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GEOMETALLURGICAL SIMULATION OF THE WORK INDEX IN A PORPHYRY COPPER DEPOSIT USING GEOSTATISTICAL TECHNIQUES

SIMULACIÓN GEOMETALÚRGICA DEL ÍNDICE DE TRABAJO EN UN DEPÓSITO PÓRFIDO CUPRÍFERO UTILIZANDO TÉCNICAS GEOESTADÍSTICAS

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Geometallurgical Simulation of the Work Index in a Porphyry Copper Deposit Using Geostatistical Techniques

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ABSTRACT

The spatial variability in the geometallurgical attributes of the deposits is a crucial parameter from the exploration stage, which conditions and influences the mineral processing. Consequently, the objective of this research is to elaborate the geometallurgical simulation of the Bond Work Index for a porphyry copper deposit. For this purpose, information of primary and response attributes corresponding to ore zones, lithologies and BWi contained in 1,449 samples of exploratory drill holes were used. An exploratory data analysis of this information was carried out, and geometallurgical units were defined based on the geological and processing knowledge that validates the behavior of each one of them within the deposit; then Sequential Gaussian Simulation was applied, running 100 realizations in each GMU, those that best reproduce the statistics of the original samples were chosen. The results show that the lithology of the deposit controls the BWi variability and according to the rock competence the ore zones are classified from the softest to the hardest in oxides, mixed and sulfides.

***Keywords*:** geometallurgy, mineral deposit, geostatistics, simulation, processing

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Simulación Geometalúrgica del Índice de Trabajo en un Depósito Pórfido Cuprífero Utilizando Técnicas Geoestadísticas

RESUMEN

La variabilidad espacial en los atributos geometalúrgicos de los depósitos es un parámetro crucial desde la etapa de exploración, lo cual condiciona e influye en el procesamiento mineral. En consecuencia, el objetivo de esta investigación es elaborar la simulación geometalúrgica del Índice de Trabajo de Bond para un depósito pórfido cuprífero. Para esto se utilizó información de atributos primarios y de respuesta correspondientes a zonas minerales, litologías y de BWi contenidos en 1,449 muestras de sondajes exploratorios. Se realizó el análisis exploratorio de datos de dicha información y se definieron unidades geometalúrgicas fundamentándose en el conocimiento geológico y de procesamiento que valida el comportamiento de cada una de ellas dentro del depósito; luego se aplicó Simulación Secuencial Gaussiana, ejecutando 100 realizaciones en cada UGM y se eligieron aquellas que reproducen mejor las estadísticas de las muestras originales. Los resultados muestran que la litología del depósito controla la variabilidad del BWi y de acuerdo a la competencia de la roca las zonas mineralizadas se clasifican desde la más blanda a la más dura en óxidos, mixtos y sulfuros.

Palabras clave: geometalurgia, depósito mineral, geoestadística, simulación, procesamiento

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INTRODUCTION

Currently, the exploratory stage of deposits faces challenges associated with geometallurgical uncertainty (Lishchuk et al., 2020; Mwanga et al., 2015) which impacts mineral processing (Dominy et al., 2018). In this context, response attributes influence the resource value because up to 70 % of the total energy consumption is used in comminution (Mohammadi et al. 2021); therefore, this impacts porphyry copper deposits characterized by high lithology hardness (Bilal, 2017). In this regard, the Bond Work Index "BWi" is frequently used for the calculation of the energy requirement (Aras et al., 2019); consequently, it is essential to evaluate its spatial variability within the deposit, however, its limited information in early stages of mining (Garrido et al., 2020) and high cost of metallurgical tests (Ranjbar et al., 2021) hinder its characterization.

In this sense Harbort et al. (2011) performed geometallurgical modeling for a porphyry copper-gold deposit located in Peru. Nghipulile et al. (2023) studied the effect of mineralogy on the milling of copper oxides and sulfides in a deposit located in Namibia. Harbort et al. (2013) applied geometallurgy to estimate comminution attributes in porphyry copper deposits.

Therefore, the objective of this work is to elaborate the geometallurgical simulation of the Bond Work Index, by incorporating primary and response attributes of a porphyry copper deposit, using geostatistical techniques.

Geometallurgy

Geometallurgy incorporates geological, metallurgical, mine planning information to improve decision making in mining projects (Mu & Salas, 2023), for which it makes use of primary and response variables (Castro et al., 2022), and predictive spatial models (Castillo et al., 2022).

A geometallurgical variable is defined as any attribute of the rock that positively or negatively affects the value of a mineral deposit and is classified into primary and response variables (Coward et al., 2009). Primary variables are intrinsic to the rock, directly measured and are used to predict metallurgical response and are additive, e.g., ore grade, lithologies, mineralized zones (Morales et al., 2019). Whereas, response variables are rock attributes that describe the response to a processes or energy application (Morales et al., 2019), they are non-additive and the characterization of their spatial variability is elaborated by geostatistical simulation (Hosseini & Asghari, 2015), e.g., Bond Work Index, throughput, reagent consumption, processing capacity, recovery.

The Bond Work Index is a variable which represents a measure of an ore´s resistance to grinding and it represents the energy (kWh/t) required to reduce the material of one short ton from a theoretically infinite feed size to size at which 80 percent of material passes through sieve with square aperture of 100 micrometers in size (Todorovic et al., 2017). Bilal (2017) classifies BWi values according to rock competence into soft (7-9), medium (9-14), hard (14-20), and very hard (>20).

On the other hand, the geometallurgical model is a 3D space that is typically synthesized from early-stage small-scale samples to predict the process response based on the location of samples in a deposit (Lishchuk et al., 2020).

