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Implicit modelling and geostatistics applied to construction of geotechnical model for a Brazilian open-pit mine

Modelagem implícita e geoestatística aplicadas à construção de um modelo geotécnico para uma mina a céu aberto no Brasil

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Abstract: The concept of a geotechnical model in open-pit mines is based on a product defined by domains or units with similar geotechnical behavior. The main objective is to support slope design processes. The construction of a geotechnical model must integrate four other models: geological, structural, geomechanical, and hydrogeological. This article aims to present a methodology for constructing these models using geostatistics and implicit modeling, and subsequently, the integration of these models to create a unified geotechnical block model. This model contains information on strength index, degree of fracturing, roughness, Geological Strength Index, anisotropy, and hydraulic conductivity. The developed methodology has proven effective in integrating the thematic models produced. The geostatistical approach reduced subjectivity in model construction, making this process more quantitative. This was one of the main differentiators of this methodology, as it allows for the classification of the reliability of geotechnical information attributed to each block.

Keywords: Geostatistics; Geotechnical Model; Open-pit mine.

Resumo: O conceito de modelo geotécnico em minas a céu aberto baseia-se em um produto definido por domínios ou unidades com comportamento geotécnico similar. O principal objetivo é apoiar os processos de design de taludes. A construção de um modelo geotécnico deve integrar quatro outros modelos: geológico, estrutural, geomecânico e hidrogeológico. Este artigo visa apresentar uma metodologia para a construção desses modelos utilizando geoestatística e modelagem implícita, e posteriormente, a integração desses modelos para criar um modelo de bloco geotécnico unificado. Este modelo contém informações sobre índice de resistência, grau de fraturamento, rugosidade, Índice de Resistência Geológica, anisotropia e condutividade hidráulica. A metodologia desenvolvida provou ser eficaz na integração dos modelos temáticos produzidos. A abordagem geoestatística reduziu a subjetividade na construção dos modelos, tornando este processo mais quantitativo. Este foi um dos principais diferenciais desta metodologia, pois permite a classificação da confiabilidade das informações geotécnicas atribuídas a cada bloco.

Palavras-chave: Geoestatística; Modelo Geotécnico; Mina a céu aberto.

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1. Introduction

The concept of a geotechnical model in open-pit mines involves creating a product that spatially defines domains or units with similar geotechnical behaviors. The main objective is to support slope design processes. The construction of a geotechnical model must integrate four other models (READ and STACEY, 2009): the geological model, which contains lithotypes; the structural model, which defines the main discontinuities and their characteristics; the geomechanical model, which defines the rock mass quality (geomechanical classes and geotechnical parameters); and the hydrogeological model, which defines the hydrogeological units and their respective parameters.

The challenge in constructing the geotechnical model lies in combining these four complex models into a single three-dimensional model. According to Read and Stacey (2009), constructing the geotechnical model by overlaying maps results in a complex and highly segmented map of geotechnical domains (Figure 1). Furthermore, the authors discuss the use of block models as an alternative but advise caution in kriging the Rock Mass Rating (RMR) scores. The RMR (BIENIAWSKI, 1989) is the most widely used geomechanical classification system in the world and consists of an overlay of qualitative ratings assigned to individual parameters (strength, fracturing, roughness, etc.). These parameters are not always effective for delineating a geotechnical domain, and data scarcity can compromise the quality of the estimate.

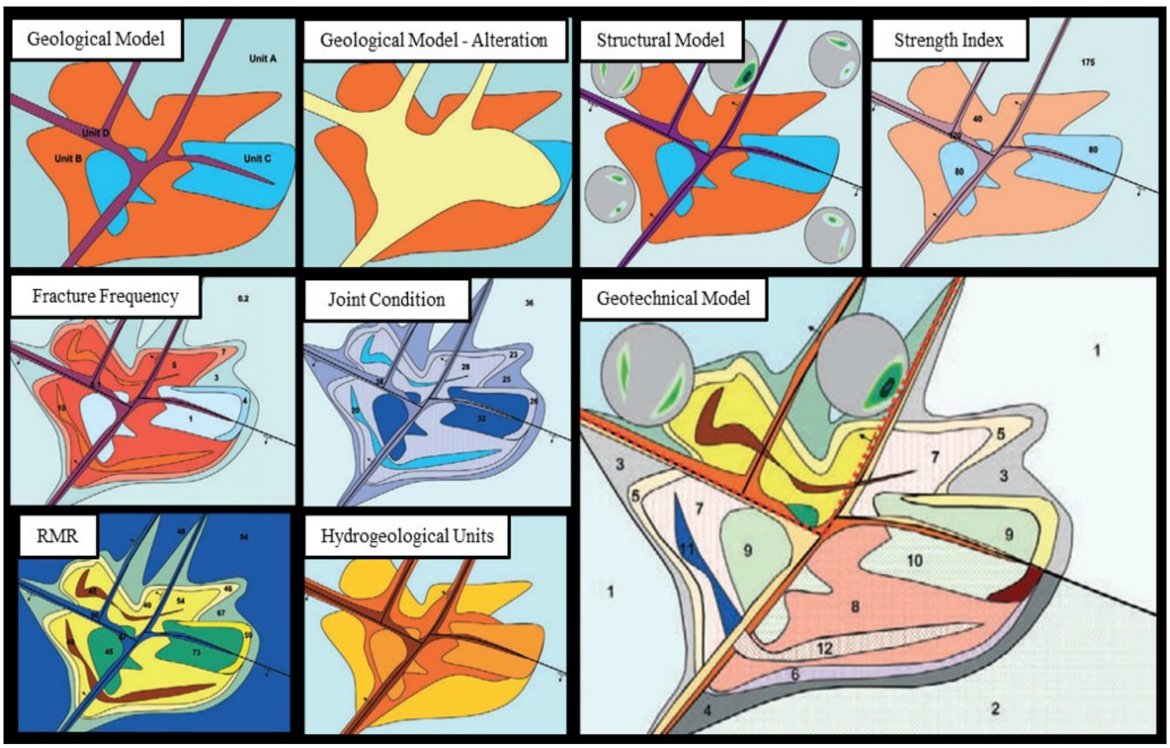


Figure 1 - Overlay of eight thematic maps to create a two-dimensional geotechnical model.
Source: modified from Read and Stacey (2009).

Among the models used in geotechnical studies, the geomechanical model is the most frequently employed by mining teams. In open-pit mines, it is traditionally developed through two-dimensional interpretation of drilling data and field surveys, projected onto vertical 2D sections and integrated into an explicit 3D model. The volume of geotechnical information at depth is generally smaller than the volume of geological information, especially in waste rock masses. The small amount of information makes the design of the two-dimensional sections even more interpretative, relying essentially on the expertise of the modeler.

Two-dimensional geotechnical sections have long been the primary source for constructing three-dimensional geomechanical models, which serve as the main basis for stability analyses, whether based on limit equilibrium or numerical methods. This traditional methodology does not employ geostatistical tools that could assist the modeler's interpretation and reduce associated subjectivity. Consequently, it is not possible to quantitatively assess the reliability of the information provided by the final model.

Quality control and geostatistical techniques are widely used in geological models, where the reliability of information is directly linked to the company's valuation due to the declaration of mineral resources and reserves. Geostatistical approaches to estimating ore volumes and grades are mandatory to comply with international standards for reserve declaration, classifying spatially distributed information as measured, indicated, or inferred.

The use of such tools in geotechnics is not yet common for preparing reports on reserve declarations for international stock exchanges; however, renowned consultants and auditors encourage further studies on quantifying and assessing data uncertainty (READ, 2013). A major challenge lies in determining which estimation methods are suitable for geotechnical variables, which are primarily categorical and may lack significant spatial continuity. Despite these challenges, the use of three-dimensional block models with geostatistical estimates has been widely discussed in the technical literature (Vatcher, McKinnon, & Sjöberg, 2016; Cruz, 2017; Kring & Chatterjee, 2020; Liu et al., 2021). This knowledge has been developed over the years by researchers and experts, primarily in the oil industry, but remains limited in its application to mining excavations.

Geostatistics has been applied in geotechnical modeling. Kring and Chatterjee (2020) introduced an integrated methodology to analyze the stability of rock structures, considering various uncertain factors that influence engineering decisions. These factors, some of which are spatially distributed in the geological area, are quantified to improve stability analysis. The study focuses on two critical factors: categorical structural parameters and continuous geotechnical parameters. To address spatial uncertainty, two geostatistical simulation methods, sequential indicator simulation and sequential Gaussian simulation, are used to generate multiple probabilistic maps for fault zones and RQD values. These spatially variable parameters are then integrated into a slope stability analysis.

The methodology was validated using synthetic data, demonstrating close alignment with stability values calculated from the simulated data. Furthermore, it was applied to a real open-pit mine design scenario with limited exploration data. Geostatistically simulated RQD maps for this case study mine were analyzed to determine a safe slope angle of 44° for open-pit mining operations. Overall, this approach can be adapted to quantify other geotechnical risks and integrated into various stability analysis frameworks.

Proposing an improved understanding of geotechnical variables and the use of geostatistical techniques in model construction, this article presents a methodology that applies geostatistical tools to quantify uncertainties and construct a three-dimensional geotechnical model of a large open-pit iron mine located in the Quadrilátero Ferrífero Mineral Province, Brazil.

