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A Multiple-Stage Algorithm to Separate Hydrothermal Alteration Zones by ASTER Satellite Data: A case Study from Kerman Province

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Abstract

Image processing of remote sensing for separation hydrothermal alteration, in the case of missing initial spectra of pixels, can be a challenge for the researcher. The previous researches has shown that accurate separation of hydrothermal alteration zones using Conventional methods of image processing based on Spectral Properties of pixels, is not possible. Therefore, this research is trying to present a multi-stage algorithm that identify and discriminate the hydrothermal alteration zones in western part of Kerman province with high accuracy. To achieve this goal, the principal component analysis method, Fractal Concentration-Area Model and Full Index Kriging (FIK) geostatistical model are used in combination. The results show the high accuracy of the FIK model in identifying and separating each of the phyllic, argillic and propylitic alterations in the study area. Also, to evaluate the classification error, the Confusion matrix was investigated. The results of the Confusion matrix showed that the FIK model performs well in terms of image classification. Also, given the high number of training pixels in the phyllic zone, the FIK model has been able to identify this type of alteration very well.

Keywords

hydrothermal alteration, multiple-stage algorithm, principal component analysis, Fractal Concentration-Area Model, Full Index Kriging.

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1- Introduction

In remote sensing using different techniques, images are processed and mineral deposits alteration, mineralization and vegetation events, etc. are identified. Previous research has attempted to more accurately distinguish alteration and identify mineral deposits using different techniques. The Methods based on geostatistical estimates have been widely used in various sciences (Remy et al. 2009; Rossi and Deutsch; 2013). One of the most important geostatistical methods is full indicator kriging (FIK). In FIK method, IK algorithm is repeated at several different thresholds. Cumulative distribution function (CDF) is usually used to select thresholds for continuous data conversion to index data. However, in order to increase the speed and efficiency of estimation using FIK method, the study uses C-A fractal method to calculate the optimal threshold. Due to the high dependence between the hydrothermal alterations in the study area, using of principal component image analysis will increase the accuracy of separation of alteration zones. This study investigates the identification and separation of phyllic, argillic and propylitic alteration zones in Kerman magmatic arc by presenting a multi-stage algorithm. Finally, the results of the proposed algorithm are validated.

2- Methods

2-1- Concentration- Area fractal model

The fractal concentration-area model is used to provide a better view of the changes and differences in the image based on the values of the pixels, the frequency distribution of the pixels, as well as the spatial and geometric characteristics of the image patterns (Cheng et. al, 2002). In this model, the goal is to establish a relationship between the area and the threshold of the reflection percentage. This relationship is described below:

(1) $$A(PR \geq S) \propto PR^{-\alpha}$$

Where A(PR[1]) is the cumulative area enclosed by pixels whose reflection percentage is greater than and equal to S. Also, S is the threshold in the log-log concentration- area plot. α is the fractal dimension (Goncalves et. al, 1998).

2-2- Full Indicator Kriging

According to Equation (2), The random variable Z (u) is transformed into an IK with a doubled distribution (Badel et. al. 2011, Isaaks and Srivsatava, 1989, Liu et. al. 2004).

(2) $$I(u;z_k) = \begin{cases} 1 & if\ z(u_\alpha) \leq z_k \\ 0 & otherwies \end{cases}$$

In this case, Z(k) is a threshold with known value content. IK is a robust method for development of a spatial distribution for uncertainty. This method bears the minimum local variance (Marshall and Glass, 2012). The full indicator kriging is as follows:

(3) $$I(u;z_k) = \sum_{\alpha=1}^{n} \lambda_\alpha I(u_\alpha;z_k) + F(z_k)[1 - \sum_{\alpha=1}^{n} \lambda_\alpha]$$

In this equation $I(u;z_k)$ is the estimated value of the FIK method. λ_α is the weight of each pixel. $I(u_\alpha;z_k)$ is the value of the index variable in the desired pixel position (α). $F(z_k)$ is the cumulative frequency values in each threshold. In FIK, IK is conducted for a set of thresholds in zk=1..., K with distinct intervals from the continuous variable z (Isaaks and Srivsatava, 1989, Leuangthong et. al, 2011).

3- Findings and Argument

According to Figure 1, the graphs represent the three background communities, weak anomalies, and severe anomalies in the distribution of phyllic, argillic, and propylitic alterations. After determining the threshold for each alteration (Table 1), in the next step, According to Equation 2 and for each threshold, an image of the study area was produced.

