

Laboratory Proximal Sensing for Mineral Identification of ornamental carbonate rocks in the Short-Wave Infrared (SWIR)

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Abstract

The use of proximal sensing hyperspectral images facilitates the compositional mapping of samples from ornamental rocks, quickly characterizing areas with mineralogical compositions that may reduce their quality. In this work, images obtained in the laboratory with a SPECIM proximal sensor in the SWIR wavelength interval were used for a classification with the Spectral Angle Mapping (SAM) algorithm based on the selection of endmembers through the use of colour compositions generated from band ratio images. The resulting mineralogical map revealed spatially coherent spectral domains associated with variations in calcite–dolomite composition, Mg-bearing phases, iron-related spectral behaviour, and water-bearing or clay mineral components that were not distinguishable macroscopically. These results confirm that proximal imaging spectroscopy offers a substantial potential for obtaining a mineral classification that helps to quickly and objectively characterize these raw materials, saving costs and facilitating a more sustainable exploitation.

1. Introduction

The exploitation of mineral raw materials is of considerable economic and industrial importance; however, it often faces significant social opposition due to the challenges of ensuring environmentally sustainable extraction. In the ornamental rocks industry, a substantial proportion of the extracted material is discarded because it does not meet the quality standards required for commercialization. Such rejection is commonly associated with the presence of impurities or mineralogical heterogeneities, including clay minerals, iron oxides, and gypsum, which adversely affect the aesthetic and commercial value of the stone.

In recent decades, remote sensing has become a fundamental tool in mineral exploration, driven by technological advances in sensors, acquisition platforms, and data processing methods. The availability of multispectral and hyperspectral images, together with radar and lidar data, has significantly improved the identification and characterization of hydrothermal alterations, lithologies, and geological structures associated with mineralized systems. Likewise, access to freely distributed satellite missions and unmanned aerial platforms has reduced costs and expanded the scale and resolution of exploratory studies. In the current context, the integration of remote sensing techniques with geographic information systems, geological models, and machine learning algorithms is transforming traditional exploration approaches, facilitating more efficient, reproducible, and decision-oriented analyses. At the same time, the development of proximal sensing instruments, such as portable reflectance spectrometers, enabled the rapid and direct acquisition of geochemical and mineralogical data in situ, facilitating the preliminary identification of minerals, alterations, and geochemical signatures associated with mineralization processes, reducing time and costs in the different stages of exploitation and operational process. However, the selection of hyperspectral data and its processing for mineral analysis in its

exploitation phase must be both an effective and rapid process in order to be a truly beneficial tool for companies in the mining sector and for society. In this context, the use of hyperspectral imaging from proximal remote sensing to generate compositional maps of rock samples, optimizing resources, holds great potential for mineral characterisation at both laboratory and outcrop scales.

Proximal hyperspectral imaging has emerged as a rapid and non-destructive technique for mineral characterization. In particular, the short-wave infrared (SWIR) region contains diagnostic absorption features that enable the identification of carbonates, clay minerals, and sulfates based on their spectral signatures, allowing the detection of compositional variations that are not discernible by visual inspection. Furthermore, the use of portable hyperspectral sensors enables real-time data acquisition both in laboratory and industrial environments, making this technology especially suitable for quality control and decision-making during stone processing.

The aim of this study is to demonstrate the potential of proximal hyperspectral sensing for generating mineralogical distribution maps of ornamental carbonate rocks through supervised image classification. By identifying subtle compositional variations within apparently homogeneous materials, this methodology provides an objective and efficient tool to support quality assessment, optimize resource exploitation, and contribute to more sustainable mining practices.

1.1 Geological context

A hand specimen of ornamental rock collected from the Cretaceous dolostones of the Prebetic Domain of the Betic Cordilleras (Murcia Province, SE Spain) was investigated. These dolostones belong to the Cuchillo Formation dolostones and the las Moratillas Formation limestones (Cenomanian-Turonian, Upper Cretaceous) (Baena, 1974).