2. Material and Methods

2.1 Data

The first step in developing the model was the survey, organization, and validation of the dataset. This step is crucial in the process, as the quality of the information directly affects all subsequent products. The geotechnical dataset used includes 944 surface mapping points and approximately 67,000 meters of drill core with geotechnical descriptions.

The definition of the composite sample size was based on the average lengths of the intervals described in the drill cores. In total, the dataset resulted in 21,975 sample points that were used to build the models (Figure 2).

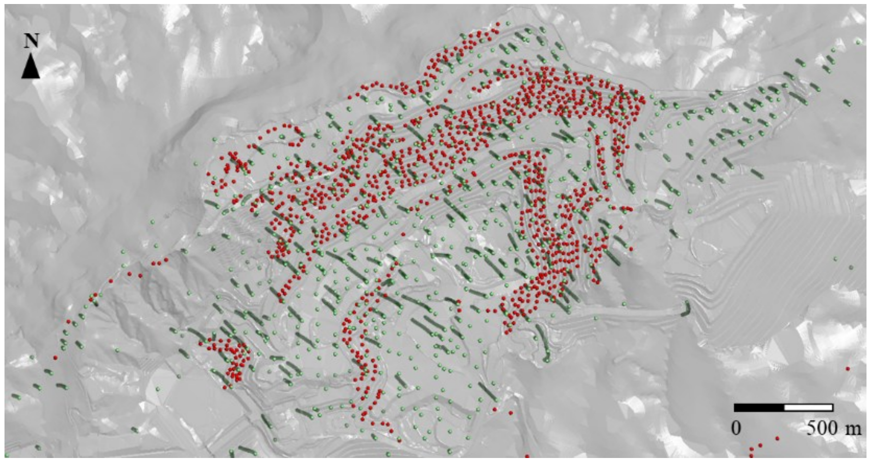


Figure 2 - Location map with the database arrangement. Red: mapping points. Green: diamond drillholes.
Source: author (2024)

Among the geotechnical parameters available in the dataset, the following were used: intact rock strength (R), Rock Quality Designation (RQD), degree of fracturing (DF), and discontinuity roughness. Therefore, three categorical variables and one numerical variable (RQD) were used. For the categorical variables, indicator transformations (0 and 1) were necessary to perform indicator kriging (IK).

2.2 Models

For the development of the geotechnical model, seven thematic models were created: geological, structural, strength, degree of fracturing, discontinuity roughness, geomechanical, and hydrogeological (Figure 3). The three-dimensional modeling of geological, structural, geomechanical, and hydrogeological data was performed using the Leapfrog Geo® software (LEAPFROG GEO, 2024).

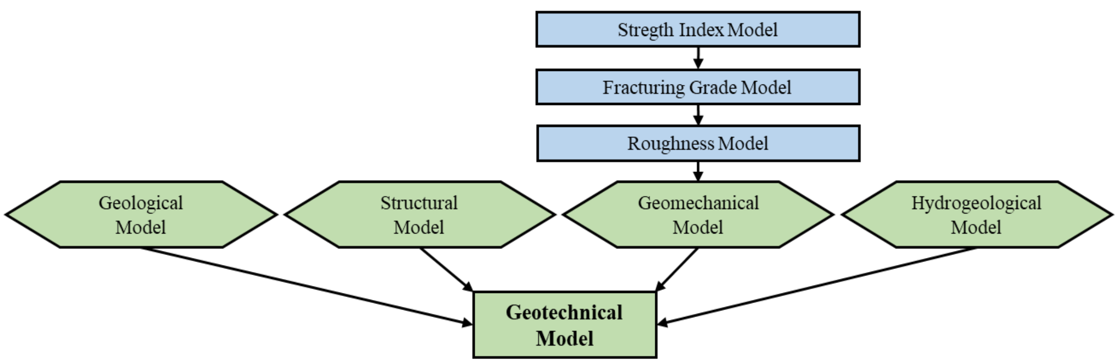


Figure 3 - Thematic models elaborated to obtain the geotechnical model.
Source: author (2024).

The geological model was developed using implicit modeling, integrating drill cores, mapping points, and the surface geological map. It delineates in three dimensions the main stratigraphic units present in the mine, primarily composed of quartzites, shales, banded iron formations (BIF), intrusive rocks, and recent covers.

The structural model was based on measurements obtained from outcrop surveys (foliations and compositional banding) and on geological contact surfaces at depth derived from drilling data. Regional and local structural maps supported the identification and interpretation of the main mine structures. Subsequently, three-dimensional surfaces representing variations in foliation attitude (anisotropic surfaces) and a fault surface with potential planar ruptures (weak layer) were generated.

The geomechanical model was constructed using the strength index (ISRM, 1981), degree of fracturing (BIENIAWSKI, 1989), RQD (DEERE, 1968), and roughness (BIENIAWSKI, 1989). From these data, three thematic models were created: the strength index model, the fracture grade model, and the roughness model. Geological model solids were defined as geostatistical domains, considering that rheological behavior and weathering degree vary by lithotype, influencing geotechnical properties.

For the strength index model, categorical variables representing seven strength ratings (R0 to R6) were used, following ISRM (1981). As proposed by Cruz (2017), these were grouped into two categories: weak (R0, R1, R2) and compact (R3, R4, R5, R6). Weak rocks were assigned a value of 1, and hard rocks a value of 0 (Table 1). This transformation was essential for preparing the dataset for variographic analysis and estimation by indicator kriging.

The final block classification was determined by the highest probability of each estimated point. The variographic model, derived from the experimental variography of weak (1) and hard (0) rocks, was applied to individual indicator krigings for each strength rating. For non-estimated blocks, the strength index was assigned based on an implicit binary model. The resulting block model contains information on both compactness (weak or hard) and rock strength index (R0 to R6).

Strength Index	Qualitative Description	UCS (MPa)	Indicator Transformation
R6	Extremely strong	> 250	0: Hard
R5	Very strong	100 a 250	
R4	Strong	50 a 100	
R3	Medium strong	25 a 50	
R2	Weak	5 a 25	1: Weak
R1	Very Weak	1 a 5	
R0	Extremely weak	< 1	

Table 1 - Strength index description and indicator transformation.
Source: ISRM (1981) and Cruz (2017).

The degree of fracturing model was developed using indicator kriging, based on the six fracturing degrees in the dataset (Table 2). The methodology involved constructing a variographic model of RQD, which is a continuous numerical variable (0–100%) and exhibits a strong correlation with the degree of fracturing in the studied mine ($R^2 = 0.89$).

This approach allowed the variographic model to be built using a larger dataset, providing a more precise understanding of the spatial distribution of fracturing. In other words, it was assumed that the spatial continuity of RQD approximates that of the fracturing degree. Indicator transformations were applied to the dataset, and using the RQD variogram, the maximum probability of each block belonging to a given fracturing degree was estimated via indicator kriging. Fracturing degree values were assigned only to blocks classified as hard in the strength index model, since in weak rocks, the rock mass behavior is predominantly controlled by the strength of the rock matrix.

Degree of Fracturing Rating	Description	Fractures / Meter
1	Massive	<1
2	Blocky	1
3	Moderately Blocky	2 a 5
4	Very Blocky	6 a 10
5	Extremely Blocky	11 a 20
6	Desintegrated / Laminated	>20

Table 2 - Degree of fracturing description.
Source: modified from Bieniawski (1989).

The roughness data available in the dataset (Table 3) are limited and pertain only to hard rock samples (strength index ≥ R2). Due to the wide spatial dispersion of these data, it was not possible to develop a consistent variographic model. Therefore, the nearest neighbor method was applied to estimate roughness, restricting assignments to within 100 meters of existing samples. For non-estimated blocks, the modal roughness value of each geological domain (Quartzites, Shales, Banded Iron Formations, and Intrusive Formations) was assigned. The resulting block model thus contains roughness information for hard rocks, based on both the sampled data and the modal values of each geological domain.

Roughness Rating	Description
1	Extremely rough
2	Rough
3	Slightly rough
4	Smooth
5	Slickensided

Table 3 - Roughness description.
Source: modified from Bieniawski (1989).

The geomechanical model was constructed by integrating the thematic models of strength index, degree of fracturing, and roughness. This integration was achieved through an adaptation of the Geological Strength Index (GSI) classification, as proposed by Hoek (2001). The GSI classification involves assessing the geological conditions of the rock mass (structure and joint conditions) and selecting the value that best represents the observed conditions by comparing them with reference cases provided in a table. The GSI system was chosen because it directly provides the parameters required for applying the Generalized Hoek-Brown failure criterion for rock masses (HOEK et al., 2002).

In this study, the GSI was adapted by using the degree of fracturing to characterize the rock mass structure and roughness to define joint conditions. Since GSI is a visual and empirical method, detailing the geomechanical model with numerous materials having different GSI values would not be practical. Therefore, only three GSI values (75, 45, and 15) were used to simplify the range of geotechnical parameters in the final model, and consequently, in the stability analysis (Figure 4).

