

# TOWARDS AN IMPROVED APPROACH OF CLAY MINERALS MAPPING IN THE NORTHWESTERN REGION OF ALGERIA

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**KEY WORDS:** Hyperspectral Imaging, Hyperion, JPL Dataset, Clay Minerals, SID, SMACC.

## ABSTRACT:

The availability of hyperspectral images has significantly facilitated clay minerals identification and mapping. Based on the Hyperion L1R hyperspectral dataset, this research aims to improve previous scientific work related to identifying and mapping clay minerals in the Djebel Meni region (northwestern of Algeria). Firstly, we enhance the dataset quality through pre-processing techniques like the removal of bad bands, radiometric calibration, and atmospheric correction. Secondly, the Spectral Information Divergence (SID) algorithm was employed by introducing endmembers derived with the Sequential Maximum Angle Convex Cone (SMACC) algorithm initially and then using Jet Propulsion Laboratory (JPL) spectral signatures of Illite, Kaolinite, and Montmorillonite. The classification results show a correspondence between areas occupied by endmembers and JPL spectral signatures, which helps in matching endmembers with specific minerals. Finally, we conducted a comparative analysis of the two classifications outcomes against a reference map. This last is generated using SID algorithm, which takes ground truth spectral signatures as input. Our proposed approach using the SID classifier has given an overall accuracy score of 97.13% and 84.17% using endmembers image and JPL library respectively. The Kappa coefficient is respectively, with endmembers image and JPL, 0.93 and 0.57. These results show that the SID classification with the endmembers image is better than the SID classification with the JPL library because extracting the endmembers from the image is more accurate than doing that from the pure minerals analyzed in the laboratory. These promising results suggest that our approach could be extended to the identification of clay minerals in diverse hyperspectral datasets.

## 1. INTRODUCTION

Identification and mapping of clay mineral resources are crucial for the scientific and economic development of any country. It has a large field of applications such as urban planning where it has a direct impact on ground stability studies (Grandjean et al., 2019). It is also widely employed in the pharmaceutical industry as an additive and in many industrial applications like ceramic, cement, and paper (Massaro et al., 2018). Geotechnical soil analyses such as the use of X-ray diffraction to determine the mineral composition are expensive and time-consuming (Fondjo and Theron, 2020). The exploration or investigation of clay minerals is possible with the help of remote sensing which is, a convenient, cost-effective, and highly efficient method (Gore et al., 2020).

Hyperspectral imagery is one of the research areas in remote sensing. Hyperspectral sensors measure reflected radiation as a series of narrow and contiguous wavelengths from 100 to around 250 bands to provide a unique combination of spatially and spectrally contiguous images. Hyperspectral imaging has been used in various earth observation applications (Alcantara et al., 2012; Gopinath et al., 2020); it is particularly well suited for mapping clay minerals because it can capture the unique spectral

signatures of different clay minerals. There are many hyperspectral satellites like NEMO (Naval Earth Map Observer), SSTI HSI (Small Satellite Technology Initiative Hyperspectral Images), and Hyperion. This last is one of the most important remote hyperspectral satellites; it covers from 0.4 to 2.5 micrometers spectral range with 242 spectral bands, 10 nm spectral resolution, and 30 m spatial resolution (Pearlman et al., 1999). The Hyperion data has two spectrometers, one Visible/Near Infrared (VNIR) spectrometer (0.4 - 1.0 micrometers) and one Short-Wave Infrared (SWIR) spectrometer (0.9 - 2.5 micrometers).

Many scientists in the field of remote sensing have developed various methods and techniques for extracting mineral information from hyperspectral data. The development of hyperspectral sensors, such as the Hyperion EO-1 sensor, facilitates the detection and mapping of hydrothermally altered surface mineralogy, such as the clay mineral group (montmorillonite, talc, kaolinite), which is based on the spectral absorption characteristics.

Govil et al. (Govil et al., 2021) demonstrated that, in conjunction with deep research, the Hyperion sensor is suitable and effective for identifying and mapping regolith and alteration minerals in

Himalayan mountainous terrain. It is also useful in identifying hydrothermal alteration zones and associated metal and non-metal deposits. Abubakar et al. (Abubakar et al., 2019) evaluated the possibility of mapping hydrothermal weathering mineral deposits associated with subtle-geothermal systems using ASTER and Hyperion satellites data as an indicator to identify potential sites of fossilized geothermal systems hidden in Yankari Park, in Nigeria's north-eastern.

