Application of remotely sensed data in detecting zinc-lead bearing mineralized zones in West Kunlun Huoshaoyun area

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Abstract. The combination of Landsat 8 Operational Land Imager (OLI) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data is an efficient tool for mapping and interpreting lead-zinc mineralization in some area with high altitude or intensely rugged topography, where conventional geological mapping and systematic geochemical sampling become limitation and time consuming. This task is completed by using band ratios (BRs), principal component analysis (PCA), and spectral matched filtering (SMF) method. And it conclude that, (6/5, 7/6, 4/7) RGB color composite and (5/4, 6/5, 7/6) RGB color composite of Landsat 8 OLI, [(6+8)/4, 8/4, 5/3] RGB color composite and [3/2, (6+8)/4, 3/6] RGB composite of ASTER image, PC 3,4,5 of Landsat8 and ASTER images, contain useful information for lithological mapping. Lead-zinc mineralization zones could be exactly discriminated by spectral matched filtering (SMF) technique and ascertained by field work and XRD analysis. Consequently, the methodology proposed demonstrates a high potential of Landsat 8 OLI and ASTER data in lithological units discrimination and lead-zinc mineralization zones extraction in west Kunlun Mountains.

1. Introduction
Remote sensing image processing plays a significant role in many aspects of the Earth sciences, geography, archaeology and environmental sciences. New generation, advanced remote sensing has been used in the past few decades in lithological mapping, mineral exploration and environmental geology [1-4]. With the development of remote sensing technology that provides detailed information on mineralogy of different rock types on the Earth’s surface [5], many image processing methodologies have been developed that attempt to map boundaries of rock bodies, weathered rock zones, and hydrothermally altered rock zones, especially in arid regions where vegetation cover is minimal [6]. Although the results from hyperspectral remote sensing in detecting alteration information are nearly perfect, such data are generally difficult to obtain and having a high cost. The multispectral image techniques with relatively high spectral resolutions have offered a vital and economically effective way in detecting and tracing the potential mineralization zones around lead-zinc bearing carbonate lodes in particular and other ores in general.

Landsat-8 was launched on 4 February 2013 from Vandenberg Air Force Base in California. It is an American Earth observation satellite and joins Landsat-7 on orbit, providing increased coverage of the Earth’s surface. It is a free-flyer spacecraft carrying two sensors, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). These two instruments collect images for nine visible,
near-infrared, shortwave infrared bands and two long-wave thermal bands (table 1). They have high signal-to-noise radiometer performance, allowing 12-bit quantification of data, thus providing more bits for better land-cover characterization. Landsat-8 provides moderate resolution imagery, from 15 to 100 m of the Earth’s surface and polar regions [7-8]. Landsat-8 data are available to the general public at no cost and can be downloaded at http://glovis.usgs.gov. And it has been successfully applied to mapping hydrothermal alteration zones by Pour et. al. [7] and Hassan et. al. [6].

Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), on board the Terra platform (EOS), was launched in December 1999. It has lower signal-to-noise radiometer performance, allowing 8 bit quantification of data, but records solar radiation in more spectral bands (table 2) than Landsat-8 and it provides useful spectral information for geologists [9]. ASTER data have been successfully used for lithological and mineral mapping [10] to aid in exploration [11]. In the VNIR and SWIR bands, iron bearing minerals, carbonates, hydrate and hydroxide minerals display molecular absorption features related to their overtones and combination tones [12]. Those minerals are some of the most common alteration related components induced by hydrocarbon seeps [13].

The main objective of this task is to compare the potentialities of ASTER and the Landsat 8 multispectral images, as well as different image processing methods, in the discrimination of lithological units and detection of lead-zinc bearing mineralization zones in the Huoshaoyun ore field, west Kunlun area. This region has great metallogenic potential and the main advantage is use the traditional BRs and PCA methods to map the lithologies and then use the new SMF method to map the lead-zinc mineralization zones.

