Mapping of bauxite mineral deposits in the northern region of Saudi Arabia by using Advanced Spaceborne Thermal Emission and Reflection Radiometer satellite data

P. Sheik Mujabar* and S. Dajkumarab

*Department of General Studies, Jubail Industrial College, Jubail, Saudi Arabia; bExploration Geoscience, Perth, Australia

ABSTRACT

Mineral deposit mapping is very essential for sustainable and eco-friendly exploitation of natural resources. The Kingdom of Saudi Arabia has abundant natural resources such as natural gas, oil and minerals. It reserves high quantity of minerals such as phosphates, bauxites, copper, gold and other industrial minerals. The red soil regions located in Hail and Qassim provinces of Saudi Arabia have rich amount of bauxite (major aluminum ore) deposits. In order to initiate the focus on mapping of mineral deposits along this area, standardized hyper-spectral analysis has been carried out by using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) satellite data. The spectral signature of gibbsite (major element in bauxite) samples is analyzed with reference to the spectral features of gibbsite in the visible near infrared and short-wave infrared bands electromagnetic spectrum. Advanced hyper-spectral transformations such as minimum noise fraction function and pixel purity index have been performed to identify the target end-member. The existence of the mineral is confirmed by comparing the spectral signatures of the end-member with the predefined spectral plots of ASTER and United States Geological Survey spectral libraries. Finally, the end-members are mapped and their abundance is estimated in 0–1 scale. The study has opened up new areas for mapping of bauxite deposits in the area and leads to eco-friendly exploitation of natural resources. It also validates the high potential of ASTER multispectral satellite data for the exploration and mapping of mineral resources.

1. Introduction

The latest development in remote sensing and Geographic Information System (GIS) leads to identify and locate the mineral resources for eco-friendly exploitation of natural resources. Lillesand and Kiefer (1987) states that the interpretation of surface features on aerial photographs and satellite images provides new information about potential areas for mineral exploration. Sanjeevi (2008) states that due to the synoptic coverage and the varying spectral and spatial resolutions offered by satellites and airborne sensors, remote sensing has proved to be an irreplaceable tool in understanding and locating mineral habitats. He also states that, from remotely sensed data, it is possible to decipher the regional lithology, tectonic fabric and the geomorphic details of a terrain, which aid precisely in targeting of metals and minerals.

Hyper-spectral remote sensing, measuring hundreds of spectral bands from aircraft and satellite platforms, provides unique spatial and spectral datasets for the analysis of surface mineralogy (Goetz et al. 1985; Krause, Boardman, and Huntington 2003). These data allow easy mapping of mineral resources in large scale with little span of time. Kariuki, Woldai and van der Meer (2004) insist that the remote sensing produces a synoptic view of a study area that is often difficult to obtain from ground observation alone. Though hyperspectral data are essential for spectral analysis, the easily accessible multispectral data can also be used to perform the lithology and mineral mapping studies. The Los Menucos gold district, with potential for low-sulfidation style gold mineralization, was discovered in 1998 using regional exploration methods employing Landsat Thematic Mapper (TM) satellite imagery and field investigation (Perry and Gemuts 2000). Multispectral Landsat 5 (TM) data have been successfully used by Zumsprekel and Prinz (2000) for lithological mapping of Archean terrain in Western Australia. Altinbas et al. (2005) performed advanced spectral analysis on multispectral Landsat enhanced Thematic Mapper (ETM) data to identify the clay minerals. Pena and Abdelsalam (2006) used a variety of remote-sensing data for lithological mapping to aid in oil and gas exploration in Southern Tanzania. They used Landsat 7 ETM, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), Radarsat and digital elevation model (DEM) data for mapping different lithological and morphological structures.

