



Common Patterns Among Different Landslide Susceptibility Models of the Same Region

Chyi-Tyi Lee and Chih-Chung Chung

Abstract

Four rain-event landslide inventories and one combined-event dataset for the mountainous terrain around the Choswei river catchment area in central Taiwan were selected for studies. A total of five event-based landslide susceptibility analyses were completed, and one multi-temporal landslide inventory was used to carry out regular landslide susceptibility analysis. The basic susceptibility of each model was compared and a common pattern of susceptibility was found among them. The results indicate that there is a common pattern of landslide susceptibility in a given region regardless of which event is used to build the susceptibility model. Also, the basic susceptibility is similar in pattern to the susceptibility model built based upon the multi-temporal landslide inventory of that region.

Keywords

Landslides • Landslide inventory • Landslide susceptibility • Logistic regression

Introduction

Regional landslide susceptibility is commonly predicted using a statistical approach based on a multi-temporal landslide inventory and various environmental factors (e.g., Carrara 1983; Guzzetti et al. 1999; Van Western et al. 2008). If a multi-temporal landslide inventory is not available, an event landslide inventory and consideration of triggering factors may be used to build a susceptibility model (Dai and Lee 2003; Lee et al. 2008a, b). The question arises as to what are the differences and similarities between traditional landslide susceptibility mapping and event-based landslide susceptibility mapping? This question is examined and comparisons made based upon a real example in this study.

A multi-temporal landslide inventory represents the landslide history of a region. If the time range is long enough, it may illustrate the slope stability at each locality in the region. This makes for good data to use to train a landslide susceptibility model for the region.

A single-period landslide inventory used for susceptibility analysis may be biased (Canuti et al. 1986), because susceptibility models trained from landslide inventories made during different periods may show different patterns (Lee and Fei 2015).

A susceptibility model trained from an event-triggered landslide inventory and triggering factors together with environmental factors is different. It was named event-based landslide susceptibility analysis, as discussed by Lee et al. (2007, 2008a, b). An event-based model is good at interpreting landslide distribution for the event. Different events may show different susceptibility patterns, because an event-based model primarily reflects the pattern of rainfall or earthquake intensity associated with the event only. However, when we remove the triggering factor component from the event-based model, the model becomes event independent, showing common susceptibility patterns between different events in a region. This common susceptibility is

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called basic landslide susceptibility by Lee et al. (2004) and Lee (2015).

Since basic susceptibility is event independent, maps derived from different triggering events but for the same region should exhibit similar patterns. Thus, the main purpose of the present study is to clarify and confirm this. The secondary purpose is to compare the similarity of the basic susceptibility to the susceptibility derived from a multi-temporal landslide inventory.

In the present study, four rain-event landslide inventories and one combined-event dataset for the mountainous terrain around the Choswei River catchment area in central Taiwan were selected to build five event-based landslide susceptibility models. A model built from a multi-temporal landslide inventory in the same region was also prepared. These will

