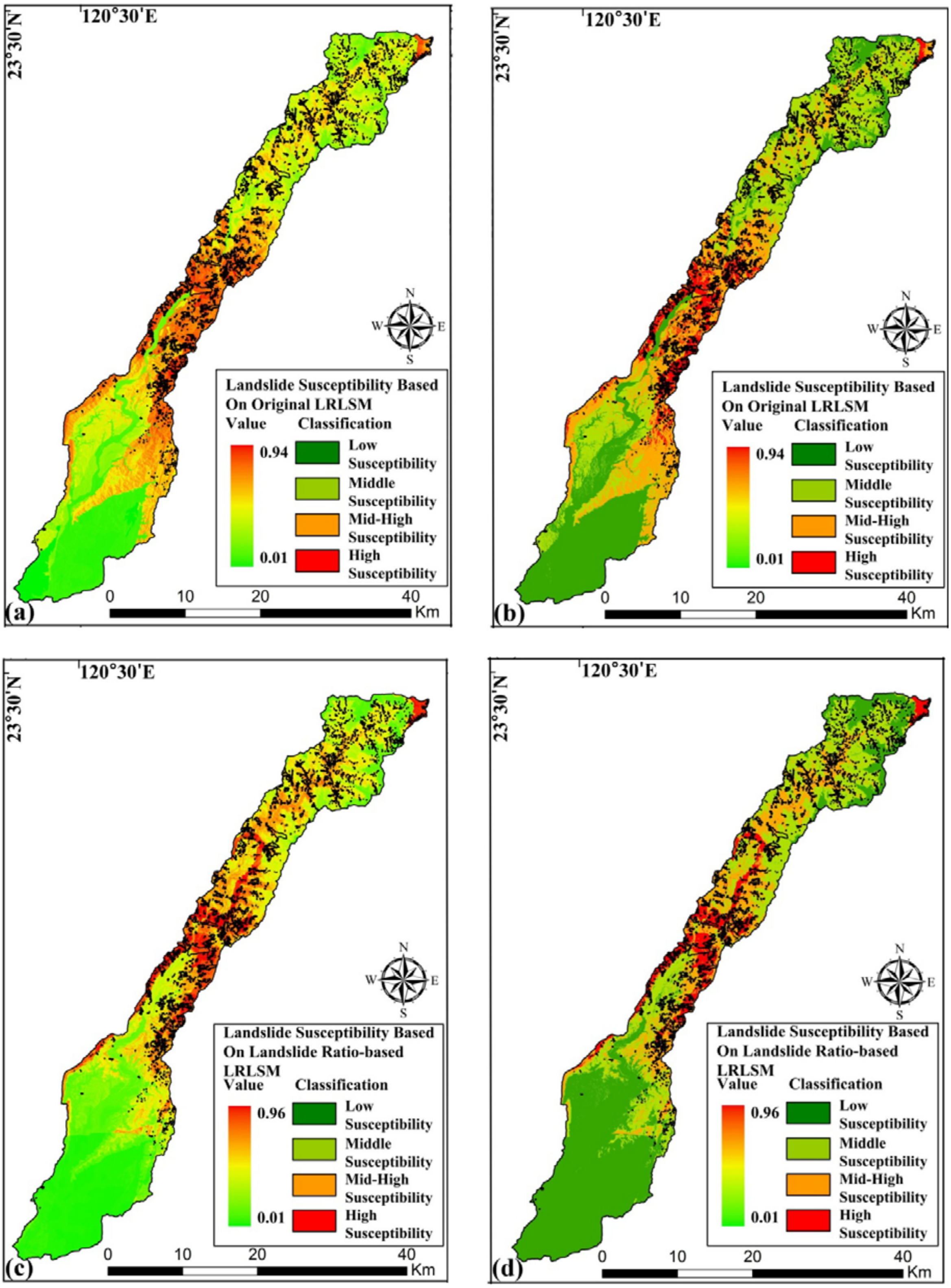


**Figure 4** The distribution (a and c) and classification (b and d) of landslide susceptibility based on or-LRLSM (a and b) and lr-LRLSM (c and d) based on the landslide inventory after 2009 Typhoon Morakot in the Chishan watershed.

can explain the difference, including the increase of PNLCR from 64.3% (or-LRLSM) to 73.3% (lr-LRLSM) and the decrease of PNLWR from 35.7% (or-LRLSM) to 26.7% (lr-LRLSM).

