Journal of Mining and Environment (JME) Vol. 13, No. 2, 2022, 325-340

Shahrood University of Technology

Iranian Society of Mining Engineering (IRSME)

Journal of Mining and Environment (JME)

journal homepage: www.jme.shahroodut.ac.ir

THOMSON REUTERS

Ore Deposit Boundary Modification in Afghanistan Aynak Central Copper Deposit using Sequential Indicator Simulation and Indicator Kriging

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Article Info

Received 10 Janury 2022
Received in Revised form 17 April 2022
Accepted 24 April 2022
Published online 24 April 2022

DOI:10.22044/jme.2022.11557.2142

Keywords

Ore reserve estimation
Geostatistics
Orebody boundary
Modeling
Indicator kriging

Abstract

The Aynak copper deposit is the most important strata-bound copper reserve in Afghanistan. The main purpose of this work is the ore deposit boundary modification and reserve estimation of the Aynak central copper deposit using the geostatistical methods. The ordinary kiging (OK), indicator kriging (IK) and sequential indicator simulation (SIS) methods were used to modify the optimum ore deposit boundary and ore reserve estimation. Then the results, accuracy and efficiency of these three methods are compared. Before the ore reserve estimation, the pre-processing, statistical and geostatistical analysis of the sampled data are performed. For a precise estimation process, it is necessary to modify the optimum ore body boundary as an estimation space. Therefore, the IK and SIS methods are applied to revise the conventional ore deposit boundary and estimation space. At the first stage, the ore body wireframe and solid model are obtained using the conventional cross-section method. The block model is created covering the mineralization space of the ore body, and firstly constrained by the conventional model (solid model). Consequently, the ore body model is adapted and bounded using the IK and SIS geostatistical methods. Finally, the log-kriging method that is basically unbiased and guarantees the minimum estimation error is used to estimate the Cu concentration in each block, and after back-transformation, the grade-tonnage curves are plotted. The total tonnage of the deposit is calculated based on different cut-off grades. Assuming the cut-off grade of 0.2% for Cu, the tonnage of ore reserve based on the conventional OK method, IK method, and SIS constrained ore body model are estimated as 453.4, 459.1, and 467.7 million tons with an average grade of 1.077%, 1.08%, and 1.05%, respectively. The proximity of the obtained reserve estimation results using different implemented methodologies is due to the low-grade variability and genetical regularity in the Aynak staratabound copper deposit and guarantees the accuracy of the results obtained in the ore reserve evaluation.

1. Introduction

The ore deposit boundary modeling and the reserve estimation are the important goals of mining exploration operations, and only after this stage, we can consider the ore reserves as the technical and economic issues. Among these, determining the ore deposit boundary and estimating the quantity and quality of reserves are the most important issues and problems frequently facing the geologists and mining engineers due to the geological complexities of ore body formation. Therefore, estimation of ore reserves is one of the most critical aspects of mining geology [1].

Evaluating the geological properties of a mineral deposit is a fundamental task for mine planning and it requires an assessment of the reserve parameters such as the thickness and grade. With the exploration progress, the reserve estimation is required from time to time in order to quantify the

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thickness and grade contained in the deposit. There are some techniques in the literature for modeling the reserve parameters thickness, tonnage, and grade. The geo-statistical methods are based on the random functions, and consider the spatial relationship of the sample data. Even though the geo-statistical methods have a high modeling capacity, these method has some limitations. The most important limitation of the geo-statistical approaches is the number of data points. In the case of small deposits, the number of boreholes is not sufficient for the calculation and modeling of an acceptable variogram [2].

There are various methods for calculating the volume and tonnage of ore reserves that can be used according to the types of reserves and the amount of depth information, calculation algorithm, accuracy, speed, ore deposit status, and characteristics of the deposit exploration works. Due to the effects of estimation error on increasing the investment risk, it is necessary to use the most accurate reserve estimation that can guarantee the minimum estimation error [3-6], and the estimation error must be known at any point of the ore deposit to categorize the reserve.

Unlike to conventional methods and/or classical statistics of ore deposit estimations, which are typically associated with a systematic error, the geo-statistical methods provide quick and reliable estimates with a minimum variance [7]. Therefore, it is possible to achieve the error distribution function. Among the geo-statistical methods, kriging provides estimation with a minimum variance and error at an unsampled location [7-9].

Kriging, as a group of geostatistical methods, is an interpolation technique that considers both the distance and the degree of variation between the known data points when estimating the values in unknown areas [10-12]. The main disadvantage of kriging is referred to smoothing, which leads to some reduction in variability. Smoothing causes overestimating of the low values and underestimating of the high values [13, 14].

The most common type of kriging that is used in the linear reserve estimation methods is ordinary kriging (OK). In this method, based on the available data, the most accurate possible estimate for the grade of the extracted blocks is calculated with the error related to the grade value of each block. Among the non-linear kriging methods, the indicator kriging (IK) method is the most used in the ore deposit boundary modification and ore reserve estimation. When the variable distributions of interest have a near-normal shape, a linear estimator is ideal. However, when the variable distribution of interest is highly skewed or contains a mixture of population, the ordinary estimation methods can be erroneous. In these case, the non-linear estimation method can more appropriately handle these more complex distributions such as log-kriging [12].

The first step in the ore reserve estimation is to determine the boundary of ore deposit or ore/waste contacts [1]. Generally, for low grade deposits in which the boundaries are highly dependent on the cut-off grade, it is vitally important to determine the ore-waste bound of a block. A number of techniques exist for boundary modeling, and some developments for reducing the uncertainty near boundaries have currently been applied [15].

Any estimation made by OK is only invaluable from the extraction view point when the estimated block is entirely extracted out. However, the conventional OK is unable to give a method for a selective extraction of the estimated block in erratic, complex boundaries, and low grade deposits because the ore/waste bound is not obvious, and is located inside the blocks. Likewise, in order to control the estimation process, it is necessary to define a specific space or search space, which has a significant impact on the outcome of the kriging estimate [16] based on the ore deposit boundary and to estimate that space using the data gathered from the deposit.

In case all the data including those of both ore and waste are used to estimate the estimation space, because of the smoothing effect of kriging, the data related to waste materials has a tendency to decrease the overall grade of the deposit while the data of ore is vice versa [17, 18]. This might result in the overestimation of tonnage and underestimation of grade, and finally distracts the ore–waste relationship from what it really is [18].

When it is required to separate the estimation blocks in an ore reserve, it is so helpful to apply IK and Sequential Indicator Simulation (SIS). IK and SIS are used in the ore deposit boundary modification and ore reserve estimation widely. The algorithm of SIS is similar to that of Sequential Gaussian Simulation (SGS), a widely used technique for the categorical and continuous variable models [19, 20]. IK and SIS are also able to help the user to draw the probability map for any grade to have the probability of happening equal to or greater than an arbitrary cut-off grade. If this cut-off grade is the same as the economic grade, then the drawn map shows the ore deposit boundary too.

The main purpose of this work is to determine the optimum ore deposit boundary using the IK and SIS geo-statistical methods and compare them with the solid model obtained by the conventional method.

