UNIVERSIDADE DE SÃO PAULO

INSTITUTO DE GEOCIÊNCIAS

Análise de incerteza para o Planejamento de Curto Prazo e Controle de Qualidade Aplicada às Minas de Capitão do Mato e Galinheiro- MG

GIULIA MARINA CERQUEIRA DIAS

Dissertação apresentada ao Programa de Pós Graduação em Geociências (Recursos Minerais e Hidrogeologia) para obtenção do título de Mestre em Ciências

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Orientador: Prof. Dr. Marcelo Monteiro Rocha

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COMISSÃO JULGADORA

Prof. Dr. Marcelo Monteiro Rocha

Prof. Dr. Giorgio Francesco Cesare de Tomi

Dra. Rita Parisi Conde Pozzi

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“Há um tempo em que é preciso
abandonar as roupas usadas
Que já tem a forma do nosso corpo
E esquecer os nossos caminhos que
nos levam sempre aos mesmos lugares
É o tempo da travessia
E se não ousarmos fazê-la
Teremos ficado para sempre
À margem de nós mesmos”

Tempo de Travessia - Fernando Pessoa

RESUMO

Dias, G. M. C., 2023. Análises de incerteza para o Planejamento de Curto Prazo e Controle de Qualidade Aplicada às Minas de Capitão do Mato e Galinheiro - MG [Dissertação de mestrado], São Paulo, Instituo de Geociências, Universidade de São Paulo,73 p.

A incorporação de análises de incertezas de teores e dos contatos geológicos por meio de métodos geoestatísticos não lineares é essencial para otimizar o sequenciamento da produção e gerir os riscos associados aos planos de lavra de forma mais adequada. O objetivo desse trabalho é investigar as aplicações de técnicas de geoestatística não linear para quantificação e análise de incerteza, com foco em aplicações para o planejamento de curto prazo. O intuito é mensurar a incerteza geológica do depósito mineral a partir da análise da variabilidade dos teores globais das principais variáveis de controle para o minério de ferro, do risco de contaminação e do risco de classificação errônea dos blocos previstos planos de lavra. Os resultados desse trabalho são apresentados na forma de dois artigos. O primeiro artigo apresenta o "indicador de risco geológico-operacional", o indicador é composto por dois componentes: (i) a continuidade dos teores, obtida por simulação sequencial gaussiana (SGS) para variabilidade do teor em relação ao limite econômico ou operacional da variável; (ii) a incerteza dos contatos geológicos, obtida pela variância da simulação sequencial de indicadores (SIS). O índice proposto é aplicado a cinco variáveis principais de um modelo de curto prazo da mina de ferro Capitão do Mato. Os resultados são satisfatórios e trazem grandes avanços na concepção de um indicador de risco geológico mais adequado para operações de médio e curto prazo, ajudando a prever e gerenciar as incertezas associadas aos planos de mineração com antecedência. O segundo artigo foi realizado mina de ferro do Galinheiro e teve como objetivo aprimorar os controles destinados a gerenciar os níveis de contaminantes no minério de ferro, por meio de mapas de probabilidade das chances de ocorrência de cada contaminante de interesse em níveis superiores aos limiares críticos. Os mapas foram gerados com base em dois métodos geoestatísticos que permitem a quantificação da variabilidade natural dos teores e da distribuição espacial das incertezas, a simulação por bandas rotativas (SBR) e a krigagem MultiGaussiana (KMG). A comparação entre os métodos mostrou resultados semelhantes, a krigagem MultiGaussiana fornece uma alternativa direta que permite acessar a incerteza local e a probabilidade de exceder os limiares críticos. A análise dos contaminantes do minério de ferro revelou a existência de zonas e lentes com níveis potencialmente elevados de contaminantes que permaneceriam não detectados em métodos tradicionais, como a krigagem ordinária. As ferramentas propostas nesse trabalho se mostraram muito eficientes para a análise de risco associada ao controle de qualidade e planejamento de lavra de curto prazo. Mensurar, analisar e gerenciar a variabilidade e incerteza geológica é essencial para o bom funcionamento de qualquer empreendimento minerário.

Palavras-chave: Simulação Geoestatística, Incerteza, Minério De Ferro, Índice De Risco, Krigagem Multigaussiana, Planejamento de Mina de Curto Prazo, Controle de Qualidade

ABSTRACT

Dias, G. M. C., 2023. Uncertainty Analyzes for Short-Term Planning and Quality Control Applied to Capitão do Mato e Galinheiro mines – MG. [Master's Tesis], São Paulo, Instituo de Geociências, Universidade de São Paulo, 73 p.

The incorporation of uncertainties analysis of the grades content and geological contacts through nonlinear geostatistical methods is essential to optimize production scheduling and manage the risks associated with mining plans more appropriately. The objective of this work is to investigate the applications of nonlinear geostatistics techniques for quantification and uncertainty analysis, focusing on applications for short-term planning. The aim is to measure the geological uncertainty of the mineral deposit from the analysis of the variability of the global contents of the main control variables for iron ore, the risk of contamination and the risk of erroneous classification of the blocks provided for mining plans. The results of this work are presented in the form of two articles. The first article presents the "geological-operational risk indicator," which comprises: (1) the uncertainty of geological contacts, determined by the variance of the sequential indicator simulation; and (2) the continuity of grades, obtained by sequential Gaussian simulation for variability of grades in relation to the economic or operational limit of that variable. The proposed index is applied to five grade variables of a short-term model of the Capitão do Mato iron mine in Brazil. The results are satisfactory and advance the concept of a geological risk indicator that is appropriate for medium- and short-term operations. This novel indicator helps to predict and manage the uncertainties associated with mining plans in advance. The second article was carried out in the Galinheiro Mine - QF and aimed to enhance the controls designed to manage contaminant levels through the development of probability maps, in which the chances of occurrence of each contaminant of interest at levels greater than critical thresholds were reflected. The maps were generated based on two methods that allows the quantification of the natural variability of contaminant contents and spatial distribution uncertainties, the turning band simulation (TBS) and the MultiGaussian kriging (MGK). The comparison between the methods showed similar results, the MultiGaussian kriging is the straightforward alternative that provides access to local uncertainty and the probability to exceed critical thresholds. The analysis of iron ore contaminants revealed the existence of zones and lenses with potentially high levels of contaminants that remained undetected in traditional methods such as ordinary kriging. The tools proposed in this work proved to be very efficient for risk analysis associated with quality control and short-term mining planning. Measuring, analyzing and managing geological variability and uncertainty is essential for the proper functioning of any mining company.

Keywords: Geostatistical simulation, Iron ore, Risk index, Uncertainty, MultiGaussian kriging, Short-term mine planning, Quality Control.

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1. Introdução

A província mineral do Quadrilátero Ferrífero (QF) está localizada na porção central de Minas Gerais, próximo às cidades de Belo Horizonte, Brumadinho, Ouro Preto, Rio Acima e Caeté, com área de aproximadamente 7000 m^2 (DORR, 1969), na região limítrofe entre o cráton do São Francisco e a faixa Araçuaí (ALMEIDA, 1977; ALKMIM, 2004). A região representa um dos maiores distritos produtores de minério de ferro no mundo. As reservas estão hospedadas em Formações Ferríferas Bandadas (FFB) metamorfizadas, denominadas de itabiritos, pertencentes à Formação Cauê (DORR, 1964).

Esse trabalho com foco em Geoestatística, é realizado nas minas de Capitão do Mato (CMT) e de Galinheiro (GAL), localizadas no QF. Investiga-se o uso de métodos de geoestatística não linear para análise de incertezas associadas a estimativa dos teores (Fe, Mn, Al, P e perda ao fogo – PF) e aos contatos de minério e estéril nos modelos geológicos. O estudo visa gerar modelos probabilísticos para incorporar a análise de incertezas no planejamento de mina de curto prazo. Os resultados desse trabalho tem como objetivo auxiliar a equipe de controle de qualidade a evidenciar zonas de alta variabilidade de ferro e contaminantes no minério e tornar a tomada de decisão a partir do modelo geológico mais assertiva, assim como os dados fornecidos às etapas subsequentes da cadeia produtiva.

A avaliação de um projeto minerário é feita a partir da construção de modelos computacionais tridimensionais de um depósito mineral, representando a forma dos corpos mineralizados, a localização espacial e todas as características geológicas (distribuição de teores, volume, massa), geotécnicas e metalúrgicas que impactam a extração dos metais ou minerais econômicos (ABZALOV, 2016). Esse modelo deve ser simples e genérico o suficiente para que seja possível trabalhar com os dados – definir domínios, planejar a explotação, tomar decisões com base no modelo – e, ao mesmo tempo, preciso e acurado o suficiente para que seja representativo da realidade. Gerar modelos simples, precisos e acurados, geralmente, é um grande desafio quando se trata de depósitos minerais, pois estes apresentam heterogeneidades naturais relacionadas aos processos formadores da rocha, que dificilmente são representadas por um modelo simplista, aumentando a incerteza e o risco associados ao depósito. As técnicas de Geoestatística, quando aplicadas seguindo as recomendações de boas práticas, podem gerar resultados fundamentais para o planejamento de um empreendimento mineral, evitando perdas de capital sem custos adicionais significativos (MATHERON, 1963).

De acordo com a Sociedade de Análise de Riscos (SRA, 2015), em uma visão ampla, risco pode ser definido como o potencial de ocorrência de uma realização indesejada, as consequências negativas de um evento e/ou desvio de um valor de referência e as incertezas associadas. Uma vez que as incertezas nunca poderão ser diretamente medidas, quaisquer análises sobre elas deverão ser feitas a partir da construção de modelos de incertezas (CAERS, 2011). Bardossy e Fodor (2004), apontam que as investigações geológicas são associadas a incertezas elevadas causadas por duas fontes principais:

a) Incertezas relacionadas a variabilidade natural do fenômeno geológico;
b) Incertezas devido a imperfeições e incompetências humanas, como amostragem não representativa, erros analíticos, modelos inadequados, interpretações enviesadas entre outras.

Consequentemente, as decisões no setor mineral apresentam riscos mais altos quando comparados às decisões semelhantes no setor econômico ou industrial (BARDOSSY; FODOR, 2004). Por isso, Abzalov (2016) indica que alto risco relacionado aos projetos minerários deve ser mensurado através dos riscos técnicos e financeiros, incluindo a quantificação da incerteza geológica na qual se deve mensurar a variabilidade de teores e deletérios e quantificação dos erros de estimativas.

Incertezas associadas à estimativas podem inviabilizar todo um empreendimento minerário, subestimando recursos produtivos ou superestimando recursos não-econômicos, além de induzir a erros na planta de operação e beneficiamento, que geram atrasos no cumprimento de metas e/ou travam a operação, acarretando prejuízos de milhões de dólares (YAMAMOTO, 2001). Conforme descrito por Vasylchuk e Deutsch (2017), o trabalho do controle de qualidade é realizar procedimentos para determinar a rota dos litotipos lavrados, uma vez que esses podem ser direcionados para vários destinos, incluindo pilhas de estocagem, pilhas de estéril, pilhas de blendagem e para a usina de beneficiamento e o direcionamento errôneo do material acarretará perdas no valor do empreendimento. Os modelos de incerteza devem expressar o desvio da realidade do sistema estudado, quanto maior for a complexidade do fenômeno, maior deverá ser a complexidade do modelo, desta forma, mais variáveis influenciarão os resultados e consequentemente maiores serão as incertezas associadas (BÁRDOSSY; FODOR, 2004, CAERS, 2011).

Serão aplicados nesse trabalho metodologias para quantificação da incerteza geológica visando aferir a confiabilidade da estimativa dos teores de elementos maiores dos depósitos de ferro estudados e identificar zonas de alta variabilidade. O objetivo é compreender melhor as variáveis no local de estudo através da quantificação da variabilidade dos teores, o que, acredita-se, possibilitará a melhor gestão do risco associado aos planos de lavra. A identificação das zonas de alto risco associado possibilita aos engenheiros de planejamento mitigar os impactos da variabilidade e excesso de contaminantes no minério que geram o aumento dos custos e das perdas operacionais. Entretanto, vale ressaltar que não é realista esperar que trabalhos desta natureza determinem o risco exato associado ao depósito mineral, pois as diferentes fontes de incertezas não podem ser definidas com precisão e exatidão e sempre restará uma proporção de risco que não se pode prever (BARDOSSY; FODOR, 2004).

1.1 Colocação do Problema e Objetivos

A variabilidade observada nos litotipos do minério é a resultante de vários processos modificadores da deposição original das formações ferríferas bandadas (FFB). Os litotipos são definidos com base em características geoquímicas e sua geometria não obedece a um padrão deposicional e/ou estrutural de fácil distinção.

As grandes oscilações de teores entre diferentes fases de lavra também se caracterizam como agravante, pois a média mensal torna-se pouco representativa do material que está alimentando diariamente a usina de beneficiamento. As predições de qualidade do minério não consideram valores extremos devido ao efeito de suavização de krigagem e, consequentemente, essas predições são pouco representativas da variabilidade real dos teores. Além disso, o indicador de risco geológico utilizado nas minas em que este estudo se baseia é a variância de krigagem, um método geométrico determinístico que não leva em consideração a variabilidade do minério, apenas a distribuição espacial das amostras. Para fins de controle de qualidade e geologia de curto prazo necessita-se determinar a incerteza geológica associada aos teores estimados para os elementos principais e, com isso, determinar o risco geológico associado ao plano de lavra. Adicionalmente, a incerteza espacial auxilia a definir campanhas de amostragem otimizadas, com foco em zonas de alta variabilidade.

Deste modo, investigar-se-á o uso das técnicas de Simulação Geoestatística (Simulação Sequencial Gaussiana, Simulação Sequencial de Indicadores e Simulação por Bandas Rotativas) para quantificar as incertezas associadas à predição de teores. Além disso, esse trabalho se propõe a comparar os resultados obtidos através da simulação geoestatística com uma metodologia alternativa de quantificação de incertezas, a krigagem MultiGaussiana.

1.2 Objetivos

O objetivo desse trabalho é investigar as aplicações de técnicas de geoestatística não linear para quantificação e análise de incerteza, com foco em aplicações para o planejamento de curto prazo. O intuito é mensurar a incerteza geológica do depósito a partir da análise da variabilidade dos teores globais das principais variáveis de controle para o minério de ferro, do risco de contaminação e do risco de classificação errônea dos blocos previstos planos de lavra. Especificamente, esse trabalho visa:

- Definir um indicador de risco baseado na variabilidade do minério (através da simulação sequencial gaussiana) e nos contatos minério-estéril (através da simulação sequencial de indicadores) para avaliar o risco operacional das frentes de lavra.
- Gerar mapas de probabilidade dos contaminantes excederem valores críticos, de acordo com as metas de qualidade do minério, através de dois métodos (simulação por bandas rotativas e krigagem MultiGaussiana) e comparar os resultados obtidos por ambos.

Os resultados desse trabalho visam fornecer métricas de controle de incerteza para o planejamento de lavra de forma a aprimorar a reconciliação entre valores reais e estimados, prever o risco associado à variabilidade do minério e auxiliar nas campanhas de amostragem para o planejamento de curto prazo.

2. Artigo I - A novel geostatistical index of uncertainty for short-term mining plan

G. M. Cerqueira Dias and M. Monteiro Rocha
Institute of Geosciences - University of São Paulo, São Paulo, Brazil

V. M. Silva
Vale S. Águas Claras Mine, Nova Lima, Brazil

giuliacerqueira@hotmail.com; +55 31 997522362

ABSTRACT: The uncertainty associated with geostatistical estimates is as important in a model as the estimated value itself. Commonly, this uncertainty is accessed through different scenarios obtained by geostatistical simulation methods. Although the applications of geostatistical simulation methods have grown significantly in recent decades in long-term modelling, the same improvement hasn't occurred in medium- and short-term modelling. This study presents the "geological-operational risk indicator," which comprises: (1) the uncertainty of geological contacts, determined by the variance of the sequential indicator simulation; and (2) the continuity of grades, obtained by sequential Gaussian simulation for variability of grades in relation to the economic or operational limit of that variable. The proposed index is applied to five grade variables of a short-term model of the Capitão do Mato iron mine in Brazil. The results are satisfactory and advance the concept of a geological risk indicator that is appropriate for medium- and short-term operations. This novel indicator helps to predict and manage the uncertainties associated with mining plans in advance.

Keywords: Geostatistical simulation, Iron ore, Risk index, Uncertainty

RESUMO: A incerteza associada às estimativas geoestatísticas é tão importante em um modelo quanto o próprio valor estimado. Comumente, essa incerteza é acessada através de diferentes cenários obtidos por métodos de simulação geoestatística. Embora as aplicações dos métodos de simulação geoestatística tenham crescido significativamente nas últimas décadas na modelagem de longo prazo, a mesmo crescimento não ocorreu na modelagem de médio e curto prazo. Este estudo apresenta o "indicador de risco geológico-operacional", o indicador é composto por dois componentes: (i) a continuidade dos teores, obtida por simulação sequencial gaussiana (SGS) para variabilidade do teor em relação ao limite econômico ou operacional da variável; (ii) a incerteza dos contatos geológicos, obtida pela variância da simulação sequencial de indicadores (SIS). O índice proposto é aplicado a cinco variáveis principais de um modelo de curto prazo da mina de ferro Capitão do Mato. Os resultados são satisfatórios e trazem grandes avanços na concepção de um indicador de risco geológico mais adequado para operações de médio e curto prazo, ajudando a prever e gerenciar as incertezas associadas aos planos de mineração com antecedência.

