Multi-stage Statistical Landslide Hazard Analysis: Rain-Induced Landslides

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Abstract

Recurrence of rain-induced landslides is controlled by the repetition of rain events. Therefore, rainfall induced landslide hazard analysis is more complicated than a conventional rainfall frequency analysis, and requires multi-stage procedures. It requires a susceptibility analysis to divide a region into successive classes at the first stage. Then, the relationship between the probability of landslide failure and rainfall intensity and/or total rainfall of an event for each susceptibility classes may be constructed, and further fit a probability of failure surface using the susceptibility value, rainfall intensity and/or total rainfall as independent variables. Then, frequency analysis for rainfall parameters at different return periods is performed. Finally, an analysis of the spatial probability of landslide failure under a certain return-period rainfall is drawn. This study selects data for Typhoon Haitang induced landslides in the Kaopin river basin as the training data set to perform a susceptibility analysis and a probability of failure surface analysis. A rainfall frequency analysis is also conducted to map different return-period rainfall intensity and 3-day rainfalls. Finally, a rainfall landslide hazard map is provided.

Keywords

Landslide • Event landslide inventory • Landslide susceptibility • Rainfall-induced landslides • Rainfall landslide hazard

Introduction

Rainfall induced landslide hazard analysis has two major approaches, statistical and deterministic. Statistical approach commonly uses a multi-temporal landslide inventory to build a statistical model (e.g., Carrara 1983; Guzzetti et al. 1999). However, most of the available hazard maps are still of qualitative nature and concentrate basically on determining the susceptibility (van Westen et al. 2006), and temporal probability is also lacking. Guzzetti et al. (2005) attempt to solve the temporal probability problem and introduced a probabilistic model which predicts where landslides will occur, how frequently they will occur, and how large they will be. But, there still are problems on incompleteness of the inventory, insufficient length of historical records, and a possible mixing of extreme events and/or earthquake disturbance.

Physical based method uses a hydrological model and an infinite slope model to form a landslide prediction model (Montgomery and Dietrich 1994; Iverson 2000; Brenning 2005; Claessens et al. 2007). It is perfect in theory, but has a difficulty in acquiring site specific data, like, failure depth, material strength, and groundwater data.

A new statistical approach called event-based landslide susceptibility analysis (EB-LSA) was introduced recently in Lee et al. (2008b). This new approach is different from the traditional susceptibility analyses in the emphasis of using an event landslide inventory and triggering factors. It is also different from the probabilistic method in the usage of event landslide inventory and triggering factors.

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EB-LSA is basically different from the physical based method, but they are similar in the multi-stage nature, including a susceptibility stage for spatial probability of landslides and a rainfall frequency analysis stage for temporal probability of landslides, and both intend to construct a landslide spatial probability or safety factor map for a certain return-period rainfalls. This means both method adopt that recurrence of rain-induced landslide is controlled by the repetition of triggering events.

To construct a 100-year rainfall landslide hazard map was routinely done in the landslide project of Central Geological Survey (CGS), Taiwan, in recent years for each river basin in Taiwan (Lee and Fei 2011). A nationwide storm landslide hazard map will be completed in the end of year 2013 (Lee et al. 2012). However, the approach in the previous studies has a weak point in that the hazard map may include the probability contributed from causative factors and produces non-zero probability at zero rainfall intensity. Therefore, a new landslide probability of failure relationship must be further developed.

The present study upgrades the study of Lee et al. (2012) by developing a probability of failure surface instead of a probability of failure curve. The new relationship should avoid mixing the contribution from causative factors. Using this new probability of failure surface and a 100-year return-period rainfall map, a new 100-year storm landslide hazard map for a major river basin in southern Taiwan is constructed. The rainfall landslide hazard map may reveal landslide spatial probability at each pixel given a certain rainfall return-period.

Methodology

Susceptibility Model

Our rainfall induced landslide susceptibility analysis method basically follows Lee et al. (2008b) which used an event landslide inventory and the triggering factors to build a susceptibility model. This model is called an event-based susceptibility model by Lee et al. (2008a, b), and is accordingly event-dependent. The effective selection of the landslide causative factors and triggering factors, as well as an analytical method, are very important for the construction of a high prediction rate model. Please refer to Lee and Fei (2011) for details of these.

