

# DETERMINATION OF ORE/WASTE BOUNDARY USING INDICATOR KRIGING, CASE STUDY: CHOGHART IRON MINE OF IRAN

J. Gholamnejad\*, A.H. Ansari, Yarahmadi Bafghi and M. Taqizadeh

Department of Mining and Metallurgical engineering, Yazd University, Yazd, Iran  
j.gholamnejad@yazduni.ac.ir, h.ansari@yazduni.ac.ir, a.yarahmadi@yazduni.ac.ir,  
majid.t80@gmail.com

\*Corresponding Author

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**Abstract** Estimation of ore reserves is one of the most critical aspects of mining geology. The accurate assessment of the tonnage and grade of run of mine may be the difference between a healthy profitable operation and an expensive early mine closure. The first step in ore reserve estimation is to determine the boundary of ore body or ore/waste contacts. This paper presents a specific mining application to estimate ore/waste boundaries, which uses usual chemical variables. In the suggested procedure, the geostatistical method of Indicator Kriging (IK) was used to determine the boundary of ore body in Choghart iron mine of Iran. Assuming a cutoff grade in terms of the iron content mode, all data values transformed to either 1 or 0. An IK estimation of transformed data was performed. These values must always lie in the interval  $[0, 1]$ , and can be interpreted as the probability that the grade is above the specified indicator. Then, the estimated probability plans were compared to the extracted plans. Results showed that blocks with the estimated probability of equal to or more than 0.85 are laid within the ore body boundary and blocks with the probability less than 0.15 should be considered as waste. This rule was then applied to the remaining ore deposit and its reserve was estimated to be about 75 million tons.

**Keywords** Indicator kriging, Ore reservoir, Ore boundary, Iron mine, Choghart

**چکیده** برآورد تقریبی مخازن سنگ معدن یکی از مسائل مهم در زمین شناسی معدن است. برآورد دقیق تناژ و درجه خلوص معدن می تواند تفاوت مابین یک فرایند سودمند صحیح و یک فرایند پرهزینه در معدن با تعطیلی زود هنگام باشد. اولین مرحله در برآورد ذخایر سنگ معدن تعیین محدوده سنگ معدن یا تماس سنگ معدن با ناخالصی هاست. در این مقاله یک کاربرد خاص معدن کاری برای برآورد محدوده سنگ معدن/ ناخالصی ارائه شده است که در آن از متغیرهای شیمیایی استفاده می شود. در این روش پیشنهادی از روش ژئو آماری IK برای تعیین محدوده سنگ معدن در معدن آهن چغارت ایران استفاده گردید. با فرض یک خلوص منقطع به صورت میزان آهن، همه اطلاعات به صفر و یک تبدیل شدند. تقریبی از IK دیتاهای تبدیل شده انجام شد. این مقادیر باید همیشه در فاصله  $[0, 1]$  باشند و می توان آنها را با احتمال اینکه خلوص بالاتر از شاخص تعریف شده باشد تعبیر کرد. سپس احتمالات تخمین زده شده با طرح های استخراج شده مقایسه گردیدند. نتایج نشان داد که بلاک هایی که با احتمال بزرگتر یا مساوی  $0/85$  دارند در محدوده سنگ معدن قرار می گیرند و آنهایی که احتمالشان کمتر از  $0/15$  است به عنوان ناخالصی لحاظ می شوند. سپس این روش برای کانسار باقیمانده استفاده شد و ذخایر آن حدود 75 میلیون تن برآورد گردید.

## 1. INTRODUCTION

Indicator Kriging (IK) as a non-parametric technique in resource estimation is over fifteen years old. IK was introduced by Journel [1], and since that time has grown to become one of the most widely-applied grade estimation techniques in the minerals industry, despite the relative difficulty in its application. Its appeal lies in the

fact that it makes no assumptions about the distribution underlying the sample data, and indeed it can handle moderate mixing of diverse sample populations. However, despite the elegant and simple theoretical basis for IK, there are many practical implementation issues which affect its application and require serious considerations. These include aspects of order relations and their correction, the change of support, issues associated

with highly skewed data, and the treatment of the extremes of the sample distribution when deriving estimates [2]. It is the prime non-linear geostatistical technique used today in the minerals industry.

