VULNERABILITY EVALUATION BY USING RAINFALL-TRIGGERED LANDSLIDE SUSCEPTIBILITY MODEL WITH SLOPE UNIT

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ABSTRACT: The purpose of this study is to integrate the remote sensing and hydro-geomorphic information to develop a rainfall-triggering landslide susceptibility model and used this model to evaluate the vulnerability at multi-scale spatial units in the up-stream of Chuo-shui River Basin, central Taiwan. Logistic regression was used to develop the susceptibility model by inputting the explanatory variables, including rainfall intensity, hydrologic conditions, topography, geologic characteristics, and the NDVIpre (normalized difference vegetation index of the pre-landslide), and the dependent variables from landslide inventory.
The results show that NDVIpre is the most critical explanatory variable, making the success rates increased from 73.7% to 84.9%, and the cross-validation of this model based on six typhoon-triggering landslide events present good accuracies with 0.815~0.873 of AUC (area under curve) by using ROC (receiver operating characteristic) curve. The results also show that moderate rainfall tends to trigger shallow landslides on the hillslopes with poor vegetation cover; Intensive rainfall can trigger deep-seated landslides on the hillslopes with well vegetation cover. This suggests that developing a landslide susceptibility model for a moderate rainfall event should use NDVIpre derived from satellite images as an explanatory variable to improve model performance.
Moreover, the slope unit, partition the territory into hydrological regions between drainage and divide lines, is appropriate to represent the spatial characteristics of landslide disasters. Comparison of standard errors of the hillslope aspect of the slope unit generated by using the four methods: watershed-overlapping, channel-extending, unchanneled valley-separation, and manual mapping, the channel-extending method has the best performances representing the topographic features on hillslopes.

1.MOTIVATION AND OBJECTIVE

Over the past few decades, global climate change and the increasing human population have deeply affected the geo-environment. In Taiwan, intense or prolonged rainfall and earthquakes induce a series of landslides. Compared with other natural hazards such as floods, landslides cause considerable damage to human beings and massive economic losses (Guzzetti, 2005). According to the High-risk disaster assessment report of the World Bank in 2005 (Natural Disaster Hotspots- A Global Risk Analysis), Taiwan may be the place on Earth most vulnerable to natural hazards, with 73 % of its land and population exposed to three or more hazards. More than 90% of the populations live in areas at high relative risk of death from two or more hazards.

Rainfall is the driving force of rainfall-triggered landslide which is an external natural phenomenon combined various environmental factors and affected by human activities. The studies of landslide assessment can be divided into two approaches (Wu Chun Hung, Tan Soo Khoon, 2004): one approach is based on the theories of physical properties and mechanics of landslide to identify the critical conditions and develop the deterministic prediction models. The prediction model was verified by the landslide data occurred in the past cases (Anderson & Howes, 1985; Dietrich et al, 1993; Xu, 1995; Fang, 2002; Zhou, 2014).

The second approach is using the statistical methods. A statistical prediction model can be constructed by correlating the landslide-related factors with landslide properties and assessing the weights of these factors. (Gupta & Joshi, 1990; Sterlacchini et al, 2011; Schicker & Moon, 2012; Cheng et al., 2013). There are various statistical models to assess the role of landslide–causative factors, including the logistic regression model. Several studies have demonstrated that the logistic regression model was commonly used for landslide susceptibility mapping and has achieved appreciated results.
The map unit will affect data processing during the preparation of factor layers to be used in susceptibility mapping. The slope units are formed by subdividing the study region based on certain hydrological criteria, where possible slope boundaries are delineated. Large mass movements can be represented more realistically in slope units because they mostly subdivide the region into uniform slope formations (Begueria and Lorente 1999). An appropriate

mapping unit is required for the development of a landslide susceptibility map and assessing the regional hazard and social impact (Turel and Frost, 2011). The main limitation of this mapping unit is the difficulties in manual identification of sub-basin boundaries. However, the use of automatic tools developed in geographical information systems (GIS) can automate the construction of slope units by the intersection of drainage lines and divides. Recently, the slope unit can be delineated automatically based on specific procedures of computation from a Digital Elevation Model (DEM).