Probability of Failure Surface

The construction of a probability of failure curve in the previous studies is simple: simply plot the mean probability of failure value at each susceptibility bin and fit a curve. A probability of failure surface is intended to show a relationship between the probability of failure and rainfall parameters at each susceptibility bin, and to obtain the fit to the surface using the rainfall parameters and susceptibility as independent variables. Note that the susceptibility values used here indicate the event-independent susceptibility without a triggering factor.

A landslide spatial probability map may be produced by transferring the event-independent susceptibility values and rainfall factors to the probability of landslide failure at each grid cell by using a probability of failure surface. When rainfall factors from the training event are used, one can produce a hazard map that reflects the rainfall event. The use of the rainfall parameters for a specific rainfall scenario, produce a hazard map that reflects the scenario rainfall event.

Temporal Probability of Landslides

Since rainfall induced landslides are induced features from the heavy rainfall, their recurrence is controlled by the repetition of the rainfall event. Therefore, we must know the likelihood of a rainfall recurrence or the rainfall values at a certain return-period. This may be obtained through a regular hydrological frequency analysis (e.g., Chow 1953; Fowler and Kilsby 2003) with a set of rainfall data from different rain gage stations.

Preparation of a certain return-period rainfall intensity map and 3-day rainfall map for the study region is the objective of the frequency analysis, and is the input data for the rainfall landslide hazard mapping. This is commonly a 100-year return period rainfall. However, it may include other choices of return period, like a 50-year return period. If rainfalls of a 100-year return-period are used, the hazard map reflects the 100-year rainfall, and may be called a 100-year rainfall landslide hazard map.

Data

Basic Data

The basic data used in the present study include: 2.5m high resolution SPOT5 images, a 5-m grid digital elevation model (DEM), 1/5,000 photo-based contour maps, 1:50,000 geologic maps, and hourly rainfall records. Digital geological maps (1:50,000) were obtained from the Central Geological Survey, Taiwan. All the vector layers were converted into raster cells of 10 m × 10 m in size and this resolution was used for all subsequent processing and analysis for each landslide factor and the hazard model.

Event Landslide Inventory

The Typhoon Haitang hit Taiwan on July 16 to 20, 2005. It brought a total rainfall of up to 2,000 mm in the Kaoping river basin, and triggered 15,864 landslides with a total area of 42.8 km^2, which occupied 1.28 % area of the river basin, or 1.75 % of the slope terrain in the river basin.

False-color SPOT5 images were used for landslide recognition. Landslides were recognized and digitized in GIS and attributes were assigned to establish a landslide map table. Each landslide table was then checked in the field and in the laboratory against 1/5,000 photo-based contour maps, and modifications were made. An event-triggered landslide was identified by comparing the pre-event and post-event landslide inventories, to produce an event-based landslide inventory. The Typhoon Haitang event-based landslide inventory is shown in Fig. 1. The event landslide inventory for the 2009 Typhoon Morakot was prepared in a similar way and will be used for validation of the Haitang event susceptibility model.

Results

Event-Based Susceptibility Model

The Typhoon Haitang induced shallow landslides (Fig. 1) and rainfall data are actually used in the susceptibility analysis. Due to the fact that an event landslide inventory and a triggering factor of the event are used in the development of the susceptibility model, this is called an event-based susceptibility model (Lee et al. 2008a, b).

Causative factors used in the susceptibility model include the following: slope gradient, slope aspect, slope roughness, tangential curvature, relative slope height, and lithology. For a detailed description of the causative factors and the triggering factor, please refer to Lee and Fei (2011).

