UNIVERSIDADE FEDERAL DO RIO GRANDE DO SUL
ESCOLA DE ENGENHARIA
Programa de Pós-Graduação em Engenharia de Minas, Metalúrgica e de Materiais (PPGE3M)

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Aplicação Prática de Fluxo de Trabalho de Scorecard de Múltiplas Camadas (MLSW) para Classificação de Recursos Minerais

Porto Alegre
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2023

CIP - Catalogação na Publicação

Rocha, Vinicius
Aplicação Prática de Fluxo de Trabalho de Scorecard de Múltiplas Camadas (MLSW) para Classificação de Recursos Minerais / Vinicius Rocha. -- 2023.
54 f.
Orientador: Marcel Antonio Arcari Bassani.

Dissertação (Mestrado) -- Universidade Federal do Rio Grande do Sul, Escola de Engenharia, Programa de Pós-Graduação em Engenharia Civil: Construção e Infraestrutura, Porto Alegre, BR-RS, 2023.

1. classificação de recurso. 2. recurso mineral. 3. risco. 4. incerteza . 5. geoestatistica. I. Bassani, Marcel Antonio Arcari, orient. II. Título.

Elaborada pelo Sistema de Geração Automática de Ficha Catalográfica da UFRGS com os dados fornecidos pelo(a) autor(a).

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Dissertação defendida e aprovada em: 22, de setembro de 2023.

Orientador: Prof. Dr. Marcel Antônio Acari Bassani

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AGRADECIMENTOS

Agradeço ao Prof. Dr. Marcel Antonio Arcari Bassani por seus ensinamentos e disponibilidade. Sua orientação foi fundamental para o desenvolvimento deste trabalho.

Agradeço também ao Prof. Dr. João Felipe Coimbra Leite Costa e aos demais professores do PPEGEM/LPM por compartilharem seu conhecimento e experiência.

Agradeço aos colegas que contribuíram com este trabalho, especialmente Diniz Ribeiro, Debora Roldao, Anderson Miyashita, Jessica Shiels, Amanda Landriault, Juan Fernandez e Bruno Afonseca.

Expresso minha gratidão aos amigos Eduardo Pinheiro e Carla Vanessa pelo apoio constante e troca de ideias.

Agradeço à minha família, especialmente à Aylime, pelo companheirismo incondicional ao longo dessa jornada.

"The only true wisdom is in knowing you know nothing." - Socrates

Resumo

A classificação de Recursos Minerais desempenha um papel crucial na divulgação pública e é fundamental para avaliar a maturidade e o risco associado a um depósito mineral, auxiliando na tomada de decisões informadas sobre a viabilidade econômica de um projeto ou operação. Para garantir precisão e abrangência, os recursos minerais devem ser classificados com base em seu nível de confiança e categorizados como Medido, Indicado ou Inferido. Nesse contexto, este estudo propõe o uso de um fluxo de trabalho via *scorecard* com múltiplas camadas para a classificação de Recursos Minerais, que leva em consideração diversos fatores provenientes de diferentes disciplinas. Essa abordagem é flexível, permitindo que o usuário adapte o fluxo de trabalho do *scorecard* às particularidades de cada depósito. No presente trabalho, foram consideradas métricas clássicas para a Classificação de Recursos, tais como o número de amostras (NS), a inclinação da reta de regressão (*slope of regression* - SR), a eficiência da krigagem (KE) e a variância da krigagem (KV), juntamente com métricas mais modernas, como o Índice de Risco, que combina a variância de krigagem e a continuidade geológica por meio de uma abordagem probabilística. Além disso, a metodologia pode incorporar informações qualitativas obtidas por meio de geomodeladores especialistas, como a complexidade geológica. O objetivo é classificar os recursos minerais considerando todos os componentes relevantes que afetam a incerteza e o risco associados a eles. O fluxo de trabalho proposto foi aplicado a dois bancos de dados diferentes estudos de caso: um caso 2D e um caso 3D. Os resultados demonstram a aplicabilidade da metodologia na classificação de recursos minerais, levando em consideração informações provenientes de diversas fontes. Essas múltiplas fontes são agrupadas por meio de uma combinação linear, em que cada fator recebe um peso. Ao adotar uma abordagem de múltiplas camadas para a classificação de recursos, este estudo tem como objetivo fornecer uma avaliação abrangente da categorização dos recursos. A metodologia do scorecard de classificação de recursos minerais oferece uma avaliação integrada de riscos, incorporando informações multidisciplinares provenientes dos departamentos de geologia e geociências. Além disso, proporciona adaptabilidade, transparência e rastreamento de auditoria. Ao considerar esses aspectos, a metodologia busca fornecer uma avaliação abrangente dos recursos minerais, auxiliando os tomadores de decisão na avaliação da viabilidade econômica de um projeto ou operação mineral

Palavras-Chave: *classificação de recurso; recurso mineral; risco; incerteza; krigagem de indicadores; geologia; código JORC; Indice de Risco.*

Abstract

The classification of mineral resources is crucial for public disclosure. It is used to evaluate the maturity and risk associated with the mineral deposit to make informed decisions about the economic viability of a project or operation. To ensure accuracy and thoroughness, mineral resources must be classified based on their confidence level and categorized as Measured, Indicated, or Inferred. To address this need, this study proposes the use of a multi-layer scorecard workflow (MLSW) for mineral resource classification that considers multiple factors from different disciplines. This approach is highly flexible as the competent user may adapt the scorecard workflow to the particularities of each deposit. This study considered classical metrics for resource classification, such as the number of samples, the slope of regression, kriging efficiency, and kriging variance, combined with more modern ones (Risk Index), which combines the kriging variance and geological continuity using a probabilistic approach. The methodology can also incorporate qualitative information from the expert geomodeler, such as the geological complexity. The goal is to classify mineral resources considering all the relevant components that affect the uncertainty and risk associated with it. The proposed workflow has been applied in two different databases: one 2D and one 3D case. The results show the applicability of the methodology to classify mineral resources considering information from multiple sources. These multiple sources are combined as a linear combination, where each factor receives a weight. Using a multi-layer approach to resource classification, this study aims to provide a comprehensive and well-rounded evaluation of mineral resources. The mineral resource classification scorecard methodology offers integrating risk assessment, incorporating input from geology and geoscience departments, in addition to its adaptability, transparency, and audit trails. Considering these aspects, the methodology aims to provide an extensive mineral resource evaluation, supporting the decision-makers in assessing the economic availability of a project or the mineral operation.

Keywords: *resource classification, mineral resource, risk, uncertainty, indicator kriging, geology, JORC code, Risk Index*

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List of Abbreviations

2D – Two dimension

3D – Three dimension

BDens – Bulk Density

BV – Block Variance

CP - Competent Person

CRIRSCO - Committee for Mineral Reserves International Reporting Standards

DIQ – Data Integrity and Quality

IK – Indicator Kriging

JORC - Joint Ore Reserves Committee

KE - Kriging efficiency

KV - Kriging variance

MLSW - Multi-layer Scorecard Workflow

NS – Number of Samples

OG – Orebody Geology

OK – Ordinary Kriging

OF – Other Factors

PGE – Platinum Group Elements

QA/QC - Quality Assurance & Quality Control

RI – Risk Index

SAMREC - The South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves

SR – Slope of Regression

SUMÁRIO

1. Introduction

Mineral resource classification is extremely relevant for investment decisions, reserve estimation, and mine planning, and helps to provide a more informed understanding of the potential risks of exploiting a deposit. The economic viability of mining projects depends on multiple factors, with resource classification playing a crucial role throughout the mining process. Accurate resource classification is essential for a reliable risk assessment within a mineral deposit. Companies typically report their economic assessment results to attract investments, and mineral resource classification standards were established to provide a clear framework for public disclosure of mineral deposits.

The classification of resources aims to determine the degree of confidence and is mandatory according to the guidelines of the international codes. The geological confidence of resources is assessed and categorized as Measured, Indicated, and Inferred in descending order of geological confidence (JORC, 2012). This classification is based on the level of geological knowledge, drilling density, and data quality available for the deposit.

Various factors influence the classification of mineral resources, including the conditions and circumstances of the mining project, as well as geological and technical considerations. Mineral resources also must have reasonable prospects for eventual economic extraction (JORC, 2012). Usually, the mineral resources classification procedure is tailored to each deposit. Despite the differences in each project, it is essential that the mineral resources classification must be robust and can be defendable by the Competent Person (CP), who is the professional responsible for the resources model.

The mineral resources classification procedure should comply with the guidelines written in international reporting codes (CRIRSCO, 2013; JORC, 2012; SAMREC, 2009). The international reporting codes inform the general principles and good practices but do not have a specific protocol for classifying mineral resources (SOUZA, 2002). Over time, various approaches have been employed, such as determining classifications based on the number of data in nearby search areas, used to estimate mining blocks, spacing between drill holes, range of variability, kriging variance, regression slope, and past experiences with similar deposits (VERLY; PARKER, 2021).

To provide a more multidisciplinary, comprehensive, and traceable approach to mineral resource classification, a multi-layer scorecard workflow is advocated (DUGGAN et al., 2017; MOHANLAL; STEVENSON, 2010; PARKER; DOHM, 2014). This systematic approach involves weighting or grading multiple linear parameters to determine the confidence level of a mineral resource estimate and derive a final score for classification. The method considers various factors that impact the estimation of resources, production scheduling, and the costs associated with the mining process.

An interesting metric used for mineral resource classification is the Risk Index (AMORIM; RIBEIRO, 1996). The Risk Index combines the estimation error and geological continuity with a probabilistic ore and waste relationship. An indicator kriging estimate measures the geological continuity, while the estimation error is characterized by the kriging variance. The Risk Index, akin to classical geostatistical metrics for resource classification, such as the number of samples, the slope of regression, kriging efficiency, and kriging variance, is generally effective in evaluating massive ore bodies. However, it can be prone to artifacts when the mineralization consists of several orebodies unconnected.

Souza (2002) emphasises the necessity for precise resource classification based on risk levels and the formidable challenge of establishing confidence limits within existing classification systems. The study investigates alternative methodologies, including the application of geostatistical techniques such as kriging and stochastic simulation, to incorporate uncertainty into resource and reserve estimates. It also underscores that while ordinary kriging offers expeditious tonnage estimates, it relies on assumptions that can be challenging to substantiate. In contrast, simulation techniques demonstrate their capacity to approximate estimation errors by generating multiple tonnage models, facilitating a more realistic evaluation of uncertainty (SOUZA 2002).

Moreover, conditional simulation generates representations of the model uncertainty at a global and local scale. These representations find relevance in tasks encompassing resource classification and risk analysis for mine production. However, fusing these representations to establish probability intervals for resource classification remains comparatively limited and not yet widespread (ROSSI; DEUTSCH, 2014). It's noteworthy that adopting probabilistic methodologies that incorporate simulated models for resource classification across different operational stages or projects could prove advantageous ((BADENHORST; ROSSI, 2012; DIMITRAKOPOULOS, 1997; GLACKEN, 1996; GUARDIANO; PARKER; ISAAKS, 1995; JOURNEL; KYRIAKIDIS, 2004; LEUANGTHONG; DEUTSCH, 2003; ROSSI, 1999; ROSSI; CAMACHO, 2004; VAN BRUNT; ROSSI, 1999). However, as highlighted by Deutsch et al. (2007), it is crucial to emphasize that uncertainty models stemming from conditional simulations should serve as a supplementary resource for other technic, such as geometric-based drill hole distance. Deutsch et al. (2007) delve deeply into several aspects of the study conducted. Firstly, they extensively examine how the level of uncertainty is intricately linked to the decisions made about models and stationarity. Even minor adjustments in these aspects can wield considerable influence. Secondly, they highlight the intricate interplay of various parameters, which affects uncertainty in ways that may not be immediately apparent. Notably, an increased nugget effect has the abrupt consequence of reducing uncertainty for larger mining scales. Thirdly, the study underscores the significant roles played by uncertainty in the histogram and spatial continuity parameters. Lastly, the paper underscores the intricate nature of selecting uncertainty parameters for classification. It emphasizes the strong reliance of this selection on the specific characteristics of the deposit under consideration. For instance, choosing between relative and absolute uncertainty can dramatically reshape how uncertainty is perceived in regions containing lower-grade resources. Furthermore, certain types of deposits inherently possess lower levels of uncertainty, yet they lack comprehensive measurement data, particularly in cases where drill hole spacing is wide.

This work shows two case studies of mineral resources classification that incorporate the Risk Index into the multi-layer scorecard framework. The case studies consider data derived from real deposits. The idea is to combine the strengths of several metrics in a robust workflow. For instance, the Risk Index incorporates the geological continuity and amount of information but does not inform the data quality used. To overcome this issue, an additional data-quality score may be added to the multi-layer scorecard.

1.1 Goals and Objectives

The objective is to investigate and explore the practical application of a multi-layer scorecard workflow with a Risk Index for the classification of mineral resources. The methodology was applied in two case studies, using real deposit data to demonstrate how the risk index can be incorporated into a multi-layer scorecard framework. Additionally, the advantages of this multidisciplinary approach and the possibility of including an additional data quality score in the multi-layer scorecard will be discussed. The goal is to develop a robust workflow that considers various parameters for robust and traceable classification of mineral resources.

1.2 Study methodology

This study employs an approach that integrates multiple metrics. The main metrics are the kriging efficiency, the slope of regression, number of samples, search volume, and Risk index, which are traditionally used for mineral resources classification. The method also uses the following complementary and qualitative criteria: orebody geometry, data integrity and quality, bulk density, and other factors. The complementary criteria are not used often in mineral resource classification but are considered important.

