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Effect of landslides on the structural characteristics of land-cover based on complex networks

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Landslides have been widely studied by geologists. However, previous studies mainly focused on the formation of landslides and never considered the effect of landslides on the structural characteristics of land-cover. Here we define the modeling of the graph topology for the land-cover, using the satellite images of the earth's surface before and after the earthquake. We find that the land-cover network satisfies the power-law distribution, whether the land-cover contains landslides or not. However, landslides may change some parameters or measures of the structural characteristics of land-cover. The results show that the linear coefficient, modularity and area distribution are all changed after the occurence of landslides, which means the structural characteristics of the land-cover are changed.

Keywords: Land-cover; landslides; topological representation; scale-free; complex networks.

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1. Introduction

Earth, as the unique living environment of human beings, is a huge and complex system. As we know, the earth is composed of the atmosphere, hydrosphere, biosphere, crust, mantle and centrosphere. The biosphere is a huge system which is an open environment of the interactions between human activities and nature. It is the link and bridges the relationship between humans' activities and the environment; it is an important part of the land-system.[1,2] It has an important role to comprehend and reveal the complex relationship of human and environment by studying the structure of land-system and properties. However, a complete land-system is composed of vegetation, inland water, glacial snow, bare rock and soil, all kinds of artificial structures and so on. Researchers have carried out extensive studies without taking into account the conditions of natural disasters.

For capturing land-cover changes on different landscapes, researchers present a new method, named as Comprehensive Change Detection Method (CCDM), which integrates spectral-based change detection algorithms including a Multi-Index Integrated Change Analysis (MIICA) model and a novel change model called Zone, which extracts change information from two Landsat image pairs. Because the method is simple and easy to operate, it is widely applied.[3] With the speeding up of urbanization, the change of land-cover is also increasing. Three land use land-cover (LULC) maps (1984, 2003 and 2014) were produced from satellite images of Cairo by using Support Vector Machines (SVM). Then, land-cover changes were detected by applying a high level mapping technique that combines binary maps (change/no-change) and post classification comparison technique.[4] Haregeweyn evaluated the dynamics of urban expansion and its impacts on land use/land-cover change by aerial photos for the years 1957, 1984 and 1994 as well as field mapping using GPS for the year 2009.[5] Researchers have produced the first 30 m resolution global land-cover maps using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data.[6] Parece summed up remote sensing applications in land use and land-cover mapping and monitoring.[7]

In recent years, earth activities seem to enter into a frequent period, the number of natural disasters is gradually increasing each year.[8] Landslide is one of the most common and frequent natural disasters, particularly it has a significant effect on the surface cover system. Therefore, scholars have launched research of effect on landslide for land-cover. Reichenbach evaluated the influence of land use change on landslide susceptibility, susceptibility maps show an increase in the areal percentage and number of slope units classified as unstable related to the increase in bare soils to the detriment of forested areas.[9] In New Zealand, scholars found some relations between rainfall-triggered landslides and changes to vegetation cover.[10] A logistic regression routine was used to assess the influence of land use and vegetation recovery in the occurrence of shallow landslides.[11] A statistical analysis for landslide frequency-area distribution was used to identify the landslide characteristics associated with different types of land use.[12] Landsliding is a natural process influencing montane ecosystems, particularly in areas with elevated rainfall and seismic activity, and has been made to quantify the contribution of this process to land-cover change.[13] An investigation was performed to reveal the spatial relationships between the occurrences of four types of landslides (slides, flows, falls and creeps) and three categories of land-cover (agricultural areas, artificial surfaces and forested and semi-natural areas) that are found in the Arno river basin of central Italy.[14]

In these researches, we find that many researchers analyzed landslide as a single object, it was not subsumed in the land-cover system. This is not conducive to study the structure change of land-cover after earthquake.

