Remote Sensing of Environment 170 (2015) 350–371

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Tracing the evolution of 2010 Merapi volcanic deposits (Indonesia) based on object-oriented classification and analysis of multi-temporal, very high resolution images

Jean-Claude Thouret [a,*], Zeineb Kassouk [a], Avijit Gupta [b,c,d], Soo Chin Liew [b], Akhmad Solikhin [a,1]

[a] Université Blaise Pascal, Laboratoire Magmas et Volcans UMR6524 CNRS, OPGC et IRD, 5, rue Kessler, 63038 Clermont-Ferrand cedex, France
[b] Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore, Singapore 119076, Singapore
[c] School of Earth and Environmental Sciences, University of Wollongong, NSW, Australia
[d] CRISP, National University of Singapore, Singapore 119076, Singapore

ARTICLE INFO

Article history:
Received 19 February 2015
Received in revised form 21 September 2015
Accepted 28 September 2015
Available online xxxx

Keywords:
VHR image
Object
Classification
Spectral indices
Change detection
Pyroclastic deposits
Lahar
Drainage
Merapi

ABSTRACT

We compare identification, delineation and recording of freshly erupted deposits around active volcanoes from very high resolution optical images with that done by traditional geologic mapping. Object-oriented classification (OOC) and normalized difference spectral indices of vegetation, moisture and soil redness (NDVI, NDWI and NDRSI) have been applied to sub-metric GeoEye-1 and Pléiades images to identify and map pyroclastic and lahar deposits and trace their spatio-temporal evolution over two years, following the 2010 eruption of Merapi Volcano, Indonesia. We could identify several categories of pyroclastic depositional areas, and also map the damaged forest and destroyed cultivated terraces and settlements in the Gendol and Opak River basins on the south flank of the volcano. More than 75% of erupted deposits were delineated semi-automatically unlike the ground geological map based on photo-interpretation of the 2010 GeoEye image and field observations. A temporal image analysis, using bivariate scatter diagrams of the three spectral indices between 2010 and 2012 and a combination of NDWI and NDVI, separated areas affected by surges from unscathed vegetation. Use of NDRSI and NDWI allowed us to differentiate overbank Pyroclastic Density Current deposits from wet lahar deposits. NDRSI values close to 0 refer to scoria-rich pyroclastic deposits.

About 40% of the devastated upper catchment was recolonized by vegetation between 2010 and 2012. The recovery also took place in the forested valley margins affected by ash-cloud surges. The morphometric analysis of the initial drainage network, digitized from the 2011–2012 images, demonstrated (1) the resurfacing of pristine 2010 PDC deposits by runoff and (2) incision or remobilization by lahars. It took two years following the eruption in the rugged upper catchment devastated by high-energy surges to fully develop the hydrographic network. It is, however, still rudimentary on gently sloping fans created by overbank PDC deposits in the middle valley, thus suggesting the importance of slope gradient, grain size, permeability and thickness of deposits. As much as 35% of the 2010 PDC deposits, emplaced in the vicinity of the river channels, were remobilized by lahars over the two post-eruption rainy seasons and also by constant mining activities. Studies on the erosion of the pyroclastic deposits after 2012 need to concentrate on the upper reach of the catchment on the south flank.

1. Introduction: scope, rationale and objectives

1.1. Remote sensing techniques of volcanic eruptions

Developments in remote sensing techniques over the past 25 years have allowed detailed mapping and safe monitoring of volcanic eruptions (Francis & De Silva, 1989; Graettinger et al., 2013; Harris et al., 2001; Pyle, Mather, & Biggs, 2013). The growing focus of recent studies on 1) detection of an eruption plume (Kahn & Limbacher, 2012), 2) monitoring thermal emissions (Wessels, Vaughan, Patrick, & Coombs, 2013), 3) measurement of volcano topography and topographic change (Ebmeier et al., 2012; McAlpin & Meyer, 2013; Wadge et al., 2011), 4) mapping surface deformation (Aly & Cochran, 2011; Howell, White, & Bohnenstiehl, 2012), 5) mapping the spatial distribution of ash and gas plume (Dacre et al., 2011), and, 6) mapping erupted deposits (Carter & Ramsey, 2009; Joyce et al., 2009; Kassouk, Thouret, Gupta, Solikhin, & Liew, 2014; Oramas-Dorta, Cole, Wadge, Alvarado, & Soto, 2012) are summarized in Table 1. In a little more than a decade,

