

PREDICTIVE ANALYSIS OF LANDSLIDE SUSCEPTIBILITY UNDER CLIMATE CHANGE CONDITIONS — A STUDY ON THE AI-LIAO WATERSHED IN SOUTHERN TAIWAN

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ABSTRACT

Among the most critical natural hazard issues, climate change caused by global warming affects Taiwan significantly for the past decade. The increasing frequency of extreme rainfall events, in which concentrated and intensive rainfalls generally cause geohazards including landslides and debris flows. The extraordinary Typhoon Morakot hit Southern Taiwan, on August 8, 2009, and induced serious flooding and landslides. The Ai-Liao watershed, a major sub-watershed of the Kao-Ping River watershed, was adopted as study area, and the typical events 2007 Krosa Typhoon and 2009 Morakot Typhoon were selected to train the susceptibility model. Based on the rainfall data, this study employs rainfall frequency analysis together with the atmospheric general circulation model (AGCM) downscaling estimation to understand the temporal rainfall trends, distributions, and intensities in the Ai-Liao River watershed. Rainfall estimates from the rainfall frequency analysis and AGCM were used in the susceptibility model to produce the predictive landslide susceptibility maps for various rainfall scenarios, including abnormal climate conditions. In addition to comparison and discussion on the susceptibility models and the predicative analyses, the results can be used for hazard remediation, mitigation, and prevention plans for the Ai-Liao River watershed.

Key words: Landslide susceptibility analysis, climate change, rainfall frequency analysis, global circulation model, logistic regression.

1. INTRODUCTION

Global warming over the past 100 years has been accompanied by changes in the physical and biological systems on the Earth (IPCC 2007). For the island of Taiwan, island-wide warming of 1-1.4°C/century was first reported by Hsu and Chen (2002). Liu *et al.* (2011) revealed the increasing rate of approximately 1.1-1.6°C/century, based on the temperature records at eight lowland meteorology stations from 1900 to 2009. In addition to the warming trend, the Climate Change in Taiwan Scientific Report (Hsu *et al.* 2011) also reveals the changes in the precipitation. The average annual rain days in Taiwan have decreased significantly over the last 100, 50, and 30 years; besides, the days with heavy rain (more than 200 mm) show a significant increasing trend in the last 50 years and 30 years. Due to the climatic abnormalities in the past few decades, Taiwan has been significantly affected by the more concentrated rainfall periods and higher rainfall intensities. The frequency of extreme rainfall events is increasing, which subsequently increases the risk of natural hazard.

With the majority of its geologically young strata fractured by the plate tectonic activities, in addition to the nature of rapid river morphological changes, it is particularly prone to landslides

and debris flows during periods of torrential rain, especially in the west foothill of Taiwan Island. The Kao-Ping River watershed is one of the major watersheds prone to geohazards in southern Taiwan. As the geology and the topography are various and strongly affected by the north-south direction geologic structures in the Kao-Ping River watershed, the conditions and landslide behavior in the sub-watersheds can be very different (see Fig. 1). Although there are studies on the landslides in this area especially after the 2009 Morakot typhoon (Chen *et al.* 2011; Lin *et al.* 2011; Tsou *et al.* 2011; Shou 2013; Lin *et al.* 2014), the impact of the climatic abnormalities is seldom considered in the landslide analysis, which motivates this study. Chiang and Chang (2011) considered the potential impact of climate change in the analysis of typhoon-triggered landslides in Taiwan. However, their study is in a national scale and based on rainfall predicted by a less mature climate model.

Shou and Yang (2015) focused on the Chingshui River watershed in central Taiwan, and analyzed the landslide susceptibility with considerations of extreme rainfall scenarios. In which the rainfall frequency analysis and the atmospheric general circulation model (AGCM) downscaling estimation were employed. In this study, the logistic regression method was the only method applied. However, it is suggested to apply other methodologies, analyze the other watersheds in a similar way, or with more extreme events, in order to confirm the robustness of the major findings.

The Ai-Liao River watershed is a sub-watershed of the Kao-Ping watershed, the largest and major watershed in southern Taiwan. Considering the differences in topographic background and geologic condition, we adopted Ai-Liao River watershed instead of the whole Kao-Ping watershed. The 2009 Typhoon Morakot is an event with rainfall over 1500 mm in 24 hours and over 3000 mm in total, which is an extreme with a recurrence period of 200 years at least (Chu *et al.* 2011) and this typhoon hit the study area seriously, which makes this study are more suitable for the study of the extreme events.

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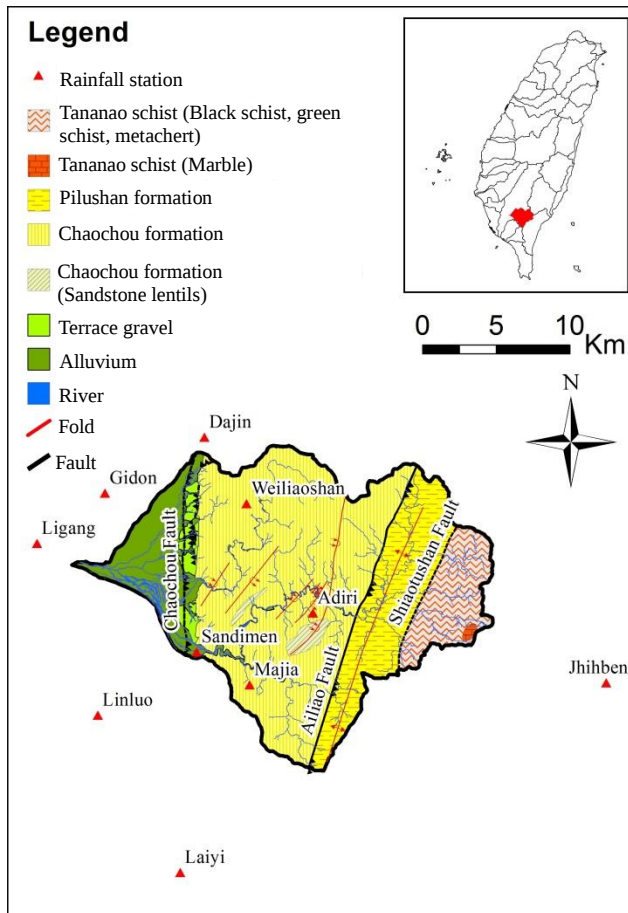


Fig. 1 The rainfall stations and the geology of the Ai-Liao River watershed

This study also aimed to determine future changes in rainfall caused by climate change as a basis for the analysis of landslide susceptibility. This study used SPOT satellite images to calculate a normalized difference vegetation index (NDVI) and identified landslides in the Ai-Liao River watershed during Typhoon Krosa in 2007 and Typhoon Morakot in 2009. The landslide interpretation results of these extreme events were used to understand the sequence of long-term geomorphologic changes and landslide reactivation induced by typhoons in the study watershed. The data of 2007 Krosa and 2009 Morakot were used as the training samples for the susceptibility model and as reference for predictive landslide analysis.

In this study, slope angle, aspect, elevation, dip slope index (I_{ds}), distance to the road, distance to river, distance to fault, and landslide-rainfall index (I_l) were selected as the controlling factors. In addition, rainfall data estimated by the rainfall frequency analysis and the dynamic downscaling global circulation model were used for the predictive landslide susceptibility calculations. The logistic regression model was compared with the instability index method before adopted for the predictive landslide susceptibility analysis. In addition to comparison of the susceptibility models and discussion on the predicative analyses, the results of landslide susceptibility analysis can be applied to design the plans of disaster remediation, mitigation, and prevention for the Ai-Liao River watershed (see the flowchart of this study in Fig. 2).

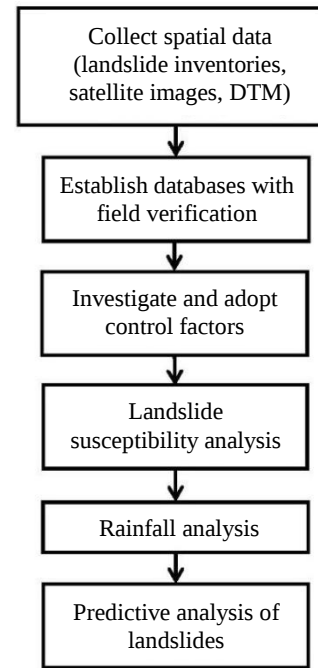


Fig. 2 The flowchart of this study

2. BASICS OF STUDY AREA

2.1 Geological Background

The Kao-Ping River catchment traverses two geological regions, including the alluvial plain and the Central Range of Taiwan Island (Ho 1994). Since the Kao-Ping River flows from the northeast to the southwest and the linear structures mainly trend in the north-south direction. As a sub-watershed, the Ai-Liao River crosses several sedimentary and metamorphic formations with different geological ages. Due to the vibrant tectonic activities, a series of imbricated structures (including folds and faults) were formed in the north-south direction. The major faults from the west to the east include Chaochou fault, Ailiao fault and Shiaotushan fault (see Fig. 1).

