Extraction of open-pit mining area based on optimal scales selection and hierarchical classification: A case of Nonoc lateritic nickel

Xian Zhang¹,²,³, Wei Li¹,², Li Chen¹ and Yaqin Sun¹

¹China Aero Geophysical Survey and Remote Sensing Center for Natural Resources, Beijing 100083, China;
²Key Laboratory of Airborne Geophysics and Remote Sensing Geology, Ministry of Natural Resources, Beijing 100083, China;
³Corresponding author’s e-mail: zhangxrs@163.com

Abstract. Traditional remote sensing extraction of open-pit mining area usually has low efficiency. To reduce time of extraction, taking laterite nickel as an example, we proposed a remote sensing extraction strategy of ground objects information in open-pit mining area. Firstly, the optimal segmentation scale parameter (SP) of each category was selected based on the local variance change rate. Secondly, the spectral feature, spatial feature and inter-object relationship feature of high spatial resolution remote sensing images were taken full advantage of feature space construction. Finally, based on the selected SPs and feature space, a top-down hierarchical classification framework was established. The overall accuracy and the Kappa coefficient of the proposed method were 95.49% and 0.9387 by the confusion matrix test, respectively. Compared with the multiple experiments to determine segmentation scales, the proposed method improves the efficiency, meanwhile guarantees the accuracy.

1.Introduction
Extraction of open-pit mining area is of great significance to monitor the mining activities and the mining situation accurately [1]. According to the content of extraction, the relevant researches can be divided into single element extraction and multi-elements extraction. The former is recognition of specific feature in the mining area, such as tailings pond, reservoir, mining area and so on. The latter generally classifies all ground objects in the mining area, which can comprehensively understand their distribution. Combined with multi-period remote sensing images, it can also establish a ground object type transfer matrix to understand the changes of various ground objects.

Traditional extraction methods are mostly manual visual interpretation or machine learning based on pixels. Gao et al extracted tailings ponds in Heilongjiang Province based on ArcGIS software [2]. Ding et al established interpretation marks of various ground objects in the mining area, and extracted various land use types based on ERDAS and ArcInfo platforms [3]. Most of machine learning methods base on pixels use Landsat or other medium spatial resolution images, and commonly use classifiers such as support vector machine and nearest neighbor algorithm [4-5]. However, the former method is usually labor-intensive and inefficient, while the latter method easily leads to salt and pepper noise, and cannot be applied to smaller mining areas due to a lot of mixed pixels in the image. With the popularization of high spatial resolution remote sensing image and the development of image processing technology, object-based image analysis (OBIA) has been applied to the extraction in
mining area. In this method, the image is first divided into relatively homogenous objects, and then the objects are used as the minimum unit for classification and extraction. This can not only effectively avoid the impact of noise, but also make full use of the shape, texture and other spatial features of high-resolution images. At present, it is more and more widely used in extraction of multi-elements in open-pit mining area [6-9]. In recent years, deep learning methods have been gradually introduced into the extraction of ground object in mining areas. However, the current relevant studies only involve single element extraction [10-11]. For multi-element extraction, deep learning methods need to be further developed.

Nickel ore is an important strategic resource and a typical open-pit mining area. Multi-element extraction of nickel ore area is helpful to understand the mining situation and environmental changes in the mining area. Therefore, in this paper, the OBIA method was used to extract the laterite nickel ore from Nonoc Island, Philippines. The determination of segmentation scale in OBIA is one of the key factors affecting the extraction accuracy. However, in the current research, the selection of segmentation scale parameter (SP) is all empirical method or multiple experimental method, which not only easily leads to local optimization, but also consumes a lot of time and manpower. This paper introduced the idea of the rate of change (ROC) of local variance (LV) proposed by Drăguț et al [12-13], to determine the SP, combined with the feature options, established a top-down hierarchical classification framework, looking forward to improving the efficiency of extraction as well as guaranteeing accuracy.