This paper presents an overview of the theory of IK, followed by some discussion of practical applications. Then, this method is applied to estimate the ore/waste boundaries in Choghart iron ore deposit in the central part of Iran.

## 2. OVERVIEW OF THE THEORY AND PRACTICAL APPLICATION OF IK

The concept of indicator coding of data is not new to science, but has only been proposed in the estimation of spatial distributions since the work of Journel [1]. The essence of the indicator approach is the binomial coding of data into either 1 or 0 depending upon its relationship to a cut-off value,  $Z_c$ . For a given value  $Z(x)$  [3]:

$$i_k(x) = \begin{cases} 1 & \text{if } Z(x) \geq Z_c \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This is a non-linear transformation of the data value, into either a 1 or a 0. Values which are much greater than a given cut-off,  $Z_c$ , will receive the same indicator value as those values which are only slightly greater than that cut-off. Thus, indicator transformation of data is an effective way of limiting the effect of very high values. Simple or ordinary Kriging of a set of indicator-transformed values will provide a resultant value between 0 and 1 for each point estimate, which can be interpreted either as [4]:

1. Probabilities (the probability that the grade is above the specified indicator) or
2. As proportions (the proportion of the block above the specified cut-off on data support).

The outcome of IK is a conditional cumulative distribution function (ccdf); a distribution of local uncertainty or possible values conditional to data in the neighborhood of the block to be estimated. This distribution of grades can be used for many purposes, in addition to simply deriving the average (or 'expected') value. Any relevant criteria may be used to derive the required estimation, not simply the arithmetic mean of the local

distribution.

The practice of IK involves calculating and modeling indicator variograms (that is, variograms of indicator-transformed data) at a range of cut-offs or thresholds which should cover the range of the input data. This approach is termed Multiple Indicator Kriging (MIK). Until recently, this has been a somewhat time-consuming exercise. One approximation is to simply infer the variograms for the median of the input data and to use this for all cut-offs. This so-called Median IK approach is very fast, since the Kriging weights do not depend on the cut-off being considered. Median IK also necessitates the solution of only one Kriging system per block in contrast to the multiple systems required for MIK. Some practical applications of IK can be stated as follows [2, 5]:

*Treatment of upper and lower tails:* An indicator Kriging program will provide an estimation of the proportion of a model block above each of the indicator grades or thresholds assessed. To reduce this data into an estimation of mean block grade or grade above a cut-off, it is a requirement that each indicator class interval be assigned a grade. A number of sensitivities must be considered when undertaking the task of class interval grade assignment. If indicator grades be carefully selected with adequate regard to the input grade distribution, then the distribution of grades within many classes will be nearly linear. The average grade of the input data or the bounding indicator grades will normally suffice for the assignment of grade in these classes.

*Use of a mineralization indicator and choice of cut-offs:* In many geological estimation problems, there may be no way to clearly define mineralogical or geological domains within which the spatial continuity and grade behavior is more consistent than elsewhere. A typical scenario is an advanced exploration prospect with demonstrated geological and grade continuity, yet in which the detailed structures controlling and constraining mineralization are unknown. Ideally, in such a situation, the preference is to allocate some forms of domain within which local controls on mineralization may be applied, even if this is only a grade envelope. However, it is sometimes physically impossible to clearly separate ore-grade material from low-grade background material. In such a situation, descriptive statistics and

geostatistics are often biased by the multitude of trace to low-grade assays, and this can also affect the choice of indicator cut-offs. One solution to this is to apply a mineralization cut-off grade to the bottom end of the grade distribution. This will separate possibly mineralized from clear-background material. Values below this cut-off are rejected for statistical and geostatistical analysis. This leads to better-defined distributions, and assists the selection of appropriate indicator cut-offs.

*Categorical Kriging:* The indicator transform also lends itself to the estimation of categorical data – in other words, variables which are not continuous but have discrete values. Some examples of categorical data are the presence or absence of a rock type (direct binary data requiring no transform), or a series of lithological or facies codes, or mineral sands hardness values [6]. In this case, instead of Kriging indicators at a set of thresholds, categorical IK will produce the probability of a given rock type or domain code occurring at a given location. Thus, it is possible to produce probability maps for given lithologies based upon actual rock code data. This may be combined with indicator estimation or simulation of grade data.

