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Comparison of Methods for Evaluating Recoverable Reserves of the Miduk Copper Deposit using Estimation Techniques and Conditional Simulations

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Abstract

In this work, various methods for evaluating recoverable reserves including estimation techniques and conditional simulation have been compared in the Miduk copper deposit using data from 55,119 blast holes and 6,178 composite samples from exploratory drillings in the supergene and hypogene zones, with a block model constructed for the analysis. Four methods were employed: UC, LUC, DCSBG, and SGS. The correlation coefficients for UC, DCSBG, and SGS methods in the supergene zone, as well as the results from extraction drill holes (extraction blocks) at a cut-off grade of 0.15%, were 0.637, 0.527, and 0.556, and the correlation coefficient for calculating tonnage and the metal content using UC was 0.364 and 0.629, respectively. For the hypogene zone, the correlation coefficients for metal content at a cut-off grade of 0.15% were 0.778, 0.788, and 0.790 for UC, DCSBG, and SGS, and at a cut-off grade of 0.65%, they were 0.328, 0.431, and 0.458, respectively. By employing The LUC method in the supergene zone with a change in SMU and comparing the results obtained from the E-Type map, the performance of this method is higher across all cut-off grades. As the cut-off grade increases in the hypogene zone, the performance of the LUC method relative to simulation methods decreases. The LUC method can be used to observe the impact of the convergence of results obtained from this method with real data from low-grade to high-grade sections, highlighting the necessity of differentiating this zone into low and high-grade segments during the estimation process.

1. Introduction

To achieve a suitable and optimal technical and economic evaluation of a mining project, all efforts must focus on estimating and foreseeing recoverable mineral resources (the portion of in-situ resources that can be economically extracted through mining) [1]. To achieve this, estimates of average grades and tonnages for economic cutoff grades should be prepared and considered for selective mining [2]. In the early stages of exploration, we often have data that is spaced far apart, which complicates the estimation process [3]. Ordinary kriging estimation, commonly used [4], is a linear estimator that can be utilized for estimating grades in larger panels (estimating in smaller panels that are not sufficiently supported by denser data may lead to smooth and biased conditional estimates) [5]. Larger panels, which are suitable for data that is widely spaced, often do not sufficiently represent the expected selective mining during extraction [6]. Selective mining (represented by the selective mining unit or SMU) depends on the type of deposit and the selected equipment and machinery [7]. Non-linear techniques, such as uniform conditioning and multi-indicator kriging, are commonly used to estimate grades at the scale of the smallest mining unit, which reflects the mining unit itself [8]. With these techniques, the ratio of the mineral material that can be economically extracted is estimated by determining the distribution of the smallest mining units within each panel based on a change model. Estimates of average grades and the extractable ratios above a specified cutoff grade for each panel are provided without precisely defining the spatial

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positions for this recoverable mineralization. A better understanding of the actual spatial positions of selective mining units will considerably simplify the application of results for mining planning purposes and will highlight the technical and economic evaluations of the project [9]. The main issue arises from the fact that many characteristics of deposits do not conform to the prerequisites of non-linear methods (for instance, the assumptions of definite stationarity). For example, in the case of porphyry copper deposits, there is often a high-grade zone that leads to preferential sampling, which can result in losses in the marginal, relatively lower-grade sections [10]. Thus, a bi-faceted problem emerges that includes the presence of a large-scale external trend and an irregular preferential sampling network. Nevertheless, this situation does not significantly affect the results of kriging estimates under general conditions. The estimated grades will provide a relatively accurate local average to some extent. In this case, the overall average of estimated grades is close to the average of the weighted data (with kriging weights or with influence zones), and the arithmetic mean of the estimated grades differs from them. Therefore, the problems with non-linear methods are quite subtle. The hypothesis of stationarity plays a fundamental role theoretically. From a practical standpoint, the transformation shape that is often applied prior to all these methods requires a histogram that represents the data conditions [11].

2. Methodology

Considering the porphyry nature of the Miduk copper mine and the dispersion of grade data in the supergene and hypogene zones, estimating the reserve and calculating the amount of mineable reserve, as well as selecting the best method for reserve estimation is of great importance. Due to the widespread distribution of grades at different points in the mine, it is first necessary to calculate the SMU for each zone or for the entire deposit in order to find the most suitable method for estimating this parameter. By doing this, it will be possible to select the economic grade threshold in the mining production planning and consequently calculate the mineable reserve with high precision. Since estimation methods are associated with varying errors, choosing the best method is inevitable due to its lower estimation error and its high validity compared to actual data values [12].

In this article, various methods for determining the recoverable reserve are employed using exploratory, extracted, and geological data, and the best method is selected for each zone to specify the reserve amount. The calculation of the tonnage and average grade of the recoverable reserve based on nonlinear geostatistical methods is as follows: If **v** is the selected general block (SMU) and **Z(v)** is its grade, then the recoverable resources at grades higher than the cutoff grade **z** for similar blocks will be:

- Tonnage of mineral material $T(z) = l_{Z(v)\geq z}$
- Metal content $Q(z) = Z(v)l_{Z(v)\geq z}$

A separate Gaussian model is used for support transformation. A standard Gaussian variable $\boldsymbol{Y}$ is dependent on each raw and primary variable $\boldsymbol{Z}$. If the sample point variable is defined as $\boldsymbol{Z(x) = \Phi(Y(x))}$, then a block model with its block transformation will be defined as $\boldsymbol{Z(v) = \Phi_r(Y_v)}$ and determined by the following integral relationship:

$$\boldsymbol{\Phi_r(y) = \int \Phi\left(ry + \sqrt{l - r^2 u}\right) g(u) du} \qquad (1)$$

where the support adjustment factor $\boldsymbol{r}$ is derived from the variance of the blocks. Then, the estimation of total resources at the cutoff grade $\boldsymbol{z}$ is as follows:

Mineral:

$$E[T(z)] = E\left[l_{Z(v)\geq z}\right] = E\left[l_{y_v \geq y}\right] = l - G(y) \qquad (2)$$

Metal content:

$$E[Q(z)] = E\left[Z(v)l_{Z(v)\geq z}\right] = E\left[l_{y_v\geq y}\Phi_r(Y_v)\right] = \int_y \Phi_r(u)g(u)du \qquad (3)$$

where g and G are the probability density function and the cumulative distribution function of the standard gaussian distribution, respectively, and $\boldsymbol{y}$ is the Gaussian grade threshold related to $\boldsymbol{z}$ via $\boldsymbol{z = \Phi_r(y)}$. As presented in other sources on non-linear geostatistical theory, only the main points are highlighted here. If the transformed grade of the blocks is denoted by Y_v , v will correspond to the selected mining unit size [1]. The main issue is to estimate $\mathrm{Q} = \sum f\left(Y_{V_i}\right)/L$, where $f(0)$ is an estimated function (for example, recoverable tonnage or recoverable metal tonnage), and L is the number of blocks within each panel. In cases where the number of blocks in each panel is very large, L is designated as the blocks that represent the overall conditions of the panel. These should be selected to provide a uniform discretization of the panel [13].

2.1. Ordinary Kriging method

Linear kriging is a technique for predicting a regional variable at any spatial location using a weighted average of the values of this variable at surrounding or encompassing locations [14]. In practice, the regional variable is often interpreted as a realization of a second-order stationary random field with a constant mean and a known spatial correlation structure, which is modeled by an automatic covariance function or a variogram. Simple kriging assumes that the mean value is known, while ordinary kriging considers this mean value as an unknown parameter, thus allowing for stronger estimation in cases where the regional variable provides a locally constant mean that varies regionally within the studied space. The kriging relationship is defined as follows, where Z_V^* is the estimated grade, λ_i is the weight attributed to the sample quantity, and Z_{V_i} is the sample grade [15].

$$Z_V^* = \sum_{i=1}^{n} \lambda_i Z_{V_i} \quad (4)$$

2.2. Sequential gaussian simulation

In sequential simulation, a random path traverses all locations once and is defined at that single instance, with each location being simulated during that single pass. With conditional simulation, the realizations that result meet the data values at their respective locations. Sequential Gaussian simulation assumes that the selected random field is multivariate normal, which implies that the data used have a normal distribution. Before applying sequential gaussian simulation, it is necessary to transform the raw initial data into standard normal form to ensure that the requirement for the normality of the data used is met. Sequential direct simulation does not rely on the assumption of multivariate normality or Gaussian of the raw initial data. Thus, there is no need to transform the raw initial data, and the simulation is carried out directly on the raw data [16].

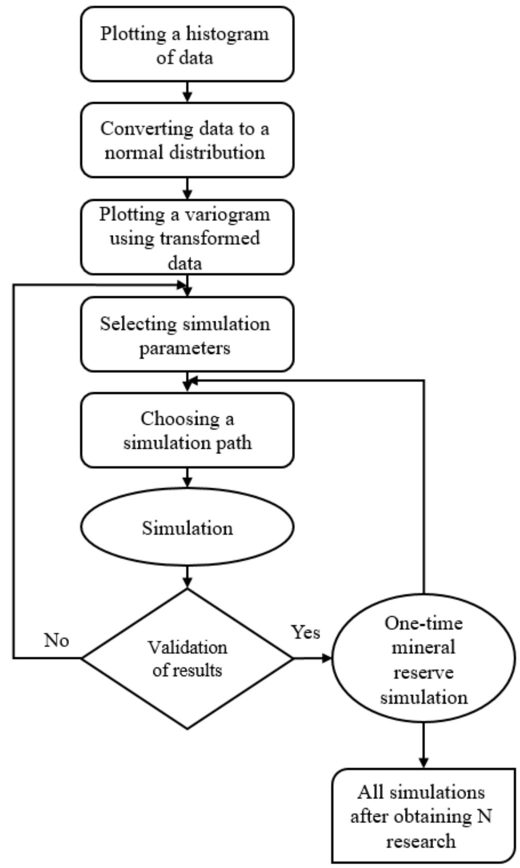

Diagram 1. Stages of implementing sequential gaussian simulation method.

