

SPECTRAL MIXTURE ANALYSIS FOR DATA VERIFICATION AND VALIDATION

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Abstract - One of the basic issues in remotely sensed data processing and their interpretation is the spectral mixture analysis. Remote sensing measurements include mainly spectral data for obtaining information about the studied objects and on this basis describe them. In the real-world scenario the land cover is a mixture of different matters and in this case the correct discrimination of a single class relies on the theory of spectral mixture analysis. The spectral properties of minerals and rocks depend on many factors such as chemical composition and texture. The goal of the paper is to study spectral mixture reflectance and emissivity from iron-containing minerals and to apply the spectral mixture decomposition technique for mineral identification and to find their proportions in context of further verification and validation. The data consists of laboratory measurements in the visible, near infrared and thermal infrared bands with multi-channel spectrometers and airborne data. Discussion is finally made on the potential applications and ways to improve the accuracy and robustness of the products.

Keywords: spectral unmixing, iron content, mineral identification, remote sensed data

INTRODUCTION

Pixels containing mixed spectral information about the objects under study are commonly found in remotely sensed data. This is due to the limitations of the spatial resolution of the airborne instruments (such as Landsat, SPOT, etc.) and the heterogeneity of features on the ground. The mixture spectra are often generated when the pixel covers more than one land cover class. This mixed classes often results in poor classification accuracy when conventional algorithms such as the maximum likelihood classifier (MLC) are used. It is possible to obtain better results if the mixed pixels are decomposed into different proportions of mineral components. In order to solve the mixed pixel problem, scientists have developed different models to unmix the pixels into different proportions of the endmembers (Mishev, 1991; Ishoku, 1996). Spectral mixture analysis (SMA) is one of the most often used methods for handling the spectral mixture problem. It assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel. This paper aims to demonstrate a practical approach in unmixing spectra of ore minerals from Kremikovtzi obtained from laboratory, in-situ and airborne instruments. Our basic assumption is that airborne data measured as reflectance in red, near infrared and mid infrared ranges of electromagnetic spectrum and emissivity spectra in thermal infrared range are a linear mixture of the mineral composition of studied area. This method has been applied with great success for classification of vegetation (Ustin, 1999) and for change detection (Rogan, 2002).

STUDY AREA

Kremikovtzi open pit mine is situated near the capital of Bulgaria, Sofia. The ores in Kremikovtzi deposit have polymetallic sulfide mineralization. The calculated deposits are estimated to be as follows: hematite ore amount to 32 million tones, goethite ore comes up to 163 million tones, barite ore amount to 29 million tones and siderite ore come up to 52 million tones.

On Figure 1 the main geology bodies are shown.

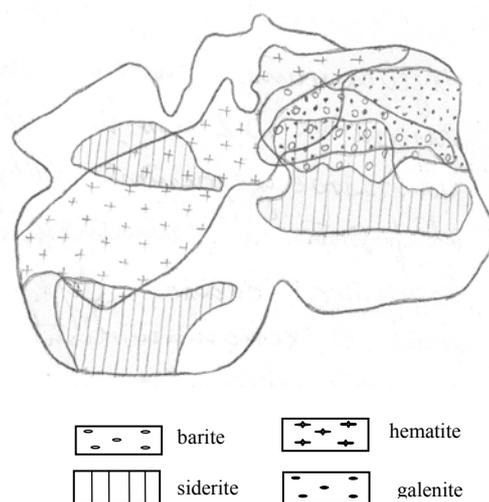


Figure 1. Geology scheme of Kremikovtzi deposit (report No274/1984, STIL-BAS)

Three kinds of iron ore occur in the deposit:

- goethite ($\text{Fe}_2\text{O}_3 \cdot n\text{H}_2\text{O}$) ore which is spread throughout the whole area of the deposit; it comprises 2/3 of all types of iron ore in the deposit and is characterized by the following chemical composition: Fe – 31,9%, Mn – 7,6%, BaSO_4 – 18,4%, Pb – 0,65%, Cu – 0,16%;
- hematite ore is about 11% of the whole Fe-ore; it is composed mainly of the mineral hematite (Fe_2O_3) – with an average quantity of 60% and is characterized by the following chemical composition: Fe – 45,6%, Mn – 1,5%, BaSO_4 – 10,9%, Pb – 0,25%, Cu – 0,08%;
- siderite (FeCO_3) ore is preserved in the deepest parts of the deposit, which are unaffected by processes of oxidation; the average chemical composition of the siderite ore is: Fe – 24,3%, Mn – 5,8%, BaSO_4 – 19,7%, Pb – 0,31%, Cu – 0,11%;
- barite bodies are found within the goethite or the siderite ore or right above the iron ore stocks; the content of BaSO_4 in the barite bodies varies from 18% to almost monomineral accumulation, and has an average value of 41,7%; for the rest

of the elements the average content is: Fe – 13,1%, Mn – 2,9%, Pb – 0,59%, Cu – 0,17%.

In Kremikovtzi open pit mine (Fig. 2) are produced iron and barite ore, iron and barite concentrate, sodium silicate solution, iron-oxide pigments, limestone, dolomite and construction materials. The production of iron ores and barite raw materials is from the "Kremikovtzi" field, dolomites from "Delyan" field; limestone from "Kozyak" field.



Figure 2. Photo of the Kremikovtzi open pit mine

MATERIALS AND METHODS

The results in this paper are based on spectral data coming from three different sources, namely laboratory, field and airborne.

Laboratory measurements of goethite, hematite, siderite and barite minerals (5 samples each) are performed with multi-channel spectrometers SPS-1 (Iliev, 2000) and IR-1 (Final Report, 1992). The SPS-1 instrument provides data in the spectral range 0,5 – 1,55 μm with bandwidth less than 0,01 μm . The statistic reliability is guaranteed by integrating 10 spectra per sample per measurement. In the stated range we put focus on NIR since for iron-containing ore minerals there is a specific minimum in the reflectance curve.

The emissivity measurements are carried out using the IR-1 instrument in thermal range 8-12 μm (Final Report, 1992). These spectral data were measured in directional hemispherical reflectance. These data can be used to calculate reflectance (R) using Kirchhoff's Law ($R=1-E$), where E is emissivity.

Field data were collected in Kremikovtzi open pit mine. Chemical analysis of the collected mineral samples was made to acquire the iron content. Spectral data were obtained with field instrument TOMS working in visible range of EMS. Unfortunately this data was of little use since more informative wavelength for the minerals studied was out of its range of operation. They were considered only as reference data with the laboratory ones.

Airborne data used in the developed models are taken from Landsat Thematic Mapper (TM) instrument acquired in June 2000. For the visual interpretation this digital image was displayed either as single band images or as additive color composites using the three primary colors; Red, Green and Blue (RGB). The band combination we found to delineate the mineral-containing ores from surrounding vegetation and urban areas is $R=TM5$, $G=TM4$, $B=TM3$. Two data sets was

formed – one comprising the whole image shown on Fig. 3 and smaller one seen as white rectangle on the same picture. From the large dataset only the data from the open pit was extracted based on topographic map and additional field information.

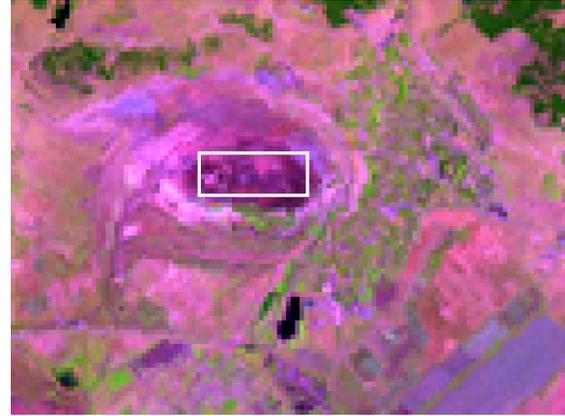


Figure 3. False color composition of Landsat TM bands - 5(red), 4(green), 3(blue)

In the Figure 3 all the pink patches mostly correspond to exposure rocks, green patches are vegetation and urban cover and violet color corresponds to bare soil.

