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On the landslide hazard and resilience with the impact of climate change in Taiwan

Sur le risque de glissement de terrain et la résilience avec l'impact du changement climatique à Taiwan

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ABSTRACT: This study aims to investigate the landslide susceptibility and resilience of the study area located in Central Taiwan, including the mountain highway and the villages in this area. After calculating the landslide susceptibility values by Logistic Regression model. By considering the core concept of resilience, the control factors were adopted and the data was collected for the study area. In order to explore the temporal behavior of landslide resilience, the population density, electricity consumption per household, and the cost of reconstruction were adopted as the indicators to establish the landslide disaster resilience model. Based on the data layers, the comprehensive linear regression model was established and used for the resilience interpretations, with suggestions on the village human mobility and the rehabilitation budget for resilience enhancement. This study can help for landslide disaster mitigation, especially for the enhancement of landslide resilience of the villages in mountain areas.

RÉSUMÉ : Cette étude vise à étudier la susceptibilité et la résilience des glissements de terrain de la zone d'étude située dans le centre de Taïwan, y compris l'autoroute de montagne et les villages de cette région. Après avoir calculé les valeurs de susceptibilité des glissements de terrain par modèle de régression logistique. En examinant le concept de base de résilience, les facteurs de contrôle ont été adoptés et les données ont été recueillies pour la zone d'étude. Afin d'explorer le comportement temporel de la résilience aux glissements de terrain, la densité de population, la consommation d'électricité par ménage et le coût de la reconstruction ont été adoptés comme indicateurs pour établir le modèle de résilience aux catastrophes des glissements de terrain. Basé sur les couches de données, le modèle complet de régression linéaire a été établi et utilisé pour les interprétations de résilience, avec des suggestions sur la mobilité humaine du village et le budget de réhabilitation pour l'amélioration de la résilience. Cette étude peut aider à atténuer les catastrophes par glissement de terrain, en particulier pour l'amélioration de la résilience des glissements de terrain dans les villages des zones montagneuses.

KEYWORDS: landslide susceptibility, logistic regression, resilience, linear regression, central taiwan.

1 INTRODUCTION.

Following the Hyogo Framework for Action, initiated on the 2005 World Conference on Disaster Reduction (WCDR), Sendai Framework for Disaster Risk Reduction (SFDRR) was presented in 2015, in which the disaster resilience was more clearly defined to improve the capability of recovering from a disaster, by the countermeasures in the aspects of social, economy, policy, etc. The most popular definition of resilience could be "the capability of an ecosystem enduring external disturbance and returning to the state before the disturbance". But it is still scarce for the research on the quantitative disaster resilience, including the geohazard-related resilience. In view of the rainfall induced landslide hazards in Taiwan, quantifying and enhancing the resilience are critical to protect the life, property, and infrastructure in the landslide area. This study comprises two major part, i.e., calculating the landslide susceptibility as a hazard factor, and collecting data of the control factors, then establishing the landslide resilience model of the research area. First paragraph (no indentation).

2 METHODOLOGIES

The study area is located in the upstream of Wu River watershed in Central Taiwan, with focuses on the mountain highway and

the six villages (see Figure 1). Data of the landslide causative factors and the resilience control factors before and after rainfall events in study area were collected, then the landslide susceptibility values were calculated and the landslide disaster resilience models were established.

2.1 Landslide Susceptibility Analysis

This study adopted the Logistic Regression method of Lin (2016), with the nine causative factors, i.e., elevation, slope, slope, dip slope index, distance to fault, distance to road, distance to river, greenness index, and 72 hour cumulative rainfall. Among them, the hourly rainfall data during 2012~2017 was further analyzed to find the largest 72-hour cumulative in a quarterly basis for each rainfall station, such that we can explore the spatial changing trend of rainfall in the study area.

