



1    **Remote sensing data processing by multivariate regression analysis  
2    method for iron mineral resource potential mapping: A case study in  
3    Sarvian area, central Iran.**

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12    **ABSTRACT**

13    This paper ~~used~~ multivariate regression to create a mathematical model (with reasonable accuracy) for iron skarn  
14    exploration in the region of the interest and ~~generalizing~~ multivariate regression in Mineral Prospectivity Mapping  
15    (MPM) field. The main target of this manuscript is to ~~exist~~ multivariate regression analysis (as a MPM method) to  
16    ~~iron outcrops mapping from~~ northeast part of the study area to discover new iron deposits in other parts. Two types of  
17    multivariate regression models as two linear equations were employed to discover new mineral deposits. The Aster  
18    satellite image bands (14 bands) ~~sets~~ as Unique Independent Variables (UIVs) and iron outcrops map as dependent  
19    variables ~~were used for MPM~~. According to the results of p-value,  $R^2$  and  $R^2_{adj}$ , the second regression model (which  
20    ~~was a~~ multiples and exponents of UIVs) was the fitted model ~~versus other models~~. ~~Also~~ the accuracy of the model  
21    was confirmed by iron outcrops map and geological observations. Based on field **observation** iron mineralization  
22    occurs as contact ~~of~~ limestone and intrusive rocks (skarn type). ~~Iron minerals consist dominantly of magnetite,~~  
23    ~~hematite and goethite.~~

24

25    **Key words:** Multivariate regression, Mineral Prospectivity Mapping, Iron, Sarvian

26



27 **1. INTRODUCTION**

28 Diagnosing futuristic zones and finding new mineral deposits ~~in the region of interest~~, is the  
29 definitive main of mineral investigation. One way to achieve this aim is Using satellite image  
30 processing for ~~identify~~ Mineral Prospectivity Mapping (MPM) (Carranza, 2008; Abedi et al., 2013;  
31 Golshadi et al., 2016 and Feizi et al., 2012).

32 ~~The utilization of~~ satellite images for mineral investigation has been extremely effective in  
33 indicating out the ~~attendanee~~ of minerals. Likewise, remote sensing gives the synoptic view; which  
34 is useful in distinguishing ~~proof and delineation of~~ different land frames, linear features, and  
35 structural elements (Feizi and Mansouri, 2013b).

36 The main objective of this manuscript is to use multivariate regression analysis (as a MPM  
37 method) to pixel values of Aster satellite image from north-east part of the study area to identify  
38 new iron deposits in other parts. Two types of multivariate regression models ~~utilized~~ to find new  
39 mineral deposits, ~~using pixel values of~~ Aster satellite image ~~bands (14 band) sets~~ as Unique  
40 Independent Variables (UIVs) and Iron outcrops surface (digitized by geology map of study area  
41 (scale 1:5000) and **check field**) data as dependent variables.

42 **Regression analyses have been utilized as a part of numerous logical fields, such as**  
43 **geosciences.**

44 **Identification** of stream sediment anomalies have been used by multiple regression analyses  
45 (e.g., Carranza, 2010a; Carranza, 2010b). Likewise, multivariate regression has been effectively  
46 utilized by Granian et al. (2015) to display subsurface mineralization from lithogeochemical  
47 information. Granian et al. (2015) utilized four types of multivariate regression models to depict  
48 significant surface geochemical anomalies for acknowledgment subsurface gold mineralization  
49 utilizing borehole data as dependent variables and surface lithogeochemical data as independent  
50 variables.

51 ~~This paper utilized multivariate regression to make a mathematical model (with sensible~~  
52 ~~precision) for iron potential zones investigation in the region of the interest and summing up~~  
53 ~~multivariate regression in remote sensing field.~~

54  
55 **2. STUDY AREA**

56 The Sarvian area is located in the Orumieh-Dokhtar magmatic arc in Central ~~of~~ Iran (Fig. 1a).  
57 This magmatic arc is the most imperative metallogenic area inside the district ~~and~~ hosts the  
58 majority of ~~the larger metals~~ deposits such as lead, zinc, copper and iron (Feizi et al., 2016 and  
59 Feizi et al., 2017).

60 The explored zone ~~determined~~ by Eocene intrusive rocks and carbonates of Qom formation.  
61 Several types of metal and non-metal mineral ore deposits have ~~as of now~~ been reported in the



62 study area. According to the 1:100,000 geological map of Kahak, the lithology of this part includes  
63 cream limestone with intercalations of marls (Qom formation), dark green, andesitic-basaltic lava,  
64 volcanic breccia, hyaloclastic limestone, green megaporphyritic andesitic-basaltic lava,  
65 rhyodacitic domes, tonalite-quartzdiorite, microquartzdiorite-microquartzmonzo-diorite, granite-  
66 granodiorite, alteration of light green, grey tuff, tuffaceous sandstone and shale with intercalation  
67 of nummulitic sandy limestone and andesitic lava, grey limestone, orbitolina bearing, thick bedded  
68 to massive (Aptian-Albian) (Feizi et al., 2016) (Fig. 1b).

69 ~~In view~~ of the current confirmations and ~~furthermore~~ contact of intrusive bodies with carbonate  
70 rocks (Qom arrangement) and Iron outcrops in the north-east of study area, Calcic iron skarn ore  
71 (Sarvian mine) is located in the northeast of study area (Feizi et al., 2017) (Fig. 2).

