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

Applying Analytical and Quantitative Criteria to Estimate Block Model Uncertainty and Mineral Reserve Classification: A Case Study: Khoshumi Uranium Deposit in Yazd

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Article Info

Received 1 january 2021
Received in Revised form 27 February 2021
Accepted 9 March 2021
Published online 9 March 2021

DOI:10.22044/jme.2021.10118.1994

Keywords

Variogram
Block model uncertainty
Kriging
Reserve classification
Fractal method

Abstract

At different stages of mining, we always face a degree of uncertainty. Some of these uncertainties, such as the amount of reserve and grade of the deposit, are due to the inherent changes in the deposit and directly affect the technical and economic indicators of the deposit. On the other hand, the heavy costs of the exploration sector often limit the amount of exploratory information, which necessitates the use of accurate estimation methods. In this work,we examines the modeling and estimation results using the conventional and simple kriging methods and the effects of the diverse indicators used in the classification of mineral storages or the parameters defining these indices. 127 exploratory boreholes with an average depth of 95 m are used to build the block model of the deposit in the Data Mine software. After the statistical studies, the 3D variographic studies are performed in order to identify the anisotropy of the region. A grade block model is constructed using the optimal variogram parameters.Then, using various methods to estimate the block model uncertainty including the kriging estimation variance, block error estimation, kriging efficiency and slope of regression, the mineral reserves are classified according to the JORC standard code. Based on different cut-off grades, the tonnage and average grade are calculated and plotted. In this work, an innovative quantitative method based on the grade-number and grade-volume fractal model is used to indicate the classification of mineral reserves. The use of fractal patterns due to the amplitude of the variation is greater and more important than the standard and provides us with a better understanding of the deposit changes per block. The existence of a minimal difference between the use of the standard and fractal patterns in the slope of the regression method indicates less error and is a proof of more reliable results

1. Introduction

In the mining industry, the economic value of a mineral reserve is estimated using a source model constructed from the direct measurements of the available resources. These models are largely influenced by the quantity, quality, and spatial distribution of the existing direct measurements for the properties in discussion such as grades. Due to the reduction of mineral resources and the increase in the extraction and processing costs, there is a requirement to improve the exploration methods for a more accurate and reliable modeling of the mineral deposits and indices [1] . Estimating the uncertainty of blocks and estimation space by the geostatistical method is one of the most important processes that unfortunately in the final parts of the geostatistical process, has been left unresolved and unstudied in most studies. Estimating the error and uncertainty of the estimation space can, on the one hand, be used to evaluate the efficiency of the geostatistical method and, on the other hand, make the classification of the storage and spatial estimation possible by the quantitative and

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mathematical methods, can make a mining designer or geologist specialized in detailed explorations and he can suggest the potential points for the future samplings [2]. The quality of resource classification is a key requirement for an accurate economic and environmental risk evaluation [3]. In the recent years, the researchers have made great efforts in order to improve grade estimation. Among these methods, the geostatistical context is perhaps one of the most commonly used methods. In the recent decades, in order to model the exploratory indices, the geostatistical techniques based on the spatial relationships between sample locations and sample components in space have been introduced [4]. Today, the fractal and geostatistical methods apply grade and some other parameters in the model. The successful application of geostatistical methods in the past decades has made it a powerful tool for estimating the distribution of many variables in different fields [2] . Fractal geometry has been used to evaluate the mineral reserves [5,7]. Mineral reserves are based on the grade and tonnage estimation through an estimation method such as simple kriging, ordinary kriging, normal log kriging, index kriging, cogriging, indicator kriging, and random simulations such as Gaussian sequential simulation and sequential index simulation [8]. Therefore, it is necessary to establish the standards for a resource classification. A number of different classification techniques have been developed, only a few of which have been used in practice[9,10]. Also, several international classification systems have been developed in the past decades [11], the main ones being the American United States Geological Survey (USGS) Circular 831 [12] and the Society for Mining, Metallurgy, and Exploration, Inc. (SME Guide) [13], the South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves (SAMREC Code) [14], the Canadian of exploration information, mineral resources and mineral reserve (CIM) guidelines [15] and National Instrument 43-101 [16], the European Code [17], and the Joint Ore Reserves Committee (JORC) Code in Australia [18].

Since estimating the error and uncertainty in the estimation of space can, on the one hand, evaluate the efficiency of the geostatistical method and, on the other hand, make the storage and spatial classification of the estimate possible by the quantitative and mathematical methods, it can involve a mining designer or geologist and future sampling will help. Estimating the uncertainty of blocks and estimation space by the geostatistical method is one of the most important processes that unfortunately in the final parts of the geostatistical process has been left unfinished and unstudied in most studies. The common methods used for examining the deposit uncertainty and segmentation in Australia and the United States are: a) error quantification, b) criging efficiency, c) regression coefficient, which in the present work for the borehole data are used to classify the blocks and estimated spaces. In this research work, the data uncertainty is classified and investigated using the two methods of kriging efficiency and regression slope, and then the mineral blocks are divided into the three categories of possible, probable and definite reserves according to the Jork's standard code and based on the grade of different limits, the tonnage and the average grade are calculated and plotted. We also propose a quantitatively innovative method based on the distribution function of the mentioned parameters and the fractal pattern of community segregation in order to classify the reserve. The mineral reserve is classified according to the Jork standard. Also, in order to evaluate the advantages of the experimental data in the uncertainty and applicability, we compare the results of the two methods of kriging efficiency and regression slope in terms of tonnage evaluation based on the geometric or geostatistical considerations for an internal uranium stock.

2. Materials and methods

The 3D modeling of the deposit and preparation of the carat block model is of great importance, so that its conscious and accurate performance leads to an accurate evaluation of the carat in different parts of the deposit. The next steps are used, so that the design, planning, and optimization of the reserves are done on the block model [19] . The various stages of a statistical method for estimating the mineral reserves that leads to the creation of the block (local) reserves and total (global) reserves are described.

2.1. Studied area

The studied reserve is located in the general area of (Khashumi) and Dareh-e-Anjir desert, 150 km NE of the Yazd city, in a block with dimensions of 400 by 400 m. The Khashumi exploration zone in the Yazd province is located in the Bafgh-Saghand metallurgical zone and the structural zone of central Iran. To access the anomalous exploration zone No. 6 of Khashumi, from the Saghand village location of the exploration camp) after 22 km of

Chadormelo asphalt road, it enters the dirt road and this dirt road is about 35 km to the exploration area. (Figure 1).

The geological and lithological units in the area include the limestone unit, tuff, lava, and volcanic strata with interlayers of marble-dolomite and gypsum, magmatites, applet-pegmatite veins, and acid dykes (Figure 2). Based on the XRD results and the study of the polished sections of radioactive ore, the most likely betafite with the chemical composition (Ca, Na, U) 2 (Ti, Nb, Ta) 2 O6 (OH, F) is a type of calcium hydroxide, sodium, uranium, titanium. , niobium and tantalum. This ore is of the primary type and belongs to the pyrochloride family and usually accompanies uranium ore along with the rare earth elements in pegmatite dikes. Another type of mineralization in this block is mainly secondary and consists of yellow boltudite and uranophane minerals at the fracture level [20].