Several studies have been carried out to map the potential minerals resources by using the ASTER...
data. Volesky, Stern and Johnson (2003) distinguished the propylitic alteration zone and gossan associated with massive sulfide mineralization in host rocks by using ASTER (4/2, 4/5, 5/6) band ratio images covering the Neoproterozoic Wadi Bidah shear zone, southwestern Saudi Arabia. Sabreen and Timothy (2007) resolved geological mapping problems by using new ASTER band ratio image 4/7, 4/6 and 4/10 for lithological mapping in the Arabian–Nubian shield, the Neoproterozoic Wadi Kid area, Sinai, Egypt. ASTER data have been used for exploring areas of hydrothermal alteration and gossan related to massive sulfide deposits in the Nuqrah area, Saudi Arabia (Assiri and Mousa 2008). They used simple color composite and band ratio methods by using the bands 4, 6 and 9 of ASTER data to detect iron-rich cap or gossan and hydrothermal alteration zones. Sanjeevi (2008) used ASTER data to map the limestone and bauxite deposits in southern India by using spectral unmixing methods. Amin and Mazlan (2011) have used ASTER data to map the muscovite, kaolinite, alunite, epidote, calcite and chlorite minerals. Guha et al. (2013) have used ASTER data to map the laterite bauxite deposits in the state of Jharkhand in India. Various studies performed on mapping of mineral deposits by using remote sensing indicate that the multispectral satellite data can be used to map the mineral resources.

The Kingdom of Saudi Arabia has abundant natural resources such as natural gas, oil and minerals. It reserves high quantity of minerals such as phosphates, bauxites, copper, lead, zinc, magnesite, gold etc. The Hail and Al Qassim provinces of the northern Saudi Arabia have rich amount of bauxite deposits. Az Zabirah mine is in the study area and producing kaolinite and low-grade bauxite deposits. The study area has a major bauxite mine in Al Bai’tha near the city of Qibah. Al-Dubaisi (2011) states that most of the minerals potential is identified to be in the Arabian shield, the geological formation on the west of the country along the Red sea extending inland to Najd and Qassim areas. He also states that in spite of extensive surveys conducted in Saudi Arabia in recent years, the amount of investment in the exploration of minerals is modest compared to other counties.

The Ma’aden (a Saudi Arabian mining company) has involved in the exploration of bauxites and kaolinite minerals along this area, and its mining license is along 192 km by 35 km wide (Al-Dubaisi 2011). Alashrah (2016) has analyzed the existence of valuable mineral contents in the red soil of Al Qassim province. He reveals that all the 30 samples collected from the red soil have significant contribution of aluminum, sodium, magnesium and silicon. He also found that more than 10% of aluminum is present in all the samples collected from the study area.

3. Data and methods

3.1. Data

3.1.1. Satellite data

The ASTER satellite data are the prime data used in the present study. The ASTER sensor, which is on board of the TERRA satellite, acquires 14 bands with medium resolution, from the visible to the thermal infrared wavelengths. The sensor also provides stereo-viewing capabilities for DEM creation (Abrams, Hook, and Ramachandran 2002). In the present study, nine spectral channels of ASTER data of wavelength ranges from 0.52 to 2.430 μm are used. Three spectral channels are in the visible near infrared (VNIR) range and the remaining six channels are...
in short-wave infrared (SWIR) range. Terrain corrected and georeferenced data provided by the United States Geological Survey (USGS) have been used for the study.

Guha et al. (2013) states that the ASTER SWIR channels are very important for detecting absorption signatures of minerals with the AlOH, MgOH and CaCO$_3$ bonds, whereas the ASTER VNIR channel can highlight the absorption features of the iron-hydroxides. Zhang, Pazner and Duke (2007) states that the ASTER sensor is better suitable for the spectral discrimination studies for mapping economic rock like bauxite than the other exiting multispectral sensors such as Landsat, SPOT and Indian remote sensing satellites since it has six spectral channels in SWIR range each of which is highly appropriate for mapping specific lithology and minerals. Also, the ASTER-derived digital elevation data can provide more accurate topographic information suitable for understanding the terrain morphology which is also essential for understanding the topographic controls for bauxite formation (Abrams 2000).

