

Application of multivariate regression on magnetic data to determine further drilling site for iron exploration

*Original*

Application of multivariate regression on magnetic data to determine further drilling site for iron exploration / Feizi, Faranak; Abbas Karbalaeei-Ramezanali, Amir; Farhadi, Sasan. - In: OPEN GEOSCIENCES. - ISSN 2391-5447. - 13:1(2021), pp. 138-147. [10.1515/geo-2020-0165]

*Availability:*

This version is available at: 11583/2974269 since: 2023-01-03T11:20:38Z

*Publisher:*

De Gruyter

*Published*

DOI:10.1515/geo-2020-0165

*Terms of use:*

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

*Publisher copyright*

(Article begins on next page)

## Research Article

Faranak Feizi\*, Amir Abbas Karbalaeei-Ramezanali, and Sasan Farhadi

# Application of multivariate regression on magnetic data to determine further drilling site for iron exploration

<https://doi.org/10.1515/geo-2020-0165>

received May 17, 2020; accepted January 16, 2021

**Abstract:** In this study, a new approach of the multivariate regression model has been applied to make a precise mathematical model to determine further drilling for the detailed iron exploration in the Koohbaba area, Northwest of Iran. Furthermore, to figure out the additional drilling locations, the ore length to the total core ratio for the drilled boreholes has been used based on the geophysical exploration dataset. Hence, different regression analyses including linear, cubic, and quadratic models have been applied. In this study, the ore length to the total core ratio of the chosen drilled boreholes has been considered as a dependent variable; besides, the outputs of the magnetic data using the UP10 (10m upward-continuation), RTP (reduction to the pole), and A.S. (analytic signal) techniques have been designated as independent variables. Based on probability value ( $p$ -value), coefficients of determination ( $R^2$  and  $R_{adj}^2$ ), and efficiency formula (EF), the fourth regression model has revealed the best results. The accuracy of the model has been confirmed by the defined ratio of boreholes and demonstrated by four additional drilled boreholes in the study area. Therefore, the results of the regression analysis are reasonable and can be used to determine the additional drilling for the detailed exploration.

**Keywords:** multivariate regression, mathematical model, drilling, iron exploration, magnetic data

## 1 Introduction

The modern mineral exploration is the definitive aim for the geophysical examination. Hence, several geophysical maps should generate to examine the underground mineral perception [1]. To determine the best zone, drilling of some boreholes is fundamental. Although the most reliable examination for the deposit potential is the drilling [2], it is the most expensive procedure of the mineral exploration [3]. Therefore, using proper methods is essential to decrease the drilling risks and improve the accuracy of the drilling sites [4,5]. Statistical methods play an important role to enhance the success rate and overcome the cost of mineral exploration [6–8].

In the past few years, the quantitative study of geoscientific data has increased rapidly [9]. There are several probabilistic, statistical, and mining models proposed for mineral exploration [4,5], such as logistic regression [2,10], ridge regression [11], multitemporal nonlinear regression [12], weight of evidence [13,14], artificial neural networks [15], Bayesian network classifiers [16], and multiple regression analyses [17,18]. All of these methods and techniques have shown promising results and have applied successfully to mineral resource appraisal [1].

Multivariate regression analysis is used successfully to model subsurface mineralization based on the geochemical dataset [19,20], iron mineral mapping [5], and rock properties predictions [21] and to improve prediction model to estimate the sediment yield [22]. In this study, a novel application of the multivariate regression method is proposed to determine additional drilling based on the geophysical exploration dataset. To this end, six different types of multivariate regression have been employed for the iron exploration by using several techniques including RTP (reduction to the pole), A.S. (analytic signal), and UP10 (Upward Continuation) to designate magnetic susceptibility concentrations. The outcomes of these methods have been compared with the log reports from eight different boreholes in the Koohbaba (Qoja-Kandi) area, and the results have

\* **Corresponding author: Faranak Feizi**, Department of Petroleum and Mining Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran, e-mail: faranakfeizi@gmail.com

**Amir Abbas Karbalaeei-Ramezanali:** Department of Geology, Science and Research Branch, Islamic Azad University, Tehran, Iran

**Sasan Farhadi:** Department of Environment, Land and Infrastructure Engineering, Polytechnic University of Turin, Turin, Italy

demonstrated the proper accuracy of the technique. The log reports of the boreholes have been used to perform further drilling for iron exploration. To achieve this goal, multivariate regression analysis of the ground magnetic data layers has been performed.

## 1.1 Geological study

This study has been conducted at the Koohbaba area within the Urumieh-Dokhtar Magmatic Arc (UDMA), located in the Northwest of Iran. The study location has a surface area of 1.44 km<sup>2</sup>, positioned between 46°59'40" and 47°1'50" east longitude and 36°51'30" and 36°53'40" north latitude, East Azerbaijan (Figure 1). Magmatic activity in UDMA was originated in the Eocene and continued to Pliocene with its climax in the Middle Eocene [23]. Moreover, concerning some recent research works [24,25], UDMA was dominated by the Eocene magmatic rocks, and this fact was confirmed by the geochemical analysis [26].

The UDMA has been dominated by plutonic rocks together with felsic volcanic rocks [23] and forms intrusive-exclusive complex with over 4 km thickness [28,29] and [30]. There is a wide range of composition in the study area, such as schist and shale (Kahar formation), dolomite and limestone (Elika formation), shale, sandstone and limestone (Shemshak formation), limestone, marl, sand stone, conglomerate, and andesite. Omrani et al. [26] have explained that UDMA volcanic rocks form a wide range in composition, which include andesite, minor basalts, and dacites. Magnetite associated with andesite units caused iron mineralization in the study area. The UDMA hosts large metal deposits such as iron and copper [32,33], as shown in Figure 2. Moreover, Mansouri et al. [31] have introduced some iron ore deposits close to the research area.

