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The Method of Detection of Clay Minerals and Iron Oxide Based on Landsat Multispectral Images (as Exemplified in the Territory of Thai Nguyen Province, Vietnam)

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Abstract: Landsat multispectral images have been successfully used for discovering some mineral deposits in different regions of the world. Some minerals, including clay minerals and iron oxide, can be detected by multispectral surveys due to their spectral characteristics. This paper presents the results of the application of principal component analysis and Crosta technique for detecting accumulations of clay minerals and iron oxide based on a Landsat 8 Oli multispectral image of Thai Nguyen Province, north of Vietnam. The obtained results have demonstrated the feasibility and suitability of prompt detecting mineral deposits based on the remote sensing data. The image processing methods and facilities tested in this study can be used to create maps of distribution of clay minerals and iron oxide for effective and expedient prospecting and exploration for minerals.

Keywords: remote sensing, principal component analysis, mineral, Landsat, Vietnam.

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Методика обнаружения глинистых минералов и оксида железа по данным многозональных изображений Landsat (на примере территории провинции Тхай Нгуен, Вьетнам)

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Аннотация: Многозональные изображения Landsat с успехом использовались для выявления месторождений некоторых полезных ископаемых в разных регионах мира. Некоторые минералы, в том числе глинистые минералы и оксид железа, могут быть обнаружены по данным многозональной съемки из-за их спектральных характеристик. В данной работе представлены результаты применения метода главных компонетов и технологии Crosta для обнаружения скоплений глинистых минералов и оксида железа на основе использования многозонального изображения Landsat 8 Oli провинции Тхай Нгуен, север Вьетнама. Полученные результаты показали возможность и целесообразность оперативного определения месторождения полезных ископаемых по данным дистанционного зондирования. Методы и средства обработки изображений, апробированные в этом исследовании, могут использоваться для создания карт распределения глинистых минералов и оксида железа, с целью эффективного и рационального поиска полезных ископаемых и разведки минерального сырья.

Ключевые слова: дистанционное зондирование, метод главных компонетов, минерал, Landsat, Vietnam.

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INTRODUCTION

Minerals are the most important natural resources of any country. Mineral resources are used in many industries: in energy generation, construction, metallurgy, agriculture, etc. Prospecting and discovery of mineral resources is a difficult task. Traditional methods based on field prospecting and exploratory surveying work, solve this problem, but bear high costs. Remote sensing technology has several advantages over ground-based reconnaissanc|exploration methods, due to coverage of a wide area and short re-observation period. The studies [1–5, 7–10, 13–18, 20–23] confirms the possibility of using multispectral images (Landsat, Aster) for monitoring and detecting minerals. Scanner images capture information about the underlying surface in the visible, near and middle infrared spectral regions [6, 11, 12]. This allows investigating physical properties of the studied surface and making assumptions about soils and rocks.

Landsat multispectral image data have been used for several years in arid and semi-arid natural conditions to identify deposits of iron oxides and hydrothermal minerals. Many authors have used the spectral index method to detect minerals. For example, the spectral indices obtained from Landsat and ASTER multispectral images were used for prospecting iron oxide, clay minerals, magnetite content, ferrous minerals and calculation of Abrams, Chica-Olma and Kaufmann indices [4, 10]. Crosta (1989) [5], Mia and Fujimitsu (2012) [16] used the principal component analysis (PCA) method to detect mineral deposits. Based on the principal component analysis method, Fraser et al. (1997) [10] developed the DPCA method (directed principal component analysis) to monitor the distribution of minerals. The DPCA method was also used by Khaleighi and Ranjbar (2011) [14] to map copper content in Iran based on ASTER multispectral images. The findings obtained in these studies show that the principal component method has higher accuracy of mineral detection than the spectral index method.

This work is devoted to the detection of clay minerals and iron oxides in the Thai Nguyen Province, northern Vietnam based on the multispectral survey LANDSAT 8 data using the method of principal components. Some other image processing methods were also used in the work, including the creation of color mosaics, stretching the histograms of brightness, decorrelation, improving the edges of contours, merging images, calculating spectral indices – to estimate the mineral content in rocks and soils.