### 3.1.2. Global DEM

The global DEM (GDEM) data are the standard data product of ASTER satellite. The data has surface elevation of earth with 30 m ground resolution with accuracies of 5–10 m. This DEM cover 99% of the land surface from 83° North latitude to 83° South latitude. The ASTER GDEM data for the study area (Figure 2) provide altitude information for understanding the slope and altitude in the formation of mineral resources. They also provide the information on surface mineral due to weathering process (Zhou and Wang 2017).

### 3.1.3. Spectral profile data

Spectroscopy is a technique that detects the absorption and emission of electromagnetic radiation as a function of wavelength. Aerial and orbital spectrometers in the satellite sensors can detect, differentiate and map the chemical differences in minerals and other compounds. A digital reflectance spectral library covers the spectral signatures of materials for wavelength range from the ultraviolet to infrared range. The spectral library (Kokaly et al. 2017) includes samples of minerals, soils, rocks, mixtures, and coatings, liquids, water, synthetic materials, plants, vegetation and microorganisms. The samples and spectra collected were assembled as a spectral profile. The present study uses the predefined ASTER spectral profile data sets of USGS spectral library (Figure 3) for identifying the gibbsite (bauxite ore) deposits in the study area.

The spectral profile of the individual pixels (Figure 4) is convolved with the ASTER spectral profile. The continuum removed spectral profiles of bauxite samples (Gibbsite HS423.3B and Gibbsite WS 214) and the end-member is analyzed. Continuum removal is a hyperspectral image analysis procedure to normalize the reflectance spectra, so individual absorption features of a target
end-member and existing standard spectra of sample minerals from a common baseline can be compared. The absorption features of both the samples and target end-member pixels are matched and analyzed.

3.2. Methodology

3.2.1. Preprocessing of ASTER data
The ASTER data are preprocessed first to obtain the reflectance image. The nine spectral bands of the terrain
corrected LIT data have been stacked together as a single data set for further processing by using the ENVI software. Then, the data are processed to remove the atmospheric effects due to the presence of water-vapor, aerosol, dust particles etc. on the satellite image by using an atmospheric correction modeling tool Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH). The reflectance calibration of the data is performed with prelaunch gains and offsets calculated for ASTER sensors. After getting suitable calibration parameters of the ASTER data, the model compensates the atmospheric effects and retrieves the spectral reflectance from the multispectral radiance images.

The quality of the final reflectance image is validated by comparing the image spectra of various pixels on land, water and vegetation with that of the ASTER convolved laboratory spectra of the same. The mineral occurrence images draped over the DEM are also helpful for confirming the target end-member. After validating the apparent reflectance image, the reflectance image is subjected to the ENVI hourglass spectral analysis which has the following steps.

### 3.2.2. Minimum noise fraction – transformation

There are various algorithms, such as band ratio technique, principle component analysis (PCA) and minimum noise fraction (MNF) transformation; shape-fitting-based algorithms are available to extract the spectral information of minerals from satellite image. The MNF transformation is used to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing (Boardman and Kruse 1994). Chen (2000) states the advantages of MNF transformation over the principal component analysis to reduce the dimensionality of hyper-spectral imagery. In this study, the MNF transformation is applied to the atmospherically corrected and calibrated ASTER data and it generates nine MNF transformed bands which can be viewed and analyzed. Figure 5 shows the plot of Eigen values corresponding to different MNF bands or Eigen number. Figure 6 shows the RGB image of the MNF bands 3, 1 and 2, which are helpful in identifying the target end-member.

### 3.2.3. Pixel purity index

The pixel purity index (PPI) is a way of finding most spectrally pure pixels in images (Boardman 1993; Boardman, Kruse, and Green 1995). It performs the spectral redundancy of data by separating most spectrally pure pixels. The PPI reduces the number of pixels to be analyzed in a data and leads to attain the spectrally unique target minerals or end-member. In this present work, the PPI analysis is performed on the MNF bands with 10,000 iterations with a threshold value of 3.