The indicator approach allows the estimation of the probability distribution of a variable within a region [7]. However, no assumptions concerning the distribution of the modeled variable(s) are needed. For this reason IK belongs to the category of nonparametric methods. [8] In this study, the ore/waste boundaries in Choghart iron ore deposit will be determined using IK method.

### 3. MINING PARAMETERS OF CHOGHART DEPOSIT

Choghart mine is located at 13 km northeast of Bafq and 120 km east of Yazd. Center longitude and latitude are 55°:28':2" and 31°:42':0", respectively. Figure 1 shows the location of the

Choghart iron ore mine. Choghart Iron Deposit is one of the largest iron ore mines of Iran. The minable reserve was more than 170 million tons. This mine is extracted by surface mining method. Mining operations usually include the five stages of drilling, blasting, loading, hauling and milling. Loading and transporting is done with truck-shovel system. Drilling and blasting operations are very important because of some reasons such as complex discontinuity system, the rock type variations and the water bearing beds. Other characteristics of Choghart mine are shape and size of pit: ellipse (840 m long diagonal and 640 m width diagonal), stripping ratio: 0.85, highest level: 1140 m, pit depth: 327.5 m, overall slope angle: 55 degree, bench height: 10 m (from 1140 to 1100 level) and 12.5 m (from 1100 to 812.5 level), shovel capacity: 7.6 m<sup>3</sup>, truck capacity: 85 tons and ore specification: ( Fe: 66% and P: 0.12% ).



**Figure 1.** Location of Choghart iron ore deposit  
Iron Ore in this mine is classified as: 1) high-grade ore, non-oxidized and low phosphor; 2) high-grade ore, oxidized and low phosphor; 3) high-grade ore, non-oxidized and high phosphor; 4) high-grade ore, oxidized and high phosphor.

Also, the low-grade ore is classified to low phosphor and high phosphor ore. High grade-high phosphor ore with P grade of up to 0.6% is removed from the pit and stored in high grade

stockpile for possible future use [9].

#### 4. INPUT DATA FOR GEOSTATISTICAL MODELING OF CHOGHART DEPOSIT

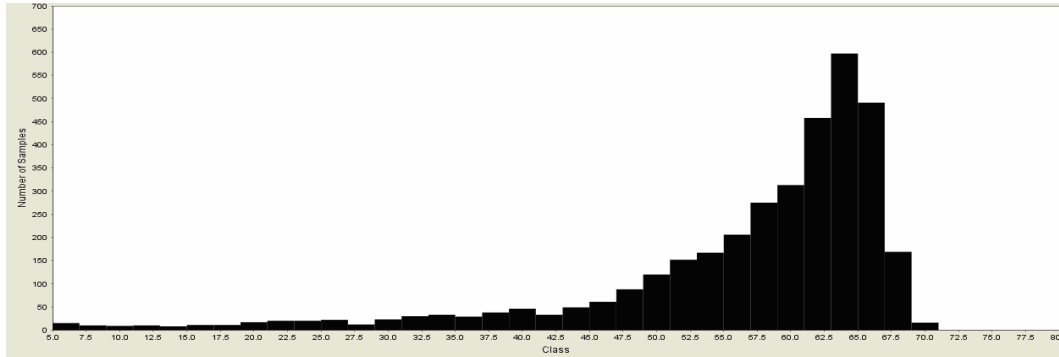


Figure 2. Histogram for Fe concentration (%) for exploration data set.

