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Optimizing Mineral Extraction in Peru: Integrating Geometallurgical Planning with Mining 4.0 Technologies

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ABSTRACT

Geometallurgy is a comprehensive approach linking geology with mineral processing, addressing orebody variability and its impact on material quality. In Peru, the absence of predictive geometallurgical planning and real-time data poses challenges. This study aims to develop effective geometallurgical planning for Peruvian mining, optimizing mineral extraction and processing through advanced techniques like geostatistics and machine learning. Using a descriptive, non-experimental approach, the study focused on open-pit and underground mines. Methodology included detailed geological and metallurgical characterization, involving chemical analysis, mineralogical studies, and metallurgical tests. Geometallurgical models were implemented, integrating machine learning and geostatistics for data management and analysis. Results showed that geometallurgical planning allowed mining companies to better understand their deposits, optimizing extraction and processing. Specifically, detailed mineralogical characterization and geometallurgical domains reduced production variability by 15%. Advanced techniques improved accuracy in resource prediction by 20% and enhanced data management, enabling informed decisions-making. In conclusion, geometallurgy is crucial for optimizing mining production and reducing environmental impact. The study emphases the importance of technological innovations for sustainable practices in the Peruvian mining industry, highlighting that effective geometallurgical planning, can significantly improve operational efficiency and resource utilization.

1. INTRODUCTION

Geometallurgy is a comprehensive, multidisciplinary approach that has become increasingly relevant in the modern mining industry [1, 2]. This approach seeks to establish a bridge between geology and mineral processing, addressing the intrinsic variability of mineral deposits and its influence on the quality of the material processed in the plant [3-6]. Mineralogical characterization provides detailed information about the minerals present in the deposit, while metallurgical characterization focuses on the properties of the mineral to be processed [7, 8]. Complementing these studies with geostatistical analysis and the application of machine learning, the management and analysis of quantitative and descriptive data is allowed, adding significant value to the planning and management of mining resources, to optimize the extraction sequence, manage resources in a manner efficient and improve the quality and recovery of minerals, protecting the environment [9].

Mining 4.0, also known as smart mining, is revolutionizing the industry worldwide by incorporating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), automation and advanced analytics [10, 11]. These innovations enable greater operational efficiency, better decision making, and a significant reduction in operating costs and environmental impact. In this context, geometallurgical planning becomes an essential component to integrate these technologies effectively in mining, ensuring that the data generated is used to improve mineral extraction and processing processes [12]. IoT-based PM monitoring systems collect data through measurement devices (sensors) and transmit it over the network, making them more efficient and reliable. Likewise, artificial intelligence (AI), automation, and advanced analytics, as seen in the paper [13], are tools that form the basis of AI today. Performance data is the foundation of data analysis, providing sufficient information for informed decision-making.

In the field of Peruvian mining, we still face the absence of geometallurgical planning supported by predictive models based on quantifiable variables and the scarcity of data measured online [13-17]. The research will focus on open pit and underground mines, adopting a descriptive and non-experimental approach. The cases analyzed demonstrate how the implementation of geometallurgical plans has allowed mining companies a deeper understanding of their deposits, optimizing their mineral extraction and treatment processes. These actions have allowed strategic decisions to be made aimed at reducing variability, anticipating more favorable results that translate into notable improvements in production [9, 12].

This study aims to fill the research gap by focusing on the implementation of effective geometallurgical planning in open-pit and underground mines in Peru. By doing so, the research will demonstrate how the integration of these advanced techniques can lead to a deeper understanding of mineral deposits, optimized extraction and treatment processes, and strategic decision-making that reduces variability and improves production outcomes [9, 12]. Furthermore, the study emphasizes the importance of adopting technological innovations in mining, aligned with principles of green and digital mining, to move towards more efficient and sustainable practices [15]. Geometallurgy is seen as a paradigm shift in the mining industry from problem solving to holistic variability management and problem prevention. This shift has driven the inclusion in geometallurgy of a wide range of disciplines, namely spatial modelling, economic modelling and a dispersion of responsibilities among a wider range of actors.

This research contributes to the existing body of knowledge by providing a framework for the effective implementation of geometallurgical planning in the Peruvian mining industry, promoting strategic decision-making and optimal resource utilization.

However, significant challenges are identified that require attention during the implementation of geometallurgical plans. Among them, the need for precise quantification of mineralogy and the effective integration of geostatistical and machine learning techniques stands out [15]. In addition, emphasis is placed on the importance of adopting technological innovations in mining, aligned with the principles of green and digital mining. This panorama highlights the importance of moving towards more efficient and sustainable practices in the mining industry, taking advantage of cutting-edge tools and developing strategies that promote continuous improvement.

Regarding the implementation of Mining 4.0 to improve mining efficiency, many cases of implementation in mining development projects are reported. Therefore, this sector is identified as the area that has the greatest potential for the integration of advanced technologies in the mining industry, through the precise determination of geometallurgical parameters and the optimization of production processes.

This is how, in the mining industry, the study carried out by Psyuk and Polyanska [14], where it is analyzed that the achievements of Industry 4.0 are penetrating increasingly widely and deeply into various spheres of economic activity. This study discusses the directions of using artificial intelligence (AI) in solving development problems in mining companies. Methods have been determined to achieve results in various directions using AI. Based on the characteristics of the neural network formation components, the model of integration of neural networks in the information system of the mining company is determined, as well as the main components of this model, their connections and dependencies. The architecture of the proposed information system is described, which consists of four zones: the corporate zone, the operational zone, the control zone and the intermediate zone. It was highlighted that the operation of the operating system of this model depends on the sensors installed on the mining equipment in the company's operational area. It is noted that the number of such sensors depends on the amount of data accumulated due to the activity of the company's equipment and the efficiency of the construction and operation of neural networks. The factors that determine the effectiveness of the model and the precision of the neural networks in the activity of mining companies are based. It was established that the main criterion is the amount of information necessary to analyze the behavior of the object and the possibility of predicting it in the future. The dependence of the effectiveness of the application of AI technologies on the level of digitalization of the company was considered, and it was also proposed to determine the indicators of accuracy and efficiency of the functioning of neural networks in the company's information systems.

