

Weighting Information Layers Using Logistic Regression for Mine Exploration Applications

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Key words: Logistic Regression, AHP, GIS, Mineral Potential Map

SUMMARY

Logistic regression can be used with spatial data as a predictor in a Geospatial Information System (GIS). Most of the other regression methods are based on the assumption that the independent variables are normally distributed which unfortunately is not always the case with the spatial data. However, this assumption is not needed in logistic regression. This paper describes an application of logistic regression for mapping the potential of existing copper in the Ali-Abad region (Taft, Yazd, Iran). The basic information layers used in this research include geological maps, geomagnetic, geoelectric and geochemical data. After preprocessing of these raw data useful information is extracted out and then integrated within a GIS using a logistic model. Borehole data is used to fit the model and find the coefficients as well as the weight of the spatial information layers. Then the model is used to determine the potential of existing copper in the other parts of the region for which the borehole information have not been used. The results show that as a data driven model logistic regression is comparable with some knowledge driven methods like Analytical Hierarchy Process (AHP) where experts decide on the importance and weight of the information. Layers weighted using both AHP and logistic regression methods are used with Index Overlay method to check the effect of the assigned weights. Predicting the minerals is the main goal of two approaches and both of them generate a mineral potential map. Logistic regression is successful in predicting the quality of minerals in most of the boreholes. While AHP strongly depends on the expert or experts and their ideas, logistic regression is relied only on the data. Being a data driven method where the relative importance of data are determined by data itself, and having no assumption on the normality of the independent variables are two main advantages of using logistic regression for prediction in a GIS environment.

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1. INTRODUCTION

The decision-making process can take advantage of using multi-criteria decision making (MCDM) techniques. These techniques can be used to facilitate the decision-making process by turning it to a more explicit, rational and efficient one (Malczewski, 1999). On the other hand, the analytical capabilities of a Geospatial Information System (GIS) especially with spatial data facilitates the decision making process in many disciplines. Moreover, the Graphical User Interface (GUI) which most of GIS are equipped with increases the decision-maker's comprehension of the spatial information that is involved in the problem being addressed. Because of these two potential added to the decision making process, a GIS is often considered as a major component in the development of Decision Support Systems (DSS).

As an example, mineral exploration is a multi-stage investigation that begins at a small scale and progresses to large scale. At each stage topographical, geological, geochemical, and geophysical data are collected, processed and analyzed to produce Mineral Potential Map (MPM). However, Mineral Potential Mapping using conventional methods is very difficult and sometimes impossible. But, as GIS has potential for storing, updating, retrieving, displaying, processing, analyzing and integrating different geo-spatial data (Karimi, 2003), it can be easily used for producing MPMs. However, the bottleneck of using GIS in producing MPMs is assigning proper weight to different information layer.

Determining the relative importance of information is called map layer weighting (Malczewski, 1999). There are two main methods for weighting the information layers, i.e, data-driven and knowledge-driven (Bonham-Carter, 1994). In data-driven methods the importance of data are decided based on the data itself while in knowledge-driven methods an expert or experts perform this task. In applications like deposit exploration one is dealing with different data with different importance which must be combined together in a particular way. The relative importance of data is taken into account by assigning weights to information layers corresponding to their relative importance. Assigning these weights is a decision making process and in this paper it is done by Analytical Hierarchy Process (AHP).

Logistic Regression (LR) is a model that can be established when some samples of the response are known (Yang et al., 2006). So it is a data-driven approach and do not depend on the opinions of experts (Bonham-Carter, 1994). Boreholes are known responses in this study. So some of randomly selected boreholes are used to fit the LR model. Then the fitted model can be used to produce MPM and the unused boreholes can be used to evaluate the performance of the model

2. IMPORTANCE

Exploring mineral deposits is a very expensive and time consuming task. In fact, even after lots of studies on a deposit, still nobody can exactly predict the location and amount of minerals under the ground. Evidently, the prediction has been more difficult using traditional methods. To find out the exact situation of the underground deposits the only way is to drill boreholes. Even though this method is precise but at the same time it is too expensive and most of the times it is even impossible. On the other hand, GIS can efficiently handle the results of different investigations such as geological, geophysical and geochemical studies. Using a powerful method for weighting of the information, GIS can provide a better prediction about the potential of mineralization under the ground.