In Vignesh and Kiran (Vignesh and Kiran, 2020), the Tirunelveli district of Tamil Nadu was selected to extract the rich mineral Limestone using Hyperion and Landsat-8 OLI (Operational Land Imager) data. The obtained reflectance imagery spectra were compared with different spectral libraries such as USGS (United States Geological Survey), JPL (Jet Propulsion Laboratory), and real field spectra. A supervised classification approach has been used to identify the minerals in both images. When compared to multispectral data, the results revealed that hyperspectral remote sensing performed well. Researchers in Govil et al. (Govil et al., 2018) identified hydrothermally altered and weathered minerals of a gossanized outcrop rich in base metal mineralization in parts of the Kumaon Himalaya (India) using an EO-1 Hyperion (hyperspectral) satellite data. The finding was checked in the field and was validated through laboratory analyses. This work showed that the remote sensing approach using Hyperspectral Hyperion EO1 data is efficient for identifying and mapping hydrothermally altered/weathered minerals. The researchers Canbaz et al. (Canbaz et al., 2021) used hyperspectral processing techniques and Hyperion satellite data to identify hydrothermal alteration zones in Köseada (Central and Eastern Anatolia – Sivas -Turkey). Using the Hyperion satellite data, the MTFM (Mixture Tuned Matched Filtering) algorithm was used to generate a comprehensive hydrothermal alteration map. This study proved that hydrothermal alteration mapping could be further developed using hyperspectral data for base metal exploration in different regions of the world.

Concerning the Algeria area, the researchers Zazi et al. (Zazi et al., 2017) used the Hyperion scene of Djebel Meni (North-western of Algeria) to identify clay minerals such as Illite, Kaolinite, and Montmorillonite using the Spectral Angle Mapper (SAM) algorithm, through introducing the spectral signatures of Illite, Kaolinite, and Montmorillonite, via JPL spectral library. These results were compared to the ones of the SAM classification, which uses spectral signatures obtained by the SMACC (Gruninger et al., 2004) endmembers extraction algorithm. Their approach allows them to detect, identify, and map the clay minerals by avoiding the manual sampling method and the tedious and expensive mineralogical analyses. However, in this research, the authors have used the Spectral Angle Mapper algorithm (SAM) which is less performant than the SID algorithm for the classification process (Ramesh et al., 2016). Even more, they did not do any qualitative evaluation of the obtained results.

Inspired by their research, we have tried in this paper to improve their approach by evaluating the SID classification using both image endmembers and JPL spectral signatures using qualitative metrics (confusion matrix and kappa coefficient).

Our method includes four main parts:

- 1- Using the SID algorithm to match pixels to the spectral signatures extracted by the SMACC algorithm in order to produce an endmembers map.
- 2- Using the SID algorithm to match pixels to the JPL library in order to produce a mineral map.

- 3- Constructing a reference map by introducing the ground truth spectral signature of the minerals to the SID algorithm.
- 4- Comparing the two classification results (endmembers and mineral maps) by two evaluation metrics: confusion matrix and kappa coefficient.

Our objective is to demonstrate that the use of endmembers instead of the JPL spectral library for classification results gives a significant improvement in accuracy. This suggests that endmembers extracted from the image itself provide a more accurate representation of the clay minerals present in the region.

The remainder of this paper is organized as follows: Section 2 provides details on the data and study area. Section 3 focuses on the description of all the steps of the proposed approach. Section 4 discusses the obtained results. Finally, section 5 concludes the paper and gives some propositions for future research.

## 2. STUDY AREA AND USED DATA

The study area is the "Djebel Meni" located in Mostaganem (western Algeria). It lies between latitudes  $36^{\circ}04'28.06''$  and  $36^{\circ}03'45.11''$  N and longitudes  $0^{\circ}23'15.02''$  and  $0^{\circ}31'08.59''$  E (see Figure 1). The choice of this region is due firstly to its geological nature, generally covered with clay minerals. Secondly, it is due to the availability of the Hyperion hyperspectral image of this region (Zazi et al., 2017).

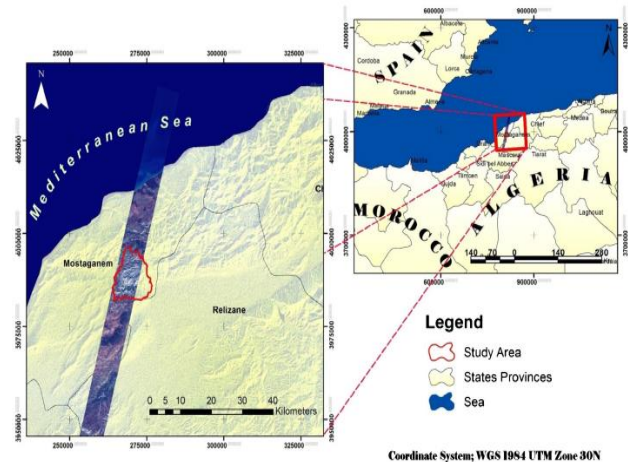


Figure 1. Location of the studied zone "Djebel Meni"

The characteristics of the Hyperion hyperspectral data (spectral and spatial resolution, number of bands, sensor type), as well as the studied area characteristics (acquisition date, image size:  $M \times N \times B$ ), are shown in Table 1.