## 1.2 Multivariate regression

The regression analysis shows the relation between one or more responses (dependent variables) and one or more predictors (independent variables) and also predicts the values of the responses for a given set of predictors. Usually, these variables are quantitative, i.e., interval or ratio. The following mathematical formula can express the simple relationship between those variables:

$$Y = F(X_i), \quad (1)$$

where  $Y$  represents dependent variables and  $X$  expresses the independent variables. It would be a linear regression if  $Y$  and  $X_i$  have a linear relation; otherwise, it would be a nonlinear regression. The main aim of the regression analysis is to represent the dependent variables as an independent variable function [34]. In this section, the mathematics approach of this technique is presented, and an in-depth presentation of this subject is available in the literature [35].

Multivariate regression is a beneficial statistical method to evaluate the linear relationships between several independent and dependent variables [5]. Therefore, it is the multiple regression expansion with an equal number of equations as the number of response variables. One advantage of using multivariate analysis is that the type 1 error can be determined, and it does not cover the number of variables [34]. Consequently, this method is applied in this study. The linear regression model can be expressed as follows [36,37]:

$$Y_i = \beta(X_i) + \varepsilon_i \quad i = 1, 2, \dots, n \quad (2)$$

where  $\beta$  is a  $p$ -dimensional column vector of unknown regression coefficients,  $Y_i$  is the  $i$ th component of the  $n$ -dimensional column vector  $Y$ ,  $X_i$  is the  $i$ th row of the  $n \times p$  design matrix  $X$ , and  $\varepsilon$  is the random error. The random error value indicates the amount of dispersion in the estimation of the  $Y$  value [19]. With  $n$  independent observation on  $Y$  and the associated values of  $Z_i$ , the complete model can be expressed as follows [38,39]:

$$\begin{aligned} Y_1 &= \beta_0 + \beta_1 X_{11} + \beta_2 X_{12} + \dots + \beta_k X_{1k} + \varepsilon_1 \\ Y_2 &= \beta_0 + \beta_1 X_{21} + \beta_2 X_{22} + \dots + \beta_k X_{2k} + \varepsilon_2 \\ &\dots \\ Y_n &= \beta_0 + \beta_1 X_{n1} + \beta_2 X_{n2} + \dots + \beta_k X_{nk} + \varepsilon_n, \end{aligned} \quad (3)$$

In the matrix form, it becomes:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_{11} & X_{12} & \dots & X_{1k} \\ 1 & X_{21} & X_{22} & \dots & X_{2k} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} & \dots & X_{nk} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}. \quad (4)$$

The error assumptions are as the following:

1.  $E(\varepsilon) = 0$
2.  $\text{Cov}(\varepsilon) = \sigma^2 I$

where  $I$  is the  $n \times n$  identity matrix. The ordinary least-square method has been used to estimate the  $\beta$  matrix [40,41], which is the regression coefficient matrix (Formula 5).

$$[\beta] = ([X]^T [X])^{-1} [X]^T [Y] \quad (5)$$

In multivariate regression, the relationship between the dependent variable  $Y$  and the independent variables  $X_i$  is measured by the coefficients of determination [35].