72

### 73 3. MULTIVARIATE REGRESSION

74 Regression analyses is a good statistical manner for analysing relationships among variables  
75 (Granian et al., 2015). This strategy can show the conduct of an event (a dependent variable) in  
76 light of related variables (some independent variables). In regression analyses, if a dependent  
77 variable called ( $Y$ ) and independent variables called ( $x_i$ ), the equation is:

78 
$$Y = f(x_i). \quad (1)$$

79  $Y$  could be linear or non-linear function. Linear regression is used for modeling mineral  
80 prospectivity in the Sarvian area. For linear regression  $Y$  is defined as follows:

81 
$$Y = a_0 + a_1x_1 + a_2x_2 + \dots + a_ix_i + \varepsilon, \quad i = 1, 2, \dots, n. \quad (2)$$

82

83 For this function, the constant factor is  $a_0$ , the random error is  $\varepsilon$ , and the regression  
84 coefficients are  $a_i$ . If there were  $n$  samples in a data set, for each sample  $t$  variables were  
85 measured. Thus, function (2) can be as follows:

86

87 
$$Y_i = \hat{a}_0 + \hat{a}_1X_{i1} + \hat{a}_2X_{i2} + \dots + \hat{a}_tX_{it} + \varepsilon_i, \quad i = 1, 2, \dots, n. \quad (3)$$

88

89

90 Equation (3) can be re-written as a matrix. The linear function matrix is:

91 
$$[Y] = [X][A] + [\varepsilon]. \quad (4)$$



92

$$93 \quad [Y] = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix}; [A] = \begin{bmatrix} \hat{a}_0 \\ \hat{a}_1 \\ \vdots \\ \hat{a}_t \end{bmatrix}; [X] = \begin{bmatrix} 1 & X_{11}X_{12} \dots X_{1t} \\ 1 & X_{21}X_{22} \dots X_{2t} \\ \vdots & \vdots \\ 1 & X_{n1}X_{n2} \dots X_{nt} \end{bmatrix}; [\varepsilon] = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}. \quad (5)$$

94

95 The least squares technique is used for estimating  $[A]$  as the coefficient matrix, as follows:

96

$$97 \quad [A] = [\Sigma]^{-1}[C] = ([X]'[X])^{-1}[X]'[Y]. \quad (6)$$

98

99 The inverse of variance-covariance samples matrix is  $[\Sigma]^{-1}$  and the covariance matrix among  
 100 independent variable and samples is  $[C]$ . Thus by equation 6, the regression coefficients model is  
 101 calculated.

102 In regression analysis, some criteria are required to review. These criteria are as follows:

103 1. The variance and the mean of the random error should be a constant value and zero,  
 104 respectively.

105 2. The coefficient of determination value ( $R^2$ ) should be examined. This value is calculated as  
 106 follows (Granian et al., 2015):

107

$$108 \quad R^2 = \frac{\sum_{i=1}^n (\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2}. \quad (7)$$

109

110 The mean of the variable ( $\bar{Y}$ ), value of  $i$ th sample ( $Y_i$ ) and estimated value of the  $i$ th sample  
 111 ( $\hat{Y}_i$ ) for dependent variables were used in equation 7. The calculated  $R^2$  value determined within  
 112 [0, 1] range. The value of  $R^2$  is close to 1 for well fitted models.

113 1. According to the fact that adding independent variables to the model will increasing  $R^2$   
 114 value, the adjusted determination coefficient ( $R_{adj}^2$ ) is defined as follows (Granian et al.,  
 115 2015):

$$116 \quad R_{adjusted}^2 = 1 - \frac{n-1}{n-t} (1 - R^2). \quad (8)$$



117 As it was mentioned,  $n$  is number of samples (or data) and  $t$  is the number of variables (or  
118 regression coefficients). If a set of explanatory variables are introduced into a regression one at a  
119 time, with the  $R_{adj}^2$  computed each time, the level at which  $R_{adj}^2$  reaches a maximum, and decreases  
120 afterward, would be a well fitted model.

121 2. In regression analyses, the model should be fitted to the data. Accordingly, the p-value of  
122 the regression model in Analysis of variance (ANOVA) test should be acceptable (less  
123 than or equal to 0.05). Also calculating p-value of final coefficients for each model, could  
124 help on optimizing and improving the model. This criterion could be considered after  
125 choosing the best model.

#### 126 4. GEO-DATA SETS PREPARATION

127 The iron ore skarn type located in the northeastern of Sarvian area. There are several iron vein  
128 and outcrop in this area. According to the regional geological conditions of the area, the data set  
129 of this iron mine is a good model for exploring the surrounding area. In this paper, satellite imagery  
130 and map the geology of the mine is used as a training area. In the training area, this method can  
131 model the iron outcrops (a dependent variable) based on Aster satellite image bands (some  
132 independent variables) (Fig. 3).

133 Figure 3 is about here.

#### 134 4.1. REMOTE SENSING DATA (INDEPENDEBT VARIABLES)

135 The ASTER sensor was propelled in December 1999 on board the Earth Observation System  
136 (EOS) US Terra satellite to record sun powered radiation in 14 spectral bands (Table 1). ASTER  
137 provides high-resolution images of the land surface, water, ice, and clouds using three separate  
138 sensor subsystems covering 14 multi-spectral bands from visible to thermal infrared. The  
139 significant resolution scales are 15m, 30m, and 90m in the visible, short-wave IR, and thermal fR,  
140 respectively. ASTER consists of three different subsystems; the Visible and Near Infrared (VNIR),  
141 the Shortwave Infrared (SWIR), and the Thermal Infrared (TIR). To find out more about each  
142 module click on the item of interest (Feizi and Mansouri, 2013b and Mansouri and Feizi, 2016).

143 Several factors influence the signal measured at the sensor, for example, float of the sensor  
144 radiometric calibration, atmospheric and topographical effects. In this way, Aster data collection  
145 was utilized and radiance correlation, such as wavelength, dark subtract and log residual by  
146 ENVI5.1 software which is basic for multispectral images, were utilized (Mansouri et al., 2015).