The first step of the methodology is to convert the multiple criteria into confidence scores using thresholds. The thresholds are empirically determined by the Competent Person (CP). Each confidence score is related to a resource category. The scores for each category are shown in Table 1. We emphasize that the categories assigned in this step are not the final classification, they are a prior classification. The prior classification is done for each criterion separately. The core idea is to evaluate how each criterion contributes to the final resource estimate confidence.

Table 1 – Confidence categories and scores.

Confidence Category	Score
High Confidence	1
Medium Confidence	2
Low Confidence	3

The final mineral resource classification is determined by the global score, which is a linear combination of the scores obtained previously. The weights are defined by the Competent Person based on experience and the deposit's characteristics. For instance, if data quality is critical for mineral resource confidence, the criterion related to data quality receives more weight than the others. Usually, the weights sum up to one or one hundred so that the contribution of each criterion to the global score is straightforward.

The last step is to assign the final resource classification based on the global score. This is accomplished by defining thresholds for the global score. Similar to the thresholds used for the individual criteria, the global score thresholds are also determined by the Competent Person (CP). The criteria used to calculate the global score are explained in Section 2.1 to 2.9.

1.3 Dissertation Organization

The dissertation is structured into chapters and organized as follows:

- **Chapter 1 - Introduction**: This chapter introduces the topic, including the motivation, goals, study methodology, and overall organization of the dissertation.
- **Chapter 2 - Bibliography Review**: This chapter focuses on the background of the scorecard method for resource classification, including a summary of the geostatistics used for each criterion within the method. It offers a concise overview of the geostatistical aspects related to resource classification.
- **Chapter 3 - Practical Application**: The objective of this chapter is to apply the proposed workflow to two different real-world datasets. The case studies are presented in two distinct sections: Section 3.1 - 2D Case Study and Section 3.2 - 3D Case Study**.** The datasets demonstrate diverse degrees of geological complexity influenced by the characteristics of the deposit. Moreover, disparities in drilling campaigns, data quality, and other pertinent factors introduce variations in the confidence levels pertaining to the resources at specific locations. On Section 3.3 - Resource Classification Criteria and Considerations it is presentaded a table that summarizes key resource classification criteria, highlighting their respective pros and cons, aiding

in the selection of the most suitable approach for specific geological contexts.

- **Chapter 4 – Discussion and Conclusions**: This chapter encompasses a comprehensive discussion on the implementation of the methods proposed in the dissertation. It further includes concluding remarks, a self-assessment of the study's outcomes, and contemplation of potential next steps and areas for improvement.

2. Bibliography Review

This chapter provides a review of the theoretical concepts related to the classification methods used in the proposed scorecard in this study. These methods include kriging efficiency, slope of regression, number of samples, kriging search volume, indicator kriging, risk index, and other risk factors that influence the classification of a mineral resource. Additionally, this chapter presents a historical background of the classification methodology via scorecard found in the literature.

2.1 Background on Scorecard for Resources Classification

The mineral resource classification process can be enhanced by implementing a multi-layer scorecard approach, which serves to evaluate the dependability and excellence of the mineral resource data. The scorecard encompasses various criteria that aid in classifying and categorizing the resource data, including but not limited to the quantity and quality of the data, the geology and geometallurgical traits of the deposit, the consistency and precision of the data, and the level of assurance in the resource estimate.

Mohanlal & Stevenson (2010), Parker & Dohm (2014), and Duggan et al. (2017) have proposed the use of scorecard methodology for resource classification. Mohanlal & Stevenson's approach combines traditional geostatistical and non-geostatistical criteria, such as QA/QC, geological aspects, the presence of geophysical surveys, and mining history, to establish confidence thresholds. These criteria are weighted based on their relative importance and combined to generate a raw scorecard, which a Competent Person then reviews for final classification.

Parker & Dohm (2014) proposes a systematic approach for the evaluation and use of several key factors in the classification scorecard that depend on the geological characteristics of the deposit and the most significant aspects for its extraction. For a thorough assessment, it is recommended to consider various aspects such as the ore body's geometry, data quality, spatial relationships, estimation methods, bulk density, and other relevant factors. To assign a resource classification to a block model, each of these factors is evaluated and given a ranking (low, medium, or high) based on its significance to the deposit. These rankings are then multiplied by confidence ratings to determine discrete scores. The cumulative score for all factors is subsequently compared to predefined ranges for Inferred, Indicated, and Measured Resources.

Duggan et al. (2017) suggested a semi-quantitative scorecard approach to evaluate complex and unique mineralization styles, covering five critical criteria in the resource estimation process: geology, grade, volume, revenue, and density. Due to the geological complexity and significant variability in grade, gemstone deposits, such as diamond deposits, pose challenges for accurate mineral resource estimation. To address this, the resource analyst completes the five scorecards, and the system is internally reviewed and finally ratified by a Competent Person (CP), providing a consistent and repeatable depiction of confidence in the company's mineral resources.

2.2 Kriging Efficiency (KE)

Kriging efficiency (KE), presented by Krige (1996), is a relevant metric for assessing the quality and precision of a kriging interpolation outcomes. It is determined by comparing the kriging variance with the theoretical variance of the variable at block scale (Equation 1) - (SILVA, 2015).

Equation 1:

$$KE = \frac{BV - KV}{BV}$$

$BV = Block\ Variance$

$KV = Kriging\ Variance$

A kriging efficiency close to one indicates that the kriging variance is close to zero. This situation occurs when many data correlated with the block to be estimated are used in the estimation process.

2.3 Slope of regression for kriging estimators (SR)

The slope of linear regression (SR) in ordinary kriging (OK) is a measure of the linear relationship between the true and estimated values. Also, the SR indicates the amount of conditional bias in the estimate. Avoiding conditional bias is crucial in resource classification as it reduces the risk of misclassifying blocks (DEUTSCH; SZYMANSKI; DEUTSCH, 2014; DEUTSCH, 2007; KRIGE, 1996; RIVOIRARD, 1987; SILVA, 2015). Equation 2 defines the slope of linear regression (SR):

Equation 2:

$$SR = \frac{Cov\ \{Z_V, Z^*{}_V\}}{\sigma^2{}_{Z^*{}_V}}$$

$SR = Slope\ of\ regression$

$Cov\ \{Z_V, Z^*{}_V\}$

$= Covariance\ the\ variable\ of\ interest\ (Z_V)\ and\ the\ estimated\ value\ (Z^*{}_V) at\ the\ same$

$volume\ V$

$\sigma^2{}_{Z^*{}_V} = Variance\ of\ the\ estimated\ value\ of\ the\ variable\ of\ interest\ (Z^*{}_V) at\ the\ same$

$volume\ V$

A slope of linear regression of one means that the estimates do not have conditional bias. Conversely, a slope of linear regression significantly lower than one indicates problems in the estimates.

2.4 Number of Samples (NS)

Ordinary kriging (MATHERON, 1963) involves estimating the value of a variable of interest at an unsampled location using a set of data. The number of samples (NS) refers to the quantity of data points utilized in this process. The number of samples directly impacts the precision and accuracy of the kriging estimate. More samples generally result in a more accurate estimate, but the ideal number of samples also depends on the spatial distribution of the data and the level of spatial autocorrelation. It is important to have sufficient samples to accurately capture the spatial pattern of the data and produce a reliable estimate at the unsampled location.

To establish confidence thresholds for this study, the range between the minimum and maximum number of samples used in the estimation process (as shown in Figure 1) was divided into three intervals. Blocks estimated with many samples were classified as high confidence for this criterion and received a score of one. Similarly, blocks estimated with an intermediate number of samples received a score of two (medium confidence), and blocks estimated with a small number of samples received a score of 3 (low confidence). This approach is in accordance with the method described by Mohanlal and Stevenson (2010).

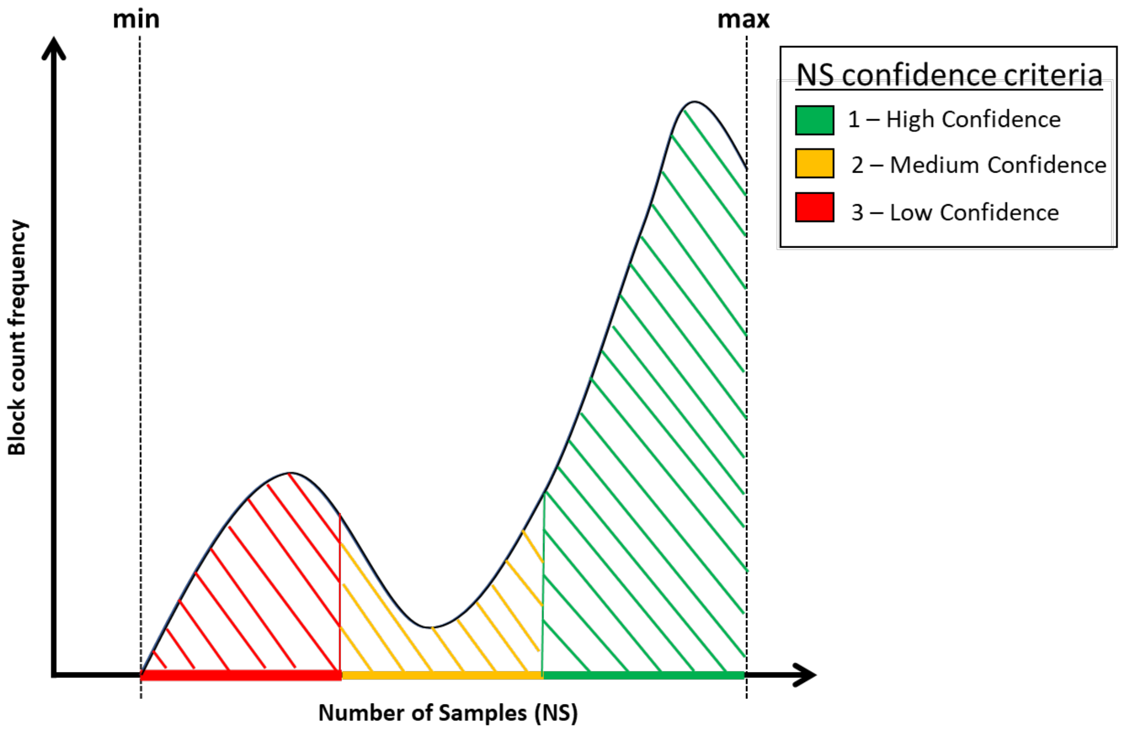

Figure 1 – Range used for categorizing the Number of Samples used during the kriging process

2.5 Search Volume (SV)

In ordinary kriging (MATHERON, 1963), the search volume is a fundamental concept used to define the search neighbourhood that comprises the set of data points employed to estimate a value at an unsampled location or point of interest. The size of the search ellipse plays a crucial role in determining the number of sample points included in the estimation process, while the orientation of the ellipse reflects the direction of maximum variability in the data. Therefore, the search volume is a critical parameter in the ordinary kriging algorithm that significantly impacts the accuracy and reliability of the estimates.

This concept of neighbourhood restrictions in resource classification is related to the spatial relationship of the data points and the influence of nearby samples. It is common practice in geostatistical resource classification to use spatial relationships and spatial continuity to inform the modelling and estimation of mineral resources. The Search Volume is correlated with the continuity of the mineralization and is often used as a metric of resource classification (PARKER; DOHM, 2014).

A common practice in mineral resource estimation is employing multiple estimation passes, each with different search parameters. The least restrictive pass is used to classify blocks as Inferred, the intermediate restrictive pass is used to define the Indicated category, and the most restrictive pass determines the Measured blocks (EMERY; ORTIZ; RODRÍGUEZ, 2006; PARKER; DOHM, 2014; SILVA, 2015). Usually, the less restrictive search volumes are obtained by multiplying the axes of the most restrictive search volume by a factor. The most restrictive search volume ranges are determined based on the ranges of the variogram (FROIDEVAUX, 1982; SOUZA, 2007).

Spatial continuity analysis is a crucial component of mineral resource estimation, often achieved through calculating and modelling of variograms. The variogram is widely recognized as the practical tool for characterizing the spatial variability of the regionalized variable, serving as a fundamental building block in the estimation process (JOURNEL; HUIJBREGTS, 1989).

The search volume criteria are often used based on the variogram range of the main element estimated. The criteria are ranked using a three-level system of confidence, with a value of 1 assigned to the first search radius (1/3 of the variogram range) for high confidence, a value of 2 assigned to the second search radius (2/3 of the variogram range) for medium confidence, and a value of 3 assigned to the third search radius (variogram range) for low confidence.

Alternatively, the criterion for confidence ranking can be established by utilizing another empirical relationship derived from spatial continuity analysis.

This involves determining the range corresponding to a specific percentage of the total variance of the variable of interest in the variogram (sill). As depicted in Figure 2, a practical guideline for establishing the confidence ranking system is as follows: assign a value of 1 to the range that corresponds to 2/3 of the variogram sill, assign a value of 2 to the range that corresponds to the modelled variogram, and assign a value of 3 to 1.5 times the range identified at the confidence level 2. This approach also provides a systematic method for determining confidence levels based on the spatial characteristics revealed in the variogram analysis.

