



Bayesian framework for mapping and classifying shallow landslides exploiting remote sensing and topographic data

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ABSTRACT

We propose a semi-automatic approach to detect, map and classify rainfall-induced shallow landslides. The approach combines the classification of a post-event multispectral satellite image with information on the morphometric signature of landslides in a Bayesian framework. We apply the approach in two steps. First, we detect and map the rainfall-induced landslides separating the stable ground from the failed areas. Next, we classify internally the landslides separating the source from the run out areas. We obtain the prior probability from the Mahalanobis discriminant function used to classify the satellite image, and the likelihood from the frequency distribution of terrain slope and cross section convexity in the pre-existing shallow landslides. We tested the approach in southern Taiwan, in a catchment where Typhoon Morakot caused abundant landslides in August 2009. Using the semi-automatic approach, we obtained a detailed event landslide inventory map that we compared to an inventory obtained through the visual interpretation of post-event ortho-photographs taken a few days after the landslide triggering rainfall event. Quantitative comparison in a Geographical Information System revealed a degree of matching between the two event inventories exceeding 90%. The approach is general and flexible, and can be used with different satellite imagery and topographic data. Best suited in landscapes where shallow landslides leave distinct radiometric and topographic signatures, the approach is expected to facilitate the production of event landslide inventory maps with positive consequences for geomorphological investigations, landslide hazard and risk modeling, and for post event recovery efforts.

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1. Introduction

Landslides are present in all continents and play a significant role in the evolution of landscapes. In many areas landslides represent a threat to the population, economy, and environment (Brabb and Harrods, 1989; Nadim et al., 2006). Knowing the geographical distribution, number and types of landslides is important for assessing landslide susceptibility (Guzzetti et al., 1999; van Westen et al., 2006; Piacentini et al., 2012), hazard (Guzzetti et al., 2005, 2006a; van Westen et al., 2006), vulnerability (Galli and Guzzetti, 2007), and risk (Glade et al., 2005); understanding the evolution of landscapes dominated by mass-wasting processes (e.g., Hovius et al., 1997, 2000; Malamud et al., 2004a; Guzzetti et al., 2008, 2009; Parker et al., 2011; Chen et al., 2012); and studying forestry, wildlife and ecology (Montgomery et al., 2000; Miller and Burnett, 2007).

A landslide inventory map portrays the location, extent, and types of landslides that have left discernable features in an area (Hansen, 1984; Guzzetti et al., 2000; Malamud et al., 2004b; Guzzetti et al.,

2012). An event inventory map shows landslides caused by a single trigger, such as an earthquake, an intense or prolonged rainfall event, or a rapid snowmelt event. Event inventory maps are used to document the extent and magnitude of a landslide event (Malamud et al., 2004b), to determine the conditions of residual risk after an event (Cardinali et al., 2006), and to validate landslide susceptibility and hazard models (Guzzetti et al., 2006b; Galli et al., 2008).

Event inventory maps can be prepared using conventional or new mapping methods (Guzzetti et al., 2012). Conventional methods include field mapping and the visual interpretation of stereoscopic aerial photographs. These methods are time consuming and resource intensive, restricting the ability to prepare event and seasonal inventory maps repeatedly and for large areas – a significant drawback for regional landslide studies (Galli et al., 2008). To overcome this limitation, investigators are experimenting new methods for preparing landslide event inventories. The new methods exploit remotely sensed data, and include qualitative (visual) and quantitative (numerical) analyses of very-high resolution (VHR) digital elevation models (DEMs) obtained through LiDAR surveys (Derron and Jaboyedoff, 2010; Van Den Eeckhaut et al., 2012), and the interpretation and analysis of satellite images, including panchromatic, multispectral, and synthetic

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aperture radar (SAR) images (Guzzetti et al., 2012, and references therein). Particularly promising are the semi-automatic image classification methods that allow investigators to prepare event landslide inventories for areas in the range from small catchments to large regions, in a limited time, with limited resources, and of a quality (i.e., accuracy, type and certainty of the information shown in the map; Guzzetti et al., 2012) comparable to that of event inventory maps prepared using conventional methods.

In this work, we propose a Bayesian framework for the semi-automatic detection, mapping, and classification of the main geomorphological features of rainfall-induced shallow landslides, including landslide source, transport and depositional areas. In our work, the probability of landslide presence in any given pixel (or a specific landslide feature), obtained from the classification of high resolution (HR) multispectral satellite images taken shortly after a landslide-triggering event, is combined with the probability of landslide occurrence (or the occurrence of a specific landslide feature) obtained from the derivatives of HR digital elevation data and pre-event landslide inventories. The approach aims at increasing the quality of the obtained event landslide inventory map, limiting classification errors (i.e., commission and omission errors) typical of landslide maps obtained from the classification of satellite images (Guzzetti et al., 2012). Adopting a stepwise approach, the Bayesian framework allows mapping separately the source areas from the travel and depositional areas of the rainfall induced shallow landslides. The separation is important for accurate geomorphological mapping, for hazard and risk assessment, and for landscape and ecological modeling.

