CREATION OF EVENT-BASED LANDSLIDE INVENTORY FROM PANCHROMATIC IMAGES BY OBJECT ORIENTED ANALYSIS

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ABSTRACT:

There has been an increase in the application of object-based image classification techniques for fast retrieval of information after natural disasters. One of the fields wherein this method has shown its potential is the detection of landslides. However, most of the studies are confined to the application of object-based image analysis techniques to multispectral images. While this application has shown tremendous potential in the early stage of disaster response, availability of high resolution multispectral images immediately after a disaster situation as reference data for change detection is not always guaranteed. In this paper, we investigated how landslides can be detected from panchromatic images, which lack spectral information of various terrain features. An object-based change detection technique developed by Martha et al. (2012) using archived panchromatic images was tested in an area in the high Himalayas where several landslides were triggered after a severe rainfall event in the year 2010. Cartosat-1 high resolution panchromatic images acquired by ISRO immediately after the event were used, and a total of 142 landslides in a catchment area of 10.5 km^2 were identified. A landslide inventory created by this method can be used for future event-based landslide susceptibility assessment of affected area.

1. INTRODUCTION

Remote sensing technology has been used extensively to provide landslide specific information to policy makers and emergency managers during a disaster period (Tralli et al., 2005). Landsliding is one such natural disaster, mapping of which supports assessing damage caused to the terrain and identifying areas prone to future landslide occurrences through hazard and risk assessment. Recent advances in computer vision and machine intelligence have led to the development of new techniques, such as object-oriented analysis (OOA) for automatic content extraction of both man-made and natural geospatial objects from remote sensing images (Akcay and Aksoy, 2008). OOA has the potential to rapidly map landslide-affected areas using high resolution satellite data and digital elevation models (DEM), which perfectly suits the requirement of decision makers in a post-disaster scenario (Benz et al., 2004; Blaschke, 2010; Voigt et al., 2007). Given the increasing number of civilian high resolution satellites, post-disaster imageries can be meaningfully used to create landslide inventories that will help in preparation of event-based landslide susceptibility maps (Lee et al., 2008; van Westen et al., 2006).

Previous workers (Barlow et al., 2006; Lu et al., 2011; Martha et al., 2010; Moine et al., 2009) have shown how to detect landslides from multispectral images by OOA. The methodology developed by Martha et al. (2010) for detection of landslides consisted of four steps: i) multi-resolution segmentation to derive image primitives, ii) identification of landslide candidates using a normalised difference vegetation index (NDVI) threshold, iii) separation of landslides from false positives by integrating spectral, spatial and contextual information in OOA, and iv) classification of landslide types based on material and types of movement. While this methodology is effective in inaccessible mountainous terrain since it uses only space data, user driven thresholds and selection of object size in an iterative manner remained drawbacks of the method. Subsequently, Martha et al. (2011) used data-driven thresholds using k-means algorithm and multiple segmentation levels identified using a plateau objective function, and overcame some of these limitations. However, in several cases panchromatic images are the only data available after an event (van Westen et al., 2008), or as pre-event reference data. Sometimes, even though multispectral data are available after a disaster, panchromatic images are preferred due to their high resolution nature in comparison to the multispectral counterpart capable of identifying small size ground objects (Chini et al., 2011). In such cases, existing methodologies cannot be used, since they rely on thresholds derived from spectral information during the detection process. Recently, Martha et al. (2012) developed another method to prepare historical landslide inventory from archived high resolution panchromatic images. In this method, they used local contextual-based thresholds instead of NDVI-based thresholds to extract landslide candidates. However, this methodology has not been tested for detection of landslides from newly acquired panchromatic images for creation of an event-based landslide inventory.

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In this paper, we present the results of the study carried out for rainfall triggered landslides using high resolution panchromatic images. The methodology developed by Martha et al. (2012) using archived IRS-1D images (5.8 m spatial resolution) for an event occurred in August 1998 in the Okhimath area in the rugged Indian Himalayan terrain, was tested for a similar event that occurred in the Almora area in September 2010, using newly acquired Cartosat-1 imagery with the same spectral band width but 2.5 m spatial resolution.

