Identification of Rainfall-Induced Slope Failures: A Case Study in Hualien

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ABSTRACT
In this paper, a physically based approach using a transient rainfall infiltration model coupled with slope stability calculation (Transient Rainfall Infiltration and Grid-based Regional Slope-stability analysis; TRIGRS developed by USGS) in conjunction with the Monte Carlo simulation technique was applied to predict the spatial and temporal distribution of landslide initiation locations as well as the corresponding failure probability. A landslide probability map was finally produced and admitted to evaluate landslide susceptibility in a GIS framework. The proposed approach was demonstrated by presenting a case study in the San Jan watershed of Hualien County, eastern Taiwan.

RÉSUMÉ
Dans cet article, une approche à base physique en utilisant un modèle pluie passagère infiltration couplée avec le calcul de stabilité des talus (Transitoire pluie et d'infiltration à base de grilles d'analyse régionale pente -stabilité; TRIGRS développé par l'USGS) en liaison avec la technique de simulation de Monte Carlo a été appliqué pour prédire la distribution spatiale et temporelle des sites d'initiation de glissements de terrain ainsi que la probabilité correspondante échec. Une carte de probabilité de glissement de terrain a finalement été présenté et admis à évaluer la sensibilité aux glissements de terrain dans un cadre SIG. L'approche proposée a été prouvée par la présentation d'une étude de cas dans le bassin de San Jan de district de Hualien, dans l'est de Taïwan.

1 INTRODUCTION

Rapid infiltration of rainfall and the increasing of pore pressure can be considered the main trigger of landslide (Wieczorek, 1987). Rainfall induced landslides are among the most dangerous natural hazards acting on hillslopes, leading to structural damage and casualties. These shallow landslides are triggered by heavy rainfall, very often falling on already wet soils.

Rainfall-induced slope failures appear to be a dominant process in hilly areas with fragile geologic and intensive rainfall conditions, especially in Taiwan. The slope failures usually cause severe damages to properties and produce a large amount of slope material which may transform into debris flows. To mitigate and manage the potential hazards of landslides and debris flows, identification of rainfall-induced slope failures should be investigated in the early stage. A variety of approaches has been utilized to estimate the hazard, such as empirical-statistical methods or physically based methods. However, the empirical-statistical approach ignores the physical process by which rainfall infiltration affects the stability of the hillslopes and limits the ability to predict the hazard.

In this paper, we examine rainfall induced landslides in the San Jan watershed of eastern Taiwan by using the physically based TRIGRS program. First, we describe the study area, its hydrological and morphological characteristics, and its landslide inventory. Next, we provide an outline of the theoretical basis of the TRIGRS model, describe its application to the study area, and present the results and the validation. Finally, we make a general discussion of the applicability of TRIGRS for the landslide susceptibility.

This study aims to predict the spatial and temporal distribution of landslide initiation locations with respect to failure probability. Results revealed the location and size of actual landslide were well predicted in compared to a recent landslide inventory map. In addition, the study showed that a probabilistic landslide map is better than a deterministic landslide map in helping account for spatial variability and uncertainty in the model parameters.

2 SLOPE STABILITY ANALYSIS MODEL

In this study, the Transient Rainfall Infiltration and Grid-based Slope-stability (called TRIGRS), which is developed by USGS, was adopted to investigate the landslide susceptibility. Then, the Monte Carlo simulation technique is implemented into the TRIGRS program. The purpose of this research is to provide a probabilistic map for slope failure by combining GIS, infinite-slope stability analysis and the Monte Carlo simulation technique.

2.1 Theoretical Basis of the TRIGRS Model

The hydrological model implemented in TRIGRS is based on solutions to a linearized form of the Richards equation (Iverson, 2000; Baum et al., 2002; Savage et al., 2003, 2004). This solution is appropriate for initial conditions where the hillslope is saturated, tension-saturated, or nearly saturated. Figure 1 is a conceptual diagram showing a hillslope inclined at an angle δ subject to time varying surface infiltration I, with a tension-saturated zone above a water table at a depth d_{wt}, vertically below the ground surface. The water table overlies an impermeable boundary at a depth d_{lb} below the ground surface.