MATERIALS

The Study Area. Thai Nguyen Province is located in the northern part of Vietnam, 80 km from the Hanoi, the capital of the country (Fig. 1). The geographic coordinates: 21°20 ′ to 22°03′ N, 105°52′ to 106°14′ E The Province is crossed by several mountain ranges, stretching in the direction from the northwest to the southeast. In the southwest of the province, Tamdao mountain range of 80 km long is located. The vegetative cover in the Province, mainly presented by newly planted forests and fruit trees, occupies about 80% of the area. Natural forests remained in a small part of the territory and are common in high mountain ranges. Mountain soil occupies 48.4% of the area, is located at heights of more than 200 m and formed as a result of weathering of hard and metamorphic rocks and other formations. The soil of the hills covers 31.4 % of the area, is formed mainly over sandstone, siltstone and some ancient tectonic formations. Thai Nguyen Province is rich in mineral resources, including iron and coal. Pictures of some mineral mines in the study area are shown in Fig. 3 [24].

Initial data. In this work, we used a multispectral image received from the Landsat 8 OLI satellites; the survey date was June 15, 2017 (Fig. 2). The image was produced in cloudless weather – a necessary condition for shooting. This image was downloaded from the site of the United States Geological Survey (US Geological Survey – USGS – http://glovis.usgs.gov) with L1T processing level [25].

Landsat 8 is the eighth satellite in the Landsat program and the seventh satellite of this series, launched into the Earth orbit. Landsat 8 receives images of the Earth's surface in the visible, near-IR and thermal IR ranges, with spatial resolution of 15 to 100 m (Table 1).

METHODS AND FINDINGS

To detect iron oxides and clay minerals from Landsat 8 multispectral image data, the principal component analysis (PCA) method was used. This method allows to reduce the data dimensionality with the least loss of valuable information for decryption.