In this study, the logistic regression model was used to construct a rainfall-triggered landslide susceptibility model, and the slope units were used as the assessment units to represent the topographic features.

2.MATERIAL AND METHODS

The upriver of Yufeng Bridge, Chuo-shui River Basin located in Nantou County, the central region of Taiwan was selected as the study area (Figure 1). This basin has an annual precipitation of 1,900~4,400 mm, with 70% of it occurring in the wet season. The main lithology in this area is comprised of argillite, slate, phyllite, and sandstone. Since 1996, there are several landslides triggered by typhoon-induced rainfall and earthquakes in this area, especially for the Chi-chi earthquake in 1999 and the Typhoon Morakot in 2009.

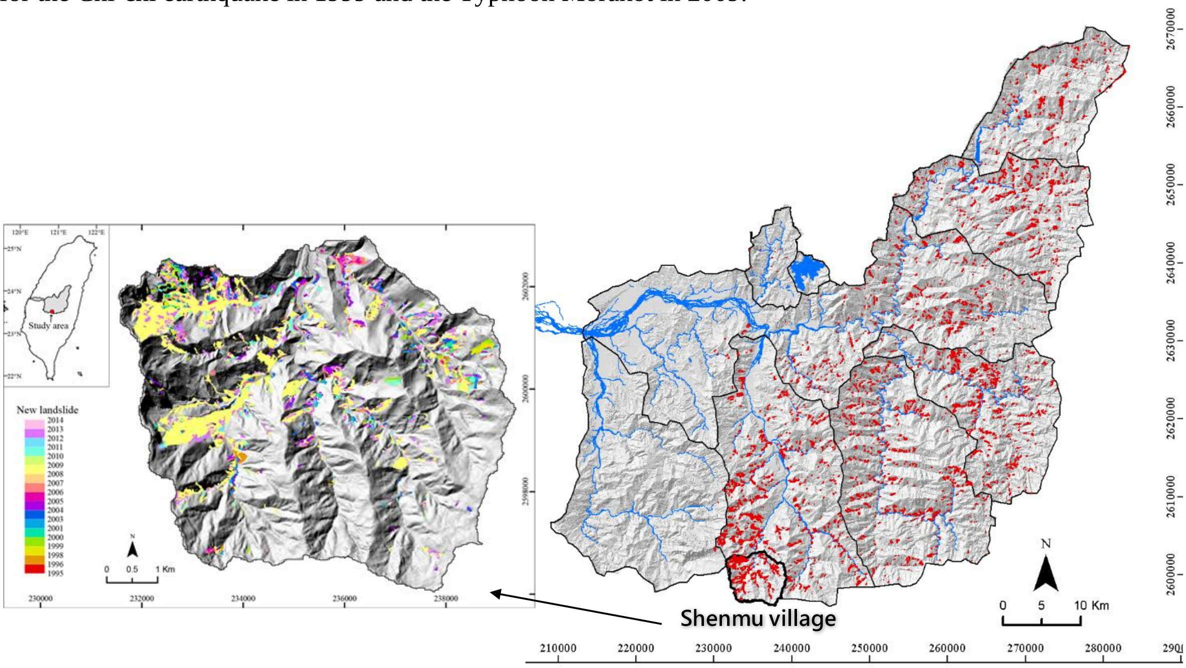

Figure 1 Study area and landslide inventory

2.1. Event-based landslide inventory

The event-based landslide inventory records the properties of new landslides associated with a specific event. The new landslides associated an event can be interpreted by comparing the landslide before and after the event. Consequently, the event-based landslide inventory can help to link landslide with its triggering and environmental factors and to establish a susceptibility model for predicting landslide triggering in an event. This study collected and mapped two sets of event-based landslide inventory. One is the landslides for Typhoon Morakot in 2009 covered the whole study area. The other is the multi-temporal landslides from 1996-2014 covered the Shenmu village, a small area in the southern part of Chuo-shui River Basin.

