

LITHOLOGICAL AND HYDROTHERMAL ALTERATION MAPPING USING TERRA ASTER AND LANDSAT-8 OLI MULTISPECTRAL DATA IN THE NORTH-EASTERN BORDER OF KERDOUS INLIER, WESTERN ANTI-ATLASIC BELT, MOROCCO

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ABSTRACT. The copper belt of Anti-Atlas is recognized with several mineral occurrences of Cu, Zn, Mn, Ag, Au, and iron. We used ASTER and OLI in lithological and mineral detection and mapping. The lithological mapping was performed using principal components analysis (PCA), minimum noise fraction (MNF), and two classifiers: maximum likelihood (ML) and support vector machine (SVM). The hydrothermally altered zones were detected based on ASTER VNIR/SWIR bands by the integration of Ninomiya indices and constrained energy minimization (CEM) algorithm. In our study area, the enhanced band combinations of ASTER MNF1, PC4, and PC2 and OLI MNF1, PC5, and PC3 were applied for lithological discrimination. The OLI and ML classification shows the best lithological mapping accuracy with an overall accuracy of 91.74% and a 0.90 Kappa coefficient, followed by SVM with an overall accuracy of 88.82% and a 0.86 Kappa coefficient using the same sensor. The hydrothermal alteration mapping reveals alunite, chlorite, calcite, epidote, illite, kaolinite, montmorillonite, muscovite, and pyrophyllite minerals, principally in phyllic and argillic altered areas. The adopted methodology for lithological and mineralogical mapping can be used in other regions with similar criteria to the study area.

Keywords: Terra ASTER, Landsat-8 OLI, spectral indices, CEM, Anti-Atlas

1. INTRODUCTION

Satellite remote sensing techniques have a key role in locating potential mineral deposits and efficiently minimizing the costs of mineral exploration (Pour & Hashim, 2012; Rowan et al, 2005). Even though various useful minerals are present in several genetic associations, commercial mineral deposits are limited in terms of genetic types and mode of occurrence (Gupta & Krishnamurthy, 1992). Based on known commercial mining models, remote sensing



can help map probable metallogenic sites and prospect areas quickly. In addition, it can help to distinguish potential areas from nonpotential areas to explore efficiently (Nafigin et al, 2022). Spatial remote sensing is useful in various geological investigations including lithological mapping (Liu et al, 2021; Pour et al, 2019a) as a preliminary stage of economic substances exploration, mineral identification (Adiri et al, 2020b; Mars & Rowan, 2006), and structural features mapping (Hajaj et al, 2022; Hejja et al, 2020; Ibrahim et al, 2016; Jellouli et al, 2021; Kelka et al, 2021). Other prospecting phases such as the mine-level exploration phase do not require the use of remote sensing since it depends on the data used and their spatial, spectral, and radiometric characteristics (Clark & Rencz, 1999; El Harti et al, 2004).

The extraction of targeted information from satellite images is achieved by using several spectral transformation methods comprising spectral classifications using machine learning and deep learning algorithms (Shirmard et al, 2022), spectral indices, band ratios, etc. Multispectral sensors such as Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Landsat-7 ETM+, and Landsat-8 Operational Land Imager (OLI) have amply demonstrated their efficiency for lithological and mineralogical mapping at a regional scale (Pour et al, 2019c). Spectral Angle Mapper, Spectral Feature Fitting, and Binary Encoding were used by Azizi et al (2010) with ASTER data to map phyllic-argillic and propylitic alteration. These mapping results, using spectral classification methods, were considerably valuable in identifying porphyry copper deposits in east Zanzan (Iran). Di Tommaso & Rubinstein (2007) demonstrated the efficiency of optical and thermal data from the ASTER sensor combined with ground-based spectroradiometric measurements to map hydrothermal alterations by applying different spectral transformation methods including Spectral Angle Mapper, Band Ratio, and False Color Composite. Moreover, Pour et al (2021) used the constrained energy minimization and mixture-tuned matched-filtering algorithms to detect the subpixel abundance of Fe²⁺-rich, Al-rich, Fe³⁺-rich, and Mg-rich phyllosilicates using the VNIR/SWIR channels of ASTER in glacier area.

Several lithological and mineralogical mapping studies using remote sensing techniques were established in the Anti-Atlas belt of Morocco (Adiri et al, 2020a; Atif et al, 2021; Bachri et al, 2019; El Janati, 2019; Hajaj et al, 2023b; Hajaj et al, 2023c; Jellouli et al, 2021; Serbouti et al, 2021). For instance, multispectral (Landsat-8 OLI and S2A) and hyperspectral (Hyperion) combined data via Color-Normalization method were used in mineral mapping, where the latter demonstrated good results by using the independent component analysis (ICA) and the mixture-tuned matched-filtering method (MTMF) (Adiri et al, 2020a). The application of optimum index factor (OIF), decorrelation stretching (DS), principal components analysis (PCA), and band rationing (BR) has led to a good discrimination of lithological units in the study area (Jellouli et al, 2019). In this study, we used ML and SVM classifiers by applying the confusion matrix based on test points to compute the overall accuracy and Kappa coefficient of the lithological mapping results.

The Kerdous inlier has been of the great interest to the mining companies due to its richness in base and precious metals (Bourque, 2016; Choubert & Faure-Muret, 1973; Maddi et al, 2011). The study area is suitable to prospect copper mineralization which is mainly represented in the western Anti-Atlas by a stratabound level in the Adoudou basal series hosted by terminal Neoproterozoic to basal Paleozoic formations (Bourque, 2016).

The aims of this study are as follows: (1) lithological mapping of the northeastern exterior of Kerdous by applying the optimal false color composite (FCC) images based on the analysis of the results of MNF and PCA; (2) the evaluation of the performance of the ML and SVM in the mapping of the lithological units; and (3) the pixel-based and the subpixel mineral mapping in the study area by applying the Ninomiya indices and CEM classification algorithm.

2. GEOLOGICAL SETTING OF THE STUDY AREA

The Moroccan Anti-Atlas belt is the most important segment of the Neoproterozoic Pan-African orogen at the West African Craton northern (Lahna et al, 2020). The Precambrian basement outcrops in several inliers, including Kerdous, Saghrou, Akka, and others. The Kerdous inlier, among the other inliers of the Moroccan Anti-Atlas belt, shows a Precambrian basement diversified by complex structural formations such as Tanalt and Anzi (Soulaimani & Piqué, 2004).

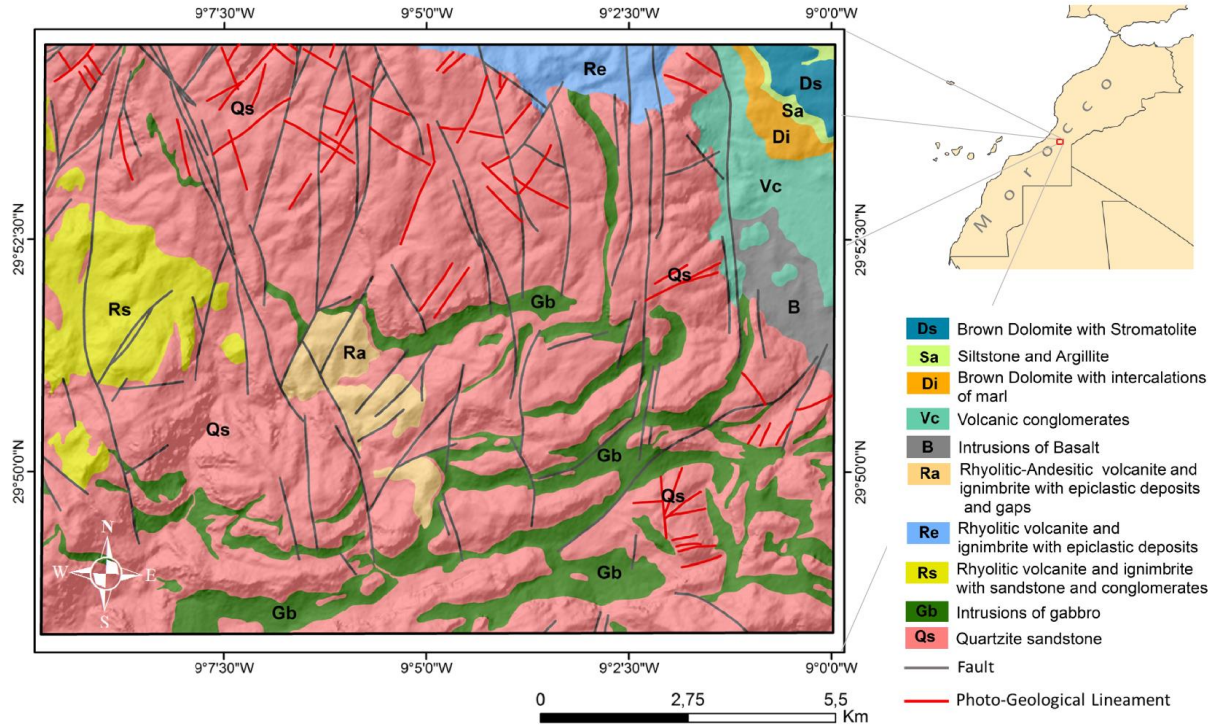


Figure 1. Lithological map of the study area (modified from the Tanalt geological map)

