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A new technique for landslide mapping from a large-scale remote sensed image: A case study of Central Nepal

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Abstract. This paper presents a new technique for landslide mapping from large-scale Landsat8 images. The method introduces saliency enhancement to enhance the landslide regions, making the landslides salient objects in the image. Morphological operations are applied to the enhanced image to remove most background objects. Afterwards, digital elevation model is applied to further remove the ground objects of plain areas according to the height of landscape, since most landslides occur in mountainous areas. Final landslides are extracted by the proposal regions from selective search. The study area covers $2^{\circ} \times 2^{\circ}$, making it more similar with practical cases, such as emergency response and landslide inventory mappings. The proposed method performs satisfactorily by detecting 99.1% of the landslides in the image, and obtains an overall accuracy of 99.8% in the landslides/background classification problem, which gets further validated in another Landsat8 image of a different site. The experiment shows that the proposed method is feasible for landslide detection from large-scale area, which may contribute to the further landslide-related research.

Keywords: Landslide detection, selective search, saliency enhancement, morphological operation.

1. Introduction

Landslide is a frequent natural hazard, causing tremendous human loss all around the world [1]. Accurate landslide susceptibility mapping and better understanding their mechanisms are notably significant in the most recent research [2]. Owing to the

development of remote sensing technology, landslides of different sizes can be visualized in images, despite of the size of research area and the surrounding backgrounds being mountainous regions or other difficult regions to reach. Remote sensing data is becoming a significant source to calculate landslide susceptibility maps. ASTER image has been proved to be highly applicable in landslide susceptibility mapping in the Kelemen catchment area [3] and it has been applied to calculate landslide susceptibility maps for the Candir catchment area [2]. Aerial photographs are another significant data source and have been widely used in many regions [4-7]. Landsat data [8], SPOT5 [9] and google earth image [10] are also widely used in landslide susceptibility mapping. Apart from that, remote sensing is playing a dominant role in exploring the relationship between earthquake and the distribution of landslides[11-17] to further understand the mechanisms and the correlation coefficient between landslide susceptibility and sediment yield[18] as well.

However, the significant role of remote sensing in landslide-relevant researches is fundamentally dependent on a reliable landslide inventory mapping. Reliable landslide locations and shapes are mainly generated by field investigation[19] or visual interpretation[20], but visual interpretation is obviously time-costly, especially for large-scale areas. Field investigation is labor-intensive and dangerous to finish [17]. Therefore, exploring an efficient method in landslide detection from remote sensed images draws more and more interest from researchers. The optical remote sensed images [21, 22], Digital Elevation Model (DEM) data [23] and Light Detection and Ranging (LiDAR) [24, 25] have been widely used in developing a reliable algorithm. Field investigation and visual interpretation are, in turn, widely used to evaluate the performance of landslide detection algorithm[20, 26].

The algorithms in landslide detection can be generally grouped to pixel-based methods and object-based methods. Change detection is the most commonly used technique in pixel-based landslide detection [27-29], because exploring pixels that have changed between images of pre and after landslide is simple but effective. Moreover, it has been synthesized with many classification algorithms and applied in the stage of post-classification[30] as well. The classification algorithms comprise

traditional methods in image processing, such as maximum likelihood classification [31], K-nearest neighbor [32], and machine learning methods[28]. However, change detection has many requirements about the bi-temporal images, such as the quality of images, clouds distribution in the images, and geometric correction, radiometric correction and atmospheric correction of the images [32, 33]. Moreover, machine learning methods have a main drawback that they require the spatial distribution of the test data to be the same with that of the training data[34]. Since remote sensed images are mostly taken under different conditions, such as air conditions, lighting conditions and sensor modes, it is hard for different remote sensed images to be similarly spatially distributed. In such case, the applicability of a trained machine learning model is limited. That can be avoided by introducing more training data and more complex models, such as transfer learning[34], but needs too much labor work to prepare data.

Object-based image segmentation is a widely used technique in landslide detection from remote sensing images as well[35]. It segments image into small regions as processing units that need to be later merged according to multiple user defined rules, such as mean intensity value of the pixels belonging to the same unit and their textural characteristics. Different sequences of applying the multiple rules may lead to different segmentation results, which are hard to define. That makes object-based method more difficult to be applied practically [36].

