Dear Editor and Referees,

Thank you for your kindly providing all these helpful comments. Our manuscript was revised and asked a native speaker for editing. Besides, we added some paragraphs to explain our methods including how we retrieve data, analyze them and also how we define the thresholds. Our replies and the corresponding revisions were all listed below.

Sincerely yours,
Lun-Wei Wei

Referee #1
Comments to author:

No.	Comment	Reply
1	The main issue of the work is the lack of a **real validation**, since authors consider only rainfall events that triggered landslides, but they should consider, if possible, even events that not triggered landslide, to validate the early warning system in terms of **false alarms, missed alarms and correct alarms**. To identify these categories, they should **define a threshold** to identify a "no alarm zone" and an "alarm zone" (e.g. green area of fig. 6, 8, 9 could be considered as no alarm zone, while yellow to red areas as alarm zone). Without such a validation a functional EWS cannot be considered as effective or ineffective.	Thanks for the comment. We agree the real validation is needed to evaluate whether this EWS is effective or not. We defined red (extreme danger level) and orange (high danger level) alerts as alarm zone, while yellow (medium danger level) and green (low danger level) alerts as no alarm zone in page 7, line 27–30. After that, the numbers of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) were counted and the skill scores including the probability of detection (POD), the probability of false detection (POFD) and the probability of false alarm (POFA) were used to evaluate the effectiveness of this EWS in the last paragraph of section 5.3 in page 10.
2	Another important point author should clarify is how they identified **the exact time of landslide**, since it is necessary to calculate the 3-hours rainfall intensity. They located landslide with several approaches as the use of SPOT5 satellite imagery, but in this case is not possible to identify the exact occurrence time of the landslides.	Thanks for the comment. During field investigations, we not only verified the correctness of landslide inventories but also tried to acquire the exact time of landslides from residents lived around. The accuracy of exact time of landslide was hard to evaluate, however, we focused on interviewing as many residents whose relatives were injured

		or houses were damaged/destroyed by the landslides as possible, so that the quality of landslide occurrence time might be improved.

Referee #1

Comments in PDF file:

No.	Comment	Reply
1	[Page 2, line 8] Please add Rosi et al. 2012;	Thanks for the comment. We added this reference in page 2, line 10.
2	[Page 2, line 14] (1) Modified as "Segoni et al, 2014, 2015" (2) Add also "Rosi et al. 2016." Rainfall thresholds for rainfall-induced landslides in Slovenia. https://doi.org/10.1007/s10346-016-0733-3	Thanks for the comment. We modified and added these important references in page 2, lines 15–16.
3	[Page 2, line 27] "region" replace with "mosaic."	Thanks for the comment. We used "mosaic" instead of "region" in page 2, line 33.
4	[Page 2, line 29] "Geological settings" replace with "Lithological units."	Thanks for the comment. We used "Lithological units" instead of "Geological settings" in page 2, line 35.
5	[Page 3, line 1] I suggest splitting this chapter into two chapters. 3: Available data. 4: Methodology. This will increase the readability of the document	Thanks for the comment. We split "Data and methodology" into "Available data" and "Methodology" to increase the readability.
6	[Page 3, line 3] Please change the number of the paragraphs according to the new chapter division	Thanks for the comment. We renewed the numbers of each paragraphs.
7	[Page 3, line 5] all the approaches you used to create a landslide DB are right, but they have a major issue: the date of the landslides are approximated and this is will affect the identification of the real rainfalls responsible of the initiation of the landslides. If you use 3 hours rainfall you need the exact time of landslide triggering. Please clarify these points.	Thanks for the comment. We agree that it is impossible to get the exact time of landslide from landslide DB. Therefore, we tried to acquire the exact time of landslide from residents lived around, especially whose relatives were injured or houses were damaged/destroyed by the landslides during our field investigations. We emphasized this in section "3.2 Landslide occurrence time and field investigation", page 3, lines 19–23.

8	[Page 3, line 21] Exact date is usually hard to identify and the exact hour is even more difficult. Do you consider the uncertainty of triggering time? How do you manage it?	Thanks for the comment. We believe that the uncertainty of triggering time is hard to evaluate due to the lack of video records. However, we tried to interview residents, especially whose relatives were injured or houses were damaged/destroyed by the landslides, to get the occurrence time of landslides during field investigation. Given the deep impressions left by such memories, we believe that the quality of landslide occurrence times might be improved. We added these descriptions in section "3.2 Landslide occurrence time and field investigation", page 3, lines 19–23.
9	[Page 3, line 25] Please describe how you performed the reduction to 10 m resolution and the smoothing. Did you use a simple GIS resample technique? Have you considered the effects of smoothing the DEM on the morphological analyses? Please clarify.	Thanks for the comment. We developed a Fortran program to obtain smoothed and resolution-reduced 10×10m DEMs (10m DEMS) by calculating the average value of each 2 by 2 grid in the 5m DEMs. The resolution-reduced 10m DEMs could generate some differences in the morphological analysis, but the expected scale of the landslide susceptibility in this study was set to 1:25,000, so differences smaller than 12.5m could be ignored according to the relationship between mapping scale and 5% acceptable error. We added these descriptions in section "3.3 Slope units" (page 3, lines 30–34).
10	[Page 3, line 26] the procedure you cited (Xie et al, 2004) identify slope units from DEM, by the use of Arc Hydro tool. Each slope unit is characterized by several homogeneous parameters. I believe that a more accurate description of the whole procedure you used to identify slope units is required, to better understand the paper.	Thanks for the comment. Slope units were delineated according to gullies and ridges. First, gullies and watersheds were analyzed by successively using spatial analysis tools in ArcGIS: fill, flow direction, flow accumulation, stream link (with 2,000 used as the threshold) and watershed. Second, reverse DEMs were generated by multiplying DEMs by -1. In the reverse

		DEMs, ridges became gullies and could be analyzed by the same methods used in the first step. Third, the watersheds of the DEMs and reverse DEMs were transformed from rasters to polygons for further editing by using the "Raster to Polygon" tool in ArcGIS and then cut by each other 5 to delineate the slope units. Finally, slope units were modified manually according to aspect and gradient. It is suggested that the aspect in a slope unit should be within three adjacent directions; e.g., northwest, north, and northeast. On the other hand, the difference in gradient should not be over 30 degrees in a slope unit, and slope units situated on flat areas, including alluvial deposits and terraces, were deleted. In addition, the area of each slope unit was set to around 5 ha; therefore, slope units smaller than 5 ha were combined with adjacent slope 10 units and those larger than 5 ha were split into several smaller ones. Moreover, slope units delineated by parallel drainage on a dip slope were combined into one slope unit. We added these detailed procedure in section "3.3 Slope units" from page 3, line 35 to page 4, line 11.
11	[Page 4, line 2] What do you mean with total rainfall? How long is the period you considered to calculate it? How did you decide to use 3 and 24 hours rainfall? Please clarify.	Thanks for the comment. Whenever Taiwan has a typhoon event, the Central Weather Bureau issues disaster prevention alerts. We therefore counted the time that the first alert was issued as the beginning of the rainfall event and the time that the alert was cancelled as the end of the rainfall event to calculate rainfall amounts. We added this in page 5, lines 6–8. For the decision of 3-hour mean rainfall intensity and 24-hour accumulated rainfall,

		we calculated the triggering rainfall, including the rainfall intensity (I_1, I_2, I_3, I_4, I_5, I_6) and accumulated rainfall (R_6, R_{12}, R_{24}, R_{48}, R_{72}) of different time windows of each landslide case according to the landslide occurrence time. The results revealed that 218 landslides occurred within the 3 hours following the highest rainfall intensity, and 242 occurred within the 3 hours following the 2nd or 3rd highest rainfall intensity (i.e., induced by high rainfall intensity), accounting for nearly 49% of the landslide cases gathered in this study (shown in Table 3). From these results, it became clear that in Taiwan, I_3 is the most important index for landslides induced by rainfall of short duration but high intensity. On the other hand, 481 landslides occurred close to the end of the rainfall events (i.e., induced by high accumulated rainfall), accounting for about 51% of the total cases. Furthermore, analysis of the different accumulated rainfall indexes showed that 24-hour accumulated rainfall had the lowest coefficient of variation (shown in Table 4), indicating that this index was less dispersive than others and might be more suitable for serving as an accumulated rainfall index for establishing rainfall thresholds. We added these details in section 4.2 (page 6, lines 9–19).
12	[Page 4, line 12] what do you mean "The ratio of steep slope was calculated by dividing the area that greater than 30 degrees by total area of slope unit."?	Thanks for the comment. As we know, shallow landslides are prone to occur on steep slopes; therefore, we used the "ratio of steep slopes" to present how many steep slopes existed in a slope unit. It was found after trial and error that a threshold of gradient higher than 30 degrees had a higher relationship with landslide susceptibility.

		Thus, we calculated the area where the gradient was greater than 30 degrees ($A_{>30}$) as well as the total area (A_{total}) of each slope unit. Therefore, the ratio of steep slope could be calculated by dividing $A_{>30}$ by A_{total}. We added these detailed descriptions in section 3.4 (page 4, lines 28–32).
13	[Page 4, line 17] Kriging interpolation method is very effective, but it has to be properly performed. You should describe how you applied it.	Thanks for the comment. We collected hourly rainfall data of 423 rain stations provided by Central Weather Bureau, Taiwan and analyzed both the 3-hour mean rainfall intensity (I_3) and the 24-hour accumulated rainfall (R_{24}) of each station. After that, we used the linear mode of ordinary kriging and applied the default setting in Surfer software to obtain the rainfall distribution of the whole study area. We added these descriptions in page 5, lines 2–6).
14	[Page 4, line 23] & [Page 4, line 25] "required" → "require"	Thanks for the comment. We corrected these sentences in page 5, lines 14–21.
15	[Page 4, line 35] please clarify how you defined the coefficient *w* in LR function.	Thanks for the comment. The index indicating landslide/non-landslide was set as the dependent variable, and all the landslide susceptibility factors were set as covariates in SPSS for training of the model. After iterative training, the regression coefficients of each landslide susceptibility factor, as well as the success rate curve (SRC), the prediction rate curve (PRC), and the area under the curve (AUC), were reported in SPSS. We added a more detailed descriptions in page 5, lines 31–34.
16	[Page 5, line 18] Why did you not use the cumulative rainfall of 3 hours? It is the same.	Thanks for the comment. We agree that using cumulative rainfall of 3 hours is similar to 3-hour mean rainfall intensity (I_3). We chose 3-hour mean rainfall intensity here instead of 3-hour accumulated rainfall

		to focus on rainfall of short duration but high intensity. Similarly, we chose 24-hour accumulated rainfall to focus on rainfall of long duration but low intensity. We added these descriptions in page 6, lines 25–27.
17	[Page 7, line 16] for a complete validation you should use also rainfall events that not triggered landslides, to calculate False alarms, correct alarm and missed alarm. See Segoni et al. 2014, Rosi et al, 2015, etc.	Thanks for the comment and kindly providing relevant references. We defined the no alarm zone from alarm zone and calculate the numbers of false alarms, correct alarms and missed alarms to make a complete validation of our EWS. It was revised in section 4.3 (page 7, lines 16–34). On the other hand, the results were shown in page 10, lines 5–15.
18	[Page 7, line 25] I believe this happened because you used rainfall intensity. If rain stops, intensity decreases, but if you try to use 3-hours cumulative rainfall you should avoid this problems.	Thanks for the comment. If rainfall stops, not only 3-hour mean rainfall intensity (I_3) but also 3-hours cumulative rainfall (R_3) decrease because only the rainfall in the nearest 3 hours (h, h-1, h-2) are taking into consideration. In this study, rainfall thresholds were set according to the I_3–R_{24} diagram shown as Figure 4. If 3-hours cumulative rainfall (R_3) were used to replace 3-hour mean rainfall intensity (I_3), the scale of y-axis and the value of new threshold will also be 3 times larger in the R_3–R_{24} diagram. It means that no matter in the I_3–R_{24} diagram or R_3–R_{24} diagram, for the same rainfall events, the snake line will all turned back to yellow when the rainfall fell.
19	[Page 14, Figure 3] this Figure is missing of some elements: scale bar, legend, orientation (North direction).	Thanks for the comment. The other reviewer suggested deleting this figure because it was not useful for the discussion. We deleted it in this revised manuscript.

Referee #2

Comments to author:

No.	Comment	Reply
1	The paper is very poorly written, with a bad English. Several typos are present everywhere in the text. Moreover, the use of past and present tenses is hardly understandable. Several sentences are not clear at all. I suggest a strong revision of the paper in this view, possibly with an editing by an English native speaker.	Thanks for the comment. We carefully checked again and asked for the editing by an English native speaker throughout the manuscript.
2	The introduction could be improved by reporting and analyzing some works that have dealt with regional early warning models and early warning systems for landslide occurrence, e.g. Segoni et al. 2014; Calvello et al. 2015, Devoli et al. 2015; Piciullo et al. 2017; Pumo et al. 2017.	Thanks for the comment. We analyzed and added these important references in the revised introduction.
3	The "Data and method" section can be improved by adding more details on data gathering. As an example, it is not clear how Authors identified rock falls from the landslide inventory. Moreover, Authors state that they gathered landslide occurrence time by inquiry residents during field investigations. This should be clarified, in particular because the occurrence time of the landslides is very important for the reconstruction of the 3-hour mean rainfall intensity. In addition, more details on the definition of landslide inventory would be useful. Furthermore, it is not clear why the Authors calculated a precipitation map for the whole study area. What is it for?	Thanks for the comment. We split "Data and methodology" into "Available data" and "Methodology" so that more details can be described in each section. For the identification of rock fall from the landslide inventories, we deleted the polygons situated on slopes having gradients greater than 55 degrees according to the classification rules proposed by the Central Geological Survey, Taiwan (Central Geological Survey, 2008). These descriptions were added in page 3, lines 7–9. For gathering landslide occurrence time by acquiring residents during field investigation, we focused on interviewing as many residents whose relatives were injured or houses were damaged/destroyed by the landslides as possible, so that the quality might be improved. These descriptions were

		added in page 3, lines 19–23. Detailed definitions including the classification and procedure for the generation of landslide inventory was added in section 3.1 (page 3, lines 4–13). The precipitation maps were produced and the triggering rainfalls of landslides were extracted for the purpose of analyzing landslide susceptibility. This was revised in section 3.4 (page 5, lines 2–8).
4	Nothing is said about rainfall data. Did authors use rain gauge series? If yes, please explain how many rain gauges.	Thanks for the comment. Yes, we used rainfall data from 423 rain gauges provided by Central Weather Bureau, Taiwan. Their distributions are shown in Figure 1. We added detailed descriptions in section 3.4 (page 5, lines 2–8)
5	The whole section regarding the landslide susceptibility analysis (section 3.2.1) should be rewritten and increased by adding more information. Several details on the adopted method are missing.	Thanks for the comment, we revised this section and asked for the editing by a native speaker again. We also added more detailed procedures in this revised version in section 3.4.
6	In the section on rainfall thresholds, Authors refer to a coefficient of variation (also reported in Table 4); please explain how it was calculated.	Thanks for the comment. We added the equation of coefficient of variation in order to explain how the calculation was made in page 6, lines 16–22.
7	In the "3.2.3 landslide early warning model" section, it is very strange that 30%, 60% and 90% thresholds correspond exactly to integer values of I_3 (30, 40, 60) and R_{24} (300, 400, 600). Is it just an example? Please explain.	Thanks for the comment. The original warning values of I_3 and R_{24} of the 90%, 60%, 30%, 15% thresholds were equal to the semi-minor axis and semi-major axis of each threshold respectively. After that, I_3 was rounded to the nearest 5 mm/h and R_{24} was rounded to the nearest 50 mm for operational purposes, such as the evacuation of residents. We added these explains in page 6, lines 32–35 as well as page 8, lines 26–27 and the caption of Figure 8.
8	In the section related to the results of landslide susceptibility analysis, the values	Thanks for the comment. For a statistical landslide susceptibility analysis, it is

	of AUC are not so high to justify that "the results showed that LR model was stable and nice in training as well as validation" (Page 6, line 20). I suggest rephrasing this sentence, acknowledging that results could be better. Moreover, I suggest avoiding the word "nice", here and elsewhere in the text.	essential to use as many samples as possible. However, we used slope units instead of grid units in this study for application to disaster prevention. This led to the reduction of samples, since one slope unit might equal hundreds of grids. Therefore, our AUC might not be considered high in comparison to a grid-based landslide susceptibility model. We added these descriptions in page 8, lines 12–15 and replaced the word "nice" with "acceptable" in this revised manuscript.
9	At the end of section 4.2 (page 7, lines 8-13), several actions to be performed in case of different warning levels are reported. This step leads from an early warning model to an early warning system; therefore, it should be remarked.	Thanks for the comment. We agree these suggested actions lead from a model to a EWS. Now we also develop a system connecting to the near real-time radar rainfall data for disaster prevention. We remarked these in section 5.2 (from page 8, line 32 to page 9, line 1).
10	Regarding validation of the model (Section 4.3), I would suggest using some indices or scores (e.g., count – and ratio – of correct and incorrect predictions, True Positive Rate, ROC analysis, etc.) to quantitatively evaluate the performance of the validation procedure.	Thanks for the comment. We agree that quantitative evaluation of the performance of early warning model is necessary. The numbers of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) were counted and the skill scores including the probability of detection (POD), the probability of false detection (POFD) and the probability of false alarm (POFA) were used to evaluate the effectiveness of this EWS. These results were shown in the last paragraph of section 5.3 in page 10.
11	Conclusions section is very short! Authors should add the main findings and the lesson learnt from their work. I suggest increasing a lot this last section.	Thanks for the comment. We increased the contents of conclusion and all major findings were also included in this section.
12	Figure 1: add more descriptions in the caption.	Thanks for the comment. We added more descriptions in this figure.

