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Feature Selection Method for Open-pit Mine Land Cover Classification Based on Multi-feature Set Using Sentinel-2

Runjie Wang, Yuhang Liu, and Xianglei Liu*

Key Laboratory for Urban Geomatics of National Administration of Surveying, Mapping and Geoinformation, Beijing University of Civil Engineering and Architecture, 1 Zhanlanguan Road, Beijing 100048, China

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The land cover map is the basis of monitoring changes in open-pit mines. However, owing to the limitation of sensor spectral resolution, the misclassification of pixels is inevitable. To reduce the influence of misclassification on the accuracy of open-pit mine land cover classification (LCC), a feature selection method for open-pit mine LCC based on a multi-feature set using Sentinel-2 images is proposed in this study. First, Sentinel-2 images and shuttle radar topographic mission (SRTM) digital elevation models (DEM) are employed to extract multi-features, including spectral features, topographic features, texture features, and filter features. Then permutation importance (PIMP) feature selection is proposed for selecting optimal features from the multi-feature set. Finally, the results of a practical experiment in Xuzhou City of China are used to verify the validity of the proposed feature selection method. The experimental results show that the multi-feature set can improve the accuracy of open-pit mine LCC and that elevation is the most important feature variable in open-pit mine LCC. Moreover, the PIMP feature selection method can effectively optimize feature combinations to obtain the optimal feature subset. This study provides a useful reference for multi-feature extraction and optimal feature selection in open-pit mine LCC using Sentinel-2 image data.

1. Introduction

As the most common mining method in the world, open-pit mining has a significant impact on the Earth's surface such as land degradation, slope instability, and environmental pollution.(1) Post-classification comparison is an important tool for detecting land cover changes in open-pit mines, which is helpful for mine planning and management.(2) Therefore, as basic components for post-classification comparison, high-precision land cover classification (LCC) mapping for open-pit mines is an important problem. However, traditional surveying and mapping techniques are unable to make large-scale and high-precision measurements.

With the development of satellite sensors, remote sensing has become the main method of LCC mapping for open-pit mines.(3) On the basis of the spatial resolution of satellite sensors, LCC mapping methods have been explored in two directions: low- or medium-resolution LCC

*Corresponding author: e-mail: liuxianglei@bucea.edu.cn
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mapping and high-resolution LCC mapping.[4] High-resolution LCC mapping relies on satellites with high-resolution sensors. Isidro *et al.*[5] applied the high-resolution satellite imagery of Pleiades-1A and SPOT-6 and produced LCC maps of small open-pit mines. However, high-resolution satellite imagery has generally been commercialized and the cost of long-term observation is high, making it only suitable for short-term monitoring of small-scale mines.[2] Low- or medium-resolution LCC mapping based on low- or medium-resolution satellite sensors has been the main method for open-pit mine LCC because they are easier to access.[4] However, moderate-resolution imaging spectroradiometer (MODIS) images are not suitable for small open-pit mine LCC due to their resolution being greater than 250 m. Landsat-8 images have a higher spatial resolution but a low spectral resolution; thus, these images are insufficiently clear. By contrast, Szostak *et al.*[6] demonstrated that the use of Sentinel-2 images in mine reclamation monitoring can support mapping in open-pit mine LCC with any time interval, and they obtained results with satisfactory precision. Therefore, in this study we selected Sentinel-2 images for open-pit mine LCC owing to their high spectral resolution and easy access. However, the misclassification of pixels is inevitable due to the lack of information in the original bands of Sentinel-2 images.

To compensate for the lack of information in Sentinel-2 images, many features have been extracted and their validity has been demonstrated. The vegetation index and building index have been applied as spectral features.[7–9] Wu *et al.*[10] applied digital elevation models (DEMs) as a topographic feature to enhance the accuracy of open-pit mine LCC. Chen *et al.*[11] introduced textural features to enhance the classification accuracy of LCC in mining areas. Chen *et al.*[12] showed that the mean filter features and standard deviation (StDev) filter features of topographic data improved slope detection. Therefore, in this study, we used layer stacking to integrate these features into a multi-feature set. However, the method of feature integration causes overfitting due to information redundancy, which decreases the accuracy of LCC.[13]

To determine whether features are redundant, it is necessary to evaluate their importance. Li *et al.*[14] evaluated the importance of different types of features in open-pit mine LCC through overall accuracy (OA) changes. However, there are complex dependences in the training data; thus, the evaluation method lacks stability if only changes in the OA are used to explain the importance of features. Zhou *et al.*[15] used out-of-bag data to evaluate the feature variable importance (VI) and conducted several tests to obtain more stable results. However, when the categorical variables have a large number of categories, VI measures based on the random forest (RF) are biased. Altmann *et al.*[16] proposed permutation importance (PIMP) as a method that can improve the prediction accuracy of the RF model and enhance its interpretability by modifying the measurement of feature importance. Therefore, we used PIMP as the evaluation criterion of feature importance to eliminate redundant features in this study.

