

Hydrothermal Alteration Zones Identification Based on Remote Sensing Data in the Mahin Area, West of Qazvin Province, Iran

R. Nouri, M.R. Jafari, M. Arain., F. Feizi

II. POSITION OF STUDIED AREA

Abstract—The Mahin area is a part of Taram- Hashtjin zone that located in west of Qazvin province in northwest of Iran. Many copper and base metals ore deposits are hosted by this zone. High potential localities identification in this area is very necessary. The objective of this research, is finding hydrothermal alteration zones by remote sensing methods and best processing technique of Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data. Different methods such as band ratio, Principal Component Analysis (PCA), Minimum Noise Fraction (MNF) and Least Square Fit (LS-Fit) were used for mapping hydrothermal alteration zones.

Keywords—Hydrothermal alteration, Iran, Mahin, Remote sensing

I. INTRODUCTION

REMOTE sensing provides information on the properties of the surface of exploration targets that is potentially of value in mapping alteration zones and lithology units. Alteration can produce distinctive assemblages of minerals that vary according to the location, degree and longevity of those flow processes. When exposed at the surface of the earth this alteration can be mapped at a zonal pattern, around a core of highest grade alteration and greatest economic interest [1].

Undoubtedly, by comparison with other exploration methods, satellite data will be the cheapest method for exploration [2]. The discrimination potential of multispectral image data depends mainly on the wavelength range and spectral resolution of the remote sensing instrument [3]. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) covers a wide spectral region with 14 bands from visible to the thermal infrared. The different band ranges can be capable of discriminating and mapping surface rocks and predicting pathfinder minerals (i.e. alunite, kaolinite etc.) on alteration assemblages of potential targets [4], [5].

This work presents the application of remote sensing digital image processing techniques for the ASTER, including band ratio, Principal Components Analysis (PCA) Least Square Fit (LS-Fit), and Minimum Noise Fraction (MNF) methods to map spectral signatures associated with the hydrothermal alterations in the Mahin area.

The studied area is located between longitudes $E49^{\circ} 22' 30'' - 49^{\circ} 30' 00''$ and latitudes $N36^{\circ} 07' 30'' - 36^{\circ} 15' 00''$ in the western part of Qazvin (NE of Quchek Khan area with 5862-II-NE 1:25000 sheet number), 230 km to the west of Tehran (Fig. 1). The Mahin area is a part of Taram- Hashtjin zone that based on 1:250000 geological map of Zanjan, the most impressive geological feature are Eocene Rocks that including members of Karaj Formation (Amand Member).

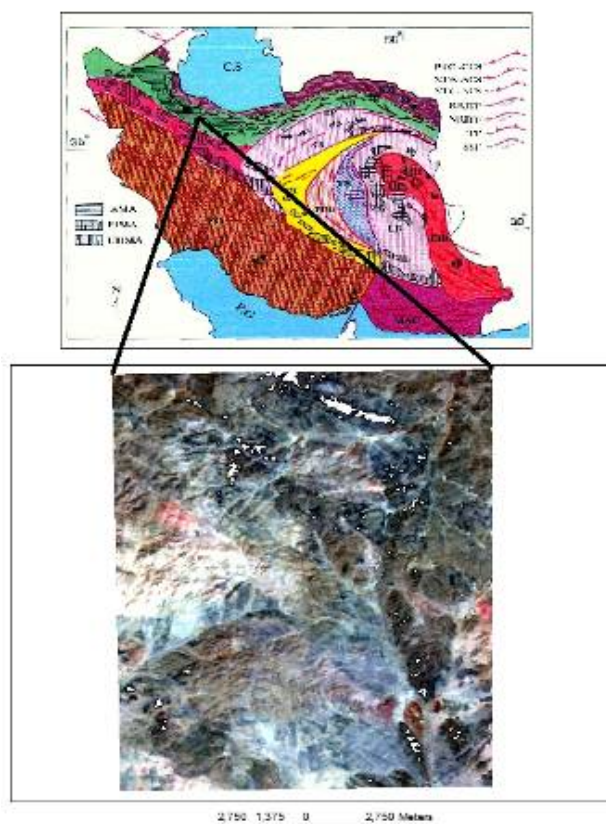


Fig. 1 Location of study area and corresponding ASTER satellite data (RGB: 468)