In this work, the accuracy and efficiency of linear (Ok), non-linear (IK) kriging, and SIS geo-statistical methods are investigated in the ore deposit boundary modification and ore reserve estimation in the Aynak central copper deposit.

2. Case study: Aynak copper deposit

Aynak is the largest know copper deposit in Afghanistan, and is comparable to those in the Zambian Copper belt in grade and tonnage [21, 22]. The Ayanak copper deposit is located about 30 km south and SE of the Kabul city, Kabul tectonic block. The center of the deposit is located at longitude 69° 18′ 18″ latitude 34° 15′ 58″ approximately (Figure 1) [23, 24].

The Kabul block is a north-northeast trending, lenticular-shaped sliver about 200 km long and 50 km wide. The block has a broadly anticlinal structure that exposes a core of Precambrian metamorphic rocks flanked by Late Paleozoic and Mesozoic rocks [24]. The Aynak deposit is hosted in rocks of the Loykhar and Gulhamid Formations that are folded into a complex asymmetric anticline [24].

The oldest rocks exposed in the studied area belong to the metavolcanic Wellayati Formation, composed of gneiss and amphibolite and are exposed to core of the anticlined.

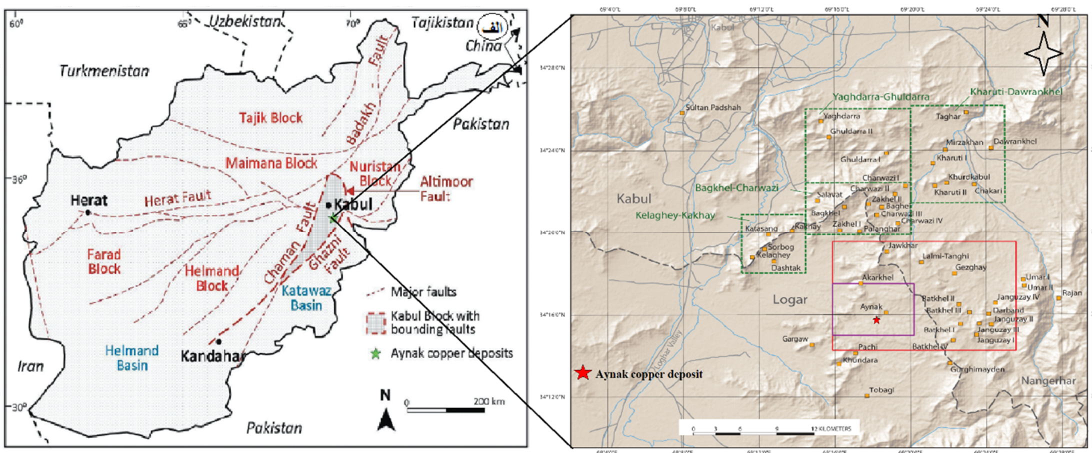

Figure 1. Tectonic map of Afghanistan with location of Kabul Block and the the Aynak copper deposit, modified from AGS and BGS [22, 23].

This formation is overlain by the thick metasedimentary sequence of the Loy Khar Formation, which is the host to the copper mineralization. The Loy khar Formation is a cyclical sequence of dolomite marble, carbonaceous quartz schist and quartz-biotite-dolomite schist, and hosts the copper mineralization. The Loy Khar Formation is post-dated by basaltic to dacitic metavolcanic rocks of the Gulhamid Formation, which are also of Vendian-Cambrian age [21-26] (Figure 2).

The upper Permian limestones and dolomites of the Khingil Formation occur at Aynak in small outcrops in the western and southern part of the area. Poorly consolidated coarse fluvial and fluvial-lacustrine intermountain basin deposits of Neogene Lataband Formation infill the valleys and depressions in the Aynak area that reaches a maximum thicknesses of about 600 m [23-26].

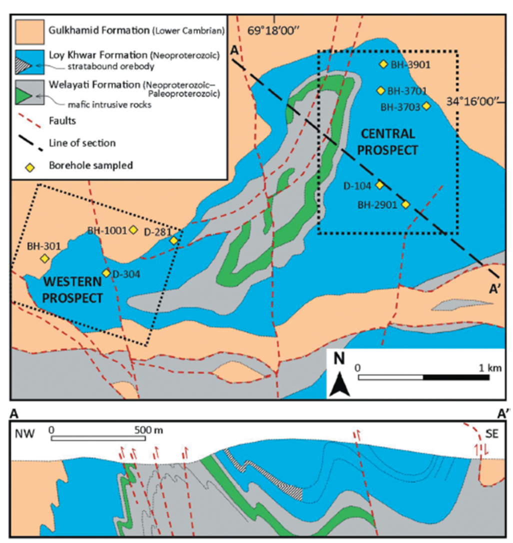

Figure 2. Geological map and cross-section of Aynak copper deposit [22].

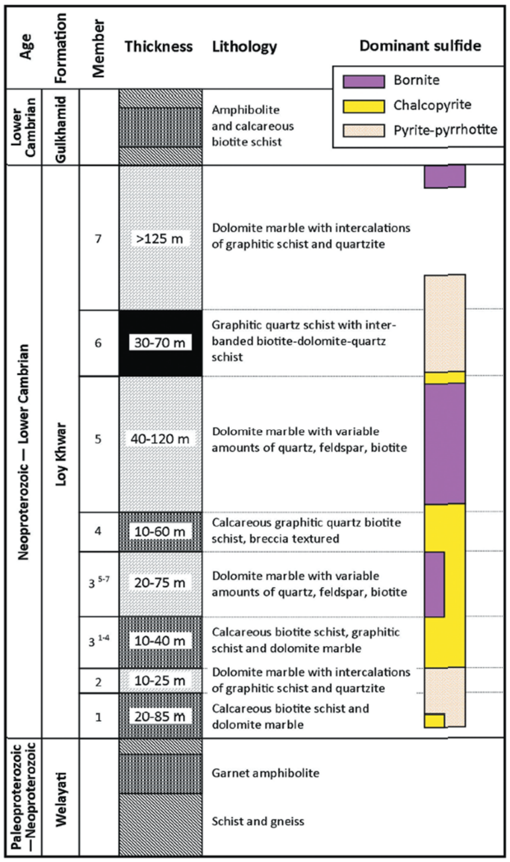

Figure 3. Stratigraphic column, showing the major rock types and sulphide mineral zonation in the Aynak copper deposit [22].

The copper mineralization at Aynak is stratabound, and characterized by chalcopyrite and bornite disseminated in dolomite marble and quartz-biotite-dolomite schists of Loy Khar formation [22-26]. The mineralization is mainly concentrated in members 3-5 of the Formation, as illustrated in Figure 3. The main ore body at Central Aynak is characterized predominantly by bornite. Chalcopyrite occurs in only minor amounts in the middle and lower parts of the orebody. Primary mineral zoning is apparent within the deposit. The central part of the deposit contains mainly bornite grading out to chalcopyrite and the pyrite and pyrrhotite. [23-26].