Where:

$M \times N$ : is the size of each band (in pixels)

$B$ : is the number of bands in the image.

| Sensor type         | HDF EO-1 Hyperion |
|---------------------|-------------------|
| Spatial resolution  | 30 m              |
| Spectral resolution | 10 nm             |
| Number of bands (B) | 242               |
| Acquisition date    | 17-12-2010        |
| Columns number (N)  | 256 pixels        |
| Rows number (M)     | 3296 pixels       |

Table 1. The characteristics of the Hyperion hyperspectral data and studied area

Figure 2 below shows the true color image of Djebel Meni.

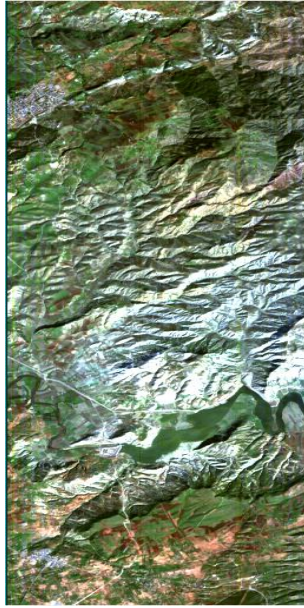


Figure 2. True color image of “Djebel Meni”

### 3. METHODOLOGY

In this section, we describe the different steps of the proposed method which is illustrated and summarized by the flow diagram in Figure 3 below.

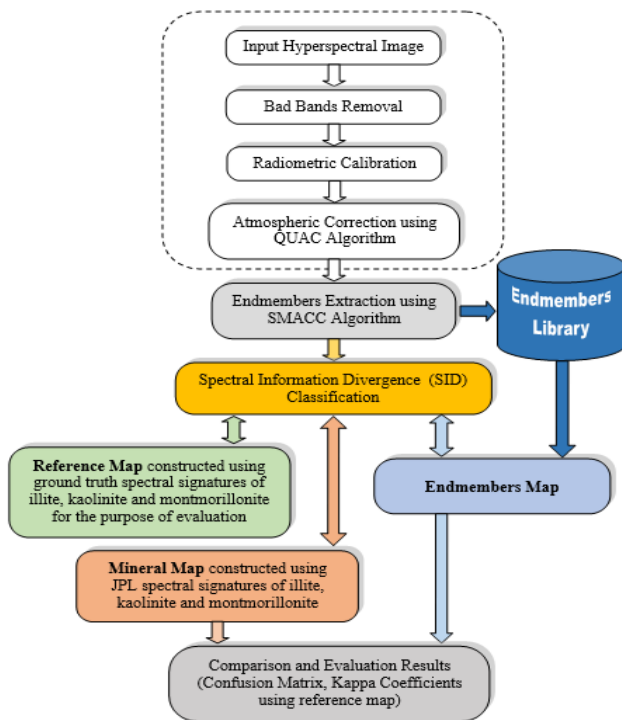


Figure 3. Flow diagram of the proposed method

**Preprocessing steps:** In hyperspectral satellite imagery, preprocessing is a crucial task to reduce atmospheric effects for better extraction of the desired information; the adopted preprocessing steps are the bad bands removal, radiometric calibration, and the Quick Atmospheric Correction method (QUAC) (Bernstein et al., 2012).

**Bad bands removal:** Hyperion hyperspectral data has 242 bands. The bands, that do not have any pixel information, are called zero bands, and we need to remove them, only 159 of 242 total Hyperion bands were used in the process. Concerning our image, bands 1 to 7 and 225 to 242 are not illuminated, and bands 58 to 78 fall in the overlap region of the two spectrometers visible/near-infrared (VNIR) spectrometer and short-wave infrared (SWIR) spectrometer i.e. bands 77, 78. We need to remove the water vapor absorption bands too. These last are identified as bands 120 to 132, 165 to 182, and 221 to 224.

The summary of removed bands is given in Table 2 below.

| Bands removed | Reason                               | Wavelength (nm)     |
|---------------|--------------------------------------|---------------------|
| 1-7           | Not illuminated                      | 355.59 - 416.64     |
| 58-78         | Overlap region                       | 976.28 - 1027.16    |
| 120-132       | Water vapor absorption band          | 1 346.25 – 1 467.33 |
| 165-182       | Water vapor absorption band          | 1 800.29 – 1 971.76 |
| 185-187       | Identified by Hyperion bad band list | 2 002.06 – 2 022.25 |
| 221-224       | Water vapor absorption band          | 2 365.20 – 2 395.50 |
| 225 – 242     | Not illuminated                      | 2 405.60 – 2 577.08 |

Table 2. Summary of removed bands in Djebel Meni image

**Radiometric calibration and atmospheric correction:** The electromagnetic signal captured by the Hyperion hyperspectral sensor is modified by the atmosphere during its path. The atmospheric effects are scattering and absorption by gases such as carbon dioxide, ozone, and water vapor. The radiance recorded by the hyperspectral sensor is influenced by the atmosphere in two ways, the first way is by attenuating the energy illumination and the second way is by adding the path radiance to the signal captured by the sensor. These two ways effects are represented mathematically by the equation (1) (Gao and Goetz, 1990).

$$R_{tot} = \frac{P \cdot E \cdot T}{2\pi} + R_p \quad (1)$$

Where:

$R_{tot}$  is the total spectral radiance measured by the sensor;

$R_p$  is the path radiance;

$P$  is the reflectance of the object;

$T$  is the transmitted energy;

$E$  is the irradiance on object caused by directly reflected sunlight and diffused skylight.