13	Figure 3: not useful for the discussion. I suggest deleting it.	Thanks for the comment. We deleted this figure.
14	Figure 5: in the label of y-axis, pleas change "hr" into "h".	Thanks for the comment. We changed "hr" into "h" in texts, figures, and tables.
15	Figure 6: it's a repetition of Figure 8b (for moderate susceptibility areas); I suggest deleting it.	Thanks for the comment. We deleted this figure.
16	Figure 7: I would suggest the following labels for x- and y-axes, respectively: "Portion of areas predicted as hazardous" for x-axis, and "portion of landslide occurred" for y-axis.	Thanks for the comment. We changed the label in Figure 6 (Figure 7 in the original manuscript) according to the suggestion.
17	Figure 8: I suggest enlarging it, and distribute the three panels vertically. Moreover, please add a), b) an c) to the three panels.	Thanks for the comment. We enlarged Figure 7 (Figure 8 in the original manuscript) and distributed them vertically. Besides, we added (a), (b), (c) in each panel.
18	Tables 5 and 6: I'm not sure that colours can be used in tables in NHESS journal. I suggest converting them into two figures, if Authors want to maintain colours.	Thanks for the comment. The colours are essential for understanding the alert. Therefore, we converted these tables into figures.
19	References: Please add DOI to each reference in the list.	Thanks for the comment. We added DOI for the references.
20	As I already stated, the manuscript is full of technical and grammatical errors, typos, and incorrect use of words. Here I list just some suggestions of technical corrections, but again I suggest a check and a language revision of the whole text.	Thanks for the comment, we carefully checked the manuscript again and asked for the editing by a native speaker.
21	● Page 1, lines 29-31: please check this sentence and rewrite. ● Page 3, line 9: correct "form". ● Page 3, lines 15, 22, 23, 30: please check plurals (e.g., slope units, landslides,: : :). ● Page 3, line 23: please check and correct the sentence "This study used slope unit that based on the features of: : :". ● Page 4, lines 11-12: please reword. ● Page 6, line 5: unclear, please rewrite.	Thanks for pointing out these unclear sentences and typos. We corrected all of them with caution in this revised manuscript. Besides, we replaced the "rounded to" with "rounded to the nearest 5 mm/h" and "rounded to the nearest 50 mm" in page 6, line 34; page 8, lines 26–27; the caption of figure 8. On the other hand, we revised the words

	● Page 6, lines 22-26: this sentence is unclear, please reword. ● Page 7, line 3: replace “rounded to” with “rounded by”. ● Page 7, line 22: correct “form”. ● Page 7, line 25 and following: authors mention “14th”, “15th”, and others; if they are days, I suggest using the format dd-mm, which results more clear. ● Page 8, line 4: “once landslide”, what does it mean? Please correct.	that expressing days in section 5.3, table 7 and table 8.

Adopting the I_3–R_{24} rainfall index and landslide susceptibility ~~on~~for the establishment of an early warning model for rainfall-induced shallow landslides

Lun-Wei Wei[1,3]~~[2]~~[3], Chuen-Ming Huang[2,] ~~Huang~~~~[12,]~~[3]~~[3]~~, Hongey Chen[1,4], Chyi-Tyi Lee~~Lee~~~~[3]~~[2], Chun-Chi Chi~~Chi~~[4]~~[5]~~, and Chen-Lung Chiu[5]~~Chiu~~[4]~~[5]~~

[1]Department~~[1]Disaster Prevention Technology Research Center, Sinotech Engineering Consultants, INC., Taiwan~~

~~[2]~~~~[1]~~~~Department~~ of Geosciences, National Taiwan University, Taiwan

[2]Institute

~~[3]~~~~[2]~~~~Institute~~ of Applied Geology, National Central University, Taiwan

[3]Disaster~~[13]~~ Disaster Prevention Technology Research Center, Sinotech Engineering Consultants, INC., Taiwan

[4]National Science and Technology Center for Disaster Reduction, Taipei, Taiwan

[5]Central~~[4]~~~~[5]~~~~Central~~ Geological Survey, MOEA, Taiwan

Correspondence to: Lun-Wei Wei (d03224007@ntu.edu.tw)

Abstract. Rainfall-induced ~~landslide is one of~~landslides number among the most devastating natural hazards in the world, and ~~the setup of~~ early warning models ~~is a pressing need for reducing~~are urgently needed to reduce losses and fatalities. Most ~~part of~~ landslide early ~~warnings~~warning systems are based on rainfall thresholds defined ~~at~~on the regional scale, regardless of the different landslide ~~susceptibility~~susceptibilities of ~~each slope~~various slopes.~~,~~ Here we ~~tried to divide~~divided slope units in southern Taiwan into three categories (high, moderate,~~,~~ and low) according to their susceptibility. For each category, we established ~~their~~separate rainfall thresholds ~~separately~~ so as to provide differentiated thresholds for different degrees of susceptibility. Logistic regression (LR) analysis was performed to evaluate ~~the~~ landslide susceptibility by using event~~-~~-based landslide inventories and predisposing factors. ~~Through the analysis~~Analysis of rainfall patterns of 941~~more than 900~~ landslide cases gathered from field investigation~~,~~ led to the recognition that 3-hour mean rainfall intensity (I_3) ~~was recognized as~~is a key rainfall index for rainfall of short duration but high intensity ~~rainfall~~; on the other hand, 24-hour accumulated rainfall (R_{24}) was recognized as a key rainfall index for rainfall of long duration but low intensity ~~rainfall~~. Thus, the I_3–R_{24} rainfall index was used ~~for the establishment of~~to establish rainfall thresholds in this study. Finally, an early warning model ~~was~~is proposed by setting ~~warning signs~~alert levels including yellow (advisory), orange (watch) and red (warning) according to ~~the concept of~~a hazard matrix. These differentiated thresholds and ~~warning signs~~alert levels can provide essential information for local ~~government on evacuating decision of~~governments to use in deciding whether to evacuate residents.

Keywords: rainfall-induced landslide, landslide susceptibility analysis, rainfall threshold, early warning

1 **Introduction**

Rainfall-induced ~~landslide is one of~~landslides number among the most perilous natural hazards, causing severe casualties and economic losses ~~all over the world~~worldwide~~world~~ (Ayalew, 1999; Evans et al., 2007; Tsou et al., 2011~~. ,~~; Petley, 2012; Wang et al., 2015; Iverson et al., 2015; Sassa et al., 2015; Fan et al., 2017). Therefore, many efforts have been made to evaluate

~~the~~landslide susceptibility and thereby set criteria ~~of~~for issuing ~~early warning for the sake of saving~~alerts that can save lives and ~~properties~~property.

~~Landslide could~~Landslides can be triggered by either rainfall or ~~earthquake~~earthquakes ~~in Taiwan~~ (Dadson et al., 2003; Lee et al., 2004; Lin et al., 2008; Chen et al., 2011). In ~~, especially the former.~~ Taiwan, ~~monsoon~~monsoons ~~was invaded by several~~ and typhoons bring ~~which brought~~ great amounts of rainfall, up to 3,000 mm/year~~every year~~, ~~causing lots of~~and numerous landslides ~~and~~cause casualties every year. Therefore, recognizing the ~~area that~~areas where rainfall-induced ~~landslide~~landslides ~~the area that~~ might occur~~have potential rainfall-induced landslide was~~ is an urgent issue. ~~important and landslide susceptibility analysis was a general method.~~ Here we~~(please check this sentence and rewrite). We~~ adopted a statistical method for the analysis of landslide susceptibility ~~model in this study~~ based on the assumption that the predisposing factors ~~caused~~that cause ~~which caused slope failure~~landslides in a region ~~were~~are ~~the same~~similar and can be used for predicting the ~~location~~locations of ~~as those which will generate~~ landslides in the future (Guzzetti et al., 1999). ~~There were~~In~~In~~ previous researches, several statistical models ~~that~~ have been proposed as well as~~and~~ widely utilized in landslide susceptibility analysis, and~~in recent years, especially~~ ~~the~~ logistic regression were one of the most used methods (Guzzetti et al., 1999; Lee et al., 2004, 2008a, 2008b, 2014). ~~Therefore, we applied logistic regression (LR) in this study.~~

On the other hand, rainfall thresholds for landslides can be categorized as either statistical approaches ~~and~~or deterministic approaches. In the former method, thresholds are decided by collecting historical landslide cases and analyzing their rainfall parameters ~~as well as~~and the probability lines of rainfall conditions (Caine, 1980; Guzzetti et al., 2008). In the latter method, thresholds are decided by calculating the safety factors of each slope or grid with geomaterial and rainfall parameters (Terlien, 1998; Kim et al., 2010).

Statistical rainfall thresholds for shallow ~~landslide~~landslides have been well discussed (Guzzetti et al., 2007). They can be classified mainly ~~classify~~ into 5 categories ~~including~~: intensity-duration (Brunetti et al., 2010; Zhou et al., 2014; Pradhan et al., 2017), accumulated rainfall-duration (Martelloni, 2011; Rosi et al., 2012; Vessia et al., 2014; Gariano et al., 2015; Rossi et al., 2017), accumulated rainfall (Corominas and Moya, 1999; Bell and Maud, 2000), intensity-accumulated rainfall (Hong et al., 2005~~)~~), and accumulated rainfall-accumulated rainfall (Osanai et al., 2010; Turkington et al., 2014).

Most of the studies ~~mentioned above~~ set ~~up~~ only one threshold for their study ~~area~~areas despite differences in ~~spite of~~ the ~~difference in~~ physical settings (geology, geomorphology, and meteorological ~~condition~~conditions) of ~~that region~~the regions. Recently, some studies have subdivided their study ~~area~~areas into several homogeneous sub-zones ~~in order~~ to discuss the influence of physical settings on thresholds (Hong and Adler, 2008; Segoni et al., 2014, 2015; Lee et al., 2015; ~~; Segoni et al., 2015;~~ Rosi et al., 2015, 2016; Peruccacci et al., 2017). However, for a smaller area ~~like~~such as slope units, ~~the difference~~differences in susceptibility may lead to ~~a~~ different warning ~~threshold~~thresholds (Yang and Adler, 2008; Segoni et al., 2015; Lee et al., 2015~~), e.g., for~~). For example, the warning threshold of a high-~~-~~susceptibility slope~~, its warning threshold may~~ is likely to be ~~probably~~ lower than that of a low-~~-~~susceptibility slope. ~~In order to reinforce~~To reduce~~address~~ ~~-~~this gap in knowledge, we focused on shallow landslides ~~including~~of the debris fall, debris topple, debris slide, earth fall, earth topple, and earth slide types proposed by Varnes (1978)~~), trying~~~~tried to divide~~). and ~~We~~ divided slope units ~~into~~according to three different landslide susceptibility levels (high, moderate, and low). After that, we ~~and establishing~~established~~established~~ their rainfall thresholds separately. ~~Besides~~Furthermore, we set ~~warning signs~~alert levels by adopting ~~the concept of~~ a hazard matrix and ~~examine if~~examined whether differentiated warning thresholds for different degrees of susceptibility existed. Moreover, ~~it is essential to validate~~given the importance of validating the performance of a landslide early warning model, especially the false alarms and missed alarms, ~~so as~~ to make it feasible for further practical application (Calvello et al. 2015; Devoli et al. 2015; Piciullo et al. 2017; Segoni et al., 2018), ~~therefore,~~ we also adopted skill scores to verify our results.

2 Study area

Taiwan is located ~~at~~in the western Pacific Ocean, on the convergent plate boundary zone of the Philippine Sea plate and the Eurasian plate. The orogenic uplift rate is 5~~ ~ ~~–7 mm/year (Willett et al., 2003~~),~~); however, the exhumation rate is also as high as 3~~ ~ ~~–6 mm/year (Dadson et al., 2003) due to the fractured geological materials and the high mean annual precipitation ~~up to~~of 2,500~~ ~ ~~–3,000 mm brought by typhoons and monsoons every year (Hsu, 2013). The frequent ~~nature~~natural disasters and high population density (23 million people ~~over~~in 36,000 km^2) ~~make~~of Taiwan make it one of the countries most exposed to multiple hazards (Dilley et al., 2005).

The study area~~ is~~, located in southern Taiwan (red box in Fig. 1), ~~including the~~includes a ~~ region ~~mosaic of 47 1:25,000 scale maps (about 7,258.5 km^2) and ~~covering~~covers densely inhabited ~~as well as~~and landslide~~-~~-threatening hillslopes. The elevation ranges from 3,243 meters in mountain ~~area~~areas to 0 meters in plain ~~area~~areas, while the gradient ranges from ~~87°~~ 87° to ~~0°. Lithological~~0°. The lithological units ~~units~~~~Geological settings~~ are mainly sedimentary rocks composed of sandstone, shale, mudstone, and conglomerate in the Western Foothills, as well as metamorphic rocks composed of slate, argillite and metasandstone in the Central Range.

3 Available data~~Data and methodology~~

~~3.1 Data~~

~~3.2~~3.1 Landslide inventory

~~Landslide~~A ~~l~~Landslide inventories~~y~~ are~~is~~ essential for the assessment of landslide susceptibility or spatio-temporal land changes (Van Westen et al., 2003; Guzzetti et al., 2012; Samia et al., 2017; Valenzuela et al., 2017).~~ ThereIn this study, ~~ ~~t~~There ~~were four~~Four procedures for the ~~construction ~~generation of rainfall-induced landslide inventories were followed in this study. ~~Firstly~~First, barren lands ~~the landslide inventories (Table 1) ~~were interpreted manually from SPOT 5 images by drawing polygons in ESRI ArcGIS software. ~~Secondly~~Second, ~~, the ~~aerial photographs and ~~the ~~satellite images ~~in~~from Google Earth ~~Ggoogle Eearth ~~software were applied to identify ~~if~~whether~~check identify if ~~the barren ~~lands~~lands~~areas~~ were landslides or agricultural ~~lands. Besides~~land. In addition~~lands~~~~the locational correctness of inventories and confirm the type of landslides. Besides~~, the polygons ~~that ~~situated ~~in the slope whose gradient is higher~~on slopes having gradients greater than 55 degrees were marked as ~~rockfall~~rockfalls according to the classification rules proposed by the Central Geological Survey, Taiwan (Central Geological Survey, 2008). Polygons ~~which were ~~marked as agricultural ~~lands~~land or ~~rockfall~~rockfalls were deleted from the inventories ~~for the purpose of ensuring ~~to ensure that ~~This study used ~~only ~~only~~ shallow landslides ~~were~~would be analyzed in ~~this~~the study. ~~Thirdly~~Third~~ study.~~~~to analyze and the other types (e.g. rockfall) were filtered. Thirdly~~, we randomly selected landslides from~~forom~~ inventories ~~randomly ~~and verified~~to verifiedy~~ the correctness of ~~location~~the locations and ~~boundary via~~boundaries by fieldwork. Finally, event-based ~~ triggered ~~landslide inventories~~inventoriess~~, including ~~new~~newly-generated landslides and expanded landslide~~landslide ~~s~~due to the event~~, were identified ~~through the comparison of~~by comparing inventories before and after each ~~rainfall ~~event. In the end, ~~there were ~~6~~ In this study, there were six~~6 heavy rainfall events that triggered ~~landslide~~landslides~~thatof triggereded landslide ~~ were chosen, and ~~totally~~a total of seven landslide inventories were generated~~built~~~~generated~~ in this study (Table 1).–

~~3.3~~3.2 Landslide occurrence time and field investigation

Rainfall conditions such as intensity, duration, and accumulated rainfall that induced ~~landslide~~landslides ~~landslides~~ are key data ~~while applying~~ in ~~the~~ application of statistical ~~method~~methods to establish the rainfall thresholds for ~~landslide~~landslides~~landslides~~ (Guzzetti et al., 2007, 2008; Brunetti et al., 2010; Peruccacci et al., 2017). ~~In order to~~To analyze the rainfall conditions for each landslide case used in this study, a flowchart was proposed ~~in this study~~ (Fig. 2). –During field ~~investigation~~investigations, we ~~not only~~ verified the correctness of the landslide inventories ~~but also tried~~and interviewed local residents to try to ~~inquire~~acquire~~identify~~ the landslide occurrence ~~time from residents lived around~~times, since ~~it is nearly impossible to get~~ this information ~~from~~is rarely included in landslide inventories. ~~We gathered landslide occurrence time by inquiring residents during field investigation or collecting reports in newspapers. Besides, detailed characteristics of landslides such as lithology, geological structure, joint, strength, area, depth and mechanism were also recorded during field work. Finally, 941 landslide cases including their occurrence time (date and hour) and characteristics of landslides were gathered for further analysis of the rainfall conditions.~~The accuracy of landslide occurrence ~~time~~times is hard to evaluate due to the lack of video records~~,~~; however, we ~~tried to interview~~ focused on interviewing as many residents whose ~~family was~~ relatives were injured or ~~house was~~houses were damaged/~~ or~~ destroyed by the ~~landslide as many~~ landslides as possible. ~~Based on these impressive~~Given the deep impressions left by such memories, we believe that the quality of landslide occurrence ~~time~~times might be improved. ~~We gathered landslide occurrence time by inquiring residents during field investigation or collecting reports in newspapers. Besides~~On the other hand, detailed characteristics of the landslides, such as lithology, geological structure, joint, strength, area, depth and mechanism, were also recorded during the field work.

Finally, ~~there are~~ 941 landslide cases, including their occurrence ~~time~~times (date and hour) and the characteristics of the landslides, were gathered for further analysis~~ of the rainfall conditions.~~

~~3.4~~3.3 Slope units

Slope units were used for the analysis of landslide susceptibility in this study ~~This study used slope unit that based on the features of geomorphology such as ridges and river valleys to analyze landslide susceptibility~~ (Carrara, 1988; Carrara et al., 1991, 1995; Guzzetti et al., 1999; Schlögel et al., 2017; Yang, 2017). ~~In order to~~To delineate the ~~boundary~~boundaries of slope units~~units~~~~correctly~~, ~~the~~ 5×5m digital elevation models (5m ~~5m~~ DEMs) were acquired from the ~~Department~~ Ministry of the Interior, Taiwan. However, ~~for the sake of reducing noises~~to reduce noise, ~~the DEM was smoothed and reduced to 10m resolution for the sake of reducing noises.~~ we developed a Fortran program to obtain ~~the~~ smoothed and resolution-reduced 10×10m ~~DEM~~DEMs (10m DEMS) by calculating the average value of each 2 by 2 grid in the ~~5×~~5m ~~DEM~~DEMs. The resolution-reduced 10m ~~DEM might~~DEMs could generate some differences ~~on~~in the morphological analysis, but the expected scale of the landslide susceptibility in this study ~~is~~was set to 1:25,000, so ~~the~~ differences~~ that~~ smaller than 12.5m could~~might~~ be ~~able to~~ ignored according to the relationship between mapping scale and 5% acceptable error.–

This study followed the method proposed by Xie et al. (2004) ~~to delineate~~in delineating slope units according to ~~the~~ gullies and ridges. ~~Firstly~~First, gullies and ~~watershed~~watersheds were analyzed by successively using ~~the~~ spatial ~~analyst~~analysis tools in ArcGIS~~ including~~: fill, flow direction, flow accumulation, stream link (~~we used~~with 2,000 used as the threshold) and watershed~~ successively. Secondly~~. Second, reverse ~~DEM~~DEMs were generated by multiplying DEMs by -1 ~~on DEM. Now~~. In the reverse DEMs, ridges became gullies ~~in the reverse DEM~~ and could be analyzed by the same methods used in the first step. ~~Thirdly, watershed~~Third, the watersheds of ~~DEM~~the DEMs and reverse ~~DEM~~DEMs were transformed from ~~raster~~rasters~~s~~ to ~~polygon~~polygons for further editing by using the “Raster to Polygon” tool in ArcGIS and then cut by each other to delineate the slope units. Finally, slope units were modified manually according to ~~Through the mapping concept proposed by Xie et al. (2004), the slope units were mapped automatically and modified manually (Fig. 3). Each slope unit was given a unique code and separated into stable or unstable unit.~~~~Slope units were delineated according to the ridges and gullies as well as their aspect and gradient.~~ aspect and gradient. It ~~is~~~~has been~~is suggested that the aspect in a slope unit should be within three adjacent directions~~,~~; e.g., northwest, north~~-west, north,~~ and ~~north-east~~northeast. On the other hand, the difference in gradient should not be over 30 degrees in a slope unit, and ~~the~~ slope units ~~that~~ situated on flat areas, including ~~alluvium~~alluvial deposits and ~~terrace~~terraces, were deleted. ~~Besides~~In addition, the area of each slope unit was~~is~~ set to around 5 ha~~.~~~~,~~; ~~–t~~Therefore, slope units ~~that some~~ smaller than 5 ha ~~slope units~~ were ~~united to~~combined with adjacent slope units and ~~slope units that~~those larger than 5 ha were split into several smaller ones. Moreover, ~~,Besides,~~ slope units ~~that~~ delineated by parallel drainage on a dip slope ~~should united as~~were combined into one slope unit. After the editing, each slope unit ~~Moreover, the area of each slope unit~~ was given a unique code ~~is set to around 5 ha. Therefore, some smaller slope units were united to adjacent slope units. Each slope unit was given a unique code and separated into stable or unstable unit~~ for ~~the sake of~~ disaster prevention.