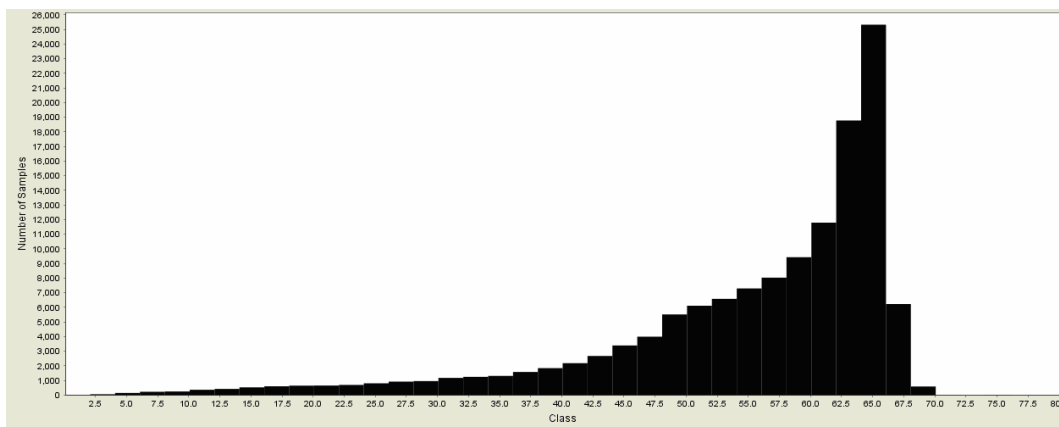


Figure 3. Histogram for Fe concentration (%) for blast-hole data set.

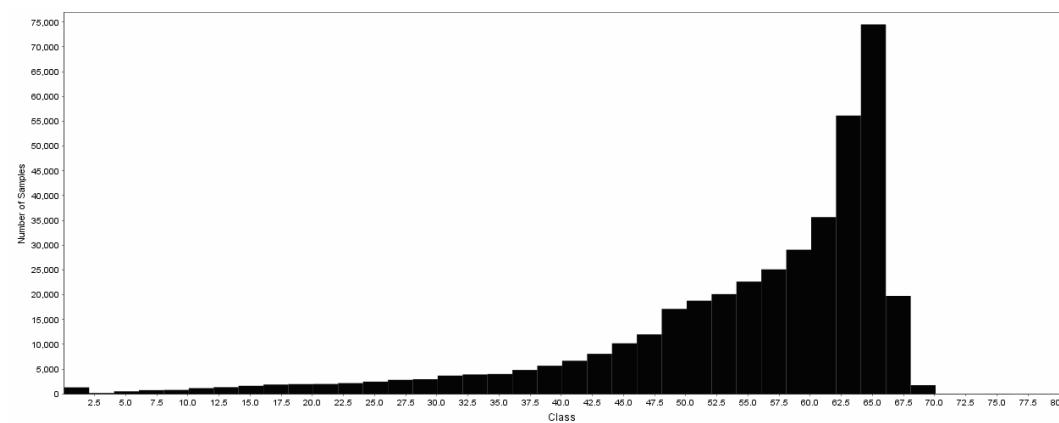


Figure 4. Histogram for Fe concentration (%) for total data set.

The mine site is included in an area extensively sampled by drill holes at 50 m by 50 m average spacing. This study also uses a 3 x 4 m (with 1 centre hole) blast hole dataset from 16 benches of the open pit with the sampling portion of each hole being 10 and 12.5 m. This dataset contains a huge amount of data that cannot be processed by today's PC; therefore, in order to reduce them, this grid changed to a 25 x 25m regular data one. To obtain this, a 25 x 25m regular grid is overlaid on the 3 x 4m data map and then, all the blast holes within each 20 x 20m cell were selected, their Fe grades were averaged and assigned to the fictive hole in the center of that block (cell). Certainly, the depth of these fictive holes was in accordance to the height of considered bench (10 or 12.5m). Prior to modeling, original drill holes and fictive samples were composited into a constant length of 3.3 m along drill holes. Compositing was configured to begin at the bottom of the hole, progressing upwards without any breaks for lithology or grade shell boundaries.

Figures 2, 3 and 4 present the spatial grade distribution of the Fe concentration for exploration, blast hole and total data set, respectively. As can be seen, Fe displays a single, negatively skewed grade distribution. The original data set must be transformed into either 1 or 0 for the purpose of variography and Kriging; therefore, cut-off grade of 20% is considered for indicator transformation of composites.

## 5. SEMI-VARIOGRAM ANALYSIS OF INDICATOR TRANSFORMED DATA

In nature the grade or value of a particular sample in three dimensional spaces is expected to be affected by its position and its relationship with its neighbors, i.e. mineralization is not usually random and is influenced by such things as rock porosity, fracturing, distance from source, etc.