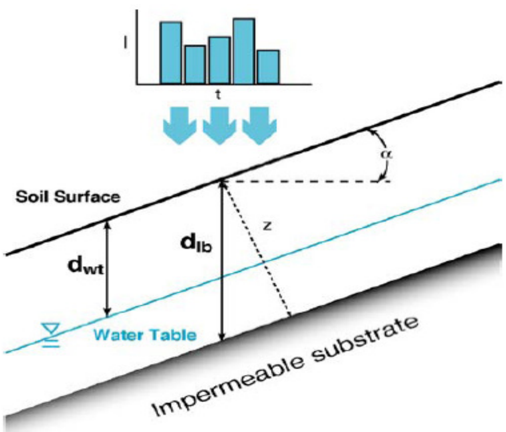

Figure 1. Conceptual diagram of the hydrological model in TRIGRS (from Salciarini et al., 2006)

The model, TRIGRS (Transient Rainfall Infiltration and Grid-based Slope-stability), is a coupled hydromechanical slope stability assessment tool, working on a regional scale. TRIGRS is raster based, and uses a time-dependent approach to assess the stability of a basin during a rainfall event. Infiltration is modelled through a simplified analytical solution of Richards' equation (Iverson, 2000), which requires a shallow, quasi-saturated soil cover at the beginning of a simulation. The built-up pore pressure is then used as an input to a slope stability model, based on the infinite-slope approach. The main output of TRIGRS is a factor of safety, indicating whether the slope can be considered stable or not. The assumption that the soil must be quasi-saturated at the beginning of a simulation can be viewed as a limitation of the model for soils that are more than a couple of meters deep, but is not an issue in the case examined.

Slope stability is calculated using an infinite-slope model, which applies where the thickness of the landslide is small with respect to its length and width. The factor of safety, FS, is defined as the ratio of the resisting and driving forces and is calculated at a depth Z by

$$FS = \frac{\tan\varphi'}{\tan\delta} + \frac{c' - \Psi(Z,t)\gamma_W \tan\varphi'}{\gamma_S Z \sin\delta\cos\delta}$$
[1]

where ϕ' is the soil friction angle for effective stress, c' is the effective cohesion, $\Psi(Z,t)$ is the pressure head as a function of depth Z and time t, d_{lb} is the depth of the impervious lower boundary, and γ_W, and γ_S are the unit weights of water and soil, respectively. The infinite slope is stable when $FS > 1$, in a state of limiting equilibrium when $FS = 1$ and $FS < 1$ denotes unstable conditions. Thus, the depth Z where FS first reaches 1 will be the depth of landslide triggering at time t.

2.2 Spatial Distribution of Soil Thickness

Due to lack of field measurement data, a linear relationship between the wetness index and soil thickness can be assumed (Lee and Ho, 2009) in this study. Since the spatial distributions for soil thickness and for the wetness index in the valley reveal identical tendency, applying the wetness index to estimate the spatial distribution of soil thickness. The soil thickness can be assumed in this study, which can be expressed as (Lee and Ho, 2009)

$$D_j = C_s \ \ln(a/\tan \beta)_j$$
[2]

where D_j is the soil thickness; C_s is a const coefficient assumed to 0.1; a is the upstream area; β is the slope.

2.3 Initial Groundwater Depth Condition

The model result is very sensitive to the initial condition. However, there is no groundwater observation station within the study watershed. During typhoon or heavy rain storm events, the rainfall induced slope stability is influenced by the increasing pore pressure. Therefore, the initial soil saturation should be considered. In this study, the SINMAP model is adopted to obtain the distribution initial groundwater depth (Pack et al., 1998).

In the SINMAP model, the relative wetness (w) defines the relative depth of the water table within the soil layer. The relative wetness has an upper bound of 1 with any excess assumed to form overland flow. According the assumption, the initial groundwater depth can be derived from the field identification of the limits of surface saturation and soil thickness.

2.4 Monte Carlo Simulation for Slope Failure Probability

Monte Carlo simulation is a technique to perform a probabilistic phenomenon that involves using random numbers and probability. The approach consists of the following steps. First, an adequately probabilistic model is selected to generate a set of random values. Next, the slope stability analysis can be calculated through N computations. Then, the failure probability can be obtained from cell by cell within the study watershed. The failure probability, PF_i from cell by cell can be expressed as.

$$PF_i = \sum_{i=1}^{N} k \Big/ N$$

[3]

where k is an index value. IF the factor of safety is smaller than unity, k is equal 1; otherwise, k is zero. The computation times N should be between 50~2000 (Heuvelink, 1993).