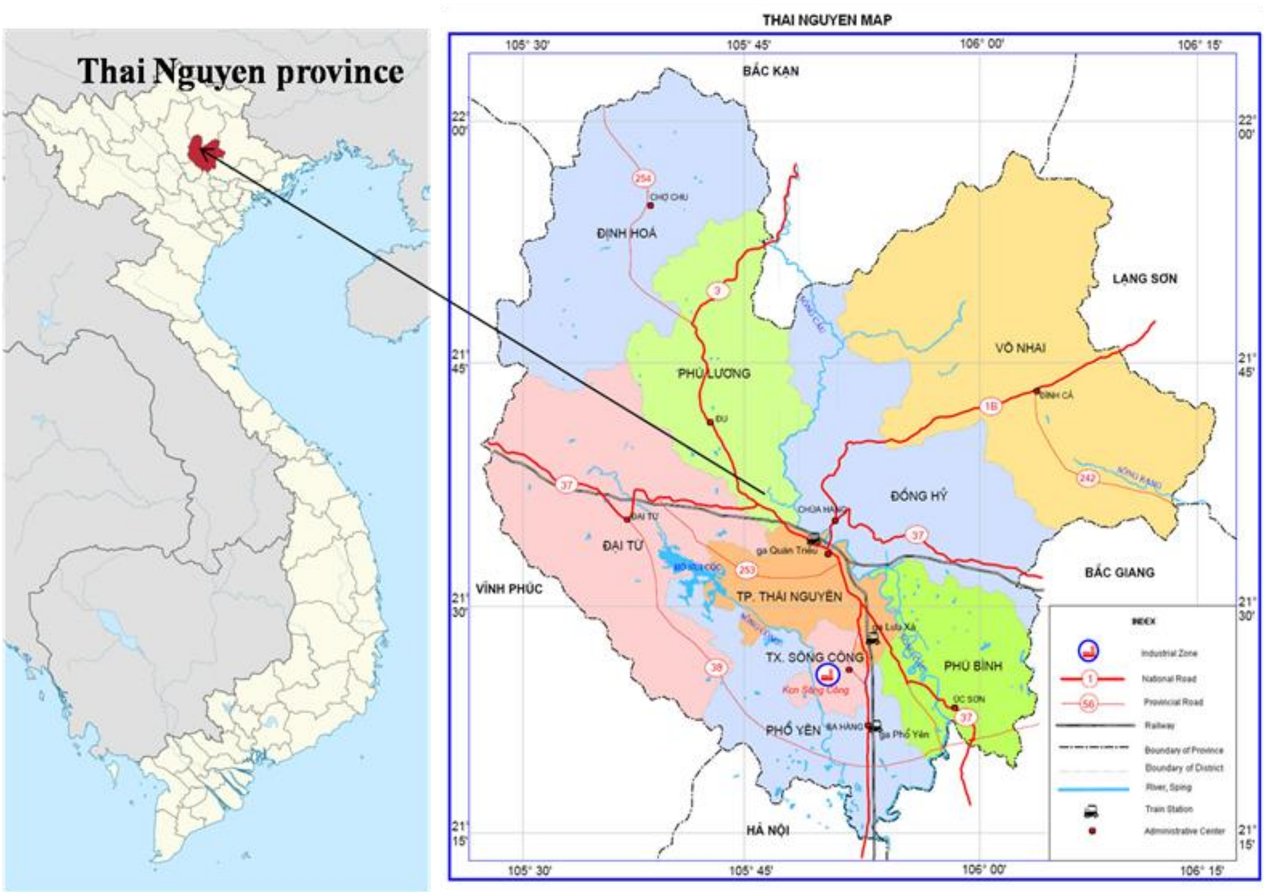


Fig. 1. Location of the study area, Thai Nguyen Province, Vietnam

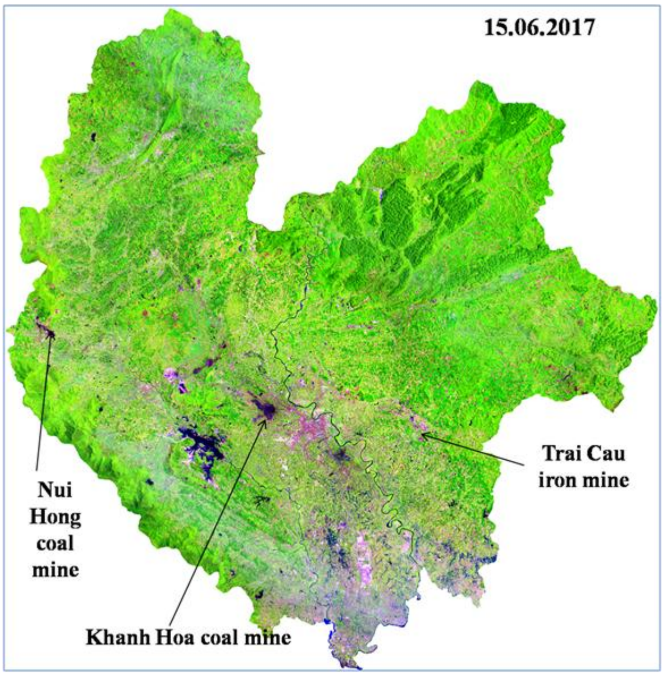


Fig. 2. Landsat 8 multispectral image in Thai Nguyen province, 15.06.2017

Fig. 3. Pictures of some mineral mines in the study area: coal mines Han Hoa (a), Nui Hong (b), and Chai Kau iron ore mine (c) [24]

Table 1

Characteristics of the multispectral image received from the Landsat 8 satellite

No.	Spectral channel	Range (μm)	Spectral resolution (m)
1	Channel 1 – shores and aerosols	0.433–0.453	30
2	Channel 2 – Blue	0.450–0.515	30
3	Channel 3 – Green	0.525–0.600	30
4	Channel 4 – Red	0.630–0.680	30
5	Channel 5 – Near-infrared	0.845–0.885	30
6	Channel 6 – Middle-infrared	1.560–1.660	30
7	Channel 7 – Middle-infrared	2.100–2.300	30
8	Channel 8 – achromatic	0.500–0.680	15
9	Channel 9 – Cirrus	1.360–1.390	30
10	Channel 10 – Thermal infrared	10.30–11.30	100
11	Channel 11 – Thermal infrared	11.50–12.50	100

In this paper, it is shown that the first principal component (PC1) consists of the positive elements of all spectral channels of the Landsat 8 image (channels 2, 3, 4, 5, 6, and 7). PC1 amounts to about 95.12 % of the eigenvalue of the total variance for the PCA data. The eigenvector for the third principal component (PC3) indicates that vegetation, which has high reflectivity in the near infrared range (channel 5) prevails in PC3. The negative value of the element in channel 5 on this principal component (−0.77223) also indicates that the vegetation pixels will be black on this principal component. Since the elements on the eigenvectors for channel 2 and channel 4 in the sixth principal component (PC6) (Table 2) are also opposite in sign, it can be assumed that the iron oxides will differ in bright pixels in PC6. Hydroxyl minerals are displayed as dark pixels in PC5 due to the fact that the contribution is negative from channel 6 and positive from channel 7 in this PC5 (Table 2). If the number of input channels is reduced to avoid a certain spectral contrast, the probability of determining an unique principal component for the detection of minerals will increase [15].

