

SEGMENT OPTIMISATION FOR OBJECT-BASED LANDSLIDE DETECTION

Tapas R. Martha^{a, b, *}, Norman Kerle^b

^a National Remote Sensing Centre (NRSC), Indian Space Research Organisation (ISRO), Hyderabad – 500625, India -
tapas_martha@nrsc.gov.in

^b Dept. of Earth Systems Analysis, Faculty of Geo-information Science and Earth Observation (ITC), University of
Twente, P.O. Box 6, 7500 AA Enschede, The Netherlands – (kerle, martha)@itc.nl

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ABSTRACT:

Advances in remote sensing technology and image analysis systems have led to an increase in automatic feature extraction technique for several novel applications. Object-oriented analysis (OOA) of high resolution remote sensing data is one such technique, wherein objects/segments are the image primitives that form the basis for automatic feature extraction, and thus have critical influence on the accuracy of the subsequent processing. In this study we assess how the fractal net evolution segmentation approach, embedded in Definiens Developer, can be optimised for automatic detection of landslides. Landslides are important natural mass wasting processes, and their fast detection using high resolution satellite and elevation data can inform disaster mitigation strategies. In recent work we showed how spectral, contextual and morphometric information can be successfully used to detect and characterise landslides of different types. However, given the complex shape and size of landslides, as well as their spectral heterogeneity, segmentation with a single set of parameters is not possible and remains a weakness in our method. Here we assess multiple segmentation strategies to derive an appropriate segmentation for various classes to be identified in subsequent rule-based classification. Segments were subjected to spatial autocorrelation analysis using Moran's I index and intrasegment variance analysis to optimise the parameter selection for multiresolution segmentation. Instead of one object level pertaining to a single parameter, multiple object levels with a set of optimum parameters were used to detect landslides of variable sizes. We test our approaches with Resourcesat-1 LISS-IV multispectral imagery (5.8 m) and a 10 m DEM derived from 2.5 m stereoscopic Cartosat-1 data for two landslide prone areas in the High Indian Himalayas.

1. INTRODUCTION

The effects of landslides on people and property have been mounting in recent decades due to increasing slope instability as a result of deforestation, road cutting and urbanisation. According to the official figures of the United Nations International Strategy for Disaster Reduction (UN/ISDR) and the Centre for Research on the Epidemiology of Disasters (CRED) for the year 2006, landslide ranked third in terms of number of deaths among the top ten natural disasters (OFDA/CRED, 2006). Recent developments in satellite technology have rendered the availability of high resolution data easier and cheaper, resulting in an increase in research on automatic content extraction of both man-made and natural geospatial objects (Akçay and Aksoy, 2008; Holt et al., 2009). Landsliding is one such natural feature, knowledge of which is a vital input for decision support systems used by policy makers and emergency managers for risk assessment. Ideally the required information on landslide occurrences is automatically and accurately extracted from satellite image data.

Unambiguous detection and classification of landslides relies on combined assessment of spectral, spatial, morphological and contextual parameters that help the analyst better to define the expert system rules, and subsequently classify a complex landscape (Minár and Evans, 2008; Navulur, 2007). Many defining landslide characteristics, such as those proposed by Varnes (1978), are not exclusively spectral in nature, but rather

relate to dimensions and spatial associations. Therefore, these characteristics need to be updated to be meaningfully employed in Object-oriented analysis (OOA), where they are included as class discriminators to detect landslides effectively.

Although OOA for landslide detection has been attempted in several earlier studies (Barlow et al., 2006; Martha et al., 2010a; Moine et al., 2009), a number of critical issues has not yet been addressed comprehensively. These concern: 1) finding reliable means to segment potentially complex landslides, including those that appear distorted, are partly obscured by topographic shadow, or are internally strongly heterogeneous; 2) identifying and extracting suitable object characteristics that allow landslide-type specific identification; and 3) hard coding of the landslide diagnostic parameters in OOA. Using high-resolution Cartosat-1 imagery (2.5 m, and along-track stereo capability), and Resourcesat-1 multispectral imagery (5.8 m), we investigate two active landslide areas in the Indian Himalayas, thereby exploring the potential of OOA for a new class of high resolution data, and in a challenging terrain where image distortion, occlusion and spectral heterogeneity are common.

