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Combining spectral and geoenvironmental information for probabilistic event landslide mapping

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ABSTRACT

Landslide mapping is important for emergency management and landslide risk assessment. In this study, we propose a new mapping method, which combines the spectral signal contained in a satellite image and the geoenvironmental information included in a landslide susceptibility map. The image analysis captures areas with spectral signatures of event landslides in the image, while the landslide susceptibility map filters subareas, which do not have landslide prone conditions. The method assigns to every pixel of the satellite image a combined probability of landslide presence. We mapped typhoon-triggered landslides in southern Taiwan using the method. To compare with a landslide inventory prepared from orthophotos, we converted the probability map to a binary map of landslides and landslide free areas. Map comparison resulted in an overall accuracy of 0.93, an area percentage of overlapped landslides of 0.84, a modified success rate of 0.89, and a kappa statistic of 0.73. The method is fast, flexible, and relatively easy to use, and the probability map the method produces is useful by itself. We expect that the method can facilitate the rapid production of event landslide inventory maps, which in turn can assist emergency management.

1. Introduction

Landslide refers to the downslope movement of rock and soil masses (Cruden, 1991), which can be triggered by earthquakes, storms, snowmelt, road construction, or a combination of these factors (Aleotti and Chowdhury, 1999). A landslide map records the location of landslides and, if known, the date of occurrence and the types of mass movements (Guzzetti et al., 2012). Landslide maps are useful for watershed management. Government agencies use them to devise plans to remove landslide deposits or to prevent further downslope rock and soil transport. They can also use the maps as a basis for landslide susceptibility, hazard, and risk assessment (Glade et al., 2005; Guzzetti et al., 2005; van Westen et al., 2006; Guzzetti et al., 2012; Piacentini et al., 2012).

Traditionally, landslides are interpreted and delineated manually on stereoscopic aerial photographs by an experienced interpreter using morphologies typical of slope movements such as scarps, deposit zones, disturbed vegetation, and disturbed channels or roads as visual cues (Dikau, 1999; Saba et al., 2010; Fiorucci et al, 2011). Manual interpretation, however, is time-consuming and expensive. In recent years, satellite images have started to replace aerial photographs for mapping landslides (van Westen et al., 2008; Saba et al., 2010; Guzzetti et al., 2012). Various techniques have been used to recognize and map landslides from satellite images by analyzing the variations in the spectral signature of the land surface (Guzzetti et al., 2012). These techniques are usually described as semi-automatic, although many of them require stepwise procedures for selecting driving datasets and/or rules (e.g., Martha et al., 2010; Lahousse et al., 2011; Stumpf and Kerle, 2011).

This study proposes a probabilistic framework to combine satellite image analysis and a landslide susceptibility map to produce an event induced landslide probability map. As for any technique of landslide mapping using satellite images, the combined method assumes that landslides leave "signs" on the ground surface, which are recorded by satellite images and can be recognized through image analysis (Guzzetti et al., 2012). In forested areas, these signs are bare soils amid vegetation. However, bare soil does not correspond to landsliding in every case as the spectral properties of bare soil inside a satellite image can be similar to other land cover classes such as plowed fields, urban areas, and sediments along the river beds (e.g., Borghuis et al., 2007). Thus, the design of the combined method is to exploit complementary information, like a landslide susceptibility map, to reduce the problem of misinterpretation (i.e., false positive) and the time necessary for the image classification.

In the following, we first describe the combined method and its two components. The semi-automatic method is then applied to map landslides triggered by Typhoon Morakot (5–10 August 2009) in a mountainous watershed in southern Taiwan. To assess the potentiality of the method, we transform the probabilistic map into a conventional

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landslide map so that it can be compared with landslides interpreted and mapped from orthophotos. Results of the comparison are presented in terms of the overall accuracy, proportion of landslides correctly classified, modified success rate, and kappa statistic. We conclude with a discussion of the combined method and its application.

2. The combined method

The combined method has the following two components: a landslide susceptibility map and an image analysis. Both are presented as probability models. The method further assumes that the two probabilistic models are independent; thus, the method can be expressed as:

$$p(L) = p(LP)p(LO) \tag{1}$$

where, for every pixel inside the satellite image, $p(L)$ is the probability of landslide presence, $p(LP)$ is the bare soil (including landslides) class membership probability, given the spectral signal captured by a satellite image, and $p(LO)$ is the probability of landslide susceptibility given the selected geoenvironmental factors associated with the pixel from past events. The following sections describe $p(LP)$, $p(LO)$, and $p(L)$ in more detail.

2.1. Bare soil class membership probability

For each pixel in the post-event satellite image, the bare soil class membership probability $p(LP)$ is extracted by using the discriminant function of the maximum likelihood (ML) supervised classifier available in the ENVI software. The probability is assigned by the equation (Richards and Jia, 1999):

$$p(\omega_i|x) = p(x|\omega_i)p(\omega_i) \tag{2}$$

where $p(\omega_i)$ is the probability that the class ω_i occurs in the image. The probability of finding a pixel belonging to the training class ω_i at a position x, $p(x|\omega_i)$, can be calculated by

$$\rho(x|\omega_i) = (2\pi)^{-N/2}\sum\nolimits_i^{-1/2} \exp\left\{-\frac{1}{2}(x-m_i)^t \sum\nolimits_i^{-1}(x-m_i)\right\} \tag{3}$$

where Σ_i and m_i are the covariance and the mean of the data in ω_i, N is the number of training classes, and t stands for "transpose."

