Applied Earth Science

Transactions of the Institutions of Mining and Metallurgy

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/yaes21

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APPLIED EARTH SCIENCE (TRANS. INST. MIN. METALL. B)
https://doi.org/10.1080/25726838.2023.2244775

REVIEW ARTICLE

Practical application of a multi-layer scorecard workflow (MLSW) for comprehensive mineral resource classification

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ABSTRACT
The classification of mineral resources is crucial for public disclosure and is used to evaluate the risk associated with the mineral deposit, enabling informed decisions. 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. In this paper, we considered classical metrics for resource classification, such as the number of samples, the slope of regression, kriging efficiency, and kriging variance, combinedwith more modern ones (Risk Index), which contemplates the combination of the estimation error, and geological continuity by a probabilistic approach. The methodology can also incorporate qualitative information such as the geological complexity. The proposed workflow has been applied in two different databases, demonstrating its transparency, auditability, and applicability.

ARTICLE HISTORY
Received 9 May 2023
Revised 25 July 2023
Accepted 31 July 2023

KEYWORDS
Resource classification; scorecard; mineral resource; risk; uncertainty; indicator kriging; JORC code; risk index

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 assessment of risk 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 (CRIRSCO 2013; JORC 2012; SAMREC 2009). The geological confidence of resources is assessed and categorised 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. 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, 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. Over time, various approaches have been employed, such as determining classifications based on nearby search areas, spacing between drill holes, range of variability, kriging variance, regression slope, and past experiences with similar deposits (Verly and 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 and Stevenson 2010; Parker and 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 and Ribeiro

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1996). The Risk Index combines the estimation error and geological continuity with a probabilistic ore and waste relationship. The geological continuity is measured by an indicator kriging estimate, while the estimation error is characterised 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 artefacts when the mineralisation consists of several orebodies unconnected.

In this paper, we show 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 quality of the data used. To overcome this issue, an additional data-quality score may be added to the multi-layer scorecard.

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 categorising 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 and Stevenson (2010), Parker and Dohm (2014), and Duggan et al. (2017) have proposed the use of scorecard methodology for resource classification. Mohanlal and 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 is then reviewed by a Competent Person for final classification.

Parker and Dohm (2014) propose 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. To ensure a comprehensive assessment, it is advisable to include the geometry of the ore body, data integrity, spatial correlation, estimation methodology, bulk density, and other factors. To assign a resource classification score to a block model, each factor is ranked (low, medium, or high) based on its importance to the deposit. Each factor is then multiplied by the confidence rating to calculate a discrete score. The total score for all factors is then compared to predefined ranges for Inferred, Indicated, and Measured Resources.

Duggan et al. (2017) suggest a semi-quantitative scorecard approach to evaluate complex and unique mineralisation 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 project geologist completes the five scorecards, and the system is internally reviewed and finally ratified by a Competent Person, providing a consistent and repeatable depiction of confidence in the company's mineral resources.

Study methodology

This paper employs an approach that integrates multiple criteria. The main criteria 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 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. Each confidence score is related to a resource category. The scores for each category are shown in Table 1. We emphasise 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.

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

Table 1. Confidence categories and scores.

Confidence category	Score
High confidence	1
Medium confidence	2
Low confidence	3

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. The criteria used to calculate the global score are explained in Sections 3.1–3.8.

Kriging efficiency

Kriging Efficiency (KE), Krige (1996), is a relevant metric for assessing the quality and precision of 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):

$$KE = \frac{BV - KV}{BV} \tag{1}$$

BV = Block Variance, KV = Kriging Variance.

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.

Slope of regression for kriging estimators

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 that the Kriging estimate is conditionally unbiased. Avoiding conditional bias is crucial in resource classification as it reduces the risk of misclassifying blocks (Deutsch et al. 2014; Deutsch 2007; Krige 1996; Rivoirard 1987; Silva 2015). Equation (2) defines the slope of linear regression (SR):

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

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.

Number of samples

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 utilised in this process. The number of samples has a direct impact on 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.