III. HYDROTHERMAL ALTERATION DETECTION

At the beginning of the path, radiance correlation such as wavelength, dark subtract and log residual by ENVI4.4 software which is essential for multispectral images, were implemented. For instance, the log-residual algorithm reduces noise from topography, instruments and sun illumination. The resulting data can be assumed to be more representative of the soils or lithologies of the exposed areas than the unprocessed data [2]. The following methods were used for alteration hydrothermal detection.

R. Nouri, Young Researchers Club, Tehran North Branch, Islamic Azad University, Tehran, Iran

M.R. Jafari, Department of Geology, Tehran North Branch, Islamic Azad University, Heravi Sq, Pasdaran Ave, Tehran, Iran; (e-mail: mr.jafari_1348@yahoo.com).

M. Arian, Department of Geology, Science and Research Branch, Islamic Azad University, Tehran, Iran; (e-mail: mehranarian@yahoo.com).

F. Feizi, Department of Mining Engineering, Southern Tehran Branch, Islamic Azad University, Tehran, Iran; (e-mail: feizi.faranak@yahoo.com).

A. Band Ratio

Band ratio method is the very simple and powerful technique in the remote sensing. Basic idea of this technique is to emphasize or exaggerate the anomaly of the target object [5]. Each object has its own spectral reflectance pattern in different wavelength portion. Spectral reflectance curve is a kind of fingerprint of the object. The object or rock unit may have high reflectance value in some spectral portion, however, it may absorb in another spectral region [6]. Because ASTER has 14 spectral channels, more ratio images, and therefore more lithologic and mineralogic indices and thus more accurate results can be derived from ASTER data [7].

In the Fig 2 showing image of compound band ratio of RGB 4/3, 4/7, 2/1 that pinkish to red color represents the presence of hydrothermal alteration in this region.

4/(5+6) and 4/6 ratios were used for choosing argillic and phyllic alteration areas that were manifest as bright pixels in Fig3 (a) and Fig3 (b). Also, propylitic alteration were distinguished by (6+9) / (7+8) ratio that were shown as dark pixels in Fig3 (c).

