Hyperspectral Data as a Tool for Mineral Exploration

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Abstract

In Geology a lot of minerals and rocks have characteristic spectral features that allow their composition and relative abundance to be recognized and mapped from space even though in sub pixels. Hyperspectral remote sensing is the measurement of the Earth's surface in hundreds of spectral images that provides a unique means of remotely mapping mineralogy. Both supervised and unsupervised spectral unmixing methods are used to detect minerals in an image. By using software of remote sensing such as ENVI (The Environment for Visualizing Images) we can represent an approach to analysis of hyperspectral data. It creates a highly accurate mineral/ lithology /alteration maps for the region to develop a better understanding of the geologic processes shaping the land surface.

Key words: Hyperspectral imagery, Alteration, AVIRIS, Mineral Mapping

1. Introduction

Hyperspectral sensors measure the intensity of solar energy reflected from materials over hundreds of wavelengths. They can record visible light (comprised of relatively short wavelengths-blue, green, and red) as well as longer, near-infrared, and short wave-infrared light. Reflected light is collected into picture elements (pixels) by flying an imaging sensor over terrain. The reflected visible and infrared light is subdivided into 100 to 200+ discrete wavelength bands within each pixel or instantaneous field of view (IFOV). This large number of spectral bands is the basis of the name "hyperspectral," which differs from multispectral sensors that have a handful of spectral bands.

Hyperspectral sensors produce a set of images. Each image is composed a range of the electromagnetic spectrum that is known as a spectral band. By merging these images, a three dimensional hyperspectral cube will form for processing and analysis. Airborne sensors like the NASA's *Airborne Visible/Infrared Imaging Spectrometer* (AVIRIS), or from satellites like NASA's Hyperion (lunched in Nov. 2000) can generate these cubes.

One of the applications from hyperspectral data is Geology and Mineral Exploration. In Classical geological map and mineral exploration we can get information about physical characteristics of rocks and soils such as mineralogy, petrology, weathering characteristics, geochemical signatures, and landforms to recognize the characteristic and dispersion of geologic units and to determine exploration targets for metals and industrial minerals.

But Subtle mineralogical differences, is important to detect differences between rock formations, or for defining bare ground versus potential economic ore, are often difficult to map in the field. Mineral exploration is turning into increasingly difficult, especially in obtaining ground access to sensitive or remote areas. A lot of minerals and rocks have characteristic spectral features that allow their composition and relative abundance to be recognized and mapped from space. The solar spectral range 0.4–2.5 nm provides abundant information about many important earth-surface minerals (clark et.al. 1990) (Boardman et.al. 1994). In particular, the 2.0–2.5 nm shortwave infrared (SWIR) spectral range covers spectral features of hydroxyl-bearing minerals, sulfates, and carbonates common to many geologic units and hydrothermal alteration assemblages.

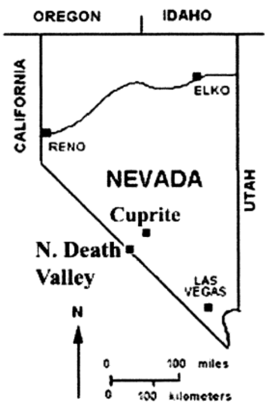
Nevertheless some silicate bearing rocks cannot display characteristics absorption features in VNIR and SWIR zones, such as quartzite, and some rocks have features that are reduced because of a low albedo, for example, basalt. It is difficult to determine these minerals or rocks accurately using VNIR and SWIR hyperspectral data. Combining multispectral thermal infrared (TIR, 8–12 μm) instruments and hyperspectral instruments with many narrow bands can improve the final results. Multispectral TIR data has been more available than hyperspectral TIR data.

Spectrally distinct minerals such as kaolinite, alunite, muscovite, and pyrophyllite all are important in natural resource exploration and characterization. Previous research has proven the ability of hyperspectral systems to uniquely identify and map these and other minerals, even in sub pixel abundances (Goetz et.al. 1985) (Kruse et.al. 1993) (Kruse et.al. 1999) (Boardman et.al. 1994).

Imaging Spectrometers or "Hyperspectral" sensors provide a unique combination of both spatially contiguous spectra and spectrally contiguous images of the earth's surface unavailable from other sources (Goetz et.al. 1985).