Furthermore, to the best our knowledge, the researches in landslides detection are mostly focusing on simple conditions or small-scale regions[26], which are far from the practical applications. Practical conditions are complicated with various objects of similar spectral characteristics of landslides, such as rocks, roads and urban area, which would decrease detection rate largely, making it hard to meet the requirement for further landslide-related analysis. That is why most researchers in preparing landslide inventory mappings would rather use visual interpretation rather than the published algorithms or methods[20].

In this paper, we are aiming to propose a work flow in landslide mapping for

large-scale remote sensed images with complex background for practical applications. The method uses single temporal landsat8 image which describes the area after landslide. It mainly consists of five steps: (1) remove clouds according to the band characteristics of landsat8; (2) enhance image according to the method FASA [37]; (3) exclude major background objects based on morphological operations; (4) further remove background objects of plain areas using DEM; (5) extract landslides by selective search [38]. As far as we know, it is the first time to introduce ‘selective search’ in landslide detection.

2. Study area and experimental data description

Nepal is a country with frequent natural hazards, such as landslides and earthquakes. Intensive plate movement and collision between Indian Plate and Eurasian Plate make Nepal a seismically active place [39]. Moreover, due to the great Himalayans blocking cold winds from Central Asia, rains are heavy especially during monsoon seasons. Since heavy rains and earthquakes are the commonly believed main causes of landslides[40, 41], landslides have become one of the most serious hazards, which have been ranked the first among other hazards by causing 32.5% mortality, according to the nationally reported losses from 1990 to 2014[42]. The Gorkha earthquake on April 25th, 2015, with a magnitude of 7.8, killed nearly 9,000 human lives. Thousands of landslides occurred due to the earthquake severely devastated the valleys around Kathmandu, the Central Nepal [43], which is our study area.

The latitude of the study area is from 26.4° to 28.4° and longitude from 84.1° to 86.4°. It covers three types of physiographic regions: Mountain Region, Hill Region and Terai Region with the elevation from 47 to 7958 meters (shown in Figure 1). The Mountain Region is located in the Himalayan Range, taking up the north of Nepal. Hill Region bridges the Mountain Region and fertile plain Terai Region, with its elevation from 800 to 4000 meters, and its climate changing from subtropical climates to alpine climates[44]. Therefore, the ground objects in the study area comprise a variety of biomes, such as rivers, savannas, broadleaf forests, shrublands, grasslands, rock and ice. Apart from biomes, in the capital Kathmandu, man-made constructions take a large portion as well. The study area not only has thousands of landslides, but

also has enormous geographic diversity, which can be regarded as a typical study area that could represent practical complicated landscapes where landslides are likely to occur. Such characteristics precisely match the aim of this study that we intend to build a method to detect landslides from a large-scale image with complicated geological environment, which is not only significant for emergency cases, such as hazard assessment and providing guidance for rescuing victims, but also helpful in investigating the organisms of hazard network among landslides, earthquakes and other geologic hazards. The experimental data used in our study comprise Landsat8 imagery acquired on June 1st, 2015 and digital elevation model (DEM). Landsat8 [45] provides global image at no charge, which can be accessed from <http://earthexplorer.usgs.gov/>. The operational land imager (OLI) of Landsat8 is used in our study, including band 9 for cirrus cloud detection, band 1 for coastal and aerosol analysis, and bands 10, 11 for surface temperature studies. The spatial resolution of all the bands used is 30m. In our work, each channel of Landsat8 images is re-scaled to 8-bit, i.e. 0-255, which is the dynamic range of the pixel values for image processing [46]. Moreover, global DEM from SRTM-datasets (Shuttle Radar Topographic Mission) [47] with a spatial resolution of 30m is released in <http://srtm.csi.cgiar.org> and used in our study to provide the spatial pattern of the research area, supplementing landslide detection. Ground truth of the earthquake-triggered landslide locations are from the inventory maps by staff at Durham University, the British Geological Survey and a volunteer group coordinated by NASA-JPL (Jet Propulsion Laboratory), the University of Arizona, and ICIMOD (International Centre for Integrated Mountain Development)[48], which are freely-available with an open Database License (ODC-ODbL). The landslide maps are identified and mapped from optical satellite images, as well as some reports from the ground. All the landslides are mapped as lines, as shown in Figure 1 with the help of software ArcGIS 10 (<http://www.esri.com/software/arcgis/new>). It can be observed that landslides are densely distributed in the valley regions next to Himalaya and sparsely in Kathmandu and Bhimphedi. Due to the low image quality in steep terrain, the mapped landslides may be inaccurate by up to 100 meters, which is acceptable for

the remote sensed images used in this study with a spatial resolution of 30 meters.

