Object-oriented monitoring of coal mine land use change

Yuan Xitun, Xing Lei, Gao Wenjin, Gao Pengwei, Zhao Xin, Chang Jinzhong
Xi'an University of Science and Technology, Xi'an, 710000, Shaanxi Province, China

Abstract. Taking Dongsheng district of Erdos City in Inner Mongolia as the research area, we used the object-oriented classification method to monitor the land use change in recent years. The images of the three periods were classified into vegetation, residential area, water body, the mining area as well as the bare land, of which the accuracy rate has reached 86%. The results were produced by statistically analyzing. From 2006 to 2011, the vegetation was badly damaged, including the expanding residential areas and mining areas. The residential area was constantly expanding between 2011 and 2018, but the total area of the mining area and vegetation cover has not changed much. The area after the mining has been re-greened, which is conducive to the coordinated development of that area.

1. Introduction
Since the 1990s, land use change has attracted the attention of international organizations and countries, which has become a hot topic in global change research. The study of regional land use change is now greatly improved in breadth and depth [1-5]. China is one of the biggest countries for coal production. Coal plays a vital role in China's energy structure. It is the main energy source and the indispensable material basis for national economic and social development of our country [6]. Coal enterprises, urban and rural construction as well as local vegetation all require the use of land, which causes the transformation of coal mine land and other enterprise land. Due to the irrationality of land use change, the ecological environment of the mining area has been greatly damaged [7-8]. Therefore, the objective data was needed as a guidance to monitor mining area real-time.

With the advancement of computer and space technology, computer-based remote sensing technology is widely used in the dynamic monitoring of coal mining and land use change around mining areas with its unique advantages of macro, rapid and dynamic [9]. In this way, real-time understanding of the geological environment, land use of the mining area, environmental restoration as well as the mining area will be accurately evaluated, thus a more effective land management plan can be formulated to provide a reasonable basis for the mining area planning. Chen Lihua et al [10] used remote sensing images to remotely monitor the ecological environment changes in the Daye mining area in Hubei; Meng Mengyuan [11] selected Wuhai as the research area of the Dynamic monitoring of coal mining, based on MSS/TM remote sensing data and combined with SPOT-VEGETATION NDVI data.

Most of the traditional remote sensing classification methods use pixel-based classification algorithms, which directly ignore the extremely rich geometric, topological and spatial features of the image. The classification results are very prone to the phenomenon of “salt and pepper”. The qualitative region is more obvious [12-13]. The object-oriented classification method not only uses image spectral features, but also combines image space, texture and shape, so that the accuracy of remote sensing classification can be further improved [14-15]. It can obviously makes remote sensing technology better serve the coal mine classification.

2. Study area and data source

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Published under licence by IOP Publishing Ltd
Some open-pit coal mines in and around Dongsheng district, Erdos City, Inner Mongolia were selected as experimental research areas. Dongsheng district is located in the eastern part of the Erdos Plateau in Inner Mongolia, which is located at 109°08′20″~110°23′00″ east longitude and 39°39′10″~39°58′18″ north latitude. The minerals in Dongsheng district are all sedimentary minerals. Most of reserves are coal. The reserves of coalfields are about 18.6 billion tons. The coal seams are thick but easy to mine. They have the reputation of coal seas.

Medium-resolution Landsat 5 TM and Sentinel-2 remote sensing images are used as data sources. The spatial resolution of Landsat 5 TM is 30 m, while the spatial resolution of Sentinel-2 is 10m, 20m, 60m. In this paper, only 10m and 20m is used, so only the two bands are fused. The three-phase remote sensing image was selected for the 18 years from 2006 to 2018. The projected coordinate system was WGS-84. The timing of each period below was September 10, 2006, September 24, 2011, and September 21, 2018.

![Figure 1. Original image of the three periods of the study area](image)

### 3. Data processing

#### 3.1. Data preprocessing

In order to obtain accurate basic data and make the final result more reliable, we downloaded remote sensing image subjected to radiometric calibration and atmospheric correction. The Sentinel-2 image requires a band of 10m and 20m resolution, so first we carried out the bands of the two resolutions subjected to radiometric calibration and atmospheric correction. Then the two resolutions bands were fused. Because of the displacement between the downloaded remote sensing images, the image registration was performed. Finally, the image was clipped by the vector boundary of the research area.

#### 3.2. Image segmentation

The segmentation operation of the study area image is performed by the multi-scale segmentation module provided in the object-oriented classification software ecognition. Multi-scale segmentation is a bottom-up segmentation method that divides an image into several parts and it ensures that the segmented objects have precise edges which do not overlap each other. The interior is also uniformly distributed, corresponding to the real objects. Therefore, the important parameter to determine the optimal segmentation scale is the basis for later work. If the segmentation scale is large, the generated object area is also large and the probability of misclassification even becomes larger; On the contrary, the segmentation scale is smaller. Although the possibility of misclassification of different categories is reduced, the number of segments of the same object increases, resulting in data volume. It is also complicated and it will affect the classification accuracy. In theory, any kind of ground object has a suitable segmentation scale and the classification of the ground objects under the optimal segmentation scale is selected and thus the precision will reach the highest.