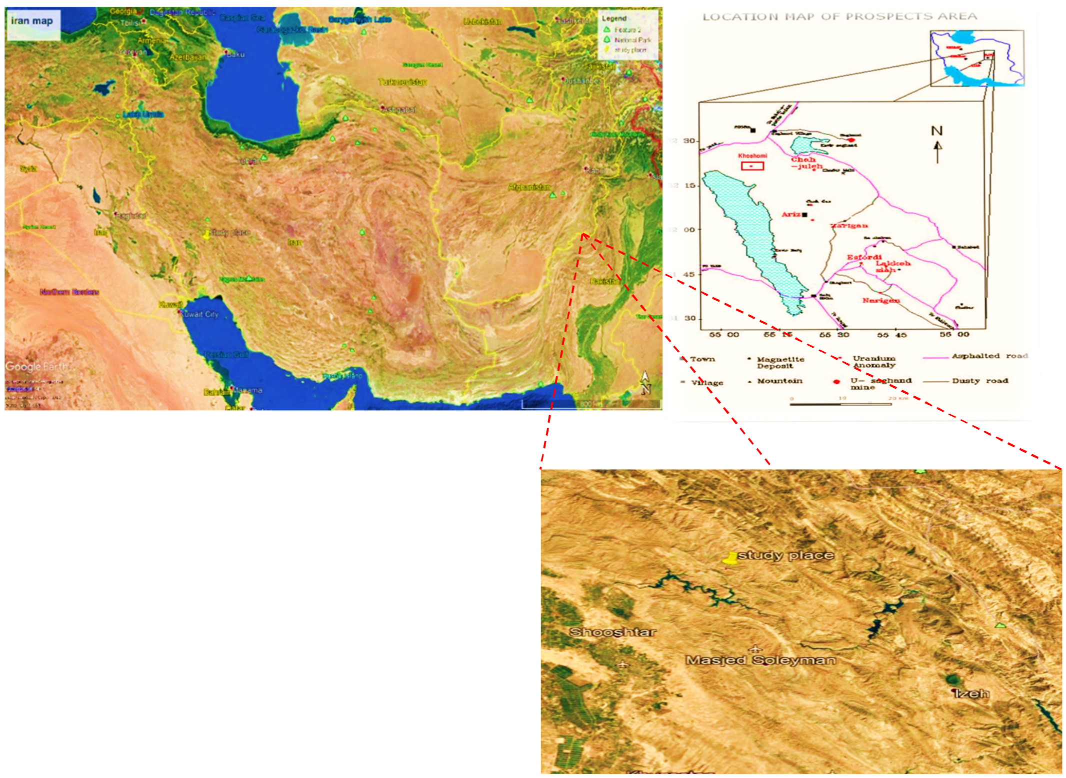


Figure 1: Geographical location of the enormous uranium exploration area in central Iran.

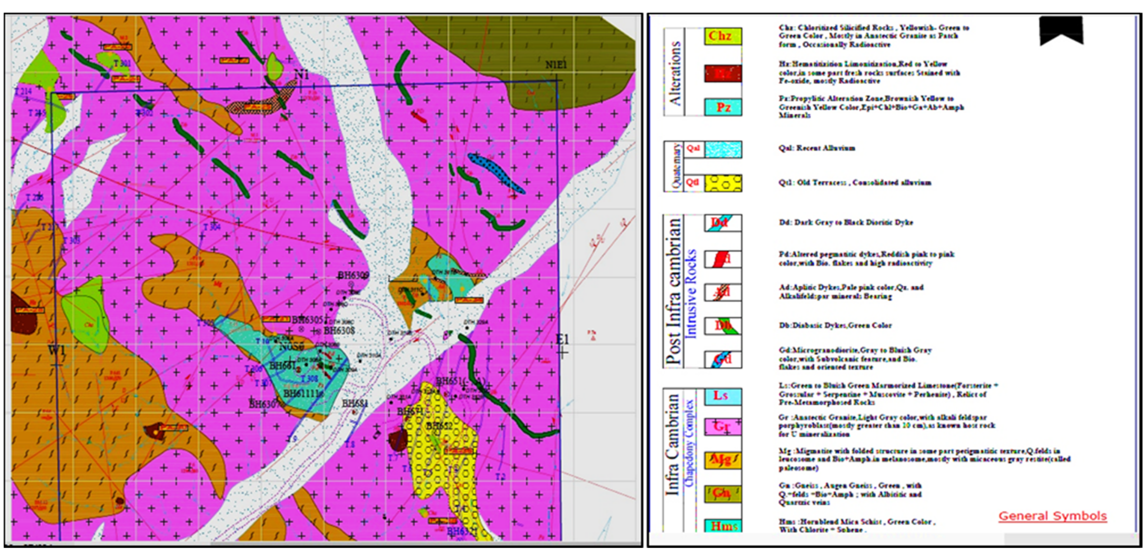


Figure 2: Geological map of Khoshumi prospect area – scale 1:500

2.2. Statistical analysis

The statistical study of the data used is the most important step towards the correct use of the geostatistical methods. The samples taken from the exploratory drilling network of the Khoshomi deposit (127 boreholes excavated at distances of 20-40 meters from each other) have been processed (Table 1).The first step in the 3D modeling of the deposit is to form a database of the exploratory boreholes. The database structure was created as follows in the Datamine software.

- Drilling data
- Drilling hole location file (collar)
- Drilling deflection file (survey)
- Drilling analysis file (assay)
- Petrology file (rock type)
- Brain recovery percentage file and stone quality index (RQD)

Preparing a topographic map, digitizing it and turning it into an elevation model of the region is one of the important databases.The topographic map of the mineralization zone in the khoshomi uranium range with outcrops sub-soil excavations are shown in Figure 3.

One source of error in a standard modeling is the existence of the out-of-row data (data with very high or low values). In order to identify the outlier data, in addition to the distribution frequency histogram, a boxplot is also used [22,23]. The statistical analysis was conducted on the composite samples. The histogram diagram after correcting the outlier values shows that all variables follow a normal distribution (Figure 4).

Table 1. Number and area of exploratory excavations in the semi-detailed and detailed phases.

Number of boreholes	62
Borehole drilling area (m)	6828
Number of wagon drill holes	65
Drill area of wagon drill (m)	5358
Total drilling area (m)	12186
Average depth of boreholes (m)	95
Number of samples	3762
Total sample size (m)	1824
Average length of samples (m)	0.5

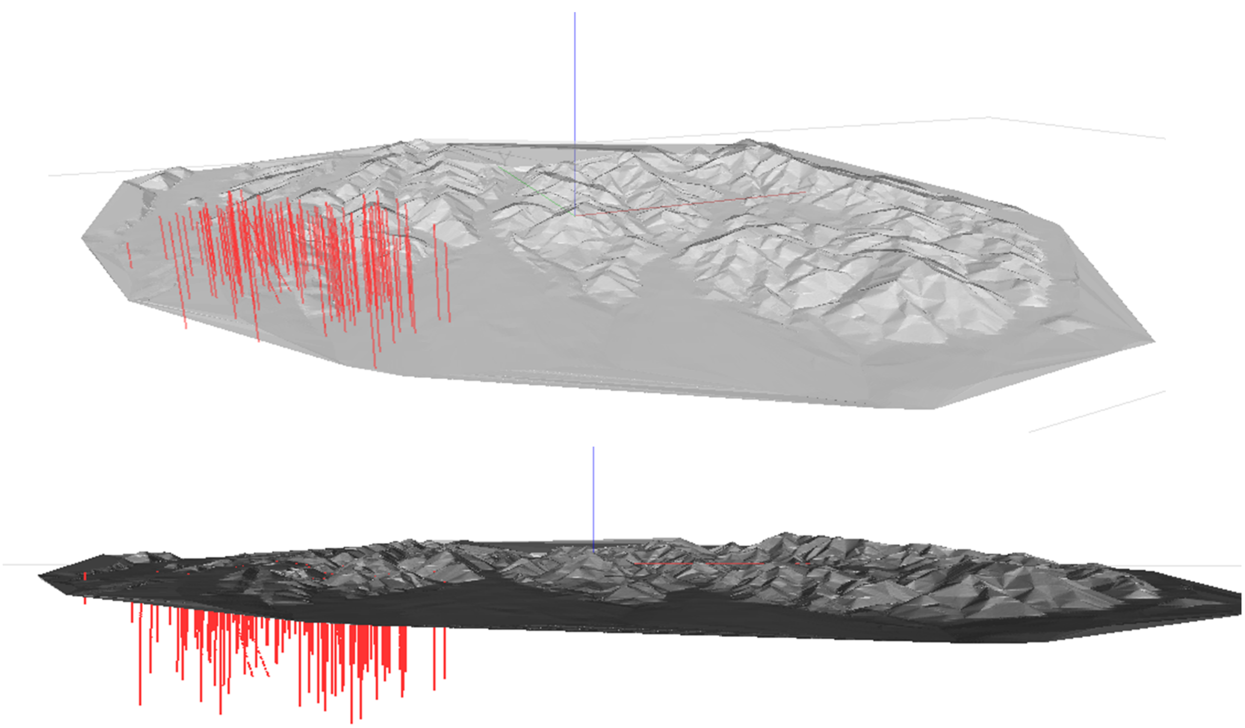


Figure 3. Position of boreholes relative to the topographic condition of the area in 3D.