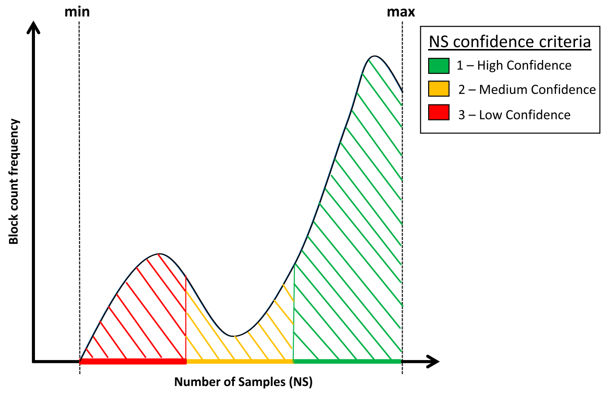

Figure 1. Range used for categorising the Number of Samples used during the kriging process.

In order 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).

Search volume

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 mineralisation and is often used as a metric of resource classification (Parker and Dohm 2014).

The resource classification usually involves using multiple estimations passes 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 et al. 2006; Parker and Dohm 2014; Silva 2015).

In this study, the search volume criteria used were based on the variogram range of the main element estimated. The criteria were 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.

Kriging variance

Kriging Variance (KV) is a measure of the uncertainty associated with a kriging estimate (Journel and Huijbregts 1978). KV is low when many samples spatially correlated with the block to be estimated are used in the estimation. It provides an indication of the degree of confidence in the estimated values, with lower values indicating higher precision and higher values indicating lower precision. The main limitation of the KV is that the variability of the grades is disregarded. Another limitation is the occurrence of artefacts, known as 'spotted dog'.

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. 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.

Risk index

The Risk Index (RI) for resource classification was proposed by Amorim and 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).

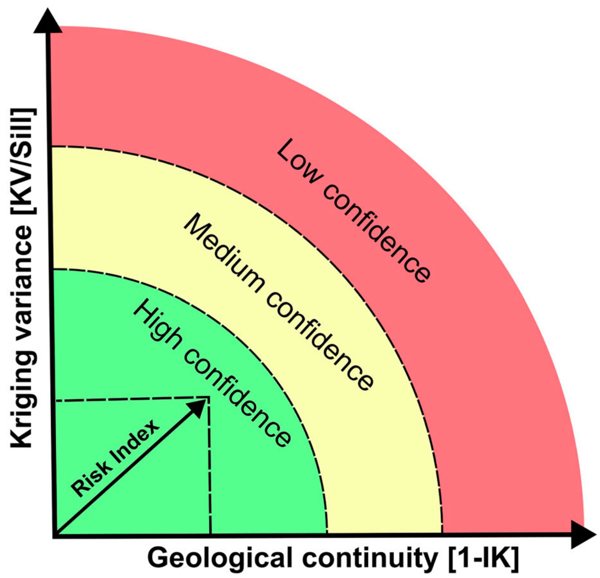

Figure 2. Risk Index vector (adapted from Amorim and Ribeiro (1996)).

The Risk Index (RI), according to Amorim and Ribeiro (1996), is calculated by combining two parameters: the Indicator Kriging (IK) for the ore material and the Standardised Kriging Variance [KV/Sill]. The kriging variance of the indicator kriging estimate is used to calculate the Standardised Kriging variance. The RI is represented as a vector in a Cartesian plane formed by the parameters [1−IK] and [KV/Sill] (as shown in Figure 2). The value of the RI vector can be calculated using the following expression:

$$RI = \sqrt{([1 - IK]^2) + \left(\left[\frac{KV}{Sill}\right]^2\right)} \qquad (3)$$

IK = Indicator Kriging,
$\frac{KV}{Sill}$ = Standardize Kriging Variance.