~~Each slope units is characterized by several homogeneous parameters. We will add these parameters and a more detailed procedure.~~

~~3.5~~3.4 Landslide Susceptibility Factors

~~Many factors could induce landslides, but each factor had different effect. This study initially selected some~~ Several predisposing factors that might lead to landslides were selected initially in this study ~~in order~~ to ~~suitable to~~ construct a landslide susceptibility model for slope units. ~~–~~These factors included~~included~~ rock mass strength-size classification (RMSSC I~~-~~–VII), dip slope, average slope, variance of slope, ratio of steep slope, total slope ~~high~~height, average elevation, average curvature, variance of curvature, fault density, fold density, average wetness, rainfall intensity, total rainfall, 3-hour mean rainfall intensity (I_3~~)~~), and 24-hour accumulated rainfall (R_{24}). The ~~relationship between~~ relationships of these factors ~~and~~to landslides ~~Whenever a typhoon attacks Taiwan, Central Weather Bureau will issue alerts for typhoon. We therefore take the time of the first alert issued as the beginning of rainfall event and the time of canceling alert as the end of rainfall event to calculate the total rainfall. The reason we choose 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) as factors will explain in section 4.2. They~~These factors could be analyzed through graphic discrimination, including ~~that included~~ success rate curve, probability of failure curve, and difference between landslide and non-landslide groups (Lee, 2014). After that, ~~Finally, we applied~~ factor correlation analyses~~analysis~~analyses were applied to delete ~~high~~highly~~and deleted the high~~ related~~ive~~ factors ~~for the sake of~~to keep the factors used in the landslide susceptibility model ~~were~~ as independent as possible (Table 2).

In terms of geological factors, the ~~lithology~~~~In terms of geological factors, L~~lithology ~~i~~~~w~~ithology of a ~~a~~is~~s always a~~ location is essential ~~essential~~~~critical – factor~~~~element~~ for the ~~when~~ analysis of~~ofzing~~~~in~~ landslide susceptibility.~~slope stability.~~ However, ~~in~~ our study area~~, there are~~ had~~were~~ more than 50 detailed types of lithology~~ in this study area~~, which ~~is~~was~~was~~ unfavorable for the analysis. Therefore, we adopted ~~t~~the 1:25,000 rock mass strength-size classification ~~(Franklin, 1975)~~ maps from ~~the~~ Central Geological Survey, Taiwan, ~~–were adopted~~ to replace the use of lithology (Franklin, 1975; Central Geological Survey, 2008). ~~Besides,~~In addition, the dip ~~Dip~~ slope inventory ~~used in this study was~~ interpreted manually from

1:5,000 aerial photographs by the Central Geological Survey, Taiwan, was~~wa~~ also adopted (Central Geological Survey, 2008). ~~On the other hand, the~~The ~~The~~ fold density was~~was~~ also calculated ~~with~~by dividing the total length of all the folds ~~divided~~ by the total area in each slope unit.

For morphological factors, the~~The~~ average slope and the variance of slope were~~were~~~~as~~ obtained by averaging and calculating the standard ~~deviation~~deviations of all the grid cells in the slope unit separately. ~~Besides~~In addition~~The ratio of steep slope was calculated by dividing the area that greater than 30 degrees by total area of slope unit.~~ Besides, shallow landslides are prone to occur on steep slopes~~,~~; therefore, we also used ~~"~~the "ratio of steep ~~slope~~slopes" to present how many steep slopes ~~are there~~existed in a slope unit. It was found after trial and error that a threshold of gradient higher than 30 degrees had a higher relationship with landslide susceptibility ~~after trial and error.~~. Thus, we calculated the area where the gradient ~~is~~was greater than 30 degrees ($A_{>30}$) as well as the total area (A_{total}) of each slope unit ~~and~~. Therefore, the ratio of steep slope ~~can therefore~~could be calculated ~~with~~by dividing $A_{>30}$ ~~divided~~ by A_{total}. On the other hand, the~~T~~~~the~~ average curvature and variance of curvature could also be calculated by the same method as slope in the ArcGIS software. The average wetness ~~is~~was calculated by averaging the wetness index of grid cells in a slope unit. This factor represents the effect of morphology on soil wetness. When the drainage area is larger and the slope is gentler, the water content in the soil ~~would~~will also be higher and therefore make a slope more prone to failure. ~~Wetness~~The wetness index can be calculated according to the method proposed by Wilson and Gallant (2000) as ~~followed~~follows:

$$\omega = ln\left(\frac{A_s}{\tan\theta}\right) \qquad (1)$$

where ω is wetness index, A_s is the drainage area of a specific grid cell, and θ is the slope of the grid.

For triggering factors, ~~The fold density was the total length of all the folds divided by the total area in each slope unit. The average wetness was calculated by following the method proposed by Wilson and Gallant (2000).~~

~~The average wetness was calculated by following the method proposed by Wilson and Gallant (2000).~~ we collected hourly ~~the~~ rainfall data of~~from~~ 423 rain stations~~gauges~~ provided by Central Weather Bureau, Taiwan~~in Taiwan~~ (96 of ~~them are~~which were located in our study area, shown in Fig. 1) and analyzed both the 3-hour mean rainfall intensity (I_3) ~~as well as~~and the 24-hour accumulated rainfall (R_{24}) of each station~~gauge~~ ~~in~~for each rainfall~~two typhoon~~ events in Table 2. After that, we used the linear mode of ordinary kriging and applied the default setting in Surfer software to obtain the rainfall distribution of the whole study area. ~~The hourly rainfall records during~~~~of two typhoon events in this study were collected from the Central Weather Bureau, Taiwan. According to these rainfall records, the 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) in each rainfall station were calculated. Besides, Kriging interpolation method was applied to generate the precipitation distribution map for the whole study area.~~Whenever Taiwan has a typhoon ~~attacks Taiwan,~~ event, the Central Weather Bureau ~~will issue alerts for the~~~~typhoon~~~~the sake of~~issues disaster prevention alerts. We therefore ~~take~~counted the time ~~of~~that the first alert was issued as the beginning of the rainfall event and the time ~~of canceling~~that the alert was cancelled as the end of the rainfall event to calculate ~~the total~~ rainfall amounts. ~~The reason we choose~~Our reasons for choosing 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) as factors will ~~explain~~be explained in detail in section 4.2.

4 Methodology

4.1 Landslide susceptibility analysis

~~There are many predisposing factors that might lead to landslides, but the effectiveness of each factor is different.~~ The main purpose of landslide susceptibility analysis is ~~determining~~to determine~~i~~~~was to determining~~~~e~~ the effectiveness of each predisposing factor and the relative possibility of landslide occurrence in a specific area. ~~There are several~~Several methods ~~for the analysis of~~can be used to analyze landslide susceptibility. The~~However, t~~~~The~~ deterministic method~~methods~~ uses a physical model and geotechnical material properties to determine the safety factor ~~of safety~~ of slopes~~,~~; however, precise parameters of materials ~~required geotechnical material properties which were~~are difficult to obtain, especially ~~for~~on ~~especially~~~~for~~ ~~for~~ a~~the~~ regional scal~~landslide susceptibility~~~~scale~~ (Montgomery and Dietrich, 1994; Van Westen and Terlien, 1996). The qualitative ~~method~~~~methods~~ and semi-quantitative ~~method~~methods rely on ~~depended on~~ the experience and knowledge of the experts who carried out the analysis~~,~~; however, these results might ~~be different~~vary from one expert to another. ~~.~~The machine learning method~~methods~~ uses ~~lots of~~multiple samples to build a model by trial and error~~,~~; however, it is ~~always~~ time consuming~~consuming~~ ~~required more training time to build model by trial and error~~ (Gorsevski and Jankowski, 2010; Yeon et al., 2010; Yilmaz, 2010; Marjanovic et al., 2011; Lee et al., 2012; Song et al., 2012). The ~~In order to avoid these difficulties, this study adopted~~ statistical method~~methods~~ ~~.~~ also requires ~~lots of~~numerous samples for the training~~,~~; however, it is more efficient, especially when dealing with regional~~-~~-scale analyses, and can avoid the uncertainty of material parameters as well as ~~the difference of~~differences in ~~-~~expert ~~experiences~~experience. Recently, nonlinear analysis, ~~one of the~~a statistical method, ~~that suitable~~has been used for the analysis of complex landslide ~~phenomenon including~~phenomena. Methods such as logistic regression (Yilmaz, 2010; Lee et al., 2012, ~~; Lee et al.,~~ 2014, ~~; Lee et al.,~~ 2015; Schlögel et al., 2017) and discriminant analysis (Lee et al., 2004, 2008a, 2008b) ~~were~~are often used to analyze landslide susceptibility. ~~Here~~In this study, we~~Here~~ ~~we~~~~logistic regression (Yilmaz, 2010; Lee et al., 2012; Lee et al., 2014; Lee et al., 2015; Schlögel et al., 2017) and discriminant analysis (Lee et al., 2004, 2008a, 2008b) were often used to analyze landslide susceptibility in the statistical methods~~~~Besides, due to landslide was a complex phenomenon, a nonlinear analysis was more suitable for this study. Recently, logistic regression (Yilmaz, 2010; Lee et al., 2012; Lee et al., 2014; Lee et al., 2015; Schlögel et al., 2017) and discriminant analysis (Lee et al., 2004, 2008a, 2008b) were often used to analyze landslide susceptibility in the statistical methods, therefore, LR was~~ applied logistic regression (LR) to evaluate the susceptibility of each slope unit (Guzzetti et al., 1999; Ayalew and Yamagishi, 2005). The LR function ~~was~~ can be expressed as ~~followed~~follows~~followed~~~~s~~:

$$\cancel{P=\frac{1}{1+e^{-z}}}\quad P=\frac{1}{1+e^{-z}}$$

(2)

$$\cancel{z=\sum_{i=1}^{m}L_i w_i+\sum_{j=1}^{n}F_j w_{m+j}+C}\quad z=\sum_{i=1}^{m}L_i w_i+\sum_{j=1}^{n}F_j w_{m+j}+C$$

(3)

$$\cancel{P=\frac{1}{1+e^{-z}}}$$

~~(12)~~

$$\cancel{z=\sum_{i=1}^{m}L_i w_i+\sum_{j=1}^{n}F_j w_{m+j}+C}$$ ~~(23)~~

where P is~~i~~~~was~~ ~~the~~ landslide susceptibility~~;~~, L_i is~~wa~~~~is~~ RMSSC factor (L01 to L07 in Table 2~~);~~), F_j ~~was~~is other factors (F01 to F10 in Table 2~~);~~), w_i and w_{m+j} ~~is~~are~~wa~~~~is~~ regression ~~coefficient~~coefficients, and C is a~~wa~~~~is~~ constant. ~~The s~~Six event-based ~~triggered~~ landslide inventories in this study were used to label ~~if~~ whether or not landslides occurred in the slope units ~~occurred landslide or not.~~. After that, all the slope units were divided randomly into two ~~parts randomly~~groups.~~,~~ ~~o~~One ~~was~~ for training the model and the other ~~was~~ for ~~the~~ validation. T he index ~~that~~ indicating landslide/non-landslide was set as the dependent variable, and all the landslide susceptibility factors were set as covariates ~~under~~in SPSS ~~software while~~ for training of the model. After ~~iterated~~iterative training, the regression coefficients of each landslide susceptibility factor, as well as the success rate curve (SRC), the prediction rate curve (PRC~~)~~), and the area under the curve (AUC~~)~~)), were reported in SPSS~~ software~~. The AUC can be used to ~~exam~~examine if the model predicts landslides well~~ or not~~, and the regression coefficients can be used for the prediction of landslide susceptibility. During the process of training, ~~there are~~ several details ~~that should pay~~required attention~~ to. Due to that~~. Because ~~The six event-based triggered landslide inventories in this study were divided into two parts randomly. One was for training model and the other was for the validation. In addition,~~ the non-landslide samples~~samples~~~~data~~ ~~were many~~~~many~~~~uch more than~~ outnumbered the landslide samples, ~~samples~~~~data, so~~ we randomly selected ~~the same amounts~~equal numbers of non-landslide and landslide samples~~samples~~~~data~~ ~~randomly~~ for the training~~–~~ so as to avoid the effect of difference in quantity. ~~Besides~~In addition, ~~quantityin SPSS software. Besides,~~ different samples ~~might lead~~could have led to different results when selecting non-landslide samples randomly. ~~In order to~~To reduce this effect, ~~Besides,~~ we prepared several sets of randomly~~–~~-selected samples ~~(especially non-landslide data) were also tested~~ for the analysis of landslide susceptibility ~~in order~~ to test if~~ensure~~ the model ~~were~~was stable enough~~,~~; i.e., the AUC would not ~~variate~~vary~~not variate~~~~ing~~ severely when validating models with different sets of samples. ~~with alternating samples.~~ Finally, the individual landslide ~~susceptibility~~susceptibilities~~distribution of each~~the ~~the failure ratio and landslide susceptibility~~ of~~in~~ ~~each~~ slope ~~unit was~~units were calculated with this model and classified into ~~plotted and then used in classifying~~~~ied~~ ~~into~~ ~~landslide susceptibility level (~~high, moderate and low susceptibility ~~level~~levels.~~.)~~

4.2 I_3–R_{24} rainfall index and thresholds

Rainfall-induced landslides are~~ always~~ triggered by either high intensity rainfall or high accumulated rainfall (Larsen and Simon, 1993; Corominas and Moya; 1999; Yu et al., 2006). ~~In order to find out~~To identify rainfall indexes responsible for landslides, the triggering rainfall, including the rainfall intensity (I_1, I_2, I_3, I_4, I_5, I_6) and accumulated rainfall (R_6, R_{12}, R_{24}, R_{48}, R_{72}) of different time ~~window~~windows of each landslide case~~,~~ w~~as~~ere analyzed according to the landslide occurrence time~~–~~. ~~It was found~~The results revealed that ~~there were~~ 218 ~~landslide cases~~landslides occurred within the 3 hours ~~right after~~following the highest rainfall intensity, and 242 ~~cases~~ occurred within the 3 hours ~~right after~~following the 2nd or 3rd highest rainfall intensity (i.e., induced by high rainfall intensity), accounting for nearly 49% of the landslide cases gathered in this study (Table 3). ~~This indicated~~From these results, it became clear that in Taiwan, I_3 is the most ~~key~~important index for landslides induced by rainfall of short duration but high intensity~~ rainfall in Taiwan.~~. On the other hand, ~~there were~~ 481 ~~landslide cases~~landslides occurred ~~at the time~~ close to the end of the rainfall ~~event~~events (i.e., induced by high accumulated rainfall), accounting for about 51% of the total cases~~ (Table 3)~~. ~~–~~Furthermore, analysis of the different accumulated rainfall indexes showed that 24-hour accumulated rainfall ~~has~~had the lowest coefficient of variation (Table 4), indicating that this index was less dispersive than others and might be more suitable for serving as an accumulated rainfall index ~~in~~for establishing rainfall thresholds.~~establishing rainfall threshold.~~ The coefficient of variation can be calculated as ~~followed~~follows:

$$C_v = \frac{\sigma}{\mu} \qquad (4)$$

where C_v is the coefficient of variation~~;~~, and σ and μ are the standard deviation and average of accumulated rainfall of all the cases used in this study respectively.

Based on these data and ~~literatures~~previous studies (Cheung et al., 2006; Liao et al., 2010), 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) were ~~therefore~~respectively chosen as the short-term and long-term rainfall ~~index~~

~~respectively~~ indexes for the establishment of the rainfall threshold (Fig. 3~~43~~). We ~~choose~~chose 3-hour mean rainfall intensity here instead of 3-hour accumulated rainfall ~~for the purpose~~to focus on rainfall of ~~emphasizing the~~ short duration but high intensity ~~rainfall~~. Similarly, we ~~choose~~chose 24-hour accumulated rainfall ~~for the sake~~to focus on rainfall of ~~emphasizing the~~ long duration but low intensity ~~rainfall~~.

Finally, rainfall thresholds were decided by plotting the I_3 and R_{24} rainfall index of historical landslides in the I_3–R_{24} diagram (Fig. 4~~54~~). Here we used the ellipse as the threshold line, and the ~~parameter~~parameters *a* (semi-major axis) ~~as well as~~and *b* (semi-minor axis) of the ellipse were set according to the slope of best fit line ~~getting~~obtained from the least square method. ~~Different thresholds~~Thresholds such as 90%, 60%, 30%, 15% were determined according to the percentage of historical cases that could be enveloped under the threshold line~~,~~; e.g., the 90% threshold ($T_{90\%}$) included 90% of the historical cases. ~~and a~~A higher threshold indicates~~also indicatesd~~ a more dangerous condition for the occurrence of ~~landslide~~landslides. The original warning values of I_3 and R_{24} of the 90%, 60%, 30%, 15% thresholds were equal to the semi-minor axis and semi-major axis of each threshold respectively. After that, I_3 was rounded to the nearest~~by~~ 5 mm/h and R_{24} was rounded ~~by~~to the nearest 50 mm for operational ~~purpose, e.g.,~~purposes, such as the evacuation of residents.

4.3 **Landslide early warning model and validation**

~~Landslide~~ The landslide early warning model in this study considered both landslide susceptibility ~~as well as~~and rainfall thresholds and ~~was given warning signs~~alerts were determined by using ~~the concept of~~a hazard matrix. As mentioned above, the LR method was applied to analyze the susceptibility of each slope unit. After that, all the slope units were categorized into high, moderate, and low susceptibility ~~level~~levels. We consequently established rainfall thresholds for each susceptibility level separately and then ~~gave warning signs including~~set alerts of red, orange, yellow and green according to the ~~dangerous~~ level of danger.

