DEVELOPMENT OF A WARNING ASSESSMENT MODEL FOR RAINFALL-INDUCED LANDSLIDES HAZARD BASED ON LANDSLIDE FRAGILITY CURVES

Meng-Hsun Hsieh[1], Tsu-Chiang Lei[2], Yi-Min Huang[3], Bing-Jean Lee[4] and Re-Yang Lee[5]
[1]Construction and Disaster Prevention Research Center, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung, 40724 Taiwan(R.O.C.),
Email: hsiehmh @fcu.edu.tw
[2]Department of Urban Planning and Spatial Information, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung, 40724 Taiwan(R.O.C.),
Email: tclei@fcu.edu.tw
[3]GIS research Center, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung, 40724 Taiwan(R.O.C.),
Email: ymhuang @fcu.edu.tw
[4]Department of Civil Engineering, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung, 40724 Taiwan(R.O.C.),
Email: bjlee@fcu.edu.tw
[4]Department of Land Management, Feng Chia University, No. 100, Wenhwa Rd., Seatwen, Taichung, 40724 Taiwan(R.O.C.),
Email: rylee@fcu.edu.tw

KEY WORDS: Landslide, Maximum Likelihood Method, Fragility Curves, Slope Unit, Rainfall Index

ABSTRACT: In Taiwan, the hillside is about over 70% of total area. These areas also have steep topography and geological vulnerability. When an event of torrential rain comes during a typhoon, the landslide disasters usually occur at these areas due to the long duration and high intensity of rainfall. Therefore, a design which considers the potential landslide has become an important issue in Taiwan. In this study, a temporal characteristic of Landslide Fragility curve (LFC) was developed, based on the geomorphological and vegetation condition factors using landslides at the Chen-Yu-Lan Watershed in Taiwan, during Typhoon Sinlaku (Sep. 2008) and Typhoon Morakot (Aug. 2009). This study introduced an effective landslide hazard assessment process, linking together the post-landslide and post-rainfall data for LFC model. The Kriging method was used to interpolate the rainfall indicates (I, R_0 and R) for numerical analysis. Remote sensing data from SPOT images were applied to analyze the landslide ratio and vegetation conditions. The 5-M DEM (digital elevation model) was used for slope variation and slope unit analysis in the watershed, and the Grid-based Clustering Maximum Likelihood Estimate (GC-MLE) was conducted to determine the median and log-standard deviation parameters of the proposed empirical LFC model. The model can express the probability of exceeding a damage state for a certain classification (or conditions) of landslides by considering a specific hazard index (i.e. I, R_0 or R) for a given event. Finally, this result can be used to assess the loss and warning from landslides, and, in the future, to manage the landslide risk in the watershed for disaster victims.

1. Introduction

Taiwan is located on the Circum-Pacific Earthquakes Belt and Western-Pacific Typhoon Path, subtropics monsoon climatic region, and the hillside is over about 70% of total area. The landslide hazard in Taiwan has become an important issue. The trigger factors of landslide are quite complex and uncertain result in difficult prediction and assessment. Thus, probabilistic assessment models will been the future trend on research and development. Landslide fragility curves (LFC) expresses the probability of the slope reaching or exceeding landslide as a function of a specific rainfall measure. In the study, based on the geomorphological and vegetation condition factors and using the slope unit as the basis for watershed landslide assessment, LFC was developed using landslide data at the Chen-Yu-Lan Watershed in Taiwan during Typhoon Sinlaku and Morakot. The "Grid-based Clustering Maximum Likelihood Estimate" (Hsieh *et al*., 2013) is used to construct LFC, different topographic factors (slope level and vegetation condition) are considered to construct landslide probability relationships with different rainfall indicates. The rainfall data of 20 weather observation stations operated by Taiwan Central Weather Bureau (CWB) was collected from 2008 to 2009. The rainfall parameters of I (maximum rainfall intensity), R_0 (antecedent effective accumulated rainfall), and R (effective accumulated rainfall) were used in the study. The R_0 is defined as the accumulated rainfall amount the beginning of typhoon event to the maximum rainfall intensity before. The R is the amount of the continuously accumulated rainfall of an event. Finally, the maximum rainfall intensity is the precipitation per unit time. The Inverse Distance Weighting (IDW) was applied to obtain rainfall value over the study area. Finally, the result shows that the LFC are a well regional assessment model for landslides assessment; and it can be apply in model of estimation, risk and warring assessment in the future.