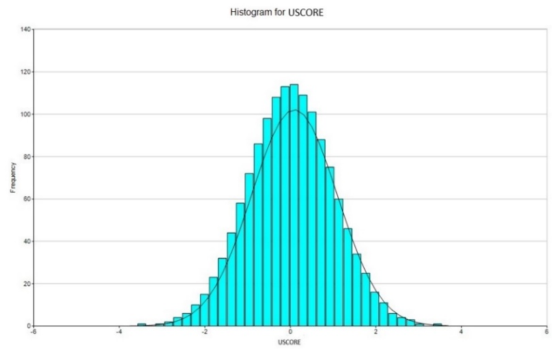


Figure 4. Histogram diagram of raw data after replacing the outlier values

2.1.1. Data Composition

In order to create the same volumes of the sample and also to reduce the volume of the kriging operations, compositing is carried out. 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 geostatistical studies. For this reason, the first step in preparing the standard data in doing the geostatistical studies is the uniformity of the statistical weight and the effect of data or composite specimens.

Comparison of the composites with various lengths through the mean and grade variance of the samples indicates the optimal composite length (0.5 m) to continue the study process (Table 2).

Table 2: The mean and grade variance based on composites with various lengths

	No.	Mean	Variance	Minimum	Maximum
RQW	29610	119.42	16393.48	0.01	2645
0.01	204901	118.41	29345	0.01	2645
0.05	39747	117.12	29030	0.01	2645
0.1	19543	117.5	28654	0.01	2645
0.5	3377	117.2	26409	0.01	2645
1	1847	107.53	21256	1.2	1886

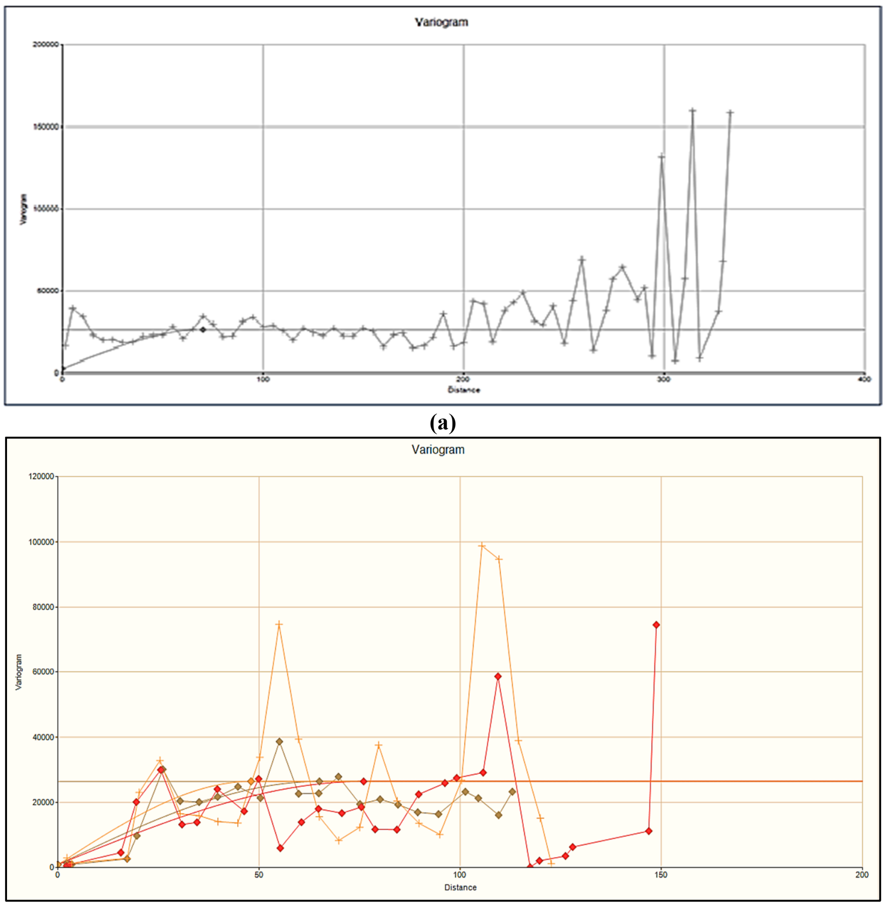
2.2. Geostatistical analysis

In order to model the deposit and to make an estimation of the grade, the geostatistical methods - experimental semivariograms, fitting the semi-variogram models and kriging were used. Variography includes the study of continuity (spatial correlation) and the rate of variation in regional variables (mineral grade, percentage disturbing elements, thickness, etc.), determining the isotropic and anisotropy status of the mineral mass and finally determining the spatial structure and estimation parameters using the variogram tools. There are several methods available for determining the spatial structure in the estimation of environment, the most common of which is drawing variograms in different directions and checking the parameters of the variograms drawn in these directions. First, a non-directional variogram is drawn to determine the spatial correlation between the uranium data (Figure 5). In order to investigate the anisotropy and unanisotropy of the mineral mass, it is necessary to draw a large number of variograms in different directions and with different conditions for each variable so that the desired spatial structure can be determined and the anisotropic ellipse distributes the measured value for the variable in the 3D space determined. The optimal directional variogram and spherical model fitted to each structure are shown in Figure 5. The variogram of the data is composed of three isotropic spherical models with ranges of 50m, 76m and 63m. The directional semi-variogram model parameters are shown in Table 3. Among the geostatistical methods, ordinary kriging (OK) is the one most used for the mineral resource estimation [24]. In order to make a geostatistical estimate, it is necessary to determine the estimation parameters according to the data distribution, spatial structure and estimation strategy. Given the optimal parameters of variogram and search ellipse, now the kriging estimator can be used to estimate the grade blocks.In this research work we investigates the alternatives for a computing estimation variance from the OK weights that account for both data configuration and data values. These estimation variances are then used to classify the resources based on the confidence levels and the results obtained are compared with those obtained by the OK variance [25].

Table 3: Different parameters of directional variogram model fitted to data

Model	Nugget effect	Sill(m)	Range (m)		
			R_1	R_2	R_3
Spherical	916.03	25501.62	50	76	63

The first step in estimating a deposit's reserves in new ways is to build a block model. The use of the 3D block model of the deposit, in addition to simplifying the calculations related to stock estimation, is also used during the extraction and operation of mines in production planning, preparation of extraction plans and feed quality control required by the processing plants. Determining the scope of expansion of the block model, optimal dimensions of each block and direction and extension of the block model in space are the three main characteristics of each block model. The Datamine Studio software was used in order to prepare the 3D models [25]. One of the most effective factors involved in determining the accuracy of mineral stock estimation in the new methods is the dimensions of the blocks used in the block model. The most important factors involved in determining the size of blocks are the geological structure and shape of the deposit, degree of grade changes in the mineral and considering the possibility of converting the exploration blocks to the extraction blocks and the blocks used in the technical and economic studies.The block size to be used for interpolation and reporting was assigned due to the distance between the boreholes and trenches, estimation space and sampling distance. The size of the blocks was selected to be 5 (m) × 5 (m) × 5 (m). After preparing the grade data (pre-estimation operation), performing variography and determining the estimation parameters, in the last step, the grade modeling method and how to assign the grade of the samples taken from the exploratory boreholes to the block model (estimation and interpolation operation) were determined by the OK method.