High~~For high High~~ susceptibility slopes ~~(Table 5Fig. 5), they)~~ might be more susceptible to rainfall~~, hence~~. Hence, the ~~warning sign was~~alerts were set as red (extreme ~~dangerous~~danger level) ~~when~~for rainfall ~~condition exceeds~~conditions exceeding the 60% threshold line~~;~~, orange (high ~~dangerous~~danger level) ~~when rainfall condition was~~for those between the 60% and 30% threshold lines~~;~~, yellow (medium ~~dangerous~~danger level) ~~when rainfall condition was~~for those between the 30% and 15% ~~thresholds~~threshold lines~~;~~, and green (low ~~dangerous~~danger level) ~~when~~for rainfall ~~condition was~~conditions lower than the 15% threshold line (Fig. 5). For moderate-~~-~~susceptibility slopes, ~~(Fig. 6),~~ the ~~warning sign was~~alerts were set as red ~~when~~for rainfall ~~condition exceeds~~conditions exceeding the 90% threshold line~~;~~, orange ~~when rainfall condition was~~for those between the 90% and 60% threshold lines~~;~~, yellow ~~when~~for rainfall ~~condition was~~conditions between the 60% and 30% ~~thresholds~~threshold lines~~;~~, and green ~~when~~for rainfall ~~condition was~~conditions lower than the 30% threshold line. ~~For low~~ Low-susceptibility slopes~~, they might~~ should be less susceptible to rainfall~~, hence~~. Hence, ~~there was no red sign and~~ the ~~warning sign was~~alerts were set as orange ~~when~~for rainfall ~~condition exceeds~~conditions exceeding the 90% threshold line~~;~~, yellow ~~when rainfall condition~~for those w~~ereas~~ between the 90% and 60% ~~thresholds~~threshold lines~~;~~, and green ~~when rainfall condition was~~for those lower than the 6~~6~~0% threshold line.

~~There are sever~~Several methods can be used for the validation of a landslide early warning model (Segoni et al., 2014, 2018; Gariano, 2015; Rosi et al, 2015; Piciullo et al., 2017; Krøgli et al., 2018). According to the analysis of Segoni et al. (2018), compiling a contingency matrix and calculating skill scores ~~are~~is the most commonly used method in recent years~~, therefore~~. Therefore, we applied this method and ~~validate~~quantitatively validated our model with probability of detection (POD, also known as hit rate), ~~probability of false alarm (POFA, also known as false alarm ratio) and~~ probability of false detection (POFD, also known as false alarm rate) and probability of false alarm (POFA, also known as false alarm ratio~~) quantitatively.~~).

The contingency matrix is ~~shown~~presented as Table 5. ~~There are four outcomes when comparing~~Comparing the observed events and the forecasted ~~event including~~events produces four outcomes: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). ~~Due to that the~~ Because in Taiwan, warnings of ~~nature~~natural hazards are always issued by taking a village as a unit ~~in Taiwan~~, here we validated our model ~~with a villages~~on the village scale. TP ~~indicates~~indicated the number of villages ~~that~~for which warnings of slope units ~~are~~were issued and landslides ~~do~~did occur, while TN ~~indicates~~indicated the number of villages ~~that~~for which no warning ~~is~~was issued and ~~there is also~~ no landslide occurred. On the other hand, FP ~~indicates~~indicated the number of villages ~~that do not occur landslides but~~for which warnings ~~are~~were issued but no landslides occurred, also known as false alarms, while FN ~~indicates~~indicated the number of villages ~~that occur landslides but~~for which no warnings ~~are not~~were issued~~,~~ but landslides did occur; i.e., missed alarms. ~~Besides~~In addition, in our study, we ~~define the warning sign of~~defined red (extreme ~~dangerous~~danger level) and orange (high ~~dangerous~~danger level) alerts as warnings issued for ~~the~~ evacuation~~,~~; i.e., the alarm zone in our model. On the other hand, ~~the warning sign of~~ yellow (medium ~~dangerous~~danger level) and green (low ~~dangerous~~danger level) ~~are~~alerts were considered ~~as~~to indicate no need for ~~the~~ evacuation~~,~~; i.e., the no alarm zone in our model. ~~The~~ POD, ~~POFA,~~ POFD, POFA can be calculated by the following equations:

$$POD = \frac{TP}{TP+FN} \quad (5)$$

$$\mathrm{POFD} = \frac{FP}{TP+FP} \quad (6\cancel{7})$$

$$\mathrm{POFA} = \frac{FP}{FP+TN} \quad (7\cancel{6})$$

$$\cancel{\mathrm{POFD} = \frac{FP}{TP+FP} \quad (7)}$$

~~T~~The ranges of POD, ~~POFA,~~ POFD, POFA are all between 0 to 1, and their optimal ~~value~~values are 1, ~~0~~0 and 0, respectively.

5 Results and discussions

5.1 Landslide susceptibility analysis

After several ~~times of calibration~~calibrations~~model calibration~~, the resultant model was obtained. The coefficients for each factor of LR ~~were~~are given in ~~table~~Table 2, and the landslide susceptibility of each slope unit was~~was~~~~ere~~ also calculated.~~defined~~~~calculated.~~ ~~In order to~~To evaluate the quality of a predicted model, the success rate curve (SRC) and prediction rate curve (PRC) (Chung and Fabbri, 1999) were mapped, and then the area under the curve (AUC) was used to describe the model's ability ~~of distinguishing~~to distinguish landslide and non-landslide (Yesilnacar and Topal, 2005). A higher AUC value indicated a better model for the prediction of landslides. If the AUC value was 0.5, it meant that the model ~~didn't~~did not predict the occurrence of the landslide better than a random approach. If the AUC value was ~~close to~~ 1.0, the capability of the model ~~that interpreting~~for predicting a landslide was perfect~~perfect~~~~nice~~.

In our study, the~~T~~the ~~AUC was~~AUCs were 0.745 and 0.691 in training and ~~validating~~validation ~~model~~ respectively, indicating that our LR model could identify 60% of the landslides in the top 25% and 30% of the highest susceptibility areas during training and validation (Fig. 6~~75~~). These results showed that the LR model was acceptable~~acceptable~~~~stable and nice~~ in both the training ~~as well as~~and the validation. For a statistical landslide susceptibility analysis, it is essential to use as many samples as possible. However, we used slope units instead of grid units in this study for ~~the purpose of the~~ application ~~on~~to disaster prevention. This ~~leaded~~led to the reduction of samples, since one slope unit might equal ~~to~~ hundreds of grids. Therefore, our AUC might not be ~~so~~considered high ~~compared~~in comparison to a grid-based landslide susceptibility model.~~It also represented that LR was useful in landslide susceptibility analysis.~~

~~Having enough samples were the foundation of statistic method. Due to our using slope units, the amount of samples were less than a traditional grid method, so it was not easy to establish a well-performed model compared with a grid-based landslide susceptibility model. For the sake of increasing more samples for analysis, we integrated the data from several events, but it might also brought some noises for the training. Therefore, filtering unfavorable or unsuitable samples were required.~~

On the other hand, ~~in order~~ to ~~not~~avoid ~~for avoiding~~ over~~-~~-training, it was necessary to validate the capability of the model. One common method ~~was dividing~~is to divide the study area into sub-regions such as left and right, one for training and the other for validation (Chung and Fabbri, 2008). But ~~it~~this method might ~~lose~~cause the loss of ~~a~~ ~~lost~~ a training pattern in a small or particular geological region if the study area ~~was~~is extensive. To overcome this problem, we ~~suggested using~~ used multi-event data ~~in~~from the same area for training and testing. The data used in this study were therefore randomly divided into two ~~parts randomly~~ portions, and several sets of data were tested. This approach would also solve the problems mentioned above.

5.2 I_3–R_{24} rainfall threshold

We gathered ~~totally~~a total of 941 landslide cases in this study and ~~picked out~~~~select~~used 240 cases located in southern Taiwan, ~~including~~consisting of 110 high-susceptibility cases, 84 moderate-susceptibility cases, and 46 low-susceptibility cases, to establish a susceptibility-based regional landslide early warning model. The ellipse-shaped I_3–R_{24} rainfall thresholds for 3 different landslide susceptibility slopes ~~were shown~~are presented in ~~Table 6 and~~ Fig. ~~8~~7~~6~~. For ~~the purpose of~~ practical use, the original threshold values of I_3 and R_{24} (as shown in the parentheses in Fig. 8) were separately rounded to the nearest~~to~~ ~~by~~ 5 mm/h~~hr~~ and the nearest 50 mm ~~separately, as shown in the parentheses in~~ ~~.Table 6~~Fig. 7. It ~~could be~~was found ~~that the threshold values gradually decreased as the susceptibility of the slope decreased for the same threshold (e.g., T90%) and~~ that the threshold values ~~also~~ gradually in~~de~~creased as the susceptibility of slope units de~~in~~creased for the same ~~warning sign~~alert level, indicating that greater rainfall amounts would be needed when issuing alters on less susceptible slope units. These~~These~~~~is~~ results showed that establishing rainfall thresholds according to different landslide ~~susceptibility~~susceptibilities and then ~~set~~setting ~~warning signs~~alert levels by adopting ~~the concept of~~a hazard matrix ~~could~~ not only ~~provide~~provided differentiated thresholds but also ~~avoid an overestimate~~avoided the over- or ~~underestimate~~underestimation of the thresholds for slopes.

After the establishment of the landslide early warning model, we ~~leaded~~converted~~led~~ the model to an early warning system (EWS) ~~which~~ connected to the QPESUMS, ~~a near~~which provides nearly real-time radar rainfall data, for disaster prevention. ~~According to~~Based on the ~~In addition, Table 7. showed the warning signs~~alerts~~w~~~~warning signs~~ present in the system, ~~and~~ the corresponding ~~dangerous~~danger levels ~~as well as~~and suggested ~~action~~actions for residents around the warning slope are shown in Table 6. During a yellow ~~sign~~alert, residents should ~~pay attention to whether there are~~ listen for further announcements ~~or not~~ and ~~ready~~prepare for ~~an~~ evacuation if the ~~sign turns~~alert is raised to orange. ~~While~~When an orange ~~sign~~alert is issued, residents should evacuate as quickly as possible because landslides are ~~prone~~likely to occur, according to the validations shown in the next section. ~~Lastly~~Finally, when ~~the warning sign goes to~~ a red~~, forced~~ alert is issued, evacuation ~~might~~may need to ~~prevent~~be enforced to protect residents from ~~getting injured~~injury.

5.3 **Validation of landslide early warning model**

We validated our model with two kinds of data: (1) three disastrous shallow landslides ~~cases~~ in 2016 and the occurrence ~~time~~times provided by witnesses; (2) a landslide inventory of two historical typhoon events and the occurrence ~~time~~times reported by newspapers.

~~For the~~The first set of validation data ~~one, it~~ showed that orange or red~~yellow~~ alerts could have been issued in advance for all of the disastrous landslides ~~cases could be warned with orange or red sign in advance~~ before ~~landslide~~the landslides occurred, according to the rainfall snake line in the I_3–R_{24} diagram (Fig. ~~9~~99~~.~~; Table ~~8~~7~~.~~).

The Shihwen landslide occurred on a low~~-~~-susceptibility slope. From~~Forom~~ the rainfall histogram and I_3–R_{24} diagram (Fig. ~~9~~98(a)), we knew that the occurrence time was quite close to the end of the rainfall event, and that the I_3 was only 2.3 mm/h~~hr~~ while the R_{24} was 507.5 mm, indicating that accumulated rainfall might ~~be~~have been the principal cause of this case. ~~Rainfall~~The rainfall snake line showed that ~~the warning sign turned~~on September 14, the alert was raised to yellow at 10:00~~, 14 Sep~~, 14th ~~(authors mention "14th", "15th", and others; if they are days, I suggest using the format dd-mm, which results more clear.)~~ and ~~soon turned~~then to orange at 11:00~~, 14 Sep~~ during the downpour~~; then it was a little bit let up~~. Then the precipitation ~~rate~~ fell for several hours, and the ~~warning sign turned back~~alert was lowered to yellow. However, when it rained again, the ~~warning sign also turned~~alert was raised back to orange ~~again~~ at 18:00~~, 14 Sep as well as~~ and at 23:00~~, 14 Sep~~ and ~~finally~~ the landslide occurred at 05:00~~,~~ on September 15~~ Sep~~. ~~15th.~~

The Zhongmin landslide occurred on a high~~-~~-susceptibility slope. From~~Forom~~ the rainfall histogram and I_3–R_{24} diagram (Fig. ~~9~~89(b)), it ~~could be~~was found that the occurrence time was also quite close to the end of the rainfall event and that the I_3 was 8.3 mm/h~~hr~~ while the R_{24} was 479 mm. The high rainfall intensity (74 mm/h~~hr~~ at 04:00~~,~~ on September 28th~~, 28-Sep~~September~~) as well as~~) and accumulated rainfall might both ~~result in~~ have contributed to this ~~landslide. Rainfall~~ case~~event~~. The rainfall snake line showed that on September 28, the ~~warning sign turned to~~ yellow ~~and then quickly turned~~alert was raised to orange and red at 04:00~~, 28 Sep~~28th during the high intensity rainfall mentioned above. After that, although ~~it let up~~the rainfall soon fell off, the landslide ~~finally~~ occurred 6 hours later, at 10:00~~,~~ on September 28~~, Sep,~~28th during ~~the~~an orange ~~sign~~alert.

The Houcuo landslide also occurred on a low~~-~~-susceptibility slope. From~~Forom~~ the rainfall histogram and I_3–R_{24} diagram (Fig. ~~9~~98(c)), we ~~knew~~found that the occurrence time was ~~almost near~~close to ~~the point of~~ time that the highest rainfall intensity showed in the rainfall event, and the I_3 was 24.3 mm/h~~hr~~ while the R_{24} was 291.3 mm, indicating that high rainfall intensity might ~~be~~have been responsible for this case. Due to this intensity, the rainfall snake line showed that the ~~warning sign turned~~alert was raised from green to yellow and then to orange ~~in~~within just one hour ~~during~~, from 03:00 ~~∼~~to 04:00, on September 28~~ Sep~~, and28th, the landslide ~~also~~ occurred at around 03:30~~, 28 Sep~~28th.

For the second set of validation data~~one~~, we applied ~~Kriging~~the kriging method to interpolate ~~spe~~spatial~~eial~~ rainfall data and analyzed the ~~warning sign of~~alerts for each slope unit hour~~-~~-by~~-~~-hour. ~~It~~The results showed that the ~~hitting ratio~~hit rates~~ios~~ in the two historical typhoon events were all ~~higher enough~~sufficiently high, according to the accumulative warning numbers relative to the numbers of landslide slopes (Fig. ~~10.~~;10;9~~.~~; Table ~~8.~~).).98~~.~~).

During Typhoon Mindulle in 2004, ~~there were~~ landslides occurred in 10,911 slope units ~~that occurred once landslide~~, including 5,129 high~~-~~-susceptibility slopes, 2,750 moderate~~-~~-susceptibility slopes and 3,032 low~~-~~-susceptibility slopes. According to ~~the~~newspaper reports ~~in newspapers~~, several landslides occurred at 10:00 and between 15:00 ~~∼~~and 16:00~~,~~ on July2nd~~, July 2~~ ~~Jul~~, 2004; however, most of the landslides occurred ~~during~~between 06:00 ~~∼~~and 13:00~~,~~ the next day, 3rd~~, July~~y 3 ~~Jul~~, 2004 (blue dashed box in Fig. 10~~10~~9(a)). From the ~~warning~~alert history (Fig. ~~10~~109(a)), it ~~could be~~was found that the peak number of orange and red ~~signs fitted~~alerts matched the reported occurrence ~~time quite well. Besides, there were~~ times quite well. In addition, orange alerts, indicating the need for evacuation, had been issued for 8,283 slope units ~~hadever been~~ ~~warned as orange sign~~ during the whole event, ~~which is the sign for evacuation, during the whole event,~~ accounting for 75.9% of the slope units ~~that~~ where landslides occurred~~once~~ ~~landslide~~ in this event.

Typhoon Haitang in 2005 was another event of concern. ~~There were~~ Landslides occurred in 10,804 slope units ~~once landslide~~, including 2,592 high~~-~~-susceptibility slopes, 2,355 moderate~~-~~-susceptibility slopes and 5,857 low~~-~~-susceptibility slopes. According to ~~the~~newspaper reports ~~in newspapers~~, landslides occurred ~~from~~between 05:00~~,~~ on July 19 ~~Jul19th to~~ and 06:00~~,~~ on July 20 ~~Jul20th, July~~, 2005 (blue dashed box in Fig. ~~10~~109(b)). From the ~~warning~~alert history (Fig. ~~10~~109(b)), it ~~could be~~was found that ~~landslide~~landslides occurred ~~right~~immediately after the number of orange and red ~~signs~~alerts increased sharply, and the peak number of orange and red ~~signs~~alerts also ~~fitted~~matched the reported occurrence ~~time~~times quite well. On the other hand, ~~there were~~orange alerts had been issued for 10,245 slope units ~~hadever been warned as orange sign~~ during the whole event, accounting for 94.8% of the slope units ~~that~~where landslides occurred ~~landslide~~ in this event.~~once landslide.~~ These results revealed that our model could provide valuable information for evacuation and disaster prevention.

~~Besides~~In addition, the second set of validation data ~~were~~was also used to validate the warnings issued for villages during two typhoon events by adopting the contingency matrix and skill scores. According to the event-based landslide inventories, if ~~there~~any landslides were ~~any landslide~~ located in a village, the village ~~would be~~was classified as "Yes" ~~of~~for observed events. ~~On the other hand, if there were any~~If orange or red warning ~~sign~~alerts were issued for slope units in a village, the village ~~would be~~was classified as "Yes" ~~of~~for forecasted events. Based on these rules, the numbers of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) ~~can be~~were counted and the skill scores ~~can also be~~were calculated (Table 9). The probabilities of detection (~~POD~~PODs) of the two typhoon events were 0.961 and 0.874 respectively, indicating that most of the villages ~~that occurred~~ where landslides occurred could ~~be~~have been warned in advance. The probabilities of false detection (~~POFD~~POFDs) of the two typhoon events were 0.280 and 0.667 respectively, suggesting that the model performed well ~~in~~for Typhoon Mindulle but might not be so ~~perfect inwell~~ideal for Typhoon Haitang. Lastly, the probabilities of false alarm (~~POFA~~POFAs) of the two typhoon events were 0.120 and 0.110 respectively, which meant that our model would not issue ~~too many~~an excessive number of false alarms and was feasible for disaster prevention.

6 Conclusions

~~In order to verify if the difference in susceptibility might lead to a difference in warning threshold, we divided slope units into three susceptibility levels (high, moderate, low) based on the results of Logistic Regression (LR) and established their rainfall thresholds separately in this study. I_3–R_{24} rainfall index, a combination of short-term as well as long-term rainfall index, were used for the establishment of rainfall thresholds. After that, three warning signs including yellow (advisory), orange (watch) and red (warning) were set by adopting the concept of hazard matrix. It was found that the warning thresholds were different for each susceptibility level and gradually decreased as the susceptibility of slope increased. Validations from three disastrous shallow landslides in 2016 showed that they can be warned in advance before landslide occurred and validations from two serious historical typhoon events also showed that the hitting ratio of our early waring model were 75.9% and 94.8% respectively. It could be concluded that classifying landslide susceptibility and establishing rainfall thresholds separately might be able to provide differentiated warning thresholds for different susceptibility levels.~~This study ~~tried~~attempted to establish regional rainfall thresholds for shallow landslides according to their landslide susceptibility ~~level~~levels and set ~~warning signs~~alerts with ~~the concept of~~a hazard matrix ~~in order~~ to provide ~~a~~ more detailed results for disaster mitigation.