GSI Adaptation			Roughness				
			Extremely Rough	Rough	Slightly Rough	Smooth	Slickensided
			1	2	3	4	5
Fracturing degree	Massive	1	85	75	65	NA	NA
	Blocky	2	75	65	55	45	35
	Moderately Blocky	3	65	55	45	35	25
	Very Blocky	4	55	45	35	25	15
	Extremely Blocky	5	45	35	25	15	10
	Desintegrated / Laminated	6	NA	NA	15	10	5

Figure 4 - Proposed GSI adaptation for geomechanical model construction of the proposed methodology.
Source: author (2024).

The hydrogeological model was developed by assigning equivalent hydraulic conductivity (K) values based on lithotype, compactness, and GSI. Although other factors, such as chemical composition, can influence hydrogeological parameters, this study focused on classifying materials according to physical characteristics that affect the geotechnical behavior of the rock mass; therefore, chemical parameters were not considered.

Additionally, by defining kriging efficiency intervals for the estimated blocks, it was possible to assess the reliability of the geotechnical information. Three classes were established, following the traditional nomenclature used in mineral resource classification: measured, indicated, and inferred. This classification helps identify areas with data gaps, guides future investigation plans, and is essential for optimizing the geotechnical drilling grid.

2.3 Case Study

The site selected for the methodology application is a large open-pit iron ore mine located in São Gonçalo do Rio Abaixo, Brazil. The main pit measures approximately 3.2 km in length, 1.5 km in width, and has a maximum overall slope height of 280 m. The planned reserve pit is expected to reach a final geometry of 4.4 km in length, 1.7 km in width, and a maximum slope height of 480 m. This significant pit expansion potential highlights the importance of the geotechnical model for ensuring pit stability and supporting technical feasibility analyses.

3. Results and Discussion

For each thematic model, the most appropriate modeling and estimation methodology was selected, considering the nature of the variables and the sample support. In blocks where no samples were available, values were assigned through implicit modeling, with lenses oriented according to the search ellipsoids of each modeled phenomenon. The modeling method applied to each individual thematic model is summarized in Table 4. Additionally, the resulting thematic models are presented alongside an example of the geotechnical model applied to a stability analysis of an open-pit geometry (Figure 5).

Model	Variography	Domain	Attributed Methodology
Geological	Not applied	All	Implicit Model
Strength Index	Indicator tranformation (Hard:0, Weak:1). Same variographic model to estimate the 7 strength indexes	Cover	Nearest Neighbor
		Intrusive	Nearest Neighbor + Implicit Model
		BIF	Indicator Kriging + Implicit Model
		Schist	Indicator Kriging + Implicit Model
		Quartzite	Implicit Model
		Basement	Implicit Model
Degree of Fracturing	RQD ordinal data (0 to 100). Same variographic model used in the 6 fracturing grades. Applicable only to blocks classified as hard rock	Cover	Not applied
		Intrusive	Modal value
		BIF	Indicator Kriging + Implicit Model
		Schist	Indicator Kriging + Implicit Model
		Quartzite	Modal value
		Basement	Modal value
Roughness	Insufficient data for variography	All, except cover	Nearest neighbor (limited to average distance of 100m) + Modal Value per lithotype
Geomechanical	Not applied	All	Model integration and assignment according to adapted GSI
Structural	Not applied	All, except cover	Anisotropic surfaces by implicit modeling, respecting the contacts between geological domains. Attitude attributed on the blocks by nearest neighbor, respecting the surface triangulations
Hydrogeological	Not applied	All	Average hydraulic conductivity (K) per lithotype

Table 4 - Modeling method applied for each thematic model.
Source: author (2024).

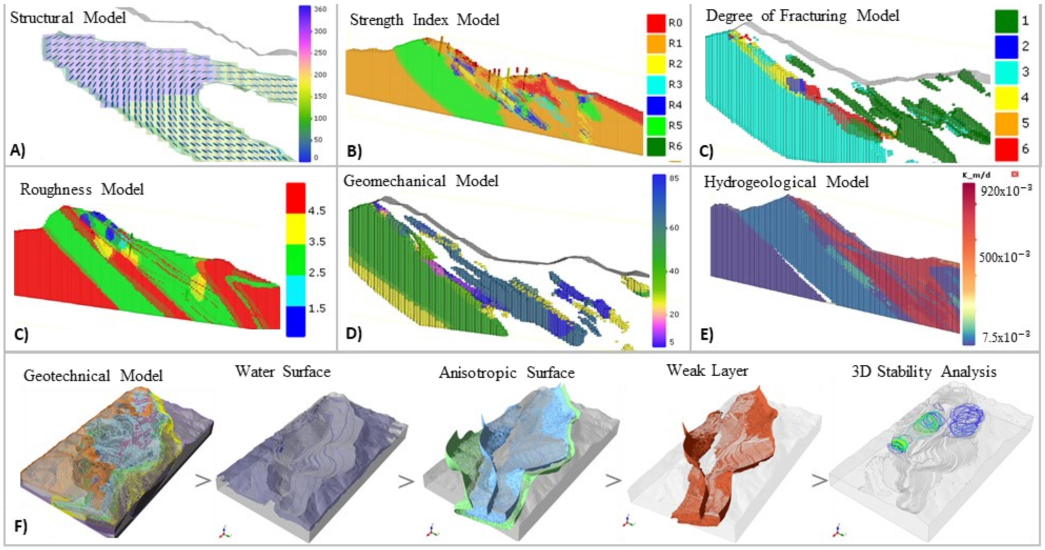


Figure 5 - (A to E) Block model sections of the thematic models and, (F) flow to import the products for a 3D stability analysis using block model and surfaces.
Source: author (2024).

3.1 Geological Model

The predominant lithotypes in the mine's stratigraphic units include basement (schists and undivided granites), quartzite, schist, banded iron formation (BIF), intrusives (diabases and gabbros), and cover (Quaternary basins and lateritic soil) (Figure 6). The mineralogical composition of each rock directly influences the material's sensitivity to weathering and, consequently, the strength index. Additionally, rocks exhibit different behaviors in response to tectonic deformations (rheology), which can result in varying structural patterns in each material. For this reason, the stratigraphic units condition the geotechnical variables and were used as geostatistical domains.

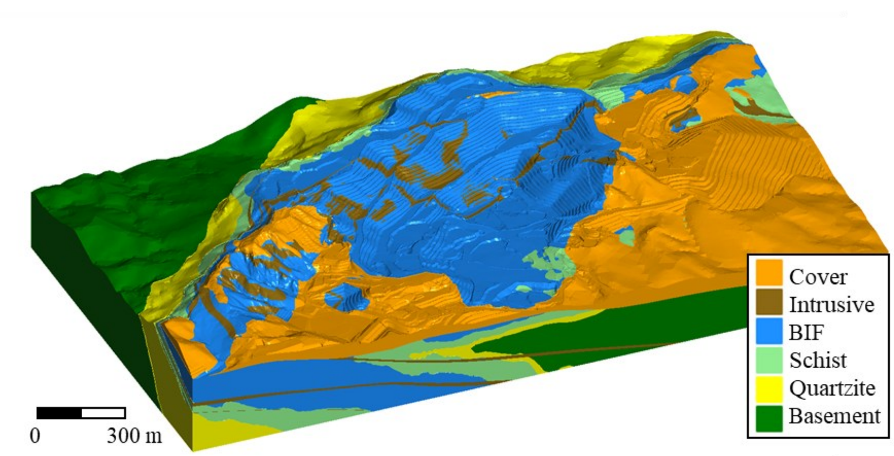


Figure 6 - Geological Model.
Source: author (2024).

3.2 Structural Model

The main structures identified in the field survey were joints, compositional banding, foliation, fold axes and mineral stretching lineation (Figure 7). However, the banding and foliation were paralleled by the tectonic processes of the region, and, for this reason, these structures are also in agreement with the main geological contacts: BIF/schist, schist/quartzite and quartzite/basement. Structural measurements and modeled surfaces are shown (Figure 8).

