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Adaptive Multi-Size Block Modeling for Mineral Resources and Ore Reserves Evaluation

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Abstract

The key input parameters for mine planning and all subsequent mining activities is based on the block models. The block size should take into account for the geological heterogeneity and the grade variability across the deposit. Providing grade models of smaller blocks is more complex and costly than larger blocks, but larger sizes cannot represent areas with high spatial variability accurately. Hence, a unique block size is not an optimal solution for modeling a mine site. This paper presented a novel algorithm to create an adaptive block model with locally varying block sizes aiming to control dilution and ore loss in Sungun porphyry copper deposit of Iran with a complex geometry characterized by multiple dikes. Three grade block models with different block sizes and simulated by direct block simulation are the inputs of algorithm. The output is a merged block model, assigning the smaller blocks to the complex zones, such as ore-waste boundaries, and larger blocks to the continuous and homogeneous zones of the ore body. The presented algorithm is capable to provide an accurate spatial distribution model with a fewer number of blocks in comparison to the traditional block modeling concepts.

1. Introduction

Designing and planning mining activities are complex processes that rely on a 3D representation of a mineral deposit referred to as a block model. The block geometry and size have different definitions depending on the stages of mining operations [1]. An extraction block or selective mining unit (SMU) is the smallest block that will be selected as the ore or waste [2, 3]. The dilution and ore loss, described as the waste mixed with ore or ore mixed with waste, resulting from the extraction of materials from different geological domains [4]. Ilyas and Madani showed that these problems depend on the parameters such as the extraction block size, geometry of the ore-waste boundaries, geological contacts, and grade spatial variability [5]. The size of blocks in the mineral deposit models dictates the geometry of the geological contacts, and as the block size decreases, the grade variability (measured, for instance, by a dispersion variance) increases. Nevertheless, creating a grade model using small blocks can enhance the resolution of the ore-waste boundary and decrease the potential dilution [6-8]. Mineral deposit modeling with improper block sizes and using inappropriate spatial prediction methods can also cause spatial variability smoothing, an incorrect determination of ore-waste boundary, and a misleading forecast of the economic potential of the ore [8].

At present, many researches exist on the optimum block size selection. These studies show that the 3D array of mining blocks is the basis of the feasibility study, and depends on the probable spacing of drill holes, scale of operation, extraction limitation, equipment size, cut-off, and average grades of metals [5]. Hekmat believed that

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variogram ranges and anisotropy ratios of the metal grade, as well as the drill hole data spacing are important parameters for selection of proper block dimension [9]. As a general rule, small block dimensions create a high-resolution image of the deposit, and the final mine model can be closer to reality, especially in the deposits with complicated geometries, provided that the drill hole spacing is not too loose [7, 8].

The distribution of ore over the entire deposit is often heterogeneous, and the model creation using small blocks increases the computational cost and the prediction error variance. In mining software, sub-cells often model the ore-waste boundaries, geological contacts, and wireframe edges: a set of sub-blocks create a large block, and if the percentage of waste sub-blocks within the considered block is more than 50%, the entire block is waste, and vice-versa is ore [10,11]. In this case, assigning the average grade value of small blocks to the block containing them provides a smooth model that does not sufficiently the deposits reality and fails at predicting the recoverable resources [9, 12]. In order to solve this problem, a model with different block sizes (i.e., with an adaptive geometry) is needed: in such a model, the small and large blocks should be inserted in structurally complex and simple areas of the ore deposit, respectively, a topic that has not been systematically studied in the literature so far.

In the current paper, an optimization algorithm simulates the grade and delineates the ore-waste boundaries of Iranian Sungun porphyry copper deposit using different block sizes, in which the ore is intersected by several barren dikes as waste. The mentioned algorithm finds areas with high and low-grade variability and areas with high and low spatial complexity and inserts a proper block size accordingly [13]. A direct block simulation method (DBSIM) with the high ability of ore feature simulation in small blocks, predicted the copper grade. DBSIM methods generates multiple realizations, reproduces the true grade variability, and prevents the smoothing of the block model, therefore the risk of ore-waste misclassification reduces. The block sizes used in this algorithm are compatible with the production plan in the case study deposit and meet the requirements of all mining stages. The following sections are, the preliminary concepts, proposed method, geology of the deposit, and evaluation of the resulted models. The details of the DBSIM method are out of the scope of this paper, and interested readers can refer to mentioned references [14, 15].