The studied sample consist of recrystallized dolostones, and limestones associated with NNE-SSW morpho-structural alignment (Baena, 1974; Jerez et al. 1974). The rock as a whole has clean calcite veinlets frequently microcrystalline that, together with the calcite coming from karstification processes, are the cause of the multi-coloured reticulated structure characteristic of the rock (Figure 1).

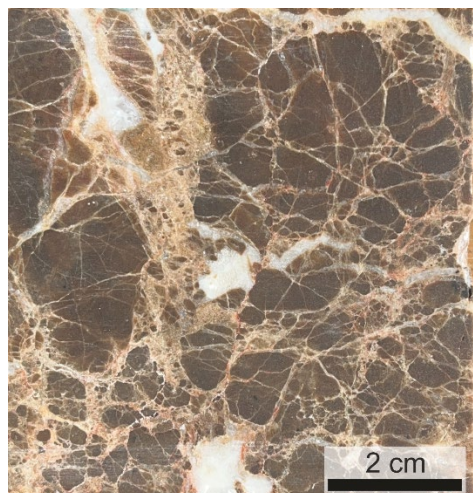


Figure 1: Photograph of the ornamental rock sample studied in this paper.

2. Methodology

Hyperspectral images were acquired under laboratory conditions using a SPECIM hyperspectral camera (Spectral Imaging Ltd.) (Figure 2) with a spatial resolution of 0.256 mm. The analysis was restricted to the Short-Wave Infrared (SWIR) spectral range, comprising 288 spectral bands with a spectral resolution of 12 nm, where the main diagnostic absorption features of the target minerals (carbonates, clay minerals, and sulfates) are located.

During image pre-processing, the raw data were converted to reflectance values and processed using the HypPy software package (Bakker et al., 2024) to remove noisy and erroneous bands, resulting in a final hyperspectral cube containing 278 spectral bands. Subsequent image processing was carried out using ENVI 5.2 (Figure 2).

Because carbonate minerals dominate the entire rock surface, conventional band ratios commonly used for carbonate discrimination were unable to distinguish the different compositional domains within the sample. Therefore, a preliminary analysis of the most representative reflectance spectra was performed based on the tonal variations observed in several false-colour composites. Although the main absorption features were common to all spectra, subtle differences in spectral slopes within specific wavelength intervals (Figure 3) allowed the definition of three diagnostic band ratios: 2234nm/2211nm, 1358nm/1443nm, and 2189nm/2155nm.

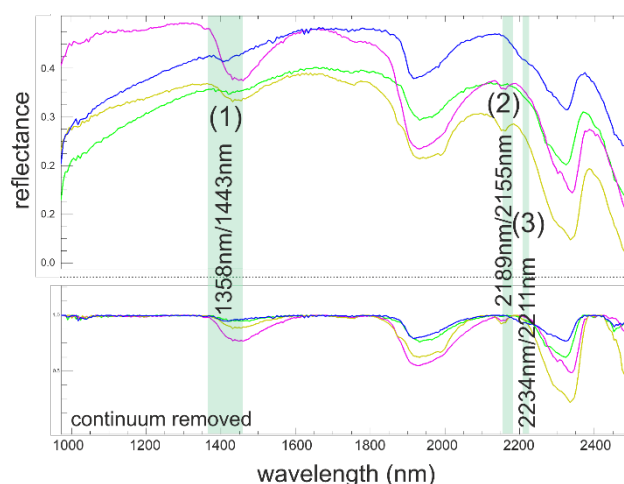


Figure 3: Curves of representative spectral signatures based on the color and tonal variations observed in several false-colour composites.

These band ratios were combined into an RGB composite image, enhancing compositional contrasts and facilitating the identification of representative spectral endmembers. Five representative spectra were extracted from each compositional domain, averaged, and stored in a spectral library. In parallel, the extracted endmembers were compared with reference spectra from the USGS Spectral Library Version 7 (Kokaly et al., 2017).