## 4 Discussion

### 4.1 The error sources of continuous variable

The continuous variables in the or-LRLSM are elevation, slope, and $R_{re}$, while no variable in the lr-LRLSM is continuous. The research made an assumption: if the distribution of weighted value of continuous variable is similar to the distribution of landslide ratio in the range of continuous variable, the LRLSM should have a good model performance. The research picks elevation and slope variables as examples to prove the assumption. Figure 5 shows the distribution of landslide ratio and weighted values in the range of elevation and slope variables by using the or- and lr-LRLSMs.

The distribution of landslide ratio in the range of elevation variable is a bell curve with the maximum value at elevation of 500 m to 1250 m and a rising curve at elevation > 2750 m (Figure 5a). The coefficient of elevation variable in the or-LRLSM is -0.001 (Table 3), while that in the lr-LRLSM ranges from 1.132 to 1.950 (Table 4). The weighted value distribution of elevation variable in the or-LRLSM is negative and linear, while that in the lr-LRLSM is positive and graded. It is quite obvious that the weighted value distribution of elevation variable in the lr-LRLSM is more similar to distribution of landslide ratio in the range of elevation variable than that in the or-LRLSM. This is the error source of elevation variable in the or-LRLSM and how the lr-LRLSM revises the error. The mean ACR in each landslide ratio classification area of elevation variable by using the lr-LRLSM is larger than that by using the or-LRLSM by 0.6% (Figure 6a).

Similar condition appears in the distribution of landslide ratio versus weighted values of slope variable in the lr-LRLSM (Figure 5b). The coefficient of slope variable in the or-LRLSM is positive and linear (Table 3), while that in the lr-LRLSM is positive and graded distribution from 0.659 to 1.457. The distribution of weighted value of slope variable is very similar to the distribution