On the other hand, there is the study of Szelążek et al. [16], where a steel manufacturing project was selected and quality management practices were evaluated in the context of Industry 4.0. Specifically, a novel proposal was formulated based on semantic data mining techniques as a step towards knowledge-based decision support and following the industrial approach of Six Sigma. Although the results of this application were positive, there are some limitations. Therefore, the addition of other indicators such as the behavior of the system in different operating conditions could be considered, which would allow establishing results of greater impact. This implementation was divided into three stages: diagnosis, implementation and control. In our research, we combine machine learning classifiers and explanation generation algorithms with the practice of Six Sigma to automate the quality assessment of steel products and determine the origin of their defects. After analyzing the results of this research, we can indicate that the combination of semantic data mining and Six Sigma techniques has a positive impact on quality management. In particular, the results of this research indicate that the implementation of these methodologies significantly improves the average values of product quality. On the other hand, the results indicated that this methodological combination produces a statistically significant reduction in the variability of the defects. Although the results of this application were positive, there are some limitations. Therefore, the addition of other indicators could be considered, such as the behavior of the system in different operating conditions, which would allow establishing results with greater impact.

Likewise, the study of Monti et al. [17], who selected a project to implement digital technologies in industrial automation and evaluated the continuous evolution of these technologies in the context of Industry 4.0. Specifically, it was analyzed how business process management (BPM) can benefit from the availability of raw data from the Industrial Internet of Things (IoT) to obtain agile processes. This implementation was divided into three stages: diagnosis, implementation and control. In our research, we combine a top-down approach based on automated synthesis and a bottom-up approach based on data mining to manage, optimize and improve production processes. After analyzing the results of this research, we can indicate that the integration of BPM with IoT data has a positive impact on the agility of industrial processes. In particular, the results of this research indicate that the implementation of these approaches significantly improves the ability of processes to react quickly to interruptions and adapt to changes. On the other hand, the results indicated that this methodological combination produces a statistically significant reduction in the variability of the processes. Although the results of this application were positive, there are some limitations. Therefore, the addition of other indicators such as efficiency in different operating conditions could be considered, which would allow establishing results with greater impact.

Based on the background studied in this study, a geometallurgy implementation project was selected in the Peruvian mining industry and its effects on the variability of the mineral deposits and the quality of the material processed in the plant were evaluated. This implementation was divided into three stages: diagnosis, implementation and control. After analyzing the results of this research, we can conclude that geometallurgy is a comprehensive and multidisciplinary approach that plays a crucial role in the modern mining industry. In particular, the results of this research indicate that mineralogical and metallurgical characterization, together with geostatistical studies and the application of machine learning, allow the management and analysis of quantitative and descriptive data, which adds significant value to the planning and management of mining resources.

On the other hand, the results indicated that the implementation of geometallurgical domains, based on mineralogical composition and other properties, is essential to optimize mineral processing and reduce variability in production. Although the results of this application were positive, there are some limitations. It has been shown that geometallurgical planning can be applied at all stages of the mining operation, from pre-project exploration to the configuration of the processing plant, helping to optimize production and reduce environmental impact. However, the great challenge is the integration of geostatistics and machine learning, according to data and digital mining, to further improve results and reduce variability in project performance.

Based on these findings, it is recommended to continue researching and developing new methodologies that integrate advanced data analysis and predictive modeling techniques, to ensure greater efficiency and sustainability in mining operations. Likewise, collaboration between academic institutions and companies in the sector can be crucial for the successful implementation of these approaches, providing a solid basis for strategic decision making and optimization of available resources in the mining industry.

2. MATERIALS AND METHODS

Below, the methodology used in each section of the article is detailed to obtain precise and valuable results, highlighting the scientific rigor and the innovative approach applied.

2.1 Geometallurgy as a comprehensive approach

The geological characteristics of a mineral deposit present intrinsic variability, associated with its formation, which can influence the quality of the minerals that will be processed [18], the benefit obtained from the exploitation of the deposit depends ore grade and efficient recovery compared to operating costs [19].

Under these conditions, geometallurgy arises, which seeks to be a bridge between geological understanding and mineral processing, playing a crucial role in the modern mining industry by reducing risks and improving economic efficiency [20].

2.1.1 Implementation of geometallurgical domains to optimize mineral processing

Geological variability can be understood and quantified with the definition of geological domains that describe mineralogy and lithology [18, 20].

Geometallurgical domains help limit variability in processing by identifying units with similar characteristics; they can be defined through chemical analysis, mineralogical characterization [18], and metallurgical testing as seen in Figure 1.