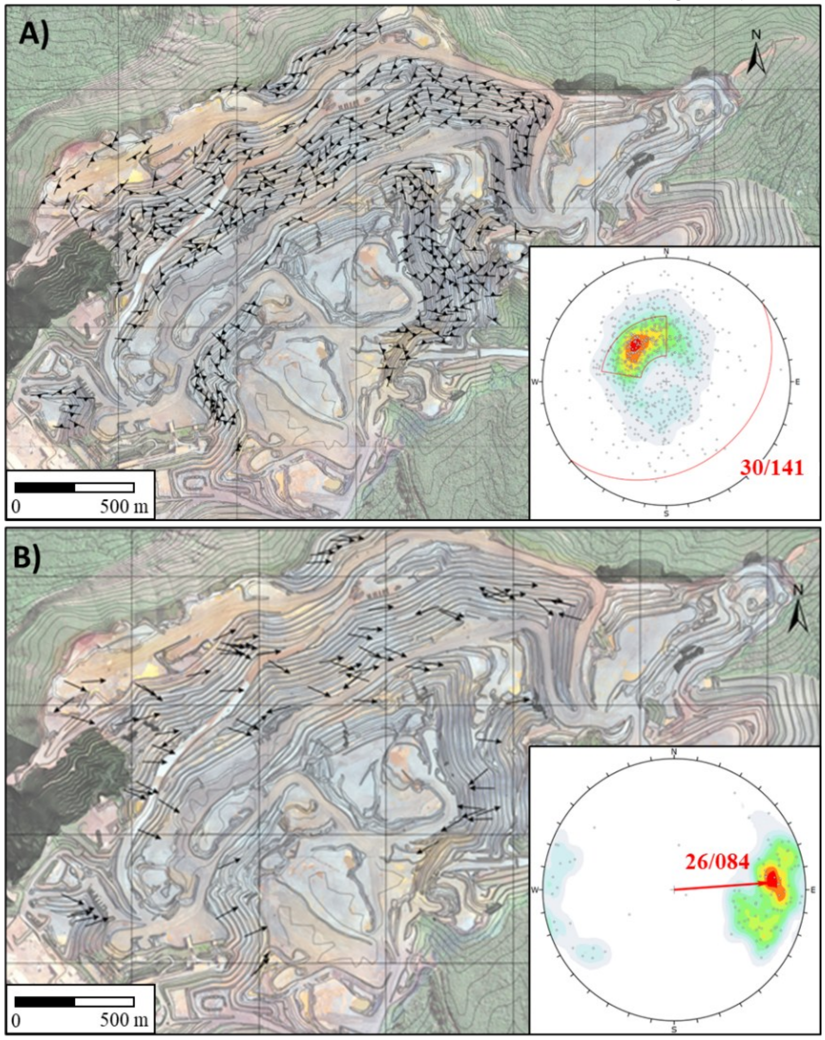


Figure 7 - A) Compositional banding and foliation, mean plane orientation 30/141. B) Fold axes and mineral stretching lineation, mean line orientation 26/084.
Source: author (2024).

Smaller-scale structures are extremely relevant for stability analyses of benches, but the model focus is to support inter-ramp and overall scale stability analyses. For this reason, joints were not considered in the model.

The anisotropic surfaces of geological contacts were elaborated by triangulation, where each mesh triangle has an attitude (dip / dip direction). These values were spatially distributed as structural data, which assumed the function of sample points and were interpolated by nearest <u>neighbor</u>, attributing dip / dip direction to the blocks.

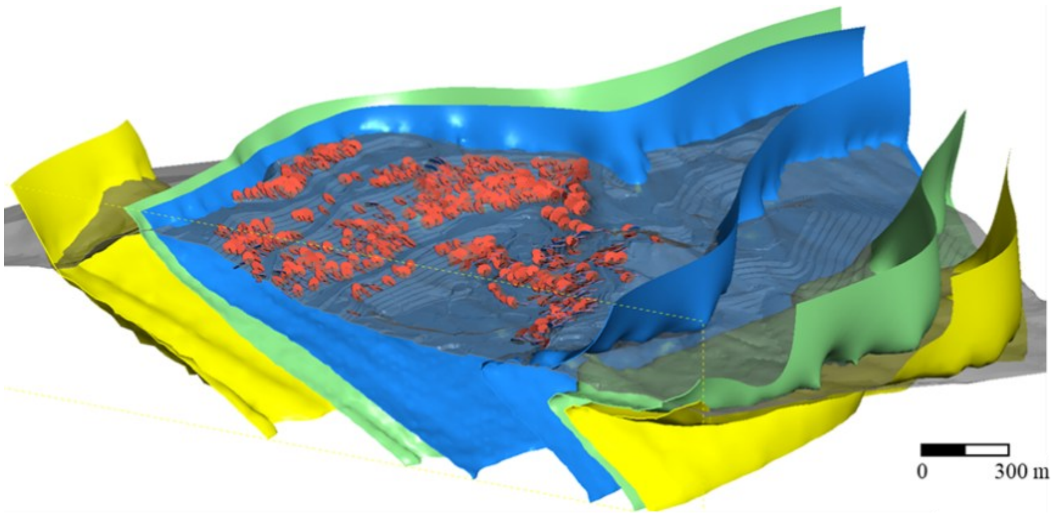


Figure 8 - Geological contact surfaces and structural measurements discs used as guides for the elaboration of the structural model.
Source: author (2024).

3.3 Strength Index Model

The strength index is categorized into seven classes (R0 to R6). As it is a categorical variable, the most suitable estimation method is indicator kriging. In this process, an indicator transformation is performed, where the category to be modeled is assigned the value 1, and the others are assigned the value 0. These binary data are then used for the variographic study and to define the spatial continuity of the phenomenon.

Initially, seven variographic studies and seven estimates were carried out using this methodology, but the results were not satisfactory. It was observed that the spatial continuity orientations varied significantly between studies, which was geologically inconsistent since the structures were formed by the same weathering and tectonic processes. As an alternative, the indicator transformation proposed by Cruz (2017) was employed. Despite being a simplified approach, this method provided results more consistent with the geology, as the obtained search ellipsoid aligned well with the general orientation of the mine's planar structures (compositional banding and foliation).

Planar structures are significant for water percolation and weathering due to the anisotropy of hydraulic conductivity generated by mineralogical differences in the compositional banding. Therefore, in addition to providing geostatistical support, the results of the variographic study showed physical coherence with the geology and structure of the mine.

The proposed variographic model aims to calculate the probability of blocks being classified as weak rock or not. If the value estimated by indicator kriging is closer to 1, the block is classified as 'weak'. If the estimated value is closer to 0, the block is classified as 'hard'. This process was replicated twice: once in the BIF domain (Figures 9 to 11) and once in the Schist domain, as these are the domains with the highest number of sampling points. Information on the ellipsoids used and the search parameters is detailed (Table 5). The variographic curve fitted the data well, resulting in consistent variographic models that confirm the spatial continuity of the modeled phenomena (Table 6). The obtained compactness variographic models were then used to estimate the individual categories (R0 to R6) and construct the strength index model.

Estimates	**Search Ellipsoid**			**Search Parameters**			
	Axes	Dip / Plunge	Range (m)	Lag Distance	n° Lags	Angular Tolerance	Band Width (m)
Compactness in BIF	Major	05/216	740	50	30	45°	200
	Semi-major	29/123	340	50	30	45°	200
	Minor	60/315	85	10	30	22.5°	-
Compactness in Schist	Major	05/054	680	100	20	45°	200
	Semi-major	29/147	200	50	20	45°	200
	Minor	60/315	80	10	50	22.5°	-
RQD	Major	12/067	450	50	20	45°	200
	Semi-major	27/163	320	50	20	45°	200
	Minor	60/315	150	10	50	22.5°	-

Table 5 - Search ellipsoids and parameters of the variography studies.

Source: author (2024).

Direction		
Dip	Dip Azimuth	Pitch
30°	135°	170°
Variogram Model		
Nugget	Structure 1 (Spherical)	Structure 2 (Spherical)
0.2269	0.2631	0.5100
Major	145.70	740.00
Semi-major	102.40	340.00
Minor	44.05	85.00

Table 6 - Variogram model.
Source: author (2024).

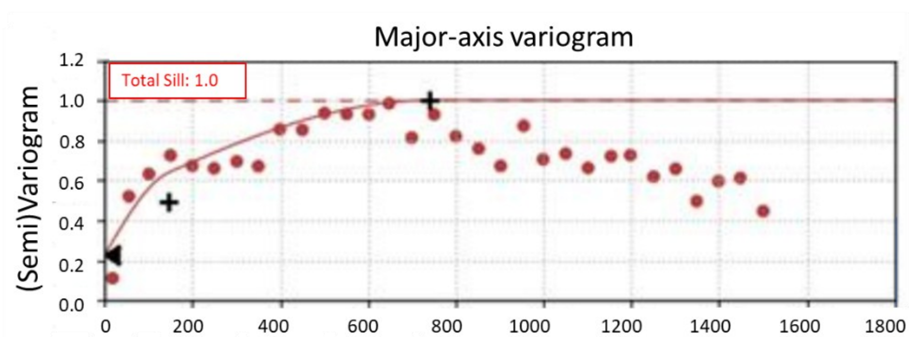


Figure 9 - Major axis variogram BIF 05/216.
Source: author (2024).

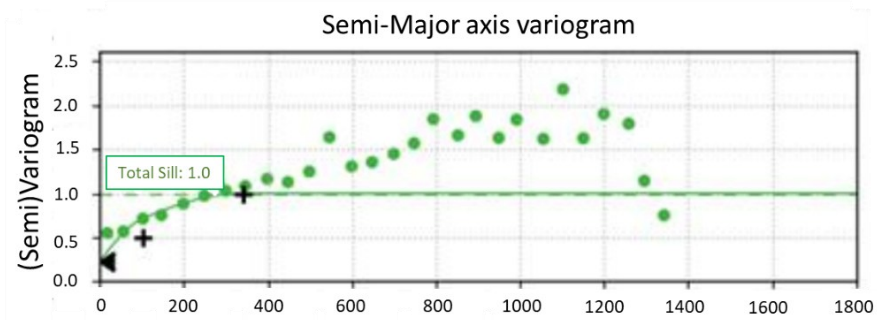


Figure 10 - Semi major axis variogram BIF 29/123.
Source: author (2024).