3. Methodology

3.1. Dataset

In all, the data about 10881 rock somples with intervals of 0.1-13.6 m with mean of 1.8 m gathered from 132 boreholes and trenches with a total length of 42185 m related to the Aynak copper deposit. The dataset included collars, lithology, down-hole survey, and assay, which are used in this work. In general, the drilling grid is irregular, and the distance between the two boreholes varies from 20 m to 100 m. Figure 4 shows a 2D view of the drill hole location in the deposit. The drill hole samples were prepared and analyzed using Atomic Absorption Spectroscopy (AAS) for copper.

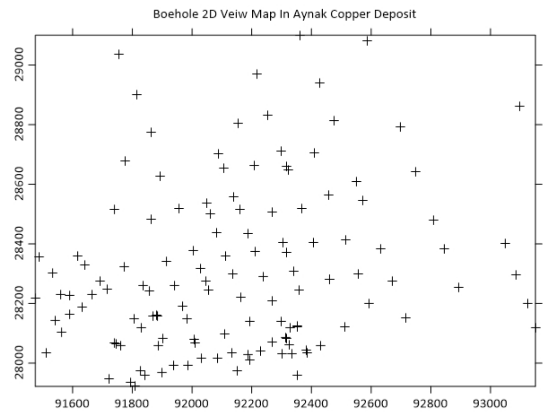

Figure 4. Drill hole 2D view in Aynak copper deposit.

3.2. Pre-processing of data

The sampled data was first pre-processed to use the reliable geo-statistical methods. Pre-processing of the data includes data validation, censored data, and outlier value analysis. In addition to the presence or absence of the censored data and outlier values, it is possible to have the missing information, illogical data entries, and others such as sample interval overlaps [27], which are required to be investigated and validated. If there are censored data and outlier values, before the statistical and geo-statistical analysis and reserve estimation, the censored data and outlier values should be replaced and corrected.

There are several methods for identifying the outlier values including box plot, Q-Q plot diagrams, computational method $X_A = \bar{x} + S.g$, and Doerffel diagrams. For this purpose, first the censored data is identified, and is replaced using the $\frac{3}{4}$ method for the minor sensitivity limit values. Then the box plot of the transformed data (ln(Cu)) is plotted and the outlier values are identified, and the replacement operation is performed (Figure 5).

After checking the censored data and outlier values, the information collected from the exploratory boreholes is inserted in the Excel software. Then four files related to the assay, geology, collar, and survey information are inserted and finally, the database is made relevant to the mining software, which is used in the modeling and reserve estimation. Figure 6 shows a 3D view of the boreholes and topographic layer of the Aynak copper deposit.

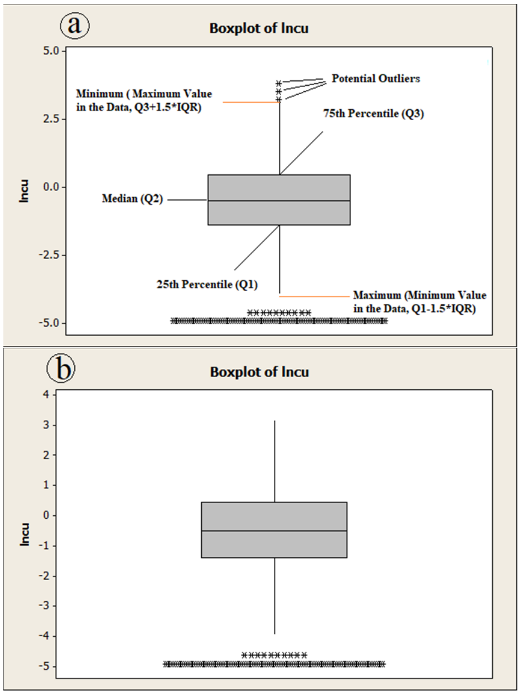

Figure 5. Box plot of ln(Cu) for investigation of outlier values; (a) before replacement, and (b) after replacement of outlier values.

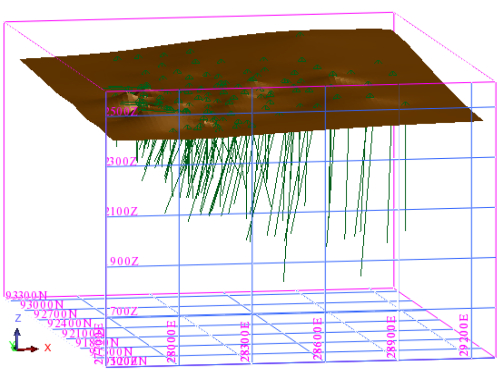

Figure 6. A 3D view of boreholes and topographic layer on Aynak copper deposit.

3.3. Statistical analysis

The statistical study of the data used is the most important step towards the correct use of the geostatistical methods [28]. The raw data distribution function or normal Gaussian transformation is one of the most important and essential control before the geo-statistical estimation that has a significant effect on the selection of the appropriate estimators. Many geo-statistical methods such as ordinary kriging are based on the assumption of stationarity [29]. The representation of the frequency histogram and the cumulative distribution function of the data are one of the most common methods in evaluating the frequency distribution and also in data normalization [10].

In this work, the data distribution function was investigated using the histogram and P-P plot of the raw data. It shows that the initial raw data does not have a normal distribution, and has a high positive skewness, which should be converted to a normal distribution with a conversion function. There are various methods for transformation of the data distribution to normal distribution such as logarithmic, three-variable logarithmic, Cox-Box, and normal score transformation. In this work, a logarithmic transformation was used to transform the abnormal distribution to a normal one; then by investigation of the statistical parameters and diagrams, it was identified that the logarithmic distribution of copper adhered to normal distribution. Thus the logarithmic transformation was used for normalizing the raw data (Figure 7).

Table 1 shows the statistical parameters of the primal raw data and the transformed one.