Risk areas: orebody geometry, data integrity and quality, and other factors

The concept of risk areas for resource estimates refers 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 mineralisation, and others (Parker and 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*: 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 better capture the complexities of the deposit and enhance the accuracy of the estimates (Isaaks and Srivastava 1989). The orebody geometry plays a key role in determining the level of geological confidence of a deposit. The complexity, shape, size, and orientation of an orebody can impact the estimation of resources, production schedules, and the costs associated with the mining process. Drill hole spacing for specific deposit-relevant factors such as the level of exploration activity and the stage of project development.
- *Data integrity and quality*: 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. Ensuring data integrity and quality throughout the entire resource classification process is vital for informed decision-making (Rossi and Deutsch 2014).
- *Bulk density*: provides valuable information on the tonnage and grade of a deposit. 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 and Deutsch 2014).
- *Other factors*: such as geometallurgical data, mineralogy, and penalty elements are all important considerations in the classification of mineral resources. This information is used to determine the best extraction and processing methods, estimate the costs associated with these methods, and to ensure the accuracy and reliability of the resource classification.

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.

Scorecard and smoothing for final classification

The individual criteria are weighted based on their 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 and 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.

Practical application

The present study applies a scorecard workflow for resource classification to two distinct datasets, 2D and 3D. This methodology serves to demonstrate and illustrate the proposed workflow. The datasets exhibit varying degrees of geological complexity that are 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.

2D case study

The proposed method was implemented on a 2D dataset that encompasses six mineralised orebodies exhibiting varying degrees of geological complexity and drilling density. The drilling grid is irregular, comprising an exploratory grid of 100 m × 100 m that was executed in different campaigns over time, and it was eventually complemented by infill drilling of a maximum 30 m × 30 m targeting high-grade areas. The block size dimensions are 10 × 10 m. where the variable lead (Pb) and the indicator Ore (1), were estimated by ordinary kriging. Thus, the criteria such as the number of samples, search volume, kriging efficiency, slope of regression, and Risk Index were used for categorisation from high confidence, medium confidence, and low confidence (Figure 3). It should