The fundamental principal behind geostatistics takes this dependence into account and is known as the theory of regionalized variables. The procedure or tool to quantify both the amount and direction of this dependence is called the semi-variogram. A semi-variogram is the fundamental autocorrelation tool of geostatistical procedures. It is defined as

half of the mean square difference of a variable for values separated by a distance  $h$  as given by the formula:

$$\gamma(h) = \frac{1}{2n} \sum_{i=1}^n [Z(x_i) - Z(x_i + h)]^2 \quad (2)$$

where,

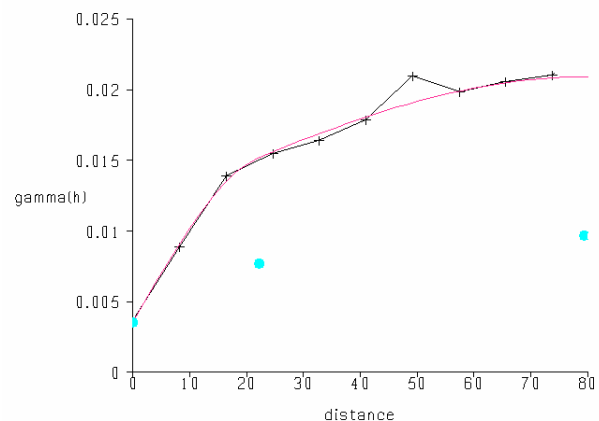
$\gamma(h)$  is the semi-variogram

$x_i$  is the value at location  $i$

$x_i + h$  is the value at a distance  $h$  from  $i$

$n$  is the number of  $Z(x_i) - Z(x_i + h)$  pairs

$\gamma(h)$  is a 3-dimensional function, commonly dependent on direction within a deposit which can also differ from a geological environment to another. An experimental semi-variogram is determined from a set of experimental data (e.g. assay values at known locations) and is shown graphically as a plot of  $\gamma(h)$  versus  $h$  (lag or sample spacing). For practical applications, a smooth mathematical model is fitted to the normally saw-toothed graph of an experimental semi-variogram.

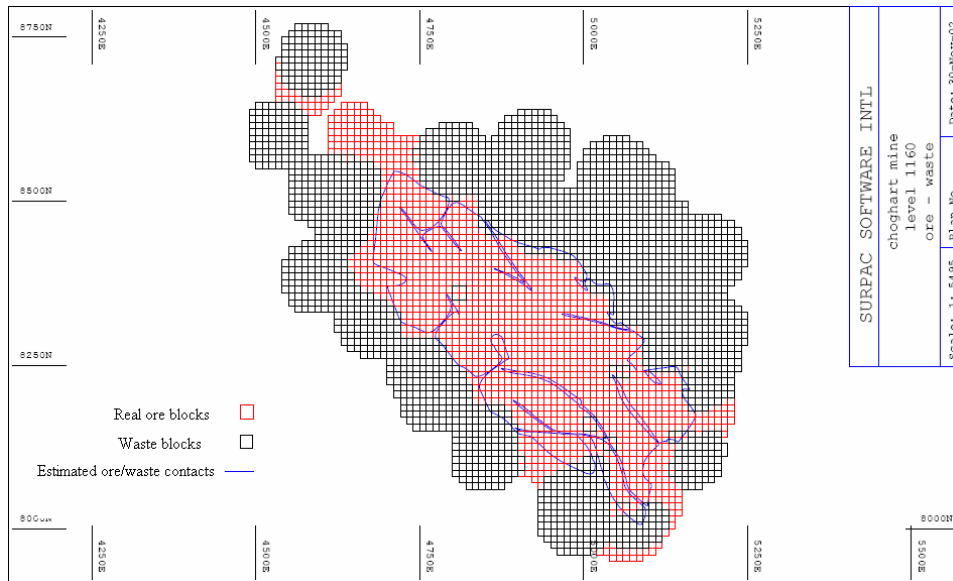


**Figure 5.** Plot of the nested variogram for indicator data set along the major axis,  $Az=180^\circ$  and  $Dip=-67^\circ$ .