Logistic Regression (LR), ~~one of the~~a statistical method, was applied in this study to analyze the landslide

~~susceptibility~~susceptibilities of slope units. The ~~area~~areas under the curve (AUC) ~~was~~were 0.745 and 0.691 in the training and ~~validating~~validation respectively. Due to our ~~using~~use of slope units instead of grid units in this study for ~~the purpose of the~~ application ~~on~~to disaster prevention, the ~~amounts~~number of our training samples ~~were less~~was less~~ow~~, since one slope unit might equal ~~to~~ hundreds of grids. Therefore, our AUC might not be ~~so~~considered high as compared to a grid-based landslide susceptibility model, but it was still acceptable for practical use.

This study also examined the ~~relationship~~relationships between rainfall indexes and the occurrence of landslides. From 941 landslide cases we gathered, it was found that 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) were the most dominant short-term and long-term parameters ~~that~~ responsible for rainfall-induced landslides in Taiwan. ~~because there were~~ ~~,~~ There were ~~for~~ 460 cases (about 49%) occurred within the 3 hours ~~right after~~following the highest, 2nd and 3rd rainfall ~~intensity~~intensities, while 24-hour accumulated rainfall had the lowest coefficient of variation ~~than other~~of the long-term rainfall indexes. The I_3-R_{24} rainfall index ~~were~~was therefore used ~~for the establishment of~~to establish rainfall thresholds.

We categorized the slope units into 3 landslide susceptibility ~~level~~levels (high, moderate, low) and then separately established a susceptibility-based regional rainfall threshold~~ separately~~. We also set three ~~warning signs~~alert levels, including red (extreme ~~dangerous~~danger level), orange (high ~~dangerous~~danger level), and yellow (medium ~~dangerous~~danger level~~)~~), by adopting ~~the concept of~~a hazard matrix for ~~the purpose of the~~ application ~~on~~to evacuation decisions. It was found that the threshold values gradually increased as the susceptibility of slope units decreased for the same ~~warning sign~~alert level, indicating that ~~it needed more~~greater rainfall amounts would be needed when issuing alters on ~~a~~ less susceptible slope ~~unit~~units.

Validations ~~of~~using three disastrous shallow landslides in 2016 and two landslide inventories of historical typhoon events showed that, for the landslide cases in 2016~~ could be warned with~~, orange or red ~~sign in advance~~ alerts could have been issued before ~~landslide~~the landslides occurred and the ~~hitting ratio~~hit rates~~ios~~ of the ~~warnings~~alerts issued for slope units in the two historical typhoon events were 75.9% and 94.8% respectively, ~~both of~~ which ~~were all higher enough~~are sufficiently high for a landslide early warning model. ~~Besides~~In addition, the skill scores ~~that~~ applied to the validation of ~~warnings~~alerts issued for villages during two typhoon events showed that the ~~probability~~probabilities of detection (~~POD~~PODs) were 0.961 and 0.874, the ~~probability~~probabilities of false detection (~~POFD~~POFDs) were 0.280 and 0.667, ~~while~~and the ~~probability~~probabilities of false alarm (~~POFA~~POFAs) were 0.120 and 0.110 respectively, indicating that our model ~~might~~could be ~~able to put in use~~used for landslide early ~~warning~~warnings.

It ~~could be~~can concluded that classifying landslide susceptibility and establishing rainfall thresholds separately not only ~~provide~~provides refined thresholds but also ~~avoid an overestimate~~avoids over- or ~~underestimate~~underestimation of the thresholds for slopes, especially when considering the application ~~on~~to disaster prevention.~~In order to verify if the difference in susceptibility might lead to a difference in warning threshold, we divided slope units into three susceptibility levels (high, moderate, low) based on the results of Logistic Regression (LR) and established their rainfall thresholds separately in this study. I_3–R_{24} rainfall index, a combination of short-term as well as long-term rainfall index, were used for the establishment of rainfall thresholds. After that, three warning signs including yellow (advisory), orange (watch) and red (warning) were set by adopting the concept of hazard matrix. It was found that the warning thresholds were different for each susceptibility level and gradually decreased as the susceptibility of slope increased. Validations from three disastrous shallow landslides in 2016 showed that they can be warned in advance before landslide occurred and validations from two serious historical typhoon events also showed that the hitting ratio of our early waring model were 75.9% and 94.8% respectively. It could be concluded that classifying landslide susceptibility and establishing rainfall thresholds separately might be able to provide differentiated warning thresholds for different susceptibility levels.~~

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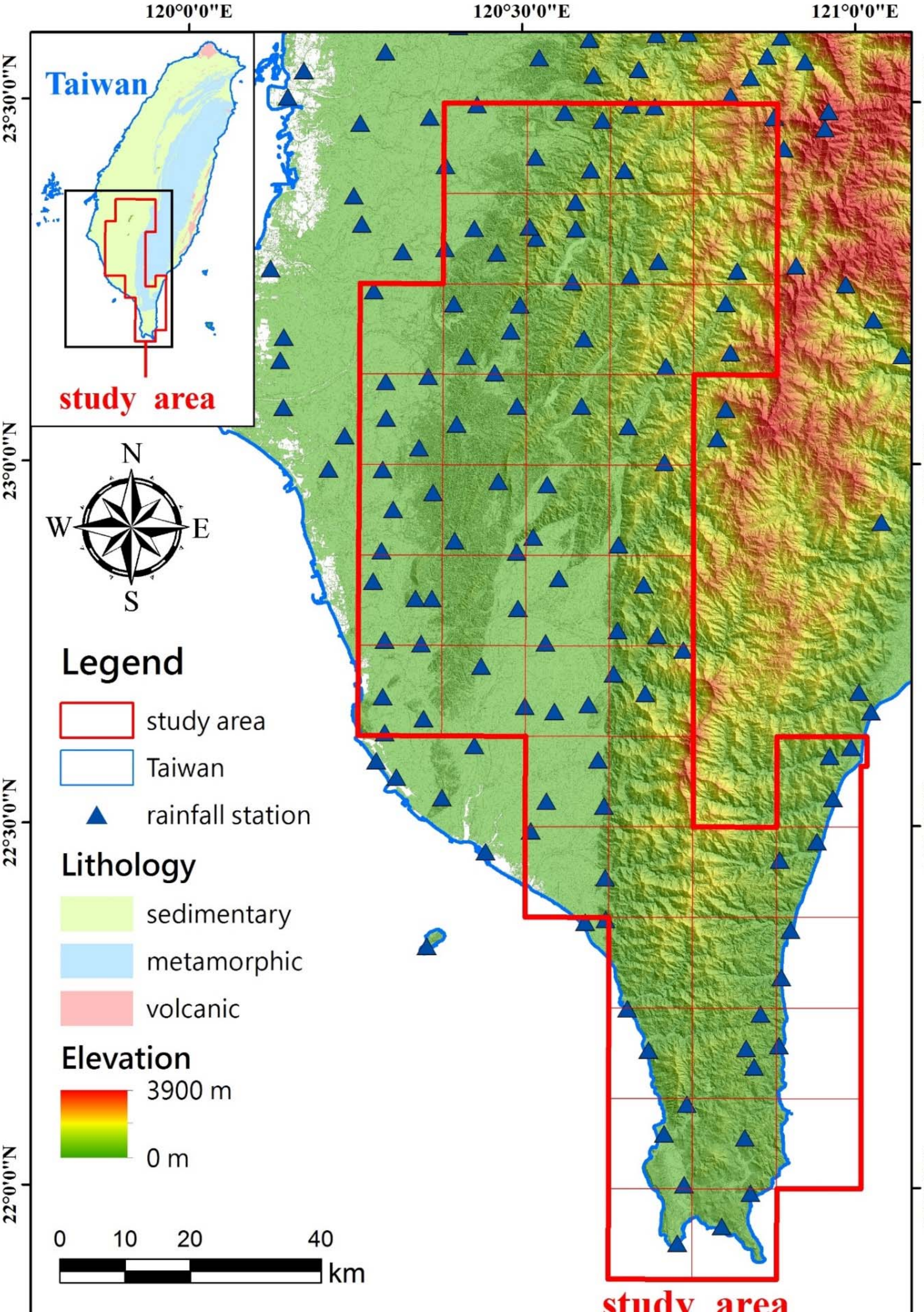
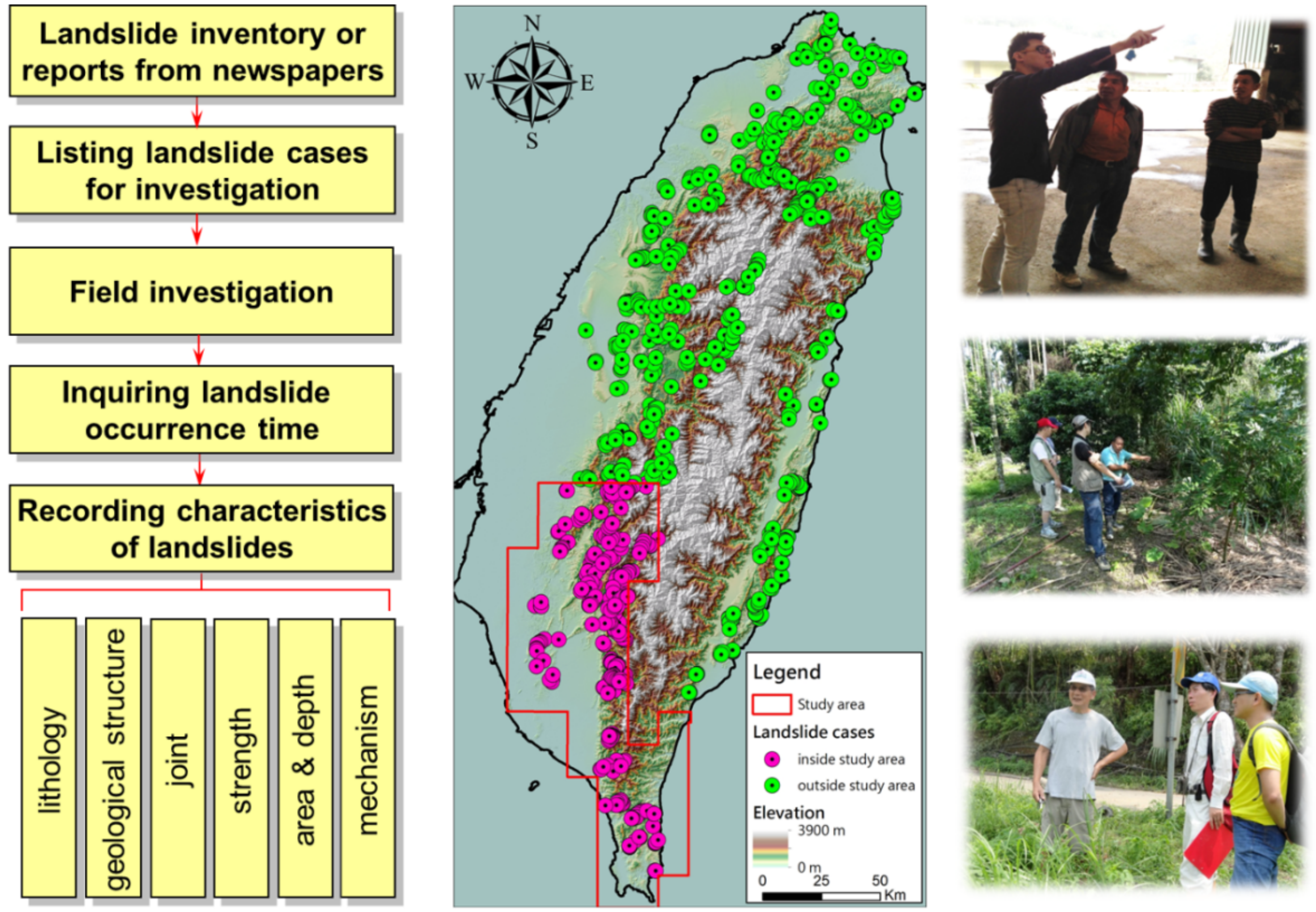


Figure 1: Geomorphological and geological settings of the study area. The elevation ranges from 3,243 meters in the eastern mountain area to ~~the~~ sea level in the western ~~plain~~plains area. Lithological units are mainly metamorphic rocks in the Central Range and sedimentary rocks in the Western Foothills. Rainfall data of 423 stations in Taiwan (96 of which are located in the study area) were collected for the interpolation and analysis of the triggering rainfall of landslides.


Landslide inventory or reports from newspapers
Listing landslide cases for investigation
Field investigation
Inquiring landslide occurrence time
Recording characteristics of landslides
lithology
geological structure
joint
strength
area & depth
mechanism
N
W
E
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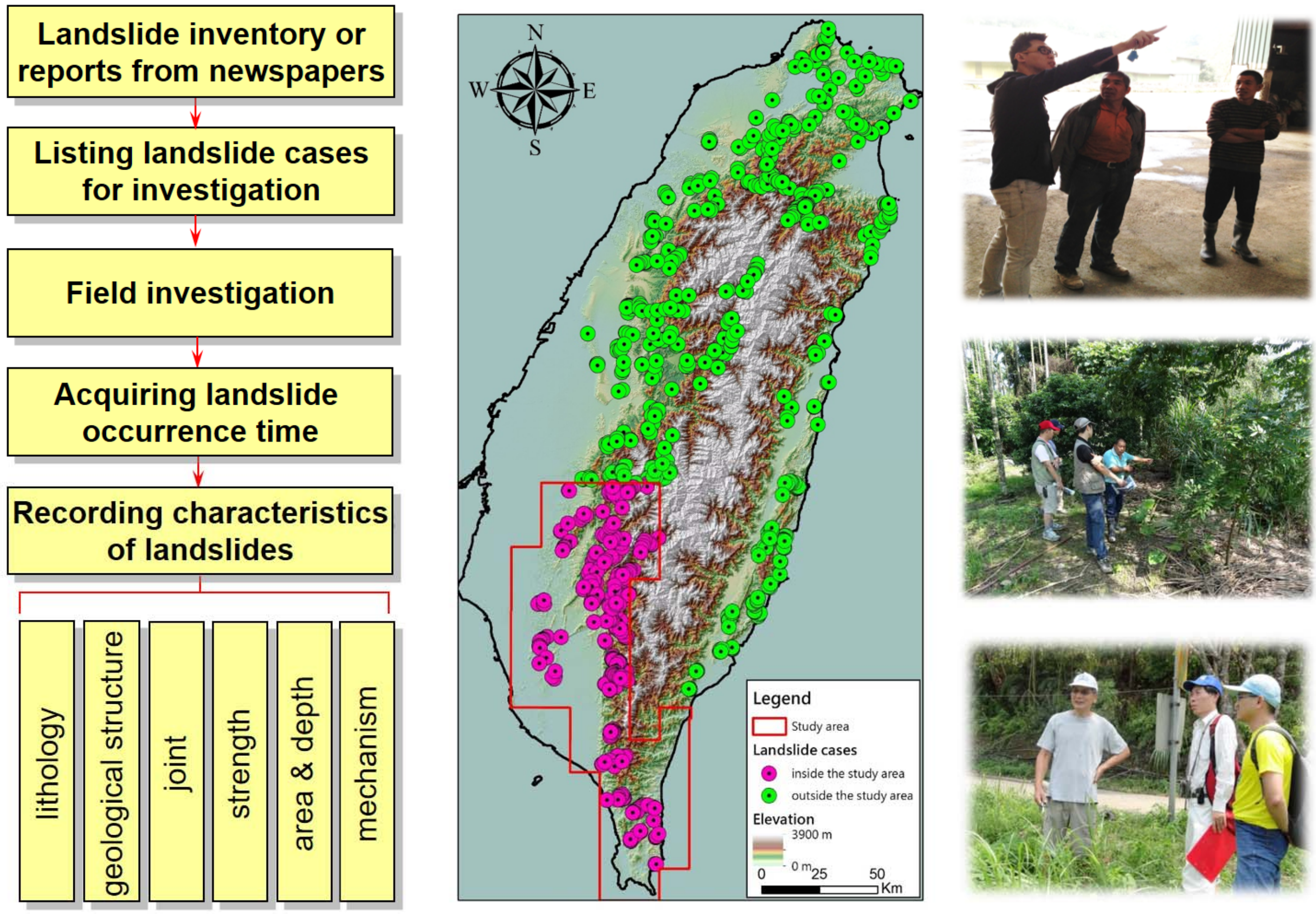
Study area
Landslide cases
inside study area
outside study area
Elevation
3900 m
0 m
0
25
50
Km


Landslide inventory or reports from newspapers
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lithology
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Study area
Landslide cases
inside the study area
outside the study area
Elevation
3900 m
0 m
0
25
50
Km

Figure 2: Flowchart of landslide occurrence time gathering during field investigation (left), ~~location~~locations of landslide cases with the occurrence ~~time~~times used in this study (middle~~)~~), and the pictures of ~~inquiring~~interviewing residents (right). ~~Landslide~~To improve the quality of this key information, landslide occurrence ~~time was inquired~~times were obtained from local residents ~~lived around~~, especially those whose ~~family was~~relatives were injured or ~~house was~~houses were damaged/~~ or~~ destroyed by the ~~landslide, in order to improve the quality of this key information~~landslides.