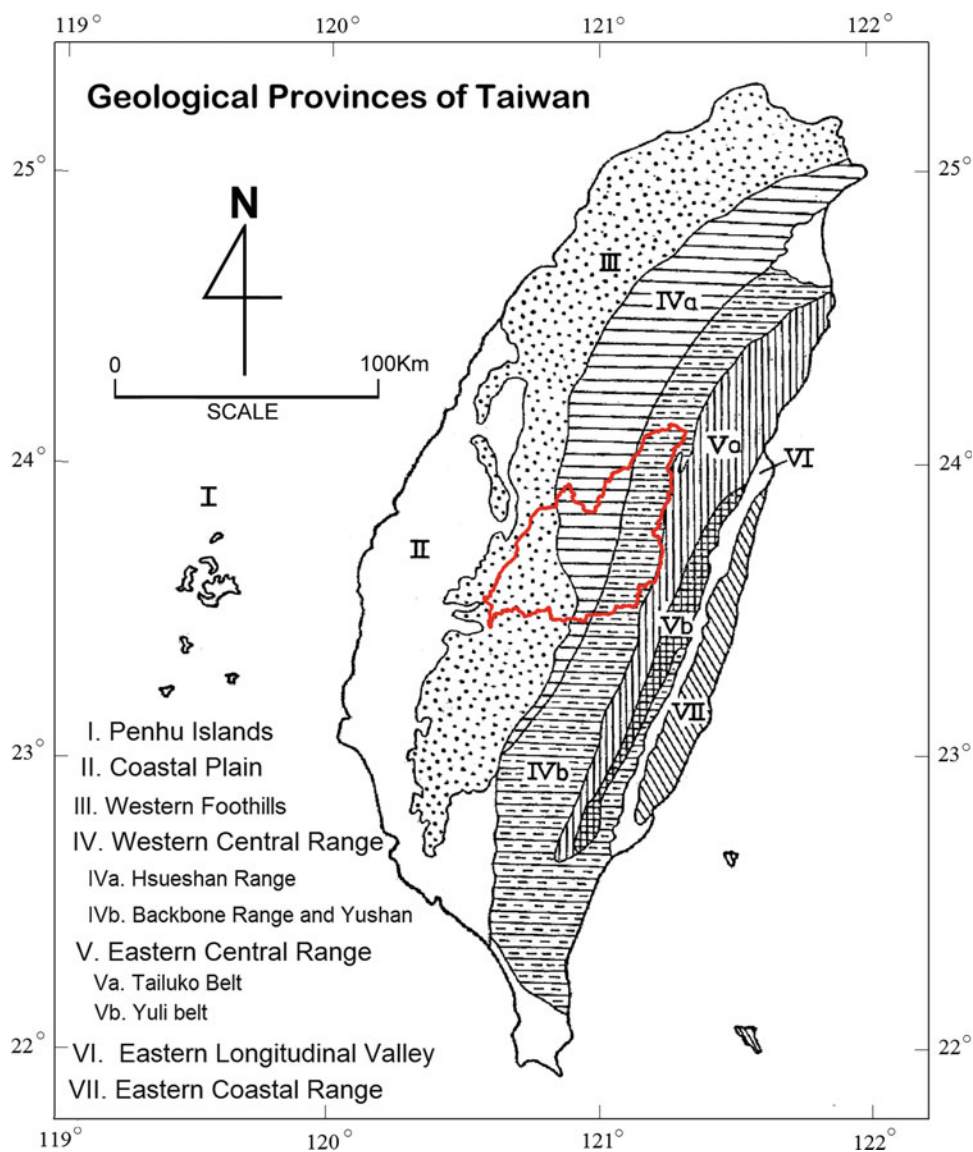
be compared and discussed in depth in the following sections.

Landslide Susceptibility Analysis

Study Area

The study area is located in the mountainous terrain of the Choswei River catchment area in central Taiwan. It falls within the Western Foothill geologic province and the Western Central Range geologic province (Fig. 1). The Western Foothill consists of Miocene sandstone and mudrock. The Western Central Range is comprised of a Paleogene slate belt.

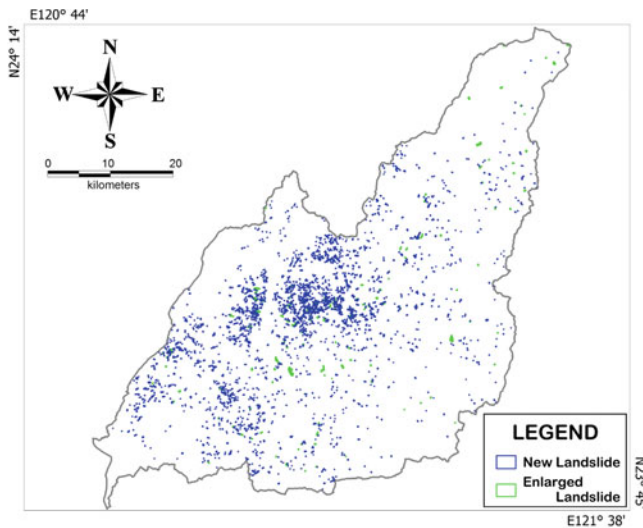
Fig. 1 Geology and location of the study area (outlined by the red line)