2. Methodology

A landslide fragility curve characterizes the probability of landslides with regard to the specific rainfall index. Thus, a probability density function must be defined to express the frequency of landslides and then converted to a cumulative distribution function. In many natural hazard researches, empirical vulnerability data from post-hazard have been commonly fitted using a simple analytical expression (e.g., Miyakoshi *et al*. 1997; Chang *et al*. 2000; Shinozuka *et al*. 2000, 2003, 2007; Rota *et al*. 2008; Tien *et al*. 2012, Hsieh *et al*., 2013, Lei *et al*., 2014). In this study, the form of a two-parameter lognormal distribution function was used for representing landslide fragility curves. For an irregular rainfall measures, the landslide fragility curve for a hillside slope is represented in the analytical function, which is determined by median and lognormal standard deviation, as below:

$$F(x;\mu,\sigma)=\frac{1}{2}+\frac{1}{2}erf\left[\frac{\ln(x/\mu)}{\sigma\sqrt{2}}\right] \tag{1}$$

where x is a rainfall index, which can be defined as I, R_0 or R; *erf* is the error function; μ and σ are the median and the log-standard deviation of the fragility curve for the typological hillside slope, respectively. The two-parameter of Eq. (2) can be determined through the Maximum Likelihood Estimate (MLE), and the landslide fragility curve can be developed for different classification of hillside slope such as slope level and VRR index.

The principle of MLE is to maximize the probability of occurrence of the vulnerability data to estimate the parameters of the distribution function, which means that the likelihood function can be constructed from different type of vulnerability data as a given distribution function. For example, Hsieh *et al*. (2013) developed a likelihood function for earthquake-induced building damage by the multinomial distribution. In this study, a binomial distribution was used to developed likelihood function for rainfall-induced landslide fragility curves of different hillside slope. For the vulnerability data, the binomial distribution expresses the probability that each trial only has two results of landslides, i.e., “occurred” or “non-occurred”, and each trial is independent and mutually exclusive. Thus, the hillside slope can be divided into K vulnerability data, and each vulnerability data is defined by two element − landslide area and non-landslide area. Hence, the likelihood function can be expressed as below：

$$L(\mu,\sigma)=\prod_{k=1}^{K}\binom{X}{x_k}[F]^{x_k}[1-F]^{X-x_k} \tag{2}$$

where K is the number of vulnerability data; X is total area of each vulnerability data; x_k is landslides area within the k^{th} vulnerability data. In Eq. (2), the term of binomial distribution express the probability of occurrence and probability of not occurrence. The median and log-standard deviation of landslide fragility curve of hillside slope can then be estimated by maximizing the likelihood function, Eq. (2), as following:

$$\frac{\partial \ln L(\mu,\sigma)}{\partial\mu}=\frac{\partial \ln L(\mu,\sigma)}{\partial\sigma}=0 \tag{3}$$

In Eq. (3), the extra binomial coefficients $\binom{X}{x_k}$ in Eq.(2) will be eliminated automatically in the differential operation.

Maximizing the likelihood function resulted in the equations as below:

$$\begin{cases}\displaystyle\sum_{k=1}^{K}R_k\left\{\frac{-e^{-\frac{1}{2}\lambda_k^2}}{1+erf\left(\frac{\lambda_k}{\sqrt{2}}\right)}\right\}+\sum_{k=1}^{K}(1-R_k)\left\{\frac{e^{-\frac{1}{2}\lambda_k^2}}{1-erf\left(\frac{\lambda_k}{\sqrt{2}}\right)}\right\}=0\\ \displaystyle\sum_{k=1}^{K}R_k\left\{\frac{-\lambda_k e^{-\frac{1}{2}\lambda_k^2}}{1+erf\left(\frac{\lambda_k}{\sqrt{2}}\right)}\right\}+\sum_{k=1}^{K}(1-R_k)\left\{\frac{\lambda_k e^{-\frac{1}{2}\lambda_k^2}}{1-erf\left(\frac{\lambda_k}{\sqrt{2}}\right)}\right\}=0\end{cases} \tag{4}$$

and:

$$\lambda_k=\ln(x/\mu)/\sigma \tag{5}$$

in which, $R_k=x_k/X$, is the vulnerability data. If vulnerability data are obtainable for each hillside slope by a rainfall index x, e.g., I, R_0 or R, then the simultaneous equations can be directly solved to obtain the median and the log-standard deviation of the landslide fragility curves.