Hydroxyl minerals reflect electromagnetic radiation in the range 1.55–1.75 μm (channel 6 of the Landsat 8 image) much more intensively than in the other studied ranges, and are intensively absorbed in the range from 2.05 to 2.35 μm (channel 7) [7]. Thus, for the detection of clay minerals, spectral channels in blue (channel 2), near IR (channel 5) and mid-infrared ranges (channels 6 and 7) of Landsat 8 image are used. Channels 3 (green) and 4 (red) are not used, to avoid the effects of iron oxides and vegetation cover. The results of the conversion of the principal components in the combination of channels 2, 5, 6 and 7 of the Landsat 8 image for the territory of the Thai Nguyen Province Vietnam) are shown in Table. 3. An analysis of the results showed that PC4 with relatively strong positive load for channel 7 (0.7384) and moderate negative load for channel 6 (−0.5791) can be used to detect hydroxyl minerals. PC4 distinguishes hydroxyl minerals as dark pixels. Using the inversion method, hydroxyl minerals are represented by light pixels on PC4 (Fig. 4, *a*).

Table 2

The findings of main component analysis for 6 multispectral image channels of Landsat 8

Channel	B2	B3	B4	B5	B6	B7	Eigenvalue (%)
PC1	0.32708	0.26698	0.22964	0.38848	0.39815	0.64149	95.123
PC2	−0.14263	0.05132	0.24151	0.03498	0.60180	0.58675	2.689
PC3	0.22824	0.23004	0.46350	−0.77223	−0.15801	0.11465	1.935
PC4	−0.09365	−0.38327	−0.56946	−0.42576	0.36687	0.33932	0.196
PC5	−0.17823	0.13023	0.12403	−0.25107	−0.54775	0.06205	0.035
PC6	−0.56011	−0.53438	0.54677	0.08179	−0.08079	0.28967	0.023

Table 3

The findings of main component analysis for identifying hydroxyl minerals

Principal components	Eigen vector				Eigenvalue (%)
	B2	B5	B6	B7	
PC1	0.3566	0.6158	0.6218	0.3270	95.481
PC2	0.1340	0.6730	−0.4379	−0.5808	3.119
PC3	−0.9072	0.2833	0.2935	−0.1024	1.310
PC4	−0.1783	0.2959	**−0.5791**	**0.7384**	0.090

Table 4

The findings of main component analysis for identifying clay minerals

Principal components	Eigen vector				Eigenvalue (%)
	B2	B4	B5	B6	
PC1	0.3680	0.2381	0.6351	0.6360	95.775
PC2	0.0992	0.4337	−0.7340	0.5132	2.410
PC3	−0.7739	−0.3509	0.0548	0.5244	1.724
PC4	**0.5058**	**−0.7951**	−0.2343	0.2389	0.091