In this study, to reduce the misclassification in open-pit mine LCC, we propose a feature selection method for open-pit mine LCC based on a multi-feature set using Sentinel-2 image data. First, multi-feature extraction is performed from Sentinel-2 satellite imagery to enrich information including spectral features and texture features. DEM is also used to provide topographic features and filter features. The importance of different types of feature sets is evaluated by using changes in OA and F1 score (F1). Then the important feature sets are integrated into a multi-feature set. Second, optimal features are selected. The importance of a single feature variable in the multi-feature set is assessed by PIMP. Features with PIMP greater than zero are considered important in open-pit mine LCC and are selected as optimal features. Based on Sentinel-2 images and DEM of the Xuzhou open-pit mine study area, these optimal features are then integrated as the optimal feature subset to build an RF classifier model. Finally, the accuracy of LCC is evaluated by a confusion matrix to verify the validity of the proposed feature selection method. The remainder of the paper is organized as follows. In Sect. 2, the proposed method of feature selection for open-pit mine LCC based on a multi-feature set is described in detail. In Sect. 3, the results of practical experiments are described and discussed. Section 4 gives the conclusions of this study.

2. Materials and Methods

Figure 1 shows the entire workflow of the feature selection method for open-pit mine LCC based on a multi-feature set. Using Sentinel-2 images, first, a series of features were extracted, including spectral, texture, topographic, and filter features, from Sentinel-2 data and shuttle radar topographic mission (SRTM) DEM. Then, the multi-feature set was integrated by layer stacking after evaluating the importance of different types of feature sets. The optimal features were selected from the multi-feature set and integrated as an optimal feature subset. To accurately select the optimal features from the multi-feature set, the proposed method of PIMP feature selection was used. Finally, the validity of the optimal feature subset with PIMP was verified by comparing and analyzing the accuracy of open-pit mine LCC.

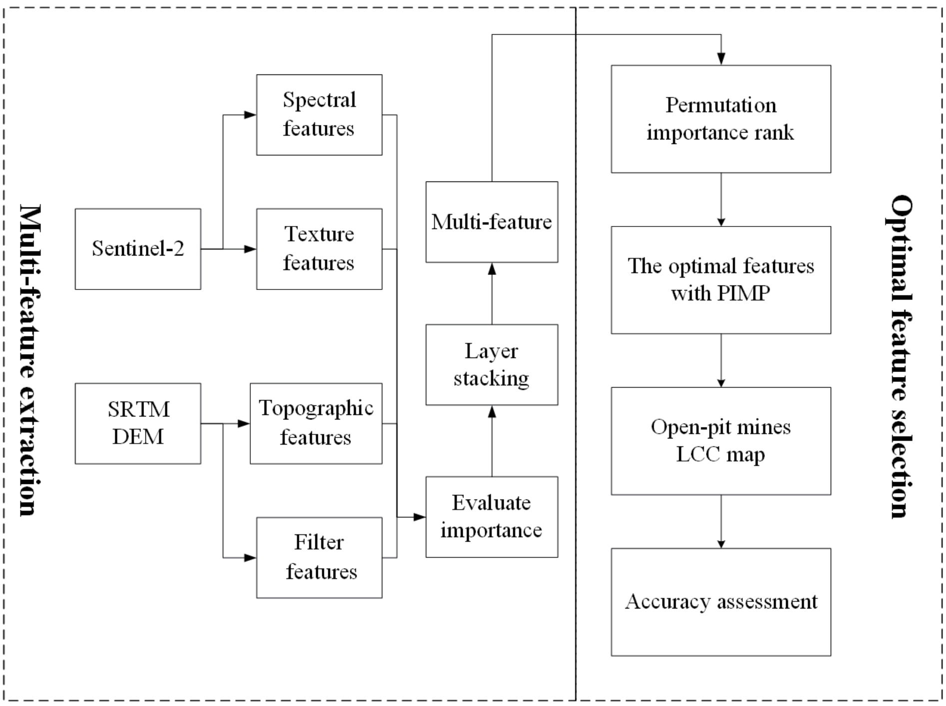


Fig. 1. Flowchart of the method in this study.