3. Study Area and Material

3.1 Study area

The watershed of Chen-Yu-Lan River, located in the central part of Taiwan, was selected to be the study site as shown in Figure 1. The Chen-Yu-Lan River originates from the north peak of Yu Mountain with an elevation of 3,910 m. Chen-Yu-Lan River is one of the headwaters of the Zhuoshui River system, which is the largest river system in Taiwan. Furthermore, Chen-Yu-Lan River has a length of 42.4 km with an average declination slope of 5%, and its watershed area is about 45,000 hectares. The heavy rainfall brought by Typhoon Herb had induced 34 debris flows in the watershed on July 31 to August 1, 1996 (Lei *et al.*, 2014).

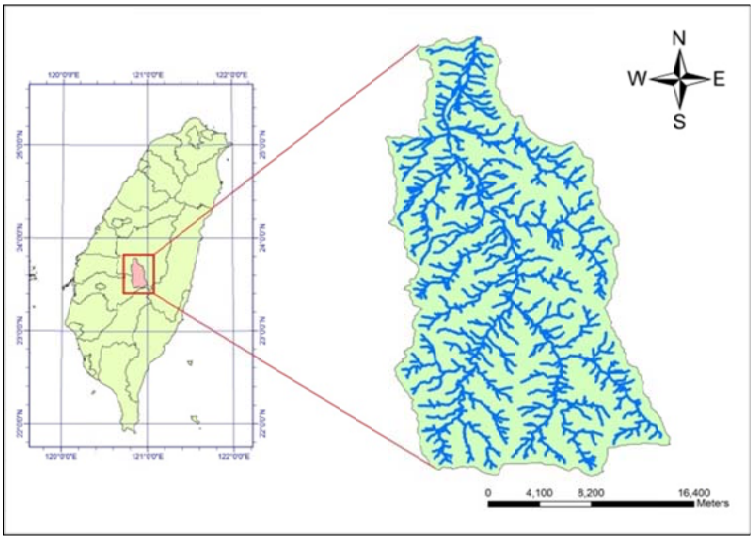


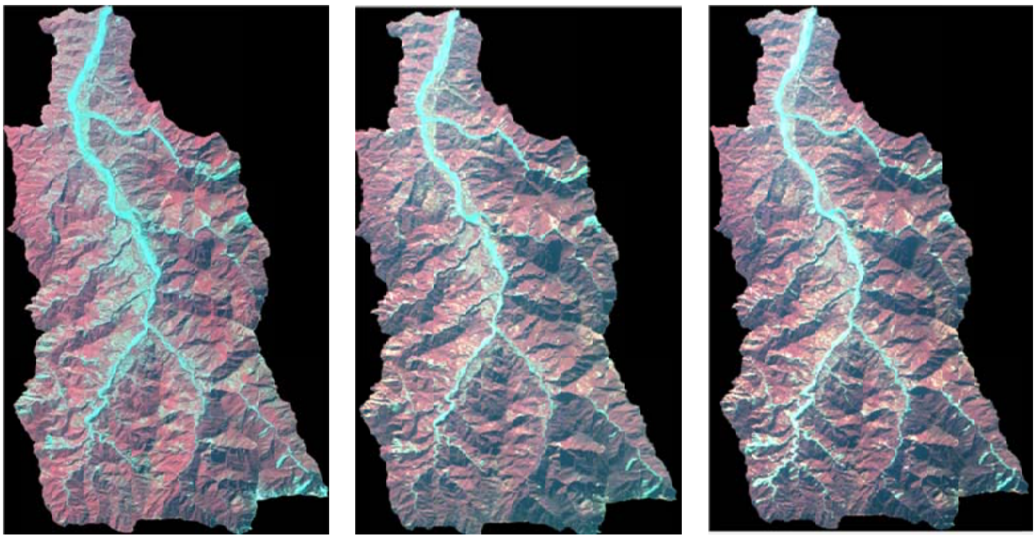
Figure 1. Chen-Yu-Lan watershed

3.2 Data acquisition

In this study, the research data consists of two major formats: vector and raster data.