2. Materials and methods

2.1. Remote sensing data

A cloud-free level 1T Landsat 8 image LC81460362013213LGN00 of the western Kunlun area was obtained from the USGS Earth Resources Observation and Science Center (http://glovis.usgs.gov) on 1 August 2013. The image projection is Universal Transverse Mercator zone 44N from WGS-84 datum. Band 9 was not used in this study because this band is intended for cirrus cloud detection. The radiance was calculated and the images were atmospherically corrected using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes module.

The ASTER data used in this study were also obtained from the USGS Earth Resources Observation and Science Center (http://glovis.usgs.gov), and consist of a cloud-free level 1B scene that were acquired on 17 October, 2013. The level 1B data product measures radiance at the sensor, without atmospheric corrections, and were produced from the original level 1A. The 1B format data also have been applied for both geometric and radiometric corrections. The images have been pre-georeferenced to UTM zone 44 North projections with WGS-84 datum. The VNIR bands were resampled to 30 m and all bands were also corrected for atmospheric effects using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes module.

2.2. Processing methods

2.2.1. Band ratio technique. Band ratios (BR) and red-green-blue (RGB) were created with both Landsat8 and ASTER bands based on laboratory spectra of the hydrothermal minerals and lithological units [14-16]. Band ratios is a technique in which the digital number value of one band is divided by another band based on absorption characters in order to highlight certain lithological unit that cannot be distinguished in the raw data. Different colour combination images were used to enhance lithological units and hydrothermally altered mineralization zones at regional scale.

2.2.2. Principal component analysis. Principal component analysis (PCA), which aims to compress a number of correlated spectral bands into a smaller number of uncorrelated spectral bands [10], is used to produce uncorrelated output bands by finding a new set of orthogonal axes that have their origin at
the data mean and that are rotated so the data variance is maximized [6]. This compression eliminates redundancy in the data, isolates the noise in the latest PCs, and therefore enhances the separation of certain types of spectral signatures from the background. PCA was applied to the proposed Landsat8 and ASTER VNIR-SWIR bands to emphasize the distribution of the different rock units and mineralization zones of the study area.

2.2.3. Spectral matched filtering. Spectral matched filtering (SMF) is a rapid method for detecting specific materials based on certain spectral reflectance curves matching with the images, and it constrains the response of the desired end member and minimizes the response of the background [17]. The result of the SMF appears as a gray-scale image with values range from 0 to 1, where 0 represents a non-match to the end member spectra and 1 represents a perfect match. Thresholds can then be identified to create binary maps from the fraction maps to show areas with relatively good matches to the end member spectra. Unlike the traditional linear unmixing, SMF does not require knowledge of all the end members within the scene. Thus in areas of highly mixed rocks, where identification of all the end members is difficult, SMF may be a better choice for identifying certain minerals such as carbonate minerals, iron oxide minerals and OH bearing minerals [18].

The carbonate minerals with abundant gypsum parts in the mineralization zones are considered to be the main target for lead-zinc exploration. And due to the spectral capabilities of the images, we collected spectral information about well-known targets as a step toward identifying the mineralization zones in the limestone rock unit. For this purpose, we used both Landsat 8 OLI and ASTER VNIR-SWIR bands to resampling spectral curves about target areas that we distinguish the field to be mineralized limestone from unmineralized limestone and other rock units.

2.2.4. Field work. Some representative rock samples of the full range of lithologies of the area were collected as reference materials in mapping and classification of the different rock units of the study area. In addition, some samples from the Huoshaoyun ore field were also gathered for spectral, mineralogical and chemical investigations. We also planed some situ X Ray Fluorescence (XRF) validation in the mineralization area.