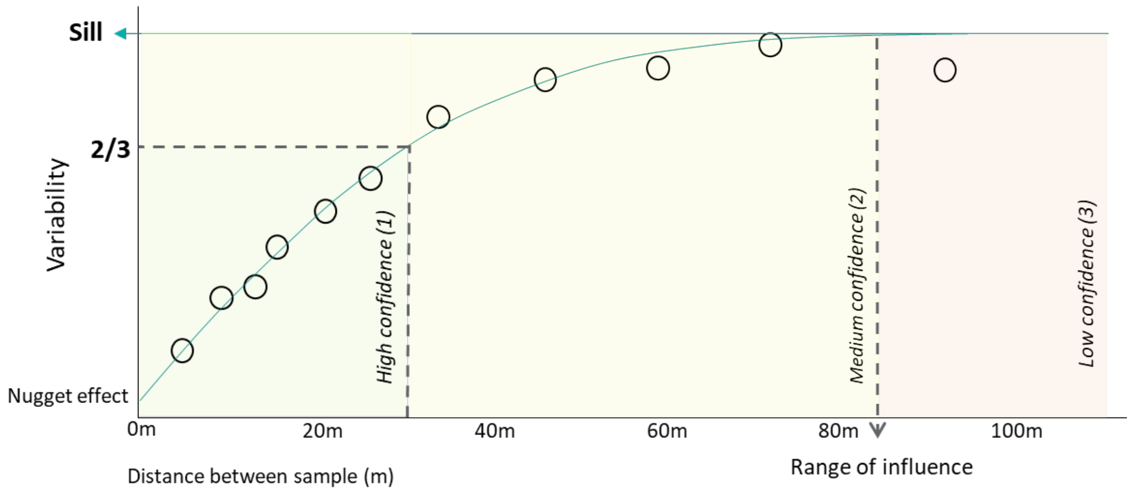

Figure 2 – Confidence ranking through variogram analysis.

It is essential to note that the selection of search parameters in Kriging can introduce certain criteria, such as minimum sample requirements, minimum samples per drill hole, and sector restrictions, which may lead to discontinuities in the resulting classification output. While these restrictions are crucial for grade estimation, they can introduce unwanted artifacts when employed for resource classification. An alternative approach involves employing a separate set of Kriging passes specifically tailored for resource classification – aiming to keep the search volume dimensions and orientations without the restrictions needed for grade estimation.

Acknowledging that these premises rely on a well-structured and modelled variogram is important. However, it is worth noting that this may not always be the case, particularly when there is limited data available. Finally, conducting a thorough analysis of ranking systems using variograms when working with high nugget effect deposits is also recommended. Examples of such deposits include gold veins with erratic distribution, narrow veins, and platinum group elements (PGE) deposits.

2.6 Kriging variance (KV)

Kriging variance (KV) is a measure of the uncertainty associated with a kriging estimate (JOURNEL; HUIJBREGTS, 1989). KV is low when many samples spatially correlated with the block to be estimated are used in the estimation. It indicates of the degree of confidence in the estimated values, with lower values indicating higher precision and higher values indicating lower precision.

Equation 3:

$$KV(x) = \sum_{i=1}^{n} \overline{\gamma}(x_i, V) * \lambda_i - \overline{\gamma}(V, V) + \mu$$

$KV\ (x) = Kriging\ variance\ at\ location\ x$

$\overline{\gamma}(x_i, V) = the\ average\ of\ variogram\ value\ for\ the\ distance\ between$

$the\ point\ (x_i)\ and\ the\ block (V)$

$\lambda_i = ordinary\ kriging\ weight$

$\overline{\gamma}(V, V) = is\ the\ average\ variogram\ value\ for\ the\ distances\ between\ each\ discretization$

$point\ in\ the\ block\ size$

$\mu = LaGrange\ multiplier$

However, it is imperative to acknowledge the limitations inherent to the Kriging Variance (KV) criteria. Owing to its fundamental nature as a measure of data density, the KV criterion possesses inherent shortcomings, notably its susceptibility to yielding artifacts referred to as "spotted-dogs" when employed as a surrogate for resource categorization. Furthermore, in congruence with this underlying principle, the criterion falls short of encompassing the grade variability. It is noteworthy that kriging variances invariably occur in the context of relative thresholds, as the raw values lack substantive physical or geological significance (ROSSI; DEUTSCH, 2014).

2.7 Indicator Kriging

Indicator Kriging (IK) is a geostatistical interpolation method proposed by Journel (1983) for the probabilities of occurrence of a categorical variable, such as the presence (ore) or absence (waste) of an ore type, or a continuous variable defined by its histogram and various thresholds. This approach provides a quantitative assessment of the geological risk. Low geological risk is related to high probabilities of being ore. For instance, if the probability of being ore is above 90% for a given block, the block is very likely ore. This block is a candidate to be classified as Measured.

2.8 Risk Index (RI)

The Risk Index (RI) for resource classification was proposed by Amorim e Ribeiro (1996) as a method to evaluate the accuracy and reliability of mineral resource estimates. The Risk Index considers the estimation error and geological continuity using an indicator kriging estimate. The idea is to provide a quantitative assessment of the level of risk associated with a resource, rank and compare different resources, and inform decision-making about the resource and its potential for further development (RIBEIRO et al., 2012).

The Risk Index (RI), according to Amorim e Ribeiro (1996), is calculated by combining two parameters: the Indicator Kriging (IK) estimated probability to be ore and the Standardized Kriging Variance [KV/Sill]. The kriging variance of the indicator kriging estimate is used to calculate the Standardized Kriging variance. The RI is represented as a vector in a cartesian plane formed by the parameters [1-IK] and [KV/Sill] (Figure 3). The value of the Risk Index (RI) vector can be calculated using the following expression:

Equation 4:

$$RI = \sqrt{([1 - IK]^2) + ([\frac{KV}{Sill}]^2)}$$

$IK = Indicator\ Kriging$

$\frac{KV}{Sill} = Standardize\ Kriging\ Variance$

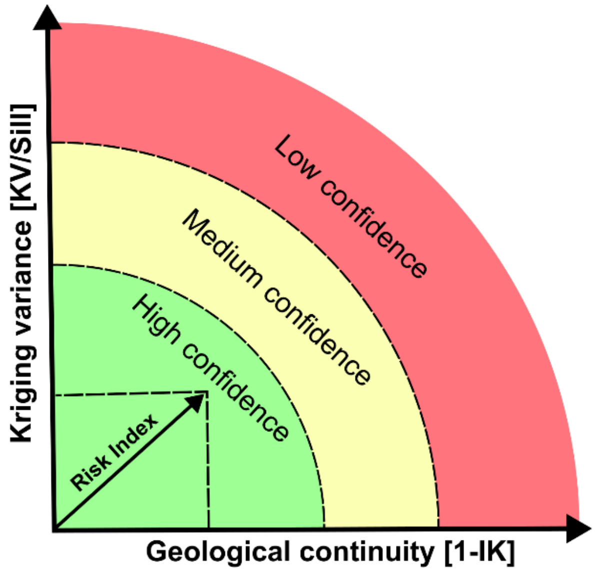

Figure 3 – Risk Index vector (adapted from Amorim e Ribeiro (1996)).

2.9 Risk Areas: orebody geometry, data integrity and quality, and other factors

Risk areas for resource estimates refer to the uncertainty surrounding the estimation of mineral resource tonnage and grades. The concept considers the various factors that contribute to this uncertainty, such as data integrity and quality, the complexity of the deposit, variability of the mineralization, and others (PARKER; DOHM, 2014). The goal is to understand the level of confidence in the resource estimate and to identify areas where further work is needed to reduce the level of uncertainty. In this workflow, the following criteria to identify risk areas were used:

- **Orebody geometry (OG):** Accurate estimation of mineral resources can be significantly influenced by geological complexity, particularly in deposits that exhibit heterogeneity and discontinuity in their geology. It is crucial to incorporate geological expertise and knowledge into the estimation process to capture the complexities of the deposit better and enhance the accuracy of the estimates (ISAAKS; SRIVASTAVA, 1989). The orebody geometry plays a key role in determining a deposit's geological confidence level. An orebody's complexity, shape, size, and orientation can impact the estimation of resources, production schedules, and the costs associated with the mining process.

- **Data integrity and quality (DIQ):** resources estimation and classification must be based on high-quality and reliable data. Maintaining data integrity through the quality assurance and control process (QA/QC), which verifies the accuracy, completeness, and consistency of the data, is essential for the accuracy and confidence of the classification. The interpretation of the data must also be consistent, accurate, and supported by high-quality data. Data integrity and quality throughout resource classifications is vital (ROSSI; DEUTSCH, 2014).
- **Bulk density (BDens)**: provides valuable information on a deposit's tonnage and metal content. It is an important characteristic that must be accurately measured and considered in the resource estimation process to ensure the accuracy and reliability of the resource classification (PARRISH, 1993; ROSSI; DEUTSCH, 2014).
- **Other factors (OF):** such as geometallurgical data, mineralogy, and penalty elements, are all important considerations in classifying mineral resources. This information is used to determine the best extraction and processing methods, estimate the costs associated with these methods, and ensure the resource classification's accuracy and reliability.

To categorise different risk criteria, confidence levels are assigned based on their respective locations and degrees of uncertainty, which can range from high confidence (1), medium confidence (2), to low confidence (3), depending on the specific purpose and context of the assessment.

2.10 Scorecard and smoothing for final classification

The individual criteria are weighted based on relative importance and then combined to form a raw scorecard. This scorecard is subsequently reviewed visually and against the data by a Competent Person for final classification. Subsequently, non-probabilistic resource classification methods typically require posterior smoothing on a block-by-block basis to produce the final classification.

To achieve smoother volumes, one method is to manually interpret, while another option is to use a smoothing algorithm based on moving window statistics. Care must be taken to avoid bias and significant alterations to the global volumes defined by established criteria. It is recommended to check overall grade-tonnage curves by resource class before and after smoothing to understand the degree of changes introduced (ROSSI; DEUTSCH, 2014). Furthermore, it is important to acknowledge that the smoothing step is considered good practice but not mandatory. The Competent Person should assess its necessity and make an informed decision accordingly.

3. Practical application

The present study applies a scorecard workflow for resource classification to two datasets, 2D and 3D. This methodology serves to demonstrate and illustrate the proposed workflow. The datasets exhibit varying degrees of geological complexity dependent on the deposit area. Additionally, differences in drilling campaigns, data quality, and other pertinent factors contribute to variations in the confidence levels associated with the resources at specific locations.

3.1 2D Case Study

The proposed method was implemented on a 2D dataset encompassing six mineralized orebodies exhibiting varying degrees of geological complexity and drilling density. The drilling grid is irregular, comprising an exploratory grid of 100m x 100m executed in different campaigns over time, and it was eventually complemented by infill drilling of a maximum of 30 m x 30m targeting high-grade areas. The block size dimensions are 10 x 10m, where the variable lead (Pb) and the indicator Ore (1) were estimated by ordinary kriging (Figure 4). As shown in Figure 4 4-A, the indicators Ore (1) and Waste (0) were assigned to the dataset, and subsequently, the variography was modelled to perform the indicator kriging (IK) – Figure 4Figure 4-A.

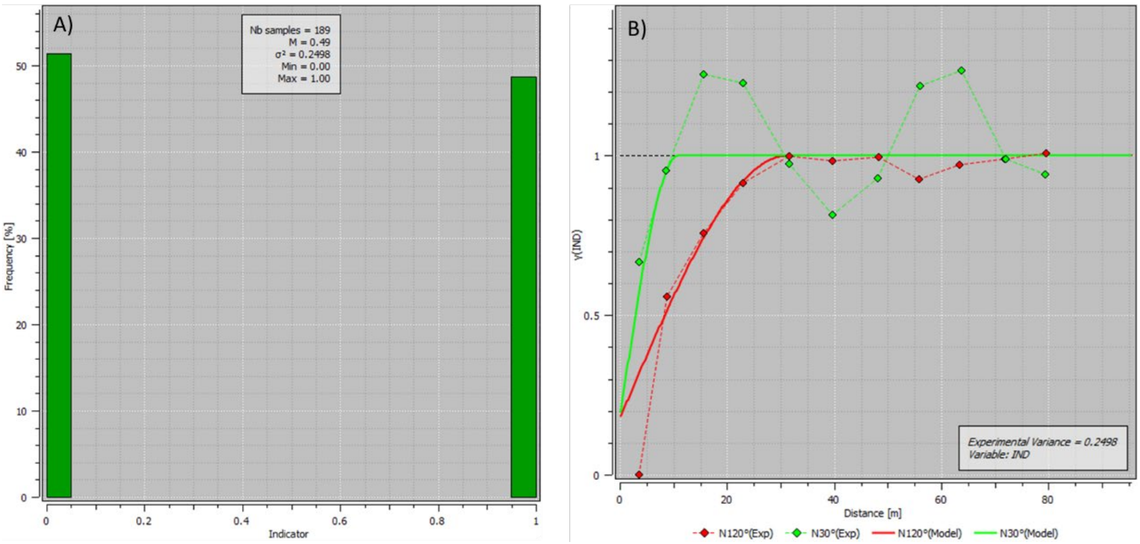

Figure 4 – The figure above displays the histogram (A) and variogram (B) of the indicator Ore. The code zero is for waste while the code one is for ore.

The Risk Index (RI) criterion (Figure 5-C) was obtained with the combination of the indicator kriging estimate of the indicator (Figure 5-A) and the indicator Kriging Variance (Figure 5-B). The blocks were then categorized into Measured, Indicated, and Inferred using thresholds (Figure 5-D). Clearly, the resources classification using the Risk Index is highly influenced by the indicator kriging estimate (see Figure 5-A and Figure 5-D, the classification view resembles the indicator kriging estimate).