In this paper our objective is to optimise segment boundaries with a combination of segmentation algorithms and classification strategy to address the complex shape and size of a landslide (Figure 1). In the following section we briefly discuss various segmentation methods from an automatic landslide detection perspective.

* Corresponding author.

1.1 Segmentation Methods

Image segmentation is an essential step for object-based automatic feature extraction techniques. It is a spatial clustering technique that completely subdivides the image into non-overlapping regions or segments. Segmentation methods can be broadly classified into two categories (Harris et al., 1998; Möller et al., 2007): 1) edge-based methods in which image edges are detected using a thresholding of the image gradient obtained from a differentiation filter, following which the detected edge pixels are connected to form the boundary of a segment; and 2) region-based methods in which a region (group of pixels) is detected either by growing a 'seed' pixel until the fulfilment of the homogeneity criteria, or by splitting the entire image initially and then merging the homogeneous regions. However, according to Harris et al. (1998), edge grouping has difficulties in producing connected boundaries.

The availability of commercial software packages, such as Definiens Developer, ERDAS Objective and Envi Zoom, and high resolution earth observation (EO) data (e.g. IKONOS, QuickBird and Cartosat-1) led to increasing research into segmentation techniques for automatic feature extraction in recent years, even though their conceptual roots go back several decades (Haralick and Shapiro, 1985). Segmentation fundamentally aims at the creation of homogenous units, using techniques as diverse as texture-based segmentation by extracting local histograms with Gabor wavelet techniques (Hofmann et al., 1998), and by Markov random fields and simulated annealing. Other approaches are edge-based, such as the method using representativeness values of each pixel proposed by Hofman and Bochner (1999). Increasingly the Fractal Net Evolution Approach (FNEA) has been used for segmentation of multispectral images. FNEA segments the image at both fine and coarse scales, depending upon the scale of interest, using a fuzzy set theory (Hay et al., 2003). FNEA, embedded in Definiens software is known as multi-resolution segmentation (Baatz and Schape, 2000). It is a bottom-up region merging technique starting with one pixel that continues in several steps until the fulfilment of an user-defined homogeneity criterion (Benz et al., 2004). One of the noticeable features of segmentation in Definiens is its capability to produce high quality, reproducible objects at different scales, also by allowing auxiliary data, such as vector layers, to be incorporated in the segmentation steps. This has led to its use in several novel applications, such as automatic vehicle detection, change detection studies, information extraction from analogue maps, and geomorphological process understanding (Barlow et al., 2006; Dragut and Blaschke, 2006; Holt et al., 2009; Kerle and de Leeuw, 2009; Laliberte et al., 2004).

Division of the image into meaningful objects, however, remains a great challenge for any image segmentation technique. Blaschke et al. (2006) emphasised the difficulty of defining the term 'meaningful object', stating that "segments in an image will never represent meaningful objects at all scales, for any phenomena". Therefore, optimisation of the phenomena (e.g. landslide) is the most plausible solution.

Spatial autocorrelation is a good indicator for the evaluation of image segments, particularly those obtained by region-based segmentation algorithms. Espindola et al. (2006) proposed an objective function, which is a combination of a spatial autocorrelation index (e.g. Moran's I index) and a variance indicator, to assess the segmentation quality and to find optimal segmentation parameters. We used this approach to find

optimum parameters for segmentation as the basis for automatic extraction of landslides, since, unlike Möller et al.'s (2007) method, it does not require a priori knowledge that is typically unavailable immediately after a disastrous event.



Figure 1. Field photographs showing the complex shape, size and land cover association for various types of landslides.