2.2 Landslides Induced by 2009 Morakot

As an extreme event, the 2009 Typhoon Morakot generated rainfall over 1500 mm in 24 hours and over 3000 mm in total, with a recurrence period of 200 years at least (Chu *et al.* 2011). This typhoon hit Taiwan and induced serious geohazards, including flooding, debris flows, and landslides. Based on the mapping of FORMOSAT-2 images (Lin *et al.* 2011), at least 22,705 landslides with a total area of 274 km² were recognized in a 7811 km² area of southern Taiwan. Out of the 22,705 landslides, there were 22,221 recognized with an area smaller than 10 ha and 22 landslides with an area of over 60 ha. In addition, Morakot-induced landslides mainly occurred in areas with cumulative precipitation in the range of 800 to 2600 mm, and the magnitude of landslide concentration is roughly linearly proportional to the amount of cumulative rainfall.

3. IDENTIFICATION OF LANDSLIDES

To identify landslides, the NDVI from satellite images and to obtain the data layer of NDVI and slope angle from digital

elevation model (DEM) are commonly used as the criterion for automatic identification of landslides. In this study, a 5 m DEM from the Department of Land Administration, the Ministry of Interior of Taiwan was used to establish the distribution of slope angle in the study area. In addition, the 20 m resolution SPOT satellite images before and after 2007 Krosa and 2009 Morakot were used (as shown in Table 1) to obtain the NDVI. The two data layers, *i.e.*, NDVI and slope angle, together with properly chosen threshold values, can be used to identify the landslide locations automatically. For the training of the thresholds, the landslide inventories from the Central Geological Survey of Taiwan were adopted, which were established by interpreting the FORMOSA-II images, and checking with the rectified aerial photographs and high resolution DEM.

According to a preliminary comparison study (Wu 2013), the most accurate threshold combination is $\text{NDVI} < 0.0$ and $\text{slope} > 40\%$. However, NDVI suffers from the poor spectral resolution in the shadow areas where most objects appear greyish so that the NDVI tends to 0. The landslides detected by NDVI might be overestimated in the shadow areas (Beumier and Idrissa 2014). Different screening indexes, including brightness (Hsieh *et al.* 2011), greenness (Liu *et al.* 2012; Lin *et al.* 2013), and vegetation mask (Beumier and Idrissa 2014), were coupled with the NDVI criteria to improve the accuracy of landslide identification in shadow areas. Based on the suggestions of Lin *et al.* (2013) and Chen (2014), the greenness of 0.14 was used as the screening criterion in this study. The performance of the additional greenness criterion is shown in Table 2.

The comparison in Table 2 is based on the landslide inventories of 2007 Krosa and 2009 Morakot provided by the Central Geology Survey of Taiwan. The results in Table 2 also reveal that the accuracy of automatic interpretation is lower for 2009 Morakot, especially for the landslide cells. The reason could be the 2009 Morakot generated more landslides with lower slope angle, which could not be totally interpreted by the criterion. The landslide interpretation accuracy of the total cells is quite reasonable; therefore, the slope-NDVI-greenness criterion could be applied in the study area in the future.

Table 1 The time and resolution of the SPOT images applied in this study

Typhoon	Event period	Image data		Resolution
Krosa	2007 10/04 ~ 10/07	before	2007/07/03 2007/09/29	20 m × 20 m
		after	2007/11/16 2007/11/20	20 m × 20 m
Morakot	2009 08/05 ~ 08/10	before	2009/05/09 2009/02/25	20 m × 20 m
		after	2009/10/28	20 m × 20 m

Table 2 The accuracy of landslide interpretation by the slope-NDVI-GI criterion

Event	Criterion	Accuracy of Landslide Cells $A1/(A1+A3)$	Accuracy of Non-landslide Cells $A4/(A2+A4)$	Accuracy of Total Cells $(A1+A4)/(A1+A2+A3+A4)$
2007 Krosa	$\text{SLOPE} > 40\%$, $\text{NDVI} < 0$, $\text{GI} < 0.14$	89.78	93.89	93.87
2009 Morakot	$\text{SLOPE} > 40\%$, $\text{NDVI} < 0$, $\text{GI} < 0.14$	62.44	95.48	93.70

* A1 is the number of landslide cells interpreted as landslide; A3 is the number of landslide cells not interpreted as landslide; A2 is the number of non-landslide cells interpreted as non-landslide; A4 is the number of non-landslide cells interpreted as landslide

4. THE CONTROLLING FACTORS OF LANDSLIDE

To examine the correlation between the major controlling factors and the landslide susceptibility, this study reviewed the references of rainfall-induced landslides (Selby 1993; Süzen and Doyuran 2004; Hsu 2007; Hung 2010; Rossi *et al.* 2010; Budimir *et al.* 2015) and adopted eight landslide controlling factors, that is, slope degree, aspect, dip slope index (I_{ds}), distance from the road, water system, distance to fault, elevation, and landslide-rainfall index (I_d). The data layers of these controlling factors were applied for the susceptibility analysis by geographic information system (GIS). Among the other common factors, for clarity, the dip slope index and the landslide-rainfall index are defined as below. In addition, the rainfall estimation methods were also described.

4.1 Dip Slope Index

As a typical slope hazard, dip slope failure is generally analyzed individually due to its specificity. Detailed data including surface topography, subsurface geology from boreholes, and mechanical properties from laboratory testing are used for the analysis of failure mechanism and stability of the slope (Ching and Liao 2013). However, this approach is not applicable for the analysis of dip slopes in a catchment scale. For a hilly area covered by less weathered geomaterial, topographic factors like slope angle and aspect might not be good enough to include the impact of dip slope failures. To consider the potential of dip slope failure, the relation between the dip direction of the slope and that of the bedding plane is critical. It is generally accepted that the more the dip direction of the slope is close to that of the bedding plane, the more the potential of dip slope failure.

In this study we introduce the dip slope index (I_{ds}) to classify the potential of dip slope failure. The dip slope index is defined as the angle difference between the dip direction of weak planes (bedding planes or joints) and the dip direction of the slope, where the resulting angles are classified as a highly-dip slope ($0^\circ \sim \pm 30^\circ$), medium-dip slope ($\pm 30^\circ \sim \pm 60^\circ$), orthoclinal slope ($\pm 60^\circ \sim \pm 120^\circ$), medium-reverse slope ($\pm 120^\circ \sim \pm 150^\circ$), and highly-reverse slope ($\pm 150^\circ \sim \pm 180^\circ$).

4.2 Landslide-Rainfall Index

Considering the rainfall induced landslides, cumulative rainfall and rainfall intensity are all important controlling factors. Keefer *et al.* (1987) used rainfall intensity-duration concept to predict the landslide occurring time, which somewhat combine the impact of cumulative rainfall and rainfall intensity. Based on peak hourly rainfall and associated 24-hour rainfall, Kay and Chen (1995) established a landslide zonation system to predict the probability of landslides. Lagomarsino *et al.* (2014) did a comparison between intensity-duration thresholds and cumulative rainfall thresholds for the forecasting of landslide.

Considering the close relationship between cumulative rainfall and rainfall intensity, which is significant for the rainfalls induced by typhoons, it is essential to consider those two factors together. In this study, the landslide-rainfall index (I_d) was introduced to accommodate these two controlling factors (Shou and Yang 2015). Figure 3 illustrates the relation between accumulated rainfall and rainfall intensity (we consider maximum hourly rainfall as the rainfall intensity in this study) of the

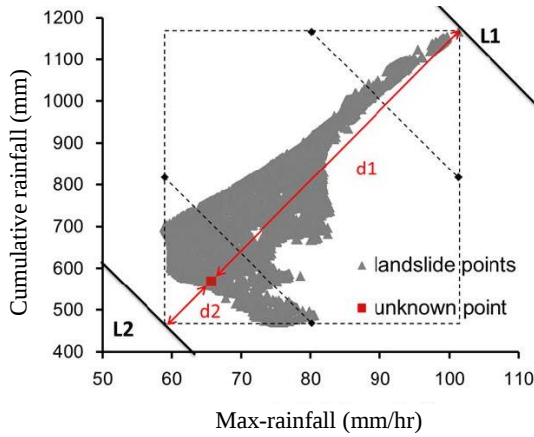


Fig. 3 The landslide-rainfall index (I_d) is defined by the distances $d1$ and $d2$ from the unknown point to the linear thresholds as $d1/(d1 + d2)$

landslide locations. For a specific typhoon event, we could establish or obtain the data layers of landslides, accumulated rainfall, and rainfall intensity. By the overlapping function of GIS, the accumulated rainfall and rainfall intensity data at the landslide locations can be extracted and plotted in graph of accumulated rainfall and rainfall intensity.