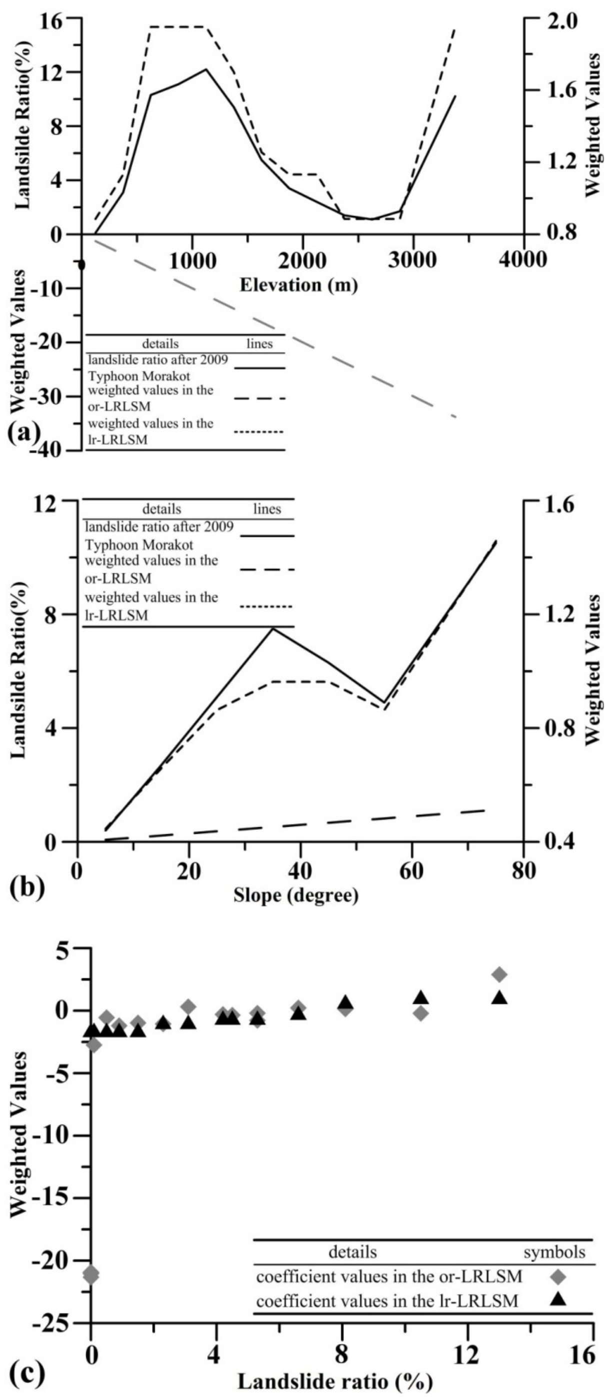


**Figure 5** The distribution of landslide ratio and weighted value in the range of elevation (a), slope (b), and geological formation (c) variables.

of landslide ratio in the range of slope variable. The mean ACR in each landslide ratio classification area of slope variable by using the lr-LRLSM is larger than that by using the or-LRLSM by 2.6% (Figure 6b). The error source of continuous variable in the or-LRLSM is the dissimilarity between the distribution of landslide ratio and weighted value, but how the error is revised in the lr-LRLSM is to make the distribution of weighted value similar to the distribution of landslide ratio.

### 4.2 The error sources of categorical variable

The categorical variables in the or-LRLSM are aspect, geological formation, and bank erosion, while all variables in the lr-LRLSM are categorical. The research made another assumption: if the relation between the coefficient and landslide ratio of each parameter in the categorical variables is positive correlation, the model performance should be good.

The main difference of adopting the categorical variables between the processes in building the or- and lr-LRLSMs is that classifying the all parameters into 6 classifications based on landslide ratio is the first step in building the lr-LRLSM. The geological formation variable, for example, in the Chishan watershed in building the or-LRLSM includes 20 classifications, while that in building the lr-LRLSM includes only 6 landslide ratio classifications. The meaning of classification based on landslide ratio in building the lr-LRLSM is gather the parameters with approximate landslide proneness together.

The research uses the geological formation variable as an example of categorical variable to explain the difference by using the or- and lr-LRLSMs. Figure 5c shows the relationship between the coefficient values and landslide ratio of each parameter in geological formation variable. The $R^2$ value of fitting equation between the coefficient values and landslide ratio of each parameter by using the or-LRLSM is only 0.38, and the over low coefficient value in five parameters (Table 3), including Liukuei formation, Nanshihlun sandstone, Wushan formation, Kaitzuliao shale, and Linkou conglomerate, should be the main reason for the low $R^2$ value. Even if the research deletes the 5 parameters with low coefficient value, the $R^2$ value of fitting equation between the coefficient values and landslide ratio of each parameter, i.e. 15 parameters used, by using the or-LRLSM is 0.64. But the $R^2$ value of fitting equation between the coefficient values and landslide ratio of each