2. DATA SET, AREA AND METHODOLOGY

2.1 Data Set

High resolution satellite data and digital elevation models (DEM) are primary requirements for modelling Earth surface processes such as landslide. In this study, Resourcesat-1 LISS-IV multispectral data were used for image segmentation and derivation of spectral characteristics of landslides. These are 8 bit data with 5.8 m ground sampling distance. The multispectral channels are in green (0.52 to 0.59 μm), red (0.62 to 0.68 μm) and near infra-red (0.76 to 0.86 μm). Stereoscopic data from Cartosat-1 were used for the extraction of a 10 m gridded DEM, using digital photogrammetric techniques. Cartosat-1 provides 10 bit along-track stereoscopic data with a 2.5 m ground sampling distance. Reduced radiometric variation between the images of the stereo pair, and the provision of rational polynomial co-efficients, make Cartosat-1 data suitable for fast and accurate extraction of DEMs (Martha et al., 2010b). These data have also been shown to be useful for mapping of major and minor landslides by visual interpretation technique in the aftermath of Kashmir earthquake in October 2005 (Vinod Kumar et al., 2006). Subsequently, DEM derivatives such as drainage, hillshade, flow direction, slope and terrain curvature, and image derivatives such as reflectance and NDVI were generated.

2.2 Study Area

In this study, we used the above mentioned datasets for automatic detection of landslides for two areas in the Himalayas (Figure 2), which are global hotspots for landslide hazard (Nadim et al., 2006). Both study areas are perennially vulnerable to landslides, since the Main Central Thrust (convergence boundary between Indian and Eurasian plates) passes through them.

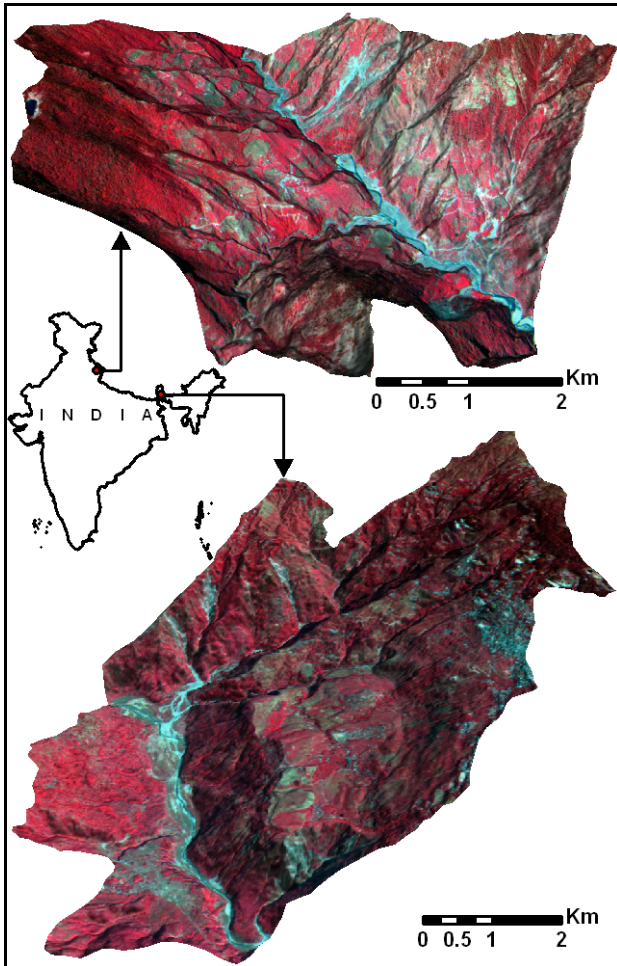


Figure 2. Location map of study areas shown in a 3D perspective. Okhimath (above) and Darjeeling (below).

2.3 Methodology

2.3.1 Optimisation of Segments: Typical optimisation procedures aim at minimising the under- and over-segmentation to increase the efficiency and accuracy of a classification technique. We specifically address segmentation as an iterative process, where an overall analysis may contain several segmentation stages of different types and for different purposes, and approach classification both explicitly and implicitly (Kerle and de Leeuw, 2009). We take full advantage of Definiens Developer's potential to segment an image without a priori knowledge, which is well suited for rapid detection of landslides in any terrain in the aftermath of an earthquake or strong rainfall event. In Definiens Developer software image segmentation is controlled by scale, colour and shape, with the shape being composed of compactness and smoothness (Benz et

al., 2004). The scale parameter is a function of resolution of the image and is used to control the maximum allowed heterogeneity of the objects. This means a lower scale parameter yields higher number of segments.