3. METHODOLOGY

The first step in this study is to determine the key elements for existence of copper under the ground. To do this three types of investigations are done: geological, geochemical and geophysical (Hassani and Shojaat, 2000). After the data is ready key information is extracted out of them. In general each layer of information has some sub-classes. In some approaches like AHP the importance of these sub-classes has to be determined before assigning weights to the layers. In some literatures this procedure is called calibration (Berry, 2002). Calibration can be done by the same methods as weighting. Methods of weighting and the process of assigning weights to the information are discussed in the next sections.

3.1 Exploring Mineral Deposits

Mineral deposit exploration is a multi-stage task. In the preliminary stages the exploration is done on small scale maps and/or aerial images and it gradually becomes more precise by using larger scale maps (Karimi, 2002). An exploration model for a particular area and class of deposit can be generated by customizing a general mineral deposit model for the area under the study (Palomera, 2002). This paper focuses on the final stage of exploration which is a large scale investigation and is done on large scale maps (e.g. 1:1000 or larger). At this scale the existence of a mineral (e.g. copper in this paper) is investigated by considering the existence of the evidences. However, these evidences should be weighted and finally integrated in a single environment to produce the MPM for the deposit.

3.2 Exploration Activities

As mentioned before, three main categories of study are done to explore a deposit: geological, geophysical and geochemical studies. In the geological study a geological map is provided which illustrates the lithology of area under study, faults, alterations, brecciated zones and/or any useful information related to geology and is often associated with some sections of the ground. In the geochemical study at first an optimal network is established and then some samples are taken from the area under the study and after chemical and statistical process, geochemical anomaly map is provided. In this paper this map is called geochemical map. Geophysical studies have different procedures and products. Like geochemical, in

geophysical studies at first a network for measurements is designed and then measurements are done based on this network. At last some products like maps of chargeability, total intensity of the magnetic field, resistivity and some other information are obtained (Saman Kave, 2001). Two efficient products of geophysical studies: geoelectric anomaly map and geomagnetic anomaly map which for simplification are called geoelectric map and geomagnetic map respectively are used in this paper.

3.3 Preparing Information Layers in GIS

In the traditional methods the investigations are done separately, therefore the first problem is to bring all of the maps (the results of investigations) in the same coordinate system. Hence, registration is the first step of processing the collected data in a GIS environment. To use the maps in other future operations it is suggested to georeference them instead of just registering them. These georeferenced maps construct the information layers which should be finally stored, integrated and weighted in a GIS environment.

3.4 Layers of Data

In this case study there are nine different information layers which need to be weighted. These information layers are considered as predictors for existence of copper and are called factor maps in some literatures (Karimi, 2003). The factor maps are illustrated in Figure 3. The geochemical anomaly map is classified into three classes of background, medium and anomaly based on the idea of the experts. Geophysical data have two categories, i.e., geomagnetic and geoelectric, and each of them is classified like geochemical data. Six different layers are extracted from geological data and include brecciated zones, dike, host rock, bed rock, alterations and faults. Among them some layers like alterations have some sub-classes. Table 1 shows the information layers. The goal is to assign proper weights to these nine information layers mentioned in Table 1.

Table 1: Studies, Layers and Classes Used for Weighting

Study	Extracted Layers	Sub-Classes
Geochemical	Geochemical	Anomaly
		Medium
		Back ground
Geophysical	Geomagnetic	Anomaly
		Medium
		Back ground
	Geoelectric	Anomaly
		Medium
		Back ground
	Brecciated zones	-----
		Phyllic

Geological	Alterations	Argillic
		Propilitic
	Dike	-----
	Host rock	-----
	Bed rock	Tuff
		Lava
		Quartzitic Sandstone and Conglomerate (QSC)
		Alteration of Sandstone and Conglomerate (ASC)
	Faults	North-West
		East-West

3.5 Weighting Methods

The information layers have to be integrated to produce MPM. Therefore, one should calibrate and weight them in order to take the relative importance of information into account. Three methods used for this purpose are discussed below.