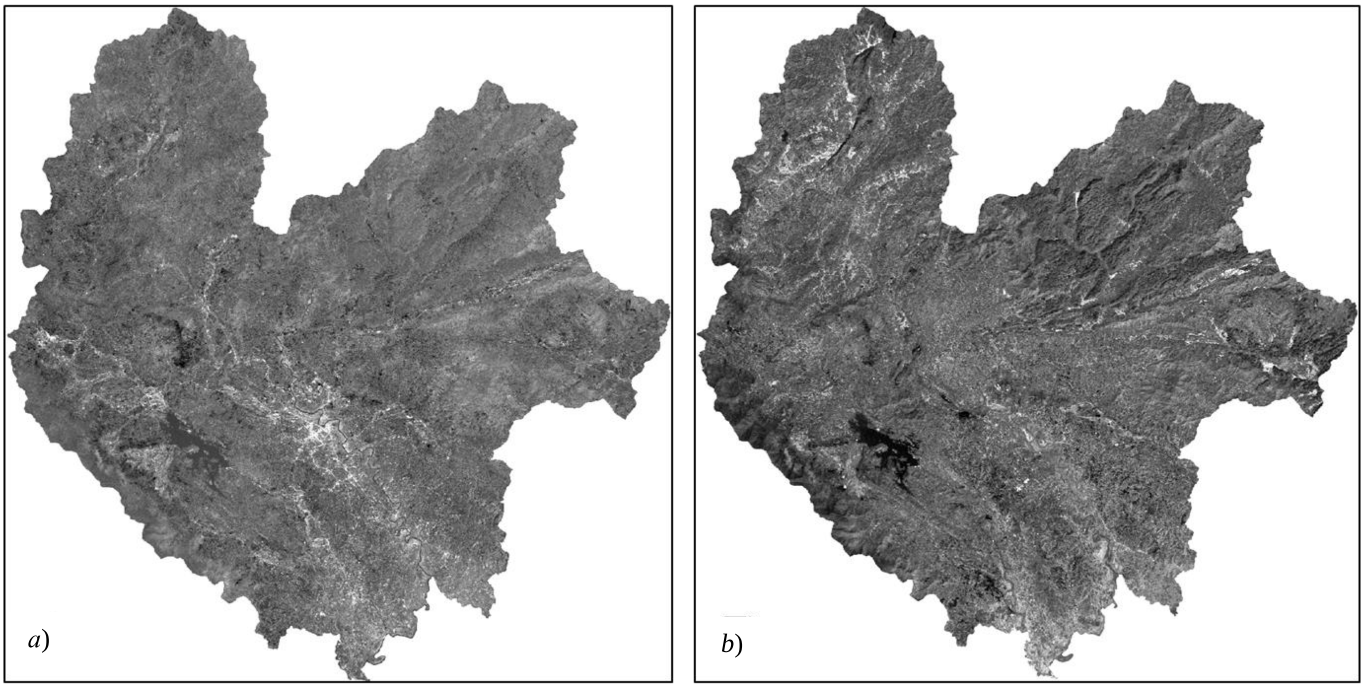


Fig. 4. Component PC4, bright pixels indicate the location of hydroxyl minerals (*a*) and iron oxides (*b*)

Similarly, for the detection of iron oxides, the spectral channels 2, 4, 5, and 6 of the Landsat 8 image are used in this study. The green channel (channel 3) is not used to avoid the effect of vegetation on the results of the detection of minerals. The results of the conversion of the principal components in the combination of channels 2, 4, 5, and 6 of the Landsat 8 image in the Thai Nguyen Province (Vietnam) are shown in Table. 4. In this case, PC4 pinpoints iron oxide as dark pixels (the eigenvector for channel 4 is −0.7951 and for channel 2, +0.5058). This image (PC4) can be inverted by brightness (brightness inverse) to show the location of iron oxides as bright pixels (Fig. 4, *b*).

Images of the principal components (PC4) for hydroxyl minerals and iron oxides are combined to create a single image displaying pixels with abnormal concentrations of both hydroxyls and oxides of iron as the brightest. This merger of two images is also obtained using the method of principal components, such as PC1, having positive eigenvalues for both input images. These images were then combined using Crosta technology to produce the three-layer image. The flowchart of the image processing method for detecting hydroxyl minerals and iron oxides from the LANDSAT 8 multispectral image data is shown in Fig. 5.

To process multispectral images, the RS-MINERALS software package was created based on the Matlab programming language. The package is intended for the analysis of satellite images by the principal component analysis method. The RS-MINERALS software package provides the ability to open and process satellite images in TIFF format, including basic modules such as View (imagery), Idicies (spectral indices), PCA (principal component analysis), DPCA (directed PCA), Interpreter (image processing). The software program interface is presented in Fig. 6.

