A remote sensing-based discrimination of high- and low-potential mineralization for porphyry copper deposits; a case study from Dehaj–Sarduiyeh copper belt, SE Iran

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ABSTRACT
This work seeks to implement surface indicators of porphyry copper deposits (PCDs) at known source regions and to apply these indicators to recognize high- and low-potential mineralization through remote sensing in other areas. Thirty copper deposits in central Iranian volcano-sedimentary complex, Kerman province, Southeast of Iran, which are different in grade and size, were selected as test sites. The abundances of alteration minerals at these deposits were discriminated using a partial sub-pixel unmixing algorithm, mixture tuned matched filtering (MTMF), on Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data to find an indicator whether the abundances of alteration minerals correspond to the grade and size of each deposit. In general, comparison of sub-pixel abundances with known mineral occurrences showed a reasonable correspondence such that areas with high abundances of alterations corresponded well with important mineralized districts. It is concluded that suggested sub-pixel analysis of ASTER data leads to identifying alteration zones with high-potential mineralization in PCDs.

INTRODUCTION
One of the most important characteristics of porphyry copper deposits (PCDs) widely used in exploration projects is the distribution of alteration zones such as zones of potassic, phyllic, argillic and propylitic. These zones are defined on the basis of their characteristic minerals, and the compositional changes observed are the consequence of the involvement of differently sourced fluids and their mixture in the formation of a deposit (Berger et al., 2008). Generally, at these deposits mineralization zones are conformable to the alteration zones such that the ore bodies (with a 0.5% Cu cutoff) overlap potassic and phyllic zones. In addition, extension and intensity of alteration can suggest the intensity of mineralization (Lowell & Guilbert, 1970). Each alteration zones characterized by assemblages of hydrothermal alteration minerals that exhibit spectral absorption features in the visible near-infrared (VNIR) through the short-wave infrared (SWIR) 0.4–2.5 μm and the thermal-infrared (TIR) (8.0–14.0 μm) wavelength regions (Abrams, 2000; Asadzadeh & De Souza Filho, 2016; Carrino, Crósta, Toledo, & Silva, 2015; Clark et al., 2007; Corumluoglu, Vural, & Asri, 2015; Hosseinjani Zadeh et al., 2014a). These characteristics cause that it is possible to discriminate alteration minerals through remote sensing science. This science has shown tremendous potential in discriminating and mapping alteration minerals through different image-processing techniques including per-pixel and sub-pixel algorithms with lower cost, time and manpower (Crosta & Filho, 2003; Debba, Van Ruitenbeek, Van Der Meer, Carranza, & Stein, 2005; Givens, Walli, & Eisemann, 2013; Hosseinjani Zadeh et al., 2014b; Hosseinjani Zadeh & Tanglestani, 2013; Hubbard & Crowley, 2005; Mars & Rowan, 2010; Sabins, 1999; Shahriari, Honarmand, & Ranjbar, 2015; Van Der Meer et al., 2012; Zhang & Li, 2014). Normally in per-pixel algorithms such as band rationing, principal component analysis and spectral angle mapper (SAM) hydrothermal altered minerals are discriminated at regional scale with little attention to sub-pixel analyses. Although image pixels are often a mixture of different materials which cannot be detected by per-pixel classification algorithms, sub-pixel analysis methods can be used to calculate the quantity of target materials within each pixel of an image. In spectral sub-pixel unmixing, the measured spectrum of a mixed pixel is decomposed into a collection of constituent spectra, or end-members and set of abundances that represent the proportion of each end-member in the pixel are determined. End-members normally correspond to pure objects in the scene, such as water, soil, rock, mineral, or any...
natural or man-made material. Spectral unmixing usually requires detailed spectral profiles of each element in a mixed pixel, and this becomes the bottleneck. Unlike unmixing algorithms such as linear spectral unmixing, partial sub-pixel unmixing hybrid method known as mixture tuned matched filtering (MTMF) does not require knowledge of all the end-members in the scene. Previous studies have demonstrated the importance of MTMF as a partial sub-pixel unmixing method in identification of mineral mapping (Bishop, Liu, & Mason, 2011; Boardman, Kruse, & Green, 1995; Hosseinjani Zadeh et al., 2014b; Hosseinjani Zadeh & Tangestani, 2011; Hosseinjani Zadeh et al., 2014c; Kruse, Boardman, & Huntington, 2003).