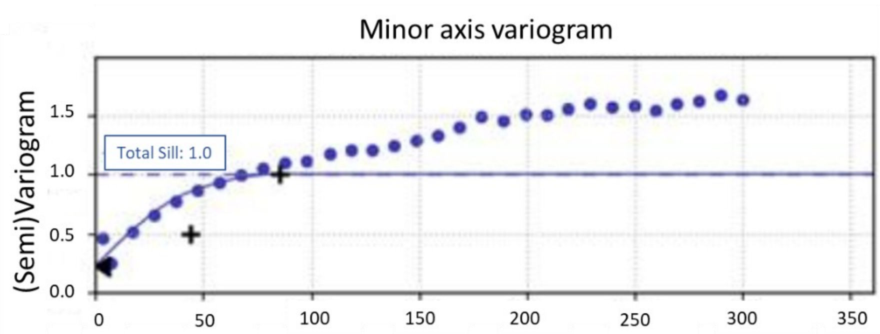


Figure 11 - Minor axis variogram BIF 60/315
Source: author (2024).

To assign strength index values to the non-estimated blocks, an implicit model was elaborated by indicator interpolation, replicating the spatial continuity identified in the variographic studies to the solids modeling parameters (Figure 12). The non-estimated blocks were assigned according to the modal value of each lithotype, respecting the compactness classification.

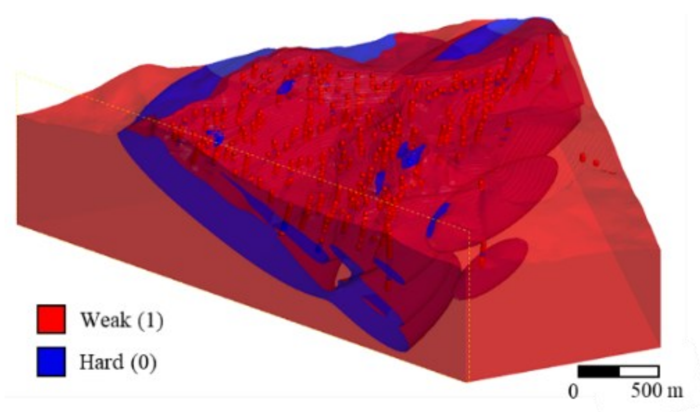


Figure 12 - Compactness implicit model. Weak (R0 to R2) and Hard (R3 to R6).
Source: author (2024).

The strength index assignments for the Cover and Intrusive domains were carried out using the nearest neighbor technique, with a maximum distance of 300 meters to avoid excessive extrapolation. For the non-estimated blocks, the strength attribute was assigned based on the modal value of the lithotype. In the Quartzite and Basement domains, where there were insufficient samples for any estimation type, the assignment was made using the implicit compactness model: R5 for hard materials and R1 for weak materials.

The validation of the estimates was conducted using four techniques: visual inspection, the sum of probabilities obtained for each block (summing up to 100%), correlation with the structural geology dataset, and swath plot analysis. Additionally, blocks with negative kriging efficiency were disregarded, and the strength assignment was made based on the implicit compactness model and modal value.

Visual validation showed a good match between the sample points and the estimated values in the blocks. The geological contacts and the orientation of the lenses are consistent with the structural geology of the area, as demonstrated in sections AB and CD (Figure 13).

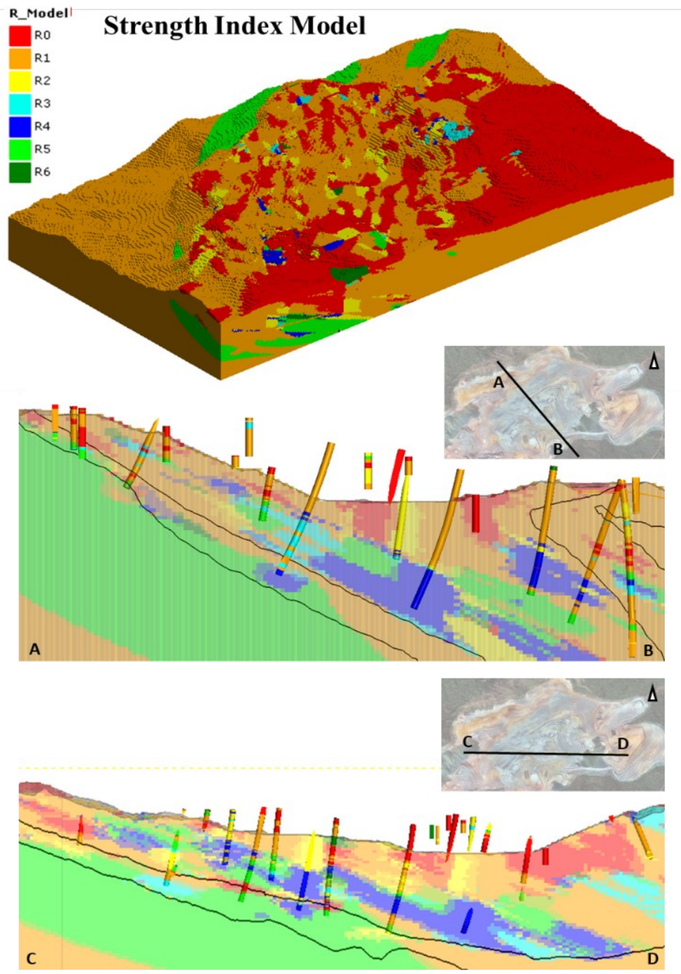


Figure 13 - Visual validation of Strength Index Model.
Source: author (2024).

The sum of the probabilities from the compactness estimates and strength categories resulted in 100%, as expected. The variography results were consistent with the area's structural geology, as the direction of greater compactness continuity aligns with the orientation of planar structures (banding and foliation). Therefore, the spatial distribution of strength is controlled by the compositional banding and the main foliation of the mine.

The analysis of the swath plots along the XYZ axes revealed a slight underestimation bias. In the indicator transformation, the value 0 represents compact rocks and 1 represents friable rocks. The underestimation indicates that the volume of compact rocks is greater than suggested by the samples. However, the behavior of the average curves of the estimated blocks and the average of the samples shows that the estimator was effective and accurately reflected the compactness behavior.

The volume of each swath is shown by the histogram below the curves and indicates a smaller amount of schist blocks compared to the iron formation. Additionally, there are fewer schist samples than iron formation samples, leading to better curve fittings for the iron formation, where the estimator showed a smaller negative bias compared to the schist estimator. The first and last swaths represent the edges of the model box, regions where the volume of sample points is noticeably smaller than in the central region, which causes a greater deviation of the mean curves in both schist and iron formation. This phenomenon is known in geostatistics as the border effect. The swath plots for the XYZ compactness estimate were performed (Figure 14).

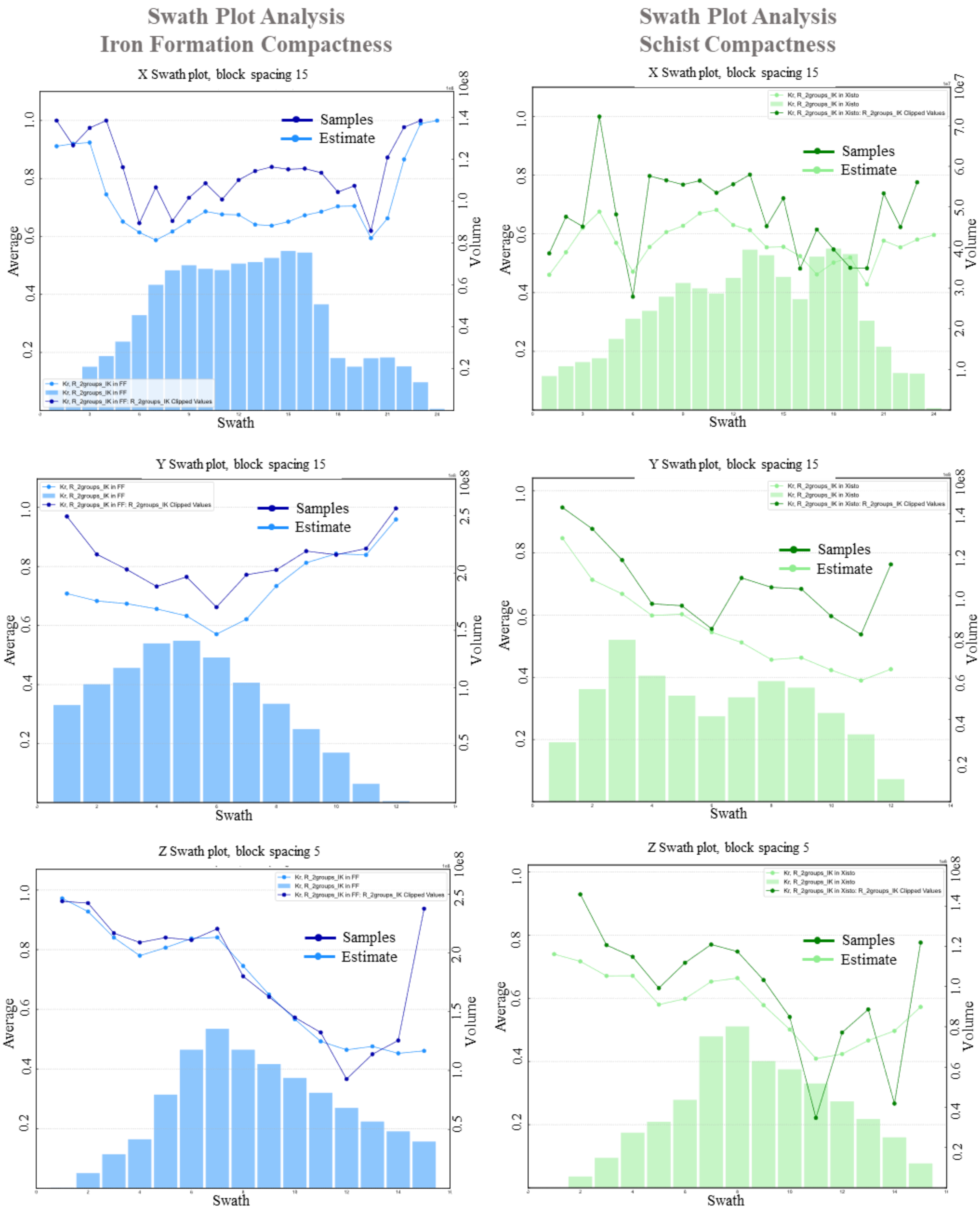


Figure 14 - Compactness swath plot analysis in schist and iron formation domains.
Source: author (2024).