Geostatistical simulation

It is a technique that allows obtaining realizations that reproduce the statistics and spatial variability of the original data (Narciso et al., 2019) achieving an unsmoothed representation of reality (Abzalov, 2016). In the study of geometallurgical variables Sequential Gaussian Simulation "SGS" is used (Hosseini & Asghari, 2015), which requires normal distribution in the samples. The simulated value Z_{SGS}^{*} is determined by Equation 1 (Abzalov, 2016).

$$Z_{SGS}^{*} = Z_{SK}^{*} + \sigma_K(U) \qquad (1)$$

Where Z_{SGS}^{*} is SGS simulated value, Z_{SK}^{*} is Simple Kriging “SK” estimate, σ_K is standard deviation of the Kriging estimate and U is a random normal function. It should be noted that Sequential Gaussian Simulation is applied to normal random functions, however, geometallurgical variables are generally not symmetrically distributed (Adeli, 2018), therefore, their gaussian anamorphosis must be performed beforehand. The Simple Kriging is used to calculate the conditional cumulative distribution function for SGS, which requires knowing the mean value ($\overline{m}$) of the variable under study, expressed through Equation 2 (Abzalov, 2016).

$$Z_{SK}^{*}(x) = \sum_{i}\left[\lambda_i^{SK} Z(x_i)\right] + \overline{m}\left(1 - \sum_{i} \lambda_i^{SK}\right) \qquad (2)$$

Where λ_i^{SK} are the SK weights assigned to each sample $Z(x_i)$. SGS involves modeling variograms to establish directions of anisotropy and model performance is evaluated by cross-validation (Ekolle et al., 2022), ensuring that the correlation coefficient in its scatter plot between predicted and actual values is close to 1 and that its error histogram tends to symmetric behavior (Rossi & Deutsch, 2014).

METHODOLOGY

Type and design of research

This is an applied and non-experimental research in which the variables have not been deliberately manipulated, that is to say, the phenomenon has been observed in its natural context (Hernández-Sampieri & Mendoza, 2018). The design is cross-sectional correlational. In addition, considering the type of data, the approach of this study is quantitative and qualitative.

Unit of analysis and study population

The unit of analysis is a porphyry copper deposit and the study population consist sixty-one exploratory drill holes.

Size and selection of the sample

The sample size is 1,449 data points for Bond Work Index, ore zones and lithologies.

Data collection techniques

The data were collected in formats established worldwide for the elaboration of the geometallurgical simulation. According to Rossi & Deutsch (2014), the information should be systematized in: Header, Survey, Assays, Lithology, Minzone.

Analysis and interpretation of information

The geological and block model for the mineral deposit was developed in RecMin software. Exploratory data analysis, definition of geometallurgical units "GMUs", sample visualization and results were performed in Jupyter Notebook. Whereas, the simulation was carried out in SGeMS software.

RESULTS

Geology of the study area

The mineral deposit is a porphyry copper located in Peru, for confidentiality, the coordinates have been modified. Its mineralization (Figure 1a) is formed by three zones: the highest zone of oxides which is underlain by a mixed zone and below this the primary sulfides zone; while the lithological model (Figure 1b) is composed of intrusive and extrusive igneous rocks.

Exploratory data analysis

Figure 2 shows the spatial distribution of the BWi samples. Their overall statistics (Figure 3) indicate that there are 1,449 data points with mean 17.07, standard deviation (Std) 2.35, minimum value 12.13. The first, second, and third quartile (Q) is 15.66, 16.40, 18.80 and its maximum value is equal to 21.99. The skewness factor (Skew) is 0.27 and kurtosis (Kurt) -0.65; therefore, the distribution of its histogram has a platykurtic behavior (Figure 3).

Figure 1. Visualization of BWi samples. **a)** Three-dimensional. **b)** Plan view

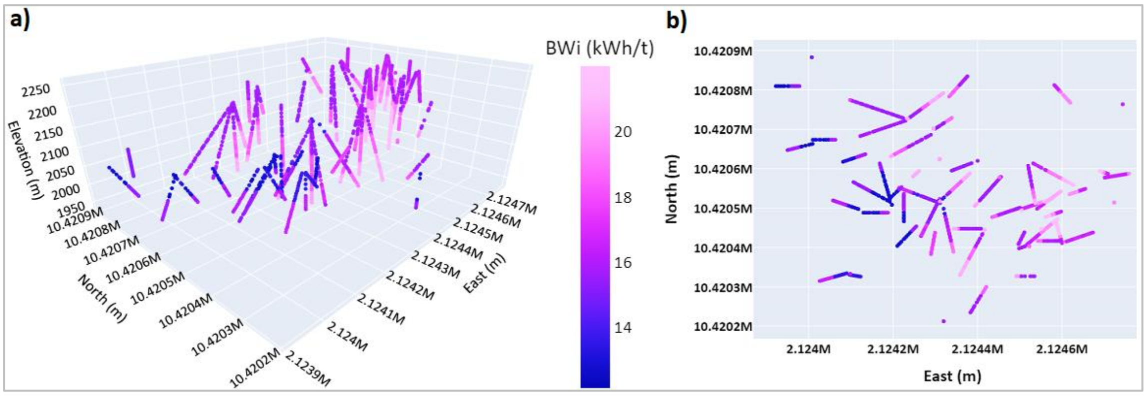
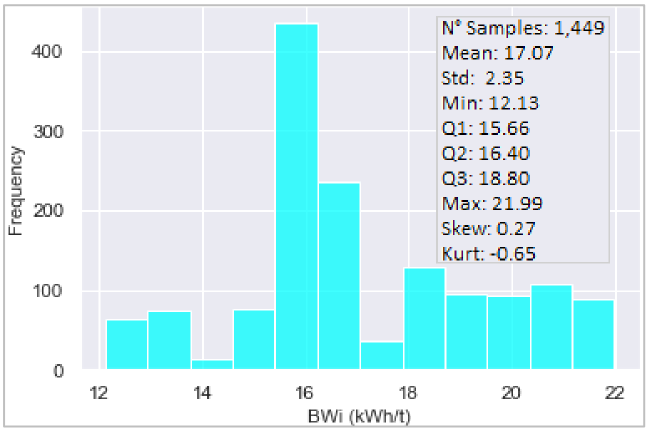


Figure 2. Histogram and samples statistics of BWi



Sample statistics (Figure 4) by ore zones show that oxides and mixed contain the most data, while sulfides contain the least. In addition, the mean BWi in each zone is well differentiated (Table 1 and Figure 5).