3.5.1 Logistic Regression

Logistic Regression (LR) is a part of statistical models called generalized linear models (Hosmer and Lemeshow, 2000). LR describes the relationship between the response (dependent) and the linear sum of the predictor (independent) variables. LR allows one to predict a discrete outcome, such as group membership, from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these (Hosmer and Lemeshow, 2000). Generally, the dependent or response variable is dichotomous like presence/absence or success/failure. Logistic regression makes no assumption about the distribution of the independent variables (Changlen et al., 2005). Using equations 1 and 2, the presence/absence of Copper potential is transformed into a continuous probability space $P(x)$ ranging from 0 to 1. Values close to 1 represent high probability of presence; whereas, values close to 0 represent high probability of absence.

The case which deals with only one predictor variable is called binary LR and the case which deals with more than one predictor variable is called multiple LR (Hosmer and Lemeshow, 2000). The LR model in binary form is an S shape curve. An example of LR curve is illustrated in Figure 1.

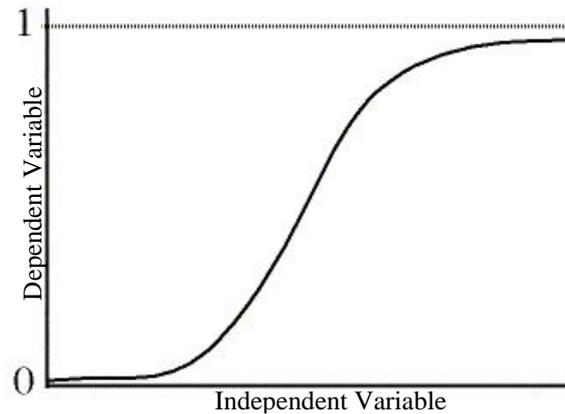


Figure 1: Logistic Curve (Menard, 2002)

Consider a collection of p independent variables denoted by vector $x' = (x_1, x_2, \dots, x_p)$. It is assumed that each of these variables is at least interval scale. Let the conditional probability that the outcome is present be denoted by $P(y = 1 | x) = P(x)$. The logit of the multiple regression model is given by the following equation (Hosmer and Lemeshow, 2000):

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p \quad (1)$$

and the logistic regression model is:

$$P(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \quad (2)$$

where β_1, \dots, β_p are the coefficients and β_0 is the constant of the model which should be computed.

3.5.2 Analytical Hierarchy Process

AHP is a powerful and flexible decision making process to help one setting the priorities and making the best decision (Ghodsi Pour, 2000). AHP is especially suitable for complex decisions which involve comparison of unquantifiable and/or difficult to quantify decision elements. It is based on the natural human reaction to the situation when one is faced with a complex decision. The natural human reaction in this situation is to cluster the decision elements according to their common characteristics. It involves building a hierarchy (ranking) of decision elements and then making comparisons between each possible pair in each cluster. The comparisons are performed by nine standard statements and the digits from 1 to 9 are assigned to these statements where the higher the number is, the stronger the preference is. The numbers are arranged in a matrix (e.g. Figure 6) and by some methods (e.g. eigenvector or geometric mean) the weights for each of the compared elements are calculated. This gives a weight for each element within a cluster (or level of the hierarchy) as well as a consistency ratio (useful for checking the consistency of the data). The AHP model has been designed by T.L. Saaty as an aid to decision making (Saaty, 1980).

After calculating weights, one should take the inconsistency of the judgments into account. This is done through using the following relations:

$$II \text{ (Inconsistency Index)} = \frac{\lambda_{\max} - n}{n - 1} \quad (3)$$

$$I.R = \frac{II}{I.I.R} \quad (4)$$

where n is the dimension of comparison matrix, λ_{\max} is the maximum eigenvalue of the comparison matrix and $I.I.R$ is the inconsistency index of a random matrix with the same dimension as the comparison matrix. Saaty has calculated $I.I.R$ for different dimensions (Saaty, 1986). Finally, $I.R$ is the inconsistency ratio and if it is lower than 0.1 the comparisons are consistent, if not they should be compared again (Saaty, 1986). The final weight of each alternative or sub-criteria is obtained by production of its weight corresponding to each criteria and summation of them. This concept is shown in Figure 2.

