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RESEARCH ARTICLE

Identification of new Landslides from High Resolution Satellite Data Covering a Large Area Using Object-Based Change Detection Methods

Tapas R. Martha[1] · P. Kamala[2] · Josna Jose[3] · K. Vinod Kumar[1] · G. Jai Sankar[2]

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Abstract Change detection using time series satellite images is one of the most widely used techniques to identify new landslides. Object-based change detection (OBCD) allows incorporation of expert knowledge in the form of spectral, morphometric and contextual criteria leading to a higher classification accuracy in comparison to pixel-based methods. In this study, an approach is developed to detect new landslides using bitemporal Resoursesat-2 LISS-IV multispectral images (5.8 m) with objects extracted from the post-landslide image by the Multi resolution segmentation (MRS) technique. A new tool developed using Python script, systematically created tiles of the input data to a user defined grid, and thus facilitated efficient analysis of large volume of high resolution satellite data. Combined use of spectral parameters such as top of atmosphere reflectance, green normalised difference vegetation index, principal component analysis and morphometric parameters such as slope and drainage derived from a 10 m digital elevation model resulted in 80.9 % detection accuracy of new landslides. Further, a low branching factor (0.09) shows that less false positives were identified by OBCD indicating the suitability of the method to detect new landslides.

✉ Tapas R. Martha
trmartha@rediffmail.com; tapas1977@gmail.com

[1] Geosciences Group, National Remote Sensing Centre (NRSC), Indian Space Research Organization (ISRO), Hyderabad 500 037, India

[2] Department of Geo-Engineering, Andhra University College of Engineering, Vishakhapatnam 530 003, India

[3] Department of Geology, Central University Karnataka, Gulbarga 585 311, India

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Introduction

Landslides are important denudational processes in mountainous areas that frequently damage means of communication and transportation besides causing loss to property and life. According to the International Landslide Centre in Durham University, majority of human losses due to landslides occur in Asia, particularly in the Himalayas (Petley 2012). Extreme rainfall and high magnitude earthquakes are the predominant triggering factors for occurrence of landslides (Vinod Kumar et al. 2003; Gorum et al. 2011; Lin et al. 2011; Xu et al. 2013; Martha et al. 2014). Immediate detection of landslides and identification of affected areas are key requirements for planning post-disaster rescue and relief operations (van Westen et al. 2008). This is mainly done through identification of landslides from post-disaster satellite images since creation of a field-based inventory in inaccessible mountainous terrains is a difficult task.

Loss of vegetation and exposure of fresh rock and soil after landsliding increases the local brightness in the image (Lu et al. 2011; Martha et al. 2012). These characteristics of landslides are mostly used during image interpretation for identification of landslide scars. However, due to increasing spatial resolution images' availability from more civilian satellites and improvement in image analysis techniques, identification of changes in terrain due to landsliding has gradually shifted from time consuming manual methods to rapid automatic methods (Cheng et al. 2004; Begueria 2006). Object-based image classification has proved to be an effective technique for fast retrieval of information from satellite images for various natural disasters (Lu et al. 2011; Stumpf and Kerle 2011;

Mallinis et al. 2012; Martha et al. 2012; Behling et al. 2014; Moosavi et al. 2014).

Detecting landslide related changes from satellite image using pixel-based or object-based approaches have been attempted by previous researchers (Nichol and Wong 2005; Lu et al. 2011; Chen et al. 2012; Martha et al. 2012; Tewkesbury et al. 2015). While pixel-based change detection methods are limited by availability of only spectral and textural information, object-based change detection (OBCD) methods exploit spectral, spatial, shape and morphometric properties of landslides, and by incorporating expert knowledge, producing highly accurate results (Lu et al. 2011; Myint et al. 2011; Hussain et al. 2013; Mahmoudi et al. 2015; Tewkesbury et al. 2015). Hussain et al. (2013) described different types of change detection techniques that can be applied to remotely sensed data. Direct comparison by image differencing and classification-based comparison are the two predominant methods used in studies that involve OBCD techniques. Object-based image analysis (OBIA) is more effective than pixel-based methods if the classes have high internal variability and classes of interest cover large area, usually more than single pixel (Blaschke 2010; Mondini et al. 2011). Natural features such as landslides are better represented by an object than a pixel because they are generally of irregular shape and variable size.