The study area is mostly formed by Neoproterozoic Quartzites belonging to the Adrar Lkest group. The Ouarzazate Group is mainly represented by volcano-detrital rock units (Soulaimani, 1998). The Cambrian cover rock units are mainly carbonates. The Neoproterozoic quartzites at Jbel Lkest are structured by a NE-dipping extension, which also appears to be associated with conglomerates of the Tanalt formation in relation with the late Ediacaran extension (Soulaimani et al, 2014b). Further structural linear features extraction based on multisource remote sensing data supports these structures occurrence at east Kerdous inlier border (Hajaj et al, 2022). The Lower Cambrian is formed by the sedimentary dolomite and argillite formations of the Taroudant Group (Adoudou and Iz'riyne formations) northeast of the study area (Jellouli et al, 2021). In addition, rhyolitic vulcanites and ignimbrites characterize the Neoproterozoic Ait-Baha group (Soulaimani & Piqué, 2004). The geological map used in this study (Figure 1) is the geological map of Tanalt region at the 1:50,000 scale. The faults and fractures in the study area present various directions and reflect the multiple deformations that have affected the region over geological time (Hassenforder, 1978). The study area demonstrated the occurrence of numerous hydrothermal alteration minerals and can be a promising area for prospecting of cupriferous mineralization (Hajaj et al, 2023a; Hajaj et al, 2023b).

3. MATERIALS AND METHODS

3.1. Remote sensing data characteristics

The ASTER image product is L1B level acquired on July 2, 2002. It has been downloaded from the Reverb platform. The ASTER image contains 14 bands in VNIR, SWIR, and TIR spectral ranges (Table 1) with a radiometric resolution of 8 and 12 bits. The OLI level-1T data product was downloaded from the USGS GloVis platform. The image comprises nine spectral bands in the three spectral ranges as shown in Table 2. It is radiometrically calibrated, geometrically co-registered, and orthorectified (Jellouli et al, 2019). Landsat-8 OLI scenes provide a high radiometric resolution with 16 bits. Figure 2 presents the flowchart of the methodology used to process ASTER and OLI data in this analysis.

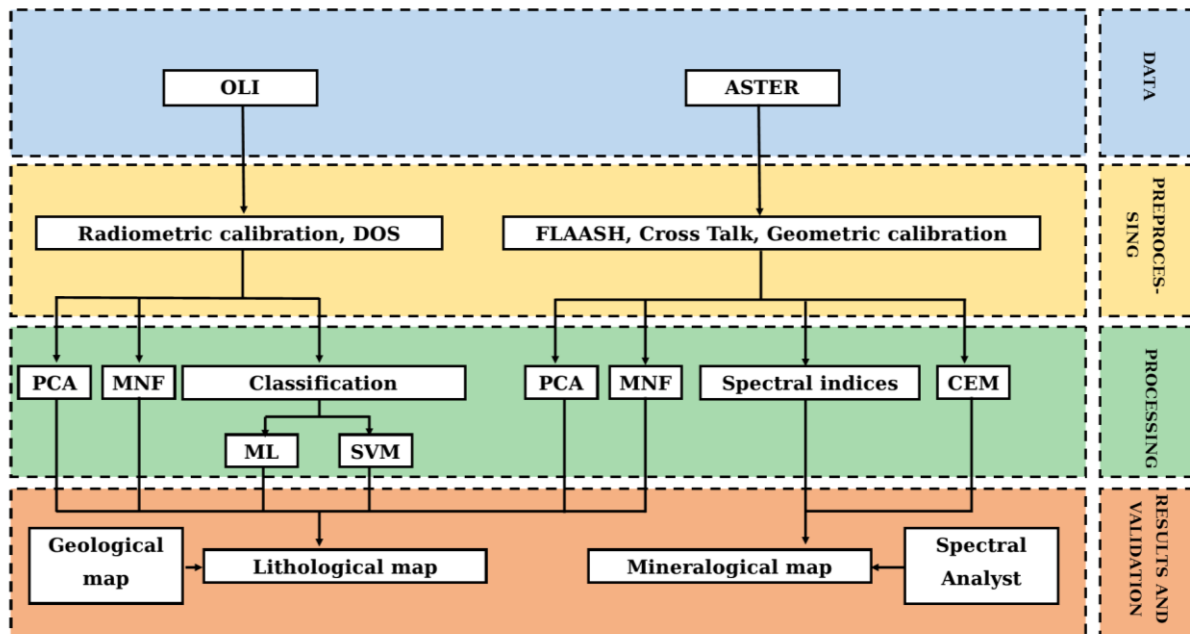


Figure 2. The methodology flowchart

Table 1. Terra ASTER data characteristics

Bands	Covered Spectrum	Wavelengths (μm)	Resolution (m)
1	VNIR	0.520–0.600	15
2	VNIR	0.630–0.690	15
3N	VNIR	0.760–0.860	15
3B	VNIR	0.760–0.860	15
4	SWIR	1.600–1.700	30
5	SWIR	2.145–2.185	30
6	SWIR	2.185–2.225	30
7	SWIR	2.235–2.285	30
8	SWIR	2.295–2.365	30
9	SWIR	2.365–2.430	30
10	TIR	8.125–8.475	90
11	TIR	8.475–8.825	90
12	TIR	8.925–9.275	90
13	TIR	10.25–10.95	90
14	TIR	10.95–11.65	90

Table 2. Landsat-8 OLI data characteristics

Bands	Wavelengths (μm)	Spatial resolution (m)
Band 1-coastal/aerosol	0.43–0.45	30
Band 2-Blue	0.45–0.51	30
Band 3-Green	0.53–0.59	30
Band 4-Red	0.64–0.67	15
Band 5-NIR	0.85–0.88	30
Band 6-SWIR 1	1.57–1.65	30
Band 7-SWIR 2	2.11–2.29	30
Band 8-Panchromatic	0.50–0.68	15
Band 9-Cirrus	1.36–1.38	30

3.2. Image preprocessing

The atmospheric correction of the Terra ASTER image was applied using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hyper-cubes) algorithm that generates the ground reflectance image. The FLAASH algorithm allows the determination of the ground reflectance from the apparent luminance (Lhissou et al, 2020), and it is based on the MODTRAN (MODerate resolution Atmospheric TRANsmission) algorithm (Cooley et al, 2002). In addition, the Terra ASTER L1B image was corrected for crosstalk effects. This crosstalk effect is caused by the dispersion of incident light in band 4, which is scattered in the focal plane of other SWIR bands and generating the noise (Iwasaki et al, 2002). The Landsat-8

OLI scenes provide a high radiometric resolution with 16 bits. The Landsat-8 OLI image was radiometrically corrected in TOA (Top Of Atmosphere) to apparent reflectance data. Atmospheric effects were corrected and converted to reflectance by using a procedure based on the Dark Object Subtraction (DOS) algorithm (Moran et al, 1992).

3.3. Image processing

3.3.1. Principal Components Analysis (PCA)

The principal components analysis (PCA) is an effective statistical method used to analyze the correlation in multispectral and hyperspectral datasets (e.g., Tripathi & Govil, 2019). Among its functionalities, the reduction of the dimensionality of input data and the separation of the noise components by suppressing irradiance effects dominate all spectral bands. Thus, PCA is an image enhancement technique that transforms correlated spectral bands into a set of uncorrelated variables called principal components or PC bands (Rajan Girija & Mayappan, 2019). In this study, we applied the PCA transform to both of ASTER and OLI VNIR/SWIR bands. Tables 3 and 4 display the eigenvalues percentages and the eigenvector loadings matrix derived from ASTER and OLI data, respectively.

3.3.2. Minimum Noise Fraction (MNF)

The Minimum Noise Fraction (MNF) transformation is a statistical method similar to the PCA method. It is used for linearly transforming the reflectance input image to reduce spectrally its dimensionality and noise (Green et al, 1988). It determines the input data noise statistics in terms of Eigen-values, and these values were used to select the lower MNF bands that contain the most spectral information. The first MNF new bands are usually used as FCC to enhance lithology due to their high eigenvalues loadings.

3.3.3. Image classification algorithms

The maximum likelihood (ML) classification algorithm is a parametric classification applied for supervised classification. It makes the assumption that the data for each class and band will be distributed normally. It determines the probability that a pixel belongs to a particular class (Fal et al, 2019). All pixels are classified, and each pixel is assigned to the class with the highest probability if the probability threshold is not selected.