2.3. Direct simulation and block simulation

Sequential simulation of a continuous variable generally requires transforming it into a binary or gaussian variable, leading to the emergence of classic algorithms such as indicator sequential simulation or sequential gaussian simulation. In 1994, André Journel demonstrated convincingly that sequential simulation of a continuous variable, without any preliminary conversion, results in the reproduction of the covariance model. In this process, the simulated values are obtained from local distributions focused on simple kriging estimates with a variance corresponding to the variance of simple kriging estimates [17]. Unfortunately, this process is unable to reproduce the histogram of the original raw variable, which is one of the fundamental requirements for any simulation method. Therefore, this issue represents one of the most significant fundamental limitations for the practical application of direct simulation. One of the ideas employed is the use of local estimates (simple kriging) of variance and mean, but not for defining the local conditional distribution function; instead, they are used to sample from the overall conditional distribution function. The simulated values of the original variable are derived from intervals of the overall conditional distribution function, calculated using the local estimates of variance and mean. One of the main advantages of the direct sequential simulation method is the ability to jointly simulate multiple variables without transforming them. Essentially, direct sequential simulation is similar to sequential gaussian simulation but lacks the standard normal transformation step [18]. Block direct simulation is another simulation option that aims to simplify the simulation process by executing it directly on a support different from the original nodes or composites. Journel and colleagues originally proposed a block direct simulation method in 1978, based on separate stages of simulation and conditioning. This method relies on using a continuous support transformation based on the continuity of the distribution technique to convert the point support data to block support. Then, conditioning occurs at the block support level [19]. The block direct simulation computer program is a means for simulating block values, while selectively determining related values within each block under a distinct Gaussian model framework. The complete framework for achieving block direct simulations is described as follows:

1. Modeling the anamorphosis of the raw initial samples and calculating the gaussian transformation data.
2. Modeling the variogram of the Gaussian data.
3. Regularizing the gaussian variogram model on block support.
4. Modeling the regularized gaussian variogram.
5. Calculating the changes in support coefficients and the block gaussian variogram related to standard normal block gaussian values.
6. Calculating block direct simulations using the modified block variogram and gaussian anamorphosis support transformation.
7. The direct block simulation module consists of three main stages: a) Concentrating the data into output network blocks, for which a new auxiliary file is created.
8. Conditional simulations (the method of circular bands) of block values using the block Gaussian variogram model and gaussian data.
9. The final stage is an elective option and involves performing block gaussian transformations using block shape or support transformation [20].

2.4. Uniform conditioning

Uniform conditioning is a non-linear estimation technique that estimates the conditional distribution of metal content and tonnage above a specified grade within a mining panel. This method does not directly estimate grades; however, grades are a common output from the metal content-tonnage distribution or results generated by local uniform conditioning. The results of uniform conditioning are usually presented as a mineral resource that is recoverable at multiple cutoff grades. The advantage of uniform conditioning is that it can be applied to datasets with widely spaced data, as well as across areas that are not absolutely steady. Additionally, this method is applicable in situations where sufficient data is available for a conditional unbiased estimation of the panel's average grade. Uniform conditioning serves as a tool for calculating recoverable reserves in panels for a specified block support in mining applications. Moreover, utilizing specific options within it, recoverable metal as a secondary variable can be computed with the cutoff grade applied to the primary variable [21].

Before executing uniform conditioning, it is necessary to first estimate the grade on the panels using kriging, and to calculate the following parameters [22]:

a. Kriged grade estimate
b. Variance of the kriged values (variance Z*)
c. For multivariate estimation, the covariance between the primary variable and the kriged secondary estimates.

Additionally, the calculated block transformation is also necessary for using this method. Then, using these values and the transformation on block support, uniform conditioning can be applied to calculate the three parameters: tonnage, metal content, and average grades for each variable at each cutoff grade.

To make various methods comparable to reality, it is first necessary to compute the real QTM variables on the panel supports. Next, a cutoff grade must be selected, and each method should be locally compared to the actual data (obtained from blasting holes) based on this cutoff grade [23].

Uniform conditioning with the panel grade is used to estimate recoverable resources within a selected sub-block in a larger block or panel V, conditioned on the panel grade or, in general, the estimated panel grade, denoted as $Z(V)^*$.

$$[T_V(z)]^* = E\left[\left(l_{Z(v)\geq z}\middle|Z(V)^*\right)\right]$$
$$[Q_V(z)]^* = E\left[\left(Z(v)l_{Z(v)\geq z}\middle|Z(V)^*\right)\right] \tag{5}$$

The idea behind uniform conditioning is to apply the grade of the panel, which has been estimated using ordinary kriging, in order to avoid the use of the average value that may be generated by certain techniques in case of deviations from stationarity. The estimation of metal content at a zero (0) cutoff grade must be met as follows:

$E[(Z(v)|Z(V)^*)] = Z(V)^*$ As long as v is uniformly distributed within V, the first stage assumes that the estimated grade of the panel $Z(V)^*$ is conditionally unbiased:

$E[(Z(V)|Z(V)^*)] = Z(V)^*$ The second stage assumes that the transformation of $Z(V)^*$ is derived from $Z(v)$ [14, 19].

$$Z(V)^* = E[(\Phi_r(Y_v)|Y_{V^*})] = \Phi_{r\rho vV^*}(Y_{V^*}) = \Phi_S(Y_{V^*}) \tag{6}$$

It is assumed that the standard gaussian variables Y_{V^*} and Y_v are jointly gaussian and denote:

$$S = r\rho_{vV^*} = r\,corl(Y_v, Y_{V^*}) \tag{7}$$

In practice, S is derived from the variance of the panel estimate. The previous relationship is used to calculate the correlation between the block and the panel estimate:

$$corl(Y_v, Y_{V^*}) = \rho_{vV^*} = S/r \tag{8}$$

Therefore, the tonnage of the mineral and the metal content at the cutoff grade $z = \Phi_r(y)$ can be calculated as follows [11]:

$$[T_V(z)]^* = E\left[\left(l_{Z(v)\geq z}\middle|Z(V)^*\right)\right] = E\left[\left(l_{Y_v\geq y}\middle|Y_{V^*}\right)\right] = l - G(a)$$
$$[Q_V(z)]^* = \int_a \Phi_r\left(\rho_{vV^*}Y_{V^*} + \sqrt{l-(\rho_{vV^*})^2 u}\right) g(u)du \tag{9}$$

With $a = \frac{y-\rho_{vV^*}Y_{V^*}}{\sqrt{l-(\rho_{vV^*})^2}}$

2.5. Local uniform conditioning

In 2006, Marat Abzalov proposed the Local Uniform Conditioning (LUC) method, which forecasts economically extractable mineral positions by assigning a single grade value to each block of size SMU. The LUC method enhances and improves upon the local modeling and results obtained from Uniform Conditioning (UC). The SMU grades are inferred from the common grade-tonnage relationships obtained from UC [24].

The key stages involved in creating and implementing a LUC estimate include the following:

- Estimating panel grades using ordinary kriging
- Fitting a discrete gaussian model to the data
- Determining support transformation. The discrete Gaussian model is used to calculate the support transformation.
- Converting panel estimates and cutoff grades to gaussian units.
- Executing uniform conditioning.
- Estimating SMU grades using an approximate estimation technique like ordinary kriging (used for ranking SMUs within each panel).
- Executing the LUC phase to localize the common grade-tonnage relationships derived from UC.

The conventional UC method estimates a tonnage and grade of mineralization that can be recovered using the Smallest Mining Unit (SMU) of size v at any selected cutoff grade. A series of grade-tonnage distributions is created by applying several cutoff grades for each panel under study.

Then, the LUC algorithm estimates the average grades of the grade classes within each panel and at a defined SMU support [25]. A grade class is a portion of the panel where the grade is greater than a specified cutoff grade (zc_i) but less than the next cutoff grade (zc_{i+1}). The next step involves ranking the SMU blocks distributed within each panel in order of increasing grades. Finally, the average grades of each grade class, inferred from the UC model, are assigned to the SMU blocks whose ranks correspond to the grade class [26].

3. Case study

The Miduk copper mine is located 42 kilometers northeast of the city of Shahrebabak and 132 kilometers northwest of the Sarcheshmeh copper mine. The Miduk area encompasses two shallow porphyry copper intrusions, each of which has its own local name. One of them is Miduk (Lachah), and the other is Sara. The main deposit of Miduk is situated about 7 kilometers northwest of the village of Miduk. The Miduk porphyry copper deposit, aged 12.5 million years, is located within Eocene volcanic and pyroclastic rocks consisting of andesite, basaltic andesite, and dacite. microscopic petrographic studies indicate that this body is composed of granodiorite, quartz diorite, and diorite [27]. Mineralogically, the associated minerals of the Miduk porphyry include plagioclase, potassium feldspar, amphibole, biotite, and quartz, while sericite, chlorite, epidote, and magnetite are also secondary minerals in this assemblage. In terms of geochemical characteristics, the granodioritic rocks of the Miduk porphyry belong to the alkaline and calc-alkaline magmatic series and are of the meta to peraluminous granite type, classified as I-type granites. Tectonic studies indicate that the Miduk deposit has characteristics typical of deposits formed at an active continental margin [28]. Additionally, the Miduk copper deposit formed and replaced in a tectonic environment following the collision of the Central Iranian and Arabian plates, during the final stages of orogeny (compressional tectonic regime), after the subduction of the Neo-Tethys oceanic crust had concluded [29].

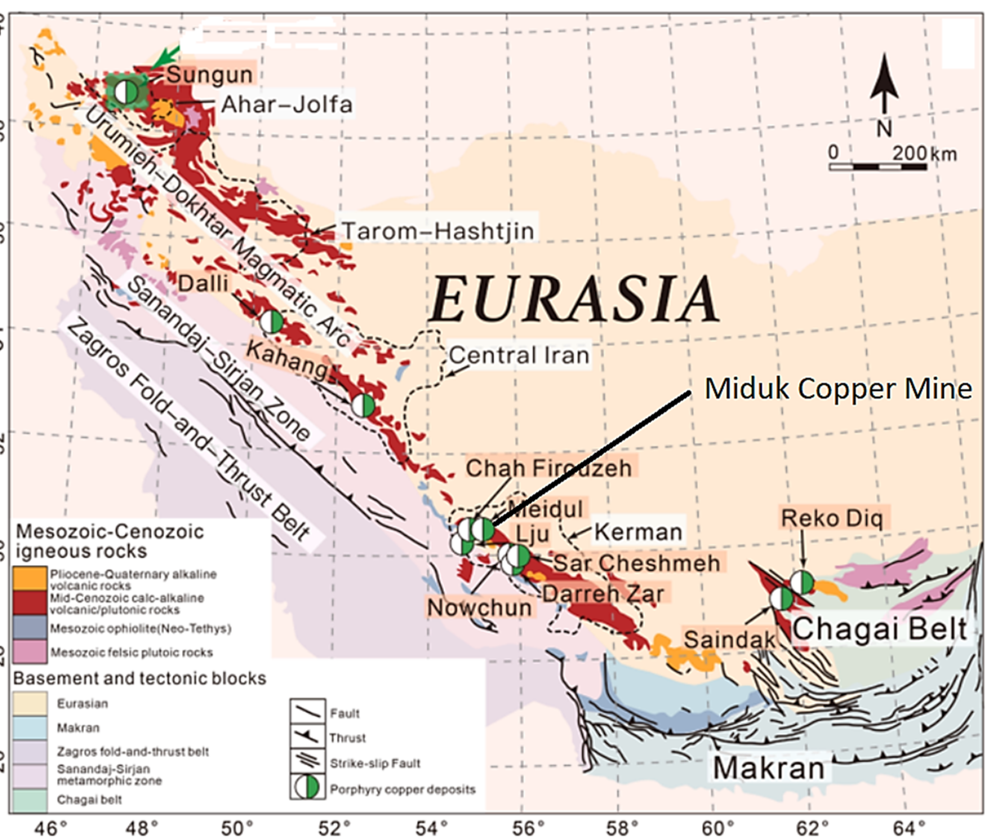

Figure 1. Location map of studied area, a location of Miduk copper deposit on Urumieh-Dokhtar magmatic arc [29].