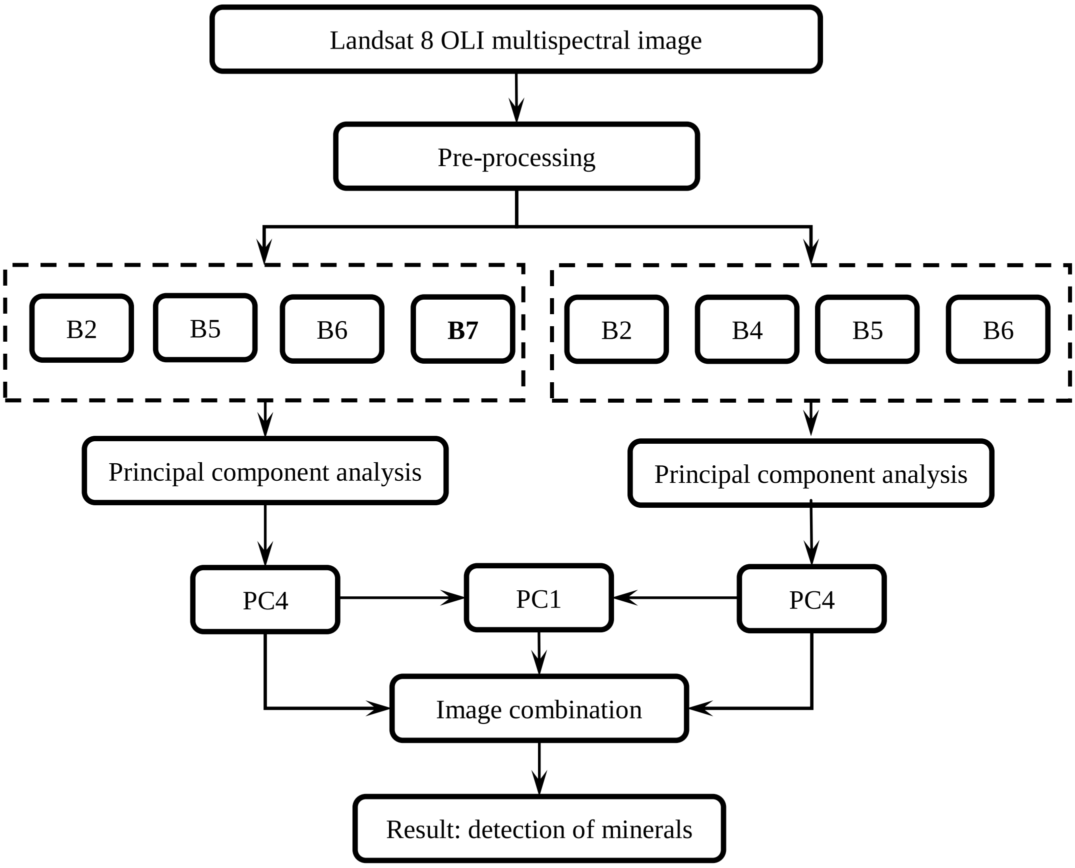


Fig. 5. Image processing method for detection of hydroxyl minerals and iron oxide using a Landsat 8 Oli multispectral image