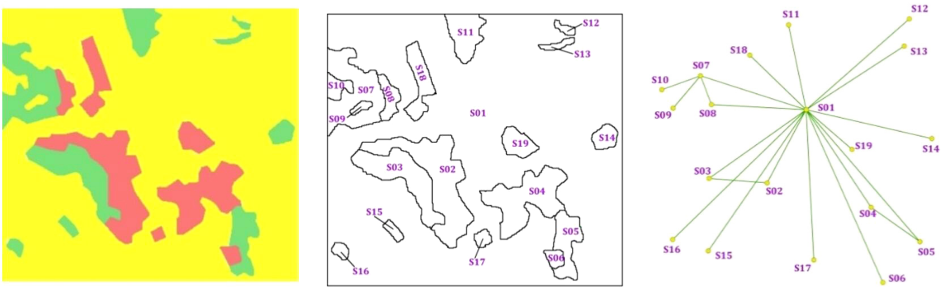
The close studies have shown that using complex networks is helpful to reveal the structure and functional characteristics of many complex systems. Complex networks are also considered to be a powerful tool for explaining the complexity of complex systems. In recent years, it has been widely used in transportation, physics, biology, communication, sociology, geography and other fields.[15–20]

Thus, in this study, we present the dual topological expression of surface coverage by complex networks and establish the specific method of modeling the surface coverage, from the viewpoint of constructing land-cover. On this basis, we tried to reveal an inherent relationship between the landslide and land-cover, through the network modeling of land-cover images of pre- and post-earthquake and analyzing the structural change of land-cover of pre- and post-earthquake by using complex network theory. This study basic theoretical support for landslide hazard assessment and automatic identification of landslide information.

2. Topological Representation of Image Maps

For true color images, the land-cover is composed of different pattern spots which can be distinguished by color. Therefore, we can see that the remote sensing image of the land-cover can be regarded as the mosaic results of lots of pattern spots without seams. Pattern spots can be obtained by image segmentation technique. Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels) and its goal is to simplify the representation of an image into something that is more meaningful and easier to analyze.[21,22] The result of image segmentation is a set of segments that collectively cover the entire image.

Using GIS (geographical information system) techniques, all the areas after segmentation are considered as polygon features which can be stored in the same polygon layer or different polygon layers (if it needs to classify the land use, different types of land use should be stored in different polygon layers). Here, we mainly focus on the land-cover without considering the land use types, therefore we can create single polygon layer for the land-cover. According to this polygon layer, we can extract the topological relationship (especially the adjacent information) between different polygon features by using the GIS topology analysis technique. Using dual graph theory, we can construct a dual topology for polygon–polygon relationships.



(a) (b) (c)

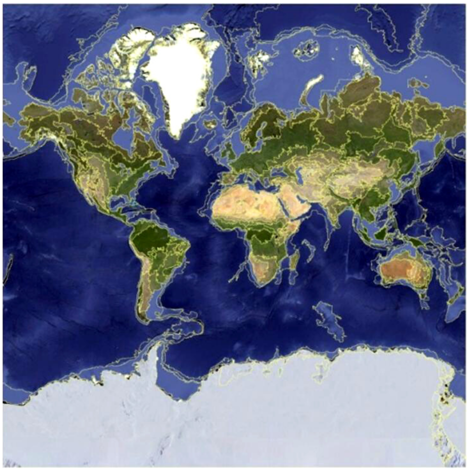
Fig. 1. Geometric and Topological representations. (a) Image map of a fictional land-cover. (b) Area map (19 polygons). (c) Area–area relationship (19 nodes and 21 lines).