3.4 Degree of fracturing Model

The degree of fracturing is a categorical variable, divided into six distinct categories. For the indicator kriging estimation, it was necessary to adopt a methodology similar to that used in modeling the strength index, grouping variables to simplify the indicator transformation. However, the degree of fracturing in the studied mine shows a strong correlation with RQD ($R^2 = 0.89$), a numerical and continuous variable (ranging from 0 to 100%), which allows for the application of ordinary kriging estimation. This significant correlation is observed in samples classified as hard (R3 to R6), where, unlike weaker rocks, the degree of fracturing plays a crucial role in determining rock quality. Thus, a variographic study of RQD was conducted, and the results are presented (Figure 15).

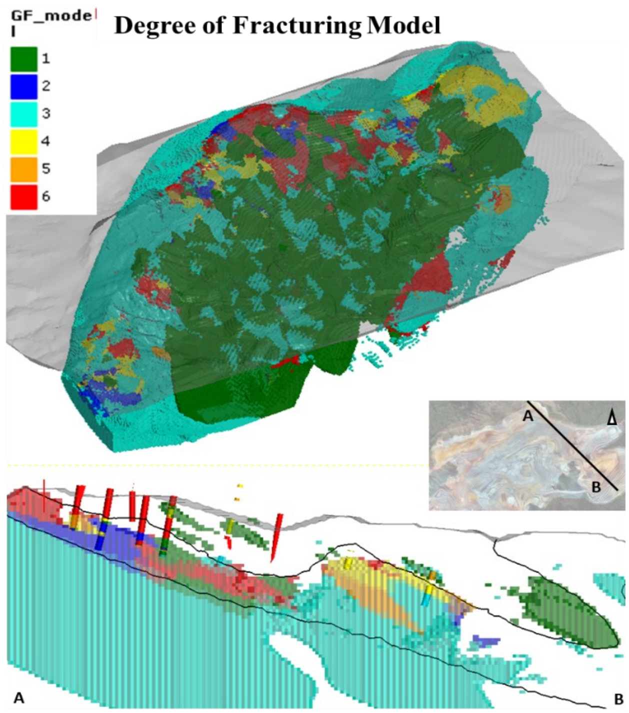


Figure 15 - Visual Validation of degree of fracturing model, with assignment of GF values only in the compact blocks (R3 to R6).
Source: author (2024).

The variographic model obtained was replicated for the indicator kriging estimation of each of the six fracturing grades, applicable exclusively to hard rocks. This approach is deemed viable because the geological and structural phenomena influencing both variables are the same, resulting in similar distribution and spatial continuity.

Generally, rock fracturing is structurally controlled by shear zones and/or regional folds. The search ellipsoid defined after the variographic study revealed a similar direction for planar features (such as compositional banding and foliation) and is aligned with linear structures (such as mineral stretching and fold axes). Thus, the spatial distribution of fracturing is controlled by the mineral stretching of the mine.

Non-estimated blocks were assigned values based on the implicit compaction model and the modal value of the fracturing grade for each lithotype. The estimation validation was performed using the same four techniques applied to the strength index model: visual inspection, the sum of probabilities in each block (totaling 100%), correlation with the structural geology dataset, and swath plot analysis. All employed techniques showed good adherence to the available dataset. Therefore, it can be stated that the estimation accurately represents the behavior of RQD in the rock mass. The swath plots of the XYZ RQD estimate are presented (Figure 16).

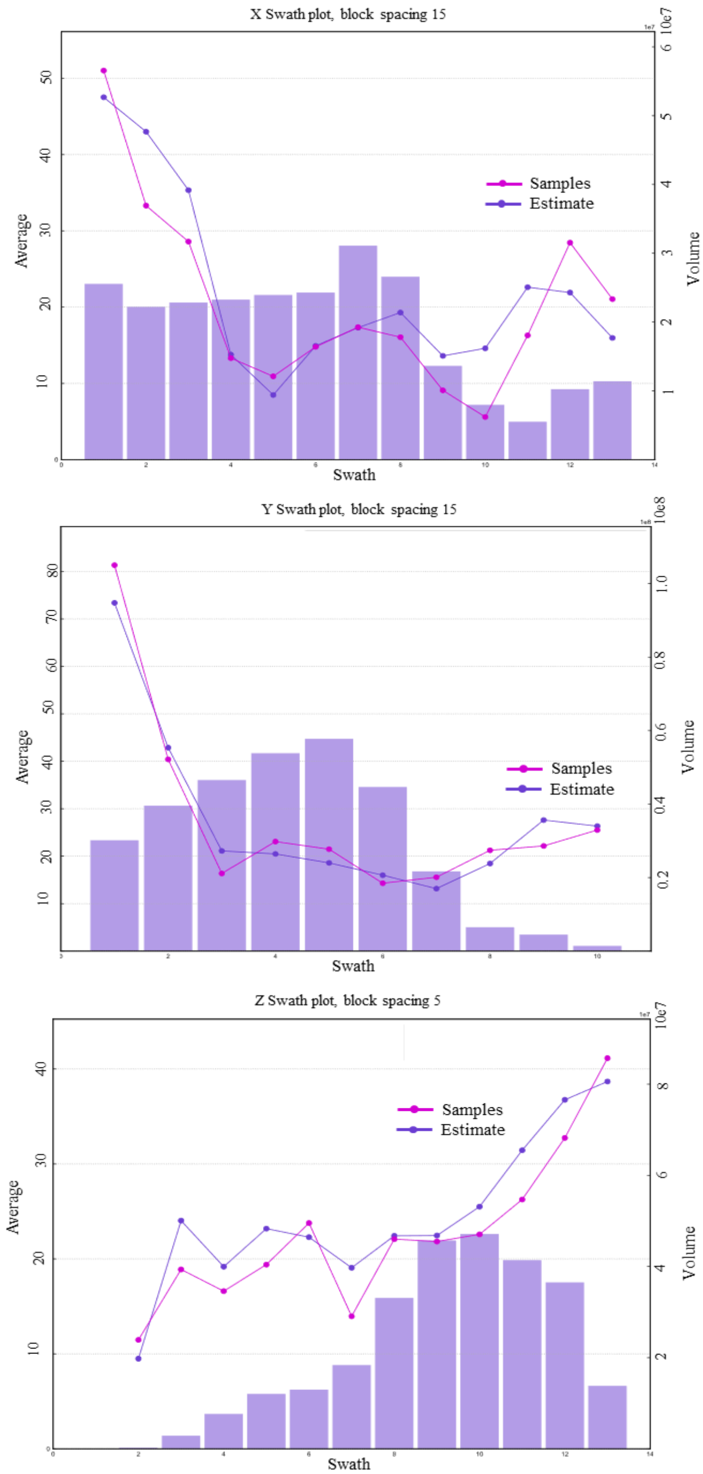


Figure 16 - RQD swath plot analysis.
Source: author (2024).

3.5 Roughness Model

Roughness data were restricted to hard rocks, but the studied mine is predominantly composed of weak rocks. As a result, the volume of available samples was insufficient to conduct a consistent variographic study. Therefore, the roughness model was developed using the nearest neighbor method, with a maximum distance of 100 m to avoid excessive extrapolation. Non-estimated blocks were assigned values based on the modal value for each geological domain (Quartzites, Schists, Iron Formations, and Intrusive Formations). The final model generated is a block model with roughness information, respecting the available sampling points and the modal values defined for each geological domain (Figure 17).