147 In this study after the corrections, pixels size of SWIR and TIR bands based on VNIR3 band  
148 (Panchromatic band) convert to 15 meter, than use layer stacking function to build a new multiband  
149 file from georeferenced images of various pixel sizes, extents, and projections.

#### 150 4.2. MAPPING OF IRON OUPCROPS (DEPENDENT VARIABLE)



151 The iron ore skarn type located in the northeastern of Sarvian area. There are several iron vein  
152 and outcrop in this area. In order to mapping of iron outcrops in the training area used from  
153 Geological map (1:1000 scale) of iron ore deposit and check field. For preparing of this layer, the  
154 shape file layer of iron outcrops convert to raster file with pixel size of 15 meter.

## 155 5. REGRESSION ANALYSES IN THE STUDY AREA

156 Regression analyses needs making proper models. Utilizing multiple, factorial, polynomial and  
157 reaction surface regressions have been utilized as a part of numerous logical fields such as  
158 geosciences (e.g. Granian et al., 2015). Thus, in this study; Model 1 ( $Y_1$ ) was generated as a  
159 multiple linear regression model and Model 2 ( $Y_2$ ) was created from  $Y_1$  plus multiplied UIVs. The  
160 formulas of two mentioned models are presented in Table 2. So in summary, two linear equations  
161 ( $Y_1$  and  $Y_2$ ) were utilized to discover new mineral deposits, using pixel values of Aster satellite  
162 image as independent variables and map of iron outcrops as dependent variables. The models  
163 which were proposed in this paper, had become more complexes respectively 1 to 2, model 2 has  
164 106 coefficients (14 for UIVs, 1 as constant, 91 for multiples of UIVs) and model 1 has 15  
165 coefficients (14 for UIVs, 1 as constant, 0 for multiples and exponents of UIVs) (Table 2).

166 For assessing the models which are exhibited in Table 2, regression analyses were performed  
167 and the critical criteria which are mentioned before, were examined. The values of the  $R^2$ ,  $R^2_{adj}$   
168 and p-value of ANOVA test of 2 multivariate regression models are provided in Table 3.  
169

170 Also, Table 4 is presented the calculated coefficients of independent variables in regression  
171 models. Other independent variables which are not mentioned in Table 4 were excluded variables.  
172 The excluded variables have no effect on the models. This means that, excluded variables didn't  
173 have any effect on iron mineralization and behavior of iron outcrop map.

174

## 175 6. DISCUSSION

176 For distinguishing the best model among 2 models, a few criteria are required to review.

177 Firstly, the variance and the mean of the random error were acceptable for all of regression  
178 models. Secondly, based on Table 4, the p-values of ANOVA test of 2 multivariate regression  
179 models were equal to 0. For regression models the acceptable p-value should be less than or equal  
180 to 0.05. Thus, this criterion confirmed the validity of models without specifying the most  
181 appropriate model.

182 On the other hand, the value of  $R^2$  is close to 1 for well fitted models. The  $R^2$  values of  
183 regression models are presented in Table 3. The lowest  $R^2$  belongs to  $Y_1$  and the highest belongs to  
184  $Y_2$ . Thus,  $Y_2$  model is better from  $Y_1$  model.



185 According to the fact that adding independent variables to the model will ~~increasing~~  $R^2$  value,  
186 the  $R^2_{adj}$  value should be checked. The  $R^2_{adj}$  values of regression models are presented in Table 3.  
187 As it was mentioned before, if a set of variables are introduced into a regression, with the  
188  $R^2_{adj}$  computed each time, the level at which  $R^2_{adj}$  reaches a maximum, and decreases afterward,  
189 would be a well fitted model. So, according to Table 3,  $Y_2$  would be the fitted model versus other  
190 models. Thus,  $Y_4$  regression model is the most appropriate model for Mineral Prospectivity  
191 Mapping.

192 **Thus** according to the results of p-value (ANOVA test),  $R^2$  and  $R^2_{adj}$ , the Second regression  
193 model ( $Y_2$ ) would be the fitted model versus other models. For generating the mineral prospectivity  
194 map the formula of  $Y_2$  was performed in ArcGIS software by raster calculator tool. The normalized  
195 mineral prospectivity map of the study area is presented in Fig. 4.

196 To assess the exactness of the selected model, the created prospectivity map was checked by  
197 the iron outcrops map in the northeast part of the study area (Fig. 5). The locations of iron outcrops  
198 have appropriate adoption with favorable areas of mineral prospectivity map. **In addition**, the  
199 adaption of prospectivity map with the iron outcrops in the northeast part of the study area, three  
200 target areas with very high favourability, were checked and the prospectivity map was confirmed  
201 by geological observations (Fig. 6). **Based on field observation** iron mineralization occurs as  
202 contact of limestone and intrusive rocks (skarn type). **Iron mineralizations consist dominantly of**  
203 **magnetite, hematite and goethite. Therefore, the accuracy of mineral prospectivity map confirmed**  
204 **in the Sarvian area.**

205

## 206 7. CONCLUSION

207

208 The conclusions of this manuscript are presented ~~in summary~~ as follows.

209 1) The application of multivariate regression analysis (as a MPM method) was confirmed in  
210 the Sarvian area. This paper ~~used~~ multivariate regression to create a mathematical model (with  
211 reasonable accuracy) for iron mineral exploration in the region of the interest and ~~generalizing~~  
212 multivariate regression in MPM field.

213 2) Two types of multivariate regression models as two linear equations were employed to  
214 discover new mineral deposits. According to the results of p-value,  $R^2$  and  $R^2_{adj}$ , the second  
215 regression model was the ~~fitted~~ model versus other models.