In the mathematical discipline of graph theory, the dual graph of a plane graph G is a graph that has a vertex for each face of G. The dual graph has a dual edge whenever two faces of G are separated from each other by an edge. Thus, each edge of G has a corresponding dual edge that connects the two faces.[23]

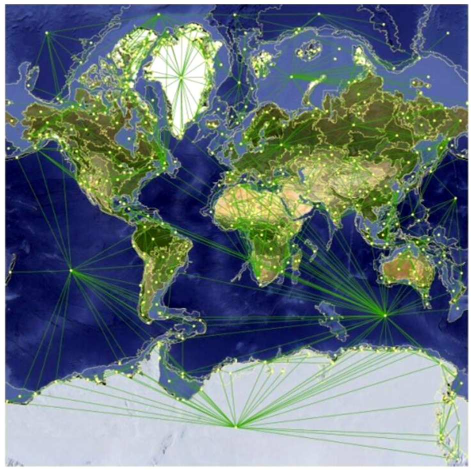
Therefore, this paper introduces the concept of land-cover network which is defined as a collection of topological relationships between different spots (i.e., polygon features) on the land-cover image. The network modeling principle for the land-cover is detailed as follows: a node corresponds to a polygon feature, and if there exists an edge between two nodes, it means that the corresponding two polygon features are adjacent to each other. Figure 1 describes the modeling principle of topological representation of the land-cover. Figure 1(a) is a fictional image that is composed by some spots. Figure 1(b) is an area map which is the segmentation result of this image. Figure 1(c) represents the dual graph for the area–area relationship.

The segmentation process is important for the network modeling of the land-cover. There are many segmentation methods in image segmentation field, such as pixel-oriented, texture-oriented and object-oriented segmentation approaches. Scholars widely agreed that the object-oriented segmentation methods are more efficient. Therefore, this paper uses the object-oriented remote sensing image segmentation for deriving polygon features of the raster image. Besides, the eCognition software is introduced to complete the work of image segmentation because the eCognition software is well known in object-oriented image analysis and is widely used for image segmentation.[24] The eCognition provides the multi-resolution segmentation technique which is an optimization procedure. After segmentation, the surface is divided into many areas which can be exported to a polygon layer. Then, we can construct the dual topology of the polygon–polygon relationships.

In the previous studies, we presented the dual graph of the earth surface and discovered some important phenomena,[23] which indicate that the proposed method has important scientific meaning. Figure 2(a) shows the geometric and topological representations of the earth's surface. Figure 2(b) shows overlay spatial results of



(a) Geometric representation



(b) Topological representation

Fig. 2. Geometric and topological representations of the earth surface.[23] The satellite image of the earth's surface is derived from Google Earth, where the map scale is 1:295,829,355.45.

the satellite image, the polygon layer and its dual graph, where each node is inside its corresponding polygon feature for the dual graph. Therefore, we can construct a dual graph for the earth surface that each area corresponds to a node of the dual graph, and the degree of a node can be calculated by the number of its adjacent nodes (namely, the number of edges connected to the node).

On the basis of the above analysis, we can see that the network modeling for the land-cover system is interesting and significant. For this, we will further study the structural characteristics of land-cover, and discuss the structural changes of the land-cover before and after landslides. In this paper, the structural characteristic of land-cover is defined as the topological structural properties of land-cover networks, which mainly describe the relationship between different pattern spots of land-cover in overall and local ways by using some topological measures.

3. Topological Measures Used for the Land-Cover Networks

The structural characteristics of networks can be illustrated using some topological measures, especially the degree information. In order to study the structural characteristics of the land-cover networks, some topological measures are introduced for researching the topological properties of the land-cover networks.

3.1. *Degree and degree distribution*

The degree of a node i is the number of edges which connects with the node, represented with k_i.[25] Here, a node corresponds to a polygon feature (or a pattern spot), and naturally the degree of a polygon feature is actually the number of its neighboring polygons. To a great extent, the degree reflects the significance of features and moreover can be used to describe the strength of interactions between the feature and its adjacent features. The larger the degree of the feature, the stronger impact the feature has on its surroundings, and also the stronger impact its surroundings have on this feature.

The most basic and important topological characterization of a graph can be obtained in terms of the degree distribution $P(k)$, defined as the probability that a node chosen uniformly at random has degree k or, equivalently, as the fraction of nodes in the graph having degree k. Obtaining the degree distribution of the land-cover networks is helpful to reveal the morphological feature of the land-cover.