Figure 3. Visualization of BWi samples by ore zones. a) Three-dimensional. b) Plan view

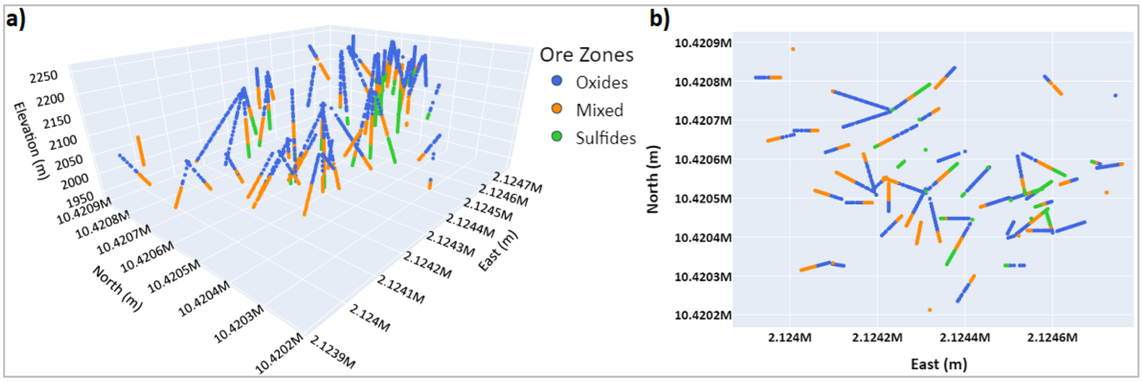
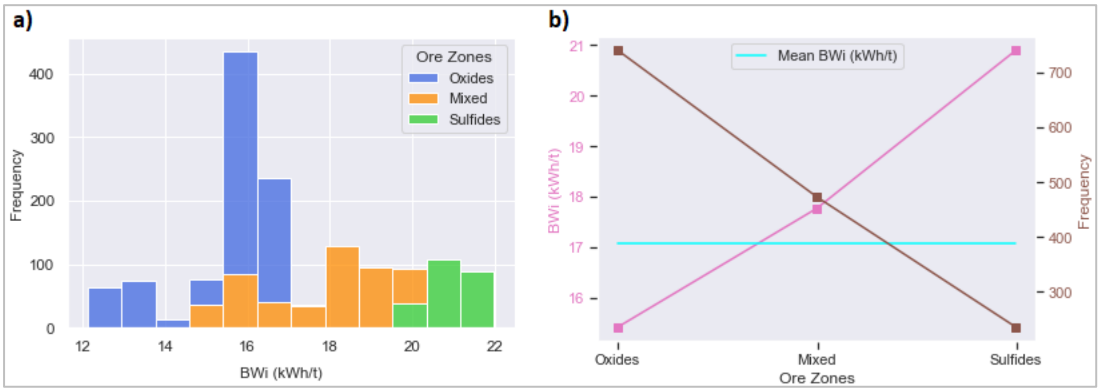


Table 1. BWi statistics by ore zones

Ore Zones	# Samples	Mean	Std	Min	Q1	Q2	Q3	Max
Oxides	741	15.42	1.25	12.13	15.38	15.76	16.28	17.35
Mixed	473	17.77	1.51	14.76	16.21	18.35	18.88	20.20
Sulfides	235	20.90	0.57	19.58	20.45	20.78	21.47	21.99

Figure 4. a) Histogram of BWi by ore zones. **b)** BWi sample mean plot



Statistics for BWi samples in lithologies (Figure 6) indicate that breccia and granite rock types are the least competent, while andesite, biotite granodiorite and granodiorite are the hardest. (Table 2 and Figure 7).

Figure 5. Visualization of BWi samples by lithologies. **a)** Three-dimensional. **b)** Plan view

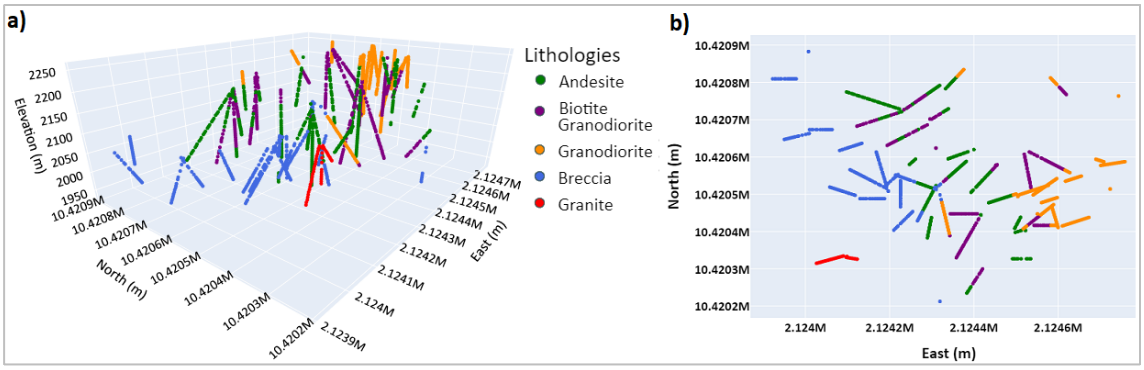
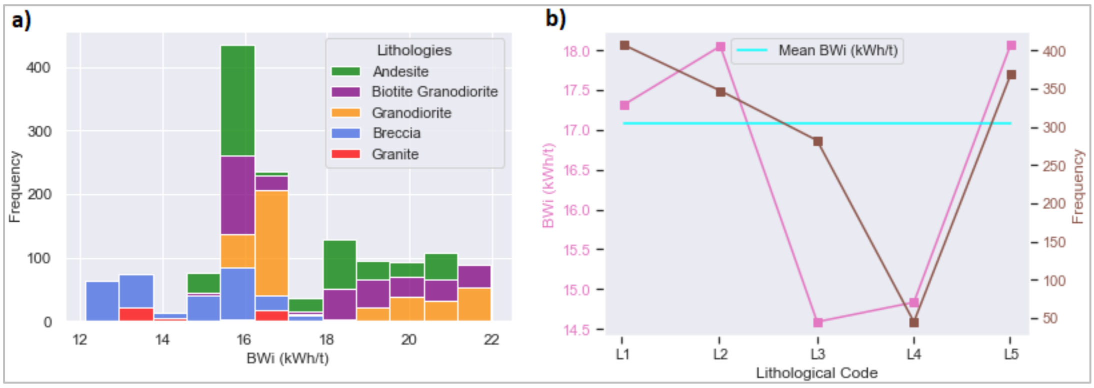


Table 2. BWi statistics by lithologies

Lithologies	# Samples	Mean	Std	Min	Q1	Q2	Q3	Max
Andesite (L1)	407	17.31	1.85	15.00	15.67	16.20	18.66	20.95
Biotite Granodiorite (L2)	347	18.05	2.13	15.20	15.85	18.41	19.80	21.99
Breccia (L3)	282	14.59	1.50	12.13	13.00	15.12	15.80	17.83
Granite (L4)	45	14.83	1.44	13.00	13.60	13.90	16.47	16.75
Granodiorite (L5)	368	18.07	2.11	15.45	16.40	16.73	19.95	21.93

Figure 6. a) Histogram of BWi by lithologies. **b)** BWi sample mean plot



Definition of geometallurgical units

To develop the BWi simulation, geometallurgical units "GMUs" of the deposit were considered, so that each GMu is a 3D spatial section of a mine body with similar geological and metallurgical characteristics.