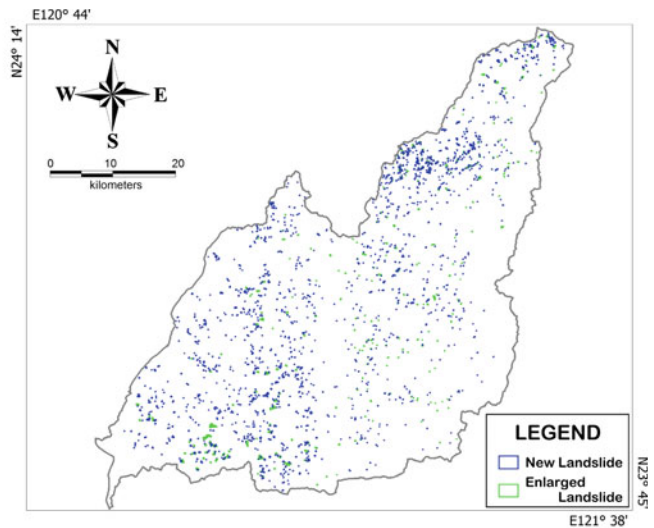
The study area covers a total area of 2775 km² with altitudes ranging from 190 to 3952 m. The average altitude is 1422 m, and typical slope angles are between 10° and 55°, with a mode of about 33°. The climate in the study area is subtropical with an average annual precipitation of about 2800 mm. Approximately three typhoons strike this area each year, mostly between July and October. Vegetation cover in the region is thick. Overburden on the bedrock is mostly slope wash or colluvium, ranging from about some tens of centimeters to less than 2 m thick.

Data

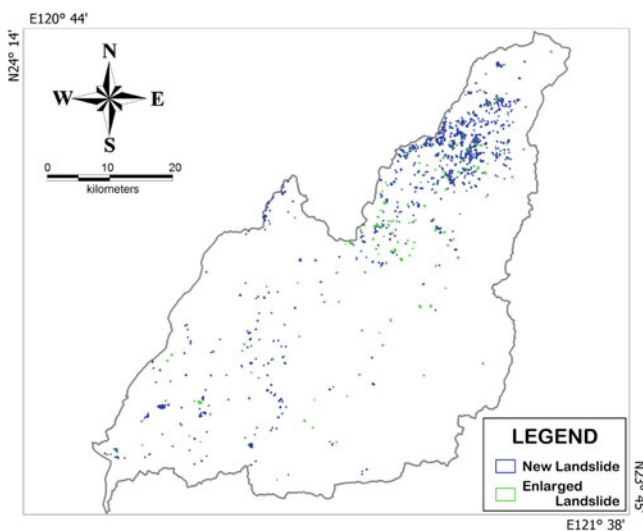
Landslide inventories were obtained and digitized from fused false-color SPOT images taken before and just after a typhoon event. Four pre-event and four post-event landslide inventories were completed in the first step. After this, the pre and post event inventories were compared to find the event-triggered landslides. Four different event landslide inventories (Fig. 2) were completed for use in the event-based landslide susceptibility analyses. The four



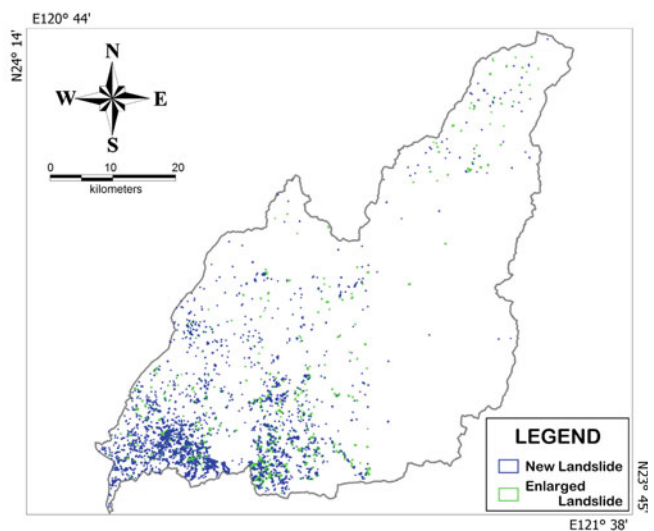
(1) Landslides triggered by the Typhoon Toraji in 2001.