216 3) **Also** the accuracy of the model was confirmed by iron outcrops map and geological  
217 observations. Based on field observation iron mineralization **occurs** **contact of limestone and**  
218 **intrusive rocks (skarn type). Iron mineralizations consist dominantly of magnetite, hematite and**  
219 **goethite.**



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224 **REFERENCES**

225 Carranza, E.J.M., 2008, Geochemical anomaly and mineral prospectivity mapping in GIS,  
226 Handbook of Exploration Environmental Geochemistry. Elsevier, Amsterdam, 368 p.

227 Carranza, E.J.M., 2010a, Catchment basin modelling of stream sediment anomalies revisited:  
228 incorporation of EDA and fractal analysis. *Geochemistry: Exploration, Environment, Analysis*,  
229 10, 365–381.

230 Carranza, E.J.M., 2010b, Mapping of anomalies in continuous and discrete fields of stream  
231 sediment geochemical landscapes. *Geochemistry: Exploration, Environment, Analysis*, 10, 171–  
232 187.

233 Feizi, F. and Mansouri, E., 2012, Identification of Alteration Zones with Using ASTER Data  
234 in A Part of Qom Province, Central Iran. *Journal of Basic and Applied Scientific Research*, 2, 73–  
235 84.

236 Feizi, F. and Mansouri, E., 2013a, Separation of Alteration Zones on ASTER Data and  
237 Integration with Drainage Geochemical Maps in Soltanieh, Northern Iran. *Open Journal of  
238 Geology*, 3, 134–142.

239 Feizi, F. and Mansouri, E., 2013b, Introducing the Iron Potential Zones Using Remote Sensing  
240 Studies in South of Qom Province, Iran. *Open Journal of Geology*, 3, 278–286.

241 Feizi, F., Mansouri, E. and KarbalaeiRamezanali, A., 2016, Prospecting of Au by Remote  
242 Sensing and Geochemical Data Processing Using Fractal Modelling in Shishe-Botagh, Area (NW  
243 Iran). *Journal of the Indian Society of Remote Sensing*, 44, 539–552.

244 Feizi, F., KarbalaeiRamezanali, A. and Mansouri, E., 2017, Calcic iron skarn prospectivity  
245 mapping based on fuzzy AHP method, a case Study in Varan area, Markazi province,  
246 Iran. *Geosciences Journal*, 21, 123–136.

247 Granian, H., Tabatabaei, S. H., Asadi, H. H. and Carranza, E. J. M., 2015, Multivariate  
248 regression analysis of lithogeochemical data to model subsurface mineralization: a case study from  
249 the Sari Gunay epithermal gold deposit, NW Iran. *Journal of Geochemical Exploration*, 148, 249–  
250 258.



251        Golshadi, Z., KarbalaeiRamezanali, A. and Kafaei, K., 2016, Interpretation of magnetic data  
252        in the Chenar-e Olya area of Asadabad, Hamedan, Iran, using analytic signal, Euler deconvolution,  
253        horizontal gradient and tilt derivative methods. *Bollettino di Geofisica Teorica ed Applicata*, 57,  
254        329–342.

255        Mansouri, E., Feizi, F. and KarbalaeiRamezanali, A., 2015, Identification of magnetic  
256        anomalies based on ground magnetic data analysis using multifractal modelling: a case study in  
257        Qoja-Kandi, East Azerbaijan Province, Iran. *Nonlinear Processes in Geophysics*, 22, 579–587.

258        Mansouri, E., Feizi, F., 2016, Introducing Au potential areas, using remote sensing and  
259        geochemical data processing using fractal method in Chartagh, western Azarbjan – Iran, E.  
260        Mansouri, F. Feizi, Arch. Min. Sci., Vol., No 2, 397–414.

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279 **Table 1.** Wavelength ranges and spatial resolutions of ASTER bands (Abrams, 2000).  
 280

Module	VNIR	SWIR	TIR
Spectral bandwidth (μm)	Band 1 0.52 - 0.60	Band 4 1.650 - 1.700	Band 10 8.125 - 8.475
	Band 2 0.63 - 0.69	Band 5 2.145 - 2.185	Band 11 8.475 - 8.825
	Band 3 N 0.78 - 0.86	Band 6 2.185 - 2.225	Band 12 8.925 - 9.275
	Band 3 B 0.78 - 0.86 (backward looking)	Band 7 2.235 - 2.285	Band 13 10.25 - 10.95
		Band 8 2.295 - 2.395	Band 14 10.95 - 11.65
		Band 9 2.360 - 2.430	
Spatial resolution (m)		15	30
			90

281  
 282

283 **Table2.** Formula of regression models used for Aster satellite image bands  
 284

Types of Regression	Number of coefficients	Formula
First-Degree	15	$Y_1 = a_0 + a_1x_1 + a_2x_2 + \dots + a_{14}x_{14}$ $Y_2 = Y_1 + a_{15}x_1x_2 + a_{16}x_1x_3 + \dots + a_{27}x_1x_{14} + a_{28}x_2x_3 + a_{29}x_2x_4 + \dots + a_{39}x_2x_{14} + a_{40}x_3x_4 + a_{41}x_3x_5 + \dots + a_{50}x_3x_{14} + a_{51}x_4x_5 + \dots + a_{60}x_4x_{14} + a_{61}x_5x_6 + \dots + a_{69}x_5x_{14} + a_{70}x_6x_7 + \dots + a_{77}x_6x_{14} + a_{78}x_7x_8 + \dots + a_{84}x_7x_{14} + a_{85}x_8x_9 + \dots + a_{90}x_8x_{14} + a_{91}x_9x_{10} + \dots + a_{96}x_9x_{14} + a_{97}x_{10}x_{11} + \dots + a_{100}x_{10}x_{14} + a_{101}x_{11}x_{12} + \dots + a_{103}x_{11}x_{14} + a_{104}x_{12}x_{13} + a_{105}x_{12}x_{14} + a_{106}x_{13}x_{14}$
First-Degree	106	