We inverted Eq. (3) to obtain:

$$p(\omega_i|x) = \frac{\exp[g_i(x)]}{\sum_{i=1}^{N}\exp[g_i(x)] = p(LP)} \tag{4}$$

where $g_i(x)$ is the discriminant function of the i class:

$$g_i(x) = \ln p(w_i) - \frac{1}{2}\ln|\Sigma_i| - \frac{1}{2}(x-m_i)^t\Sigma_i^{-1}(x-m_i) \tag{5}$$

provided by ENVI as intermediate result (rules) of the ML classifier.

The ML supervised classifier must be trained by using visually selected training areas ω_i for different classes inside the satellite image (e.g., bare soil and built-up area), before a class membership probability is assigned to each pixel. Section 4.1 covers in more detail how this procedure was performed in this study.

2.2. Probability of landslide susceptibility

The probability map of landslide susceptibility $p(LO)$ is derived by using a historical landslide inventory and a set of geoenvironmental factors. In this study, logistic regression (Menard, 2002) is used to prepare a landslide susceptibility map:

$$logit(y) = \mathrm{a} + \mathrm{b}_1x_1 + \mathrm{b}_2x_2 + \mathrm{b}_3x_3\ldots \tag{6}$$

where y is the dependent variable representing the presence or absence of landslide in the inventory, a is a constant, and b_i is the i-th regression coefficient. The explanatory variables x_i are the selected geoenvironmental factors. $logit(y)$ can be converted to the probability p by:

$$p(LO) = \frac{\exp(\mathrm{a} + \mathrm{b}_1x_1 + \mathrm{b}_2x_2)}{1 + \exp(\mathrm{a} + \mathrm{b}_1x_1 + \mathrm{b}_2x_2)} \tag{7}$$

The performance of a logit model can be evaluated by the area under the receiver operating characteristic curve (AUC), which is based on the proportions of incidences correctly reported as positive (true positive) and incidences erroneously reported as positive (false positive). Using the AUC value, a predictive logit model can be classified as acceptable ($AUC > 0.7$), excellent (>0.8) or outstanding (0.9) (Hosmer and Lemeshow, 2000).

2.3. Probability of landslide presence

For every pixel of the satellite image, the probability of landslide presence $p(L)$ is assigned based on its spectral and geoenvironmental properties. The probability map can be used by itself. To transform it into a conventional binary map, it must be further processed to separate landslide and landslide free into two categories.

3. Study area

The 256 km^2 study area is located in the middle of the 2868 km^2 Kaoping watershed in southern Taiwan, covered by the satellite image (Section 4.3) used in this study (Fig. 1D). Elevation within the study area ranges from 250 to 2647 m with a mean elevation of 966 m and a standard deviation of 457 m. Slope (Fig. 1C) derived from a 5-m DEM (Fig. 1B; see Section 4.3) ranges from 0° to 81°, and averages 30°. Annual precipitation averages 2000 mm, with 90% of the rainfall generated by typhoons and thunderstorms between May and October.

Based on the 1:50,000 geologic maps, four main geological units crop out in the area, including the Changchikeng Formation (37%), encompassing layered alternations of sandstone and shale, Miocene in age; the Chaochou Formation (27%), consisting of argillite and/or slate intercalated with sandstone lentils, Middle Miocene in age; the Pilushan Formation (23%), comprising slate with meta-sandstone with igneous rock, Eocene in age; and the Sanming Shale Formation (10%), shale intercalated with thin-bedded siltstone, Miocene in age (Fig. 1A). Terrace gravel and alluvium, Holocene in age, make up the remaining 3%. The bedrock in the area is highly fractured due to the presence of folds, faults, joints, and cleavage systems. According to the 2007 land use survey, most of the area (81%) is covered by bamboo and broadleaf forest, followed by croplands and orchards (9%), and by water, built-up areas, roads, or bare ground (10%).

The study area is often affected by landslide-triggering typhoons. From 2001 to 2009, nine relevant typhoons of different rainfall intensities impacted the study area (Table 1). The average cumulative rainfall recorded at 24 rain gauge stations within the Kaoping watershed ranges from 304 to 1803 mm, with typhoons Toraji and Nari at the lower end and Typhoon Morakot at the higher end. Typhoon Morakot set a new rainfall record of 2900 mm, triggered thousands of landslides in mountainous areas, and caused 711 fatalities and missing persons, including 500 inhabitants of a village buried by a single landslide (Lin et al., 2010). In this study, we mapped landslides triggered by Typhoon Morakot by using the combined method and a landslide susceptibility map derived from information on the previous eight typhoon events.