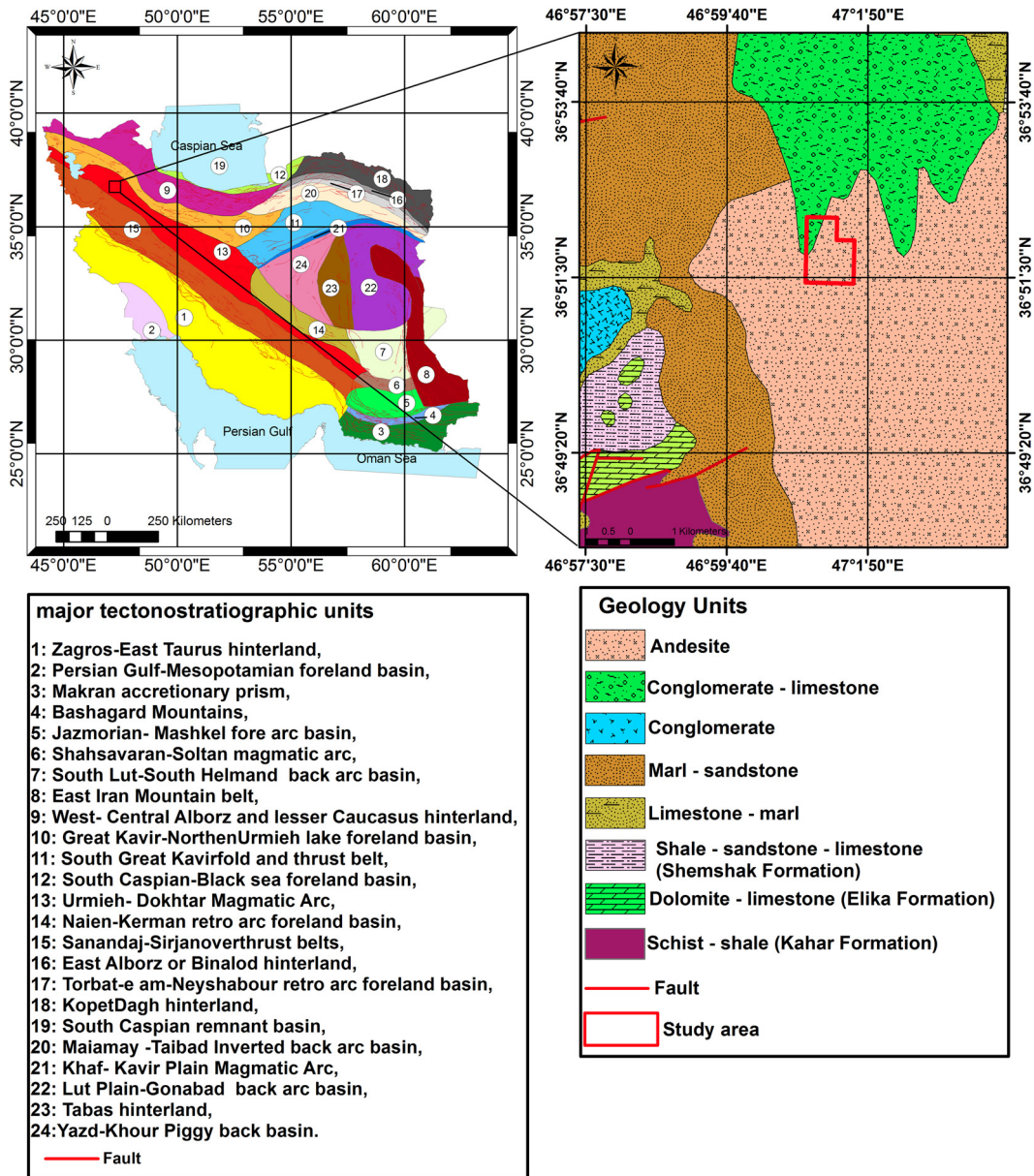


Figure 1: The Koohbaba position in the physiographic-tectonic zoning map [27].

This is the most frequent statistical approach to estimate the fitness of the model [42]. The mathematical expressions are as follows:

$$R_2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}. \quad (6)$$

where SSR shows the regression sum of squares, SSE represents the residual (error) sum of squares, and SST is the total sum of squares total. The model can fit the data more reliable as the value of  $R^2$  increases [43]. The  $R^2$  value may increase by adding a new independent variable to the function, although its presence can be required or not.

Therefore, it looks complicated whether an increase in  $R^2$  value is significant. In that case, the adjusted determination of coefficients is expressed as follows [19]:

$$R_{adj}^2 = 1 - \frac{(1 - R^2)(n - 1)}{(n - p)} \quad (7)$$

where  $n$  is the number of samples (data) and  $k$  represents the number of coefficients. The adjusted coefficient of determination  $R_{adj}^2$  has been submitted to decrease the bias in  $R^2$  [42]. By adding a different independent variable to the regression model, if the mean square residual (MSR) reduces, the  $R_{adj}^2$  will increase.

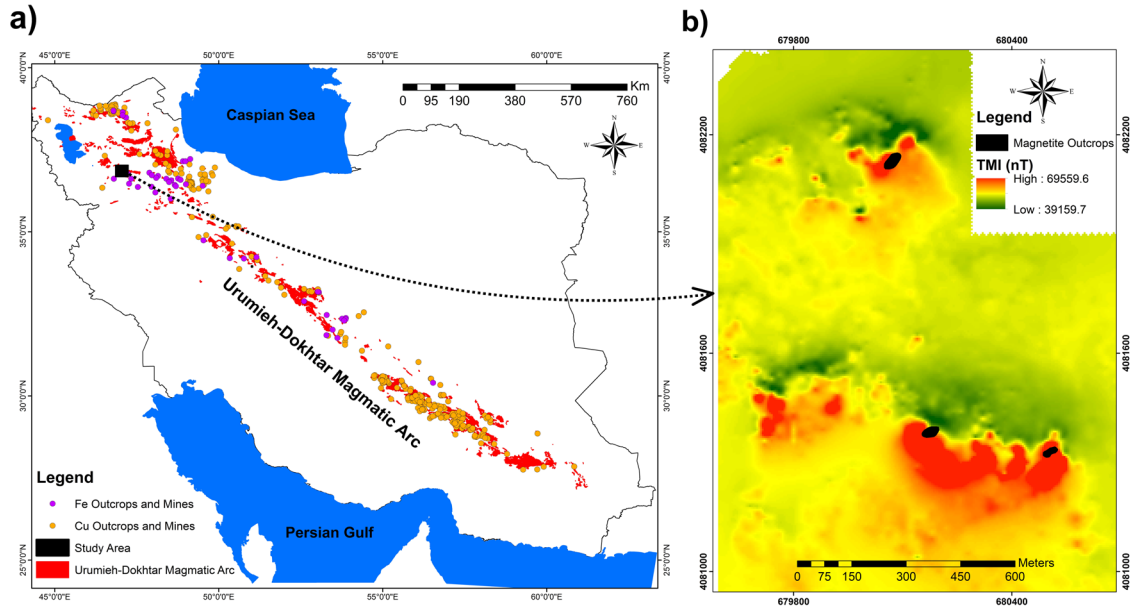


Figure 2: (a) Cu and Fe outcrops of the Urumieh-Dokhtar Magmatic Arc (UDMA) and (b) magnetite outcrops in the study area.

## 2 Materials and methods

### 2.1 Data analysis

Ground magnetic data were collected by following the same method used by Mansouri et al. [31] in the Kooh-baba area. The required geophysical data have provided by magnetometer GSM-19T in the research region ( $\pm 0.2$  nT absolute accuracy). As shown in Figure 3, the total magnetic intensity (TMI) represents the magnetic anomalies in the E–W direction in the north and center of the site. In general, there are three dipolar magnetic anomalies (one magnetic anomaly in the north and two magnetic anomalies in the west and east of the center). These three dipolar magnetic anomalies are 130 related to magnetite dikes in andesite units [5]. Accordingly, the multivariate regression method has been used to determine further drilling sites for iron exploration.

#### 2.1.1 Preparing dependent variables

The output of the drilled boreholes has been considered as the dependent variable because this variable reveals the accuracy for defining the drilling points. The value for the ratio  $\left(\frac{\text{Ore Length}}{\text{Total Core}}\right)$  is between 0 and 1, and for the best boreholes, it is closer to one. The log reports have been

collected, and the magnetite thickness of each has been measured respect to the total core (Table 1). The accepted boundary for the ore length is 20% of the total Fe. Besides, Table 2 presents the statistical factors of the ratio using the regression analysis.