(a)

(b)

Figure 5. Non-directional variogram drawn with an impact radius of 70 (a) and optimal directional variogram and spherical model fitted (a). (Red represents the first axis of directional variogram anisotropy with the following parameters (step distance of 5 m, with step tolerance of 20 m and angle tolerance of 15 degrees), gray represents the second axis of directional variogram anisotropy with the following parameters (step distance of 5 m, with step tolerance of 20 m and angle tolerance of 15 degrees) and orange represents the third axis of directional variogram anisotropy with the following parameters (step distance of 5 m, with step tolerance of 20 m and angle tolerance of 15 degrees).

2.3. Fractal method

The fractal geometry-based methods in the earth sciences are used to analyze the complex shapes of the geological structures, especially for the separation of the geochemical and mineralization communities. Among these, the methods of grade-area, grade-environment, grade-number and power-area spectrum are widely used in the earth sciences. Today, the fractal and geostatistical methods and some other parameters are applied in the model. The fractal analysis methods are also used to describe and explain the relationships between the mineral, geochemical and geological communities with spatial data from the deposit analysis [2]. In fact, the fractal method is a way to identify different possible communities in the databases. Based on this method, a model can be developed in order to identify the communities through the number, area or volume of the data. The grade-number model is one of the most widely used fractal models [27]. In this research work, the grade-number and grade-volume models are used.

3. Discussion

Uncertainty is an integral part of the exploration and development of mineral resources. The mining projects face many uncertainties due to the changing nature of the deposit. In the field of mining engineering, the design, classification, estimation and interpretation are associated with error. These uncertainties are the main risk factors in various parts of the mining projects. The most important uncertainties in mining projects,are the uncertainties in the quality and quantity of minerals (grade and reserve). Among the mentioned cases of uncertainty in the mining projects, it is more important to study the uncertainty in the deposit model and its dependence on the grade changes,since all the design algorithms are performed on the deposit block model, its estimation is very important. The estimates were kriged (OK) into a sub-celled block model. The data presented was fed into the geostatistical techniques such as the block error estimation, kriging estimation variance, kriging efficiency, and slope of regression against each other. Also, the tonnage and grade estimates according to the differing degrees of geosientic confidence and economic evaluation was performed. The fractal models belonging to nonlinear mathematics are effective tools for describing the natural variability and skewed distribution of the geological objects as used for separation of the assay communities.

3.1. Investigating uncertainty grade estimation of blocks and their classification based on JORC codes

The mineral resource classification is fundamental in the uncertainty estimation and risk analysis of mineral resource development. Using the parameters obtained from geostatistical relations such as the estimation variance, block variance, Lagrange coefficient, and average function Fisher can be quantitatively categorized errors and calculated relationships [4]. These classifications are in accordance with the standard JORC codes [26]. The categorization of mineral resources in the JORC standard generally depends on the geological model of the deposit, sampling quality and data spacing [25]. The other parameters available in the estimation, such as the number of data helping to estimate a block or the number of bumps involved in estimating a block, can also be used in order to perform innovative quantifications.

3.2. Kriging estimation variance

One of the unique features of kriging is determining the variance of the estimate or determining the amount of error in each estimate. This feature is used in the classification of reserves (definite and probable), determining the distribution of errors at the exploration range level and optimizing the supplementary drilling network. Using the error variance distribution method, it is possible to identify the parts of the storage where the error rate is high and to dig new boreholes and take more samples [28]. The variance of the estimate is fitted to the variogram model and also the distance between the samples depends on each other and not on the variable value, so it is possible to determine the reduction in the estimate per drill before drilling [29]. There are several methods available for classifying resources, mostly based on the OK variance. The relative kriging standard deviation, defined as the ratio between the kriging standard deviation and the estimated value of a block is one option [30]. Figure 6 shows the 3D model of kriging estimates and kriging errors in the Khoshumi uranium deposit.

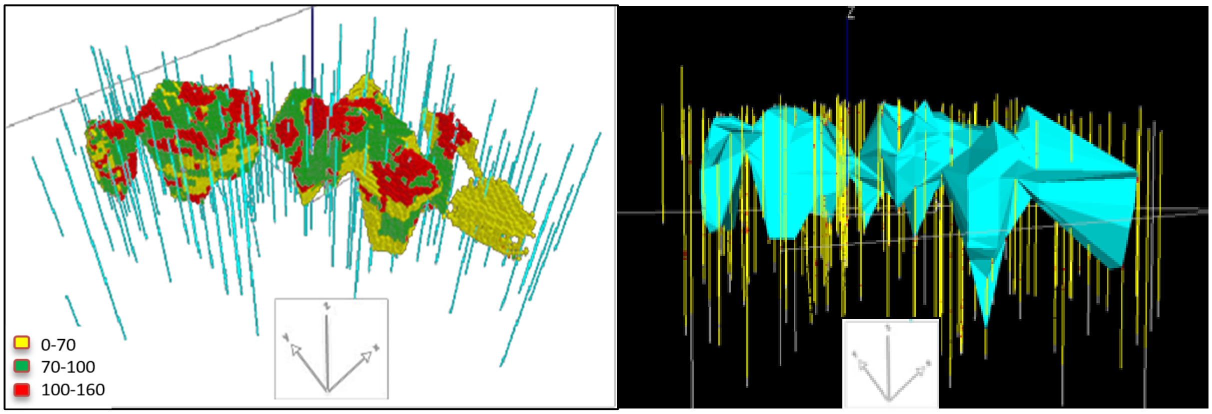
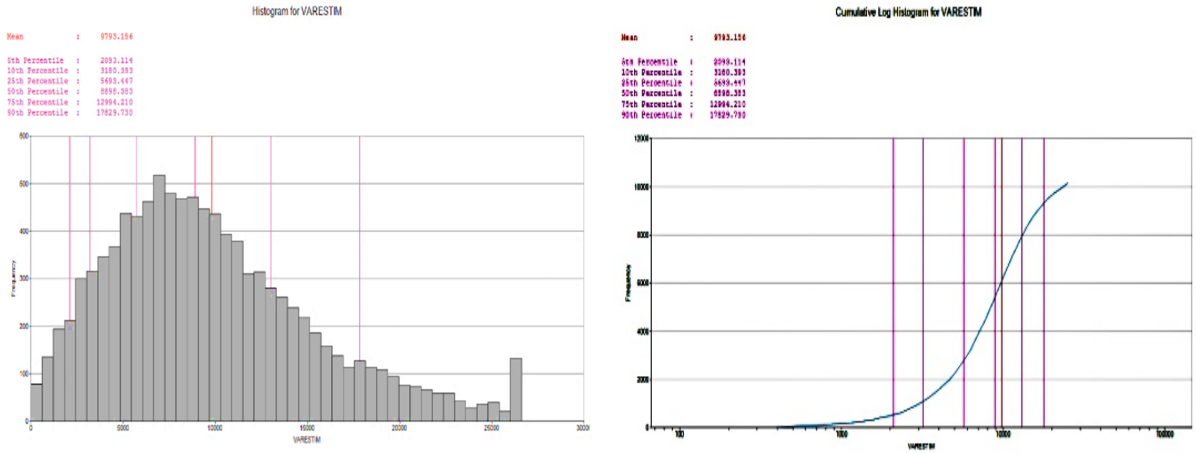


Figure 6. A view from above the assay block model built in 3D.