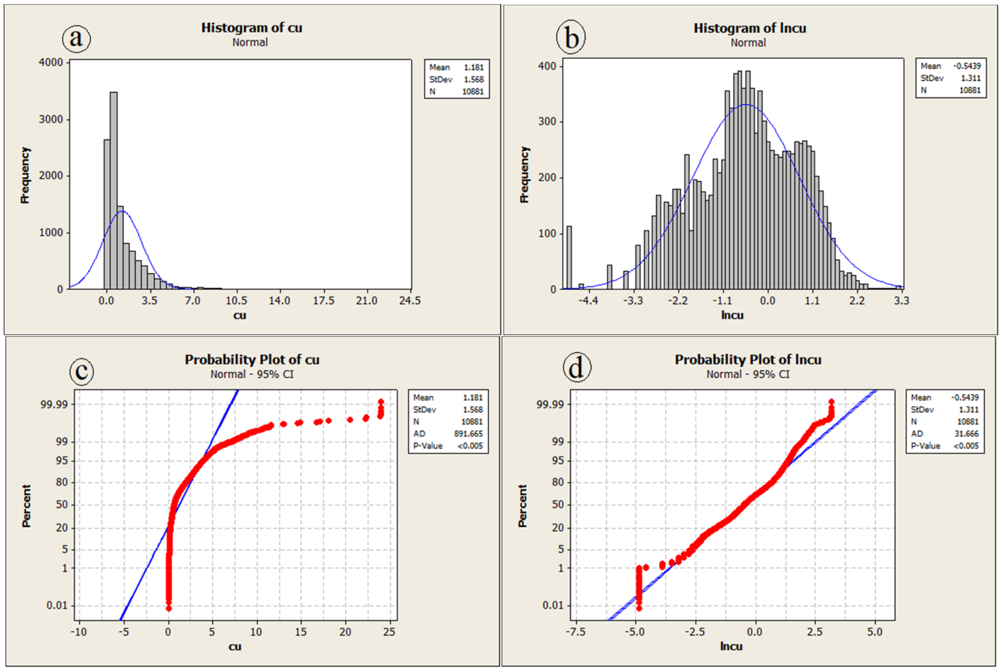

Figure 7. Histogram and P-P plot of primary raw data to investigate data distribution before and after logarithmic transformation (a) histogram of Cu, (b) histogram of ln(Cu), (c) P-P plot of Cu and (d) P-P plot of ln(Cu).

Table 1. Statistical parameters of Cu and Ln(Cu).

Parameters	Cu	Ln(Cu)
No. of data	10881	10881
Mean	1.1811	-0.5439
Median	0.61	-0.4943
Standard Deviation	1.5682	1.3107
Variance	2.4593	1.7179
Skewness	4.48	-0.46
Kurtosis	41.6	0.26
Minimum	0.0075	-4.8929
Maximum	24	3.1781

Finally, in order to create the same volume of the samples, creating a homogeneous environment, the same probability in terms of the size of the samples, compositing is carried out. It is very important in estimation to work with equal support samples, and therefore, the data was composited to equal lengths [30]. In other words, the samples taken from the drilling cores should be statistically homogeneous in length and effect So that they can be used in the geo-statistical studies. For this reason, the first step in preparing the standard data in doing the geo-statistical studies is the uniformity of the statistical weight and the effect of data or composite specimens [10, 28]. In this work, based on the plotted histogram of sampling length, for having and equal volume of the samples and creating iso-probability space, all the data was composited into 2.5 m in length.

3.4. Geological modeling

Prior to grade estimation, it is necessary to construct the geological model of the constraints and border of the mineralization zones. Usually 3D representation of the volume of mineralization must be constructed [9, 15, 31]. A 3D geological modeling can reflect the result and properties of the ore deposit, enabling the geologists to have a more intuitive and clear understanding of the ore deposit. The purpose of a geological model construction is to determine the grade, boundaries, and geological structures of an ore deposit. The first step in geologic modeling is to plot the cross-sections with the geologic data of each drill hole on sections [32].

Therefore, in order to know the status of geometry of mineralization and ore grade distribution in the Aynak copper deposit and finally to estimate the ore reserve, 23 northwest-southeast cross-sections were plotted using and exploratory borehole information. Then in each section, the mineralization zones were identified, and the sections were connected to each other manually, and finally, the volumetric model of the mineralization domain was prepared for the usual ordinary kriging (Figure 8).

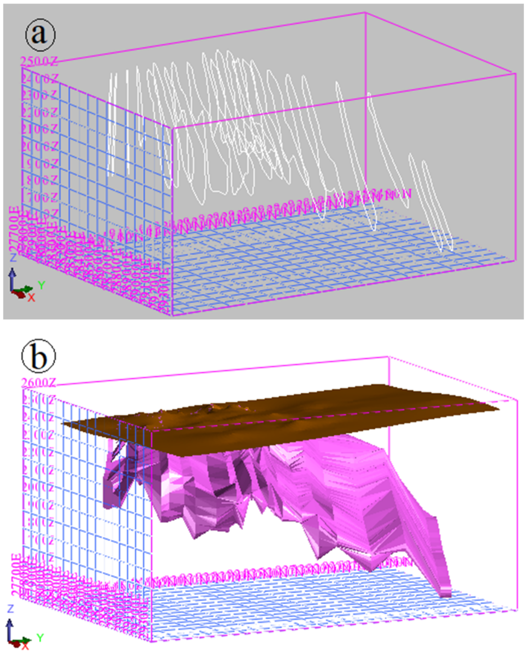

Figure 8. Exploration cross-sections and geological model of ore deposit domain in Aynak copper deposit (a) cross-sections (b) wireframe model.

3.5. Variogram analysis

The geo-statistical methodologies are based on the theory of regionalized variables [7, 33], which states that the attributes within an area exhibit both the random and spatially structured properties [34, 35]. A semi-variogram is the fundamental tool of geo-statistical procedures to investigate the spatial structure[36]. It is defined as half of the mean square difference of a variable for values separated by a distance h [1, 7, 12, 13]. In practice, an experimental variogram is computed as [1, 7, 11, 15, 34, 35, 37]:

$$\gamma_i\,(\mathrm{h})=\frac{1}{2\,N\,(h)}\sum_{i=1}^{N\,(h)}[z\,(x_i)-z\,(x_i+h)]^2 \qquad (1)$$

where γ_i (h) denotes the variogram for an interval lag distance class h, N(h) represents the number of pairs for an interval lag distance class h, and $z\,(x_i)$ and $z\,(x_i+h)$ are the values of the regionalized variables of interest at locations x_i and x_i+h, respectively.

The variogram can be computed in different directions to detect any anisotropy of the spatial variability [35, 38]. The directional variogram model provides a better understanding of the deposit and helps in identifying the anisotropy [10]. An anisotropy model generally includes the geometric anisotropy and zonal anisotropy [35, 38]. The former type of anisotropy yields the variogram having the same structural shape and maximum variability (sill) but a direction-dependent range for the spatial correlation. The latter type, however, is defined by sills varying with direction [35].

In this work, variographic operations were performed to study the structural analysis, anisotropy, and geo-statistical estimation with respect to the spread of the ore deposit in the Aynak copper deposit, and thus the direction of the medium and small axes of the anisotropic ellipsoid was determined. After computing and plotting the experimental variogram, a theoretical model should be fitted to the obtained experimental variogram. In the current work the best theoretical exponential model was fitted to find three parameters including the nugget effect (C_0), the sill ($C + C_0$), and the range. The variogram parameters and variogram model are illustrated in Table 2 and Figure 9.

Table 2. Variogram parameters related to Cu variogram model in Aynak copper deposit.

