A new fast method for earthquake-triggered secondary geological hazard information extraction from high-resolution remote sensing imagery

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Abstract. Earthquake-triggered secondary geological hazards usually significantly augment the destruction caused by an earthquake due to their rapid impact, long duration and high repeatability. Seismic disaster losses are often exacerbated and can cause substantial difficulties for rescue, relief and post-disaster reconstruction. The quick acquisition of disaster information is important to aid relief efforts in the 72 critical hours after an earthquake occurs. Currently, computer-aided interpretation of remotely sensed imagery of a single time phase plays a central role in information extraction for geological hazards, whereas automated interpretation is relatively limited. Because high-resolution remotely sensed imagery is rich in textures and spatial details of the imaged objects, such as their size, shape and neighborhood relationship, geologic hazard investigations employing such imagery can offer more accurate results. In this paper, a rapid method for earthquake-triggered secondary geological hazard information extraction from high-resolution remotely sensed imagery is proposed and is demonstrated to be a fast and automatic method that uses multiple image features of a hazard.

1. Introduction
China is significantly affected by earthquakes. Rainfall frequently occurs after an earthquake and readily induces secondary geological hazards, such as landslides, collapses, and debris flows. Earthquake-triggered secondary geological hazards exacerbate seismic disaster loss and cause serious difficulties for rescue, relief, and post-disaster reconstruction.

With the development of space technology and sensors, the spatial resolution of remote sensing imagery has greatly improved in recent years. A high spatial resolution of 1 to 5 meters has become a requirement of new-generation remote sensing sensors in the first decade of the 21st century. High-resolution remote sensing imagery is more effective in image interpretation for revealing information about image objects, such as spatial structures, textures, edges, and other subtle inner details. Remote sensing technology has recently played an important role in emergency responses to serious natural disasters in China, such as the Wenchuan and Yushu earthquakes. Remote sensing technology also provides decision support related to disaster relief and post-disaster reconstruction to state and local governments.

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Various geological hazard mapping methods of remote sensing have been developed, such as visual interpretation [1], image enhancement [2-4], image classification [5-7], change detection [4, 8], object-based image analysis [9-12] and terrain analysis [13-16]. Currently, a primary method for geological hazard information extraction is computer-aided interpretation of single time phase remotely sensed imagery, although its automation is relatively limited. It is difficult to automatically extract landslide bodies, as there are several types of land covers that are anomalies on a landslide body in addition to landform and drainage changes. The accuracy of visual interpretation generally suffers from the inexperience of the interpreters, and its efficiency is limited when dealing with large amounts of remote sensing data. To meet the urgent need for efficient geological hazard extraction from high-resolution remotely sensed imagery, a new fast geological hazard mapping method based on multiple features of landslides in high-resolution remote sensing imagery and DEM (Digital Elevation Model) is proposed in this paper.

![Figure 1. Spatial patterns in a geological hazard region impacted by the Wenchuan earthquake. (a) Stripped vegetation patches and bare soil patches and (b) high-light patches and bare soil patches.](image)

2. Methodology
Landslides have distinct features in regard to color, shape, topography, texture, and spatial pattern. The color of a landslide body is different from other parts of the mountain. Vegetation, rocks, and bare soil cover a landslide body, and the latter is off-white or white, revealing the color of the rocks and bare soil. A hillside with a large slope contributes to the occurrence of a landslide. In a landslide, the sliding direction is the same as the aspect of the landslide debris back-wall, and the bottom of its sliding zone is relatively rougher than the upper part because rock-soil bodies accumulate on the bottom when a landslide happens. Most landslides occur along rivers. The internal spatial patterns of a landslide mainly represent the spatial relationship between the land covers of a landslide body, such as vegetation, rock, and soil.

Based on the characteristics of landslides mentioned above, a method based on the Comprehensive Utilization of Multiple Image Features (CUMIF) for earthquake-triggered secondary geological hazard information extraction is proposed in this paper. This method consists of four steps, including supervised classification, mathematical morphological reconstruction, filtering using DEM and shape characteristics, as shown in figure 2.
The first step of the CUMIF method is supervised classification of the high-resolution remotely sensed imagery. The land cover categories of the research area generally include water bodies, bare soil, vegetation, farm, roads, buildings, and high-light features. The high-light feature category refers to the bare rocks or bare soil regions after the occurrence of the landslide. Classification accuracy is important, as supervised classification is the basic step of the entire process.

The second step is post classification. Morphological filtering is applied to the three classes of high-light features, bare soil, and vegetation to remove small patches within the high-light feature and bare soil classes as well as reserve small patches in the vegetation class. The small vegetation patch regions experience stripped vegetation after the landslide happens. The morphological opening operation along with a square structure element is employed in the filtering process.