The radiometric calibration is performed in order to remove the path radiance; we also need to compensate the atmospheric attenuation effect. For that, we have used the QUAC atmospheric correction method (Bernstein et al., 2012) to get the true reflectance energy of the ground object. The QUAC method determines the atmospheric compensation parameters directly from the observed pixel spectra in the hyperspectral image.

This method is based on the empirical finding that the mean spectrum of a collection of diverse material spectra, such as the endmember spectra in a scene, is not dependent on each scene (Bernstein et al. 2012).

**Endmembers extraction:** Endmembers are spectra that are chosen to represent pure surface materials in a spectral image. The SMACC algorithm extracts the most abundant spectral signatures in the selected area by using the following convex cone expansion (Kale et al. 2019) for each pixel spectrum (Endmember), defined by equation (2).

$$H(c, i) = \sum_{k=1}^N R(c, k) \cdot A(k, j) \quad (2)$$

Where:

$i$ : is the pixel index;

$j$  and  $k$ : are the endmember indices from 1 to the expansion length  $N$ ;

$R$ : is a matrix that contains the endmember spectra as columns;

$c$ : is the spectral channel index;

$A$ : is a matrix that contains the fractional contribution (abundance) of each endmember  $j$  in each endmember  $k$  for each pixel.

**Spectral Information Divergence Classification:** The SID algorithm is a spectral classification method that compares the similarity between two pixels by measuring the probabilistic discrepancy between two corresponding spectral signatures, the smaller the divergence, the more likely the pixels are similar (Chang, 1999).

In our study, we used the SID algorithm with a divergence measure for three different purposes:

- 1- Matching pixels to spectra extracted with the SMACC algorithm (endmembers map): We first used the SID algorithm to match pixels to the spectral signatures extracted using the SMACC algorithm. This step produced an endmembers map.
- 2- Matching pixels to JPL spectral signatures of illite, kaolinite, and montmorillonite (mineral map): We then used the SID algorithm to match pixels to the Jet Propulsion Laboratory (JPL) spectral signatures corresponding to illite, kaolinite, and montmorillonite. This produced a mineral map.
- 3- Matching pixels to ground truth spectral signatures of illite, kaolinite, and montmorillonite (reference map): Finally, we used the SID algorithm to match pixels to the ground truth spectral signatures of illite, kaolinite, and montmorillonite. We used this reference map to evaluate the two classification results (endmembers map and mineral map).

**Evaluation of SID classification using both image endmembers and JPL spectral signatures:** To assess the impact of using both image endmembers and JPL spectral signatures on the SID classification results, we used the reference map to calculate the confusion matrix and kappa coefficient.

#### 4. RESULTS AND DISCUSSION

According to the proposed approach illustrated in the previous section (Figure 3), we have first removed bad bands from the Djebel Meni hyperspectral image. Secondly, we have applied a radiometric calibration and an atmospheric correction to remove

the atmospheric effects from this image. The visual result of this second processing step of the proposed approach is illustrated in Figure 4.

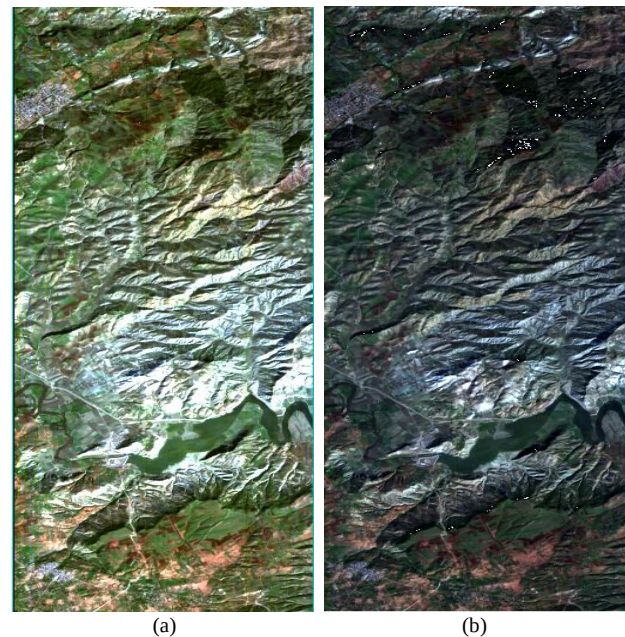
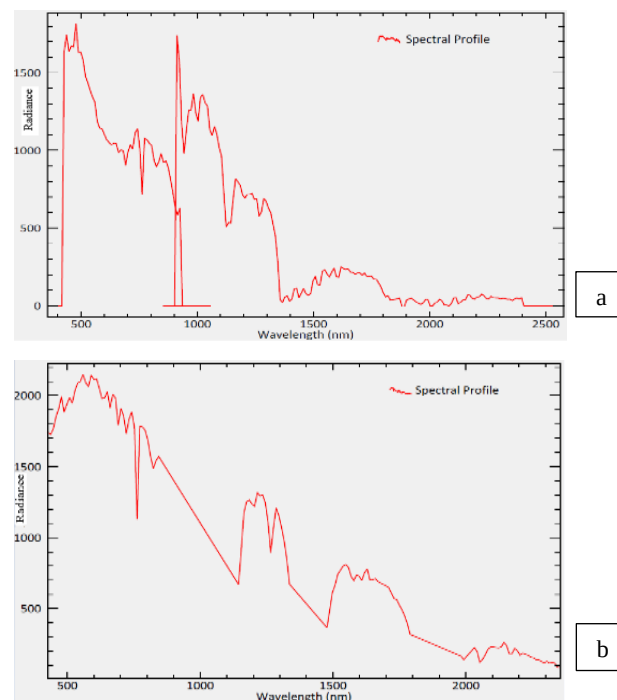