The Support Vector Machine (SVM) classification algorithm is one of the broadly applied supervised classification algorithms based on statistical learning theory (De Boissieu et al, 2018). The SVM machine learning logic is based on a maximized hyperplane to classify the image according to the given regions of interest. The selection of the hyperplane is the one that represents the largest separation between two classes to minimize the spectral mixture (Ge et al, 2018). Commonly, the use of the SVM method in the geological and mineralogical studies provides good mapping accuracies (Bachri et al, 2019; Ge et al, 2018; Soulimani et al, 2014a).

3.3.4. Spectral indices

The spectral indices are computed by dividing the multiplied or added reflectance value of pixel bands by the corresponding values of pixels in another band (or another physical quantity, e.g., spectral radiance) displaying the result as a grayscale image (Corrie et al, 2011; Ninomiya, 2010). The band ratios are computed based on distinctive spectral band characteristics, resulting in an output image that identifies the targeted mineralogical composition in the image. The VNIR and SWIR spectral characteristics of various minerals associated to hydrothermal processes were analyzed. Ninomiya (2002) used several spectral bands for mapping quartz-rich, carbonate, and silicate rocks using TIR data from the ASTER sensor. The applied spectral

indices were developed on the basis of SWIR data by Ninomiya (2004), including hydroxyl-bearing minerals, calcite, and alunite.

3.3.5. Constrained energy minimization (CEM) classification method

The CEM classification method is a target signature approach, which limits the desired target signature with a specific gain while minimizing the effects caused by other unknown signatures (Chang et al, 2000; Farrand & Harsanyi, 1997; Liu et al, 1999). This classification method has been applied to the ASTER image to enhance the target signatures. The ENVI 5.3 software was used to apply this method in the study area. The image generated by the CEM method is in gray levels, where each pixel gray level value in the image reflects the amount of the targeted mineral fraction abundance that was identified. The mineral detection is then performed based on the resulting grayscale image, and thematic classification is performed by detecting the desired mineral in a separate image (Pour et al, 2019b).

4. RESULTS AND DISCUSSION

4.1. Lithological mapping

4.1.1. PCA and MNF results

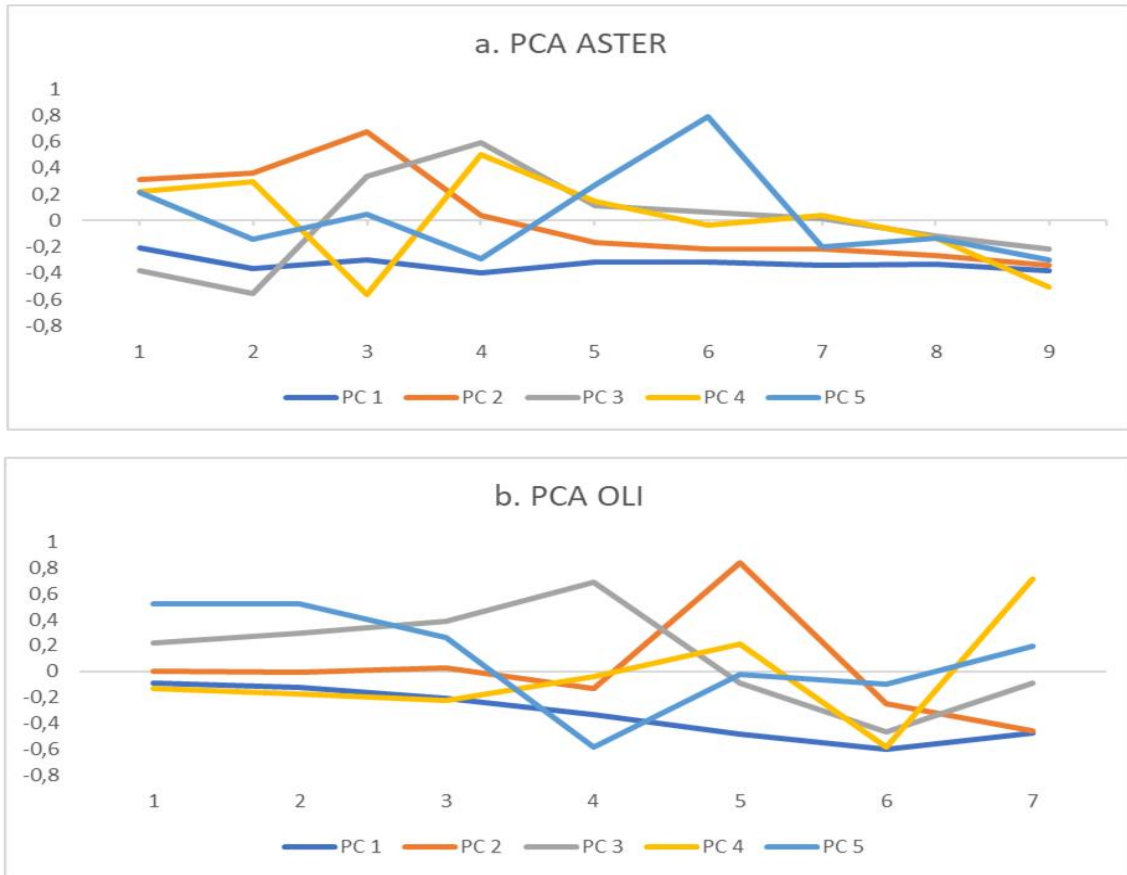
The PCA transformation is applied to the nine bands of ASTER and the seven bands of Landsat-8 OLI (Tables 3 and 4). The first three principal components (PC1, PC2, and PC3) contain more than 96.05% and 99.49% of all the inner information in ASTER and OLI images, respectively. Figure 3 shows the eigenvector loading trend of the first five ASTER and OLI PC images for better visualization of the data in Tables 3 and 4.

Table 3. PCA eigenvector matrix of ASTER bands

Eigenvectors	Eigenvalues (%)	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7	Band 8	Band 9
PC 1	83.49	-0.2073	-0.3643	-0.3000	-0.4017	-0.3157	-0.3159	-0.3434	-0.3354	-0.3779
PC 2	8.61	0.3157	0.3620	0.6760	0.0359	-0.1632	-0.2192	-0.2168	-0.2680	-0.3425
PC 3	3.95	-0.3816	-0.5550	0.3412	0.5935	0.1125	0.0629	0.0189	-0.1203	-0.2144
PC 4	2.31	0.2198	0.2946	-0.5600	0.5047	0.1437	-0.0375	0.0426	-0.1342	-0.5046
PC 5	0.54	0.2128	-0.1446	0.0484	-0.2907	0.2730	0.7915	-0.1968	-0.1344	-0.2983
PC 6	0.4	0.1262	-0.2003	0.1268	-0.2920	0.1665	-0.2261	0.5204	0.4782	-0.5139
PC 7	0.34	-0.7725	0.5273	0.0629	-0.1636	0.0905	0.1434	0.1037	-0.0191	-0.2333
PC 8	0.20	0.0066	-0.0244	0.0206	-0.1657	0.8205	-0.3631	-0.0296	-0.3749	0.1572
PC 9	0.15	-0.0722	0.0395	0.0020	0.0785	0.2378	-0.1289	-0.7152	0.6287	-0.0825

Table 4. PCA eigenvector matrix of OLI bands

Eigenvectors	Eigenvalues (%)	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
PC 1	94.505	-0.09192	-0.12474	-0.2078	-0.33462	-0.48452	-0.60072	-0.47457
PC 2	3.398	0.000397	-0.00519	0.024592	-0.13446	0.842454	-0.25154	-0.45639
PC 3	1.620	0.222355	0.292138	0.389118	0.690656	-0.08932	-0.46946	-0.09177
PC 4	0.279	-0.12715	-0.17061	-0.22221	-0.03729	0.213198	-0.58625	0.717502
PC 5	0.176	0.519782	0.523961	0.26547	-0.58028	-0.01976	-0.096	0.196193
PC 6	0.018	-0.44877	-0.26373	0.815732	-0.2339	-0.04026	-0.05046	0.068967
PC 7	0.003	-0.67407	0.72517	-0.13975	-0.01132	0.00846	-0.00293	0.004203

**Figure 3.** Eigenvector loading trend graphical representation extracted from the first five (a) ASTER and (b) OLI PC bands from data in Tables 3 and 4

The PC1 image usually enhances the main information in the image, such as the general geological contrast, topography, and structural features. The ASTER PC1 eigenvector loadings show negative contributions for all bands (Figure 3a) with a little decrease from the first band (-0.20736) and the ninth band (-0.37795). As demonstrated in the study area on the extracted PC1 image (Figure 4a), the Cambrian formations (Sa, Ds, and Di) are highlighted by dark pixels, while Neoproterozoic units (B, Vc, Re, Gb, Qz, Rs, and Ra) are highlighted by relatively bright pixels. PC2 highlights the Ds unit with dark pixels following the high negative contribution in the bands 8 and 9 of ASTER (-0.26804) and (-0.34255), respectively (Figure 3). This is due to CO₃ absorption feature in 2.33 μm corresponding to ASTER band 8 (Hunt &

Ashley, 1979). Iron-bearing minerals exhibit distinctive absorption features at ASTER bands 1, 2, and 3 and reflectance in band 4 (Pour & Hashim, 2012). Gabbro intrusions are discriminated by bright pixels in these two PCs (Figure 4c and d) due to their richness in basic ferrous minerals.