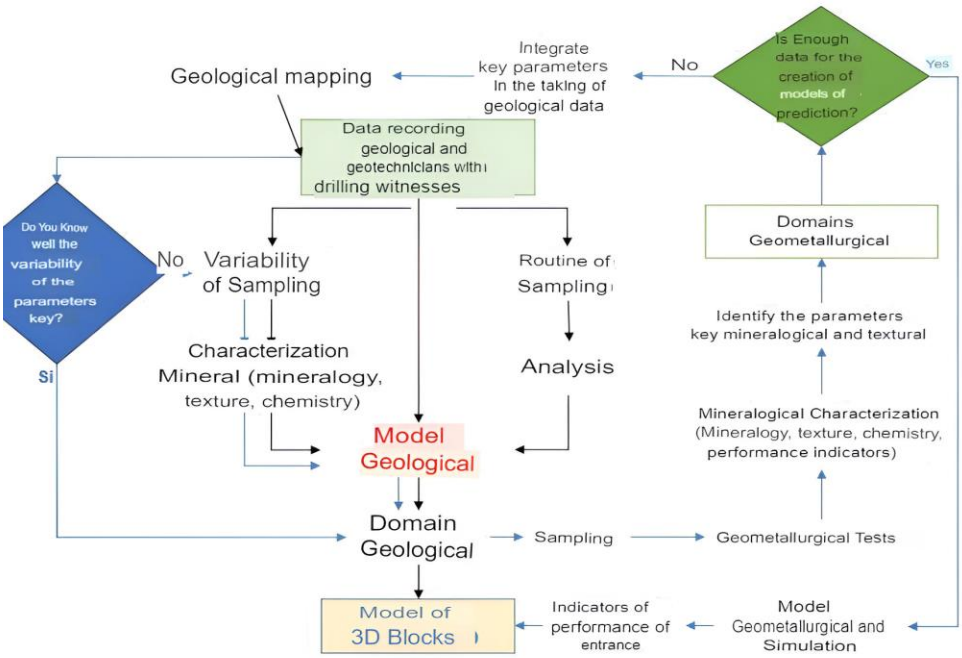

Figure 1. Approach to defining geometallurgical domains, comparing the traditional workflow (black lines), with the approach that considers geological data (blue lines) [18]

The geometallurgical domains must be implemented in production, in conjunction with the standardization of data communication and adaptation to new raw material management trends [20], applying it at different levels of the operation to the link mineral yield with the beneficiation process in the block model [21], reducing uncertainty when processing the mineral.

2.2 Key parameters of geometallurgical characterization

2.2.1 Mineralogical characterization

Within the mineralogical characterization, considers:

- **Visual Logging:** Describes on a macroscopic scale the sample, type of rock, mineralized zone, alteration, structures and textures present, to obtain the geological parameters of the deposit as seen in Figure 2.

Figure 2. Drill holes with massive texture, bands of chalcopyrite and amphibolite

- **Compositional Mineralogical Study:** Shortwave infrared spectrometry (SWIR) and X-ray diffraction can be used, as seen in Figure 3.

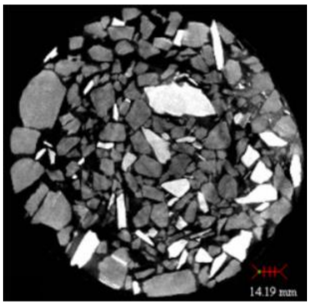

Figure 3. Two-dimensional CT - X-ray sectional slice from 3D high-speed computed tomography data for coal particles [22]

- **Textural Analysis:** It focuses on the influence of factors such as the genesis of minerals for geometallurgical purposes as seen in Figure 4.

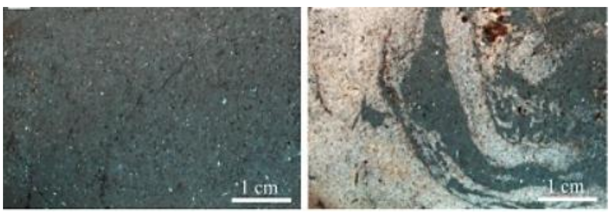

Figure 4. Textural patterns of drill cores identified at Mont-Wright (a) Massive (Ms); (b) Banded (BBd)

- **Optical Microscopy of Reflected and Transmitted Light:** Allows petrographic, mineragraphic and petromineragraphic studies to be carried out.
- **Degree of Release (P80):** From the mineralogical perspective, knowing the distribution of particles based on the degree of release allows predicting the distribution of the release from the texture of the mineral.
- **Scanning Electron Microscopy (SEM):** Allows the quantitative or semi-quantitative determination of the chemical composition, using the EDS detector, complemented by the backscattered electron detector.

2.2.2 Metallurgical characterization

It is based on the information obtained from the description of the properties of the mineral to be processed. The tests that can be performed are:

- Determination of humidity and specific gravity of a mineral (pulps)
- Radio-reduction tests
- Comminution tests
- Flotation tests
- Acid leaching
- Basic leaching (Cyanidation)
- Solvent extraction
- Electrodispersion tests
- Sulfide roasting tests

2.2.3 Chemical analysis

Parian et al. [23] point out that the result of the analysis is the chemical composition of each sample, among these tests we can consider:

- X-ray fluorescence spectroscopy (XRF). In this sense, in the study by Comelli et al. [7], these tests give us the scope that they accurately, results of their composition from the metallographic analysis of the treated material
- Dissolution + Atomic Absorption Spectroscopy (AAS)
- Inductively Coupled Plasma Optical Emission Spectrometry (ICP-OES)
- Inductively Coupled Plasma Mass Spectrometry (ICP-MS)

2.2.4 Physical-mechanical characterization

The geomechanical studies allow an adequate characterization of the rock mass for the adequate design and support that will be used, it is made up of:

- Uniaxial tests
- Triaxial compression tests
- Classification of rock massifs

2.2.5 Environmental studies

The geometallurgical model must incorporate the characterization of the extracted material through environmental tests, to achieve an effective design of the mine components using materials that do not generate acid drainage for the work carried out.

2.2.6 Statistical analysis, geostatistics and machine learning

Statistics involves data management, but in the analysis of geometallurgical data, quantitative and descriptive data are considered (hardness, lithology and other aspects related to mineralogy), Figures 5, 6 and 7 are presented below, which outlines the process of analysis.