Similar to other object-based land cover studies with optical remote sensing data, we have given maximum weights for spectral heterogeneity, i.e. colour, and minimum weights for shape heterogeneity, since shape and size are not the characteristic features of a landslide, unlike for man-made features such as buildings, roads and vehicles or highly textured, panchromatic SAR images. The weights for heterogeneity of compactness and smoothness were maintained equal due to similar reasons. Most uncertainty lies in the selection of scale factors to adequately derive the landslide segments, given their large size variability.

We used Espindola et al.'s (2006) objective function, which is a combination of intrasegment variance and Moran's I index, to select scale parameters for the creation of landslide defining objects. The highest value of the objective function is a statistical indicator of the most appropriate segmentation of the image. However, a feature of variable sizes, such as landslide, can typically not be delineated with a single scale parameter. Therefore, instead of selecting a single scale factor with highest objective function value, we considered scale factors corresponding to peak values in the plateau area of the objective function curve (Figure 3). In the analysis, the scale factor with the highest objective function (e.g. 16 for the Okhimath area) is treated as the main object level, and others are considered as sub-object levels (e.g. 13 for Okhimath area) (Figure 3). Scale factors higher than the statistically optimum scale factor (e.g. 23 for Okhimath area) in the plateau area were not considered since larger segments, in principle, can not effectively delineate small size landslides. This means super objects with scale factor higher than the statistically optimum objects are not considered for analysis. Initially we used objects obtained with the lowest scale factor in the plateau region for first level classification using NDVI values, and subsequently these landslide candidates were again segmented with a highest scale factor in the plateau region, with the resulting objects being used for further classification. This helps reducing oversegmentation of some of the larger landslides and application of shape parameters to their classification and elimination of false positives.

2.3.2 Creation of landslide candidates: One of the other significant features observable on the ground after the occurrence of a landslide is the loss of vegetation, and exposure of the fresh rock and soil. This change in land cover leads to an increase in local brightness of the image, and can very well be represented by normalised difference vegetation index (NDVI), which is sensitive to low levels of vegetation change. For this reason, previous researchers have used NDVI as an effective discriminator for separating landslides from vegetated areas e.g. (Barlow et al., 2006; Moine et al., 2009). We estimated NDVI from the top of atmosphere (TOA) reflectance.

To separate landslide candidates from vegetated areas for reduction of oversegmentation, an iterative thresholding method was used. This method is simple since the problem of selecting a bin size, an essential requirement for histogram-based thresholding methods, can be avoided and also no human intervention is required. This method is suitable since the objective is to separate dark objects (lower NDVI corresponding to landslide candidates) from bright objects

(higher NDVI corresponding to vegetation). Therefore, we initially selected mean NDVI as threshold with an assumption that if the objects are darker than the background, then they should lower than the mean (Figure 4). This iterative algorithm is a special one-dimensional case of the k-means clustering algorithm, which has been proven to converge at a local minimum. NDVI thresholding was performed in following three steps.

1. $T_v = \text{meanNDVI}$
2. $f(\text{Object}) = \begin{cases} LC & \text{if } f(\text{Object}) \leq T_v \\ VA & \text{if } f(\text{Object}) > T_v \end{cases}$
3. $T'_v = \frac{\text{meanNDVI}_{LC} + \text{meanNDVI}_{VA}}{2}$

Now T'_v , which is an average of mean of landslide candidates (LC) and vegetated areas (VA) becomes the new threshold. The iteration with classification and thresholding continues until the new threshold becomes equal to the old threshold value i.e. the threshold becomes stable.