2. Data and Material

Cuprite, NEVADA, located approximately 200 km northwest of Las Vegas in USA; Nevada is a relatively undisturbed acid-sulfate hydrothermal system in volcanic rocks exhibiting well-exposed alteration mineralogy consisting principally of a Jurassic-age intrusion exhibiting kaolinite, alunite, and hydrothermal silica (fig.1).



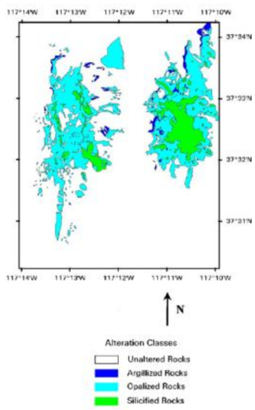


Fig.1 Location map for the Cuprite Alteration map of Cuprite

The data was gathered by AVIRIS (*Airborne Visible/Infrared Imaging Spectrometer).* AVIRIS, flown by NASA/Jet (JPL), is a 224-channel imaging spectrometer with approximately 10-nm spectral resolution covering the 0.4–2.5

nm spectral range. AVIRIS is the premier imaging spectrometer. The sensor is a whiskbroom system (a scanning mirror to sweep back and forth). At an altitude of approximately 20 km, resulting in approximately 2-4-m spatial resolution and a 10.5-km swath width.

3. Research Methodology

The hyperspectral analysis methodology includes:

1) Data preprocessing (radiometric calibration, atmospheric and topographical effects);
2) Correction of data by ENVI software;
3) Use of Linear transformation of the reflectance data to suppress noise and determine data dimensionality (MNF) (Green et.al. 1988);
4) Location of the most spectrally pure pixels (PPI) (Boardman et.al. 1993);
5) Extraction and automated identification of endmember spectra (Kruse et.al. 2004);
6) Spatial mapping and abundance estimates for specific image endmembers (SAM, SFF… methods) (Kruse et.al. 2003).

After pre-processing was completed, the data was processed to (1) extract mineral end-member spectra and (2) to map the relative abundance of these minerals. This procedure was accomplished in two ways. The first is an unsupervised method such as K-Means, Isodata and the second method is supervised unmixing and classification such as Spectral Angle Mapper (SAM), Spectral Feature Fitting (SFF).

ENVI software provides the interactive tools to spatially and spectrally browse through any hyperspectral data set, but also includes a comprehensive set of tools for quantitative analysis. ENVI Software makes it possible to use these data without a priori knowledge.

4. Results and Analysis

Spectral bands covering the shortwave infrared spectral range (2.0–2.4 m) will select, and these bands will linearly transform using the MNF transformation. Fig.1 shows plots of the MNF eigenvalues for the datasets. Higher eigenvalues generally indicate higher information content.

The top MNF bands for dataset, which contain most of the spectral information (Green et.al. 1988), will use to determine the most likely endmembers using the PPI procedure (fig.2)

Fig.2 Output PPI

These potential endmember spectra will then load into an n-dimensional (n-D) scatterplot and will rotate in real time on the computer screen until “points” on the scatterplot will be exposed (Boardman et.al. 1993). The projections will paint using region-of-interest (ROI) definition procedures and then rotates again in three or more dimensions to determine if their signatures are unique in the MNF data (fig.3)

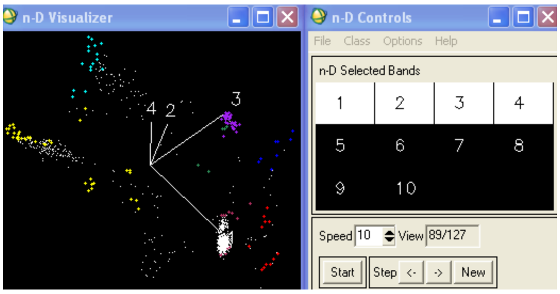


Fig. 3 painted endmember

Once a set of unique pixels will define using the n-D analysis technique, then each separate projection on the scatterplot will export to a ROI in the image. Mean spectra will then extract for each ROI from the apparent reflectance data to act as endmembers for spectral mapping for the Cuprite Site. These endmembers or a subset of these endmembers will use for subsequent classification and other processing. The supervised and unsupervised classification method will use to produce image maps showing the distribution and abundance of selected minerals (fig.4).