Logistic regression is used in the susceptibility analysis and the results of this analysis include a logistical function and the coefficients,

$$\ln\left[\frac{p}{1-p}\right] = \begin{array}{l} 0.726L_1 + 0.175L_2 + 1.072L_3 + 3.673L_4 \\ +2.520L_5 + 2.575L_6 + 2.856\,L_7 + 2.205L_8 \\ +3.044L_9 + 3.053L_{10} + 2.940\,L_{11} + 2.812A_1 \\ +3.595A_2 + 4.146A_3 + 4.333A_4 + 4.240A_5 \\ +3.987A_6 + 3.297A_7 + 2.790A_8 + 1.182F_1 \\ +0.061F_2 + 0.299F_3 - 0.761F_4 + 0.446F_5 \\ -7.317. \end{array} \quad (1)$$

where L_1–L_{11} are lithological units; A_1–A_8 are slope aspects; F_1–F_4 are causative factors; F_5 is a triggering factor; and p is the occurrence probability. During the establishment of the logistic equations, the input p is 1 for a landslide grid and o for a non-landslide grid. After the regression, when the set of factors is given a score at a grid point, the occurrence probability p at that point is derived. It will be in the range of 0 to 1. This occurrence probability is taken as a susceptibility index λ in this study. Larger values of an index indicate a higher susceptibility to landslides.

The event-based susceptibility model (Fig. 2) goes a good way to explaining the event-induced landslide distribution. The probability of failure curve shows a good fit to the hyperbolic sine function (Fig. 2b). The area under the curve (AUC) of the success rate curve is 0.776. The model is further validated utilizing the Typhoon Morakot rainfalls and its event landslide inventories; the AUC of the prediction rate curve is 0.728 for the model.

Event Independent Susceptibility Model

The event-based susceptibility model is dependent on the event itself. However, if we extract the triggering factor from the model, then the model becomes event independent, provided that the triggering factor is an independent factor having only small correlation coefficient with any causative factors. This option must be carefully examined before a causative factor is selected.

In this case, the event-based susceptibility model is reduced to an event-independent model by removing the component of the triggering factors from the original model. Here, we call this reduced model an event-independent susceptibility model for the region. Different event-independent susceptibility models for the same region have been compared and good agreement has been found among them (Lee et al. 2004). On this basis, we can use an event-independent susceptibility model to represent the susceptibility of the region with confidence.

Probability of Failure Surface

We tested the relationship between probability of failure and rainfall intensity, as well as total rainfall at each event-independent susceptibility bin. It was found that the relation is good; the probability of failure increases with an increase in the rainfall and also with an increase in the susceptibility. After this finding, it was necessary to find a global fitting surface using a rainfall parameter and event-independent susceptibility as two independent variables. The result is shown in Fig. 3 and (2) and (3) as follows:

$$y = 16.808\lambda\left(1 - e^{-5.924\lambda^{0.942}}\right)\left(1 - e^{-0.0132x_1^{2.907}}\right) \quad (2)$$