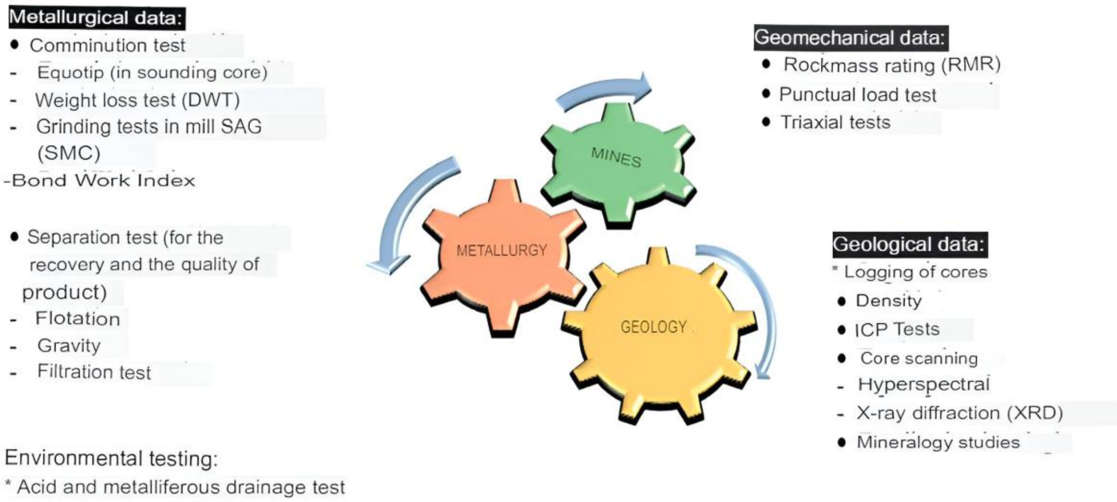

Figure 5. Information collected in geometallurgical programs

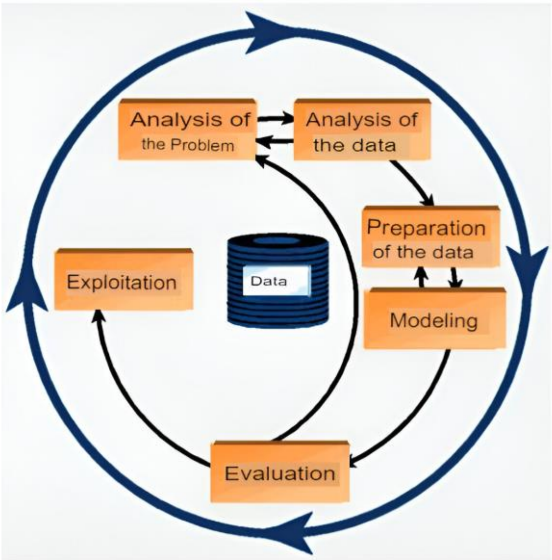

Figure 6. CRISP-DM statistical analysis methodology flowchart [24]

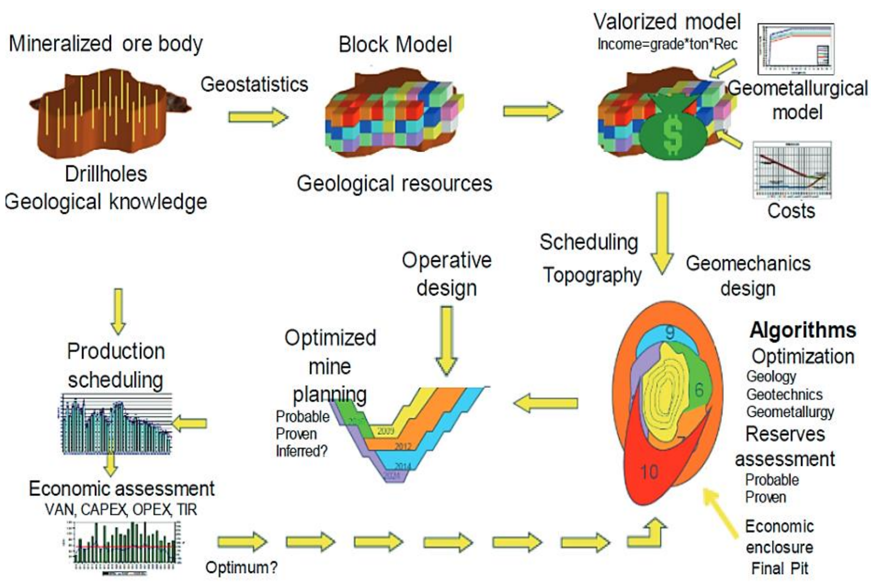

Figure 7. Value chain for generation of geostatistical models [24]

2.3 Geometallurgical planning: A comprehensive perspective

As a mine enters production, deposit data collection becomes more detailed, allowing geometallurgical models to be optimized, managing resources efficiently and decreasing environmental impact and increasing confidence in the mineral production plan [18, 20].

The geometallurgical planning and its high value as a management resource in mining are manifested in multiple contexts:

- In the pre-project exploration stages
- During the extraction of minerals in the deposit
- As a basis for the configuration of the plant in the metallurgical process selected according to the nature of the deposit.

Performing this analysis mitigates uncertainty during processing, being crucial to develop different operation plans based on the geometallurgical model [20].

In this perspective, the document by Monti et al. [17], gives the scope to allow linking the main techniques of process mining are discovery and conformity verification. The discovery starts from an event log and automatically produces a process model that explains the different behaviors observed in the log, without assuming any prior knowledge about the process. Today, while a large number of process discovery solutions have been successfully developed and employed in various application domains, existing techniques are suitable for discovering processes that do not have a data perspective built into them.

For the geometallurgical campaign to be successful, it is necessary to design it on experimental and practical bases.

- **Experimental design:** involves understanding the data analysis options from the beginning and planning to eliminate technical limitations, taking statistical technical bases to collect meaningful data, establishing achievable objectives to develop meaningful predictive relationships, this process is outlined in Figure 8.