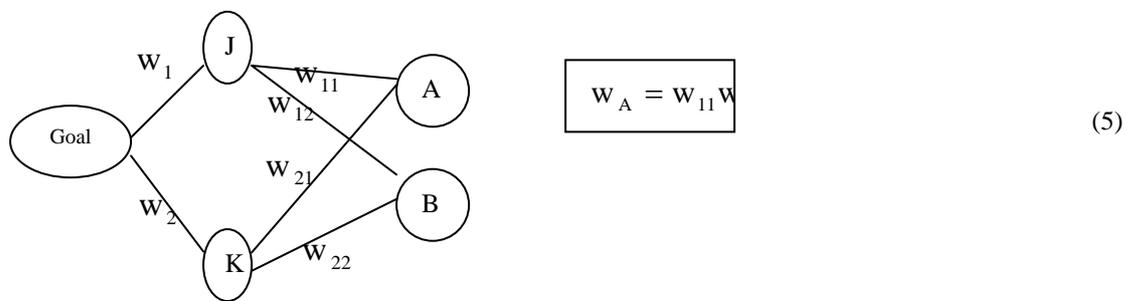


Figure 2: Calculating the Final Weights in Hierarchy of AHP (Ghodsi Pour, 2000)

Sum of calculated weights for each comparison matrix is equal to 1.

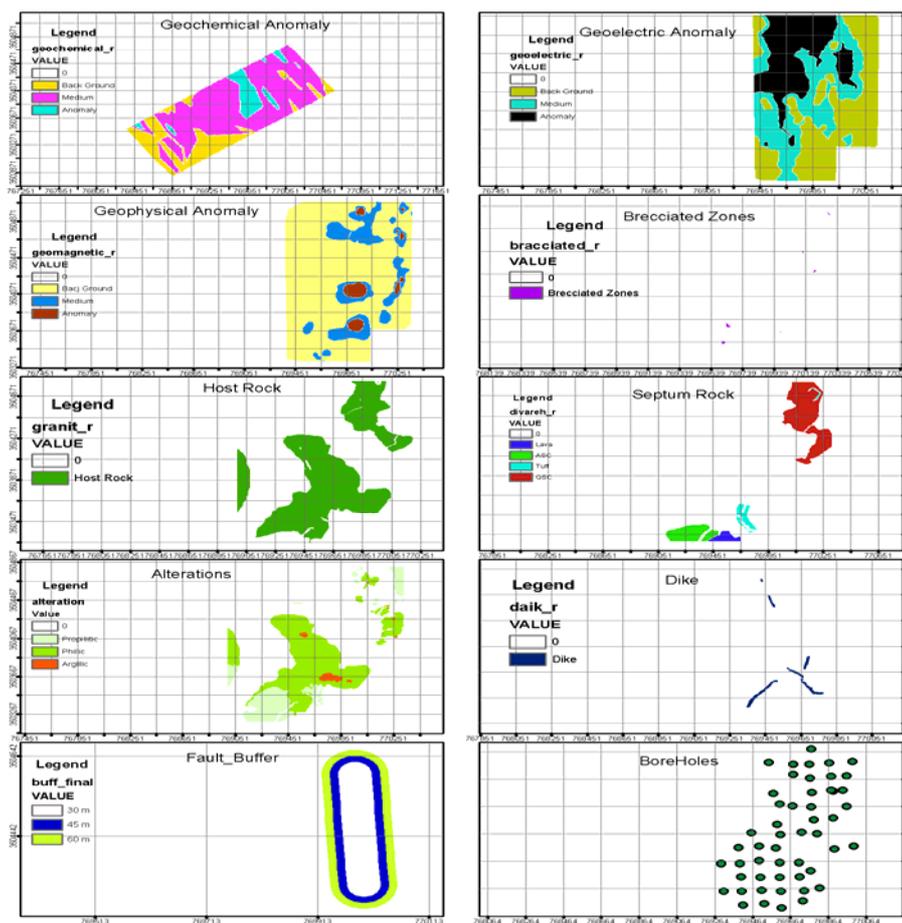


Figure 3: Factor maps and boreholes

The following ten steps for the Delphi method are described:

3.6 Index Overlay

In Index overlay method, each class of maps is given a different score allowing for a flexible weighting system. The table of scores and the map weights can be adjusted to reflect the judgment of an expert in the domain of the application under consideration (Bonham-Carter, 1994). At any location, the output score \bar{S} is defined as:

$$\bar{S} = \frac{\sum_{i=1}^n S_{ij} W_i}{\sum_{i=1}^n W_i} \quad (6)$$

where \bar{S} is the assigned score for the pixel, W_i is the weight of the i th map, and S_{ij} is the weight of j th class from the i th map. The biggest disadvantage of this method probably lies in its linear additive nature. However, as the method is the same for both of the weighting methods it would not have a biased effect.