The PPI method takes an arbitrary vector through the n-dimensional data cloud (each random vector is controlled to pass through the mean value of the data cloud) and then projects each pixel in the image onto the random vector. A histogram of this process shows how the pixels are projected onto the random vector. The pixels are considered pure if they fall into the tails of the histogram distribution. The histogram tails are defined by the PPI threshold value applied by the user. Each time the same pixel is recognized as pure using a new random vector, its value in the output image is incremented by one. At that moment, a new random vector is chosen, and the process is continued.

The result of the PPI continues is an image where the value of each pixel corresponds to the number of times it was recognized as a pure pixel during all of the PPI iterations. The PPI generates an image in which pixel values correspond to the number of times that a pixel in the input data recorded as extreme. The PPI plot is shown in Figure 7. The generated PPI image can be viewed and analyzed for locating the end-members in image.

![Figure 5](image-url). Eigen value plot for different MNF bands.
3.2.4. n-Dimensional visualizer
The n-dimensional visualizer is an interactive tool used to generate the clouds of pixels in n-dimensional space defined by the MNF bands. The generated pixel clouds can be rotated and visualized in different directions and angles. The 2D scatterplots of different MNF bands shown in Figure 8 help to identify and isolate the target end-members present in the data from the main clusters. The confirmed end-members are verified by comparing and analyzing their spectral signatures with the existing spectral reflectance data generated from ASTER spectral libraries.

The verified end-members are mapped by using Spectral Angle Mapper (SAM) method. SAM is an automated method for comparing image spectra to individual spectra or to a spectral library (Boardman and Huntington 1996). It is also a per-pixel mapping method, which attempts to determine whether one or more target end-members are abundant within each pixel in a hyper-spectral (or multispectral) image on the basis of the spectral similarity between the training (reference) pixel and target (unknown) spectra. This provides a good trial at mapping the predominant spectrally active material present in a pixel. The algorithm determines the similarity between two spectra by calculating the spectral angle between them, treating them as vectors in n-dimensional space, where n is the number of bands. Smaller angles represent closer matches to the reference spectrum. van der Meer and de Jong (2003) claim that the SAM is the most used mapping method for minerals using hyper-spectral data.

4. Results and discussions
The presence of bauxite deposits along the study area is mapped by using SAM mapping method and the occurrence is draped over the DEM of the study area (Figure 9).
The abundance of the bauxite minerals along the study area is mapped in a 0–1 scale (Figure 10). The abundance is density sliced and characterized into five categories such as 0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8 and 0.8–1 corresponding to 0–20%, 20–40%, 40–60%, 60–80% and 80–100%, respectively. The bauxite occurrence image and the index-based abundance of minerals deposits draped over the DEM of the study area (Figures 9 and 10) also help to confirm the mineral distribution with reference to the topographic variations of the study area. This result is then validated by comparing the abundance with the existing literature (Mahmoud Ali and Nazir 1996; Al-Dubaisi 2011) on the chemical composition of samples collected from the study area.

The generated data space of the MNF transformation (Figure 5) can be divided into two parts; one part is associated with large Eigen values and coherent Eigen images. The other part is a complementary part with near unity Eigen values. Among the nine transformed MNF bands, the last three bands have least information but noise dominated and they are omitted for further processing. Due to the application of MNF transformation, the redundancy and noise in the data were eliminated and more interpretable images are obtained. The 2D scatterplots of the different MNF bands are shown in Figure 8. The scatterplot of different MNF bands helps to locate the unique target material along the study area. The scatterplots with MNF bands indicate the presence of separate clusters or arms of pixels. These separate clusters of pixels helped the process to identify the areas of high probability by allowing a visual comparison with the MNF bands and to locate the spectrally unique target materials present in the data. These arms are studied carefully and their position can be identified with in the image.