Considering the villages as the analysis units, the Thiessen's Polygon method was used to obtain the rainfall distribution, as shown in Figure 2. By introducing the seasonal rainfall data to the following Logistic Regression model of Lin (2016), as described in Eq. (1), we can obtain the seasonal landslide susceptibility values of each village.

$$\ln [P/(1-P)] = -0.577 * F1 + 1.545 * F2 + 0.077 * F3 - 0.038 * F4 - 0.242 * F5 - 0.102 * F6 - 0.458 * F7 - 3.564 * F8 + 0.560 * F9 - 0.406 \quad (1)$$

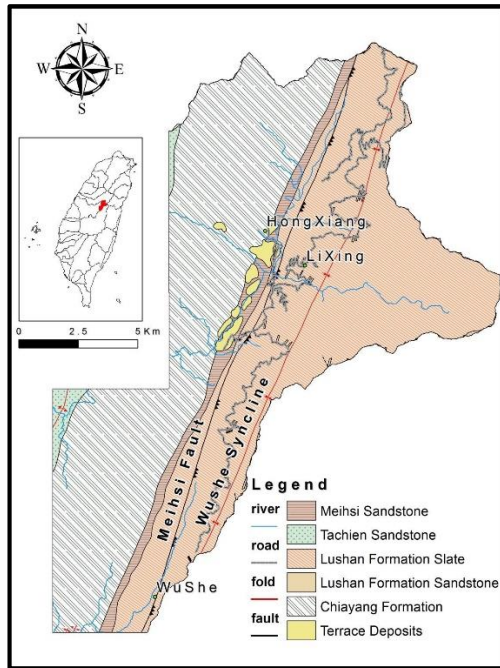


Figure 1. The location and geology of the study area study are in the upstream of Wu River watershed in Central Taiwan.

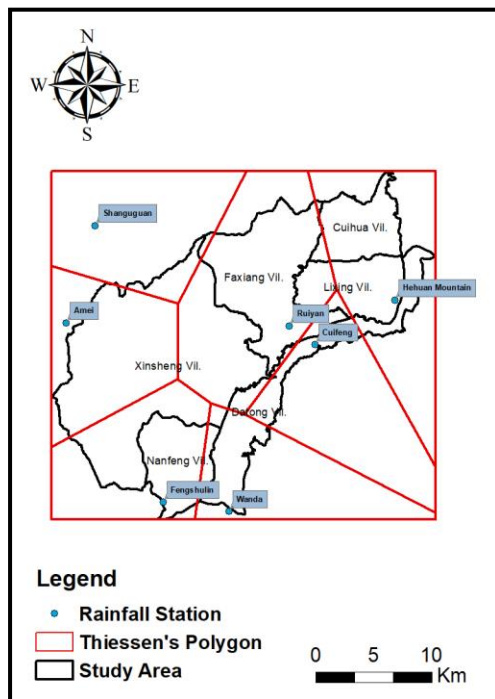


Figure 2. The Thiessen's Polygons to obtain the rainfall distribution of the six villages in the study area

2.2 Landslide Disaster Resilience

Based on a review of the behavior of landslide hazard, nine control factors were selected for assessing the landslide resilience in the study, including population density, average electricity consumption per household, elder ratio, shelter ratio,

fire fighter ratio, medical manpower ratio, income tax, and reconstruction budget.

This study further applied linear regression analysis based on the resilience of landslide disasters defined by Eq. (2) and Eq. (3). Karen (2011) quantified the resilience of landslide disasters with time dependence, using Eq. (2) to define the incremental resilience $r(t)$, as the cost per unit time $C(t)$ multiplying unit time $Inc(t)$ and dividing by total time NI . In Eq. (3), by integrating $r(t)$ according to time, the resilience Re can be obtained.

$$r(t) = \frac{C(t)Inc(t)}{NI(t)} \quad (2)$$

$$Re(t_s) = \int_{t_0}^{t_s} r(t)dt \quad (3)$$

3 LINEAR REGRESSION ANALYSIS

In order to more properly establish the landslide resilience model, this study tried to use different control factors and divided the data into high season and low season for linear regression analysis. Before further establishment of resilience model, the correlation of those control factors for the major resilience indicators were analyzed.

3.1 Population Density

The linear regression analysis was carried out for the high season and low season of different time periods, namely 2012-2016, 2016-2017, 2012-2017, 2012-2015, and 2015-2017. The independent control factors include landslide susceptibility (RI1), elder ratio (RI2), shelter ratio (RI3), fire fighter ratio (RI4), medical manpower ratio (RI5), income tax (RI6), and rehabilitation budget (RI7).

