Land Cover Change Monitoring of Mine City Using Multi-Temporal Satellite Remote Sensing Images

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***Abstract*—Exploitation of mine resources has great damage to the earth surface and has impact on the regional ecological environment, which led to serious land collapse, soil degradation, vegetation damage and so on. Land cover distribution and change can directly reflect the ecological status of mining region. Therefore, this paper presented a framework to obtain more detailed classification results and monitor land cover change of mining city using multi-temporal high spatial resolution remote sensing images. The presented method had two major steps. First, the multi-temporal remote sensing images were classified by object-oriented semi-automatic classification method. Second, the spatial distribution and change of land cover were analyzed based on multi-temporal classification results. The Liaoning Anshan Iron Ore of Northeast China was selected as the study area. Two temporal high spatial resolution remote sensing images spanning ten years were collected, including ALOS, SPOT-2 and Landsat-7. The experimental results showed that multi-temporal high spatial resolution remote sensing images can be effectively used to monitor the land cove change of mining city. The land cover of Anshan had great changes over the ten years. The mining, building and bare land area increased. The arable land and grassland area decreased, and the forest land area remained stable. From the change of land cover distribution and types, the ecological quality of Liaoning Anshan was declined with mining and urbanization.**

***Index Terms*—multi-temporal, high spatial resolution remote sensing images, classification, land cover change detection**

I. Introduction

The natural resource was the most basic material and energy foundation for the human society survival and development. The production and consumption of mineral resource made great contributions to the development of human economy and society. However, a series of ecological environment problems have been brought up by human resource exploitation activities, especially for mining [1]. Mineral resource exploitation has destroyed the earth surface, which led to serious land collapse, soil degradation, vegetation damage, even worse ecological environment deterioration [2].

With the development of economic, a lot of environmental problems had been appeared, such as soil erosion, land desertification, vegetation degradation, and so on. The ecological environment problems caused by mining exploitation were serious and had gained wide spread attention. The quality of the regional ecological environment becomes more and more important to regional sustainable development and human survival.

How to evaluate the ecological environmental conditions is a complex procedure because it involves in the knowledge of many subjects. Many studies have been carried out on different spatial scales and from different perspectives [2]. The exploitation of opencast mines made greater damage to the earth surface. Land cover change can directly reflect the ecological status of mining regions. Regular monitoring and analysis of land cover change for mining city has important practical significance to the ecological environment recovery and management.

Remote sensing technology play an important role in understanding the impact of mining activity on the region ecological environment with the capabilities of repeatability, large area, low cost and so on. The classification results of remote sensing images were usually applied to investigate the land-use/land-cover distribution and change in area of different activities before, during and after the mining project [3]. Many studies evaluated the environment status of mining region using multi-temporal remote sensing images. David et al. monitored the environmental impact of remote location mining using the remote sensing data [1]. The landscape transformation of copper-gold mine was obtained from multi-temporal satellite remote sensing images. The environmental impact of opencast iron mines in India was analyzed using multi-temporal remote sensing data and limited ground based information by Venkataraman et al. [3]. The change trend of land use was observed from multi-temporal remote sensing data. Li and Wu applied

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fused high spatial and spectral resolution remote sensing images to monitor the subsidence induced by mining and achieved good results [4]. Erener presented a method to monitor vegetation cover and assess the vegetation health using multi-temporal Landsat TM data sets [5]. Many vegetation indexes were computed and analyzed from TM images. The experimental results showed that the remote sensing data was useful and cost-effective in monitoring the progress of rehabilitation for mining regions. Li et al. applied multi-temporal remote sensing Landsat data to monitor the increase of coal mining activity [6]. The land cover information was obtained by visual interpretation and digitization from remote sensing images. The spatial and temporal evolution trends of mining activity were concluded from the classification results. Petropoulos et al. applied multi-temporal Landsat TM images to monitor the change of surface mining activity and reclamation. The support vector machine classifier was selected to classify multi-temporal TM images. The change trend of mining area was analyzed throughout the whole 23 years [7].