2.1 Multi-feature extraction

Owing to the strong temporal-spatial variability of open-pit mines causing the misclassification of pixels, only relying on the original band information of Sentinel-2 images may result in the misclassification of pixels.(3) To overcome the lack of information and reduce the misclassification of pixels, we propose a multi-feature set including spectral features, topographic features, filter features, and texture features. Each feature obtained in this study corresponds to a layer, and the method of layer overlay is used for feature integration.

(1) Spectral features: On the basis of the original bands, the mathematical transformation of some bands is used as spectral features to strengthen the ability to classify specific land cover types. The enhanced vegetation index (EVI) and normalized difference index (NDVI) can serve as suitable alternatives for extracting vegetation accurately.(17,18) They are expressed as follows:

$$EVI = 2.5\left(\frac{NIR - RED}{NIR + 6RED - 7.5BLUE + 1}\right), \tag{1}$$

$$NDVI = \frac{NIR - RED}{NIR + RED}. \tag{2}$$

Moreover, three spectral indices are commonly used to improve LCC accuracy for water, built-up areas, and bare soil, namely, normalized difference water index (NDWI), normalized difference built-up index (NDBI), and soil index (SI).(19–21) They are calculated using the following expressions:

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR}, \tag{3}$$

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}, \tag{4}$$

$$SI = \frac{(SWIR + RED) - (NIR + BLUE)}{(SWIR + RED) + (NIR + BLUE)}, \tag{5}$$

where *NIR*, *RED*, *BLUE*, and *SWIR* are bands 8, 4, 2, and 11 of the Sentinel-2 multispectral imager (MSI), respectively.

(2) Topographical features: The application of DEM provides other information different from the optical information to compensate for the lack of information. Using the four adjacent pixels of each pixel in the SRTM DEM, the local slope of each pixel is calculated. The elevation and slope information are integrated as topographical features in the study area.

(3) Texture features: Guo *et al.*(22) extracted eight texture features based on the grayscale co-occurrence matrix (GLCM) to describe the texture information in an image. These features,

such as contrast (con), correlation (corr), entropy (ent), and angular second moment (asm), are also widely used as texture features in LCC.[23–25] In the process of spectral feature extraction, we found that some bands were sensitive to specific landcover objects. To examine whether the texture information of these bands is also effective for these landcover objects, we applied bands 8, 4, 3, and 2 of the Sentinel-2 satellite MSI to calculate the above four texture features based on the GLCM.

(4) Filter features: Previous studies have shown that the mean filter and StDev filter features of topographic data improved slope detection.[12] In this study, we applied the mean filter and StDev filter to the topographic features as filter features.

2.2 Selection of optimal features

RF can provide the VI to quantify the importance of features. This approach could effectively assist us to evaluate the importance of single feature variables. However, when the categorical variables have a large number of categories, VI measures are biased. To improve the reliability of feature selection results, it is necessary to correct the bias of the VI in RF models. Altmann *et al.*[16] proposed PIMP, which can enhance the interpretability of the importance of features. In this study, we proposed a feature selection method based on PIMP for open-pit mine LCC. The optimal feature selection process based on PIMP is as follows:

(1) Build the input feature matrix of RF models. A matrix of features was constructed by using 70% of the samples, with each column representing a feature and each row representing a sample. This matrix was applied to the RF model as an input matrix. Two important parameters of the RF model, the number of trees and the number of nodes, were set to 100 and 1, respectively. At this point, the construction of the RF model was completed.

(2) Evaluate the PIMP of the variable. We shuffled one column of the input matrix and left the other columns unchanged. Using the remaining 30% of samples as test samples, the loss function of the RF model predictive value and the true value were calculated. The value of the loss function represents the importance of the column that was shuffled, that is, the PIMP value of the feature. Considering outliers may increase the PIMP of irrelevant features or decrease the PIMP of relevant features. The same calculation process was conducted 10 times and the average value of 10 results was taken as the final PIMP value to avoid these outliers.