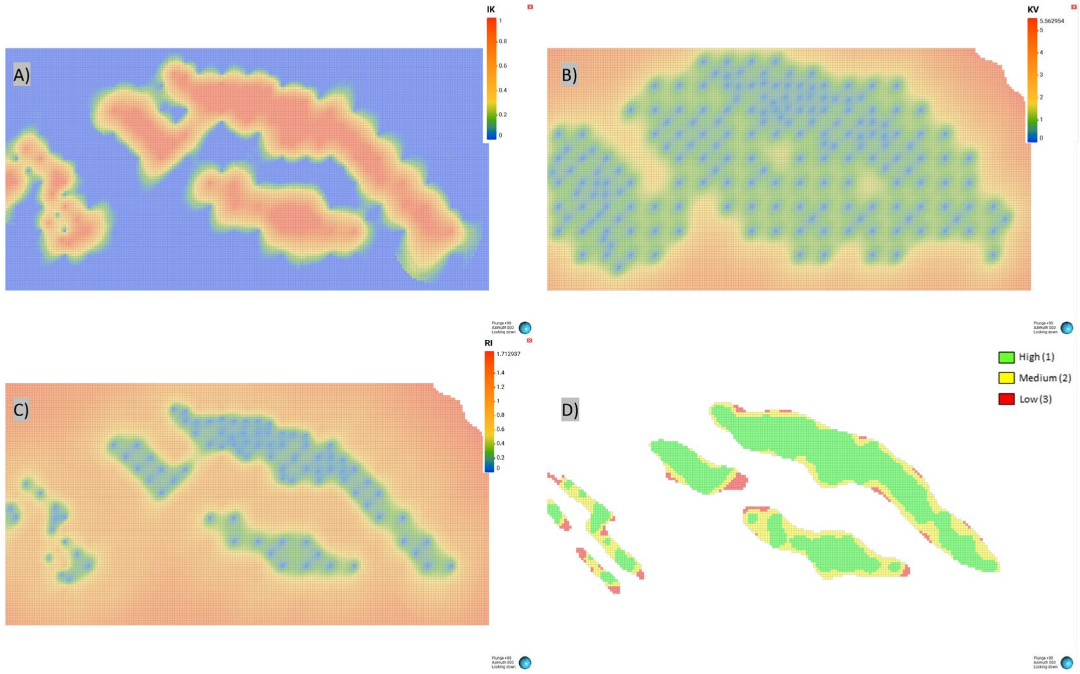

Figure 5 – The figure above displays the Risk Index (IR) process. The criteria is built up using the IK of the Ore(1) indicator (A). Kriging Variance (B), which are combined resulting in the Risk Index (C). Thus, Risk Index is classified in the confidence range (D).

The search volume criterion was based on the variogram range of the main element estimated (Figure 6). The range of the first search volume is one-third of the variogram range, the range of the second is two-thirds of the variogram range, and the range of the third equals the variogram range. The scores 1, 2, and 3 are linked to the first, second, and third search volumes.

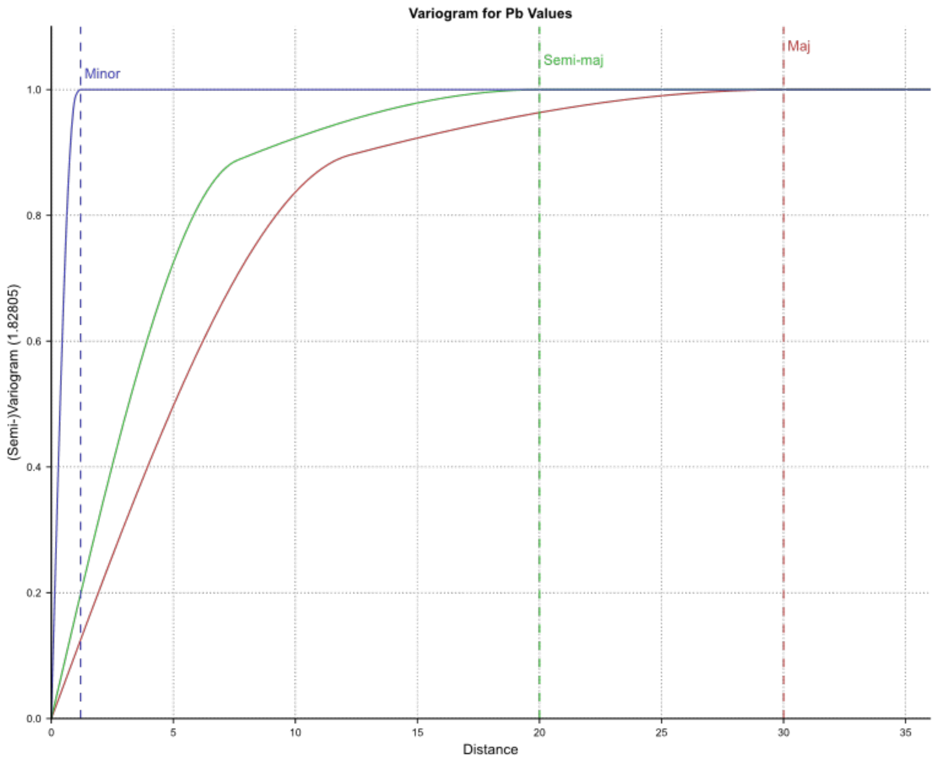

Figure 6 – Variogram for the variable of interest showing a range of 30m for the major and 20m for the semi-major. Important to note that the data is 2D.

The application of the search volume criterion resulted in some discontinuities in the resource classification (Figure 7). These discontinuities will likely occur when the search volume is divided into sectors. Despite these discontinuities, dividing the search volume into sectors is advisable. This division mitigates the problem of negative weights and prevents the estimate from being dominated by clusters (groups of redundant samples). The Kriging configuration for the SV criteria was established with the following parameters: Minimum number of samples (4), Maximum number of samples (24), Sector Search (Octant), Maximum samples per octant (3), and a Maximum of samples per drill hole (2).

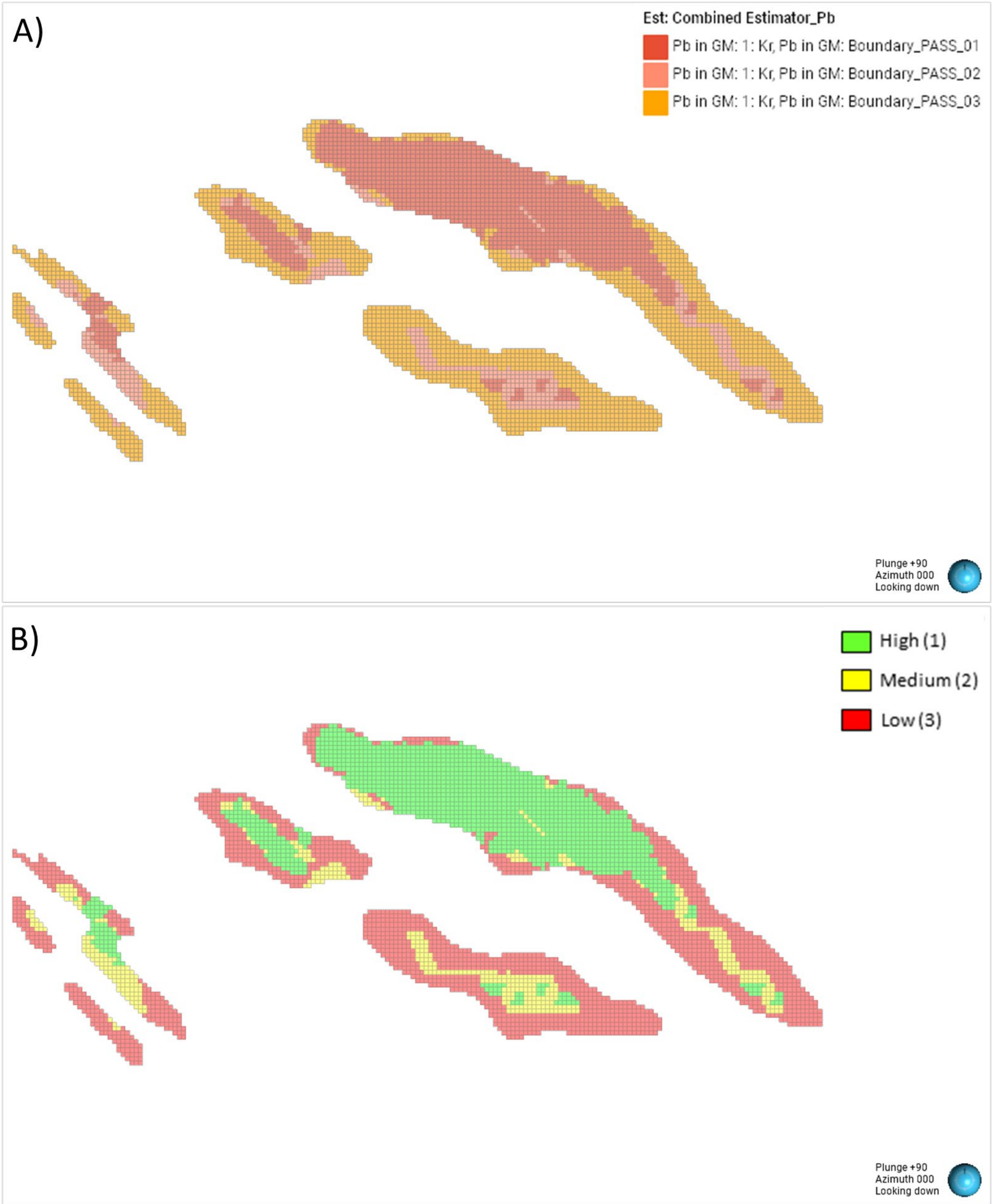

Figure 7 – This illustration depicts the raw search ratio criteria (A), which is then further refined by the application of the confidence level (B).

Subsequently, as discussed on section 2.4, the application of the NS criteria can be seen on Figure 8, which is an output of the kriging process of the variable of interest. The NS criterion clearly defines the most sampled area, which occurs in the middle of the orebody. As expected, fewer samples are found near the boundaries of the ore.

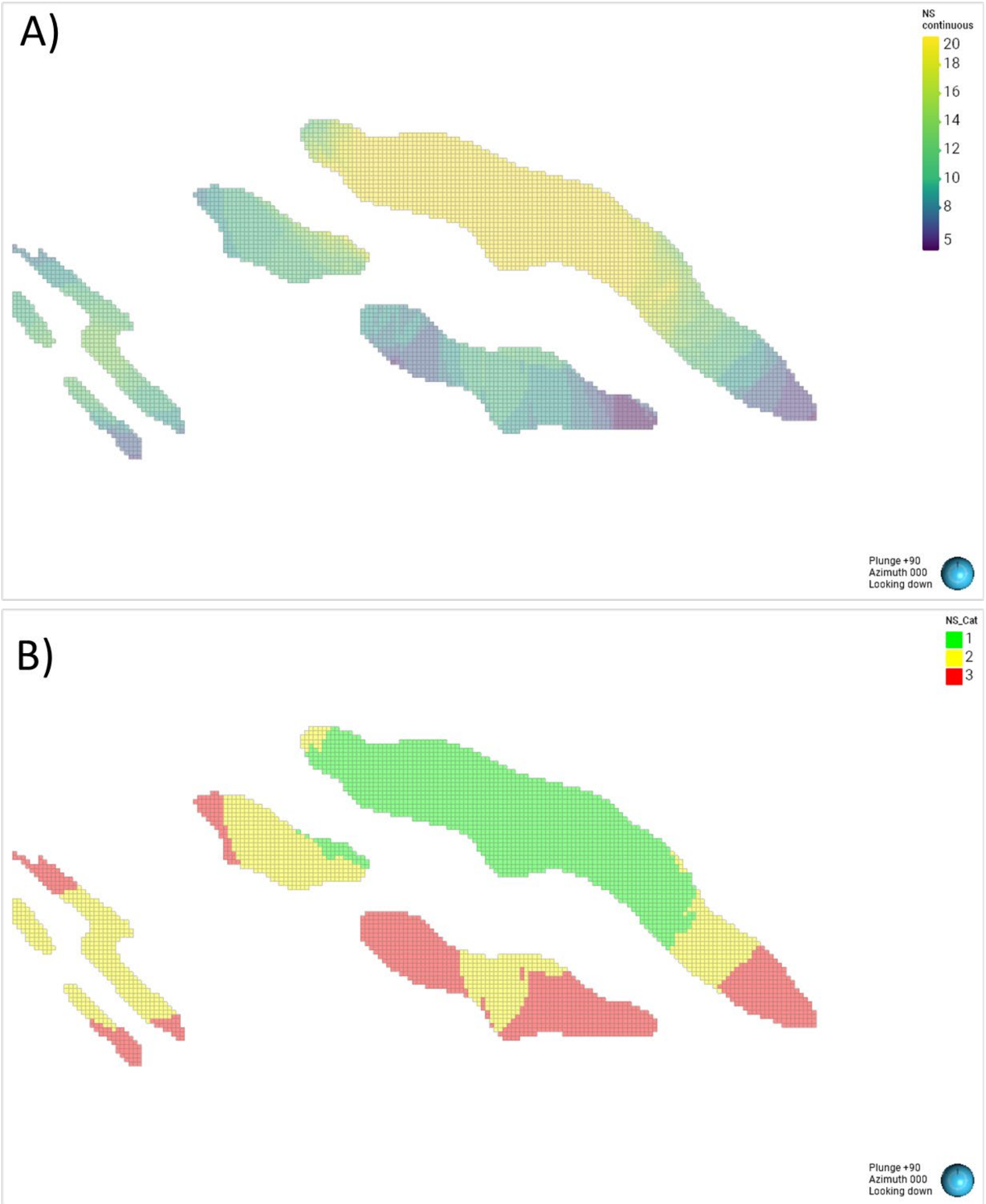

Figure 8 – This figure illustrates the unprocessed NS criteria (A) alongside the same criteria after the application of the confidence level (B).