As a higher landslide potential always associated with higher accumulated rainfall and rainfall intensity (towards the upper-right direction in Fig. 3), it is essential to have a linear threshold with a negative slope (higher rainfall intensity with lower accumulative rainfall possess similar landslide potential as the case with higher accumulative rainfall with lower rainfall intensity). This study proposed a rectangular frame to wrap the landslide data point, and use the bisecting points to determine the slope of the linear thresholds. Then we can graphically obtain the upper and lower boundary linear thresholds from this graph. This study assumes that the landslide will occur at the points above the upper linear threshold, and the landslide will not occur at the points below the lower linear threshold. For the points between those two thresholds, the landslide potential can be quantified by their positions, *i.e.*, the closer to the upper threshold the more landslide potential. Based on this concept, the landslide susceptibility of a point can be quantified by its distances to the upper and lower thresholds, *i.e.*, the values $d1$ and $d2$ (see Fig. 3). The landslide-rainfall index (I_d) is defined as

$$I_d = d2 / (d1 + d2) \quad (1)$$

The landslide-rainfall index (I_d) ranges between 0 and 1. As I_d approaches 1, the slope becomes increasingly susceptible to rainfall-induced landslide. On the contrary, as the point of the rainfall of potential landslide approaches the lower threshold, or as I_d approaches 0, the slope becomes less susceptible to rainfall-induced landslide. It is worth noting that the sparse distribution of data points is due to the nature of rainfall distributions, more data points from more typhoon events could make the criterion more mature and more accurate for landslide susceptibility analysis.

4.3 Rainfall Estimation

This study used the method of Kriging to estimate the spatial distributions of rainfalls. And the estimation of rainfalls primarily employs (1) historical data from rainfall stations and various rainfall frequency analysis methods and (2) the climate change model estimates.

4.3.1 Rainfall Frequency Analysis

The rainfall data from the weather monitoring stations of the Central Weather Bureau in the Kuo-Ping River watershed was collected for the rainfall analysis and prediction (see Fig. 1). The K-S (Kolmogorov-Smirnov) test was employed to eliminate unsuitable distributions, and the standard error was used to select the optimal rainfall distribution from normal distribution, logarithmic normal distribution, the Pearson type III, the logarithmic Pearson type III, and the Gumbel distribution (Hosking and Wallis 1997; Koutsoyiannis 2004; Wallis *et al.* 2007; El Adlouni and Ouarda 2010; Shou and Yang 2015). The selected statistic distributions for the rainfall stations can be applied for the return period frequency analysis.

According to the studies of Hung (2010) and Shou (2011) on the rainfall return period in Taiwan area based on the rainfall data for the past 20 years, among the other methods, the Hazen method (Hazen 1930) is better in the goodness of fit test. The Hazen method (Hazen 1930; Haan 1986) is a common method for estimating the return period for a given rainfall intensity or rainfall duration. This method consists of determining the statistic distribution of rainfall amounts for the duration of interest, and obtaining the rainfall estimations associated with the return period of interest by interpolating or extrapolating. For a set of rainfall data, the data can be listed in order from the highest to the lowest. A ranking number is then given to each rainfall amount. From the ranking, a plotting position or probability of occurrence F_a (%) for each event can be determined by

$$F_a = \frac{2m-1}{2y} \times 100(\%) \quad (2)$$

where y is the total number of events and m is the rank of each event. The plots of rainfall amount against probability of recurrence can be used to draw a straight line, which can be extended to estimate large return period. The frequency analysis model obtained by the Hazen method was used to predict the rainfall (maximum hourly rainfall, cumulative annual precipitation, and 24-, 48-, and 72-hour cumulative rainfall) in the Ai-Liao River watershed for the return periods of 10, 20, and 100 years.

To obtain the spatial distributions of rainfall intensity and cumulative rainfall for various return periods, the results of the rainfall frequency analysis for each station, *i.e.*, the rainfall values for different return period, were interpolated by the Geostatistical Analyst Kriging function of the GIS. Although there are options of Kriging, including ordinagry Kriging, simple Kriging, universal Kriging, *etc.* The ordinary Kriging was applied as it has remarkable flexibility and easy to use. The spatial distributions of rainfall intensity and cumulative rainfall for various return periods in the Ai-Liao River watershed were illustrated in Figs. 4 to 6.

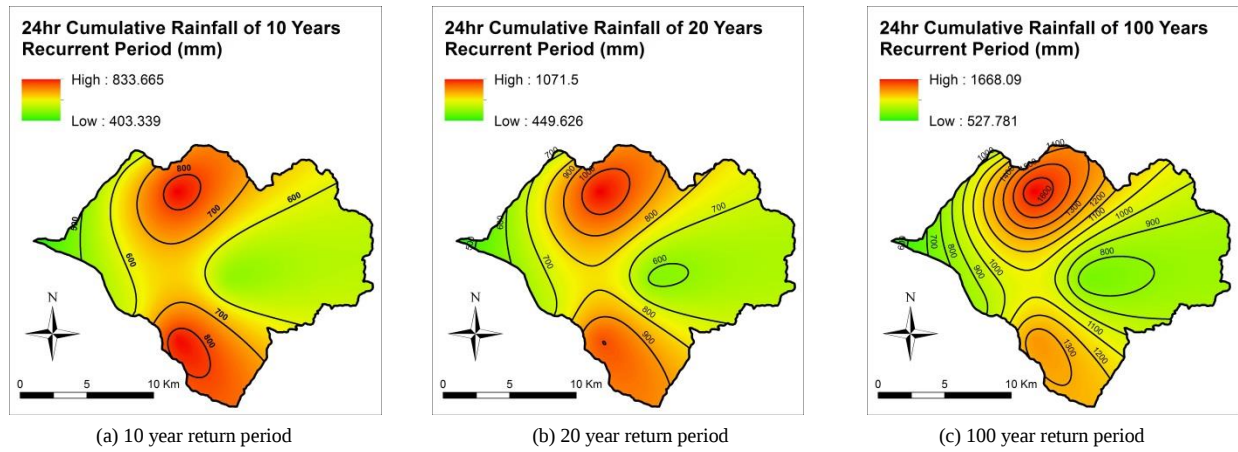


Fig. 4 The spatial distributions of 24-hour cumulative rainfall for various return periods in the Ai-Liao River watershed

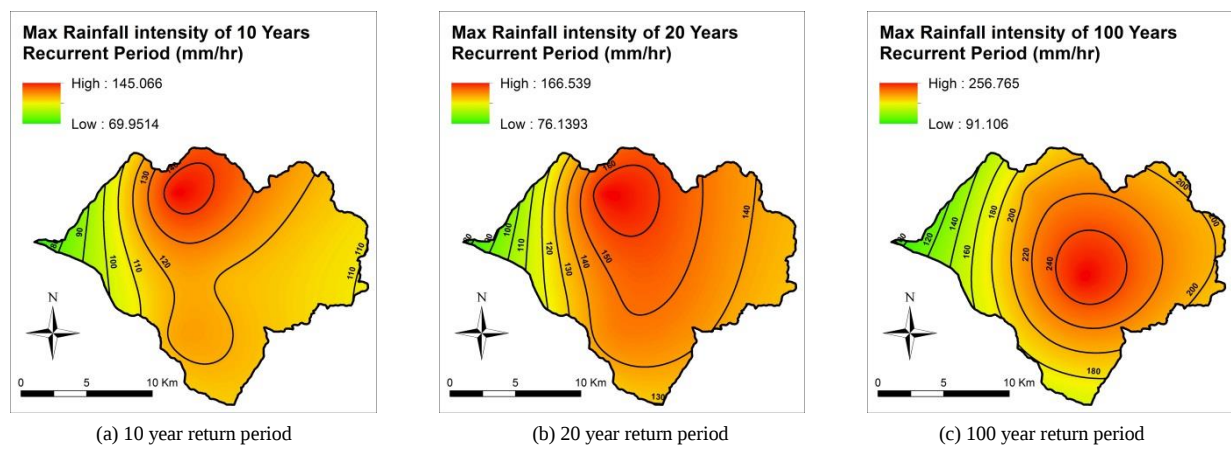


Fig. 5 The spatial distributions of the maximum rainfall intensity for various return periods in the Ai-Liao River watershed