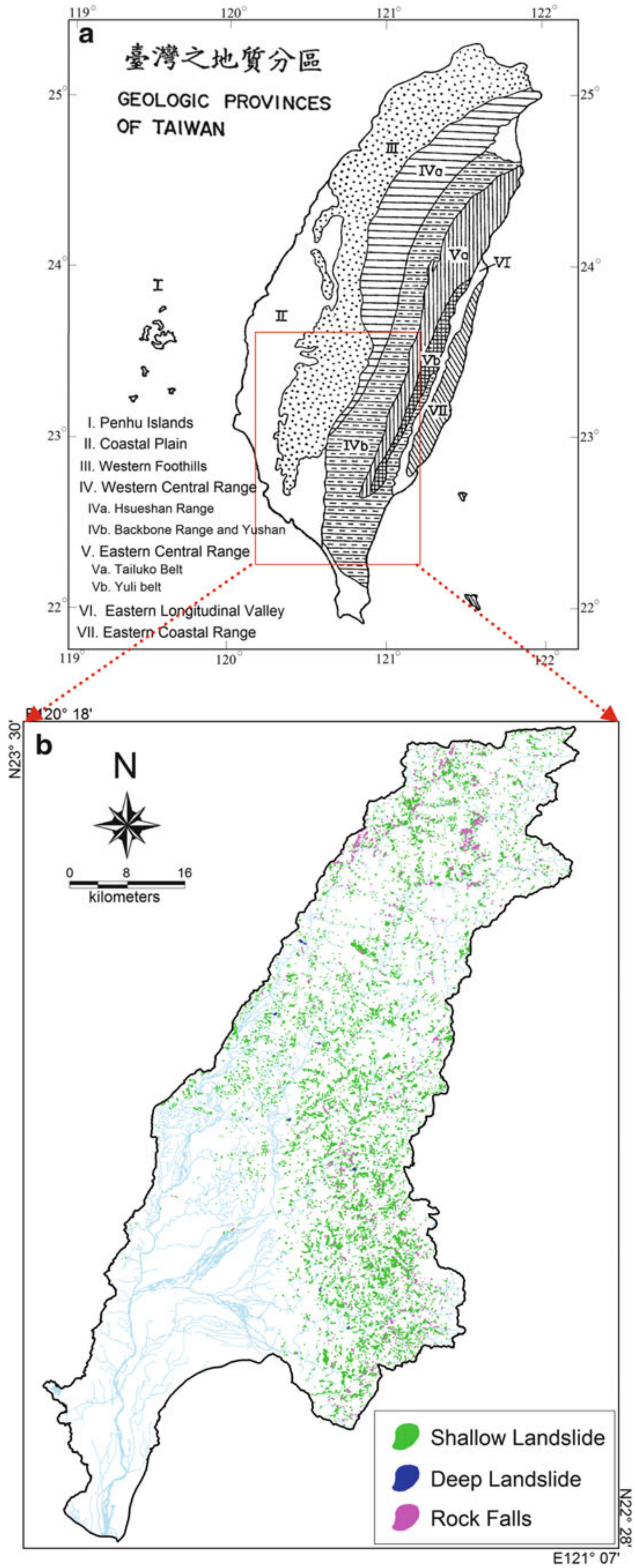

Fig. 1 Geology of the Kaoping river basin (**a**) index map showing the geology of Taiwan, (**b**) landslide distribution of the Kaoping river basin