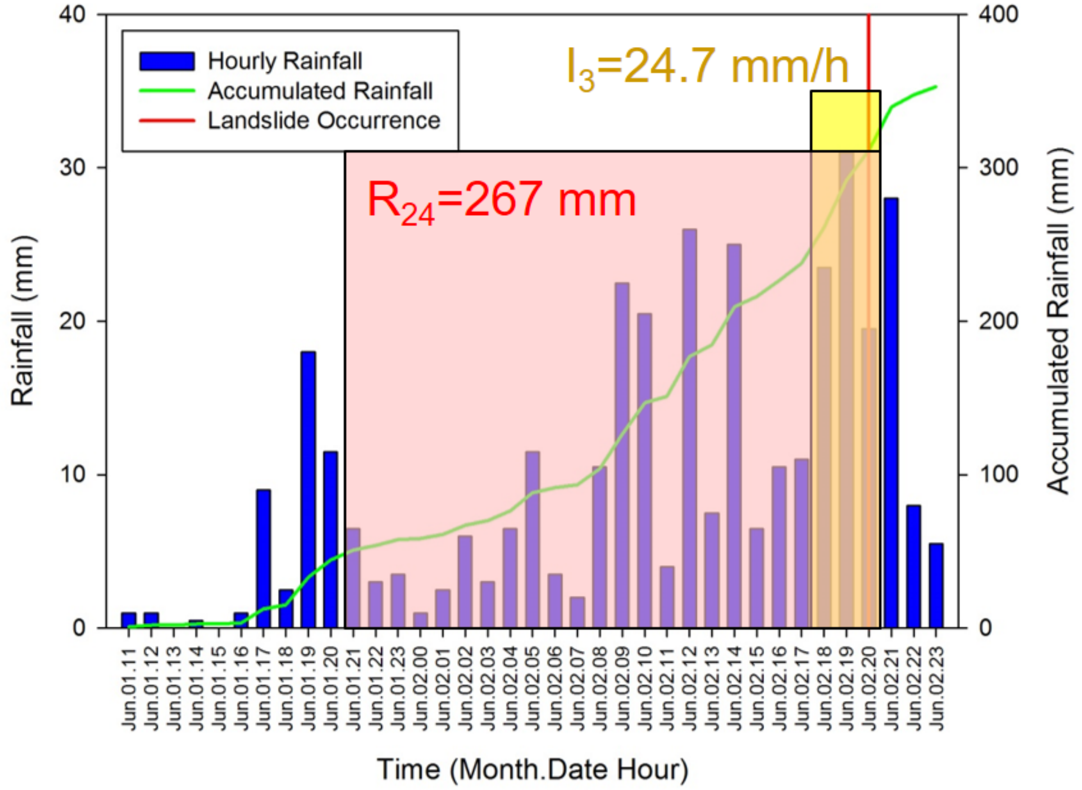
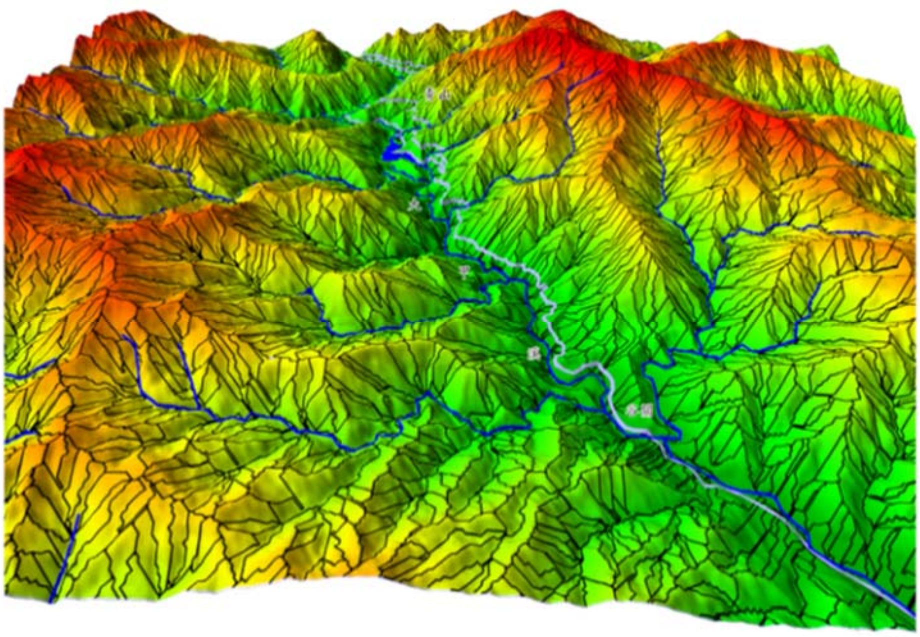
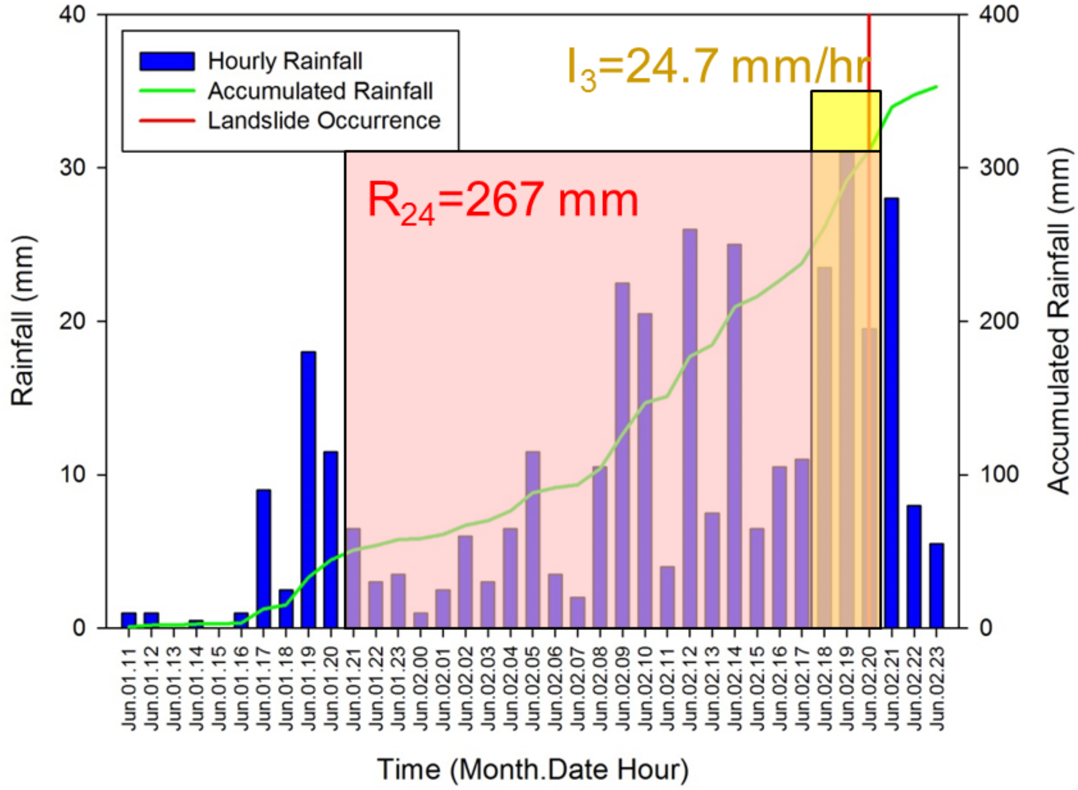


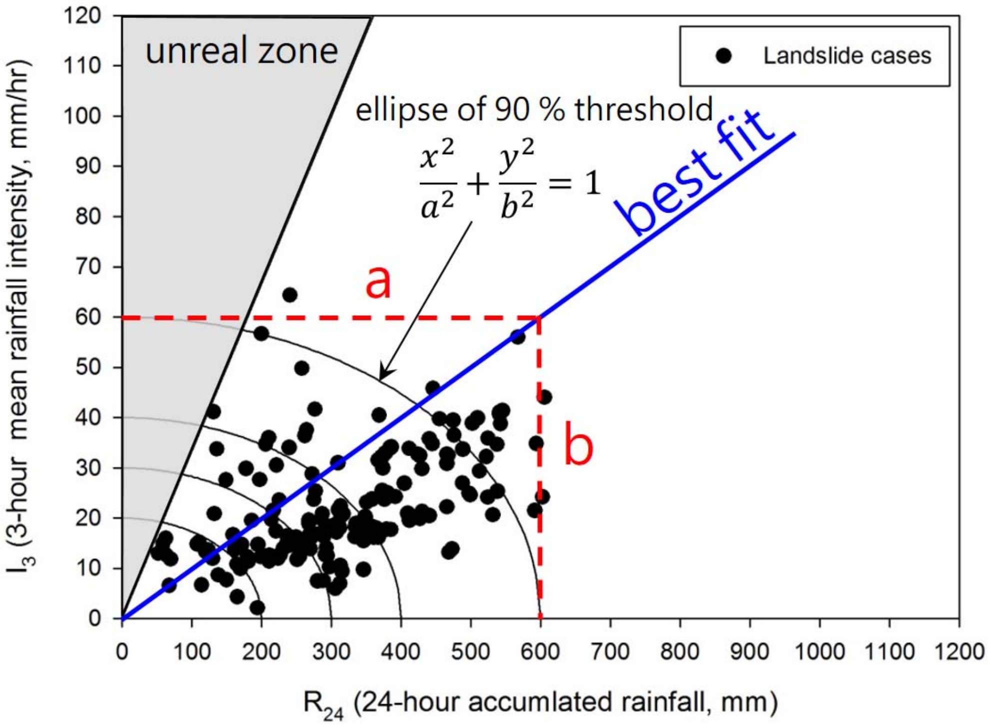
Figure 3:



~~**Figure 3: A display of Slope unit.**~~



~~Figure 4~~3~~:~~ 3-hour mean rainfall intensity (I_3) and 24-hour accumulated rainfall (R_{24}) were used as short-term and long-term rainfall ~~index~~indexes for the establishment of rainfall thresholds.



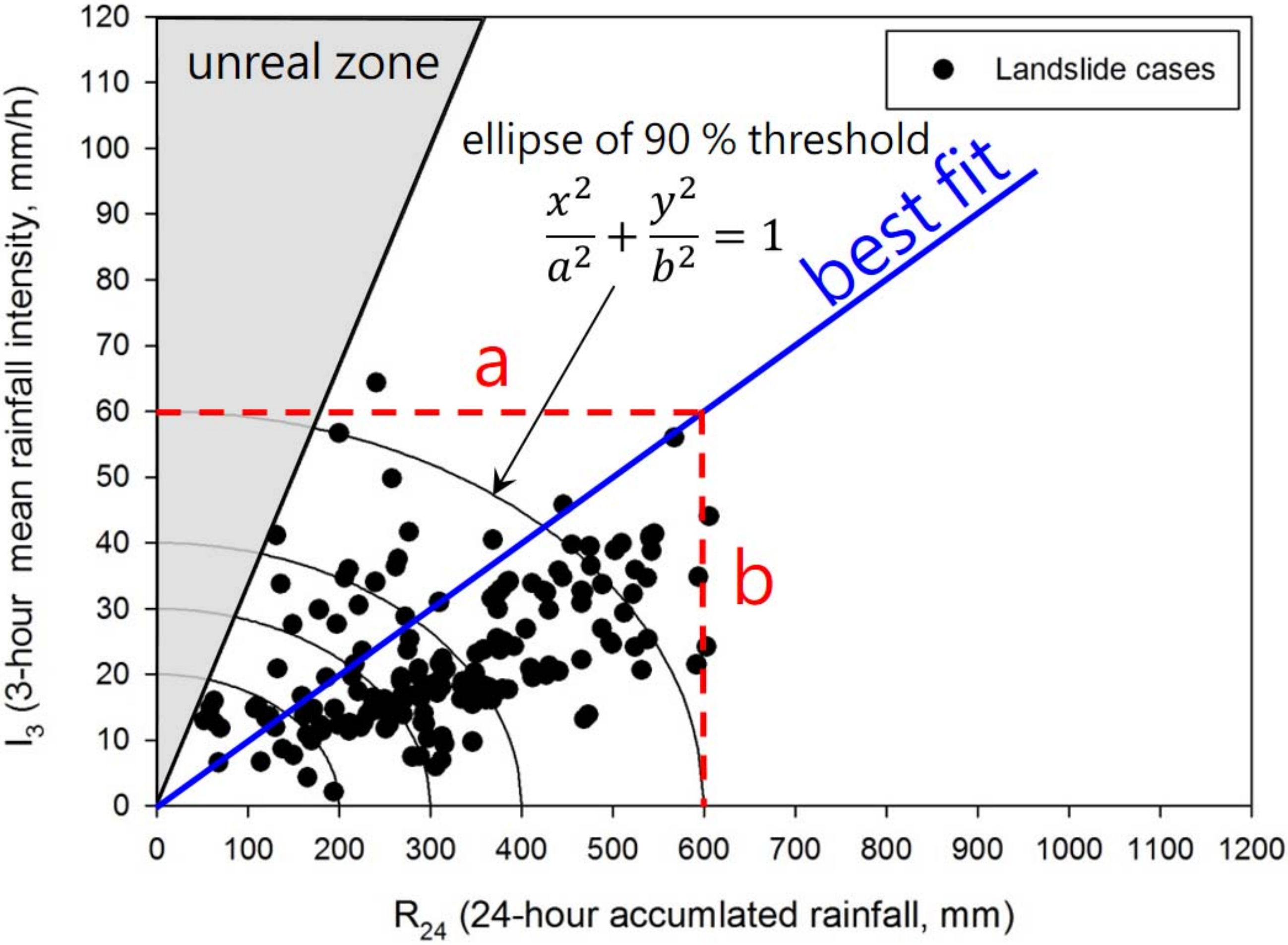


Figure 4~~5~~4: Establishment of I_3–R_{24} rainfall thresholds for shallow landslides. The best fit line was derived ~~-~~by least square method, and the ratio of a and b ~~were~~was used as the ratio of the semi-major axis and semi-minor axis in the ellipse threshold line.

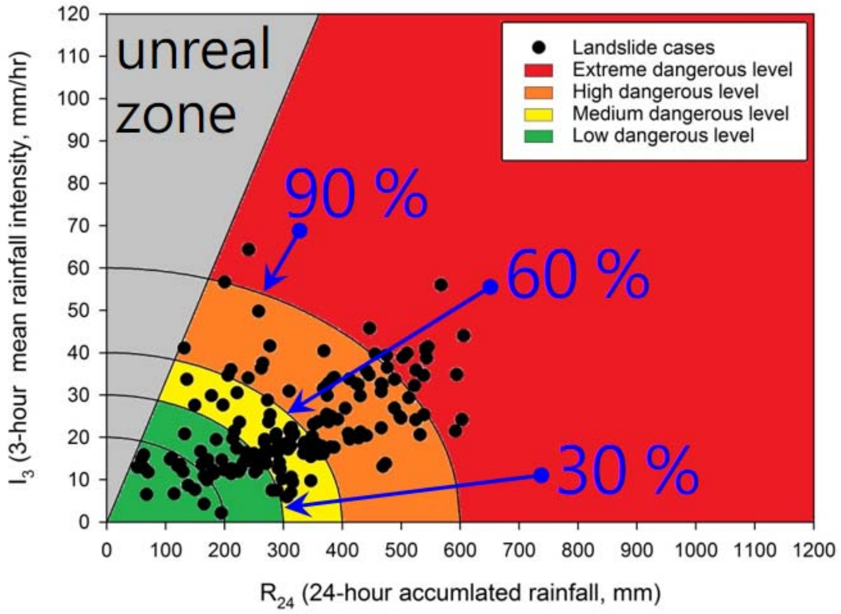
		Rainfall threshold (T)			
		$T_{90\%}$	$T_{60\%}$	$T_{30\%}$	$T_{15\%}$
Landslide susceptibility	High susceptibility	Extreme dangerous level	Extreme dangerous level	High dangerous level	Medium dangerous level
	Moderate susceptibility	Extreme dangerous level	High dangerous level	Medium dangerous level	Low dangerous level
	Low susceptibility	High dangerous level	Medium dangerous level	Low dangerous level	Low dangerous level

~~**Figure 5: Landslide early warning model and the warning signalerts considering both landslide susceptibility and rainfall thresholds.**~~

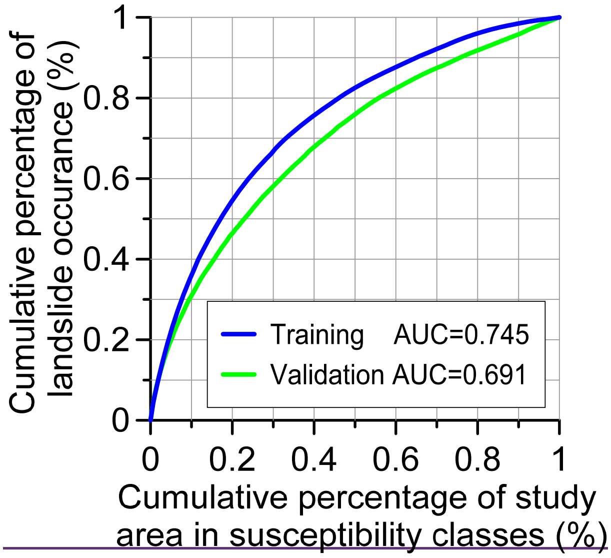
		Rainfall threshold (T)			
		$T_{90\%}$	$T_{60\%}$	$T_{30\%}$	$T_{15\%}$
Landslide susceptibility	High susceptibility	Extreme dangerous level	Extreme dangerous level	High dangerous level	Medium dangerous level
	Moderate susceptibility	Extreme dangerous level	High dangerous level	Medium dangerous level	Low dangerous level
	Low susceptibility	High dangerous level	Medium dangerous level	Low dangerous level	Low dangerous level

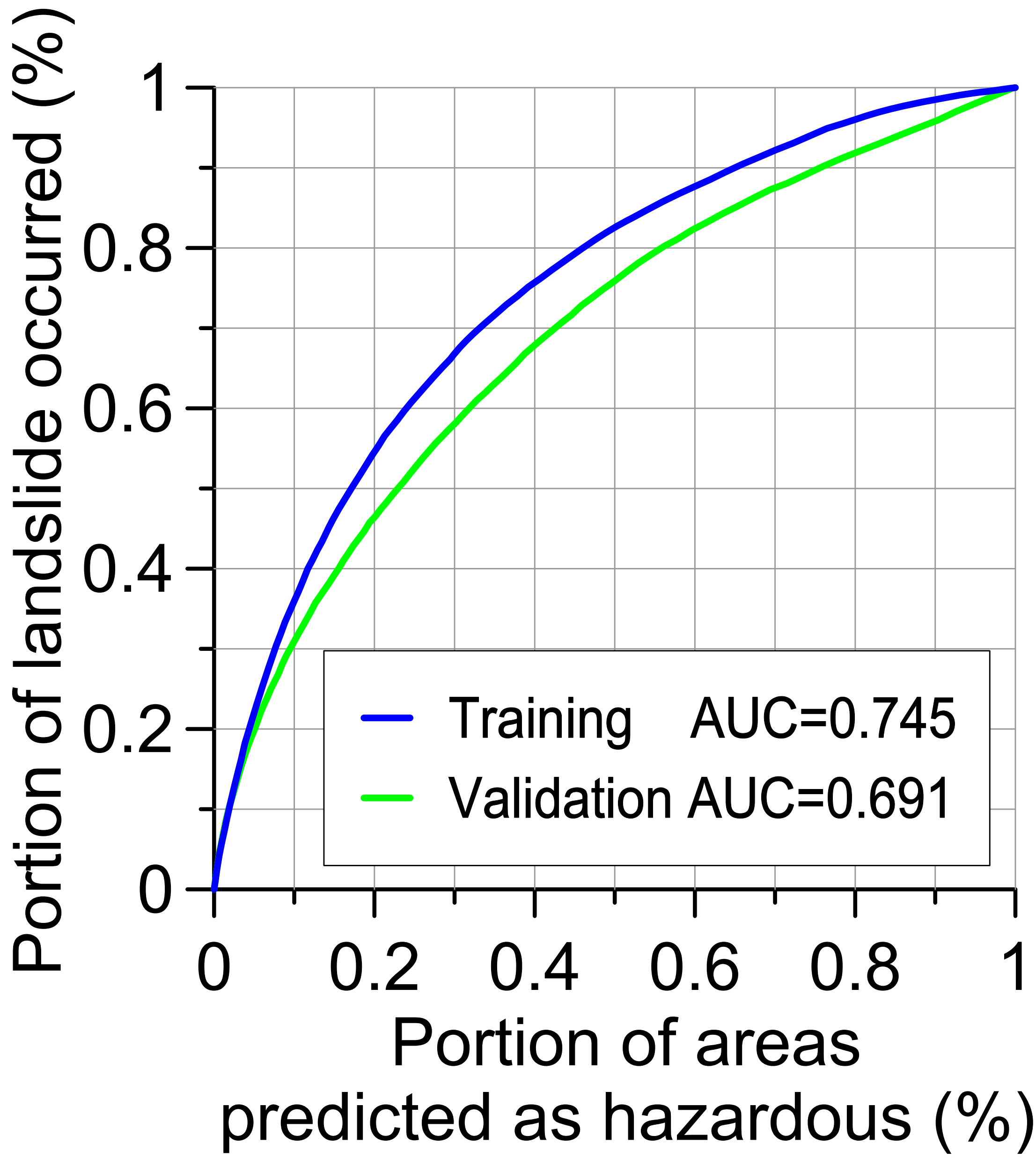
		Rainfall threshold (T)			
		$T_{90\%}$	$T_{60\%}$	$T_{30\%}$	$T_{15\%}$
Landslide susceptibility	High susceptibility	Extreme danger level	Extreme danger level	High danger level	Medium danger level
	Moderate susceptibility	Extreme danger level	High danger level	Medium danger level	Low danger level
	Low susceptibility	High danger level	Medium danger level	Low danger level	Low danger level

Figure 5: Landslide early warning model and ~~the warning sign~~alert considering both landslide susceptibility and rainfall thresholds.