3. Results and discussion

3.1. Selection of band combinations for discriminating lithologies
The bands used in the ratios are selected on the basis of the spectral signatures extracted from the two corrected images OLI and ASTER, where the highest reflectance is found in band 6 of OLI and band 4 of ASTER. The ratios (5/4 of OLI and 3/2 of ASTER) are allowed to discriminate alluvium, explained by the absorptions in red bands (band 4 of OLI) and (band 2 ASTER), at 650 and 660 nm, respectively, which are related to the presence of iron oxides [19-21]. The sandstone-to-mudstone, which is rich of mica and clay minerals, is mapped by the ratios (6/5 of OLI) and (5/3 of ASTER), since its spectra show high reflectance in band 6 of OLI and band 5 of ASTER, against an absorption at 860 nm (band 5 of OLI) and 800 nm (band 3 of ASTER), corresponding to the near infrared region. This type of absorption is also due to the presence of iron oxides [22-24]. In comparison with other spectra, conglomerate shows a high reflectance in band 4 of OLI and band 3 of ASTER, and intense absorption of Al-OH type at 2200 nm (band 7 of OLI and band 6 of ASTER) due to mica or clay minerals [9, 23, 25], hence the ratios of (4/7 of OLI) and (3/6 of ASTER) are used to map this rock unit. The limestone is discriminated by the ratio (8/4) of ASTER, because its spectrum represents deep absorption in band 8, while the OLI sensor does not cover this region. In addition, mineralized limestone spectra show high reflectance in band 6 (OLI) and 4 (ASTER), and a weak absorption at 2200 nm, which coincides with bands 7 of OLI and 6 of ASTER, possibly due to the weak gypsum and clay alteration [20, 26]. The spectral signature extracted from the ASTER data, which is also characterized by a deep absorption at 2330 nm (band 8), can be related to the presence of carbonate minerals [12, 24]. The [RBD [(6 + 8))/4] of ASTER and the ratio (7/6) of OLI are used to map the mineralized limestone.
After examining different combinations of ratios, two Color Components (CCs) RGB (for each sensor) were chosen to better discriminate the existing lithological units and mineralized zones \cite{9, 27, 28, 29}. In CC1 \((6/5, 7/6, 4/7)\) of OLI, the mudstone-sandstone is distinguished by a yellow-orange color, and it appears purple in CC3 \([(6 + 8)/4; 8/4; 5/3]\) of ASTER, and it appears light blue-green in CC2 \((5/4, 6/5, 7/2)\) of OLI. The mineralized limestone is mapped by a light blue-white color in CC3, while it appears light yellow in CC1. Alluvium and lake deposits appears dark blue in CC2 \((5/4, 6/5, 7/6)\) of OLI, while in CC4 \([3/2, (6 + 8)/4, 3/6]\) of ASTER, they appear light blue to light green. Regarding limestone, it is mapped by the green in CC1 and pink-magenta in CC4. Finally, conglomerate is mapped by the dark blue color in CC3 and green-yellow in CC2 (figure 1).

![Figure 1. RGB composite of Landsat 8 OLI and ASTER images.](image)

3.2. Selection of PCA bands for discriminating lithologies

Based on the covariance matrix, the results obtained from the calculation of the PCA are shown in table 1 and 2, including PC bands, eigenvectors, and eigenvalues \cite{19, 25}. PC1 contains the highest percentage of information (variance) contained in images (82.97% for OLI and 97.55% for ASTER). PC2 highlights the difference between the VNIR bands \((2, 3, 4, 5\) of OLI and \(1, 2, 3\) of ASTER) and SWIR bands \((6, 7\) of OLI and \(4, 5, 6, 7, 8, 9\) of ASTER), having opposite signs \cite{30}. In the other PCs, an object is discriminated on the basis of signs and magnitude of eigenvectors \cite{31}. It is mapped by bright pixels if the eigenvector values are positive in the bands of reflectance and negative in the bands of absorptions 25. On the other hand, the magnitude describes the significance of the spectral band in that PC. A large value indicates more significance \cite{30}. 

By examining the eigenvectors in the table of OLI sensor, the mudstone-sandstone, which is rich of micas and clays, can be distinguished by bright pixels in PC3, because it has a high reflectance in band 6 having a positive contribution (0.076) and absorption in the band 5 having a very strong negative contribution (−0.686) (figure 2a). In PC4, the lake deposits may be discriminated by bright pixels, despite the positive eigenvector in band 6 (0.375) of absorption and negative in band 7 (−0.360), probably due to small discrepancies in the magnitude in these bands (figure 2b). Mineralized limestone can be distinguished by bright pixels in PC5, since it is characterized by an absorption in band 4 (−0.194) and a high reflectance in band 7 (0.564) (figure 2c).