* Corresponding author.
[1] Now at Centre of Volcanology and Geological Hazard Mitigation (CVGHM), 57 Jalan Diponogero, Bandung, Indonesia.

http://dx.doi.org/10.1016/j.rse.2015.09.028

Table 1
Recent (post 2003) case studies of pyroclastic density current (PDC) and lahar deposits identified and/or mapped on the basis of remote sensing techniques applied to optical images.

Techniques	References	Data imagery	Aims
Principal component	Kerle et al. (2003)	SPOT-3 MS	Delineation and characterization of the 1998 Casita lahar deposits, Nicaragua
Analysis (PCA)	Dávila Hernandes et al. (2007)	ASTER	Lahar delineation, Colima Volcano, Mexico
Normalized difference vegetation index (NDVI)	Castro and Carranza (2005)	SPOT5	Spatial distribution of pyroclastic-flow and lahar deposits, West Pinatubo, Philippines
	Joyce et al. (2009)	SPOT5	Lahar path detection, Mt. Ruapehu, New Zealand
	Harris et al. (2006)	Landsat TM ASTER	Temporal and spatial variations in valleys conveying lahars on Santiaguito Volcano, Guatemala
Tonal contrast analysis	Torres et al. (2004)	SPOT4 Pan	Mapping the extent of lahar deposits, Pasig–Potrero alluvial fan, Pinatubo Volcano, Philippines
Normalized difference lahar index	Dávila Hernandes et al. (2011)	SPOT5	Spectral enhancement of lahar deposits, Colima Volcano, Mexico
Visual photo-interpretation	Thouret et al. (2010)	IKONOS	Pyroclastic deposits, 2006 eruption of Merapi Volcano, Indonesia
	Lube, Cronin, Thouret, and Surono (2011)	IKONOS	PDC deposits, 2006 eruption of Merapi Volcano
	Solikhin et al. (2012)	SPOT5, ASTER	Pyroclastic deposits, Semeru Volcano, Indonesia (2002–2003)
	Jenkins et al. (2013)	SPOT5, ALOS	Outlining PDC impacts, 2010 eruption of Merapi Volcano
	Thouret et al. (2013)	GeoEye-1	PDC and lahar deposits, 2010 eruption of Merapi Volcano
	Charbonnier et al. (2013)	GeoEye-1	PDC and lahar path detection, 2010 eruption of Merapi Volcano
Supervised classification	Solikhin, Thouret, et al. (2015)	GeoEye-1	PDC and lahar deposit detection, 2010 eruption of Merapi Volcano
SLC interpolation & classification	Seul-Ki et al. (2015)	Landsat 7 ETM+	Evolution of Merapi 2010 lahar and pyroclastic deposits using Landsat 7 images and simulation runs using LaharZ code

remote optical sensors equipped with different categories of visible, near-infrared, mid-infrared and thermal channels, have made it possible to map and describe tephra fall and pyroclastic density current deposits (PDCs, including pyroclastic flows and surges), and lahar (debris flow) deposits at active volcanoes. Synthetic Aperture Radar (SAR) data from C-band ERS-1/2, RADARSAT-1, ENVISAT, L-band JERS-1 and ALOS PALSAR sensors are now used for imaging PDC and lahar deposits irrespective of weather conditions (Calder et al., 2004; Harris et al., 2006; Joyce et al., 2009; Saepuloh, Koike, Omura, Iguchi, & Setiawan, 2010; Saepuloh, Koike, Urai, & Sri Sumantyo, 2015; Samsonov et al., 2014; Solikhin, Pinel, Vandemeulebrouck, Thouret, & Hendrasto, 2015), although the spatial resolution remains 10 m at best.