2.1.1. Basin-scaled landslide for Typhoon Morakot

A set of basin-scaled landslide inventories were provided by the Forestry Bureau of Taiwan government. The landslides were mapped from the FORMOSAT-II satellite mosaic images taken in May to June each year and were interpreted by a semi-automatic classified procedure. The minimum map unit is 0.1 hectares. We verified that no other significant rainfall occurred during the interval between the time the image was collected. Therefore, the new landslides triggered by Typhoon Morakot can be produced by comparing the landslide inventory in 2009 and 2010 (before and after Typhoon Morakot).

2.1.2. Multi-temporal landslide in Shenmu village

To mapping the Multi-temporal landslide, cloudless SPOT satellite images after each typhoon event from 1995—2014 was selected to analyze the vegetation condition and extract the new landslides. Normalized Difference Vegetation Index (NDVI) after typhoon events was calculated to examine the relationship between vegetation and rainfall intensity. NDVI value ≤ 0.05 was defined as the classification threshold of no-vegetation (Liu, 2008). After the candidate landslides were extracted based on NDVI, artificial editing and revising was conducted to remove the areas of the channel and human activities, like buildings, farmland, and etc. (Figure 1).

2.2. Model development and verification

Logistic regression employs the independent variables to create a mathematical formula that predicts the probability that an event occurs on any given parcel of land which is widely adopted in the literature. Based on the previous study (Chang et al., 2007), nine independent variables, including elevation, terrain complexity, slope gradient, aspect, curvature, topographic wetness index (TWI), geology, maximum 24-h rainfall (rm24), and NDVI before the landslide event (NDVIpre) were used. The logistic regression has the following form:

$$logit(\lambda) = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n$$

$$P = \frac{1}{1 + e^{-\lambda}}$$

To verify the accuracy of the model, an area under the receiver operating characteristic (ROC) curves was applied. The ROC curve is a useful method of representing the quality of deterministic and probabilistic detection and forecast systems (Swets, 1988). Verification by ROC is carried out by first sorting the landslide susceptibility in a descending order. The ordered indexes are then divided into 100 classes and set on the y-axis, with accumulated 1% intervals on the x-axis. The resulting graph shows a curve that explains how well the model and factors predict the future landslide. The accuracies of the prediction models are represented by the area under the curves (AUC). An AUC value can be categorized as acceptable (AUC > 0.7), good (AUC > 0.8), or excellent (AUC > 0.9).

2.3. Generation of slope units

Three slope-units delineation methods: (1) watershed-overlapping, (2) channel-extending and (3) unchanneled valley-separation were compared in this study. At the first step of the three methods, the watershed-units, upslope area that contributes flow to a channel or drainage outlet, can be delineated by computing the flow direction and determining a threshold of contributing area from a DEM. Then, the following steps of the three methods are described separately as below:

(1)Watershed-overlapping method: the method delineated the inversed watershed-units from an inversed DEM by the same procedure. By overlapping the boundaries of normal and inversed watershed-units in GIS, the ridge and channel lines can divide the terrain surface into the slope unit.

(2)Channel-extending method: the method delineated the longest flow path extending to drainage divides determined from a DEM within a watershed-unit. The longest flow line was used to divide a watershed-unit into the left and right side of slope unit.

(3)Unchanneled valley-separation: The method segmented a watershed-unit into unchanneled valley areas based on the contributing area flowing into the upstream of a channel line. The residual watershed-unit was, then, divided into the left and right side of the slope unit by the channel line.