Concerning the table of ASTER sensor, the very clayceous or micaceous lake deposits can be distinguished by bright pixels in PC3 due to the positive contribution of band 8 (0.527) and the negative contribution of band 4 (−0.271) of reflectance and absorption, respectively (figure 2d). In this PC, the mudstone-sandstone can be distinguished by gray pixels, because of the positive contribution of band 7 (0.480) of reflectance and negative contribution of band 6 (−0.464) and 5 (−0.372) of absorptions. Conglomerate appears in bright pixels in PC5, following the negative contribution of band 3 (−0.605) of absorption and the positive one of band 4 (0.407), which coincides with reflectance. Also in this PC, limestone with calcite and dolomite can be distinguished by gray pixels because of the positive contribution of band 1 (0.606) and negative contribution of band 7 (−0.204) (figure 2e). Finally, mineralized limestone appears in bright pixels in PC4, following the positive contribution of band 6 (0.458) of reflectance. In the same PC, Alluvium can be discriminated by bright pixels, despite the weak positive contributions in band 7 (0.062), which represent the absorption band of this rock unit [9, 25, 27, 31]. For both sensors, the other remaining PCs contain only noise, and therefore cannot provide any information (figure 2f).

### 3.3. Spectral Matched Filtering for discriminating mineralization zones

For discriminating mineralization zones of limestone, we also used the SMF technique for both OLI and ASTER images. Because the ASTER data has more bands in SWIR than Landsat 8 OLI data, it can show more detail in spectral features. In this case, the ASTER data is more efficient to use SMF method for the identification of mineralized limestone unit. The results of the method, which are shown on figure 3 and figure 4, indicate that mineralized limestone can be matched well by this method. Thus, spectral curves of the mineralization zones are selected using the spectral data of the samples collected by field work.

As is shown in the image mapping results based on spectral matched filtering using Landsat 8 OLI 7 bands data and ASTER 9 bands data, the ASTER 9 bands data generally produced a better separation of mineralized limestone rock unit. On the other hand, the Landsat 8 OLI data could also exactly separate carbonate rocks (limestone and mineralization limestone) from other types of rocks, but it fail to distinguish mineralized limestone from other carbonate rocks and lake deposits.

### Table 1. The matrix of eigenvectors extracted after calculating the PCA on OLI image.

| Eigenvector | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 | Band 6 | Band 7 | Eigenvalue(%) |
|-------------|--------|--------|--------|--------|--------|--------|--------|---------------|
| PC 1        | -0.257 | -0.268 | -0.353 | -0.417 | -0.459 | -0.452 | -0.386 | 82.97         |
| PC 2        | -0.412 | -0.384 | -0.319 | -0.224 | -0.038 | 0.555  | 0.470  | 16.63         |
| PC 3        | 0.379  | 0.337  | 0.127  | -0.273 | -0.686 | 0.076  | 0.419  | 0.25          |
| PC 4        | 0.372  | 0.238  | -0.268 | -0.594 | 0.331  | 0.375  | -0.360 | 0.07          |
| PC 5        | 0.171  | 0.043  | -0.346 | -0.194 | 0.410  | -0.570 | 0.564  | 0.05          |
| PC 6        | 0.389  | -0.062 | -0.695 | 0.549  | -0.198 | 0.123  | -0.082 | 0.02          |
| PC 7        | 0.549  | -0.778 | 0.288  | -0.100 | 0.019  | -0.012 | 0.009  | 0.00          |

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Figure 2. Spectral signatures of lithological units extracted from (left) OLI and (right) ASTER images.