(2) Landslides triggered by the Typhoon Mindulle in 2004.



(3) Landslides triggered by the Typhoon Shinlaku in 2008.



(4) Landslides triggered by the Typhoon Morakot in 2009.

Fig. 2 Event landslide inventories in the study area

events were Typhoon Toraji in 2001, Typhoon Mindulle in 2004, Typhoon Sinlaku in 2008, and Typhoon Morakot in 2009. The four pre-event inventories and the four post-event inventories were also used to form a multi-temporal landslide inventory for building a susceptibility model. In addition to the SPOT images, the basic data utilized in this study included a 5 m × 5 m grid digital elevation model (DEM), 1/5000 photo-based contour maps, 1/50,000 geologic map sheets, and hourly rainfall data. These data were used in the processing of environmental and triggering factors. All data were finally transformed to 10 m raster cells for susceptibility analysis. There are 31 rain gauge stations located in the study area. Hourly rainfall data at each station were first processed to find the rainfall parameters. Then, the regression kriging method was used to interpolate rainfall values into each 10-m grid, using elevation value as an auxiliary variable.

Analysis

All landslide cells and similar numbers of non-landslide cells in the landslide inventory were selected for training of a susceptibility model. Conventional multi-variate statistical analysis through logistic regression was adopted to build the susceptibility model. Effective causative factors including the slope gradient, slope aspect, slope roughness, tangential curvature, and relative slope height were determined and were used in the analysis. The maximum rainfall intensity and total event rainfall were selected as the two triggering factors for each event. The correlation coefficient between each pair of these two factors was calculated. If a correlation coefficient was larger than 0.5, then one of the factors was not selected. Also, it was found that for most selected causative factors the correlation with each triggering factor was very low (at most <0.1). It is best if a triggering factor is statistically independent of a causative factor. The occurrence probability p obtained after the logistic regression is used as the susceptibility index in this study. Larger values of an index indicate higher potential for a landslide.

Results

Four event-based susceptibility models and a combined-event model were built for the study region in the first step. Then we extracted the triggering factor component from the event-based model, and an event-independent susceptibility map was constructed [Fig. 3(1–5)]. A model trained from the multi-temporal landslide inventory was also built, but without the triggering factors [Fig. 3 (6)]. The combined-model was trained by combining the inventories

and triggering factors from the Toraji event and the Mindulle event.

The constructed event-based models are compared with the landslide data used to build the model, and the success rate (Chung and Fabbri 1999, 2003) are 0.791 (area under the success rate curve), 0.750, 0.743, 0.696, and 0.784 for the Toraji, Mindulle, Sinlaku, Morakot, and combined event models. These models are ranked as fair in fitting the landslides used to build the model. The success rate for the model built from multi-temporal landslide inventory is 0.810 and is ranked as good.

When an event landslide inventory and triggering factors are used to build a landslide susceptibility model, the resulting model goes a very good way towards explaining the distribution of event-triggered landslides, and the model is automatically dependent on the event itself. However, if the trigger factor component is removed from the model, then the model becomes event independent, provided that the triggering factor is an independent factor having only a small correlation coefficient with each causative factor.