2. Relationships of block size and mining operation parameters

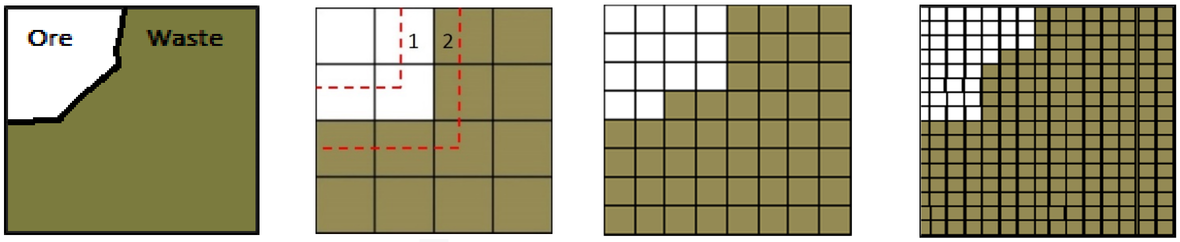
The block dimensions relate with the error variance of grade predictions, profitability, the efficiency of machinery, machinery capacity, operating costs, and geometric constraints of the mine design such as the slope and width of the roads and the height of the benches, so it is necessary to consider all these parameters in determining the block dimensions [9, 16]. There is an association between the block sizes and some essential parameters of mining activities such as prediction error variance, dilution, calculation time, pit geometrical features, size of extraction equipment, operation costs and efficiency, tailing ratio, processing plant capacity, the outcome of selling, geotechnical features, size of extraction equipment, mineralogical and geological variations, ore deposit type and information effect [6, 16]. The subsequent paragraphs provide brief descriptions of some of these parameters.

2.1. Dilution and ore loss

Mining selectivity is the process of separating ore from waste (materials with higher or lower grades than a considered cut-off grade) based on the selective mining units [11]. To visualize the effect of dilution in ore evaluation, Figure 1b illustrates an area around the boundary of ore and waste (Figure 1b, area delimited by red dash lines). If we suppose all of this area is waste, the tonnage of part 1 (which is ore) will be subtracted from the ore tonnage and transferred to the waste dump (ore loss). If we suppose all this area is ore, the tonnage of part 2 (which is waste) will be transferred to the mineral processing cycle (ore-waste dilution) [6, 17]. In order to avoid this event and its economic consequences, an algorithm should model the ore-waste boundary precisely. In deposits with simple geometry, the mentioned boundary is identifiable, and large blocks can model it. For complex structured deposits, small blocks separate the ore from the waste more accurately (Figures 1c and 1d) [7, 8].

2.2. Cut-off grade

In ore reserve evaluation, if the cut-off grade of the considered metal is less than its average grade, a small block size selection will result in less dilution and less ore tonnage estimation. If the cut-off grade of the considered metal is higher than its average grade, the result will be contrariwise [18]. In this way, the recoverable metal grade in a model with small blocks will be greater than the recoverable metal grade in a model created with large blocks. Therefore, the cut-off grade relative to the average grade is an effective parameter on block size selection [19]. Also, the cut-off grade is highly dependent on the ore continuity: as the cut-off grade increases, the ore continuity and exploitable volumes tend to decrease. In ore bodies with a disconnected geometry, the cut-off grade is an effective parameter in selecting the appropriate block dimensions [16].



(a) (b) (c) (d)

Figure 1. The effect of block size on ore-waste separation. Ore blocks are white, waste blocks are brown.

2.3. Support and information effects

The volume covering the modelled or deposit feature is the support [18]. The change of support (e.g., from the drill hole sample support to block support) alters the frequency distributions of ore attributes, in particular their shapes and variances, and consequently the number of recoverable resources, a feature known as the support effect [20].

Prediction methods rely on sampling data to assign a metal grade or any other parameter to a block model. As predictions differ from reality, misclassifications are likely to occur, which causes the so-called information effect. This effect is less pronounced when the block size is large or when the sampling data are abundant, implying a higher prediction accuracy [19, 21].

2.4. Type of deposit

In bedded or layered deposits, the block dimension along the height should be limited to the layer thickness. In expanded tabular deposits, the increase in block dimensions results in an increased dilution [6]. Pyramid shape or honeycomb blocks can be useful, but they will create many computational problems to design the final pit [22].