Since each mineralized zone has a different distribution in the response variable (Figure 8a), samples from different ore zone will not be considered to define GMUs. Furthermore, as specified in Figures 8b, 8c and 8d, lithology controls the distribution of BWi in the ore deposit; therefore, considering the number of mineralized zones and lithologies there could be thirteen GMUs. However, when verifying the rock types present per mineral zone there can be up to thirteen GMUs and among these five GMUs (Table 3) have been defined taking into account the similarity in the behavior of the BWi.

Figure 7. Violin plots. **a)** Ore zones. **b)** Oxides – Lithologies. **c)** Mixed – Lithologies. **d)** Sulfides – Lithologies

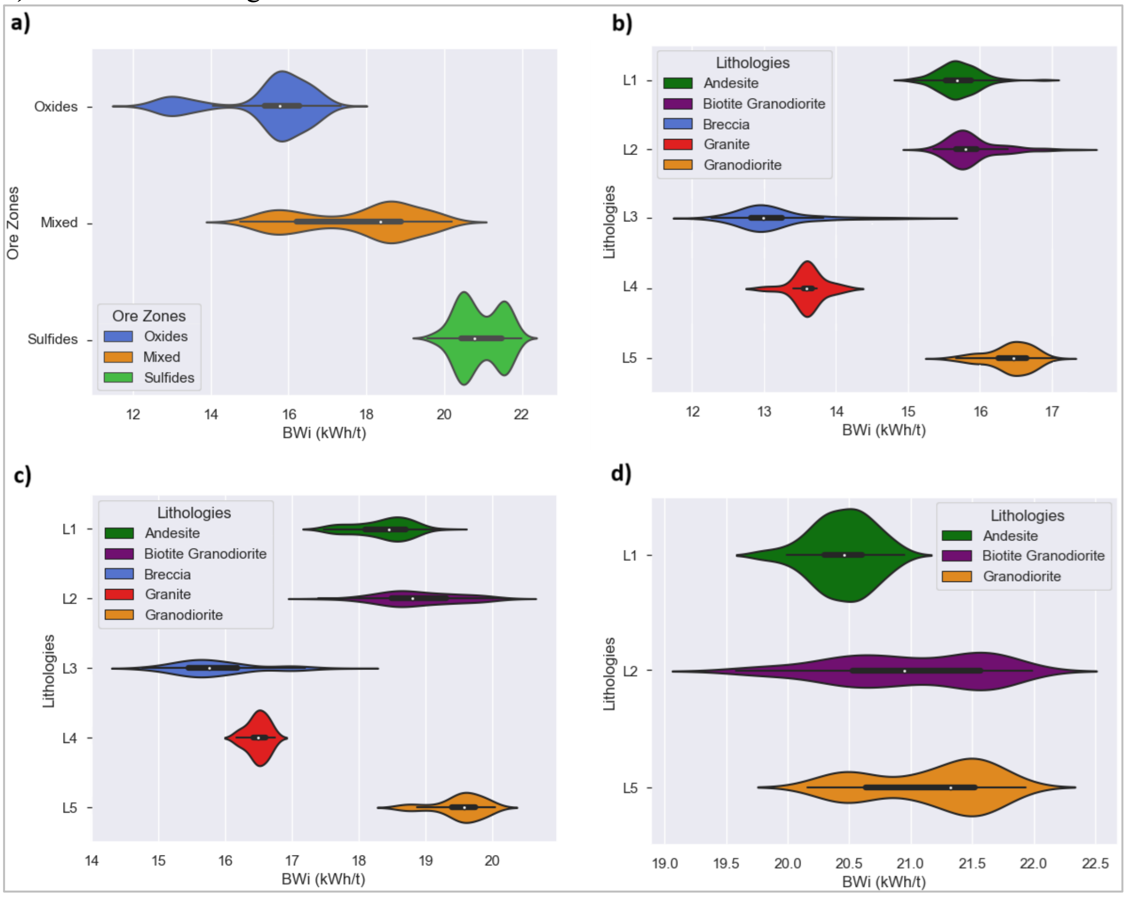


Table 3. BWi statistics by GMUs

GMUs	Ore Zones	Lithologies	# Samples	Mean	Std	Min	Q1	Q2	Q3	Max
GMU 1	Oxides	L1, L2, L5	584	16.01	0.45	15.00	15.67	15.90	16.40	17.35
GMU 2		L3, L4	157	13.19	0.54	12.13	12.86	13.05	13.57	15.26
GMU 3	Mixed	L1, L2, L5	303	18.79	0.64	17.40	18.40	18.70	19.31	20.20
GMU 4		L3, L4	170	15.95	0.62	14.76	15.50	15.81	16.34	17.83
GMU 5	Sulfides	L1, L2, L5	235	20.90	0.57	19.58	20.45	20.78	21.47	21.99