3 A CASE STUDY

Taiwan, an island full of mountainous watersheds, is featured by steep slope and torrential rainfall brought by frequent typhoons (3–4 typhoons/year). Landslides often occur during or after typhoons. The landslide susceptibility and failure probability of the San Jan watershed corresponding to the Typhoon MiDuLi will be demonstrated by using the approach proposed in this study.

3.1 Study Watershed Description

San Jan watershed is located at Hualien county, eastern Taiwan (Fig. 2). The watershed area is 122 km^2 with an average slope of 0.552. Elevations range from 13 m to 3098 m. 99% areas of the study watershed are mountainous, and the other is flat area. There is no rain gauging station within the watershed. Therefore, the three nearest rain gages were selected in this study. The average annual rainfall is approximately 2517 mm as measured by these three stations.

Rainfall records show that heavy rainfall caused by typhoons and thunderstorms occurs mostly between June and October in these areas. During June 28–July 3, 2004, Typhoon MinDuLi attacks Taiwan, resulting in 24 deaths and agricultural losses of US $ 3 millions.

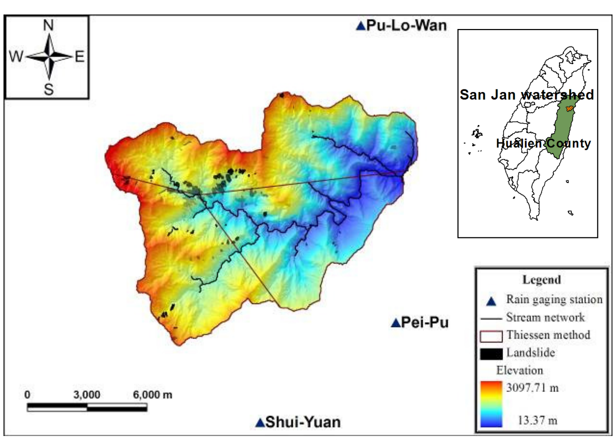

Figure 2. Location map of the San Jan watershed

3.2 Landslide Inventory

An inventory map of landslide occurrence in San Jan watershed from the MinDuLi Typhoon was available for validating the landslide simulations. The map was compiled from the interpretation of a historical series of aerial photographs and from field surveys. We carefully compare pre-event and post-event landslide inventories to produce an event-based landslide inventory. We select data for the shallow landslides triggered by the 2004 typhoon MinDuLi in the Hualien region of eastern Taiwan to complete the susceptibility model.

The results show that there is 1.83% of landslide area identified in the San Jan watershed. As shown in the Figure 2, spatial distribution of landslide region is almost centered on the upstream area.

3.3 Input Parameters for the Study Watershed

There are ten parameters in the TRIGRS model, including the effective cohesion (c'), the friction angle (ϕ'), the soil unit weight (γ_s), the water unit weight (γ_w), the soil thickness (d_{lb}), the initial water condition, the hydraulic conductivity, the diffusivity, the slope, and the long term infiltration rate.

The slope is calculated by using grided DEMs (20-m resolution). The spatial distribution of soil thickness calculated from Eq. 2 can be shown as Figure 3. The soil thickness ranges from 0.45 m to 2.49 m. The steeper area increases the soil thickness whereas the flatter area the thinner soil thickness. As shown in the Figure 4, the initial groundwater depth is obtained from the relative wetness index in the SINMAP model. Hydraulic conductivity K can be set as 10^{-5} m/s according to the literature (SWCB, 2009). The diffusivity value is assumed to be 400 times the K of soil. The long term infiltration rate is set as 10^{-7} m/s calculated from the PART program (Rutledge, 1992).