Recent advances in remotely sensed mapping have been possible by the use of very high resolution (VHR), sub-metric images from modern sensors launched over one decade: QuickBird (2002), GeoEye-1 (2009), Worldview (2010), and Pléiades (2012) as illustrated by Castro and Carranza (2005), Joyce et al. (2009), Solikhin, Thouret, Harris, Liew, and Gupta (2012) and Oehler, Thouret, Solikhin, and Ettinger (2014). Several methods for mapping and differentiating PDC and lahar deposits using very high resolution (VHR) optical data have been proposed (Table 1): principal component analysis (Dávila Hernandes, Capra, Gavilanes, Varley, & Norini, 2007; Dávila Hernandes, Lira, Capra-Pedol, Zucca, 2011; Torres et al., 2004), image subtraction (Torres et al., 2004), image rationing (Lopez, Paringit, & Lim, 1998). In addition to spectral reflectance (i.e. color or tone), other factors as visual hues, texture, shape and pattern were also used for the visual–cognitive delineation of pyroclastic deposits (Solikhin et al., 2012; Solikhin, Pinel, et al., 2015; Thouret et al., 2010; Torres et al., 2004). However, such studies essentially used pixel-based classifications which do not account for feature characteristics (i.e. geometry) and contextual information (i.e. topographic, geomorphic and hydrologic characteristics) contained in the VHR image, as increasing resolution makes it difficult to derive objects that are made up of several pixels. Robust object-oriented classification algorithms tend to solve this problem.

1.2. Object-oriented classification and object-based image analysis

The concept of the object-oriented approach was developed to overcome difficulties in pixel-based classification, which rose with increased satellite resolution (Blaschke, 2010; Blaschke, Lang, & Hay, 2008). This approach has evolved towards object-based image analysis (OBIA) which delineates readily usable objects from imagery, and at the same time combines image processing and Geographic Information System (GIS) functionalities in order to utilize spectral and contextual information in an integrative way. Object-oriented image classification involves identification of image objects, or segments, that are spatially contiguous pixels of similar texture, color, and tone (Congalton & Green, 2009). It starts by grouping neighboring pixels into meaningful multi-pixel objects of various sizes based on both spectral and spatial characteristics of pixel groups (Aplin, Atkinson, & Curran, 1999; Baatz & Schape, 2000). An object is a region defined by spatial, spectral (brightness and color), and/or textural characteristics. Once an image is segmented, the classification is done by using spatial information such as textural, shape, size and neighborhood properties simultaneously. This OBIA approach allows for consideration of both context and spectral content (Lang, 2011). In the classification process, all pixels in the entire object are assigned to the same class, thus removing the problem of spectral variability and mixed pixels.

Several researchers have developed object-based image analysis using VHR multi-spectral IKONOS and QuickBird images for classification of vegetation or constructions in dense urban areas (Chen, Li, & Sun, 2009; Shackelford & Davis, 2003; Teo & Chen, 2004), forest patterns and other land cover/land use (Lang & Langanke, 2006), and bird habitats (Jobin, Labrecque, Grenier, & Falardeau, 2008). A limited number of publications addressed the problem of segmentation and classification of VHR images for delineating the effects of natural hazards: building damage due to earthquake (Gusella et al., 2005; Turker & Sumer, 2008), tornadoes (Myint, Yuan, Cerveny, & Giri, 2008), coastal recovery after a large tsunami (Liew, Gupta, Wong, & Kwoh, 2011) and flood risk and damage assessment (Ettinger, Zeghdoudi, Manrique, Yao-Lafourcade, & Thouret, 2015; Van de Sande, de Jong, & de Roo, 2003). To our knowledge, however, the delineation of spatial impacts of explosive eruptions and classification of pyroclastic and lahar deposits is covered in a very limited number of publications.

1.3. Rationale and objectives

This paper compares the ability of the object-oriented classification (OOC) and object-based image analysis (OBIA) applied to VHR (50-cm spatial resolution) images to the traditional geologic mapping of volcanic deposits. We attempt to determine the extent to which multi-temporal VHR images enable us to detect a variety of 'fresh' pyroclastic deposits produced by a large eruption, and trace the initiation of drainage following this event on volcanic slopes in a wet environment. In a cloud-free situation, PDC and lahar deposits are identifiable in visible, infrared, and thermal infrared images, as their colors (typically grayish-