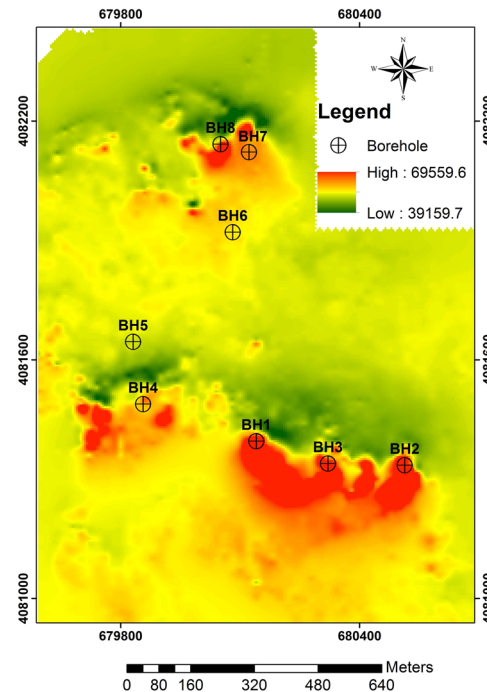


Figure 3: TMI map of the study area with the location of eight drilled boreholes.

**Table 1:** Log report of boreholes with RTP classification based on fractal method [31]

Borehole id	Total core (m)	Magnetite range (m) (grades greater than 20% Fe total)		Magnetite thickness (m) in total core (grades greater than 20% Fe total)	Ore length/total core
		From	To		
		BH1	136.5		
BH2	171.2	4 50.2 130.6	12.2 53.5 166.3	47.2	0.27
BH3	151.2	80 112	102 122	32	0.21
BH4	106	44 81	48 89.5	12.5	0.11
BH5	58.9	—	—	0	0
BH6	136.5	69	72	3	0.02
BH7	172	44 61.5 156	47 63.5 164	14	0.08
BH8	157	70 133	90 142	29	0.18

### 2.1.2 Preparing independent variables

In the regression analysis, selecting the independent variable is essentially important as these variables must be relevant to the models. Therefore, to make the model, three geophysical raster maps such as upward continuation (UP10), reduce to pole (RTP), and analytic signals (A.S.) have been generated by using Oasis Montaj V.8.4. The upward continuation method is a proper method for deep and semi-deep iron and porphyry-Cu deposit exploration [44]. This method distinguishes the magnetic field far away from the source, and it can decrease the effect of shallow magnetic frequency to create a better map. Figure 4a shows the UP10 map in the Koohhbaba area.

The RTP approach converts magnetic anomalies to a symmetrical pattern, and it can make the magnetic anomalies shape with higher accuracy to the spatial site. Therefore, the magnetic anomalies can interpret much easier [44,45]. In this study, the TMI map has been converted to RTP by using a magnetic declination (4.93) and inclination (55.43). Figure 4b shows the RTP raster map of the study location. The A.S. technique is a widely known filter to enhance the magnetic field and for locating the magnetic anomalies edges. The basic concept of this method has been discussed in the literature [29,46,47]. The A.S. raster map is shown in Figure 4c.

After generating maps, the values of UP10, RTP, and A.S. raster layers have been extracted in the exact location of eight boreholes (dependent variable); consequently, the values of three unique independent variables (UIVs) have been obtained. The statistical parameters of UIVs (UP10, RTP, and A.S.) have been used in the regression modeling (Table 2).