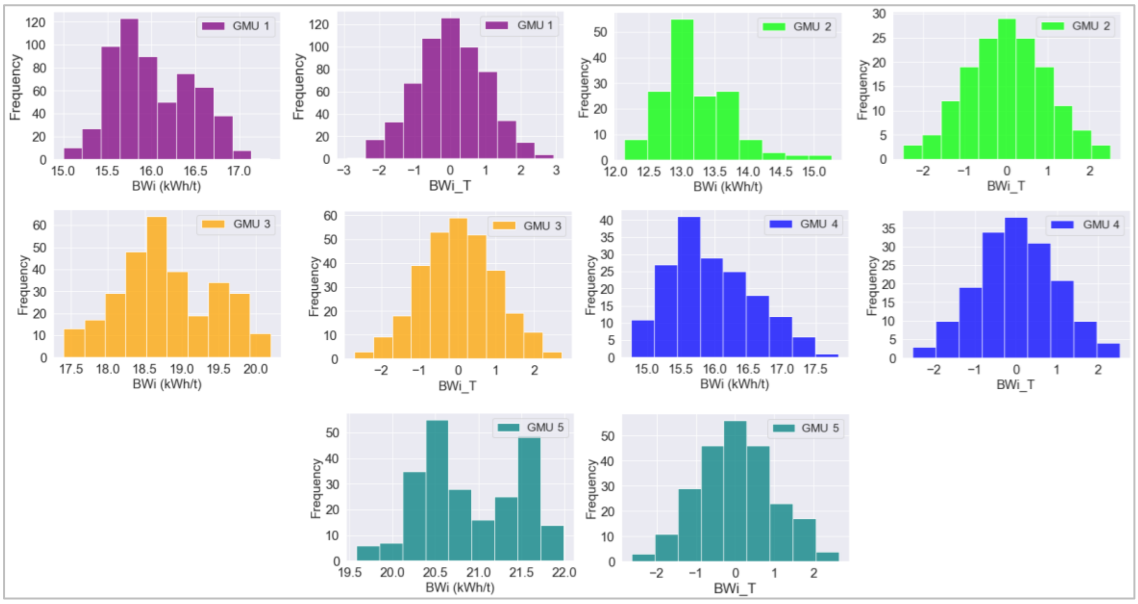
Geometallurgical simulation of BWi

Preliminary gaussian anamorphosis was performed on the BWi data shown in Table 3, to obtain a symmetrical distribution in the samples (Table 4 and Figure 9).

Table 4. Statistics of BWi transformed into gaussian variable

GMUs	# Samples	Mean	Std	Min	Q1	Q2	Q3	Max
GMU 1	584	0	1	-2.927	-0.665	0.011	0.676	2.927
GMU 2	157	0	1	-2.493	-0.665	0	0.665	2.493
GMU 3	303	0	1	-2.717	-0.664	0.016	0.669	2.717
GMU 4	170	0	1	-2.521	-0.634	0	0.665	2.521
GMU 5	235	0	1	-2.633	-0.648	0	0.674	2.633

Figure 8. Histograms of original and transformed samples to gaussian variable by GMUs



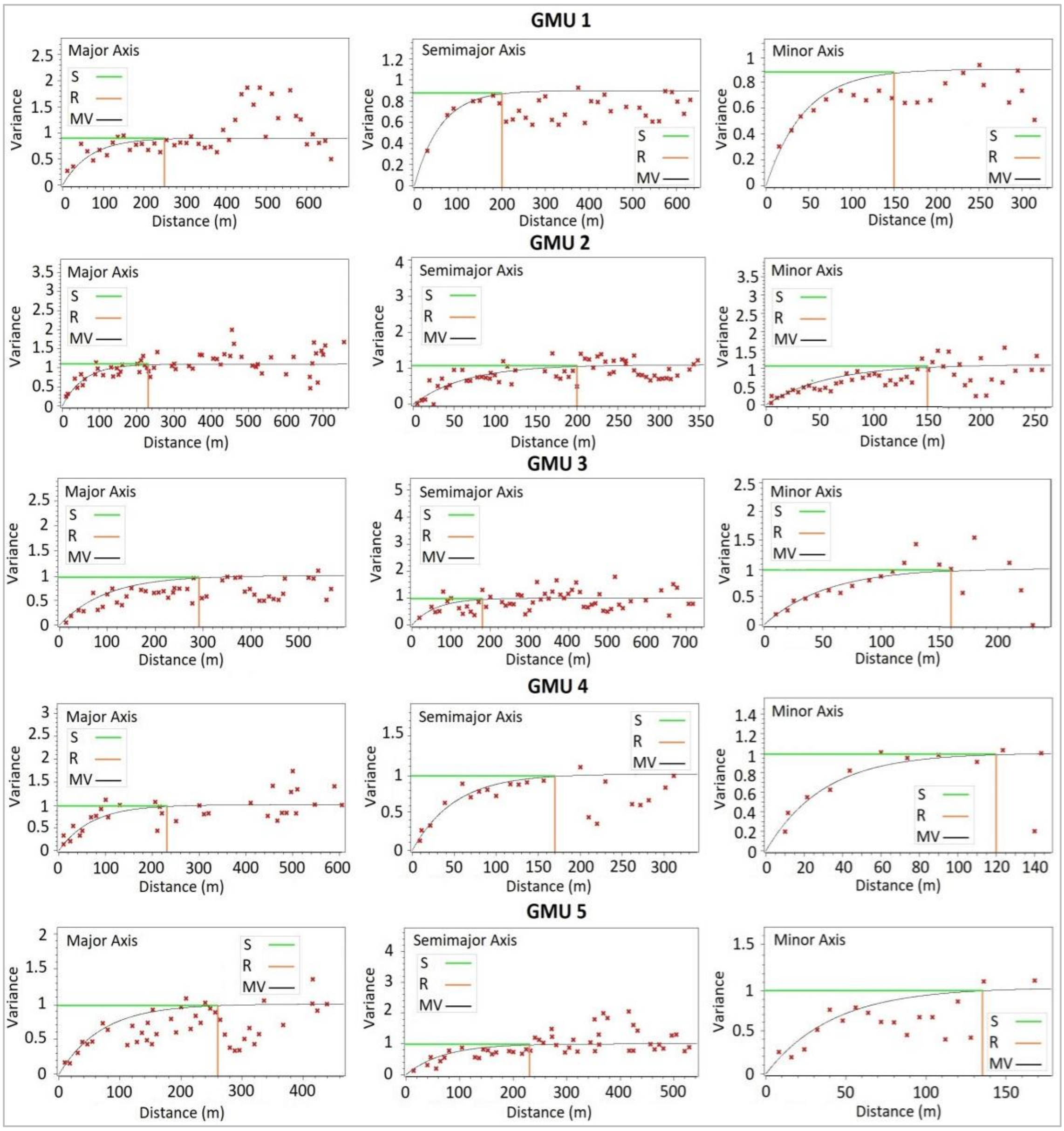
Note: BWi_ T (BWi transformed)

Exponential-type variograms were modeled in each GMU (Table 5 and Figure 10) to identify the spatial continuity and directions of anisotropy (major axis, semimajor axis and minor axis) that will form the search ellipsoid. In addition, a leave-one-out type cross-validation (Figure 11) of the modeled variograms was performed, that is to say, each known sample is successively removed from the dataset and a new value is predicted by Simple Kriging at that location using the other samples, indicating the difference between the actual and predicted value to what extent the data value fits the neighborhood of the nearby samples. Subsequently, the BWi simulation was performed on the block model developed for the GMUs (Figure 12).