Given the significant extraction of oxidized, leach, and supergene zones, only the exploratory and extraction data from the supergene and hypogene zones have been used as the main mineralization zones in the present study. Additionally, because blasting data will be used to compare different methods, the exploratory data has been limited to the levels where blasting data has been available in each zone. Figures (2) illustrate an overview of the location of these zones and the exploratory data pertaining to each of them. Aghazadeh et al. (2015) quote a resource at Miduk of 500 Mt with 0.8% Cu and 0.007% Mo [30].

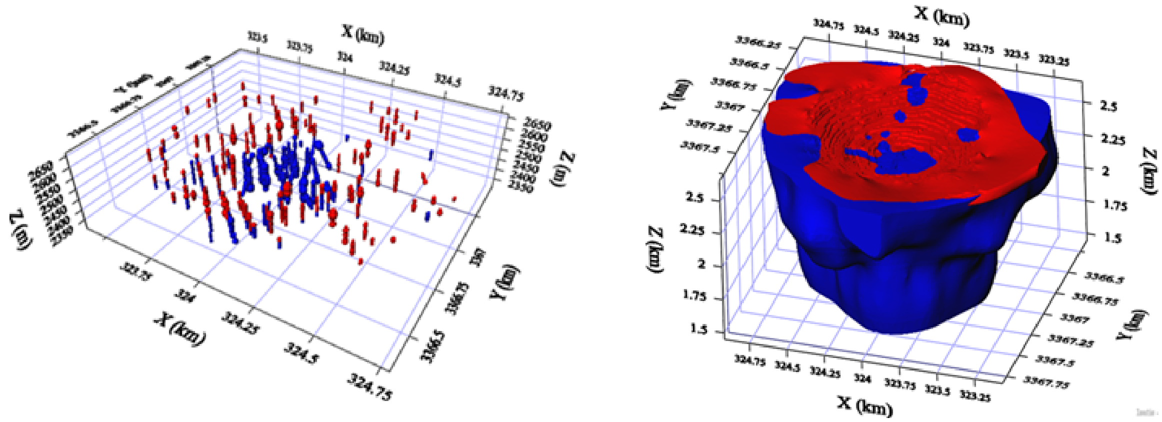

Figure 2. A 3D model of the supergene (red) and hypogene (blue) mineralization zones as the main ore zones (below) and the distribution of exploratory data in each of the zones, limited to the levels containing the blasting data for each area.

The Miduk porphyry copper deposit was formed due to the injection of a Quartz diorite stock into Eocene volcanic and pyroclastic rocks. The porphyry-style mineralization in the Miduk porphyry stock has created multiple zones, which from the surface to depth include the leached zone, oxide zone, supergene zone, and hypogene zone. Additionally, supergene-oxide and supergene-hypogene transition zones are also distinguishable within this deposit. The leached zone of the Miduk porphyry body has formed due to alteration and leaching by ferruginous solutions, evidenced by mineralization resulting from the dissolution of sulfides, which can be easily seen in rock samples. The oxide zone has a limited extent within the Miduk porphyry deposit, with much of it eroded away. The minerals observed in this zone include Malachite, Azurite, Tenorite, Chrysocolla, goethite, and Calcantite, which appear in both disseminated and vein forms. The supergene-oxide zone is a transitional zone between supergene and oxide, characterized by the paragenesis of oxide zone minerals alongside pyrite and chalcopyrite. The supergene zone is exposed in some areas of the Miduk porphyry copper deposit, and has developed in the phyllic alteration section of the porphyry body, with mineralization occurring in both vein and disseminated forms. In the samples from the supergene zone, chalcopyrite, along with pyrite, constitutes the primary ores. The supergene-hypogene zone is a gradual and transitional zone located between the supergene and hypogene zones, marked by a decrease in Chalcopyrite and an increase in Bornite and chalcopyrite from top to bottom. Mineralization occurs in both disseminated and vein forms, with the alteration of Chalcopyrite to covellite and Chalcopyrite frequently observed in this zone. In the Miduk porphyry deposit, the supergene-hypogene zone overlaps with potassium-phyllic alteration zones. The hypogene zone in the Miduk porphyry deposit generally aligns with potassium-phyllic and potassium alteration zones. The mineral paragenesis in this zone includes pyrite, chalcopyrite, bornite, and to some extent, molybdenite and magnetite. Chalcopyrite crystals are observed in massive, stringer, and disseminated forms.

3.1. Data description

For the current work, data from blasting holes have been used, separated for each zone. These data have been transformed into blocks, the smallest units in mining, and were utilized to assess the results of nonlinear methods and simulations on the panels. During the transfer of block information to the panels, the panels that included very few blocks were excluded from the analyses conducted for the comparison of the results of the present work. To evaluate the accuracy of each approach, data from 65,535 blasting holes located at different levels in parallel spaces, similar to exploration holes, have been used. In fact, using data from 265 exploratory boreholes, one can predict the copper grade at the position of 20 thousand blasting holes and compare the estimated results with the actual values using bar charts and scatter plots. The sampling method for extraction holes is one sample for every 15 meters, while the sampling in exploratory holes is one sample for every 2 meters. To ensure the accuracy of sampling and the repetition of sampling from each extracted blast, a re-assay test has been conducted on 20% of the extracted boreholes, and for each exploratory borehole, a re-assay test is performed for every 10 meters.

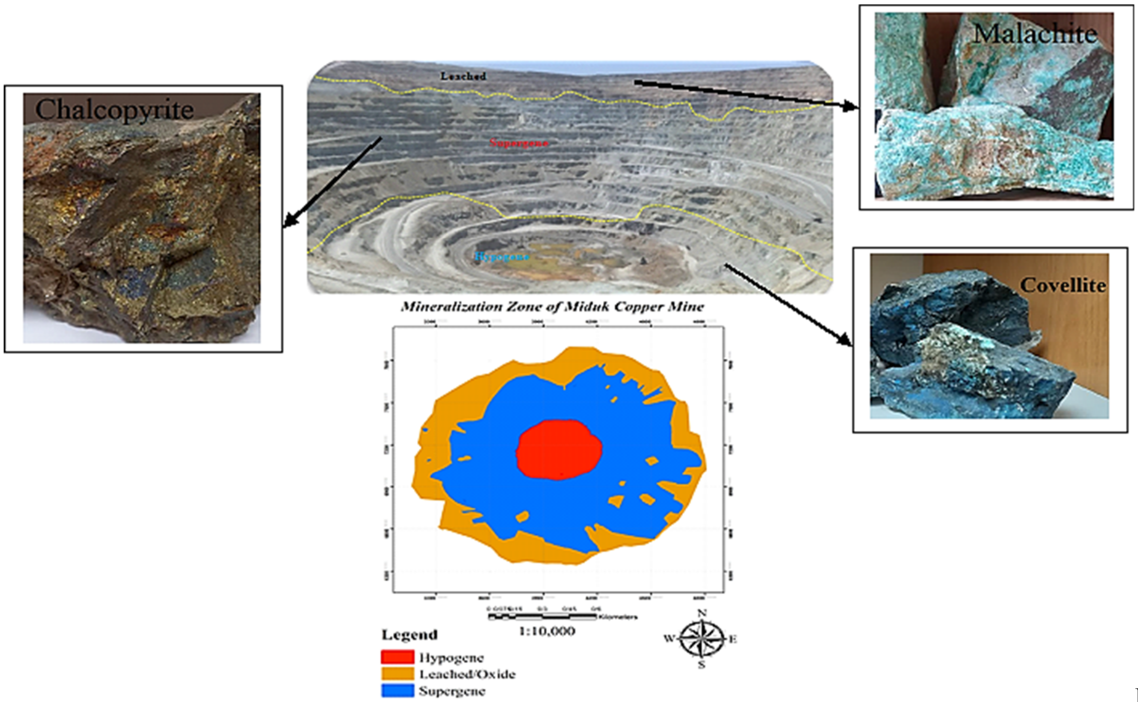

Figure 3. The zoning of mineralization in the Miduk copper deposit, from top to bottom, includes the leach, supergene, and hypogene zone.

Table 1. Data used from blasting holes and exploratory boreholes

Zone	Quantity	Average Grade	Variance	Minimum grade	Maximum grade
Supergene	27,653	0.23	0.04	0.01	3.05
Hypogene	14,236	0.54	0.13	0.01	3.05
Supergene	6,187	(222 boreholes)	0.25	0.06	0.01
Hypogene	3,495	(226 boreholes)	0.44	0.18	0.01

The methods examined in this writing include linear kriging, simulation, direct simulation, block simulation, uniform conditioning, and local conditioning.

3.2. Variography of raw exploration Data in the supergene and hypogene zones

This work explores non-linear geostatistical estimation methods and conditional simulation techniques applicable to mineral deposits. These methods are applied to the active Miduk copper porphyry deposit for comparison and selection of the most effective approach. The efficiency of these methods is evaluated by comparing them with the actual data obtained from drilling blasts conducted over three years. Direct block simulation methods and sequential conditional simulation, along with a non-linear conditional uniform kriging estimation method and local uniform conditioning, have been applied to the Miduk deposit. To implement the uniform conditioning methods, the composite data from the exploratory boreholes were divided into the supergene and hypogene zones. Subsequently, these data were modified by replacing out-of-row values and were used for variography. The experimental variogram for each zone was calculated, and a suitable theoretical model was fitted to each, as shown in Figure (3), which displays the variogram models of the raw data for each zone.