3.2.1 Vector data

The vector data includes (a) river system, (b) boundary line of sub-watershed, (c) land use map, and (d) weather observation stations. The data was used to construct a knowledge rule for landslides.



(a) 2008/02/21 (b) 2008/11/28 (b) 2009/12/02

Figure 2. The original SPOT 5 image with different periods at Chen-Yu-Lan Stream.

3.2.2 Raster data

The raster data consists of Digital Elevation Model (DEM) data (5m×5m resolution) and remote sensing (SPOT 5) data of 2008/02/21, 2008/11/28 and 2009/12/02, from Center for Space and Remote Sensing Research of National Central University in Taiwan. The data was used to obtain land cover categories by image classification, as shown in Figure 2.

3.2.3 Slope unit

Xie *et al*. (2004) divided the slope unit considered part of the slope, or right and left of catchment area. In view of the terrain, the slope units were watershed ridge line and valley (stream line) divided. The study uses geographic information system (GIS) software of hydrology and terrain slope element analysis tools. The catchment area obtained from the DEM data, in catchment area, polygonal contour is the ridge line, and valley lines using inversion of DEM. The slope units of Chen-Yu-Lan watershed were analyzed as shown in Figure 3. The results show that the 7,374 slope units in the Chen-Yu-Lan watershed; but 3,322 slope units never landslide events occur, and therefore, 4,052 slope units satisfied the GC-MLE method and involve the fragility analysis.

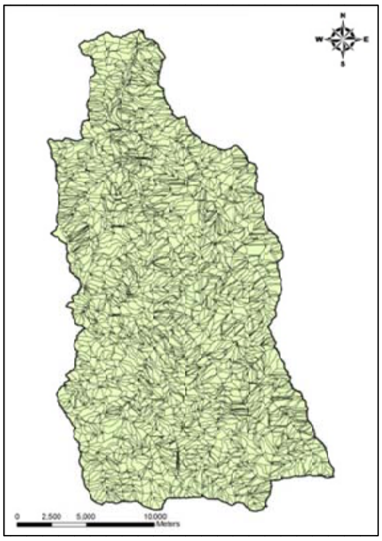


Figure 3. The results of slope unit analysis at Chen-Yu-Lan Stream

4. Result and Discussion

In this study, the degree of slope and vegetation may be a prominent factor of triggering landslides. The slope was classified based on the Soil and Water Conservation Bureau (SWCB 2013) manual. On the other hand, to determine the density of vegetation on a patch of land, Normalized Difference Vegetation Index (NDVI) are estimate the vegetative recovery of different periods using linear transformation. The definitions of slope indexes are given in Table 1, based on slope and vegetation factors. With previously described 2 environmental factors (slopes of S1 to S4 and vegetation indices of NDVI0 and NDVI1) and 3 rainfall indices (I, R_0, R), there were 24 combinations of environmental conditions. The probability of landslide then was estimated and the fragility curves of all possible conditions (24 in this study) were obtained. With the derived fragility curves, the landslide probability of each grid cell in the study area was determined for a given rainfall condition, asTable2 and Figure3.

Table 1. The code of slope classification and its levels of hillside slope and normalized difference vegetation index (NDVI)

Levels of slope	Vegetation Index	Code	Levels of slope	Vegetation Index	Code
S1(30%＜S≦40%)	NDVI0	S4N0	S3(55%＜S≦100%)	NDVI0	S6N0
	NDVI1	S4N1		NDVI1	S6N1
S2(40%＜S≦55%)	NDVI0	S5N0	S4(S＞100%)	NDVI0	S7N0
	NDVI1	S5N1		NDVI1	S7N1

Table 2. The two parameters of landslide fragility curves in the study

	I		R_0		*R*	
	μ(mm)	σ	μ(mm)	σ	μ(mm)	σ
S4N0	195	0.663	2,338	0.805	6,792	1.154
S4N1	210	0.665	2,877	0.917	7,431	1.104
S5N0	188	0.729	2,234	0.812	6,958	1.203
S5N1	214	0.762	2,684	0.881	7,802	1.149
S6N0	156	0.680	1,932	0.742	5,672	1.058
S6N1	182	0.696	2,352	0.801	7,550	1.178
S7N0	179	0.755	2,167	0.838	6,851	1.115
S7N1	249	0.912	3,020	0.972	8,046	1.180