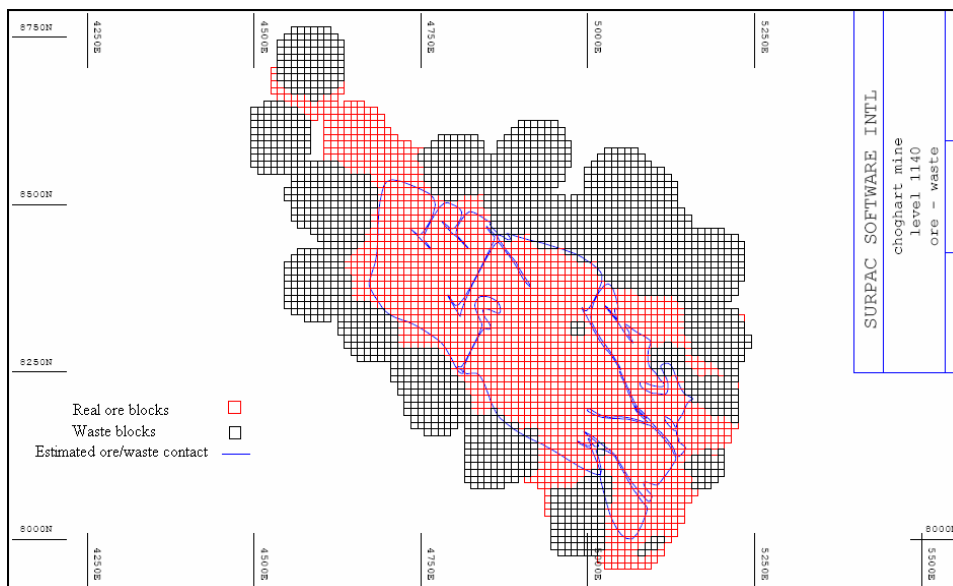
The indicator semi-variograms values are estimated at several directions and dips to detect any anisotropy in the data. Checking and detecting anisotropy is important process as it has larger or shorter spatial correlation (range) in some directions, and can be useful in selecting neighboring data to improve the performance of IK estimates (interpolation techniques). Figure 5 shows the major semi-variogram model axis for indicator data in azimuth and dip of 180 and -67

degree, respectively, which is in accordance to the major anisotropy axis.

two spherical structures and maximum range of 71m. Table 1 presents the specifications of



**Figure 6.** Estimated and real ore boundary in level 1160m of Choghart open pit.



**Figure 7.** Estimated and real ore boundary in level 1140m of Choghart open pit.

As can be seen from Figure 5, the empirical semi-variogram does not seem to follow any of the standard structures; it is possible to combine structures to obtain a variogram with the characteristics of more than one of the standard structures. A linear combination of valid variogram structures is also a valid variogram model and is called a nested variogram structure. In this variogram we have a nested structure with

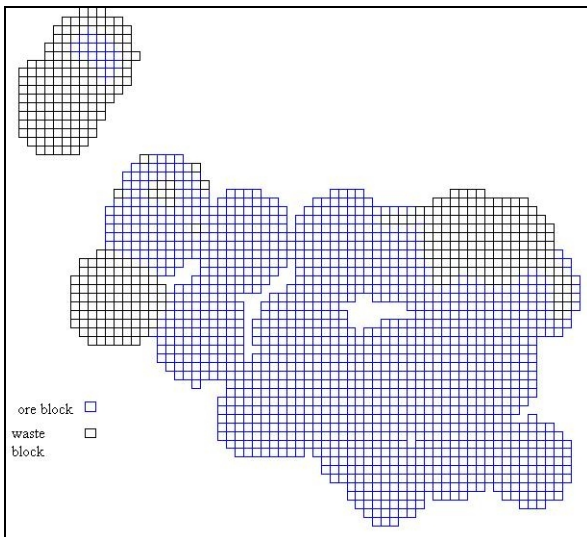
anisotropy ellipsoid axis.

**TABLE 1. Specifications of anisotropy ellipsoid axis.**

| Anisotropy axis | Azimuth | Dip | Anisotropy factor |
|-----------------|---------|-----|-------------------|
| Major axis      | 180     | -67 | 1                 |
| Semi-major axis | 90      | 23  | 1.15              |

### 6. INDICATOR KRIGING ANALYSIS

Indicator Kriging (IK) is the Kriging of indicator-transformed values using the appropriate indicator variogram as the structural function. In general, the Kriging employed is Ordinary Kriging (OK). IK was initially selected as the preferred method of resource estimation in this study. Block model in this analysis consisted of two kinds of blocks, 12.5 x 12.5 x 10m blocks from level 1160 to 1100m and 12.5 x 12.5 x 12.5m blocks from level 1100 to 812.5m, with regard to the bench height of the open pit. IK analysis of data was performed and probability maps were produced in each level for the whole deposit.