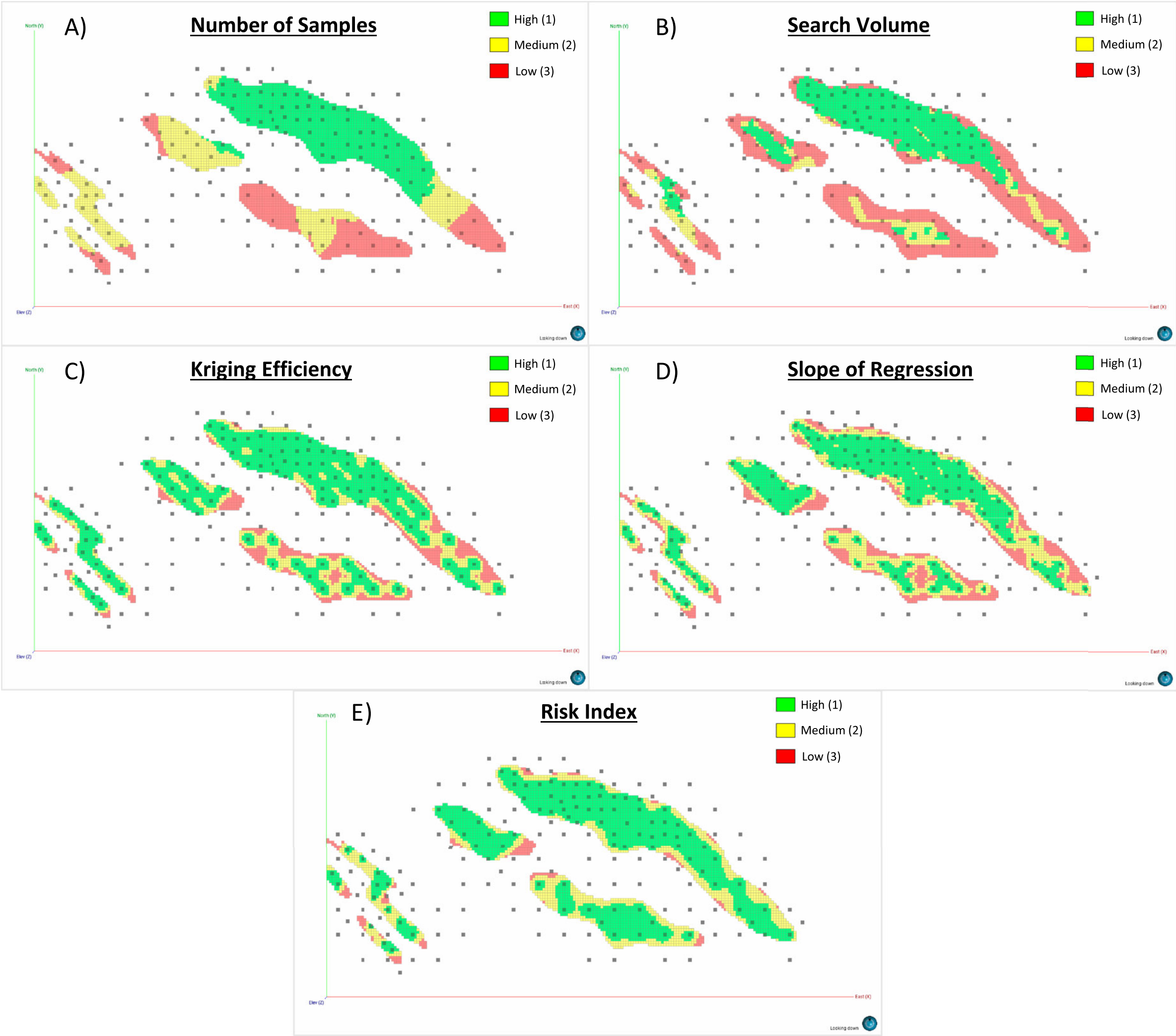

Figure 3. This figure shows the different elements of the workflow that are categorised based on their level of confidence criteria. The elements include (A) the Number of Samples, (B) Search Volume, (C) Kriging Efficiency, (D) Slope of Regression, and (E) Risk Index. These criteria are used to assess the level of confidence in the mineral resource.

be noted that the presence of drilling artefacts affected the classification for criteria such as KE (Figure 3(C)) and SR (Figure 3(D)). However, for criteria such as NS (Figure 3(A)), Search Volume (Figure 3(B)), and RI (Figure 3(E)), stronger continuity was observed along the orebody.

The areas with the highest risk were identified and classified according to their level of confidence for each criterion (Figure 4). Geological areas with low confidence in interpretation, as well as regions with poor confidence in lithological logging, were identified as having lower confidence (Figure 4(A)). Moreover, historical data that lacked appropriate materiality and quality assurance/quality control (QA/QC) protocol were given different confidence levels (Figure 4 (B)). Additionally, areas with historical drilling that lacked density measurements were also identified (Figure 4(C)). Finally, two different areas of confidence were identified regarding geometallurgical and mineralogical components, which could potentially impact the ore processing (Figure 4(D)).

Once all the criteria were compiled, weight values were assigned to each one based on its relative importance. These weights were then used to calculate the final score. It's important to note that all individual criteria were categorised into confidence categories ranging from 1 to 3.

$$\begin{aligned} \text{Scorecard} = {} & [NS * 0.1] + [KE * 0.05] \\ & + [SR * 0.05] + [SV * 0.05] \\ & + [RI * 0.2] + [OG * 0.2] \\ & + [DIQ * 0.25] + [BD * 0.05] \\ & + [OF * 0.05] \end{aligned} \tag{4}$$

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, BD = Bulk Density, OF = Other Factor.