The difference between low season and high season is that the impact of landslide susceptibility on population density is reduced, that is, it shows that the impact of landslides on the study area is relatively lower during the period when the population density is lower. The results suggest that, whether in high season or low season, the best model for forecasting is the 2012-2015 period, as they can properly to predict the population density in 2016-2017. Therefore, the population density could be considered as a dependent factor to assess the recovering from a landslide disaster.

$$Y = -0.731*RI1 - 0.594*RI2 + 0.434*RI3 - 0.260*RI4 + 0.820*RI5 - 0.543*RI6 - 0.124*RI7 + 1.879 \quad (4)$$

3.2 Electricity Consumption

Similarly, the linear regression analysis for the resilience indicator, i.e., electricity consumption, was carried out for the high season and low season of different time periods. Comparing the R^2 coefficients of five models of electricity consumption, i.e., 0.597-0.436, it shows the regression is barely acceptable. The weightings of the control factors on the electricity consumption for the 2016-2017 model (as shown in Eq.(5)) can be ranked as: landslide susceptibility, medical manpower ratio, shelter ratio, reconstruction budget, income tax, elder ratio, and fire fighter ratio.

$$Y = -0.199*RI1 - 0.617*RI2 + 0.419*RI3 - 1.310*RI4 + 0.820*RI5 - 0.505*RI6 - 0.138*RI7 + 1.486 \quad (5)$$

Based on the highest R^2 value, it suggested the best mode for both high season and low season is the 2012-2015 model. This model was applied to predict the population density of 2016-

2017 with error between 1~53 %, best for Xinshen village and worst for Nanfeng village. For the low season, the error is between 0~66%, 0% for Faxiang village and 66% for Nanfeng village. The results suggest there are variation of error temporally and spatially.

Table 1. The prediction errors of regression models for different seasons in 2016-2017.

Year	Season	% of Error				
		Xinsheng	Lixing	Faxiang	Nanfeng	Cuihua
2016	1	2%	3%	10%	45%	8%
	2	6%	5%	9%	46%	7%
	3	6%	5%	12%	44%	17%
	4	4%	6%	18%	53%	12%
	Ave	5%	5%	12%	47%	11%
2017	1	6%	19%	8%	8%	28%
	2	2%	19%	1%	24%	19%
	3	3%	27%	8%	10%	23%
	4	1%	26%	2%	13%	27%
	Ave	3%	23%	5%	14%	24%

4 LANSIDE RESILIENCE ANALYSIS

This study applied the model of Karen(2011) to study the resilience of landslide disasters, to explore the differences in reconstruction budget in different time scales.

4.1 Model Based on Reconstruction Budget

In order to compare the performance of the reconstruction budget on the resilience, the linear regression analysis was carried out by letting reconstruction budget as the dependent variable. The cases of analyses were numbered as shown in Table 2. Case A is for the reconstruction budgets in 2008-2011 and 2012-2016; Case B is for the reconstruction budgets in 2012-2015 and 2016-2017; Case C is based on the reconstruction budget as dependent variable for linear regression, for the periods of 2012-2015 and 2016-2017, and matching with Eqs. (2) and (3).

The linear regression analysis model with R^2 of 0.623 was used to estimate the 2012-2017 reconstruction budget (see Figure 3); then introduce the data into the formula of Karen (2011) to obtain the resilience, as shown in Figures 4-6. The results show that the resilience of Lihang, Datong, Nanfeng and Cuihua villages changed from negative to positive in the post-2015 period, while that of the remaining two villages (Xinshen and Faxiang) was positive and increasing. In terms of the concept of disaster resilience, the lower the cost of rehabilitation, the higher the resilience, indicating that its villages do not need too much money to deal with natural disasters. However, it is suggested to have more evidence to support the findings of this study.

Table 2. Different group settings for the resilience analyses.

Case	Groups of data	
A	2008-2011	2012-2016
B/C	2012-2015	2016-2017

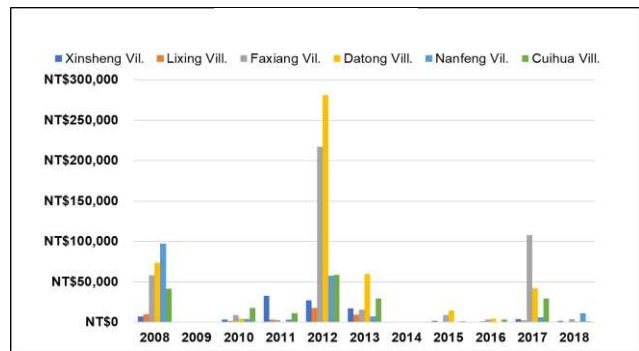


Figure 3. The 2008-2018 reconstruction budgets for the villages in the study area.