Variable	Variogram	Model	Nugget-effect	Sill ($C + C_0$)	Range (m)	
					Minimum	Maximum
Ln(Cu)	Directional	Exponential	0.1012	1.0262	45.66	82.66

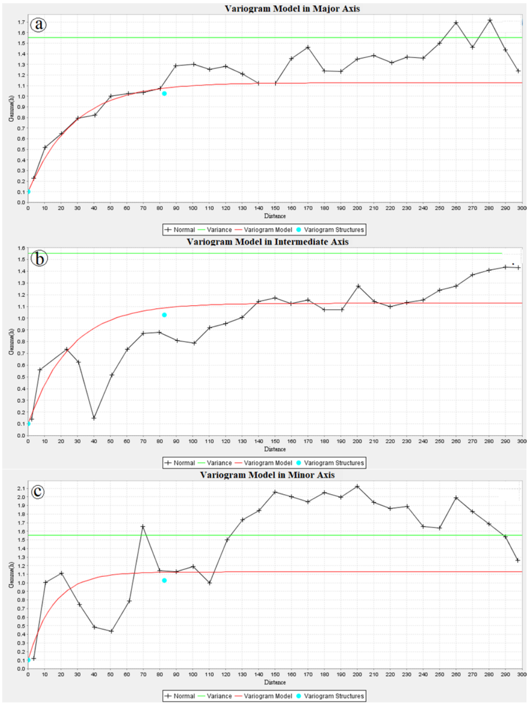

Figure9. Directional variogram of ln(Cu) in Aynak copper deposit (a) dip = -10°, Azimuth = 110° (b) dip = -29.5°, Azimuth = 14°, and (c) dip = 58.5°, Azimuth = 36.7°

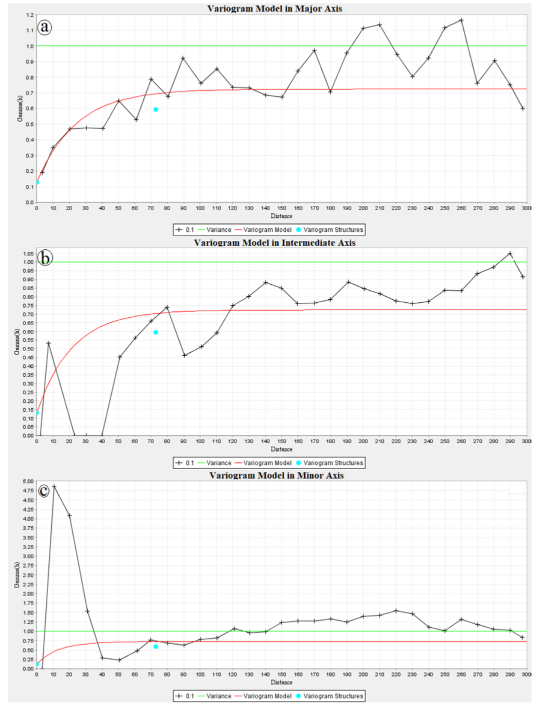

Figure10. Indicator variogram of Cu in Aynak copper deposit (a) dip = -10°, Azimuth = 110° (b) dip = -29.5°, Azimuth = 14° and (c) dip = 58.5°, Azimuth = 36.7°

In order to draw the indicator variogram, the first step is to transform the data into the indicator values, and the variogram should be plotted using the values for the indicators. The variogram must be calculated in different directions to detect the anisotropy of spatial variation [18].

In this work, in order to determine the ore deposit boundary using the indicator kriging method, the indicator variogram was calculated and the experimental variogram model was obtained. Then on the experimental variogram, the appropriate theoretical model (here, the exponential model) was fitted. The results of this indicator variogram analysis are illustrated in Table 3, and Figure 10.

3.6. Cross-validation

After performing the estimation process using each geostatistical method, validation is performed to examine the accuracy of the results [34, 35, 39]. In other words, the accuracies of the variogram model and the estimation method are determined via the validation techniques. In a cross-validation procedure or leave-one-out [18, 38], the measured data is dropped one at a time and re-estimated from some of the remaining neighboring data [13, 34, 35]. Each datum is replaced in the dataset once it has been re-estimated. The two parameters are computed as follow [34, 35].

$$\text{KME} = \frac{1}{N}\sum_{i=1}^{N}[I^*(u_i;z_k) - I(u_i;z_k)] \quad (2)$$

$$\text{MSSE} = \frac{1}{N}\sum_{i=1}^{N}\frac{[I^*(u_i;z_k) - I(u_i;z_k)]^2}{\sigma(u_i;z_k)^2} \quad (3)$$

where $I^*(u_i; z_k)$ and $I(u_i; z_k)$ are the estimated and measured values at the location, respectively, N is the number of measured data, and $\sigma(u_i;z_k)^2$ is the kriging variance.

Table 3. Indicator variogram parameters related to Cu variogram model in Aynak copper deposit.

Variable	Cut-off grade	Variogram	Model	Nugget-effect	Sill	Range (m)	
						Min	Max
Cu	0.1	Directional	Exponential	0.129	0.594	39.245	72.762

The KME (kriging mean error) and MSSE (mean square standard error), which are close to zero and one, respectively, denote the best fitting models and parameters of the variogram. In this work, the validity of the variogram models were checked using a cross-validation method.

Based on the results of the variogram validation, the amounts of uncertainty and error are determined in the sampled data. Ideally, the following conditions should be met in the results of comparing the estimated data with the initial data.

1- The mean error should be close to zero 2- The variance error should be close to the average kriging variance 3- The error histogram should have a normal distribution, and approximately 95% of the error should be in the range of -2 to +2 of kriging variance 4- High correlation between the estimated values and the actual values, and 5- There is no correlation between the estimated values and the error.

The cross-validation results show that KME and MSSE are close to 0 and 1, respectively, indicating that the fitted variable function parameters are reliable and can be used for ordinary kriging estimation. The results are shown in Table 4 and Figure 11.

Table 4. Summary statistics of Kriging error using cross-validation.

Summary statistics of Kriging errors	
Parameters	ln(Cu)
Mean	0.0034
Variance	0.2557
STD.Deviation	0.5057
Skewness	-0.1212
Kurtosis	6.082
AVG. Krig variance	0.2896
Two. STD. Deviation	95.65

Figure 11. (a) Scatter diagram between estimated and residual values (b) correlation diagram of kriged values and initial values.

3.7. Indicator Kriging

Indicator Kriging, as introduced by Journel, is a non-parametric geostatistical method for estimation of the probability of exceeding a specific threshold value, Z_k, at a given location. In indicator kriging, the stochastic variable, Z(u), is transformed into an indicator variable with a binary distribution, as follows [2, 14, 15, 34, 35, 38-43]:

$$I\,(u;z_k)=\begin{cases} 1 \rightarrow z_u \le z_k \\ 0 \rightarrow otherwise \end{cases} \tag{4}$$

k=1, 2, 3,…, m

where I (u; z_k) is index value of the sample I, and Z_k is the given cut off grade.

Indicator kriging estimates the probability of the grade of a given block to be smaller than a specific cut-off grade. The merit of this method is that the estimation process is independent from the distribution of the data.

Prior to applying this method, the raw data should be transformed into the index values, based on the upper mentioned equation (4).

Indicator kriging is almost similar to ordinary kriging except in indicator kriging; the indicator variogram values are used instead of the ordinary variogram. The indicator variogram can provide information about the spatial distribution of each class of values, allowing the evaluation of the probability to exceed the cut-off values [42]. The indicator variogram is calculated for each given cut-off grade using the following equation:

$$\gamma_i^*(h,z_k) = \frac{1}{2\,N\,(h)} \sum_{i=1}^{N\,(h)} [I\,(x_i\,, z_k) - I\,(x_i + h, z_k)]^2 \tag{5}$$

where $N(h)$ is the number of pair of samples separated by vector “h”.