The ecological environmental status can be evaluated through the analysis of land cover change. The traditional evaluation methods applied multi-temporal low or medium-spatial resolution remote sensing images, such as Landsat series, MODIS and so on. However, with the development of remote sensing technology, a series of high spatial resolution remote sensing satellites had been launched. The data acquisition ability has been increased greatly, and the acquisition of multi-source high spatial resolution earth observation data has come to a new era. How to use multi-source and multi-temporal high spatial resolution remote sensing images to obtain more detailed classification results and monitor land cover change of mining city become a hotspot and it needs to be further studied.

The aim of this study was to monitor the land cover change of mining city using multi-temporal high spatial resolution remote sensing images. The Liaoning Anshan Iron Ore of Northeast China was selected as the study area and two temporal high spatial resolution remote sensing images spanning ten years were collected. The experimental results proved that multi-temporal high spatial resolution remote sensing images and related techniques can effectively monitor the land cove change of mining city.

II. METHOD

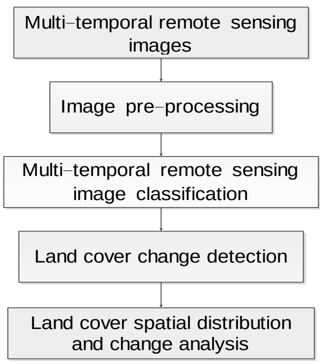

Figure 1. The flowchart of the proposed monitoring method.

This section introduced the technological process of land cover change monitoring of mine city using multi-temporal high spatial resolution satellite remote sensing images. The image pre-processing, multi-temporal remote sensing image classification, land cover spatial distribution and change analysis were detailed. The flowchart of the proposed method is shown in Fig. 1.

A. Study Area and Remote Sensing Data

The Liaoning Anshan Iron Ore development area, which is located in northeast of China, was selected as the study area. Two temporal high and moderate spatial resolution remote sensing images were collected in the year of 2000 and 2010, including ETM+, SPOT-2 and ALOS. The details of remote sensing satellite data can be seen in Table I.

TABLE I. MULTI-TEMPORAL SATELLITE REMOTE SENSING IMAGES FOR MONITORING LAND COVER CHANGE IN ANSHAN

No.	Satellite Sensor	Spatial resolution	Date of acquisition
1	SPOT-2	10 m	2000.09.24
2	ETM+ MS	30 m	2000.09.25
3	ETM+ Pan	15 m	2000.09.25
4	ALOS Pan	2.5 m	2010.05.20
5	ALOS MS	10 m	2010.05.20

B. Multi-temporal Images Pre-processing

Image pre-processing was the foundation of successfully using the multi-temporal data sets, which include geometric correction, data fusion, image resample and image clip.

In order to analyze remote sensing images from different dates and sensors, the datasets must be firstly geometrically corrected to the same spatial reference frame [8]. Different satellite remote sensing images need different geometric correction models. The RPC (Rational Polynomial Coefficient) model was used to geometrically correct ALOS images for 2010. Then, the corrected ALOS images were selected as reference images and the image-to-image registration method was applied for SPOT-2 and Landsat 7 images correction using strict physical imaging model and multinomial model.

Image fusion is the process of combining relevant information from two or more images into a single image. The resulting fusion image will be more informative than any of the input images. For multi-source remote sensing images, the data fusion method was used to improve the multi-spectral bands resolution integrating the high spatial resolution panchromatic image.

After co-registration and fusion, both temporal high spatial multi-spectral remote sensing images were clipped by the shape of study area. Fig. 2 and 3 show two temporal results of image pre-processing.

Figure 2. Pre-processed remote sensing image of 2000, band combination (RGB-543)

Figure 3. Pre-processed remote sensing image of 2010, band combination (RGB-342)

C. Multi-temporal Images Classification

Following the images pre-processing, a semi-automatic classification method was used to classify these two temporal remote sensing images. The classification process of multi-temporal remote sensing images mainly included three steps. First, the latest temporal remote sensing image was classified by object-oriented automatic classification and manual correction. Second, the latest temporal classification result was mapped to the former temporal segmentation result. Third, the change information of the second temporal was corrected by human manual correction. The flowchart of multi-temporal images classification method can be seen in Fig. 4.

1) Image segmentation

Image segmentation is the basis of object-oriented image analysis for high spatial resolution remote sensing images. Image segmentation is a process of dividing an image into meaningful homogenous regions [9]. The region-based multi-resolution segmentation method in eCognition software is used to segment the multi-temporal images. The multi-resolution segmentation process is controlled by the scale, shape and compactness parameters specified by users [10]. The most suitable parameters are determined by users' subjective assessment.