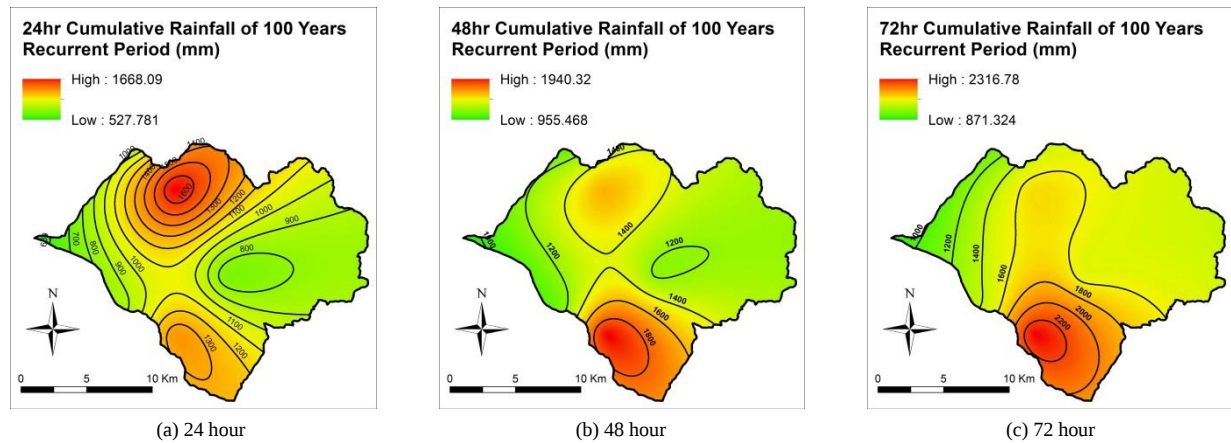


Fig. 6 The spatial distributions of cumulative rainfall for various rain periods (with recurrent period of 100 years) in the Ai-Liao River watershed

4.3.2 The Climate Change Models for Rainfall Estimates

The Taiwan Climate Change Projection and Information Platform Project (TCCIP) analyzes the results from the assessment reports of the United Nations Intergovernmental Panel on Climate Change (IPCC), which intended to assess the information concerning climate change, including the scientific and socio-economic information and the options for management and mitigation (IPCC 2013; TCCIP 2013). TCCIP applied the meth-

od of statistical downscaling to 24 Global Climate Models (GCMs) from the IPCC assessment report to obtain regionally downscaled results for Taiwan. In this study, the rainfall prediction including climate change was provided by the TCCIP, which uses the high-resolution climate simulation of MRI-JMA AGCM (Matsueda *et al.* 2009) as the initial and boundary conditions for the dynamical downscaling to produce 5 km high-resolution climate simulations of the near future

(2015-2039) and the far future (2075-2099). Dynamical Downscaling requires simulation by high-resolution climate models on a regional sub-domain, with boundary conditions by observational data or lower-resolution climate model output. These models apply physical principles to reproduce local climates, but are computationally intensive.

MRI-JMA AGCM was developed based on the numerical model used by the Japan Meteorological Agency for weather forecasts. With a horizontal resolution of approximately 20 km, the MRI-JMA AGCM is a super high-resolution global model (Matsueda *et al.* 2009). The model simulates climate estimates for three time periods, *i.e.*, the present (1979-2003), the near future (2015-2039), and the far future (2075-2099). For the future emission consideration of the IPCC data, this study adopted the Scenarios A1B which emphasizes economic growth and a convergence of global socioeconomic conditions (IPCC 2013). The ocean-atmosphere general circulation modeling with the Scenario A1B suggests that sea-surface temperatures exhibit a linearly increasing trend. The variation of present sea-surface temperatures was added to the linearly increasing sea-surface temperature for the AGCM estimation.

The estimation of MRI-JMA AGCM (Matsueda *et al.* 2009) was used as the initial and boundary conditions for the dynamic downscaling. The regional model used to execute dynamic downscaling was the Weather Research and Forecasting (WRF) modeling system developed by the National Center for Atmospheric Research (NCAR). By the coupled MRI-AGCM dynamic downscaling approach, we can estimate the seasonal rainfall changes in Taiwan at the end of the twenty-first century (TCCIP 2013).

Based on the MRI-WRF dynamical downscaling data provided by TCCIP, we can estimate the future rainfall distributions of extreme event (TOP1 represents the typhoon route with the heaviest rainfall) with the consideration of climate change. The ordinary Kriging interpolation was conducted on the data of the thirty five 5 km × 5 km domains within the Ai-Liao River watershed to estimate the distribution of cumulative rainfall and rainfall intensity of the future typhoons (see Figs. 7 and 8).

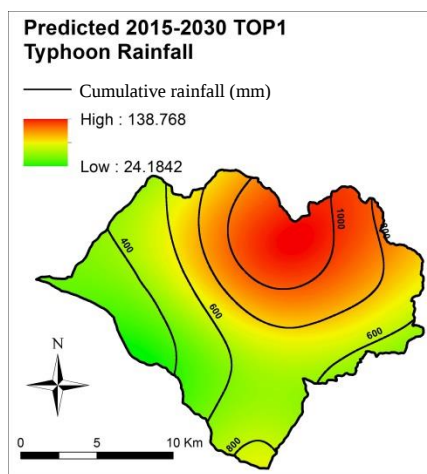


Fig. 7 The predicted rainfall distributions in the Ai-Liao River watershed for the near future (2015 ~ 2039), based on the MRI-WRF dynamical downscaling data provided by TCCIP

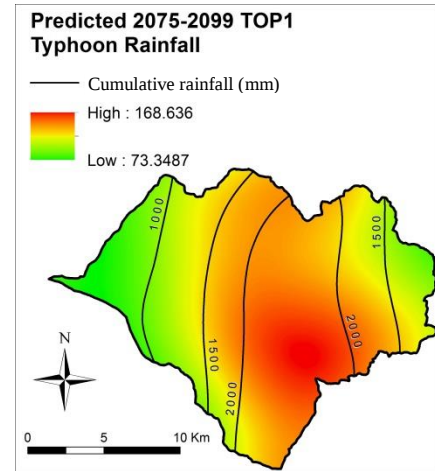


Fig. 8 The predicted rainfall distributions in the Ai-Liao River watershed for the far future (2075 ~ 2099), based on the MRI-WRF dynamical downscaling data provided by TCCIP

5. LANDSLIDE SUSCEPTIBILITY ANALYSIS METHODS

This study applies two methods, *i.e.*, the Instability Index Method and Logistic Regression Method, for the landslide susceptibility analysis. Their performance was compared for the analyses of 2007 Krosa and 2009 Morakot. Then the method with better accuracy was applied for the predictive landslide susceptibility analysis.

5.1 Instability Index Method

Instability Index Method (IIM), also called Multiple Nonlinear Regression Analysis, or Dangerous Value Method, was proposed by Jian (1992). As it is easy to implement with the GIS systems, this approach was commonly applied for landslide susceptibility analysis (Lee and Min 2001; Jiménez-Perálvarez 2009; Youssef *et al.* 2015). There might be shortcomings, if the control factors were not chosen properly or the quality of the data was not good enough. IIM describes the degree of slope instability by landslide causative factors. For IIM, there is no limit for the number of the factors and no limit for the type (continuous or discontinuous) of the factors; which is one of the major advantages of IIM. The processing steps of IIM include: dividing the value of each factor into different ranks, calculating the landslide density (X_i) in a grid basis, *i.e.*, the ratio of landslide grids to total grids, for every rank. For a specific factor, the normalized grade (D_i) is defined as:

$$D_i = \frac{9(X_i - X_{\min})}{(X_{\max} - X_{\min})} + 1 \quad (3)$$

in which $X_{\min}$ is the minimum landslide density rank, and $X_{\max}$ is the maximum landslide density rank by calculating the number of grids in the specific rank.

The weighting factor w_i of the i -th factor is defined as the ratio of individual variation coefficient to the sum of all factors:

$$w_i = \frac{V_i}{(V_1 + V_2 + \dots + V_n)} \quad (4)$$

where V_i represents coefficient of variation of the i -th factor. In this model, for the unbiasedness, the total weight was set to unity, i.e., the values of weighting factors (w_i , $i = 1 \sim n$) are all less than 1 and their sum equals 1.

The landslide susceptibility index I_p , a normalized value of the total instability index number D_{total} , is proposed to include the influence of all controlling factors. The instability index I_p is defined in terms of weighting values w_i ($i = 1 \sim n$) and grading values D_i ($i = 1 \sim n$) of all controlling factors as

$$I_p = \log(D_{total}) = \log(D_1^{w_1} \times D_2^{w_2} \times \dots \times D_n^{w_n}) \quad (5)$$

The value of D_{total} is between 1 and 10 and the value of P is between 0 and 1. The higher the values of D_{total} and P , the higher the landslide susceptibility. It can be an index for the probability of landslide or the potential of landslide hazard.

5.2 Logistic Regression Method

In this study, the method of logistic regression was also adopted to analyze the landslide susceptibility. Based on the training samples, which comprised a group of data points or data locations, categorized as landslide and non-landslide. The data layer of each factor was then placed upon the landslide and non-landslide layers, and the correlation between each factor and landslides was used to conduct binary logistic regression (Atkinson and Massari 1998; Süzen and Doyuran 2004; Lee et al. 2008; Mathew et al. 2009; Rossi et al. 2010; Akgun 2012; Lee 2012; Devkota 2013; Budimir et al. 2015).