3. Case study: Sungun copper deposit

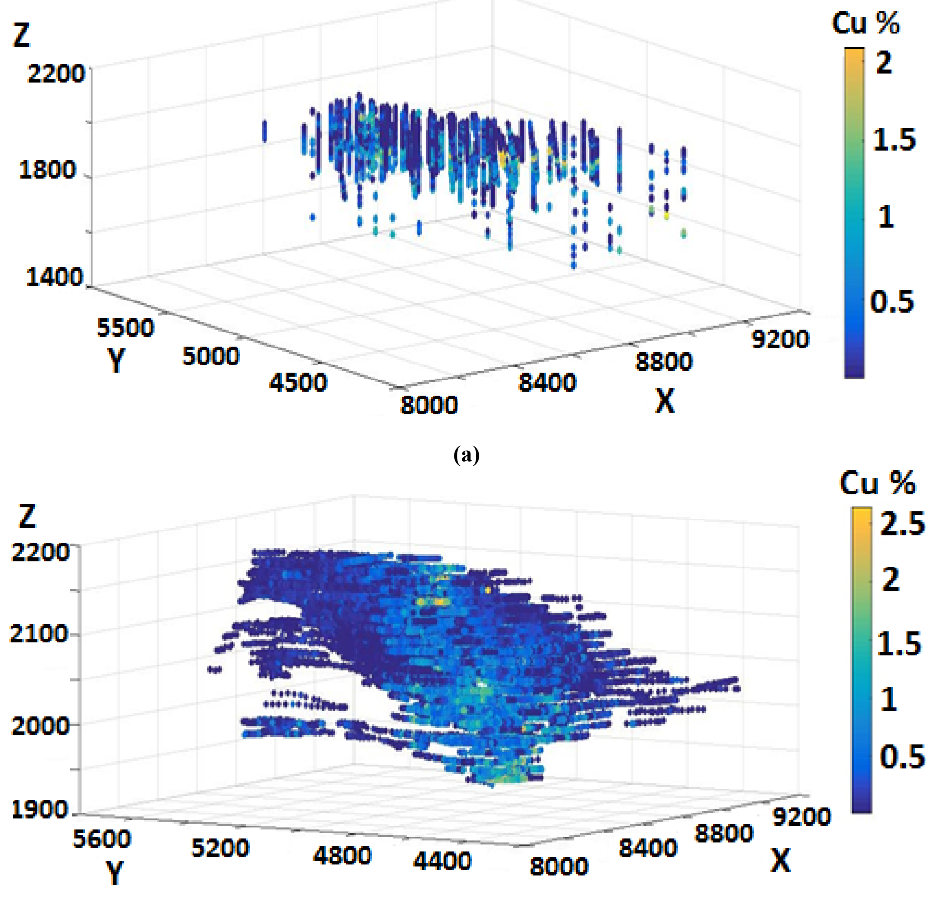
3.1. Geological description

The Sungun porphyry copper deposit is in the northwestern Iran, on the Urmia-Dokhtar magmatic arc. The magmatic activities of this arc created most of the Iranian porphyry copper deposits [23]. The positioning of alterations and mineralization domains of Sungun does not follow the simple models of porphyry systems [24]. Early hydrothermal alterations were generally potassic and propylitic, which were accompanied by later phyllic and argillic alterations. Skarn-type mineralization and its related alterations appear in the eastern and northern sides of the stock. Late-injected dikes are located in the northern and eastern parts of the deposit. The dikes do not bear any economic mineralization (0.08% copper on average), and their thicknesses range from a centimeter to several meters [23, 24].

Three main rock types control the copper grade distribution: skarn (SK), Sungun porphyry (SP) stock, and dikes (DK). In our case study, DK corresponding to waste and SP mainly to ore. Also, three mineralization zones of the porphyry stock are: leached, supergene, and hypogene. The copper mineralization in the hypogene zone comes with potassic, and phyllic alterations. In the potassic alteration, the main minerals are chalcopyrite and bornite. These minerals were dissolved during the supergene activity and substituted by secondary minerals, such as cuprite, malachite and chalcocite [24].

3.2. Presentation of the data set

Geological domaining divides the estimation area into homogeneous regions, and part of the phyllic and potassic alteration is the case study area. This domain covers an area with 0.6 km longitude distance, 1 km latitude distance, and with depths up to 0.3 km below the surface. Fig. 2 illustrates the location map of drill holes and blast holes of the case study area, 48 drill holes are available in this area, and the composition length for grade assays is 2-meter for all drill holes. Furthermore, 4591 blast-hole samples are true data for validation of results.



(a)

(b)

Figure 2. Location maps of the available data, colored according to copper grades: (a) drill holes, (b) blast holes.

4. The proposed solution to define a block model with an adaptive geometry

As explained before, mining selectivity is the ore-waste separation based on the smallest exploited block (selective mining unit). Carrying out mining activities near ore-waste boundaries makes a problem in selectivity, resulting in the extraction of materials with different inherent characteristics and leading to the mixing of ore and waste during operation (dilution and ore loss). This issue plays an essential role in structurally complex deposits, and sub-blocks or partial blocks near the geological boundaries control it. The sub-blocking procedure can improve the resolution of geological contacts, provide more accurate predictions, and reduce ore-waste dilution. Subdividing the blocks into other parts of the ore deposit with low complexity (i.e., low spatial variability or areas within a single geological domain) is unnecessary and only increases computational cost.

Current algorithm creates an adaptive model; in this model the size of blocks relates to the spatial variability of the modeled area. The largest assumed size of blocks (parent blocks) is $30\times30\times15$ m^3, and sub blocks are $15\times15\times7.5$ m^3 or $10\times10\times5$ m^3 that adjusts with the mine production planning. The average grade values of blast hole samples in a block volume is the true grade of that block. The steps of the algorithm are as follows:

1. Input the grade values of the drill hole samples.
2. Classify the spatially heterogeneous mine area into different homogeneous domains, and run the algorithm in each domain.
3. Execute the direct block simulation method (DBSIM) on the $30\times30\times15$ m^3, $15\times15\times7.5$ m^3, and $10\times10\times5$ m^3 block sizes.
4. Scan all the large ($30\times30\times15$ m^3) blocks throughout the simulated model to find blocks that are more likely to be entirely ore or entirely waste.

