Hyperspectral Imaging, Data Processing and Prediction of Bauxite Samples from Paragominas, Brazil

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Abstract

The use of hyperspectral sensors has become increasingly popular for mapping ground targets. Due to the large number of spectral bands present in these sensors and the narrow spectral bandwidth, mineralogical identification and quantification are possible with precision according to the spectral signature of each mineral through a known and specific pattern of reflection and absorption at different wavelengths. To evaluate the potential use of these sensors in bauxite mining areas, mining fronts were imaged in Paragominas, in the northeast region of the State of Pará, Brazil, using the HyspeX hyperspectral sensor (SWIR 970–2500 nm). 72 samples were collected for scanning and construction of the spectral library with the assistance of a FieldSpec 3 Jr. spectroradiometer that captures 2151 bands between 350 and 2500 nm (vis-NIR). The chemical results were subjected to statistical and discriminant analysis using SAS software, and the images were processed in CaliGeo PRO and ENVI Classic software. Algorithms developed in the Python language (libraries available in Scikit Learn, MatLab, and Orange software) were used to evaluate, model, and predict the spectral curves with the chemical contents of the samples. The results showed a moderate distinction between the layers evaluated by the reflectance spectrum in the laboratory, both in shape and intensity. The use of neural networks for prediction presented the best results (60 to 90 % accuracy), and the spectral range of 1000–2500 nm established more robust models for the analyzed data, attesting to the potential for application of the hyperspectral methodology for characterization and quality control of bauxite mining. However, a larger set of samples and a more robust spectral library would allow refinement and improvement of the prediction model's performance, reducing the areas of overlap in the spectral responses.

Keywords: Hyperspectral imaging, Model prediction, Bauxite exploration.

1. Introduction

The use of hyperspectral sensors has become increasingly popular for mapping ground targets. Due to the large number of spectral bands present in these sensors and their narrow spectral bandwidth, they can accurately provide information that is not obtained with multispectral sensors. Different minerals have a specific pattern of reflection and absorption at a wide range of wavelengths. In this way, many minerals can be identified according to their spectral response, which in some cases is specific to each species, also known as spectral signature [1].

Over the past three decades, there have been great advances in imaging hyperspectral data with improved identification and quantification capacity for geological materials on the earth's surface [2, 3, 4]. However, most of the works where these images are used refer to those obtained by sensors installed on space platforms, such as the Hyperion sensor, and more recently, data acquired from platforms installed on airplanes.

Through the years, imaging technological advances have allowed the acquisition of data from sensors mounted on platforms based in the field [5,6,7]. This condition made it possible to use images in open-pit mining areas since the equipment has become increasingly smaller and easily transportable. The use of these imaging sensors has great potential for applicability because it allows the identification and, in some cases, the quantification or abundance of minerals in mining sites [8, 9]. This starts to play a relevant role when, increasingly, we seek, within the exploration process, methods that can reduce the exposure of people who carry out inspection, collection, and evaluation of material within mined areas, whether for reasons of safety or health [10]. Furthermore, the increased use of images obtained by remote sensors installed on platforms that can be operated in the field has been used, particularly, for the possibility of evaluating and obtaining values in a non-destructive way in areas that require minimum spatial scale.

In this context, this project aimed to evaluate the potential use of hyperspectral imaging sensors in bauxite mining owned by Hydro Paragominas, in the northern region of Brazil, and present the positive and negative points for possible automation in the process assessment of the quality of the mined material.

2. Methodology

2.1 Study Area

The study area is located in the central domain of the Paragominas Bauxite Province (PBP), in the northeast region of the state of Pará, in the Eastern Amazon, Brazil. The PBP represents one of the most important, extensive, and dense groupings of bauxite deposits in Brazil, with a potential of more than 3 billion tonnes of metallurgical ore, about 70 % of Brazil’s total bauxite reserves. The PBP is characterized by plateaus covered by a thick layer of clay (Belterra clay) and ferroaluminous crusts. These deposits were formed by the lateritic alteration of siliciclastic deposits from the Cretaceous, specifically sediments from the Itapecuru and the Ipixuna Formation, during the Paleogene [11] (see Figure 1).

The central domain of the Paragominas Province comprises several bauxite deposits, including the Miltonia 5 and Miltonia 3 plateaus, where the Hydro Paragominas bauxite mine has been in operation since 2012. The mine is located in the municipality of Paragominas, 356 km from the capital, Belém do Pará. The lateritic profile consists of eight main lithotypes with clear textural, compositional, and color differences and well-defined contacts. Starting from the bottom to the top of the lateritic profile, the lithotypes are as follows: a) The bottom clay (ARV), which transitions gradually from the fine-grained kaolinitic sandstone bedrock of the Itapecuru/Ipixuna formations. This layer includes a saprolitic and mottled zone ending in the main bauxite zone; b) The amorphous bauxite (BA) is found in pseudo nodules and columnar features with a microcrystalline texture, along with a mottled clay matrix. It represents the transition from the bottom clay to the main ore zone; c) The ore zone is a massive layer of reddish bauxite containing numerous gibbsite crystals and iron oxides. It is divided into crystallized bauxite with "amorphous" bauxite (BCBA) and crystallized bauxite (BC); d) Ferruginous Laterite (LF) is composed of goethite and hematite pisolites in a massive texture; e) Crystallized Nodular Bauxite (BNC) presents gradual contact with the horizon above and discordantly overlaps with the level of ferruginous laterite. It is characterized by concretions of irregular size and shape, composed of crystallized gibbsite and iron oxides, and commonly occurs as lenticular and discordant bodies; f) Nodular Bauxite (BN) consists of gibbsite nodules formed by amorphous bauxite in a kaolinitic matrix; g) Belterra clay (CAP) is discordant and contains ferruginous pisolites among gibbsite

5. References

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