Four bands (TM3, TM4, TM5 and TM6) were used model the spectral mixture of minerals. First three are compared with data from SPS-1 and field data, while the thermal band (see Fig.4) was used in conjunction with IR-1 data.

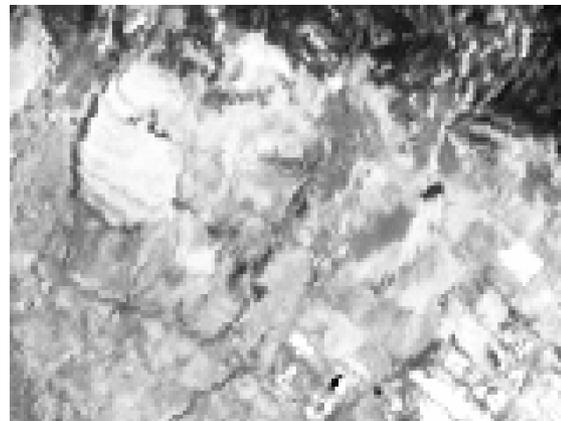


Figure 4 Grey scale image of TM6

The laboratory spectral data for the minerals were numerically modeled as linear mixture using the theory of mixed classes (Mishev, 1991). Linear combinations of goethite with the other three minerals starting from 5% goethite and 95% other ending in 95% goethite and 5% other were computed for each wavelength with step 0,01 μm :

$$r_{\text{comb}}(\lambda_i) = p_{\text{goethite}} r_{\text{goethite}}(\lambda_i) + p_{\text{other}} r_{\text{other}}(\lambda_i)$$

For correct comparison between the laboratory and TM data the further was averaged in the same ranges as TM bands.

RESULTS AND DISCUSSION

Plot of NIR = 0.76-0.9 um versus red = 0.63-0.69 um reflectance for laboratory reflectance spectra are presented in Figure 5. The mineral baseline is established with linear regression (n=54).

If using only the red and NIR reflectance all ore-forming minerals fall on a well-defined line which resembles well-known soil-rock baseline (Elvidge,1985).

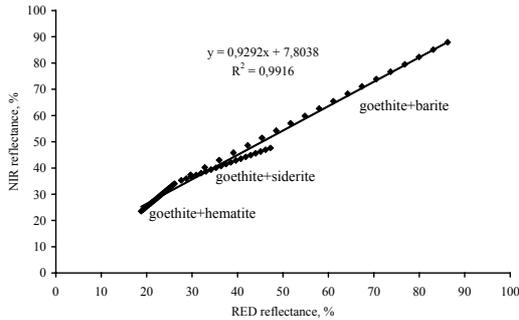


Figure 5. Plot of NIR vs. red reflectance

Similar results were obtained with TM data from large (n=1180) and small (n=140) datasets. We consider that there is correct representation of all ore minerals in the large dataset since the angle between the regression lines is less than 10 degree.

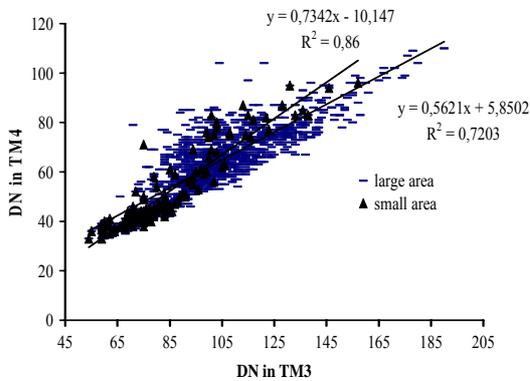


Figure 6. DN corresponding to red and NIR

Numerical models of different mineral composition for the ore materials based on geological and lithological maps (see Fig.1). We find to be appropriate to model all possible combinations since this hypothesis was proved by chemical analysis too. On Fig.7 the modeled reflectance in NIR for variable amount of goethite in the mixtures could allow the researcher to make correct interpretation of field and airborne collected spectral data. The mixture goethite/barite is clearly distinguished if the reflectance is more than 50% and on this basis data from TM4 could be used for identification of iron containing minerals. The same conclusion is valid for the mixture goethite/hematite but the reflectance should be less 35%. These results greatly facilitate the spectral analyst on the stage of multiple sources data verification and validation.