Figure 4. Hyperspectral image of “Djebel Meni”,  
(a) Original image, (b) Obtained image after radiometric calibration and atmospheric correction

For a better representation of this obtained result, Figure 5 offers a spectral profile comparison between randomly selected pixel from the original image and those obtained after the preprocessing steps. Graphs (a), (b), and (c) in Figure 5 show the improvement in the quality of the pixel spectral signature after these preprocessing steps. This facilitates the identification and classification of clay minerals in hyperspectral images.



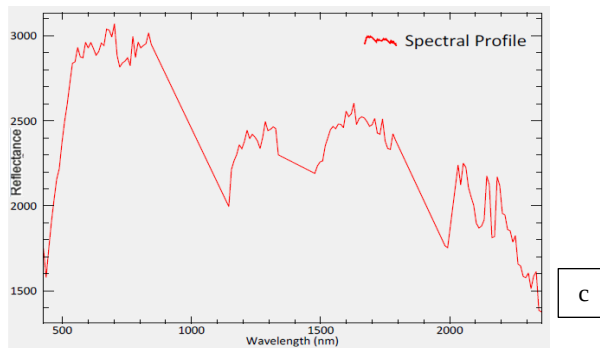


Figure 5. Spectral profile of randomly selected pixel from “Djebel Meni” image: (a) Original image, (b) After bad bands removal, (c) After radiometric calibration and atmospheric correction

After that, the SMACC endmembers extractor algorithm is applied to extract the most abundant spectral signatures from the Djebel Meni image. The obtained results are shown in Figure 6. We have applied the SID algorithm that uses a divergence measure to match pixels to spectra extracted with the SMACC algorithm to construct the endmembers map of the Djebel Meni image. The smaller the divergence, the more likely the pixels are similar. The result is represented by a color-coded image in Figure 7.

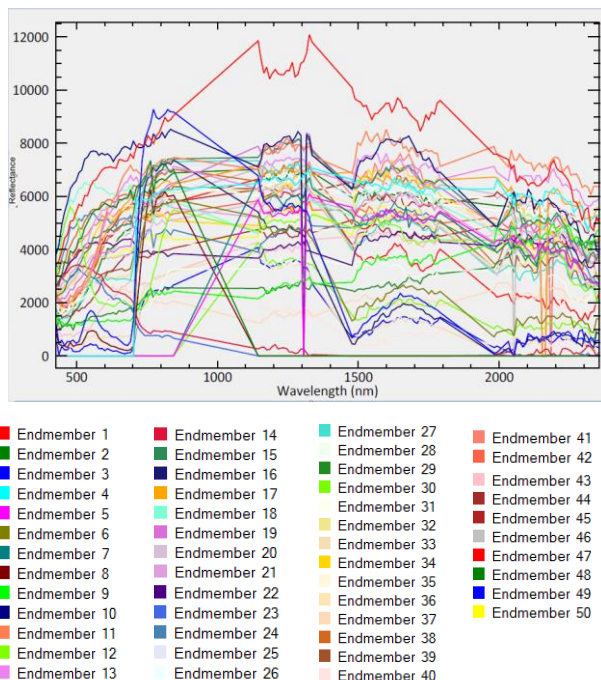


Figure 6. Extracted spectral signatures from Djebel Meni hyperspectral image using SMACC algorithm

To construct the mineral map of the Djebel Meni image, we have used the SID method which uses a divergence measure to match pixels to spectra of clay minerals introduced via the JPL spectral library (Figure 8). These clay minerals are illite, kaolinite, and montmorillonite. They have been chosen due to the geological nature of this region, which is usually covered by this kind of mineral. A mineral map using the JPL spectral library is represented by a color-coded image shown in Figure 9.