In OBIA, classification is done on objects instead of single pixels and image segmentation is the first step for such classification methods. Success of OBIA depends upon the segmentation technique that meaningfully extract objects which can accurately describe the properties of the features of interest. Multiresolution segmentation (MRS), is the most common segmentation technique used in OBIA for classification of remote sensing images (Kumar and Roy 2013; Blaschke et al. 2014; Dragut et al. 2014). MRS partitions an image into spatially contiguous, mutually connected and homogeneous regions at various segmentation levels (Baatz and Schäpe 2000; Blaschke et al. 2006). MRS starts considering each pixel as an object and merges them to create larger objects based on homogeneity thresholds defined by the analyst (Benz et al. 2004; Blaschke 2010). MRS also produces objects at different scales and has been used in object-based detection of landslides by previous researchers (Martha et al. 2010; Stumpf and Kerle 2011). However, significant challenges still persist when OBIA for landslide detection has to be performed for a large area using high resolution satellite data. Only recently few researchers (e.g. Behling et al. 2014) have attempted to detect landslides over a large area by OBIA using high resolution satellite data.

In this study, we applied OBCD technique to identify new landslides by comparing the pre-and post-landslide Resourcesat-2 LISS-IV multispectral images of 5.8 m spatial resolution. The method was tested in the Uttarakhand state of India where several landslides occurred due to a rainfall event during 15–17 June, 2013. Object-based analysis of a full scene high resolution LISS-IV multispectral image over a large area (~6000 km^2) demanded high computational requirement due to large volume of image data. To address this issue, a new tool was developed in ArcGIS using Python script to automatically generate image tiles from a full scene of image and applying OBCD technique to individual tiles, resulting in increase in efficiency of the whole procedure.

Materials and Methods

Study Area

An area in the Chamoli and Rudraprayag districts of Uttarakhand state in India was selected for identification of recent landslides (Fig. 1). This area is historically known for occurrence of landslides and related damage to roads and buildings besides death of people (Vinod Kumar et al. 2003; Martha and Vinod Kumar 2013). In the year 1998, several parts of Uttarakhand Himalayas witnessed large scale occurrence of landslides due to heavy rainfall (Paul et al. 2000). Recently, during 15–17 June 2013, this area again witnessed a large number of landslide occurrences due to an extreme rainfall event (Martha et al. 2013). Alaknanda river and its tributaries such as Mandakini, Pindar, Nandakini and Birahi constitutes the main drainage system of this area. Gopeshwar, Okhimath, Agastmuni, Guptkashi, Karnaprayag and Joshimath are some of the major settlements within the study area. The maximum and minimum elevations are 7000 m and 520 m, respectively.

Data Used

Resourcesat-2 LISS-IV multispectral satellite data having three spectral bands (green, red and near infrared) corresponding to pre- and post-landslide event were used for identification of landslides by OBCD techniques. DEM was extracted from the stereoscopic Cartosat-1 images. Cartosat-1 carries two panchromatic cameras, Pan-Aft (−5°) and Pan-Fore (+26°), which acquire images along the track of the satellite pass. The data are provided with rational polynomial coefficients (RPCs) for block triangulation and creation of DEMs. In this study, an available 10 m DEM extracted from stereoscopic Cartosat-1 satellite data was used for detection of landslides. Details of the satellite data used in this study are given in Table 1.

Methodology

A knowledge-based approach was developed in eCognition 9.0 software to perform image segmentation and OBCD for detection of landslides. Hydrology module of ArcGIS software was used to derive drainage network from DEM. The methodology adopted in this study is shown in Fig. 2.