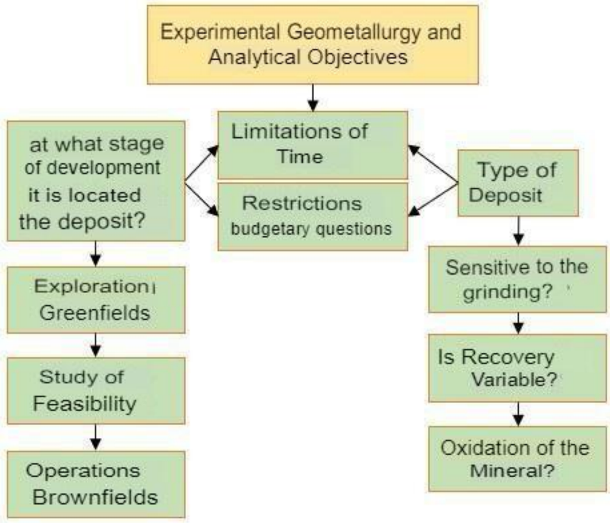

Figure 8. The development of objectives and purposes of the geometallurgical campaign

In a geometallurgy campaign, drill core samples are collected and integrated with other existing data (geophysics and geotechnics) and analyzed into a data matrix as seen in Figure 9.

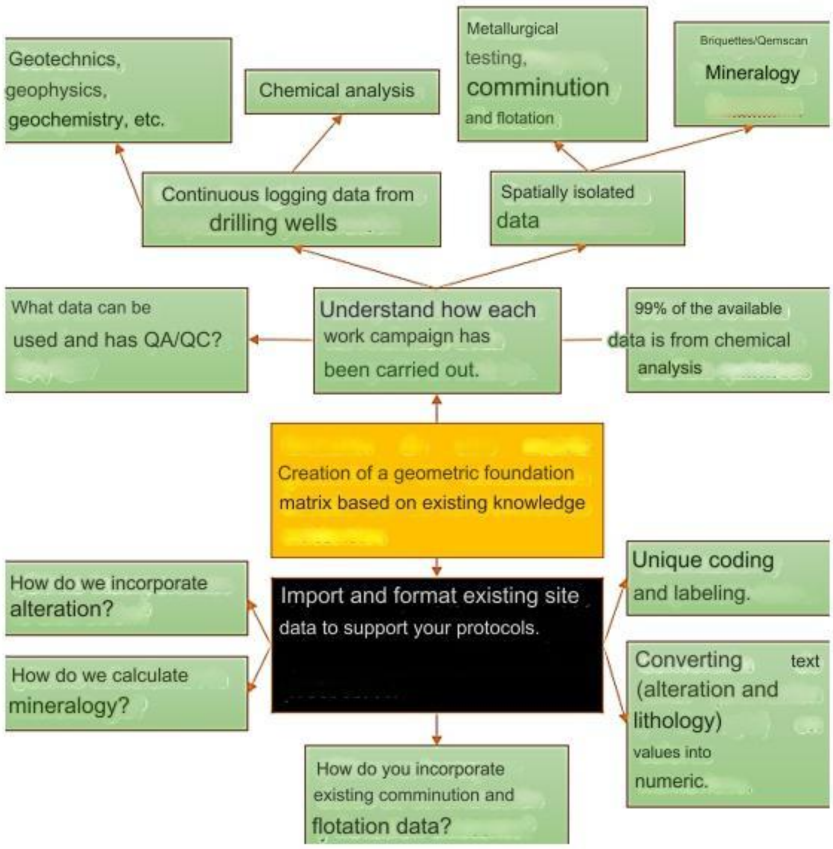

Figure 9. Development of a data set that will be the basis of the geometallurgical data set

2.3.1 Development of geometallurgical planning programs

We reviewed 25 geometallurgical programs from different mining companies around the world and developed a classification system to understand how geometallurgy is used and what methods are applied. Table 1 is presented below as an instrument, which will organize the classification of geometallurgical programs according to approach and application, and Figure 10, which outlines the definition of a geometallurgical program.

Table 1. Classification of geometallurgical programs based on approach and application

CLASSIFICATION SYSTEM: Try to answer the following questions: What type of data is used (approach)? How is the data used (application)?		
GEOMETALLURGICAL APPROACH		Defined by the type of data use in the geometallurgical program.
Traditional		- Chemical tests form the basis of the program. - The metallurgical response is calculated based on the chemical composition of the mineral. - The recovery of the metal is based on the chemical composition of the mineral. - They work on ore minerals with a good degree of release.
Indirect		- Common in the pre-feasibility stage. - Uses semiquantitative geometallurgical tests to characterize metallurgical behavior. - Collect information about mineral variability.
Mineralogical		- The geometallurgical model is built based on mineralogy. - Needs quantitative mineralogical data from the entire site. - Links the geological model and the process model.
APPLICATIONS		It is defined by how geometallurgical data is used in production management.
Passive Geometallurgy	***0: None***	They do not collect geometallurgical data, there are no geometallurgical programs, they do not use a geometallurgical model.
	1: Data collection	Geometallurgical data systematically collected, but not used in production planning.
	2: Display	Geometallurgical variability is visualized and studied based on the geometallurgical data collected.
Active Geometallurgy	***3: Identification of production constraints***	Geometallurgical data is used to identify quality constraints of the material that feeds production.
	4: Prediction prediction	Geometallurgical data is used to forecast production.
	5: Changes based on the quality of the Feed Mineral	Geometallurgy is used to plan changes in the process based on variations in the mineral that feeds the plant.
	6: Production Planning	The mining production plan is made taking into consideration the geometallurgical data.
	7: Simulation of production scenarios	Investment decision making, selection of uses of alternative techniques, production flow based on the application of geometallurgical data.

Fountain: Adapted from Andrade et al. [24].