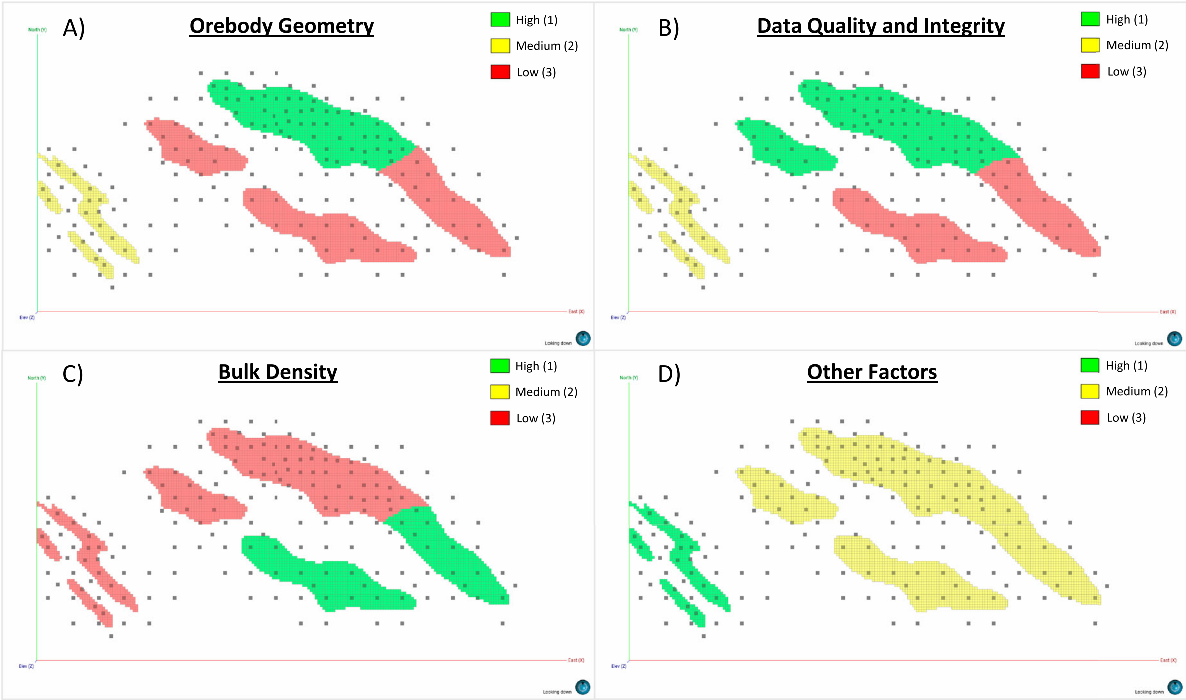

Figure 4. The figure above displays the risk areas identified in the proposed workflow for classifying mineral resources. These areas are categorised into (A) Orebody Geometry, (B) Data Quality and Integrity, (C) Bulk Density, and (D) Other Factors.

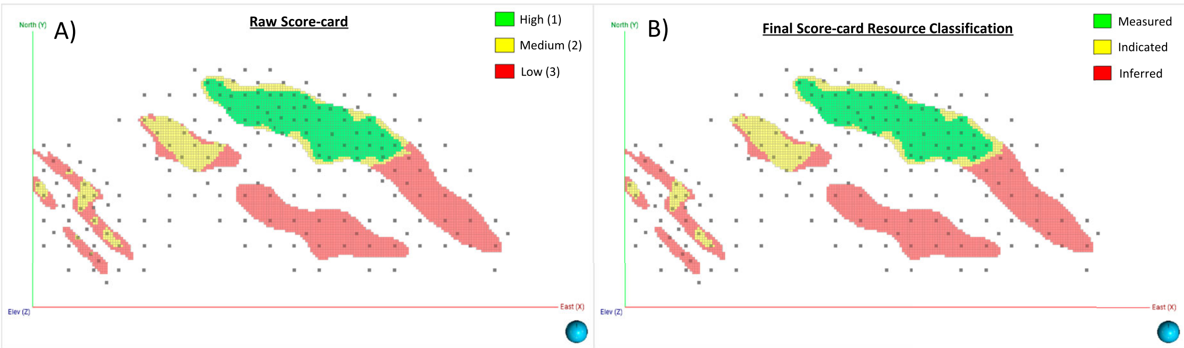

Figure 5. The figure above illustrates the results of the final scoring workflow (A), and (B) the final scorecard resources classification where the smoothing and 'spotted dog' treatment have been applied.

The final classification of the deposit is determined based on the scores obtained from the scorecard. Scores falling between 1 and 1.3 are considered Measured, scores ranging from 1.3 to 1.8 are considered Indicated, and scores exceeding 1.8 are classified as Inferred. However, the raw scorecard model (Figure 5(A)) may contain 'spotted-dog' patterns or other irregularities that need to be post-processed before the final resource classification. Therefore, the scorecard model was smoothed to remove these patterns and ensure a more accurate final classification (Figure 5(B)).