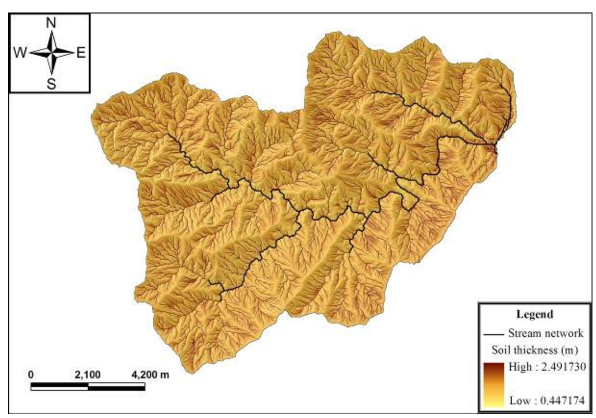

Figure 3. Spatial distribution of soil thickness

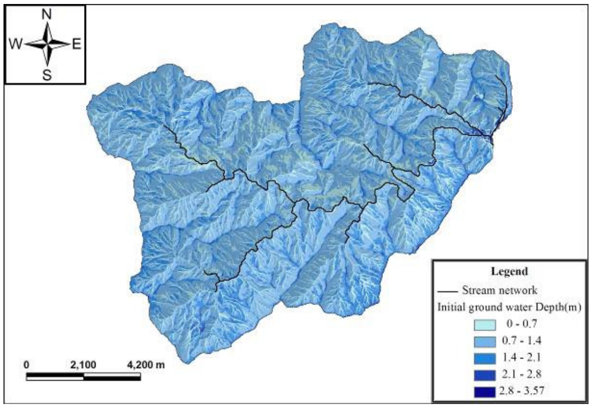

Figure 4. Spatial distribution of the initial groundwater depth

Thus, only two parameters (c' and ϕ') calibrated in the TRIGRS model remain unknown. The sampling of parameter c' and ϕ' in the study area should be taken into consideration. The reasonable value ranges are set as Table 1. Uniform probability distribution is also adopted for the parameter sampling. In this study, the Monte Carlo simulation is used to deal with the parameter uncertainty problem and produce a spatial slope failure probability distribution.

Table 1. Range values of the sampling parameter.

Parameter	Range value	Distribution
effective cohesion, c'	3-11 kPa	Uniform
friction angle, ϕ'	25-36 °	Uniform

4 RESULT AND DISCUSSION

4.1 Model Calibration

To demonstrate the capability of the proposed landslide prediction model, hydrological records of MinDuLi typhoon shown in the Figure 5 were collected to conduct the failure probability map. The rain storm event is classified into 13 periods by interval of 6 hr for the model input. The hydrogeologic parameters were set as the above section mentioned. The uncertain parameters, c' and ϕ' , were sampling 55 set of parameters in this study. The sampling parameters should be at less 50~2000 for the probability susceptibility (Heuvelink, 1993).

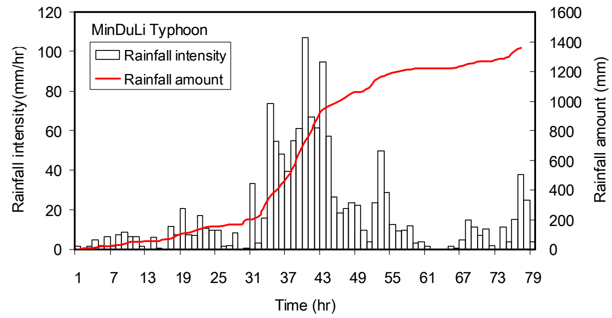

Figure 5. MinDuLi Typhoon (2004/6/28~7/3)

After finishing 55 computations, the temporal and spatial distributions of the safety factor can be obtained from cell by cell within the watershed. By integrating the safety factor distribution by using Eq. 3, the predicted failure probability map can finally be obtained.

4.2 Slope Failure Calculation Results

Figure 6 shows the predicted temporal and spatial distribution of the failure probability map in the San Jan watershed during different rain storm periods. The failure probability of Figure 6 has been divided into 5 classes of equal width. It shows that the initial period (Fig. 6a) of the study watershed is generally stable with low failure probability (0~20%). In the beginning period, failure probability begins to increase.

When it starts to rain, the failure probability increases to the maximum (Fig. 6f&6g) until the heavy rain happens (T=37-43 hr as seen in the Figure 5). In Figure 6f&6g, the maximum probability of failure computed over the entire period is represented. This corresponds to a worst case assessment of the landslide hazard. Therefore, the worst case (Fig. 6f&6g) can be taken as a comparison of sample. Compared with the actual landslide map, the statistics results can be shown in the Figure 7. It is found that if 20 percent of failure probability has been defined the unstable region, 94 percent of successful rate would be matched with the actual landslide map. If the 40 percent of the failure probability has been changed to the threshold value, 50 percent of success rate left would be matched. If 80 percent of the failure probability has been identified, 6.6 percent of success rate left would be matched left. From the results of different threshold values, it can be found that the higher threshold we define, the less success rate can be reached.