3.2. *Clustering coefficient*

Clustering coefficient is a topological measure introduced by Watts and Strogatz. Let G be a graph; $\pi(i)$ be the set of neighbors of node i in G; G_i is the subgraph of the original graph G, which is composed of the neighbors of node i and the edges between these neighbors; e_i be the actual number of edges in graph G_i. Therefore, the clustering coefficient C_i of node i is defined as the ratio between e_i and $k_i(k_i-1)/2$ (the maximum possible number of edges in G_i):

$$C_i = \frac{2e_i}{k_i(k_i-1)}. \tag{1}$$

Clustering coefficient is used to describe the local structural characteristics of the network and reflects the clustering degree of nodes. For the land-cover spots, clustering coefficient can illustrate the local structural compactness of spots.

3.3. *Modularity*

Modularity is a topological measure that is used to assess the strength of community structures in a network. Therefore, modularity is one of the most important measures of community detection, represented with Q. The modularity is often defined as follows:

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta(C_i, C_j), \tag{2}$$

where A_{ij} is the adjacent matrix of the network such that if nodes i and j connect to each other, then $A_{ij}=1$, otherwise $A_{ij}=0$; m is the number of edges of the network; $\delta(C_i, C_j)$ is the Kronecker delta such that if nodes i and j belong to the same community, then $\delta(C_i, C_j)=1$, otherwise $\delta(C_i, C_j)=0$.

By introducing modularity, we can study the community features of the land-cover network, and evaluate the change of community features if the land-cover is destroyed seriously.

4. Experiments and Discussions

4.1. *Data source description*

The experimental region is located in Wenchuan county, Sichuan province, Yinxiu township taoguan village (31° 17′ 51.28″ N, 103° 27′ 15.51″ $E \sim$ 31° 15′ 18.16″ N, 103° 33′ 28.46″ E), where it is about 88 km^2. The images are derived from Google Earth, image resolution is 2 m, imaging time is on 9 September 2005 (Fig. 3 for the pre-earthquake image) and 26 April 2011 (Fig. 4 for the post-earthquake image). The entire region of altitude difference is relatively large, the lowest elevation is 1100 m, it is located in the bottom of the Minjiang river valley, the highest elevation is 3300 m, it is located in northeast of image.

Before the earthquake occurred, the land-cover was not destroyed, the denser the vegetation in the region, the less the landslides happened. But in post-earthquake images, we find that a large number of landslides in the entire area have taken place, the land-cover is severely damaged. In our experiments, according to the size of surface elements in image and verification results by visual interpretation, the segmentation scale is defined as 60, compression parameter 0.6 and shape parameter

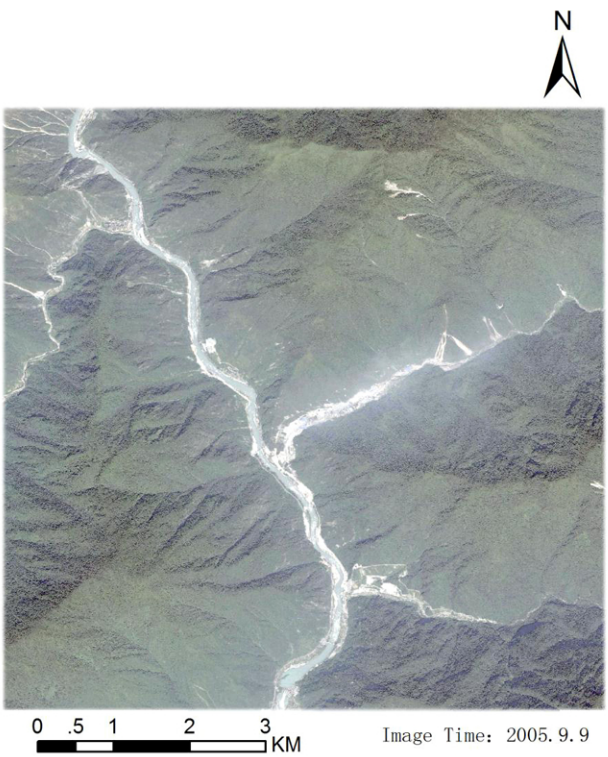


Fig. 3. Pre-earthquake image.