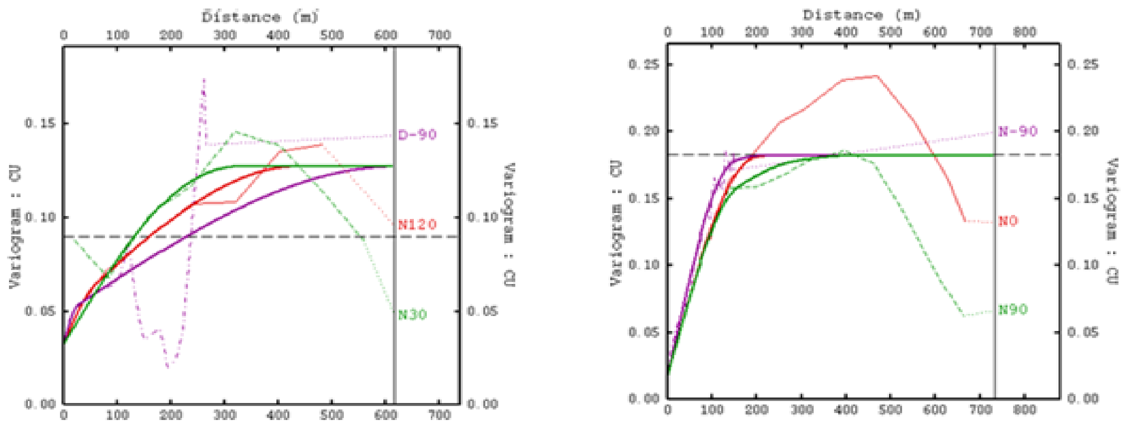

Figure 4. Model of variogram for raw exploration data of the supergene zone (top) and hypogene zone (bottom).

The support change has been carried out from the point support of the initial raw data to a block support with dimensions of 15×15×15 for each SMU. This was done to implement uniform conditioning and subsequently use its output for local uniform conditioning. A summary of the resulting outcomes for each zone can be seen in Table (2).

Table 2. Results of support change calculations for the supergene zone (top) and hypogene zone (bottom).

Block support correction calculation:	CU
Punctual variance (Anamorphosis)	0.182971
Variogram sill	0.219923
Gamma (v, v)	0.031302
Real block variance	0.151669
Real block support correction (r)	0.9224
Kriged block support correction (s)	0.9224
Kriged-real block support correction (s)	1
Zmin block	0.01
Zmax block	3.58
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Real block variance	0.151669
Real block support correction (r)	0.9224
Kriged block support correction (s)	0.9224
Kriged-real block support correction (s)	1
Zmin block	0.01
Zmax block	3.58

3.2. Variography of transformed (gaussian) data in the supergene and hypogene zones

To implement sequential gaussian simulation and direct block simulation, the initial raw data were transformed into gaussian-shaped data, and variographies were performed on the transformed data. The variogram models and the transformed data were then used for the sequential gaussian simulation of each zone. For direct block simulation, the experimental gaussian variogram was calculated as a regularized block variogram. Subsequently, an appropriate theoretical model was fitted to it and used for the simulations. The structured block gaussian variogram models can be seen in Figure (4).

The simulations (both sequential gaussian and direct block simulations) are performed on the SMU support, their results have been re-blocked into a panel support format of (15×90×90) for comparability with the uniform conditioning method. At this stage, threshold grades similar to those defined for uniform conditioning need to be established to enable a comparison of results. To compare the results against actual data, a significant number of blast hole data can be utilized. A grid similar to that of the SMUs is defined, and the data located within each SMU are averaged and assigned to each SMU. Then, by defining each of the threshold grades and calculating the number of SMUs within each panel that exceed the defined threshold, the tonnage of the mineral can be obtained as a ratio or percentage of the total tonnage of the panel. Using the tonnage of each panel and its average grade, the metallic content of each panel for the defined threshold grade can also be determined. To calculate the grade of each panel at the defined threshold grade, the averages of the SMUs within each panel that exceed the threshold grade are taken. Thus,s for each threshold grade, the actual data on grade, tonnage, and metallic content for each panel can be obtained, which can be used to compare the results of non-linear methods and simulations. To increase the accuracy of the comparisons, panels with fewer than ten SMUs containing grades above the specified threshold (for example, 0.15 percent) are disregarded and not considered as actual data. The actual data with panel support for the supergene and hypogene zones, with the distribution of average grade for each panel, are illustrated in Figure (5).

3.3. Uniform conditioning method, direct block simulation, and sequential gaussian simulation for the supergene zone.

The results of all three aforementioned methods, after the necessary post-processing to enable comparability with actual data, were analyzed at a cutoff grade of 0.15 percent copper. These results were compared with the real data (transferred to block support and then averaged, calculating the metallic content and recoverable tonnage on panel support at cutoff grades similar to those used in the results of the three studied methods). This comparison was made through scatter plots and correlation coefficients, with the results for the supergene zone illustrated in Figure (6). As can be seen from these results, the correlation coefficient of the uniform conditioning method's results was better than those of the other two simulation methods. The comparison of the results of uniform conditioning, direct block simulation, and sequential gaussian simulation with the actual data from blast holes showed correlation coefficients of 0.637, 0.527, and 0.556, respectively.

As the results of the uniform conditioning method performed better for the supergene zone on panel support, the scatter plots of this method's results for the metallic content and recoverable mineral tonnage are displayed in Figure (7). The correlation coefficients for these results with the actual data were 0.629 and 0.364, respectively.

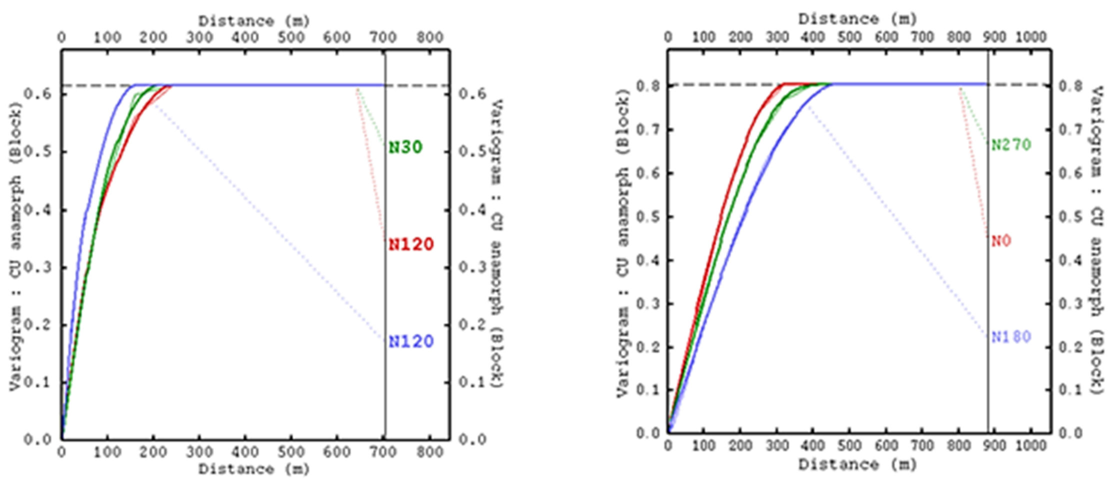

Figure 5. Model of regularized block gaussian variogram for the supergene Zone (top) and hypogene zone (bottom).

To more comprehensively evaluate all three methods against actual data, various grade-tonnage diagrams were prepared to assess different parameters of recoverable resources, as shown in Figure (8). From the comparison of these diagrams, it is evident that the uniform conditioning method performs better than the other two simulation methods in most cutoff grades for the supergene zone. However, both simulation methods yielded relatively similar results. The better performance of the uniform conditioning method can be attributed to the sparse data density (relative to the larger area of the supergene Zone) and the relatively narrow range of the grade data for the Supergene Zone during the current study period. In other words, considering that a significant portion of the supergene zone has been extracted and the blast hole data is limited due to the restricted time frame (older data could not be used due to the limited model of the ore body and topography used in the modeling), the higher-grade areas that were previously extracted and located at higher elevation levels are unavailable in the present study. In fact, the grade range of the content data for the supergene zone has not varied significantly, which has led to poor results due to the smoothing effects of kriging. In contrast, the lack of smoothing in the simulations has not been prominent for this zone in the current study.

In addition to the aforementioned factors, preferential sampling in higher-grade sections has also influenced the obtained results. In fact, more dense drilling and sampling from the higher-grade areas have increased the density of samples from these sections, which has enhanced the accuracy of the kriging-based estimator. This can be clearly seen in the greater discrepancies between the simulation results and actual data at higher grades (cutoff grades exceeding the average grade). Meanwhile, the results of the uniform conditioning method have shown relatively better performance in higher-grade areas for the parameters of recoverable tonnage and metallic content compared to the simulation methods. Estimations and assessments are conducted using exploratory data, and the comparisons in the current study are based on data obtained from blast holes, which are analyzed after exploratory drilling and understanding the overall distribution conditions of the ore's grade. Thus, during the sampling of blast holes, there is an awareness of the position and distribution of higher-grade sections, leading to more sampling from these areas. Additionally, the results of grade analyses for these sections are recorded with greater care and precision. However, very high-grade sections during the geostatistical study of exploratory drill holes are often replaced by outlier values through the process of deleting or substituting out-of-range values. Yet, in the process of assigning the grade data from blast holes to SMU blocks and subsequently calculating the parameters of grade, tonnage, and metallic content for the panels, this process occurs without replacing outlier values (very high grades). This factor itself significantly affects the underestimation of the results of recoverable resource assessments compared to actual data. Since the supergene zone in the current study encompasses two approximate sections, larger low-grade areas with fewer exploratory drill holes, and smaller high-grade areas with more exploratory drill holes, the results obtained from non-linear methods and simulations for the supergene zone are therefore more favorable.