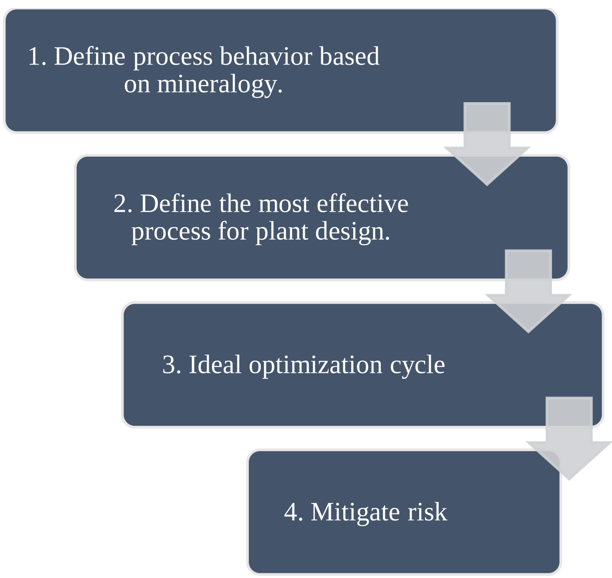

Figure 10. Definition of a geometallurgical program

To implement a geometallurgical program, the following steps must be considered:

The behavior of the process based on mineralogy considers:

- Efficiency based on measurements of each individual process in a context of textural mineralogical assemblages.
- Different metallurgical responses based on the type of mineral processed, which conditions the recovery of the ore mineral.
- Allows monitoring of the behavior of the process based on the type of mineral present in the deposit.
- Considers degrees of alteration and mineralogical domains in a geological model.

The integrated approach involves linking geometallurgy to characterize the reservoir and circuit simulation to predict metallurgical performance.

3. RESULTS

3.1 Application of geometallurgical studies in mining operations in Peru

Geometallurgy allows for a better understanding of deposits and more precise decision making in mining operations. In this context, various examples of the application of geometallurgical studies in mining operations in Peru are presented in Table 2, which highlights the importance of the characterization of geological and metallurgical properties to implement a geometallurgical plan that maximizes efficiency and profitability in the extraction and processing of minerals.

3.1.1 Challenges of operational geometallurgy in Cerro Corona, Cajamarca, Peru (Copper-Gold Porphyry)

The geometallurgical classification of the Cerro Corona mining deposit is a relevant factor to anticipate how metallurgy will behave in processing and its main objective is to maximize economic benefits, which is achieved through the creation of Geometallurgical Units (UGM) based on criteria such as the composition of the rocks, their alteration, structural characteristics, types of minerals present and metallurgical data.

These UGMs allow forecasts to be made on aspects such as mineral recoveries, the amount of material processed, the concentration of contaminating elements and the number of reagents used, as shown in Figure 11. The implementation of production strategies based on geometallurgical models benefits the company by improving mine planning, maintenance, impurity reduction and process optimization.

Table 2. Geometallurgical studies in mining operations

Application of Geometallurgical Studies in Mining Operations		
Location	Deposit Type	Optimization plan
Cerro Corona, Cajamarca	*Copper-Gold Porphyry*	Implementing production strategies based on geometallurgical models benefits the company by improving mine planning, maintenance, impurity reduction, and process optimization.
Cerro Lindo Mining Unit, Ica	*Volcanogenic Mass – VMS*	Identify, zone and characterize these resources through diamond drilling, which will allow geometallurgical studies to be carried out to evaluate the viability of exploitation of the deposit.
Ferrobamba and Chalcobamba-Las Bambas, Apurímac	*Skarn*	Identify Geometallurgical Units (UGMs) known as End Members, to adjust the operating parameters of the metallurgical plant for the treatment of different materials that reach it, considering the lithological variations within Ferrobamba.
Cuajone, Moquegua	*Copper Porphyry*	Implementing a geometallurgical evaluation, three main factors that affect copper recovery were identified: the work index, the abundance of micas and clays, and the chalcopyrite grain size.
Huarón Mining Unit, Pasco	*Silver, Zinc, Lead and Copper Polymetallic Deposit*	Implement a geometallurgical characterization in the northern zone veins where lead and copper metallurgy is deficient due to the lead/copper head association. Silver recovery is strongly affected by gangue inclusions and the presence of class 5 sphalerite.

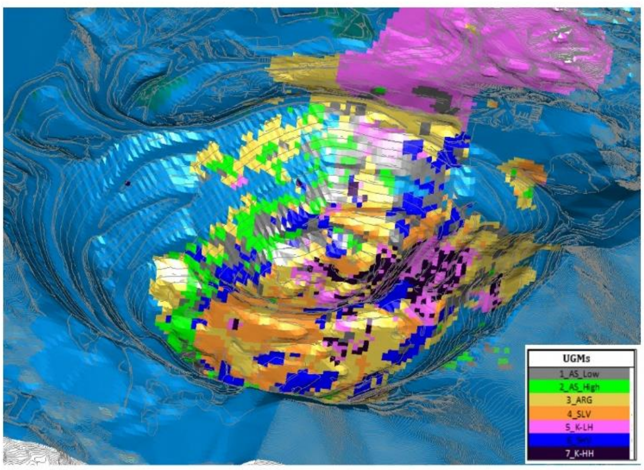

Figure 11. Distribution of the UGMs in Cerro Corona

3.1.2 Geometallurgy study of secondary coppers and impacts on resources and production of the Cerro Lindo mining unit (Vulcanogenic Mass Deposit – VMS)

In the geometallurgical study, carried out by Navarra et al. [20], they have identified that the mineral compound has moderate hardness and abrasiveness due to its high massive sulfur content, which makes it suitable for processing in a conventional concentrator plant. It is identified that the higher the soluble copper content, the lower the zinc recovery obtained. The quality of zinc and copper is affected by the difficulty of mechanically separating covellite from sphalerite.