The Standard Error of the Mean Aspect (SEMA) was calculated to determine the homogeneous degree of hillslope aspect within a slope unit. The SEMA is formulated as the following form:

$$e_j = \frac{\sum_{i=0}^{n} |A_{mean} - A_i|}{n} \; ; \; SEMA = \frac{\sum_{j=0}^{N} e_j}{N}$$

3. RESULTS

3.1. Landslide Susceptibility Model

The independent variables determined by forward stepwise logistic regression are as follows:

$$P = \frac{1}{1 + e^{-\lambda}}$$

$$\lambda = -0.107 * elevation - 0.050 * dem_{rug} + 0.047 * slope + 1.072 * aspsin - 1.252 * aspcos + 0.056 * twi - 6.897 * NDVI + 0.00233 * RM24 + geology - 2.328$$

Table 1 Logistic regression coefficients and the significance level of independent variables

Independent variable	Abbreviation	Coefficient (B)	Wald	Sig.
geology	geology		894.57	0.000
elevation	elevation	-0.107	5.79	0.016
terrain complexity	dem_rug	-0.050	21.27	0.000
Slope gradient	slope	0.047	102.46	0.000
Sin of apect	sinapect	1.072	1077.11	0.000
Cos of apect	cosapect	-1.252	1410.12	0.000
topographic wetness index	twi	0.056	19.27	0.000
NDVI before landslide event	ndvi	-6.897	3935.88	0.000
Maximum 24-h rainfall	rm24	$2.33x10^{-3}$	327.37	0.000
Constant	Constant	-2.328	217.30	0.000

The classification results were obtained by logistic regression analysis with nine significant independent variables (shown in table2). The overall accuracy of the classification is 73.7% without NDVI before the landslide (NDVIpre). The overall accuracy can be increased to 84.9%, which is quite appreciated if the NDVIpre was added into the model. It means that the NDVI value before landslide was a critical factor to the Landslide Susceptibility Model.

Table 2 Performances of logistic regression models without- and with NDVIpre

Without NDVIpre				With NDVIpre			
Observation	prediction			Observation	prediction		
	Non-landslide	Landslide	Accuracy (%)		Non-landslide	landslide	Accuracy (%)
Non-landslide	7143	2857	71.4	Non-landslide	8456	1544	84.6
Landslide	2396	7604	76	Landslide	1471	8529	85.3
Overall Accuracy (%)			73.7	Overall Accuracy (%)			84.9

3.2. Model verification

Verification samples were selected from six typhoon- rainfall events from 2006 to 2012 (Morakot typhoon in 2009 was excluded as an extreme event). A set of 1,000 pixels was randomly selected from each event to check the prediction accuracy and the model performance was evaluated by using the AUC (shown in Table 3). The verification represents good accuracy with AUC values of 0.815 ~ 0.873.