~~**Figure 6: I_3–R_{24} landslide early warning model and the warning sign (moderate susceptibility as example)**~~

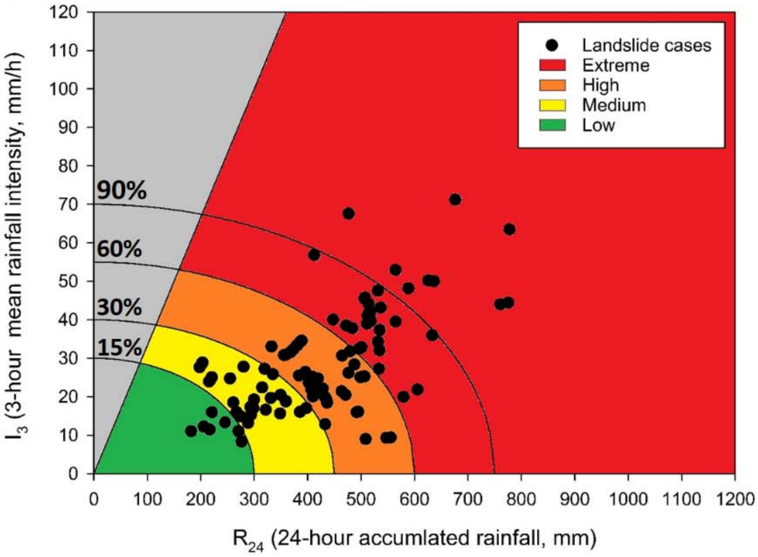




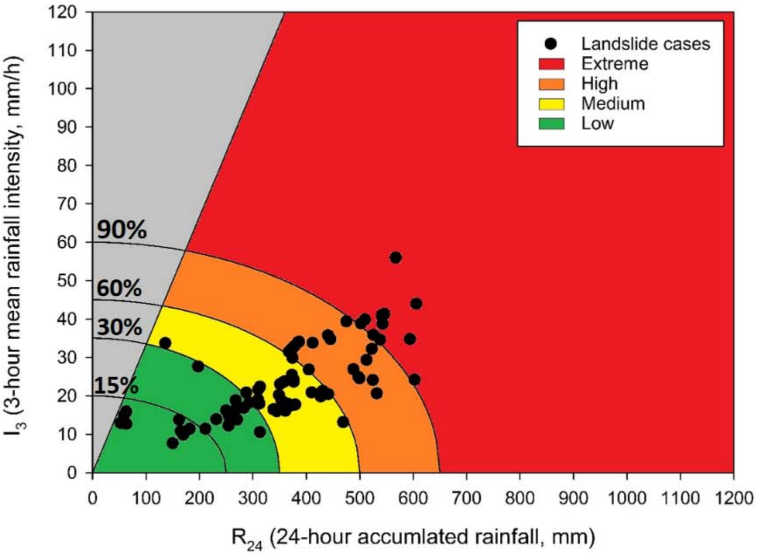
~~Figure~~

5 Figure 6: ~~5~~7: Area under the curve (AUC) ~~Result~~ of training and validation of landslide susceptibility analysis.

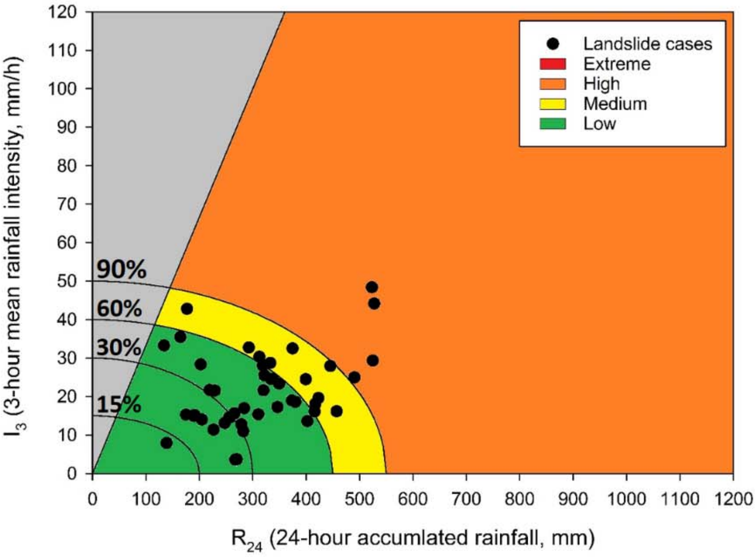
(a) High susceptibility



(b) Moderate susceptibility



(c) Low susceptibility



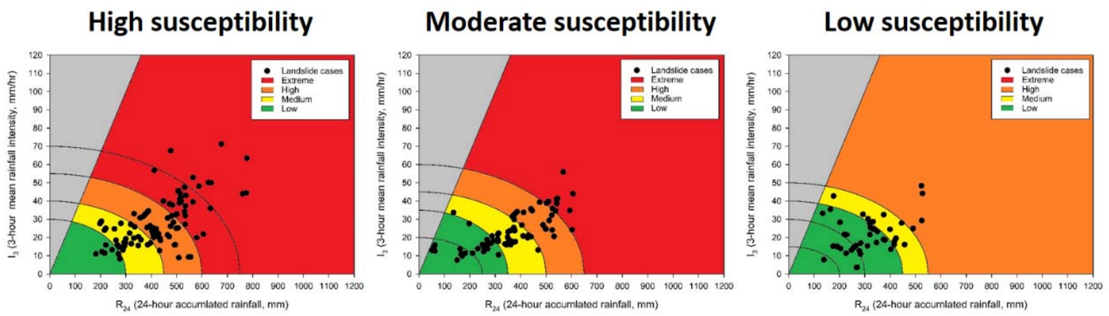
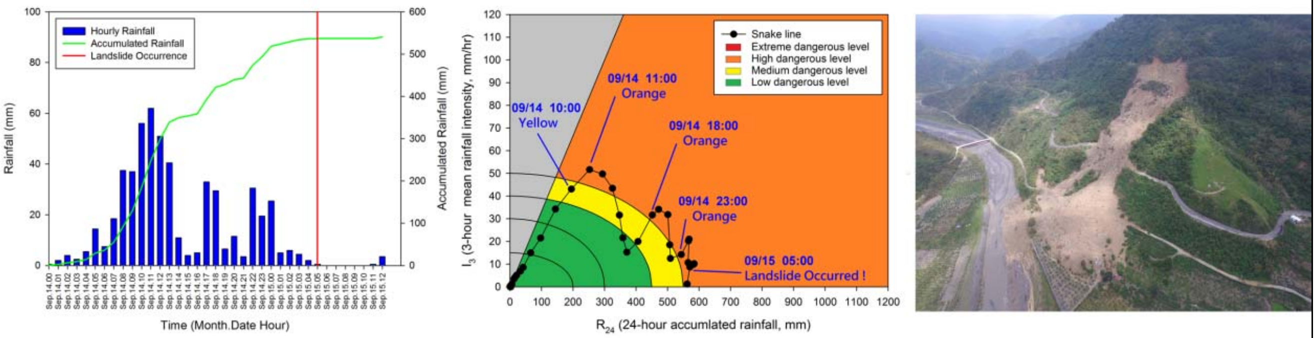


Figure ~~8~~7~~6~~: I_3–R_{24} rainfall thresholds and alert of (a) high-~~-~~susceptibility slope units (b) moderate susceptibility slope units and (c) low-~~-~~susceptibility slope units for southern Taiwan~~.~~.

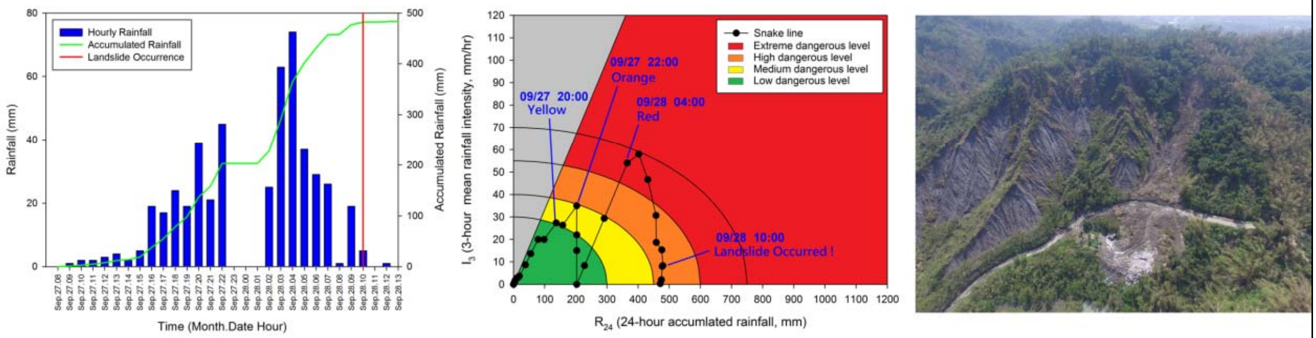
		Rainfall threshold (T)							
		$T_{90\%}$		$T_{60\%}$		$T_{30\%}$		$T_{15\%}$	
		I_3	R_{24}	I_3	R_{24}	I_3	R_{24}	I_3	R_{24}
Landslide susceptibility	High susceptibility	70 (68)	750 (745)	55 (56)	600 (610)	40 (40)	450 (438)	30 (27)	300 (291)
	Moderate susceptibility	60 (61)	650 (657)	45 (46)	500 (498)	35 (34)	350 (368)	20 (22)	250 (236)
	Low susceptibility	50 (50)	550 (539)	40 (40)	450 (430)	30 (29)	300 (316)	15 (15)	200 (167)

Figure 8~~7~~: Rainfall thresholds for southern Taiwan. The values were calculated as 90%, 60%, 30%, and 15% of the original threshold respectively.~~The original values were calculated from 30%, 60% and 90% thresholds respectively.~~ After that, I_3 was rounded to the nearest~~by~~ 5 mm/h and R_{24} was rounded ~~by~~to the nearest 50 mm for operational purpose (e.g., evacuation). The original values are shown in parentheses.

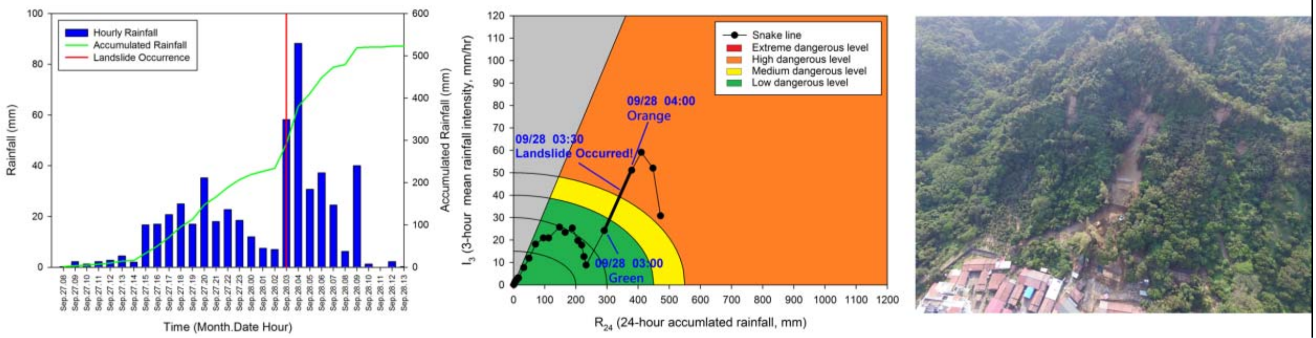
(a) Shihwen landslide



(b) Zhongmin landslide



(c) Houcuo landslide



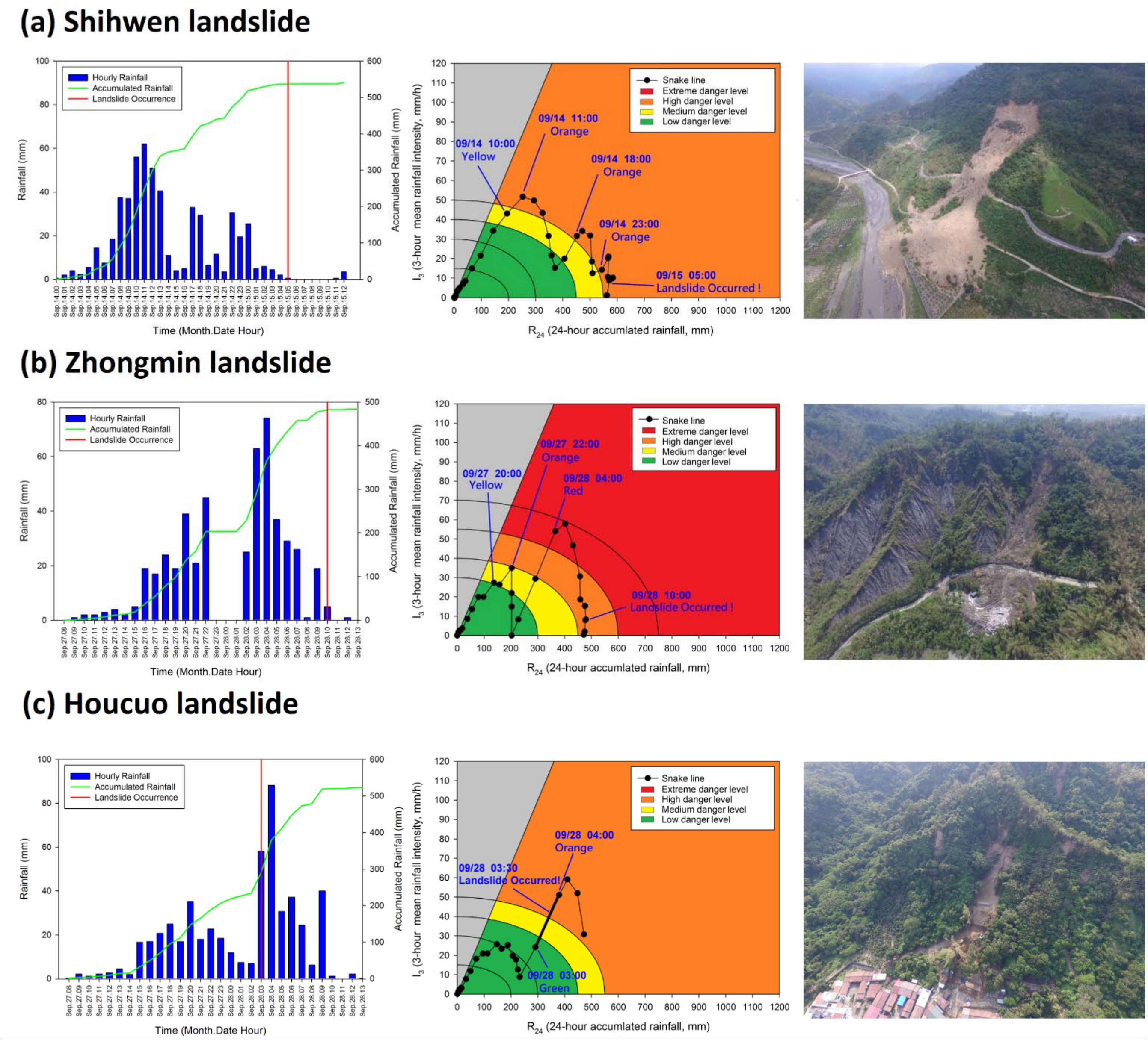
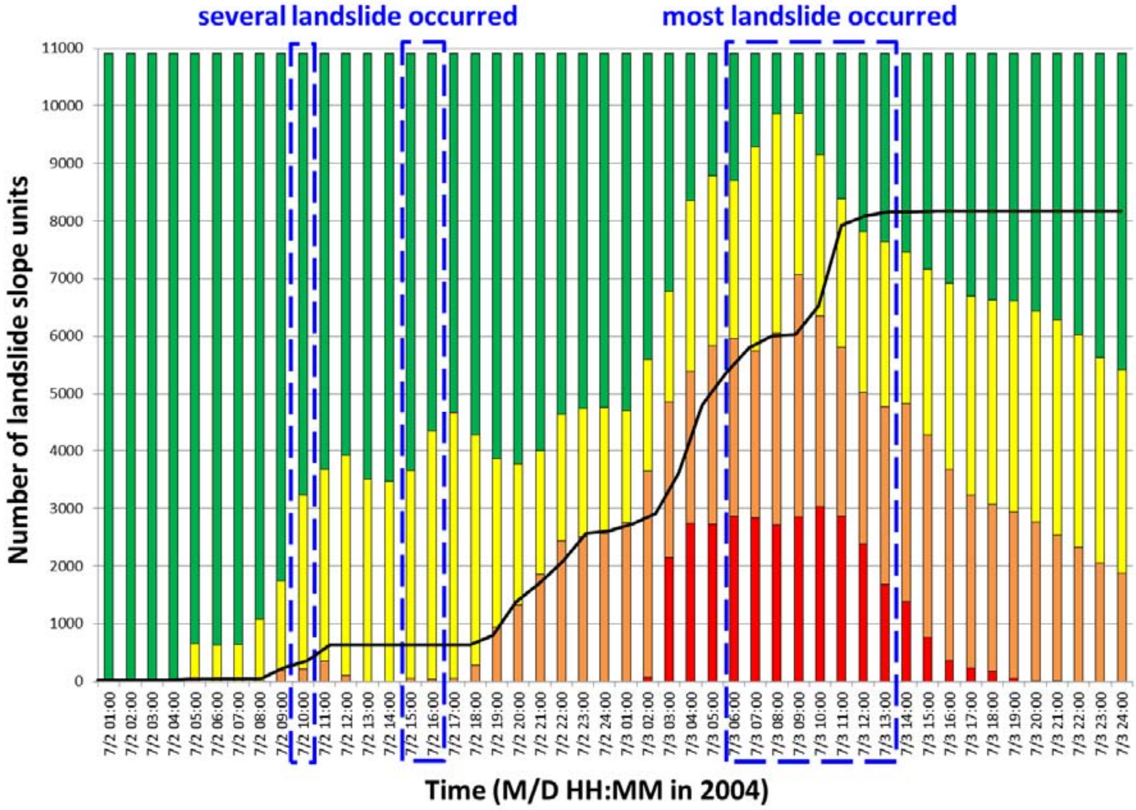
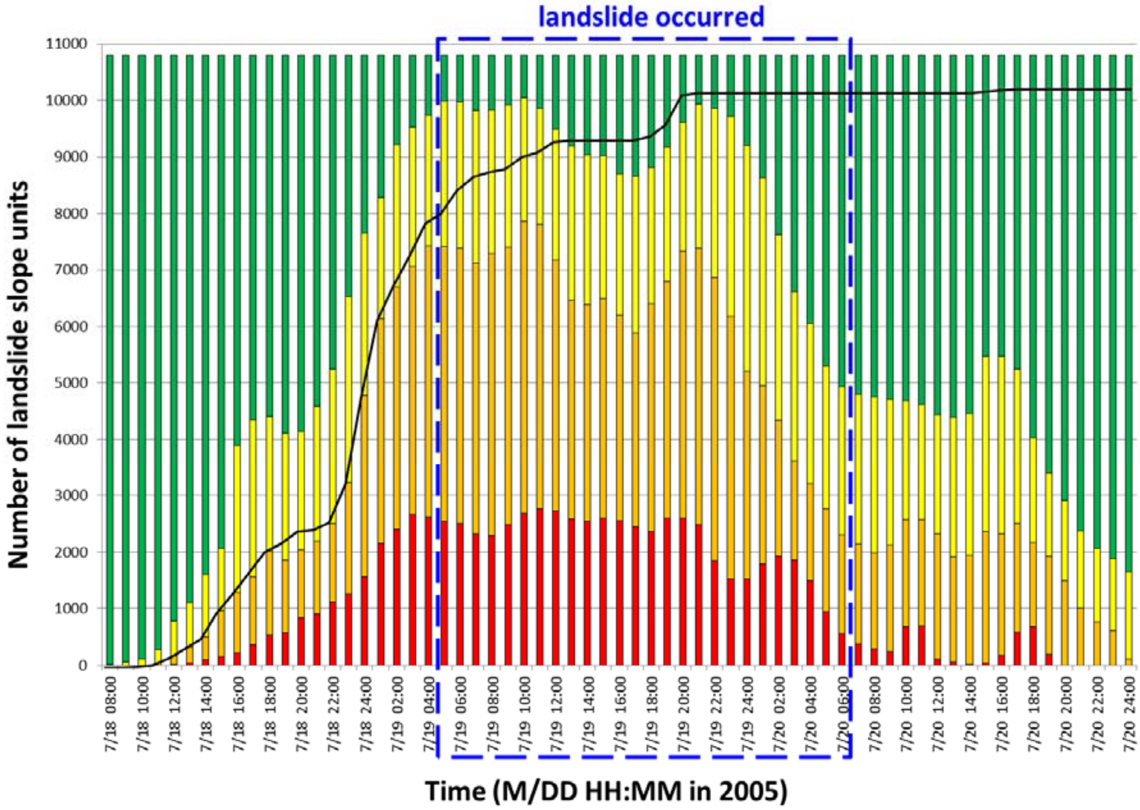