In the logistic regression model, the probability of landslide occurrence is expressed by

$$\text{Pr} = \frac{e^z}{1 + e^z} \quad (6)$$

The logit Z is assumed to contain the independent variables on which landslide occurrence may depend. The logistic regression model assumes the term Z to be a combination of the independent set of variables X_i ($i = 1, 2, \dots, n$) acting as potential controlling factors of landslide. The term Z is expressed by the linear form

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad (7)$$

where coefficients β_i ($i = 1 \sim n$) are representative of the contribution of single independent variables X_i to the logit Z and β_0 is the intercept of the regression function. It must be noted that the logistic regression approach does not require, or assume, linear dependencies between Pr and the variables involved. The coefficients β_i are estimated through the maximum likelihood criterion and correspond to the estimation of the more likely unknown factors. Although the processing of the geographical data used in this study was performed in the GIS environment, the logistic regression analysis was carried out by the SPSS statistical package.

The logistic regression method is particularly suitable for the analysis of categorical variables and, when working with geographical data, requires sampling of the dataset using a regularly spaced grid. Although it is not strictly required, the transformation of continuous variables into categorical data is commonly applied in the logistic regression analysis of landslide susceptibility. The categorization of the independent variables (the controlling factors) can be based on the distribution of the

dependent variable (presence/absence of landslides) under the criterion of maximizing differences among the classes formed. After such a classification, possible relationships between classes of independent variables and the dependent variable under study are more easily detectable.

This study employed the receiver operating characteristic (ROC) curve (Swets 1988) and the success rate (SR) curve (Chung and Fabbri 2003) to verify the model. The area under the curve (AUC) of the ROC curve or the SR curve can be used to evaluate the prediction accuracy of a susceptibility model. Generally, the larger the AUC values the better. As the area approaches 0.5, the result may not necessarily be superior to that of a random selection. AUC values of less than 0.5 are not worth employing.

6. RESULTS

For the comparison and future applicability of landslide susceptibility models, this study applied landslides interpreted by the same slope-NDVI-greenness criterion for 2007 Krosa and 2009 Morakot. Based on the collected geology, topography, and rainfall data, the data layers of the eight controlling factors were generated and illustrated in Fig. 9. The data layers were introduced to the landslide susceptibility analysis methods described in the previous sections. In addition, the predictive rainfalls suggested by the rainfall frequency analysis and the climate change models were applied in the predictive landslide susceptibility analysis.

6.1 Landslide Susceptibility Analysis

Based on the methodology described in section 5.1 and the data layers of the eight controlling factors, the instability index analysis can be performed for the 2007 Krosa and 2009 Morakot. In order to eliminate the bias due to the order of the controlling factors (their values could be very different), a normalization procedure (divided by their mean values) was performed before applied to the analyses. The results of the instability index analysis can be expressed as below:

$$I_p = F_1^{0.115} \times F_2^{0.094} \times F_3^{0.124} \times F_4^{0.145} \times F_5^{0.093} \times F_6^{0.235} \times F_7^{0.108} \times F_8^{0.086} \quad (8)$$

for 2007 Krosa typhoon, and

$$I_p = F_1^{0.117} \times F_2^{0.098} \times F_3^{0.073} \times F_4^{0.150} \times F_5^{0.160} \times F_6^{0.222} \times F_7^{0.102} \times F_8^{0.079} \quad (9)$$

for 2009 Morakot typhoon, where I_p is the instability index, F_1 is the slope angle, F_2 is the elevation, F_3 is the aspect, F_4 is the distance to fault, F_5 is the distance to river, F_6 is the distance to road, F_7 is the dip slope index (I_{ds}), and F_8 is the landslide-rainfall index (I_d). The exponent for each factor were calculated by Eq. (4). The results, i.e., Eqs. (8) and (9), suggest the major controlling factors are slope angle, aspect, distance to fault, and distance to road. For the extreme 2009 Morakot, the distance to road becomes significant and the aspect becomes less significant. Based on Eqs. (8) and (9), the landslide susceptibility maps can be generated as shown in Fig. 10.

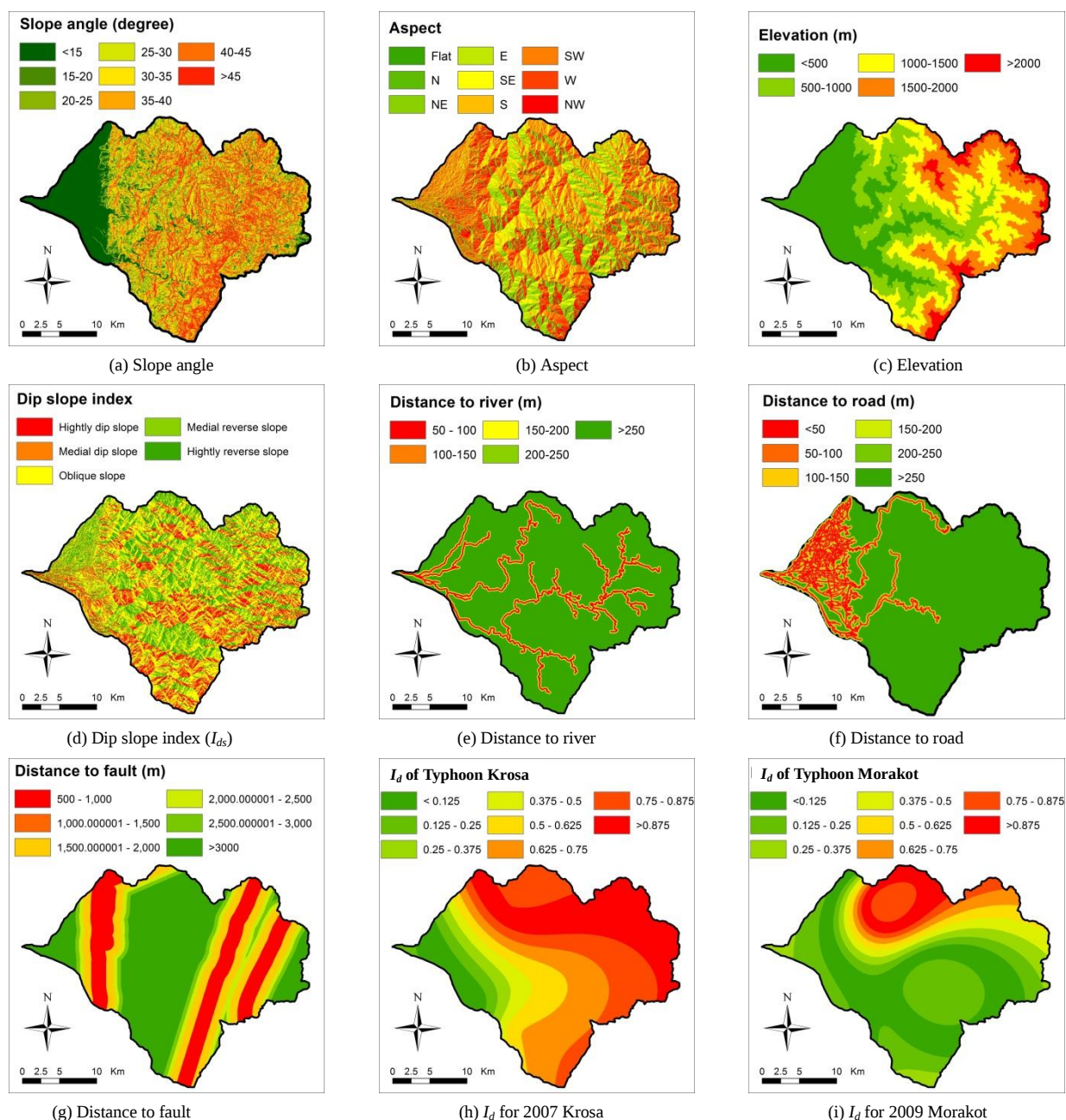


Fig. 9 The data layers of the selected controlling factors in the Ai-Liao River watershed