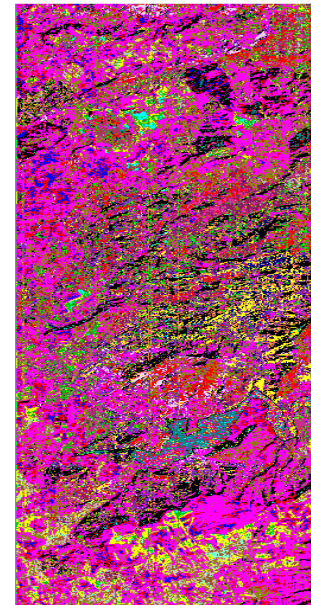


Figure 7. Endmembers map of “Djebel Meni” region (SID classification using endmembers image)

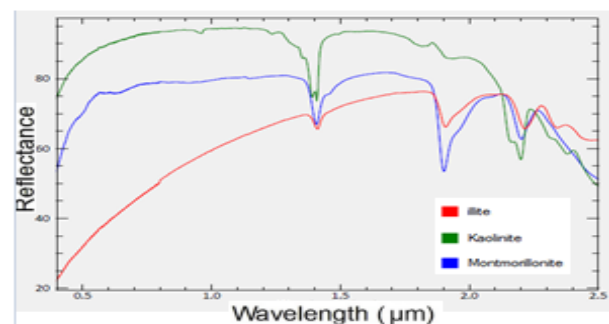


Figure 8. Spectral signatures of clay minerals from JPL spectral library used in mineral map construction of Djebel Meni hyperspectral image

We have noticed that the Endmembers classes existing in the endmembers map have no attribute of mineral (endmember 1, endmember 2, etc.). To evaluate the SID classification using endmembers' image in the studied region, we need to match each endmember class with its mineral class. For that, a comparison between the Endmembers map and the mineral map using the JPL spectral library has been done. The result of this processing step is illustrated in Figure 10. This figure shows that the endmember 43 represents the illite area. Kaolinite and montmorillonite are covered by endmembers 18 and 1 respectively.

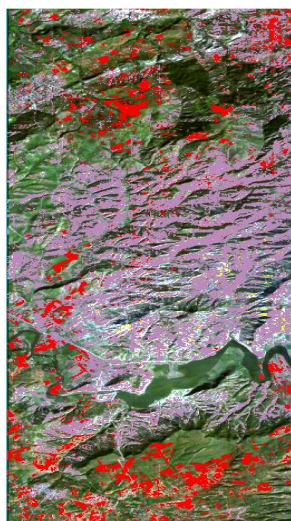


Figure 9. Mineral map of "Djebel Meni" region (SID classification using JPL spectral library)

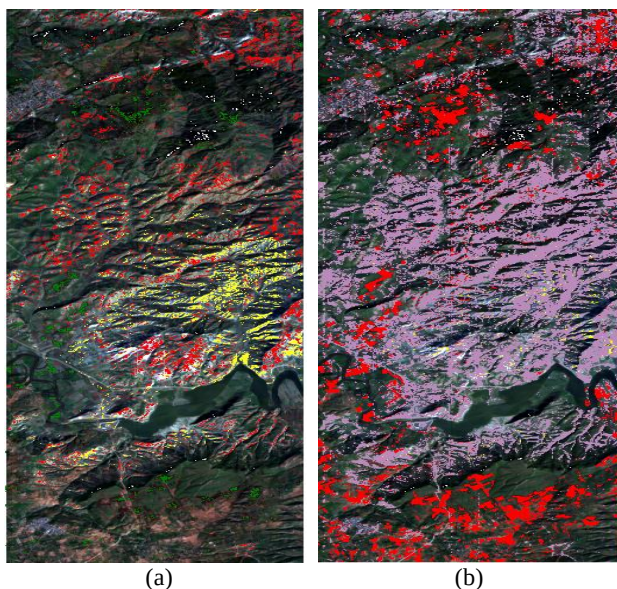


Figure 10. Comparison between (a) Endmembers map: Endmember 1 (red), Endmember 18 (yellow), Endmember 43 (green) and (b) Mineral map using JPL library: Montmorillonite (purple), Kaolinite (yellow), Illite (red)

To evaluate the two classification results (endmembers map and mineral map), a reference map (Figure 11) is constructed by using the SID classifier via introducing the ground truth spectral signatures of illite, kaolinite, and montmorillonite shown in Figure 12. The overall accuracy of the SID classification using image endmembers is 97.13%, which is significantly higher than the 84.17% accuracy achieved using the JPL spectral library. This indicates that 97.13% of the image pixels were accurately classified using the SID classification based on endmember signatures, whereas 84.17% of the pixels were correctly classified when using the SID classification with JPL spectral signatures area. Additionally, the kappa coefficient is respectively with endmembers image and JPL spectral library 0.93 and 0.57 (Table 3). This indicates a stronger correlation between the ground truth and the classification results when

using image endmembers compared to using JPL spectral signatures. These results further support the conclusion that the SID classification using endmembers image is a more accurate method for classifying these clay minerals in the Djebel Meni region. The higher accuracy of the SID classification using the endmembers image is because the endmembers image represents more the ground truth contrary to JPL spectral signatures that represent pure minerals that are analyzed in the laboratory conditions.