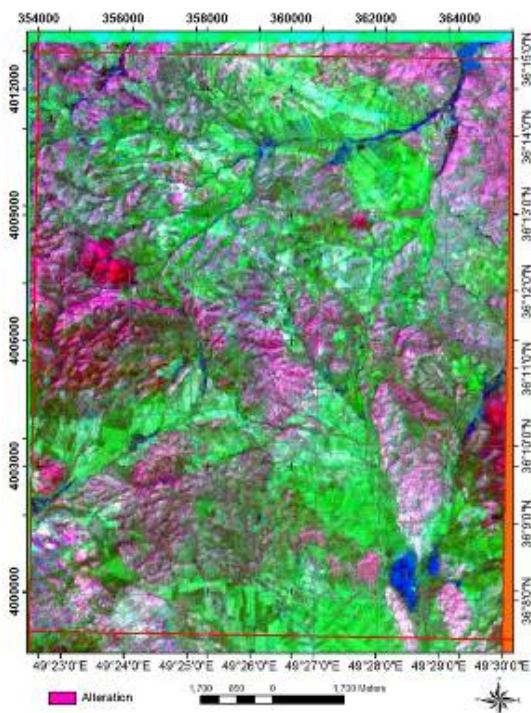


Fig. 2 RGB color composite ratio image of 4/3, 4/7, 2/1

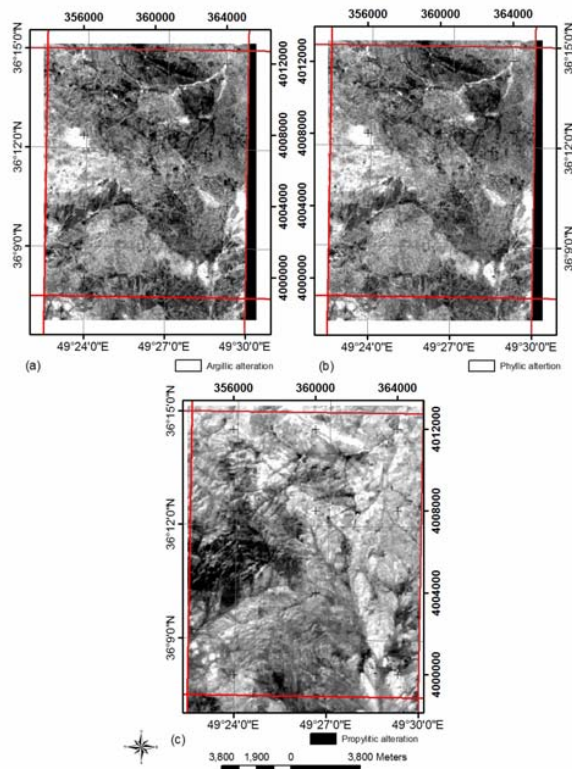


Fig. 3 (a) Argillic, (b) phyllic (c) propylitic images that is prepared based on band ratio method

B. Principal Component Analysis

The Principal Component Analysis (PCA) determines the eigenvectors of a variance-covariance or a correlation matrix. The resulting components are often more interpretable than are the original images. PCA is widely used for mapping the distribution of alteration in metallogenic provinces. PCA can be applied to multivariate datasets, such as multispectral remote sensing images, with the aim of highlighting spectral responses related to specific minerals produced by hydrothermal alteration [8], [9]. In selective PCA analysis, only certain bands are chosen that contain absorption and reflection features of the mineral of interest. A reduction in the number of input channels results in an increased chance of defining a unique principal component for a specific mineral class [9], [10], [11].

PCA technique has been applied in this study. An approach based on the examination of eigenvector loadings in each PC image is used for determining which image contains information related to the spectral signatures of specific target minerals [12], [13]. Table I, shows the eigenvector loadings for bands 4, 5 and 7. In according to the results, image related to PC3 shows the argillic alteration (See Fig4 (a)). Table II shows the eigenvector loadings for bands 4, 6 and 7. PC3 can show the areas with phyllic alteration (See Fig4 (b)). Comparison of Fig.4 (a) and Fig.4 (b) shows that the areas of phyllic and argillic alterations are almost overlapping. Table III shows the eigenvector loadings for bands 7, 8 and 9. PC1 can show the areas with propylitic alteration (See Fig4 (c)).

TABLE I
THE RESULT OF PCA FOR ENHANCING ARGILLIC ZONE

	B4	B5	B7
PC1	0.596286	0.565483	0.569800
PC2	0.801477	-0.379049	-0.462555
PC3	0.045584	-0.732497	0.679243
Eigen value	0.213933	0.001887	0.000350

TABLE II
THE RESULT OF PCA FOR ENHANCING PHYLLIC ZONE

	B4	B6	B7
PC1	0.594603	0.569934	0.567119
PC2	0.784155	-0.255251	-0.565639
PC3	0.177619	-0.781039	0.598689
Eigen value	0.215608	0.001688	0.000387

TABLE III
THE RESULT OF PCA FOR ENHANCING PROPYLITIC ZONE

	B7	B8	B9
PC1	0.580281	0.587163	0.564371
PC2	0.397613	0.400523	-0.825521
PC3	-0.710759	0.703435	-0.001048
Eigen value	0.207264	0.000505	0.000301