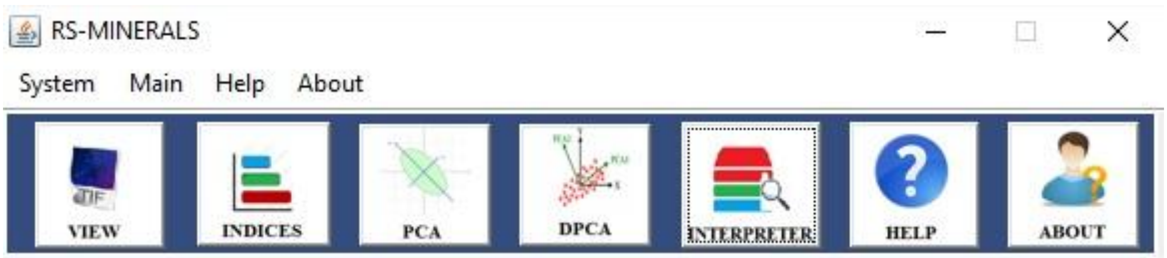
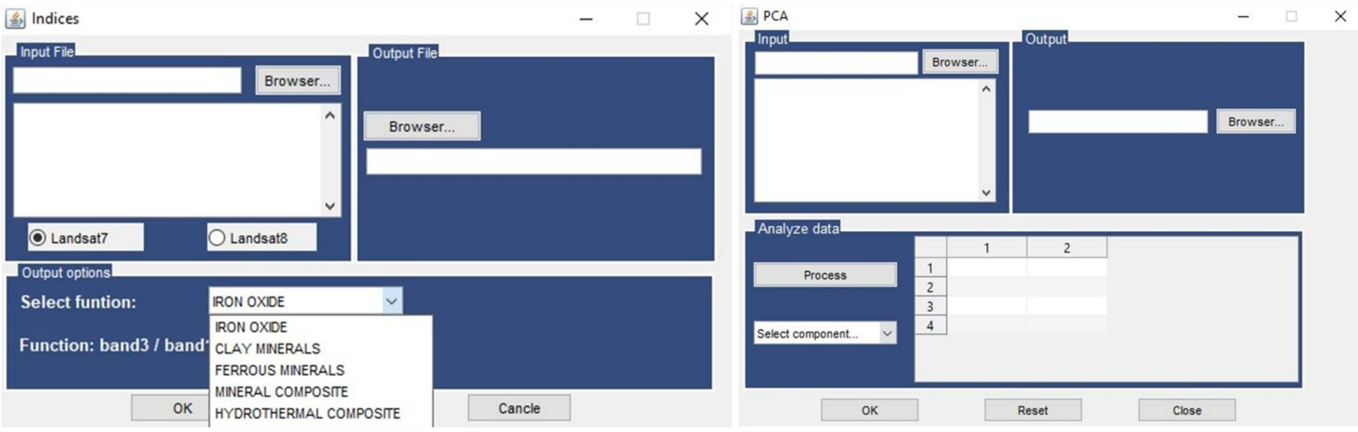


Fig. 6. RS-MINERALS software program interface



а *б*

Fig. 7. PCA (*a*) and Indices (*b*) modules in the RS-MINERALS software package

The PCA module allows calculating the principal components for Landsat images. At the output, the program displays eigenvectors and eigenvalues for the selected principal components containing the most valuable information about minerals (Fig. 7, *a*).

The Indices module allows calculating mineral indices such as those for clay minerals, iron oxide, ferrous minerals, mineral composites, Abramm index, Kaufmann index and Chica-Olma index (Fig. 7, *b*).

The Interpreter module has tools for combining the spectral channels of a multispectral image (Band combinations) and Brightness inversion. The Brightness inversion tool allows inverting the brightness of pixels to highlight the location of minerals in the image of the principal component.

The DPCA module allows highlighting the location of minerals using the DPCA method described by Fraser and Green (1987). In this method, PC1 is calculated from the ratios of the Landsat TM spectral channels: (channel 4/channel 3) and (channel 5/channel 7). The image (channel 5/channel 4) and the image (channel 7 + channel 1) were used to create the color RGB image.

The result of the combination of the images for the detection of hydroxyl minerals and iron oxide was shown in Fig. 8. In this image, white pixels represent areas rich in both hydroxyl and iron minerals. The areas containing many hydroxyl minerals are shown by bright red to orange color, and the areas rich in iron are shown in bright blue to blue color [15].

To assess the accuracy of the detection of hydroxyl minerals and iron oxide from Landsat 8 multispectral survey data, we used the mineral map of Thai Nguyen Province, Vietnam, at a scale of 1:200,000 (Fig. 9). The obtained results showed that iron minerals are distributed over most of the Thai Nguyen Province. The location of large iron ore mines such as Trai Cau, Hoa Trung, Linh Nham, Thanh Chu, Tien Bo is clearly displayed in the image after color combination with the use of Crosta technology. The results also showed that hydroxyl minerals are concentrated in the areas where large coal mines are located, such as Nui Hong, Khanh Hoa, Phan Me (see Fig. 8).