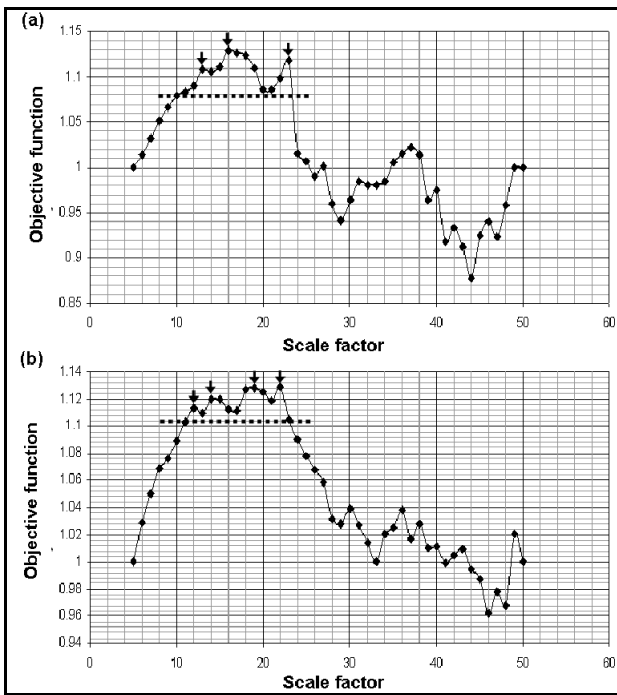


Figure 3. Graph showing variation of objective functions due to change in scale factor for (a) Okhimath and (b) Darjeeling. Scale factors corresponding to the peaks (shown with arrows) in the plateau area (above dotted line) were considered for analysis.

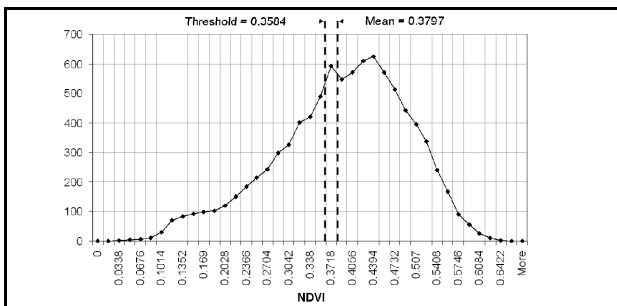


Figure 4. Threshold value obtained by iterative method.

2.3.3 Automatic Landslide Detection Technique: Landslides are a natural mass wasting process, and terrain characteristics have a major influence on their occurrence. Detection of landslides in object-based analysis strongly depends on many factors, such as their typology, frequency of occurrence, size, land cover, or relief. Therefore, a DEM and its derivatives, such as slope and flow direction, are critical to the successful detection of landslides. However, since NDVI is used as a threshold, false positives having lower or equal NDVI values such as road, river sand, built-up area and barren rock are also detected. These false positives can sequentially be eliminated by integrating other contextual information (Martha et al., 2010a).

Barlow et al. (2006) used high resolution SPOT 5 data, DEM and image segmentation to classify landslides into debris slide, debris flow and rockslide. Only recently, Martha et al. (2010a) comprehensively characterised the spectral, spatial and morphometric diagnostic features of landslides in order to recognise and classify them using OOA. They successfully identified landslides and false positives and used adjacency conditions of some of the false positives to classify landslides based on its typology. In this paper, we adapted the methodology of automatic landslide detection proposed by Martha et al. (2010a) to the optimised segments for detection of landslides. Subsequently, unsupervised/supervised thresholding was applied to the critical landslide diagnostic features, such as NDVI, relative relief, slope, terrain curvature, hillshade and flow direction, derived from a high resolution multispectral image and DEM (Figure 5). Landslide impurities such as very small undisturbed areas with vegetation within larger landslide bodies were removed with chessboard segmentation (Martha et al., 2010a). Thus an accurate outline and area of a landslide is identified which is essential for landslide hazard zonation studies. The object-based algorithm developed for detection of landslides is available on our website (www.itc.nl/OOA-group).