To address this situation, it is proposed to identify, zone and characterize these resources through diamond drilling, which will allow geometallurgical studies to be carried out to evaluate the viability of exploitation of the deposit. The importance of considering a geometallurgical plan from the deposit exploration stages is emphasized, as shown in Figure 12.

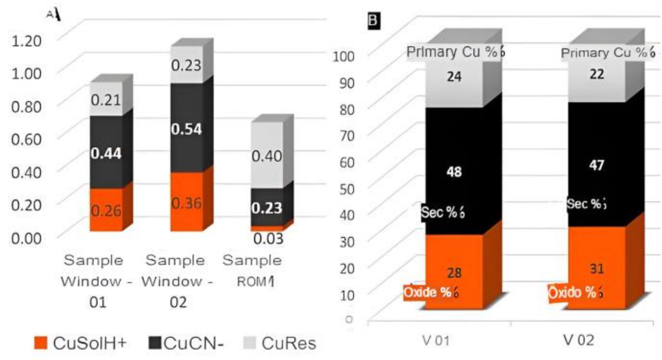

Figure 12. Distribution of soluble copper (A) and copper in the samples (B)

3.1.3 Geometallurgy of the ferrobamba and chalcobamba deposits, Las Bambas Mining Project (Skarn Copper)

Fabián-Salvador et al. [8] carried out a study where Geometallurgical Units (UGMs) known as End Members are identified, based on lithological and mineralogical criteria in the context of copper mining in the areas of Ferrobamba and Chalcobamba. The presence of a better developed mixed zone in Ferrobamba (called SKOX) compared to Chalcobamba stands out. The main focus is copper mining, with an emphasis on primary sulfides (bornite and chalcopyrite) as the primary ores.

They determine that the metallurgical recovery method for the future Las Bambas plant will be flotation due to the predominance of primary copper sulfides. Characterization and variability tests are carried out, both in comminution and flotation, in order to represent the common characteristics of an End and highlight the differences within them. These data will be used to adjust the operating parameters of the metallurgical plant for the treatment of the different materials that arrive at it, considering the lithological variations within Ferrobamba as can be seen in Figure 13.

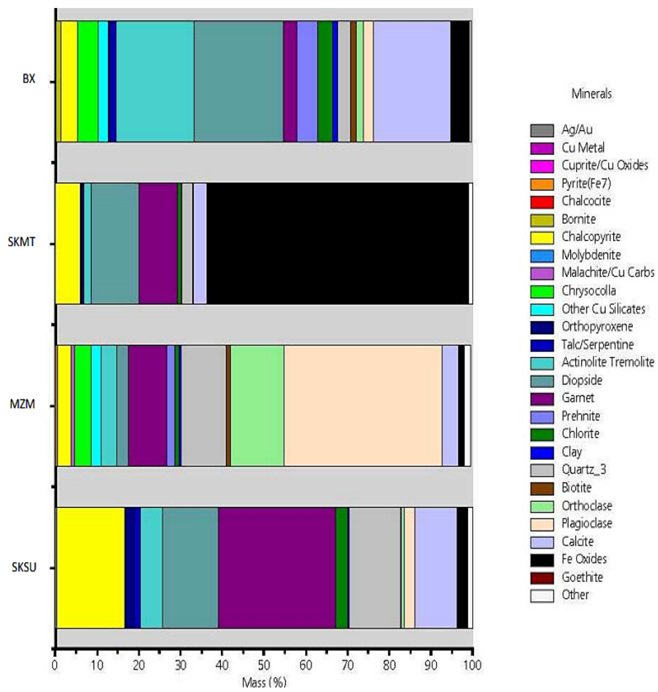

Figure 13. QEMSCAN image of the modal mineralogy for the different end members in Chalcobamba

3.1.4 Petrominerагraphic-textural and geochemical characterization of the geological units of mineralized lithological units in the Cuajone copper porphyry

Koch and Rosenkranz [21] present a geometallurgical analysis of 9 samples of mineralized lithological units at the Cuajone mine, as shown in Figure 14 where they identified three main factors affecting copper recovery: work rate, abundance of micas and clays, and the grain size of chalcopyrite, concluding that the energy necessary to crush a rock is linked to the energy between the minerals of the rock, where the intercrystalline energy decreases when the crystals develop properly, resulting in a lower index of work. On the contrary, a rock with abundant matrix and chaotic growth of minerals will have a higher work rate.

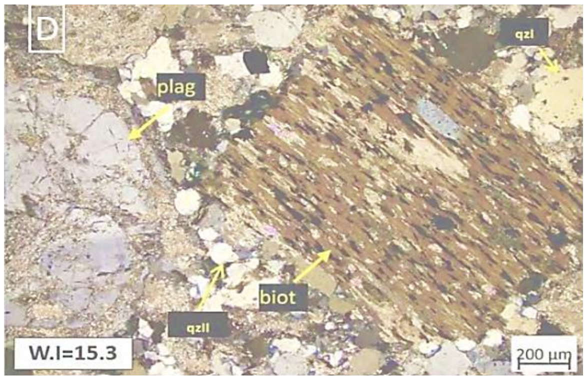

Figure 14. Photomicrographs of rocks from the Cuajone Mine

D: LP PTK; F: BA PTK. The variation of the Work index according to the texture is shown.