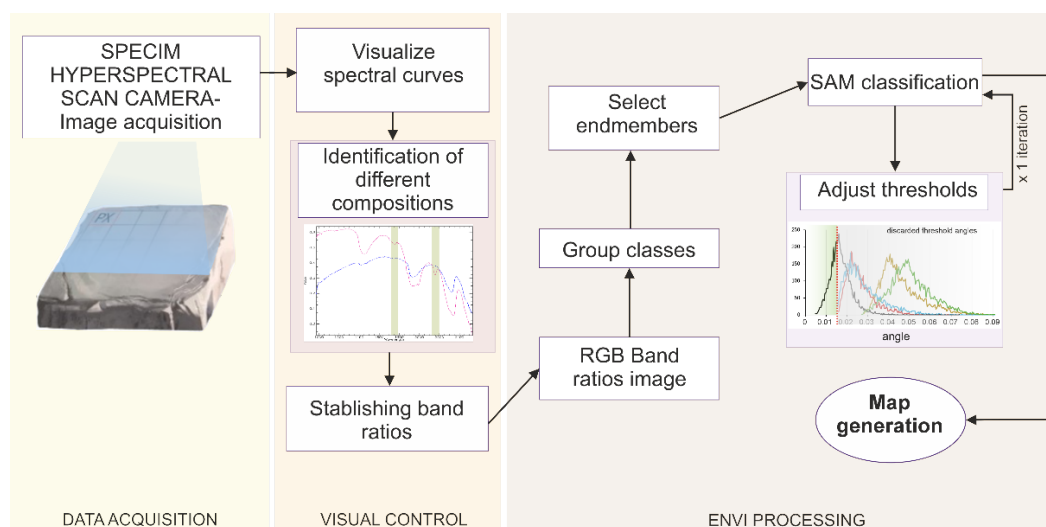


Figure 2: Outline of the methodology used

The Spectral Angle Mapper (SAM) algorithm (Kruse et al., 1993) was subsequently applied as a supervised classification method. The SAM algorithm evaluates the spectral similarity between image pixels and reference spectra by calculating the spectral angle between them in multidimensional spectral space. Smaller angles indicate higher spectral similarity, whereas pixels exceeding the specified angular threshold remain unclassified.

An initial SAM classification was performed using a threshold angle of 0.1 radians for all classes, ensuring that all pixels were assigned to a class. The resulting histograms were then analysed to identify overlapping classes (Figure 4). Based on these results, a second SAM classification was carried out using class-specific angular thresholds, thereby improving class separability and reducing spectral ambiguity.

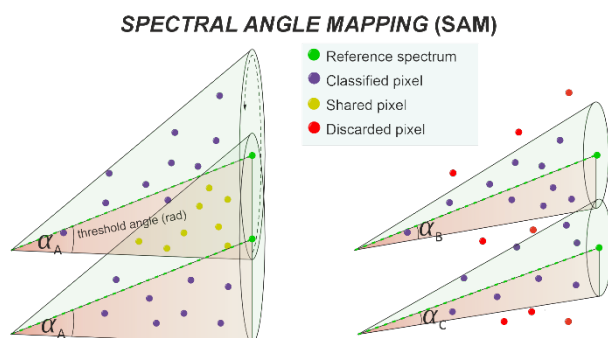


Figure 4: Spectral endmembers of five different classes.

3. Results and Discussion

The RGB composite generated from the three selected band ratios (Figure 5) successfully enhanced subtle spectral variations across the sample, revealing compositional domains that were not evident from visual inspection alone.

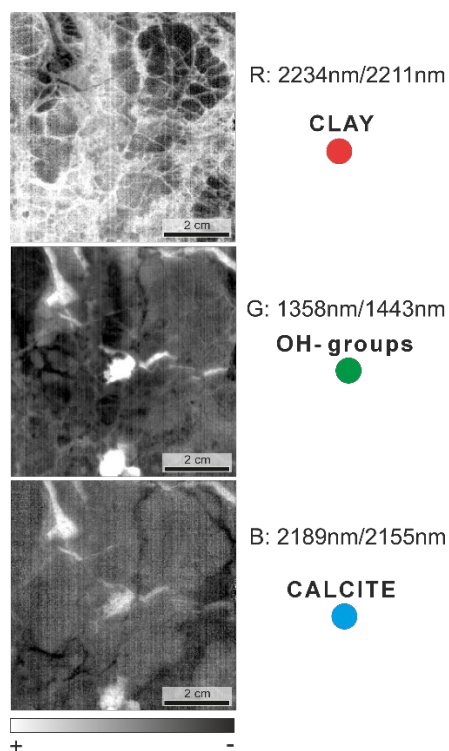


Figure 5: Band ratio images.