The MNF and PPI transformed images help to identify the target end-members. The brighter pixels of these...
transformed images represent the most spectrally extreme pixels. In order to identify and locate the endmembers, the data clouds are also visualized through $n$-dimensional visualizer. The spectral signatures of the identified end-members are compared with ASTER spectral profile of bauxite samples. It was observed that the absorption and reflection features of the spectra are identical. Also, the bauxites have specific characteristic around 2.27 μm. This characteristic absorption is more helpful to confirm the bauxite mineral. Guha et al. (2013) also states that the matching of spectral profiles derived from the image locations of the bauxite exposures derived from the PC-image with the laboratory spectra of bauxite specially for the diagnostic absorption signature at 2.26 μm helps in clarifying the bauxite enrichment map. After careful identification, they end-members are mapped by using SAM classification method.

Thus, the study implies that the abundance of bauxite minerals in the 0–1 scale is more suitable for delineating the bauxite deposits along the study area. The occurrence of bauxite mineral deposits is dropped over the DEM of the area leads to understand the topographic deposition of the bauxite revelations in the area. The study also reveals that low topographic and geologically stable surface exposed to tropical weathering activities for long time has more chances for the bauxite enrichment.

The present study has also demonstrated the potential use of multispectral ASTER data for mapping the bauxite mineral resources by using their spectral signature. The minerals which show significant variation of reflectance for different spectral bands can be effectively mapped by using multispectral satellite data. The predominant mineral resources along the study area are identified and mapped by using SAM per-pixel method. The present study on mapping the bauxite deposits along the study area by using ASTER data has been very useful to perform further exploration of minerals by using advanced hyper-spectral data like AVIRIS and Hyperion. The study leads to perform further advanced subpixel mineral mapping methods like mixture-tuned matched filtering and spectral unmixing methods. In addition, the study is useful for the purpose of quantifying and exploration of the bauxite mineral resources along the study area.

5. Conclusions

In this present study, the potential use of multispectral ASTER data for mapping the bauxite mineral resources has been demonstrated. The classified image shows that large amount of bauxite mineral is deposited along the
study area. The abundance image implies amount of bauxite mineral deposits. The bauxite mineral, which shows significant variation in reflectance at different spectral bands, can be effectively mapped by using multispectral data. Even though the number of spectral bands and the alteration characteristics of minerals are significantly influenced the identification and mapping process, the chemical composition studies on the soil samples done by researches on the study area are in agreement with the obtained results. It is very helpful to identify and locate the abundance of minerals, which leads to the eco-friendly and sustainable exploitation of bauxite mineral resources along the study area. It also emphasizes the ability and application of ASTER data to investigate the potential mineral resources.

Acknowledgments

The authors sincerely thank the managing director, Jubail Industrial College, Jubail Industrial City, Saudi Arabia for his kind support and encouragement to the applied scientific research and development and to the deputy directors, chairmen and faculty members of the college for extending effective provisions and support for performing the work.

Notes on contributors

P. Sheik Mujabar is working in the Department of General Studies, Jubail Industrial College, Jubail Industrial City, Kingdom of Saudi Arabia. He is teaching physics for the last 15 years and involved in research in the field of applied geophysics, satellite remote sensing and GIS technologies. His research area includes advanced hyper-spectral analysis on mineral exploration, thermal energy flux analysis and geophysics.

S. Dajkumar is working as a principal geologist in Exploration Geosciences, Terra SearcH Pty Ltd. Perth, Australia. His research area includes sedimentology, mineralogy and geomorphology.