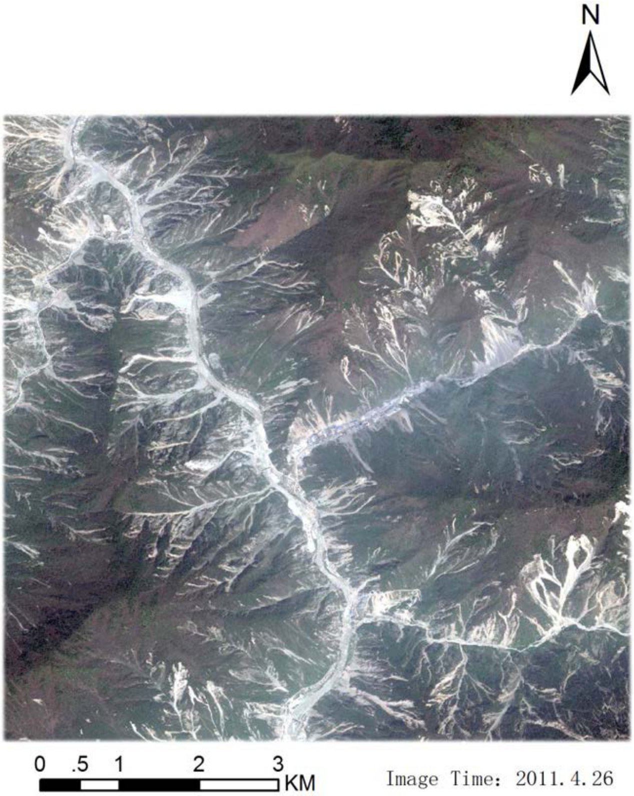


Fig. 4. Post-earthquake image.

0.4. We get 68,357 elements from the pre-earthquake image, the biggest element of area is 63,749 pixels, and the smallest element of area is 49 pixels. Figure 5 shows the partial segmentation results before the earthquake image, river segmentation is more complete than other objects in the figure, it is the main reason that the consistency of water surface is better. The other blue polygon is vegetation coverage region, its border has more curve than the water's border, the main reason is that the vegetation of texture is not stable, the differences in the height of trees are obvious. Overall, the segmentation result is all right that reserves the integrity of different features.

The entire experimental area is seriously destroyed by the earthquake, it caused a number of landslides, a lot of high bright spots are increased in the image. We extracted the surface elements from post-earthquake image, where the rule is the same with the segmentation rule of the pre-earthquake image. The result contains 134,681 elements, the biggest area of element is 4598 pixels and the smallest is 27 pixels (as shown in Fig. 6). The experimental region and segmentation parameters are the same, but the result is very different. The main reason is that the land-cover completeness is destroyed.

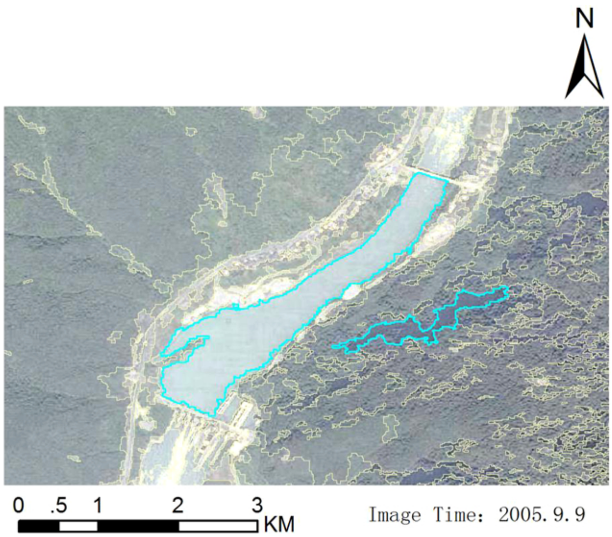


Fig. 5. Segmentation result of the pre-earthquake image.