MTMF combines the strength of the matched filter (MF) method with physical constraints imposed by mixing theory in which the signature at any given pixel is a linear combination of the individual components contained in that pixel. Results of this algorithm are two sets of gray images for each end-member including the MF image score and the infeasibility image. The MF images help to estimate relative degree of match to the reference spectrum and the approximate sub-pixel abundance with values from zero to one. Pixels with a high infeasibility are likely to be MF false positives. MTMF maximizes the response of the end-member of interest and the composite unknown background to match the known signature (Chen & Reed, 1987; Research, & Systems.Inc, 2003).

Among remote sensing data, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) has been effectively used for identification of various surface features and mineralogical classification especially hydrothermal minerals (Amer, Kusky, & El Mezayen, 2012; Dalm, Buxton, Van Ruitenbeek, & Jack, 2014; Gabr, Ghulam, & Kusky, 2010; Hosseinjani Zadeh et al., 2014c; Mars & Rowan, 2010; Mondino, Lessio, & Gomarasca, 2016; Ranjbar, Masoumi, & Carranza, 2011; Zhang, Pazner, & Duke, 2007). In most of remote sensing studies, hydrothermal alteration minerals have been discriminated without attention to size, grade and potential of mineralization. Although mineral abundances which can be derived through sub-pixel analyses may be used as a clue to discriminate hydrothermal alteration zones of high-potential mineralization from those with low potentials, rare publications are available for distinguishing high-potential mineralization through sub-pixel analysis such as MTMF algorithm. Although Hosseinjani Zadeh et al., (2014c) showed that MTMF can be used to discriminate alteration minerals and their apparent abundances on a sub-pixel basis, many efforts remain to be done in other mineralized areas for verifying accurate determination of mineral abundances and to prove its ability for determination of high-potential mineralization.

Since extension and intensity of alteration can suggest the intensity of mineralization, it could be possible to use mineral abundances, which can be derived through sub-pixel analyses, as a clue to discriminate hydrothermal alteration zones of high-potential mineralization from those with low potentials. The main objective of this research was to implement surface indicators of PCDs through sub-pixel analysis of ASTER data at known source regions for recognition of high-potential mineralization and to establish markers of potential in other areas. In order to reach these aims, 30 copper occurrences with a variety of economic potential in Dehaj–Sarduiyeh copper belt were investigated. The study area is a potential zone for exploration of PCDs in which most of the important PCDs of Iran are situated. These deposits were assessed with the aim of mapping alteration minerals through sub-pixel processing of ASTER data. Discriminated areas were investigated in order to determine whether the abundances of alteration minerals correspond to the grade and size of each deposit.

**Geology and mineralization**

The study area is situated at the southern part of the central Iranian Urumieh–Dokhtar magmatic arc, Kerman province, Iran (Figure 1a)). This magmatic belt, known as Dehaj–Sarduiyeh copper belt in Kerman province, has considerable economic potential for porphyry copper mineralization. The largest porphyry copper mine of Iran, Sarcheshmeh, and 30 other deposits, such as Meiduk, Darrehzar, Nowchon, Sara and Iju are located at this area (Figure 1b).

The study area is concentrated on three established porphyry copper regions including: (a) some parts of merged geological maps of the Pariz and Chahar Gonbad, (b) geological map of the Sarduiyeh and (c) some parts of merged geological maps of the Anar, Shahr-e Babak, Dehaj and Robat (Figure 1c–e)). The scales of these maps are 1:100,000 (Geological Survey of Iran (Cartographer), 1971a, 1971b, 1972a, 1972b, 1973a, 1973b, 1995).