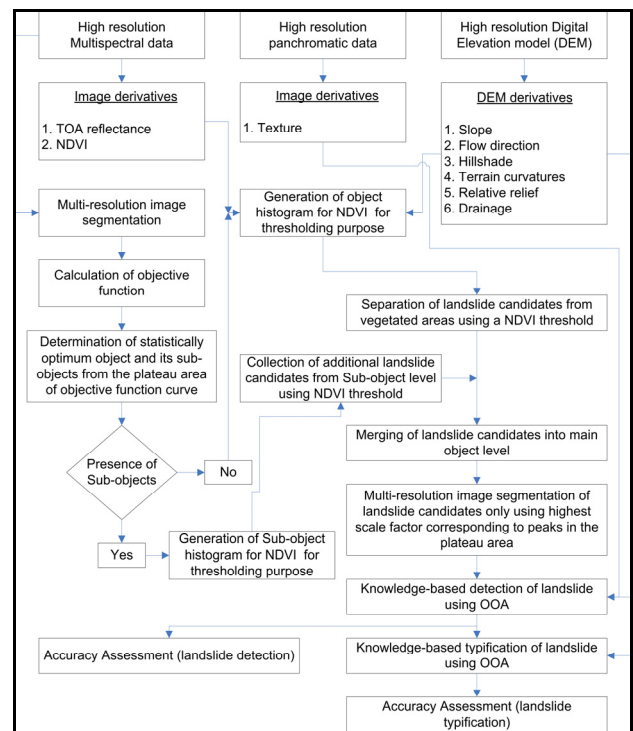


Figure 5. Methodology for landslide detection.

3. RESULTS AND DISCUSSION

The method was tested in two landslide affected areas having different geomorphological set up and land use / cover association with respect to landslides. Objects obtained from multiresolution segmentation of 5.8 m multispectral data with a statistically optimal scale factor were able to delineate major landslide boundaries in both study areas. However, a few landslides could not be delineated. For example, objects obtained with scale factor 23 were not able to completely delineate the flank of a large landslide in the Darjeeling area due to relatively poor contrast with surrounding area (Figure 6). However, scale factor 12 provides landslide defining objects for such areas. Therefore, the latter was used to create landslide candidates using a NDVI threshold value 0.3584 obtained using iterative threshold method. The value was stored as a global variable and is independent of data types and classification strategy. Subsequently, all landslide candidates were resegmented with scale factor 23 for sequential elimination of landslide false positives. The resegmentation helped in reduction of over segmentation while preserving the outline of landslides (Figure 6).

The smallest and largest landslide detected by this method in Okhimath and Darjeeling areas are 706 and 292591 m², and 1400 and 92725 m², respectively. An expert system rule set developed using characteristic landslide features was applied to classify landslides. In total five types of landslides were detected using OOA (Figure 7). We observed that few landslides were missed from detection and few are wrongly detected as landslides. This occurred due to lack of adequate landslide diagnostic features, although, they were outlined as segments by the optimisation procedure.

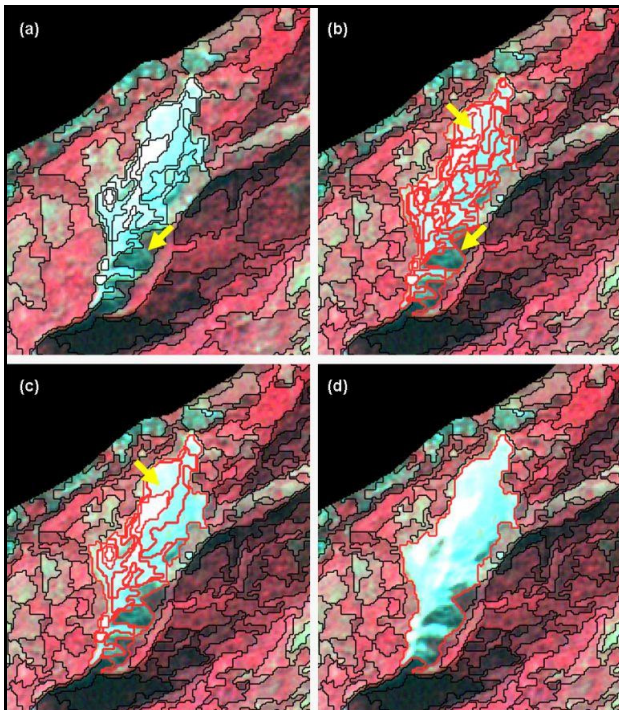


Figure 6. Effect of segment optimisation on a large landslide in the Darjeeling area. (a) Objects with scale factors 23, (b) Objects with scale factor 12 and classification based on NDVI thresholding (outlined in red), (c) merging and segmentation of landslide candidates with scale factor 23, and (d) merging of

landslide candidate objects of large landslide into single object for classification into landslide types. Major changes are highlighted with yellow arrows.