2) Image classification of the first temporal

The Support vector machine classifier was adopted to automatically classify the first temporal image. Support vector machine is a supervised nonparametric statistical learning technique. It works well at solving nonlinear, high dimensional and limited training samples and widely applied to classification of remote sensing images [11]. The automatic classification method can quickly get the classification result, but the classification precision cannot satisfy the need of application. Therefore, in order to improve the automatic classification precision, the automatic classification result was corrected by manual operation.

3) Image classification of the second temporal

Comparing the 2000 and 2010 images, it can be seen that most land-cover classes remained largely unchanged over the past ten years. Hence, the high precision classification result of 2010 can be backtracked to help to get the classification result in 2000. The high precision classification result in 2010 was firstly mapped to the segmentation result of 2000 by the majority spatial mapping mechanism presented in [12]. After spatial mapping, the initial mapping classification result of 2000 was obtained. And the final classification result was obtained by manual correction for changing information.

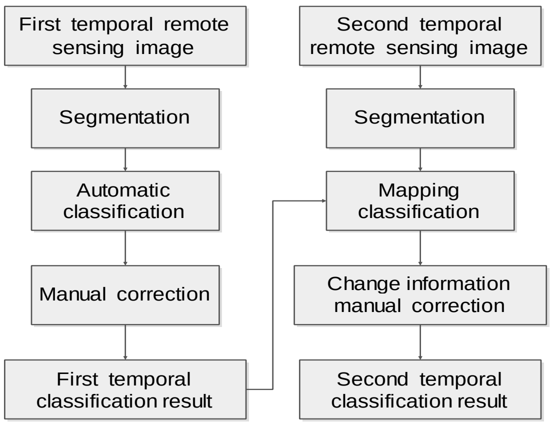

Figure 4. The flowchart of multi-temporal images classification method.

D. Land Cover Spatial Change Analyse

The impact of mining activity on the land cover change was analyzed from 2000 to 2010 through a post-classification change detection method. The analysis was applied to the land cover maps derived from those two temporal remote sensing images. The area and change of each land cover class were computed from these two temporal classification results. The land cover change transfer matrix was computed for analyzing the land cover change trend.

III. Experiments and Discussion

Fig. 5 and 6 show the final classification results for 2000 and 2010. To evaluate the classification accuracy of these two temporal remote sensing images, the confusion matrices of these two temporal classification results were constructed by selecting points with stratified random sampling. The reference classification results were generated through precise manual interpretation of more high spatial resolution images from Google Earth and field survey. The producer, user and overall classification accuracies were calculated from the confusion matrix.

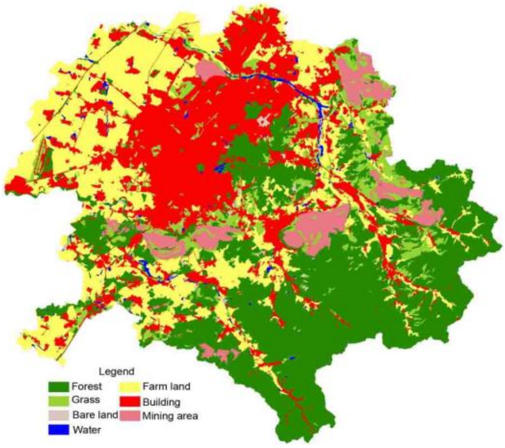

Figure 5. Land cover classification results of 2000.

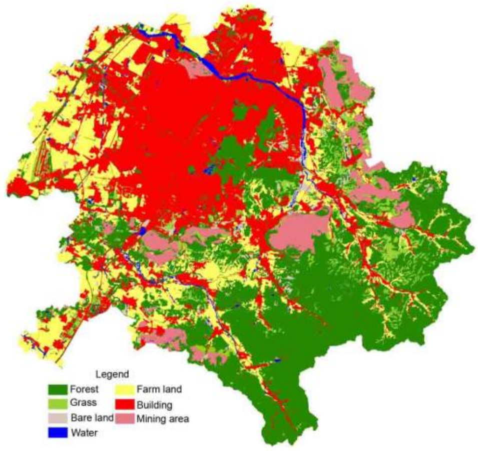

Figure 6. Land cover classification results of 2010.