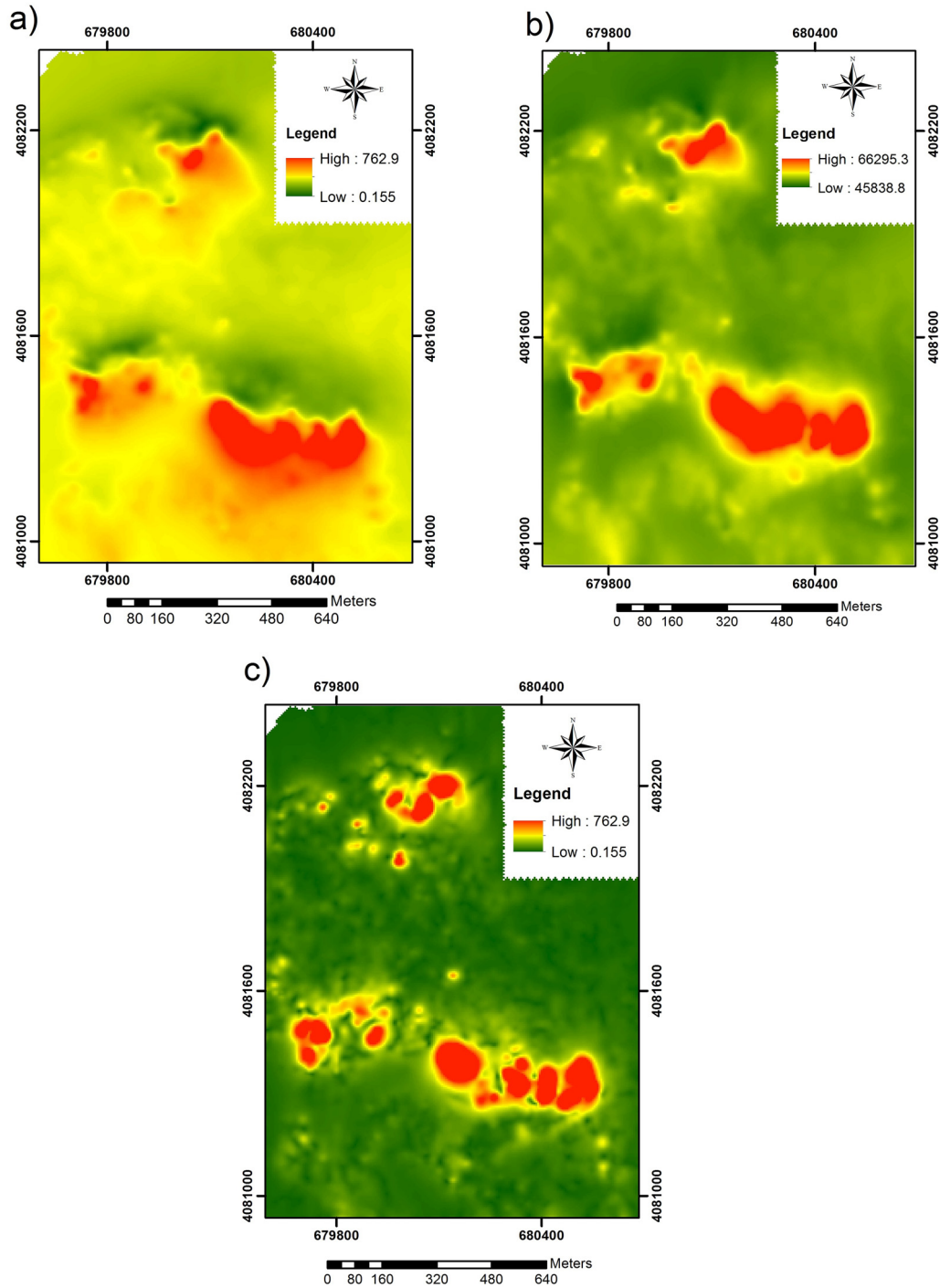
## 2.2 Regression analysis

In the regression analysis such as linear regression, to have the best model, it is essential to create many models [19]. In this study, six types of multivariate regression analyses, including linear, quadratic, and cubic models, have been employed (Table 3) to find out the best drilling points for iron exploration.

The models became more complex, from  $Y_1$  to  $Y_6$  as the coefficients increased too. To select the best model, there are some criteria considered for the regression analysis. The values for  $R^2$ ,  $R_{adj}^2$ , and  $p$ -value (ANOVA test) for different regression models is presented in Table 4. Besides, the unknown regression coefficients values are presented in Tables 5 and 6. Other independent variables, which are not presented in tables, are excluded, and they do not affect the statistical models.

**Table 2:** The statistical parameters of dependent (ore length/total core) and unique independent (UP10, RTP, and A.S.) variables used in the regression modeling

Variables			<i>N</i>	Mean	St. Dev	Skewness	Kurtosis	
Dependent	Sample	$Y$	ore length/total core	8	0.156	0.13	0.522	-0.436
Unique independent	Raster maps (pixel)	$X_1$	UP10	8	52261.8	3464.8	0.065	-1.273
		$X_2$	RTP	8	56116.5	7494.7	0.170	-1.793
		$X_3$	A.S.	8	279.7	276.04	0.356	-2.035



**Figure 4:** Raster maps of the Koohbaba area: (a) upward continued to 10 m (UP10), (b) reduction to the pole (RTP), and (c) analytic signal (A.S.).

### 3 Results and discussions

To select the best model, some criteria have to be considered. First, the computed variance and random error mean values confirmed the acceptable value for all regression models. Furthermore, based on Table 3, the

$p$ -value (ANOVA test) of the models is acceptable ( $\ll 0.05$ ). Therefore, all these values demonstrated the accuracy of the regression models.

As Table 4 represents, the lowest value for  $R^2$  has been obtained by the first model ( $Y_1$ ), and the highest one has been achieved by the last three models ( $Y_4$ ,  $Y_5$ , and  $Y_6$ ).

**Table 3:** Multivariate regression formula used for detailed iron exploration

Types of regression	Number of coefficients	Formula
First degree	4	$Y_1 = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + \varepsilon$
First degree	7	$Y_2 = Y_1 + a_4x_1x_2 + a_5x_1x_3 + a_6x_2x_3$
Second degree	10	$Y_3 = Y_2 + a_7x_1^2 + a_8x_2^2 + a_9x_3^2$
Second degree	13	$Y_4 = Y_3 + a_{10}x_1^2x_2^2 + a_{11}x_1^2x_3^2 + a_{12}x_2^2x_3^2$
Third degree	16	$Y_5 = Y_4 + a_{13}x_1^3 + a_{14}x_2^3 + a_{15}x_3^3$
Third degree	19	$Y_6 = Y_5 + a_{16}x_1^3x_2^3 + a_{17}x_1^3x_3^3 + a_{18}x_2^3x_3^3$

**Table 4:** Values for multivariate regression models

Models	$R^2$	$R^2_{adj}$	$p$ -value (ANOVA)
$Y_1$	0.910	0.887	0
$Y_2$	0.93	0.912	0.003
$Y_3$	0.937	0.917	0.001
$Y_4$	0.986	0.966	0.001
$Y_5$	0.986	0.955	0.001
$Y_6$	0.986	0.948	0.005

$$EF = \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (\bar{O}_i - O_i)^2}, \tag{8}$$

The fourth model is a second-degree function, and it has lower complexity than other models (Table 3). Even though  $R^2$  is a proper parameter for examining the model with the same number of independent variables, it cannot be adequate for comparing the models with different numbers of independent variables as increasing the number of independent variables will increase the  $R^2$  values. Hence,  $R^2_{adj}$  has been computed, and model number 4 has indicated a fitted model with the highest value (0.966). Therefore, based on the results obtained by coefficients of determination, model  $Y_4$  is the most appropriate model in this study, and it can be applied to determine further drilling exploration sites in the study area.