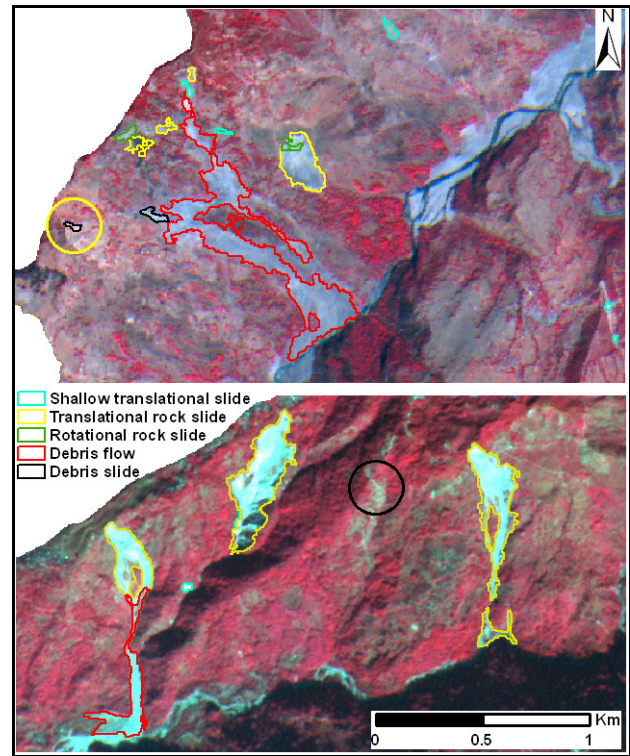


Figure 7. Landslides detected using object-based image analysis in Okhimath (above) and Darjeeling (below) areas. Landslides which could not be detected and wrongly detected are highlighted with black and yellow circles, respectively.

4. CONCLUSION

High resolution satellite data and DEM were used to detect landslides using OOA. Objective function was found to be a suitable indicator to select parameters for segmentation in the beginning of the analysis and helps in avoiding subjectivity. However, instead of a single parameter corresponding to the highest objective function value, multiple scale parameters in the plateau region, i.e. with minor difference to the highest objective function value, were found to be more suitable for the detection of landslides, given their greatly varying shape and size. Segment optimisation using the result of intermediate classification is not only able to create objects for small landslides, but also reduces oversegmentation of large landslides and classifies landslides based on material and movement characteristics. Finally, landslide objects were further optimised with chessboard segmentation. The main advantage of the methodology demonstrated in this paper is that no *a priori* knowledge is required to optimise segments, which makes it suitable typically suitable for a rapid response to disastrous landslide events. The segment optimisation procedure was created using Definiens developer software and responded well to delineate segments for both small and large landslides surrounded by vegetated areas. We are further working on how to optimise landslide segments, particularly in areas where it is surrounded by unvegetated land and how to remove use of hard thresholds during landslide detection.