4. IMPLEMENTATION

Exploring mines is an ancient activity. Nowadays new approaches have made it simpler and faster. The studies are done on the surface of the ground, however, some parts of geological and geophysical studies just tries to make a guess about the underground situation. So mine exploration methods are practically stochastic methods and all of the studies just look for evidences of existence of minerals under the ground. The information which determines the situation under the ground is the information gained from the boreholes. These information have been used in this paper to compare the results of weighting methods. The boreholes for this case study are shown in Figure 3.

4.1 The Area of Study

The area under study is the copper deposit of Ali-Abad (Taft, Yazd, Iran). It is a porphyric deposit and the most important indicator for geological alterations in the area of study is Dehshir fault. The area of study is about 1 squared kilometers wide. Figure 4 shows the area.



Figure 4: Area of Study

4.2 Building the Logistic Regression Model

LR is categorized as a data-driven weighting model, so some results must be used to build the model (Yang, 2006). Then the constructed model will be used to predict the results in other parts. For this purpose 16 boreholes from 26 existence boreholes in the common area of study are randomly chosen. The quality of copper in the boreholes is the basis to call a borehole good or bad. By taking the statistics of the boreholes into account an expert determines if the

boreholes are good or bad. The value of 1 is assigned to good boreholes and value of 0 is assigned to bad ones.

The input data used in a knowledge-driven method are not always appropriate for a data-driven model. In the knowledge-driven models, the expert defines the effective data and they themselves determine the relative importance of input data through a model like AHP. However, this is not the case in a data-driven model. In a knowledge-driven model, primarily the spatial dependency among data has to be considered and the dependent data must be removed from the model. Furthermore, if none of the results or evidences lies in a spatial layer, that layer will have no effect on the results from data-driven point of view.

As no borehole is located in some layers, they are removed from the input data. The remained layers are: Geoelectric, Geomagnetic, Geochemical, Host Rock and Phillic alteration. These layers are tested for spatial correlation. Pair-wise method and χ^2 test reveal that Host Rock and Phillic alteration have significant spatial correlation. Therefore, these two layers are integrated using Boolean *AND* operator to build the Host Rock And Phillic Alteration (HRAPA) layer. At last the natural values of Geoelectric, Geomagnetic and Geochemical maps are normalized to lie between 0 and 1. This action brings data into an equivalent rational scale unless the target coefficients will have different ranges. The HRAPA layer has binary values, i.e., 1 when the point is in the HRAPA and 0 when it is not. The input values for building a LR model is illustrated in Table 2.

Table 2: The used value for building a logistic regression model

BOREHOLE NAME	GEOCHEMICAL	GEOELECTRIC	GEOMAGNETIC	HRAPA	EVALUATION
D32	0.412	0.6	0.46025	0	0
D34	0.4	0.6	0.46025	0	0
E26	1	0.4	0.46025	1	1
E30	0.6	0.8	0.46025	1	0
E32	0.6	0.8	0.46025	1	0
F26	0.8	0.2	0.46025	0	1
F30	0.8	0.4	0.46025	1	1
F35	0.8	0.405	0.46025	1	1
G28	0.6	0.994	0.46020	0	1
G30	0.8	0.962	0.46039	0	1
G33	0.8	0.709	0.46027	1	1
H22	0.6	0.398	0.46025	0	0
H24	0.4	0.347	0.46002	0	0
H32	0.575	0.968	0.46095	0	0
I26	0.4	0.929	0.45900	0	0
IJ21	0.987	0.6	0.460391	0	0

For Building the LR model, the values shown in Table 2 are entered in SPSS 9 software. The process shows that values of Geomagnetic layer can not pass the test of significance therefore this layers is neglected in the processing. The other three remained fields are contributed in the process. They pass the tests of significance of coefficients and the model passes the tests of goodness of fit such as Hosmer and Lemeshow test and likelihood ratio test. At last the results are calculated. The constant value is calculated as -6.813, and the coefficients for Geochemical, Geoelectric and HRAPA are obtained as 8.975, 0.281 and 0.927, respectively. Table 3 shows these values after they are normalized to lie between 0 and 1.