3D case study

In accordance with confidentiality requirements, this paper 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 mineralisation 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 (100 m × 100 m) and the modern campaigns (25 m × 25 m). Furthermore, bulk density measurements were only taken during the modern campaigns, which are crucial for the deposit due to the presence of a specific mineral alteration, with a high-density mineral that can diminish ore processing performance. The block size dimensions are $8 \times 8 \times 8$ m, which are sub-blocked to a suitable minimum of $2 \times 2 \times 2$ m. Additionally, ordinary kriging was employed to estimate the interested variable and the indicator Ore (1).

The results of the methodology are depicted in Figure 6, which categorises the confidence levels into high (1), medium (2), and low (3) based on each criterion. The classification using KE (Figure 6(A)) and NS (Figure 6(D)) presents artefacts and a 'spotted dog' effect surrounding the drilling data. Furthermore, the NS criteria exhibit artefacts on the orebody boundaries due to drilling complexity and the OK kriging anisotropy setup. On the other hand, the SR (Figure 6(B)), RI (Figure 6(C)), and Search Volume (Figure 6(E)) criteria have shown higher spatial continuity in high and medium confidence levels within the high-density drilling grid area. Additionally, Figure 6(F,G) illustrates the classification criteria for Data

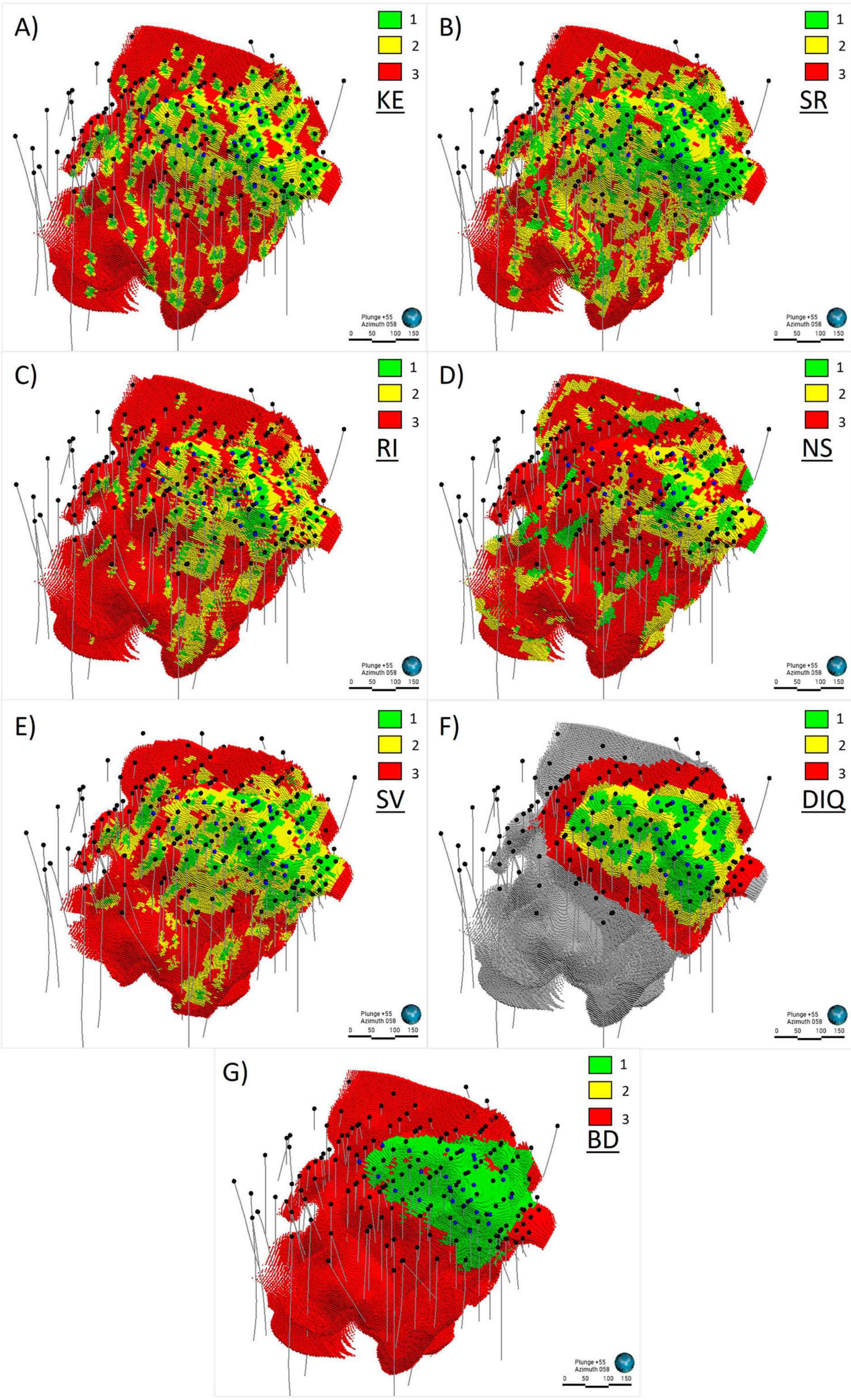

Figure 6. This figure illustrates various components of the workflow that are categorised based on their confidence level criteria. The elements include (A) Kriging Efficiency, (B) Slope of Regression, (C) Risk Index, (D) Number of Samples (E) Search Volume, (F) Data integrity and quality, and (G) Bulk Density. These criteria are utilised in combination to develop the scorecard classification.