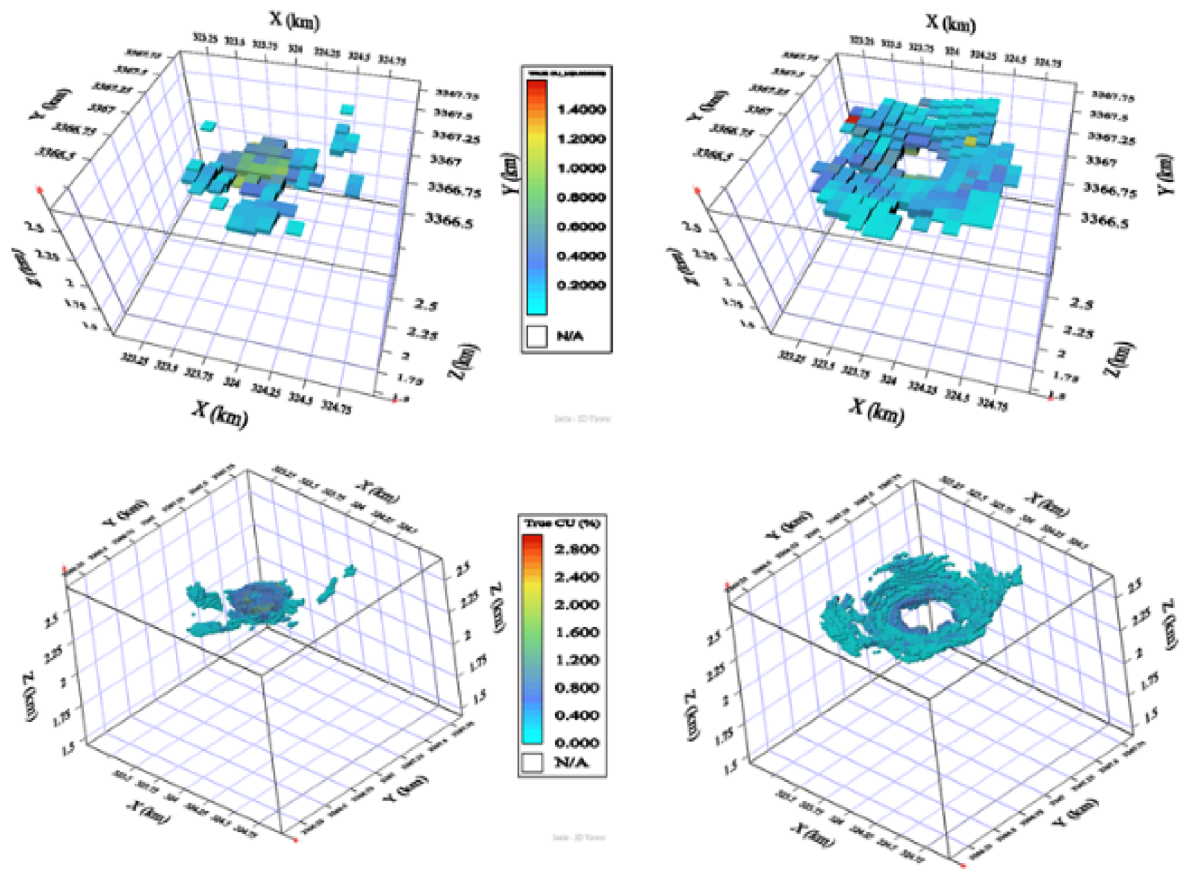

Figure 6. Three-dimensional view of the distribution of actual grade data (copper) on panel support (top figures) and block support or SMU for the supergene zone (right) and hypogene zone (left)..

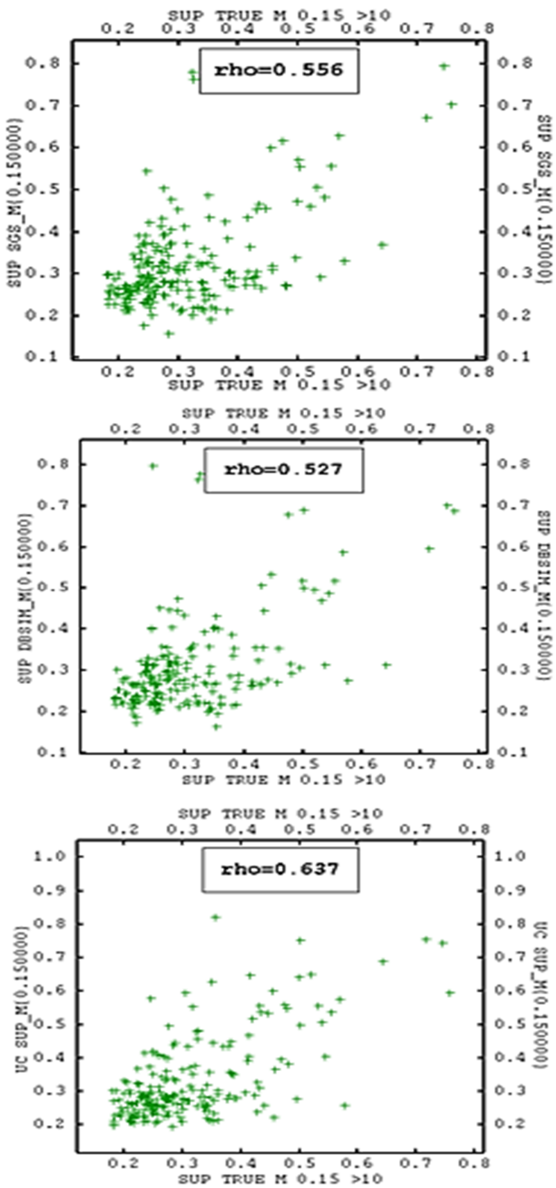

Figure 7. Scatter plot between actual data and estimated recoverable resource grade results for the supergene zone using the uniform conditioning method (bottom), direct block simulation (middle), and sequential gaussian simulation (top).

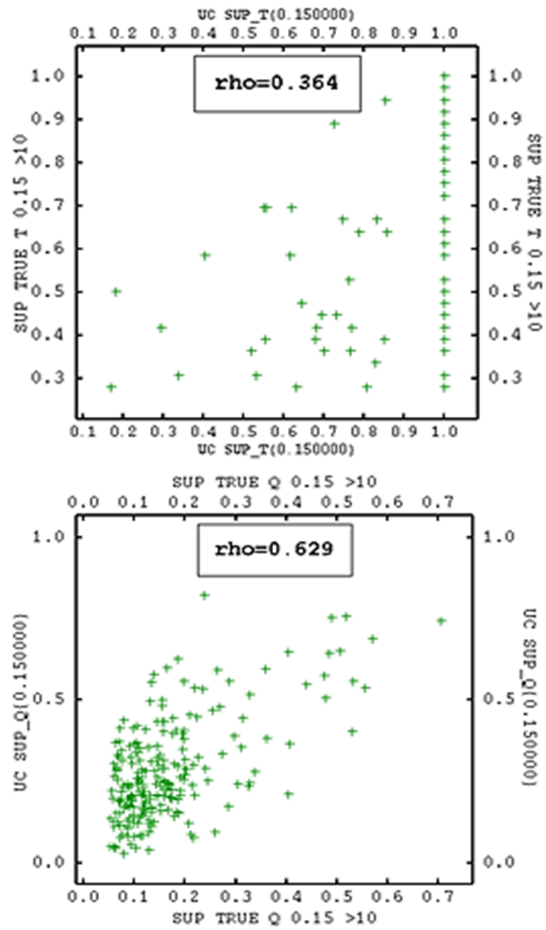

Figure 8. Scatter plot of the uniform conditioning method results compared to actual data at a cutoff grade of 0.15 percent for the supergene zone: recoverable ton metallic content (top) and content (bottom).

3.4. Uniform conditioning method, direct block simulation, and sequential gaussian simulation for the hypogene zones

Similar analyses were conducted on the results obtained from all three methods for estimating recoverable reserves in the hypogene zone after the necessary post-processing. In the hypogene zone, the selected cutoff grade for comparisons was 0.15 percent copper, with actual data (grade, metallic content, and tonnage) prepared on panel support for this cutoff within the hypogene zone. The results of each method at a cutoff grade of 0.15 percent were compared with this data, and the results are presented as scatter plots along with the corresponding correlation coefficients in Figure (9). At this stage, the comparisons focused on the metallic content results from each method to evaluate the recoverable reserves.

The comparison was made on metallic content, which, unlike the supergene zone, showed that for the cutoff grade of 0.15 percent, the simulation methods provided better results than the uniform conditioning method. Furthermore, to analyze all cutoff grades, various graphs of recoverable reserves were prepared, which depict the overall performance of all three methods compared to the actual data across all cutoff grades and parameters. The results of this analysis are shown in Figure (10).

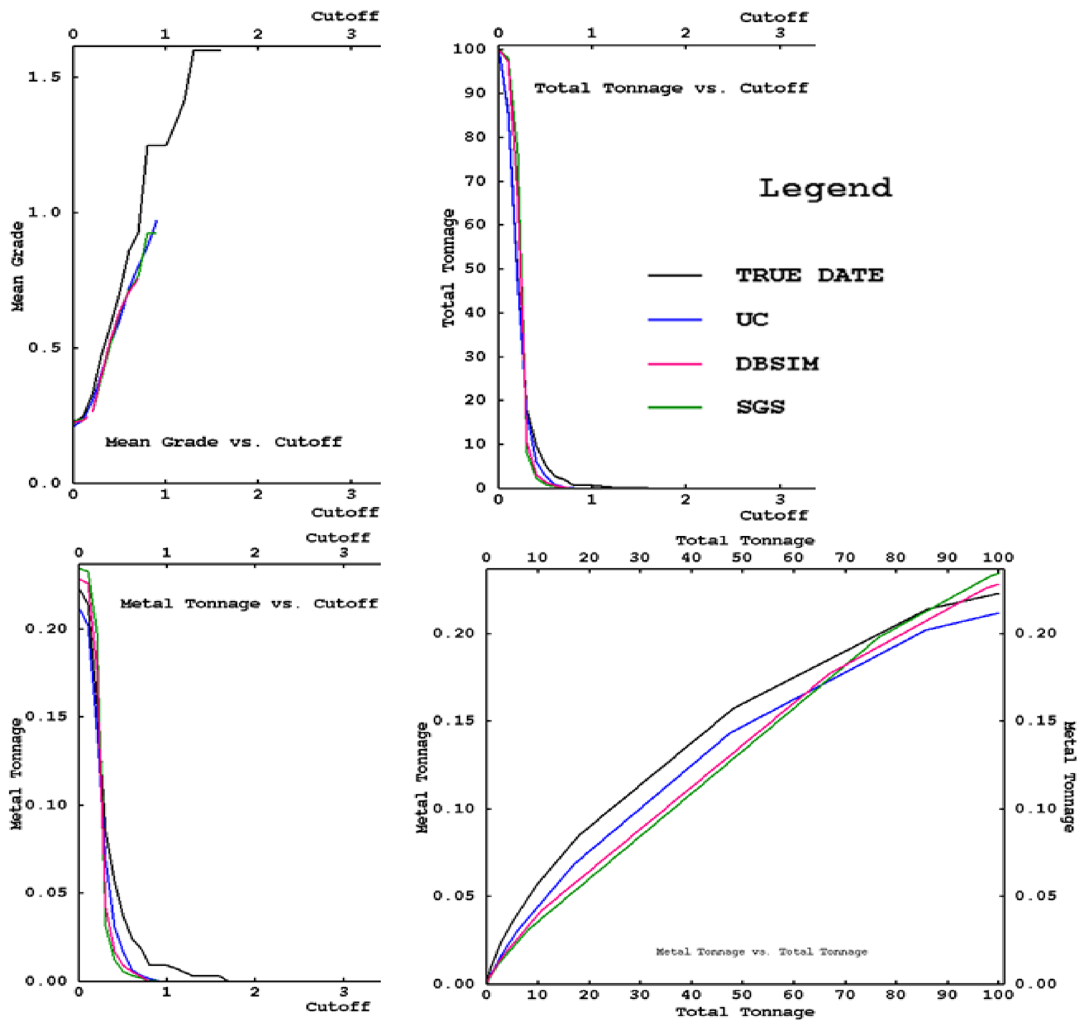

Figure 9. Graphs of recoverable reserves for the supergene zone using the uniform conditioning method, direct block simulation, sequential gaussian simulation, and actual Data (from blast hole data)

As can be seen from the comparison of various grade-tonnage diagrams for assessing recoverable reserves in the hypogene zone across all grades simultaneously, at low cutoff grades, the performance of the uniform conditioning method, except for the metallic content parameter, is nearly similar to that of the simulation methods. However, at higher cutoff grades, the performance of the simulation methods has been better than that of the uniform conditioning method, with sequential gaussian simulation performing better than the other simulation method. Additionally, the results from direct block simulation have, at some intermediate cutoff grades, been weaker than those of the uniform conditioning method. This issue relates to the prerequisites concerning the reliability of the data used in direct block simulation, which may have lower reliability in the hypogene zone due to the presence of very high-grade data alongside low-grade data. This is reflected in the slightly weaker results of direct block simulation compared to sequential gaussian simulation. Overall, the results of these two methods are close, and they are quite similar in low-grade and medium-grade sections, providing nearly identical results. In contrast to the simulation methods, at higher cutoff grades above the average grade, the uniform conditioning method shows greater divergence from the actual data. This is attributed to the significant variance of the initial raw data, which poses challenges for kriging-based methods. Nonetheless, in non-linear methods like uniform conditioning, the effects of this issue are reduced. These observations are well-illustrated in the scatter plots of the results (recoverable tonnage) obtained from the methods used in the current study compared to the recoverable tonnage from actual data at a cutoff grade of 0.65 percent for the corresponding panels in the hypogene zone. In other words, at the relatively high cutoff grade of 0.65 percent, the correlation of results from the simulation methods with the actual data has been greater compared to those from uniform conditioning, as demonstrated in Figure (11).