The approximate value of the index variable in each point is given by the following equation [34, 35]:

$$I^*(u_o, z_k) = \sum_{j=1}^{n} \lambda_j(z_k) I(u_k, z_k) \tag{6}$$

where $I(x_i, z_k)$ represents the values of the indicator at measured locations, u_j, and λ_j is the weighting factor of $I(u_k, z_k)$ in estimating $I^*(u_o, z_k)$.

The approximate value of the index, $I(u_k, z_k)$, varies between 0 and 1, and suggests the probability of the grade of the estimated block to be smaller than the cut-off grade [1, 35, 42].

The indicator is then estimated using OK to give the probability estimate of exceeding or not exceeding the thresholds of interest. The IK estimate of each single indicator lies in the interval

[0,1] [1, 12, 40, 44], and can be interpreted as [1, 12, 40]:

1. Probability that the grade exceeds the indicator threshold or
2. As proportions (the proportion of the block above the specified cut-off on the data support).

3.8. Sequential indicator simulation (SIS)

SIS is an invaluable tool for providing the spatial models by combining the sequential paradigm with indicator formalism to simulate nonparametric categorical or continuous distributions. The objective in SIS is to generate realizations $\{z(x_1), z(x_2), \ldots, z(x_n)\}$ at un-sampled locations $\{x_1, x_2, \ldots, x_n\}$ for a set of random variables z(x) of a property. In this simulation approach, the IK estimator is used for providing the model. Like Full Indicator Kriging (FIK), SIS utilizes many thresholds for transforming data into the indicator values to perform the simulation [38, 45].

In general, the SIS algorithm can be implemented as follows [38, 45]:

1. Transformation of the data of Cu grade in to the indicator codes (o or 1) by the indicator function at each threshold z_k.
2. Preparation of the indicator variograms for each threshold.
3. Definition of a random path.
4. Application of the IK estimator at each unsampled location from all other values (known and simulated) to approximate the probability of variable being lower than a given cutoff value.

$$F[z_k; x'_m|(n+m-1)]=prob_{IK}[z(x'_m) \leq z_k] \quad (7)$$

where n is the number of observed data, m-1 is the number of previous simulated values, and F $[z_k; x'_m|(n)]$ is the conditional cumulative distribution fuction (CCDF).

5. Simulation at other locations sequentially.

A flow chart illustrating the SIS procedure is shown in Figure 12.

3.9. Ordinary kriging

Ordinary Kriging (OK) is probably one of the most common geo-statistical methods being applied in estimation since it has gained much recognition and has proven to be a very good estimator [29]. OK is an estimation method often associated with the normal distribution [46]. OK is a linear geo-statistical method that provides local estimation by interpolation. Krige and Matheron have introduced this linear estimation technique to reduce the volume variance effect. OK assumes that the regionalized variables are stationary where the mean is unknown [3-5, 41, 43]. Ordinary kriging can be estimated by linear combination of the observed values with weights as follows [11, 33]:

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \quad (8)$$

where $Z^*(x_0)$ is the kriging estimation at location x_0, $Z(x_i)$ is the sampled value at location x_i, and λ_i is the weighting factor for $Z(x_i)$. The estimation error is:

$$Z^*(x_0) - Z(x_0) = R(x_0) = \sum_{i=1}^{n} \lambda Z(x_i) - Z(x_0) \quad (9)$$

where $Z(x_0)$ is the unknown true value at x_0, and $R(x_0)$ is the estimation error. For an unbiased estimator, the mean of the estimation error must be equal to zero. Therefore, $E\{R(x_0)\} = 0$ and,

$$\sum_{i=1}^{n} \lambda_i = 1 \quad (10)$$

The parameters of the search ellipsoid are shown in Table 5.

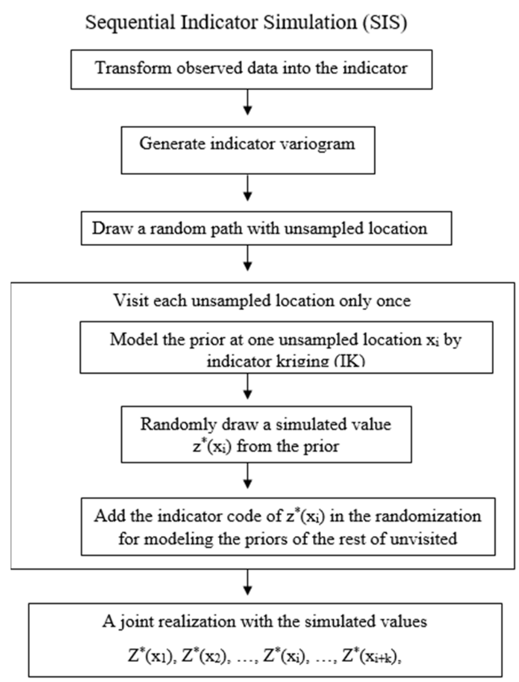

Figure 12. A flow chart illustrating procedure of (SIS).

Table 5. Search ellipsoid parameters.

Range	Rmaj/Rsemi	Rmaj/Rmin	Azimuth	Dip	Plunge
82.66	1.083	1.81	110	30	-10

3.10. Block modeling

Block modeling is performed to determine the volume of the ore deposit, limit the estimation space, and finally, to estimate the ore reserve. The factors that determine the size of the block are mainly to fully reflect the changing characteristics of the ore body. The ore body should have a large vaiability, the unit block should be small, the ore body should be in a lower vaiablility, then the unit block could be large. If the block size is too large or too small, the sample evaluation result will be average, and it cannot accurately reflect the characteristics of grade changes [47]. The size of these blocks is selected based on several factors, such as the drill hole spacing, mining method (bench height), and ore deposit geological settings [12]. In the Aynak copper deposit, the distance between boreholes varies from 20 m to 100 m in different parts of the deposit.

Table 6. Block model parameters in Aynak copper deposit.

Type	X	Y	Z
Minimum	27808	91215	1486
Maximum	29248	93335	2496
Main-block size	10	10	10
Sub-block size	2.5	2.5	2.5

Therefore, the dimensions of the main block size were selected as 10 × 10 × 10 m and the sub-block size 2.5 × 2.5 × 2.5 m throughout the ore body extent (Table 6). The 3D block model of the Aynak copper deposit is shown in Figure 13.

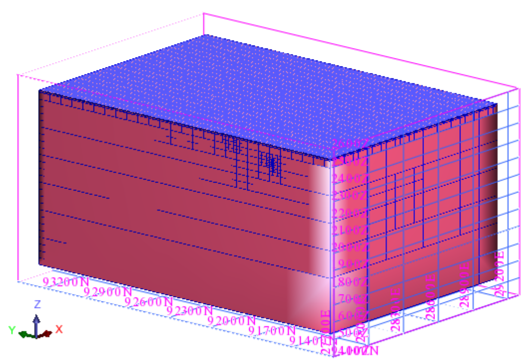

Figure 13. Block model of Aynak copper deposit.