(3) Eliminate redundant features. After evaluating the PIMP of a feature, we decided that a value of less than or equal to zero means that this feature is unrelated to LCC. Therefore, such redundant features were eliminated and the retained features were integrated.

3. Practical Experiment and Analysis

3.1 Study areas and datasets

In this study, a study area of 85.7 km^2 located in Xuzhou City, China, was selected for the analysis (117°10′10″ E–117°16′32″ E and 34°26′32″ N–34°22′41″ N). Owing to open-pit mining, the maximum height difference in the study area was 121 m. The study area also covers areas where a variety of agricultural activities have resulted in damage to the natural forest. Major land cover types include forest, farmland, urban areas, open-pit mines (including bare soil and rock), and water. The locations of open-pit mines are shown in Fig. 2. We used the 2021 Sentinel-2 images and SRTM DEM. The training set involving 1400 points was sampled by a stratified random sampling method from the high-spatial-resolution images of Google Earth.

3.2 Results of multi-feature extraction

Multiple features were extracted from Sentinel-2 and SRTM DEM, including spectral features, topographic features, texture features, and filter features. Table 1 shows the 11 original bands and the total of 27 auxiliary features extracted in this study.

We first evaluated the effectiveness of the multi-feature set. The multi-feature set integrated all the auxiliary feature sets by layer stacking. As shown in Fig. 3 and Table 2, the multi-feature set basically eliminated the misclassification of a large number of pixels. The OA was improved by 7.87%. The F1 scores of open-pit mines, farmland, urban areas, and forest were improved by

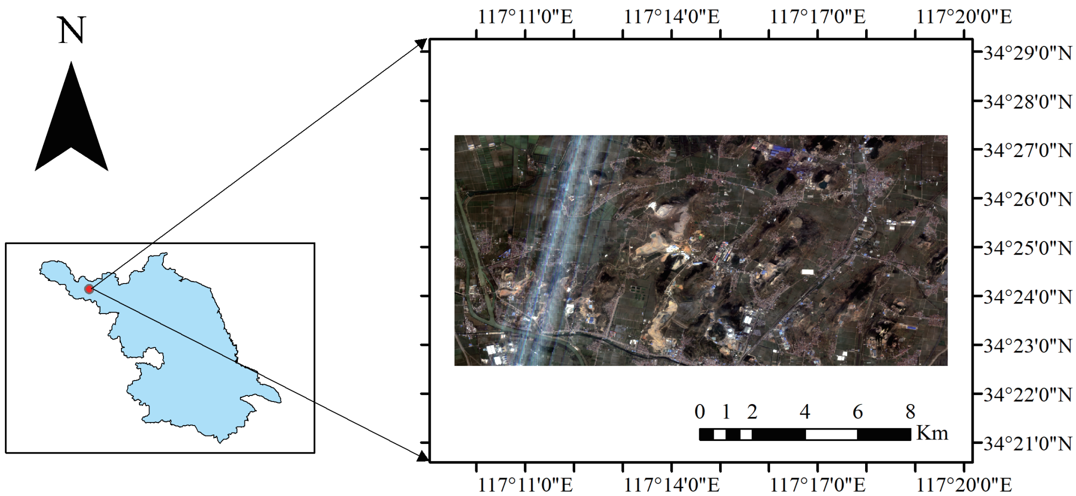


Fig. 2. (Color online) Google Earth image of study area.

Table 1
Result of multi-feature extraction.

	Feature type	Name	Number
A	Original bands	B1, B2, B3, B4, B5, B6, B7, B8, B9, B11, B12	11
B	Spectral features	EVI, NDVI, NDWI, NDBI, SI	5
C	Topographic features	Elevation, Slope	2
D	Texture features	B2_asm, B2_ent, B2_contrast, B2_corr B3_asm, B3_ent, B3_contrast, B3_corr B4_asm, B4_ent, B4_contrast, B4_corr B8_asm, B8_ent, B8_contrast, B8_corr	16
E	Filter features	slope_mean, slope_stdDev elevation_mean, elevation_stdDev	4