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.

After compiling all the criteria, weight values were assigned to each one based on their relative importance. These weights were subsequently utilised to calculate the final score (Figure 7(A)), considering the varying degrees of confidence assigned to each criterion, which was categorised into confidence categories ranging from 1 to 3. This approach consists in factoring in the level of confidence assigned to each criterion and its respective weight. The weight values assigned to each criterion were based on the empirical nature of the deposits described above, as well as previous background knowledge. 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. Therefore, smoothing and 'spotted dog' treatment has been implemented to result in the final resource classification (Figure 7(B)). By utilising a weighted scoring system, we were able to ensure that more important criteria were given a higher degree of importance when calculating the final score, ultimately providing a comprehensive resource classification.

Figure 8 illustrates the tonnage of each criterion that make up the scorecard and the final resource classification. Note that there the proportion of tonnages distribution within the DIQ criterion is similar to the final scorecard classification due to its high importance in the process (40% weight assigned).

Figure 8 provides an insightful illustration of the distribution of tonnage across each criterion that constitutes the scorecard and the final resource classification. It is worth noting that the proportion of tonnage distribution within the Data Integrity and

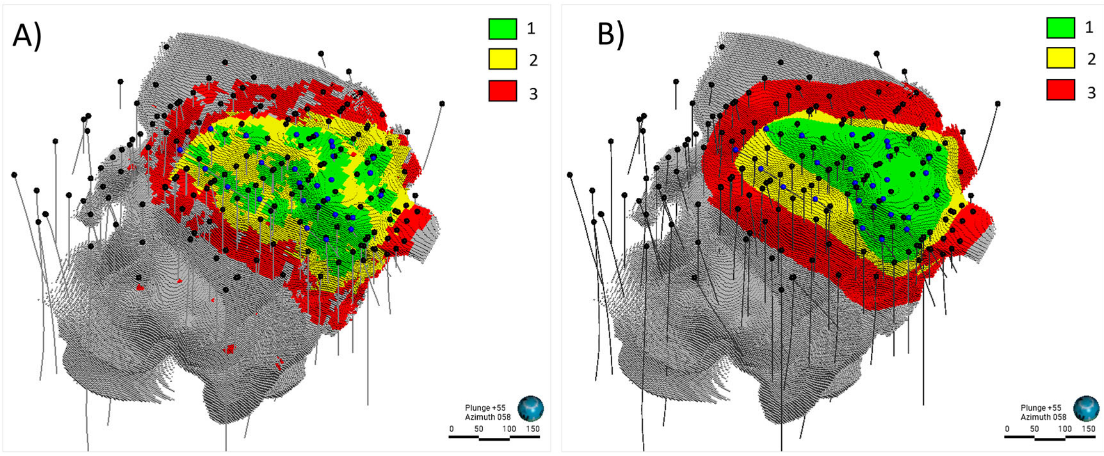

Figure 7. The figure above displays the outcome of the final scoring workflow (A) Scorecard, and (B) the final Resource Classification, where smoothing and 'spotted dog' treatment have been implemented.