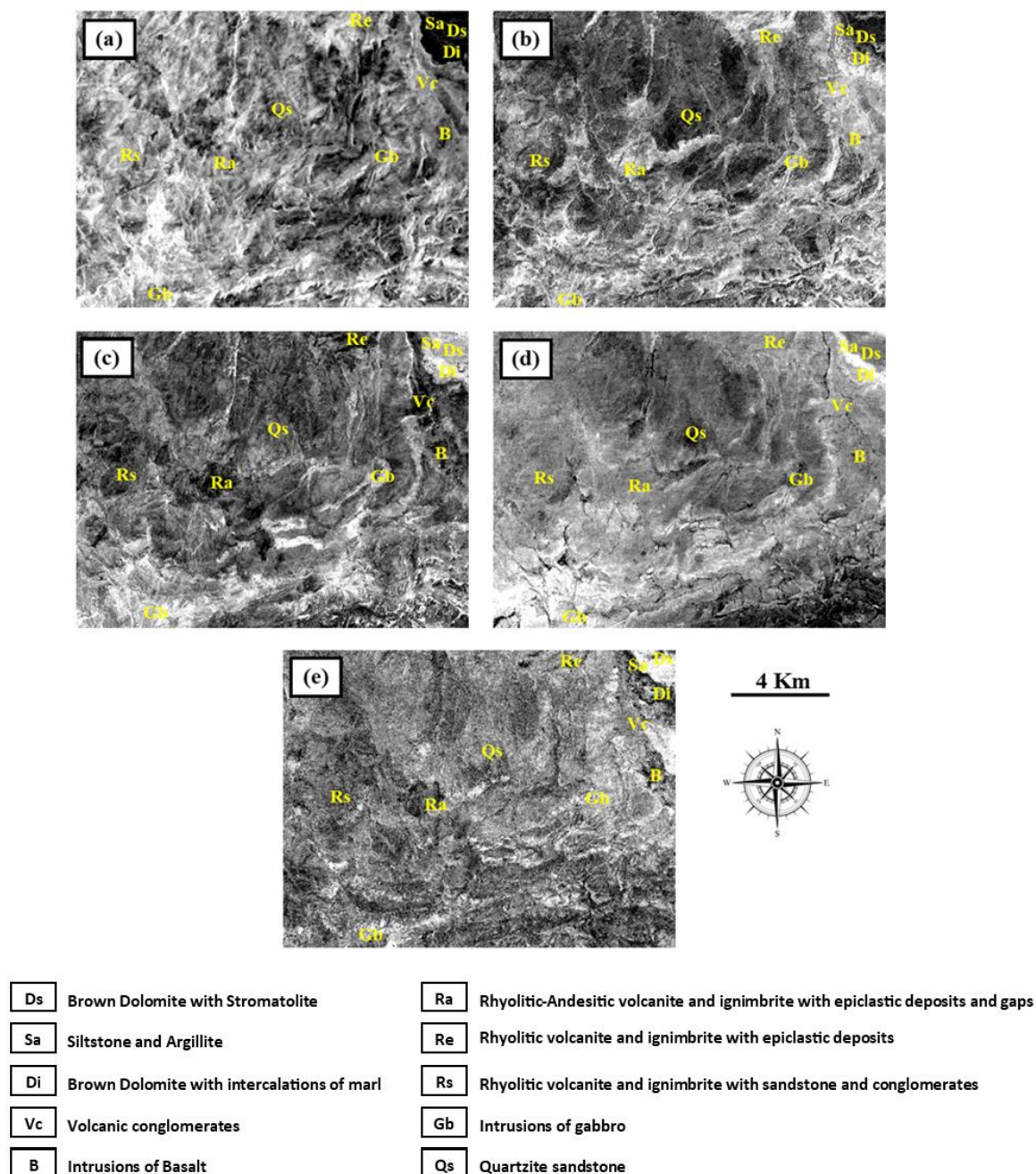


Figure 4. PC images of ASTER: (a) PC1; (b) PC2; (c) PC3; (d) PC4; (e) PC7

The PC1 eigenvectors demonstrated a negative contribution in all the seven bands with a maximum value of (-0.09192) in band 1 and a minimum value of (-0.60072) in band 6 (Figure 3b). PC2 shows vegetation in white pixels due to the high positive contribution in the band 5 (0.842454), and the units of Ds, Sa, and Di are enhanced by dark pixels due to the high negative contribution in band 7 (-0.45639) (Figure 3b).

PC3 highlights the units of Vc and Ra with white pixels due to the high positive contribution in band 4 (0.690656), and Gb lithological unit was identified with a dark tone due to the negative contribution (-0.46946) in band 6 (Figure 3b) (Fe-bearing minerals reflectance band). Thereafter, PC4 (Figure 5d) shows the Qs and Ds lithological units with bright pixels due to the high positive contribution in band 7 (0.717502) and the Gb lithological unit with black pixels due to the high negative contribution in band 6 (-58625) (Figure 3b).

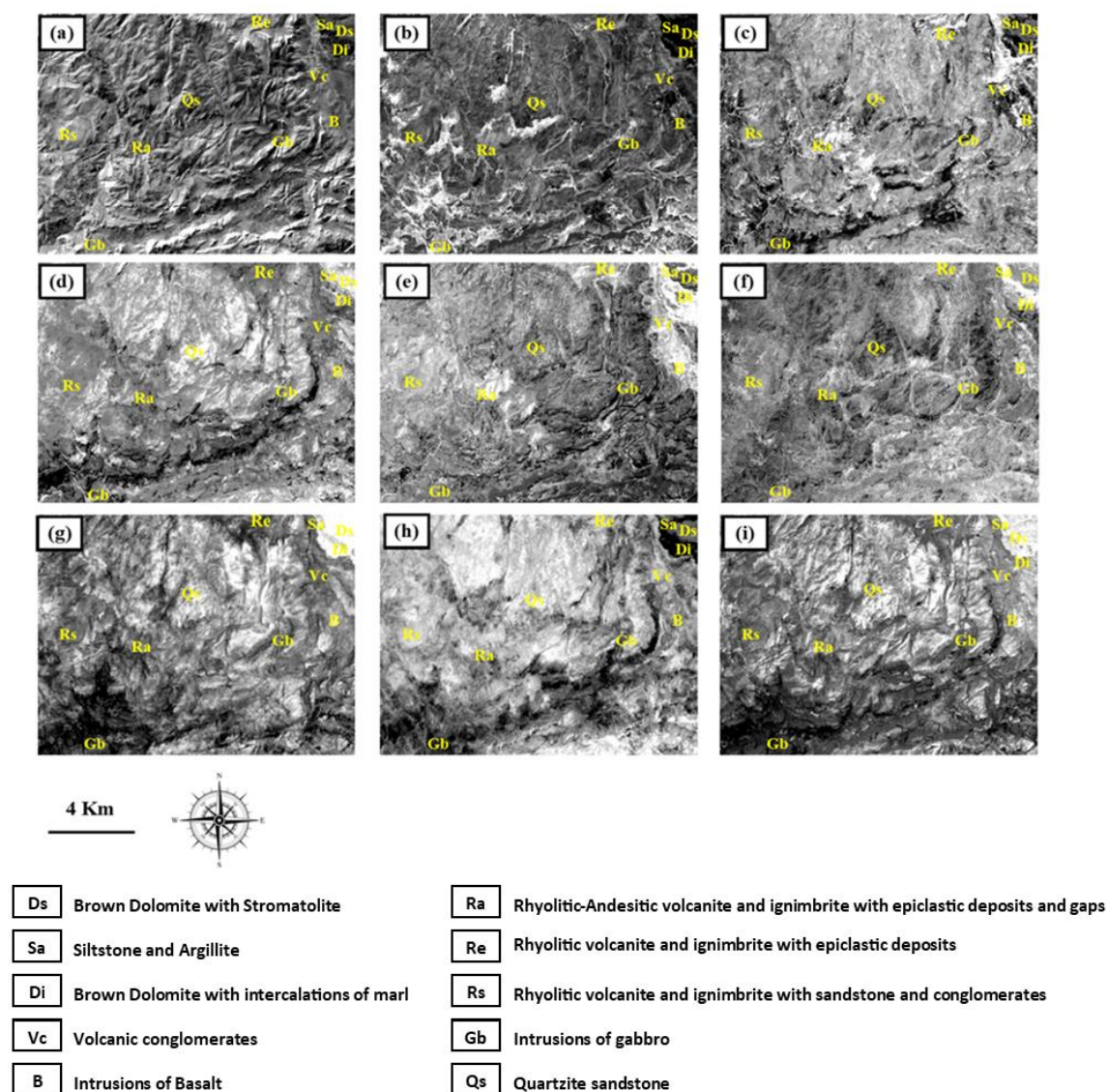


Figure 5. PCA and MNF extracted images of: (a) OLI PC1; (b) OLI PC2; (c) OLI PC3; (d) OLI PC4; (e) OLI PC5; (f) OLI PC6; (g) ASTER MNF 1; (h) ASTER MNF 2; (i) OLI MNF1

Besides, PC5 displays the Ra, B, and Sa in bright pixels due to the high positive contribution in band 2 (0.523961) (Figure 3b). PC6 (Figure 5f) shows a good capability to differentiate Sa formation in white tone due to the high positive contribution in band 3 (0.815732).