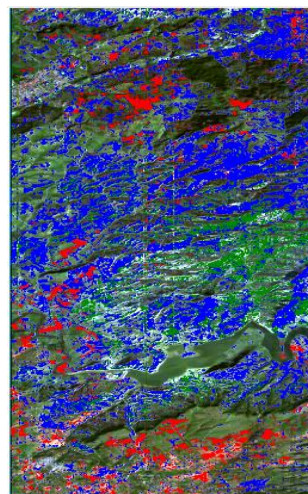


Figure 11. Reference map

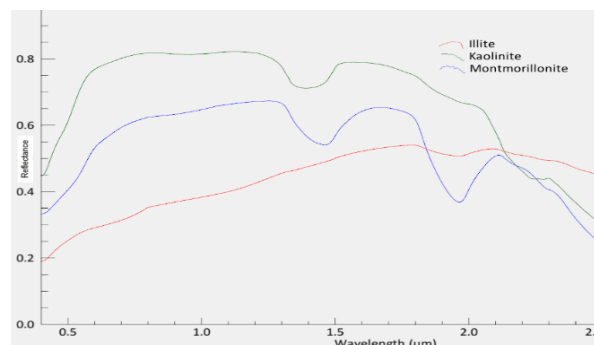


Figure 12. Ground truth spectral signatures of illite, kaolinite and montmorillonite

|                   | Image endmembers | JPL spectral signatures |
|-------------------|------------------|-------------------------|
| Overall accuracy  | 97.13 %          | 84.17%                  |
| Kappa coefficient | 0.93             | 0.57                    |

Table 3. SID classification accuracies

The confusion matrices in Tables 4 and 5 demonstrate that SID classification using image endmembers achieved higher accuracy for montmorillonite (90.43%), illite (99.31%), and kaolinite (76.50%) compared to classification using JPL spectral signatures (43.40%, 99.98%, and 5.29%, respectively).

The SID classification using endmembers image generally has lower omission and commission rates for all classes compared to the SID classification using JPL spectral signatures. This suggests that the SID classification using endmembers image is better at identifying positive cases (i.e., pixels that belong to the class of interest).

| (a)                           | Ground truth (pixels) |                          |                 |                    |                |
|-------------------------------|-----------------------|--------------------------|-----------------|--------------------|----------------|
| Class                         | Unclassified (pixels) | Montmorillonite (pixels) | Illite (pixels) | Kaolinite (pixels) | Total (pixels) |
| Unclassified                  | 114486                | 729                      | 75              | 1001               | 116291         |
| Endmember 1 (Montmorillonite) | 420                   | 18421                    | 0               | 64                 | 18 905         |
| Endmember 43 (Illite)         | 11                    | 190                      | 10781           | 0                  | 10982          |
| Endmember 18 (Kaolinite)      | 393                   | 1031                     | 0               | 3466               | 4890           |
| Total                         | 115310                | 20371                    | 10856           | 4531               | 151068         |

| (b)                           |  | Unclassified (%) | Montmorillonite (%) | Illite (%) | Kaolinite (%) | Total (%) |
|-------------------------------|--|------------------|---------------------|------------|---------------|-----------|
| Unclassified                  |  | 99.29            | 3.58                | 0.69       | 22.09         | 76.98     |
| Endmember 1 (Montmorillonite) |  | 0.36             | 90.43               | 0.00       | 1.41          | 12.51     |
| Endmember 43 (illite)         |  | 0.01             | 0.93                | 99.31      | 0.00          | 7.27      |
| Endmember 18 (Kaolinite)      |  | 0.34             | 5.06                | 0.00       | 76.50         | 3.24      |
| Total                         |  | 100.00           | 100.00              | 100.00     | 100.00        | 100.00    |

| (c)                           |  | Commission (%) | Omission (%) | Commission (pixels) | Omission (pixels) |
|-------------------------------|--|----------------|--------------|---------------------|-------------------|
| Class                         |  |                |              |                     |                   |
| Unclassified                  |  | 1.55           | 0.71         | 1805/116291         | 824/115310        |
| Endmember 1 (Montmorillonite) |  | 2.56           | 9.57         | 484/18905           | 1950/20371        |
| Endmember 43 (illite)         |  | 1.83           | 0.69         | 201/10982           | 75/10856          |
| Endmember 18 (Kaolinite)      |  | 29.12          | 23.50        | 1424/4890           | 1065/4531         |

| (d)                           |  | Prod. Accuracy (%) | User Accuracy (%) | Prod. Accuracy (pixels) | User Accuracy (pixels) |
|-------------------------------|--|--------------------|-------------------|-------------------------|------------------------|
| Class                         |  |                    |                   |                         |                        |
| Unclassified                  |  | 99.29              | 98.45             | 114486/115310           | 114486/116291          |
| Endmember 1 (Montmorillonite) |  | 90.43              | 97.44             | 18421/20371             | 18421/18905            |
| Endmember 43 (illite)         |  | 99.31              | 98.17             | 10781/10856             | 10781/10982            |
| Endmember 18 (Kaolinite)      |  | 76.50              | 70.88             | 3466/4531               | 3466/4890              |