4.3 Calibrating and Weighting Layers by AHP

To use AHP one needs to build a hierarchy of goal, criteria, sub-criteria and alternatives. The hierarchy is usually built by the aid of experts and for this case study it is illustrated in Figure 5.

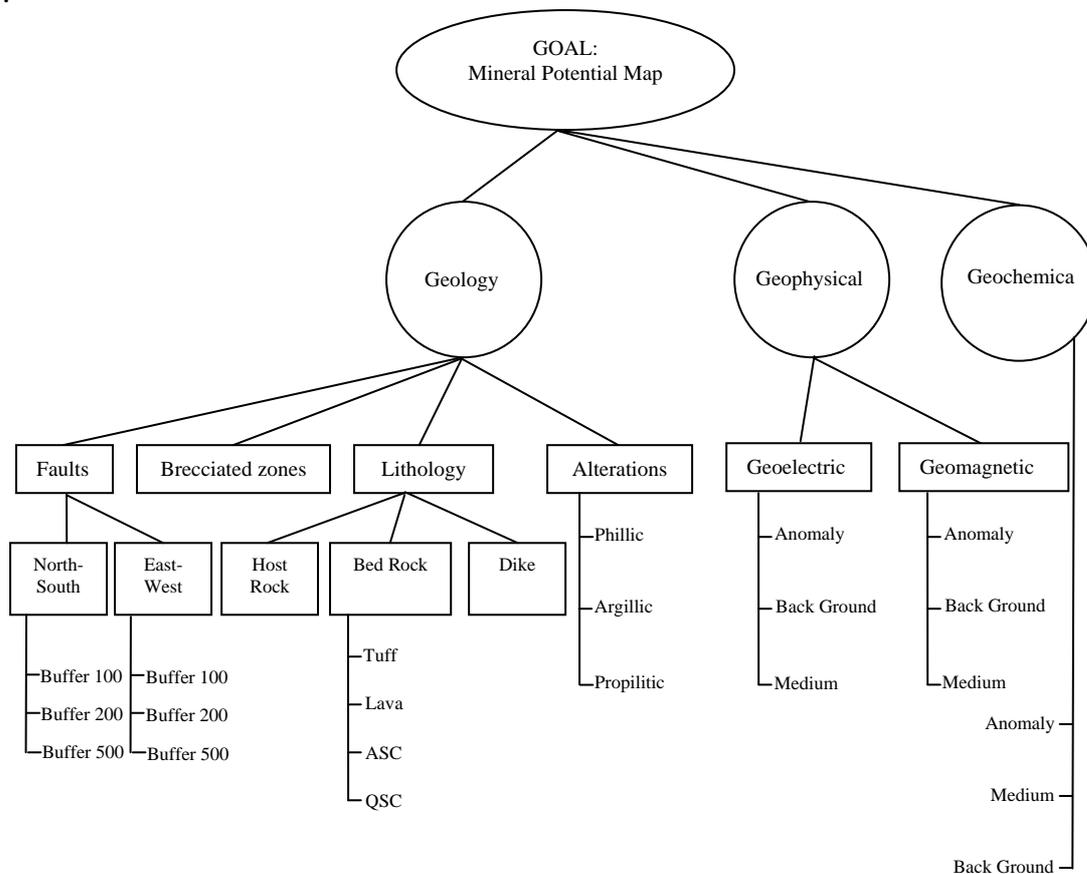


Figure 5: Hierarchy Used for Producing MPM with AHP

	Tuff	Lava	QSC	ASC
Tuff	1	a	b	c
Lava	1/a	1	d	e
QSC	1/b	1/d	1	f
ASC	1/c	1/e	1/f	1

Figure 6: Pair-wise Comparison Matrix to Bed Rock Calibration

In the model shown in Figure 5, all of the criteria/sub-criteria in the same level are compared pair-wise. The pair-wise comparisons are put into a matrix and the weights are obtained using eigenvector method. For example from the bed rock point of view four different rocks can be compared. Figure 6 shows the comparison matrix. The final weights and inconsistencies are listed in Table 3.