Palavras-chave: incerteza, simulação geoestatística, minério de ferro, índice de risco

2.1. Introduction

The term “uncertainty” is widely used in many fields of study, such as economics, engineering, and geology. Uncertainty involves imperfect or unknown information about the study target. In the mining industry, the main source of uncertainty is imperfect information regarding the actual variability in geological behavior, which is commonly assessed as the difference between the modelled and observed behavior of the variables of interest. This difference may be due to a lack of sufficient data, sampling and analytical errors, and imperfect understanding of geological behavior, among others.

Geological models and their related uncertainties directly affect decision making in the mining industry. Therefore, the mining industry generally needs to manage more associated risks than other industries because of the high uncertainty of the geological modelling and the ore body itself (Bárdossy & Fodor, 2004; Snowden, Glacken & Noppé, 2002). The chances of success of mining scheduling and operational plans are proportional to the correct quantification and management of the uncertainty of the mineral content of interest and of deleterious elements.

Beginning in the early 1970s, methodologies to quantify and manage geological uncertainty and its impact on mining operations and decision making were developed, including the application of the stochastic simulation methods to spatially correlated data, that is, modelling spatial uncertainty by generating multiple realizations of the joint distribution of attribute values in space (Goovaerts, 1997). Methods of stochastic simulation conditioned by available data and parameters are considered the best at quantifying uncertainty in geological modelling for the mining industry, and could be used in mineral resource classification (Snowden, 1996). The generation of conditional realizations was introduced by Journel (1974) based on: 1) drawing equiprobable realizations conditioned to the data, 2) globally reproducing the random-function parameters to honor the locally available data in terms of spatial variability, and 3) and histogram distribution. The measured uncertainty is proportional to the variability between these realizations (Goovaerts, 1997; Journel & Huijbregts, 1978; Rossi & Deutsch, 2014).

The use of geostatistical simulation methods to quantify uncertainties and classify mineral resources has significantly increased in recent decades and is becoming commonplace (Deutsch, 2018). Although simulation should be a standard method to quantify uncertainties, the industry still struggles with managing multiple realizations of a variable. The application of simulation methods to uncertainty assessment in medium- (quarterly, annual, bi-annual) and short-term (daily, weekly, monthly) mine planning is even more restricted. Concerns primarily center on high computational requirements for models that need to be frequently updated, the non-uniqueness of multiple realizations, and the high number of calculations, including mine planning algorithms, within a single block model (Deutsch, 2018). Another limit to widespread use of simulations is the availability of software used to implement them. Different algorithms could be written to produce simulations from a given model, but they are not equally efficient. The implementation of certain algorithms may lead to inefficient programs, especially in terms of numerical precision, speed, and memory (Lantuéjoul, 2002).

In the twenty-first century, computational limitations have been overcome, and computer performance has improved by a factor of 1.7–76 trillion compared to manual computing (Nordhaus, 2007). The ability to use multiple cores and graphics processing units means that it is not necessary to compromise on complexity to consider all realizations in downstream calculations, that is, pass all realizations through a transfer function to construct a distribution of responses for resource estimates (Deutsch, 2018). However, working with multiples scenarios remains a shortcoming in the industry. Simple summary models could be useful, such as the modelling the probability of meeting an economic threshold or modelling the local variance. For example, the realizations could be passed through a decision tree structure to help support a decision. Another approach is to collapse uncertainty into a few summary measures and base plan on them. These approaches will never be as good as using all the realizations simultaneously but they provide a practical solution using available software (Deutsch, 2018). Based on these concerns, geostatistical simulations are commonly overlooked in real mining-industry applications (Dominy, Noppé & Annels, 2002; Ortiz, Magri & Libano, 2012; Verly, 2005; Yamamoto, 2001).

Analysis or decision-making will be suboptimal if the uncertainty inherent to any geological model is ignored. Therefore, many kriging-based methods were developed as more convenient and easy-to-implement uncertainty assessment methods (Arik, 1999; Deutsch, Szymanski & Deutsch, 2014; Miguel-Silva, 2021; Ribeiro et al., 2010). Uncertainty analysis using kriging quality metrics involves the same assumptions as kriging estimation, making the best linear unbiased estimate, minimizing the local error variance, and setting the mathematical expectation of the error to zero. This methodology results in a smoothed interpolation, which is a serious deficiency if the goal is to detect extreme values and highlight the variability of the attribute (Goovaerts, 1997). Another drawback of kriging is that the smoothing is not uniform, which may produces artifact structures: it is minimal close to the data locations and increases with distance from the sample (Goovaerts 1997).

Considering the limitations of kriging-based methods to measure uncertainty and the rapid evolution of computational performance, this paper proposes to compare the geostatistical risk index (RI) proposed by Ribeiro et al. (2010) to a full simulation-based approach. The method, called the Operational-geostatistical Risk Index (ORI), is composed of two components. The first component is the spatial continuity of the modelled geological domains, such as packages of rocks with similar properties. It is obtained by sequential indicator simulation (SIS; Isaaks, 1983). The second is the variability of the grades of interest and their chance of being above or below defined threshold values based on cutoff grades or operational constraints. It is obtained by sequential Gaussian simulation (SGS; Isaaks, 1990; Deutsch & Journel, 1997).

The primary purpose of this paper is to propose the ORI for short-term mining planning. First, the literature is reviewed in terms of the RI and the SIS and SGS geo-statistical simulation methods. Next, the fundamentals of the ORI are presented. Finally, the proposed approach is tested for a real mining deposit, the Capitão do Mato mine in Brazil.

2.2. Literature review

2.2.1. The RI

The RI proposed by Ribeiro et al. (2010) is a kriging-based method to support mineral resource classification. The index combines the estimation error through a kriging variance and geological continuity through an indicator kriging approach. This method was developed to mineral resource classification at Vale Ferrous (Ribeiro et al., 2010). The RI has been applied to risk analysis of a gold deposit (Gomes, 2021) and to adapt the equation incorporating the specific volume to reduce the effect of block size (Rivoirard, et al., 2017).

The RI is performed at each kriged node or block (x_0). The kriging variance (S_{IK}^2) and the kriged indicator (I_K) are merged through equation 1:

$$RI\ (x_0) = \sqrt{[1 - I_K(x_0)]^2 + [S_{IK}^2(x_0)]^2} \tag{1}$$

S_{IK}^2 is a geometric index that depends on the variogram model used and the spatial data configuration—two excellent features to assess risk estimates. It is proportional to the number of samples in the neighborhood of the estimated block or node. Spatial continuity anisotropy will affect the variability distribution of the estimated grades: the variability is higher in the lower continuity direction. The uncertainty also increases where there are too few samples to properly estimate grades. However, S_{IK}^2 is independent of data values—a harmful feature because the areas surrounded by data with high or low variability have the same S_{IK}^2 (Figure 1). Thus, S_{IK}^2 will only reflect the variogram model anisotropy and the data spatial distribution. Therefore, we consider S_{IK}^2 a good summary of the spatial configuration given the modelled variogram structural distance (Goovaerts, 1997) but a poorly indicator of data variability.

I_K handles transformed data within a chosen stationary domain (Journel, 1983). Observations are coded as 1 if their values are above a given threshold grade; otherwise, they are assigned 0. The estimated indicators can be interpreted as the probability or proportion of each point belonging to each class (1 or 0). It is worth noting that I_K estimates depend on indicator variability but are not influenced much by data spacing (Figure 2).

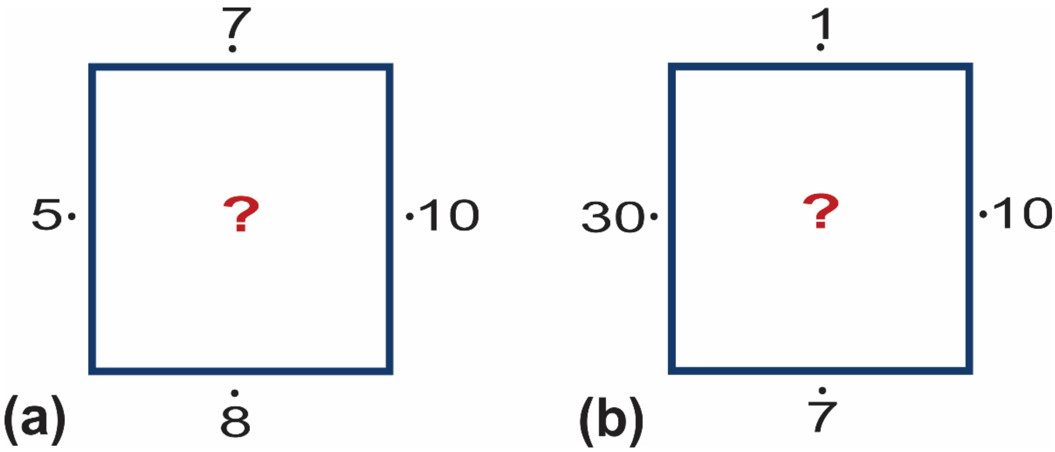

Figure 1 – Estimation of blocks from the same data configuration. The Kriging Variance of A and B is the same due to its independence to data values (Armstrong, 1998).

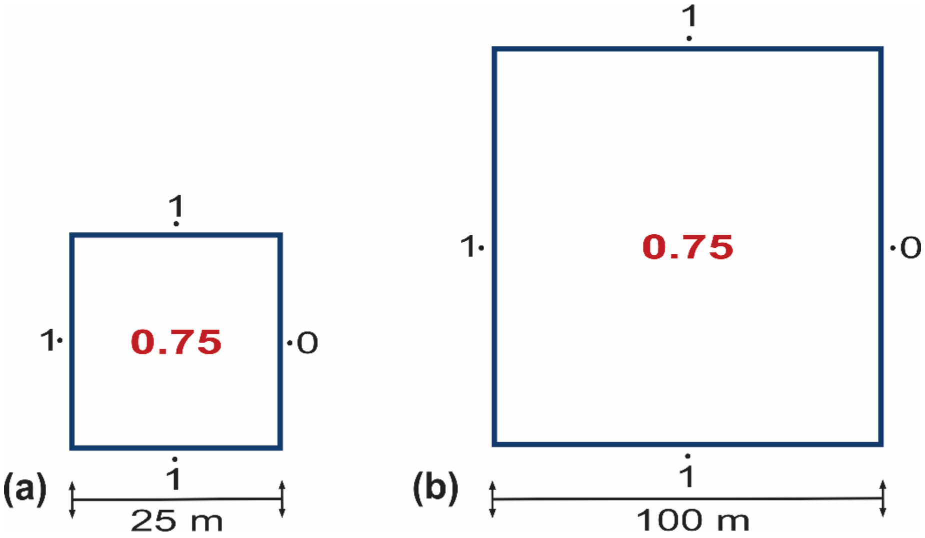

Figure 2 – Estimation of blocks from the same indicator values. See that in A the estimation is the same of B, regardless of the increasing distance between data and kriged node (Miguel-Silva, 2021).

Thus, RI is represented by a two-dimensional graph, where the results between geological continuity $(1 - I_K)$ and variability (S_{IK}^2) are related to each other (Figure 3). The proposed ORI overcomes the limitations of the RI in terms of assessing geological uncertainty, that is, S_{IK}^2 does not properly represent the data variability, and I_K is only weakly influenced by data spacing.

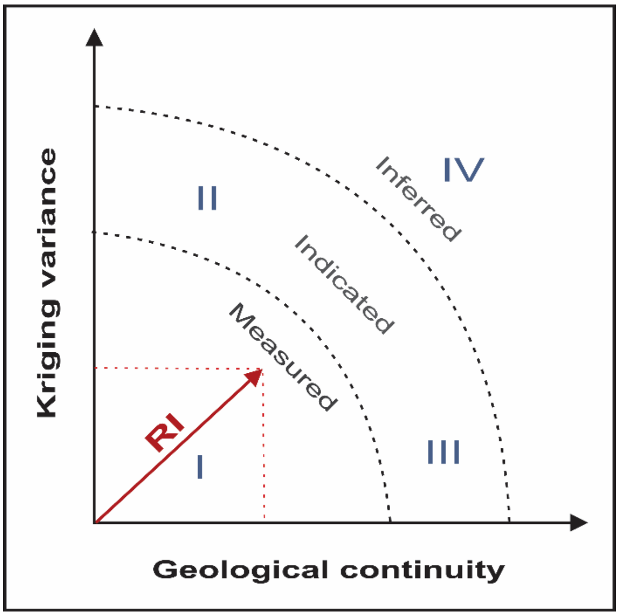

Figure 3 – Mineral resource classification based on sectorization of the Risk Index based on its kriging variance (y-axis) and geological continuity (x-axis) component (Ribeiro et al., 2010).

2.2.2. Geostatistical simulation – SIS and SGS

The regionalized variable of interest, z(x_0), may be assumed as a realization of the random variable function, Z(x_0). Z(x_0) is characterized by a cumulative distribution function and a covariogram or variogram model that controls z(x_0). The conditional simulations may draw other realizations, $z^l(x_0)$, of Z(x_0). The realization $z^l(x_0)$ will honor the sampled values at locations X_i and each realization must honor the same variogram model and histogram as the original input data. The simulated and data-sampled realization will thus be equiprobable and can be viewed as two possible variants of the same geological process from Z(x_0). The simulated realization, however, is known at all simulated nodes and not only at the data points X_i as the data-sampled realization (Journel & Huijbregts, 1978).

Evaluating uncertainty is required as best practice in mineral resource estimation. Uncertainties in any of the criteria that could lead to under- or over-statement of Mineral Resources should be disclosed (JORC, 2012). The JORC code also states that the choice of the appropriate category of Ore Reserve is determined primarily by the relevant level of confidence in the mineral resource and after considering any uncertainties in modifying factors. Therefore, methods of geostatistical simulation are starting to be more widely accepted and implemented in the last decades to quantify uncertainty and classify mineral resources. Conditional simulation is an ideal tool for uncertainty and risk assessment: the risk and uncertainty may be determined as a probability distribution assembled from the drawn realizations (Emery, Ortiz & Rodríguez, 2006). The simulated nodes may be averaged into blocks or production areas of any shape to assess their uncertainty.

The sequential simulation approach is a generalization of the conditioning idea. It is extended to include all data available in the neighborhood, including the original samples and previously simulated values (Deutsch & Journel, 1997). SGS and SIS are the most widely used methods for sequential simulation (Deutsch & Journel 1997; Goovaerts 1997; Isaaks 1983, 1990). In both algorithms, a random path is defined to visit all nodes to be simulated. A value randomly drawn from the conditional distribution is then used as conditioning data for the next node to be visited.

In SIS, indicator kriging (Journel, 1983) is used to sequentially characterize the conditional distribution at each node to be simulated. The indicator simulation algorithm is a nonparametric method originally designed for categorical variables where the Gaussian random function model is inappropriate. The method was later extended to continuous variables, for example, a continuous variable discretized over K classes, where $I_k = 1$ if the category k above a given threshold occurs at x_0, otherwise $I_k = 0$ (Journel, 1983; Goovaerts, 1997).

In SGS, the distribution at each node to be estimated is fully characterized by its conditional mean and variance given by simple kriging. The method relies on the multi-Gaussian property in which a Gaussian random function is fully characterized by its mean vector and covariance matrix. In general, experimental data are not Gaussian. Therefore, the original data may need to be transformed into a Gaussian distribution, usually by normal score transformation (Deutsch & Journel, 1997). The simulated nodes are then back-transformed to their original units.

2.3. The ORI

In the ORI, the geological uncertainty is evaluated by taking into account model-based operational decisions, such as classifying a block as ore or waste or defining an infill-drilling campaign based on areas of higher uncertainty. Similar to the RI, ORI is based on combining two components. First, SIS generates several realizations of the domains of interest to define the variability in each node of the category k that it belongs to. Second, considering the random function properties of each node and its category k, SGS is used to draw realizations of the variables of interest. In this way, the output considers the uncertainty associated with the distribution of rocks and/or domains and then the uncertainty of the grades within each domain. Thus, the uncertainty of the variables or grades of interest within each geostatistical domain are modelled by SGS, while the geological continuity of those domains are modelled through SIS. The domains may be based on rock type, ore /waste packages, or other criteria.

The local uncertainty on a point is assessed by the probability of this point exceeding a defined threshold value in several realizations (equation 2):

$$Prob[z^l(x_0) \leq z_c] = \frac{n(x_0)}{L} \tag{2}$$

where $z^l(x_0)$ is the simulated value at point x_0, z_c represents the defined threshold value, $n(x_0)$ is the number of realizations in which the variable exceeded z_c, and L is the total number of realizations.