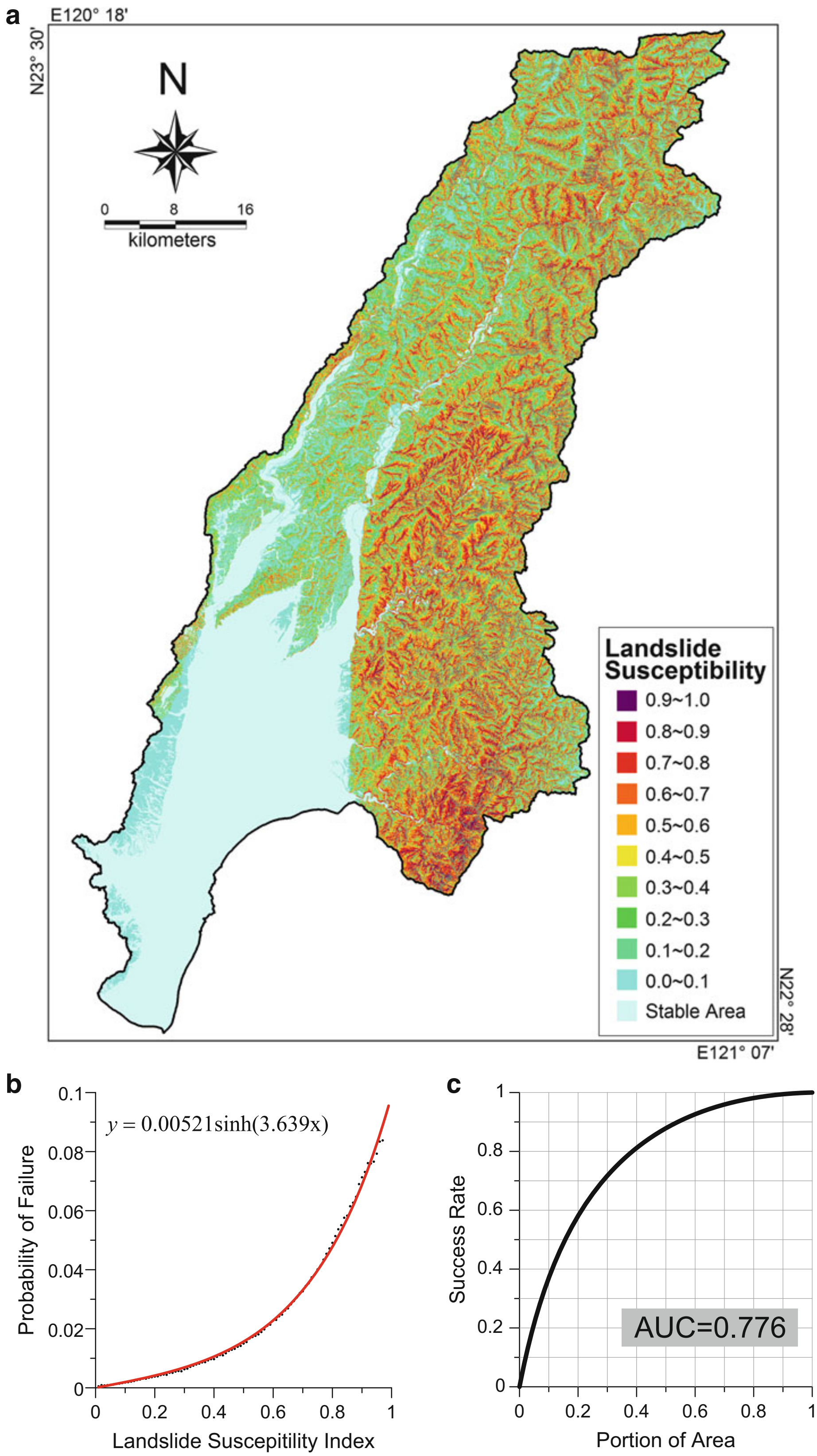

Fig. 2 Susceptibility model for the Haitang event landslides (**a**) event-dependent landslide susceptibility map; (**b**) probability of failure curve; and (**c**) success rate curve

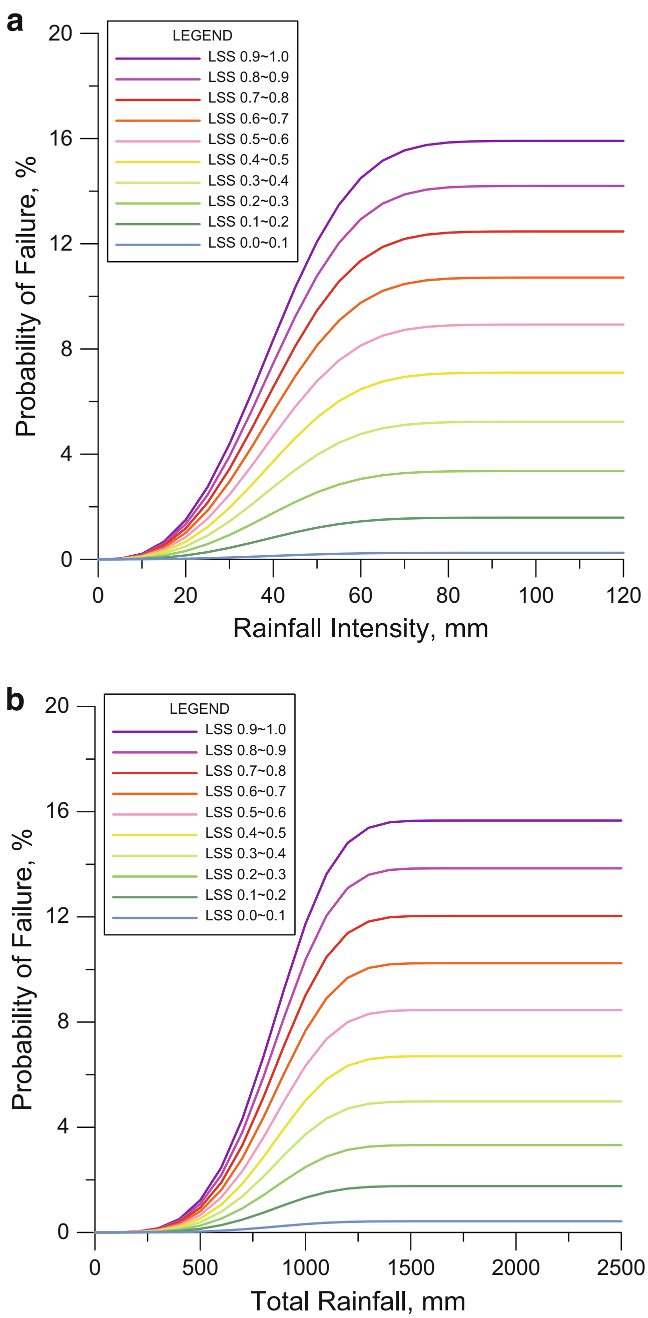

Fig. 3 Probability of failure surface (**a**) rainfall intensity; (**b**) total rainfall. Equation shown in the text