This region is characterized by the presence of several copper mineral deposits and many occurrences. Two types of mineralization including porphyry and vein types have been identified in these areas. Porphyry types are more important and are located mainly in the post Eocene intrusive bodies in the Eocene volcanic–sedimentary complex. The vein-type mineralization has been found both in the intrusive and in the volcanic rocks and has been controlled by faults of different trends (Dimitrijevic,
The occurrences and deposits located in the study area are indicated in Figure 1.

Hydrothermal alterations are intensive, widespread all over the study area and developed both in the intrusive and volcanic rocks. The following types of hydrothermal alterations such as chloritization, biotization, sericitization, argillization, silicification, sulphatization, epidotization, pyritization and carbonatization were identified. The intensity of alterations is not of the same type in all locations. Sericitization which is mainly developed around the copper mineralization like Darrehzar, Jju and many other occurrences is the most intensive and most common alteration in this area. This alteration is usually associated with silicification, argillization and bleaching of the surrounding rocks. Argillization is also very common although not intensive as sericitization.

Silicification, nearly always present, most intensively occurred near copper mineralization and is developed into different degrees in all types of rocks. Chloritization and epidotization are usually absent from the most intensively altered zones where sericite, quartz and clay minerals are present but have usually occurred in the propylitized zones (Dimitrijevic, 1973).

Methods

Three principal sources of information including ASTER images, existing geological/exploration maps and geological exploration data have been used in this research. The study areas cover three frames of ASTER-level 1B data which were acquired on 13 March 2002, 1 September 2003 and 9 August 2004.
Since the data were acquired in different time, the processing of the data was implemented on each frame separately. The procedure of preprocessing and processing was similar to Hosseinjani Zadeh et al., (2014c). The preprocessing such as crosstalk correction and Internal Average Relative Reflection calibration were implemented on the data in order to remove noise and acquire surface reflectance. Spectra of diagnostic alteration minerals including sericite–illite, pyrophyllite–alunite, kaolinite–dickite, chlorite–calcite–epidote and the jarosite were extracted from the preprocessing imagery using Environment for Visualizing Images (ENVI) software, n-dimensional visualizer tool, and a-priori knowledge of the geology. The extracted spectra, in minimum noise fraction (MNF) space, were used to identify alteration minerals and to generate abundance thematic mineral maps through partial sub-pixel unmixing algorithm known as MTMF (Hosseinjani Zadeh and Tangestani, 2011, Hosseinjani Zadeh et al., 2014b, 2014c). These processes were implemented for three frames of ASTER separately. In order to determine and investigate whether the grade and size of each deposit correspond to the results obtained from processing of ASTER data, the discriminated areas for each spectrum and abundances were converted to vector and saved as shape files. The accuracies of the discriminated areas were verified by field surveys and laboratory analyses such as X ray diffraction (XRD), microscopy and spectroscopic studies. Important analogic information from previous studies such as geological/exploration maps and geological exploration data (grade and size of each deposit) was also available at different scales ranging from detailed to regional. These maps were georeferenced and digitized and were introduced along with the rest of the ancillary georeferenced information and discriminated abundances of altered minerals into the ArcGIS v. 10.3 database. Then, the discriminated areas were investigated and compared in the case of extension, abundance, size and grade of each deposit. The flowchart of the study procedure is shown in Figure 2.