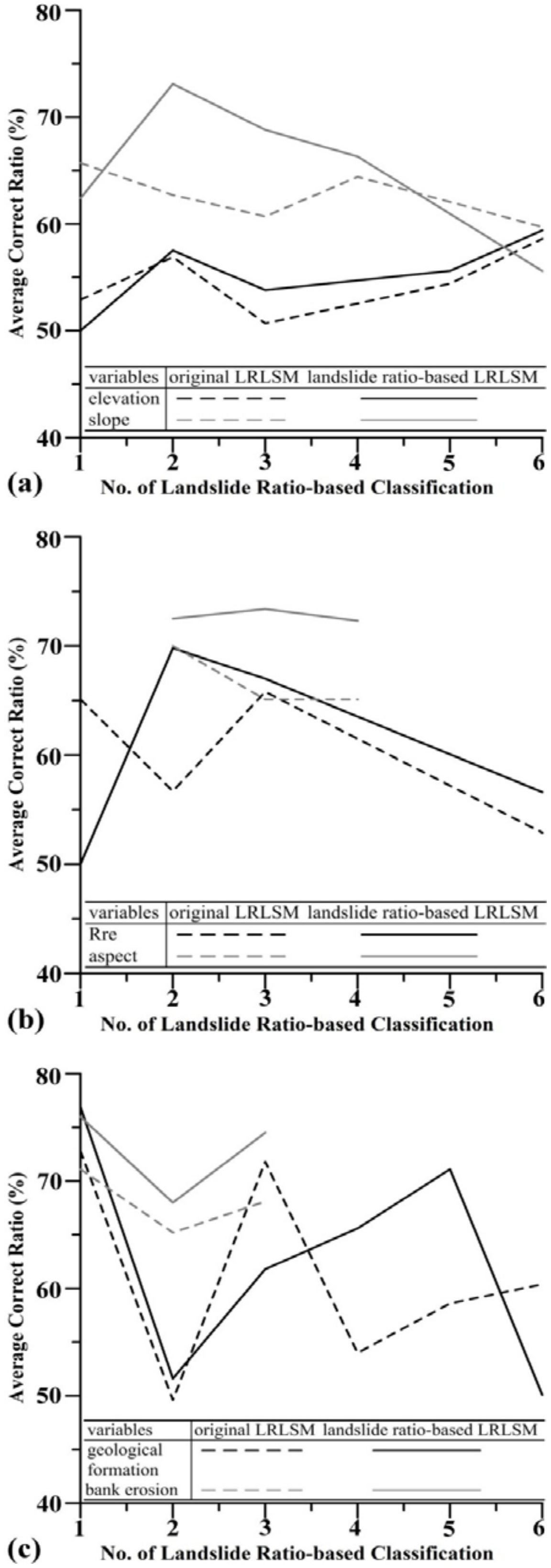


**Figure 6** The distribution of ACR based on the landslide ratio-based classification in the range of each variable.

parameter by using the lr-LRLSM is 0.95. Furthermore, the mean ACR in each landslide ratio classification area of geological formation variable by using the lr-LRLSM is larger than that by using the or-LRLSM by 1.7% (Figure 6a).

Similar condition appears in the $R^2$ value of fitting equation between the coefficient values and landslide ratio of each parameter in aspect variable by using the or- and lr-LRLSM. The $R^2$ value of fitting equation between the coefficient values and landslide ratio of each parameter by using the or-LRLSM is 0.65, while that by using the lr-LRLSM is 0.88. The mean ACR in each landslide ratio classification area of aspect variable by using the lr-LRLSM is larger than that by using the or-LRLSM by 6.0% (Figure 6a). This also proves that classification based on landslide ratio in building the lr-LRLSM is useful to promote the model performance.

## 4.3 Model performance of each variable

The heavy rainfall during 2009 Typhoon Morakot is an extreme rainstorm event with the return period of over 200 year. The extreme rainstorm event unexpectedly resulted in serious disaster events in the Chishan watershed. The research discusses the model performance of or- and lr-LRLSMs in the high- and low-landslide ratio areas to understand the applicability of lr-LRLSM.

The ACR distribution of each variable based on the LRC is shown in Figure 5. The mean ACR of or- and lr-LRLSMs is 55.0% in elevation variable, 63.9% in slope variable, 60.5% in $R_{\mathrm{re}}$ variable, 69.7% in aspect variable, 62.0% in geological formation, and 70.5% in bank erosion variable. The mean ACR difference of or- and lr-LRLSMs is -1.2% in elevation variable, 2.6% in slope variable, 0.8% in $R_{re}$ variable, 6.0% in aspect variable, 1.7% in geological formation, and 4.7% in bank erosion variable. This means that the performance difference of bank erosion and aspect variables in the LRLSM is apparent, while that of elevation and $R_{re}$ variables is not apparent, especially the elevation variable.