In the present work, the grade-number method was used to separate the communities. First, the data was arranged in an ascending order and then their cumulative distribution diagram was drawn. The points at which the cumulative function curve showed an index fracture were considered as an index population. As shown in Figure 7, the use of statistical distribution of the variance of the estimation parameter makes it possible to separate different groups of the society and compare more similar societies through the data dimension. It is clear that the dimensional data fits into a community (fractal statistical community separation). The use of different statistical methods helps one to separate the communities more accurately. As shown in Figure 6, different percentages are plotted from 5 - 90 %. For example, the fifth percentile is equal to 2093, which indicates that 95% of the total data is greater than this number. The classification based on the kriging variance is performed with threshold setting for each group. Obviously, the co-dimension data is in a population (separation of statistical population by the fractal technique). Using various statistical methods helps in the community separation with a higher accuracy. It should be noted that the blocks were selected for the classification that had a lower error estimation. Based on the results of the amount and distribution of the kriging estimation error variance, 65% of the estimated reserve was considered to be the proven reserve category (Figure 8). The grade-tonnage curve is a visual representation of the effect of grades on the mineral reserves. The grade and tonnage curves can consider several modifiers simultaneously in order to estimate the mineral reserves.The grade-tonnage curve is one of the most important tools that enable the mine managers to provide the correct long-term, medium and short-term plan for the production process in mineral reserves. Drawing the tonnage-grade curves is required to obtain tonnage in different grades. Given the grade data of each block, we can calculate the mineral reserves based on different cut-off grades. It can also be observed that the tonnage-grade curve based on the variance estimation uncertainty parameter is also found in the proven reserve class (Figure 9). In other words, the blocks with a kriging variance below 35% of the block variance are classified as measured while the blocks with a kriging variance below 65% of block variance, but higher than 35% are classified as indicated. The results obtained show the differences in tonnages within each class of resources when different measures of uncertainty are used.



(a) (b)

Figure 7. Histogram(A) and cumulative frequency(B) plot of the kriging estimation variance for segregate of communities by fractal pattern

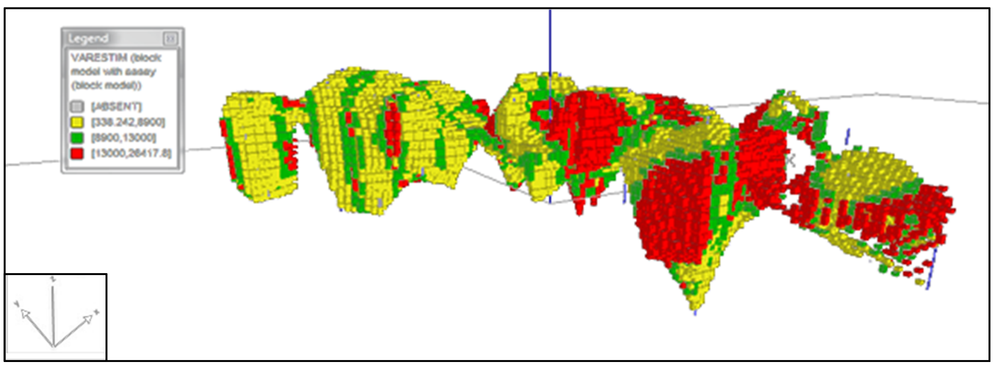


Figure 8. 3D block model based on the estimation variance parameter using the fractal method.

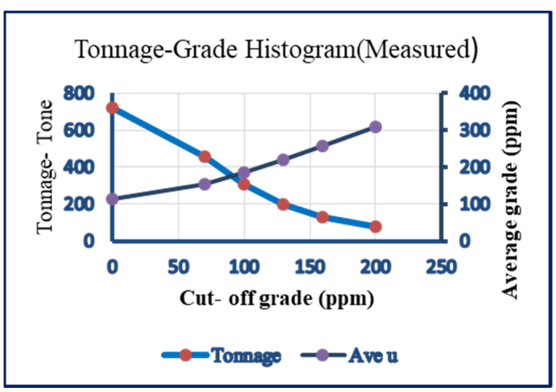


Figure 9. Grade- tonnage curve; proven reserve class based on distribution of block estimation variance

3.3. Block Error estimation

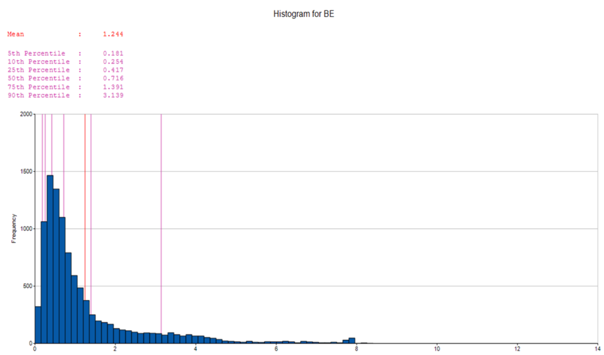
The block error estimation is another parameter involved for quantifying the geostatistical process uncertainty. Since this parameter depends on the spatial distribution and data dimension, using the specific standard for it cannot be reliable [31]. Therefore, in addition to using the existing standard, the analytical and numerical parameters were also used. Based on the statistical distribution of these parameters, as described in the previous section, and by comparing the results obtained from the standard and quantitative methods, the deposits can be classified into three categories : proven, probable and possible. The formula for calculating the block error estimate parameter is shown in Equation 1:

$$BE = \frac{\sigma_E * t_{95\%}}{Z * \sqrt{n}} \tag{1}$$

where, BE: block error estimation; σ_E :kriging estimation variance; Z: estimated grade; n: number of samples; t: the 95% coefficient of confidence equals to 1. 96 %.

For a reliable modeling and description of a given mineral deposit, the measured uncertainty must be an intrinsic part of the geo-modeling method. The 3D block model of the deposit was constructed based on the uncertainty parameter of the estimation error, and the current standard was used.

Based on this,the estimated uncertainty and the amount of the proven reserve were calculated. As shown in Figure 10, it is possible to calculate the amounts of the definite, probable and possible reserves using the statistical parameters and separation analysis of the fractal communities . Figure 11 shows a 3D block model obtained from the separation of the statistical communities by the distribution of the block error estimation. Based on the results obtained from the comparison of the two methods, the proven reserve amount in relation to the total reserve amount in the standard method is 33% and based on the statistical analysis of the error estimation distribution, it is 72%, which is closer, more tangible and reliable to the reality than the available standard.



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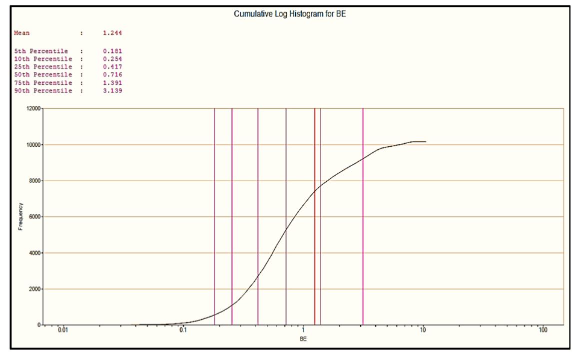
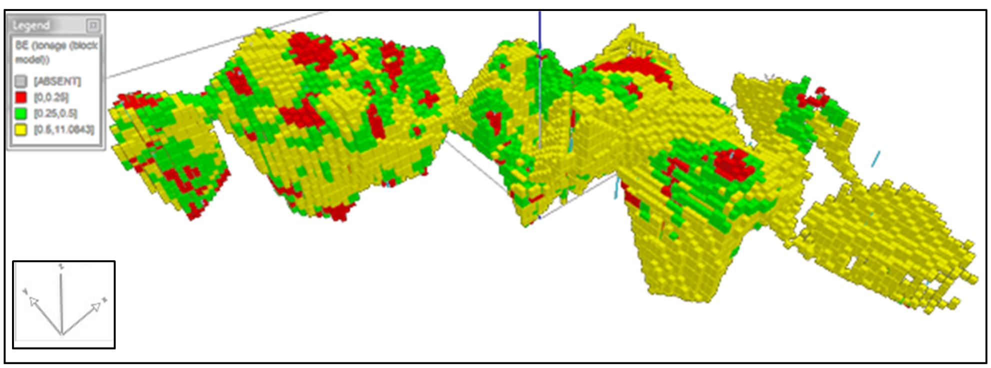