TABLE II. PRODUCER AND USER CLASSIFICATION ACCURACIES OF 2000 CLASSIFICATION RESULT

Class	Producer's Accuracy %	User's Accuracy %
Mining area	100. 00%	98. 00%
Building	86. 21%	100. 00%
Farm land	95. 56%	86. 00%
Bare land	97. 87%	92. 00%
Forest	92. 16%	94. 00%
Grass	86. 54%	90. 00%
Water	100. 00%	96. 00%
Overall Accuracy	94. 89%	

TABLE III. PRODUCER AND USER CLASSIFICATION ACCURACIES OF 2010 CLASSIFICATION RESULT

Class	Producer's Accuracy %	User's Accuracy %
Mining area	98. 04%	100. 00%
Building	100. 00%	88. 00%
Farm land	91. 67%	88. 00%
Bare land	95. 45%	84. 00%
Forest	87. 27%	96. 00%
Grass	65. 67%	88. 00%
Water	100. 00%	88. 00%
Overall Accuracy	91. 56%	

TABLE IV. AREA STATICS OF EACH CLASS

	Area (Unit: Km^2)		
Class	2000	2010	Change
Mining area	33.6187	40.0374	6. 4187
Building	157.1561	212.2991	55. 1430
Farm land	156.4042	107.4050	−48. 9992
Bare land	3.7373	21.7346	17. 9973
Forest	217.2511	205.9547	−11. 2964
Grass	52.3338	29.3527	−22. 9811
Water	5.3002	9.0179	3. 7177
All	625.8014	625.8014	0

Table II and III presented the producer, user and overall accuracies of those two temporal classification results. The overall accuracies were higher than 90%, and were able to apply for land cover change analysis.

From 2000 to 2010, the land cover of Liaoning Anshan changed greatly. The mining, building and bare land area increased over the ten-year period. The farm land and grassland area decreased, and the forest land area remained stable. The land cover change trend can be obtained from Table IV.

The mining regions of Liaoning Anshan Iron Ore were located in the southeast of main urban area. As shown in Table IV, the mining area increased only about 20 percent of the iron mining region from 2000 to 2010. The reason of limited increasing was that land reclamation was applied in the mined region.

The building area increased about 30 percent from 2000 to 2010. The direction of urban extension was north-west, because the distribution of mining regions limited the direction of urban extension towards the south-east. Besides, there is a highway running through the north-east of Anshan.

TABLE V. THE LAND COVER CHANGE TRANSFER MATRIX (AREA UNIT: KM2)

Year	2010							
2000	Class	Mining area	Building	Farm land	Bare land	Forest	Grass	Water
	Mining area	26.9043	0.7497	0.0639	0.3083	4.7807	0.7594	0.0524
	Building	0.3784	147.7845	0.9212	6.0367	0.877	0.3372	0.8211
	Farm land	0.8611	37.7923	93.8948	6.2571	10.9938	4.4103	2.1948
	Bare land	0.0537	0.7545	0.2416	1.7657	0.3383	0.2711	0.3124
	Forest	4.7173	10.6145	9.1116	2.5921	181.6283	7.6846	0.9027
	Grass	7.1077	13.9152	2.666	4.296	7.0112	15.6803	1.6574
	Water	0.0149	0.6884	0.5059	0.4787	0.3254	0.2098	3.0771

It can be seen from Table V that the new building and mining area was mainly transformed from arable, grass and forest land. Some abandoned mining regions were reclaimed to grass and forest land.

Generally, the vegetation cover was decreasing and the building, mining and bare land area was increasing. The quality of Liaoning Anshan ecological environment was declined with the land cover changes by mining and urbanization.

IV. CONCLUSION

In the present study, the multi-temporal satellite remote sensing images and relevant techniques were used to analyze the land cover change of mining city. The Liaoning Anshan Iron Ore of Northeast China was selected as the study area, and two temporal high spatial remote sensing images spanning ten years were collected. The experimental results proved that multi-temporal remote sensing images, especially high spatial resolution satellite remote sensing image, has the unique advantage in land cover information extraction and change detection of mining city.

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