285  
 286

287 **Table 3.** The values of the  $R^2$ ,  $R^2_{adj}$  and p-value of ANOVA test of 2 multivariate regression  
 288 models

Models	$R^2$	$R^2_{adj}$	p-value (ANOVA)
$Y_1$	0.738	0.715	0
$Y_2$	0.847	0.829	0

289



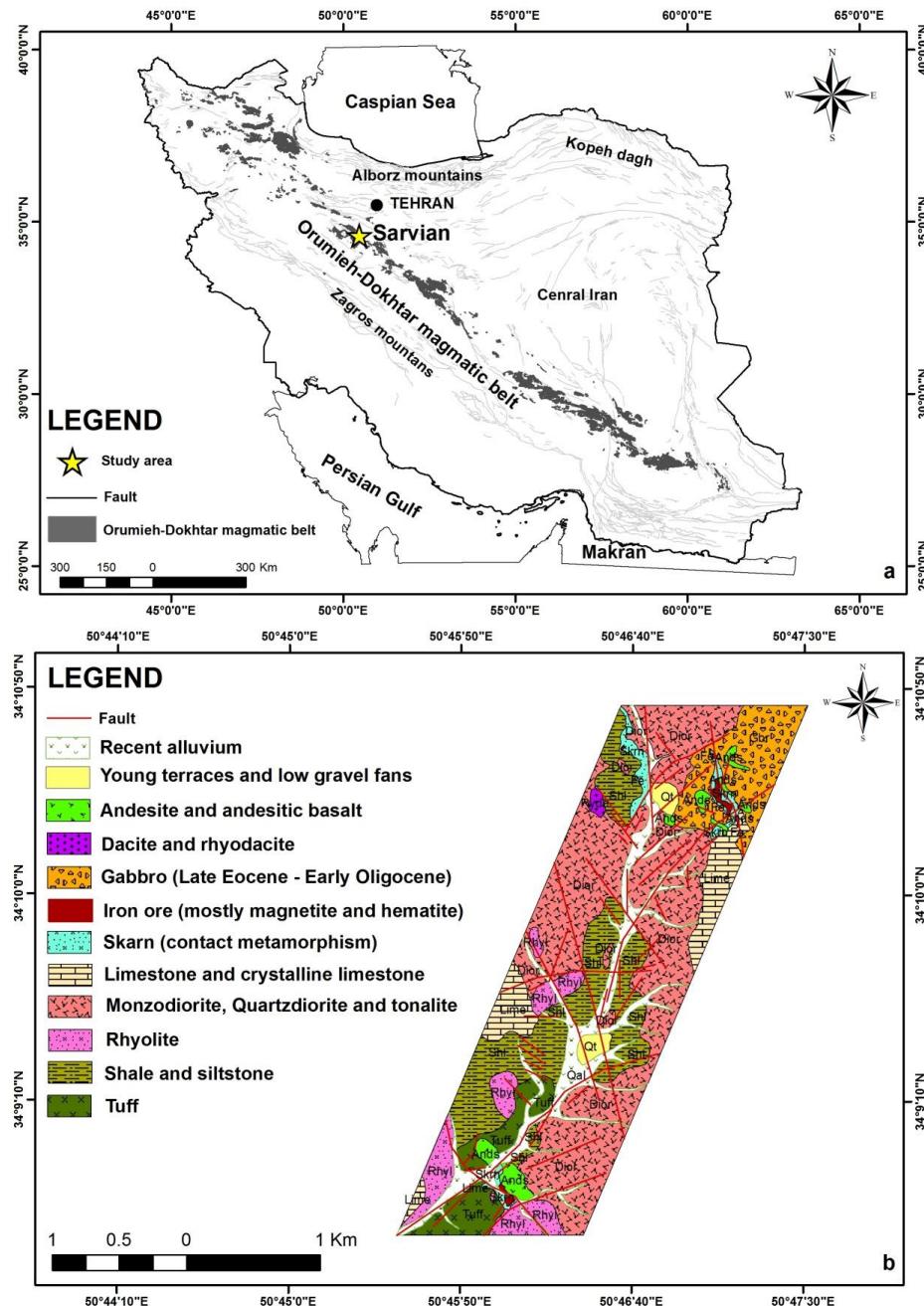
290

291 **Table 4.** The calculated coefficients of regression models 1 and 2.

Model 1		Model 2	
variables	Coefficients ( $a_i$ )	variables	Coefficients ( $a_i$ )
CST	0.275	CST	0.677
$x_1$	-0.01	$x_1$	-0.014
$x_2$	-0.12	$x_2$	-0.019
$x_3$	-0.019	$x_3$	-0.045
$x_4$	0.003	$x_4$	0.022
$x_5$	-0.006	$x_5$	-0.017
$x_6$	-0.005	$x_6$	-0.001
$x_7$	-	$x_7$	-
$x_8$	-0.004	$x_8$	-0.02
$x_9$	-0.005	$x_9$	-0.006
$x_{10}$	0.009	$x_{10}$	-0.014
$x_{11}$	0.005	$x_{11}$	0.024
$x_{12}$	0.016	$x_{12}$	0.024
$x_{13}$	0.002	$x_{13}$	0.018
$x_{14}$	0.022	$x_{14}$	0.036
-	-	$x_1 x_4$	-0.0009
-	-	$x_1 x_6$	-0.0002
-	-	$x_4 x_9$	-0.0009
-	-	$x_7 x_8$	0.00082