The threshold value is established for each variable of interest based on criteria that influence the block classification or geological domains. For each block, values are assigned for the quantiles of 5% (Q05) and 95% (Q95) and the average of all realizations. Then, the simulation uncertainty is calculated confining 90% of distribution ($IC_{90\%}$) in each block for each variable (equation 3):

$$IC_{90\%} = \frac{Q95 - Q05}{2 \times Simulation\ mean} \tag{3}$$

Often, more than one variable affects operational risk. Thus, the $IC_{90\%}$ values of all variables need to be combined to assess the total uncertainty. Auxiliary variables define which variables from each block will be considered in the ORI equation. If the block has a high probability (> 50%) of exceeding the threshold, its auxiliary variable is associated with 1; otherwise, it is associated with 0. Then, the accumulated simulation uncertainty calculated at 90% confidence (IC_{ac}) is calculated (equation 4):

$$IC_{ac} = \frac{(Aux_x \times IC_x) + (Aux_y \times IC_y) + (Aux_z \times IC_z)}{(Aux_x + Aux_y + Aux_z)} \tag{4}$$

where IC_i, IC_j, and IC_k are the simulation uncertainty calculated at 90% confidence for variables i, j, and k, respectively, and Aux_i, Aux_j, and Aux_k are their auxiliary variables (0 or 1), respectively. The auxiliary variables are coded as 1 if z(x_0) is greater than a defined cutoff or threshold.

The geological continuity of the domains is modelled through SIS, and variability is incorporated on the ORI equation through the simulation variance between the domain classification (Var_{sis}). After simulating the grade and indicator uncertainty, ORI is computed through (equation 5). The higher the variance within the drawn realization, the higher the uncertainty associated to the block and the higher the associated risks.

$$ORI(x_0) = \sqrt{[\,Var_{sis}(x_0)]^2 + \ [IC_{AC}(x_0)\ ]^2} \tag{5}$$

where $Var_{sis}(x_0)$ is the variance within SIS realizations. It evaluates the uncertainty in which the simulated node x_0 belongs to the geological domain. The component $IC_{AC}(x_0)$ is the accumulated simulation uncertainty of the variables of interest at 90% confidence of exceed a defined cutoff or threshold.

2.3. Case study

2.3.1. Geological background

The case study compares the RI and ORI in a real iron ore deposit owned by Vale. The Capitão do Mato mine is located in the Quadrilátero Ferrífero, Brazil (Figure 4). The deposits comprise metamorphosed banded iron formations hosted in itabirites. The Quadrilátero Ferrífero is considered one of the most important sources of iron ore to the global market with several world-class iron ore deposits. It consists of sedimentary rocks, such as conglomerates, quartizites, and phylites from the Minas Supergroup overlain by marine sedimentary rocks, banded iron formations, and carbonates from the Itabira Group (Dorr, 1969). Intrusive bodies and an iron-rich duricrust (canga) are also present crossing and covering the stratigraphy, respectively. The iron-ore deposits resulted from 1) weathering of itabirite rocks, which formed friable contaminated ores (soft ore), and 2) hydrothermal overprint of the itabirite, which formed compact hematite (hard ore) (Hensler et al., 2015).

At Capitão do Mato mine, iron-ore mineralization is described based on mineralogical and chemical compositions, resulting in 10 ore types: friable itabirite, high-grade friable itabirite, compact itabirite, goethite itabirite, aluminous itabirite, manganiferous itabirite, goethite-aluminous–hematite, compact hematite, friable hematite, and canga. There are also five waste lithotypes: intrusive rocks, phyllite, dolomite, dolomitic phyllite, and laterite.

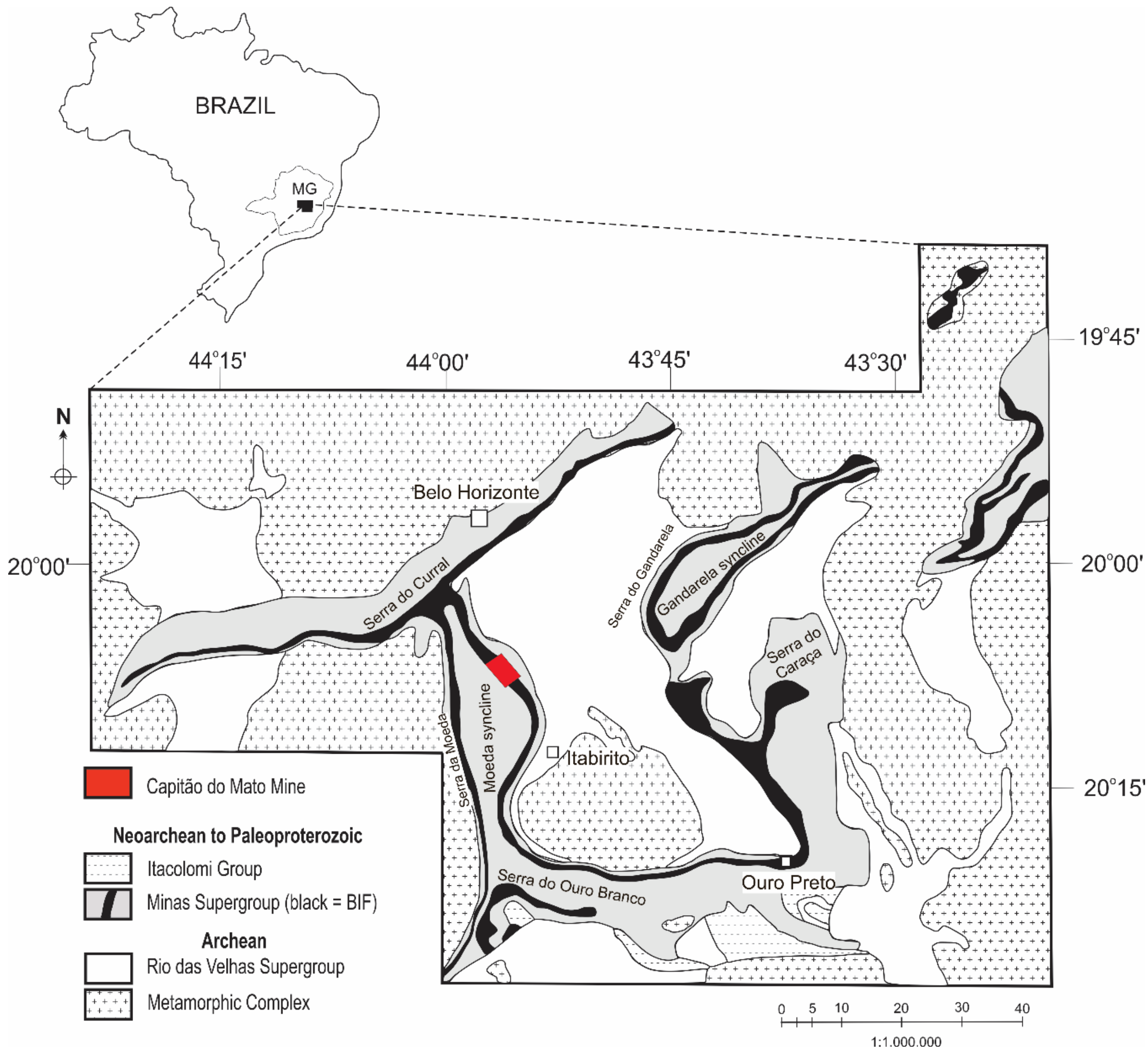

Figure 4 - Simplified geological map of the Quadrilátero Ferrífero, modified from Dorr et al. (1969), showing the location of the study area, Capitão do Mato mine. Inset abbreviation: BIF = Banded Iron Formation; MG = Minas Gerais State.

2.3.2. Operational aspects

In the Capitão do Mato mine, six ore variables are monitored daily: Fe_2O_3, SiO_2, Al_2O_3, P_2O_5, and MnO_2 content and loss on ignition. Although SiO_2 content is monitored, it was disregarded because it has a strong negative correlation with Fe_2O_3. Iron is the main ore product. Keeping contaminants below the values negotiated on the global market is essential and a challenge for quality control. Iron formations outside the requirements in Table 1, and other lithologies are classified as waste. There is a greater tolerance in the acceptable limits of each grade to classify the block as ore or marginal ore because the monthly run-of-mine (ROM) comprises several blended blocks. However, in the daily ROM for feeding the beneficiation plants, the acceptable contents are more restrictive.

Table 1. Destination classification key for iron formations at Capitão do Mato mine (%); ROM: run-of-mine

Classification	**Fe_2O_3**	**Al_2O_3**	**P_2O_5**	**MnO_2**	**Loss on ignition**
Ore	≥37	≤ 6	-	≤2	≤ 6
Marginal ore	≥32	> 6	-	>2	> 6
Avg. ROM feed	>40	<1.5	<0.09	<0.15	<2

2.3.3. ORI Implementation

To implement ORI in this case study, 30 scenarios were simulated for each component.

The component simulated by SIS ($Var_{sis}(x_0)$) was obtained from the simulation of the destination classification indicator according to Table 1. For each block, there were three possible destination classifications (ore, marginal ore, and waste) in each realization. Each component was simulated independently by its indicator variable. The most probable destination classification was assigned to each block in each realization according to the simulated classification indicator. Then, the categorical variables were transformed to a numerical variable to calculate the variance from the realizations results: ore was assigned 1, marginal ore 0.5, and waste 0. The variance between the realizations represents the destination classification uncertainty.

For the SGS component (IC_{AC}), the five variables in Table 1 were simulated. The grade contents were combined according to equation 6:

$$IC_{ac} = \frac{IC_{Fe}+(Aux_{Al}\times IC_{Al})+(Aux_{P}\times IC_{P})+(Aux_{Mn}\times IC_{Mn})+(Aux_{LOI}\times IC_{LOI})}{(Aux_{Fe}+Aux_{Al}+Aux_{P}+Aux_{Mn}+Aux_{LOI})} \quad (6)$$

where IC_{Fe}, IC_{Al}, IC_{P}, IC_{Mn}, and IC_{LOI} are the simulation uncertainty calculated at 90% confidence for Fe_2O_3, Al_2O_3, P_2O_5, MnO_2 and LOI, respectively, and Aux_{Fe}, Aux_{Al}, Aux_{P}, Aux_{Mn} and Aux_{LOI} are their indicator auxiliary variables, respectively, in terms of the probability of exceeding the thresholds. Each indicator auxiliary variable is defined as 1 when the chances of the respective study variable exceeding the critical thresholds of beneficiation plant quality specifications are > 50%; otherwise, it is defined as 0.

2.4. Results and discussion

It is possible to distinguish two sectors in the mine. In the eastern sector, itabirite and hematite predominate with little contamination and higher grades and are mainly classified as ore (Figure 5a). The southern sector, on the other hand, has a greater variability of ore lithotypes, predominantly contaminated materials, such as canga, goethitic and aluminous itabirites, and low-grade itabirites. We can expect from this visual analysis that the southern sector will present more associated operational risks due to the predominance of lower grade and contaminated rocks. Considering the intrusive (waste) rocks as a physical boundary between the two sectors, and the materials classification as ore, marginal ore, and waste (Figure 5b), it can be stated that the eastern sector is dominated by blocks classified as ore while southern sector predominates marginal ore.

The borehole sampling mesh is sufficiently regular enough and covers the area, with a few gaps in the mesh at the bottom of the eastern sector and southwest portion of the southern sector (Figure 6).

The kriging variance is the first component of the RI (equation 1). The kriging variance and areas with lower risk have the same preferential orientation as the samples (N26°E), suggesting that this could be an artifact of the data spacing (Figure 7a). The probability of the block to be ore, computed through indicator kriging, is the second component of the RI. Approximately 70% of the blocks are classified as ore (Figure 7b). The probabilities to be ore for blocks that are near barren lithotypes samples are close to zero; they are classified as waste. A “halo” of blocks with intermediate values can be observed around these blocks. Combining the variables in Figures 7a and 7b yields the RI (Figure 7c). Its behavior is strongly influenced by the sampling design and does not adequately represent the grade variability and lithotypes observed in the area.

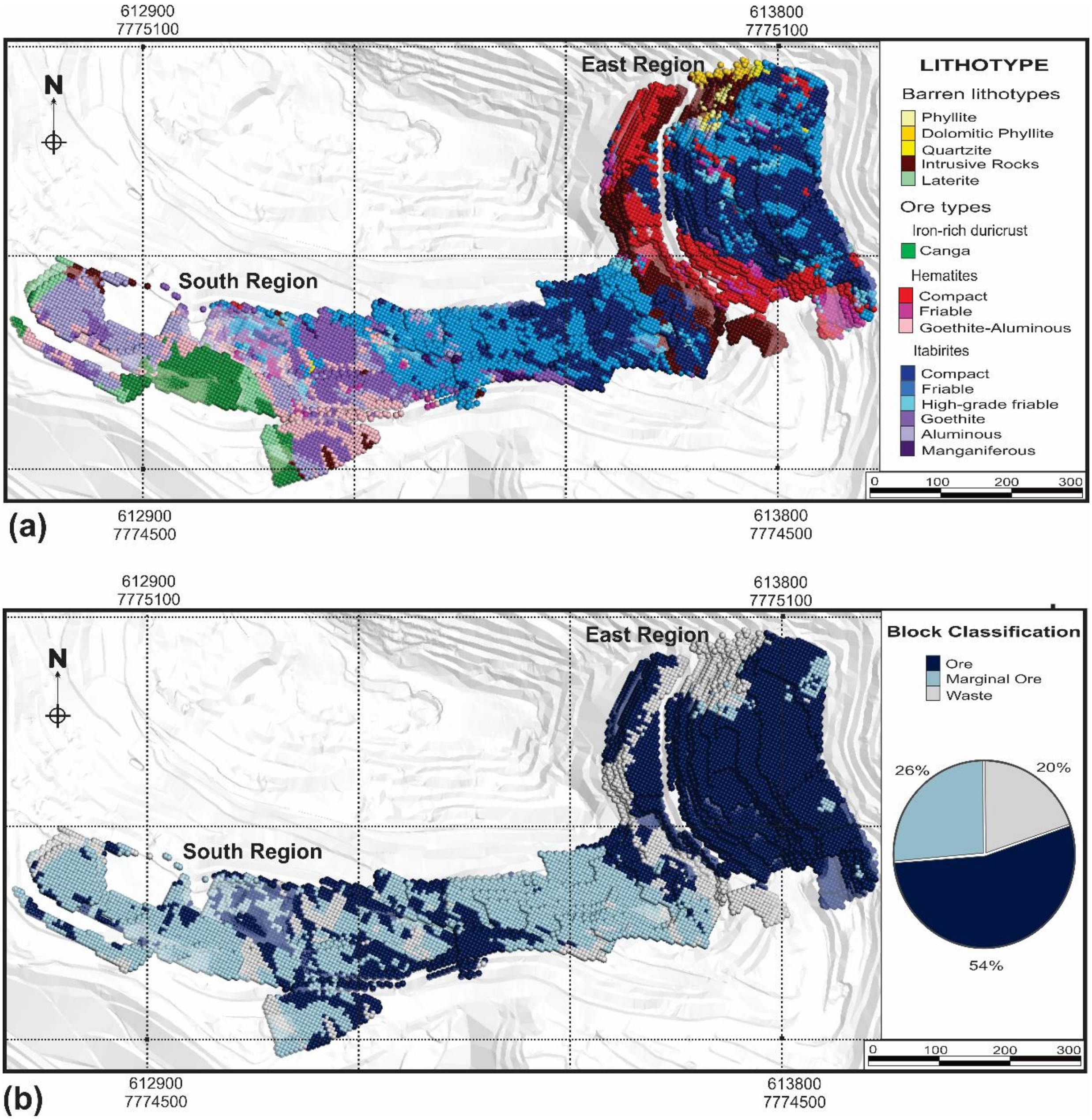

Figure 5 – Distribution of the proposed ore for annual mining plan at the Capitão do Mato mine, shown as lithotypes distribution (a) and block classification distribution (b). As the boundary between the eastern and the southern region isn't visually easy to define, we could consider the intrusive rocks (brown color) as a physical boundary between them.

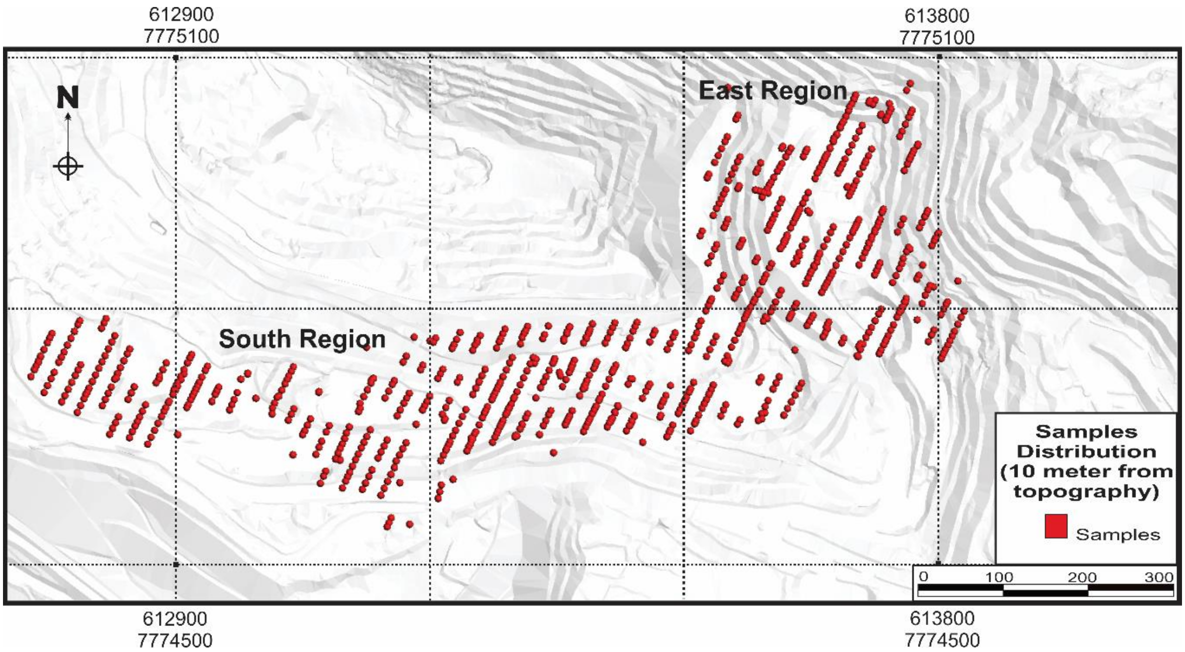

Figure 6 – Sample distribution (10 m from topography) at the Capitão do Mato mine.