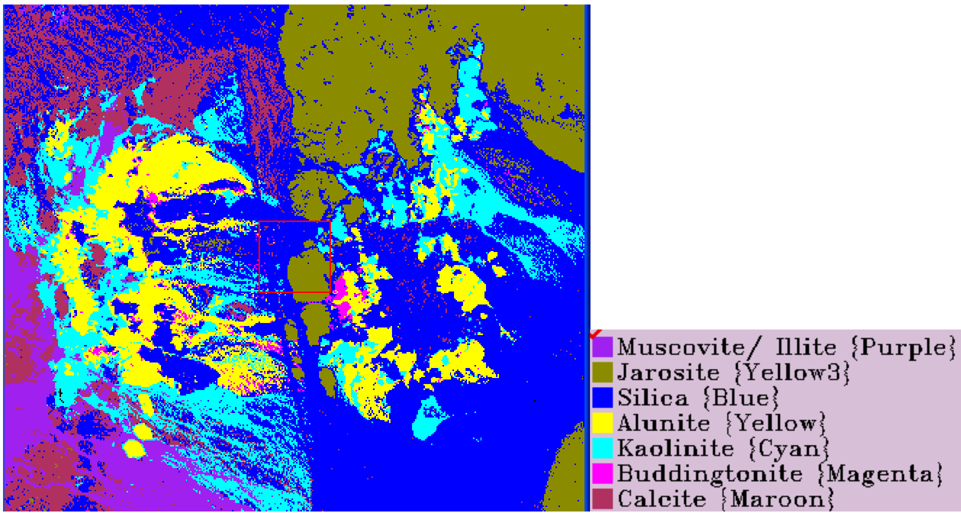


Fig. 4 SAM classification image

Hydrothermal alteration zones in Iran

Hydrothermal alteration involves mineralogical changes resulting from the interaction of hot fluids and rocks, and provides important information concerning the location and prospectively of geothermal resources. The existence, abundance, and stability of hydrothermal alteration minerals depend on the temperature, pressure, lithology, permeability and chemical composition of the fluids in the system.

Hydrothermal alteration zones cover an area of 145,948km2, or about 10% of Iran, mostly in the northwestern, central and eastern regions of the country.

Since most of hydrothermal minerals are almost the same in different areas, we can follow this methodology in Iran by using satellite data.

In Iran, satellite data such as TM, ETM+, and ASTER SWIR bands have been used for geology exploration purposes. Undoubtedly, by comparison with other exploration methods, satellite data will be the fast and cost efficient acquisition of surface (fig. 5).

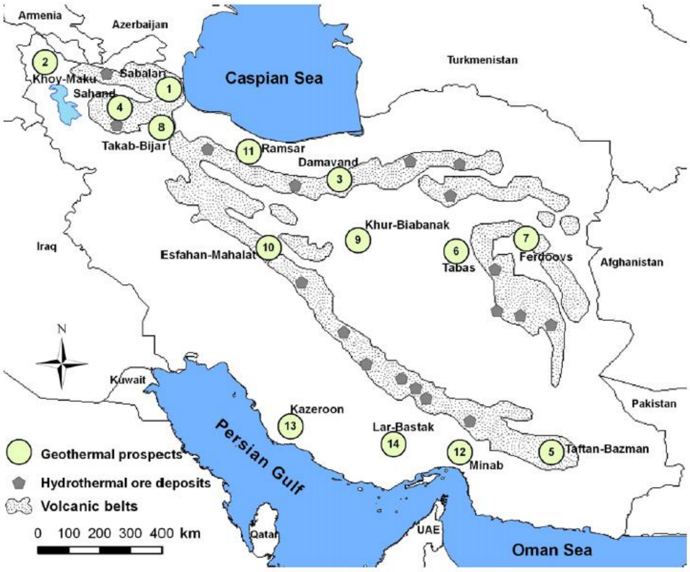


Fig.5 Map of Hydrothermal zones of Iran (Noorollahi et.al., 1998)

5. Conclusions

The classification map generated with SAM could effectively be used for geological mapping and potentially be used for exploration in unexplored areas. AVIRIS images would be helpful for visualizing the study area with great details. This demonstrates that for geological mapping, it is much more important to have a high spectral resolution rather than a high spatial resolution. Spectral remote sensing has the potential to provide the detailed physicochemistry (mineralogy, chemistry and morphology) of the earth's surface. Recent advances in optical remote sensing sensor technology have led to the development of hyperspectral sensors, which acquire images data in many narrow, contiguous spectral bands. Certainly, this new technology would be very valuable for geological and mineralogical mapping.

Acknowledgements

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