Figure 9 shows the results regarding the KE. The criterion represents an outcome of the kriging process of the variable of interest and is shown in Figure 9-A. As the kriging variance highly influences the KE, the KE map shows abrupt changes as the distance between the blocks and the samples increases. These abrupt changes resulted in artifacts in the resource classification defined by this criterion (Figure 9-B).

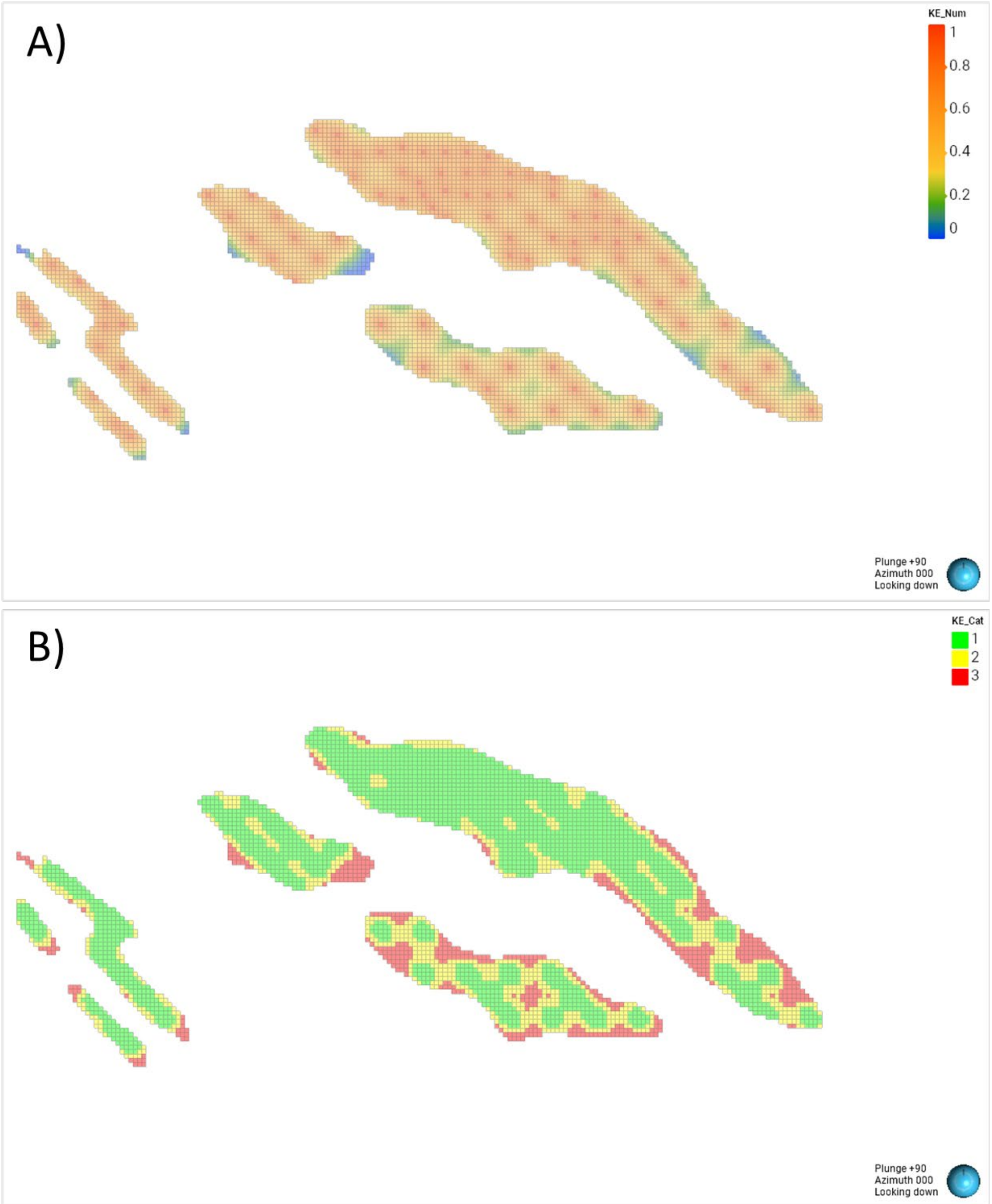

Figure 9 – This figure depicts the initial, unprocessed KE criteria (A) juxtaposed with the same criteria post the integration of the confidence level (B).

Finally, the application of the SR criterion is visually presented in Figure 10. The SR criterion also led to some artifacts (Figure 10-B). The main difference is that the artifacts are less pronounced than those obtained by KE.

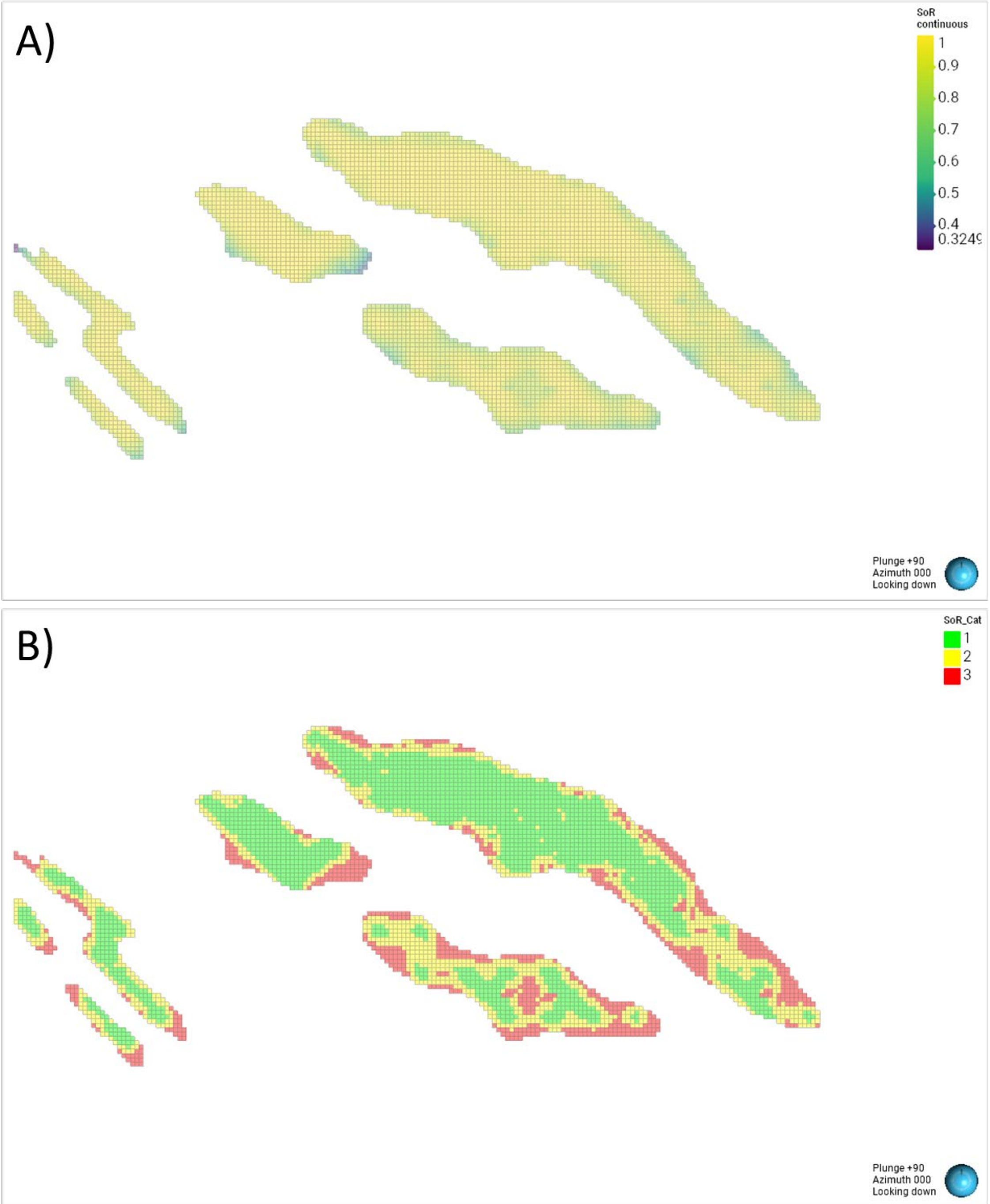

Figure 10 – This figure portrays the initial, unprocessed SR criteria (A) in parallel with the same criteria after incorporating the confidence level (B).

Table 2 details the specific classification rules employed in the present study to transform the raw criteria into the scores 1, 2, and 3 – when a numerical threshold is needed. For instance, the blocks whose risk index was below 0.3 received a score of 1, which is destined for the high-confidence blocks. These thresholds play a role in categorizing individual blocks through the estimation process, contributing to the determination of the criterion for which a threshold is needed. The classification rules are defined empirically based on the experience of the qualified/competent person.

Table 2 – Classification rules applied to the criterion necessary to define the confidence levels.

Description	Scorecard (confidence level)	Number of Samples	Slope of Regression	Kriging Efficiency	Risk Index
High confidence	**1**	>= 14	>= 0.96	> 0.65	< 0.3
Medium confidence	**2**	< 14 and >= 9	< 0.96 and >= 0.88	<= 0.65 and >= 0.3	>= 0.3 and < 0.6
Low confidence	**3**	<9	< 0.88	< 0.3	>= 0.6 and < 1.5

Figure 11 compares the classification obtained using the number of samples, search volume, kriging efficiency, slope of regression, and Risk Index (Figure 11). As opposed to the categorization obtained by the number of samples, Search Volume, and Risk Index (Figure 11-A, Figure 11-B, Figure 11-E), the KE and SR categorizations resulted in artifacts (Figure 11-C and Figure 11-D).

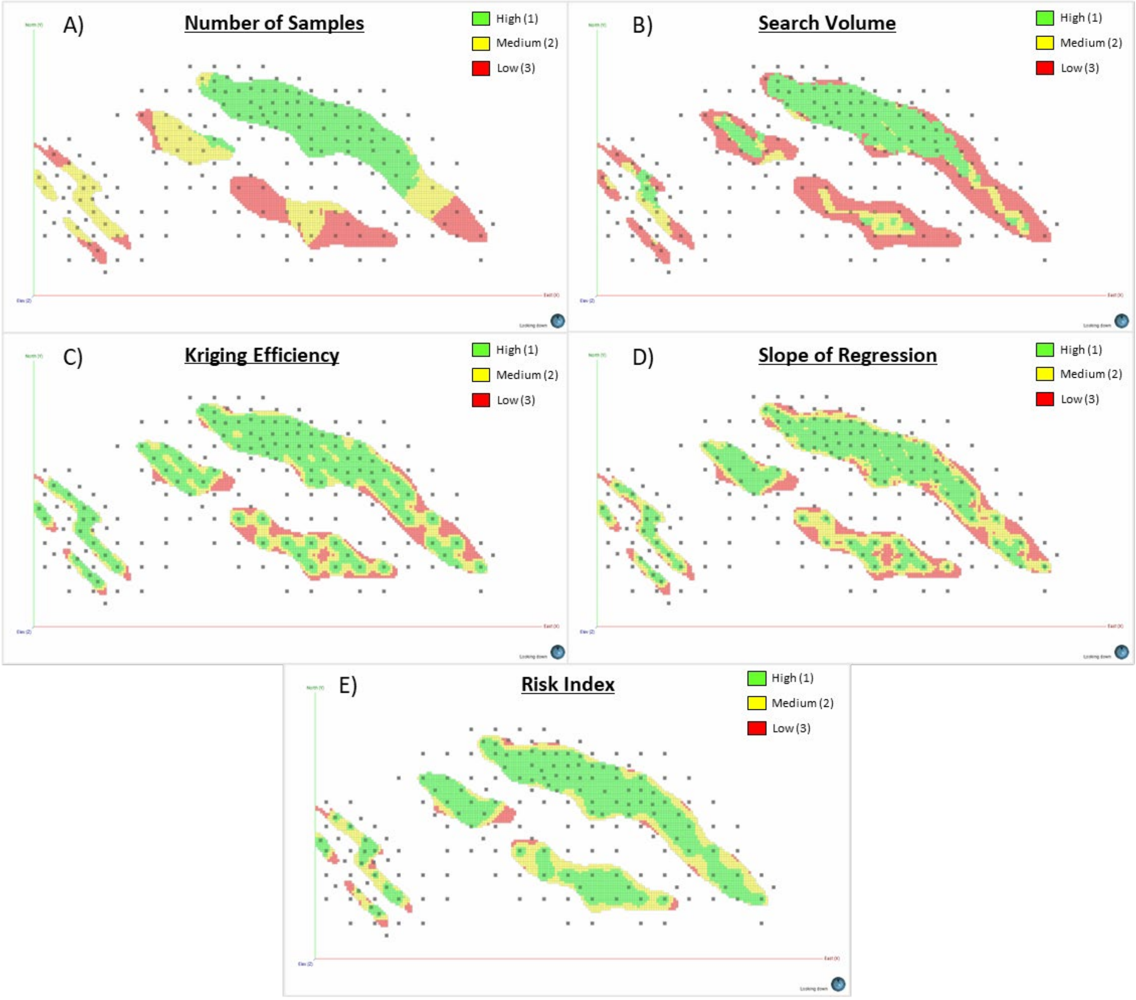

Figure 11 – This figure shows the different workflow elements that are categorized based on their level of confidence criteria. The elements include (A) the Number of Samples, (B) Search Volume, (C) Kriging Efficiency, (D) Slope of Regression, and (E) Risk Index. These criteria are used to assess the level of confidence in the mineral resource

Moreover, other criteria that are not linked with the estimates were used. These criteria are shown in Figure 12 and represent the Orebody Geometry, the QA/QC aspect, Bulk Density, and other factors. Similar to the criteria based on the estimates, these criteria were also divided into high, medium, and low confidence (Figure 12). Geological areas with low confidence in interpretation, and regions with poor confidence in lithological logging, were identified as having lower confidence (Figure 12-A). Furthermore, historical data that lacked appropriate materiality and quality assurance/quality control (QA/QC) protocol were given different confidence levels (Figure 12-B). Additionally, areas with historical drilling lacking density measurements were identified (Figure 12-C). Finally, two different areas of confidence were identified regarding geometallurgical and mineralogical components, potentially impacting the ore processing (Figure 12-D).