**Results and discussion**

The question of which discriminated areas contain high-potential mineralization is important for locating deposits. Identifying the areas of high economic potential for copper mineralization using ASTER data in the Urumieh–Dokhtar was applied to three ASTER scenes covering the Meiduk, Sarcheshmeh and Daralu mining districts. Regarding previous analysis by authors (Hosseinjani Zadeh et al., 2014c) on VNIR + SWIR wavelengths to identify iron oxide/hydroxide and clay minerals in some parts of the study sites, the present study focuses to implement surface indicators of PCDs at known source regions and to apply these tools to recognize high-potential mineralization through remote sensing in other areas. Surface indicators of PCDs include mineral spectral signatures as well as spectral abundances mapped through ASTER imagery. Spectral abundances mapped were generated from a partial sub-pixel unmixing algorithm on ASTER data. The abundant maps for some of important deposits are displayed in Figure 3. Hereafter, the discriminated areas were investigated and compared in the case of extension, abundance, size and grade of each deposit (Table 1).
Table 1 shows location, grade and size of 30 known PCDs which were compared with the abundances and extensions of discriminated minerals extracted from processing of ASTER data. Investigation and comparison of the size and grade of each deposit with the abundances of discriminated minerals revealed an excellent correlation with coefficient between 0.533 and 0.646 for each mineral (Table 2). So that it is possible to find relationship between extension and intensity of alteration with the intensity of mineralization through remote sensing studies.

The alteration minerals including hydrated aluminum silicates (clay alteration minerals) and gossan mineral (jarosite) were successfully mapped with ASTER data using MTMF algorithm. The zoned alteration pattern suggests a change from phyllic (e.g. sericite) to argillic (e.g. kaolinite) to propylitic alteration (e.g. epidote) from the center to outwards. High abundances (0.75–1) of five diagnostic alteration minerals including sericite, kaolinite, alunite, jarosite and chlorite were found at giant deposit like Sarcheshmeh. The discriminated minerals at this mine illustrated elliptical shapes with sericite and argillic zones surrounded by propylitized rocks and have abundances from high to low (0.35–1). Big deposits such as Meiduk revealed high abundances of four minerals including sericite, kaolinite, alunite and jarosite. Distributions of altered minerals are high with elliptical shape and have abundances from high to low. Medium deposits such as Darrehzar, Iju and Nowchon show high abundance of one mineral at
Table 1. Location, grade and size of porphyry copper deposits in the study area (extracted from Dimitrijevic, 1973; Shafiei & Shahabpour, 2008).