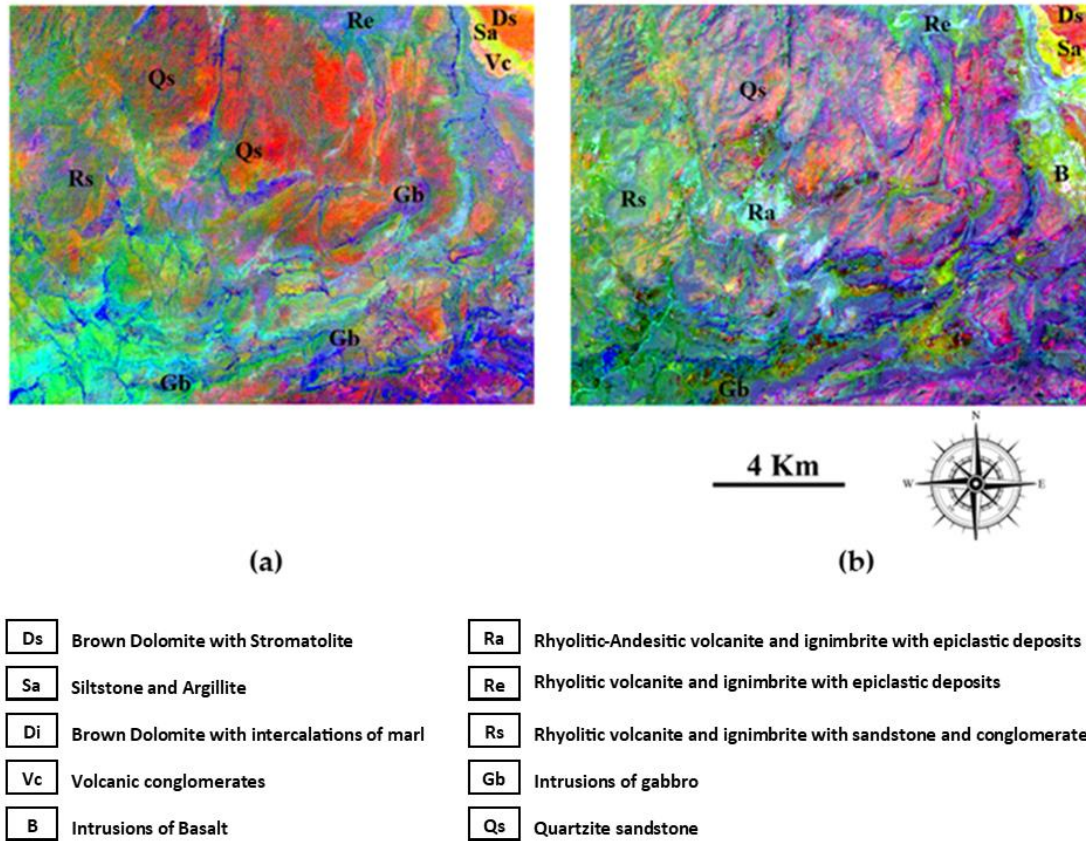


Figure 6. (a) FCC ASTER MNF1, PC4, and PC2; (b) FCC OLI MNF1, PC5 and PC3

The FCC of the selected bands is used for discrimination of the different lithologies. The resulting MNF images of ASTER MNF1 and MNF2 as well as MNF1 of OLI are presented in Figure 5g, h, and i. Furthermore, the FCC is used for both PCA and MNF images (Figure 6). The best combination for discriminating lithological units of the study area using ASTER data is MNF1, PC4, and PC2 as RGB images (Figure 6a). On the other hand, the OLI (MNF1, PC5, and PC3) as RGB shows a high capability to enhance lithology visualization in the study area (Figure 6b).

4.1.2. Image classification results

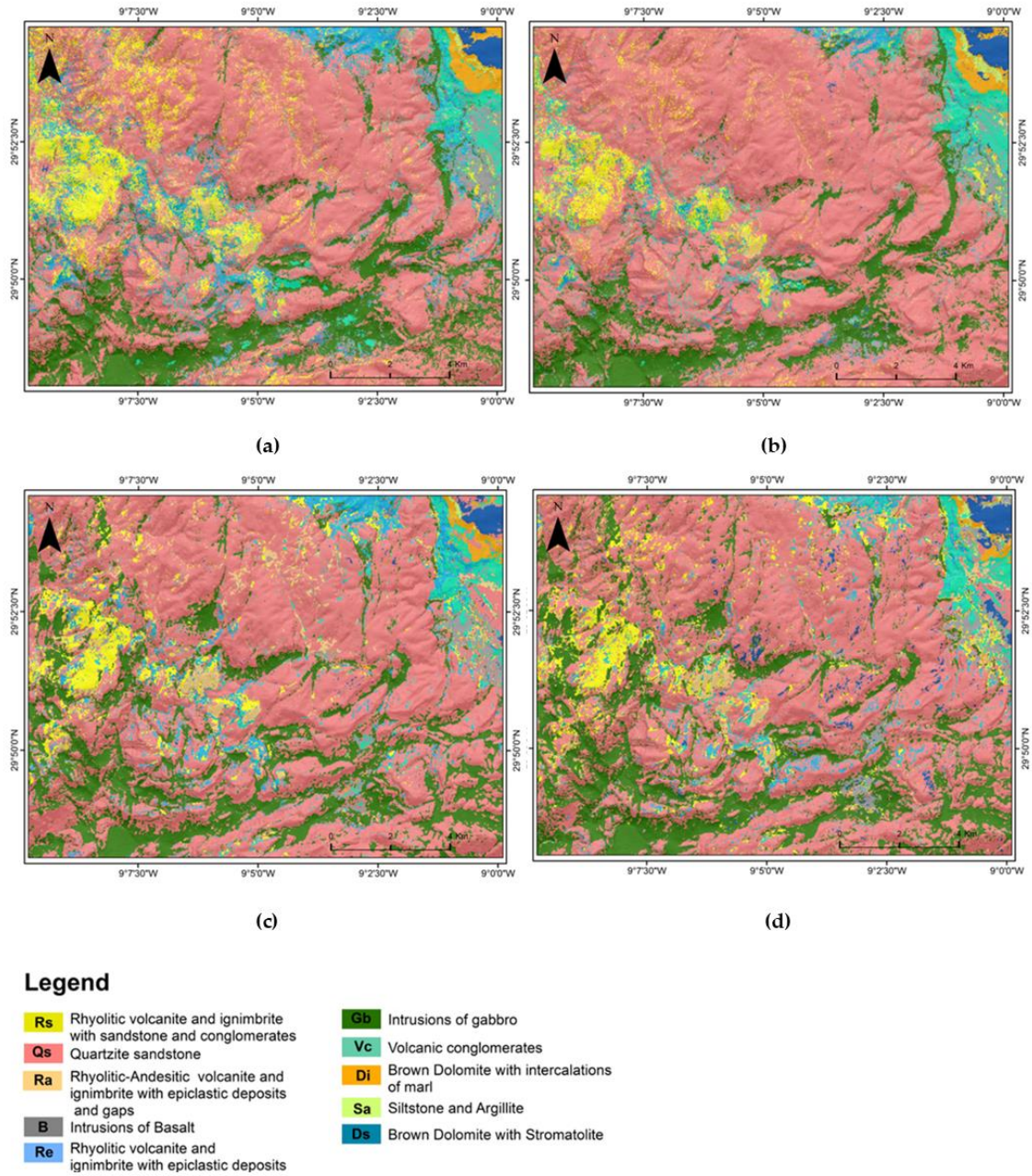


Figure 7. Lithological classification maps: (a) MLC classification using ASTER image; (b) SVM classification using ASTER image; (c) MLC classification using OLI image; (d) SVM classification using OLI image

The analysis of the results from the OLI image shows that both ML and SVM classification methods demonstrated good discrimination of the study area lithology (Figure 7). According to the resulting lithologic maps, the five lithological units, brown dolomite with stromatolite (Ds), brown dolomite with marl intercalations (Di), rhyolitic-andesitic volcanic and ignimbrite with epiclastic deposits (Ra), siltstone and argillite (Sa), and quartzite sandstone (Qs), are well mapped in both classification methods. These units show high values of overall accuracy and Kappa coefficient.