The paper is organized as follows. In Section 2, we present the rationale for our new approach to the semi-automatic detection and mapping of rainfall-induced shallow landslides from satellite images. In Section 3, we propose a general Bayesian probabilistic model for the detection, mapping, and internal classification of shallow landslides. This is followed, in Section 4, by a description of the satellite, terrain, and landslide information used for the study. Next, we show how the proposed model was applied in the Huaguoshan watershed, Taiwan, to detect and map landslides caused by the August 2009 Typhoon Morakot (Section 5), and to classify the mapped landslides internally into landslide source and run out areas (Section 6). In Section 7 we analyze the landslide event inventory obtained by adopting the proposed stepwise, semi-automatic Bayesian approach, and in Section 8 we discuss the results obtained.

2. Rationale

Traditionally, to prepare an event landslide inventory map, geomorphologists interpret visually stereoscopic aerial photographs taken shortly after an event (e.g., Harp and Jibson, 1996; Bucknam et al., 2001; Cardinali et al., 2001; Guzzetti et al., 2004; Lin et al., 2004; Cardinali et al., 2006). They recognize and map landslides on aerial photographs aided by vertically exaggerated stereoscopic vision, which amplifies the morphological appearance of terrain, reveals morphological (topographical) and land cover (geographical) changes caused by landslides, and facilitates the interpretation of landslide signatures (Pike, 1988; Guzzetti et al., 2012). A trained interpreter can recognize typical landslide signatures based on a complex set of characteristics shown on the images, including the shape, size, photographic color, tone, mottling, texture, and pattern of objects as well as site topography and setting (Guzzetti et al., 2000, 2012). Other topographical, morphological, geological, structural, and land use/cover information can also be considered if available.

Methods for the semi-automatic recognition of landslides from optical satellite images exploit radiometric information captured by a satellite sensor to attribute individual pixels (or group of pixels) to specific terrain classes, including one or more landslide classes (Guzzetti et al., 2012). Supervised and unsupervised classification schemes can be adopted, and classifications can be performed using

single (post-event) (Borghuis et al., 2007) or multiple (pre-event and post-event) images (e.g., Cheng et al., 2004; Yang and Chen, 2010; Mondini et al., 2011a,b; Stumpf and Kerle, 2011). Both pixel-based (e.g., Cheng et al., 2004; Yang and Chen, 2010; Mondini et al., 2011b) and object-oriented (e.g., Barlow et al., 2006; Blaschke et al., 2008; Park and Chi, 2008; Moine et al., 2009; Martha et al., 2010; Lu et al., 2011; Parker et al., 2011; Stumpf and Kerle, 2011) classification methods can be used, with various degrees of success (Guzzetti et al., 2012).

The semi-automatic methods for the recognition of landslides from optical satellite images exploit only part of the information used by a trained interpreter of stereoscopic aerial photographs or stereoscopic satellite images of corresponding quality (Fiorucci et al., 2011). More specifically, the information used is limited to radiometric data captured by satellite sensors. Information on morphological (e.g., terrain elevation, gradient, and curvature), geological (e.g., rock type, bedding attitude, and presence of faults/joints), and land cover (e.g., vegetation type, height, density, and seasonal variations) settings is used to filter specific terrain conditions e.g., flat areas where landslides are known not to have occurred (Martha et al., 2010; Mondini et al., 2011b), or to classify landslides through expert driven, supervised rules (Stumpf and Kerle, 2011).

Here, we propose a new, stepwise, semi-automatic, image classification method for (i) the recognition and mapping of shallow rainfall-induced landslides, and for (ii) the recognition and classification of geomorphological features inside the mapped landslides. For the internal classification of the mapped landslides, we subdivide the landslides in two geomorphological features: (i) the landslide source area, where the slope failure was initiated, and (ii) the landslide transport and depositional areas, where the failed material traveled and was deposited (Crosta et al., 1990). For convenience, and adopting a nomenclature common in Taiwan where we tested our method, we use the term “run out area” for the ensemble of the transport and depositional areas. We acknowledge that the separation among the source, transport, and depositional areas is uncertain, and does not reflect a single process active in each area.

Our proposed new method adds to the traditional pixel-based approaches that use single post-event images (e.g., Borghuis et al., 2007) existing a priori geomorphological knowledge on where event landslides are expected to be more (or less) abundant in a region. As a result, the method exploits a significant part of the terrain and environmental information used heuristically by a geomorphologist when interpreting stereoscopic aerial photographs to prepare an event landslide inventory map. This makes the method similar to the heuristic approach used – often unconsciously – by a geomorphologist to prepare an event landslide inventory map. Our method exploits a Bayesian probabilistic model, which we introduce in the next section.

3. Bayesian probability model

Let us consider a region R represented by a single pixel in a multispectral satellite image for which m terrain conditions are known e.g., slope, curvature, lithology, and land cover/use. Exploiting the pixel spectral and local terrain information (v_1, \dots, v_m), and using one of several machine classification methods (Michie et al., 1994), it is possible to assign the pixel R to one of several pre-defined terrain classes ω_i , e.g., a landslide area u , a landslide-free area Θu , a landslide source area s , and a landslide run out area r . The classification assigns the pixel R to a terrain class ω_1 with a membership probability $p(\omega_1)$. In this work, we adopt a Bayesian inference approach to determine ω_i and $p(\omega_i)$ (Chung and Fabbri, 1999).

Let us consider the proposition:

$$S_1 : \text{“A landslide – related feature } f \text{ is present in a region } R\text{”} \quad (1)$$

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