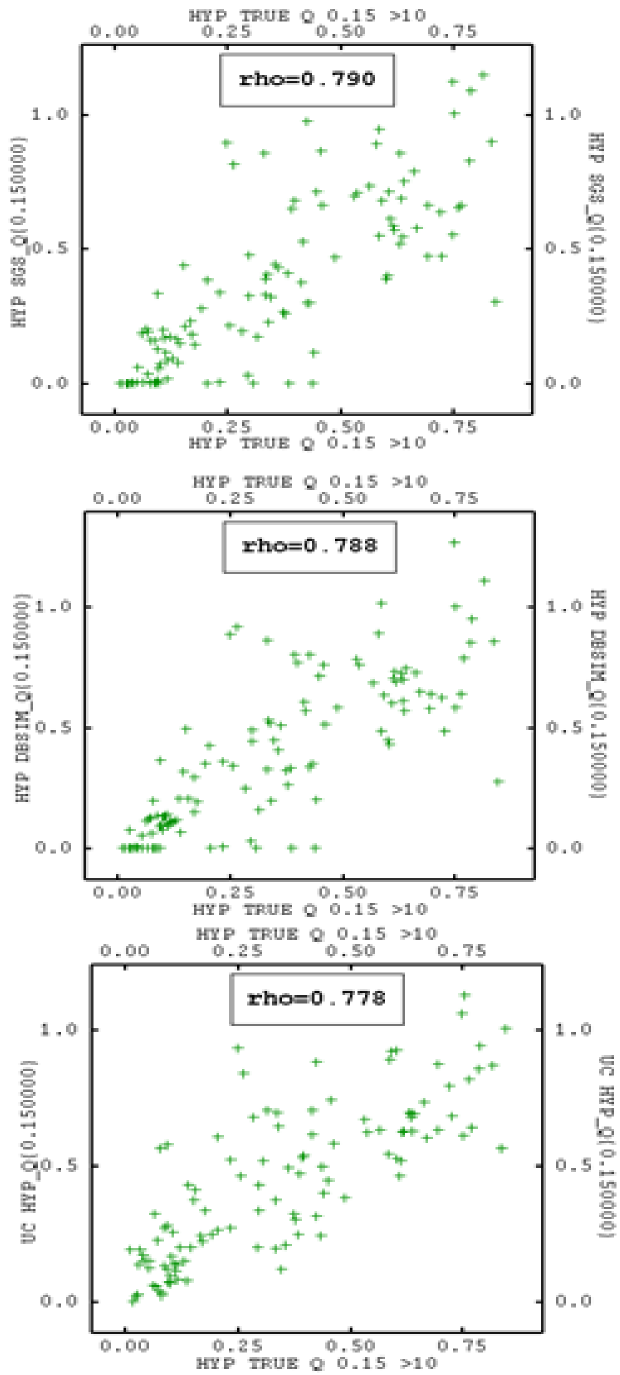

Figure 10. Scatter plot between actual data and estimated metallic content of recoverable reserves in the hypogene zone at a cutoff grade of 0.15 percent copper using the uniform conditioning method (bottom), direct block simulation (middle), and sequential gaussian Simulation (top).

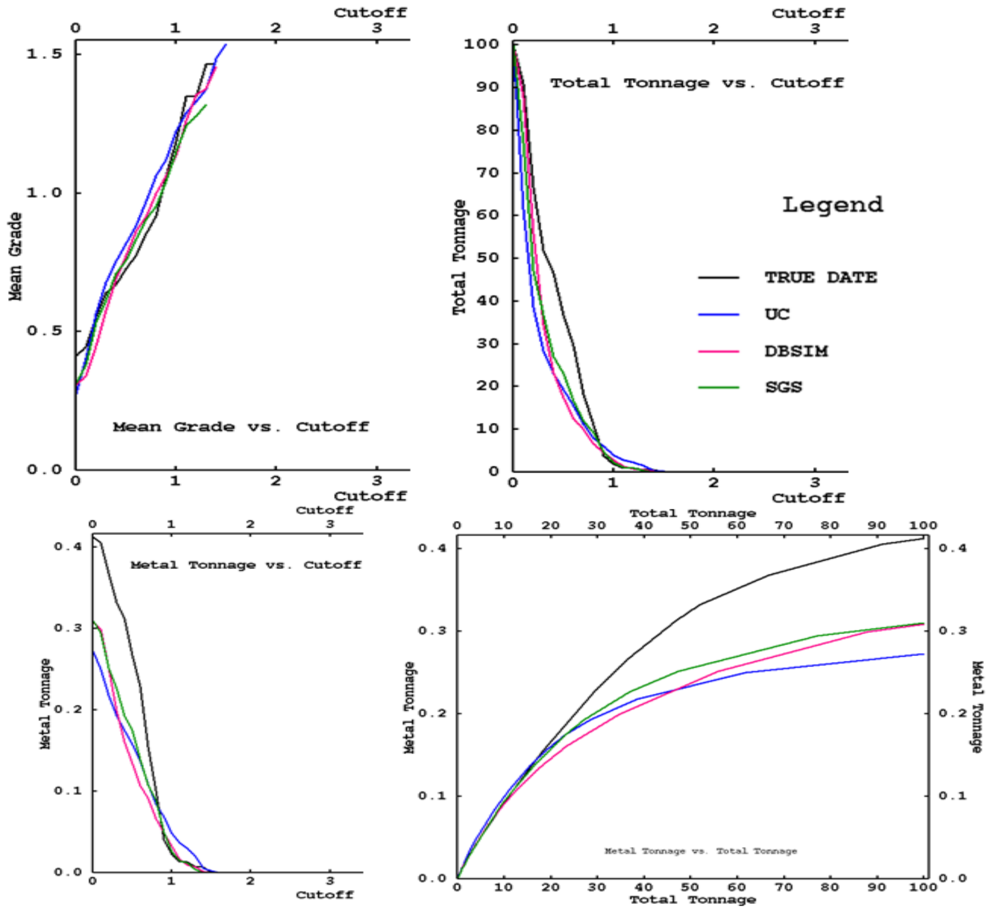

Figure 11. Graphs of recoverable reserves in the hypogene zone for the uniform conditioning method, direct block simulation, sequential gaussian simulation, and actual data (from blast hole data).

As indicated by the results of the scatter plots at a cutoff grade of 0.65 percent, the simulation methods provided better results compared to the uniform conditioning method, which is consistent with the results obtained for various recoverable reserves diagrams. In fact, the hypogene zone consists of two parts: a low-grade section on the periphery and a very high-grade section in the central part of the zone. The low-grade sections on the margin have a larger extent (more drill holes and samples included in the estimation), and the variance of the assay data in this section is very low, which increases the accuracy of estimations even with kriging-based methods. In contrast, in the central parts that are richer in grade; the variance of the assay samples is significantly higher due to the simultaneous presence of low-grade, average-grade, and high-grade samples. Consequently, this area undergoes considerable smoothing in estimations with kriging-based methods. However, the simulation methods exhibit less smoothing, and their results deviate less from reality. Another reason for the greater smoothing observed in high-grade areas and the increased discrepancy between these areas and the actual data—seen in the results for both the supergene and hypogene zones—can be attributed to the influence of the defined search radius in the estimation and simulation processes. When estimating certain blocks and panels located in high-grade areas, data from average- and low-grade sections are included in the estimate due to the defined search radius (derived from the variogram model for each zone) and the number of points participating in the estimation, which results in underestimating the grade. This issue affects the estimates of metallic content and recoverable tonnage in the blocks and panels of each zone. In contrast, to calculate actual data, or to assign blast hole data to SMUs and the subsequent calculations, only the samples contained within each SMU are used in the averaging process and assignment of grades to the corresponding block or SMU. Thus, for estimating grade, tonnage, and metallic content of panels, only the SMUs encompassing each panel are utilized for calculating the parameters. As a result, the grade of average- and low-grade sections does not affect the high-grade areas.