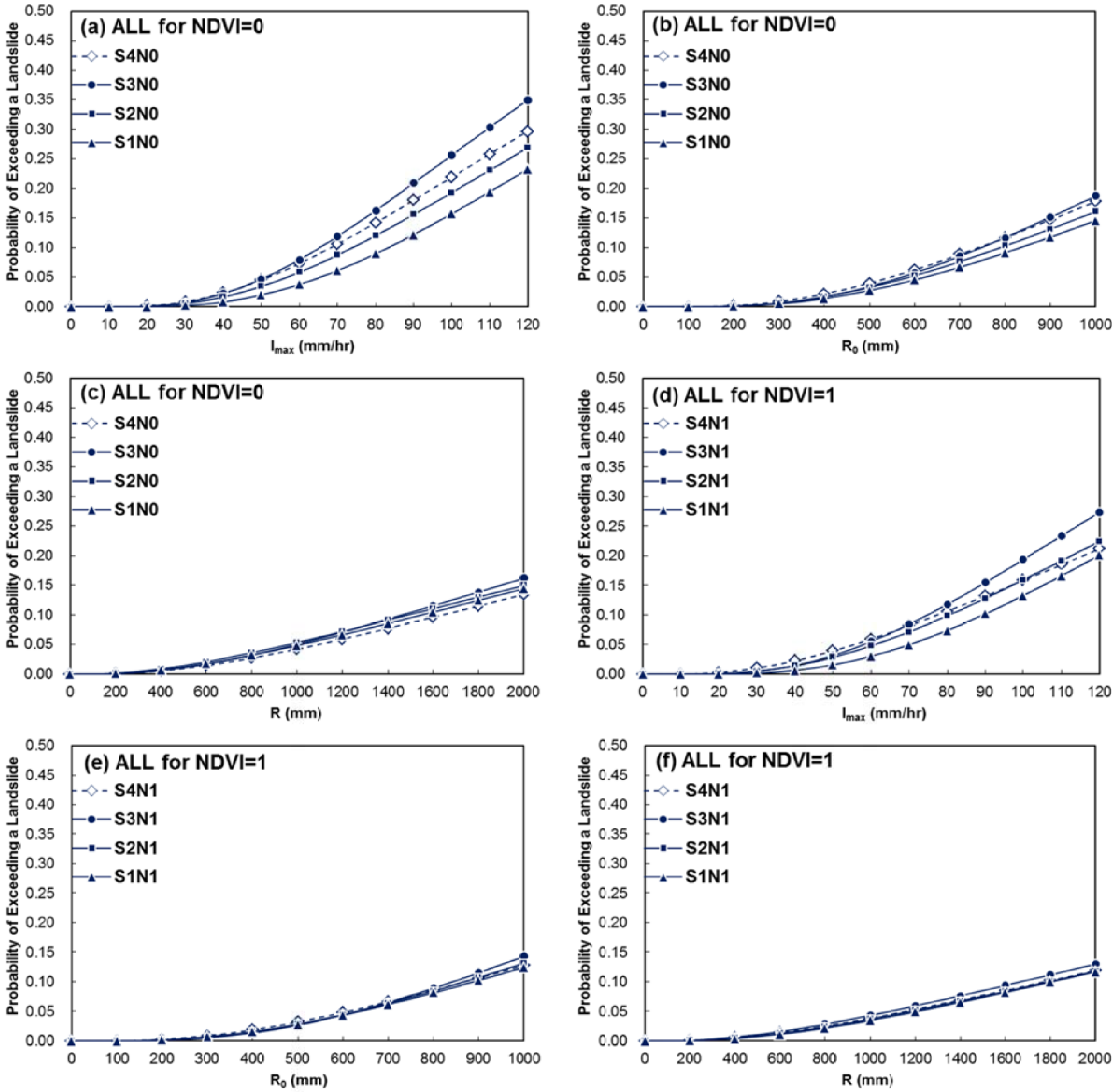


Figure 4. Landslide fragility curves by I, R_0, R factors under different classification of slope and vegetation indices.