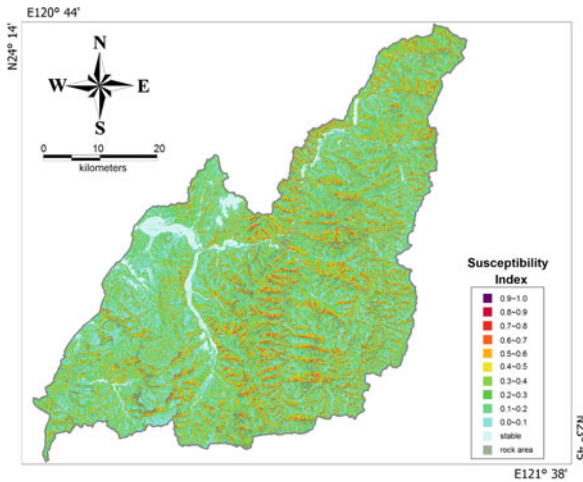
From Fig. 3, we can see the similarity in the patterns among the four event-independent susceptibility models and the combined-event model. It is worth mentioning there is not only a similarity between all of the event-independent susceptibility model, but they also have similar patterns to the model built using the multi-temporal landslide inventory. Note that the histogram matching technique has been applied to each event-independent model, because we consider that landslide susceptibility values only reflect the relative potential of landslides for a specific region.

Discussions

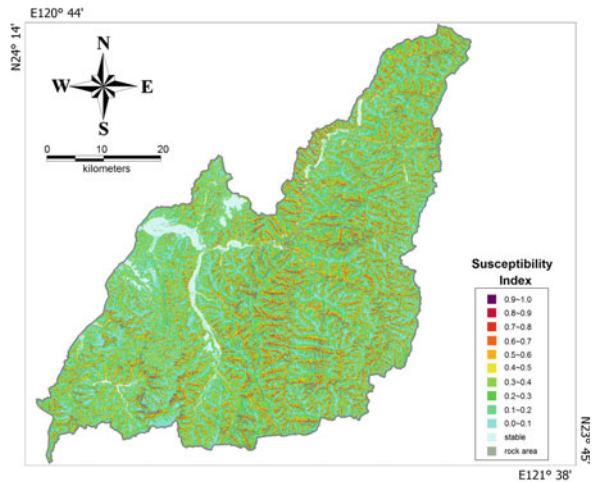
What are the differences and similarities between traditional landslide susceptibility mapping and event-based landslide susceptibility mapping? It is clear that although triggering factors were used in the event-based analysis, the susceptibility patterns shown were similar when the triggering factor component was removed from the event-based model.

However, attention must be paid to the independence of a triggering factor to any one environmental factor. If the correlation coefficient of two factors is larger than 0.5, then the causative factors should not be selected for the susceptibility analysis. Also, most selected causative factors should have a very low correlation (say <0.1) with a triggering factor.

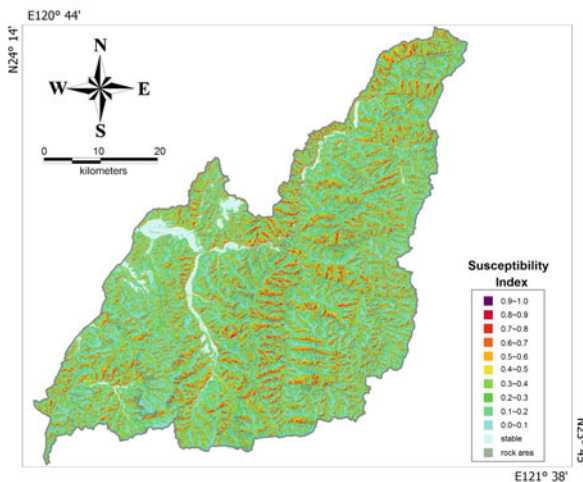
Since triggering factors are control factors for landslide occurrence during a rain event or an earthquake event, the resolution and quality of these factors are very important for the production of a high quality susceptibility map. For a rain event, sufficient data from a large enough number of rain gauge stations and high quality interpolation methods,