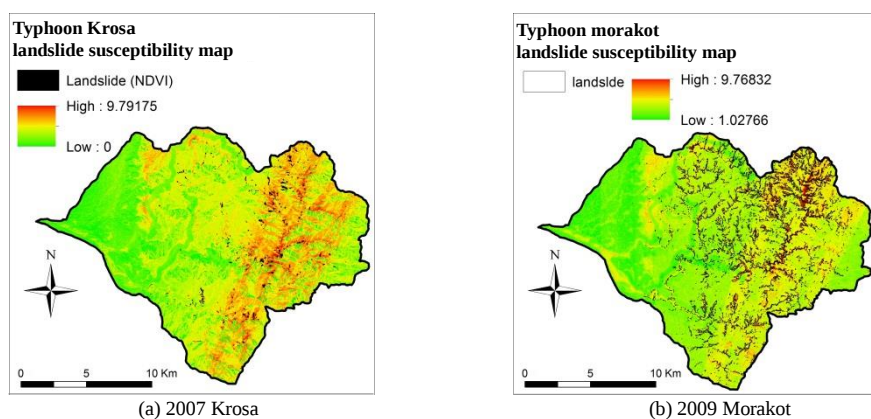


Fig. 10 The landslide susceptibility maps obtained by the instability index method for 2007 Krosa Typhoon and 2009 Morakot Typhoon

Similarly, the same data layers of the eight controlling factors were applied for the logistic regression analysis. As mentioned in section 5.2, the logistic regression analysis was performed by the SPSS software. The results of logistic regression analysis can be expressed as below:

$$\ln \left[\frac{P}{1-P} \right] = 0.856F_1 - 0.280F_2 - 0.361F_3 - 0.373F_4 - 0.460F_5 + 0.414F_6 - 0.199F_7 + 0.292F_8 - 0.081 \quad (10)$$

for 2007 Krosa typhoon, and

$$\ln \left[\frac{P}{1-P} \right] = 0.944F_1 + 0.155F_2 - 0.244F_3 - 0.090F_4 - 0.506F_5 + 0.190F_6 - 0.208F_7 + 0.145F_8 - 0.072 \quad (11)$$

for 2009 Morakot typhoon, where P is the logistic function; $F_1 \sim F_8$ are the same controlling factors defined previously. Equation (10) suggests the major controlling factors are slope angle, aspect, distance to fault, distance to river, and distance to road. For 2009 Morakot, similar to Eq. (9), an increasing weighting of the distance to road and a decreasing weighting of the aspect can be found in Eq. (11), in which distance to fault and distance to road also become less significant. The landslide susceptibility maps induced by Krosa and Morakot using Eqs. (10) and (11) are shown in Fig. 11.

Figures 10 and 11 show the areas in the watershed that are susceptible for sliding under similar rainfall scenarios. Comparing the two figures, a larger area with high landslide susceptibility during Morakot than during Krosa, indicates that Typhoon Morakot generated more severe landslides in the Ai-Liao River watershed. From the perspective of disaster potential, although the areas downstream in the Ai-Liao River watershed are mainly low-susceptibility areas, the susceptibility maps of the two time periods show that the high-susceptibility areas of the river are concentrated in the upstream sub-watersheds.

According to the field investigations, landslides mainly distributed in the upstream, including the steep slopes at river banks and source areas, which is consistent with the susceptibility analysis. In addition, a considerable amount of sediments accumulate on riverbed and slopes in the upstream, as the primary source for sediment in the Ai-Liao River watershed is landslides. Sediments that accumulate in the upstream may be transported downstream during heavy rains, creating a serious sediment hazard to the downstream. Furthermore, the upstream sediments may deposit at the downstream, creating potential flooding during extreme heavy rains.

The landslide susceptibility models were verified using the AUC values of the ROC curves. The results in Figs. 12 and 13 show that the AUC values of the instability index method are 0.655 for 2007 Krosa and 0.620 for 2009 Morakot, and the AUC values of the logistic regression method is 0.680 for 2007 Krosa and 0.672 for 2009 Morakot. For both typhoon events, the logistic regression method can obtain higher AUC values. Although the results suggest that the logistic regression susceptibility models with Eqs. (10) and (11) are all reasonable and acceptable, the model with higher AUC value, i.e., the Eq. (10) of 2007 Krosa was adopted for the predictive landslide analyses.

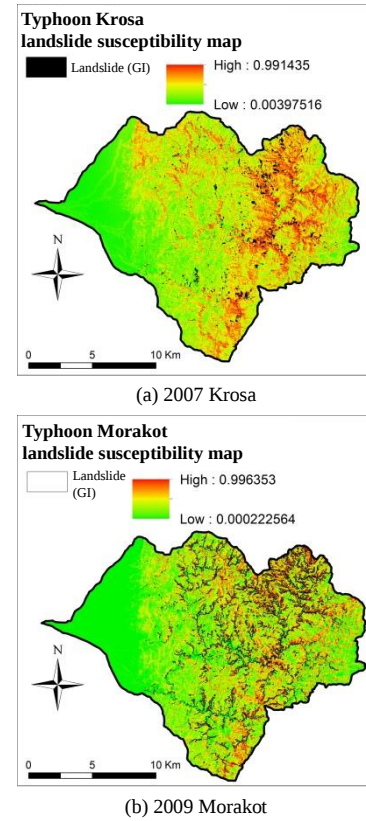


Fig. 11 The landslide susceptibility maps obtained by the logistic regression analysis of 2007 Krosa Typhoon and 2009 Morakot Typhoon

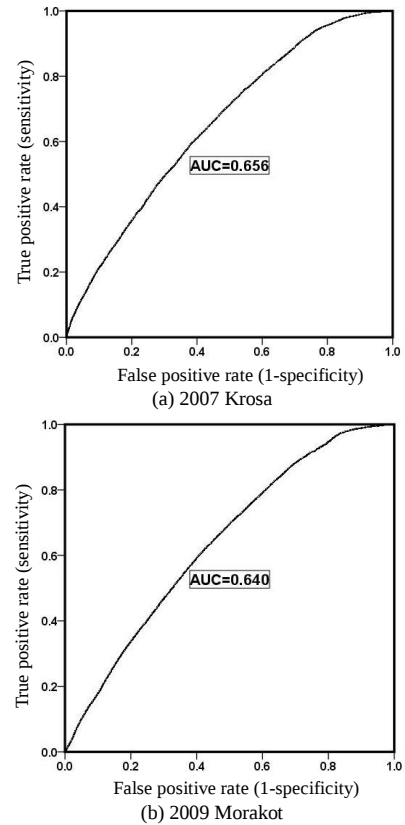


Fig. 12 The ROC curves of the landslide susceptibility results by Instability Index method for 2007 Krosa Typhoon and 2009 Morakot Typhoon

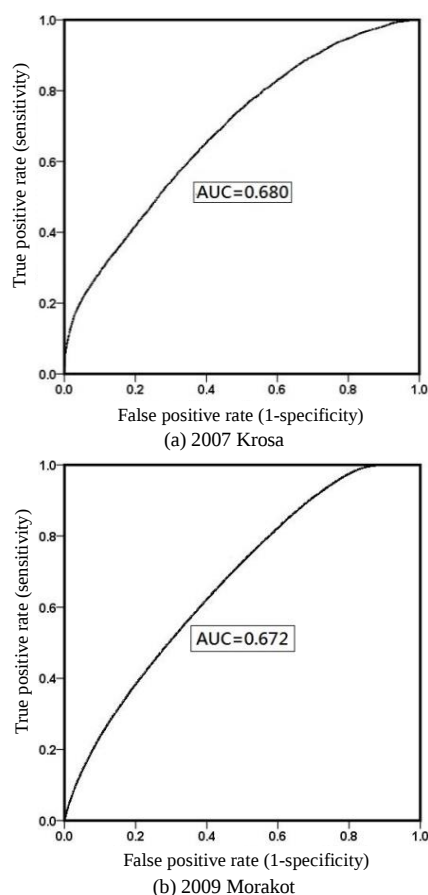


Fig. 13 The ROC curves of the landslide susceptibility results by Logistic Regression method for 2007 Krosa Typhoon and 2009 Morakot Typhoon

For comparison, the AUC values for the Ai-Liao River watershed and the Chingshui River watershed (Shou and Yang 2015) are summarized in Table 3. The results show that the AUC values are always lower for the extreme typhoon event. In other words, the landslide susceptibility model can better predict the hazard for the rainfall event comparable to the training event. The difference between the predicted event and the training event is critical for the prediction inaccuracy. On the other hand, logically, if we use the 2009 Morakot as a training event, then the prediction could be better for the event with the size comparable to that of 2009 Morakot. It is also worth noting that the AUC values for both cases by the logistic regression method are in the range of 0.65 ~ 0.70.

Table 3 The comparison of the AUC values of ROC curves for different watersheds by different susceptibility analysis method

Watershed		Chingshui river		Ai-Liao river	
Typhoon	2001 Toraji	2004 Mindulle	2009 Morakot	2007 Krosa	2009 Morakot
AUC of logistic regression method	0.750	0.768	0.665	0.680	0.672
AUC of instability index method	N/A	N/A	N/A	0.656	0.640

This study aims to establish a reliable susceptibility model that can be used to predict the landslide susceptibility with more extreme climate conditions possibly happened in the future. Although the rainfall and the induced landslide hazard of 2009 Morakot are heavier than those of 2007 Krosa, they can be used to test the robustness of the susceptibility model. In other words, the 2009 Morakot can be used as an extreme sample for testing. The results show that the susceptibility model based on 2007 Krosa is slightly better than the one based on 2009 Morakot. However, it suggests that the selected susceptibility model is practically acceptable for predictive analyses of various extreme rainfall scenarios.