2. Study area and data
The Nonoc nickel deposit is located in Nonoc Island, which is one of the largest laterites nickel ore in the Philippines [14]. It is estimated there are 112 million tons of nickel ore which is mainly laterite oxide ore [15]. The laterite regolith is thicker and the thickness is generally 3~10 m [16]. This study selected the eastern region of Nonoc nickel deposit (about 10 km²) as the study area. There are seven types of ground object, including water, vegetation, tailing ponds, road, bare land, mining area and pending mining area.

The PLEIADES image was employed as data source to extract the mineral elements from the study area. It has multispectral imagery with 4 bands (B, G, R, and NIR) of 2 m spatial resolution and panchromatic image of 0.5 m spatial resolution. The pre-processing was carried out by ENVI5.3, including radiometric correction, geometric correction, clip and image fusion.

3. Methods and result
3.1. Selection of optimal segmentation scales
The optimal SP selection method proposed by Drăguț is based on the rate of change(ROC) of local variance(LV). It is widely recognized that the LV of an image can reveal the spatial structure of an image. Therefore, the rate of change of local variance(ROC_LV) between different segmentation scale levels can measure the change of segmentation results at different levels. At the peaks of ROC_LV graph, the segmentation objects characterized by relative homogeneity. ROC_LV is defined as:

\[ \text{ROC}_L = \frac{LV_i}{LV_{i-1}} \times 100\% \]  

where \( LV_i \) is the LV at target level and \( LV_{i-1} \) is the LV at next lower level.  

Draw a line chart of the LV and ROC_LV with the change of SP. When the ROC_LV is located at the local maximum value, it can be considered as a more appropriate SP.

Taking 3 as the step size, the ROC_LV with the SP of 80~530 was calculated and the line chart was drawn (Figure 1). As can be seen from the Figure 2, when the SP was 95, 113, 155, 329, 524, ROC_LV was the maximum value of a certain range around it, and it was also the higher value of ROC_LV in the whole range of segmentation scale. Therefore, the image was segmented at these scales. The results are shown in Figure 2. As shown in Figure 2, when SP=95, 113 and 155, the segmentation results were more fragmented, which were suitable for bare land scattered among vegetation areas. By contrast, the SP of 95 was smaller, and there was over-segmentation in the extraction of bare land,
while the SP of 155 had under-segmentation areas (Figure 2 (a) - (c)). Therefore, bare soil was extracted at the scale of 113. SP of 278 and 329 were in the middle, which were suitable for the extraction of road and vegetation in mining area. The results of 278 scale had some over-segmentation areas, so 329 was adopted (Figure 2 (d), (e)). The result of 524 scale segmentation was large patch, which was suitable for large and homogenous categories, such as mining area, water body and tailing ponds(Figure 2 (f)).

3.2. Hierarchical classification
Considering that the ground objects in the study area are relatively complex and there is no unified optimal SPs for all of them, adopting the selected SPs above, a top-down hierarchical classification framework was established to extract all types of ground objects, so as to improve the overall extraction accuracy.

3.2.1. Feature space construction. The spectral feature, shape feature and inter-object relationship feature of high spatial resolution remote sensing images were fully utilized to construct feature space. First, samples for each category were selected, and then the separabilities of various features were analysed. Finally, the following features were selected from more than 100 features: mean spectral value of all objects in band 2 (B2), mean spectral value of all objects in band 3(B3), mean spectral value of 4 bands (Brightness), normalized difference vegetation index(NDVI), normalized difference
water index (NDWI), length-width ratio (LWR) and adjacency relationship between two categories (Border to). The formulas of NDVI, NDWI and LWR are as follows:

\[
NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{2} \\
NDWI = \frac{(G - NIR)}{(G + NIR)} \tag{3} \\
LWR = \frac{e_{1g_1}}{e_{1g_2}}, \quad e_{1g_1}(S) > e_{1g_2}(S) \tag{4}
\]

where NIR, R and G are spectral value of band 4, band 3 and band 2, respectively; eig is the eigenvalue of the covariance matrix of an object.

It should be noted that although the texture features of high spatial resolution images are relatively obvious, the calculation of texture features is very complex and time-consuming. Especially for large area like this study area, the efficiency is very low if the texture features are adopted. Therefore, based on the three optimal segmentation scales selected above, the author proposed a top-down hierarchical classification strategy. The bare land and pending mining areas differentiated by texture features in past studies were extracted at different scale levels, combined with inter-object relationship feature, thereby avoiding the utilization of texture features and further improving extraction efficiency.