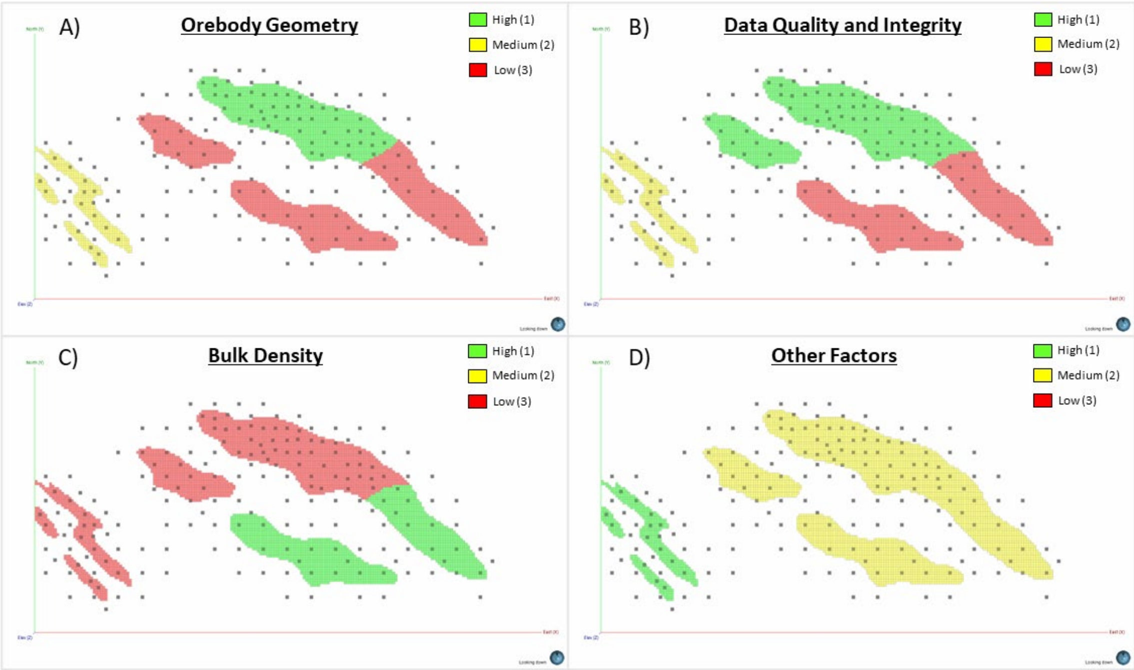

Figure 12 – The figure above displays the risk areas identified in the proposed workflow for classifying mineral resources. These areas are categorized into (A) Orebody Geometry, (B) Data Quality and Integrity, (C) Bulk Density, and (D) Other Factors.

An individual score was assigned to the categories of each criterion. One is the individual score for the high-confidence blocks, two is the score for the medium-confidence blocks, and three is the score for the low-confidence blocks. The individual scores are combined using weights to obtain the final score. The final score is a linear combination of the individual scores and weights. In this case study, the final score was obtained by Equation 5:

Equation 5:

$$Final\ Score = [NS * 0.1] + [KE * 0.05] + [SR * 0.05] + [SV * 0.05] + [RI * 0.2] + [OG * 0.2] + [DIQ * 0.25] + [BDens * 0.05] + [OF * 0.05]$$

$NS = Number\ of\ samples$

$KE = Kriging\ Efficiency$

$SR = Regression\ of\ slope$

$SV = Search\ Volume$

$RI = Risk\ Index$

$OG = Orebody\ Geology$

$DIQ = Data\ Integrity\ and\ Quality$

$BDens = Bulk\ Density$

$OF = Others\ Factor$

Figure 13 shows the block model coloured by the final score. This score is the main parameter for the final resource classification.

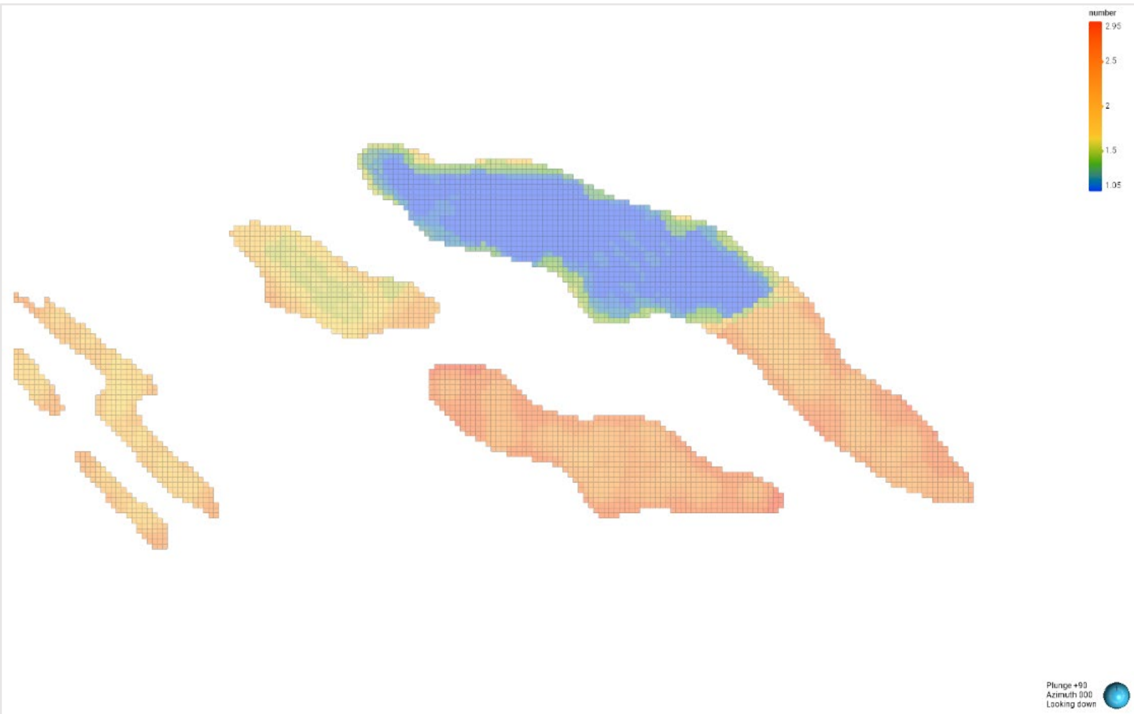

Figure 13 - The figure above illustrates the application of the scorecard to each block, as outlined in Equation 4

The final classification of the deposit is based on the final score and a series of thresholds. In this case study, the blocks with a final score between 1 and 1.3 were considered Measured, scores ranging from 1.3 to 1.8 were considered Indicated, and scores above 1.8 were classified as Inferred.

The classification obtained by the final score (Figure 14-A) may contain *"spotted-dog"* patterns or other irregularities that need to be processed before the final resource classification. Therefore, the scorecard model was smoothed manually to remove these patterns and ensure a more accurate final classification (Figure 14-B).

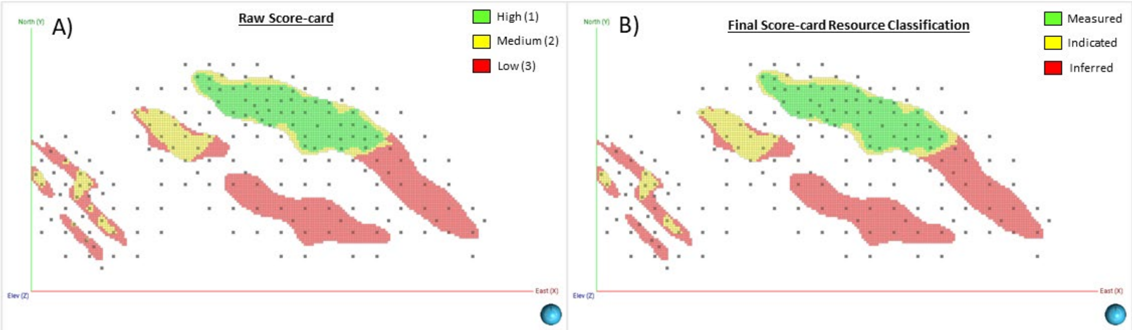

Figure 14 – The figure above illustrates the results of the final scoring workflow (A), and (B) the final scorecard resources classification where the smoothing and "spotted dog" treatment have been applied.

3.2 3D Case Study

Due to confidentiality requirements, this study withholds the name, location, and commodities of the studied deposit. The proposed methodology was applied to a 3D dataset that encompasses a highly structured polymetallic mineralization with seven known orebodies juxtaposed with a weathering profile. The drilling grid is irregular and comprises an exploratory grid executed in different campaigns over time, which was eventually complemented by infill drilling targeting high-grade and shallow areas.

A confidence level difference exists between the historical drilling (with a data spacing of 100 x 100m) and the modern campaigns (with a data spacing of 25 x 25m). Furthermore, bulk density measurements were only taken during the modern campaigns. The bulk density is crucial for the resource assessment of the deposit, as a specific mineral alteration combined with a high-density mineral worsens the ore processing performance. The block size dimensions are 8 x 8 x 8m, sub-blocked to a suitable minimum of 2 x 2 x 2m. Additionally, ordinary kriging was employed to estimate the variable of interest and the indicator Ore (1).

The results of the methodology are depicted in Figure 17, which categorizes the confidence levels into high (1), medium (2), and low (3) based on each criterion. The high-confidence blocks receive a score of one, the medium-confidence blocks receive a score of two, and the low-confidence blocks receive a score of 3.

Figure 15 provides a visual representation of two distinct components. The first element features a histogram (Figure 15-A) that illustrates the indicators, specifically Ore (1) and Waste (0), within the dataset. The second aspect of the figure highlights the variogram model (Figure 15-A) pertaining to the Ore (1) variable. This figure collectively offers insights into the distribution of indicators and the variogram characteristics of the Ore (1) variable. The variogram modelled (Figure 15-A) has been used to perform the indicator kriging which is part of the Risk Index (RI) criteria – section 2.8.

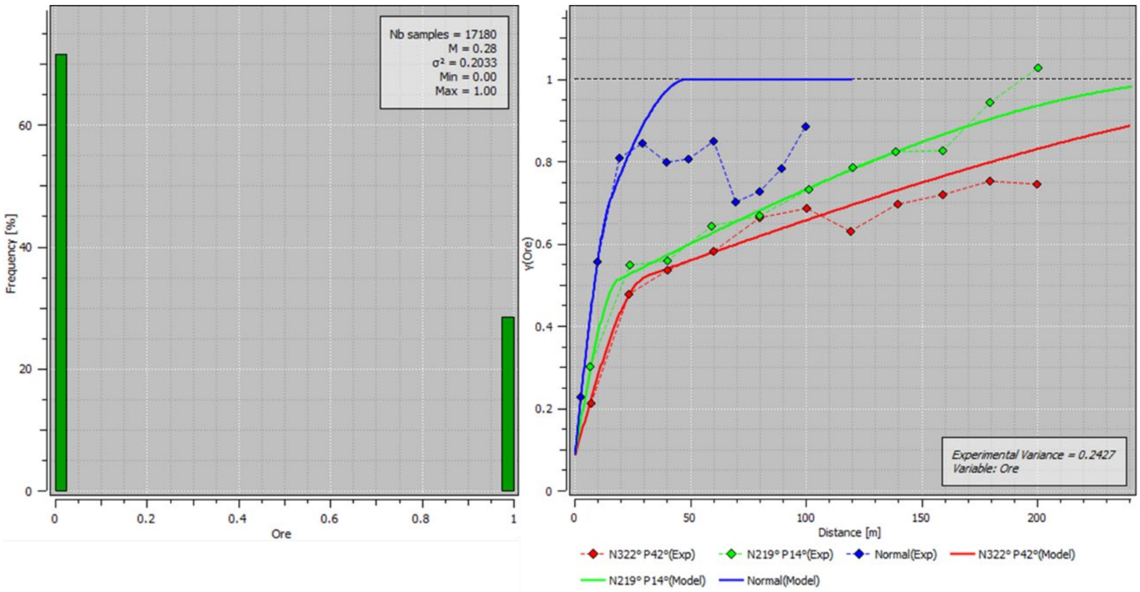

Figure 15 – The depicted figure showcases two elements: firstly, the histogram (A) representing the assignment of the indicators Ore (1) and Waste (0) to the dataset, and secondly, the modelled variogram (A) of the Ore (1) variable.