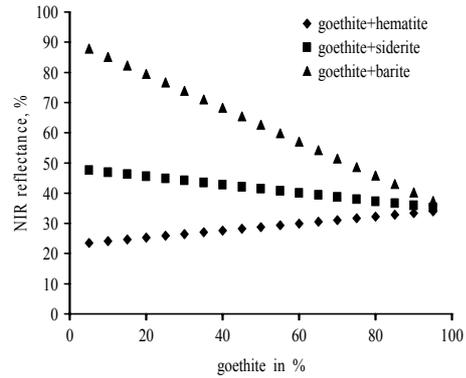


Figure 7. Numerical models of mixtures

Data for the studied minerals obtained under laboratory conditions with IR-1 (Fig.8) exhibit coincidence with similar data from other sources (TES, 2005). This promising result guarantee that the data from IR-1 are reliable and could be used in mineral composition investigation.

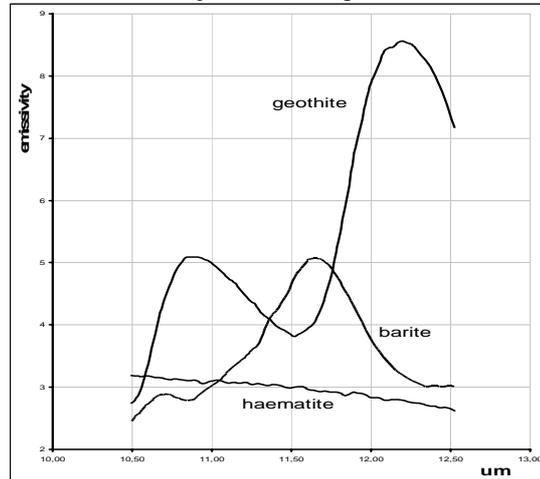


Figure 8. Emissivity spectra as measured by IR-1

On the figure below the laboratory data was used to calculate the MIR/NIR ratio which confirmed the known iron absorption line in the range 0.8- 1 um (Clark, 1999).

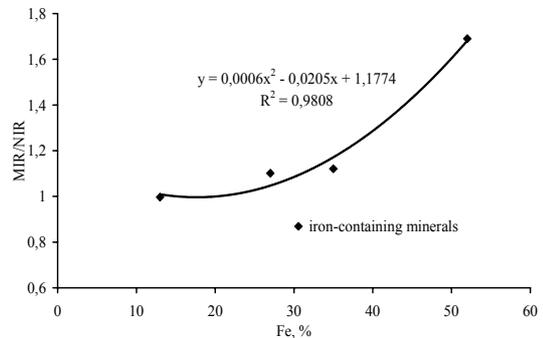


Figure 9. Relationship between iron content and MIR-NIR ratio

Using ground information two lines of TM4 data from the small dataset was extracted. These data expected to be from the pit slope and the graph shows good correlation with the modeled mixture of goethite/hematite. We consider this result as evidence in applying numerical models for prediction of unknown mixtures. This is particularly useful on the stage of airborne data verification with filed measured spectral data.

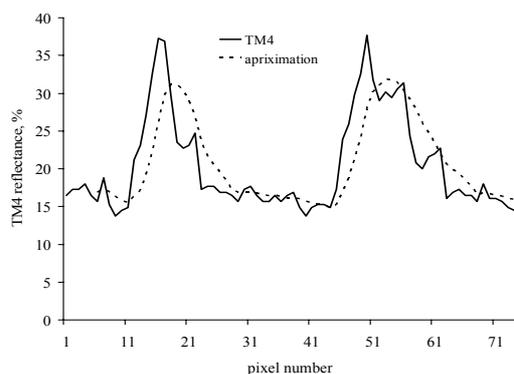


Figure 10. Two lines from small dataset for TM4

CONCLUSIONS

In this paper a practical approach to establish correspondence between laboratory, field and airborne measurements for ore minerals has been discussed. A two-component linear model (e.g. goethite+hematite) for mineral composition found in open pit and satellite data over same area was created. In our future work we shall consider more detailed models including more minerals.

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