3.2.2. Classification processing. According to the 3 selected SPs in 2.1, the classification was performed with 3 levels. The flowchart of multi-scale segmentation and hierarchical classification processing is shown in Figure 3.

![Figure 3. Flowchart of multi-scale segmentation and hierarchical classification.](image-url)
The objects whose NDWI>0.05 were classified as the water and tailing ponds, where the objects whose B3>237 were water, while the objects whose B3<237 were tailing pond.

When the NDWI<0.05, if NDVI<0.23 and B2<309, the objects would be a part of mining area (MA1). In the rest of the objects, if LWR>4.3 and Brightness>318, they would be classified as cement road.

In the rest of the unclassified objects, the objects whose LWR>3.8 and NDVI<0.34 were classified as dirt road1, while the (LWR<3.8 or NDVI>0.34) and B2>329 were classified as refuse dump.

In the rest of the unclassified objects, the objects whose LWR>3.8 and NDVI<0.34 would be the dirt road2, while the (LWR<3.9 or NDVI>0.34) and NDVI>0.35 were classified as vegetation.

The rest of the unclassified objects were the mixtures of bare land and a part of mining area (MA2), which could be distinguished by the Brightness and Border to. If Brightness>314 and (Border to mining area or MA1), the objects would be MA2, the rest of the unclassified objects were classified as bare land.

Finally, the MA1 and MA2 composed mining area, and the cement road, dirt road1 and dirt road2 composed road.

### 3.2.3. Classification result and accuracy evaluation

In order to evaluate the accuracy of classification result comprehensively and objectively, 13×18 test sample areas were selected from the original image at equal interval. The classification result and distribution of test samples are shown in Figure 4. Indicators such as producer accuracy, user accuracy, Kappa coefficient and overall accuracy of various categories are shown in Table 1.

![Figure 4. Classification result and distribution of test samples.](image)
Table 1. Evaluation indicators.

| Ground objects      | producer accuracy | user accuracy | Kappa per class | overall accuracy | kappa       |
|---------------------|-------------------|---------------|-----------------|-----------------|-------------|
| water               | 100%              | 100%          | 1               | 95.49%          | 0.9385      |
| tailing pond        | 100%              | 100%          | 1               |                 |             |
| vegetation          | 99.26%            | 98.10%        | 0.989           |                 |             |
| refuse dump         | 90.35%            | 84.72%        | 0.8973          | 95.49%          | 0.9385      |
| mining area         | 95.90%            | 86.64%        | 0.9544          |                 |             |
| road                | 74.57%            | 98.78%        | 0.7368          |                 |             |
| bare land           | 78.90%            | 90.77%        | 0.7679          |                 |             |

It can be seen from Figure 4 and Table 1 that the extraction accuracy of each category is relatively high on the whole, with overall accuracy and Kappa coefficient of 95.49% and 0.9385 respectively. For categories of water, vegetation and tailing pond, the producer accuracy and user accuracy are higher than 98%. Among the other four categories, the producer accuracy of refuse dump and mining area is higher (90.35% and 95.90% respectively), while the user accuracy is relatively low (around 85%). On the contrary, the user accuracy of road and bare land is 98.78% and 90.77% respectively, while the producer accuracy is lower (around 75%). The Kappa coefficient of these two categories is also significantly lower than that of other categories. The reason is the confusion of the road and bare land categories with mining area and refuse dump.

4. Conclusions

Based on optimal scale selection, a hierarchical extraction strategy for ground objects in open-pit mining area is proposed in this paper. By selecting the optimal scale in advance, the inefficiency caused by multiple experiments is avoided. In addition, through the design of a top-down three-layer extraction framework, not only avoid over-segmentation and under-segmentation effectively, but also other features were selected based on the feature optimization method that can replace the texture features, thus refrain from complex calculation and further improving the extraction efficiency. The extraction accuracy is also guaranteed, the overall accuracy is 95.49%, and the Kappa coefficient is 0.9385.

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