For this purpose, in each realization, algorithm will assign 1 to the large size block if the following two conditions are true (otherwise 0):

a. The eight medium sub-blocks contained in it are all waste or all ore.

b. The 27 small sub-blocks contained in it are all waste or all ore.

If across the set of realizations, the large size block is one more often than 0, then this block will more likely contain only ore or only waste, and a division into sub-blocks is not necessary. Otherwise (0 more often than one), a subdivision is preferable.

5. For every large size block, the decision of using small size or medium size sub-blocks relies on which subdivision provides a more stable ore-waste classification across the realizations, indicating a lower risk of dilution or ore loss:

a. for each of the eight medium sub-blocks (i=1… 8), define the indicator $M(i,r) = 1$ if the i_{th} sub-block is ore in realization r, 0 if it is waste; calculate the variance of this indicator over all the realizations, then the average variance over the eight sub-blocks;

b. to each of the 27 small sub-blocks (j=1… 27), define $S(j,r) = 1$ if the j_{th} sub-block is ore in realization r, 0 if it is waste; again, calculate the variance of this indicator over the realizations, then the average variance over the 27 sub-blocks;

c. if the average variance of M is less than that of S, then the ore-waste classification into medium sub-blocks is less variable across the realizations (the medium block size is more effective in delineating the ore-waste boundary), and the subdivision into medium sub-blocks is preferred; otherwise, a subdivision into small sub-blocks.

Figure 3 is a schematic diagram of the relationship between the intersection of medium and small blocks with a hole and the resulted simulation uncertainty. The resulting adaptive block models are validated with the average blast-hole data in the large, medium, and small blocks, and also by local visual matching with the true data.

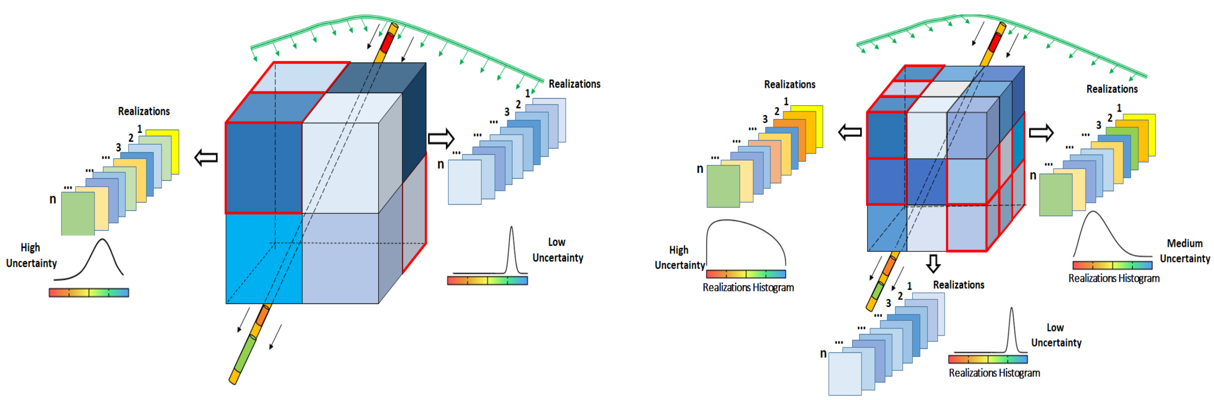


Figure 3: Simulation uncertainty in different blocks, red highlighted blocks are not intersected with hole and do not include any true data, top) medium blocks; bellow) small blocks.

Figure 4 shows the result of running the algorithm in a small area, with a hypothetical cut-off grade of 0.4. As can be seen, the segmented blocks are mainly near the predicted ore-waste boundary, and the blocks that are completely in ore or waste zone do not need division.

5. Results and discussion

Based on the variograms of the metal grades along with the directions with 0°, 45°, 90°, 135° azimuths and 0°, 45°, 90° dips with 22.5° tolerance, the major anisotropy axis has azimuth 0° and dip 45°. The direct block simulation algorithm models the grades on $30\times30\times15$ m^3 (large), $15\times15\times7.5$ m^3 (medium) and $10\times10\times5$ m^3 (small) blocks (Figure 5a, b, c). The proposed algorithm creates adaptive block models for different cut−off grades (Figure 5d); as it is clear, large blocks are in the high-grade (hypothetical ore) and low-grade (hypothetical waste) areas, indicating that the large block dimensions are sufficient to represent these areas without much ore-waste dilution.