Based on these spectral differences, five representative classes (Classes 1–5) were identified (Figure 6), each characterized by a distinct spectral endmember (Figure 7).

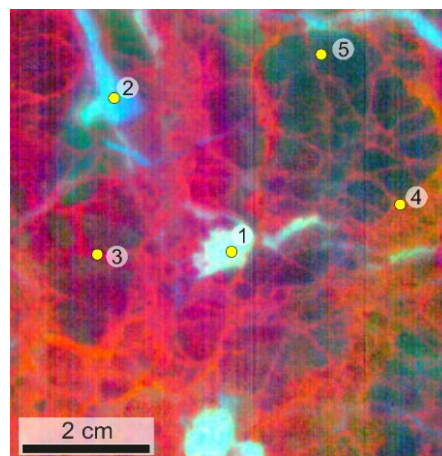


Figure 6: RGB composite image of combined band ratios.

The resulting RGB composite image (Figure 6) illustrates the spatial distribution of these spectral classes and reveals the mineralogical heterogeneity within an apparently homogeneous ornamental carbonate rock.

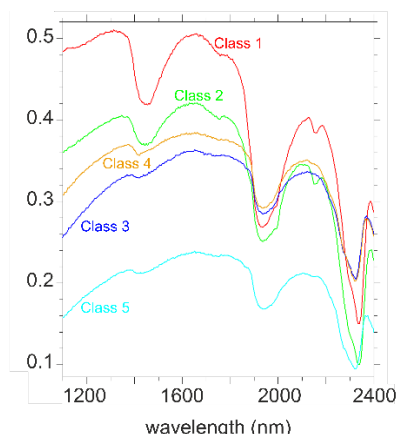


Figure 7: Spectral endmembers of five different classes.

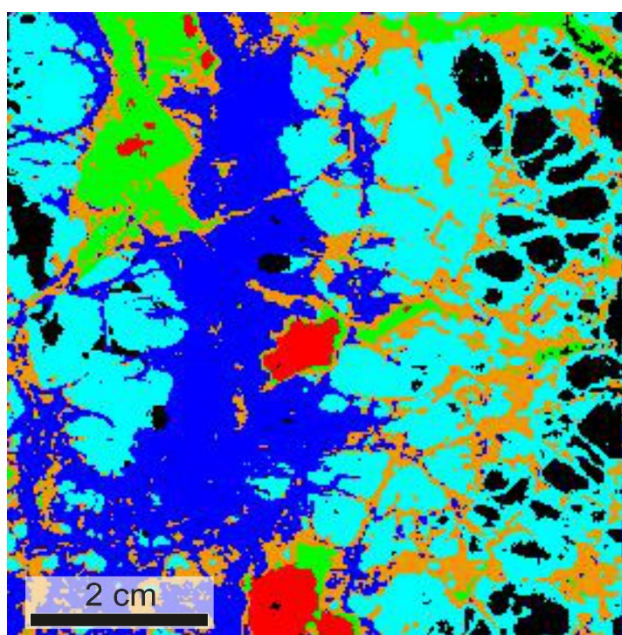
The main spectral differences among the endmembers are associated with the carbonate absorption features in the SWIR region. As reported by Gaffey (1984), the position of these absorption bands is primarily controlled by the cation composition of the carbonate mineral. In particular, the substitution of Ca by Mg shifts the principal carbonate absorption feature from approximately 2335 nm, characteristic of calcite, to around 2315 nm in dolomite. This spectral behaviour made it possible to distinguish pure calcite, dolomite, and intermediate calcite-dolomite mixtures displaying different Mg content.