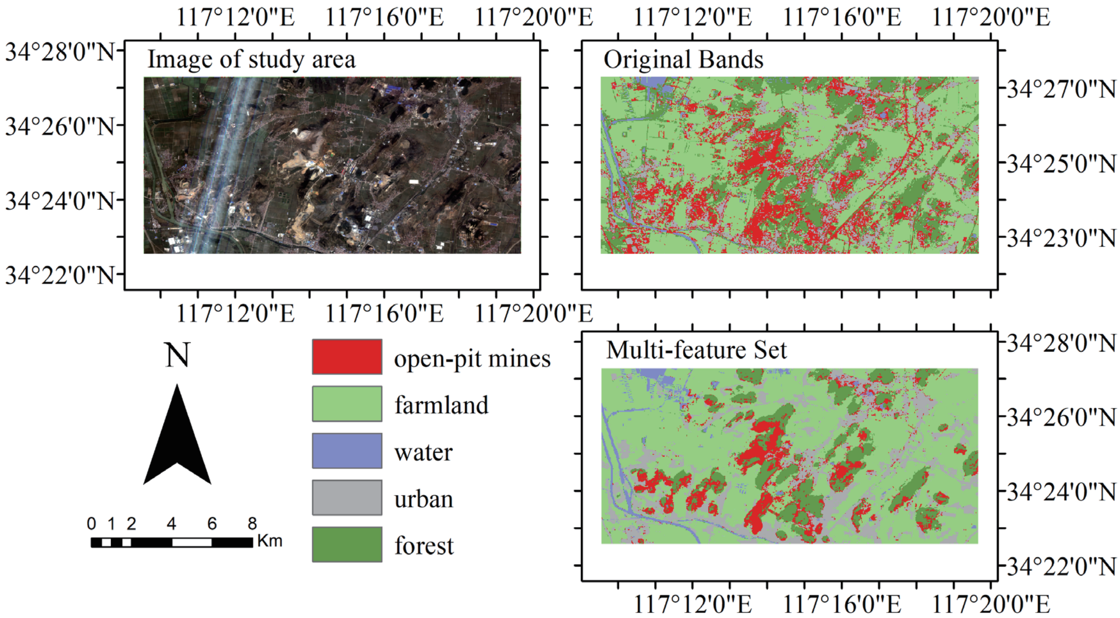


Fig. 3. (Color online) LCC maps of original bands and multi-feature set.

Table 2
F1 and OA (%) for open-pit mine LCC using original bands and multi-feature set.

	Original bands	Multi-feature set
Open-pit mine F1	0.6092	0.7135
Farmland F1	0.8515	0.8626
Water F1	0.6667	0.6207
Urban F1	0.7785	0.8705
Forest F1	0.6250	0.7531
OA (%)	72.03	79.90

17.12, 1.3, 11.82, and 20.5%, respectively, and only the F1 of water decreased. Thus, not all auxiliary feature sets had a positive effect on improving the classification accuracy, and it was necessary to evaluate the importance of every feature set.

To evaluate the importance of the different types of feature sets, we performed four classification experiments based on RF using the following feature combinations as input data: (1) A + B, (2) A + C, (3) A + D, and (4) A + E. The results are shown as classification maps (Fig. 4) and a statistical table (Table 3) of the OA and F1 of different feature sets.

Compared with the OA for feature set A, the percentage changes in the OA for the above four combinations are −3.86, 2.78, −2.36, and 7.68%, respectively. The addition of spectral and texture features decreased the OA in open-pit mine LCC. This was because spectral and texture features were calculated linearly from original bands, which introduced redundant information. Conversely, the other feature sets were extracted from DEM, and these data may have provided some information from different angles, thus improving the classification accuracy.