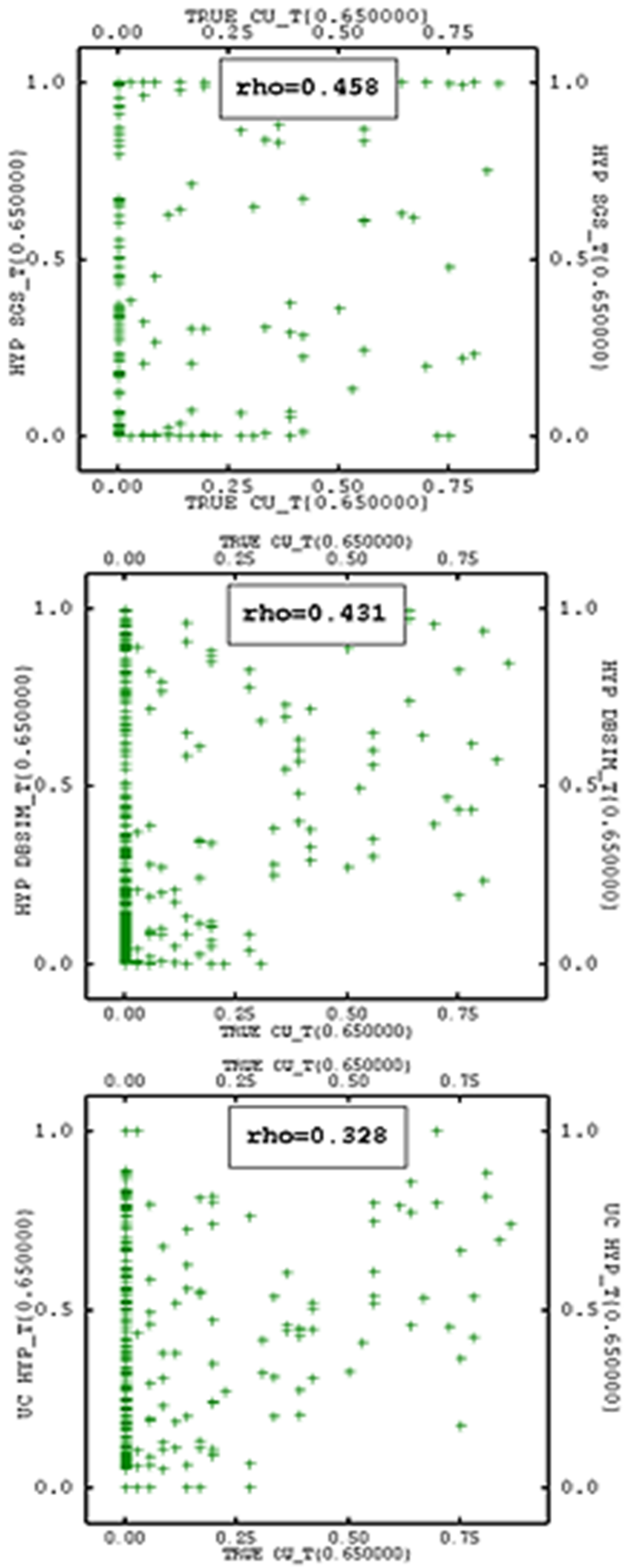

Figure 12.Scatter plot between actual data and estimated recoverable tonnage in the hypogene zone at a cutoff grade of 0.65 percent using the uniform conditioning method (bottom), direct block simulation (middle), and sequential gaussian simulation (top).

The notably high values of recoverable tonnage from actual data compared to the results obtained from methods for estimating recoverable reserves at medium to high cutoff grades, despite the overestimation of average grades in this range, are significant. This discrepancy arises from the greater abundance of average grades in actual data derived from blast hole results compared to exploratory data. In other words, the very high prevalence of average grades in the actual data not only compensates for the tonnage deficit caused by the lower average grade (relative to the evaluation methods used) but also leads to an increase in recoverable tonnage at medium cutoff grades. In the obtained results, the metallic content from actual data is also higher at low and medium cutoff grades than the results from reserve estimation methods. Two factors influence this outcome: the first is the higher average grade of the actual data at low cutoff grades, and the second is the significantly higher tonnage of the actual data at medium cutoff grades. This situation, apart from compensating for the lower metallic content resulting from the lower average grade of the actual data at medium cutoff grades, has contributed to the increase in their metallic content as represented in the graphs. As previously mentioned, this effect is logically consistent due to the abundance of average grades in the actual data, because the total number of data points obtained from blast holes is at least four times that from exploratory drillings within the overlapping regions of the two datasets in both the supergene and hypogene zones. The higher average grade of the actual data at low cutoff grades is also attributed to the lower accuracy of assay and registration of blast hole data compared to exploratory data. Low-grade sections are sampled, analyzed, and recorded with less precision and care compared to high-grade and average-grade sections, which have a higher density of sampling. Additionally, the differing conditions supporting the samples collected from blast holes compared to those obtained from exploratory drill holes, along with the differing sample lengths—15 meters for blast holes and 2 meters (most common length) for exploratory drill samples—affect these discrepancies.

3.5. Local uniform conditioning method, direct block simulation, and sequential gaussian simulation of the supergene zone

The local uniform conditioning method is designed for non-linear estimation in mining and is derived from post-processing the results obtained from uniform conditioning. The parameters for grade, metallic content, and local tonnage are calculated using the local uniform conditioning method for various cutoff grades, with the grade distribution for each block guided by the ranking of estimated grades for the Small Mining Units (SMUs). To implement this method, the estimated grade parameters for each block and metallic content are applied over a panel grid along with options for constraining the estimation space. The block grid or SMUs defined for this method perfectly aligns with the panel grid; in other words, a block is part of a panel. In the present study, the local uniform conditioning method has been implemented for each of the zones in the Miduk deposit using the aforementioned parameters relevant to each zone. The results obtained were compared with the actual data assigned to the blocks of the block grid, which are of the same dimensions as the SMUs. Simulation methods were also executed in a block support framework for the conducted comparisons and were post-processed at this stage. The post-processing of the simulation results was performed by averaging the realizations from 100 iterations and preparing the E-type for each method. Thus, the outcomes of these post-processed results were utilized for comparison with the results from the local uniform conditioning method against the actual data. Figures (13) depict various diagrams evaluating recoverable reserves for the results of each method and actual data in the supergene zone. As can be seen from these results, the local uniform conditioning method has provided better results for all copper cutoff grades. The results obtained for the supergene zone were nearly similar to the results of the comparisons made in the panel support, which is not surprising, considering that the local uniform conditioning method is essentially a post-processing outcome of the uniform conditioning method results.

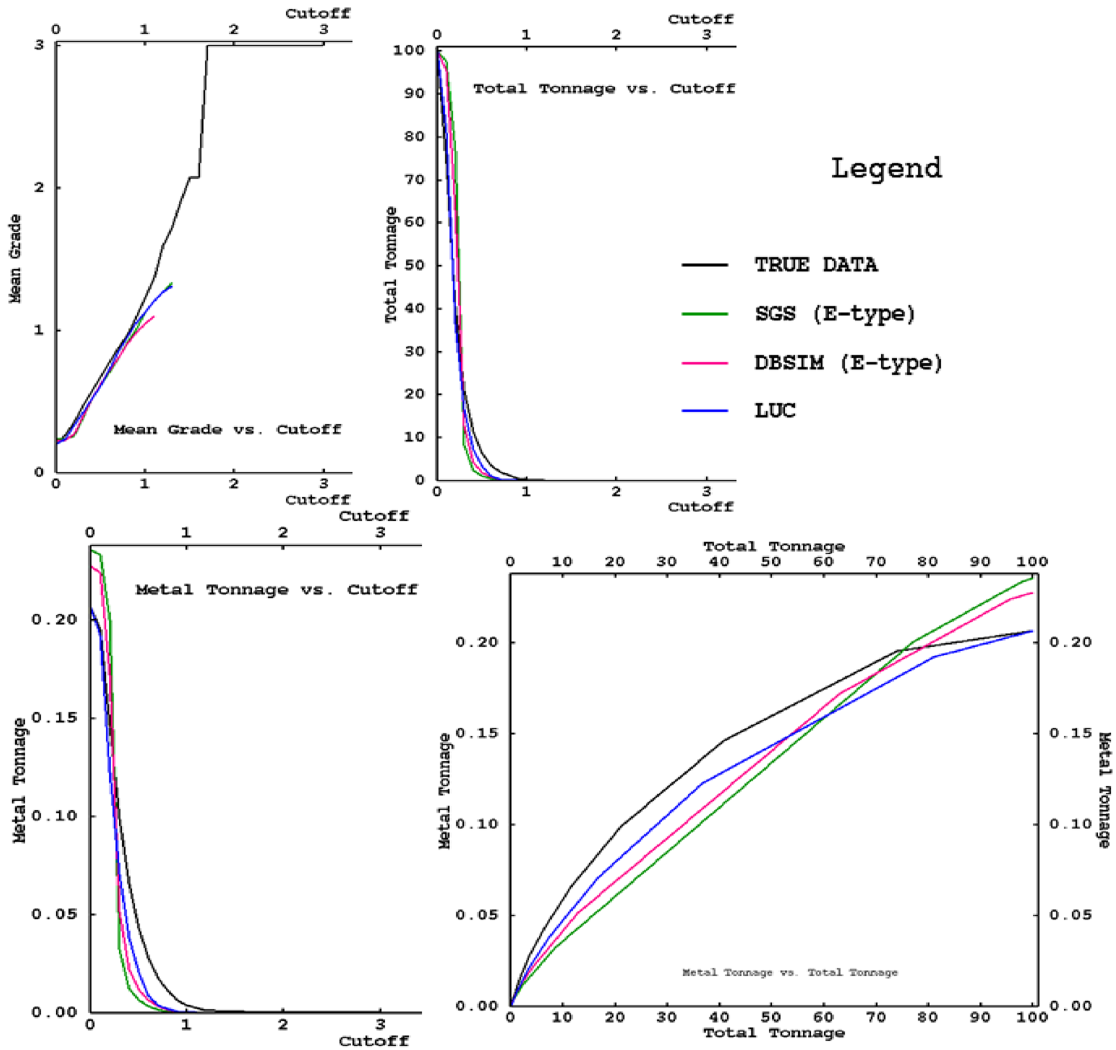

Figure 13. Recovery reserve graphs for the supergene zone for all three methods: local uniform conditioning, direct block simulation, sequential gaussian simulation, and actual data (derived from blast hole data).

3.6. Local uniform conditioning method, direct block simulation, and sequential gaussian simulation of the hypogene zone

For the hypogene zone, similar calculations have been carried out using the specific data and parameters for that zone to execute local uniform conditioning. The results obtained, along with the simulation results (for the hypogene zone) in SMU support, were subjected to necessary post-processing for comparison with actual data. Figures (13) show the results of various recovery reserve evaluation graphs. As indicated by these graphs, for cutoff grades lower than the average grade, the results of the simulations were better than those from local conditioning. However, for medium cutoff grades, the simulation results improved in comparison to actual data. For cutoff grades higher than average or high-grade cutoff values; both methods exhibited weak convergence with the actual data. However, overall, the conditions of the simulations were better than local conditioning methods. Thus, based on the results obtained, the smoothing effect of kriging-based methods can be clearly observed. If linear methods were used to estimate recoverable reserves, the results would face significantly greater smoothing. Since the local uniform conditioning method, unlike uniform conditioning, showed considerable overestimation in the average grade estimation across most cutoff grades, and one of its inputs is derived from uniform conditioning output, this highlights the influence of linear kriging estimates whose results guided the distribution of grades for each block (via ranking of estimated SMU grades). In addition to the aforementioned points, due to the changes in conditions (convergence to actual data), the estimates across all three methods, especially the local conditioning method, clearly indicate the necessity for re-examining the raw initial data and distinguishing low-grade and high-grade sections in the estimation process. If low-grade and high-grade sections are concentrated in one area or separable sections, they can be segregated, allowing for simultaneous modeling of each region for each zone.

The results of the correlation coefficient assessment using different methods are presented in the table below.