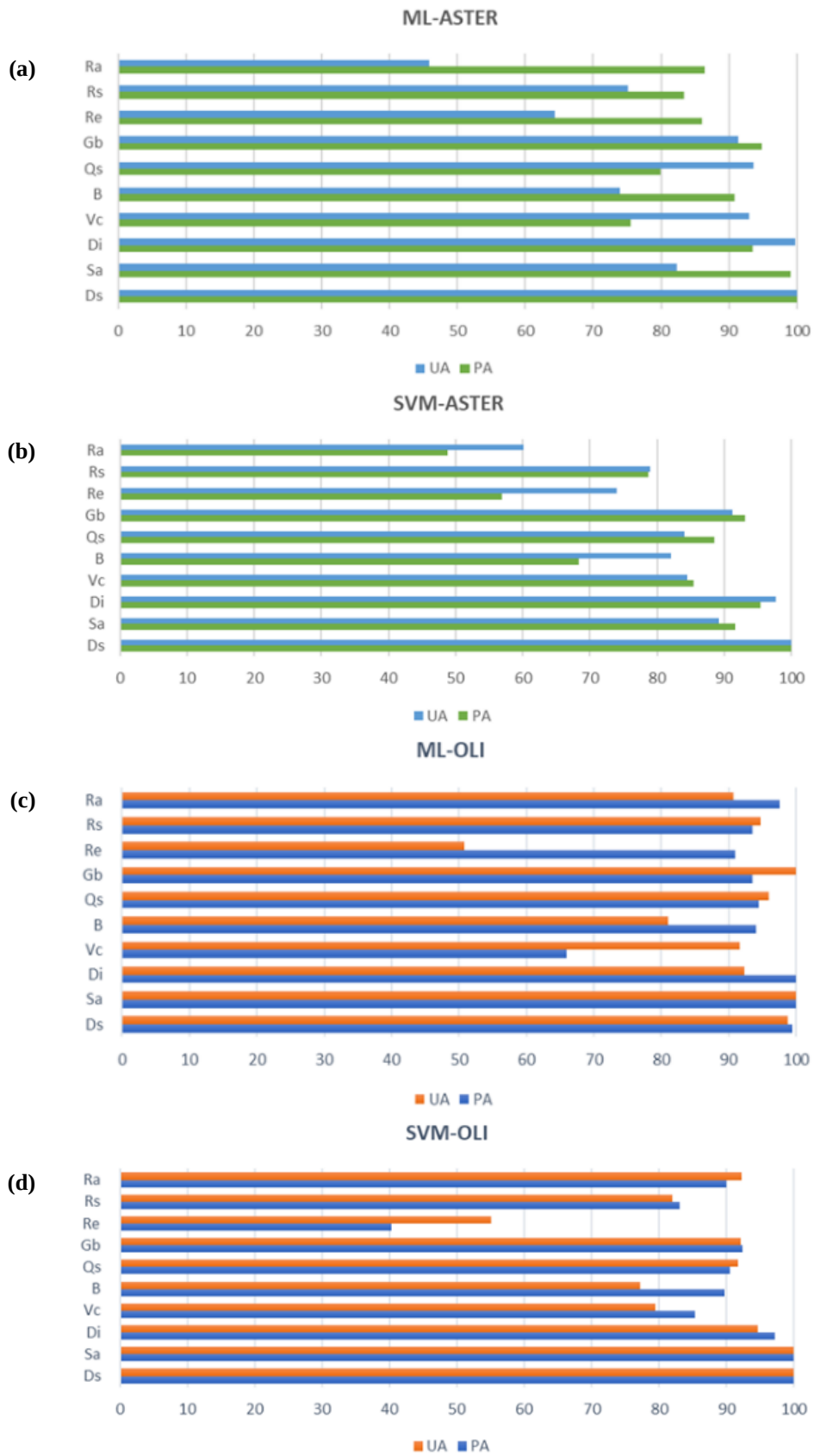


Figure 8. User and producer accuracies: (a) ML ASTER; (b) SVM ASTER; (c) ML OLI; (d) SVM OLI

Based on the confusion matrix results, the ML classification method has an overall accuracy (of 91.74%) and a Kappa coefficient (of 0.90) higher than the SVM classification method with an overall accuracy of 88.82% and a Kappa coefficient of about 0.86 (Figure 9).

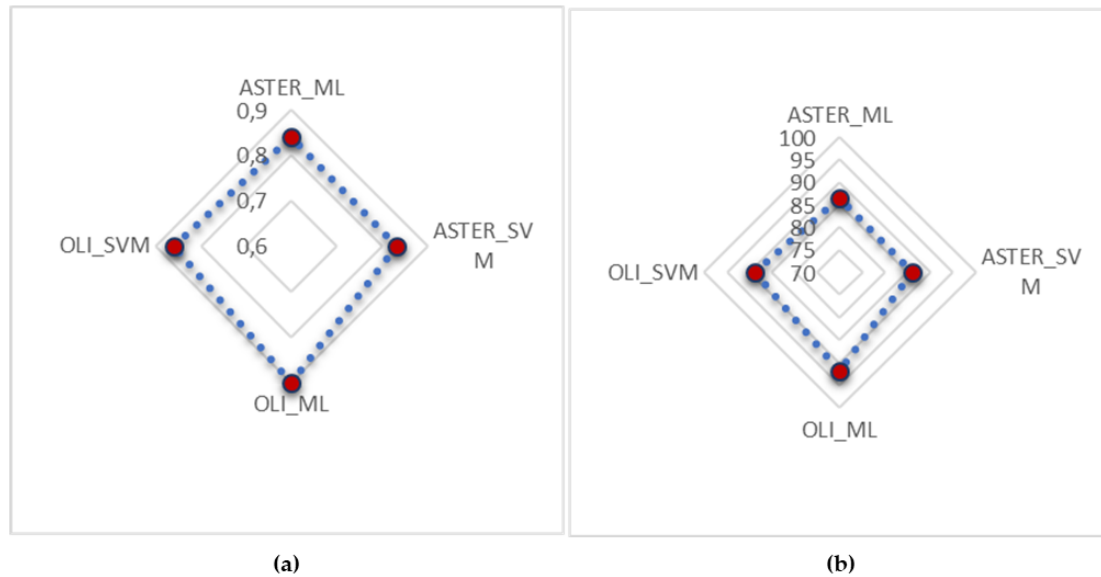


Figure 9. Overall accuracy and Kappa coefficient of MLC and SVM classifications using ASTER and OLI: (a) overall accuracy; (b) Kappa coefficient

In addition, several lithological units were well enhanced by both classification methods, and the results are presented in Figure 7. The ML classification method has well enhanced two lithological units: brown dolomite with stromatolite (Ds) and brown dolomite with marl intercalations (Di) (Figure 7a and 7c), as observed in the ML classification results compared to the SVM classification. The results obtained from both ML and SVM classification methods using the ASTER data did not show satisfactory lithological discrimination compared to that from the OLI data.

On the other hand, siltstone and argillite (Sa) and volcanic conglomerates (Vc) are well mapped by the SVM classification (Figure 7b and 7d). According to the resulting accuracies (Figures 8 and 9) of the ASTER image, the lithological units of rhyolitic volcanic and ignimbrite with epiclastic deposits (Re) are better classified using the ML method than the SVM method. The ML method showed a spectral mixture between the lithologic units of rhyolitic volcanic and ignimbrite with sandstones and conglomerates (Rs) and quartzite sandstones (Qs).

4.2. Hydrothermal alteration mapping

4.2.1. Ninomiya spectral indices

The abundance images of hydrothermal alteration mineral occurrences were calculated. For the mineralogy of Ninomiya (2004), the pseudocolor ramp image of the calcite mineral discriminates Ca-bearing alteration minerals as bluish pixels (Figure 10a). In addition, the kaolinite-rich zones characterize the argillic and phyllic alteration zones which are highlighted by OH(a) and OH(b) that moreover enhance the pyrophyllite and montmorillonite (Figure 10b and c). Then, the index images were thresholded to extract all pixels with reflectance values well above the threshold value to be combined as shown in Figure 11.