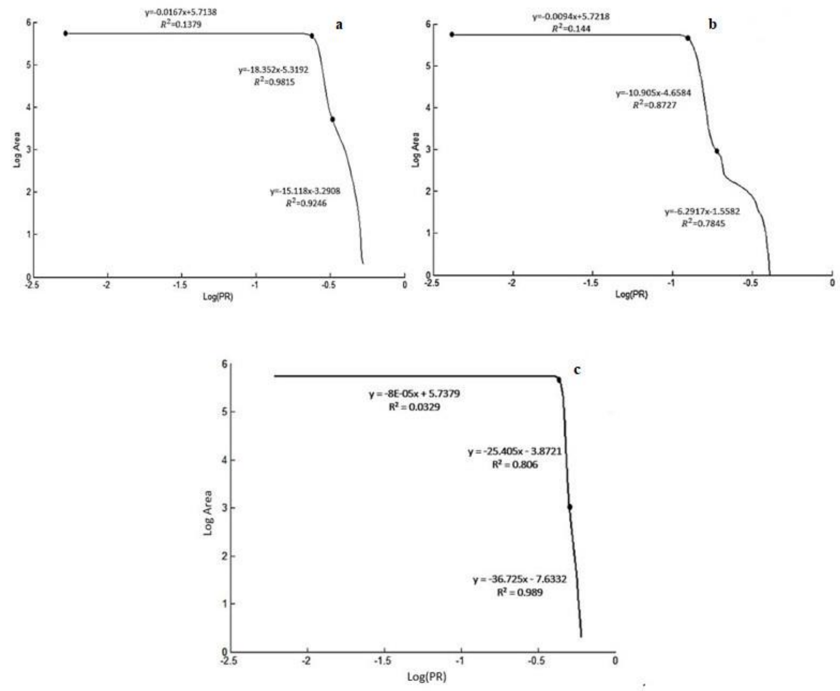

**Fig. 1. The log-log plot of percent reflection versus area,
a. phyllic alteration, b. propylitic alteration, c. argillic alteration.**

Table 1. Threshold of mineralized areas and background for phyllic alteration

alteration	Mineralized	Background
phyllic	0.054 - 0.266	-0.255 - 0.0538
propylitic	-0.132 - 0.0659	0.0659 - 0.272
argillic	0.543 - 0.604	0.006 - 0.543

Fig. 2. Full indicator kriging map of phyllic alteration in study area.

Fig. 3. Full indicator kriging map of argillic alteration in study area

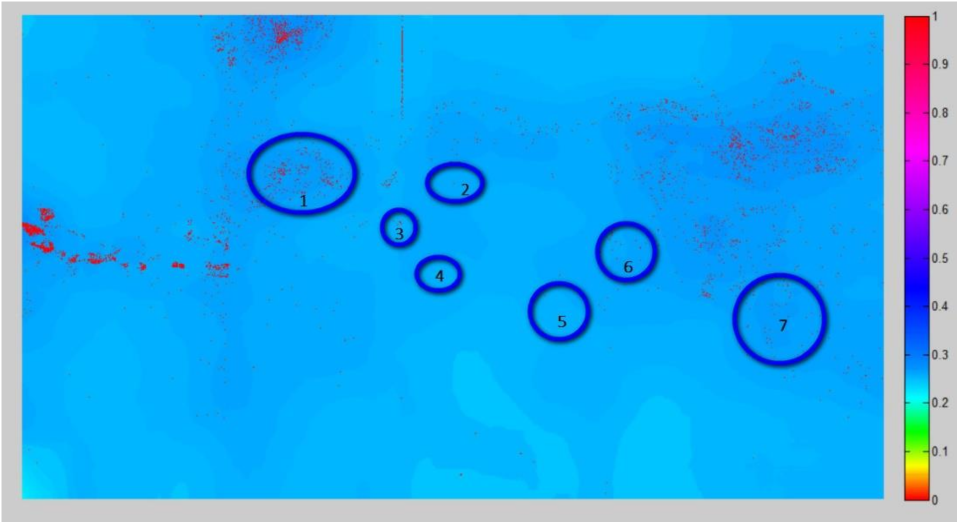

Fig. 4. Full indicator kriging map of propylitic alteration in study area

In order to evaluate the quality of the classification, the FIK model will be quantified in the form of a fusion matrix. According to Table 4, the error of removing the argillic zone is found to be 54.16%, which means that 54.16% of the pixels that belonged to the argillic zone, have classified in other zones mistakenly. The reason of this high error can be attributed to the lower number of traning pixels compared to other zones. However, given that the error rate of the argillic zone was zero, it can be concluded that the FIK model performed well in relation to image classification. Also, due to the large number of training pixels in the Phyllic zone, the FIK model has been able to identify this type of alteration.

Confussion matrix	Phyllic (field)	Argillic (field)	Propylitic (field)	total	Error of commission
Phyllic (FIK)	507	51	0	558	9.13%
argillic (FIK)	0	66	0	66	0%
propylitic (FIK)	24	27	279	330	15.45%
No alteration	60	0	213	273	
total	591	144	492	1227	
Error of omission	4.51%	54.16%	0%		Total accuracy: 89.30%

4- Conclusions

The results show the appropriate capability of the algorithm presented in identifying and distinguishing between phyllic, argillic, and propylitic alterations. In order to evaluate the classification error, the confusion matrix was investigated. The results of the confusion matrix show that the error of removing the argillic zone is 54.16%. This high error is due to the lower number of training pixels in this zone compared to other zones. However, given the zero error value of the argillic zone, it can be concluded that the proposed algorithm performed well in relation to image classification. Also, due to the large number of training pixels in the Phyllic zone, the proposed algorithm has been able to identify this type of alteration.

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