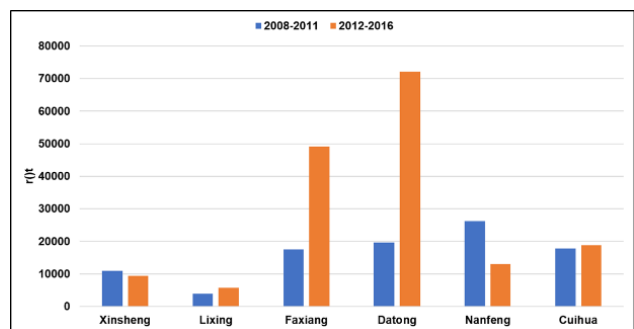


Figure 4. The resilience values of the six villages in the study area, for Case A with the reconstruction budget model.

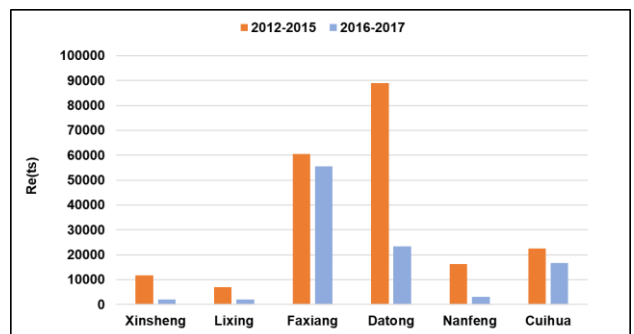


Figure 5. The resilience values of the six villages in the study area, for Case B with the reconstruction budget model.

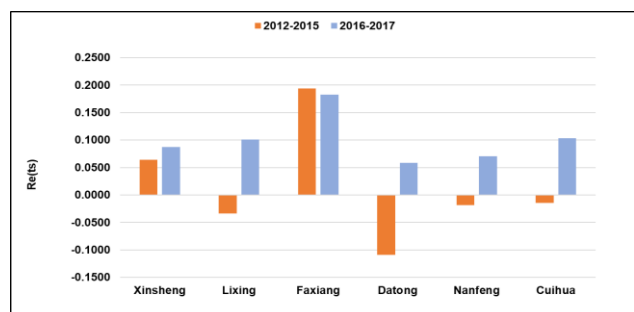


Figure 6. The resilience values of the six villages in the study area, for Case C with the reconstruction budget model.

4.2 Model Based on Population Density

For the population density model, the applied data was obtained by the best regression formula, with the largest R^2 value. The seasonal data of 2012-2017 was used as $C(t)$. In order to compare the temporal behavior of population density of each village, two periods of time, i.e., 2012-2015 and 2016-2017, were considered. The unit time of an increment $Inc(t)$ is one season, and the total time (seasons) $NI(t)$ is 16 seasons in 2012-2015 and 8 seasons in 2016-2017.

The results in Figure 7 indicate Nanfeng village is obviously different from the other villages. It could be due to the high regression error of 54%, that also reflects an abnormal behavior of population density. Unlike the other villages, there is no significant variation of population density in Xinsheng and Faxiang villages. Similar to electricity consumption, the population density is an indicator of economic activity. The larger of those two indicators, the larger disaster resilience.

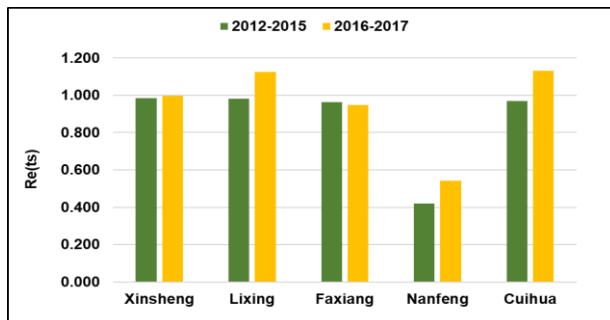


Figure 7. The resilience values of the six villages in the study area, for Case B with the population density model.