Figure 1. Study area with ground truth landslides from [48]

3. Proposed method

3.1 Work flow of the proposed method

The technology proposed in our paper is mainly composed of three parts, the first one is saliency enhancement of the image, the second one is contour-based potential landslides extraction by morphological operations, and the third one is selective search for landslides from potential landslides. Moreover, in this paper, the composition of bands 7, 5 and 4 (shown in Figure2) is used as base image for landslide detection, because such shortwave infrared composition is commonly used for investigating geologic structures [49] by strengthening the difference between landslides and other similar bared soil ground objects, such as human settlements. The general work flow is shown in Figure 3.

Figure 2 Original image composed of bands 7, 5 and 4.

Figure3. Flow chart of the proposed method

3.2 Clouds re-movement

According to the spectral characteristics of each band in Landsat8 imagery, the shortwave infrared band 9 with a spectral range from 1.360 to 1.390 micrometers is

suitable for cloud detection, due to its strong characteristic of water vapor absorption. As shown in Figure 4(a), there are only two objects: clouds and non-clouds. Moreover, the spectral intensity between the two objects has a large gap. In such case, most clouds can be extracted using a fixed threshold. The threshold can be a variety of values, such as 100, 101 or 110, as long as it is not too high, such as higher than 200, or too low, such as lower than 50, to group the two objects into one. Although there may be minor differences in clouds extraction using different thresholds, the minor differences can be ignored compared with the major clouds extracted. In this study, we use a threshold of 100 to segment the image by assigning the pixels whose intensity is higher than 100 to be 255, otherwise, assign 0, and obtain the detected clouds in Figure 4(b). Correspondingly, the original image in combination of bands 7, 5 and 4 after clouds re-movement is shown in Figure 5.

Figure 4 Clouds extraction: (a) Band 9 of Landsat8; (b) Clouds extracted from Band 9.

Figure 5. Image combination of bands 7, 5 and 4 after clouds re-movement.

3.3 Saliency enhancement by FASA

From Figure 5, we can realize that there are three main ground objects: vegetation, bare soil and urban area. It is hard to distinguish between urban area and bare soil from Landsat8 images using spectral characteristics only, because they take on similar characteristics at a spatial resolution of 30 meters. Since landslides belong to bare soil regions, in this step, we are aiming to enhance non-vegetation area by treating bare soil and urban area as saliency regions. Saliency regions are what attract us most when we view an image at first sight, which tend to be areas of high contrast with neighboring objects. Saliency enhancement is introduced to enhance non-vegetation area, especially the bare soil in the background of vegetation.. In this paper, the method FASA is used to do saliency enhancement by calculating the probability of each pixel in the image belonging to non-vegetation area.

The general pipeline of FASA in our study [37] is composed of three steps: (1) transform color domain from RGB to CIEL*a*b*, which is commonly used for image segmentation [50]; (2) quantify the original color histogram of each channel into 32 color bins and calculate the spatial center and variances for each pixel; (3) calculate saliency probability map using multivariate Gaussian function. The spatial center and color variances of each quantized color are calculated as follows:

$$S_{xn}(P_i) = \frac{\sum_{j=1}^N w^c(Q_{cn}, Q_{cj}) \cdot \sum_{\forall x_i | C_i \rightarrow Q_{cj}} x_i}{\sum_{j=1}^N h_j \cdot w^c(Q_{cn}, Q_{cj})} \quad (1)$$

$$V_{xn}(P_i) = \frac{\sum_{j=1}^N w^c(Q_{cn}, Q_{cj}) \cdot \sum_{\forall x_i | C_i \rightarrow Q_{cj}} (x_i - S_{xn})^2}{\sum_{j=1}^N h_j \cdot w^c(C_i, C_j)} \quad (2)$$

wherein $S_{xn}(P_i)$ and $V_{xn}(P_i)$ are the horizontal spatial center and variances of pixel $P_i(x_i, y_i)$ belonging to n th color after quantification, which can be accordingly used to calculate the vertical spatial center and color variances. h_j is the number of pixels quantified to j th color Q_{cj} from original color C_i in the space of CIEL*a*b*, which can be expressed by $h_j = |\forall x_i | C_i \rightarrow Q_{cj}|$. $w^c(Q_{cn}, Q_{cj})$ measures the color difference by applying Gaussian function with its variance σ_c being 16 [37]. according to equation (3):

$$w^c(Q_{cn}, Q_{cj}) = e^{-\frac{\|Q_{cn} - Q_{cj}\|^2}{2\sigma_c^2}} \quad (3)$$