Comparison between the extracted endmembers and the reference spectra from the USGS Spectral Library confirmed the mineralogical interpretation of the classified units. The characteristic calcite absorption feature at approximately 2335 nm (Hunt and Salisbury, 1971) is dominant in several classes, whereas the diagnostic dolomite feature at 2315 nm, together with the shoulder near 2275 nm, is consistently observed in both the reference library and the measured spectra. The progressive shift between these two absorption positions provides a robust

criterion for identifying compositional variations associated with different calcite-to-dolomite ratios.

Reflectance spectra also exhibit absorption features related to water at approximately 1400 and 1900 nm. Most spectra display both absorption bands, although the 1400 nm feature is generally weaker and, in some locations, barely distinguishable. These observations suggest the presence of trace amounts of hydrated clay minerals, such as illite and/or montmorillonite. Alternatively, the pronounced absorption near 1900 nm may also be related to microscopic fluid inclusions, which are commonly found in carbonate rocks (Gaffey, 1984).

Based on the histograms obtained from the preliminar SAM classification (Figure 8), class-specific angular thresholds were defined for the second classification (Figure 9): 0.04 radians for Classes 1, 2, and 4, 0.05 radians for Class 3, and 0.06 radians for Class 5. These more restrictive thresholds reduced spectral overlap between classes and improved their separability.



Legend

Unclassified	3 Dolomite veins + H ₂ O
1 Pure calcite + H ₂ O	4 Dolomite + Mg-Clay
2 Calcite + Mg-Clay	5 Dolomite

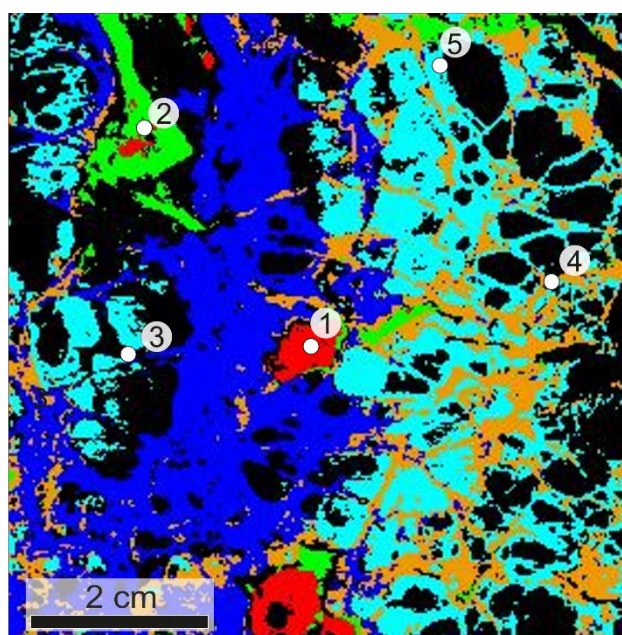
Figure 8: SAM classification using a threshold angle of 0.1 radians for all classes.

Taking Class 1 as an example (Figure 9), the histogram analysis shows that, when a threshold angle of 0.10 radians is applied, pixels belonging to Classes 2 and 4 exhibit spectral angle values that overlap with those of Class 1, leading to potential misclassification. In contrast, reducing the threshold to values below 0.05 radians eliminates this overlap, so that no pixels from other classes are assigned to Class 1. The same procedure was applied to the remaining classes, adjusting the spectral angle threshold individually according to their histogram distributions. These optimized thresholds were subsequently used to perform the second SAM classification (Figure 10), improving class separability and reducing spectral confusion between units.



Figure 9: Pixel histograms that fit an endmember as a function of angle. The yellow shadow shows the angle used in the second SAM classification, which allows for discrimination between classes. The similarity to the other endmembers is also shown.