Figure 16 depicts the model from the variable of interest which was used in the ordinary kriging process. Noteworthy is the major range of 230 meters, the semi-major range spanning 130 meters, and a minor range extending to 50 meters. As discussed in section 2.5, the assessment standards are organized according to a three-tiered confidence framework.

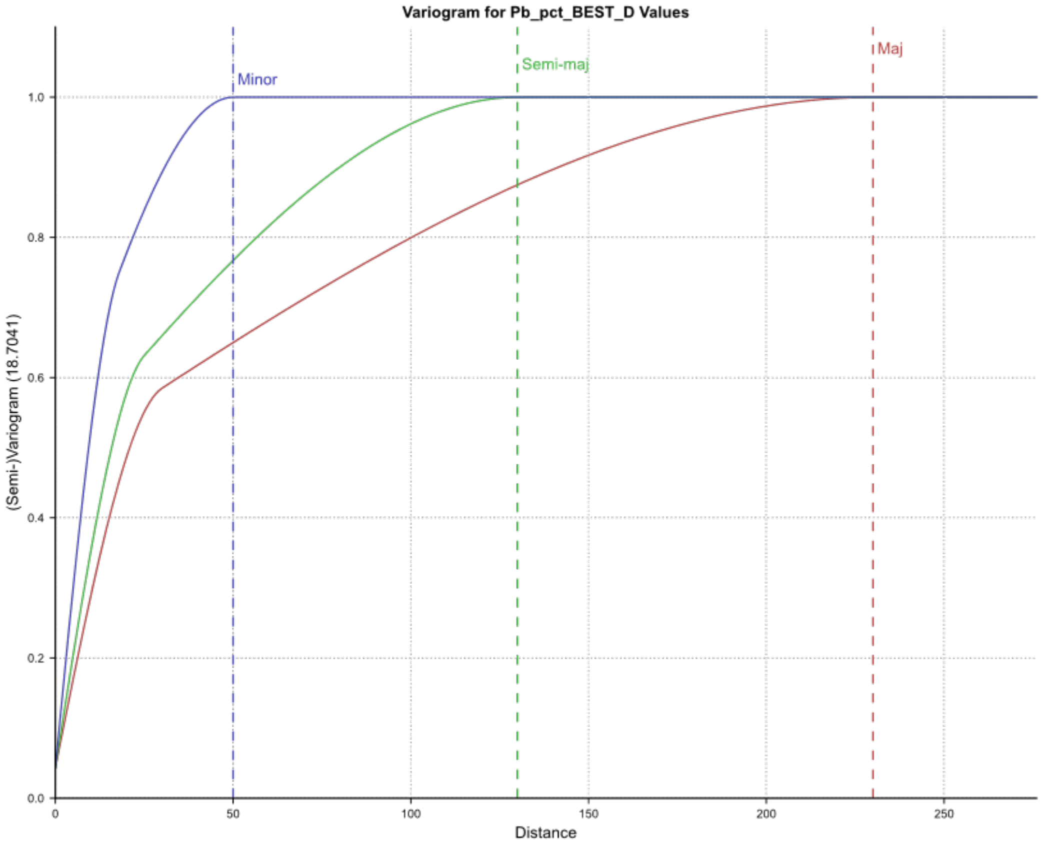

Figure 16 – The variogram presented illustrates the variable of interest, indicating a major range of 230 meters, a semi-major range of 130 meters and 50 meters as minor.

As expected, the classifications using KE (Figure 17-A) e NS (Figure 17-D) present artifacts and a "spotted dog" effect surrounding the drilling data. Furthermore, the NS criteria exhibit artifacts on the orebody boundaries due to drilling complexity and the OK kriging anisotropy setup. On the other hand, the SR (Figure 17-B), RI (Figure 17-C) and Search Volume (Figure 17-E) criteria have shown higher spatial continuity in high and medium confidence levels within the high-density drilling grid area. Additionally, Figure 17-F and Figure 17-G illustrate the classification criteria for Data Integrity and Quality (DIQ) and Bulk Density (BD), respectively. The DIQ criterion assesses the impact of the new drilling based on distance, while the BD classification examines the availability of bulk density measurements.

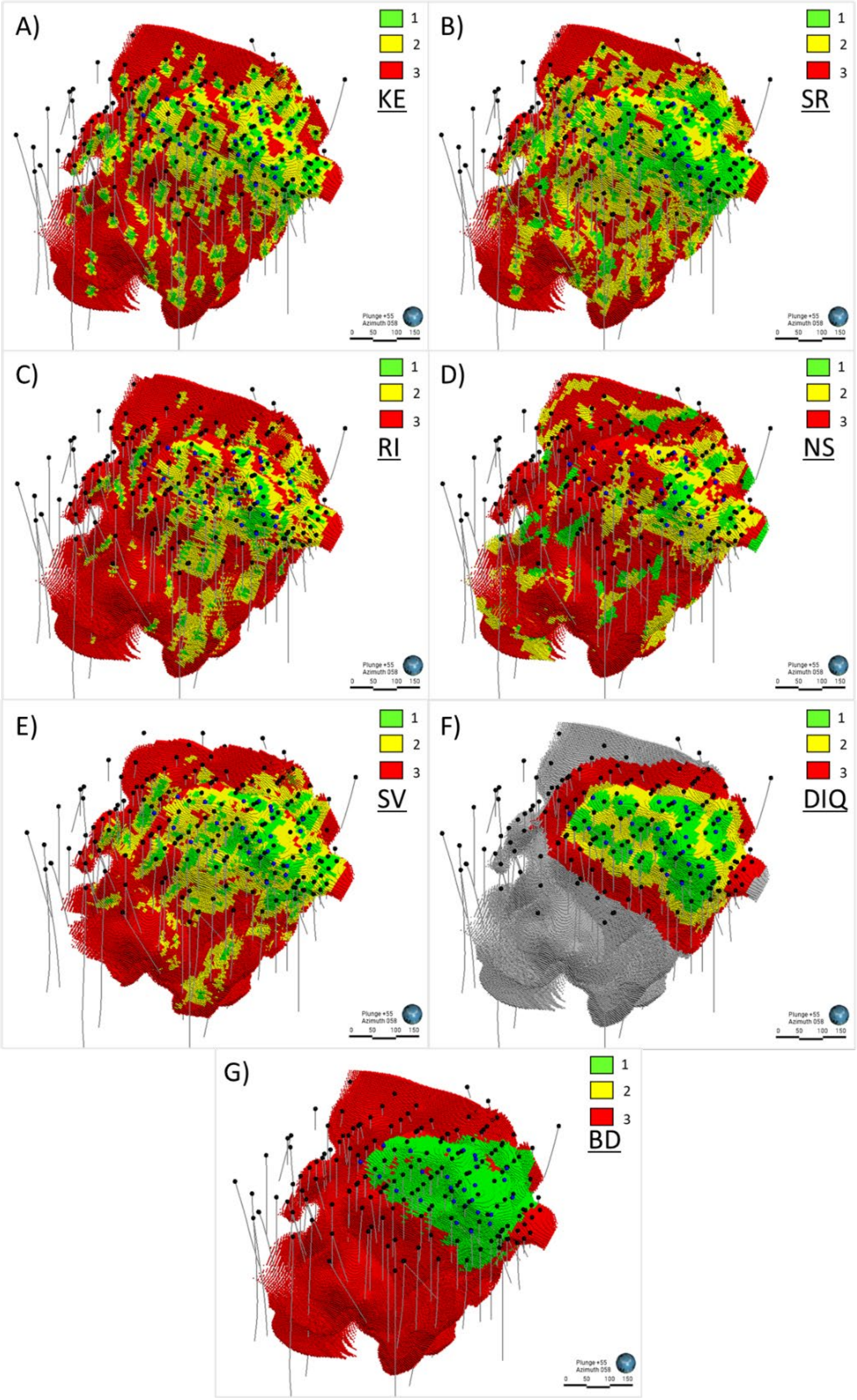

Figure 17 – This figure illustrates various components of the workflow that are categorized based on their confidence level criteria. The elements include (A) Kriging Efficiency, (B) Slope of Regression, (C) Risk Index, (D) Number of Samples (E) Search Volume, (F) Data integrity and quality, and (G) Bulk Density. These criteria are utilized in combination to develop the scorecard classification.

The next step consisted of assigning weights for each criterion based on their relative importance. The weights assigned to each criterion were based on the empirical nature of the deposits described above and on the experience of the competent person. In this case, the following weights were applied to each criterion: 5% for Search Volume, 5% for Kriging Efficiency, 5% for Slope of Regression, 5% for Number of Samples, 15% for Risk Index, 25% for Bulk Density, and 40% for Data Integrity and Quality.

These weights were then used to calculate the final score (Figure 18-A), which is a linear combination of the scores obtained from each criterion separately. Then, a smoothing step ("spotted dog" treatment) has been applied to the final score to obtain the final resource classification (Figure 18-B). The weighting system is essential to guarantee that important criteria influence the final score more. Another benefit of the weighting system is that it increases the transparency of the method. Even though many factors are combined, an external auditor is able to recognize the influence of each factor quickly.

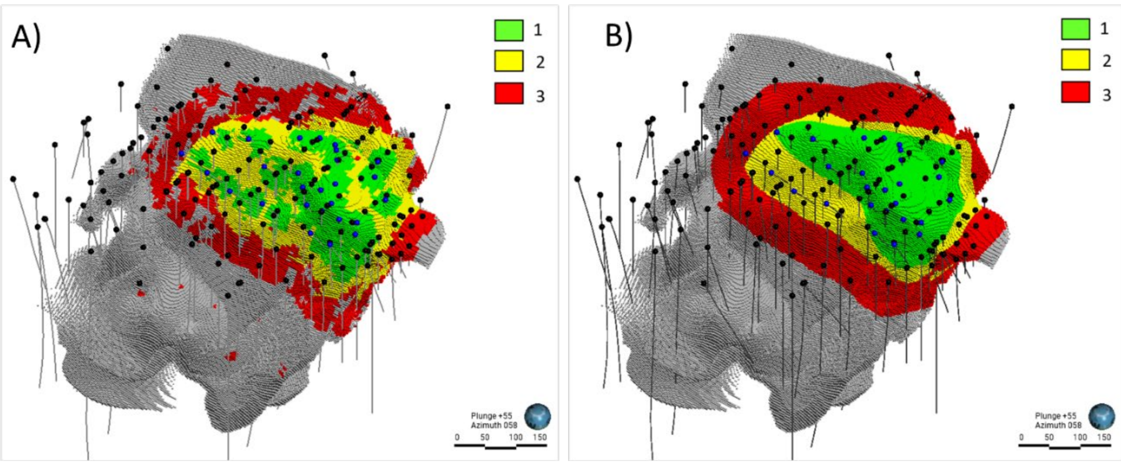

Figure 18 – The figure above displays the outcome of the final scoring workflow (A) scorecard, and (B) the final resource classification, where smoothing and "spotted dog" treatment have been implemented

Figure 19 presents the tonnage allocation within each criterion comprising the scorecard and the final resource classification. Notably, the distribution of tonnages within the Data Integrity and Quality (DIQ) criterion closely aligns with the final resource classification. This observed similarity can be attributed to the significant weight purposely assigned to the DIQ criterion, accounting for 40% of the overall scorecard evaluation.

The DIQ criterion is paramount in the resource evaluation process, as it is a crucial determinant of the final classification. Its high weighting signifies its critical role in assessing the integrity and quality of the data associated with the resources under consideration.

Furthermore, it is noteworthy to highlight that the need for post-processing, ("smoothing") is minimal after the evaluation process. This implies that the classification derived from the scorecard aligns well with the observed tonnage distribution, and extensive adjustments or corrections through post-processing are not required. The findings depicted in Figure 19 provide insights into the resource classification methodology, underscoring the influence of the DIQ criterion and emphasizing the efficiency of the evaluation process in generating a reliable and accurate final classification within the deposit.

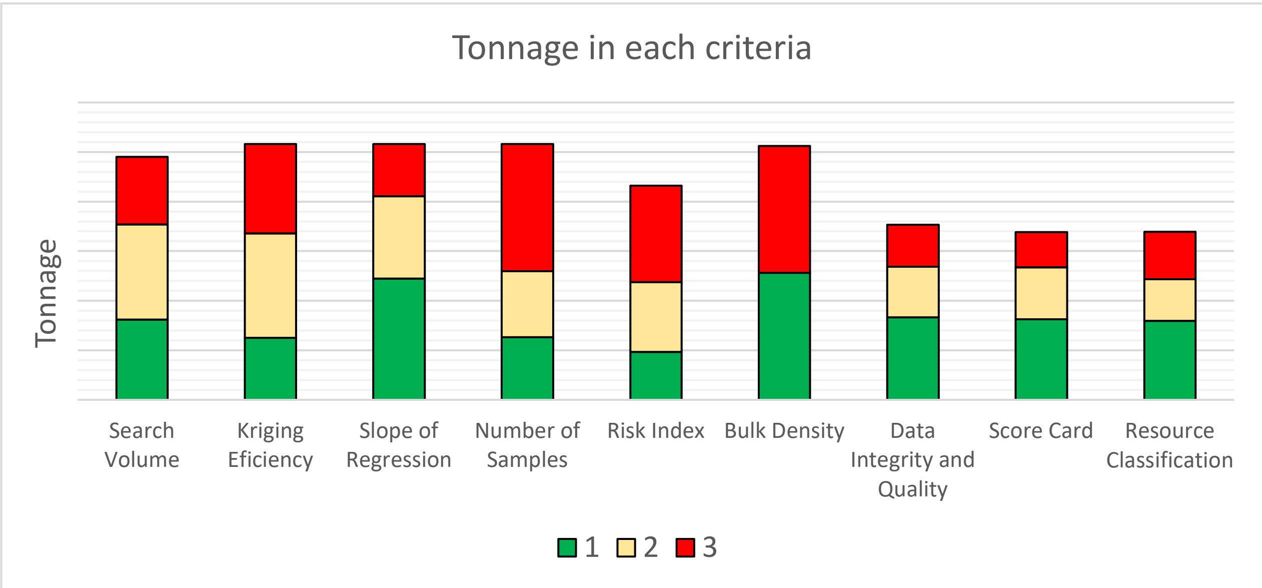

Figure 19 – The graph showcases all the different criteria that are utilized to create the scorecard and, subsequently, the final Resource Classification. These criteria include Search Volume, Kriging Efficiency, Slope of Regression, Number of Samples, Risk Index, Bulk Density and Data Integrity and Quality. After applying smoothing techniques to the Scorecard, the final Resource Classification is produced.