The saliency probability of each pixel can be calculated according to equations (4)-(6).

$$\text{Pr ob}(P_i) = \frac{1}{(2\pi)^2 \sqrt{|\Sigma|}} \exp\left(-\frac{(g_i - \mu)^T \Sigma^{-1} (g_i - \mu)}{2}\right) \quad (4)$$

$$g_i = \left[\frac{\sqrt{12 \cdot V_{xn}(P_i)}}{n_w} \frac{\sqrt{12 \cdot V_{yn}(P_i)}}{n_h} \frac{S_{xn}(P_i) - \frac{n_w}{2}}{n_w} \frac{S_{yn}(P_i) - \frac{n_h}{2}}{n_h} \right]^T \quad (5)$$

wherein $S_{yn}(P_i)$ and $V_{yn}(P_i)$ are vertical spatial center and color variances that can be calculated corresponding to equations (1) and (2). n_w and n_h are the width and height of image, and the coefficients μ and Σ are obtained from [37].

$$\mu = \begin{bmatrix} 0.5555 \\ 0.6449 \\ 0.0002 \\ 0.0063 \end{bmatrix}, \quad \Sigma = \begin{bmatrix} 0.0231 & -0.0010 & 0.0001 & -0.0002 \\ -0.0010 & 0.0246 & -0.0000 & 0.0000 \\ 0.0001 & -0.0000 & 0.0115 & 0.0003 \\ -0.0002 & 0.0000 & 0.0003 & 0.0080 \end{bmatrix} \quad (6)$$

After calculating probability of each pixel in the image, the probabilities are rescaled to 0-255 to enlarge the gaps among all the probabilities of all the pixels. With a multitude of trials, pixels, whose intensity values are higher than 190, can cover the most landslides and eliminate other ground objects. Therefore, pixels with intensity value lower than 190 are re-assigned to zero, as shown in Figure 6.

Figure 6. Non-vegetation area after saliency enhancement

3.4 Background objects re-movement using morphological operations

Referring to Figure 1, from Figure 6 we can realize that most bare soil regions and urban area are not of our interest, which can be recognized as background objects. The non-landslide bare soil regions and urban area take up quite a large proportion and the landslides in Figure 6 are small and separated from each other. Considering this and the characteristics of morphological operations, we apply six-time iteration of dilate operation with a structuring element of size 11x11 to fill up the closely decentralized non-landslide regions and merge them into several large areas. The landslide regions are still small and separated from major non-landslide regions (as shown in Figure 7(a)). By iterating each contour of the merged regions, major

non-landslide regions are selected and filled with 255 to demonstrate obviously in Figure 7(b) and removed (shown as Figure 7(c)) if any contour has a height or width larger than 10 percent of the height or width of the image.

Figure 7 Major non-landslide region re-movement by morphological operations: (a) original image after dilation; (b) contours selected as non-landslide regions; (c) bare soil after removing major non-landslide regions.

3.5 Further background objects re-movement using DEM

Since most landslides occur in mountainous regions, DEM is further used to remove ground objects in plain area. According to the DEM in Figure 1 and landscape pattern introduced in Section 2, the ground objects with an elevation less than 65 meters are removed, as demonstrated in Figure 8. 65 is a conservative threshold that can maintain the landslides and remove as many non-landslide objects as possible.

3.6 Figure 8. Further background objects re-movement by DEMLandslides extraction by selective search

Selective search is a widely used technique in computer vision for image segmentation [51]. It makes detection easier and more efficient by proposing many potential regions that have the object of interest. Selective search synthesizes the ideas of exhaustive search [52] and segmentation, and proposes proposals more efficiently compared with traditional methods. The proposals cover all the regions that are highly probable to cover the object of interest. The specific workflow of selective search [53] is described below:

(1) Segment image according to an efficient graph-based image segmentation method [54], and get initial regions $R = \{r_1, r_2, \dots, r_n\}$

(2) Calculate the similarity between each pair of neighboring regions $s(r_i, r_j)$ and store all the pairs into set S , i.e. $S = S \cup s(r_i, r_j)$

(3) Find the pair of neighboring regions with the maximum similarity in S , i.e. $s(r_m, r_n) = \max(S)$ and merge r_m, r_n into r_t

(4) Remove all the pair of regions relevant with r_m and r_n in S

(5) Calculate the similarity of region r_t with each of its neighboring regions

(6) Update S and R

(7) Iterate steps (2)-(6) until S is empty.