The ecognition plug-in ESP is used to determine the optimal segmentation scale. The principle is to calculate the local variation of image segmentation homogeneity under different segmentation scales. As the average standard deviation of the segmentation target layer, the segmentation effect is judged by
the standard deviation of the object layer. When the value of the rate of change reach a peak value, it is generally considered that the value corresponding to the point is the optimal segmentation scale result as follows:

![Figure 2. Determination of the optimal segmentation scale](image)

Combined with the figure above, the image is divided into three layers by dividing the image at different segmentation scales. The first layer is divided into three layers, which are used to distinguish between vegetation and buildings. The second layer has a segmentation scale of 200, which can be used to distinguish between water and bare land. The third layer has a segmentation scale of 340, which is used to distinguish mining areas.

3.3 Feature selection
(1) Normalized difference vegetation index (NDVI)

The normalized vegetation index is an indicator used to detect vegetation growth status and vegetation coverage. Its value is between -1 and 1, and the greater the vegetation coverage, the higher the value. The formula is:

$$\text{NDVI} = (\text{NIR} - \text{Red})/(\text{NIR} + \text{Red})$$

Where, NIR is the reflectance in the near-infrared band; Red is the reflectance in the red band (Figure 3).

(2) Normalized difference Building Index (NDBI)

The normalized building index can accurately reflect the information of the construction land, and the higher the proportion of the building land is, the larger the value is. The formula is:

$$\text{NDBI} = (\text{MIR} - \text{NIR})/(\text{MIR} + \text{NIR})$$

In the formula, MIR is the reflectance of the mid-infrared band (Figure 4).

As can be seen from Figure 4, the value of the normalized building index in the mining area is apparently high.

(3) Normalized Water Index (NDWI)

The normalized water body index is used to highlight the water body information in the image. The formula is:

$$\text{NDWI} = (\text{Green} - \text{MIR})/(\text{Green} + \text{MIR})$$

In the formula, Green is the reflectance of the green band (Figure 5).
(4) Other features
The average of the characteristics of blue, green, red, near red, medium red, and brightness of the original image automatically generated by ecognition software.

3.4. Nearest neighbor classification
The classification method used in this study is the nearest neighbor classification, which selects the sample region and classifies the image. The process is similar to the traditional pixel-oriented supervised classification method, but there are differences: the object-oriented nearest neighbor classification method is selected after image segmentation. The outcome is the object, however, the traditional supervised taxonomy choose the pixel.

Principle of nearest neighbor taxonomy: In the feature space, each segmented image object searches for the nearest sample object. If the most recent image object belongs to a certain class, the object is also classified into this class.

Through the classification above, the land use situation in the three periods of the study area is obtained, as shown in the figure:

4. Results analysis

4.1. Accuracy analysis
Comparing the objects in the classified image with the re-selected verification samples, we finally get the confusion matrix for accuracy analysis as shown in Table 1 (in 2011). The accuracy of the other two years is above this result. The results show that the overall accuracy is above 86%.

| Table 1. Confusion matrix and classification accuracy of nearest neighbor classification (%) |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|---------------|
| class\sample                   | Water | Vegetation | Residential | Mine | Bare land | Water | Vegetation | Residential | Mine | Bare land | Sum  |
| Water                          | 11    | 0           | 0           | 0    | 0         | 11    | 0           | 0           | 0    | 0         | 11   |
| Vegetation                     | 1     | 28          | 2           | 1    | 0         | 32    | 28          | 2           | 1    | 0         | 32   |
| Residential                    | 0     | 0           | 25          | 2    | 5         | 32    | 0           | 25          | 2    | 5         | 32   |
### 4.2. Analysis of land use change in the study area

| Area       | 2006       | 2011       | 2018       |
|------------|------------|------------|------------|
| Vegetation | 833.9869   | 669.3150   | 678.2333   |
| Residential| 27.6192    | 79.5844    | 95.5152    |
| Mine       | 19.3689    | 120.3561   | 104.9224   |
| Bare Land  | 120.8854   | 132.4996   | 122.6488   |
| Water      | 0.8973     | 1.0026     | 1.438      |

**Overall Accuracy = 0.898, Kappa = 0.86569**

As can be seen from the figure and table above, the main land use type in the study area is vegetation. In 2006, 2011 and 2018, it respectively accounted for 83%, 67% and 68% of the total area, which can be seen that the vegetation area decreased significantly between 2006 and 2011. In addition, the residential area has increased significantly from 3% in 2006 to 8% in 2011, and then to 10% in 2018, which is generally on the rise.