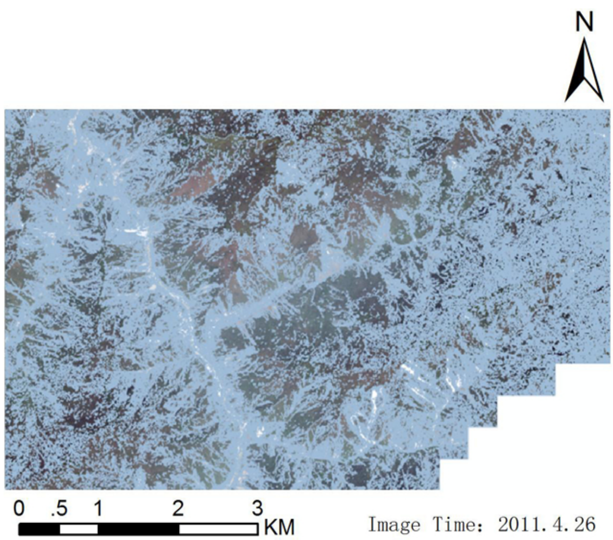


Fig. 6. Segmentation result of the post-earthquake image.

4.2. *Experimental results*

Studying the topological properties of real systems is very significant to understand their structures and dynamics. For this, this paper uses some topological measures for comparison experiments between the pre-earthquake and post-earthquake images. Figure 7 shows the degree distributions of the land-cover features. The results indicate that the degree distribution satisfies power-law distribution both

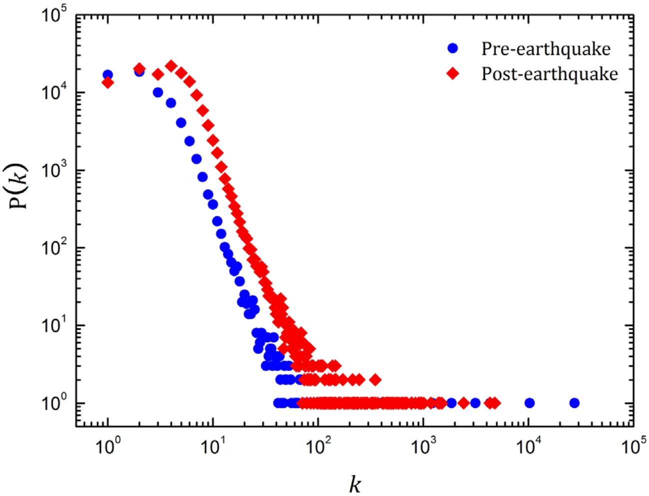
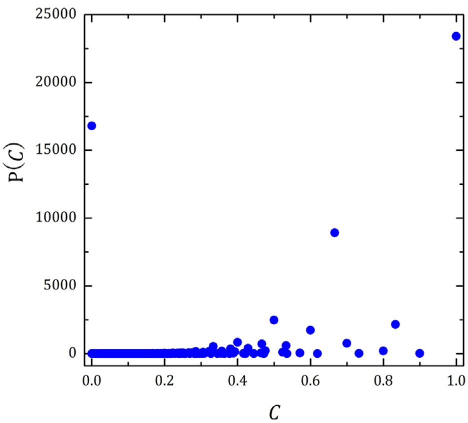