However, images in computer vision are small and have simple background. Selective search can be used as first-step processor before further recognition or detection. For the cases of large-scale remote sensed image with a size of 7721x7821, it is difficult to apply selective search directly to an image with complicated ground objects before detection or recognition. Therefore, in this study, selective search is applied after removing most non-landslide regions. The window size of smallest and the largest region in the process of selection in our study are 50 and 10000 pixels after a multitude of trials, where most landslides are well maintained. The results of selected regions with bounding boxes are demonstrated in Figure 9(a), and the corresponding regions in the proposals are extracted as final landslides, as shown in Figure 9(b).

Figure 9. Landslide detection by selective search: (a) proposals by selective search; (b) landslide detection result

4. Experiment evaluation and discussions

4.1 Performance evaluation

To explore the robustness of the proposed work flow in landslide detection from large-scale image, we applied the same technique on another Landsat8 image with a latitude range of 26.36° - 28.49° and a longitude range of 82.58° - 84.91° , located next to the study area. It was taken on June 5th, 2015, with a similar complex background (as shown in Figure 10(a)). The corresponding landslide detection result by the proposed work flow is shown in Figure 10(b).

Figure 10. Application of the work flow on another Landsat8 image: (a) original image combination of bands 7,5 and 4; (b) landslide detection result.

Referring to the landslides mapped from [48], we visually interpreted by drawing regions for each landslide as ground truth for both study area and the test image.. Since the number of landslides is one of the key characteristics of landslide inventory mapping[12], we compared the number of landslides of the study area and the test image, detected by our method with that from the ground truth[48] and demonstrated the results in Table 1.

Table 1 Comparison of number of landslides between our method and ground truth

	Ground truth	Proposed method	Difference Ratio (DR)
NO. of Landslides for study area	5578	5528	0.896%
NO. of Landslides for test image	130	179	37,7%

DR here is used to measure the difference between the proposed method and ground truth, in terms of the number of landslides. It is calculated using the following equation:

$$DR = \frac{|NO. (Method) - NO. (Ground_truth)|}{NO. (Ground_truth)} \times 100\% \quad (7)$$

It is obvious to note that, in terms of collecting the number of landslides from

large-scale images, the proposed method is able to get satisfactory results when landslides are thousands or hundreds distributed, as shown in the cases of study area and the test image in Table 1. Moreover, the detection in thousands distributed landslide area has less bias than that in hundreds distributed by gaining a DR of 0.896% over 37.7%. One of the most possible reasons is that images with fewer landslides but similar complex background are more difficult to detect, because more bared soil regions with similar characteristics are easy to be miss-classified as landslides by the proposed method. However, the general magnitude of landslide distributions in the image can be well reflected by the proposed method, which validates that the method can be useful for exploring the relationship between the number of landslides and the magnitude of the earthquake or the research relevant to landslide inventory mappings.

Furthermore, the performance of landslide detection in terms of the locations and the exact areas is calculated as well, and listed in Table 2.

Table 2 Evaluation of landslide detection in terms of area

		Commission Error (%)	Omission Error (%)	Overall Accuracy (%)	Kappa Coefficient
Study Area	Background	0.03	0.12	99.8447	0.4244
	Landslide	67.78	37.58		
Test Image	Background	0.01	0.01	99.9890	0.2511
	Landslide	74.76	75.00		

The overall accuracies of landslide and background classification for both cases are higher than 99.8%, indicating only at most 0.15% of the pixels in the image are miss-classified. Moreover, the frequently used evaluation parameter Kappa Coefficients are higher than 0.25, which turn out to be satisfactory in solving the classification problem. It can be obviously observed from Figure 1 and Figure 10 that the proportion of background is quite large compared with landslides. The commission and omission error of background objects both validate the efficiency of the proposed method in background re-movement. Only 0.15% of the background object pixels is miss-classified as landslides, and 0.03% or even 0.01% are wrongly committed from landslides. However, due to the large size of the image with

7721x7871 pixels and the sparsely distributed landslides, a small portion of background pixels will take up a large percentage of landslide pixels, leading to a relatively high commission error and omission error in the view of landslide pixels. That also indicates that the proposed method is influenced by the complicated ground objects, whose characteristics are similar with landslides. The similar ground objects puzzle the proposed method to miss-classify them as landslides. One of the possible reasons that may lead to this phenomenon is that the proposed method intends to maintain as many as landslides as possible from Step 1 to Step 5, so that small landslides are less likely to be miss-removed, but the similar background objects are maintained as well. Despite the general satisfactory landslide detection for the entire image and the size of the image is too large to display in details, it is difficult to visualize the performance of landslide detection in details, and we randomly selected four sub regions with landslides from study area and two sub regions with landslides from test image for further analysis.