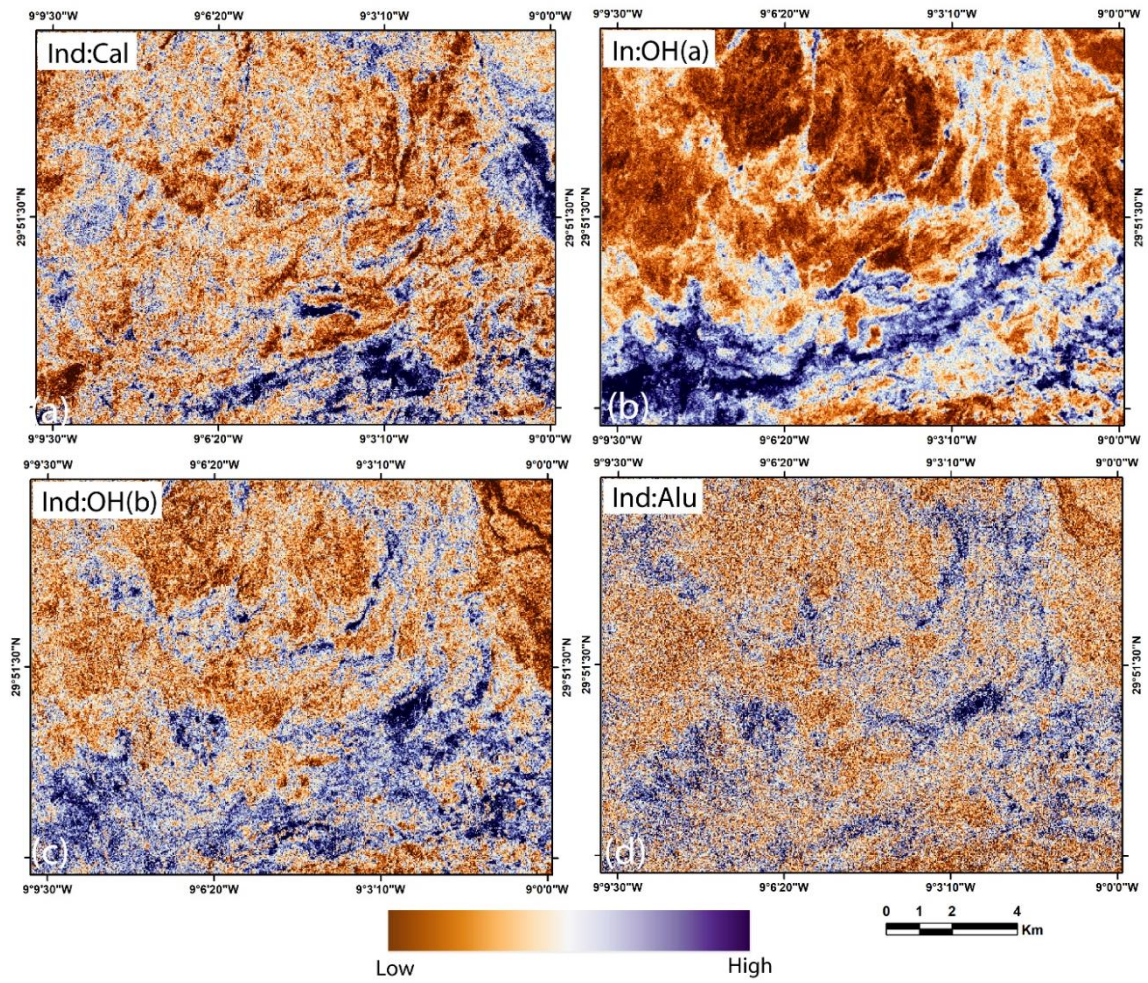


Figure 10. Resulted images of the Ninomiya spectral indices: (a) Calcite; (b) OH(a); (c) OH(b); (d) Alunite

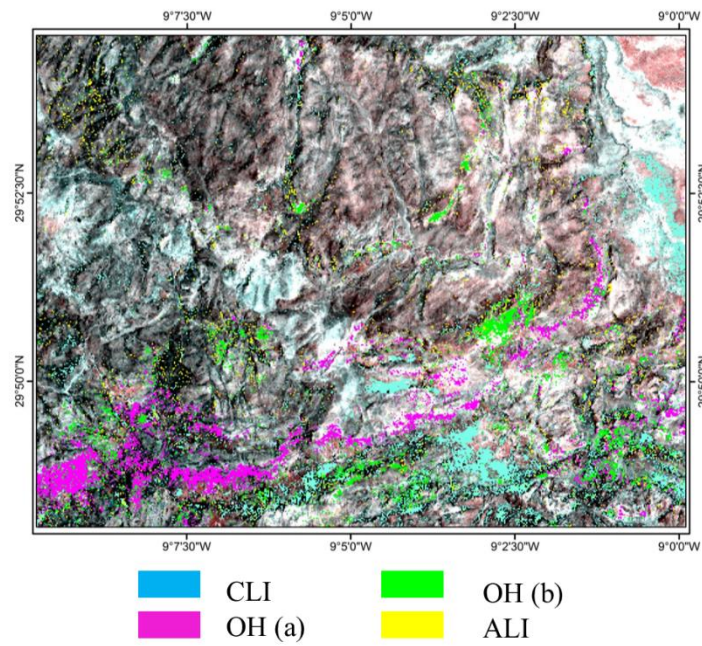


Figure 11. Images of the Ninomiya spectral indices superimposed on the true color composite of ASTER image

4.2.2. CEM mapping results

The CEM classification allows the enhancement of alteration minerals separately to identify each specific mineral (Pour et al, 2019b). The Precambrian basement-hosted cupriferous mineralization can be presented in the vein structure, where the porphyry alteration systems are common (Azmi et al, 2014). Azmi et al. (2014) proposed a genetic model for the Hercynian-remobilized porphyry-type mineralizations. Following this model, nine hydrothermal alteration minerals have been selected for classification to highlight argillic, phyllic, and propylitic alteration features (Figure 12). The spectral signatures of the hydrothermal alteration minerals were extracted from the USGS spectral library. This spectral library includes spectral signatures of minerals with a spectral resolution of 3 nm (Kokaly et al, 2017). The spectral signatures are resampled to the ASTER bands (Figure 12). The resulting pseudocolor ramp images of the CEM classification are shown in Figure 13. The results show a good correlation with those of the Ninomiya spectral indices presented in Figures 10 and 11. This confirms that the CEM classification is an efficient method of classification for mineralogical aspects (Moradpour et al, 2020; Pour et al, 2019b). The CEM images of the argillic hydrothermal alteration-related minerals (e.g., alunite, kaolinite, montmorillonite, and pyrophyllite) in addition to the images of the CEM classification of phyllic hydrothermal alteration-related minerals (e.g., illite, muscovite) show a very good correlation with the images of the OH(a) and OH(b) spectral indices, respectively (Figure 13). The Di (dolomite with marl) lithological unit shows an abundance of calcite, illite, kaolinite, montmorillonite, muscovite, and pyrophyllite. Sa (siltstone and argillite) unit is marked by chlorite, calcite, muscovite, and montmorillonite. On the other hand, the dolerites intercutting the quartzite sandstone unit are associated essentially with alunite, illite, kaolinite, muscovite, and montmorillonite (argillic/phyllic alteration).

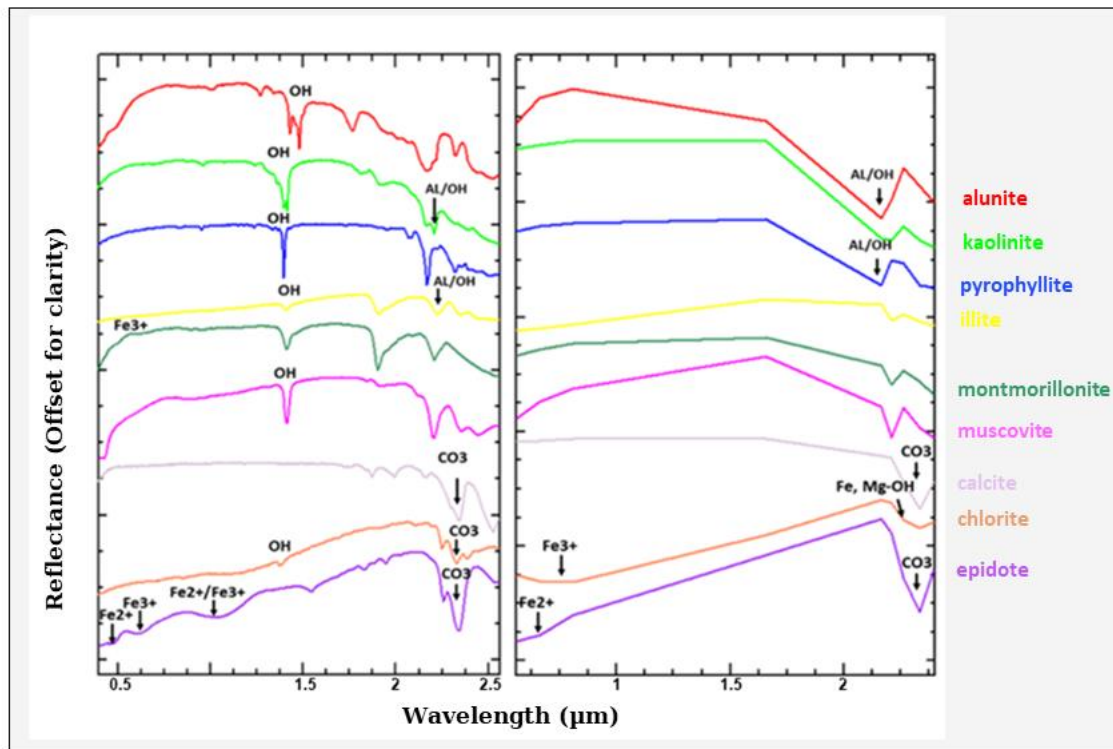


Figure 12. Laboratory reflectance spectra of hydrothermal alteration minerals from USGS spectral library (left) and spectra resampled to ASTER bands (right)

This region highlights a high density of tectonic lineaments extracted from HH and HV polarization images of ALOSPALSAR (Jellouli et al, 2021), which suggest a structural control

of the hydrothermal alteration process. Furthermore, the eastern Kerdous (Amlen Valley shear zone) presents several hydrothermally altered regions that show high similarity with our findings. Hyperspectral data with high-spatial resolution (5 m) allow the detection of several zones of Al-OH, Fe³⁺-Fe²⁺, and Mg-Fe-OH/CO₃ hydrothermal alteration minerals. Some detected zones were depicted as a potential sites for copper and manganese mineralizations after applying fuzzy logic modeling for 20 layers derived from hyperspectral dataset (Hajaj et al, 2023b).