| Deposit       | Location (Zone 40R) | Reserve and grade | Size          | Abundance of discriminated altered minerals | Extension of discrimination areas |
|---------------|---------------------|-------------------|---------------|---------------------------------------------|----------------------------------|
| Sarcheshmeh   | 392,000E, 3,313,529N | 1200 Mt, 0.7% Cu and 0.03 Mo | Giant         | H: Au, Jrs, MsC, Chl and Kln              | 2.5 × 3.7 km² large oval         |
| Darrehzar     | 393,800 E, 3,306,089N | 49 Mt, 0.64% Cu and 0.04 Mo | Medium        | High: Au, Jrs, MsC, Chl and Kln           | 1.8 × 1.3 km² large oval         |
| Nowchon       | 389,315E, 3,310,754N | 80 Mt, 0.32% Cu | Medium        | H: Chl                                      | 1.9 × 1.3 km Chl large           |
| Sereidun      | 394,370E, 3,315,134N | 0.1–0.3% Cu | Small         | L: Jsc                                      | 1.8 × 1.1 km oval               |
| Kuhpanj       | 409,850E, 3,305,174N | 0.1–0.3% Cu | Small         | M: MsC, Kln                                | 2 × 0.8 km² disseminated patches |
| Baghkhoshk    | 402,500E, 3,300,464N | 24 Mt and 0.27% Cu | Small        | M: Chl                                      | Disseminated patches            |
| Sarbagh       | 407,045E, 3,317,294N | 0.1–0.3% Cu | Small        | M: Chl, Kln                                | Disseminated patches            |
| Dehsiahan     | 403,175 E, 3,318,404N | Porphyry 20–200 ppm | Small         | M: Kln, Jsc                                 | Disseminated patches            |
| Iju           | 303,508E, 338,085N  | Vein 300,000 t, 1.5% | Medium       | H: MsC, Jsc, Chl                            | 0.78 × 0.78 oval medium          |
| Gode Kolvari  | 307,603E, 3,386,835N | According to eight hole, Cu is less than 0.1% | Small       | M: Alu, Jsc, Chl, Kln                       | Disseminated patches            |
| Serenu        | 306,658E, 3,374,565N | Low Cu average 0.14%, Mo 10–50 ppm | Small       | M: Msc (S)                                  | Low 0.3 × 0.6 disseminated patches |
| Sara (Parkam) | 321,613E, 3,369,855N | Low 0.16% (0.01–2.01) Cu, 12 ppm (0.5–489) | Small       | H: Alu (S), MsC (M)                         | 1.1 × 1.1 km² oval shape         |
| Meiduk (Lachah) | 324,373E, 3,367,560N | 150 Mt and 1.1% Cu | Big          | M: Kln, Chl                                 | Large 2 × 2 km, oval shape km²   |
| Chah Mesi     | 323,473E, 3,365,280N | Vein 1,554,585 t, 1.27% Cu, gold up to 7 ppm 359,151 t, 0.49% Cu | Small       | L: MsC                                      | –                                |
| Bondare Baghu | 401,525E, 3,316,664N | Vein type 100,000 t, 1.85% Cu | Small       | –                                           | –                                |
| Bande Bagh    | 404,195E, 3,308,249N | Vein lead zinc    | Small        | H: MsC, Jsc                                 | –                                |
| Daralu        | 510,241E, 3,254,044N | 25 Mt, 0.46% Cu, 65 ppm Mo 50–80 Mt, 0.4 Cu | Small       | M: Kln, Alu                                 | 2.5 × 0.6 elongated oval         |
| Sarmeshk      | 513,704E, 3,252,101N | Low 0.25 Cu, 26, ppm Mo | Small       | M: Alu (seven pixels), Jsc, Kln, MsC         | 0.8 × 0.5 km² oval               |
| Bondare Hanza | 520,229E, 3,244,526N | Low 0.1–0.4% up to 0.6% Cu, 2–870 ppm Mo | Small       | H: MsC (three pixels)                       | Disseminated patches            |
| Hanza         | 520,529E, 3,249,881N | –                 | Small        | M: Jsc                                      | Disseminated patches            |
| Guru          | 529,304E, 3,248,186N | Low 0.1% Cu, 2–134 ppm Mo | Small       | M: Jsc, Kln, MsC                            | Disseminated patches            |

(Continued)
| Deposit     | Location (Zone 40R) | Reserve and grade* | Size | Abundance of discriminated altered minerals | Extension of discrimination areas |
|-------------|---------------------|--------------------|------|---------------------------------------------|----------------------------------|
| Godar Siah  | 542,534E, 3,260,231N| Low 0.1–0.5% Cu, up to 30 ppm Mo | Small | M: Msc, Kin | Disseminated patches |
| Surakhe Mar1| 542,639E, 3,243,641N| 0.32% Cu           | Small | H: Jsc | 0.8 × 0.7 higher temperature than surakh 2 |
| Surakhe Mar 2| 5,466,74E, 3,240,146N| 0.1–0.4% Cu, 19–93 ppm Mo | Small | L: Alu, Chl, Kin, M: Jsc, Msc | Disseminated patches |
| Damaneh     | 519,644E, 3,230,756N| –                  | Small | L: Jsc, Msc | Disseminated patches |
| Sin Abad    | 526,619E, 3,230,786N| –                  | Small | M: Alu, Jsc, Kin | 1.1 × 0.8 km² |
| Zamin Hossein | 530,144E, 3,214,376N| Soil sample up to 3000 ppm Cu | Small | M: Msc, Kin, Jsc, L: Alu, Chl | Disseminated patches |
| Baghrai     | 523,739E, 3,213,776N| –                  | Small | – | – |
| Sargard     | 531,644E, 3,218,606N| –                  | Small | – | – |
| Babnam      | 533,519 E, 3,221,126N| Soil sample 200–850 ppm Cu | Small | M: Msc, Kin, Jsc, L: Chl | Disseminated patches |
| Janga       | 545,249 E, 3,219,701N| 0.38–0.7% Cu       | Small | M: Kin, Msc, L: Alu, Chl | Disseminated patches |