The final SAM classification produced a mineralogical distribution map that accurately represents the spatial variability of the sample (Figure 10). Most of the rock surface is dominated by Classes 3 and 5, whereas Classes 1 and 2 are located in secondary fractures that gave place to macroscopic porosity. Class 4 is distributed throughout the sample with a greater abundance in the eastern sector.



Legend

Black	Unclassified	Blue	Dolomite veins + H ₂ O
Red	Pure calcite + H ₂ O	Orange	Dolomite + Mg-Clay
Green	Calcite + Mg-Clay	Cyan	Dolomite

Figure 10: SAM classification.

Comparison of the extracted endmembers with reference spectra from the USGS Spectral Library enabled the mineralogical interpretation of the identified classes. Class 1 corresponds to a relatively pure carbonate enriched in water, where the main feature has de maximum depth at 2335 nm (Hunt and Salisbury, 1971), and spectral features at 1400 and 1900 nm indicates presence of water. The strong band at 1900 nm could be explained by the presence of clay minerals an also of liquid water in microscopic fluid inclusions, which are very common in carbonates (Gaffey, 1984), and it is coherent with the position in the sample. Classes 3, and 4 represent different compositional variants of the dolomitic matrix. The steeper spectral slope observed in these Classes at wavelengths below 1200 nm suggests probably a high iron content (iron oxides like hematite and goethite, which have absorption features around 900 nm). Furthermore, the absorption feature observed near 2380 nm in all endmembers except Class 1 is consistent with the presence of Mg-rich clay minerals.

A large portion of the sample's surface appears as unclassified pixels, demonstrating that SAM classification with adjusted thresholds does not force pixels into a class; rather, those without a clear match will not be assigned to any class. In the samples from this same quarry, it has been possible to classify carbonates with varying amounts of magnesium carbonate. An example of classification with proximal hyperspectral images of carbonates ranging from pure calcite to dolomite with a high magnesium content has been published (Rodríguez et al., 2025). By studying the wavelengths at which the minima occur in the carbonate features, it can be seen that the classified calcite and dolomite have values of 2335 and 2315 nm, respectively. This may explain the occurrence of unclassified pixels in the final map. The selected endmember for Class 1 exhibits its main absorption minimum at 2335 nm, whereas the endmember for Class 5 is characterized by an absorption minimum at 2318 nm. Because the spectral angle thresholds were deliberately constrained to

maximize class separability, pixels corresponding to dolomites with absorption minima between 2318 and 2335 nm did not satisfy the classification criteria for either class and therefore remained unclassified. This result reflects the presence of intermediate spectral compositions that were excluded by the strict threshold selection adopted in the second SAM classification.

These results demonstrate that proximal hyperspectral imaging, analysed with tailored band-ratios and supervised classification, is capable of detecting subtle mineralogical variations that are not discernible by visual inspection and therefore represents a valuable tool for the objective quality assessment of ornamental carbonate rocks.

4. Conclusions

The results demonstrate that proximal hyperspectral imaging combined with supervised image classification is an effective approach for the rapid mineralogical characterization of ornamental carbonate rocks. Although the studied sample appears compositionally homogeneous at the macroscopic scale, hyperspectral analysis successfully identified subtle mineralogical variations associated with differences in iron, magnesium, and water-bearing mineral phases.

The study also highlights that standard spectral libraries are not always sufficient for selecting representative endmembers in heterogeneous carbonate materials. Instead, the detailed analysis of image-derived reflectance spectra proved essential for defining representative endmembers and achieving an accurate supervised classification.

The use of class-specific angular thresholds in the Spectral Angle Mapper (SAM) algorithm significantly improved class separability, reducing spectral overlap and minimizing pixel misclassification. The resulting map of spectrally defined compositional classes revealed spatially coherent domains associated with variations in calcite–dolomite composition.

These findings demonstrate the potential of proximal hyperspectral sensing as a rapid, non-destructive, and objective tool for quality assessment in the ornamental stone industry. Its implementation during extraction and processing could contribute to reducing material rejection, optimizing resource utilization, lowering production costs, and promoting more sustainable exploitation of ornamental stone resources.

5. Acknowledgements

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