Table 3 Model verification by AUC from 2006 to 2012

year	2006	2007	2008	2010	2011	2012
AUC	0.815	0.872	0.873	0.844	0.847	0.862

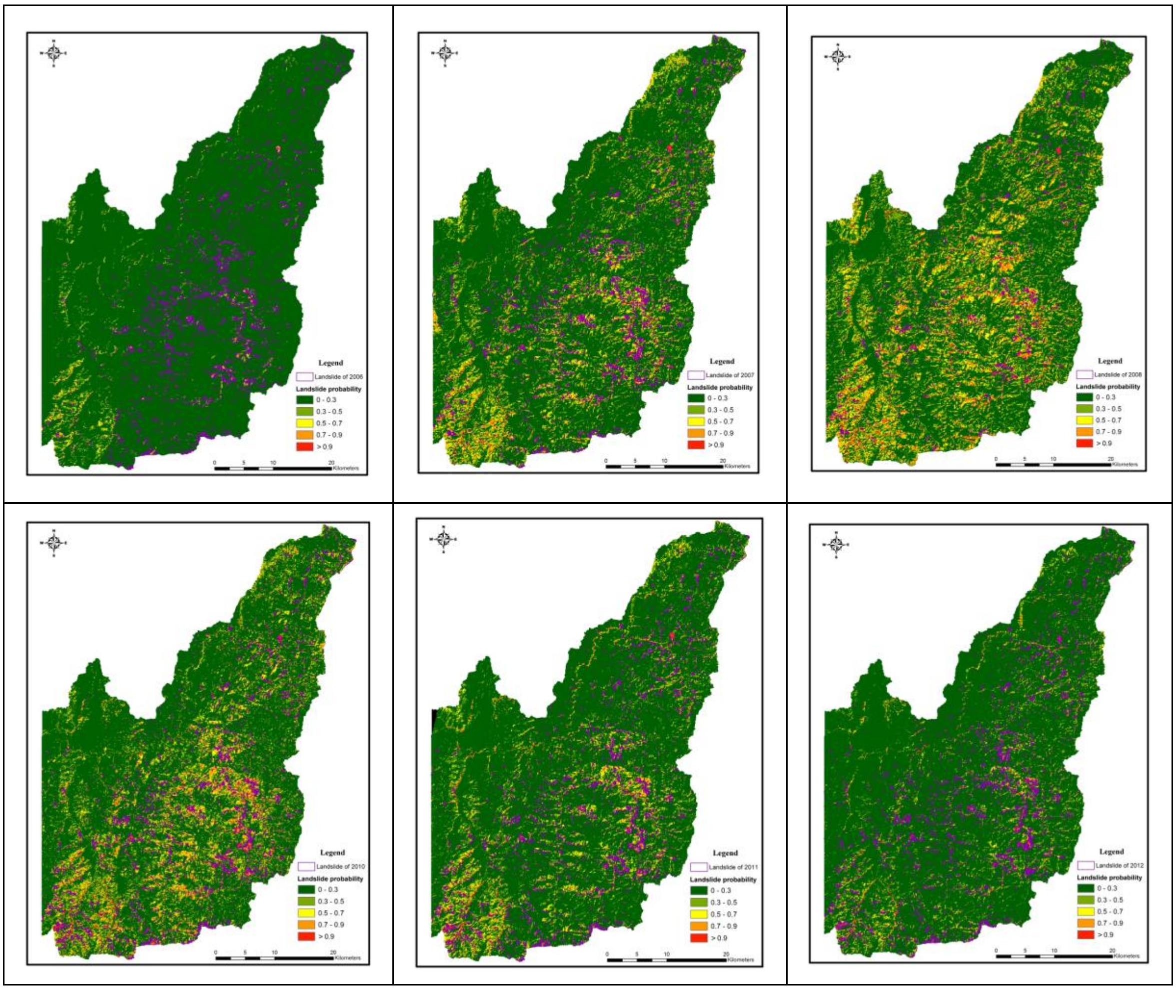

Figure 3. Landslide susceptibility map in 2006 to 2012.

3.3. The relationship among NDVIpre, rainfall and landslide area

Since the NDVIpre is a critical factor of the landslide susceptibility model, the result may reveal that the root cohesion increases the resistance force that stabilizes hillslopes (Chang and Chiang, 2009). However, the effect of root cohesion is valid for the shallow and soil landslide, but deep and bedrock landslide. Moreover, deep landslide may be triggered by prolonged and intensive rainfall and shallow landslide by short duration and moderate rainfall. To reveal this issue, the relationship among NDVIpre, rainfall and landslide area was drawn in Figure 4 and Figure 5.