The spatial distribution and uncertainty of the block destination classification obtained by the variance of the SIS realizations (Figure 8a) is correlated with geological continuity. Elevated values indicate the probability of misclassification of the block is high and vice versa. The high SIS variance values (red) are correlated with the boundary regions observed at Figure 5b. The second component of the ORI, the grade variability obtained by SGS, highlights those regions with a high probability of exceeding critical thresholds (Figure 8b). This component numerically quantifies the phenomena described by the visual analysis of the lithotypes and block classification. The southern region has high grade variability because there are more contaminants and diffuse contact relationships between the ore and marginal ore classifications. In contrast, the east region has low grade variability since there is less lithotype variability and less contamination.

The ORI is obtained by a quadratic equation of the spatial continuity and grade variability components. It allows the practitioner to distinguish between two sectors with different geological impacts during mining operations at Capitão do Mato mine. In the east region, there are high risk values near the contact with the barren lithotypes (intrusive rocks and phyllite) because this contact is transitional (Figure 8c). Losses by dilution in iron content and contamination by Al_2O_3 commonly occur. In the southern region, the high risk values are more comprehensive since there are several lenses of marginal ore and waste among the blocks classified as ore as well as contaminated ores that present high values of Al_2O_3, P_2O_5, MnO_2, or loss on ignition.

The proposed use of ORI to replace the RI presents advantages with respect to the assessment of the actual geological uncertainty of the deposit. The RI exhibited a strong correlation with the sampling spatial distribution, indicating areas of high risk where there is no sampling or close to the limits between ore and waste blocks. Although the lack of sampling is, in general, a source of risk, the quantification of risk during mining should not be based only on number of samples or proximity to waste blocks, for two reasons (Figures 6 and 8c). 1) Some regions as the south/central area have a dense sampling grid and still present operational problems due to the great variability of lithotypes and contents. Consequently, a high risk is associated with the natural variability of the deposit in that region. 2) The uncertainty levels may be acceptable even in the presence of sparser samples in regions lacking high grade variability or transitions within lithotypes, as was observed in the lower east region.

Furthermore, the classification of the block as waste should not in itself be treated as a risk. If the block is classified as waste but has greater reliability in classification and estimated value, it is not a high risk. What should be incorporated as a risk factor is the low reliability in the classification of the block. If there is an ore block with low reliability of classification, this equates to a high risk: there is a high chance of misclassification.

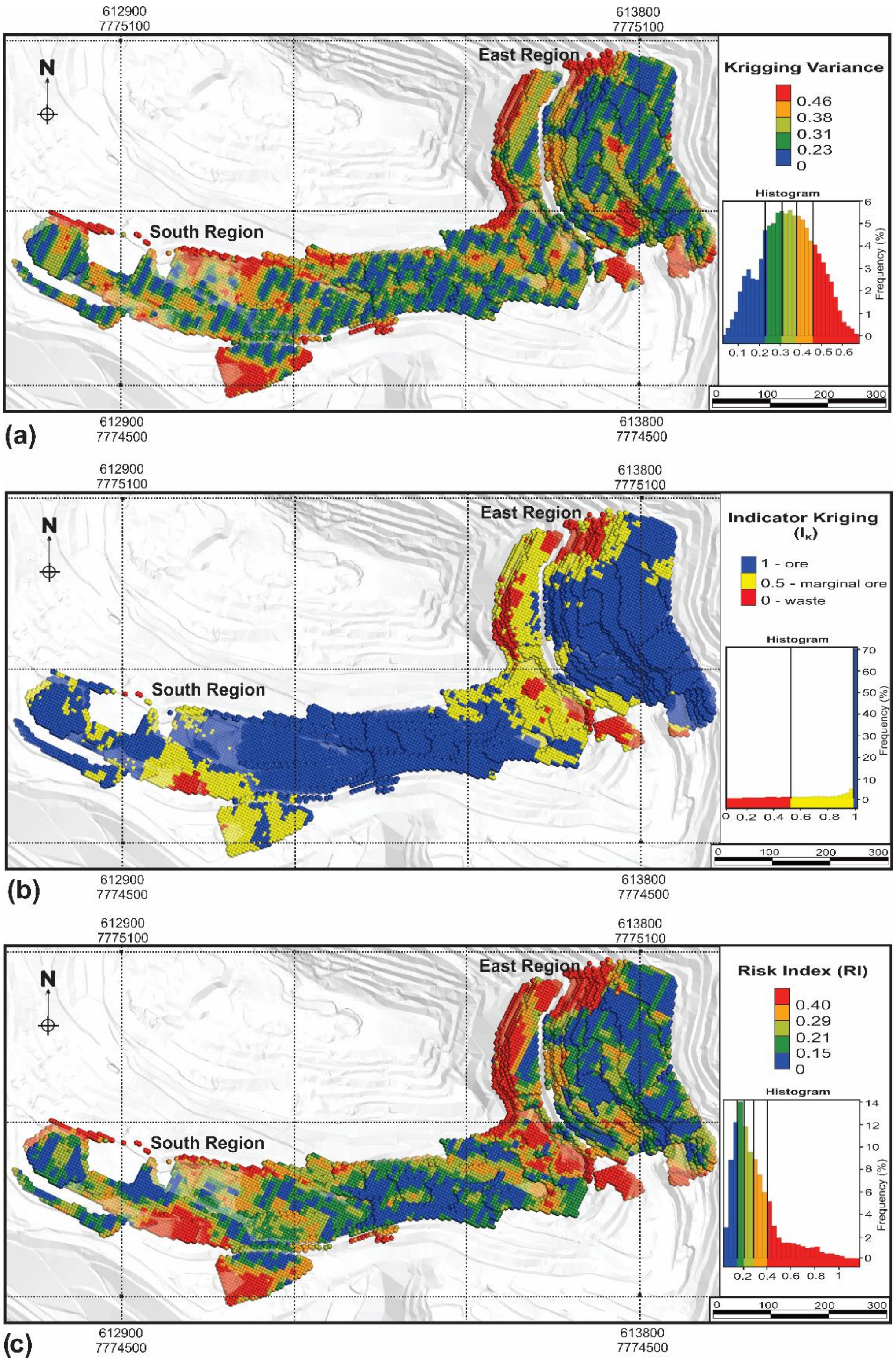

Figure 5 – Spatial distribution and histograms of the components of the risk index (RI), Kriging Variance (a), Ore Indicator (Ore = 1, Marginal Ore = 0.5 and Waste = 0) (b) and the risk index (c).

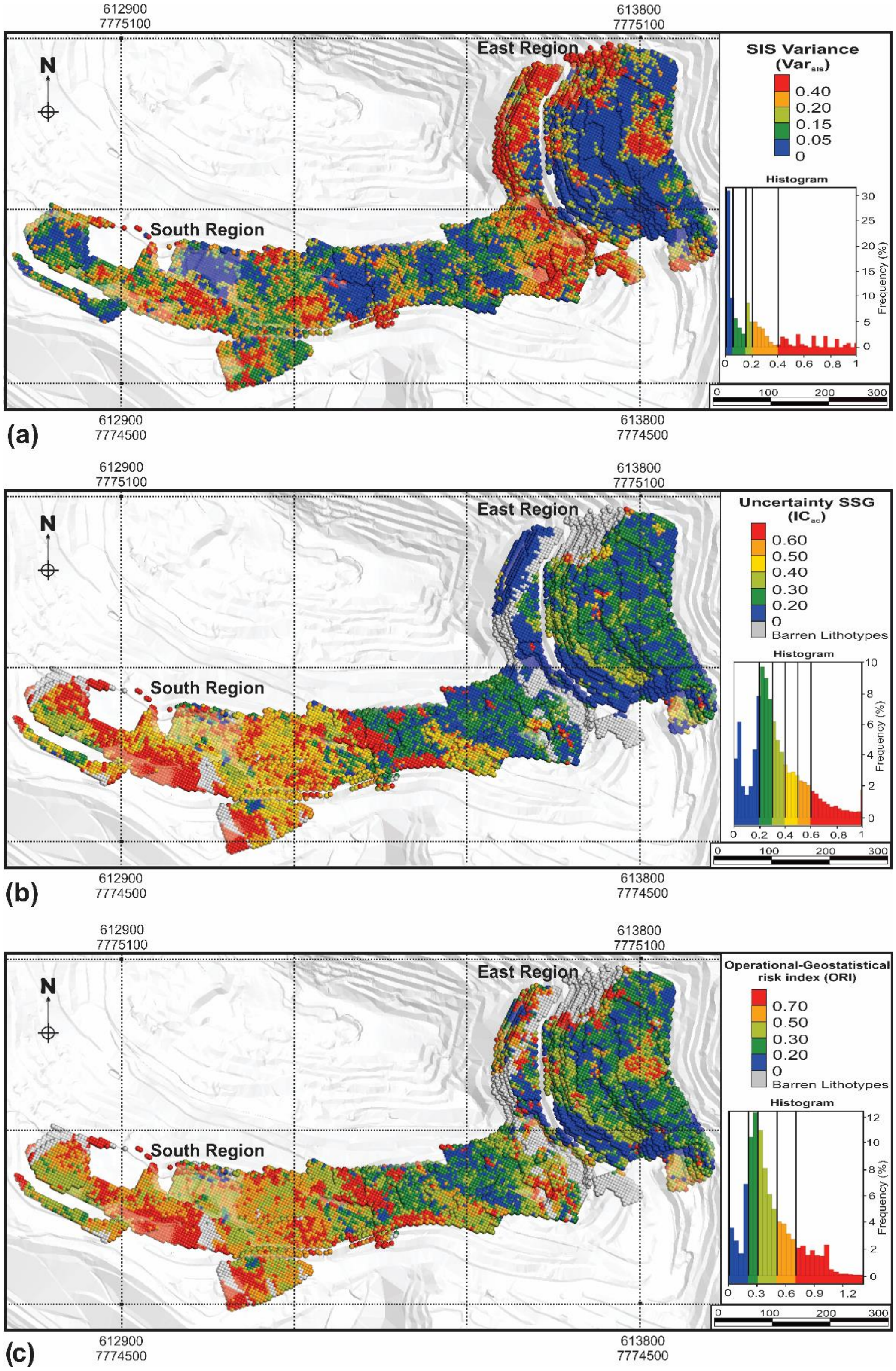

Figure 6 – Spatial distribution and histograms of the components of the operational-geological risk index, geological continuity (a), grade variability (b) and the ORI (c).

2.5. Conclusions

Although geostatistical simulation is currently used for resource classification, in the short-term routines of the mineral industry, its applications are very limited. Within this context, incorporating uncertainty of grade and geological contacts through simulation methods advances the concept of a more appropriate geological operational risk index. The management of risks related to geological uncertainty in the short term can minimize incorrect decisions and consequently, financial losses that can reduce a mine's profit and productivity. In general, such gains are far greater than the expenses associated with the additional time and increased computational demands required by simulation methods.

The ORI summarizes the variability of ore content and the reliability of the block classification. It provides essential information for mine planning engineers to incorporate uncertainties into the mine schedule. Short-term planners could use the ORI to make better decisions during mine planning in several ways. 1) Blocks that presents high ORI values could be downgraded in the ore classification. 2) Blocks that are classified as ore but present high ORI values could be destined for blending stockpiles. 3) The sampling mesh could be optimized using the ORI values: regions with high ORI values could be sampled with a dense mesh while regions with low ORI values could be sampled with a sparse mesh. 4) The mine plan with uncertainties within operational tolerance could be achieved by combining areas with high and low ORI values.

This work explores a preliminary application of the ORI. However, there is room for improvement and further investigation. Future studies should review how the two components (SIS and SGS) are combined. The geometric method of joining geological continuity (Var_{sis}) and grade variability (IC_{ac}) could be investigated to understand the relative contribution of each variable to the overall risk. In this study, the contaminants in the IC_{ac} were given equal weight. Future studies could weight variables based on their impact on an economic factor (e.g., impact of a given contaminant on the final price of ore). The uncertainty related to geological continuity could be improved through analysis of geological boundary variability by comparing different modelling techniques such SIS versus implicit modelling. Finally, although the ORI was created with a focus on short-term mine planning, it could be incorporated into the resource classification framework to better predict uncertainties related to mineral resources.

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3. Artigo II - Quantification of spatial uncertainties associated with iron ore contaminants to short-term quality control: a comparison between turning band simulation and Multi-Gaussian kriging.

G. M. Cerqueira Dias and M. Monteiro Rocha

Institute of Geosciences - University of São Paulo, São Paulo, Brazil

D. Q. Rossi

Vale S.A., Iron Resource Management, Vargem Grande Complex, Nova Lima, Brazil

giuliacerqueira@hotmail.com; +55 31 997522362

ABSTRACT: Iron ore is the main mineral commodity produced in Brazil, and the Quadrilátero Ferrífero (QF) ranks among the largest iron-producing regions of the world. For almost the entire 20th century and into the early 21st century, Brazilian iron ore has been known for its high iron content. However, dwindling high-grade iron ore reserves have pushed mining companies into exploring ores with lower iron and higher contaminant contents. For this reason, quality control of iron ore in mining operations has become an essential element in managing contaminant levels and ensuring compliance with international market requirements, since elements such as alumina and manganese directly affect steelmaking processes and the final properties of steel products. This study was carried out in the Galinheiro Mine - QF and aimed to enhance the controls designed to manage contaminant levels through the development of probability maps, in which the chances of occurrence of each contaminant of interest at levels greater than critical thresholds were reflected. The maps were generated based on two methods that allows the quantification of the natural variability of contaminant contents and spatial distribution uncertainties, the turning band simulation (TBS) and the MultiGaussian kriging (MGK). The comparison between the methods showed similar results, the MultiGaussian kriging is the straightforward alternative that provides access to local uncertainty and the probability to exceed critical thresholds. The analysis of iron ore contaminants revealed the existence of zones and lenses with potentially high levels of contaminants that remained undetected in traditional methods such as ordinary kriging. The findings derived from this study will help quality control and short-term planning teams make better, more informed decisions.

Key-words: Turning Bands Simulation, MultiGaussian kriging, Iron Ore, BIF, Short-term mine planning, Quality Control.

RESUMO: O minério de ferro é a principal commodity mineral produzida no Brasil, e o Quadrilátero Ferrífero (QF) está entre as maiores regiões produtoras de ferro do mundo. Por quase todo o século 20 e no início do século 21, o minério de ferro brasileiro tem sido conhecido por seu alto teor de ferro. No entanto, a redução das reservas de minério de ferro de alta qualidade levou as empresas de mineração a explorar minérios com teor de ferro mais baixos e teores mais altos de contaminantes. Por essa razão, o controle de qualidade do minério de ferro nas operações de mineração tornou-se um elemento essencial na gestão dos níveis de contaminantes e na garantia do cumprimento dos requisitos do mercado internacional, uma vez que elementos como alumina e manganês afetam diretamente os processos siderúrgicos e as propriedades finais do aço. Este estudo foi realizado na Mina do Galinheiro - QF e teve como objetivo aprimorar os controles destinados a gerenciar os níveis de contaminantes no minério, por meio de mapas de probabilidade das chances de ocorrência de cada contaminante de interesse em níveis superiores aos limiares críticos. Os mapas foram gerados com base em dois métodos geoestatísticos que permitem a quantificação da variabilidade natural dos teores e da distribuição espacial das incertezas, a simulação por bandas rotativas (SBR) e a krigagem MultiGaussiana (KMG). A comparação entre os métodos mostrou resultados semelhantes, a krigagem MultiGaussiana fornece uma alternativa direta que fornece acesso à incerteza local e a probabilidade de exceder os limiares críticos. A análise dos contaminantes do minério de ferro revelou a existência de zonas e lentes com níveis potencialmente elevados de contaminantes que permaneceriam não detectados em métodos tradicionais, como a krigagem ordinária. Os resultados derivados deste estudo ajudarão as equipes de controle de qualidade e planejamento de curto prazo a tomar decisões assertivas.

Palavras-chave: Simulação por Bandas Rotativas, Krigagem MultiGaussiana, Minério de Ferro, BIF, Planejamento de Mina de Curto Prazo, Controle de Qualidade

3.1. Introduction

Located in Southeastern Brazil, the Quadrilátero Ferrífero (QF) is one of the largest banded iron formations (BIFs) of the world (Figure 1). In 2020, Brazil ranked second in the world as the nation produced about 400 million tons of iron ore, backed up by reserves estimated at 34 billion tons (USGS, 2020). The chemical composition of iron ore and its concentrates varies substantially, particularly in regard to the contents of Fe (56 – 67%) and key contaminants SiO_2 (0.6 – 5.7%), Al_2O_3 (0.6–3.7%), Mn (0.03 – 0.8%), and P (0.015 – 0.154) (Clout; Manuel, 2015). A trend towards declining iron ore grades has been observed in recent years, which pushed mining companies into exploring ores with lower iron and higher contaminant contents (Lu et al., 2007; Clout; Manuel, 2015).