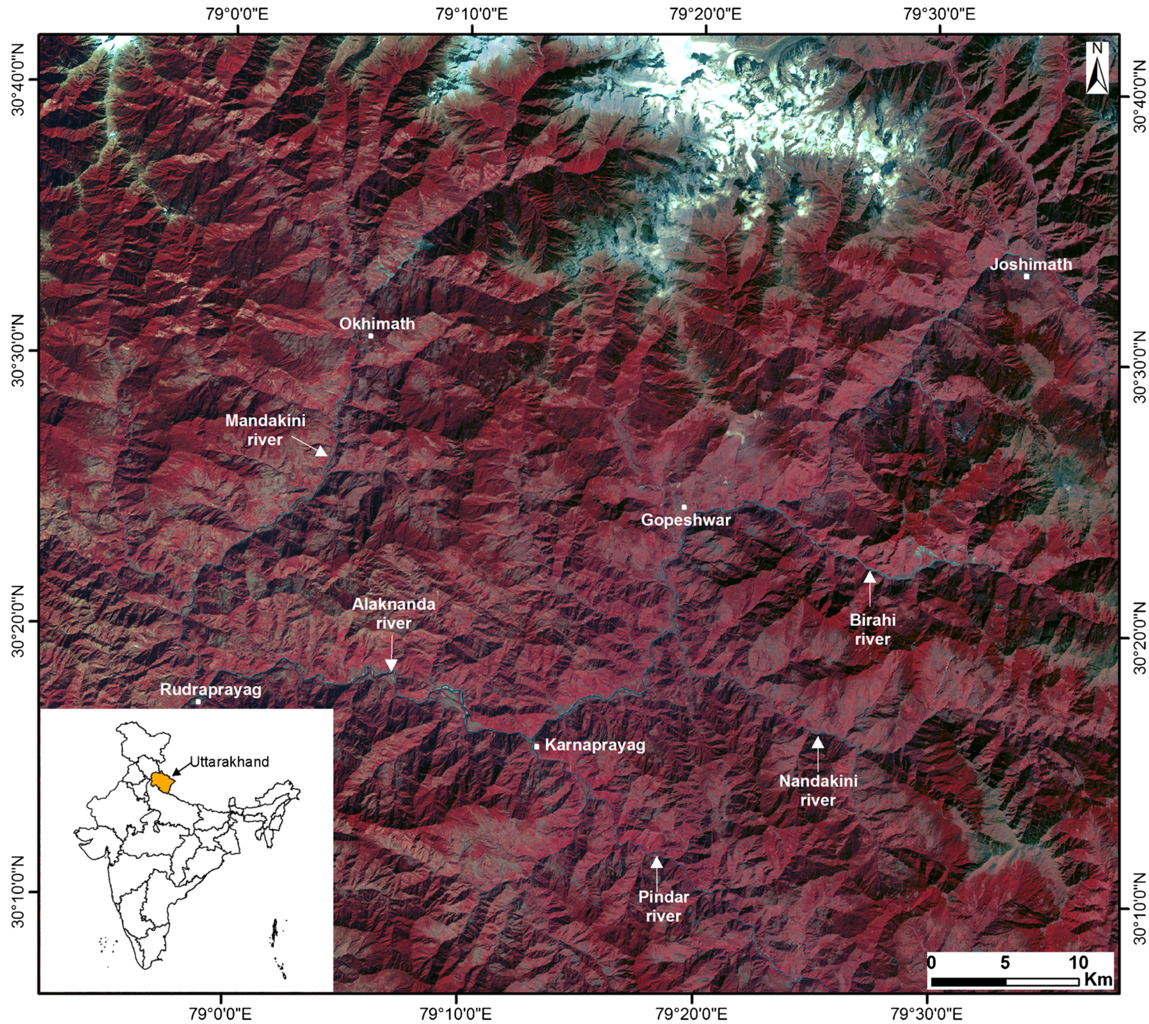

Fig. 1 Map showing location and extent of the study area

However, to apply this methodology to a large area, we developed a new tool in ArcGIS using Python script that partitions the input data such as high resolution satellite image, DEM and its derivatives into tiles, which were then processed separately in eCognition 9.0 software.

Image Pre-Processing

Image-to-image registration of time series satellite data is a primary requirement in any change detection study (Prenzel and Treitz 2004). Orthorectified Resourcesat-2 LISS-IV multispectral pre- and post-landslide images were further corrected using the AutoSync module of ERDAS Imagine software to have a better pixel level match. The RMS error obtained after the image co-registration was 0.92 pixel, which is adequate for change detection study (Xu et al. 2010). Other image pre-processing procedures adopted in this study include calculation of top of atmosphere (TOA) reflectance, which is necessary to compensate for variable sun illumination condition due to seasonal difference in image acquisition (Mondini

Table 1 List of data used for identification of landslides

Data used	Date of acquisition	Bands	Path/Row	Source	Resolution
Resourcesat-2 LISS IV multispectral	01 December 2013 (post-landslide)	Green (0.52–0.59 μm) Red (0.62–0.68 μm) Green (0.77–0.86 μm)	97/49D	ISRO	5.8 m
Resourcesat-2 LISS IV multispectral	23 May 2013 (pre-landslide)	-do-	-do-	-do-	-do-
DEM	—	—	—	-do-	10 m