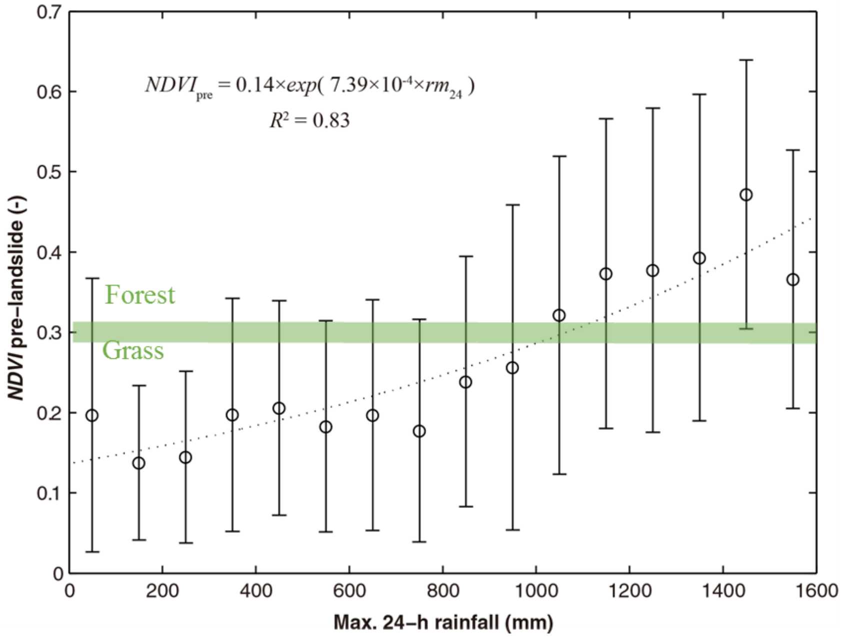

Figure 4. Relation between maximum 24-h rainfall and NDVIpre-landslide

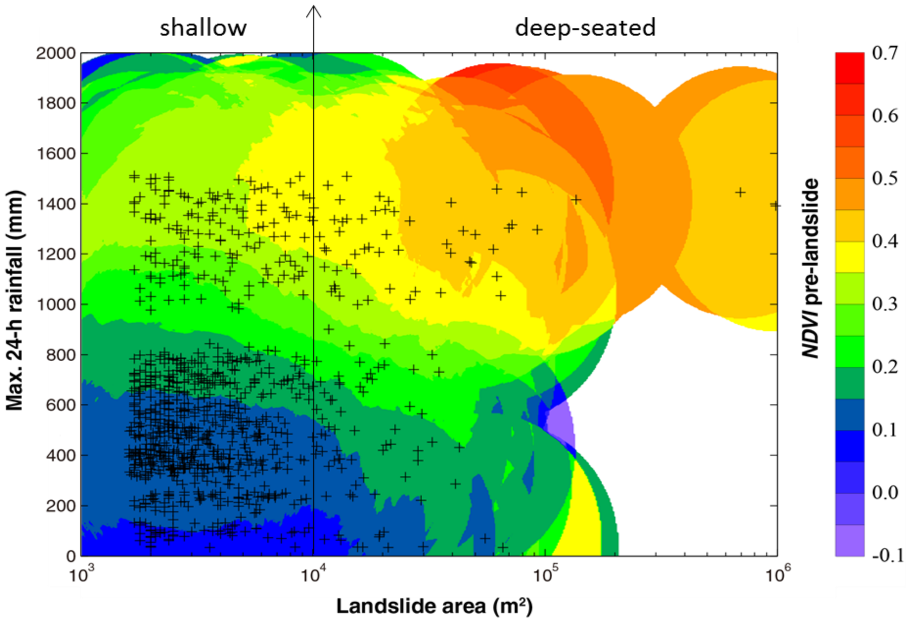

Figure 5. Relationship among NDVIpre, rainfall and landslide area

According to the volume-area scaling relationship (Chen et al., 2013), when the landslide area is larger than 10,000 square meters, the average depth is greater than 2.4 meters. Thus, the landslide area can be considered as the criteria for distinguishing the deep-seated and shallow landslide. About 13% was being classified as deep-seated landslide and shallow landslide was the absolute majority in this study area. The larger landslide area or heavier rainfall presented, the greater the value of NDVIpre was observed. It means that the deep-seated landslide may occur in forest land. Although it is well known that vegetation can play a major role in slope stability through hydrological and mechanical processes, this study showed that the benefit of vegetation may limit to the shallow landslide.

3.4. Slope unit

The results showed that the slope unit generated by using channel-extending method have smallest SEMA among the slope unit delineation methods, followed by unchanneled valley-separation method, and watershed-overlapping is the worst (Figure 6). Since channel-extending delineated the longest flow path extending to drainage divides determined from a watershed and sub-watershed unit, it's much consistent with the natural terrain feature and has the best performances (Figure 7).