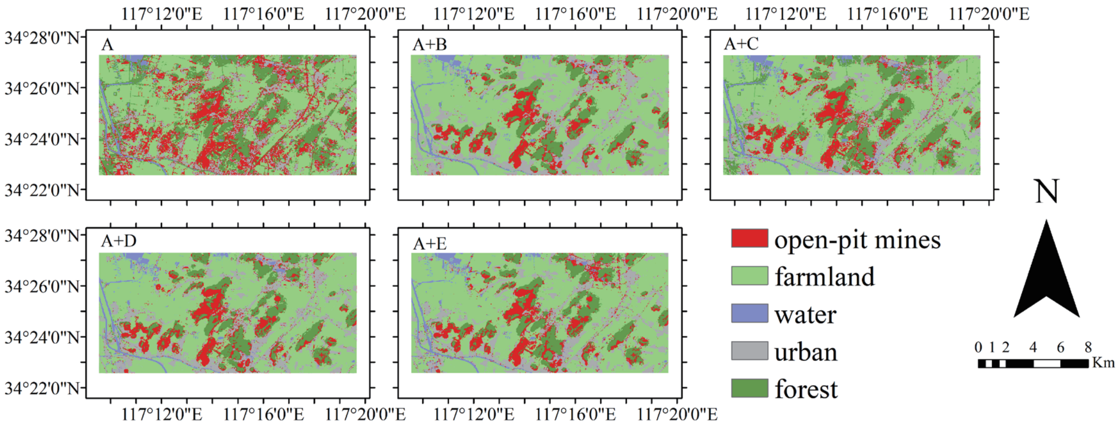


Fig. 4. (Color online) LCC maps for different feature combinations.

Table 3
F1 and OA (%) for open-pit mine LCC using original bands and different feature sets.

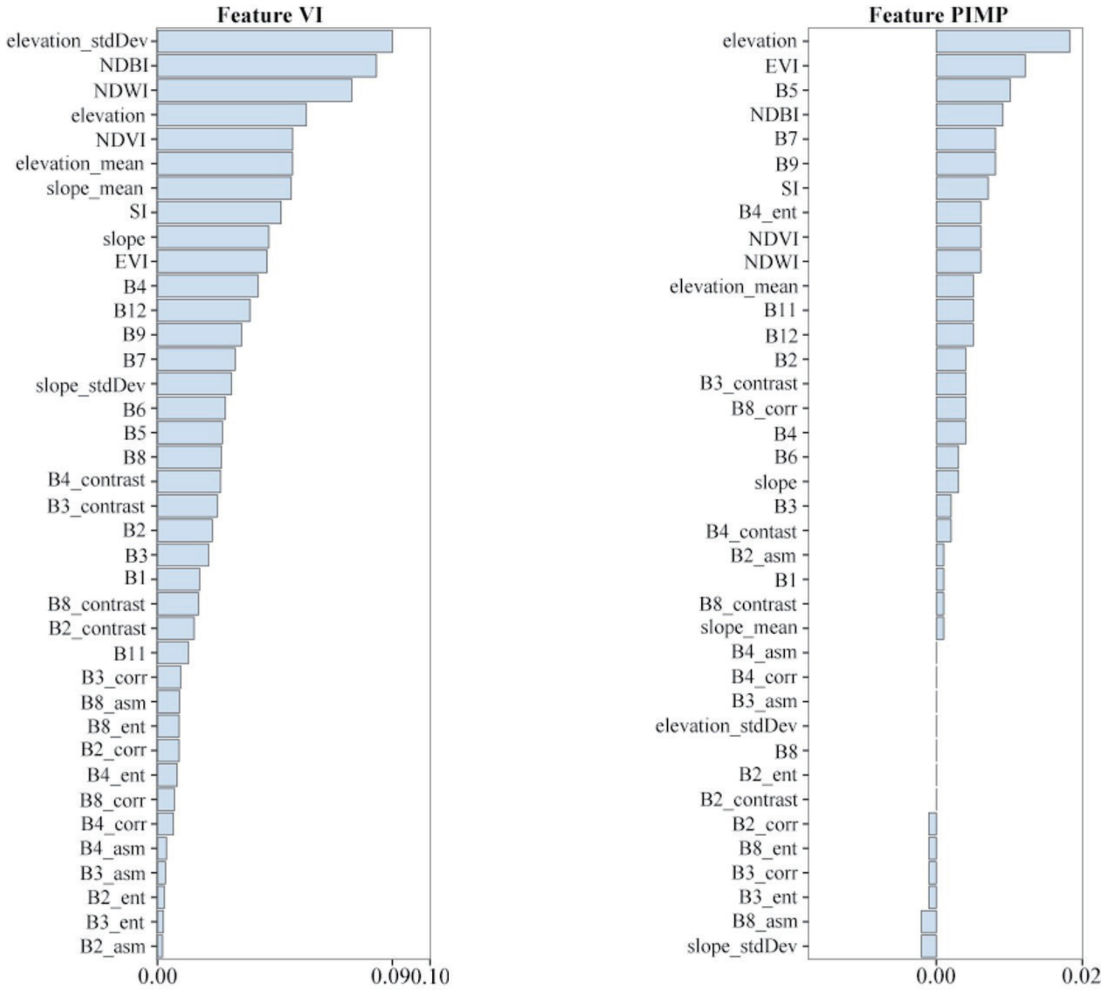
	A	A + B	A + C	A + D	A + E
Open-pit mine F1	0.6092	0.6339	0.6919	0.6304	0.7515
Farmland F1	0.8515	0.7310	0.8286	0.8333	0.8525
Water F1	0.6667	0.6667	0.7234	0.6452	0.6667
Urban F1	0.7785	0.6871	0.8506	0.6923	0.8571
Forest F1	0.6250	0.6719	0.5972	0.6241	0.7448
OA (%)	72.03	68.17	74.81	69.67	79.71

