

Abstract

- Study of the spectral signature of different minerals in a porphyry-copper deposit.
- Discussion of challenges in the application of semantic segmentation to mineral classification from high-resolution vis-NIR-SWIR hyperspectral data.

Objectives

- Automate the process of mineral identification from image data
- Automatically segment images per mineral composition
- Produce mineral maps from hyperspectral data

Mineral Hyperspectral Data

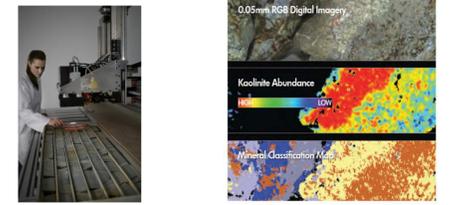


Fig. 1 - Hyperspectral data are collected by scanning rock core slabs from drillholes. The products from this scanning are high-resolution RGB images, the hyperspectral datacubes, and 3D profiler data.

The Nature of Hyperspectral Data

A spectral measurement corresponds to the percentage of reflected light by the surface of a material, in response to the incidence of a beam of light; these measurements are normally collected at different wavelengths.

Multispectral data (MSI) are images that are scanned at 3 to 5 discrete wavelengths.

Hyperspectral data (HSI) are images that contain hundreds of measurement at contiguous wavelengths.

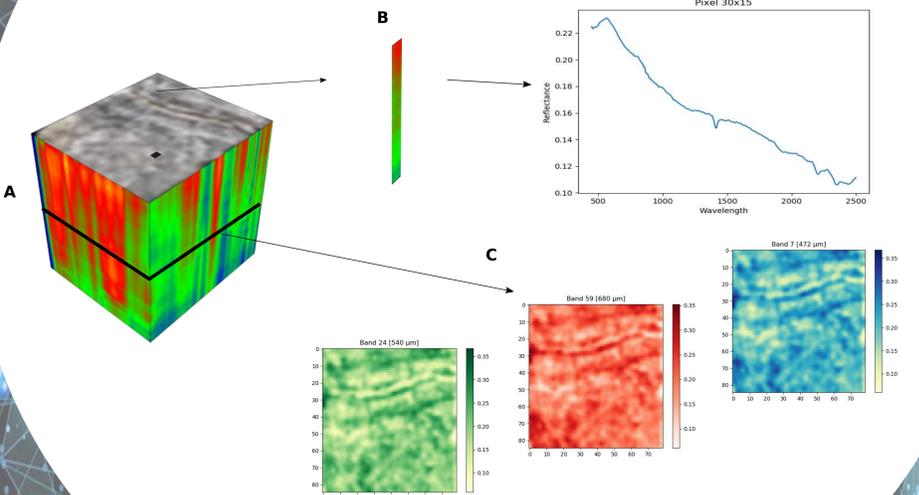


Fig. 3 - Hyperspectral images can be perceived as a datacube (A). For each pixel, at a given spatial position x and y, there are hundreds of values on a third dimension, which correspond to the reflection measured at different wavelengths - the spectra of that pixel (B). The datacube can also be seen as a stack of rasters (bands), where each value corresponds to the percentage of the reflection at each wavelength (C).

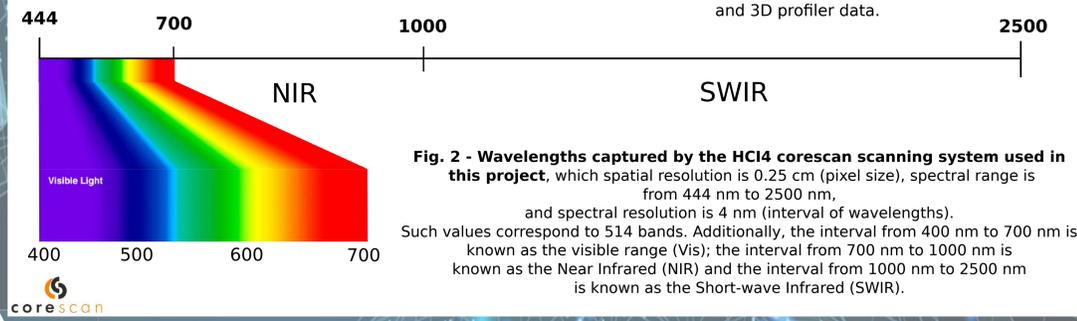


Fig. 2 - Wavelengths captured by the HCl4 corescan scanning system used in this project, which spatial resolution is 0.25 cm (pixel size), spectral range is from 444 nm to 2500 nm, and spectral resolution is 4 nm (interval of wavelengths). Such values correspond to 514 bands. Additionally, the interval from 400 nm to 700 nm is known as the visible range (Vis); the interval from 700 nm to 1000 nm is known as the Near Infrared (NIR) and the interval from 1000 nm to 2500 nm is known as the Short-wave Infrared (SWIR).

Hull Quotient calculation for spectral data

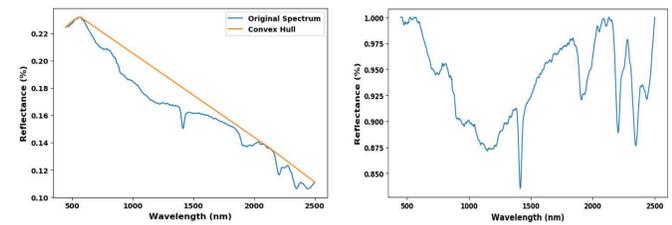


Fig. 5 - How the Hull Correction works. (A) The convex hull and the original spectrum of a pixel. The convex hull corresponds to the upper limit of the pixel spectrum, without its absorption features. (B) Spectrum of the same pixel, with the convex hull removed. Corresponds to a quotient: the original spectrum is divided by the convex hull to produce the hull removed spectrum.