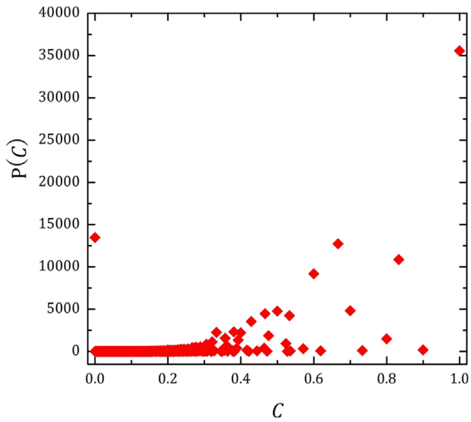
Fig. 7. Degree distribution of land-cover networks.

for the land-cover features of pre-earthquake and post-earthquake images; more importantly, their power-law exponents are basically identical. Therefore, we can see that the land-cover networks of the pre-earthquake and post-earthquake are both scale-free networks. Compared with the pre-earthquake, the degree distribution of the post-earthquake network moves toward the positive k direction slightly, which indicates that the constants of the power-law functions is different that the constant of land-cover network of the post-earthquake is greater than that of the pre-earthquake. In other words, the average degree of the post-earthquake land-cover network is greater than that of the pre-earthquake land-cover network. Before earthquake, the average degree is equal to 3.865. But after earthquake, the average degree is equal to 5.348. Therefore, we can conclude that the land-cover is destroyed after earthquakes; although the land-cover networks for pre- and post-earthquake images are both scale-free network, the structural properties of the land-cover networks are still different to some extent, especially the average degree increased remarkably after earthquake.

Figure 8 is the clustering distribution of land-cover networks for the pre-earthquake and post-earthquake images. The results show that the clustering distribution morphologies of two land-cover networks are similar, only the number of large clustering nodes increases to some extent. The reason for this is that the original spots in the pre-earthquake image are broken after earthquake and the number of new generated spots is more than that of the original spots. Therefore, we can see that for pre- and post-earthquake images, the structural characteristics of land-cover spots possess similarity and some disciplines. On the basis of this, it suggests that the change of structural characteristics of land-cover after earthquake can be measured according to the pre-earthquake image and its topological properties.



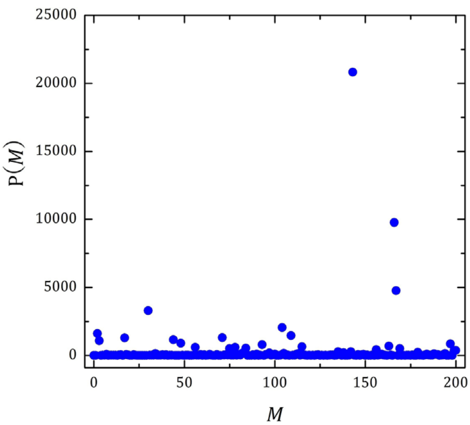
(a) Pre-earthquake



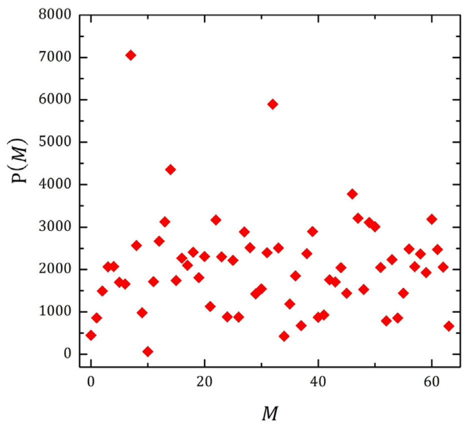
(b) Post-earthquake

Fig. 8. Clustering distribution of land-cover networks.