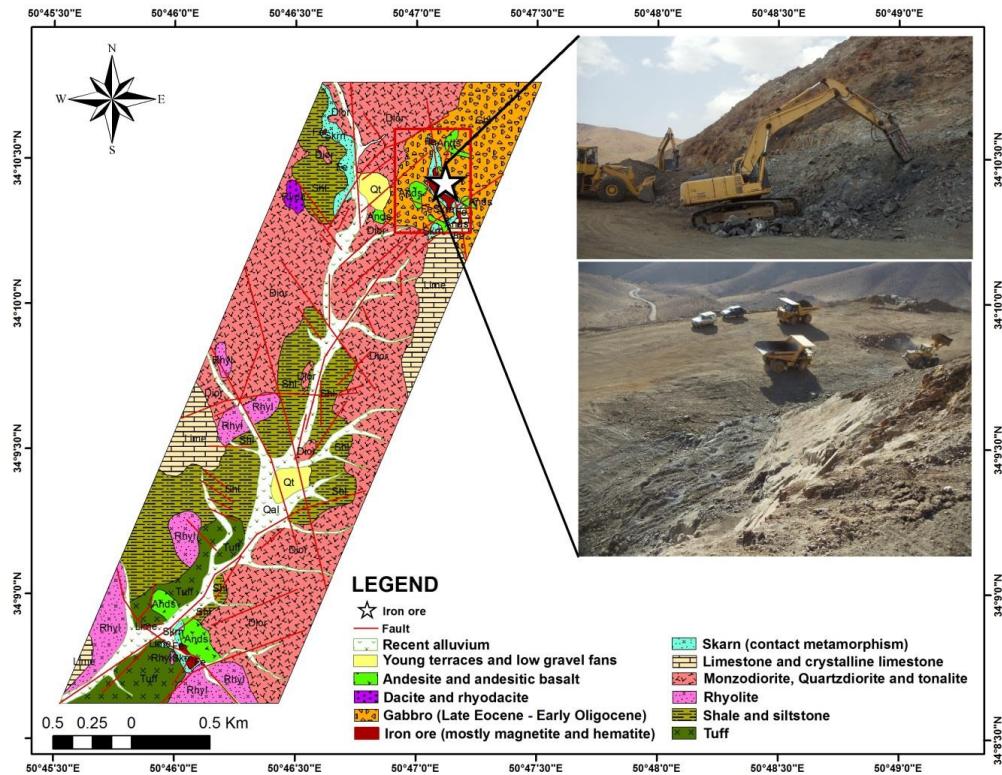
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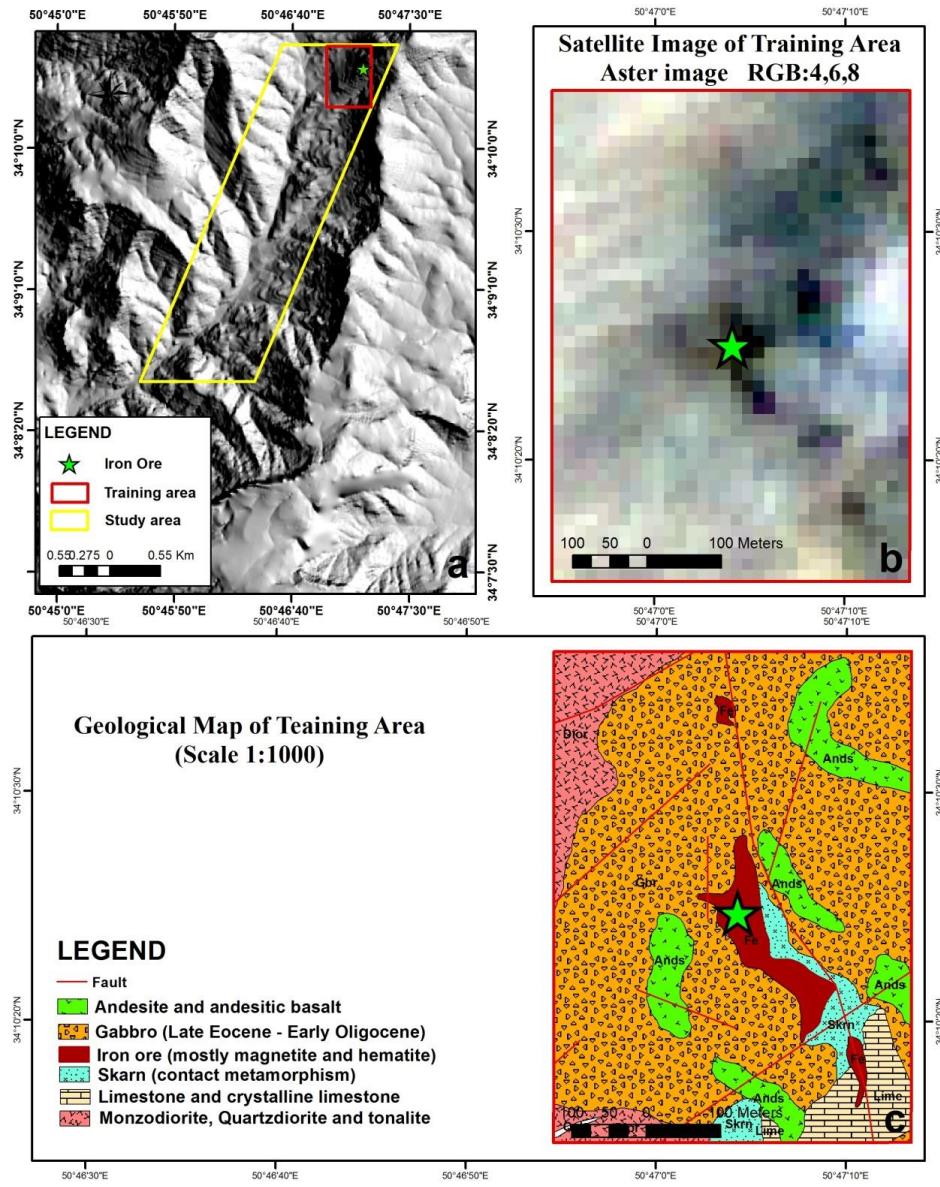
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296 **Fig. 1. a)** The location of the Sarvian area in the Urumieh–Dokhtar magmatic belt, Iran **b)** Geological map  
 297 of Sarvian area (scale 1:25000)