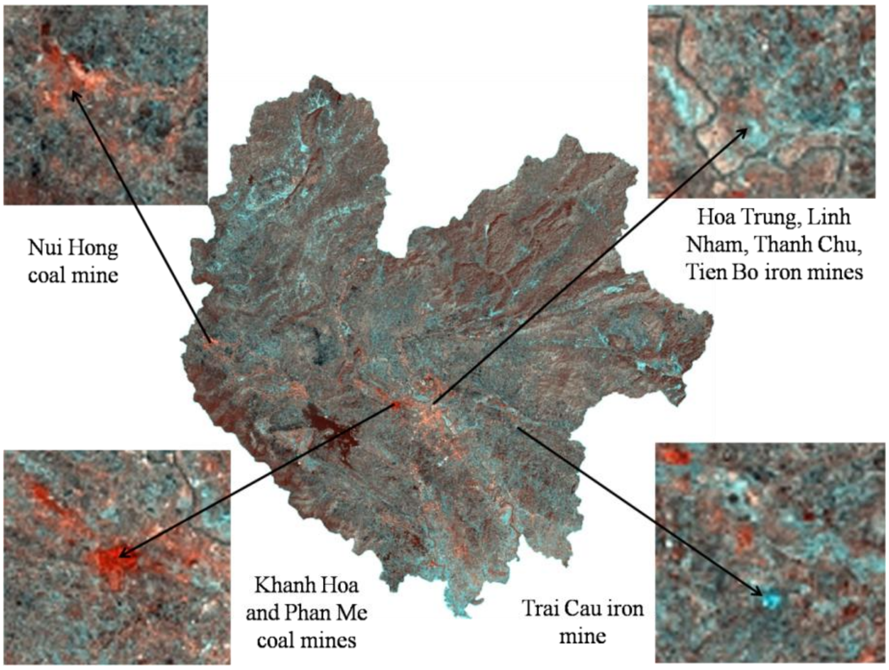


Fig. 8. Crosta-based image combination

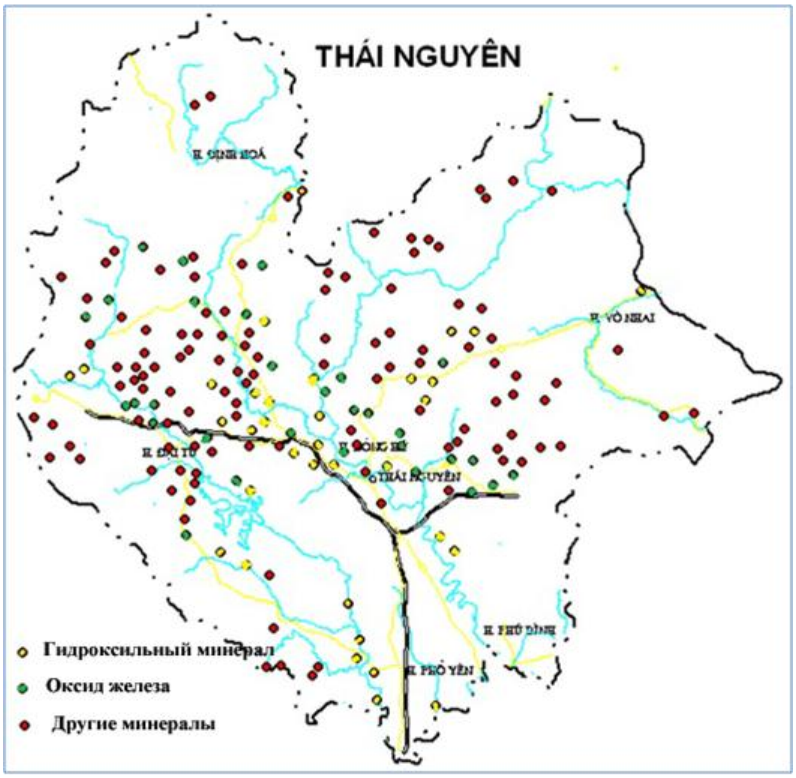


Fig. 9. Map of minerals of Thai Nguyen province (Vietnam), scale 1 : 200.000

CONCLUSIONS

LANDSAT 8 multispectral images can be effectively used to detect and forecast the hydroxyl mineral and iron oxide deposits. The method of the principal component analysis is capable to detect minerals with greater reliability due to the elimination of duplicate information in the spectral channels. In this study, hydroxyl minerals and iron oxide were detected in rocks, as well as in open soils in the vicinity of mining enterprises. Rock emissions around mines are very well decrypted on images of the principal components based on Crosta technology. In the Thai Nguyen Province, in the territory with sparse vegetation, hydroxyl minerals and iron oxide can also be detected based on decryption of hard rock and arenacaous formations. The findings obtained in this study can be used to create and update a map of minerals distribution for forecasting new concentrations of mineral raw materials.

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