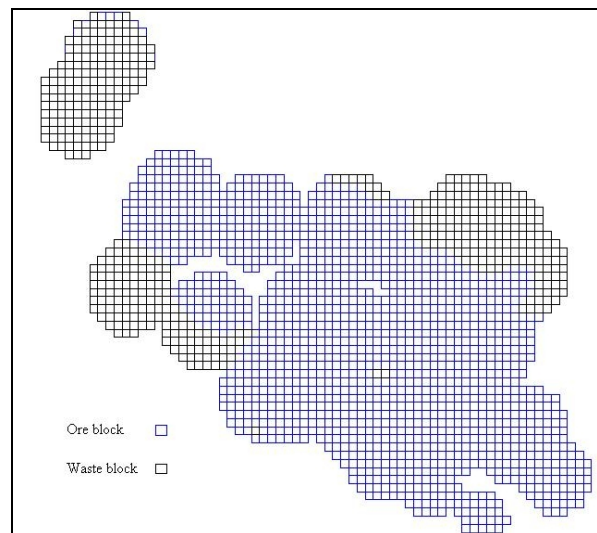


**Figure 8.** Estimated ore boundary in level 970m of Choghart open pit.

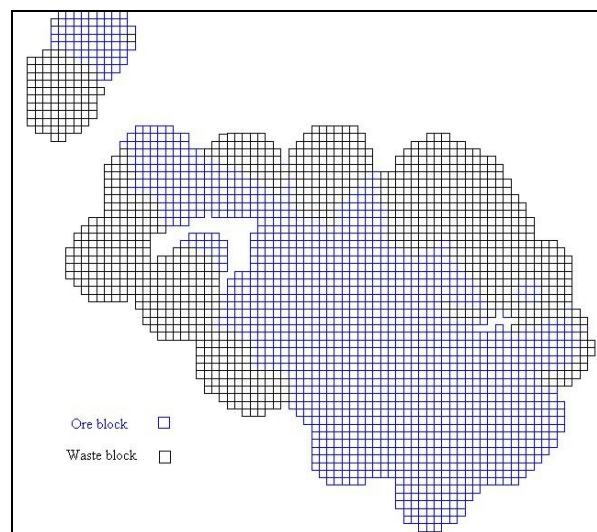
As explained before, the calculated probabilities are between 0 and 1 for each estimated block, which can be interpreted as the probability that the block grade is above the specified cut-off grade, which is considered 20% in this analysis. In the other words, each probability reflects the probability that supposed block to be an ore block. In order to distinguish the ore/waste boundaries in Choghart deposit, the probability map of each previous extracted bench is overlaid on the real ore/waste boundary of the same bench obtaining from blast holes Fe analysis. Results showed that in all plans, blocks that are within the true

boundary of ore have the probability index of equal or more than 0.85. Figures 6 and 7 show the estimated and real ore boundary in levels 1160m and 1140m of Choghart open pit. As is clear from these figures, there is a good conformity between estimated and real ore/waste boundaries except in the southeast of orebody. This is attributed to the lack of bore holes in this part of the deposit.

By applying this index to the unexploited levels (1100 to 812.5), the ore/waste boundaries for the remaining ore body were estimated. Figures 8, 9 and 10 show the ore/waste boundaries of levels 970, 1000 and 1050m, respectively. Results show that the total unexploited ore in Choghart deposit is about 75 million tons.



**Figure 9.** Estimated ore boundary in level 1000m of Choghart open pit.



**Figure 10.** Estimated ore boundary in level 1050m of Choghart open pit.

## 7. CONCLUSION

Indicator Kriging is now widely used in the mining industry as an estimation technique over a wide range of deposits and environments, because it offers practical solutions to some common estimation problems. In this paper, IK was used in order to determine the ore/waste boundaries in Choghart Iron mine of Iran. Assuming the cut-off grade of 20% for iron, all the data composites are converted to 0 or 1 by using indicator transformation function. Then, Ordinary Kriging applied to the transformed data and the probability number was calculated for each block. Comparison of the resultant probability maps with the real ore/waste boundaries on the extracted levels showed that blocks with the probability of more than 0.85 lay within the ore body and remaining blocks can be considered as waste. This approach was applied to the rest of levels and concluded that the total amount of remaining iron ore is 75 million tons. This method can also be applied to the sedimentary and base metal deposits.

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