The research analyzed in detail the ACR difference in each LRC area of each variable. The mean ACR difference of 6 variables in the or- and lr-LRLSMs is -2.5% in LRC = 1 area, 5.2% in LRC = 2 area, 2.9% in LRC = 3 area, 6.9% in LRC = 4 area, 4.7% in LRC = 5 area, and -3.6% in LRC = 6 area. This means the performance of lr-LRLSM is better in the area with landslide ratio = 2.0% - 10.0% and worse in the area with landslide ratio < 2.0% or > 10.0% than that of or-LRLSM. The ACR difference of or- and lr-LRLSMs ≧ 10.0%, i.e. ACR of lr-LRLSM ≧ ACR of or-LRLSM, occurred in LRC = 2 area of Rre variable (13.1%), LRC = 5 area (12.5%) and LRC = 4 area (11.6%) of geological formation variable, and LRC = 2 area of slope variable (10.4%) while that ≦ -10.0%, i.e. ACR of lr-LRLSM ≦ ACR of or-LRLSM, occurred in LRC = 1 area of $R_{\mathrm{re}}$ variable (-15.1%), LRC = 6 area (-10.3%) and LRC = 3 area (-10.0%) of geological formation variable. The occupied percentage of the area with ACR difference of or- and lr-LRLSMs ≧ 10.0% in the Chishan watershed ranges from 10.5% - 30.2%, while that with ACR difference of or- and lr-LRLSMs ≦ -10.0% ranges from 0.0% - 23.9%. This explains why the ACR of lr-LRLSM is better than that of or-LRLSM by 5.0%.

The negative ACR difference of or- and lr-LRLSMs in LRC = 6 area is an interesting topic to discuss. Because the research adopts the landslide ratio classification, the ACR of lr-LRLSM in the area with higher landslide ratio should be better than that of or-LRLSM. The ACR difference of or- and lr-LRLSMs in LRC = 6 area is -3.5% in elevation variable, -4.1% in slope variable, 3.7% in $R_{\mathrm{re}}$ variable, and -10.3% in geological formation variable, and that in the highest LRC area is 6.4% in LRC = 3 area in bank erosion variable and 7.2% in LRC = 4 area in aspect variable.

The occupied percentage of LRC = 6 area in the Chishan watershed is 20.7% in elevation variable, 0.3% in slope variable, and 3.6% in geological formation variable. The LRC = 6 area in each variable is usually small, and the landslide susceptibility in the LRC = 6 area is affected by other variables. The area of LRC = 6 in slope variable, for example, is 2.77 km$^2$, but 27.6% of the LRC = 6 area in slope variable locates in the LRC = 2 area in geological formation variable. And the percentage of high and high-middle landslide susceptibility (predicted landslide) area in the LRC = 2 area in geological formation variable is only 12.1%. This also explains the landslide susceptibility of LRLSM is the accumulated influence of 6 variables and not dominated by only 1 variable.

## 5 Conclusions

The object of the research is to compare the performance of or- and lr-LRLSMs, explain the error source of or-LRLSM and how the errors were been revised in the lr-LRLSM. The original assumption in the research is if the distribution of landslide ratio and weighted value of each variable is similar, the LRLSM should have a good performance. The research does the landslide ratio classification at first, uses LRC as the database instead of the original characteristic value of each variable, and builds the lr-LRLSM. All data, including Cox & Snell $R^2$, Nagelkerke $R^2$, AUC, and ACR values, show that the performance of lr-LRLSM is better than that of or-LRLSM, and this also proves the research's assumption. The error sources of or-LRLSM are all related to the dissimilarity between the distribution of landslide ratio and weighted values, including continuous and categorical variables, and the lr-LRLSM revises and reduce the errors by using landslide ratio classification. The increase of the ACR difference from or-LRLSM to lr-LRLSM shows in slope, $R_{re}$, aspect, geological formation and bank erosion variables, and only light decreases in elevation variable. The increase of the ACR difference from or-LRLSM to lr-LRLSM also shows in LRC = 2, 3, 4, 5 area, and light decreases in LRC = 1 and 6 area. The important finding of the research is that doing appropriate classification, i.e. landslide ratio classification in this research, to let the distribution of weighted value of every variables similar to the distribution of landslide ratio is useful to promote the performance of LRLSM.

## Acknowledgment

I would like to thank Ministry of Science and Technology in Taiwan for providing budget for my project (project number: NSC 103-2313-B-035-001).

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