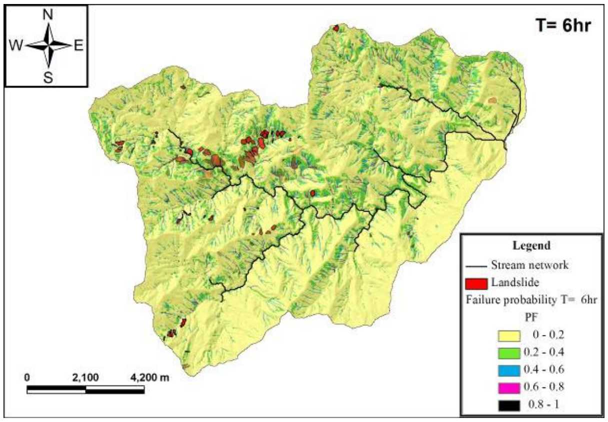

Figure 6(a). Predicted failure probability (T=6hr)

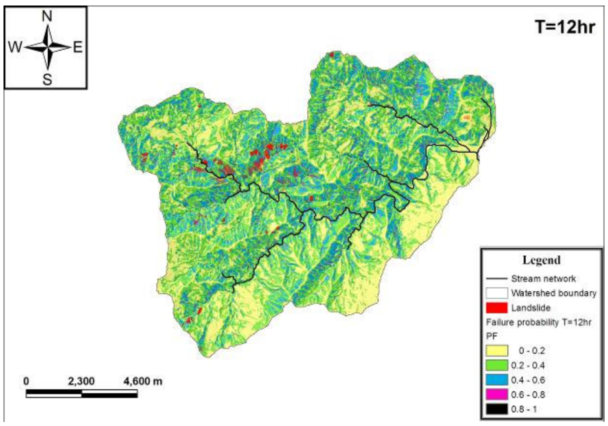

Figure 6(b). Predicted failure probability (T=12hr)

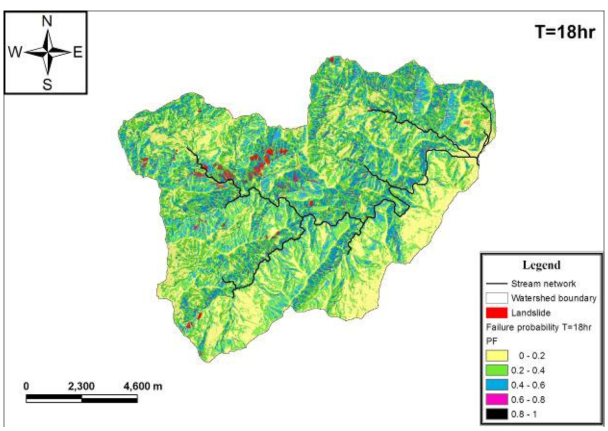

Figure 6(c). Predicted failure probability (T=18hr)

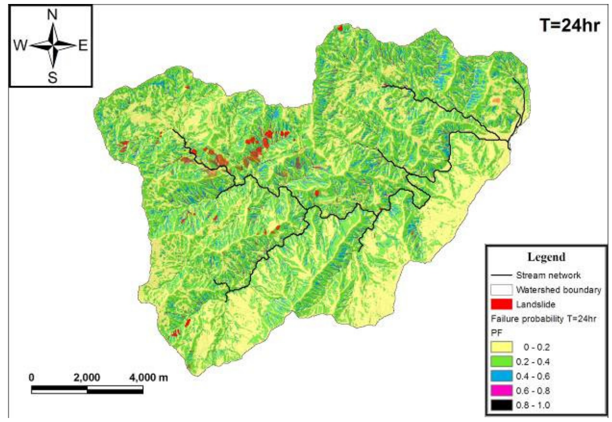

Figure 6(d). Predicted failure probability (T=24hr)