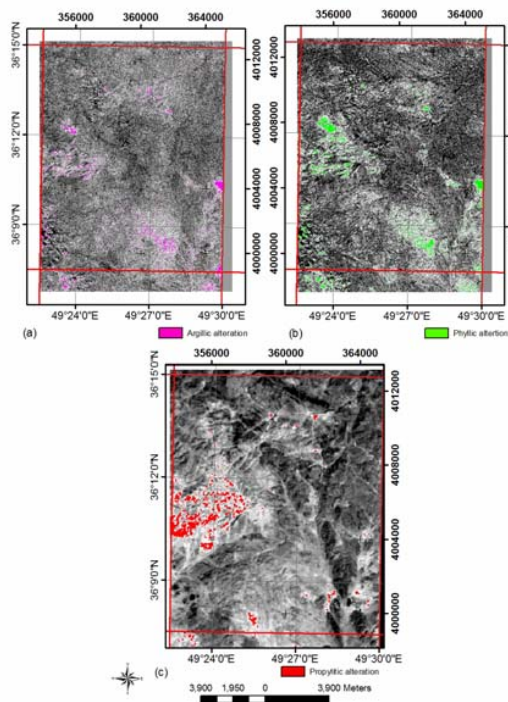


Fig. 4 (a) Argillic, (b) phyllic (c) propylitic images that is prepared based on PCA method

C. Minimum Noise Fraction

The Minimum Noise Fraction (MNF) transformation is used to determine the inherent dimensionality of image data, segregate noise in the data, and reduce the computational requirements for subsequent processing [14], [15], [16]. MNF involves two steps; in first step which is also called noise whitening, principal components for noise covariance matrix are calculated. This step decorrelates and rescales the noise in the data. In second step principal components are derived from the noise whitened data. The data can then be divided into two parts. One part associated with large Eigen values and the other part with near unity Eigen values and noise dominated images. Using data with large Eigen values separates the noise from the data, and improves spectral results [15], [16].

MNF analysis can identify the locations of spectral signature anomalies. This process is of interest to exploration geologist because spectral anomalies are often indicative of alterations due to hydrothermal mineralization [16]. MNF bands 7, 6 and 4 were used for argillic, phyllic, and propylitic alterations (Fig5).

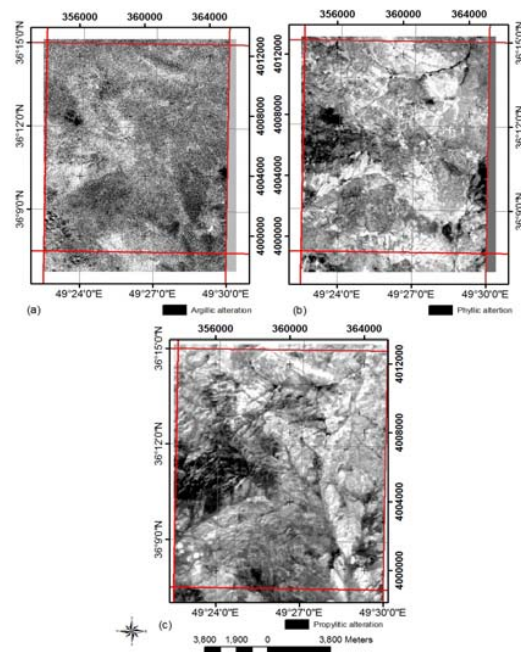


Fig. 5 (a) Argillic, (b) phyllic (c) propylitic images that is prepared based on MNF method

D. Least Squares Fitting (LS-Fit)

LS-Fit method performs a linear band prediction using a least squares fitting technique. It is used to find regions of anomalous spectral response in a data set. It calculates the covariance of the input data and uses it to predict the selected band as a linear combination of the predictor bands [17], [18].

Fig6 (a) illustrates an output image of the LS-Fit model to map the distribution of argillic alteration (dark pixels). This map was created by using all the 6 visible and short wave infrared (SWIR) bands as the input bands and SWIR-b3 as the modeled band. Fig6 (b) and Fig6 (c) show phyllic (bright pixels) and propylitic (dark pixels) alterations were mapped by using residual band SWIR-b1 and residual SWIR-b6. Final map of alteration is shown in Fig7.