2. DATA SET, AREA AND METHODOLOGY

2.1 Data Set

High resolution satellite data and DEM are primary requirements for modelling Earth surface processes such as landsliding. High resolution Cartosat-1 data were shown to be useful for mapping major and minor landslides by visual interpretation in the aftermath of the Kashmir earthquake in October 2005 (Vinod Kumar et al., 2006). Cartosat-1 has several distinct features, such as along-track stereoscopy, unique sensor geometry (PAN-Aft and PAN-Fore, with an off-nadir viewing angle of -5° and +26°, respectively), 10-bit radiometric resolution, rational polynomial co-efficients (RPC), on-demand tilting capability, and five days revisit period with dedicated stereoscopic cameras, making it a suitable choice for DEM generation in any part of the world (Radhika et al., 2007). In this study, both pre- and post-landslide stereoscopic data of Cartosat-1 were used for the extraction of a 10 m gridded DEM, specifically a digital surface model (DSM), using digital photogrammetric techniques. Since RPCs are terrain independent, GCPs collected from the DGPS survey were used to improve the geo-location accuracy. Subsequently, DEM derivatives such as drainage, hillshade, flow direction, slope and terrain curvature, and image derivatives such as reflectance were generated. Datasets used in this study are listed in table 1.

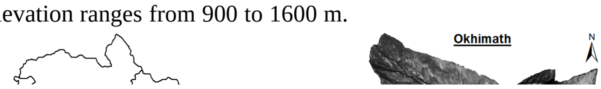
Table 1: Details of data used in this study

Data type	Source
Pre-landslide satellite data	Cartosat-1 (02 April 2010)
Post-landslide satellite data	Cartosat-1 (30 September 2010)
DEM	Cartosat-1 (2.5 m resolution)
Relief	10 m DEM
Slope	
Flow direction	

2.2 Study Area

The study area is located in the high Himalayas of the Uttarakhand state in India (Figure 1). The methodology was developed by Martha et al. (2012) using pre- and post-landslides images for a small catchment of the Madhyamaheswar river in the Okhimath area of the Rudraprayag district, where severe rainfall in August 1998 triggered 466 landslides that killed 103 people and damaged 47 villages (Naithani, 2002).

Testing of the methodology developed by Martha et al. (2012) was done for an event of similar magnitude that took place in September 2010 in a small catchment of the Kosi river in the Almora district (Figure 1), where thousands of tourists and pilgrims were stranded at many places due to road blockage. A total of 37 people were killed due to landslide related incidences. A part of the Kosi river catchment near Suyalbari village north of Nainital town, a famous hill station in India, was selected to rapidly detect landslides using Cartosat-1 data. This area has witnessed the largest number of landslides due to this event. The dominant land use of this area is agricultural land through terrace cultivation and rocky barren land. The elevation ranges from 900 to 1600 m.



Change analysis was carried out in an object-based environment, wherein brightness of the objects obtained through multi-resolution segmentation of the post-landslide satellite image was compared with brightness of the same area in the pre-landslide image. Increase in image brightness after landsliding is a universal property, which was therefore used for thresholding of the panchromatic images. However, instead of applying brightness as a global threshold, we adopted a two-fold strategy to identify landslide candidates; i) change detection using the difference in object brightness of pre- and post-landslide images, and ii) local brightness threshold of the post-landslide image using a contextual criterion. Specifically, we used the high brightness contrast to darker neighbours to detect brightness anomalies, i.e. relative tonal variation between a landslide and its neighbours caused due to the landsliding process. While the first strategy was useful in the identification of large landslide candidates, the second strategy was useful to identify smaller ones.

For reactivated landslides, we created a sub-object level below the main object level by segmenting the pre-landslide image, which allowed better object comparison. Once all landslide candidates were identified, brightness in conjunction with GLCM textures was used to eliminate landslide false positives, such as road, agricultural and barren lands. Figure 2 shows the procedure used for landslide detection from panchromatic images.