ORCID

P. Sheik Mujabar  http://orcid.org/0000-0003-1449-0939

References

Abrams, M. 2000. “The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER): Data Products for the High Spatial Resolution Imager on NASA’s Terra Platform.” International Journal of
Remote Sensing 21 (5): 847–859. doi:10.1080/
0143116020130326.
Abrams, M., S. Hook, and B. Ramachandran. 2002. ASTER
User Handbook. Version 2. Pasadena, CA: Jet Propulsion
Laboratory Press.
Alashra, S. A. 2016. “Radiation Properties for Red Soil in
Qassim Province, Saudi Arabia.” Journal of Radiation
Research and Applied Sciences 9 (4): 363–369.
doi:10.1016/j.jrras.2015.12.006.
Al-Dubaisi, A. G. 2011. Light Metals: Development of
Bauxite and Alumina Resources in the Kingdom of
Saudi Arabia. Wiley.
Altinbas, U., Y. Kurucu, M. Bolca, and A. H. El-Nahry.
2005. “Using Advanced Spectral Analyses Techniques as
Possible Means of Identifying Clay Minerals.” Turkish
Journal of Agriculture & Forestry 29 (1): 19–28.
Amin, B., and H. Mazlan. 2011. “Application of Advanced
Spaceborne Thermal Emission and Reflection
Radiometer (ASTER) Data in Geological Mapping.”
International Journal of the Physical Sciences 6 (33):
7657–7668.
Assiri, A., and H. Mousa. 2008. “Using ASTER Imagery for
Massive Sulphide Deposits Exploration.” Paper
presented at Microwaves, Radar and Remote Sensing
Symposium, Ukraine, September 22–24.
Boardman, J. W. 1993. “Automated Spectral Un-Mixing of
AVIRIS Data Using Convex Geometry Concepts.” Paper
presented at 4th Annual JPL. Airborne Geoscience
Workshop, Washington, D.C., October 25–29.
Boardman, J. W., and F. A. Kruse. 1994. “Automated
Spectral Analysis: A Geologic Example Using AVIRIS
Data, North Grapevine Mountains, Nevada.” Paper
presented at 10th Thematic Conference on Geologic
Remote Sensing, Las Vegas, February 27–29.
doi:10.3168/js thành S0022-0302(94)77044-2.
Boardman, J. W., F. A. Kruse, and R. O. Green. 1995.
“Mapping Target Signatures via Partial Un-Mixing of
AVIRIS Data.” Paper presented at 5th Annual JPL.
Airborne Geoscience Workshop, California, January
23–26.
Boardman, J. W., and J. F. Huntington. 1996. “Mineral
Mapping with 1995 AVIRIS Data.” Paper presented at
6th Annual JPL Airborne Research Science Workshop,
California, January 12–16.
Chen, C. M. 2000. “Comparison of Principal Components
Analysis and Minimum Noise Fraction Transformation for
Reducing the Dimensionality of Hyper-Spectral Imagery.”
Geographical Research 35 (2): 163–178.
Goetz, A. F. H., G. Vane, J. E. Solomon, and B. N. Rock.
1985. “Imaging Spectrometry for Earth Remote
Sensing.” Science 228 (4704): 1147–1153. doi:10.1126/
science.228.4704.1147.
Guha, A., V. K. Singh, R. Parveen, K. V. Kumar, A. T.
Jeyaseelan, and E. N. D. Rao. 2013. “Analysis of ASTER
Data for Mapping Bauxite Rich Pockets within High
Altitude Lateritic Bauxite, Jharkhand, India.”
International Journal of Applied Earth Observation and
Geo Information 21: 184–194. doi:10.1016/j.
jag.2012.08.003.
Kariuki, P. C., T. Woldai, and F. van der Meer. 2004.
“Effectiveness of Spectroscopy in Identification of
Swelling Indicator Clay Minerals.” International Journal
of Remote Sensing 25 (2): 455–469. doi:10.1080/0143116031000084314.