Managing contaminant levels in iron deposits is a fundamental element in controlling the quality of end products and optimizing the profitability of a mining operation, since contaminants adversely affect steelmaking processes and decrease the prices paid for iron ore in the international market. Slight increases in the content of alumina in sinter feed may lead to significant impacts in characteristics such as strength and reduction degradation index, causing the deterioration of gas permeability in the upper portion of the blast furnace (Lu et al., 2007). Although present in some types of steel, manganese in extremely high contents increases the need for dilution through blending with cleaner materials to preserve the expected properties of the desired steel products (Clout; Manuel, 2015).

Therefore, production targets set based on iron ore quality and quantity are essential for the success of mining operations. However, the natural variability of iron ore grades and spatial distribution uncertainties may cause deviations in production and financial losses (Benndorf; Dimitrakopoulos, 2018). Estimation of local recoveries such as tonnage and ore grade in a selective mining operation is a challenging geostatistical problem, it is necessary to calculating local probability distributions where the distributions are conditioned to a local data environment (Verly, 1983). This study compares two different methodologies used to uncertainty quantification of a spatially distributed variable, in this case, the contents of contaminants Al_2O_3 and MnO_2 in the Galinheiro Iron Ore Mine. The first method is the Turning Bands Simulation (TBS), a commonly used simulation method and the second method is the MultiGaussian Kriging (MGK), a flexible alternative to simulation. Both methods allowed the development of probability maps, in which the chances of occurrence of each target contaminant at levels greater than critical thresholds are reflected.

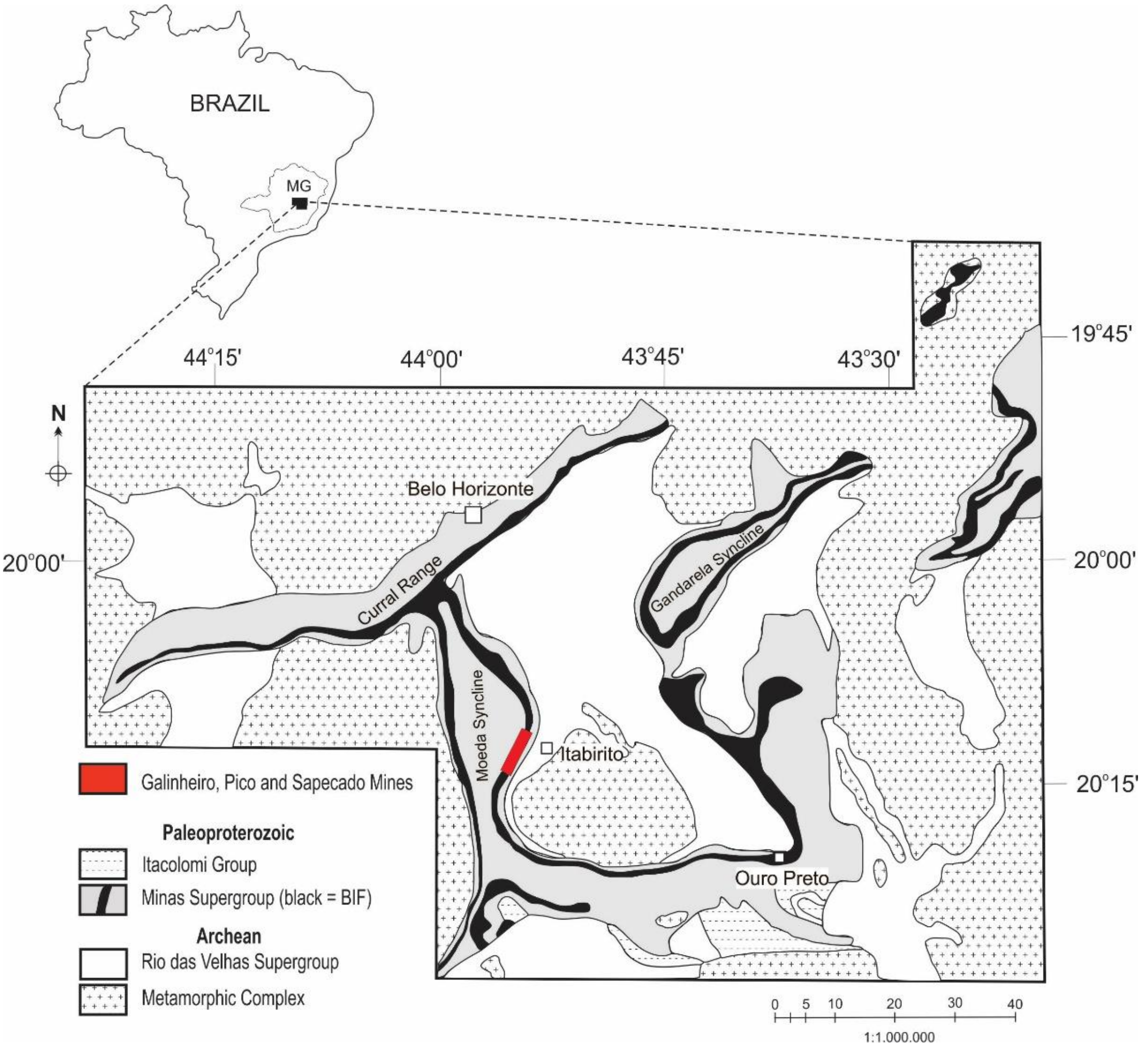

Figure 1: Plot Plan of Quadrilátero Ferrífero and location of Galinheiro and Sapecado Mines – M.G, adapted from Dorr et al. (1969). Approximated study area delineated in red.

3.2. Literature review

The turning bands simulation is a commonly used method of simulation proposed by G. Matheron (1973) and developed by Journel (1974). The method generates a series of one-dimensional independent simulations along lines (which could be rotated in 3-D space) to performs simulations in a multi-dimensional space (Chilès; Delfiner, 1999). TBS is based on a decomposition of the random function defined by a variogram. The width of the bands is proportional to the range of the variogram, but its rotation and its "rhythm" are random. Simulations are performed using a gaussian distribution, and they reproduce the covariance from the gaussian data and original data after the back-transformation. A post processing is required to conditioning the unconditional simulation realizations through kriging residuals between input data and non-conditional simulation (Journel; Huijbregts, 1978) (Figure 2). The methodology implementation consists the following steps: 1) The spatially distributed are declustered and transformed to normal score values distribution; 2) Variogram calculation and modelling of the normal values; 3) Unconditional simulation in Gaussian units, with the experimental histogram reproduced by transformation and the covariance or variogram from the data being also reproduced; 4) Condition the turning bands simulation through a post-processing using kriging; 5) Backtransformation of the gaussian simulated values to the original units of the variable.

MultiGaussian kriging applies simple kriging to a Gaussian or normal transformation of the original sample data to amounts the conditional distribution of uncertainty, that is fully defined by their mean and variance under the multiGaussian assumption. (Ortiz et al., 2004). A Gaussian random field, or multigaussian random function, is characterized by the fact that any weighted average of its variables follows a Gaussian distribution, which means that its spatial distribution is entirely defined by its first- and second-order moments (mean and covariance function or variogram). In this method, the conditional distribution of the variable of interest is Gaussian-shaped, with mean equals to its simple kriging (SK) result and variance equals to the simple kriging variance (Emery, 2005). The methodology implementation consists of the following steps (Ortiz; Deutsch, 2003): 1) The spatially distributed are declustered and transformed to normal score values distribution; 2) Variogram calculation and modelling of the normal values; 3) Kriging estimation of the mean and variance of the normal score values in a regular grid; 4) The shape of a gaussian distribution is known by its means and variance, hence the full conditional distribution in the original units of the variable can be retrieved by backcalculating the z values for given percentiles (Figure 3).

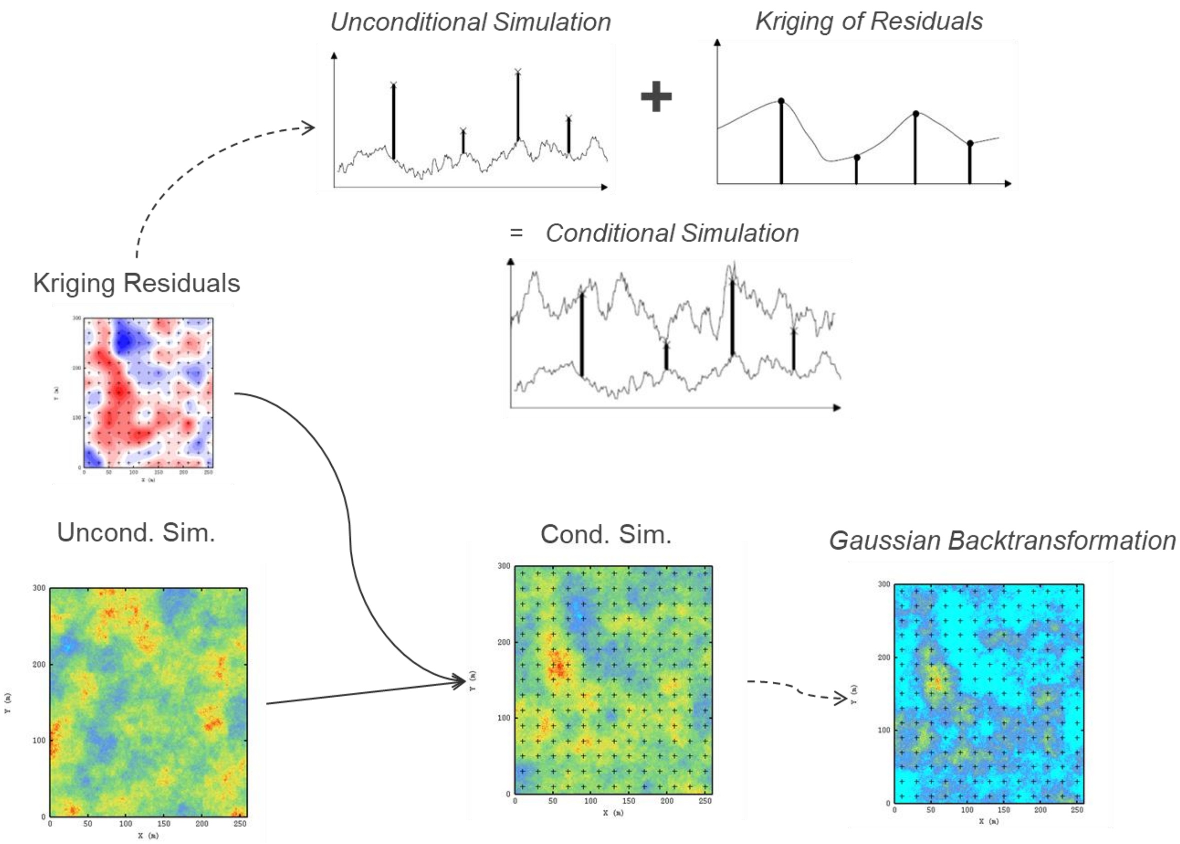

Figure 2: Ilustration of the TBS approach to develop uncondicional simulations of gaussian values, then post process the simulation results to conditioning the unconditional simulation realizations through kriging residuals between input data and non-conditional simulation. The conditional simulations are backtransformated to the original units of the variable using the global normal score anamorphosis of the data as reference.

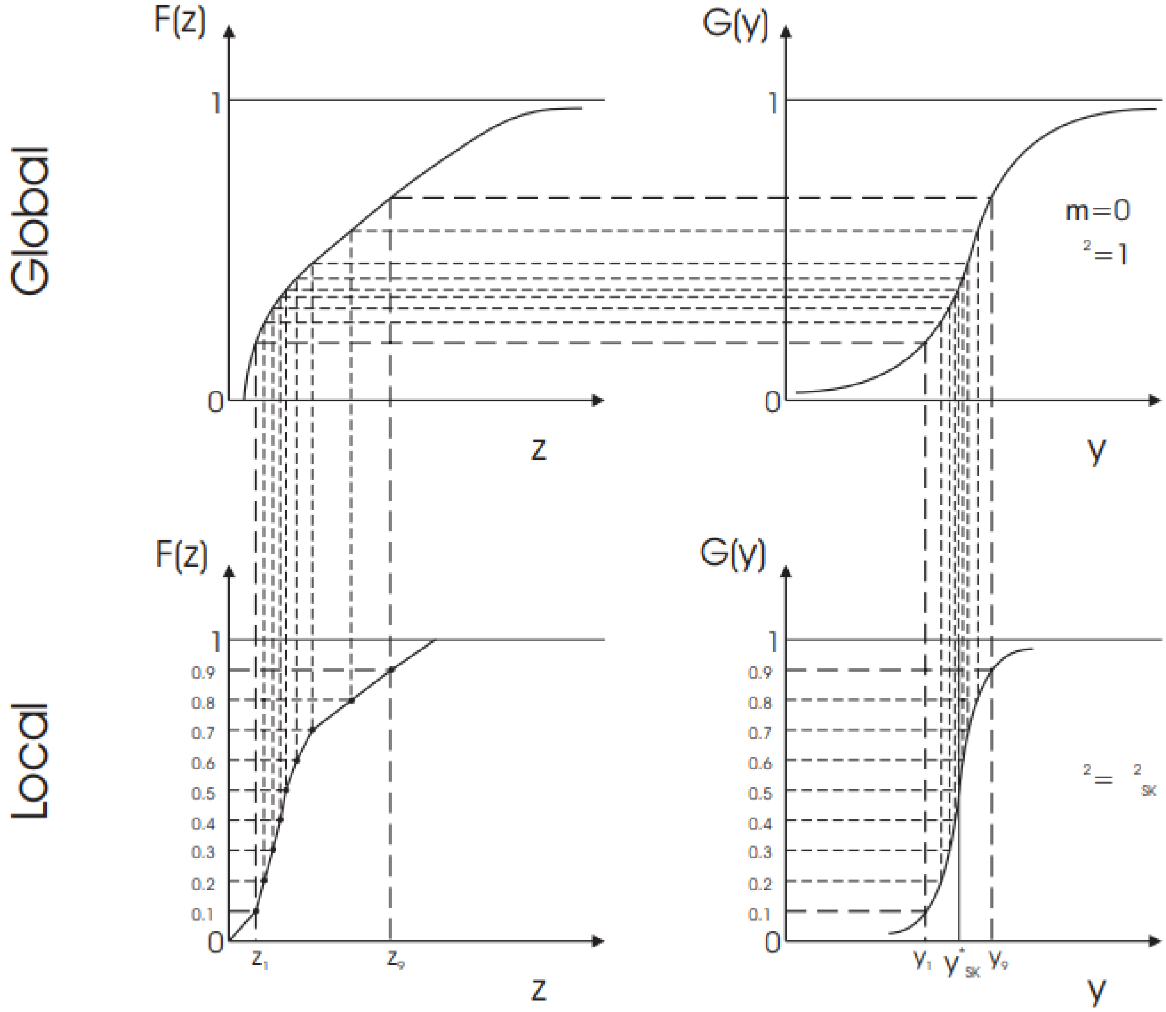

Figure 3: Ilustration of the MGK approach to backtransformation of the local gaussian estimation to the local estimation in original units of the variable using the global normal score anamorphosis os the data as reference, image and caption from Ortiz and Deutsch (2003): Calculation of the mean by numerical integration. The local uncertainty distribution is given by the kriging estimate and variance and the assumption that the shape is normal (bottom right). Several quantiles are calculated in the illustration. The nine deciles of the distribution, y1, ..., y9, are back-transformed (top) and the corresponding values, z1, ..., z9, are used to calculate the mean (bottom left).

3.3. Case of Study

This study was carried out in the Galinheiro Mine, an iron deposit located in a site close to the municipality of Itabirito, in the southeast flank, inverse fold, of the Moeda syncline – QF (Figure 1). The mine owned by VALE produced about 12 million tons of iron ore in 2020. Previous studies described the mineral body as the product of supergene alteration of itabirites, which formed friable contaminated ores (soft ore), and hydrothermal alteration, which formed veins of compact hematite (hard ore) (Hensler, et al. 2014; Hensler, et al. 2015). Ore lithotypes were described based on geochemical characteristics, yielding a total of 12 ore types: compact itabirite (IC), friable itabirite (IF), goethite-bearing itabirite (IGO), alumina-bearing itabirite (IAL), manganese-bearing itabirite (IMN), high-grade friable itabirite (IFR), friable hematite (HF), compact hematite (HC), goethite-bearing hematite (HGO), alumina-bearing hematite (HAL), canga (CG), and rolado (RO).

Although, the company geological team described the ore into to 12 different types, there is a weak stationarity within them. Once, they are discretized by geochemical cut-offs, there is not a clear separation between these domains in the data distribution and nether visually in the field, and the contact analysis showed a soft transition between them. The geochemical distribution is mostly related to supergene activity than lithological or structural controls. Iron ore from the Galinheiro mine site has higher contents of contaminants such as Al_2O_3 and Mn, especially in nearby the topographic surface.

For purposes of geostatistical analysis, there are not enough samples to properly estimated each individual ore type, thus the ore types were arranged in three groups based on mutual similarities, such as geological context, spatial distribution, and the range of the grades. The ore lithotypes were integrated into contaminated ore group (IGO, IAL, IMN, HGO, HAL and CG), rich ore group (HF, HC and IFR) and poor ore group (IF and IC).