3.3 Resource Classification Criteria and Considerations

Table 3 below provides an overview of this study's key criteria for resource classification. The pros and cons associated with each criterion are outlined, shedding light on the factors that must be weighed when choosing the most suitable approach for a specific geological context.

Table 3 – Overview of the benefits and drawbacks of each criterion.

Criteria	Upsides	Drawbacks
Slope of Regression	· Directly related to the possible bias of the estimation · Correlation between the estimated value vs the data sampled	· Sensitive to the variogram and estimation parameters · Does not consider the grade variability · Prone to artifacts
Kriging Variance	· Highly correlated with the data density/availability · Proxy to estimation error · Considers the spatial variability of the data.	· Sensitive to the variogram and estimation parameters · Does not consider the grade variability · Prone to artifacts
Kriging Efficiency	· Considers the spatial variability of data · Inversely related to Kriging Variance	· Sensitive to the variogram and estimation parameters · Does not consider the grade variability · Prone to artifacts
Number of Samples	· Higher sample numbers generally lead to more reliable estimates · Simple and intuitive	· Uneven, biased or poorly treated sample distribution can lead to poor estimate · Disregard the redundancy between the samples · After a threshold the increasing sample size might not significantly improve accuracy
Search Volume	· Directly related with the spatial continuity of the deposit ad anisotropy	· Sensitive to the choice of variogram and estimation parameters, · Sensitive quantity data available within the search volume, which can be a challenge in certain areas

	· Can be adjusted to capture different scales of spatial variability (short/long term models)	· May cause discontintituities when the search is divided into sector, which is usually the case
Risk Index	· Considers the geological continuity (through a probabilistic approach) and the drilling density (KV) · Emphasized the difficulty in estimating blocks near the contacts, which usually have higher uncertainty.	· Relies on the quality of the geological model and continuity of wireframing (in cases of overextrapolation could be harmful) · Prone to artifacts when the mineralization consists of several orebodies unconnected · The impact of each factor on the final index is not intuitive;
Risk Areas: Orebody Geometry, Data integrity and quality, and Other Factors	· Qualitative aspects can be beneficial to de-risk know areas based on previous knowledge · Holistic approach considers various risk factors that could impact resource classification, tailored and adaptable for different scenarios	· Empirical and manual approach

4. Discussion and Conclusions

The classification of mineral resources is a fundamental step in evaluating their economic viability and the associated risk in a mineral project. In this study, we proposed a multi-layer scorecard workflow for mineral resource classification that considers multiple factors from different disciplines to ensure a comprehensive and well-rounded evaluation of mineral resources. The methodology combines classical metrics, such as the number of samples, the slope of regression, kriging efficiency, and kriging variance, with modern ones, such as the Risk Index, which incorporates the estimation error and geological continuity by a probabilistic approach. Additionally, the workflow can also integrate qualitative information obtained from the expert geomodeler, such as the geological complexity, to improve the accuracy of the classification.

The proposed workflow was applied to two different databases: one 2D and one 3D. The results showed the applicability of the methodology in classifying mineral resources while considering information from multiple sources. The combination of multiple factors is weighted, and the competent user can adapt the scorecard workflow to the particularities of each deposit. Therefore, the Competent Person (CP) needs to evaluate the thresholds that are applicable to each parameter.

In addition to the proposed methodology, other techniques such as simulation and uncertainty analysis could be integrated to provide a more comprehensive approach. By incorporating these approaches, the workflow could further improve the evaluation of mineral resources by capturing additional sources of uncertainty and reducing the impact of bias on the final score.

Overall, the proposed methodology offers several advantages, including:

- **Integrating risk assessment**: The methodology considers multiple factors that can affect the risk associated with a mineral deposit, such as the geological continuity and the estimation error.
- **Incorporating input from geology/geoscience departments**: The methodology allows for the integration of qualitative information from experts in geology and geoscience, such as the geological complexity of the deposit.
- **Adaptability**: The methodology can be adapted to the particularities of each deposit by adjusting the weights of the different factors.
- **Transparency**: The methodology is transparent and auditable, as it clearly explains how the score is calculated.
- **Robustness**: The methodology is robust and can be used to classify mineral resources of different types and sizes. The methodology also provides a framework to combine the strengths of several metrics. For instance, the kriging variance describes the areas more densely drilled but not to capture the ore/waste boundaries. The scorecard workflow may combine the kriging variance with an indicator kriging estimate to promote the synergy between multiple metrics.

In resource classification methodologies, many criteria have emerged, each bringing its own set of advantages and considerations. These criteria play a pivotal role in shaping the accuracy, comprehensiveness, and reliability of resource classification outcomes. In the pursuit of optimal decision-making, it becomes imperative to understand both the strengths and limitations inherent in these criteria.

In conclusion, each metric brings its own advantages and limitations to resource classification. Choosing the most appropriate metrics depends on the specific characteristics of the mineral deposit, available data, project goals, and the level of detail required for decision-making. Combining multiple metrics with care can provide a more comprehensive understanding of resource distribution and associated uncertainties.

Metrics obtained through Kriging may exhibit redundancies, including Kriging Efficiency, Kriging Variance, and Slope of Regression. As a result, it is essential to assess their performance under these conditions and select the most suitable one for Resource Classification purposes.

The objective of this study was to employ and showcase a wide range of criteria, both qualitative and quantitative. However, in practical applications, it is advisable to exercise conciseness by carefully choosing a subset of criteria that are both feasible and sensible for characterizing the deposit.

Despite its strengths, the method does not completely evaluate a mining project. The economic feasibility of a project involves aspects beyond the area of mineral resource classification. These aspects include the community operating license, permitting, infrastructure constraints, safety, market analysis, technical feasibility, financial viability, and social/environmental impact assessments.

Overall, the proposed methodology offers flexibility to incorporate factors obtained from different sources (estimates, geological interpretation, QA/QC). The multi-layer approach to resource classification can help decision-makers evaluate the maturity and risk associated with the mineral deposit and make informed decisions about the economic viability of a project or operation.

5. References

AMORIM, L. Q.; RIBEIRO, D. T. An Useful Ore Reserve Classification Criterion Based on Indicator Kriging. **Proceedings of Mine Planning and Equipment Selection. In: HENNIES, A. da Silva, CHAVES.(Ed.). Balkema**, p. 117–121, 1996.

BADENHORST, C.; ROSSI, M. Measuring the impact of the change of support and information effect at Olympic Dam. **Geostatistics Oslo 2012**, p. 345–357, 2012.

CRIRSCO. **International reporting template for the public reporting of exploration results, mineral resources, and mineral reserves.** . , 2013. Disponível em: <http://www.crirsco.com/templates/crirsco_international_reporting_template_2013.pdf>. Acesso em: 2 abr. 2023

DEUTSCH, J. L.; SZYMANSKI, J.; DEUTSCH, C. V. Checks and measures of performance for kriging estimates. **Journal of the Southern African Institute of Mining and Metallurgy**, v. 114, n. 3, p. 223, 2014.

DEUTSCH, C. V. The Slope of regression for Kriging estimators. **Centre for Computational Geostatistics**, v. 9, p. 311, 2007.

DEUTSCH, C. V; LEUANGTHONG, O.; ORTIZ, J. M. Case for geometric criteria in resources and reserves classification. **Transactions-society for mining metallurgy and exploration incorporated**, v. 322, n. 1, 2007.

DIMITRAKOPOULOS, R. Conditional simulations: Tools for modelling uncertainty in open pit optimisation. **Optimizing with Whittle, Perth, Whittle Programing Pty. Ltd**, p. 31–42, 1997.

DUGGAN et al. Development of a best-practice mineral resource classification system for the De Beers group of companies. **Journal of the Southern African Institute of Mining and Metallurgy**, v. 117, p. 1127–1132, 2017.

EMERY, X.; ORTIZ, J. M.; RODRÍGUEZ, J. J. Quantifying uncertainty in mineral resources by use of classification schemes and conditional simulations. **Mathematical geology**, v. 38, p. 445–464, 2006.

FROIDEVAUX, R. Geostatistics and ore reserve classification. **CIM BULLETIN**, v. 75, n. 843, p. 77–83, 1982.

GLACKEN, I. Change of support by direct conditional block simulation. **Master's thesis, Stanford Univ.**, 1996.

GUARDIANO, E.; PARKER, H. M.; ISAAKS, E. H. Prediction of recoverable reserves using conditional simulation: a case study for the Fort Knox gold project, Alaska. **Unpublished Technical Report, Mineral Resource Development, Inc**, 1995.

ISAAKS, E. H.; SRIVASTAVA, R. M. **Applied geostatistics**. [s.l.] Oxford university press New York, 1989. v. 561

JORC. **Australasian Code for Reporting of Exploration Results, Mineral Resources and Ore Reserves (The JORC Code)**. **The Joint Ore Reserves Committee of The Australasian Institute of Mining and Metallurgy, Australian Institute of Geoscientists and Minerals Council of Australia**, 2012. Disponível em: <http://www.jorc.org>. Acesso em: 8 mar. 2023

JOURNEL, A. G. Nonparametric estimation of spatial distributions. **Journal of the International Association for Mathematical Geology**, v. 15, p. 445–468, 1983.

JOURNEL, A. G.; HUIJBREGTS, C. J. Mining geostatistics. Academic Press, New York. **Mining geostatistics. Academic Press, New York.**, 1989.

JOURNEL, A. G.; KYRIAKIDIS, P. C. **Evaluation of mineral reserves: a simulation approach**. [s.l.] Oxford University Press, 2004.

KRIGE, D. G. A practical analysis of the effects of spatial structure and of data available and accessed, on conditional biases in ordinary kriging. **Geostatistics Wollongong**, v. 96, n. 2, p. 799–810, 1996.

LEUANGTHONG, O.; DEUTSCH, C. **Multivariate geostatistical simulation of red dog mine, alaska**. [s.l.] usa. Technical report, Centre for Computational Geostatistics, University of …, 2003.

MATHERON, G. Principles of geostatistics. **Economic geology**, v. 58, n. 8, p. 1246–1266, 1963.

MOHANLAL, K.; STEVENSON, P. **Anglo American Platinum's approach to resource classification case study—Boschkoppie/Styldrift minewide UG2 project**. The 4th International Platinum Conference, Platinum in transition 'Boom or Bust'. **Anais**...The Southern African Institute of Mining and Metallurgy, 2010.

PARKER, H. M.; DOHM, C. E. **Evolution of Mineral Resource classification from 1980 to 2014 and current best practice**. FINEX 2014 Conference. **Anais**...2014. Disponível em: <www.crirsco.com/docs/H_Parker_Finex.pdf>. Acesso em: 8 mar. 2023

PARRISH, I. S. Tonnage factor- a matter of some gravity. **Mining Engineering**, v. 45, n. 10, p. 1268–1271, 1993.

RIBEIRO, D. T. et al. Utilização de critérios geoestatísticos para comparação de malha de sondagem visando à maximização da quantidade de recursos. **Rem: Revista Escola de Minas**, v. 65, p. 113–118, 2012.

RIVOIRARD, J. Two key parameters when choosing the kriging neighborhood. **Mathematical geology**, v. 19, p. 851–856, 1987.

ROSSI, M. E. **Optimizing grade control: a detailed case study**. Proceedings of the 101st annual meeting of the Canadian Institute of Mining, Metallurgy, and Petroleum (CIM), Calgary. **Anais**...1999.

ROSSI, M. E.; CAMACHO, J. E. Application of conditional simulations to resource classification schemes. **CIM BULLETIN**, p. 62–68, 2004.

ROSSI, M. E.; DEUTSCH, C. V. **Mineral resource estimation**. [s.l.] Springer Science & Business Media, 2014.

SAMREC. The South African Code for the Reporting of Exploration Results, Mineral Resources and Mineral Reserves. 2009.

SILVA, D. S. F. Mineral Resource Classification and Drill Hole Optimization Using Novel Geostatistical Algorithms with a Comparison to Traditional Techniques. 2015.

SOUZA, L. E. DE. Estimativa de incertezas e sua aplicação na Classificacao de Recursos Minerais. 2002.

SOUZA, L. E. DE. Proposição Geoestatística para quantificação do erro em estimativas de tonelagens e teores. 2007.

VAN BRUNT, B. H.; ROSSI, M. E. **Mine planning under uncertainty constraints**. Proc. of the Optimising With Whittle'99 Conference. **Anais**...1999.

VERLY, G.; PARKER, H. M. Conditional simulation for mineral resource classification and mining dilution assessment from the early 1990s to now. **Mathematical Geosciences**, v. 53, n. 2, p. 279–300, 2021.