Table 5. Parameters for modeled variograms

GMUs	Major Axis				Semimajor Axis				Minor Axis			
	Azimuth (°)	**Dip (°)**	**Range (m)**	**Sill**	**Azimuth (°)**	**Dip (°)**	**Range (m)**	**Sill**	**Azimuth (°)**	**Dip (°)**	**Range (m)**	**Sill**
GMU 1	67.5	0	250	0.9	157.5	0	200	0.9	0	-90	150	0.9
GMU 2	135	0	230	1.1	45	0	200	1.1	0	-90	150	1.1
GMU 3	22.5	0	290	1	112.5	0	180	1	0	-90	160	1
GMU 4	0	0	230	1	90	0	170	1	0	-90	120	1
GMU 5	67.5	0	260	1	157.5	0	225	1	0	-90	135	1

Figure 9. Modeled variograms (MV) by GMUs



Note: S (Sill), R (Range)

Figure 10. Histogram of errors and scatter plot between true values and predicted values by GMUs

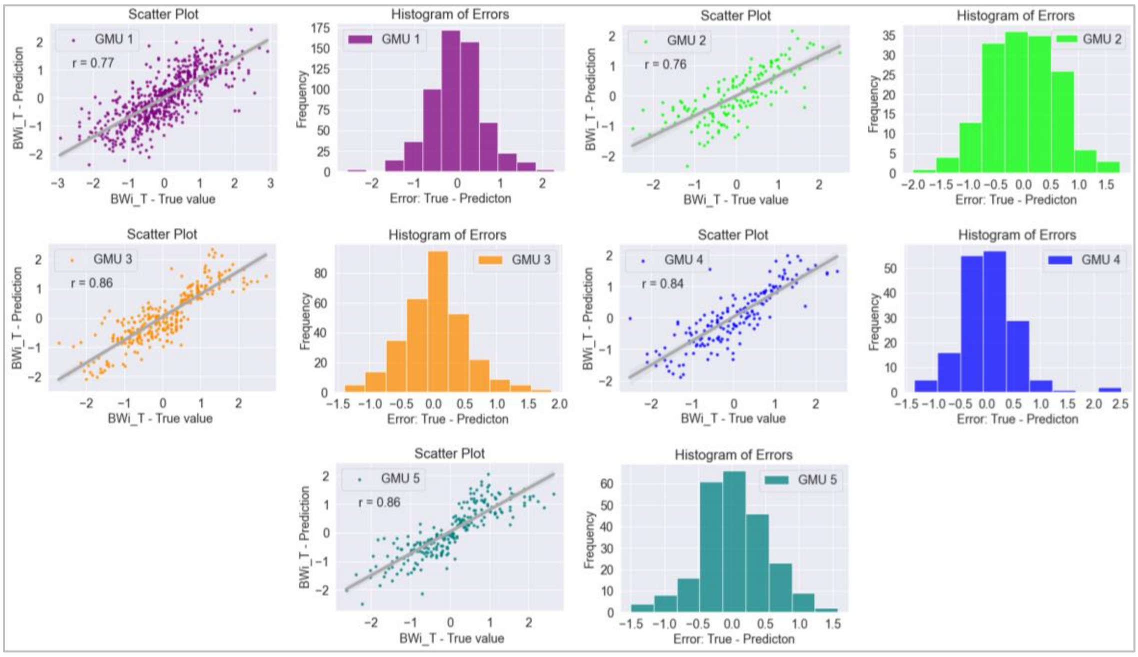
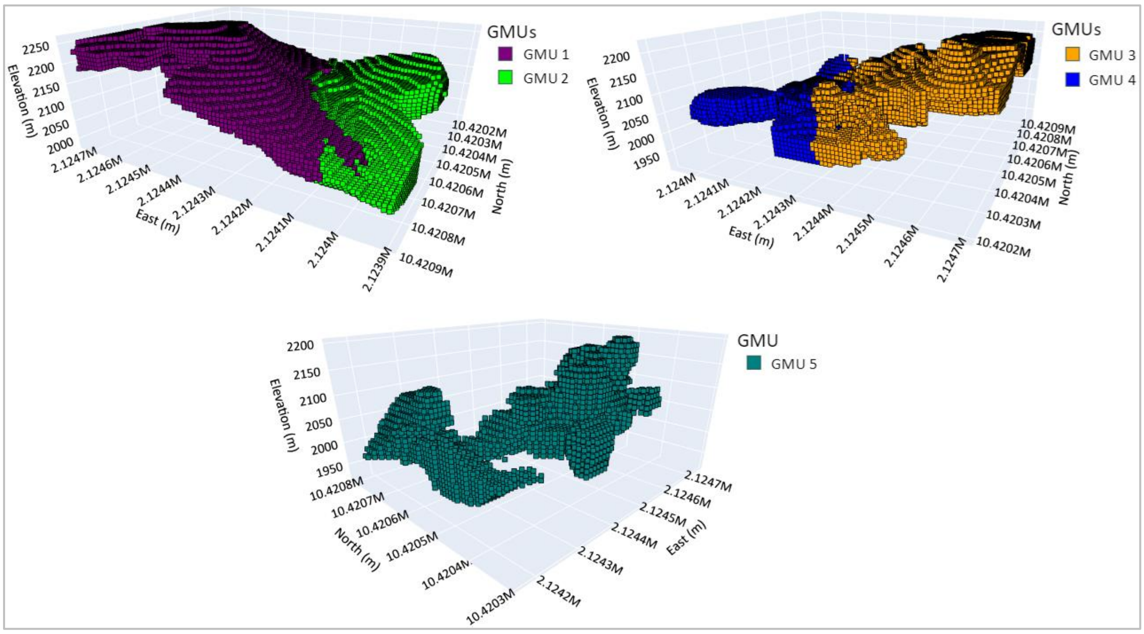