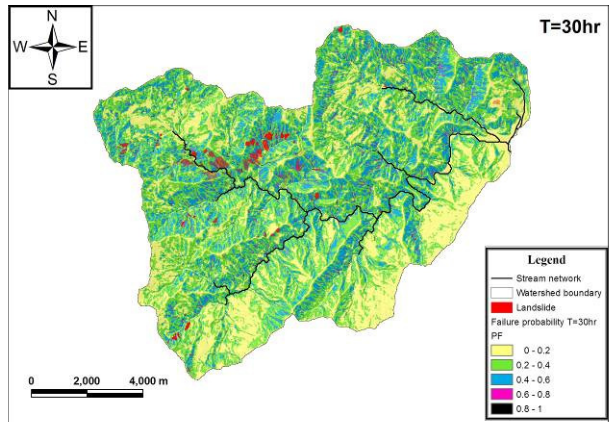

Figure 6(e). Predicted failure probability (T=30hr)

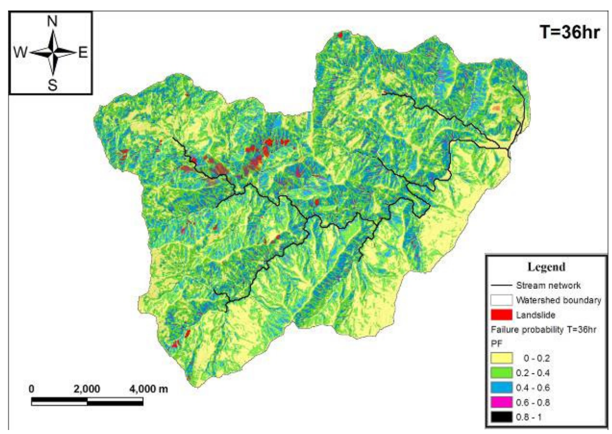

Figure 6(f). Predicted failure probability (T=36hr)

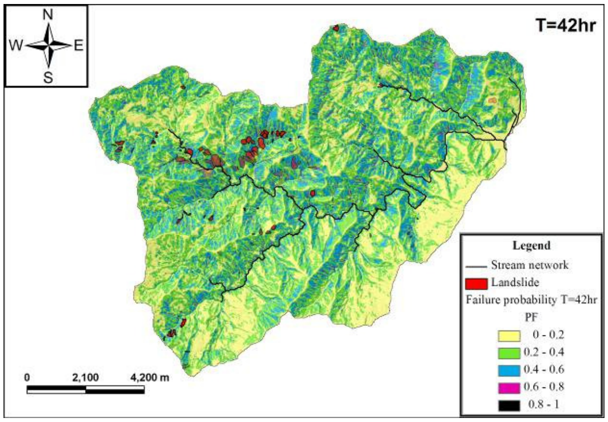

Figure 6(g). Predicted failure probability (T=42hr)

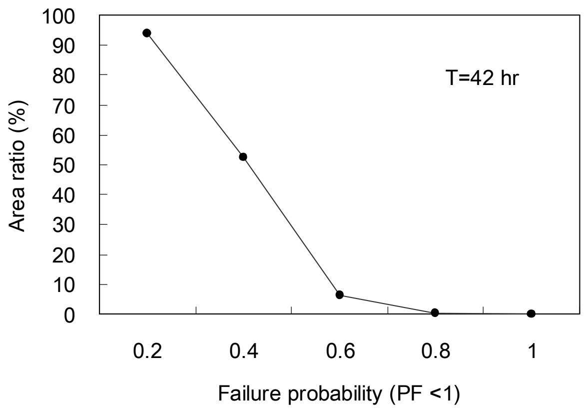

Figure 7. Accumulative area ratio of failure probability at time T=42 hr

5 CONCLUSION

This research presents an integrated GIS based methodology of spatial probabilistic modeling for slope failures with probability concept. The failure probability was proposed into a landslide model to generate and integrate landslide susceptibility maps. The probability of choosing an appropriate threshold to distinguish between stable sliding and potential areas of instability will depend on the reason for the difference.

For example, a landslide degree of correspondence approaching 100 percent can be achieved by conservatively using a low threshold value (PF$\leq$ 0.2). Nevertheless, only at the identifying approximately 6 percent of the landslide map unit can be as being unstable. Conversely, nearly all areas in which no slope hazards were mapped can be modeled as stable by optimistically using a high threshold value, but at modeling almost none of the active landslide map unit as unstable. For situations in which it may not be even possible to specify a threshold probability, image-processing techniques can be used to objectively delineate zones of high probability or slope reliability.

It has enabled the preparation of a slope failure probability hazard map, which can provide important information on landslide mitigation. This integration process promotes the representation of landslide susceptibility map.

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