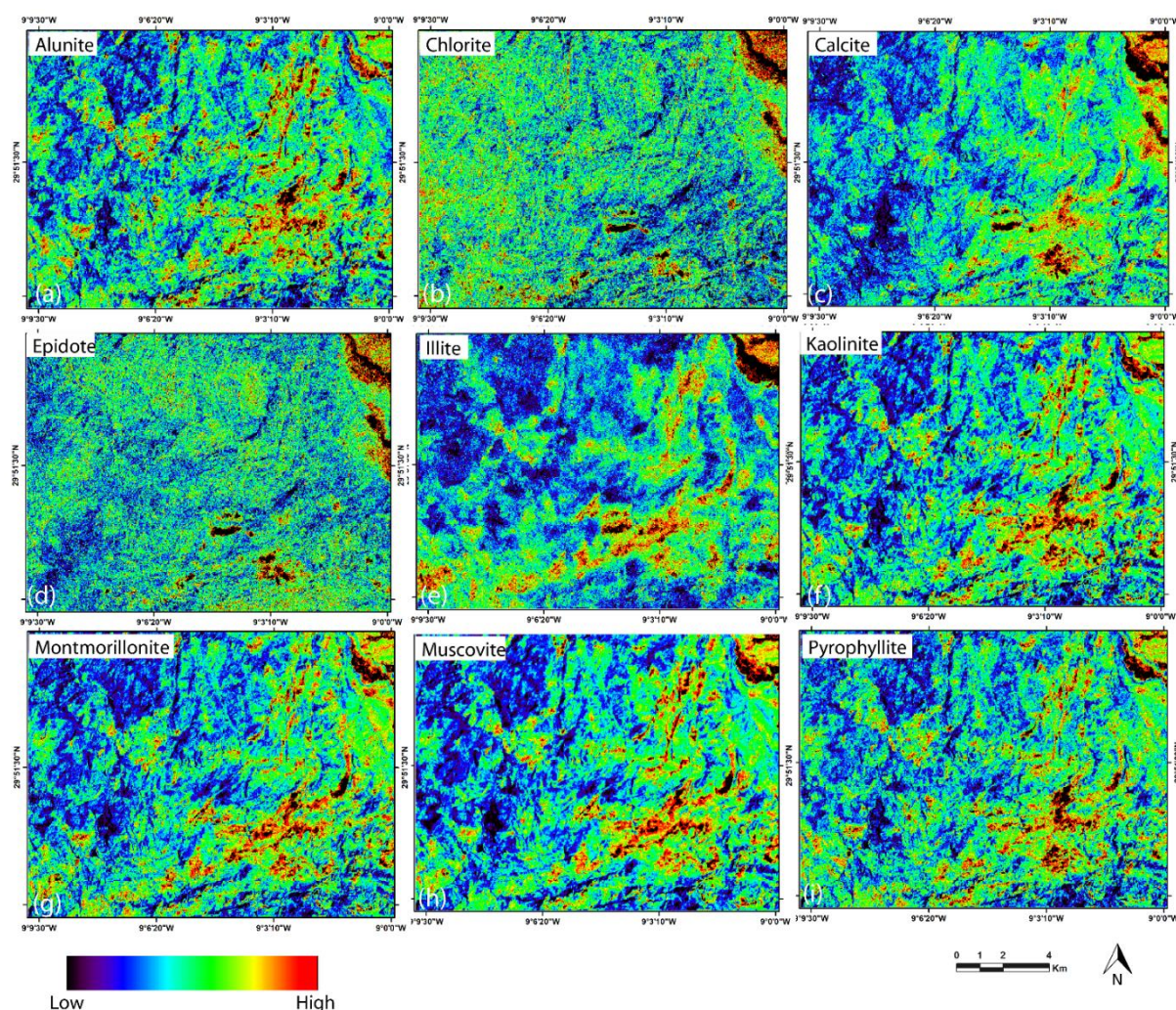


Figure 13. ASTER resulting images of a high abundance of hydrothermal alteration minerals using CEM: (a) alunite; (b) chlorite; (c) calcite; (d) epidote; (e) illite; (f) kaolinite; (g), montmorillonite; (h) muscovite; (i) pyrophyllite

In addition, kaolinite developed in argillic alteration zones correlates well with the CEM images and spectral indices (Figure 13). To verify the accuracy of the CEM classification, the USGS library spectra were used for validation. The analysis using spectral angle mapper (SAM) allowed us to identify the matching scores. Table 5 (Hitlist) shows the matching score of the selected image spectra of the highly altered regions. The computed matching scores are ranging from 0.73 to 0.91.

Table 5. Selected end-member minerals (within the mapped hydrothermally altered zones) and USGS spectra matching scores computed using the SAM method and geographic coordinates

Mineral	Score (%)	Geographical coordinates
Alunite	81.6	29°51'3.56"N, 9°1'16.63"W
Calcite	90.3	29°52'17.62"N, 9°0'13.03"W
Chlorite	73.3	29°50'20.48"N, 9°4'16.54"W
Epidote	80.2	29°49'18.45"N, 9°2'51.28"W
Illite	89.3	29°54'35.83"N, 8°59'56.01"W
Kaolinite	91.1	29°49'18.45"N, 9°2'51.28"W
Montmorillonite	90.1	29°54'35.83"N, 8°59'56.01"W
Muscovite	84.6	29°50'48.65"N, 9°2'38.17"W
Pyrophyllite	74.1	29°51'7.29"N, 9°1'12.16"W

5. CONCLUSIONS

Overall, the ASTER and Landsat-8 OLI data combined with different pixel and subpixel methods have well discriminated the lithological units and alterations in the study area. However, due to the low spectral resolution that characterizes multispectral data, the spectral mixing could explain the erroneous argillic abundances located over the gabbro formations. Hence, future work using hyperspectral data will complete and refine the obtained maps in the present work.

The FCC using both the MNF and PCA new-bands computed from ASTER and OLI data shows a good separation of lithological units for ASTER MNF1, PC4, and PC2 and OLI MNF1, PC5, and PC3. The lithological classification using ASTER and OLI data demonstrated comparable results. The best results were obtained using the ML classifier for both ASTER and OLI images. The accuracy assessment of ML shows that the highest classification accuracy in north-eastern Kerdous is derived from the use of OLI data with an overall accuracy of 91.74% and a 0.90 Kappa coefficient.

The mineralogical mapping using Ninomiya indices and the CEM algorithm allowed the identification of several zones of hydrothermal alterations. The argillic/phyllitic is the most abundant alteration type in the study area. The detailed subpixel scale mapping by CEM reveals the hydrothermal alteration minerals including alunite, chlorite, calcite, epidote, illite, kaolinite, montmorillonite, muscovite, and pyrophyllite.

The methodology applied in this investigation allows the detection of new hydrothermal alteration zones that can be related to cupriferous mineralization. The distribution of mineral alteration in the north-eastern part of the study area near the siltstone and argillite units located at the Precambrian/Cambrian passage is compatible with the stratabound mineralization type that occurred around different inliers in the western Anti-Atlas (Pouit, 1966). Besides, a strong hydrothermal alteration associated with gabbro intrusion is detected, which suggests a possible genetic link.

Furthermore, the results of this study demonstrated the beneficial use of Ninomiya indices with the CEM algorithm in the initial stages of exploration for a complex area with less metallogenic studies. The processing of ASTER data provides important insights into the distribution of alteration minerals. Machine learning methods applied in lithological and mineralogical mapping may be of great importance for the automatic extraction of spectral and spatial

information, which will subsequently help to answer a number of scientific questions. The combination of multispectral and hyperspectral data will certainly improve the obtained results.

Acknowledgements. This research was supported by the laboratory of Geomatics, Georesources and Environment at Sultan Moulay Slimane University. This research work is part of the PhD thesis of the senior author. The authors thank the reviewers for their helpful comments and recommendations.

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Received: 2024-10-21

Reviewed: 2024-11-21 (undisclosed name); 2024-12-10 (undisclosed name);
2024-12-10 (H. Bouzekraoui)

Accepted: 2025-03-28