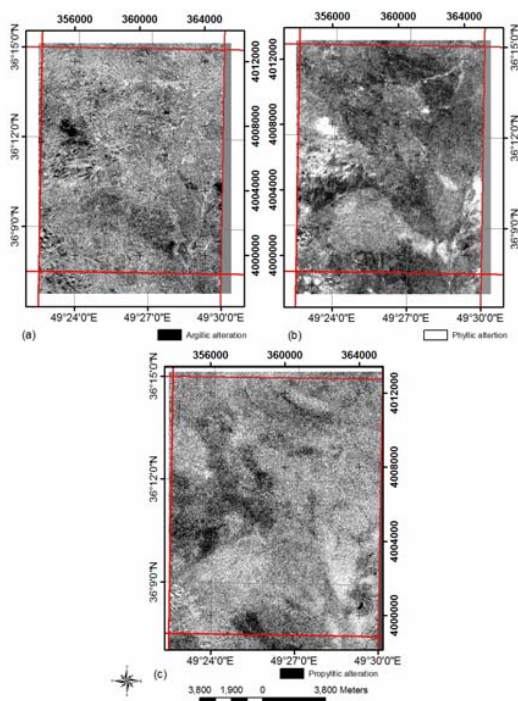


Fig. 6 (a) Argillic, (b) phyllic (c) propylitic images that is prepared based on LS-Fit method

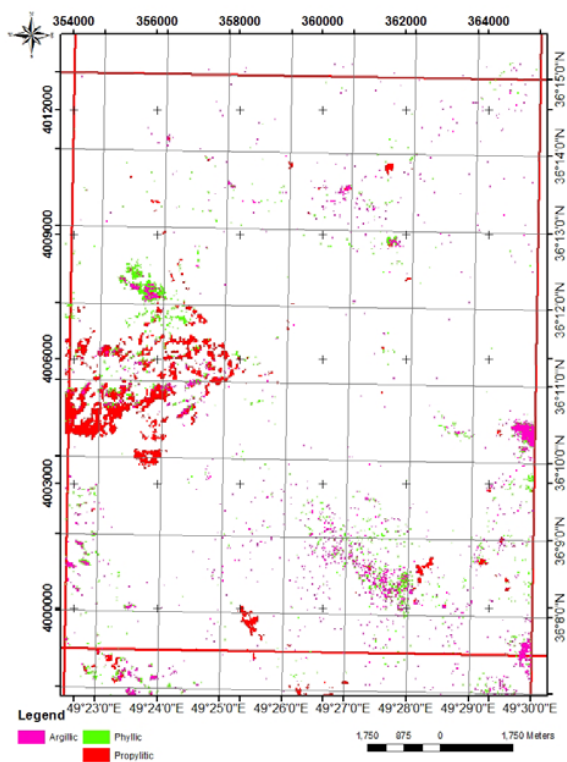


Fig. 7 Final alteration photo map of studied area

REFERENCES

[1] A. G. Dehnavi, R. Sarikhani and D. Nagaraju, Image Processing and Analysis of Mapping Alteration Zones In environmental research, East

of Kurdistan, Iran, World Applied Sciences Journal 11 (3): pp. 278-283, 2010.

[2] H. Azizi, M.A. Tarverdi and A. Akbarpour , Extraction of hydrothermal alterations from ASTER SWIR data from east Zanzan, northern Iran, Advances in Space Research, pp. 99–109, March 2010.

[3] A. I. Lianes Castro, An assessment on the potential of mapping hydrothermal alteration from ASTER short wavelength infrared image data based on image simulation experiments, International institute for geo-information science and earth observation Enschede, The Netherlands, February 2004.