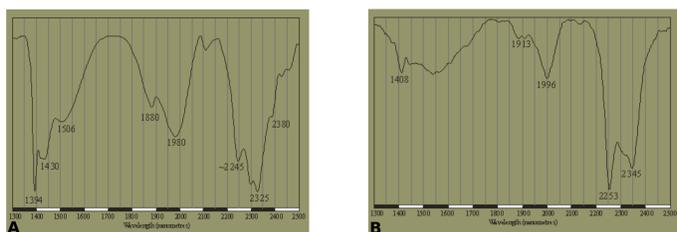


Fig. 4 - How spectral geologists identify minerals from spectral data: observing the distinctive absorption features. (A) Absorption features for chlinocore (Mg-rich chlorite) and (B) chamosite (Fe-rich chlorite).

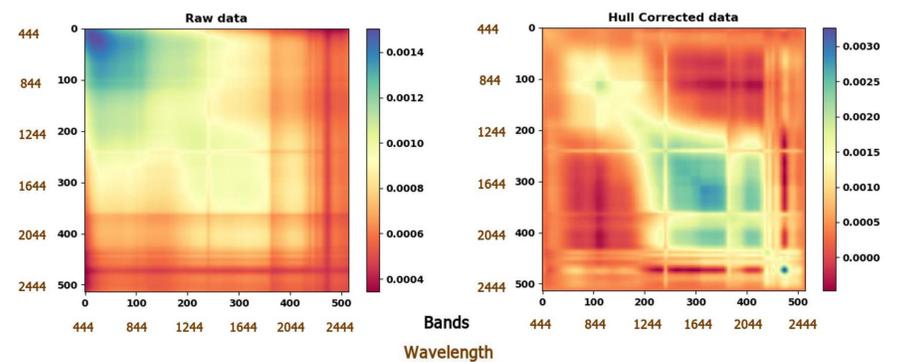


Fig. 6 - Co-variance Matrixes of the raw data (A) and of the Hull-corrected data (B) for the rock presented in figure 5.

The co-variance matrix for the raw data shows that there is a high variance on the visible range of the hyperspectral data, but less variance on the NIR, and even lesser on the SWIR. The SWIR response of minerals is normally highly important, since different minerals exhibit different characteristic absorption features (Fig. *). The co-variance matrix for the same data corrected with the hull removal shows that most of the variance belongs at the SWIR range. Such variance is important and necessary when trying to perform mineral classification.

Hyperspectral data represents an unique type of data. The reflection values measured at each pixel are indexed by wavelength. In other words, the value measured at a certain position on the wavelength is strictly dependent from the values around it (on the previous and subsequent wavelengths). Any analysis and interpretation of this type of data should have into account the autocorrelation between a measured point and those points preceding and following it. An example is given in Fig. *, where the difference between two different minerals of the same mineralogical family are presented. If we remove the wavelength stamps of the hyperspectral data and treat the measured points as independent attributes, a traditional machine learning algorithm will return a low accuracy predicting these types of data. Therefore, the classification methods need to have into account the wavelength stamps associated with the measurements.

Acknowledgements

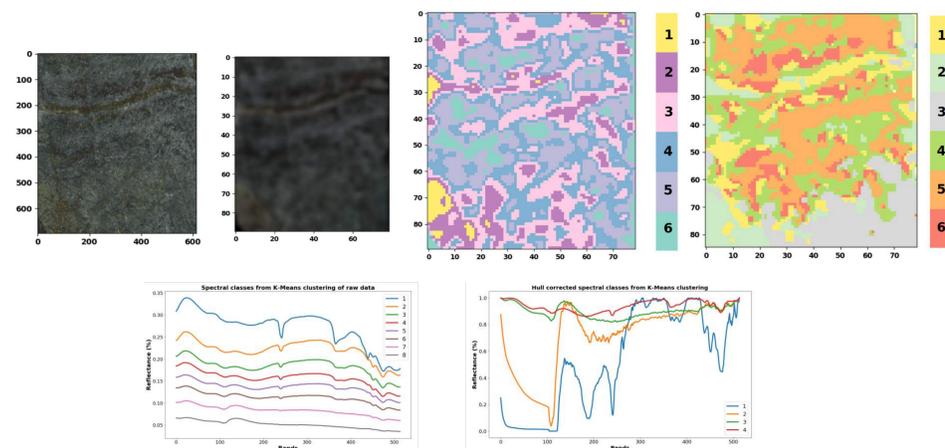


Fig. 7 - Unsupervised semantic segmentation of hyperspectral data (K-means). (A) High resolution RGB image of a core slab from a drillhole. Note the chalcopyrite vein, with oxidized chalcopyrite surrounding it, and the epidote and chlorite alteration. (B) Equivalent hyperspectral image of the same rock slab. Note the difference in resolution. (C) Results for mineralogical domains' classification from raw spectral data. (D) Results for the classification on the hull corrected spectral data. (E) Spectral classes of the raw data classification depicted in 7.C. (F) Hull corrected spectral classes of the classification depicted in 7.D.

Unsupervised semantic segmentation of hyperspectral data (K-means).

- (A) High resolution RGB image of the core slab. Note the textural contrast evident on the higher portions of the picture relatively to the lower portion.
- (B) Equivalent hyperspectral image.
- (C) Results for mineralogical domains' classification from raw spectral data.
- (D) Results for the classification on the hull corrected spectral data.
- (E) Spectral classes of the raw data classification depicted in 8.B.
- (F) Hull corrected spectral classes of the classification depicted in 8.C.