Figure 11. Geometallurgical block model



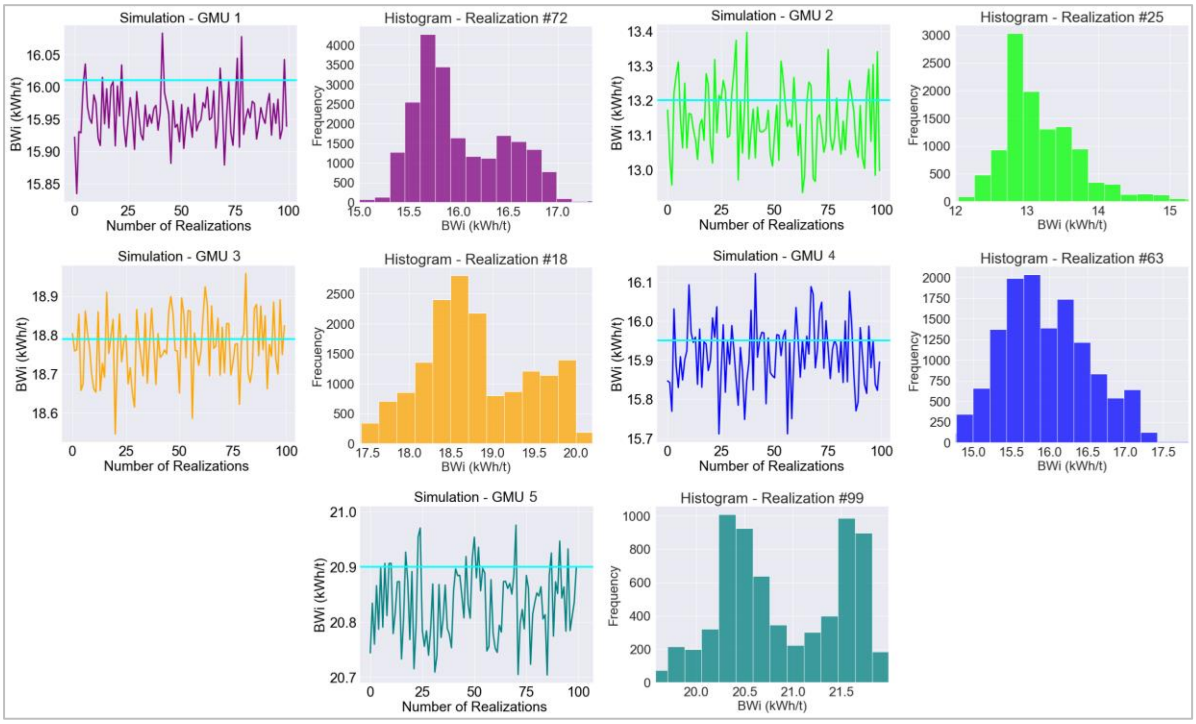
Note: The size of each block is 10 meters

Sequential Gaussian Simulation was applied to elaborate BWi realizations using its data transformed to a normal distribution with a mean of 0 and variance of 1. The number of realizations for BWi in each GMU was 100 as recommended by Bai & Tahmasebi (2022); then the values were brought to their initial units through inverse anamorphosis and finally, the optimal simulations were defined, considering those that best reproduce the mean and histogram of the original samples. The results obtained are shown in Table 6 and Figures 13 and 14.

Table 6. Statistics for original samples and optimal realizations by GMUs

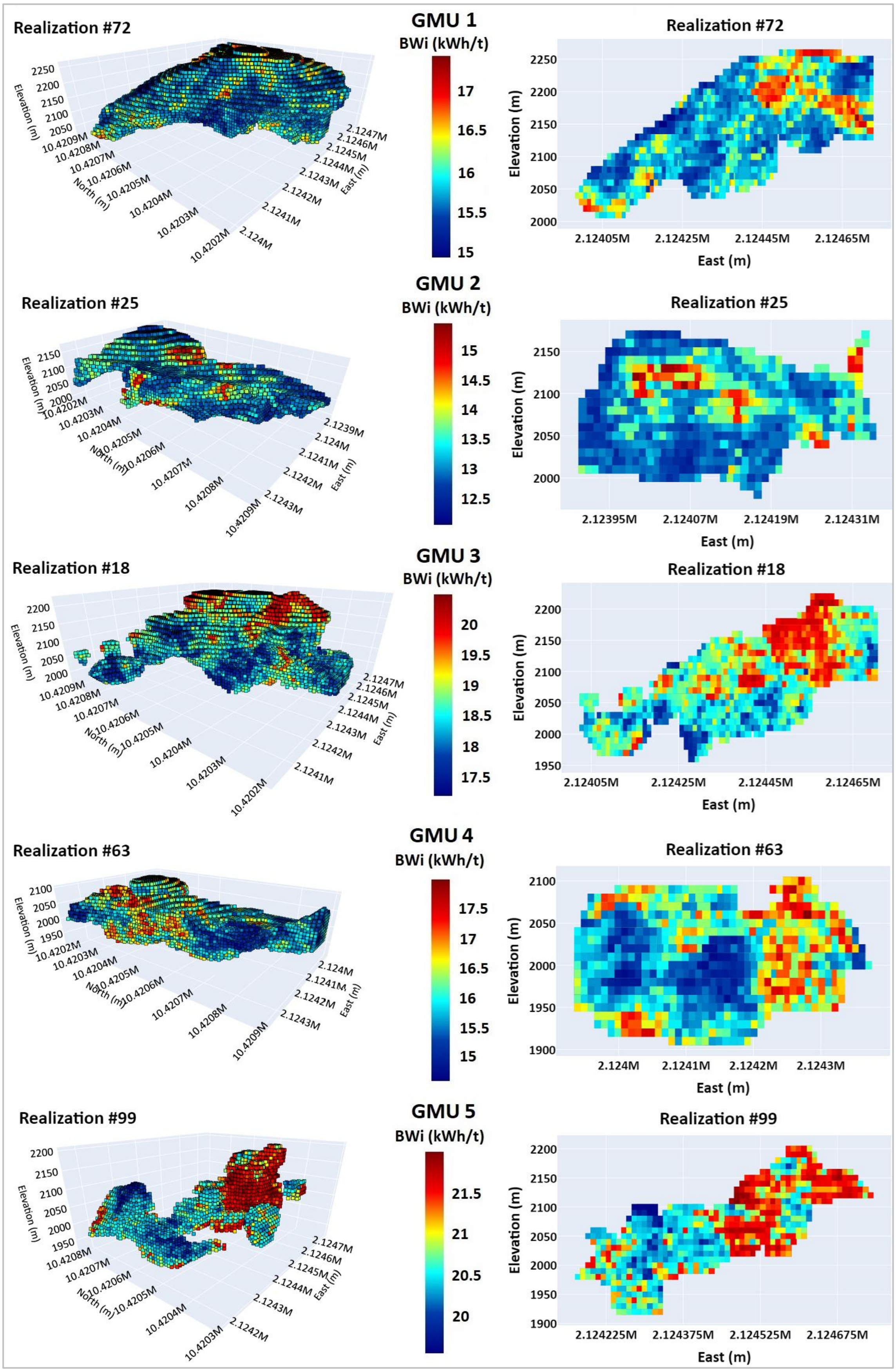
Description	# Samples	Mean	Std	Min	Q1	Q2	Q3	Max
GMU 1	584	16.01	0.45	15.00	15.67	15.90	16.40	17.35
Realization #72	21,224	16.01	0.45	15.00	15.66	15.87	16.39	17.35
GMU 2	157	13.19	0.54	12.13	12.86	13.05	13.57	15.26
Realization #25	11,247	13.20	0.57	12.13	12.87	13.06	13.58	15.26
GMU 3	303	18.79	0.64	17.40	18.40	18.70	19.31	20.20
Realization #18	16,276	18.80	0.63	17.40	18.41	18.70	19.33	20.20
GMU 4	170	15.95	0.62	14.76	15.50	15.81	16.34	17.83
Realization #63	13,024	15.95	0.57	14.76	15.53	15.87	16.30	17.83
GMU 5	235	20.90	0.57	19.58	20.45	20.78	21.47	21.99
Realization #99	6,710	20.89	0.62	19.58	20.38	20.75	21.50	21.99