3.11. Ore deposit boundary modification using IK and SIS methods

The simplest method to identify ore against waste is to draw the ore-waste boundaries manually in cross-sections based on the borehole information [13]. Generally, for low grade deposits in which the boundaries are highly depended on th cut-off grade, it is vitally important to determine the ore deposit bound of a block. When it is required to separate the estimation blocks in an ore reserve, it is so helpful to apply the IK and SIS interpolation methods. IK and SIS are non-parametric techniques that are used in ore deposit boundary determination and ore reserve estimation widely. IK and SIS are also able to help the user to draw the probability map for any grade to have the probability of happening equal to or greater than an arbitrary cut-off grade.

In this work, in order to determine the ore deposit boundary and reserve estimation using the IK and SIS methods, the exploratory borehole information related to the Aynak central copper deposit was used. For this purpose, by applying a cut-off grade (0.1% Cu), that below of 0.1% is considered as waste and above it, as ore; all the data was converted to 0 and 1, and the ore deposit boundary was estimated using the indicator kriging method.

Finally, the estimation domain was cut with an 80% probability of occurrence, and the ore deposit boundary was determined. The results of this estimation as a probability map are shown in Figure 14.

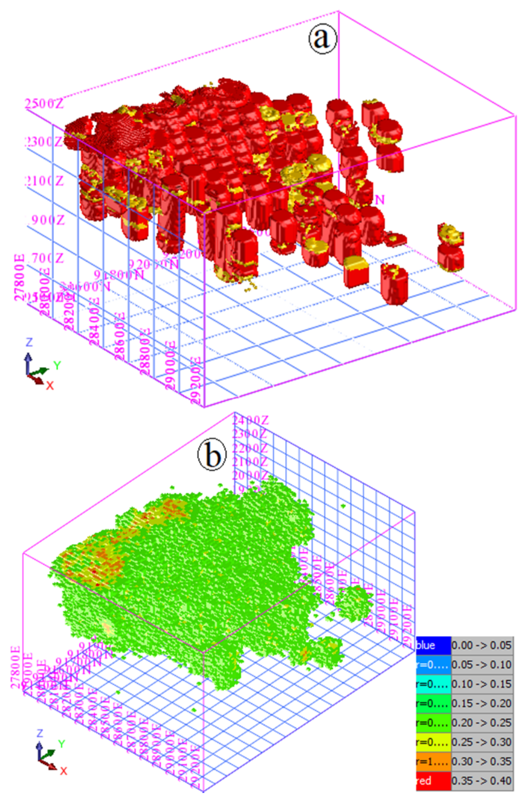

Figure 14. 3D ore deposit model in Aynak copper deposit using IK (a) and SIS (b) methods with probability of 80%.

4. Results and Discussion

Before the ore deposit estimation, it is required to perform the statistical and geo-statistical analysis of the sampled data. Also to control the estimation process, it is necessary to modify a 3D model as the estimation space. To define the estimation area, the conventional, IK and SIS interpolation methods were applied, and the ore body solid models were obtained. Then the block model was created covering the mineralization space of the ore body, and constrained by the ore body solid model (Figure 8).

In this work, the IK and SIS methods were used to modify the optimum ore deposit boundary, and estimate the Cu concentration in the Aynak copper deposit. IK and SIS were used to estimate the probability of ore occurance based on 3D the anisotropic indicator variogram models.

Then the ore body probability map to exceed the chosen 0.1% cut-off grade with a probability of 80% presence of ore deposit was obtained (Figure 14). Based on the SIS method, one hundred realizations were calculated, and the E-type map that illustrates thah the point-by-point average of all realizations was obtainted. Figure 15 shows a 3D view of Cu concentration in the Aynak central copper deposit constrained using the SIS approach.

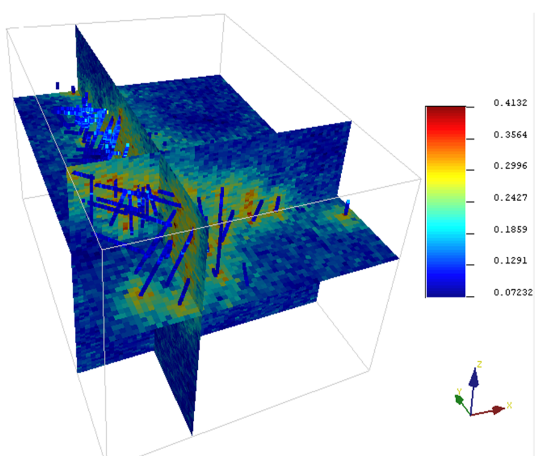

Figure 15. 3D view E-type map.

Finally, the ore reserve estimation was performed using the OK method on the transformed values with the conventional and geo-statistical (IK and SIS) constrained block model. Then the results were back-transformed to the primal raw values. After estimating the Cu concentration in the Aynak copper deposit, the estimated block model was performed by transformed (ln(Cu)) and back-transformed (Cu) values, which illustrated in conventional 3D block model (Figures 16 a & b).

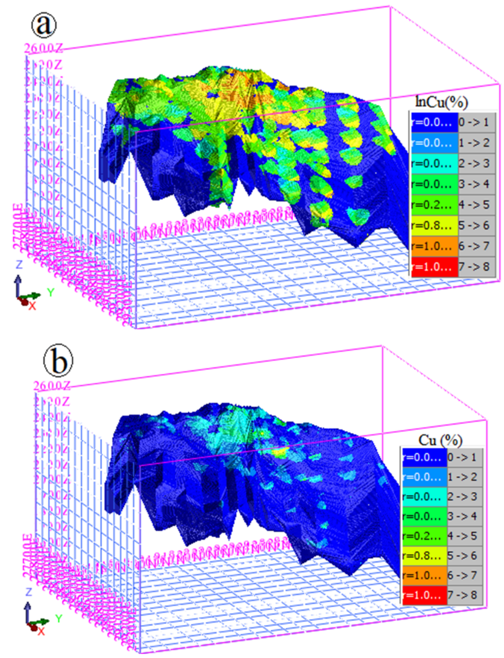

Figure 16. Ore reserve estimation using OK method (a) transformed values (ln(Cu)) and (b) back-transformed values (Cu).

In this work, the tonnage of ore deposit was calculated in different cut-off grades using the OK method. For a cut-off grade of 0.2% Cu, the tonnage of ore reserve based on Ok method with the conventional, IK and SIS constrained ore body model was estimated as follow (Table 7).

Finally, the grade-tonnage curves were plotted. According to these curves, on the basis of an special cut-off grade, the average grade and tonnage of a mineral deposit can be estimated all together. Figure 17 presents the grade-tonnage curves of ore reserve in the Aynak copper deposit.

Table 7. Ore reserve estimation of Aynak copper deposit using OK method (with 0.2 % cut-off grade).