4.3 Model Based on Electricity Consumption

Similarly, the regression formula with the highest R^2 value is also used to calculate the average electricity consumption per household for each season of 2012-2017 as $C(t)$. The unit time of an increment $Inc(t)$ is one season, and the total time (seasons) $NI(t)$ is 16 seasons in 2012-2015 and 8 seasons in 2016-2017. According to the results of the regression analysis, although the R^2 value is acceptable, but the average error in the performance of the forecast results is up to 68% (Faxiang Village). However, Cuihua village possesses the largest increases in population density and electricity consumption, also has the highest disaster resilience out of the six villages.

Two different interpretations are summarized according to different indicators of disaster resilience. First of all, the reconstruction budgets are as the cost of post-disaster repair, the more budget invested the more time the region needs to return to a stable state. Therefore, as a wayward evaluation value the greater the disaster resilience is lower. Based on the results of Cuihua Village, the population density and electricity consumption are the highest compared with other villages, and the comparison with the calculation results of the village's reconstruction budget shows that the reconstruction budgets of the village in 2008-2018 were relatively large compared with other villages. In order to compare the performance of the reconstruction budget.

5 CONCLUSIONS AND DISCUSSIONS

This study adopted the upstream of Wu River as the research area, and chose the control factors by to establish the resilience model by linear regression method. In order to incorporate the concept of disaster resilience, population density, electricity consumption, and reconstruction budget were used as the

indicators of resilience. And the following conclusions are drawn from the analysis results:

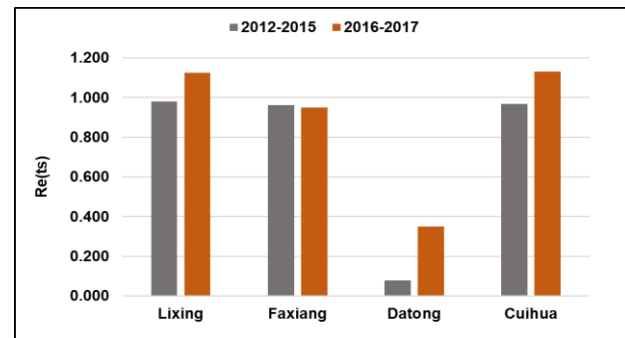


Figure 8. The resilience values of the villages in the study area, for Case B with the electricity consumption model.

For the landslide susceptibility, this study adopted the Logistic Regression model of Lin (2016) to produce landslide susceptibility values. The 99% percentile susceptibility value of the grid unit was conservatively considered as the landslide susceptibility of the village. In the establishment of landslide disaster resilience assessment indicators, covering the hazard, preservation, response and reconstruction indicators. The following four groups of control factors were adopted for the resilience analysis, i.e., (i) landslide susceptibility, (ii) population density and electricity consumption, (iii) elder ratio, shelter ratio, fire fighter ratio, and medical manpower ratio, (iv) income tax and reconstruction budget.

Based on the analysis results using the resilience model of Karen (2011), with considering reconstruction budget, population density, and electricity consumption as resilience indicators, it suggests the smaller the value calculated by the reconstruction budget represents higher resilience. On the other hand, for population density and electricity consumption, the smaller the calculated value the smaller the resilience.

Through the analysis of population density as a dependent variable, it is possible to find the time at which the villages return to the pre-event stable state. However, for the quantitative analyses, the number of samples is crucial to obtain promising results. It is suggested to optimize and simplify the resilience model of the most important indicator factor. Such that the error of the model can be reduced and the efficiency of the evaluation can be increased.

6 ACKNOWLEDGEMENTS

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7 REFERENCES

- Karen, S.R., 2011. *On Landslide Risk, Resilience and Vulnerability of Mountain Communities in Central-Eastern Nepal*, Thesis, University of Lausanne.
- Lin, J.F., 2016. *On the Rainfall Factor for the Landslide Susceptibility Analysis in Central and Southern Taiwan Areas*, Thesis, National Chung-Hsing University.
- UNISDR, 2015. Sendai framework for disaster risk reduction 2015–2030 *UN World Conference on Disaster Risk Reduction*, 2015 March 14–18, Sendai, Japan.