To approve this fact, initially, the efficiency formula (Formula 8) has been computed as follows [48]:

where  $n$  is the number of observations,  $O$  is the observed values,  $\bar{O}$  mean of absolute value, and  $P_i$  is the estimated value. The mean value of the observation becomes more reliable than the estimated values if the model efficiency (EF) approaches zero; therefore, to avoid the model limitations, EF values should be closer to 1 to have a workable model [49].

According to the EF values (Table 4),  $Y_4$  is considered as the best model, followed by  $Y_5$  and  $Y_6$ . This result confirmed the output result from the regression analysis by considering the coefficients of determination and  $p$ -values (ANOVA test). To determine the further drilling sites in the study area (Koohbaba), the raster map is obtained from  $Y_4$ . To generate the intended figures, ArcGIS V.10.1 has been employed (with using the raster calculator toolbox). Figure 5a represents the final raster map of the study by considering the fourth regression model.

Moreover, four new boreholes (borehole No. 9–12) have been drilled in the study area, belonging to class 5. The result is presented in Table 7 and Figure 5. The accepted boundary for the magnetic thickness is 20% of the total Fe. Concerning this information, the final results are very promising and appropriate.

**Table 5:** The calculated coefficients of regression models (1–3)

Model 1		Model 2		Model 3	
Variables	Coefficients ( $a_i$ )	Variables	Coefficients ( $a_i$ )	Variables	Coefficients ( $a_i$ )
CST	-0.866	CST	-0.59	CST	-6.333
$x_1$	5.504	$x_1$	-3.351	$x_2$	-0.014
$x_2$	4.016	$x_2$	1.628	$x_3$	-0.022
$x_3$	4.016	$x_3$	-3.354	$x_2^2$	-1.469
—	—	$x_1x_3$	2.051	$x_3^2$	2.292
—	—	—	—	$x_1^2$	-7.266

**Table 6:** The calculated coefficients of regression models (4–6)

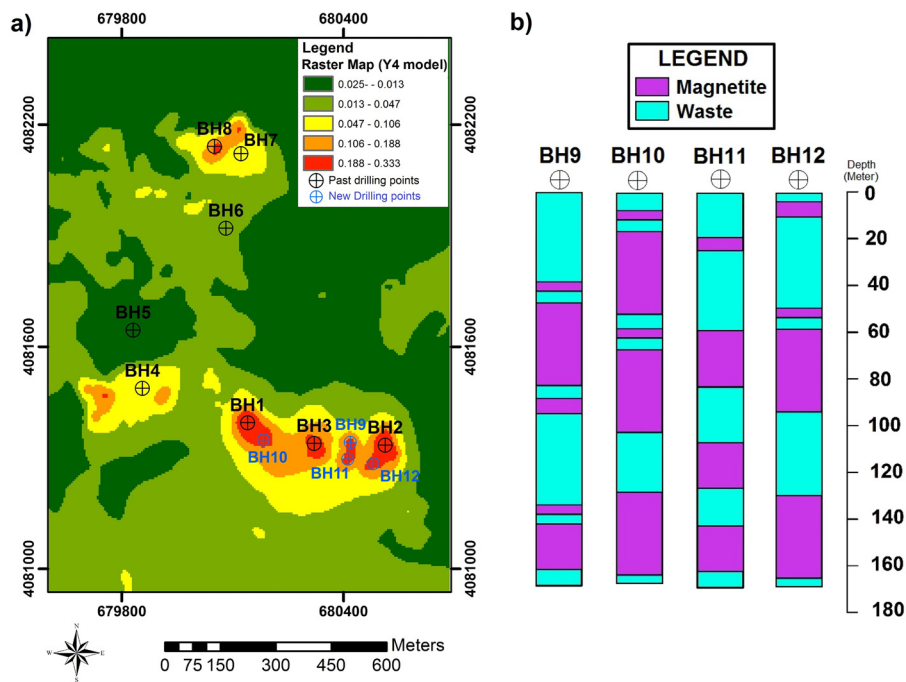
Model 4		Model 5		Model 6	
Variables	Coefficients ( $a_i$ )	Variables	Coefficients ( $a_i$ )	Variables	Coefficients ( $a_i$ )
CST	-4.481	CST	-2.210	CST	-1.413
$x_1$	-1.540	$x_2$	6.206	$x_1$	-2.839
$x_2$	0.018	$x_3$	0.016	$x_2$	6.188
$x_3$	-0.024	$x_1^2 x_3^2$	-8.798	$x_3$	-2.539
$x_1^2 x_2^2$	-2.012	$x_1^3$	-5.654	$x_1^2 x_3^2$	-7.294
$x_1^2 x_3^2$	6.215	$x_2^3$	-9.229	$x_1^3 x_2^3$	-1.299
—	—	$x_3^3$	4.354	$x_1^3 x_3^3$	-1.974

### 4 Conclusion

The conclusions are presented as follows:

1. Regression analysis is a proper and direct statistical method to identify the potential favorable drilling exploration sites with high accuracy in Koohbaba, Northwest of Iran.
2. The application of the multivariate regression analysis has been confirmed in this area. In this research study, multivariate regression has been developed to create a mathematical model (with reasonable accuracy) for iron mineral exploration by using geophysical data as a new approach.

3. Six different types of multivariate regression models such as two linear, two quadratic, and two cubic equations have been employed to identify the additional drilling area. According to the results of the coefficients of determination ( $R^2$  and  $R_{adj}^2$ ),  $p$ -value, and EF, the fourth regression model (quadratic equation) has been the best response, and it has been confirmed by the ratio (ore length/total core) values of the former drilled boreholes and the further drilled boreholes.
4. The accuracy of the model has been approved by drilling four new boreholes. This additional field investigation has shown promising results.