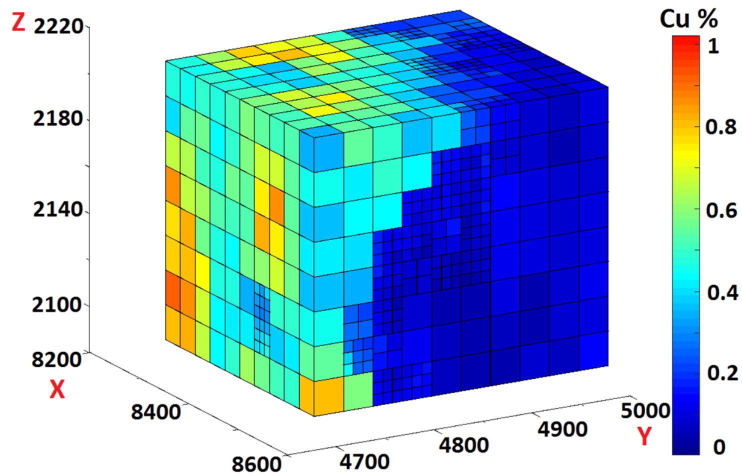
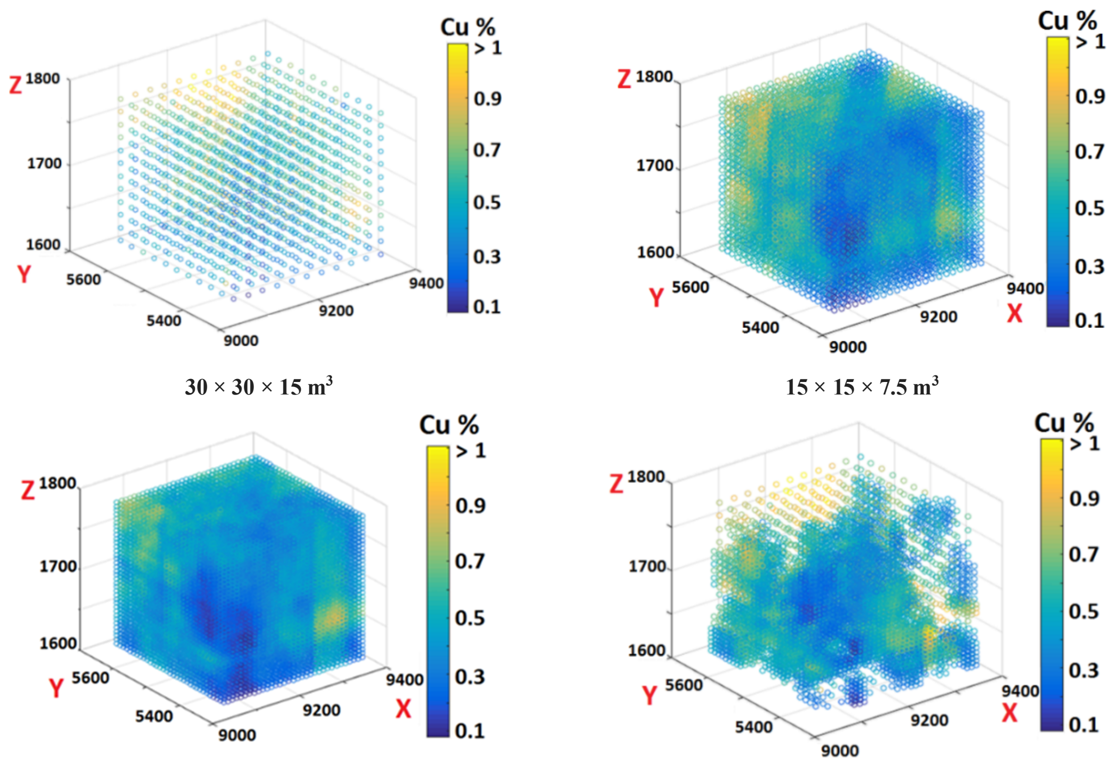


Figure 4. Predicted block model of copper grade (average of DBSIM realizations) with adaptive block size algorithm (cut-off grade 0.4).



30 × 30 × 15 m³ 15 × 15 × 7.5 m³

10 × 10 × 5 m³ Adaptive block size (cut-off 0.3)

Figure 5. 3D representation of copper grade at different supports. Only the block centroids are represented and colored according to the average of DBSIM realizations.

Figure 6 shows the adaptive block model that results from implementing the proposed algorithm for a cut−off grade of 0.15 together with the exploration drill holes. The segmented blocks located in the low-grade areas correspond to the areas close to the ore-waste boundary, and the high-grade areas are not segmented at all. Also, in this figure, the matching between the areas with the high aggregation of dikes (especially in a drill hole and a column of signed blocks with the red stars) and the smaller blocks are evident. As the dimensions of the block decrease, the resolution of the model increases.

