

Raw materials' detection using hyperspectral remote sensing techniques. Case study W. Milos, Greece

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Introduction

The goal of this research is to evaluate the potential of using hyperspectral airborne data for geological mapping, focusing on rock formations, ore deposits and raw materials identification, hence formations with a significant economic value. Moreover, it aims at identifying the limitations and the key factors in the process. Finally, this work can act as a compass for young scientists that want to combine outcomes from hyperspectral remote sensing methods and techniques with classic geological mapping techniques, as in this paper the linear spectral unmixing steps of the hyperspectral data are outlined.

Study Area

The study area of this research is the western part of Milos Island, situated in the southwestern corner of the Cyclades islands in the Aegean Sea, Greece. This area is a part of the Natura 2000 network and the natural habitat of protected species, like the Mediterranean seal and the Milos' red viper (Liordos et al., 2017). It is also characterized by the existence of very few small villages and hamlets, active or abandoned quarries and extractions sites and a lot of vegetation.

Milos Island is a part of the active Hellenic volcanic arch and is characterized by calc-alkaline mafic rocks, the most common being andesites, dacites, rhyolites, obsidians and tuffs (Alfieris et al., 2013). Apart from those, the island is one of the most densely mineralized areas in the Aegean Sea, containing economically viable occurrences of both metallic and non-metallic minerals, with reported exploitation since antiquity. These include perlite, bentonite, kaolin, deposits of manganese and barite.

Materials

The hyperspectral images, which have been used in this work for the identification and characterization of the island's surface deposits, have been acquired with a Digital Airborne Imaging Spectrometer (DAIS) 7915 sensor that has 79 spectral bands between $0.5 - 14 \mu m$. (Ganas et. al, 2002). The hyperspectral imagery has 5m spatial resolution, is comprised of 4 independent strips N-S oriented with side overlap of 20% and it was acquired on the 25th of August 1998. Apart from the airborne image, the ASTER GDEM has been also used during orthorectification and atmospheric correction in order to minimize the geometric and atmospheric errors. Due to lack of ground measurements, geological maps of the Institute of Geology and Mineral Exploration (IGME) have been used as the main source of ground truth information, regarding the island formations. USGS Spectral Signatures have been downloaded for these formations as well.

Methods and Results

Prior to the implementation of the spectral unmixing, preprocessing took place in order for the data to be homogenous and free of radiometric or geometric errors. Atmospheric correction using ATCOR4 was carried out for the elimination of the atmospheric effects and the estimation of the real surface reflectance. Orthorectification using GDEM and at least 15 ground control points for each image strip has also been carried out leading to a single mosaic image.

The first step of the unmixing procedure is the dimensionality reduction. More specifically Principal Component Analysis (PCA) and Minimum Noise Fraction (MNF) were used for this purpose. The PCA method demonstrated that almost all information is concentrated in the first four PCA bands. Aiming at the same purpose, the MNF method was implemented, resulting to 16 MNF bands containing substantial information.

The lack of matching between the hyperspectral image spectra and USGS standard signatures for various rock formations led to the selection of spectral targets either from the user using auxiliary sources or by applying endmember extraction techniques, which is the second step of the spectral unmixing. In the manual selection, both training and validation data were selected by the user using the geological map of IGME, due to the lack of in situ measurements. Three main ore deposits that had distinct spectral signatures among them were selected. Namely, two or three pure outcrops of kaolin, barite and pozzolan were manually selected for training areas and another couple or trio (depending on the area) that were used for evaluation.

Regarding the automatic extraction of endmembers, three different extraction algorithms were implemented; the embedded in the ENVI program Pixel Purity Index (PPI) method, the Simple Endmember Extraction (SEE) method (Andreou et al., 2011) and the N-FindR algorithm (Winter, 1999). These three methods were tested for two different scenarios, the first including a mask in the aquatic environment and the second a wider mask covering water and dense vegetation areas. The result of this procedure was the extraction of 14 and 16 endmembers (for the sea mask and the mixed masked respectively) through the PPI method and 13 endmembers for the other two algorithms. These endmembers

were compared with the user's targets, in order to identify those that correlated best to each raw material. The assessment was carried out measuring the spectral angle difference between the extracted and the reference spectral signature.

The aggregate result (Table 1) was 6 cases (3 different extraction methods with 2 different masks applied for each one), where the total number of endmembers, the closest endmember (number) to each material's signature and a mean score as a credibility index were identified.

Endmember extraction method	Number of endmembers	Barite best endmember	Barite best score	Kaolin best endmember	Kaolin best score	Pozzolan best endm.	Pozzolan best score	Mean best score
N-FindR (sea mask)	12	12	0.829	11	0.884	7	0.854	0.856
N-FindR (sea+veg mask)	13	3	0.791	6	0.906	10	0.794	0.830
PPI (sea mask)	17	17	0.838	1	0.925	8	0.830	0.864
PPI (sea+veg mask)	16	9	0.864	1	0.843	11	0.839	0.867
SEE (sea mask)	13	13	0.834	4	0.952	12	0.798	0.861
SEE (sea+veg mask)	13	12	0.825	6	0.952	12	0.824	0.867

Table 1. Summary table comparing endmembers

It is observed that:

- SEE (sea+veg) assigned two different materials for the same endmember.
- The PPI method outperformed.
- SEE (sea mask) produced satisfactorily results, and detected kaolin with the highest accuracy.

In order for the automatic extraction of endmembers to be accurate, the endmembers must be discrete, hence to have wide angle differences. The methods that fulfilled this criterion were PPI and N-FindR, due to the fact that only a few endmembers display an angle difference <0.1. Moreover, the 3 endmembers of the materials of interest, presented wide angle differences with the rest endmembers

The final step of the spectral unmixing was the creation of abundance maps for each of the three aforementioned materials (barite, kaolin, pozzolan). For this, three methods, the Constraint Linear Spectral Unmixing method (CLU), Mixture Tuned Match Filtering (MTMF) and Network Based Method (NBM) (Karathanassi et. al., 2011), have been applied. Among these, CLU and NBM produced the most accurate maps.

Discussion and Conclusions

The current study had a high difficulty level in terms of mapping due to the wide vegetation areas in Western Milos that hid a wide variety of formations and hinder a complete geological mapping. Another burden was the quite similar formations, since the volcanic island of Milos is characterized by mafic rocks and volcanic tuffs, formations that need in situ mineralogical analysis and higher resolution data, making it quite difficult to be correctly identified with the current remote sensing dataset.

Nevertheless, every endmember extraction methodology tested was successful as it managed to produce pure endmembers that matched the user's endmembers and have wide spectral angle differences between them thus making them easily distinguishable.

Regarding the abundance mapping of the pure raw materials, the most reliable method was the NBM method, with the CLU being second in terms of accuracy.

To sum up, the utility of hyperspectral data in identifying ore deposits is unambiguous, especially when talking about areas with difficult access. It is clear that in order to achieve a high level of accuracy, in situ measurements are prerequisite. Furthermore, an ideal case would be a sensor whose spectral resolution would match the USGS spectral library, so that every mineral in the area could be matched with a mineral of the spectral library.

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