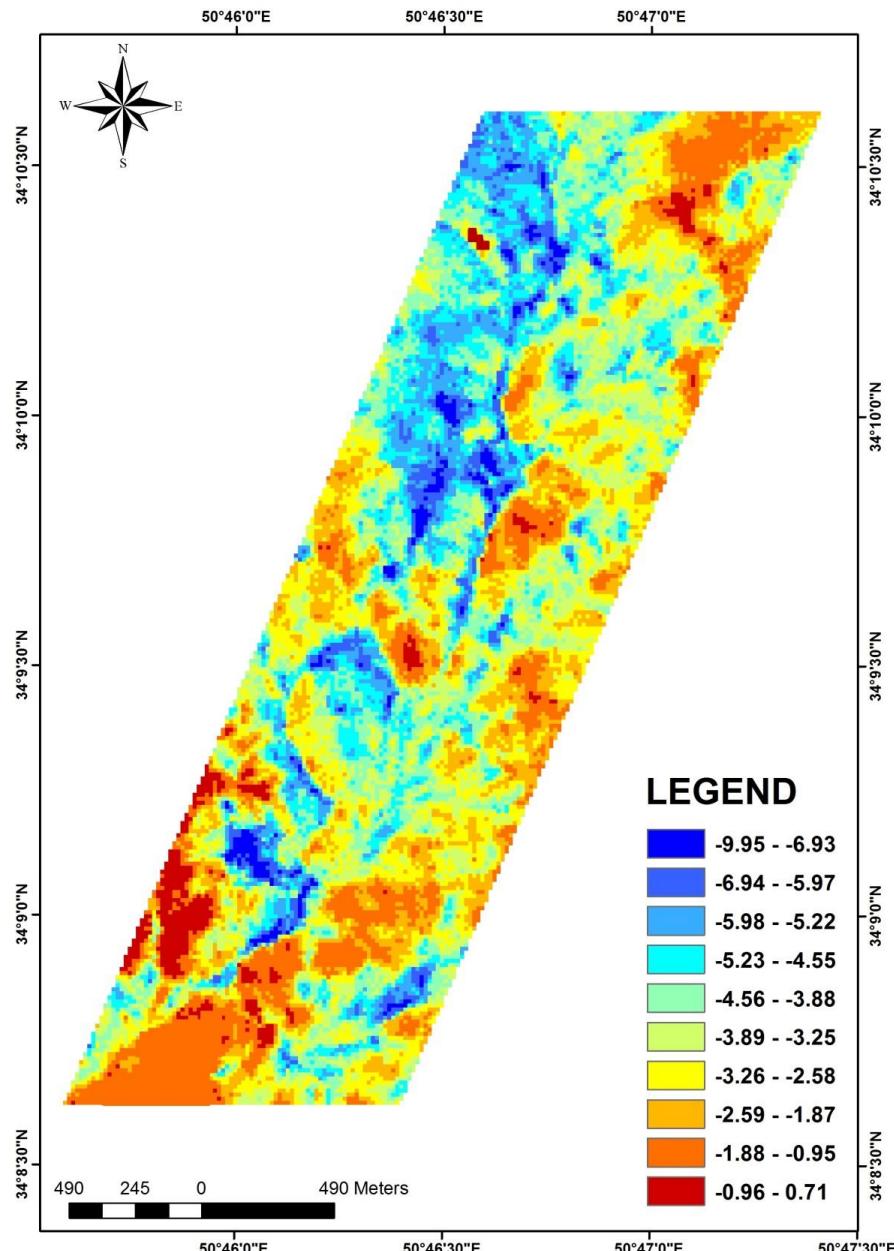


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299 **Fig. 2.** Location of Sarvian iron mine in the study area