Figure ~~9~~98: Disastrous landslide cases in 2016, ~~and~~ their rainfall ~~histogram as well as~~ histograms, and their snake ~~line~~lines in the I_3–R_{24} diagram. ~~it~~The results showed that ~~these disastrous landslide cases could be warned with~~ orange or red ~~sign~~ alerts could have been issued in advance ~~before landslide occurred~~for these disastrous landslides.

(a) Typhoon Mindulle

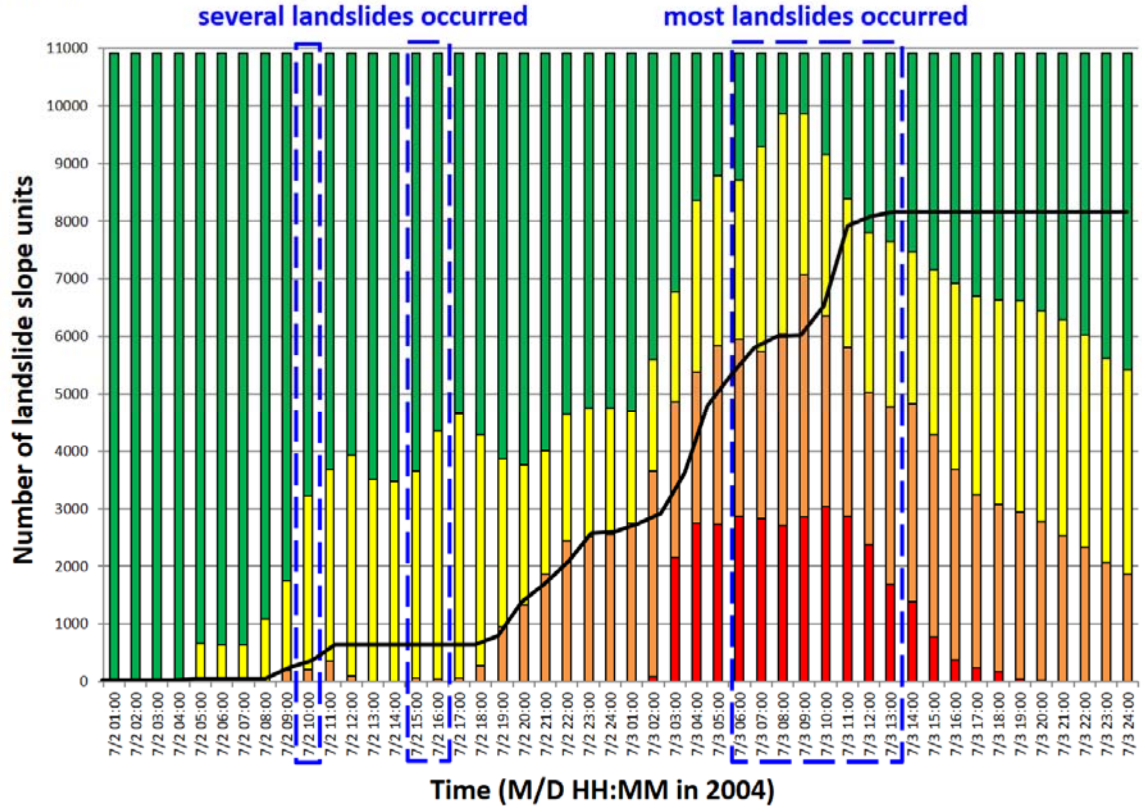


(b) Typhoon Haitang



Red Orange Yellow Green — Accumulated number of slope units that ever be warned as orange sign

(a) Typhoon Mindulle



(b) Typhoon Haitang

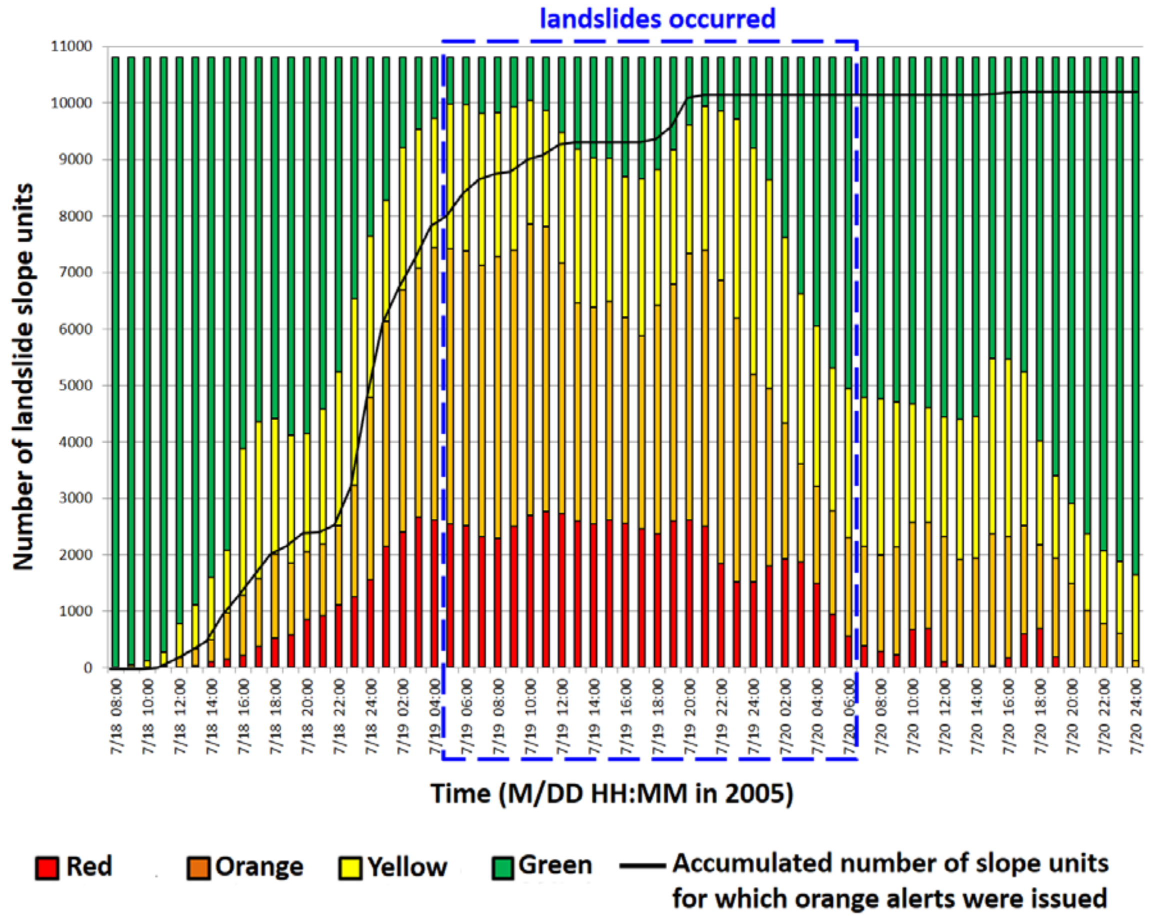


Figure ~~10~~109: Warning history of (a) Typhoon Mindulle and (b) Typhoon Haitang~~. It showed~~ showing that the time at which our model issued ~~warning~~alerts matched the landslide occurrence ~~time~~times reported by newspapers.

Table 1: List~~The multi-year~~~~List~~ of landslide inventories~~ that~~ generated in this study~~studyy~~.

Year	Event
2004	Before Typhoon Mindulle
2004	After Typhoon Mindulle
2005	After Typhoon Haitang
2006	After 0609 torrential~~Torrential~~ rainfall
2007	After Typhoon Sepat
2008	After Typhoon Sinlaku
2009	After Typhoon Morakot

Table 2: Predisposing ~~F~~factors ~~items~~ and their ~~logistic function~~ coefficient in logistic regression analysis.

Code	Factor item	coefficient
L_{01}	RMSSC I	-
L_{02}	RMSSC II	-
L_{03}	RMSSC III	-0.874
L_{04}	RMSSC IV	-0.099
L_{05}	RMSSC V	0.314
L_{06}	RMSSC VI	-0.384
L_{07}	RMSSC VII	-
F_{01}	dip slope	0.207
F_{02}	average slope	0.265
F_{03}	variance of slope	0.098
F_{04}	ratio of steep slope	0.344
F_{05}	average curvature	0.016
F_{06}	variance of curvature	0.161
F_{07}	fold density	0.013
F_{08}	average wetness	0.061
F_{09}	3-hour mean rainfall intensity (I_3)	-0.817
F_{10}	24-hour accumulated rainfall (R_{24})	0.665
C	Constant	0.057

Table 3: Type and the proportion of landslide occurrence ~~time~~times.

type of landslide occurrence time	amount (percentage)
Type A: within the 3 hours ~~right after~~following the highest rainfall intensity (landslide induced by high rainfall intensity)	218 (23%)
Type B: within the 3 hours ~~right after~~following the 2nd or 3rd highest rainfall intensity (landslide induced by high rainfall intensity)	242 (26%)
Type C: near the end of the rainfall event (landslide induced by high accumulated rainfall)	481 (51%)

~~total~~Total	941 (100%)

Table 4: Coefficient of variation of different accumulated rainfall ~~index~~indexes.

Accumulated rainfall Indexes	Coefficient of Variation
6-hour accumulated rainfall (R_6)	0.68
12-hour accumulated rainfall (R_{12})	0.47
24-hour accumulated rainfall (R_{24})	0.38
48-hour accumulated rainfall (R_{48})	0.41
72-hour accumulated rainfall (R_{72})	0.45

Table 5: Contingency matrix for the validation of landslide early warning model. ~~Four~~Shown are four outcomes ~~including~~: True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) ~~are shown.~~).

		Observed events	
		Yes	No
Forecasted events	Yes	True Positive (TP)	False Positive (FP)
	No	False Negative (FN)	True Negative (TN)

Table 6: Alerts and the corresponding ~~dangerous~~danger levels, as well as suggested actions.

~~Table 5: Landslide early warning model and the warning sign considering both landslide susceptibility and rainfall thresholds~~

		~~**Rainfall threshold (T)**~~			
		~~$T_{90\%}$~~	~~$T_{60\%}$~~	~~$T_{30\%}$~~	~~$T_{15\%}$~~
~~**Warning sign**~~**Alert**~~**Landslide susceptibility**~~		~~Dangerous~~Danger~~Extreme dangerous level~~	Suggested action~~Extreme dangerous level~~		
	~~Moderate susceptibility~~	~~Extreme dangerous level~~	~~High dangerous level~~	~~Medium dangerous level~~	~~Low dangerous level~~
	~~Low susceptibility~~	~~High dangerous level~~	~~Medium dangerous level~~	~~Low dangerous level~~	~~Low dangerous level~~

~~Table 6: Rainfall thresholds for southern Taiwan. I_3 was rounded to 5 mm/hr, R_{24} was rounded to 50 mm and parentheses referred to the original value.~~

	~~**Rainfall threshold (T)**~~			
	~~$T_{90\%}$~~	~~$T_{60\%}$~~	~~$T_{30\%}$~~	~~$T_{15\%}$~~

		~~I_3~~	~~R_{24}~~	~~I_3~~	~~R_{24}~~	~~I_3~~	~~R_{24}~~	~~I_3~~	~~R_{24}~~
~~Landslide susceptibility~~	~~High susceptibility~~	~~70 (68)~~	~~750 (745)~~	~~55 (56)~~	~~600 (610)~~	~~40 (40)~~	~~450 (438)~~	~~30 (27)~~	~~300 (291)~~
	~~Moderate susceptibility~~	~~60 (61)~~	~~650 (657)~~	~~45 (46)~~	~~500 (498)~~	~~35 (34)~~	~~350 (368)~~	~~20 (22)~~	~~250 (236)~~
	~~Low susceptibility~~	~~50 (50)~~	~~550 (539)~~	~~40 (40)~~	~~450 (430)~~	~~30 (29)~~	~~300 (316)~~	~~15 (15)~~	~~200 (167)~~

~~Table 7~~6~~: Warning signs and the corresponding dangerous levels as well as suggested actions.~~

~~Warning sign~~	~~Dangerous level~~	~~Suggested action~~
Alert	Danger level	Suggested action
Green	Low	-
Yellow	Medium	Notice announcements
Orange	High	Evacuation
Red	Extreme	Forced evacuation

Table ~~8~~7: Disastrous landslide cases in 2016 and the results of validation ~~results~~. ~~These~~ Warnings could have been issued for all landslide cases ~~could all be warned~~ in advance or ~~just on~~at the time of occurrence.

Landslide susceptibility	Lithology	Landslide area	~~Warning sign & warning~~Alert & issuing time	Occurrence of Landslide	Early (+) Late (-)
Shihwen landslide (Shihwen villiage, Chunri Township, Pingtung County)					
Low	Weathered sandstone	61,500 m^2	Orange, ~~firstly at~~ 11:00, 14-Sep~~14th September~~, 2016	05:00, 15-Sep~~15th September~~, 2016	+18 hours
Zhongmin landslide (Zhongmin Rd., Yanchao District, Kaohsiung City)					
High	Mudstone interbedded with thin sandstone	3,500 m^2	Orange and red, 04:00, ~~28th~~ 28-Sep~~September~~, 2016	10:00, 28-Sep~~28th September~~, 2016	+ 6 hours
Houcuo landslide (Houcuo Ln., Qishan District, Kaohsiung City)					
Low	Conglomerate	4,000 m^2	Orange, 03:00~~ ~ ~~ – 04:00, 28-Sep~~28th September~~, 2016	03:30, 28-Sep~~28th September~~, 2016	0 hour

Table ~~9~~8: Validation of warnings issued for slope units and the ~~hitting ratio~~hit rate ~~ios of~~ during ~~Typhoon~~Typhoons Mindulle and Haitang.

Typhoon event (year)	Landslide occurrence time reported by newspapers	Number of landslide slope units (Number of high~~;~~-, moderate~~;~~-, low-~~-~~susceptibility slope units)	Number of slope units ~~ever~~ ~~had be warned~~ ~~as~~for which orange ~~signal~~alerts had been~~were~~ issued	~~Hitting Ratio~~Hit rate~~io~~
Mindulle (2004)	Mainly 06:00~~~~~ – 13:00, 3~~3^rd^~~, ~~-~~Jul, 2004~~y~~	10,911 (5,129; 2,750; 3,032)	8,283	75.9%
Haitang (2005)	From 05:00, 19-Jul~~19th~~ to 06:00, 20-Jul~~20th, July~~, 2005	10,804 (2,592; 2,355; 5,857)	10,245	94.8%

Table 9: Validation of ~~warnings~~alerts issued for villages during Typhoons Mindulle and Haitang by using contingency matrix and skill scores.

		Observed events				
		Typhoon Mindulle (in 2004)			Typhoon Haitang (in 2005)	
		Yes	No		Yes	No
Forecasted events	Yes	220	30	Yes	194	24
	No	9	77	No	28	12
POD		0.961			0.874	
POFD		0.280			0.667	
POFA		0.120			0.110	