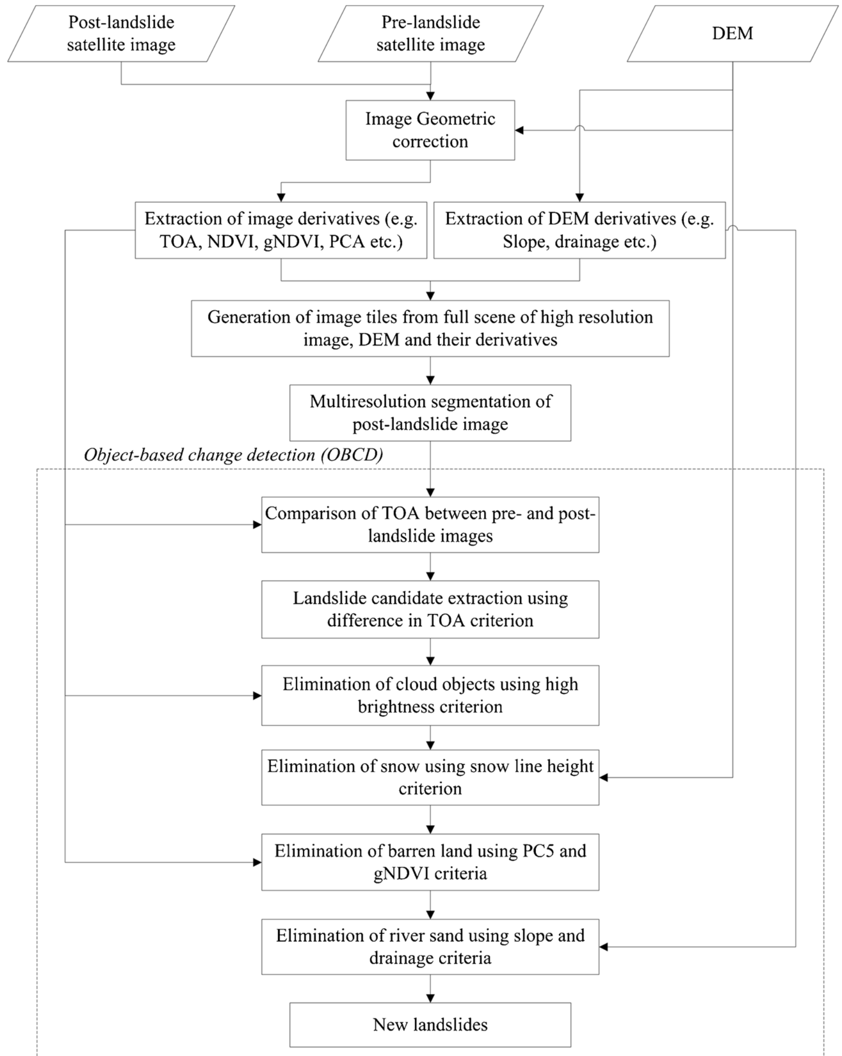

Fig. 2 Methodology flowchart to detect new landslides for a large area using object-based change detection (OBCD) method

et al. 2011; Martha et al. 2012). Subsequently, green normalised difference vegetation indices (gNDVI) were derived from the TOA images and used for identification of landslide false positives (Holbling et al. 2015). Additional spectral parameters such as temporal principal component analysis (PCA) using stacked pre- and post-landslide Resourcesat-2 LISS-IV multispectral images were also extracted. Temporal PCA is effective for detection of landslides as well as elimination of landslide false positives (Lu et al. 2011).

Creation of Image Tiles

Multi-spectral high resolution images have a large data volume. For example, a three band 5.8 m resolution Resourcesat-2 LISS-IV multispectral image with 70 km swath has approximately 1.6 GB file size. MRS with a small scale parameter and OBIA of satellite image of such large file size requires considerable time even with a fast processor. Therefore, it is a challenging task to provide immediate results from high resolution images immediately after a landslide disaster for large areas such as the Himalayas. In this type of situations, it is better to divide the high resolution image covering a large area into tiles and then carry out the analysis of each tile independently. Finally, the result of each tile can be combined to produce the output of the entire area in a reasonably less time.

Every country has a gridded (e.g. 1°×1° or 0.25°×0.25°) referencing system for topographic maps with each grid having a unique code. The topographic grid adopted by the Survey of India (SOI) was used in this study for systematic tiling of the input data that covers a large area (Fig. 3). We developed a tiling tool using Python script. The tool is compatible with ArcMap 10.1 and its subsequent versions. The tile tool automatically clips the input data such as satellite image, DEM and its derivatives into multiple files depending upon the selection of a grid. The tool developed to generate subsets or tiles for a given large dataset has three options. The first option allows the user to create one degree tiles of the input data, then the tool searches first three characters of the unique grid code and dissolves the smaller grids within the one degree grid into one polygon and then performs the clipping operation. The second option allows the user to create 0.25°×0.25° tiles, then the tile tool searches all characters of the grid code and then performs the clip operation. The third option allows the user to tile within an area of interest (AOI) instead of full area, then the tool will only create tiles of the input data within the AOI instead of full image scene (Fig. 3). The user also has an option to specify a buffer distance around the grid boundary, which is provided since image segmentation and OBIA sometimes are influenced by the border pixels. The buffer option is also useful if landslides occur in the grid boundary. All outputs of the tile tool are stored in a user defined folder with grid codes assigned automatically as prefix to the filename.

Image Segmentation

We used the MRS technique available in eCognition 9.0 to segment the image and extract objects for change detection and identification of landslides. MRS is a bottom up region merging technique and is demonstrated to be effective for segmentation of multispectral image (Baatz and Schäpe 2000; Benz et al. 2004). We used scale parameter 20 to segment the LISS-IV Mx data by assigning equal weightages to all three bands of the satellite image. The scale parameter was selected using the plateau objective function (POF) method proposed by Martha et al. (2011). Colour i.e. spectral property, was given maximum (0.9) weightage while shape was given minimum (0.1) weightage since landslides occur with variable shapes.