6.2 Landslide Susceptibility Predictions

The comparison in section 5.1 shows that the prediction capability of the logistic regression susceptibility model of Eq. (10) is within an acceptable range. The predicted rainfalls from section 4.3 can be introduced to this model to calculate the landslide susceptibility maps for future rainfall scenarios. Introducing the results of rainfall frequency analysis (Figs. 4 and 5) into the landslide susceptibility model, 9 rainfall scenarios (24-, 48-, and 72-hour with return periods of 10, 20, and 100 years) can be analyzed. It should be noted that, due to the length limitation of the paper, only the major landslide susceptibility maps with the predicted rainfall scenarios were included. The major landslide susceptibility distributions for various return periods are shown in Figs. 14 and 15. The results in Figs. 14 and 15 show that the area with higher landslide susceptibility will increase if the rainfall is longer or the return period is longer. In Table 4, the detailed results also show that the number of low susceptibility cells decreases as the rainfall period increases or the returning period increases. The number of cells with susceptibility 0.8 ~ 1.0 increases about 8% from 10 year return period 24-hour rainfall to 100 year return period 24-hour rainfall. However, the increase is up to about 23% from 100 year return period 24-hour rainfall to 100 year return period 72-hour rainfall. In other words, the influence of the rainfall period is more significant than that of the return period (for the period range around 100 years).

Table 4 The comparison of the numbers of cells of different landslide susceptibility for different predictive scenarios

Landslide susceptibility	Scenario						
	24hr/10yr return	24hr/20yr return	24hr/100yr return	48hr/100yr return	72hr/100yr return	2015 ~ 2039 Top1 Typhoon	2075 ~ 2099 Top1 Typhoon
0.0 ~ 0.1	256488	265584	264081	206831	193139	210287	209161
0.1 ~ 0.2	165603	176197	175056	167256	160790	169325	165444
0.2 ~ 0.3	209536	218144	217871	206171	197116	208519	202104
0.3 ~ 0.4	232316	225247	226614	229034	224206	229305	224335
0.4 ~ 0.5	218519	205199	204879	219584	220490	215321	215293
0.5 ~ 0.6	181056	169031	168287	188532	194283	183151	185983
0.6 ~ 0.7	135344	130920	130982	149447	157823	146491	150545
0.7 ~ 0.8	88773	91534	92203	105242	114744	105953	110563
0.8 ~ 0.9	51442	54631	55791	62141	68850	64317	67620
0.9 ~ 1.0	17196	19785	20508	22035	24832	23277	24898

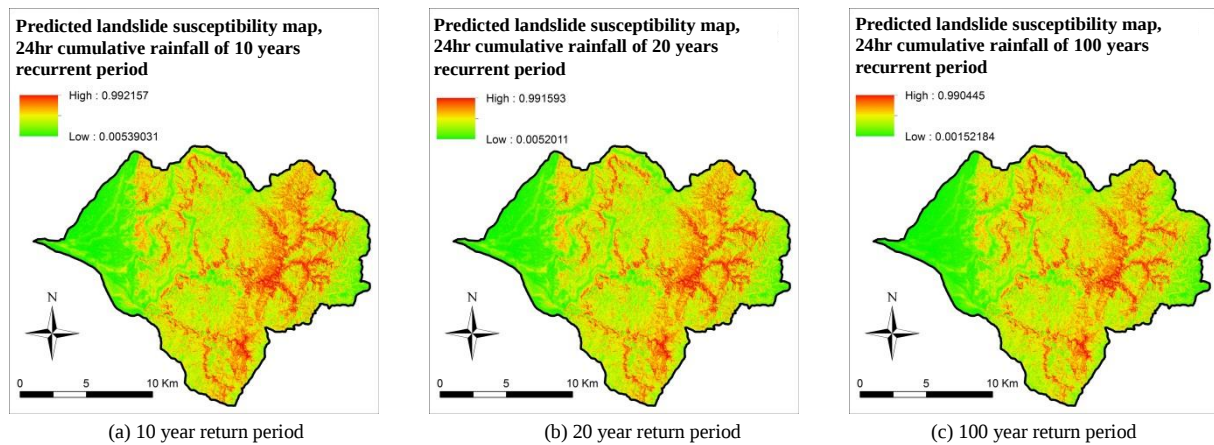


Fig. 14 The spatial distributions of landslide susceptibility with 24-hour cumulative rainfall and rainfall intensity for various return periods in the Ai-Liao River watershed

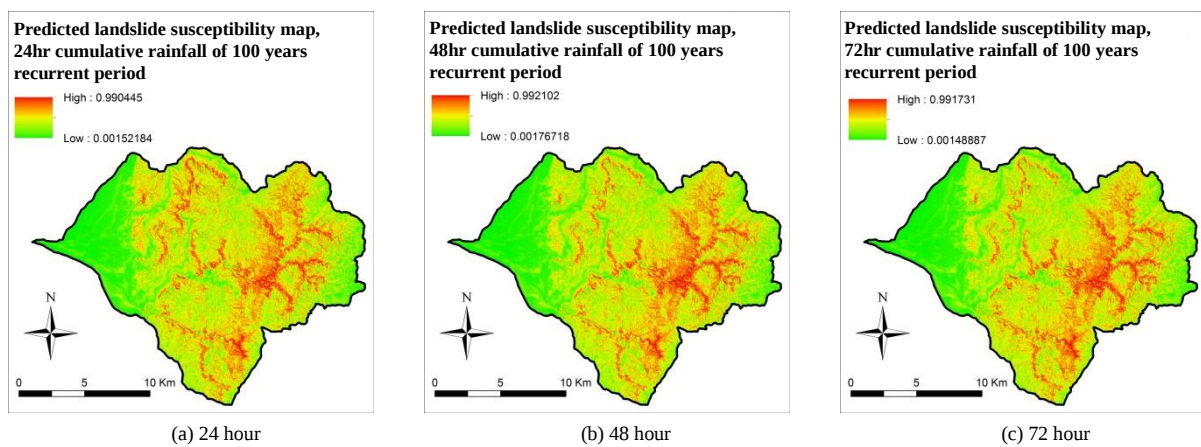


Fig. 15 The spatial distributions of landslide susceptibility with 100 year return period for various rainfall periods in the Ai-Liao River watershed

The rainfalls predicted by the climate change dynamic downscaling method (Figs. 6 and 7) can also be introduced to the landslide susceptibility model. It can help to identify the potential landslide hazards for the Ai-Liao River watershed in the near future (2015-2039) and in the far future (2075-2099). The predictive landslide susceptibility distributions with the consideration of climate changes are shown in Fig. 16. The results in Fig. 16 suggest that the landslide susceptibility is higher in the far future (2075-2099) than in the near future (2015-2039). The high landslide susceptibility area increases significantly in the upstream area, *i.e.*, the southeastern side of the watershed. This finding suggests more attention should be paid in this area for long-term hazard management and mitigation. The detailed results in Table 4 show that the estimation of the far future (2075-2099) is close to the estimation of 72-hour accumulative rainfall 100 year return period with a discrepancy of about 3%. However, the estimation of the near future (2015-2039) is larger than the estimation of 24-hour accumulative rainfall 20 year return period with a discrepancy of about 10%. It is worth noting that the results in Table 4 suggest that the landslide susceptibility prediction based on the AGCM is higher than that based on the rainfall frequency analysis. And it is because that the rainfall intensities predicted by the AGCM are much higher than those predicted by the rainfall frequency analysis.

The results of predictive analysis for the Ai-Liao River in this study can be compared with those for the Chingshui watershed (Shou and Yang 2015), where the estimation of the far future (2075-2099) is close to the estimation of 72-hour 100 year

return period accumulative rainfall with a discrepancy of about 5%, and the estimation of the near future (2015-2039) is less than the estimation of 24-hour 20 year return period accumulative rainfall with a discrepancy of about 15%. The comparison reveals that the estimation of the far future is more accuracy than that of the near future, with overestimation around 3 ~ 5%. On the other hand, the prediction of the near future is more inconsistent, can be is overestimated or underestimated.