*a http://www.nicico.com/DesktopModules/Articles/ArticlesView.aspx?TabID=1&Site=DouranPortal&Lang=fa-IR&ItemID=539&mid=14767.

Msc: muscovite; Kin: kaolinite; Chl: chlorite; Jrs: jarosite; Alu: alunite; H: high abundance; M: moderate abundance; L: low abundance.
least. Darrehzar revealed high abundances with large extension of the five diagnostic alteration minerals. Iju showed high abundances with medium extension of muscovite and chlorite, while Nowchon showed high abundances with large extension of chlorite. The discriminated areas around Darrehzar, which is known as medium deposits (Shafei & Shahabpour, 2008), are similar to giant and big deposits (Sarcheshmeh and Meiduk). Therefore, it requires supplementary investigation and should consider more. In fact, according to the latest study at the area, the tonnage of Darrehzar is higher than (96 Mt with 0.42%) \(^1\) what reported previously (49 Mt with 0.64%).

Small and low-grade deposits such as Sereidun, Kuhpanj, Baghkhoshk, Sarbagh, Serenu, Sarmeshk, Hanza, Guru, Surakhe Mar2, Damaneh, Zamin Hossein, Babnam and Janga are associated with moderate to low abundances of minerals (0.75–0.35). However, small deposits such as Daralu, Surakhe Mar1, Bondare Hanza and Sara show high abundance of one and two minerals with low extension of discrimination areas. The exception is for Daralu which are known as small deposits and show high abundances of three minerals including muscovite, kaolinite and jarosite with moderate extension of altered minerals. Therefore, this deposit needs extra investigation and should consider more. According to the latest work on this deposit, the tonnage of Daralu is also higher than (133 Mt with 0.4% Cu)\(^2\) what reported previously (25 Mt, 0.46% Cu). Based on discriminated areas, there is no evidence of alteration minerals around vein-type deposits such as Bondare Baghu, Bande Bagh, Sargoad and Chah Mesi. It may be due to the fact that the alteration is weak and small around these vein deposits.

Jarosite which is associated with gossan of PCDS and muscovite is important for exploration of PCDS. According to the discriminated minerals, high abundance of jarosite and clay minerals especially muscovite is associated with giant, big and medium deposits such as Sarcheshmeh, Darrehzar, Meiduk (Lachah) and Daralu. However, Surakhe Mar1 which is a small deposit indicates high abundances of jarosite with moderate to low abundances of other clay minerals. Medium abundances of jarosite are associated with Iju, Gode Kolvari, Serenu, Sara (Parkam), Sarmeshk, Bondare Hanza, Hanza, Guru, Surakhe Mar2, Sin Abad, Zamin Hossein and Babnam. Low abundance of jarosite is observed at Nowchon, Sereidun, Kuhpanj, Sarbagh, Dehsiahan, Godar Siah and Damaneh. In general, it can be extracted from the discriminated areas that have high abundance of jarosite associated with high abundance of clay minerals in important deposits like Sarcheshmeh, Darrehzar, Meiduk and Daralu. Many exploration works revealed the economic importance of these deposits. The exception is for Nowchon which is considered as medium deposit but contains low abundance of jarosite. This may be due to the absence of supergene zone and the existence of only a few meters thick of weathered zone at Nowchon. In addition, copper mineralization is associated with potassic alteration in Hypogene zone, and the copper concentration is accomplished by the higher molybdenum as well (Dimitrijevic, 1973).