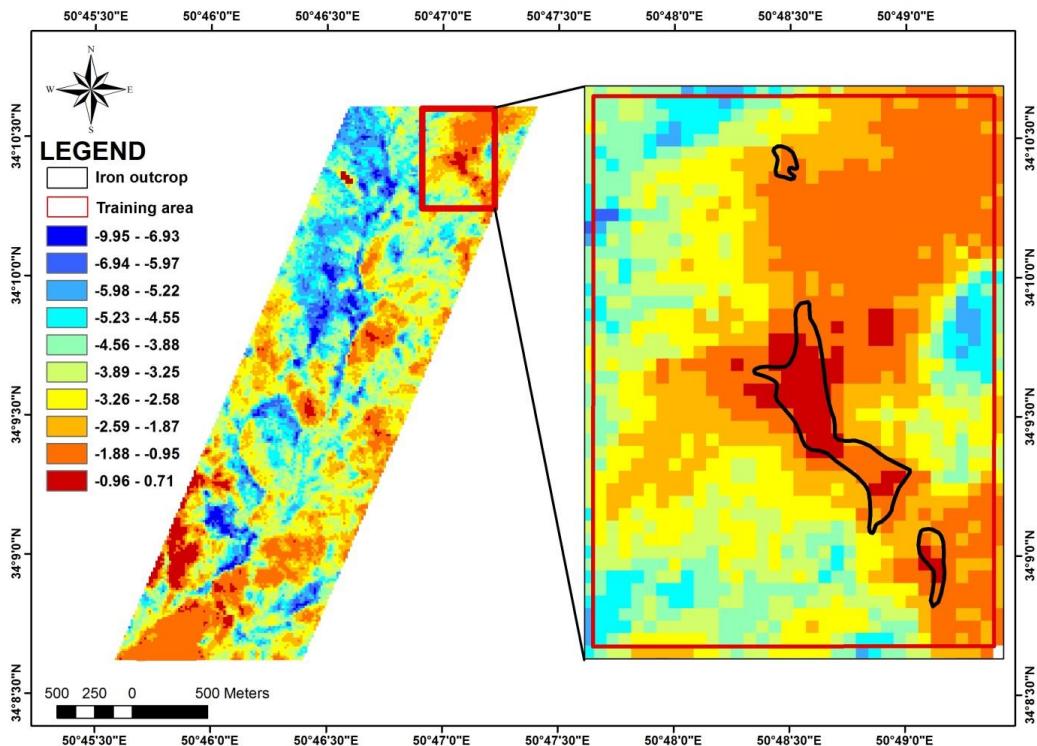
300  
 301 **Fig. 3.** a) Location of training area in the study area. b) Aster satellite image in the training area  
 302 (RGB:4,6,8). c) Geological map (scale 1:1000) of training area.



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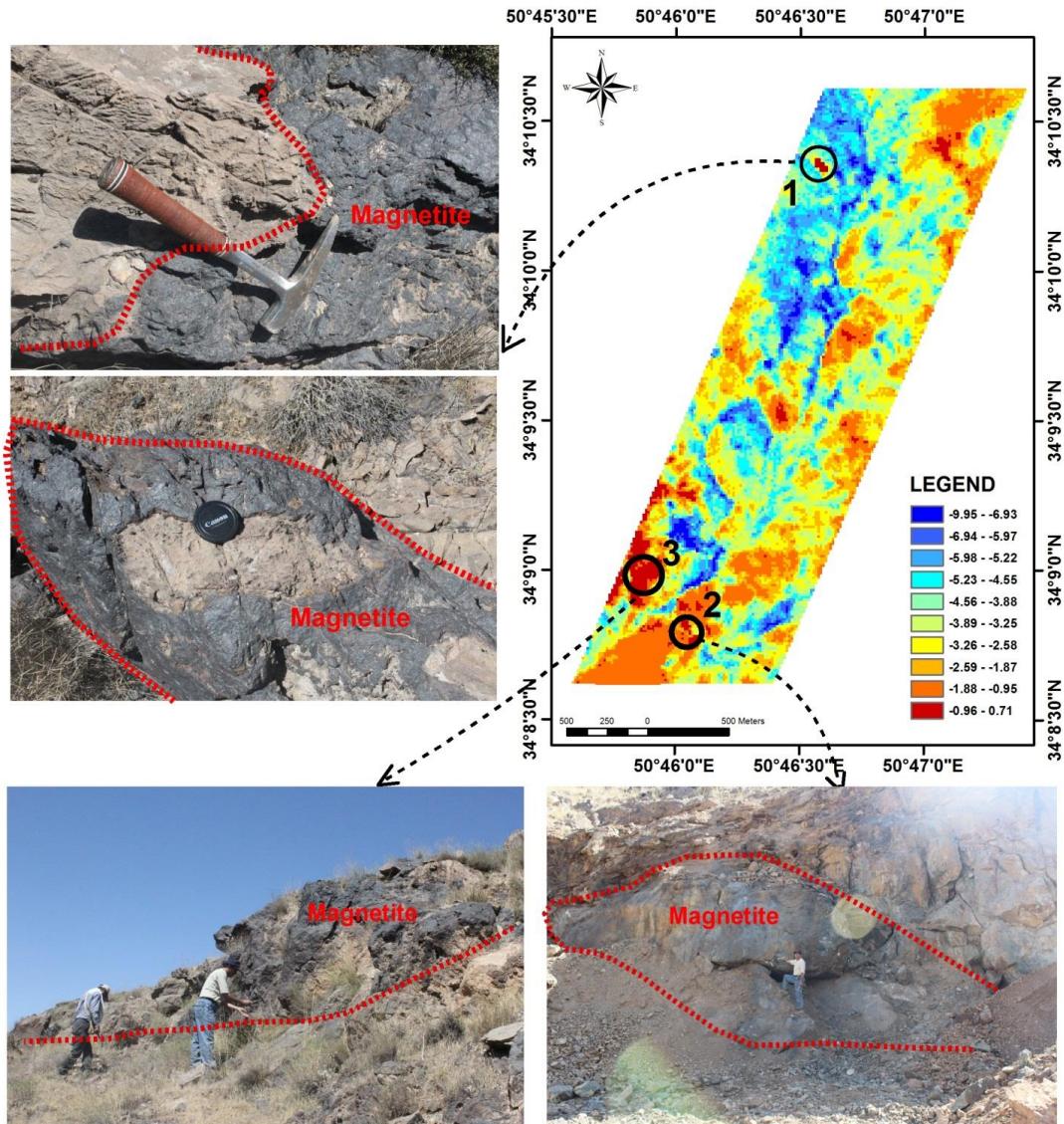
**Fig. 4.** Mineral prospectivity map of the Sarvian area.



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306 **Fig. 5.** Mineral prospectivity map of the Sarvian area which confirmed by iron outcrops.

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309 **Fig. 6.** Mineral prospectivity map of the Sarvian area which confirmed by check field of three target  
310 areas.

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