Kokaly, R. F., R. N. Clark, G. A. Swayze, K. E. Livo, T. M.
Hoeven, N. C. Pearson, R. A. Wise, et al. 2017. USGS
Spectral Library Version 7: U.S. Geological Survey Data
Series. https://pubs.er.usgs.gov/publication/ds1035.
Krause, F. A., J. W. Boardman, and J. F. Huntington. 2003.
“Evaluation and Validation of EO-1 Hyperion for Mineral
Mapping.” IEEE Transactions Geoscience Remote Sensing
41 (6): 1388–1400. doi:10.1109/TGRS.2003.812908.
Lillesand, T. M., and R. W. Kiefer. 1987. Remote Sensing
and Image Interpretation. USA: John Wiley & Sons.
Mahmoud Ali, D., and A. B. Nazir. 1996. “Mineral
Resource Potential and Its Development in Saudi
Arabia.” JKAU: Engineering Sciences 8 (1): 107–120.
Pena, S. A., and M. G. Abdelsalam. 2006. “Orbital Remote
Sensing for Geological Mapping in Southern Tunisia:
Implication for Oil and Gas Exploration.” Journal of
African Earth Sciences 44 (2): 203–219. doi:10.1016/j.
jafrar.2005.10.011.
Perry, S., and I. Gemuts. 2000. “New High Sulfdation Gold
District: Los Menucos, Rio Negro Province, Argentina –
A Landsat Discovery.” Paper presented at 14th
International Conference, Applied Geologic Remote
Sensing, Las Vegas, Nevada, November 6–8.
Ralph, J. R., G. W. Ronald, C. W. D. Franklin, and H. K. Thor.
1975. “Mineral Deposits in Western Saudi Arabia (U.S. Geological Survey, Jiddah,
Saudi Arabia, Project Report 201).” https://pubs.er.usgs.
gov/publication/ofr75654.
Sabreen, G., and K. Timothy. 2007. “ASTER Spectral
Ratios for Lithological Mapping in the Arabian–
Nubian Shield, the Neoproterozoic Wadi Kid Area, Sinai,
Egypt.” Gondwana Research 11 (3): 326–335.
doi:10.1016/j.gr.2006.02.010.
Sanjeevi, S. 2008. “Targeting Limestone and Bauxite
Deposits in Southern India by Spectral Unmixing of
Hyperspectral Image Data.” Paper presented at
Conference of International Archives of the
Photogrammetry, Remote Sensing and Spatial
Information Sciences, Beijing, China, July 3–11.
van der Meer, F., and S. de Jong. 2003. “Spectral Mapping
Methods: Many Problems, Some Solutions.” Paper
presented at 3rd EARSeL Workshop on Imaging
Spectroscopy, Herrsching, May 13–16.
Volesky, J. C., R. J. Stern, and P. R. Johnson. 2003.
“Geological Control of Massive Sulfide Mineralization in the
Neoproterozoic Wadi Bidah Shear Zone, Southwestern
Saudi Arabia, Inferences from Orbital Remote Sensing and
Field Studies.” Precambrian Research 123 (2–4): 235–
247. doi:10.1016/S0301-9268(03)00070-6.
Zhang, X., M. Pazner, and N. Duke. 2007. “Lithologic and
Mineral Information Extraction for Gold Exploration
Using ASTER Data in the South Chocolate Mountains
(California).” ISPRS Journal of Photogrammetry and
Remote Sensing 62 (4): 271–282. doi:10.1016/j.
ISPRSjprs.2007.04.004.
Zhou, K. F., and S. S. Wang. 2017. “Spectral Properties of
Weathered and Fresh Rock Surfaces in the Xiemitai
Metallogenic Belt, NW Xinjiang, China.” Open
Geosciences 9 (1): 322–339. doi:10.1515/geos-2017-0027.
Zumbrule, H., and T. Prinz. 2000. “Computer Enhanced
Multi-Spectral Remote Sensing Data: A Useful Tool for
the Geological Mapping of Archean Terrains in (Semi)
Arid Environments.” Computers and Geosciences 26 (1):
87–100. doi:10.1016/S0098-3004(99)00042-4.