(b)

Figure 10. Histogram (A) and cumulative frequency(B) curves of block error estimation for segregate of communities by fractal pattern



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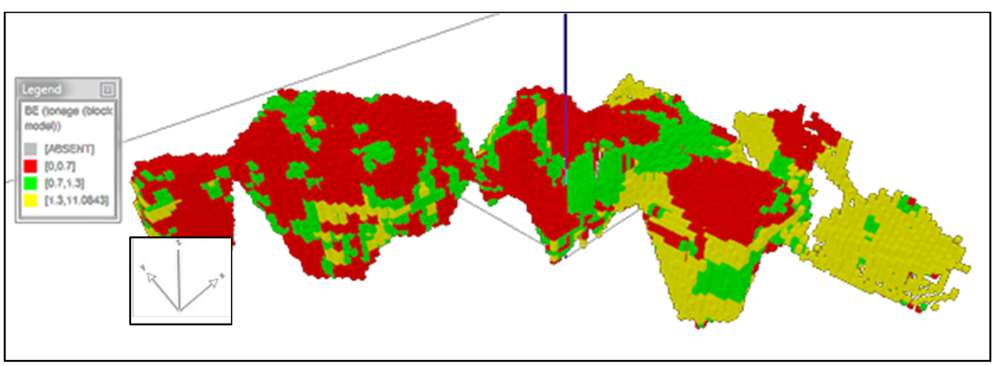


(b)

Figure 11. Demonstration of block model uncertainty in a standard method (A) and quantitative method (B) based on the block error estimator parameter

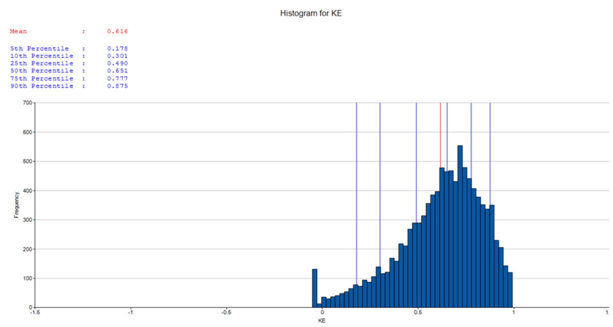
3.4. Kriging efficiency

The term kriging efficiency was first coined by Weifantis et al to evaluate the three sampling patterns square, triangular and hexagonal . However, for the first time Craig [24] expressed the efficiency of block estimation. This parameter is used as a measure to ensure the dimensions of blocks and network distances and is directly related to the kriging variance. Actually, KE is another definition of variance that is proportional to the true variance of the blocks. For a complete estimation algorithm, the efficiency would be 100%, which would require zero estimation variance. In real studies, the return is usually less than 100%. In some cases where the variance of the estimate is greater than the variance of the blocks, the value of the estimate can be negative. KE is the best parameter to check the modeling error. KE can be calculated by the following formula (Equation 2):

$$KE = \frac{(BV - KV)}{BV} \tag{2}$$

where, BV= is the theoretical variance of blocks within the domain; KV=is the kriging variance; and KE= is the kriging efficiency;

KE of the assay data in the Khoshumi deposit was calculated. Figure 12 shows the cumulative frequency curve of the KE parameter, which can be a well quantity' measure to estimate the actual separation threshold of the statistical community and the reserve classification in accordance with the actual distribution of data.



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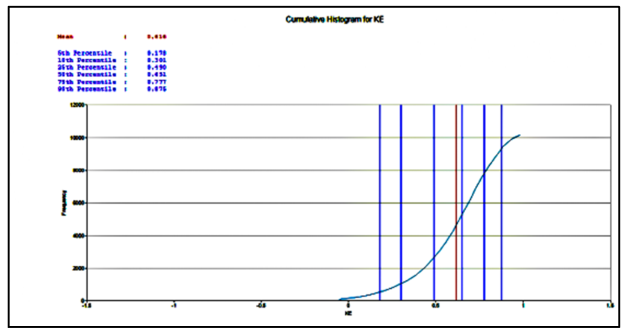

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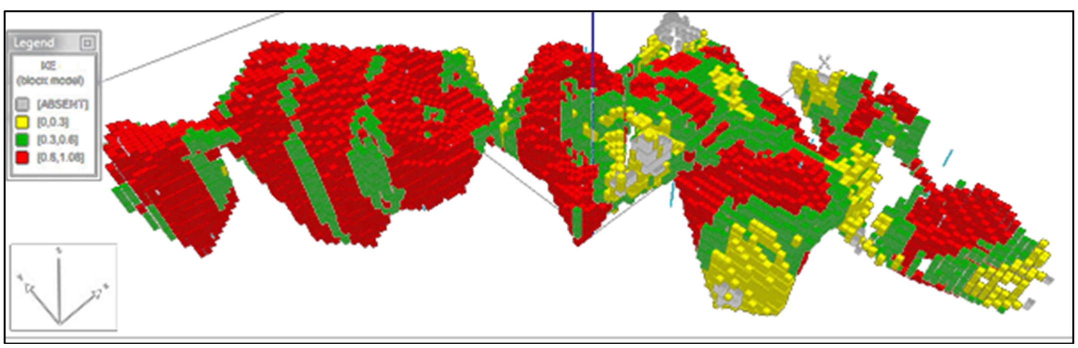
Figure 12. Histogram (A) and cumulative frequency(B) curves of the KE parameter for segregate of communities by fractal pattern



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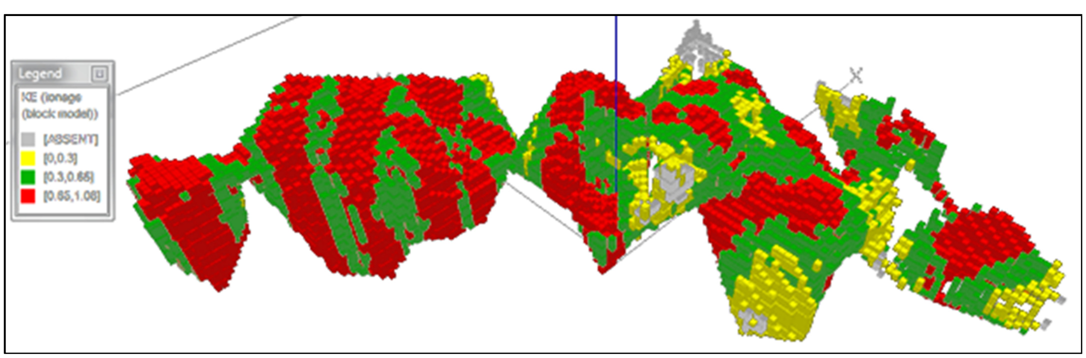


(b)

Figure 13. Demonstration of block model uncertainty in a standard method (A) and quantitative method(B) based on the KE estimator parameter.