In order to enhance the applicability of the landslide susceptibility maps, it is common to classify the susceptibility to different categories such that we can apply different countermeasures. The classifications can be made according to the levels of landslide ratio, *i.e.*, the density of landslide in an area. The levels A, B, C, D, and E represent high, medium high, medium, medium low, and low landslide susceptibility respectively. The criteria of these classifications are defined according to the cumulative landslide ratios, *i.e.*, high level for more than 50%, medium high level for 15 ~ 50%, medium for 5 ~ 15%, medium low level for 1 ~ 5%, and low level for less than 1% of cumulative landslide ratios (as shown Fig. 17). The distributions of landslide susceptibility levels for various return periods are shown in Fig. 18, and the predictive distributions of landslide susceptibility classes with the consideration of climate changes are shown in Fig. 19. Comparing with Figs. 14 ~ 16, it more clearly illustrates that the high landslide susceptibility area (level A and level B) increases significantly in the mid-stream and upstream areas, *i.e.*, the southeastern side of the watershed.

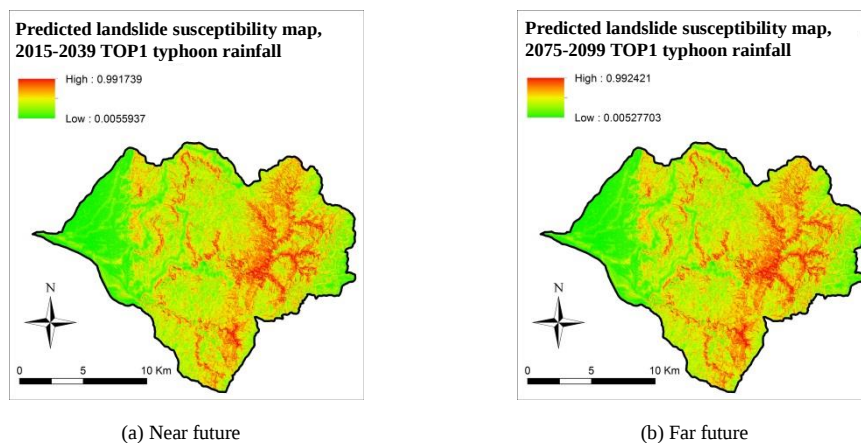


Fig. 16 The spatial distributions of predicted landslide susceptibility for the near future (2015 ~ 2039) and the far future (2075 ~ 2099) in the Ai-Liao River watershed

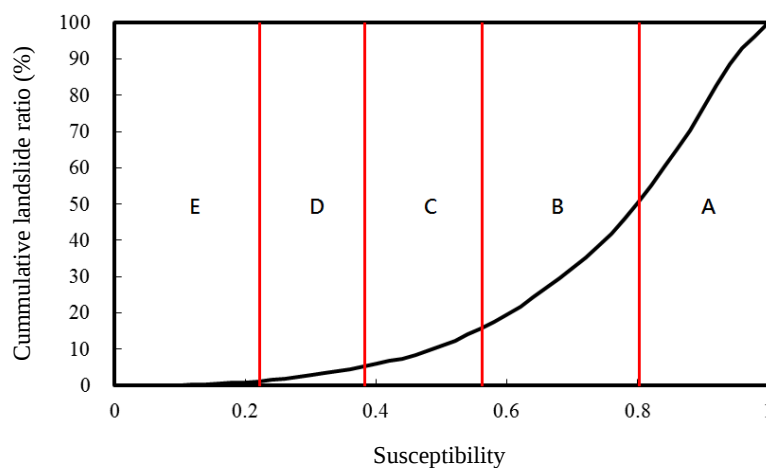


Fig. 17 The classifications of landslide susceptibility

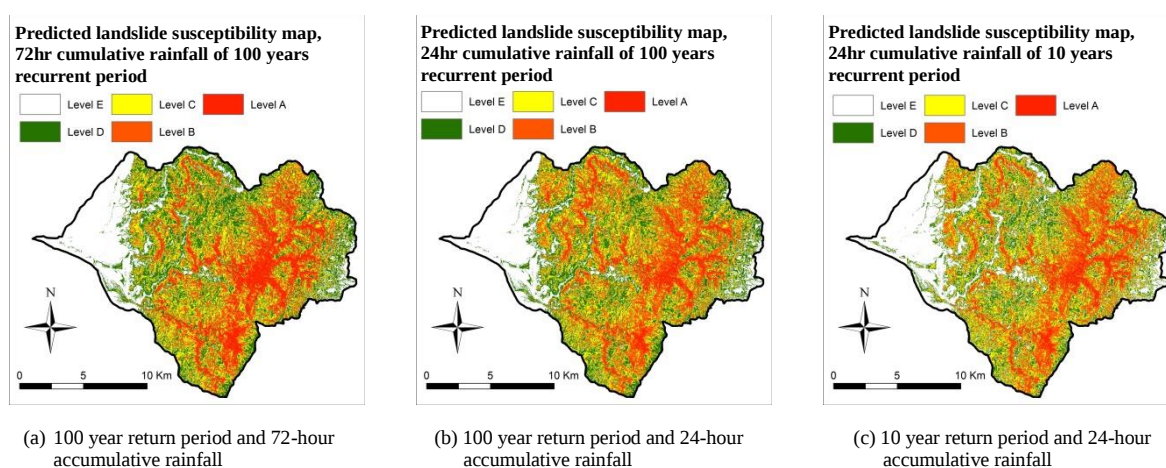


Fig. 18 The spatial distributions of landslide susceptibility levels for various return periods in the Ai-Liao River watershed

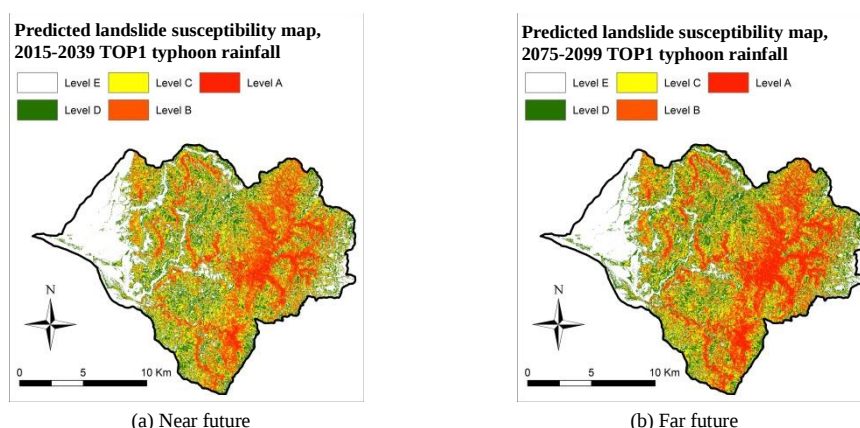


Fig. 19 The spatial distributions of predicted landslide susceptibility levels for the near future (2015 ~ 2039) and the far future (2075 ~ 2099) in the Ai-Liao River watershed

7. CONCLUSIONS AND SUGGESTIONS

In this study, focusing on the Ai-Liao watershed, predictive analyses of landslide susceptibility were performed with the consideration of climate change. The conclusions and suggestions of this study can be summarized as below:

1. Trained by the 2007 Krosa and 2009 Morakot, the logistic regression susceptibility model was developed in this study. The AUC of the model is in the range of 0.65 ~ 0.70, which indicates its applicability for identify potential landslides. This model can be used as a reference for designing disaster prevention plans.
2. Based on the comparison of AUC values for the Ai-Liao River watershed and the Chingshui River watershed, it reveals that the landslide susceptibility model can better predict the hazard for the rainfall event comparable to the training event. The difference between the predicted event and the training event is critical for the prediction inaccuracy.
3. The susceptibility maps calculated by the susceptibility model all showed that the mid-upstream and upstream areas of the Ai-Liao River were highly susceptible to landslides. The predictive susceptibility analyses suggest that the new high landslide susceptibility areas are mainly distributed in the up-streams, including the south side and the southeast side of the watershed. The southeast side of the watershed is more critical because the analysis results of the far future also reveal the same finding.
4. The results of predicative analysis for the Ai-Liao River in this study and the Chingshui River in the previous study reveals that the estimation of the far future is more accuracy than that of the near future, with overestimation around 3 ~ 5%. On the other hand, the prediction of the near future is more inconsistent and with a higher discrepancy.
5. The prediction capability of the susceptibility model is influenced by the weight of landslide-inducing factors, the limit of these factors (e.g., I_d has a maximum value of 1.0), and rainfall distributions. Therefore, there is a limitation of the model's prediction capability. Training of the susceptibility model with enough good quality training data is essential to have prediction with better accuracy.

6. This study used rainfall frequency analysis and AGCM to estimate rainfall and predict future rainfall trends and intensity under climate change conditions. Rainfall frequency analysis with more data and a better AGCM can help to obtain a better rainfall estimation to more accurately predict the landslide susceptibility.
7. This study adopted a slope-NDVI-greenness criterion for automatic landslide interpretation and obtained an acceptable accuracy. However, the interpretation accuracy of landslide cells is still improvable, especially for the extreme events. More effort is suggested for a better landslide interpretation accuracy (Martha *et al.* 2010).

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