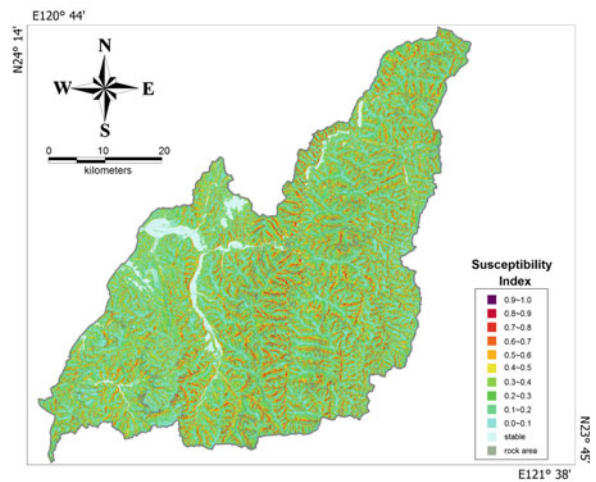
(1) Event-independent landslide susceptibility map trained from Typhoon Toraji data.



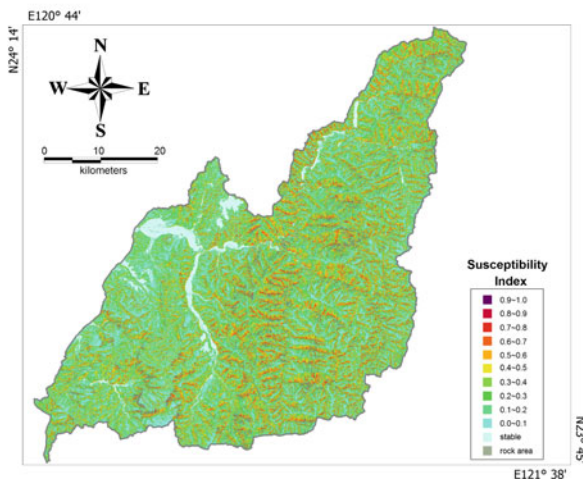
(2) Event-independent landslide susceptibility map trained from Typhoon Mindulle data.



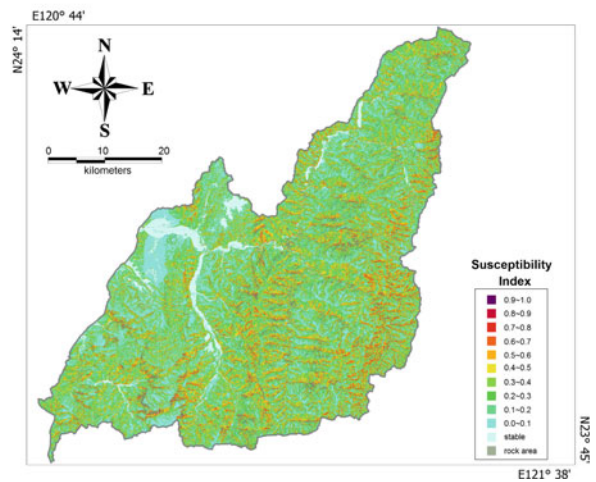
(3) Event-independent landslide susceptibility map trained from Typhoon Shinlaku data.



(4) Event-independent landslide susceptibility map trained from Typhoon Morakot data.



(5) Event-independent landslide susceptibility map trained from combined Typhoon Toraji and Midulle data.



(6) Landslide susceptibility map trained from a multi-temporal landslide inventory.

Fig. 3 Event-independent landslide susceptibility maps for the study area

like cokriging or regression kriging with elevation data, should always be used. In the present case, the density of rain gauge stations in the study area is 89.5 km² per station on average. For an earthquake event, a sufficient amount of strong-motion stations are required. It is also important to take into consideration topographic amplification (e.g., Lee et al. 2008a).

Conclusions and Recommendations

Although event-based landslide susceptibility analysis is different from the traditional method in terms of the usage of landslide inventory and triggering factors, the resultant landslide susceptibility map is similar in pattern after the removal of triggering factors during the modelling process. It is suggested that either a model trained by a multi-temporal landslide inventory or an event-independent susceptibility model which was trained from a single event landslide inventory with consideration of triggering factors, may be suitable to represent the landslide susceptibility of the study region. This common susceptibility may be considered to illustrate the basic susceptibility of the region.