In Figure 4, the LFC of I, R_0 and R show that the landslide probability increases with increasing rainfall indices, as well as the increasing slopes (e.g., (a) and (d)). However, it is noticed that the landslide probability doesn't increase obviously with increasing slopes, especially, rainfall indices with R_0 and R. It is shows that the maximum rainfall intensity has high correlation between with landslide. In addition r, the landslide probability at bare land is higher than at the healthy vegetation area. The area of lower vegetation coverage have higher ratio of incremental landslide than the better vegetated areas. The result implies that the status of vegetation considerably contributes to the soil conservation on a slope.

5. Summary and conclusions

This study had developed the Landslide Fragility Curve (LFC) model by using the spatial data, slope unit and statistical methods. The fragility curves of the study area were derived for all combinations of environmental and triggering factors. The analysis results had shown that the landslide has high correlation with rainfall, slope, and vegetation conditions. Moreover, the landslide probability increases with increasing rainfall of I, R_0 and R. Generally, the LFC curves indicated that the ratio of incremental landslide was proportional to the increasing slopes and rainfall. The LFC results also indicated that the better vegetation condition is, the lower the ratio of incremental landslide. From the analysis results, the proposed rainfall-induced landslide model can describe the relationships between rainfalls with the landslide. The model also provides basic prediction to landslide areas. The model then can be developed to include more influence factors regarding landslides. Overall, the LFC model from this study provides assessment method for landslides in the catchments. The model later can be developed for susceptibility and applied in model of estimation, risk and warring assessment in the future.

References

Chang, S.E., Shinozuka, M. & Moore, J., 2000. Probabilistic Earthquake Scenarios: Extending Risk Analysis Methodologies to Spatially Distributed Systems. Earthquake Spectra 16(3), pp. 557-572.

Hsieh, M.H., Lee, B.J., Lei, T.C. & Lin, J.Y., 2013. Development of Medium- and Low-rise Reinforced Concrete Building Fragility Curves Based on Chi-Chi Earthquake Data. Natural Hazards, 69(1), pp. 695-728.

Lei, T.C., Huang, Y.M., Lee, B.J. Hsieh, M.H. & Lin, K.T., 2014. Development of an Empirical Model for Rainfall-induced Hillside Vulnerability Assessment- A Case Study on Chen-Yu-Lan Watershed, Nantou, Taiwan", Natural Hazards, DOI 10.1007/s11069-014-1219-z.

Miyakoshi, J., Hayashi, Y., Tamura, K. & Fukuwa, N., 1997. Damage Ratio Functions of Buildings Using Damage Data of The 1995 Hyogo-Ken Nanbu Earthquake. In: Proceedings of the 7th International Conference on Structural Safety and Reliability (ICOSSAR), pp. 349-354.

Rota, M., Penna, A. & Strobbia, C.L., 2008. Processing Italian Damage Data to Derive Typological Fragility Curves. Soil Dynamics and Earthquake Engineering, 28, pp.933-947.

Soil and Water Conservation Bureau web site, 2013. Handbook of Soil and Water Conservation, Taiwan, from http://www.swcb.gov.tw/form/index.asp?m1=14&m2=96. Accessed 10 June 2013

Shinozuka, M., Feng, M.Q., Lee J., & Naganuma, T., 2000. Statistical Analysis of Fragility Curves, Journal of Engine. Mech., 126(12), pp. 1224-1231.

Shinozuka, M., Feng, M.Q., Kim, H., Uzawa, T. & Ueda, T. 2003. Statistical Analysis of Fragility Curves. Technical Report MCEER-03-0002, multidisciplinary center for earthquake engineering research, The State University of New York at Buffalo.

Shinozuka, M., Dong, X., Chen, T.C. & Jin, X., 2007. Seismic Performance of Electric Transmission Network Under Component Failures. J Earthq Eng Struct Dyn 36(2), pp. 227-244.

Tien, Y.M., Juang, C.H., Chen, J.M. & Pai, C.H., 2012. Isointensity–isoexposure Concept for Seismic Vulnerability Analysis—A Case Study of The 1999 Chi–Chi, Taiwan Earthquake. Eng Geol 131, pp. 1-10.

Varnes, D.J., 1984. Landslide Hazard Zonation: A Review of Principles And Practice. UNESCO Press, Praris, 63p.

Xie, M., Esaki, T. & Zhou, G., 2004. GIS-Based Probabilistic Mapping of Landslide Hazard Using A Three-dimensional Deterministic Model. Natural Hazards, 33, pp. 265-282.