### Accuracy assessment

In order to verify the accuracy of the discriminated areas, a field reconnaissance was carried out at the altered areas and 200 samples were collected. These samples were taken from different altered areas through a stratified random sampling of fresh and surface-weathered sides of representative hydrothermally altered rocks. The samples were used for laboratory analyses such as XRD, microscopic and spectroscopic studies, and the veracities of identified minerals via ASTER were checked by comparing with the results obtained by these analyses (Figure 4 and Table 3). In addition, the predicted and actual class labels for a set of specific sites were compared statistically. In order to reach this purpose, while the result of ASTER data was similar to filed data, the value of 1 was adopted and if the results were different, the value of 0 was taken. The value 1 and 0 mean the areas were mapped correctly and incorrectly, respectively, which suggest that the result of ASTER data was similar or dissimilar to filed data value. In order to determine the numbers which the result of ASTER data was similar to filed data, the frequency was applied. The percentage of correctly classified areas for muscovite, kaolinite, jarosite–muscovite, alunite and chlorite are 70%, 73%, 88%, 86% and 74%, respectively. For example, the 70% of muscovite indicates the percentage of times that identified as muscovite in both ASTER and filed data for a

\(^{1}\)http://nicico.com/DesktopModules/Articles/ArticlesView.aspx?TabID=1&Site=douranPortal&Lang=fa-IR&ItemID=542&mid=14767.

\(^{2}\)http://www.nicico.com/DesktopModules/Articles/ArticlesView.aspx?TabID=1&Site=douranportal&Lang=falR&ItemID =563&mid =14767.

**Table 2. Correlation coefficient between size and grade of each deposit with the abundances of discriminated minerals.**

| Kaolinite | Muscovite | Jarosite | Alunite–pyrophyllite | Chlorite |
|-----------|-----------|----------|---------------------|----------|
| Grade     | 0.533     | 0.604    | 0.604               | 0.575    | 0.582 |
| Size      | 0.622     | 0.537    | 0.537               | 0.537    | 0.636 |
set of specific sites. These percentages showed that alteration minerals were identified with a relative accepted level of accuracy.

**Summary and conclusions**

In this paper, it is shown that how discriminated minerals through remote sensing data can be used to determine the potential of mineralization. It further demonstrates that remote sensing imagery and sub-pixel processing play an important role in mineral potential analysis, specially, on the spatial distribution of hydrothermal alteration zones. Investigation of 30 known deposits showed that mineral abundances which derived through sub-pixel analyses of ASTER data are a reasonable surface indicator to discriminate hydrothermal alteration zones of high-potential mineralization. The investigation revealed that high abundances of sericite, kaolinite, jarosite and chlorite were discriminated at giant, big and medium ore deposits such as Sarcheshmeh, Darrehzar, Meiduk and Nowchon, while small and low-grade deposits such as Sereidun, Kuhpanj, Bagkhoshk and Sarbagh are associated with moderate to low abundances. Low abundances of altered minerals are discriminated at deposits with no economic importance for porphyry copper such as Dehsiahan and Damaneh. The alteration minerals were not discriminated around small vein deposits such as Bondare Baghu, Bande Bagh, Sargoad and Chahmesi. In general, comparison of sub-pixel abundances with known mineral occurrences showed a reasonable correspondence such that areas with high abundances of alterations corresponded well with important mineralized districts. It is concluded that suggested sub-pixel analysis of ASTER data leads to identifying alteration zones with high-potential mineralization in PCDs. This should lead to further refinements in the use of remote sensing data for evaluating potential mineralization. Since sub-pixel analysis of ASTER data leads to identifying alteration zones with high-potential mineralization, it seems that applying appropriate thresholds on the results of other spectral processing techniques such as SAM, and etc. may be also useful in determination of high-potential mineralization.

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