The selected sub regions and their corresponding detection results are shown in Figure 11. Also, the accuracy analysis is calculated and listed in Table 3.

Figure 11. Landslide detection for sub regions: (a), (d), (g), (j), (n) and (r) are original images of sub regions; (b), (e), (h), (k), (p) and (s) are ground truth of sub regions; (c), (f), (i), (m), (q) and (t) are detection results of the corresponding sub region.

Table 3. Evaluation of landslide detection in six sub regions

Sub Region	Object of Interest	Commission Error (%)	Omission Error (%)	Overall Accuracy(%)	Kappa Coefficient
Figure 11(a)	Background	0.64	0.65	98.7265	0.6061
	Landslide	38.89	38.59		

Figure 11(d)	Background	2.04	2.39	95.8890	0.6940
	Landslide	29.96	26.73		
Figure 11(g)	Background	0.70	3.52	95.9398	0.5441
	Landslide	56.50	20.05		
Figure 11(j)	Background	0.94	0.79	98.3227	0.6983
	Landslide	27.50	31.02		
Figure 11(n)	Background	0.45	0.09	99.4672	0.4923
	Landslide	24.54	63.21		
Figure 11(r)	Background	0.17	0.02	99.8107	0.5586
	Landslide	11.11	59.18		

Visually, landslides in the original sub regions in Figure 11 are mostly extracted, as shown in Figure 11(c), (f), (i), (m), (q) and (t). For cases of Figure 11(d) and (j), the background objects of landslide are simpler than the other four cases, and the corresponding detected landslides are more neat and integrated. The landslides detected from Figure 11(a), (g), (n) and (r) are influenced more heavily by the background objects with similar characteristics, which hinder exact landslide detection to a large extent.

Statistically, the overall accuracy and kappa coefficient of the six sub regions from study area and the test image both indicate a satisfactory performance of the proposed technique. Corresponding with the visual performance, the commission and omission error of landslide classification in Figure 11(a), (g) and the two sub regions from test image are comparatively large, due to the severe impact of similar characteristics of background objects. In terms of background classification, the proposed method performs quite well in all the sub regions. Therefore, for the practical purpose of landslide detection, especially for a large area with complicated background, the proposed work flow in this paper can be a pretty useful trial to deal with this issue, because to the best of our knowledge, there has not been many researches focusing on such cases yet.

4.2 Limitations of our method

Despite the practical advantages of our method in landslide detection compared with other relevant researches, especially for large-scale complicated landslide detection for emergency cases and landslide inventory mapping, it still has several

limitations in landslide detection that hinder its performance. (1) The background objects with similar characteristics of landslides are the main obstacles of the proposed method;(2) the work flow is not self-adaptive, because there are several thresholds need to be subjectively determined according to different cases. Adding more data and applying more statistical models may be a nice trial to deal with the limitations, which provide potential routes for future research.

5. Conclusions

This paper demonstrates a practical method for large-scale landslide detection by synthesizing saliency enhancement, morphological operations, contour-based potential landslide detection, DEM and selective search for exact landslide detection. Generally, the proposed method has the following advantages: (1) it is simple and feasible for different images with complicated background, which is more approximate to practical cases, making it practical for large-scale research area; (2) its source data Landsat8 is world-wide freely accessible, and it is a single-temporal image based method, which requires little about image pre-processing for landslide detection. The experiment in our study demonstrates the efficiency and feasibility of the proposed method in terms of not only collecting the number of landslides, but also detecting the areas and locations of the landslides from different images. That shows there are several potential benefits to apply the proposed method in emergency cases or landslide inventory mapping. Moreover, more statistical models should be considered to make the detection more accurate in the future research.

Acknowledgement

This work has been supported by the Hundred Talents Program of Chinese Academy of Sciences [grant number Y34004101A]; the Comparative Study on Global Environmental Change Using Remote Sensing Technology [grant number 41120114001]; and the National Natural Science Foundation of Major International (regional) Collaborative Research Project, and High Resolution Earth Observation Systems [grant number 14CNIC-032079-32]. We are grateful for the NASA's Earth observation program for providing Landsat data from the website <http://landsat.usgs.gov>. There are no conflicts of interest among the researchers.

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