Moreover, owing to the addition of information to the original bands, all feature sets improved the F1 score of the open-pit mines. However, the addition of information did not improve the classification accuracy of all land cover objects. This indicated that some features in the multi-feature set were redundant. However, this does not mean that all the features in the feature set are effective, and the effectiveness of each feature requires further evaluation.

3.3 Results of optimal feature selection

The scores and ranking results of feature PIMP are shown in Fig. 5(b). Also, the scores and ranking results of feature VI are shown to verify the effectiveness of PIMP. If the value of PIMP is less than or equal to 0, this feature has almost no influence on classification results. To compare the difference between PIMP and VI, we also calculated VI of all the features' variables on the basis of the RF model, as shown in Fig. 5(a).

There are some similarities between PIMP and VI. Because the PIMP and VI scores of the five spectral features are among the top ten scores, it can be considered that the spectral features are important. Topographic features also rank highly in both methods; in particular, the score for elevation is very high in both methods. There is also a large gap between the results of the two methods. Compared with PIMP, the VI of texture features is generally low. Note also that slope_stdDev and elevation_stdDev rank highly in VI but are excluded in the PIMP results. Their



(a) (b)

Fig. 5. (Color online) Scores and ranking results of feature importance: (a) VI and (b) PIMP.

PIMP indicates that these features might be less important than expected. The reliability of the two methods is analyzed from the following results.

To verify the validity of the proposed feature selection method, we performed four classification experiments based on RF using the following input data: (1) original bands (OB), (2) multi-features (MF), (3) optimal features based on VI (OFVI), and (4) optimal features based on PIMP (OFPIMP).

We eliminated the 14 features whose PIMP value was less than or equal to zero and integrated the remaining features with the original band into an optimal feature subset that contained 25 feature variables named OFPIMP. Similarly, to ensure comparability, we extracted the top 25 features from the feature selection results based on VI to construct another optimal feature subset named OFVI. The classification maps were used to evaluate the visual effects of different input data. The results are shown in Fig. 6.

It can be seen in all schemes that the features of water are accurately extracted. However, OB has the lowest performance, with a large number of misclassified pixels. MF and OFVI have

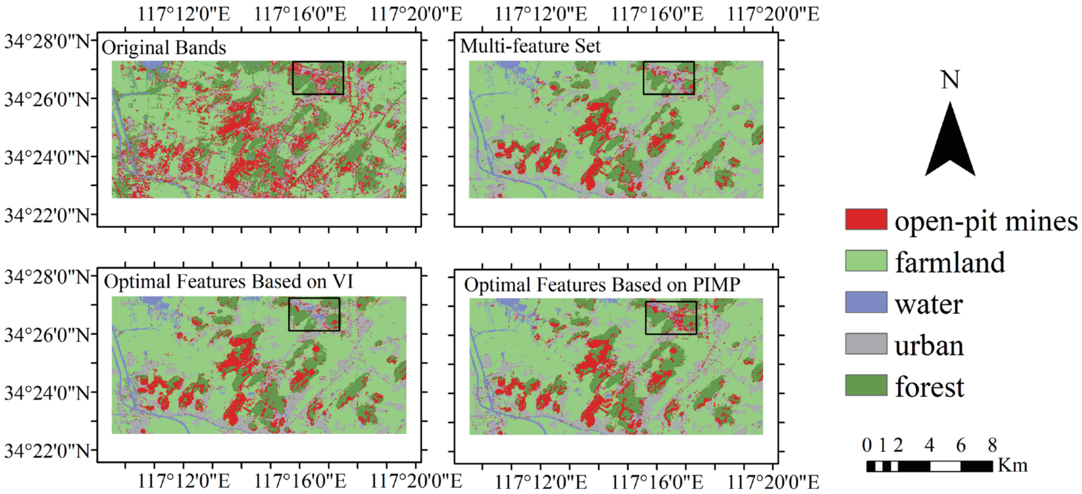


Fig. 6. (Color online) LCC maps of different optimal feature subsets.

similar results, with misclassification in both urban areas and open-pit mines (see the black rectangle in Fig. 6). OFPIMP accurately distinguishes the open-pit mines from the urban areas.