The correlations between variables were analyzed before the choice between simulation and co-simulation methods was made. Therefore, the correlation matrix between variables presents a low linear correlation between them (Table 1). Based on the obtained results, the choice was made to run an independent data simulation.

Table 1: Correlation matrix between the variables of interest.

	Al_2O_3	MnO_2
Al_2O_3	1	0.02
MnO_2	0.02	1

Once, the samples are clustered into domains and there is a low correlation between the variables, the samples were declustered and transformed to a normal distribution. The variograms of the gaussian values of the Al_2O_3 and MnO_2 were modelled for each variable in each group independently. The simulation was performed on the resource pit considering the next five years of production. A total of 100 scenarios were run for each variable.

Table 2: Neighborhood parameters used in TBS and MGK for all the ore groups.

Elipsoid orientation	Dip = 00° Dip Azimuth = 120° Pitch = 00°
Elipsoid range	200 m, 150 m, 35 m
Anisotropic distance	Yes
Angular Sectors	4
Optimum number of samples per sector	8
Split elipsoid vertically	yes
Number of bands	1000
Minimum of samples	4

For TBS, the local uncertainty of a variable in a given point could be assessed from the frequentist probability of such point to exceed a given critical threshold in various simulated scenarios (Equation 1).

$$Prob[z(x_0) \leq z_c] = \frac{n(x_0)}{L}$$ *Equation 1*

Where $z(x_0)$ is the value of variable z on point x_0, z_c equivalent to the critical threshold, $n(x_0)$ is the number of realizations in which the variable exceeded z_c , and L is the total number of realizations.

For MGK, the probability of exceed the thereshold is obtained by integrating the probability distribution function within an interval. The area resulting from the integration equals the probability of x_0 in the integration interval (Equation 2).

$$P(z_c \leq x_0) = \int_{-\infty}^{z_c} f_X(x_0)dx \qquad \textit{Equation 2}$$

The spatialization of the results derived from equation 1 and equation 2 generates probability maps, which provide for a practical way of visually integrating and validating the data obtained from the simulated scenarios and the MultiGaussian kriging results. Local uncertainty distribution is generated based on the analysis of the results by the calculation of the probability of each given point to exceed the critical threshold from the local distribution. A value of z_c was assigned to each element based on the iron ore and beneficiation plant quality control specifications: Alumina above 1.8% and Manganese above 0.2%.

3.4. Results and Discussion

Figure 4 shows the spatial configuration of iron ore and waste rock lithotypes in the simulated region (a), as well as the spatial distribution of the three arranged groups of ore based on mutual similarities (b). Contaminated ore is predominantly found in the upper central area of the site, while in the South portion poor ore prevails. The rich ore occurs sparsely in the whole area in form of lenses.

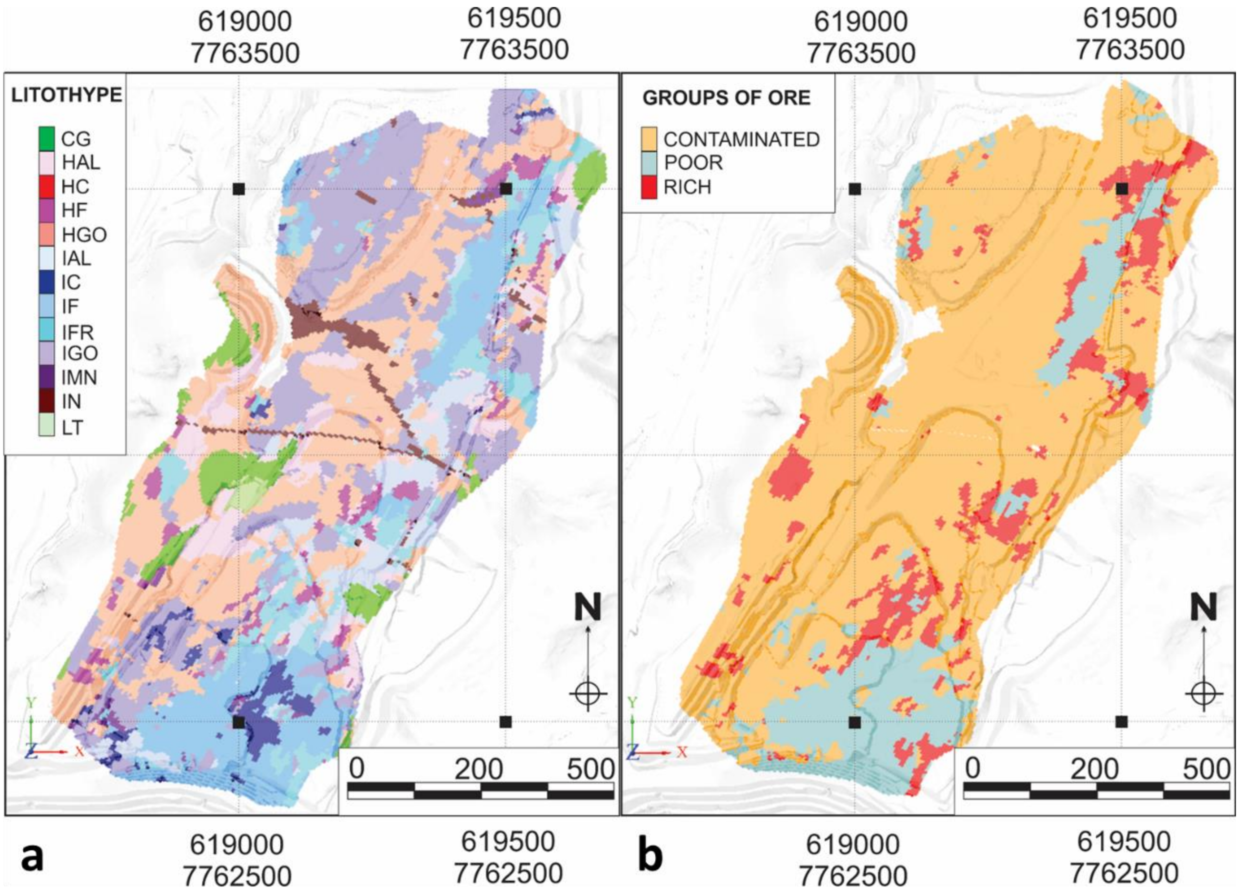

Figure 4: (a) Spatial distribution of lithotypes in the Galinheiro Mine, contaminated lithotypes are predominantly present in the North area, while hematites and friable itabirites prevail in the southern portions of the site. (b) Spatial distribution of the grouping of lithotypes in contaminated ore, poor ore, and rich ore.

The spatial distribution of the samples grades through the area is presented in Figure 5 and the statistics of the grades for each ore group before and after declustering are presented in Table 3. The samples present a regular distribution along the area and the desclustering process doesn't change the statistics significantly. The distribution of the Al_2O_3 grades is disseminated, but there is a concentration of high grades in the central region. The high grades of MnO_2 occurs mostly as spots in south region of the study area.

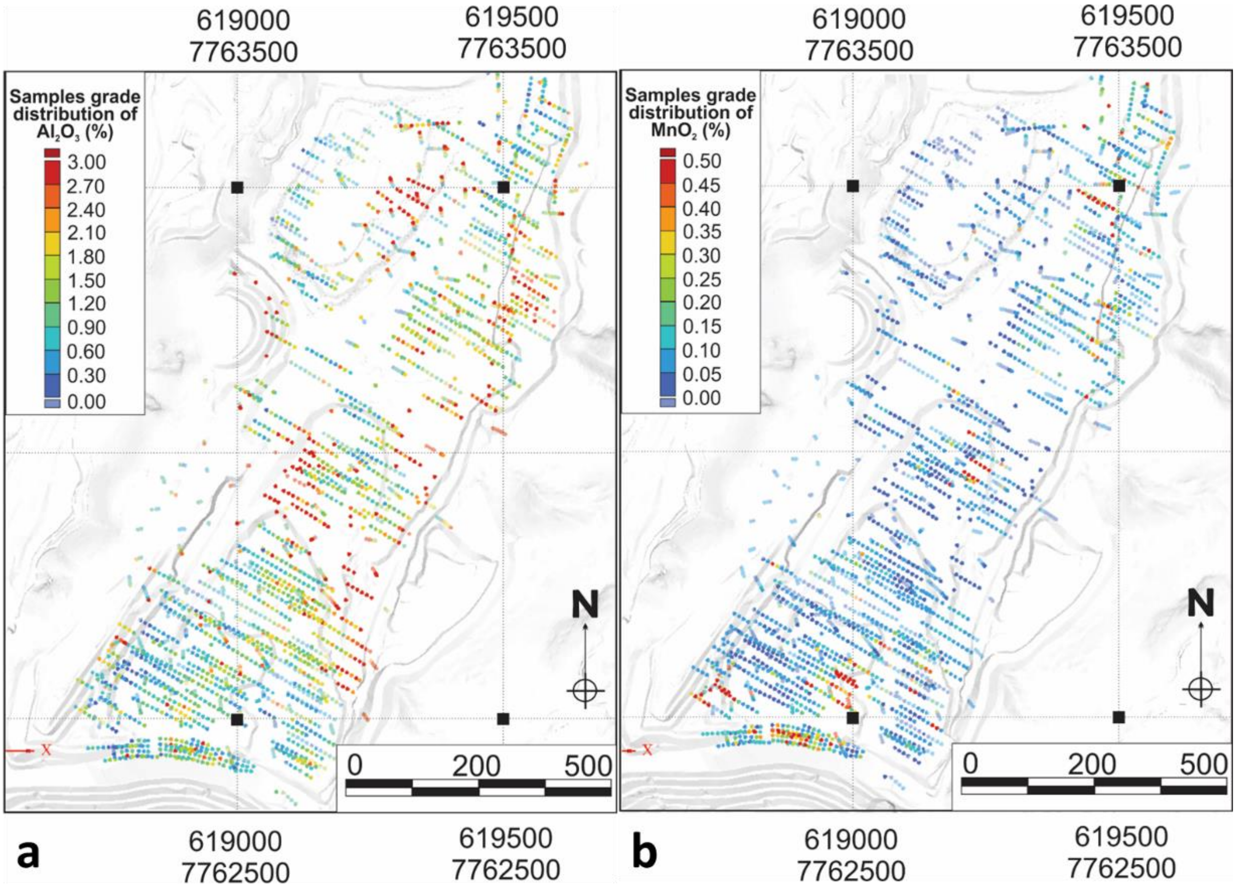

Figure 5: Spatial distribution of the grades of the variables of interest in the samples. (a) Alumina content distribution in the samples; (b) Manganese content distribution in the samples.

Figure 6 and Figure 7 shows the validation graphics (histogram and variograms) of simulation results versus samples data of each ore group for Al_2O_3 and MnO_2, respectively. There is a dispersion cloud of the simulated scenarios around the samples data which indicates the uncertainty space of the results. The graphics show that the simulation scenarios were able to reproduce the morphology of the distribution by reproducing the histogram, and the spatial continuity by reproducing the variograms models.

Table 3: Samples statistics for the interest variables with and without declustering for each ore group.

Group	Variable	Declus-ter	Num. of samples	Mean	Var	Std Dev	CV	Min	Max
Contaminated ore	**Al_2O_3**	**No**	3609	2.34	5.590	2.36	1.01	0.1	36.06
Contaminated ore	**Al_2O_3**	**Yes**	3609	2.29	4.502	2.12	0.93	0.1	36.06
Contaminated ore	**MnO_2**	**No**	3609	0.21	1.521	1.23	5.84	0.01	31.51
Contaminated ore	**MnO_2**	**Yes**	3609	0.25	1.665	1.29	5.12	0.01	31.51
Poor ore	**Al_2O_3**	**No**	1212	0.83	0.227	0.48	0.57	0.1	3.33
Poor ore	**Al_2O_3**	**Yes**	1212	0.81	0.240	0.49	0.61	0.1	3.33
Poor ore	**MnO_2**	**No**	1212	0.1	0.039	0.2	1.98	0.01	2.98
Poor ore	**MnO_2**	**Yes**	1212	0.09	0.031	0.18	1.89	0.01	2.98
Rich ore	**Al_2O_3**	**No**	1375	1.14	0.334	0.58	0.51	0.12	3.4
Rich ore	**Al_2O_3**	**Yes**	1375	1.15	0.353	0.59	0.52	0.12	3.4
Rich ore	**MnO_2**	**No**	1375	0.09	0.037	0.19	2.19	0.01	5.57
Rich ore	**MnO_2**	**Yes**	1375	0.09	0.024	0.15	1.72	0.01	5.57

The E-type comparison between the TBS and the MGK results of the distribution of the Al_2O_3 content in the study area is presented in Figure 8. Figure 8a shows the spatial distribution of the E-Type of the TBS scenarios and Figure 8b shows the spatial distribution of the E-Type of the MGK results. The higher alumina contents were concentrated in the central portion and outer east rim area of the site in both methods. Both figures highlighted the same areas of high and low grades and the scatterplot of the results (Figure 8c) present a coefficient of linear correlation of 0.98.

Similarly, Figure 9 presents the spatial distribution of the standard deviation of TBS (Figure 9a) and the MGK (Figure 9b) results, a comparison between both distribution of the Al_2O_3 variability in the study area. MGK results showed a slighted smoother transition between regions with extreme values, while the simulation provided for a crisper line around extreme contents with a lower smoothing around the edges of the ore body. Although, both results are very similar and the scatterplot (Figure 9c) shows a high linear correlation of 0.95.

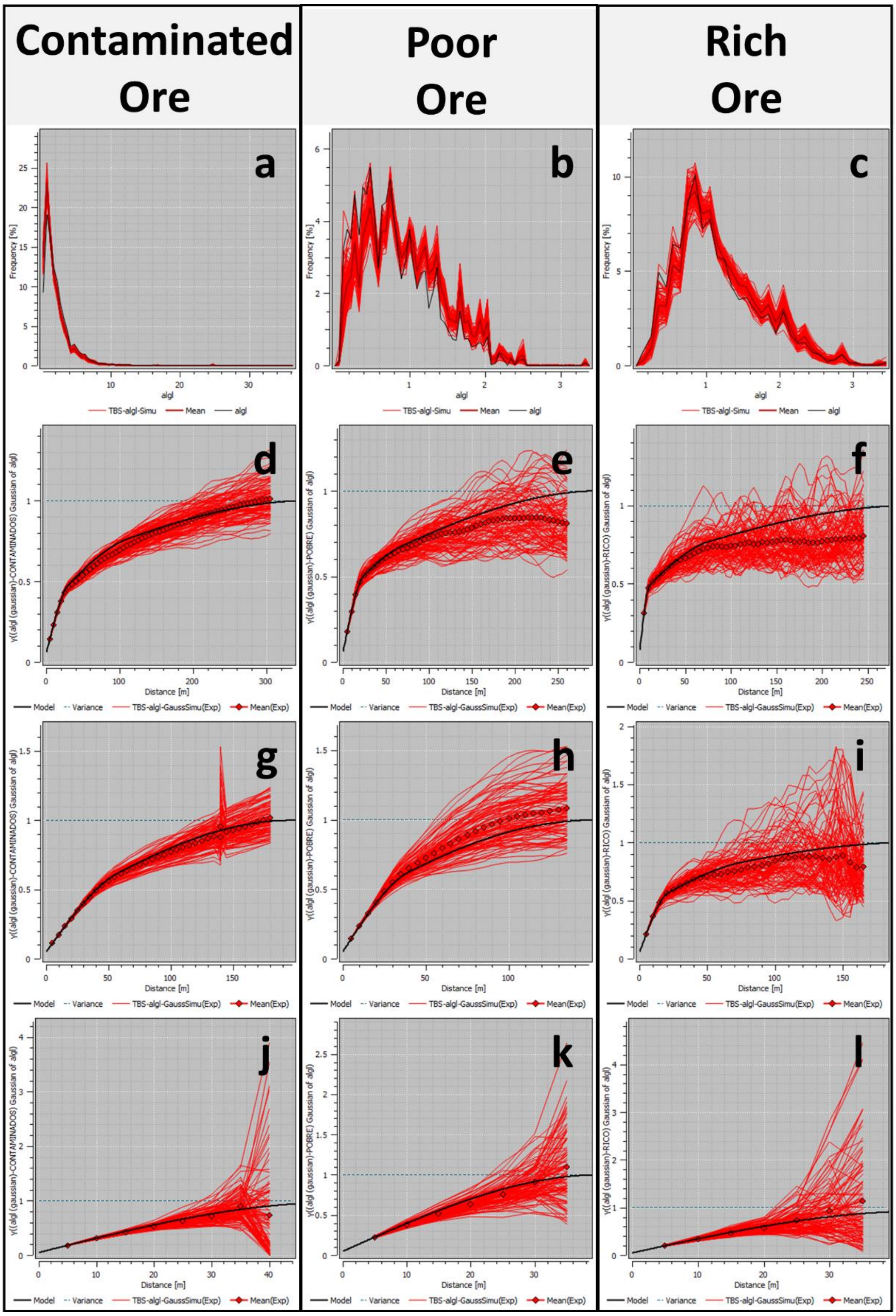

Figure 6: Validation graphics of the alumina simulation results for each ore group. Red lines represent the simulation scenarios and the black line represent the samples data. (a,b,c) Raw histogram of the samples vs. simulation results; (d,e,f) Variogram model vs. simulation results for the main direction; g,h,i) Variogram model vs. simulation results for the intermediate direction; (j,k,l) Variogram model vs. simulation results for the minor direction.