Constrain method	Tonnage (ton)	Average grade (%)
Conventional	453459000	1.0774
IK	459157000	1.0801
SIS	467742000	1.0514

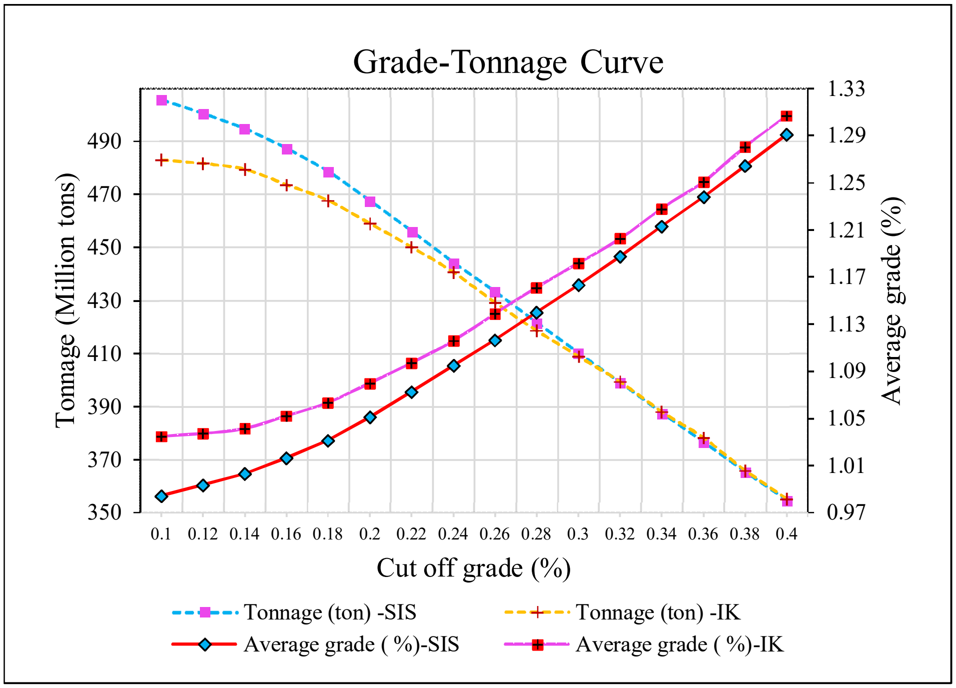

Figure 17. Grade-tonnage curves constrained on the basis of IK and SIS estimations.

5. Conclusions

Choosing the robust geostatistical methods with a minimum error is a very vital step for the ore deposit boundary modification and ore reserve estimation. In order to model the ore deposit boundary and define the estimation space, the conventional and geo-statistical (IK and SIS) methods were used, and the ore body solid model was obtained. The results of this work show that the traditional ore body modeling methods, generally due to low accuracy, is time-consuming; the user intervention in ore deposit boundary modeling, and also impelementing the same interpolation rules for different ore deposit types, in some cases, could be imprecise and locally erroneous. In this work, the traditional linear OK and non-linear IK and SIS geo-statistical methods were implemented and compared for ore deposit boundary modification and ore reserve estimation in the Aynak copper deposit.

Overal, in comparison, the SIS method was be able to much properly model the orebody with a higher continuity and the local fluctuation that had a better conformity with the Aynak staratabound deposition. The proximity of the obtained reserve estimation results using different implemented methodologies is probably due to a low-grade variability, and genetical regularity in the Aynak copper deposit, and guarantees the accuracy of the obtained results in the ore reserve evaluation. However, in the low-grade deposits with higher irregularity and ore grade variability, ore boundary modeling with traditional methods could be much complicated, and we are required to implement the proposed non-linear geo-statistical and simulation methodologies to reduce the risk of estimation.

Acknowledgment

The authors would like to specially appreciate Hossaindad Shafayi, Deputy of Afghanistan Geological Servey and Abdul Majeed Rasikh for providing the Aynak copper deposit data.

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تعدیل مرز کانی‌سازی کانسار مس عینک مرکزی افغانستان با استفاده از شبیه‌سازی شاخص متوالی و کریجینگ شاخص

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ارسال ۲۰۲۲/۰۱/۱۰ پذیرش ۲۰۲۲/۰۴/۲۴

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چکیده:

کانسار مس عینک یکی از مهم‌ترین کانسارهای مس استراتی باند در افغانستان است. هدف اصلی این تحقیق، تعیین مرز کانی‌سازی و تخمین ذخیره کانسار مس عینک مرکزی با استفاده از روش‌های زمین‌آماری است. تعیین مرز بهینه و ارزیابی ذخیره این کانسار با استفاده از روش‌های کریجینگ معمولی، کریجینگ شاخص و شبیه سازی شاخص متوالی صورت پذیرفت. سپس نتایج، دقت و کارآیی این سه روش باهم مقایسه شد. قبل از ارزیابی ذخیره، پیش پردازش داده ها شامل تجزیه و تحلیل آماری و زمین‌آماری روی داده‌ها صورت پذیرفت. برای فرآیند دقیق تخمین، لازم است که مرز بهینه کانسنگ که بیانگر فضای واقعی تخمین است، مشخص شود. بنابراین، روش‌های کریجینگ شاخص و شبیه‌سازی شاخص متوالی جهت اصلاح و تعیین مرز بهینه کانی‌سازی (که ابتدا با روش سنتی بدست آمده بود)، مورد استفاده قرار گرفت. در ابتدا، مدل رویه سه‌بعدی با استفاده از روش سنتی (روش مقاطع قائم) بدست آمد تا مدل بلوکی که دربرگیرنده‌ی فضای کانی‌سازی است، توسط مدل سه‌بعدی محدود شود. سپس مدل سه‌بعدی کانسنگ با استفاده از روش‌های زمین‌آماری (کریجینگ شاخص و شبیه‌سازی شاخص متوالی) تعدیل شده و بهبود یافت. در نهایت تخمین مس در هر بلوک با استفاده از روش لاگ‌کریجینگ که یک تخمین‌گر ناااریب است و حداقل خطای تخمین را تضمین می‌کند، صورت پذیرفت و منحنی تناژ- عیار رسم شد. در این مطالعه، تناژ کانسار بر اساس عیارحدهای مختلف محاسبه شد. با درنظر گرفتن عیارحد ۰/۲ درصد مس، تناژ ذخیره براساس روش‌های کریجینگ معمولی، کریجینگ شاخص و شبیه‌سازی شاخص متوالی به ترتیب ۴۵۳/۴، ۴۵۹/۱ و ۴۶۷/۷ میلیون تن با عیار متوسط ۱/۰۷۷، ۱/۰۸ و ۱/۰۵ درصد مس، برآورد شد. نزدیکی نتایج تخمین به‌دست آمده با استفاده از روش‌های مختلف به‌دلیل تغییرپذیری کم عیار و نظم ژنتیکی در کانسار مس چینه‌کران عینک است که صحت و دقت نتایج ارزیابی ذخیره را تضمین می‌کند.

کلمات کلیدی: ارزیابی ذخیره، زمین‌آمار، مدل‌سازی مرز ماده معدنی، کریجینگ شاخص، شبیه‌سازی شاخص متوالی، کانسار مس عینک.