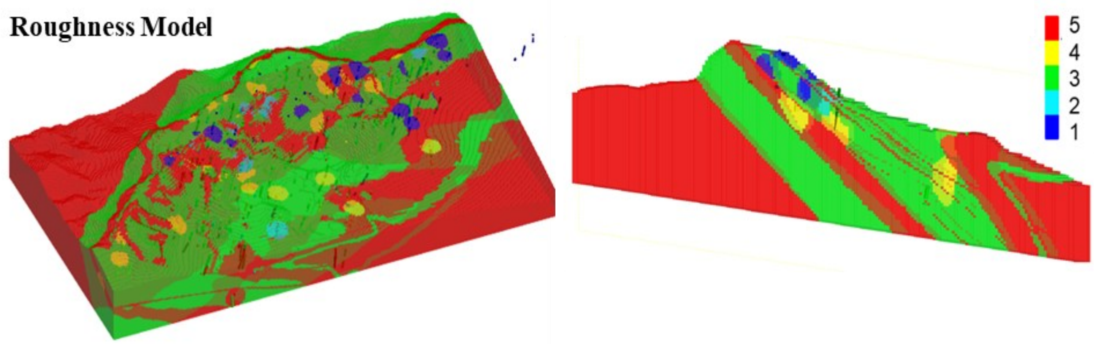


Figure 17 - Roughness Model.
Source: author (2024).

3.6 Geomechanical Model

The geomechanical model integrated the following models from the previous stages: strength index, degree of fracturing, and roughness. The GSI methodology is primarily applicable to rock masses and, therefore, was not used for weak rock blocks with soil-like behavior. The assignment of GSI values to hard rock blocks was carried out through computational logic, following the proposed adaptation of the GSI table. For example, a block with a degree of fracturing of 3 and roughness of 2 was assigned a GSI value of 55 (Figure 18).

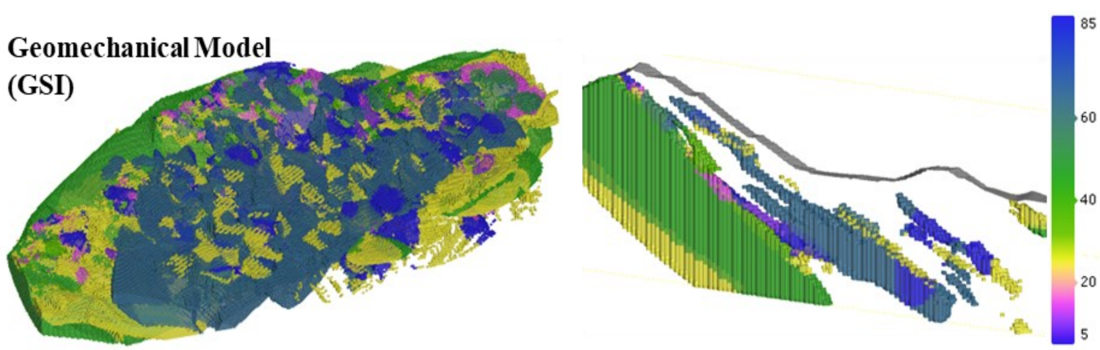


Figure 18 - Geomechanical Model.
Source: author (2024).

3.7 Hydrogeological Model

The hydrogeological model was elaborated by attribution of equivalent values of hydraulic conductivity (K) based on the lithotype, rock strength and GSI values. The values attributed to each material (Table 7) and the final model (Figure 19) are presents.

Lithotype	Strength	GSI	Geotechnical units	Hydraulic Conductivity
				K (m/d)
Cover	Hard	-	COV_COMPAC	0,530
	Weak	-	COV_WEAK	0,530
Intrusive	Hard	15	IN_GSI_15	0,049
	Weak	-	IN_WEAK	0,0075
Banded Iron Formation (BIF)	Hard	75	BIF_GSI_75	0,660
	Hard	45	BIF_GSI_45	0,800
	Hard	15	BIF_GSI_15	0,920
	Weak	-	BIF_WEAK	0,740
Schist	Hard	75	SC_GSI_75	0,049
	Hard	45	SC_GSI_45	0,073
	Hard	15	SC_GSI_15	0,089
	Weak	-	SC_WEAK	0,0075
Quartzite	Hard	45	QT_GSI_45	0,041
	Weak	-	QT_WEAK	0,046
Basement	Hard	15	BAS_GSI_15	0,089
	Weak	-	BAS_WEAK	0,0075

Table 7 - Hydraulic conductivity (K) attributed to materials.
Source: author (2024).

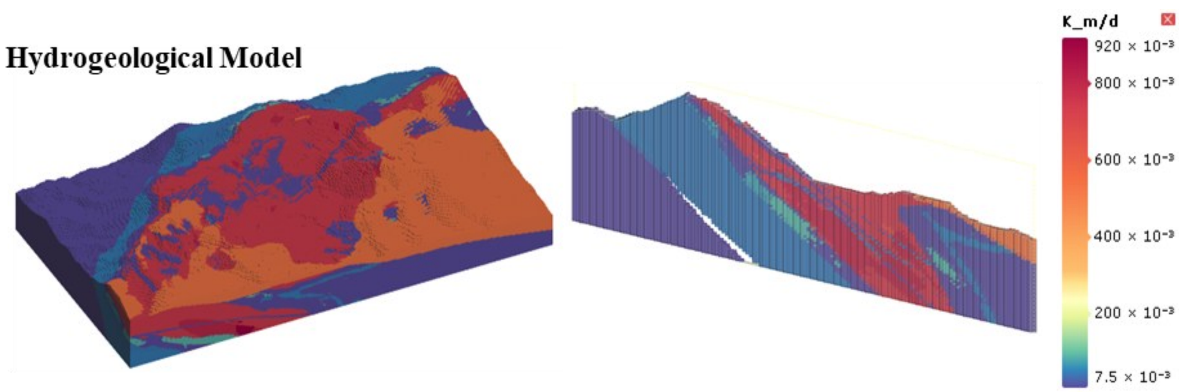


Figure 19 - Hydrogeological Model.
Source: author (2024).

3.8 Geotechnical Model

The geotechnical model was developed by integrating all thematic models into a single point in space, represented by the block centroid. To facilitate the application of the model in stability analyses and considering computational utility, a simplification was applied to the geomechanical model to reduce the number of materials. Before this simplification, the same lithotype could have up to ten different GSI values, resulting in ten materials with distinct geotechnical parameters. After simplification, the GSI values were reduced to three options (75, 45, or 15).

A flowchart illustrates the computational logic used in the model integration (Figure 20), consolidating all necessary information into a single product, the block model (Figure 21). The final model resulted in sixteen materials, each with distinct geotechnical parameters to be used in stability analyses (Figure 5F).

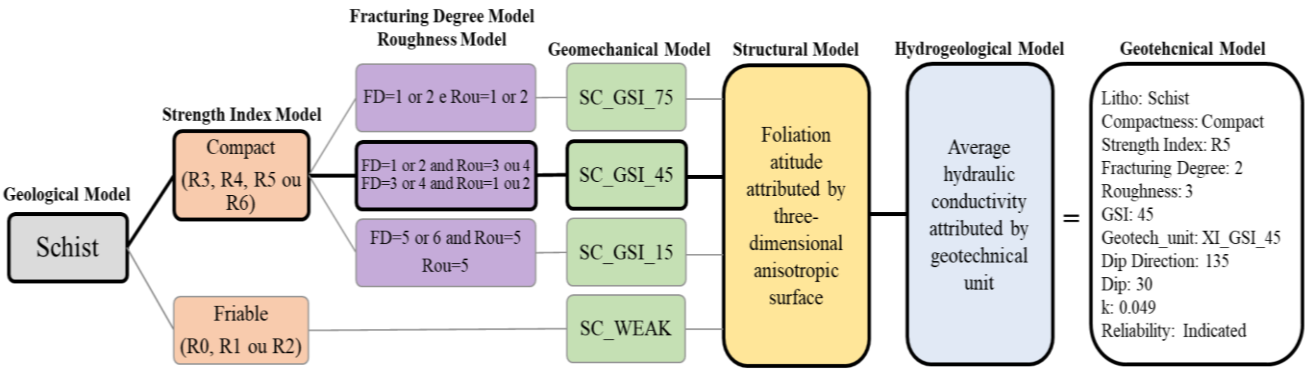


Figure 20 - Flowchart exemplifying the computational logic used for model integrations.
Source: author (2024).