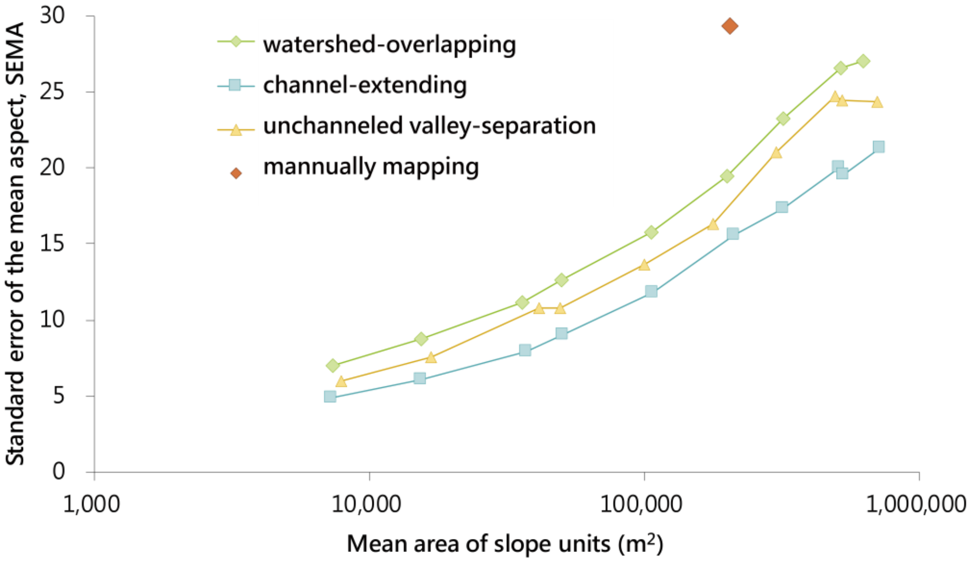

Figure 6. The standard error of the mean aspect of the slope unit generated by using different procedures

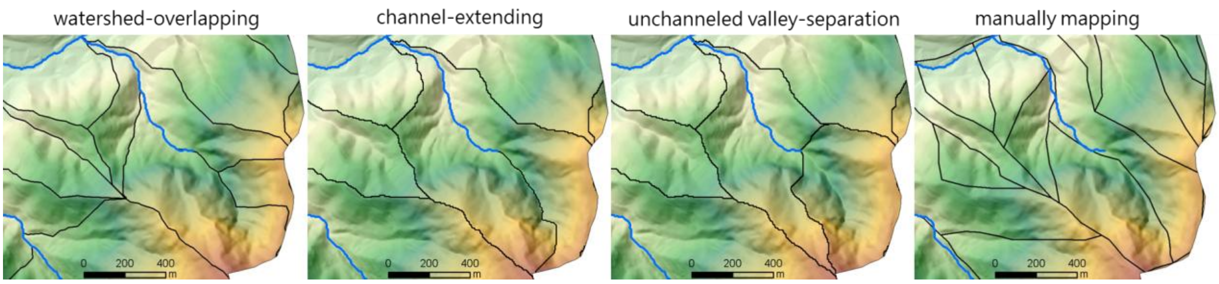

Figure 7. Slope unit generated by using different procedures

4. CONCLUSIONS

The Landslide Susceptibility Model was developed by logistic regression and employed nine independent variables, including elevation, terrain complexity, slope gradient, aspect, curvature, topographic wetness index, geology, maximum 24-h rainfall, and NDVI before landslide event. NDVIpre is the most critical variable which making the prediction success rates increased from 73.7% to 84.9%. This model also verified by six typhoon- triggering landslide events and present good accuracies with 0.815~0.873 of AUC by using ROC. The validation result strongly supports the Landslide Susceptibility Model. The results also show that moderate rainfall tends to trigger shallow landslides on the hillslopes with poor vegetation cover; Intensive rainfall can trigger deep-seated landslides on the hillslopes with well vegetation cover. This suggests that developing a landslide susceptibility model for a moderate rainfall event should use NDVIpre derived from satellite images as an explanatory variable to improve model performance.