Table 4. Confusion matrix - Classification of Djebel Meni image pixels using Endmembers image: (a) Unit = pixels, (b) Unit = %, (c) Omitted pixel rate (number of pixels and %),

## 5. CONCLUSION

The main goal of this scientific research is to improve a previous paper (Zazi et al., 2017) related to clay minerals identification and mapping of the Djebel Meni region in northwestern of Algeria. The proposed approach outperformed the previous one by using the SID algorithm for the classification process. The SID algorithm was found to be more accurate than the SAM algorithm, which was used in a previous study (Ramesh et al., 2016). Additionally, our approach includes a qualitative evaluation, unlike the previous research (Zazi et al., 2017).

| (a)             |  | Unclassified (pixels) | Montmorillonite (pixels) | Illite (pixels) | Kaolinite (pixels) | Total (pixels) |
|-----------------|--|-----------------------|--------------------------|-----------------|--------------------|----------------|
| Class (JPL)     |  |                       |                          |                 |                    |                |
| Unclassified    |  | 601959                | 62777                    | 14              | 2939               | 667689         |
| Montmorillonite |  | 8442                  | 49344                    | 0               | 17276              | 99891          |
| Illite          |  | 40460                 | 1586                     | 57845           | 0                  | 1134           |
| Kaolinite       |  | 6                     | 0                        | 0               | 1128               | 75062          |
| Total           |  | 650867                | 57859                    | 21343           | 113707             | 843776         |

| (b)             |  | Unclassified (%) | Montmorillonite (%) | Illite (%) | Kaolinite (%) | Total (%) |
|-----------------|--|------------------|---------------------|------------|---------------|-----------|
| Class           |  |                  |                     |            |               |           |
| Unclassified    |  | 92.49            | 55.21               | 0.02       | 13.77         | 79.13     |
| Montmorillonite |  | 1.30             | 43.40               | 0          | 80.94         | 8.90      |
| Illite          |  | 6.22             | 1.39                | 99.98      | 0.00          | 11.84     |
| Kaolinite       |  | 0.00             | 0.00                | 0.00       | 5.29          | 0.13      |
| Total           |  | 100.00           | 100.00              | 100.00     | 100.00        | 100.00    |

| (c)             |  | Commission (%) | Omission (%) | Commission (pixels) | Omission (pixels) |
|-----------------|--|----------------|--------------|---------------------|-------------------|
| Class           |  |                |              |                     |                   |
| Unclassified    |  | 9.84           | 7.51         | 65730/66769         | 48908/650867      |
| Montmorillonite |  | 34.26          | 56.60        | 25718/75062         | 64363/113707      |
| Illite          |  | 42.09          | 0.02         | 42046/99891         | 14/57859          |
| kaolinite       |  | 0.53           | 94.71        | 6/1134              | 20215/21343       |

| (d)             |  | Prod. Accuracy (%) | User Accuracy (%) | Prod. Accuracy (pixels) | User Accuracy (pixels) |
|-----------------|--|--------------------|-------------------|-------------------------|------------------------|
| Class           |  |                    |                   |                         |                        |
| Unclassified    |  | 92.49              | 90.16             | 601959/650867           | 601959/667689          |
| Montmorillonite |  | 43.40              | 65.74             | 49344/113707            | 49344/75062            |
| Illite          |  | 99.98              | 57.91             | 57845/57859             | 57845/99891            |
| kaolinite       |  | 5.29               | 99.47             | 1128/21343              | 1128/1134              |

Table 5. Confusion matrix - Classification of Djebel Meni image pixels using the JPL spectral library: (a) Unit = pixels, (b) Unit = %, (c) Omitted pixel rate (number of pixels and %), (d) Accuracy (number of pixels and %)

Our study solves the cost and time processing issues encountered by geologists using manual techniques. The preprocessing steps include bad bands removal, radiometric calibration, and atmospheric correction using the QUAC method. After that, we applied the SID algorithm on both the spectral signatures (Endmembers) obtained from the SMACC algorithm (Endmembers map) and JPL spectral signatures of Illite, Kaolinite, and Montmorillonite (mineral map). A comparison between the endmembers map and the mineral map is performed. The qualitative evaluations of the two classification results (endmembers map and mineral map) show the higher accuracy

of SID classification using image endmembers than using JPL spectral signatures.

The results of this study suggest that the SID classification using the endmembers map is a promising method for mapping clay minerals. This method could be used to improve the accuracy of clay mineral maps in other areas, particularly in regions where the JPL spectral library is not as accurate. In addition, unlike static spectral library (JPL), our use of image endmembers provides flexibility to accommodate temporal variations, rendering our approach well-suited for continuous monitoring in dynamic and ever-changing environments. Also, we are planning for the future to apply the same method using airborne hyperspectral remote sensing data such as the Airborne visible-infrared Imaging Spectrometer-Next Generation (AVIRIS-NG) to identify and map minerals in other regions in the world.

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