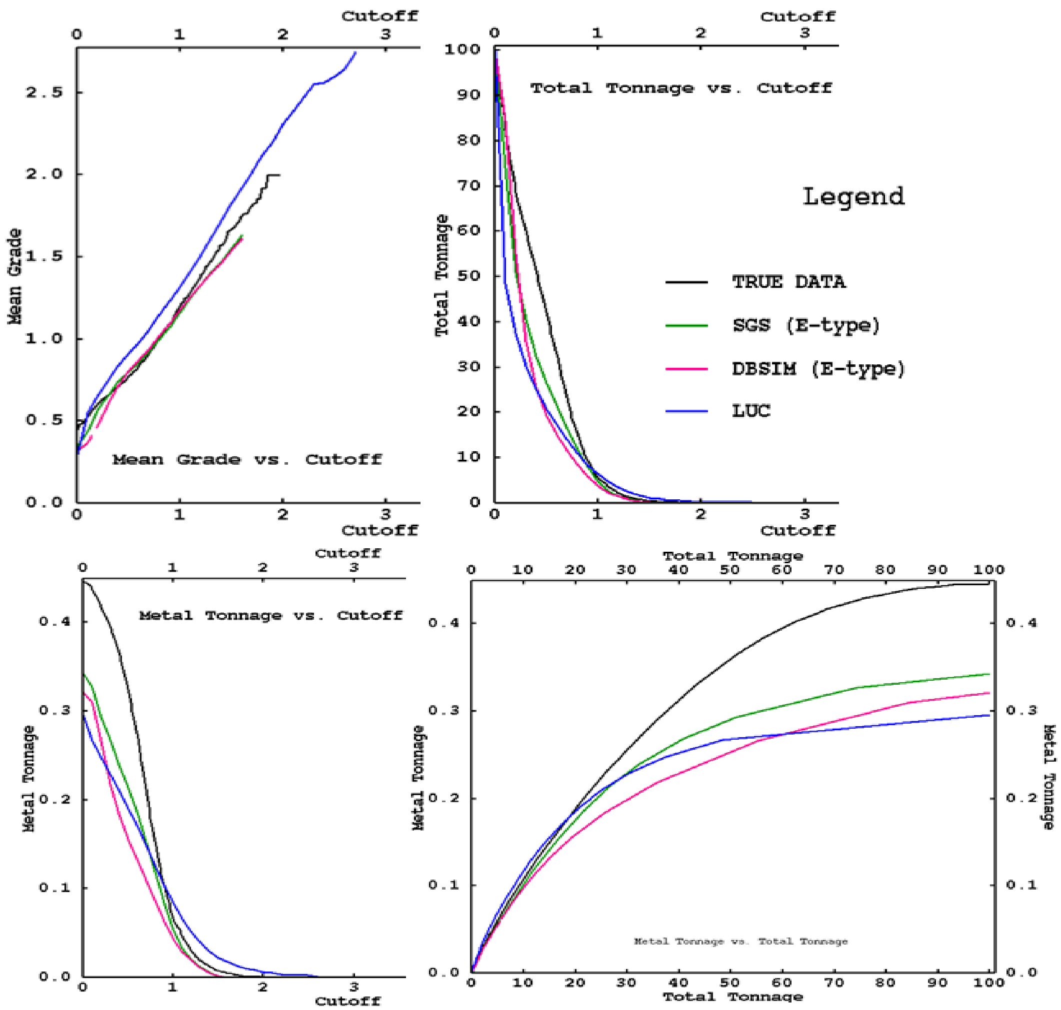

Figure 14. Recovery reserve Graphs for the hypogene zone for all three methods: local uniform conditioning, direct block simulation, sequential gaussian simulation, and actual data (derived from blast hole data).

Table 3. The results of the correlation coefficient assessment using different methods across hypogene and supergene zones, with cut-off grades of 0.15% and 0.65%.

Method	Dimensions of SMU	Grade CC			Tonnage CC	Metal content CC
		Supergene with cutoff 0.15%	Hypogene with cutoff 0.15%	Hypogene with cutoff 0.65%		
UC	15×15×15	0.637	0.778	0.328	0.364	0.629
LUC	15×15×15	-	-	-	0.328	0.778
DCSBG	90×90×15	0.527	0.788	0.431	-	0.788
SGS	90×90×15	0.556	0.79	0.458	-	0.79

4. Conclusions

In this work, the focus is on investigating non-linear geostatistical estimation methods and conditional simulation to assess recoverable mineral resources of the porphyry copper deposit in the active Miduk mine, utilizing uniform and local conditioning methods, direct block simulation, and sequential gaussian simulation. The data comprises 55,119 samples from blasting boreholes and 6,187 samples obtained from exploration drill holes. The effectiveness of these methods is evaluated by comparing the actual data from blasting boreholes in two zones: supergene and hypogene, over three years (since 2018). Compositing of exploration boreholes was conducted along with variography in both the supergene and hypogene zones. The comparison of results from the uniform conditioning, direct block simulation, and sequential gaussian simulation methods against actual data from blasting boreholes shows correlation coefficients of 0.637, 0.527, and 0.556, respectively. Since for the supergene zone, the results from the uniform conditioning method performed better on panel support, the correlation coefficients for metal content and the tonnage of recoverable ore were 0.629 and 0.364, respectively. To provide a more comprehensive evaluation of all three methods against the actual data, various grade-tonnage curves were prepared to assess different parameters of recoverable reserves. The comparison conducted on metal content indicates that unlike the supergene zone, for a cut-off grade of 0.15%, simulation methods yielded better results compared to the uniform conditioning method. At a relatively high cut-off grade of 0.65%; the correlation of results from simulation methods was greater compared to that of the uniform conditioning method with the actual data. The correlation coefficients for estimated tonnage and metal content using the UC method are 0.364 and 0.629, respectively. Therefore, the UC method in the supergene zone is more effective due to the significant extent of low-grade sections in exploration boreholes. The correlation coefficients for metal content using the UC, DCSBG, and SGS methods in the hypogene zone at a cut-off grade of 0.15% are 0.778, 0.788, and 0.790, respectively, and at a cut-off grade of 0.65%, they are 0.328, 0.431, and 0.458. At lower cut-off grades, the performance of the UC method (except for metal content) is better than other methods, and unlike the simulation methods, at higher cut-off grades than the average grade of the deposit, the performance of the UC method decreases, while the correlation coefficients of other methods, particularly SGS, increase. By employing the LUC method in the supergene zone while varying the SMU and comparing the results with the E-Type map, the effectiveness of this approach is found to be higher across all cut-off grades. However, as the cut-off grade increases in the hypogene zone, the performance of the LUC method decreases relative to the simulation methods. The LUC method allows for observing the convergence of results from low-grade to high-grade data, emphasizing the necessity of distinguishing between low-grade and high-grade sections in the estimation process. The results obtained for the supergene zone are nearly similar to the outcomes observed in panel support comparisons, which is not surprising, as local uniform conditioning is essentially a post-processing of the uniform conditioning results. The shift in conditions (convergence with actual data) in all three methods, particularly the local conditioning method, highlights the clear need for further examination and re-evaluation of the raw data, as well as the separation of low-grade and high-grade sections in the estimation process.

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مقایسه روش¬های ارزیابی ذخایر قابل بازیابی کانسار مس میدوک با استفاده از تکنیک¬های تخمین و شبیه‌سازی‌های شرطی

مجتبی دهقانی جوزم* و محمد رضا شایسته‌فر

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کلمات کلیدی

ذخایر قابل بازیابی
شبیه‌سازی شرطی
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بهینه‌سازی یکنواخت
بهینه‌سازی یکنواخت موضعی

چکیده

روش¬های ارزیابی ذخایر قابل بازیابی شامل تکنیک¬های تخمین و شبیه¬سازی شرطی در کانسار معدن مس میدوک با استفاده از داده¬های ۵۵۱۱۹ چال آتشباری و ۶۱۷۸ نمونه گمانه¬های اکتشافی کامپوزیت شده در دو زون سوپرژن و هایپوژن با ساخت مدل بلوکی مقایسه شده است. روش¬های مورد استفاده UC، LUC، DCSBG و SGS می¬باشد. با حذف مقادیر خارج از ردیف و واریوگرافی داده¬های خام برای هر زون انجام شده است. ابعاد SMU در روش¬های UC و LUC برابر با ۱۵×۱۵×۱۵ و در روش¬های DCSBG و SGS برابر با ۱۵×۹۰×۹۰ تعیین شده است. مقدار ضرایب همبستگی روش¬های UC، DCSBG و SGS در زون سوپرژن و نتایج چال¬های استخراجی (بلوک¬های استخراجی) در عیار حد ۰/۱۵٪ به ترتیب برابر با ۰/۶۳۷، ۰/۵۲۷ و ۰/۵۵۶ می¬باشد. که نشان¬دهنده دقت بالاتر روش UC جهت تخمین ذخیره قابل بازیابی در این عیار حد نسبت به سایر روش¬ها می¬باشد. ضریب همبستگی محاسبه تناژ و میزان فلز محتوی روش UC به ترتیب برابر با ۰/۳۶۴ و ۰/۶۲۹ می¬باشد. بنابراین روش UC در زون سوپرژن بدلیل وسعت زیاد بخش کم¬عیار در گمانه¬های اکتشافی کاربرد بهتری دارد. میزان ضریب همبستگی فلز محتوی روش¬های UC، DCSBG و SGS در زون هایپوژن با عیار حد ۰/۱۵٪ به ترتیب ۰/۷۷۸، ۰/۷۸۸ و ۰/۷۹۰ و در عیار حد ۰/۶۵٪ به ترتیب ۰/۳۲۸، ۰/۴۳۱ و ۰/۴۵۸ می¬باشد. در عیار حدهای پایین کارآیی روش UC (بجز فلز محتوی)، بهتر از بقیه روش¬ها می¬باشد و برخلاف روش¬های شبیه¬سازی، در عیار حدهای بالاتر از عیار متوسط کانسار، کارآیی روش UC کم و ضریب همبستگی روش¬های دیگر به خصوص SGS بیشتر شده است. برعکس روش¬های شبیه¬سازی، کارآیی روش¬های مبتنی بر کریجینگ در جامعه آماری با عیار پایین، بهتر از عیار بالا می¬باشد. با بکارگیری روش LUC در زون سوپرژن با تغییر SMU و مقایسه نتایج حاصل از نقشه E-Type، کارآیی این روش در تمامی عیار حدها بالاتر می¬باشد. با افزایش عیار حد در زون هایپوژن کارآیی روش LUC به نسبت روش¬های شبیه¬سازی کمتر می¬شود. با استفاده از روش LUC می-توان تاثیر همگرایی نتایج حاصل از این روش با داده¬های واقعی از کم¬عیار به پرعیار مشاهده نمود که لزوم تفکیک این زون به بخش کم¬عیار و پرعیار در فرآیند تخمین می¬باشد.

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