Figure 12. Mean plots for BWi realizations and histograms of optimal realizations



Note: Sky blue color indicates mean of original samples in each GMU

Figure 13. Spatial (left) and 2D (right) visualization of optimal realizations for GMUs

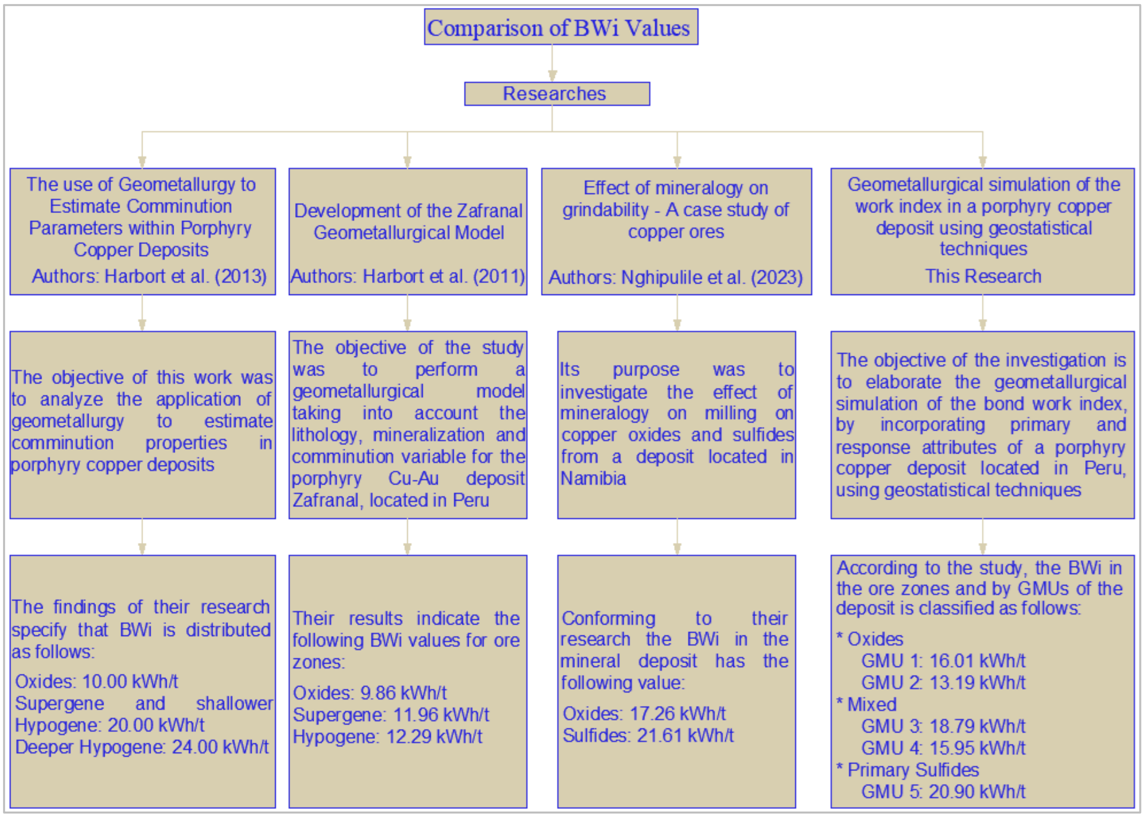


DISCUSSION

The application of Sequential Gaussian Simulation shows results in accordance with the reality of the phenomenon, since the statistics and spatial variability of the original BWi samples are better reproduced; in this sense, the degree of uncertainty is significantly reduced.

Likewise, through the findings found in this research it is established that the mineralized zones in the porphyry copper deposit studied in terms of hardness, the primary sulfide zone is the most competent, followed by mixed and finally oxides; which is related to the works developed by Harbort et al. (2013), Harbort et al. (2011) and Nghipulile et al. (2023) ; however, in each study, there is a variation in the values for BWi due to the specific characteristics of deposits (Figure 15).

Figure 14. BWi values determined for different porphyry copper deposits by ore zones



CONCLUSIONS

Through the research carried out, it was determined that the lithology of the porphyry copper deposit studied is a geometallurgical attribute that influences and controls the variability related to comminution in each ore zone.

According to the results obtained and considering the competence of the mineralized zones by way of BWi, these are classified from the softest to the hardest in oxides, mixed and sulfides.

By means of the simulation elaborated in GMUs, it has been possible to obtain multiple realizations of the BWi and evaluate its variability, adequately representing the proportion of high and low values, the spatial complexity of the deposit and the continuity of the geometallurgical variable three-dimensionally.

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