4.4 Integration of Layers

Maps and information layers prepared in GIS are weighted with the two mentioned methods. For AHP a professional expert carries out the procedures and the final weights are calculated. All of the maps and layers are transformed into 1x1 m raster data model as this data model is simpler for integrating and overlaying purposes. The coefficients obtained from LR model are normalized to fall between 0 and 1 and then is treated as weights. The layers are then integrated using Index Overlay approach in Arc GIS 8.3 software with the weights calculated from both methods. Calculated MPM with weights extracted from LR and combination of them with Index Overlay is abbreviated as LRI in this paper. For AHP approach the score of each class prepares values of all pixels in it. For LR approach each pixel in each map has its own value related to its value in the nature like the case used for building the model (Table 2).

On the other hand, LR can produce the MPM itself. When the coefficients are obtained, each pixel can be introduced to the model and the probability of having potential is obtained from the model. This method of integration layers by LR is also used in this study.

4.5 Producing MPM

The boreholes are holes drilled into the ground (Saman Kave, 2001). When the evidence for existence of a mineral is sufficient and satisfies the economical aspects, the boreholes are drilled in the region to discover the reality of the underground. These boreholes are used to check the efficiency of each weighting method. Table 3 shows the weights assigned to the layers according to each method. The expert who carries out the AHP judgments recognized that faults have no effect on mineralization in this case. Therefore, the information layer of faults is omitted from this method.

For LR model, 16 boreholes are used to build the model. From them 7 boreholes are good ones so primary probability of being good are $7/16=0.4375$. When the model is fitted, it is able to correctly predict the situation of 14 boreholes. This is equal to 87.5%. Then for each pixel in the area, the corresponding values of it in each of three used layers are entered into the model and the probability of being a high potential point is calculated. If the probability for each pixel passes the value of 0.4375, it is considered as a high potential pixel.

Also the weights for three layers extracted by LR model are entered to the Index Overlay model as well as the weights calculated by AHP for all of the layers and classes. Then the MPMs are produced by Index Overlay. Three produced MPMs are displayed in Figure 7.

Table 3: The Calculated Weights by LR and AHP

Layer or class Method		AHP Weights		LR Weights
Geochemical Anomaly		0.157		0.881
Geomagnetic Anomaly		0.063		-----
Geoelectric Anomaly		0.187		0.028
Barecciated zones		0.087		-----
Alterations		0.392		0.091
Host Rock		0.087		
Dike		0.013		-----
Septum Rock		0.014		-----
Faults		0		-----
Geophysical and Geochemical	Anomaly	0.749	I.R	-----
	Medium	0.198	0.087	
	Back Ground	0.053		
Alterations	Phillic	0.739	0.012	-----
	Argillic	0.167		
	Propilitic	0.094		
Bed Rock	Tuff	0.220	0.030	-----
	Lava	0.096		
	QSC	0.625		
	ASC	0.059		

Unfortunately, the factor maps of different studies shown in Figure 3 do not have a complete overlap because of georeferencing issues. Therefore, results of just the common area are used. The final MPMs produced for copper deposit of Ali-Abad by two weighting methods are displayed in Figure 7. LR has two products, one with integrating data with Index Overlay approach using the weight extracted from LR (LRI) and another by integrating data directly by fitted LR.

Saaty comments that an individual person cannot have a correct comparison between more than 7 ± 2 options simultaneously (Saaty, 1980). In this case there are 8 criteria for weighting, and especially with building a hierarchy, AHP is an appropriate approach.