Moreover, the slope unit which can represent the topographic features on hillslopes is appropriate to display the spatial characteristics of landslide disasters. The slope unit generated by using channel-extending method is the best delineation approach with smallest SEMA, followed by unchanneled valley-separation method, and watershed-overlapping is the worst. Therefore, the slope unit should be integrated with the landslide susceptibility model to improve the connection between disasters description and vulnerability assessment in the future.

REFERENCES

Anderson MG, Howes S., 1985. Development and application of a combined soil water-slope stability model. Journal of Engineering Geology and Hydrogeology, 18, pp. 225–236.

Begueria S., Lorente A., 1999. Landslide hazard mapping by multivariate statistics: comparison of methods and case study in the Spanish Pyrenees Damocles.

Chang KT, Chiang SH, Hsu ML, 2007. Modeling typhoon-and earthquake-induced landslides in a mountainous watershed using logistic regression. Geomorphology 89, pp. 335–347.

Chang KT, Chiang SH, 2009. An integrated model for predicting rainfall-induced landslides. Geomorphology, 105, pp. 366–373.

Chen YC, Chang KT, Chiu YJ, Lau SM, Lee HY, 2013. Quantifying rainfall controls on catchment-scale landslide erosion in Taiwan. Earth Surface Processes and Landforms, 38, pp. 372–382.

Cheng CC, Wu CD, Chuang YC, Jihn JF, 2013. Land-use dynamics of Shihmen Reservoir Catchment using photogrammetry and Markov Model. Journal of Photogrammetry and Remote Sensing, 16(4), pp. 289-297.

Chou LS, 2014. The Mechanism of Shiaolin Landslide Induced by Typhoon Morakot. Master thesis, Department of Civil Engineering, National Taiwan University.

Dietrich, W. E., C. J. Wilson, D. R. Montgomery, and J. McKean, 1993. Analysis of erosion thresholds, channel networks and landscape morphology using a digital terrain model, J. Geology, Vol.101, No.2, pp. 161-180.

Fang CF, 2002. The Study of the Physics and Mechanics Characteristics of Landslide of Lichi Melange in Chishan Aera. Master thesis, Department of Soil and Water Conservation, National Chung Hsing University.

Frost, J.D., and Turel, M., 2011. Satellite, airborne and ground based imaging of earthquake damage and Geotechnical hazards. Journal of Highway & Transportation Research & Development, Vol.28, No.6, pp. 41-48.

Gupta & Joshi, 1990. Landslide hazard zoning using the GIS approach—A case study from the Ramganga catchment, Himalayas. Journal of Engineering Geology, Vol.28, Issues 1–2, pp.119-131.

Guzzetti, F., 2005. Landslide Hazard and Risk Assessment. PhD Dissertation, Department of Geography,University of Bonn, Germany.

Liu Y C,2008. Estimation Vegetation Recovery and Landslide Potential with Satellite Images in Jou-Jou Mountain after Chi-Chi Earthquake. Master thesis, Department of Civil Engineering, National Chung Hsing University.

Schicker R, Moon V., 2012. Comparison of bivariate and multivariate statistical approaches in landslide susceptibility mapping at a regional scale. Geomorphology, 161–162, pp. 40–57.

Sterlacchini S., Ballabio C., Blahut J., Masetti M., Sorichetta A., 2011. Spatial agreement of predicted patterns in landslide susceptibility maps. Geomorphology , 125(1), pp.51–61.

Swets JA., 1988. Measuring the accuracy of diagnostic system. Science 92, pp. 38–59.

Xu M L, 1995. A grid-based model for predicting dynamic soil pore pressure. Journal of Geographical Science, 18, pp. 1-21.

Wu C H, Chen SC, 2004. The evaluation of the landslide potential prediction models used in Taiwan. Journal of Chinese Soil and Water Conservation, 36(4), pp. 295-306.

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