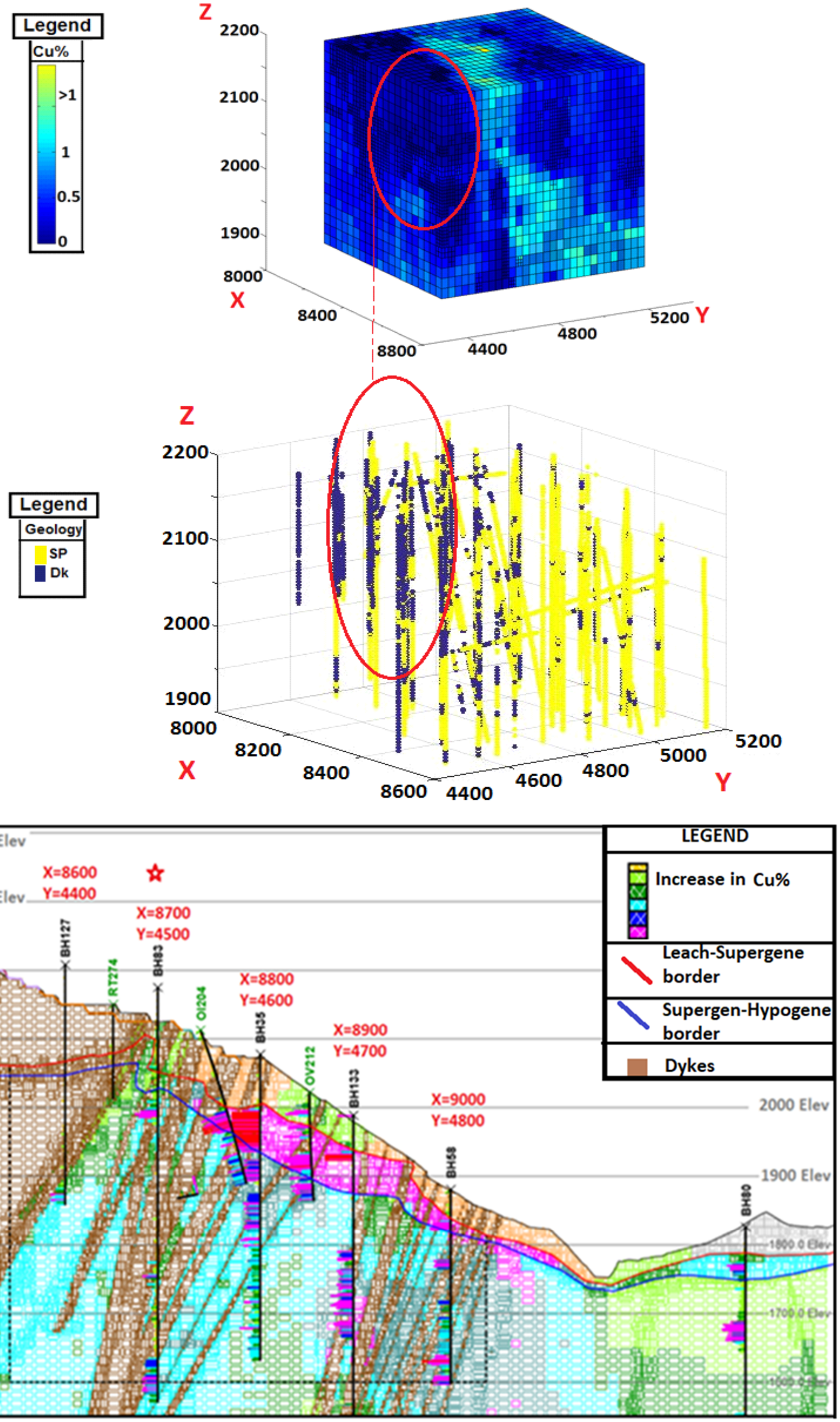


Figure 6. Adaptive block model and ore and waste in core samples (top); a section of the geological map (bellow) [13].

A plan view of the adaptive block model at an elevation of 2000 m is shown in Figure 7, and related geological map. The areas intersected by dikes correspond to the sub-divided blocks. The mentioned comparisons are only for a visual validation of the results. Figure 8 shows a mining level of our adaptive model. To extract every one of these blocks, its special machines must be applied. For example, for the parts of the marked model in red, yellow, and green, the machines A, B, and C are used, respectively. The order of ore and waste block extraction depends on the restriction of access to the desired block. For example, in medium and large-size block extraction, that small-size blocks surrounded them, it is practically not economical to use machines B and A, and the machines dedicated to extract small blocks will be used. Therefore, the mentioned results are presented without considering the economic and operational parameters, and only have a computational aspect.

The simulated grades of the large (30×30×15 m^3), medium (15×15×7.5 m^3), small (10×10×5 m^3), and adaptive block models accurately reproduce the statistical variability (histogram) of the true grades at the same support. Figure 9 illustrates its Q-Q plots.