$$y = 17.990\lambda\left(1 - e^{-2.542\lambda^{0.461}}\right)\left(1 - e^{-0.000114x_2^{4.085}}\right) \qquad (3)$$

where x_1 is the rainfall intensity in centimeter, x_2 is the total rainfall in decimeter; y is the probability of failure, and λ is the event-independent susceptibility. Equation (2) is for rainfall intensity and (3) is for total rainfall.

A global probability of failure surface for two rainfall variables may be built by combining (2) and (3). If the two rainfall variables are totally independent, then the square of global probability of failure is the sum of the square of (2) and the square of (3). If the two rainfall variables are totally dependent, then the square of global probability of failure is the product of (2) and (3). In actual cases, the two rainfall variables are, commonly, in between dependent and independent, but have a correlation coefficient between 0 and 1. In the present study, we propose,

$$y = \left((1 - r)\left({y_1}^2 + {y_2}^2\right) + r(y_1 y_2)\right)^{0.5} \qquad (4)$$

where y_1 is y of (2), y_2 is y of (3), and r is the correlation coefficients between rainfall intensity and total rainfall.

Rainfall Frequency Analysis

The temporal probability of a rainfall landslide hazard model may be accounted for by the recurrence of the rainfall events. Rainfall values at different return-period may be obtained through a conventional rainfall frequency analysis.

A hydrological team in the CGS landslide project was responsible for rainfall frequency analysis and providing different return-period rainfall values at each study area and also a set of maps for the whole of Taiwan. The present study selects 1-h rainfalls and 3-day rainfalls of 100-year return-period for final mapping of the rainfall landslide hazard. 3-day rainfalls are evaluated as proper to represent the total rainfall of a Typhoon storm event in Taiwan.

Rainfall Landslide Hazard Map

The previously built susceptibility model, which is event-dependent, is good for interpretation of the event landslide distribution. With the addition of the probability failure surface, this model is capable of predicting landslides during a scenario event, provided that the rainfall values are known for each study grid cell. However, for hazard mapping, a certain temporal probability or return period for rainfall values should be adopted. This is commonly a 100-year return period. Other choices of return period, like a 10-year, 20-year, 50-year return-period may also be used.

The 1-h rainfall map and 3-day rainfall map of 100-year return-period, and the event independent susceptibility model are then applied to the probability of failure model to construct a 100-year rainfall landslide hazard map for the Kaoping river basin (Fig. 4).