**Figure 5:** The final raster map of the study area based on the  $Y_4$  regression model with drilled boreholes.

**Table 7:** Log report of new drilled boreholes

Borehole ID	Total core (m)	Magnetite range (m)		Magnetite thickness (m)	Ore length/total core
		From	To		
BH9	170.8	39.3	41.8	69.9	0.41
		43.5	81.2		
		82.6	92.3		
		136.5	138.4		
		142.4	160.5		
BH10	169.2	9.4	12.1	107.7	0.63
		18.2	52.5		
		59.3	62.1		
		68.3	102.4		
		129.2	163		
BH11	171.3	19.8	23.2	65.5	0.38
		59.8	82.3		
		108.2	128.4		
		143.2	162.6		
BH12	170.7	3.3	11.1	77.1	0.45
		51.1	53.4		
		59.2	93.4		
		130.4	163.2		

- The results confirm that the regression analysis model using the geophysical data is an effective approach as it can reduce the time and cost of exploration.
- Conclusively, 17092.11 m<sup>2</sup> of the study area has been considered as a suitable candidate zone for the detailed studying and determining additional drilling for iron exploration in the area of interest.

## References

- Oh HJ, Lee S. Regional probabilistic and statistical mineral potential mapping of gold–silver deposits using GIS in the Gangreung area, Korea. *Resour Geol.* 2008 Jun;58(2):171–87.
- Harris DV, Pan G. Mineral favorability mapping: a comparison of artificial neural networks, logistic regression, and discriminant analysis. *Nat Resour Res.* 1998 Aug;8(2):17.
- Marjoribanks RW. *Geological methods in mineral exploration and mining.* 2nd edn. Berlin, New York: Springer; 2009.
- Xiong Y, Zuo R, Carranza EJM. Mapping mineral prospectivity through big data analytics and a deep learning algorithm. *Ore Geol Rev.* 2018 Nov;102:811–7.
- Mansouri E, Feizi F, Rad AJ, Arian M. Remote-sensing data processing with the multivariate regression analysis method for iron mineral resource potential mapping: a case study in the Sarvian area, central Iran. *Solid Earth.* 2018 Mar;9(2):373–84.
- Chen Y, Wu W. Mapping mineral prospectivity using an extreme learning machine regression. *Ore Geol Rev.* 2017 Jan;80:200–13.
- Ramezanali AK, Feizi F, Jafarirad A, Lotfi M. Application of best-worst method and additive ratio assessment in mineral prospectivity mapping: a case study of vein-type copper mineralization in the Kuhshah- e-Urmak area, Iran. *Ore Geol Rev.* 2020 Feb;117:103268.
- Feizi F, KarbalaeeiRamezanali A, Mansouri E. Calcic iron skarn prospectivity mapping based on fuzzy AHP method, a case study in Varan area, Markazi province, Iran. *Geosci J.* 2017 Feb;21(1):123–36.
- Chen C, Dai H, Liu Y, He B. Mineral prospectivity mapping integrating multi-source geology spatial data sets and logistic regression modelling. *Proceedings 2011 IEEE international conference on spatial data mining and geo- graphical knowledge services.* Fuzhou, China: IEEE; 2011 Jun. p. 214–7
- Xiong Y, Zuo R. GIS-based rare events logistic regression for mineral prospectivity mapping. *Comput Geosci.* 2018 Feb;111:18–25.
- Hang R, Liu Q, Song H, Sun Y, Zhu F, Pei H. Graph regularized nonlinear ridge regression for remote sensing data analysis. *IEEE J Sel Top Appl Earth Observ Remote Sens.* 2017 Jan;10(1):277–85.
- Kim HJ, Seo DK, Eo YD, Jeon MC, Park WY. Multi- temporal nonlinear regression method for landsat image simulation. *KSCE J Civ Eng.* 2019 Feb;23(2):777–87.
- Tangestani MH, Moore F. Porphyry copper potential mapping using the weights- of- evidence model in a GIS, northern Shahr-e-Babak, Iran. *Aust J Earth Sci.* 2001 Oct;48(5):695–701.
- Agterberg FP, Bonham-Carter GF. Measuring the performance of mineral-potential maps. *Nat Resour Res.* 2005 Mar;14(1):1–17.
- Singer DA, Kouda R. Application of a feedforward neural network in the search for Kuroko deposits in the Hokuroku district, Japan. *Math Geol.* 1996 Nov;28(8):1017–23.
- Porwal A, Carranza EJM, Hale M. Bayesian network classifiers for mineral potential mapping. *Comput Geosci.* 2006 Feb;32(1):1–16.
- Carranza EJM. Catchment basin modelling of stream sediment anomalies revisited: incorporation of EDA and fractal analysis. *Geochem Explor Environ Anal.* 2010 Nov;10(4):365–81.
- Carranza EJM. Mapping of anomalies in continuous and discrete fields of stream sediment geochemical landscapes. *Geochem Explor Environ Anal.* 2010 May;10(2):171–87.
- Granian H, Tabatabaei SH, Asadi HH, Carranza EJM. Multivariate regression analysis of lithochemical data to model subsurface mineralization: a case study from the Sari Gunay epithermal gold deposit, NW Iran. *J Geochem Explor.* 2015 Jan;148:249–58.
- Ramezanali AK, Feizi F, Jafarirad A, Lotfi M. Geochemical anomaly and mineral prospectivity mapping for vein-type copper mineralization, Kuhshah-e-Urmak area, Iran: application of sequential gaussian simulation and multivariate regression analysis. *Nat Resour Res.* 2020 Feb;29(1):41–70.
- Ma YZ. Pitfalls in predictions of rock properties using multivariate analysis and regression methods. *J Appl Geophys.* 2011;75:390–400.
- Grauso S, Pasanisi F, Tebano C, Grillini M, Peloso A. Investigating the sediment yield predictability in some Italian