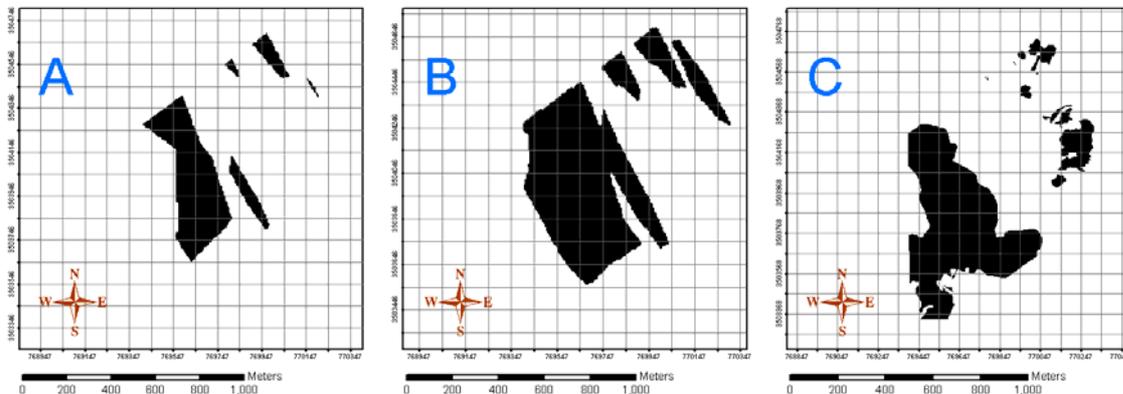


Figure 7: Mineral Potential Maps, produced by three methods, (A) the MPM produced by LR for integrating layers, (B) the MPM produced by Index Overlay using the weights calculated by LR, (C) the MPM produced by Index Overlay using the weights and scores determined by AHP.

After integrating data, the MPM will be a raster map containing different pixels values which lie between 0 and 1. The higher the pixel value is, the higher is the predicted copper potential. As mentioned before, when using the LR, the probability of 0.4375 is considered as a cut off value. The pixels with higher values are categorized into the category of high potential area (Figure 7 (A)). Two other MPMs produced by Index Overlay integrating method are categorized in a different way. The pixel values in these two maps do not have the concept of probability. A judicious for such classification is to search for abrupt changes in values (Kanungo et al., 2006). So in the two remained maps the high potential area are determined by the major change in pixel values.

5. CONCLUSIONS AND RECOMMENDATIONS

The whole common area of study is about 890639 squared meters. The high potential area predicted by each procedure is around 152430, 362901 and 358986 squared meters, respectively for maps produced by LR, LRI and AHP approaches. These amounts show that the first procedure is the most pessimistic and the second procedure is the most optimistic approach. The effect of Geochemical anomaly factor map is obvious in the map (A) while the phallic alteration and host rock have the major role in map (C). Nevertheless, using the boreholes can lead to the amount of success of each procedure. Ten boreholes which aren't used in the LR are used here for this aim. The classification tables show the predicted as well as the correct situation of boreholes for all three methods (Table 4). LR and AHP have 9 correct predictions or 90% correctness while for LRI approach this is 70%. It is worth mentioning that LR has 90% correctness in a very small area in compare to the area corresponding to AHP method. Therefore, it can be concluded that building a logistic regression and using it to integrate data leads to the best results. Also, using the coefficients of fitted logistic regression in Index Overlay is not so appropriate. However, for knowledge-

driven methods like AHP, Index Overlay is a simple and fast method of integrating data. Even though, other methods of integrating data such as Fuzzy logic can be used too.

Table 4: Classification Tables of three applied methods

(A) Classification Table for Boreholes Using LR Method			
	Good	Bad	Total
Good	3	1	4
Bad	0	6	6
Total	3	7	10

(B) Classification Table for Boreholes Using LR and Index Overlay			
	Good	Bad	Total
Good	4	0	4
Bad	3	3	6
Total	7	3	10

(C) Classification Table for Boreholes Using AHP and Index Overlay			
	Good	Bad	Total
Good	4	0	4
Bad	1	5	6
Total	5	5	10

Though the LR approach has the best results in this case it may contains other problems. As a data-driven approach the major limitation of this method is unavailability of evidences (e.g. boreholes in this study) in many cases. Furthermore, the LR model usually needs more data to be fitted and in some cases it may not be fitted at all.

AHP needs just the pair-wise comparisons of an expert and is a simple and almost reliable approach for weighting because it can check the consistency of judgments.

Generally speaking, selection of a proper weighting method depends on a particular decision situation. Particularly, it is very important to consider a number of factors such as, accuracy, degree of understanding on the part of decision maker, the theoretical foundation underlying a given method, the availability of computer software, and the way the method can be incorporated into GIS-based multicriteria decision analysis (Malczewski, 1999).

It is recommended that these methods especially LR to be used in other case studies and with more evidence data. Also multinomial LR can be used when the response variable is not binary. Integrating weights by other integrating methods like Fuzzy sets can be another option.

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BIOGRAPHICAL NOTES

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