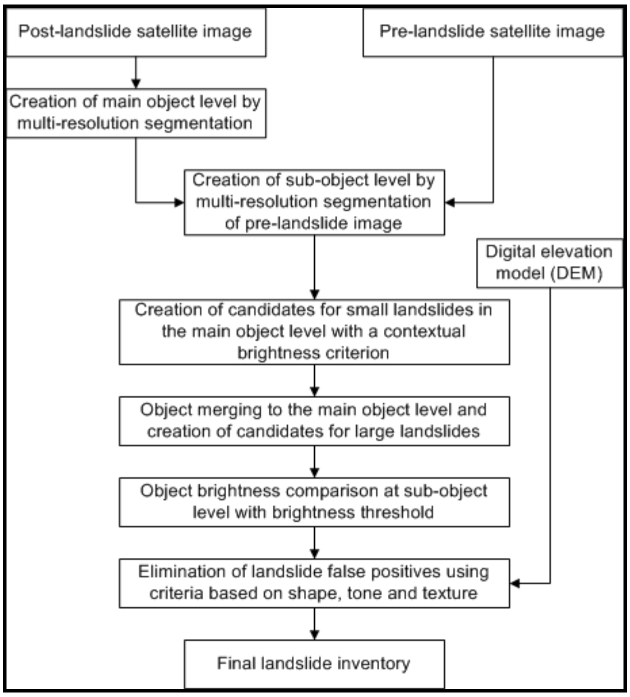


Figure 2. Methodology flowchart for detection of landslides from panchromatic images.

3. resultS and discussion

After processing both pre- and post-landslide Cartosat-1 images, the object-based change detection methodology developed for the Okhimath area by Martha et al. (2012) was applied to the Almora area. This area was mainly affected by several shallow translational landslides, wherein a layer of thin soil or weathered rock had slid down under the impact of heavy rainfall. Therefore, the landslides in the Almora area were mostly of smaller size in comparison to a mixture of small and large landslides in the Okhimath area. Hence, the object-based contextual criterion '*mean difference to darker neighbour*' was used to extract landslide candidates. Martha et al. (2012) had already highlighted the usefulness of this criterion in the identification of shallow translational landslides.

After extraction of landslide candidates using the change detection technique, landslide false positives were identified using tone, shape, texture and contextual criteria. For example agricultural terraces, although similar in tone to landslides, could be identified as a separate class using additional criteria such as GLCM dissimilarity, GLCM homogeneity, GLCM standard deviation and slope. Roads were identified using shape properties, such as high asymmetry, orthogonal relationship between flow direction and main direction, and very low standard deviation of the DEM. After elimination of all landslide false positives, the remaining candidate objects represented landslides. The method was able to discriminate narrow and elongated landslides lying adjacent to each other and creates individual polygons rather than identifying them as a single polygon, which might exaggerate the statistics of total area of the mapped landslides (Figure 3).

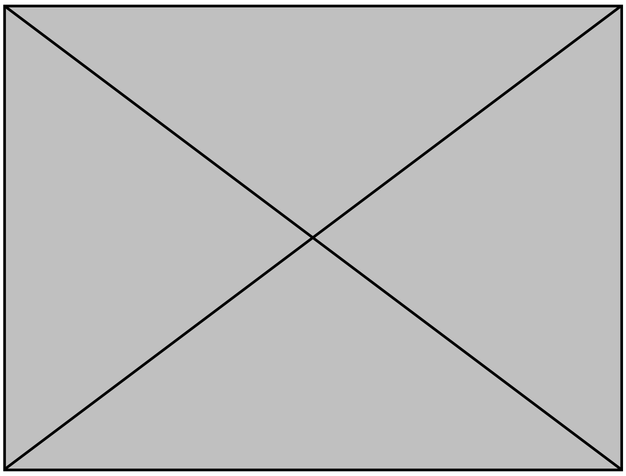
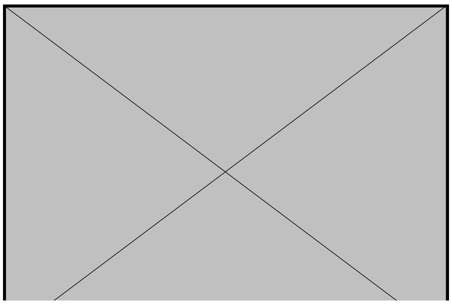


Figure 3. Detection of shallow translational landslides. a. pre-landslide Cartosat-1 image and b. identified landslides (red outlines) superimposed over the post-landslide Cartosat-1 image. Yellow circle highlights individual detection of adjacent landslides.

The 10 m DEM derived from Cartosat-1 data was found to be very useful, particularly for the detection of landslides in the Kosi river valley floor. For example, landslides highlighted in Figure 4 would have been classified as river sand had relief derived from the DEM not been used in addition to adjacency to the river as criteria to classify bright objects as river sand.



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References

Akcay, H.G. and Aksoy, S., 2008. Automatic detection of geospatial objects using multiple hierarchical segmentations. IEEE Transactions on Geoscience and Remote Sensing, 46(7): 2097-2111.