Object-Based Change Detection (OBCD)

Two frequently used methods of OBCD are: i) direct object change detection and ii) classified object change detection (Hussain et al. 2013). In the first approach, objects derived from the image acquired at time T_1 were compared for change in geometrical and spectral properties with respect to the image acquired at time T_2. This approach is generally used when comparison is made between images acquired from same satellite sensors and generation of full change matrix is not an absolute requirement (Hussain et al. 2013). In the second approach, segmentation and classification are performed independently using time series images and the change matrix is derived after classification. The second approach is mostly used in land use/land cover change analysis and also when time series data are acquired by different satellite sensors. In this study, we used the first approach, since, the objective of

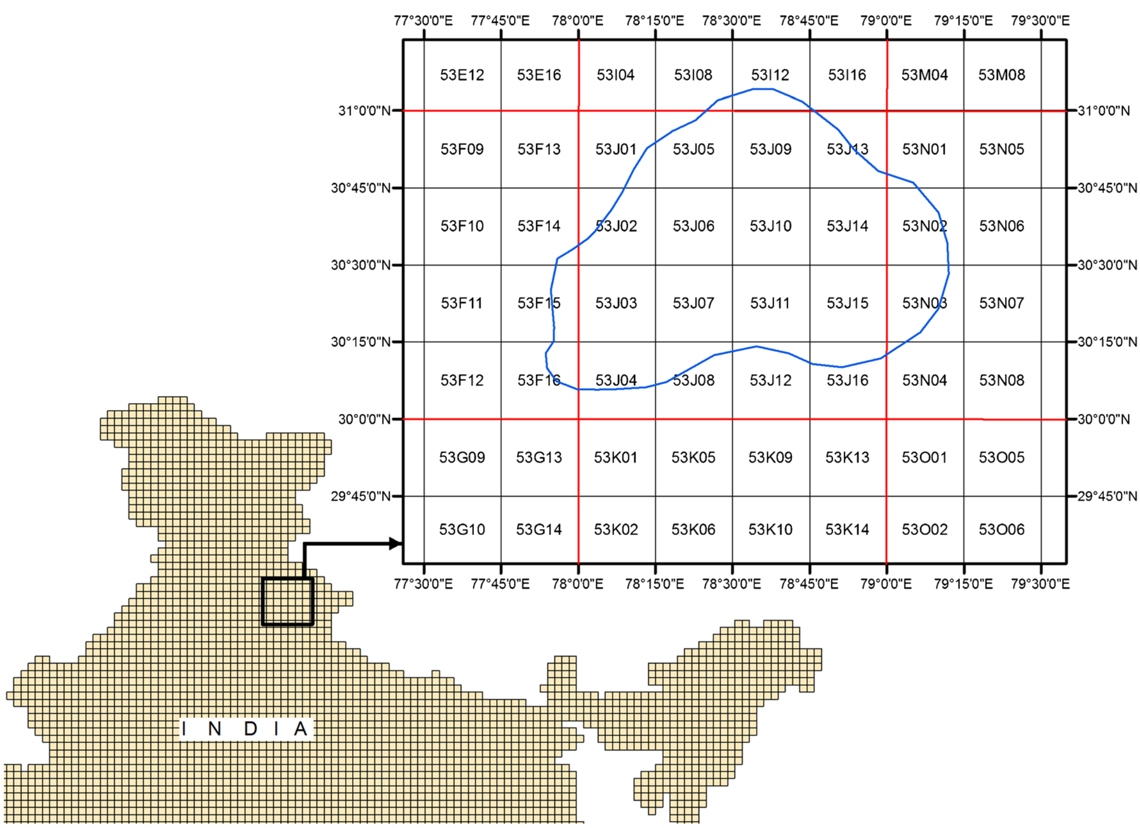

Fig. 3 Topographic mapping grid of northern part of India. Each one degree grid contains sixteen 0.25 degree grids. The area of interest (AOI) is shown as blue polygon

change detection was to identify only one feature viz. landslide, and the change was estimated from images acquired from the same sensor.

Using the MRS technique, we first segmented the post-landslide satellite image. Then, for each object we compared the TOA reflectance value of the post-landslide image with the pre-landslide image (Fig. 2). New landslides exhibit high reflectance/brightness due to loss of vegetation and exposure of fresh rock or soil to the sunlight. Therefore, those objects having higher brightness values in post-landslide image in comparison to the pre-landslide image were identified as landslide candidates. However, landslide debris derived from upstream areas and deposited in The Valley floor as river sands also had high brightness. Similarly, temporary bright objects such as snow has high brightness in the post-disaster image in comparison to pre-landslide image. These false positives were classified separately using spectral and contextual criteria (Fig. 2).