References

- Akçay, H.G. and Aksoy, S., 2008. Automatic detection of geospatial objects using multiple hierarchical segmentations. *IEEE Transactions on Geoscience and Remote Sensing*, 46(7), pp. 2097-2111.
- Baatz, M. and Schape, A., 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. In: Strobl, L.J., Blaschke T. and Griesebener T. (Eds.), *Angewandte geographische informationsverarbeitung XII, Beitrage zum AGIT Symposium Salzburg 2000*. Herbert Wichmann Verlag, Heidelberg, pp. 12-23.
- 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), pp. 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), pp. 239-258.
- Blaschke, T., Burnett, C. and Pekkarinen, A., 2006. *Image segmentation methods for object-based analysis and classification*. In: S.M. de Jong and F.D. van der Meer (Editors), *Remote sensing image analysis: including the spatial domain*. Springer, Dordrecht, The Netherlands, pp. 211-236.
- Dragut, L. and Blaschke, T., 2006. Automated classification of landform elements using object-based image analysis. *Geomorphology*, 81(3-4), pp. 330-344.
- Espindola, G.M., Camara, G., Reis, I.A., Bins, L.S. and Monteiro, A.M., 2006. Parameter selection for region-growing image segmentation algorithms using spatial autocorrelation. *International Journal of Remote Sensing*, 27(14), pp. 3035-3040.
- Haralick, R.M. and Shapiro, L.G., 1985. Survey: Image segmentation techniques. *Computer Vision, Graphics, and Image Processing*, 29(1), pp. 100-132.
- Haris, K., Efstratiadis, S.N., Maglaveras, N. and Katsaggelos, A.K., 1998. Hybrid image segmentation using watersheds and fast region merging. *IEEE Transactions on Image Processing*, 7(12), pp. 1684-1699.
- Hay, G.J., Blaschke, T., Marceau, D.J. and Bouchard, A., 2003. A comparison of three image-object methods for the multiscale analysis of landscape structure. *ISPRS Journal of Photogrammetry and Remote Sensing*, 57(5-6), pp. 327-345.
- Hofmann, T. and Bohner, J., 1999. Spatial pattern recognition by means of representativeness measures. *IEEE*, 6/99.
- Hofmann, T., Puzicha, J. and Buhmann, J., 1998. Unsupervised texture segmentation in a deterministic annealing framework. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(8), pp. 803-818.
- Holt, A.C., Seto, E.Y.W., Rivard, T. and Gong, P., 2009. Object-based detection and classification of vehicles from high-resolution aerial photography. *Photogrammetric Engineering and Remote Sensing*, 75(7), pp. 871-880.
- Kerle, N. and de Leeuw, J., 2009. Reviving Legacy Population Maps With Object-Oriented Image Processing Techniques. *IEEE Transactions on Geoscience and Remote Sensing*, 47(7), pp. 2392-2402.
- Laliberte, A.S. et al., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sensing of Environment*, 93(1-2), pp. 198-210.
- Martha, T.R., Kerle, N., Jetten, V., van Westen, C.J. and Vinod Kumar, K., 2010a. Characterising spectral, spatial and morphometric properties of landslides for automatic detection using object-oriented methods. *Geomorphology*, 116(1-2), pp. 24-36.
- Martha, T.R., Kerle, N., van Westen, C.J., Jetten, V. and Vinod Kumar, K., 2010b. Effect of sun elevation angle on DSMs derived from Cartosat-1 data. *Photogrammetric Engineering and Remote Sensing*, 76(4), pp. 429-438.
- Minár, J. and Evans, I.S., 2008. Elementary forms for land surface segmentation: The theoretical basis of terrain analysis and geomorphological mapping. *Geomorphology*, 95(3-4), pp. 236-259.
- 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. Rémaitre and T. Bogaard (Editors), *Landslide Processes: from geomorphological mapping to dynamic modelling*. CERG, Strasbourg, France, pp. 63-68.
- Möller, M., Lymburner, L. and Volk, M., 2007. The comparison index: A tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation*, 9(3), pp. 311-321.
- Nadim, F., Kjekstad, O., Peduzzi, P., Herold, C. and Jaedicke, C., 2006. Global landslide and avalanche hotspots. *Landslides*, 3(2), pp. 159-173.
- Navulur, K., 2007. *Multispectral image analysis using the object oriented paradigm*. CRC Press, Boca Raton.
- OFDA/CRED, 2006. EM-DAT International Disaster Database - [\(2007-03-26\)](http://www.em-dat.net)
- Varnes, D.J., 1978. *Slope movements types and processes*. In: R.L. Schuster and R.L. Krizek (Editors), *Landslides: Analysis and Control*. Special Report 176. Transportation Research Board, National Academy of Sciences, Washington D.C., pp. 11-33.
- 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), pp. 4449-4459.