[4] Y. Ninomiya, Mapping quartz, carbonate minerals and mafia-ultramafic rocks using remotely sensed multispectral thermal infrared ASTER data. Proceedings of SPIE, 4710, pp. 191-202, 2002.

[5] B. T. San, E. O. Sumer and B. Gurcay, Comparison of band ratioing and spectral indices methods for detecting alunite and kailinite minerals using ASTER data in Biga region, Turkey, Geo-Imagery Bridging Continents XXth ISPRS Congress, Istanbul, Turkey, July 2004.

[6] J.M. Abrams, Remote sensing for porphyry copper deposits in Southern Arizona. Economic Geology, 78, pp. 591-604, 1983.

[7] M. Hashim, M. Pournamdary and A. Beiranvnd Pour, Processing and interpretation of advanced space-borne thermal emission and reflection radiometer (ASTER) data for lithological mapping in ophiolite complex, International Journal of the Physical Sciences Vol. 6(28), pp. 6410-6421, November 2011.

[8] A.P. Crosta, C.R. DE Souza Filho, F. Azevedo, and C. Brodie, Targeting key alteration minerals in epithermal deposit in Patagonia, Argentina, using ASTER imagery and principal component analysis. Int. J. Remote Sens., 10(21): 4233-4240, 2003.

[9] M. Honarmand, H. Ranjbar, and J. Shahabpour, Application of Spectral Analysis in Mapping Hydrothermal Alteration of the Northwestern Part of the Kerman Cenozoic Magmatic Arc, Iran, University of Tehran, Journal of Sciences, Islamic Republic of Iran 22(3): 221-238, 2011.

[10] W. Loughlin, Principal component analysis for alteration mapping. Photogramm, Eng. Remote Sens., 57(9): 1163–1169, 1991.

[11] J. R. Ruiz-Armenta , and R.M. Prol-Ledesma, Techniques for enhancing the spectral response of hydrothermal alteration minerals in Thematic Mapper images of central Mexico. Int. J. Remote Sens., 19(10): pp.1981–2000, 1998.

[12] A.P. Crosta and J.M. Moore, Enhancement of Landsat Thematic Mapper imagery for residual soil mapping in SW Minas Gerais State, Brazil: a prospecting case history in Greenstone Belt Terrain. In Proceedings of the Seventh Thematic Conference on Remote Sensing for Exploration Geology, 2- 6 October, 1989.

[13] M. Khaleghi, and H. Ranjbar, Alteration Mapping for Exploration of Porphyry Copper Mineralization in the Sarduiyeh Area, Kerman Province, Iran, Using ASTER SWIR Data, Australian Journal of Basic and Applied Sciences, 5(8): pp. 61-69, 2011.

[14] J.W. Boardman, F.A. Kruse and R.O. Green, Mapping target signatures via partial unmixing of AVIRIS data, Summaries, Proceedings of the Fifth JPL Airborne Earth Science Workshop, Pasadena, California, JPL Publ., 95-1, 1: 23–26. 1995.

[15] A.A. Green, M. Berman, P. Switzer and M.D. Craig, A transformation for ordering multispectral data in terms of image quality with implications for noise removal, IEEE Tran. Geo. Rem. Sen., 26(1): pp.65-74, 1988.

[16] A. Beiranvnd Pour, M. Hashim and M. Marghany, Using spectral mapping techniques on short wave infrared bands of ASTER remote sensing data for alteration mineral mapping in SE Iran, International Journal of the Physical Sciences Vol. 6(4), pp. 917-929, 2011.

[17] H. Asadi Haroni and A. Lavafan, Integrated Analysis of ASTER and Landsat ETM Data to Map Exploration Targets in the Muteh Gold - Mining Area, IRAN, 5th International Symposium on Spatial Data Quality, Enschede, The Netherlands, June 2007.

[18] R.Poormirzaee and M. Mohammady Oskouei, Use of spectral analysis for detection of alterations in ETM data, Yazd, Iran, Applied Geomatics, pp. 147–154, 2010.