Results and Discussion

Input Data Tiles

A new tool was developed to create tiles of input data such as satellite image, DEMs and its derivatives. The graphic user interface (GUI) of the tool created as a toolbox for ArcGIS 10.1 software is shown in Fig. 4. Using this tool, we created 0.25°×0.25° tiles of input data by selecting the 'grid(50)' option available in the toolbox. Subsequently, the input data for each 0.25°×0.25° grid were processed separately for detection of landslides (Fig. 5). The advantage of this tool in comparison to the clip tool available in ArcGIS 10.1 or similar other softwares is that systematic tiling of input data covering a large area and file nomenclature of each tile is done at once for the whole scene/frame without user interaction. Tile wise processing of images not only helped efficient handling of data over a large area but also facilitated effective use of object parameter thresholds for identification of landslide false positives resulting in overall increase in the landslide detection accuracy.

Object Extraction and Detection of Landslides

Segmentation is an important component of the OBIA process flow that is used to extract objects as image primitives for classification. We used the MRS technique to derive objects for detection of landslides as done by previous workers (e.g. Martha et al. 2010; Stumpf and Kerle 2011). Objects derived from post-landslide image tiles by the MRS technique were compared for their brightness with the pre-landslide image. Only those objects having higher brightness value in post-disaster image in comparison to the pre-disaster image were classified as landslide candidates.

Landslide candidates with high brightness value include false positives such as river sand, snow and barren land. Identification of these false positives is essential to increase the accuracy of landslide detection method. River sands were identified using criteria such as adjacency to drainage lines and low slope angle (< 20°) as shown by Martha et al.