We believe that after the earthquake, the land-cover information is changed. For this, this paper further studies the modularity of both land-cover networks. Using the same modularity algorithm, we extract some important results. For the land-cover network of the pre-earthquake image, the modularity $Q = 0.809$ with 206 community structures; however, for the land-cover network of the post-earthquake image, the modularity $Q = 0.952$ with 62 community structures. We can see that after earthquake, the degree of community structure is greater than before earthquake and the communities have better structural characteristics. As shown in Fig. 9, it presents the modularity classes and the number of nodes of each class. The results indicate that before earthquake, only few communities have a lot of nodes, many other communities just have a few nodes; after earthquake, most of

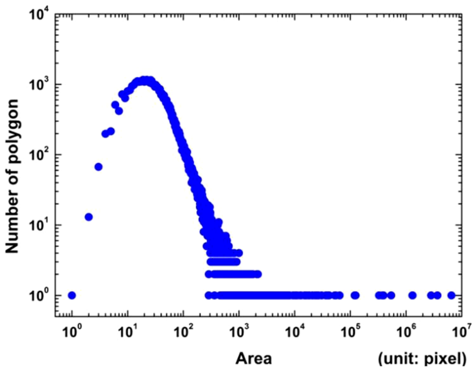


(a) Pre-earthquake

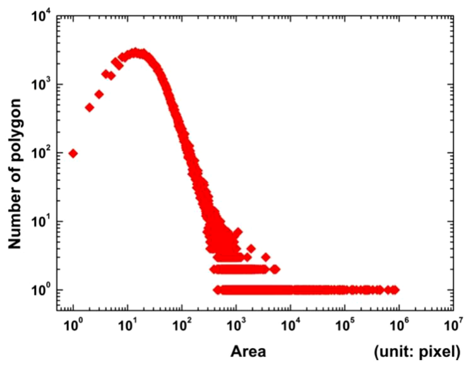


(b) Post-earthquake

Fig. 9. Modularity distribution of land-cover networks.



(a) Pre-earthquake



(b) Post-earthquake

Fig. 10. Area distribution of land-cover networks.

the communities have thousands of nodes. Therefore, it can be concluded that the modularity of the post-earthquake land-cover network is greater than that of the pre-earthquake land-cover network; after earthquake, the size of each community is larger, the strength of community structure is greater and the results of community division are more effective. Moreover, this result is helpful to study the change of structural characteristics of land-cover and the identification of the landslide group.

In order to further study the land-cover networks, we calculate the area information of all spots, as shown in Fig. 10. The results show that the area information of spots meets power-law distribution both for the pre-earthquake and post-earthquake images. Although the plots of Figs. 10(a) and 10(b) are very similar (that means the power-law exponent is same approximately), the maximum number of polygon is different considerably. In Fig. 10(a), the maximum number of polygon is equal to 1159. However, in Fig. 10(b), the maximum number of polygon is equal to 2970. The reason for this is that after earthquake, the land-cover features are broken and the number of features with smaller area increases greatly. Moreover, the maximum area of polygons decreases from 6,542,491 to 844,303 and the corresponding polygon is covered by woodland, which indicates that the area of the maximum woodland feature reduced by 87%. Therefore, we can see that the structural characteristics of land-cover were destroyed seriously by the earthquake.

5. Conclusions

The land-cover has some structural characteristics that can be measured by using complex networks and GIS techniques. However, when some disasters occur, especially massive landslide, whether the land-cover's structure will change and how to measure the change remain an important subject.

This paper introduces the complex networks theory to study the structural properties of the land-cover, and proposes a dual graph for the land-cover map. By taking Taoguan village as an experimental region, we construct the dual graphs of the pre-earthquake image and post-earthquake image, respectively. The results indicate that the land-cover network meets power-law distribution; after earthquake, the communities of the land-cover network are divided efficiently with greater strength; and the land-cover is destroyed seriously that the degree distribution, clustering distribution and modularity distribution of the land-cover network are all changed if lots of landslides occur. This paper explores the research idea of land-cover, which is helpful for studying the image segmentation, landslide hazard assessment, etc. Importantly, our work reveals the topological structural characteristics of land-cover, presents a method for measuring the change of structural characteristics of land-cover and provides a research idea for the identification of landslides.

Acknowledgments

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