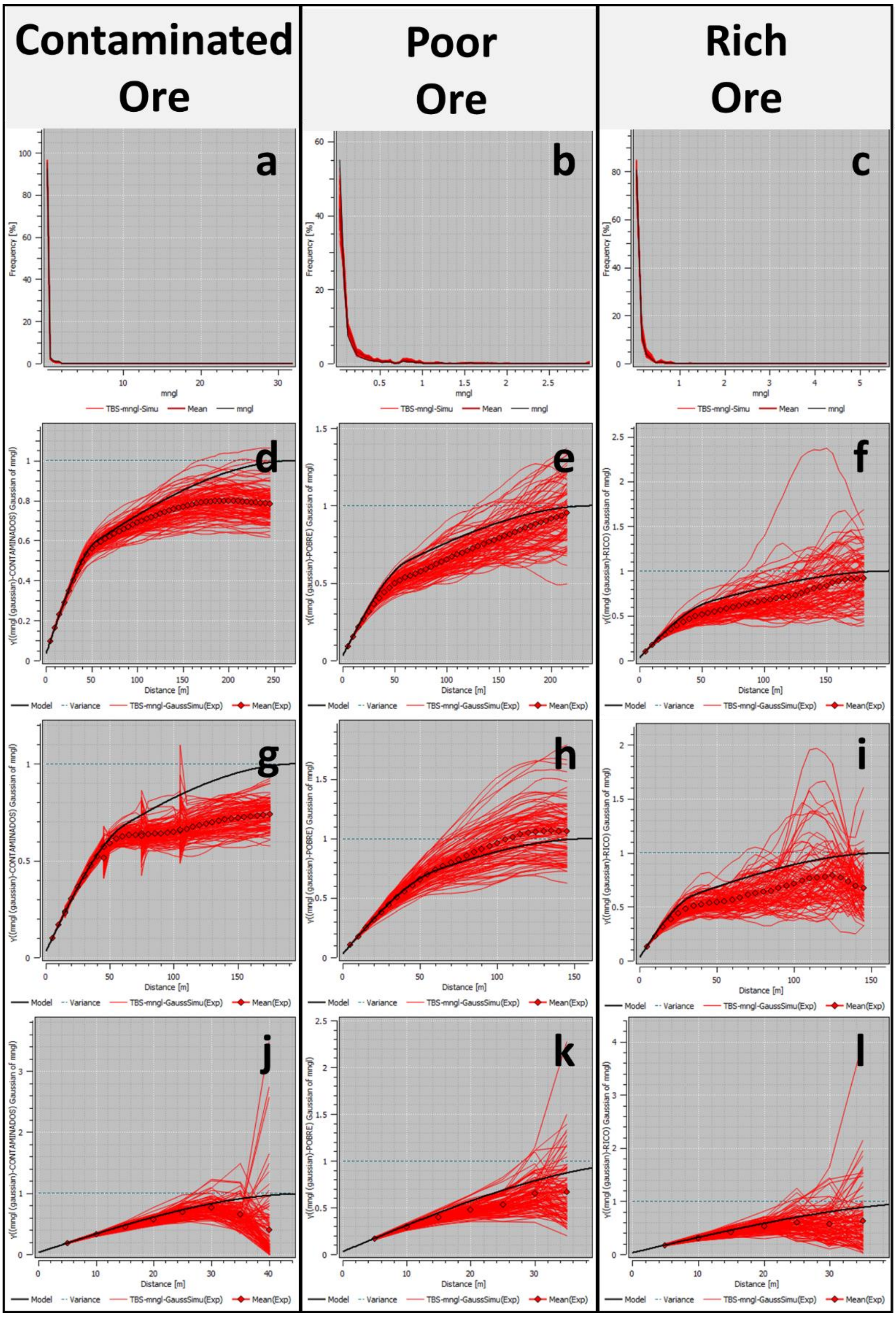

Figure 7: Validation graphics of the manganese simulation results for each ore group. Red lines represent the simulation scenarios and the black line represent the samples data. (a,b,c) Raw histogram of the samples vs. simulation results; (d,e,f) Variogram model vs. simulation results for the main direction; g,h,i) Variogram model vs. simulation results for the intermediate direction; (j,k,l) Variogram model vs. simulation results for the minor direction.

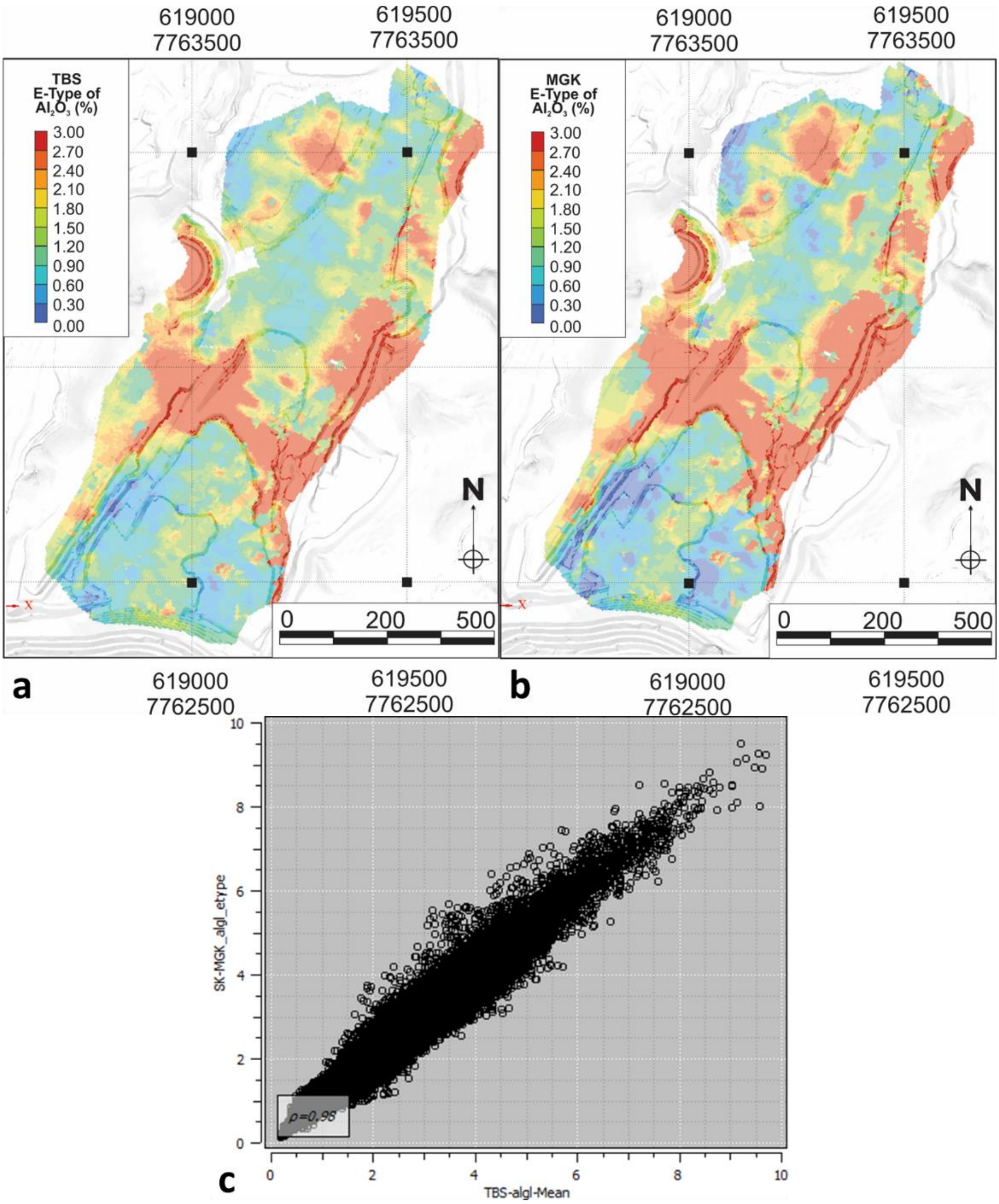

Figure 8: E-Type comparison for alumina grades. (a) Spatial distribution of TBS results; (b) Spatial distribution of MGK results; (c) Scatterplot of the results of both methods showing a high linear coefficient of correlation equals to 0.98.

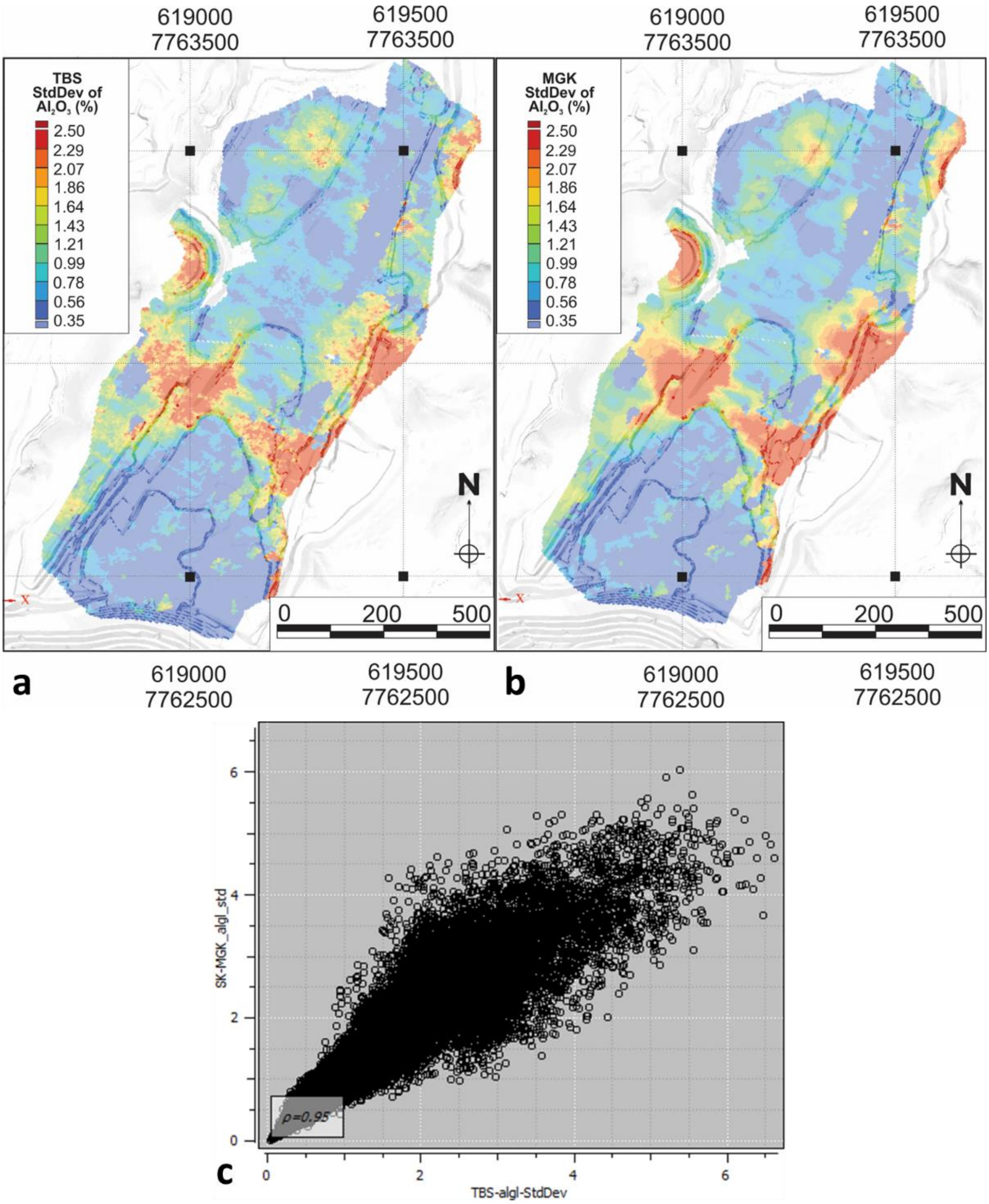

Figure 9: Standard deviation comparison for alumina grades. (a) Spatial distribution of TBS results; (b) Spatial distribution of MGK results; (c) Scatterplot of the results of both methods showing a high linear coefficient of correlation equals to 0.9

Figure 10 a and b show the borders of the domains with a high probability of exceeding the critical threshold of 1.8% Al_2O_3 in the iron ore for TBS and MGK, respectively. The highlighted areas are mostly the same for both methods, showing that both methods are equally efficient to access the local uncertainty and local risk analysis. Contents above this threshold may jeopardize wet beneficiation processes and clog screens and transfer chutes in the plant. The distribution of domains with a high probability of exceeding the percent threshold was correlated with bodies of canga, alumina-bearing hematite and itabirite grouped into the contaminated ore group, mostly in the central and east region of the site.

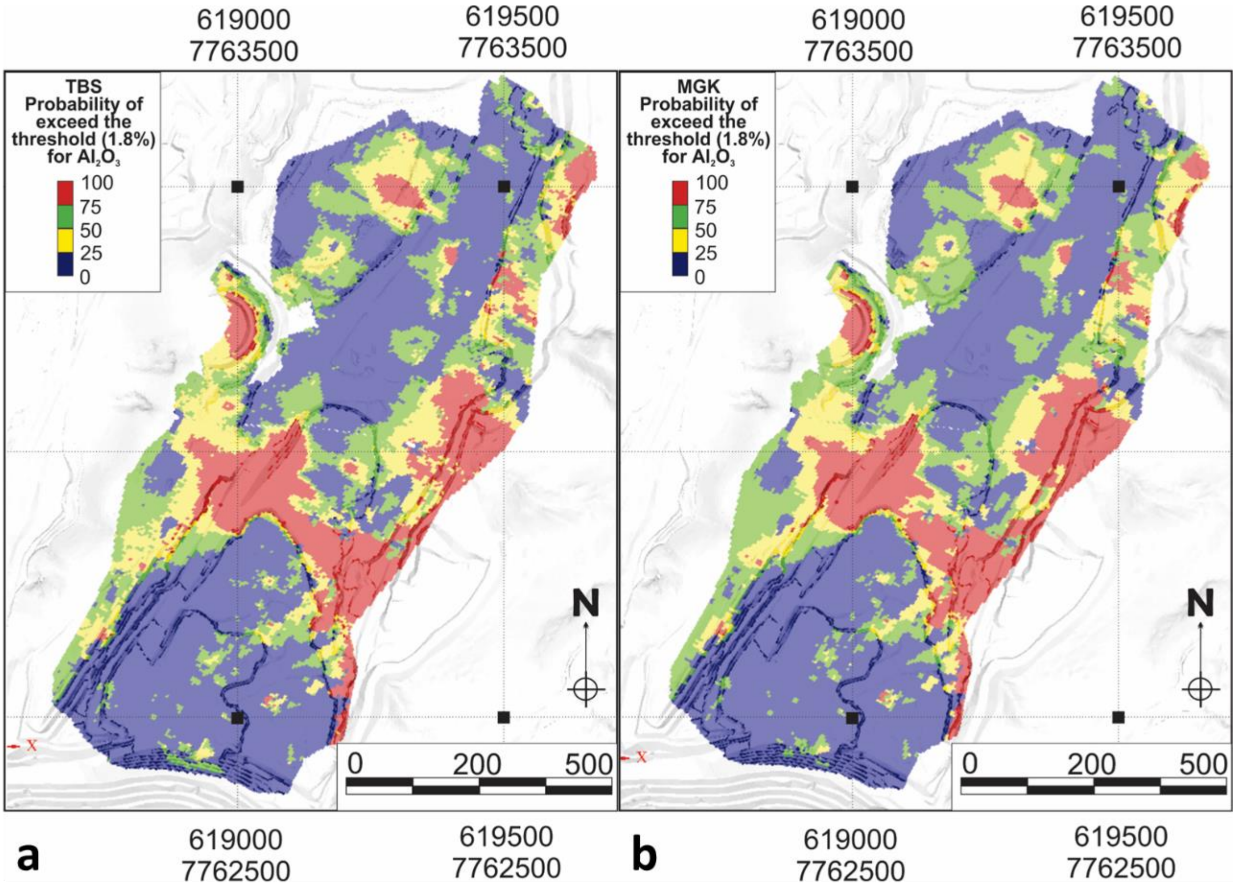

Figure 10: Probability map showing chances of occurrence of alumina contents greater than 1.8 %. (a) Results by TBS; (b) Results by MGK. Low risk was ascribed to areas with probabilities of up to 25%; medium risk to areas with probabilities between 25% and 50%; high risk to areas with probabilities between 50% and 75%; and very high risk to areas with probabilities greater than 75%.

The E-type comparison between the TBS and the MGK results of the distribution of the MnO_2 content in the study area is presented in Figure 11. An analysis of Figure 11a and b show the differences in the spatial distribution of manganese contents from both methods. The overall trends are very similar between both methods, with higher contents concentrated in areas closer to the extremely South and North regions. The main difference is in the central-west region, where TBS shows a few spots with medium to high grades, that do not appear in the MGK results. Although, both figures highlighted mostly the same areas of high and low grades and the scatterplot of the results (Figure 11 c) present a coefficient of linear correlation of 0.91, slightly lower and more scattered than the Al_2O_3 results.