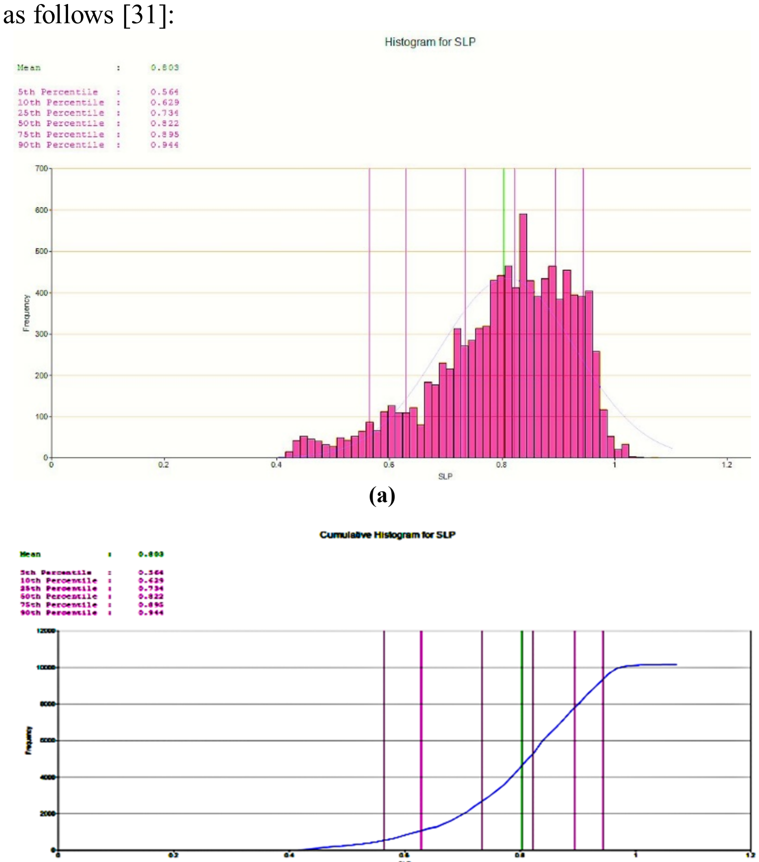
3.5. Regression slope

This criterion is a theoretical experiment based on the linear shadow assumption of real values relative to the estimated values and is used in order to evaluate the quality of estimates. When the estimated values (Z*) are exactly equal to the actual values (Z), the regression slope of the actual values of the block in terms of the estimated values is linearly equal to one. This method is one of the most up-to-date tools for quantifying the uncertainty and reserve classification parameters due to the use of various parameters for uncertainty[32]. SLP approximates the conditional bias of the kriging estimation results.

In this section, we propose an alternative approach that quantifies the overall uncertainty on the mineral resources by means of the conditional simulations of the grades that can also be used to classify each block as measured, indicated, or inferred resource. The SLP method was applied in order to examine the uncertainty of the data in this work. Its formula is as follows [31]:

$$R = \frac{BV - KV + |\mu|}{BV - KV + |2\mu|} \quad (3)$$

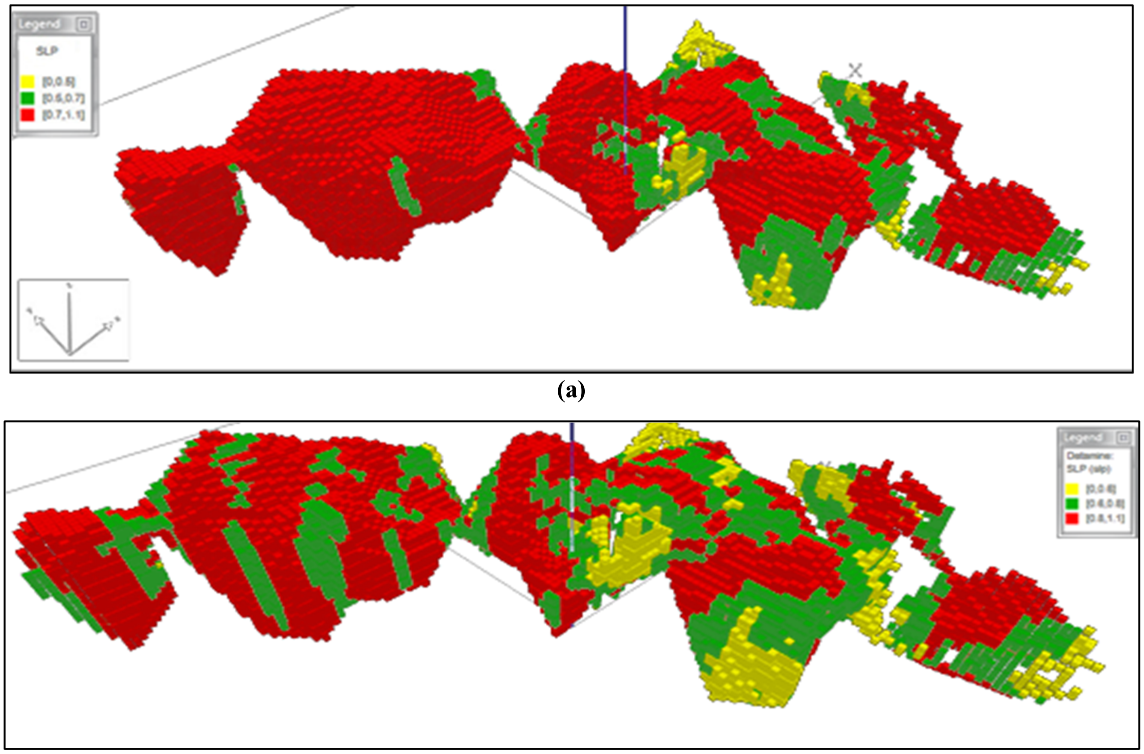
where, BV: is the sill value; KV: is the kriging variance; and μ: is the lagrange multiplier. The mean regression slope for our analysis was calculated to be 0.65 and the blocks were plotted and colored according to the regression slope value. After plotting the cumulative frequency curve and based on the separation of the communities by the fractal method (Figure 14), the values of the SLP parameter more than 0.8 were classified as the proven reserves, between 0.6 and 0.8 as the probable reserve, and 0 to 0.6 as a possible reserve. Figure 15 presents the block model of the deposit based on the SLP uncertainty estimation parameter. Using the results obtained from the quantification of the SLP measure we can obtain the tonnage and the average grade curves in terms of grade (Figure 16).



(a)

(b)

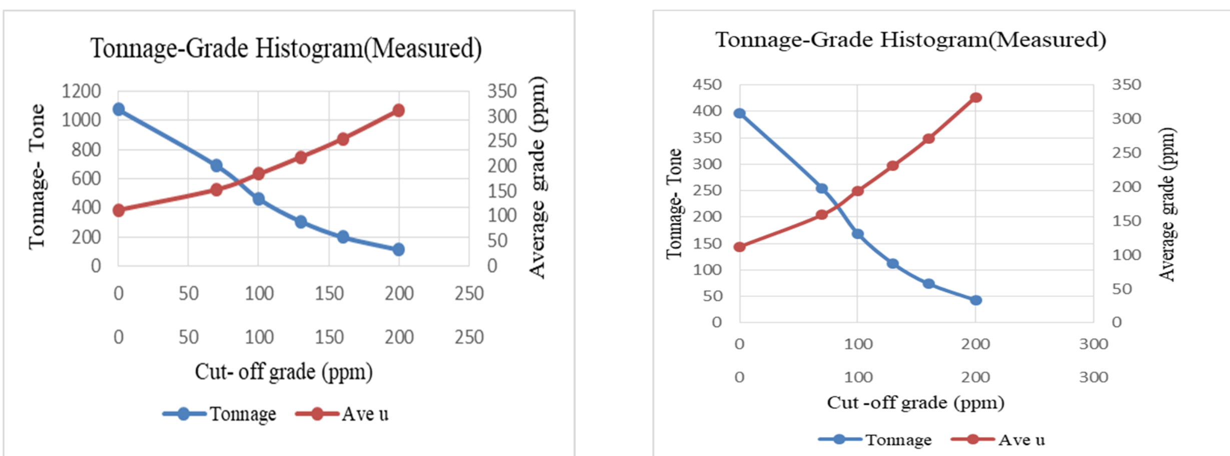
Figure 14. Histogram (a) and cumulative frequency(b) curves of SLP for segregate of communities by fractal pattern.