- rivers by means of hydro-geomorphometric variables. *Geosciences*. 2018 May;8:249.
- [23] Kananian A, Sarjoughian F, Nadimi A, Ahmadian J, Ling W. Geochemical characteristics of the Kuh-e Dom intrusion, Urumieh–Dokhtar magmatic arc (Iran): implications for source regions and magmatic evolution. *J Asian Earth Sci*. 2014 Aug;90:137–48.
- [24] Yeganehfar H, Ghorbani MR, Shinjo R, Ghaderi M. Magmatic and geodynamic evolution of Urumieh–Dokhtar basic volcanism, Central Iran: major, trace element, isotopic, and geochronologic implications. *Int Geol Rev*. 2013 April;55(6):767–86.
- [25] Babazadeh S, Ghorbani MR, Cottle JM, Bröcker M. Multistage tectono-magmatic evolution of the central Urumieh–Dokhtar magmatic arc, south Ardestan, Iran: insights from zircon geochronology and geochemistry. *Geol J*. 2019 July;54(4):2447–71.
- [26] Omrani J, Agard P, Whitechurch H, Benoit M, Prouteau G, Jolivet L. Arc-magmatism and subduction history beneath the Zagros mountains, Iran: a new report of adakites and geodynamic consequences. *Lithos*. 2008 Dec;106(3–4):380–98.
- [27] Arian M. Physiographic-tectonic zoning of Iran's sedimentary basins. *Open J Geol*. 2013;3(3):169–77.
- [28] Alavi M. Tectonics of the Zagros orogenic belt of Iran: new data and interpretations. *Tectonophysics*. 1994;229:211–38.
- [29] Ramezani AK, Mansouri E, Farnak F. Integration of aeromagnetic geophysical data with other exploration data layers based on fuzzy AHP and C-A fractal model for Copper porphyry potential mapping: a case study in the Fordo area, central Iran. *Boll di Geofisica Teorica ed Applicata*. 2017;58(1):55–73.
- [30] Feizi F, Mansouri E, Ramezani AK. Prospecting of Au by remote sensing and geochemical data processing using fractal modelling in Shishe-Botagh, area (NW Iran). *J Indian Soc Remote Sens*. 2016 Aug;44(4):539–52.
- [31] Mansouri E, Feizi F, Karbalaeei-Ramezani A. Identification of magnetic anomalies based on ground magnetic data analysis using multifractal modelling: a case study in Qoja-Kandi, East Azerbaijan province, Iran. *Nonlinear Process Geo-Phys*. 2015 Oct;22(5):579–87.
- [32] Feizi F, Karbalaeei-Ramezani A, Tusi H. Mineral potential mapping via TOPSIS with hybrid AHP–shannon entropy weighting of evidence: a case study for porphyry-Cu, Farmahin area, Markazi province, Iran. *Nat Resour Res*. 2017 Oct;26(4):553–70.
- [33] Feizi F, Mansuri E. Separation of alteration zones on ASTER data and integration with drainage geochemical maps in Soltanieh, Northern Iran. *Open J Geol*. 2013;03(02):134–42.
- [34] Duleba A, Olive D. Regression analysis and multivariate analysis. *Sem Reprod Med*. 1996 May;14(2):139–53.
- [35] Rencher AC. *Methods of multivariate analysis*. Wiley series in probability and mathematical statistics. 2nd edn. New York: Wiley; 2002.
- [36] Chung CF, Agterberg FP. Regression models for estimating mineral resources from geological map data. *J Int Assoc Math Geol*. oct 1980;12(5):473–88.
- [37] Zhang D. A coefficient of determination for generalized linear models. *Am Stat*. 2017 Oct;71(4):310–6.
- [38] Johnson RA, Wichern DW. *Applied multivariate statistical analysis*. 6th edn. New Jersey: Pearson; 2007.
- [39] Chung CJF, Van Westen CJ. *Multivariate regression analysis for landslide hazard zonation*. Geographical information systems in assessing natural hazards, vol. 5. Netherlands, Dordrecht: Springer; 1995. p. 107–33.
- [40] Scott AJ, Holt D. The effect of two-stage sampling on ordinary least squares methods. *J Am Stat Assoc*. 1982;77(380):7.
- [41] Chang J, Olive DJ. OLS for 1D regression models. *Commun Stat Theory Methods*. 2010 May;39(10):1869–82.
- [42] Akossou AYJ, Palm R. Impact of data structure on the estimators R-square and adjusted R-square in linear regression. *Int J Math Comput*. 2013;20:10.
- [43] Cornell JA. Factors that influence the value of the coefficient of determination in simple linear and nonlinear regression models. *Phytopathology*. 1987;77(1):63.
- [44] Abedi M, Norouzi GH. Integration of various geophysical data with geological and geochemical data to determine additional drilling for copper exploration. *J Appl Geophys*. 2012 Aug;83:35–45.
- [45] Golshadi Z. Interpretation of magnetic data in the Chenar-e Olya area of Asadabad, Hamedan, Iran, using analytic signal, euler deconvolution, horizontal gradient and tilt-derivative methods. *Boll di Geofisica Teorica ed Applicata*. 2016 Dec;57(4):329–42.
- [46] Nabighian MN. The analytic signal of two-dimensional magnetic bodies with polygonal cross-section: its properties and use for automated anomaly interpretation. *Geophysics*. 1972 Jan;37(3):507–17.
- [47] Nabighian MN. Additional comments on the analytic signal of two-dimensional magnetic bodies with polygonal cross-section. *Geophysics*. 1974 Feb;39(1):85–92.
- [48] Li J, Heap AD. *A review of spatial interpolation methods for environmental scientists*. Canberra: Geoscience Australia; 2008. p. 154.
- [49] Vicente-Serrano SM, Saz-Sanchez MA, Cuadrat JM. Comparative analysis of interpolation methods in the middle Ebro valley (Spain): application to annual precipitation and temperature. *Clim Res*. 2003;24:161–80.