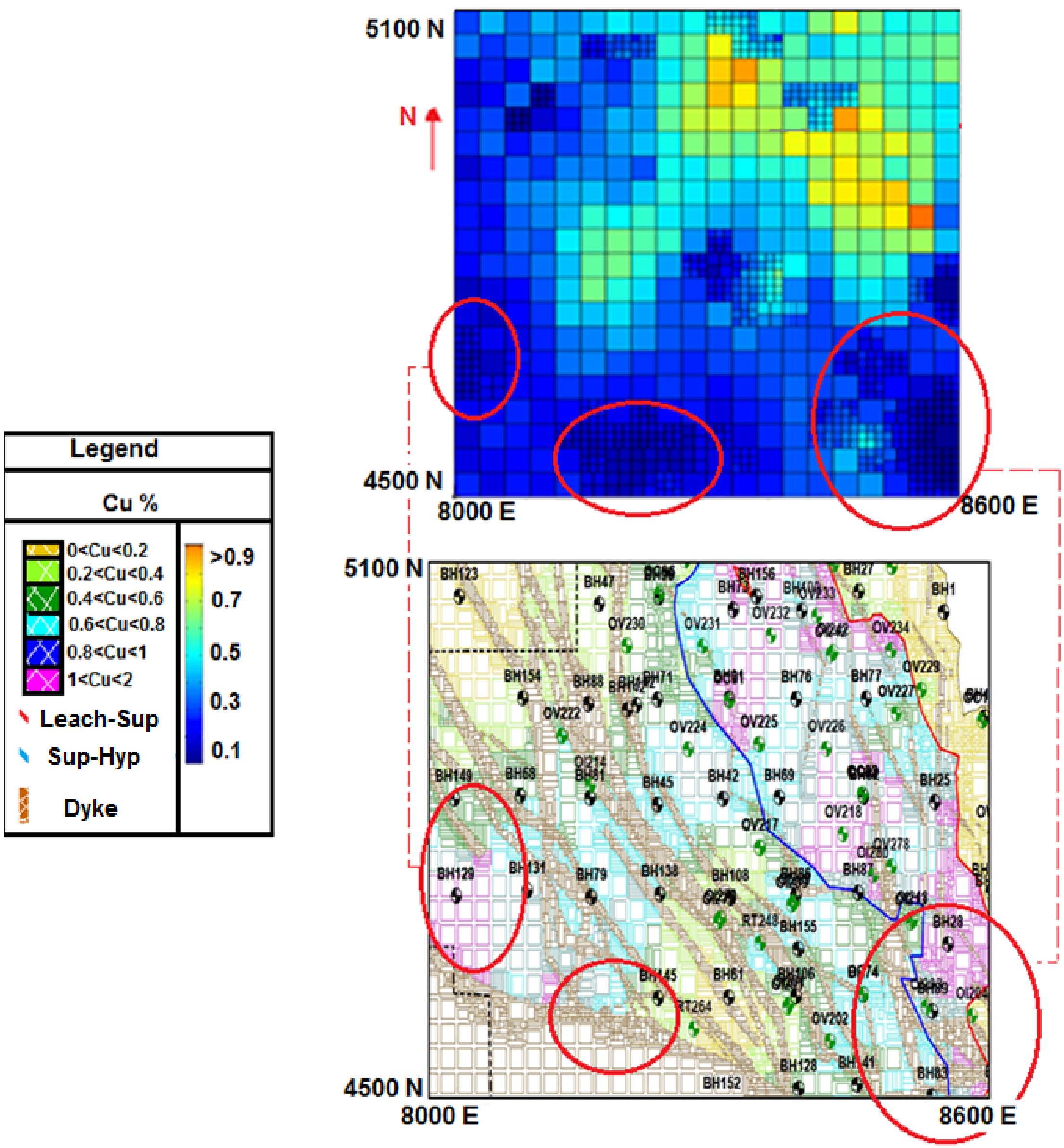


Figure 7. Plan view of the adaptive block model at an elevation of 2000 m. Sub-divided blocks occur in areas intersected by dykes and leach as well as hypogene and supergene contact areas (Figure 6) [13].

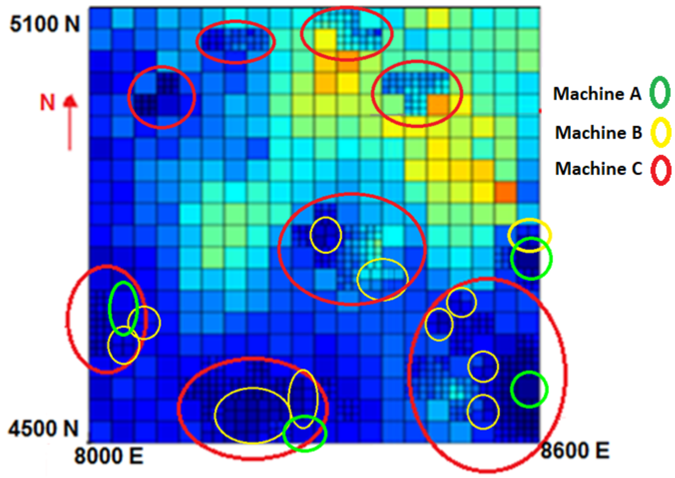


Figure 8. Application of different exploitation machinery for this level of mine.