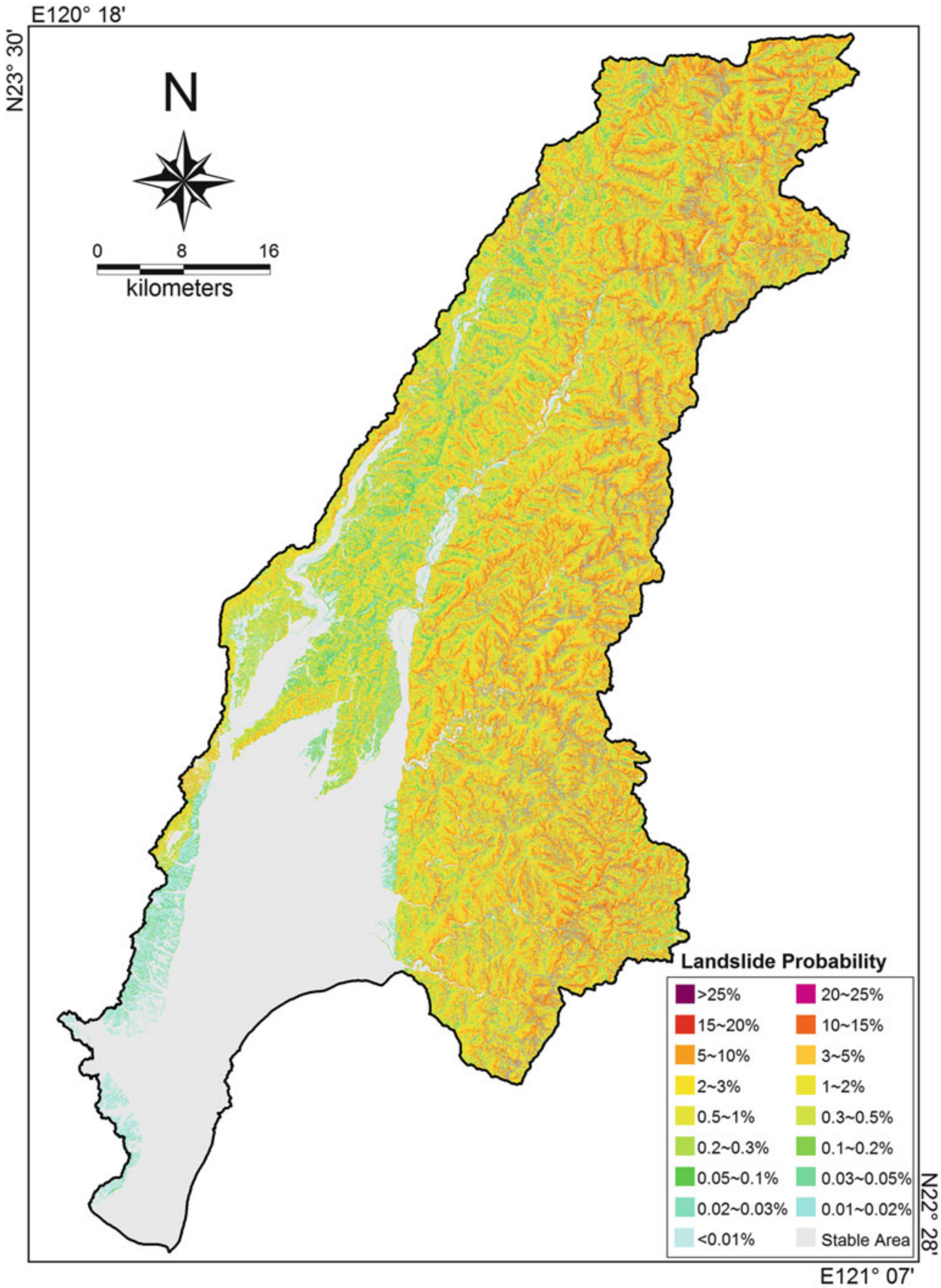

Fig. 4 100-year rainfall landslide hazard map for the Kaoping Basin

Conclusion and Recommendation

A multivariate statistical approach with logistic regression has been used to analyse the Typhoon Haitang induced shallow landslides and their controlling factors, and to build an event-dependent susceptibility model. The event-independent model (without a triggering factor), rainfall intensity map, total rainfall map, and the actual landslides from the Haitang event, are used to construct a relationship, using the event-independent susceptibility and rainfall parameters as independent variables, and it is fitted with a probability of failure surface. Then, the 100-year rainfall maps together with the event-independent susceptibility model are input into the probability of failure relationship to complete a 100-year rainfall landslide hazard map for the Kaoping river basin. The results of the analysis are good, provided that careful validation of the Typhoon Morakot induced landslides is made. We conclude that this statistical approach is feasible for rainfall landslide hazard analysis, and that the hazard model can be used to predict landslides after a rainfall event and can be used to produce a rainfall landslide hazard map of a wider region.

The statistical approach to rainfall landslide hazard has advantages over deterministic methods in that it does not require failure depth, material strength, or groundwater data, and may have a better prediction rate. On the other hand, a deterministic model can be used anywhere once the parameters required by the model are available. The statistical approach, in contrast, may be applicable only in the vicinity of the study region where the model was trained, and may be limited to within or near to the rainfall intensity range for which they were trained.

The present proposed hazard model is good for the prediction of landslide spatial probability during a rainfall event, the mapping of the rainfall landslide hazard probability for a certain return-period rainfall, decision making for regional planning, site selection, hazard mitigation, and the estimation of sediment products for a river basin after an extreme event. However there is still a lack of output in regards to the landslide magnitude which is very important in risk assessment. This problem needs further study.

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