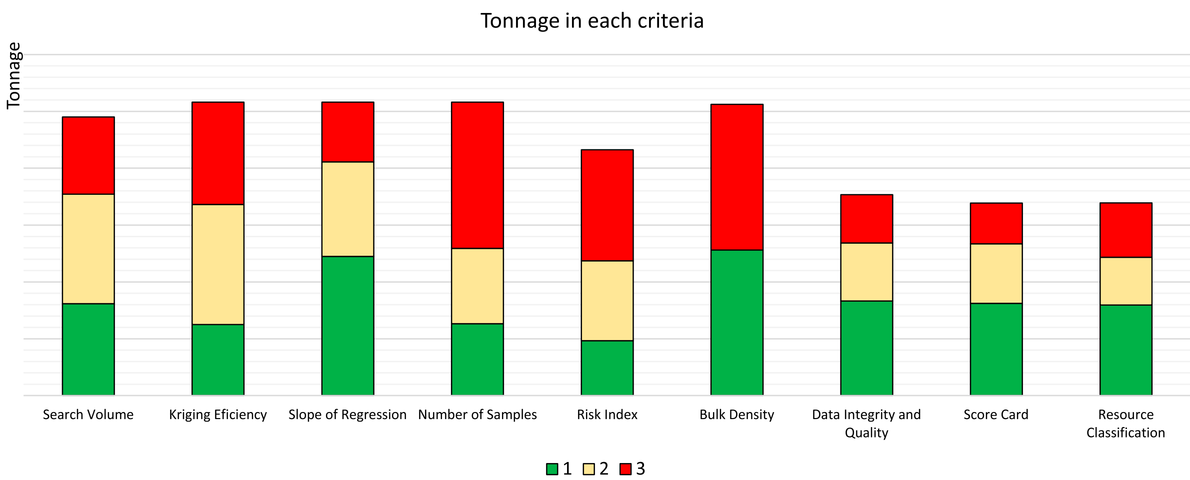

Figure 8. The graph showcases all the different criteria that are utilised to create the Scorecard and, subsequently, the final Resource Classification. These criteria include Search Volume, Kriging Efficiency, Slope of Regression, Number of Samples, Risk Index, Bulk Density and Data Integrity and Quality. After applying smoothing techniques to the Scorecard, the final Resource Classification is produced.

Quality (DIQ) criterion is notably similar to the final Resource Classification. This is due to the high significance of the DIQ criterion in the resource evaluation process, as it carries a weight of 40% in the scorecard.

Discussion and conclusions

The classification of mineral resources is a fundamental step in the evaluation of their economic viability and the associated risk. In this paper, it is proposed a multi-layer scorecard workflow (MLSW) 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 has been applied to two different databases: one 2D and one 3D case, and 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, it is essential for the Competent Person to evaluate the thresholds that are applicable to each parameter.

Moreover, additional techniques such as simulation and uncertainty analysis could be integrated into the methodology 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.

We emphasise that a complete evaluation of a mining project in terms of economic feasibility must consider other qualitative aspects that play a pivotal role in ensuring the project's success and sustainability. These aspects are analysed after the resources model is built and include community license to operate, permitting, infrastructure constraints, safety, market analysis, technical feasibility, financial viability, and social/environmental impact assessments.

Overall, the proposed methodology offers integrating risk assessment, incorporating input from geology and geoscience departments, adaptability, transparency, and audit trails. 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.

Acknowledgement

The authors would like to kindly thank UFRGS for supporting this study.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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