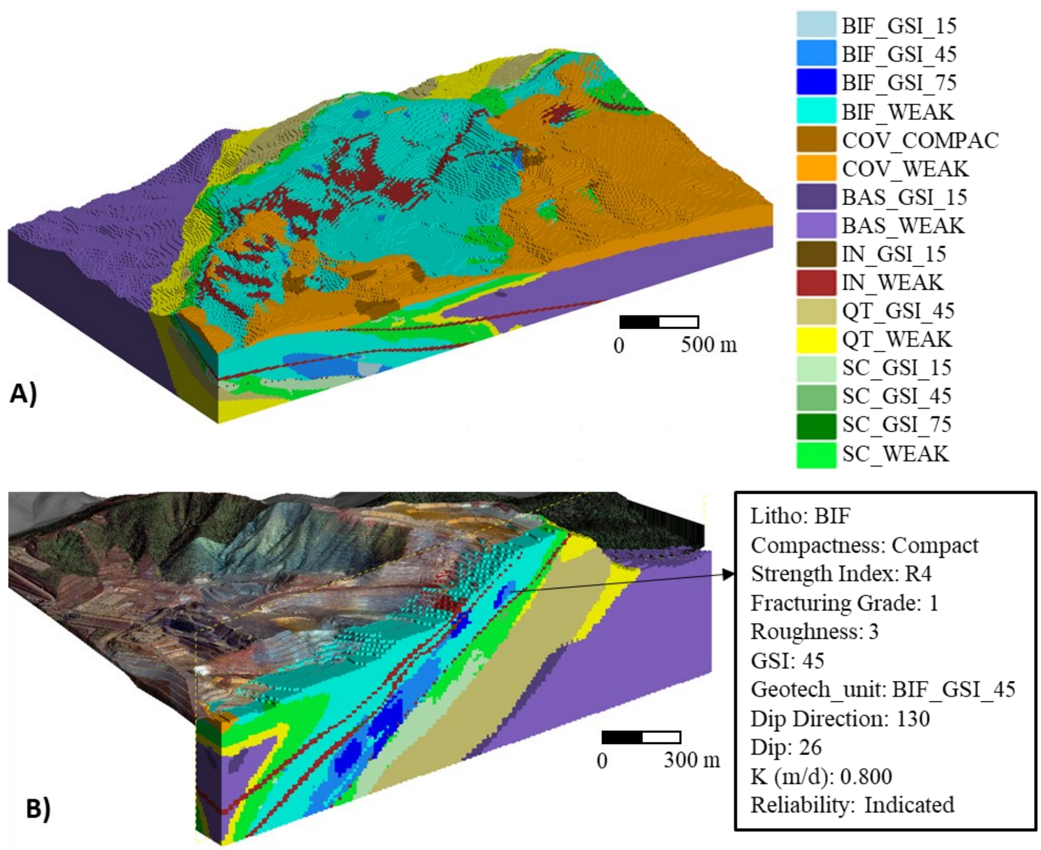


Figure 21 - A) Geotechnical Model with all geotechnical units. B) Model cross section and information contained in each block.
Source: author (2024).

3.9 Reliability of Geotechnical Information

The geostatistical approach allowed for the measurement of estimation error and, consequently, the assessment of the reliability attributed to the blocks. This method is widely used in the classification of mineral resources and reserves, with various methods available for defining classification criteria (ROSSI and DEUTSCH, 2013). The reliability classification of the geotechnical information estimated for each block in a geotechnical model is an innovation with great potential to optimize geotechnical investigations, as it identifies areas with insufficient information and guides drilling and field survey plans.

The classification criteria adopted were kriging efficiency (KE) (KRIGE, 1966) for blocks estimated by kriging and average distance (AvgD) for blocks interpolated by nearest neighbor. Based on this concept, a reliability classification for the strength index assigned to the blocks was developed. The strength index was selected because it is the most relevant variable for the stability of the mine slopes, which are predominantly excavated in weak rocks. The adopted classification criteria (Table 8) and the obtained results (Figure 22) are presented.

Domain	Criteria	Reliability Classification
Cover and Intrusive	AvgD <= 50m	Measured
	AvgD <= 100m	Indicated
	AvgD > 100m	Infered
BIF and Schist	0.6 < KE <= 1	Measured
	0.2 < KE <= 0.6	Indicated
	KE <= 0.2	Infered
Quartzite and Basement	Sample scarcity	Infered

Table 8 - Reliability classification criteria.
Source: author (2024).

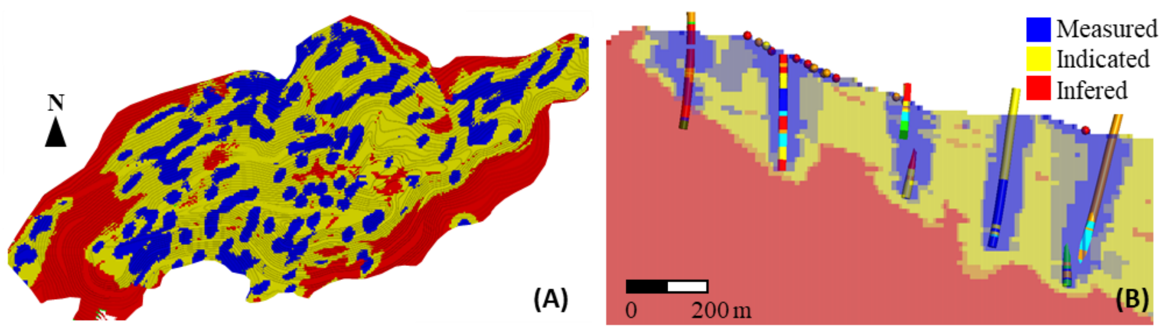
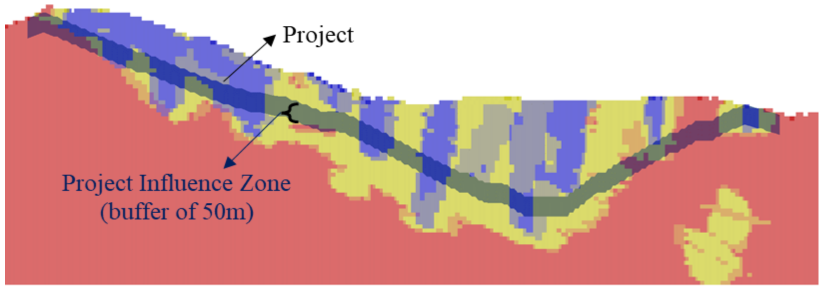


Figure 22 - A) Pit geometry project with prediction of geotechnical data reliability. B) Block model section with geotechnical data reliability, mapping points and drillholes.
Source: author (2024).

The proposed methodology enables the integration of multiple models into a single product. Integrating such complex models in a three-dimensional solid framework would be virtually unfeasible due to the creation of an immense number of small volumes and the storage requirements of surface-based formats (resulting in very large files). Therefore, the block model approach was chosen, as it allows multiple variables to be assigned to the same point while storing the information in lightweight file formats (csv, xls, dat, txt).

The developed geotechnical model is multidisciplinary and provides valuable information for various teams, including geotechnical engineers, geologists, hydrogeologists, mine planners, and drilling personnel. In a mineral excavation project, asset maturity progresses through the following phases: conceptual, pre-feasibility, feasibility, operational, and closure. Each phase requires different levels of information maturity to adequately support decision-making.

The proposed reliability classification for the blocks offers significant potential, providing a means to quantify data uncertainty within projects. These values can be used to assess project maturity. For instance, conceptual and long-term projects are more flexible and can tolerate a higher percentage of inferred blocks, whereas operational projects demand greater precision and data reliability. Accordingly, based on the results obtained and discussed, the reliability classification within the project's influence zone is presented in Figure 23.



		Reliability	Block Count	%	
Project Influence Zone (buffer 50m)	Waste 61%	Measured	17320	14%	43%
		Indicated	35595	29%	
		Infered	70081	57%	57%
	Ore 39%	Measured	18411	23%	81%
		Indicated	46375	58%	
		Infered	14828	19%	19%

Figure 23 - Reliability classification within project influence zone.
Source: author (2024).

4. Conclusions

In this study, an integrated methodology for the construction of a three-dimensional geotechnical model applied to open-pit mining was presented and validated, combining implicit modeling techniques with geostatistical estimates within a block model framework. The proposed approach proved effective in integrating geological, structural, geomechanical, and hydrogeological thematic models into a single coherent product, suitable for slope stability analyses and mine planning applications.

The systematic use of geostatistical tools for modeling predominantly categorical geotechnical variables, such as the strength index and degree of fracturing, constituted a central contribution of this work. Through the application of indicator kriging, supported by variographic models consistent with the structural geology of the mine, the subjectivity traditionally associated with geotechnical model construction was significantly reduced. The resulting spatial distributions exhibited strong geological coherence, with continuity directions aligned with the main planar and linear structural features of the deposit.

Additionally, a reliability classification of geotechnical information at the block scale was incorporated, based on kriging efficiency and interpolation distance. This approach, widely applied in mineral resource evaluation but still uncommon in geotechnical modeling, allowed for the quantification of data uncertainty. The reliability classification proved to be a practical tool for identifying areas with insufficient information, guiding future drilling campaigns, and supporting decision-making throughout the different stages of project maturity.

The application of the methodology to a large open-pit iron ore mine demonstrated that, within the main zone of influence for slope stability (approximately the first 50 m from the project surface), waste rocks accounted for the majority of the excavated material. However, only 43% of the waste rock blocks were classified as measured or indicated, compared to 81% of the ore blocks. This imbalance indicated a relevant challenge in open-pit mine geotechnical projects, as slope stability was predominantly controlled by the behavior of waste rocks, which exhibited lower data density and higher uncertainty.

The final geotechnical block model, simplified to a manageable number of geotechnical units and GSI classes, proved suitable for direct integration into three-dimensional stability analyses. In addition to supporting geotechnical design, the model provided relevant information for multidisciplinary teams, including mine planning, hydrogeology, and drilling, reinforcing its applicability throughout the entire life cycle of the mining project, from conceptual studies to operational decision-making.

Overall, the proposed methodology represented an advance in the quantitative characterization of geotechnical conditions in open-pit mines. By explicitly addressing uncertainty and information reliability, it contributed to the development of more transparent, auditable, and risk-oriented geotechnical models. As future perspectives, it is indicated that geostatistical simulation techniques may be incorporated to enable a more comprehensive uncertainty assessment, as well as that the methodology may be extended to include additional structural features and time-dependent hydrogeological effects.

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