Barlow, J., Franklin, S. and Martin, Y., 2006. High spatial resolution satellite imagery, DEM derivatives, and image segmentation for the detection of mass wasting processes. Photogrammetric Engineering and Remote Sensing, 72(6): 687-692.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. and Heynen, M., 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing, 58(3-4): 239-258.

Blaschke, T., 2010. Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65(1): 2-16.

Cheng, K.S., Wei, C. and Chang, S.C., 2004. Locating landslides using multi-temporal satellite images. Advances in Space Research, 33(3): 296-301.

Chini, M., Cinti, F.R. and Stramondo, S., 2011. Co-seismic surface effects from very high resolution panchromatic images: the case of the 2005 Kashmir (Pakistan) earthquake. Natural Hazards and Earth System Sciences, 11: 931-943.

Lee, C.-T. et al., 2008. Statistical approach to earthquake-induced landslide susceptibility. Engineering Geology, 100(1-2): 43-58.

Lu, P., Stumpf, A., Kerle, N. and Casagli, N., 2011. Object-oriented change detection for landslide rapid mapping. IEEE Geoscience and Remote Sensing Letters, 8(4): 701-705.

Martha, T.R., Kerle, N., Jetten, V., van Westen, C.J. and Vinod Kumar, K., 2010. Characterising spectral, spatial and morphometric properties of landslides for automatic detection using object-oriented methods. Geomorphology, 116(1-2): 24-36.

Martha, T.R., Kerle, N., van Westen, C.J., Jetten, V. and Vinod Kumar, K., 2011. Segment Optimisation and Data-Driven Thresholding for Knowledge-Based Landslide Detection by Object-Based Image Analysis. IEEE Transactions on Geoscience and Remote Sensing, 49(12): 4928-4943.

Martha, T.R., Kerle, N., van Westen, C.J., Jetten, V. and Vinod Kumar, K., 2012. Object-oriented analysis of multi-temporal panchromatic images for creation of historical landslide inventories. ISPRS Journal of Photogrammetry & Remote Sensing, 67: 105-119.

Moine, M., Puissant, A. and Malet, J.-P., 2009. Detection of landslides from aerial and satellite images with a semi-automatic method-Application to the Barcelonnette basin (Alpes-de-Haute-Provence, France). In: J.-P. Malet, A. Remaitre and T. Bogaard (Editors), Landslide Processes: from geomorphological mapping to dynamic modelling. CERG, Strasbourg, France, pp. 63-68.

Naithani, A.K., 2002. The August, 1998 Okhimath tragedy in Rudraprayag district of Garhwal Himalaya, Uttaranchal, India. GAIA, 16: 145-156.

Prenzel, B. and Treitz, P., 2004. Remote sensing change detection for a watershed in north Sulawesi, Indonesia. Progress in Planning, 61(4): 349-363.

Radhika, V.N., Kartikeyan, B., Gopala Krishna, B., Chowdhury, S. and P.K., S., 2007. Robust Stereo Image Matching for Spaceborne Imagery. IEEE Transactions on Geoscience and Remote Sensing, 45(9): 2993-3000.

Tralli, D.M., Blom, R.G., Zlotnicki, V., Donnellan, A. and Evans, D.L., 2005. Satellite remote sensing of earthquake, volcano, flood, landslide and coastal inundation hazards. ISPRS Journal of Photogrammetry and Remote Sensing, 59(4): 185-198.

van Westen, C.J., Castellanos, E. and Kuriakose, S.L., 2008. Spatial data for landslide susceptibility, hazard, and vulnerability assessment: An overview. Engineering Geology, 102(3-4): 112-131.

van Westen, C.J., van Asch, T.W.J. and Soeters, R., 2006. Landslide hazard and risk zonation—why is it still so difficult? Bulletin of Engineering Geology and Environment, 65(5): 167-184.

Vinod Kumar, K., Martha, T.R. and Roy, P.S., 2006. Mapping damage in the Jammu and Kashmir caused by 8 October 2005 Mw 7.3 earthquake from the Cartosat–1 and Resourcesat–1 imagery. International Journal of Remote Sensing, 27(20): 4449-4459.

Voigt, S. et al., 2007. Satellite Image Analysis for Disaster and Crisis-Management Support. IEEE Transactions on Geoscience and Remote Sensing, 45(6): 1520-1528.