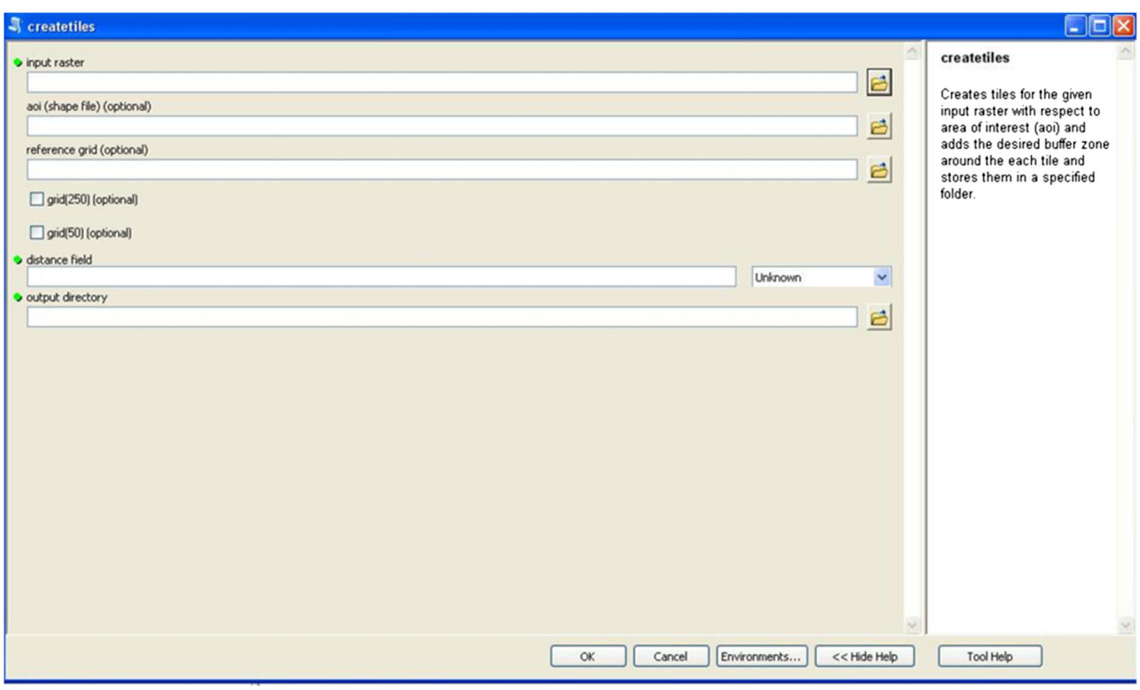

Fig. 4 Graphic user interface (GUI) of the tiling tool

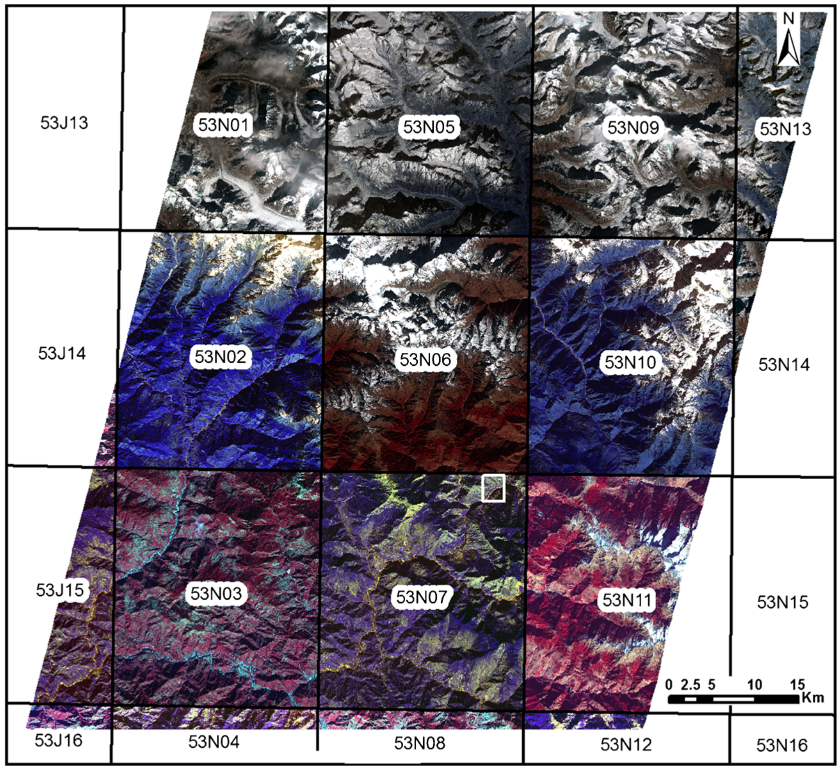

Fig. 5 Tiling of one frame of Resourcesat-2 LISS-IV multispectral image into 0.25°×0.25° grid. Images in each grid is shown alternatively with band combinations RGB = Green-Red-NIR and RGB = NIR-Red-Green to highlight that each grid corresponds to a separate file created by the tool

(2010). By combining these two criteria, landslides in steep slope but adjacent to river as well as landslides in gentle slope but away from the river were successfully detected (Fig. 6). Snow has high reflectance similar to landslides, and therefore is difficult to be eliminated as a false positive using the three band spectral information of LISS-IV. However, since snow accumulation is controlled by altitude, we used elevation criteria based on our local knowledge i.e. height of the snow line instead of spectral criteria to identify the snow cover.

Lu et al. (2011) have shown that PCA analysis is useful for detection of landslides as well as identification of false positives. In this study, we found that the fifth principal component (PC5) has a good correlation with barren land. Similarly, difference in gNDVI values between pre- and post-landslide images was also used to identify barren lands, particularly the escarpment areas. Therefore, to identify barren lands, we used a combination of PC5, gNDVI and low brightness values of the post-landslide image (barren lands were less brighter than new landslides). The criteria and thresholds used for identification of landslide candidates and false positives in grid no. 53 N07 are provided in Table 2. Once all false positives were identified, remaining landslide candidates correspond to new landslides.

Accuracy Assessment

To assess the accuracy of landslide inventory prepared by the OBCD method, we compared the change detection result with the landslide inventory prepared manually through image interpretation. We intersected both sets of landslide inventory database and calculated the following accuracy parameters for quantitative assessment of the landslide detection result (Shufelt 1999; Martha et al. 2012).

$$\text{Branching factor} = \frac{\text{False positive}}{\text{True positive}} \tag{1}$$

$$\text{Miss factor} = \frac{\text{False negative}}{\text{True positive}} \tag{2}$$

$$\text{Detection percentage} = 100^* \frac{\text{True positive}}{(\text{True positive} + \text{False negative})} \tag{3}$$

$$\text{Quality percentage} = 100^* \frac{\text{True positive}}{(\text{True positive} + \text{False negative} + \text{False positive})} \tag{4}$$

Detection percentage is treated as the measure of the performance of OBCD method. Branching factor is a measure of degree to which the change detection method overclassifies landslides and ideally should be zero (Shufelt 1999). Miss factor is a measure of the degree to which change detection method underclassifies the landslides and ideally should also be zero. Quality percentage indicates how likely a landslide identified by the change detection method is true (Lee et al. 2003). For the grid no. 53 N07 (Fig. 5), which shows maximum occurrence of landslides after the rainfall event of 15–17 June 2013, 80.9 % landslides could be detected by the OBCD method