Similarly, Figure 12 presents the spatial distribution of the standard deviation of TBS (Figure 12a) and the MGK (Figure 12b) results, a comparison between both distribution of the MnO_2 variability in the study area. The results obtained by TBS (Figure 12a) presents a lot of spots, regions were less continuous and had higher levels of variability and concentrated in lenticular bodies distributed in close proximity to each other. Otherwise, the MGK results showed a slighted smoother transition between regions with extreme values, with larger and more continuous areas of high standard deviation. The MGK presented smooth boundaries and a well-defined lenticular geometry, while TBS shows crisp borders and discontinuous lenses of high variability. In comparison to the Al_2O_3 distribution, the results are less similar and the scatterplot (Figure 12 c) shows a lower linear correlation of 0.82. However, despite the differences, it is still a good correlation between the methods.

Figure 13 shows the manganese risk map based on the probability of contents surpassing the 0.2% threshold for TBS results (Figure 13a) and for MGK results (Figure 13b). Despites the differences in the standard deviation results, the probability maps of both methods highlighted the same areas, showing that both methods are equally efficient to access the local uncertainty and local risk analysis. Manganese content occurs mostly as local spots with low spatial continuity, concentrated in the South and North regions of the study area.

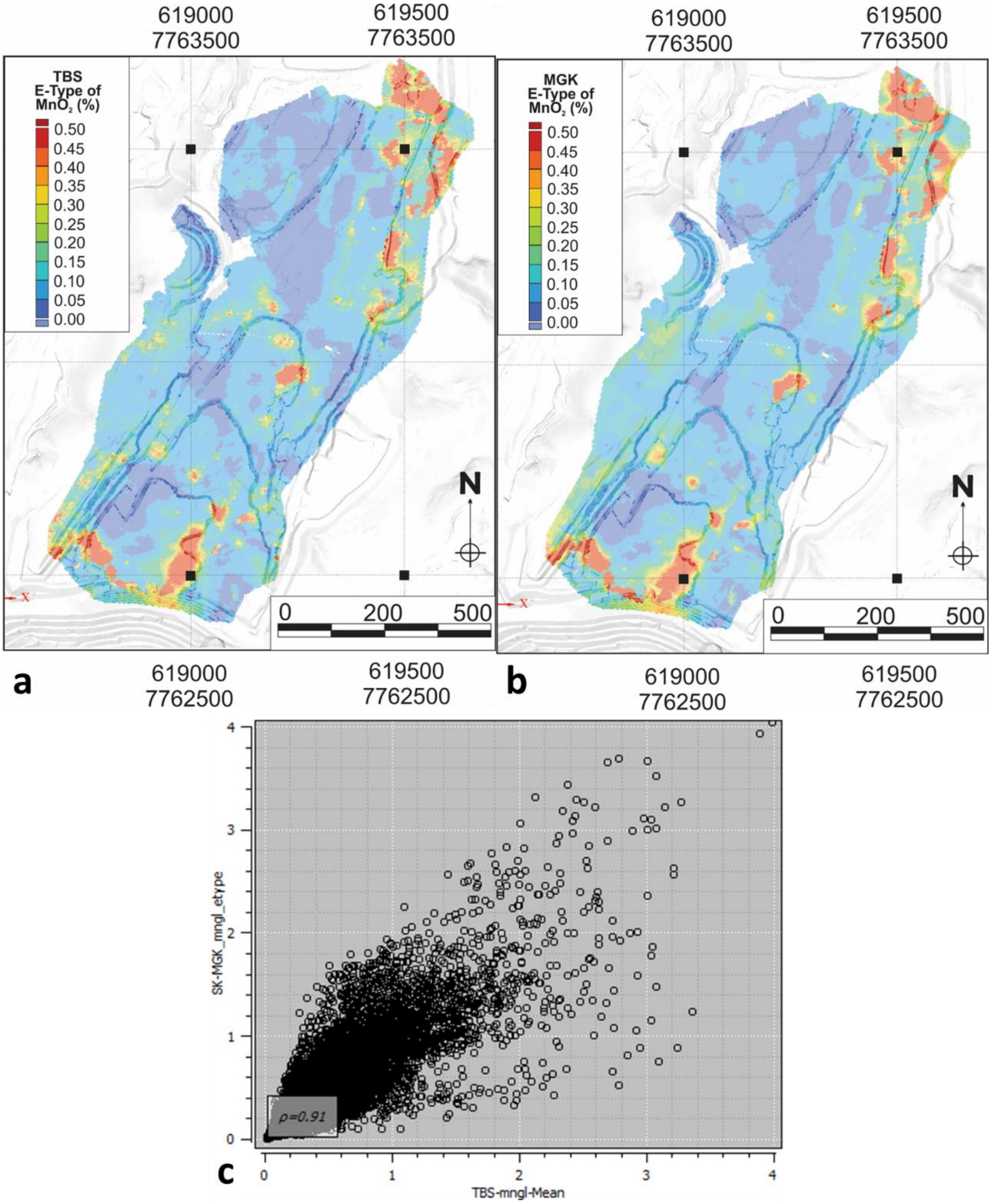

Figure 11 – E-Type comparison for manganese grades. (a) Spatial distribution of TBS results; (b) Spatial distribution of MGK results; (c) Scatterplot of the results of both methods showing a high linear coefficient of correlation equals to 0.91.

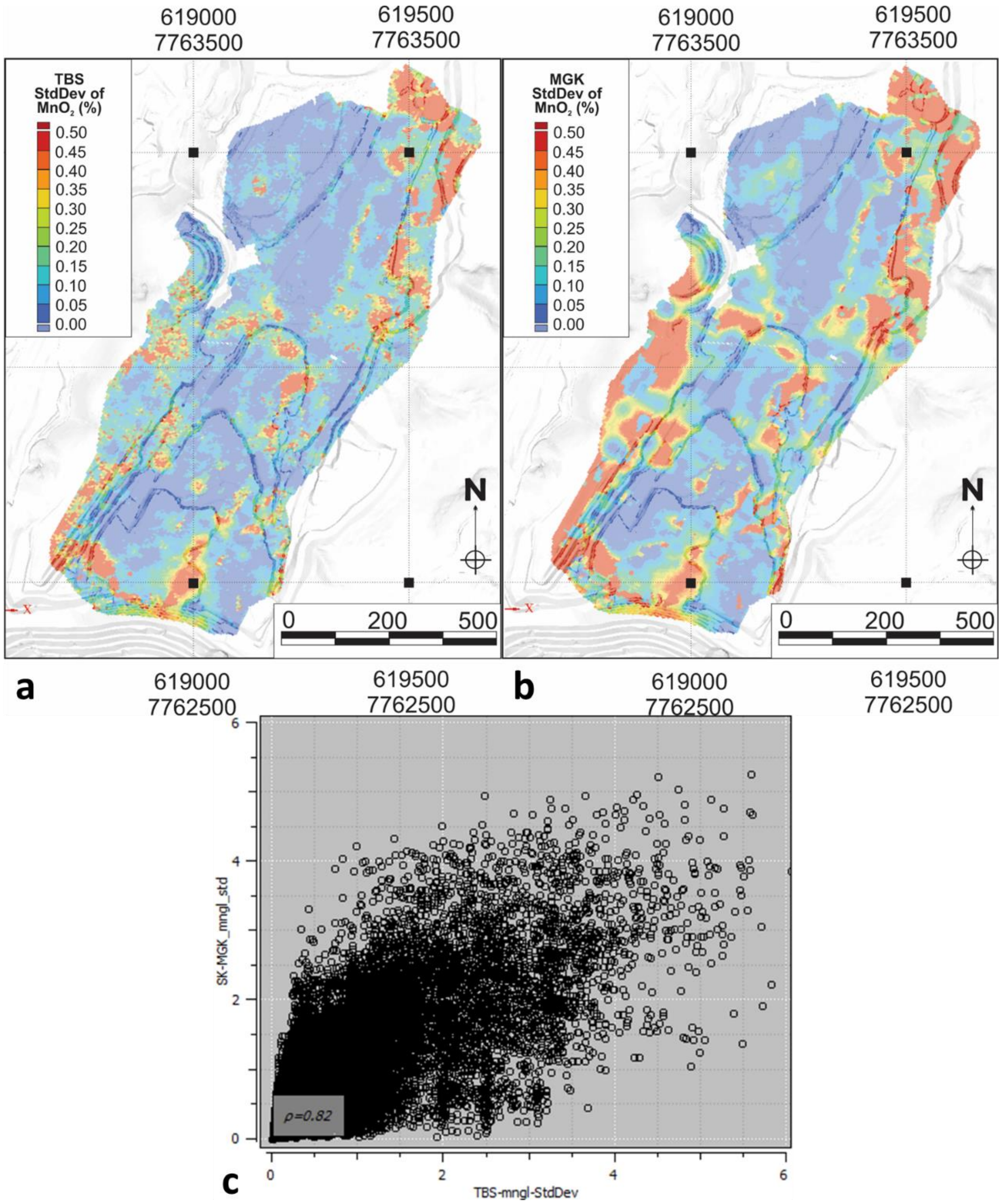

Figure 12 – Standard deviation comparison for manganese grades. (a) Spatial distribution of TBS results; (b) Spatial distribution of MGK results; (c) Scatterplot of the results of both methods showing a high linear coefficient of correlation equals to 0.82.

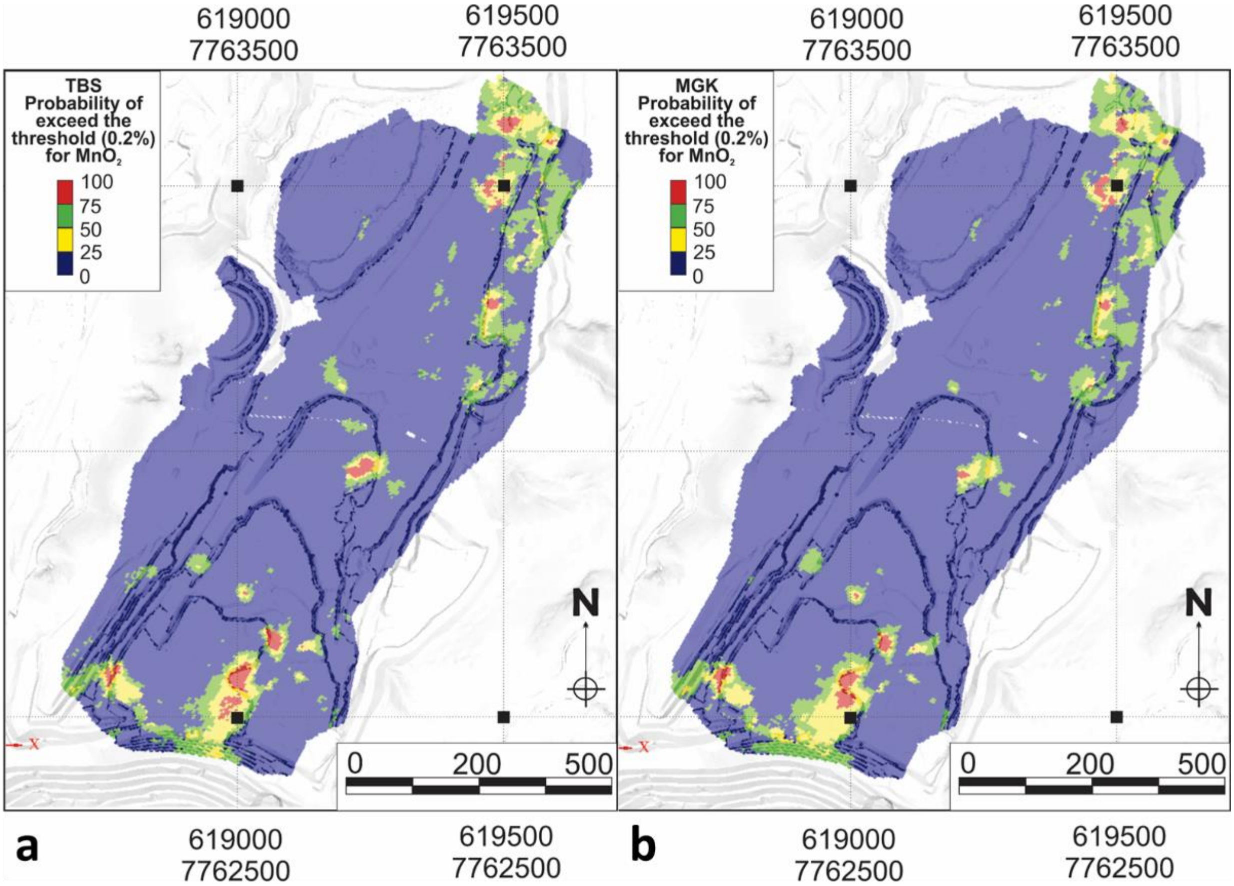

Figure 13: Probability map showing chances of occurrence of manganese contents greater than 0.2%. (a) Results by TBS; (b) Results by MGK. Low risk was ascribed to areas with probabilities of up to 25%; medium risk to areas with probabilities between 25% and 50%; high risk to areas with probabilities between 50% and 75%; and very high risk to areas with probabilities greater than 75%.

3.5. Conclusions

The tools described in this article added value to the analysis of the risks managed by quality control and short-term mine planning teams. The probability maps in clearly depicts the trends described by the E-type distributions and makes analysis much faster and more intuitive. Manganese occurs in lenses along the N-S trend, primarily in two areas, extremely Northeast border and in the South region of the site. The results for alumina revealed the contaminant occurred mainly in the central region and in the borders of the mineralized body. The analysis of iron ore contaminants by both methodologies evinced the same zones and lenses with high probability of occurrence of contaminants, which shows that both methods are properly adequate to measured local uncertainty. The maps generated by both methods are similar, and both provides key information to follow critical areas of the mine plans. Geostatistical simulations are well known to uncertainty quantification for spatially distributed variable at any scale. Although MGK proved to be a flexible alternative to simulation since it is easy to implement and request less computational time. For short term mine planning, faster computational time represents a great advantage because models updates are frequently necessary. The findings derived from this study will help quality control and short-term planning teams make better and more informed decisions.

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3.6. References

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4. Conclusões

Embora a simulação geoestatística seja atualmente mais utilizada para classificação de recursos, as aplicações das técnicas de simulação geoestatística nas rotinas de curto prazo da indústria mineral ainda são limitadas. Nesse contexto, a incorporação de análises de incertezas de teores e dos contatos geológicos por meio de métodos geoestatísticos não lineares é essencial para otimizar o sequenciamento da produção e gerir os riscos associados aos planos de lavra de forma a otimizar sua adequação. As ferramentas propostas nesse trabalho se mostraram muito eficientes para a análise de risco associada ao controle de qualidade e planejamento de lavra de curto prazo. O sucesso obtido nos resultados da simulação estocástica condicional deve-se ao método destacar as heterogeneidades e variabilidade dos dados. Além disso, os resultados obtidos adicionam clareza e previsibilidade em relação aos riscos geológicos associados aos planos de lavra.

Conforme apresentado nos resultados do primeiro artigo, análises pautadas apenas na variância de krigagem (indicador geométrico proporcional ao espaçamento amostral) como indicador de risco, não permitem ações preventivas e mitigatórias dos impactos gerados pela alta variabilidade de teores e contatos observados durante a lavra do minério. O ORI resume a variabilidade dos teores e a confiabilidade da classificação do bloco como minério ou estéril. Este índice fornece informações essenciais para os engenheiros de planejamento de lavra incorporarem incertezas no cronograma da mina. A comunicação entre geólogos e engenheiros de minas frequentemente torna-se laboriosa pela ausência de um fator numérico para incorporação da variabilidade geológica observada pelo geólogo para os engenheiros de minas utilizarem nos softwares de sequenciamento de lavra. Dessa forma, o ORI torna-se uma ferramenta essencial para comunicação entre as equipes e transmissão da incerteza geológica do depósito mineral de maneira quantitativa através de índice numérico que sumariza a variabilidade dos teores e a confiabilidade da classificação do bloco para o planejamento de lavra incorporar como condicionante no sequenciamento da mina

Se o risco operacional não é incorporado no sequenciamento de lavra, formando planos onde se busca minimizá-lo através do *blend* entre diferentes regiões, frequentemente irão ocorrer problemas, ou até mesmo paralisar as operações, por alta variabilidade e classificação errônea da destinação do material lavrado.

A comparação dos resultados da simulação por bandas rotativas e a krigagem Multi-Gaussiana realizada no segundo artigo evidenciou as mesmas zonas de riscos e as análises de incerteza oriunda de ambos os métodos foi bastante semelhante. Dessa forma, considera-se a krigagem MultiGaussiana uma alternativa flexível à simulação, uma vez que é mais simples de implementar e necessita menos tempo computacional. Para o planejamento de minas de curto prazo, um tempo computacional mais rápido é vantajoso, porque as atualizações de modelos são frequentemente necessárias.

Mensurar, analisar e gerenciar a variabilidade e incerteza geológica é essencial para o bom funcionamento de qualquer empreendimento minerário. A gestão de riscos relacionados à incerteza geológica no curto prazo pode reduzir decisões incorretas e, consequentemente, perdas financeiras que podem influenciar negativamente no lucro e na produtividade de uma mina. Em geral, tais ganhos são muito maiores do que as despesas associadas ao tempo adicional e ao aumento das demandas computacionais exigidas pelas metodologias propostas nesse estudo para quantificação e análise de incertezas.

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