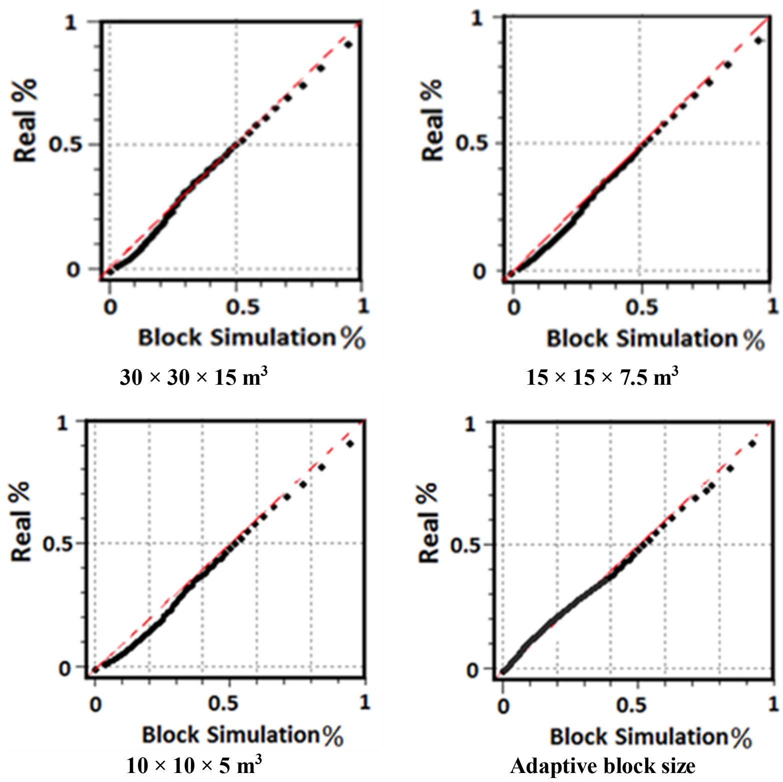


Figure 9. Q-Q plots between simulated and true grades for different block sizes.

All in all, the proposed algorithm finds the geologically complex areas in the deposit, and selects the appropriate block size to display these areas. The best block size for an area is a size that minimize the ore loss and the dilution in that area. All the used block sizes in this algorithm are compatible with the production program of the case study mine. The algorithm allows minimizing the risk of ore-waste misclassification by improving the resolution of the ore-waste boundary.

6. Conclusions

Mine planning and designing are based on a block model. A key parameter of this model is the block size, which affects the mining operation costs and has been a topic of interest in the recent decades. We proposed a multi-resolution approach to create an adaptive block model, rather than traditional unique-sized block models. The presented algorithm will partition some large blocks near the ore-waste boundary into the smaller sub-blocks to reduce the dilution or ore loss, if sufficient conditions of algorithm are met. Direct block simulation (DBSIM) has modeled the grades at all the blocks and sub-blocks. The most apparent finding of this study was the high conformity of sub-blocks with some areas that include dikes (waste), and uncertain and anisotropic areas (the mineralization and dike zones).

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ارائه مدل بلوکی با ابعاد متنوع و تطبیقی، به منظور ارزیابی منابع و ذخایر معدنی

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چکیده:

پارامترهای کلیدی ورودی برای برنامه‌ریزی معدن و کلیه فعالیت‌های استخراجی بر اساس مدل‌های بلوکی برآورد می‌شوند. اندازه بلوک باید ناهمگنی و پیچیدگی زمین‌شناسی و تنوع عیاری موجود در کانسار را در نظر بگیرد. ارائه مدل‌های عیاری در بلوک‌های کوچکتر نسبت به بلوک‌های بزرگ پیچیده‌تر و پرهزینه است، اما بلوک‌های بزرگتر نمی‌توانند مناطق با پیچیدگی زمین‌شناسی بالا را به طور دقیق نشان دهند. از این رو، استفاده از اندازه بلوک یکسان در سراسر معدن راه حل مطلوبی برای مدل‌سازی نیست. در این مقاله یک الگوریتم جدید برای ایجاد یک مدل بلوک با ابعاد متنوع و تطبیقی با هدف کنترل ترقیق و هدررفت کانه در کانسار مس پورفیری سونگون ایران ارائه شده است. ورودی الگوریتم سه مدل بلوکی با اندازه های مختلف، برآورد شده توسط شبیه سازی بلوک مستقیم و خروجی آن یک مدل بلوک ادغام شده است. الگوریتم، بلوک‌های کوچکتر را به مناطق پیچیده مانند مرزهای کانه و باطله و بلوک‌های بزرگتر را به مناطق یکنواخت به طور مثال بدنه کانسار یا بدنه باطله اختصاص می‌دهد. الگوریتم ارائه شده قادر است مدل توزیع فضایی عیار را دقیق‌تر و با استفاده از تعداد کمتری بلوک در مقایسه با روش های سنتی مدل‌سازی بلوکی ارائه دهد.

کلمات کلیدی: مدل‌سازی کانسار، مدل بلوکی با ابعاد متنوع، مرز کانه و باطله، ترقیق، هدررفت کانه.