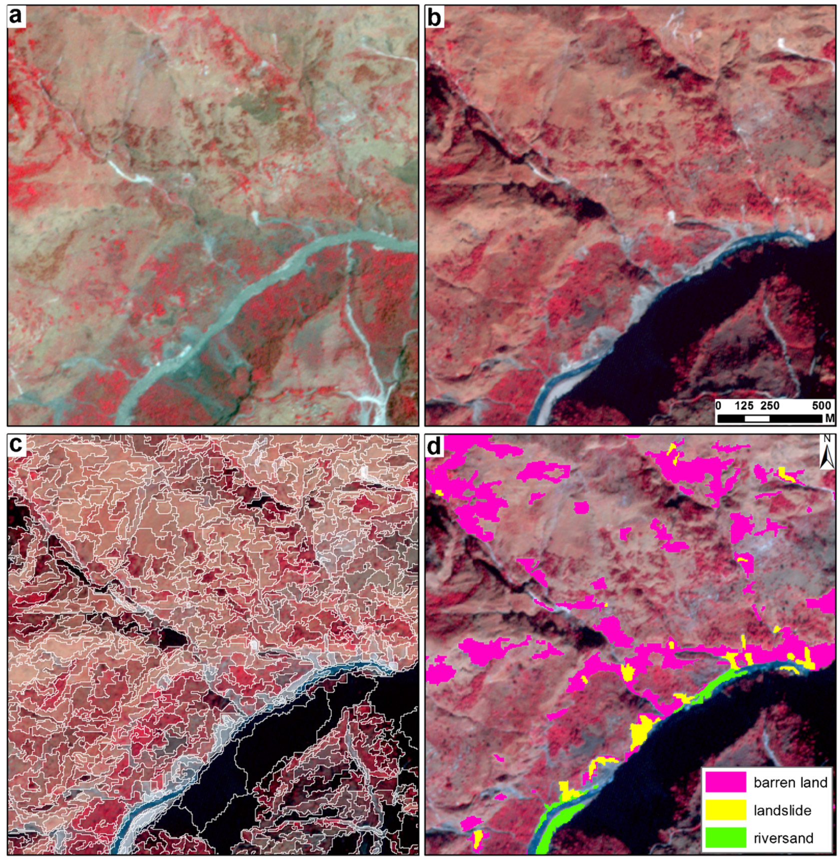

Fig. 6 Detection of landslides by direct object change detection. a. pre-landslide Resourcesat-2 LISS-IV multispectral image, b. post-landslide Resourcesat-2 LISS-IV multispectral image, c. Multi-resolution segmentation of the post-landslide image and d. new landslides and false positives detected using OBCD method. The area corresponds to white box in grid no. 53 N07 of fig. 5

with 75.3 % quality. As can be seen in Table 3, low values of branching factor (0.09) and miss factor (0.23) indicate an insignificant over and under classification of landslides.

Conclusions

In this study, OBCD method was applied to detect new landslides from post-event image by comparing the TOA reflectance values with the pre-event image. Segmentation of the post-landslide satellite image by the MRS technique was done to create objects for direct comparison. Difference in reflectance between pre- and post-landslide image was used to find landslide candidates. Subsequently, false positives such as snow, river sand and barren land were removed with the help of spectral, morphometric and contextual criteria derived from image and DEM.

OBCD over a large area using very high resolution images such as Resourcesat-2 LISS-IV was a challenging task. The new tile tool developed in this study could systematically partition the high resolution image and ancillary datasets into tiles which were then processed separately. The tool is created as a ready to use toolbox and can be used by any user to perform the clip operation using ArcGIS software.

Table 2 Criteria used to detect landslides by OBCD method

Class	Criteria	Threshold
Landslide candidates	TOA reflectance	Difference TOA reflectance ≥ -0.04
False positives		
Snow cover	Elevation	DEM $\geq$ 3500 m
Barren land	gNDVI	Difference gNDVI $\geq$0.08
	PC5	PC5 ≥ -17
	Post brightness	Post brightness $\leq$100
River sand	Slope	Slope $\leq$ 13°
	Drainage	$\leq$ 5 m

Table 3 Accuracy assessment of number of new landslide detected by OBCD method

Reference landslide	Detected landslide	True positive (Tp), False positive (Fp) and False negative (Fn)	Branching factor	Miss factor	Detection percentage	Quality percentage
377	334	Tp = 305 Fp = 29 Fn = 72	0.09	0.23	80.9	75.3

The detection accuracy of landslides achieved by this method was 80.9 %. A low value of branching factor (0.09) shows that spectral parameters such as TOA reflectance, PC5 and gNDVI were able to identify false positives effectively. Similar to any other satellite-based landslide inventory, the method described in this study could not detect landslides below cloud cover or topographic shadow regions. Additionally, some of the new landslides in the post-landslide image, although in a cloud and shadow free region, may not have been detected due to the presence of small patches of clouds in corresponding area of the pre-landslide image.

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