According to the three-year classification image and the land use area statistics of Table 2, in 2006, the main vegetation cover of the study area was the main one. At this time, the proportion of the mining area and the residential area only accounted for 5%. From 2006 to 2011, due to the continuous improvement of mining technology, the area of mining area expanded rapidly, increasing by 100 hm². At the same time, the vigorous exploitation of the mining area led to the development of the local economy, which also led to the expansion of the residential area. It can be seen that the occupied land in mining areas, residential areas and some bare land is mainly evolved from vegetation. The exploitation of open pit mines directly causes the destruction of surface vegetation. If the land restoration measures are not carried out in time, the ecological balance will be seriously affected.

From 2011 to 2018, land use change is not very obvious. The area of residential areas has increased and the total area of mining areas is not much different. In addition, the vegetation has begun to appear in the mined areas. In some places, vegetation cover is obvious. This shows reflect three thing. First, that the land reclamation work in the mining area has been improved. Second, the land planning and utilization work is relatively in place. Third, the layout is relatively reasonable, which is conducive to the coordinated development of the mining area.

### 5. Conclusion

The study area is located in the Inner Mongolia Autonomous Region, which belongs to arid areas. Ecological environment is fragile and Coal mining leads to serious damage to the surface vegetation. In addition, the natural conditions are so poor that population is small and the output is low. There is no advantage in developing other industries, so it's the best choices for local development to recover the...
original ecological functions. Therefore, we should establish and improve the government supervision mechanism in order to strengthen the governance work; We still have lots of things to do, including raising the awareness of the whole society on land governance, vigorously publicizing the significance of land governance, promoting scientific development and sustainable development, enhancing the legal awareness and responsibility of the whole people, actively participating in land management as well as achieving a good situation of equal emphasis on development and governance.

References
[1] Wang Xiulan, Bao Yuhai. Discussion on research methods of land use dynamic change. Progress in Geography, 1999, 18(1): 81-87.
[2] Wang Siyuan, Zhang Zengxiang, Zhou Quanbin et al. Temporal and spatial characteristics of land use based on remote sensing and GIS technology. Journal of Remote Sensing, 2002, 6(3): 224-228.
[3] Hu Zhenqi. Land use/cover change in coal mining area based on remote sensing image. Journal of China Coal Society, 2004, 33(5): 44-48.
[4] Bian Zhengfu, Zhang Yanping. Analysis of land use pattern evolution in Xuzhou coal mining area. Acta Geographica Sinica, 2006, 61(4); 349-358.
[5] Hu Zhaoling, Du Peijun, Guo Dazhi. Analysis of spatio-temporal changes of land use in Xuzhou city based on remote sensing. Journal of China University of Mining & Technology, 2006, 16(2): 151-155.
[6] Liang Xiaoye, Wang Zhihua, Zhou Zhijun, Huang Zhenyu, Junhu Zhou, Cen Kefa. Up-to-date life cycle assessment and comparison study of clean coal power generation technologies in China, Cleaner Production, 2013, 39: 24-31.
[7] Fan Yinghong, Lu Zhaohua, Cheng Jianlong, et al. Main ecological and environmental problems in China's coal mining areas and ecological reconstruction technology [J]. Ecological Science, 2003, 23(10): 2144-2152.
[8] DUTTA R K, AGRAWAL M. Restoration of Open Cast Coalmine Spoil by Planting Exotic Tree Species: A Case Study in Dry Tropical Region [J]. Ecological Engineering, 2003, 21(1): 143-151.
[9] Wang Xiaohong, Nie Hongfeng, Yang Qinghua, et al. Comparison of high-resolution satellite data in mine development status and environmental monitoring [J]. Remote Sensing of Land and Resources, 2004(1): 15-18.
[10] ChengLihua, ChenGang, LiJinglan, et al. RS based Ecological Environmental Dynamic Monitoring Mining Area[J]. Resources Science, 2004, 26(5): 132-138.
[11] Meng Mengyuan, Xu Xinhong, Jiang Dong, et al. Remote sensing monitoring of the impact of coal mining on ecological environment in Wuhai City from 1979 to 2010 [J]. Remote Sensing Technology and Applications, 2012, 27(6): 933-940.
[12] Zhong Bo, Ma Peng, Nie Aihua, et al. Land Cover Classification Method Based on Time Series HJ-1/CCD Data[J]. Science in China, Earth Science, 2014, 44(5): 967-977.
[13] Yang Hao, Huang Wenjiang, Wang Jinhua, et al. Monitoring of rice growth period based on HJ-1A/1B CCD time series imagery[J]. Transactions of the Chinese Society of Agricultural Engineering, 2011, 27(4): 219-224.
[14] Laliberte AS, Rango A, Havstad KM, et al. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico[J]. Remote Sensing of Environment, 2004, 93(1/2): 198-210.
[15] Wu Qianzheng, Liu Jianzheng, Huang Xiulan, et al. Automatic identification of farmland irrigation and drainage system in land consolidation area based on object-oriented classification[J]. Transactions of the Chinese Society of Agricultural Engineering, 2012, 28(8): 25-31.