(a)

(b)

Figure 15. 3D model of uncertainty by SLP based on the standard (A) and quantitative(B) analysis.



(a)

(b)

Figure 16. Grade- tonnage curve; proven reserve class based on the SLP method (a: quantitative; b: standard).

4. Conclusions

Almost all the reported standards have introduced the geostatistical methods as quantitatively powerful methods for estimating and classifying stocks, but have not introduced a fixed criterion for classifying sources or stocks. In this work, the results of estimating the uncertainty in the block model by the geostatistical methods were discussed and analyzed. The existing standard criteria for the classification of mineral reserves, due to the lack of consideration of the stock status and statistical distribution of estimates, undoubtedly have problems that make the reliability of the estimation results with certain doubts. Therefore, using a fractal analysis model based on the statistical distribution of data and segregation of communities, an innovative quantitative method was proposed in order to estimate the uncertainty parameters and finally the classification of mineral reserves (Table 4).

Table 4: Comparison of the results obtained from the current proposed standards

Uncertainty index	Kriging estimation variance(KV)	Block error estimation(BE		Kriging efficiency(KE)		Slope of regression(SLP)	
	Quantitative analysis	Standard	Quantitative	Standard	Quantitative	Standard	Quantitative
Proven reserve ratio to total reserve (%)	60	33	72	64	69	76	79
Measured reserve ratio to total reserve (%)	18	45	10	15	12	11	14
Indicated reserve ratio to total reserve (%)	22	22	18	21	19	13	7

From the results obtained, It can be seen that the multiple grade models of a deposit enable the mining planners to evaluate the best estimation method in the classification of mineral resources and reserves. The analysis results show which SLP method can be used in order to develop the mining strategies that have a lower risk of grade uncertainty. However, in order to show the difference between the methods, the tonnages in the realizations of the four methods were calculated depending on the cut-off grades of uranium.

The main purpose of this research work was to compare the most common techniques and methods proposed to estimate the uncertainty of the block model using the sub-surface data from the Khoshumi uranium deposit in order to highlight the advantages and disadvantages of each method in the classification of mineral resources. Using geostatistics to determine the correlations between the data as well as interpolation and estimation is very appropriate, but the statistical estimates such as kriging have smoothing. Therefore, the estimation error should be determined by the appropriate methods. The kriging estimator provides the kriging variance along with the estimation data. The kriging variance is a good tool for error detection. A good estimator must be inexperienced .i.e. the difference between the estimated data and the actual data has a normal distribution and the variance and mean are close to the original data. The post-estimation operation included a distribution map of the variable estimation diffraction distribution. For the ordinary kriging estimates, the kriging variance, kriging efficiency, regression slope, actual cut-offs and estimated cut-offs are all performed relatively well, and these are usually acceptable measurements of the error used in the conventional kriging. The uncertainty measurements in the final section can be used to define the resource / resource classification criteria. The existing standard criteria for classifying mineral reserves, regardless of the stock status and statistical distribution of the estimate, are certainly associated with the problems that cast doubt on the reliability of the estimate results. The use of quantitative analyses based on the statistical data distribution and fractal community separation techniques can effectively help to better understand the storage conditions and estimate the quantitative uncertainty parameters and ultimately classify the mineral reserves.

Comparing the results of the proposed standards so far and the innovative quantitative methods based on the distribution function, shows the fact that the results of the existing standards can definitely not be used in all deposits with different conditions and the need for a quantitative analysis depends on the deposit conditions. The special must be felt. The slope regression (SLP) method is one of the most up-to-date tools for quantifying the uncertainty and stock classification parameters due to the application of various uncertainty parameters. The kriging estimation variance, block error estimation, kriging efficiency, and slop of the regression parameter methods were compared and employed in the mineral resource classification of a uranium deposit. Using a fractal analysis model in that it recognizes the parameter distribution pattern and separates the groups from each other and this can be an innovative approach and closer to reality. However, in practice, the results of the SLP method are more reasonable and satisfactory, and the use of this method is encouraged for the classification of the mineral resources in the underlying uranium deposit into measured, indicated and inferred resources based on the JORC code. The maximum proven reserve ratio to the total reserve can be obtained by the SLP method. Thus, this method can be considered for the resource classification for an improved accuracy of the final classification models.

Acknowledgements

This research work is part of the PhD Tez of the first author at Shahid Bahonar University of Kerman. (Postal Code: 7616913439 PO Box: 76169133) .The authors of the article appreciate the advice and guidance of Dr. Ali Rezaei and Dr. Mohammad Jalali in conducting the work. The authors of the article also wish to thank the editor of the journal for reviewing and reviewing this article, and the esteemed reviewers for their helpful and constructive comments on improving the article.

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بکارگیری معیارهای تحلیلی و عددی به منظور برآورد عدم قطعیت مدل بلوکی و کلاسه بندی ذخیره: مطالعه موردی: کانسار اورانیوم خشومی یزد

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ارسال ۲۰۲۱/۰۱/۰۱، پذیرش ۲۰۲۱/۰۳/۰۹

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چکیده:

در مراحل مختلف عملیات معدنکاری، همواره با درجه‌ای از عدم اطمینان روبرو هستیم. برخی از این عدم قطعیت‌ها مانند میزان و عیار ذخیره به دلیل تغییرات ذاتی کانسار است و مستقیماً بر شاخص‌های فنی و اقتصادی کانسار تأثیر می‌گذارد. از طرف دیگر، هزینه‌های سنگین بخش اکتشاف اغلب میزان اطلاعات اکتشافی را محدود می‌نماید، که استفاده از روش‌های دقیق تخمین را ضروری می‌سازد این پژوهش به بررسی نتایج مدلسازی و تخمین عیار بلوک‌های اکتشافی بر اساس تکنیک‌های متداول و ساده کریجینگ و همچنین تأثیر معیارهای گوناگونی که در طبقه بندی ذخایر معدنی استفاده می‌شود و یا پارامترهایی که این ملاک‌ها را تعریف می‌کند، می‌پردازد. برای ساخت مدل بلوکی کانسار در نرم افزار دیتاماین، از اطلاعات ۱۲۷ گمانه اکتشافی با میانگین عمق ۹۵ متر استفاده شد. پس از مطالعات آماری، مطالعات واریوگرافی سه بعدی به منظور شناسایی ناهمسانگردی منطقه ای انجام شد. یک مدل بلوکی عیاری با استفاده از پارامترهای بهینه واریوگرام ساخته شد. سپس ، با استفاده از روش های مختلف برآورد عدم قطعیت مدل بلوکی از جمله واریانس تخمین کریجینگ، خطای تخمین بلوک، کارایی کریجینگ و شیب رگرسیون، ذخایر معدنی بر اساس کد استاندارد JORC طبقه بندی شدند. سپس بر اساس عیارحد های متفاوت، تناژ و عیار میانگین محاسبه و رسم شد. در این مطالعه، از یک روش کمی مبتکرانه‌ای مبتنی بر الگوی تحلیل فرکتال عیار- تعداد و عیار –حجم، جهت طبقه بندی ذخایر معدنی استفاده شده است. استفاده از الگوهای تحلیل فرکتال بعلت دامنه تغییر بیشتر از الگوهای استاندارد ، درک بهتری از تغییرات عیار در هر بلوک به ما ارائه می‌دهد. وجود حداقل اختلاف بین استفاده از الگوهای استاندارد و فراکتال در شیب رگرسیون نشانگر خطای کمتر و نتایج قابل اعتمادتر بود.

کلمات کلیدی: واریوگرام، عدم قطعیت مدل بلوکی، کریجینگ، رده بندی ذخایر معدنی، روش فرکتال.