Table 2. The matrix of eigenvectors extracted after calculating the PCA on ASTER image.

| Eigenvector | Band 1 | Band 2 | Band 3 | Band 4 | Band 5 | Band 6 | Band 7 | Band 8 | Band 9 | Eigen values (%) |
|-------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|-----------------|
| PC 1        | -0.244 | -0.300 | -0.333 | -0.416 | -0.350 | -0.345 | -0.359 | -0.309 | -0.317 | 97.55           |
| PC 2        | 0.554  | 0.506  | 0.417  | -0.223 | -0.167 | -0.109 | -0.264 | -0.209 | -0.245 | 1.72            |
| PC 3        | 0.187  | 0.066  | -0.106 | -0.271 | -0.372 | 0.464  | 0.480  | 0.527  | 0.117  | 0.38            |
| PC 4        | 0.277  | -0.074 | -0.287 | -0.701 | 0.350  | 0.458  | 0.062  | 0.077  | 0.049  | 0.12            |
| PC 5        | 0.606  | -0.080 | -0.605 | 0.407  | 0.103  | -0.188 | -0.204 | -0.040 | 0.074  | 0.08            |
| PC 6        | 0.100  | -0.027 | -0.125 | 0.140  | -0.039 | 0.137  | 0.659  | -0.357 | -0.610 | 0.06            |
| PC 7        | 0.051  | -0.013 | 0.050  | -0.135 | 0.009  | -0.211 | 0.298  | -0.667 | 0.632  | 0.04            |
| PC 8        | -0.087 | 0.013  | 0.115  | -0.096 | 0.759  | -0.587 | 0.041  | 0.031  | -0.216 | 0.03            |
| PC 9        | 0.366  | -0.798 | 0.474  | 0.013  | -0.035 | -0.012 | -0.004 | 0.048  | -0.032 | 0.01            |
Figure 3. Result of SMF to distinguish mineralized limestone of ASTER.
3.4. Field validate work
According to the mapping results, we deployed some field work for situ XRF measurement and validation. The mineral components of the mineralization area were measured using Skyray Genius 7000XRF instrument. In this area, we found abundant lead and zinc components than limestone units in the periphery of the ore body. Table 3 shows the result of the situ XRF measurement in the field work.

Table 3. Situ XRF measurement of the mineralization areas.

| Measurement No. | Pb (%)  | Zn (%)  |
|-----------------|---------|---------|
| HSY16-01        | 1.0254  | 38.2727 |
| HSY16-02        | 2.1339  | 0.157   |
| HSY16-03        | 7.128   | 3.7247  |
| HSY16-04        | 4.197   | 3.9666  |
| HSY16-05        | 0.7443  | 60.179  |
| HSY16-06        | 0.8596  | 62.8469 |
| HSY16-07        | 18.7559 | 39.4437 |
| HSY16-08        | 6.9946  | 32.3956 |
| HSY16-09        | 1.0355  | 59.992  |
4. Conclusions
This study used the multispectral Landsat 8 OLI and Terra ASTER for mapping existing lithological units and lead-zinc mineralization zones in west Kunlun Huoshaoyun ore field, and it was accomplished by the exploitation of VNIR and SWIR regions of the two sensors by using three image processing techniques. Analysis of the results showed that the OLI and ASTER sensors both have great potential for lithological mapping and mineralization zones discrimination. A comparison of the two sensors showed that the ASTER data gave better results than OLI data in using SMF method because of the spectral richness of ASTER sensor especially in SWIR region.

The findings of this research reported interesting image processing methods, which are more effective in geological mapping and lead-zinc mineralization locating. These appropriate image processing techniques have provided a reliable, simple, robust, very low cost and user-friendly approach for exploration geologists to identify carbonate mineral assemblages associated with lead-zinc ore and related host rock.

In conclusion, the presented methodology appears to be effective and can be applied in other types of ore fields, especially with the absence of vegetation cover. In addition, the resulting maps of this work can be used as an aid in mineral exploration and enhancement of the geological map. The use of hyper spectral data with higher spectral resolution, spatial resolution, and geochemical analyses will allow, without doubt, a more accurate mapping at mineral scale.

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