Table 4 provides a better understanding of the open-pit mine LCC results. When using only original bands, there is obvious misclassification among different land cover types. In the open-pit mine samples, 23 pixels are classified into urban areas. However, after the integration of MF, this number reduces to four. The integration of MF increases the OA and Kappa coefficient by 8.4% and 0.1099, respectively. This result indicates that the integration of MF can effectively improve the classification results by reducing the misclassification between open-pit mines and urban areas.

The proposed feature selection method has certain advantages in improving the accuracy of classification results. For OFPIMP, when using feature selection results, the OA increases from 79.90 to 81.69% and the Kappa coefficient improves from 0.7375 to 0.7639. For OFVI, when using feature selection results, the OA increases from 79.90 to 80.36% and the Kappa coefficient is improved from 0.7375 to 0.7429. In the case of sufficient training samples, feature selection removes the features of redundancy and poor performance to improve the classification accuracy. The accuracy of OFPIMP is higher than that of OPVI, which demonstrates that the optimal feature selection method based on PIMP is more suitable for open-pit mine LCC.

Table 4
Confusion matrices for the open-pit mine LCC.

	Original bands				
	Open-pit mines	Farmland	Water	Urban	Forest
Open-pit mines	64	1	0	9	3
Farmland	13	90	0	1	3
Water	4	3	14	0	0
Urban	23	2	0	52	6
Forest	19	8	3	4	52
	OA: 71.51%		Kappa coefficient: 0.6276		

Table 4
(Continued) Confusion matrices for the open-pit mine LCC.

	Multi-feature set using layer stacking				
	Open-pit mines	Farmland	Water	Urban	Forest
Open-pit mines	61	8	0	11	13
Farmland	2	91	1	2	2
Water	2	2	9	4	2
Urban	4	1	0	84	0
Forest	9	11	0	3	61
	OA: 79.90%			Kappa coefficient: 0.7375	

	Selected optimal feature based on VI				
	Open-pit mines	Farmland	Water	Urban	Forest
Open-pit mines	56	2	0	14	4
Farmland	5	90	0	3	2
Water	3	2	11	2	1
Urban	2	5	0	69	0
Forest	14	4	3	0	44
	OA: 80.36%			Kappa coefficient: 0.7429	

	Selected optimal feature based on PIMP				
	Open-pit mines	Farmland	Water	Urban	Forest
Open-pit mines	74	5	0	5	8
Farmland	5	81	1	1	0
Water	4	8	16	2	0
Urban	3	4	0	73	1
Forest	12	8	0	0	58
	OA: 81.69%			Kappa coefficient: 0.7639	

4. Conclusion

High-precision LCC mapping is a basic component of detecting changes in land cover in open-pit mines. The misclassification of different land cover types has long been a technical problem when using remote sensing in open-pit mine LCC mapping. To overcome this problem, it is necessary to integrate MF and select optimal features. In this study, we proposed a feature selection method for open-pit mine LCC using Sentinel-2 image data that was based on a multi-feature set. The following conclusions were obtained.

(1) The use of MF can improve open-pit mine LCC accuracy. Spectral, texture, topographical, and filter features all improve the F1 score of open-pit mines. The filter features are the most important feature set in open-pit mine LCC, which improved the OA by 7.68%. The multi-feature set obtained by integrating these features improved the OA and Kappa coefficient by 8.4% and 0.1099, respectively. Therefore, the multi-feature set used in this study is effective.

(2) Feature selection based on PIMP plays an important role in optimizing the feature combination. Feature selection based on PIMP improved the OA by 10.18%, whereas feature selection based on VI improved the OA by only 8.85%. The optimal feature subset based on PIMP thus had a stronger generalization ability and visual effect. Therefore, the optimal feature selection method based on PIMP is more suitable for open-pit mine LCC.

In conclusion, the proposed method can effectively reduce the misclassification of different land cover types and improve accuracy in open-pit mine LCC. In addition, the optimal feature subset based on PIMP obtained in this study can provide a valuable reference for future open-pit mine LCC.

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