In the third step, morphological reconstruction is engaged to utilize the internal spatial patterns of the landslide. The morphological reconstruction iteratively performs dilation of the label image until the edges of the mask image are reached. The two label images are the small vegetation patch regions and the high-light feature regions. The related mask image is the union of the small vegetation patches, bare soil, and high-light feature regions. Finally, two morphological reconstruction processes are separately performed with the two label images, and the two resulting images are merged to obtain the preliminary landslide regions.

In the last step, the previous preliminary landslide regions are refined by eliminating regular regions, such as farm regions, with reference to DEM and shape parameters. These regions are refined with reference to the fact that the sliding direction of a landslide is virtually the same as the aspect of the debris back-wall; the difference between the two directions is less than 90 degrees. The sliding direction is estimated using the DEM data and shape parameters of the preliminary landslide regions, as both the back-wall and slip tongue of a landslide have arcs. While the back-wall region has greater DEM values, the slip tongue is relatively lower. The aspect is calculated from the DEM as follows:

First, calculate the slope image and the aspect image from the DEM; then, calculate the mean slope value of each preliminary landslide region and remove the regions with low slope values. Finally, estimate the difference between the sliding direction and the aspect. As shown in figure 3, the point $H$ is the center of the edge with high DEM values and high curvature values, and $L$ is the center of the edge with low DEM values and high curvature values. The angle $\theta_1$ is the angle from the vertical dotted line to the line $HL$ along the clockwise direction, and $\theta_2$ is the aspect of point $H$. The difference is estimated by the formula $|\theta_1 - \theta_2|$, and a region is removed once the difference is larger than 90 degree.
3. Analysis and discussion

The study area is located in Pingwu County, Mianyang City, Sichuan Province, and the airborne imagery of the study area was acquired in May 2008, with a spatial resolution of 2 m and three visible spectral bands. The imagery was both geometrically and orthographically corrected. Several landslides in this area were triggered by the Wenchuan earthquake and can be identified from the high-resolution remotely sensed imagery.

3.1. Secondary geological hazard extraction

First, the airborne imagery was classified into water, bare soil, vegetation, farm land, road, building, and high-light feature categories by the SVM (support vector machine) classification method [5]. The high-light feature, bare soil, and vegetation categories were then filtered by the morphological opening algorithm with a rectangular structure element. The morphological reconstruction algorithm was subsequently performed to obtain the preliminary geological hazard regions. Finally, the preliminary regions were refined to obtain the final result, referencing DEM and shape parameters, as introduced in section 2.

3.2. Accuracy evaluation

The final result was compared with the result obtained using the IGCS method based on GrabCut segmentation [17]. The IGCS method yielded the same hazard regions but produced more accurate boundaries compared to the visual interpretation method.

### Table 1. Accuracy analysis of the CUMIF method

|                | Count               | Area (Square Kilometers) |
|----------------|---------------------|--------------------------|
|                | Total number        | Correct ratio            | Error ratio | False ratio | Total area | Correct area | Effectiveness ratio | Correct ratio |
| IGCS           | 33                  | 33/33                    | —           | —           | 1.77       | —            | —                   | —            |
| CUMIF          | 22                  | 14/33                    | 7/22        | 19/33       | 1.41       | 1.38         | 0.981               | 0.781        |

The resulting images generated by the CUMIF and IGCS methods are shown in Figure 4, and their statistics are listed in Table 1. The correct ratio and error ratio under the 'Count' heading represent the correct and error counts of the CUMIF-generated result, respectively, divided by the total region number of the IGCS-generated result. The false ratio is equal to the un-sliding region counts divided by the total region number of the CUMIF result. The correct area represents the intersection of the two resulting images generated by using the IGCS and CUMIF methods, and the effectiveness and correct ratios represent the correct area divided by the total area of the CUMIF-generated and IGCS-generated resulting images, respectively. Because the un-sliding regions can be visually removed and the correct area can be achieved by splitting polygons, the correct ratio of the area can be viewed as an
effectiveness indicator to evaluate the CUMIF method. The correct ratio of the area is 0.781, indicating that the CUMIF method is an effective and automatic method for geological hazard information extraction.

![Image of original image and reconstructed results](image)

**Figure 4.** (a) The original image, (b) the result of morphological reconstruction, (c) the result of the IGCS method, and (d) the result of the CUMIF method.

4. Conclusion
To extract the secondary geological hazards caused by earthquakes, a method was proposed in this paper to comprehensively utilize the spectrum, inner spatial neighborhood, and topological features of image objects. This method consists of four steps, including supervised classification, post classification, mathematically morphological reconstruction, and filtering using DEM and shape parameters. The method efficiently extracts large landslide regions compared to other computer-aided interpretations. The accuracy of the extracted landslide results is dependent on the supervised classification employed in the method. Although high-resolution remotely sensed imagery is rich in texture and spatial details, it is difficult to obtain satisfactory accuracies for a supervised classification method based only on pixel spectra. To improve the accuracies of extracted landslides, object-based classification should be employed in further research.

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