When we removed the triggering factor component from an event-based model, the model becomes event independent, provided that the triggering factor is an independent factor with only a small correlation coefficient with each causative factor.

Since landslide susceptibility values could reflect the relative potential of landslides occurring at a specific region, after the basic susceptibility of a region is determined, we can then analyze the relationship between the probability of landslide failure and the triggering factor of a certain event at each basic susceptibility bin and build their relationship. The relationship can then be used as a prediction model for predicting the likelihood of rain-induced and earthquake-induced landslides. Examples of these kinds of relationships and predictions can be found in Lee (2014a, b, 2015). This type of landslide prediction model is good for (1) mapping the landslide hazard for a certain return-period due to rainfall or earthquake, (2) prediction of landslide failure probability triggered by a rainfall or earthquake event, (3) decision making for regional planning, site selection and hazard mitigation, and (4) estimation of sediment yield for a drainage basin after an event (Lee and Fei 2015).

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References

- Canuti P, Focardi P, Garzonio CA, Rodolfi G, Vannocci P (1986) Slope stability mapping in Tuscany, Italy. In: Gardiner V (ed) *International geomorphology*, vol 1. Wiley, pp 231–240
- Carrara A (1983) Multivariate models for landslide hazard evaluation. *Math Geol* 15(3):403–427
- Chung CF, Fabbri AG (1999) Probabilistic prediction models for landslide hazard mapping. *Photogram Eng Remote Sens* 65 (12):1389–1399
- Chung CF, Fabbri AG (2003) Validation of spatial prediction models for landslide hazard mapping. *Nat Hazards* 30:451–472
- Dai CF, Lee CF (2003) A spatiotemporal probabilistic modeling of storm-induced shallow landslide using aerial photographs and logistic regression. *Earth Surf Process Landf* 28:527–545
- Guzzetti F, Carrara A, Cardinali M, Reichenbach P (1999) Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy. *Geomorphology* 31:181–216
- Lee CT (2014a) Multi-stage statistical landslide hazard analysis: earthquake-induced landslides. In: Sassa K et al (eds) *Landslide science for a safer geoenvironment*, vol 3. Springer International Publishing, pp 205–211 (ISBN 978-3-319-04998-4)
- Lee CT (2014b) Multi-stage statistical landslide hazard analysis: rain-induced landslides. In: Sassa K et al (eds) *Landslide science for a safer geoenvironment*, vol 3. Springer International Publishing, pp 291–298 (ISBN 978-3-319-04998-4)
- Lee CT (2015) Review and perspectives on methodology for landslide hazard analysis. In: *Proceedings of 10th Asian regional conference of IAEG*, 6 p
- Lee CT, Fei LY (2015) Nationwide landslide hazard analysis and mapping in Taiwan. In: Lollino G et al (eds) *Engineering geology for society and territory*, vol 2. Springer International Publishing, pp 971–974 (ISBN 978-3-319-09302-4)
- Lee CT, Huang CC, Lee JF, Pan KL, Lin ML, Liao CW, Lin PS, Lin YS, Chang CW (2004) Landslide susceptibility analyses based on three different triggering events and result comparison. In: *Proceeding of international symposium on landslide and debris flow hazard assessment*, Taipei, pp 6–16
- Lee CT, Huang CC, Lee JF, Pan KL, Lin ML, Dong JJ (2007) Event-based landslide susceptibility analysis—an example from central western Taiwan. *Geophys Res Abstr* 9:06216
- Lee CT, Huang CC, Lee JF, Pan KL, Lin ML, Dong JJ (2008a) Statistical approach to earthquake-induced landslide susceptibility. *Eng Geol* 100:43–58
- Lee CT, Huang CC, Lee JF, Pan KL, Lin ML, Dong JJ (2008b) Statistical approach to storm event-induced landslide susceptibility. *Nat Hazard Earth Syst Sci* 8:941–960
- Van Westen CJ, Castellanos E, Kuriakose SL (2008) Spatial data for landslide susceptibility, hazard, and vulnerability assessment: an overview. *Eng Geol* 102:112–131