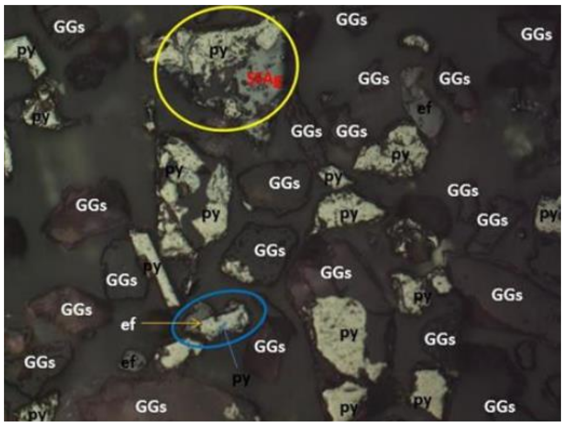

Figure 15. Mixed particle of silver sulfosalts and pyrite (SFAg/py) in yellow circle and mixed particle of sphalerite and pyrite (ef/py) in the blue circle

3.1.5 Geometallurgical characterization in the veins of the north zone Huarón mining unit (Silver, Zinc, Lead and Copper Polymetallic Deposit)

In research by Merrill-Cifuentes et al. [19], they carried out the geometallurgical characterization of two veins:

- **Pozo D Vein Branch Labor sublevel (SN) 200B:** It has high contents of silver (Ag), regular content of zinc (Zn), low grade of lead (Pb) and copper (Cu), and low content of iron (Fe), with a high Work Index (Wi), which indicates considerably high hardness. Mineralogy shows the presence of silver and sphalerite sulfosalts in the gangue, which affects silver and zinc recoveries. Zinc flotation tests show acceptable performance in Figure 15, but silver displaces zinc due to type 5 sphalerite and its relationship to pyrite. Lead metallurgy has low quality due to the low quality of the head.

- **Llacsacocha Vein Pit 251:** It has a high content of silver and zinc, a regular content of copper and lead, and a high content of iron. It has a low Work Index, indicative of low hardness. Mineralogy shows a shift of zinc and silver into the tailings due to inclusions of silver sulphosalts and mixtures of sphalerite with pyrite, affecting recoveries. Although zinc flotation tests are acceptable, lead and copper metallurgy are poor due to the association of lead and copper heads. The recovery of silver is influenced by gangue inclusions and the presence of class 5 sphalerite as seen in Figure 16.

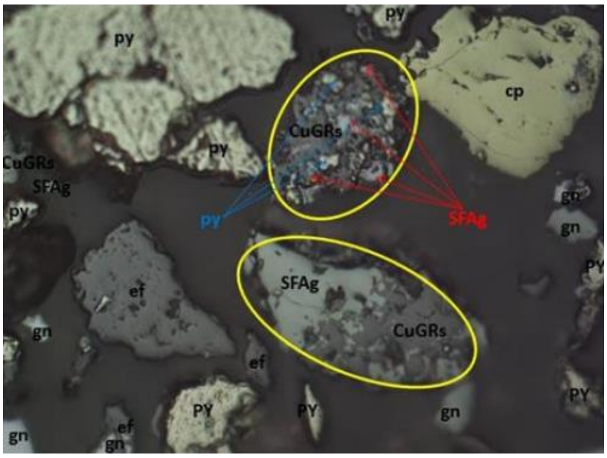

Figure 16. Impact of ganga and sphalerite on silver recove Particle composed of silver and gray copper sulfosalts (SFAg/CuGRs) in the yellow circle and small particles of silver and pyrite sulfosalts with inclusions. Presence of galena (gn) as free particles in the concentrate.

3.2 Challenges and opportunities in the implementation of geometallurgical planning in Perú

In the implementation of geometallurgical planning in Peru, significant challenges arise due to the complexity of the mineralogy in deposits. The lack of precise mineralogical information is an obstacle. To address this, we will consider the following aspects:

3.2.1 Quantification of mineralogy and its influence on mineral processing

In deposits with complicated mineralogy, geometallurgy plays a fundamental role in evaluating projects, since this information helps design extraction plans and configure concentration plants to address challenges of recovering valuable minerals [19]; With the proper categorization of minerals, there is a greater understanding of the entire mineral valuation process [21], however, this represents a challenge because mineralogical information is scarce [18]. The use of automated mineralogy techniques and chemical analysis at the particle and concentrate level is essential to determine the grinding conditions, the ideal release degree and other properties that influence the recovery process [23]. A clear example is the study in Sweden [18], where UGMs are classified in a way that allows their mineralogical classification and influence on the process. Problematic minerals can be mixed with other types of minerals to improve their recovery or avoid penalties.

The textural characterization of minerals should be quantitative and provide information about the particles that form during comminution and their composition (distribution of mineralization and degree of release) [23].

There is the study of Dominy et al. [6], where the textures of the ore influence its beneficiation and flotation performance, the quality of the concentrate and provide an indication of the characteristics of the tailings. A common understanding of the term "texture" relates to the size of the grain, which can be coarse, medium, or fine-grained, with varying grain.

3.2.2 Integration of geostatistics and machine learning for the creation of geometallurgical programs

Traditional geostatistical techniques consider a single geological scenario (ordinary kriging, simple griging, etc.) for long-term production planning, therefore, they do not measure the confidence of net present value (NPV) estimates, under variability geological [24].

Geostatistical techniques, as explained in the report of Huang et al. [9], give us scope of populations and directions by categories of population variabilities, in such a proposal this study finds univariate Bayesian geostatistical models for the continuous or categorical form of each continuous predictor and chooses the form with the minimum log score being the best functional form. Second, it uses the backward elimination method to identify the best set of fixed effects covariates for the final model. This assessment of geostatistics is correct, as mentioned in the article [20]. Two-stage optimization algorithms can be used to evaluate alternative operating modes, and therefore different plant configurations, under conditions of geological uncertainty. However, the implementation of these algorithms requires specialized data structures and is an area of ongoing research. Innovative data structures enable more detailed representation of mineral processing operations while maintaining the computational efficiency of the algorithms. The current framework is now capable of supporting geometallurgical models in terms of different modes of operation and processing capabilities as can be seen in Figure 17.

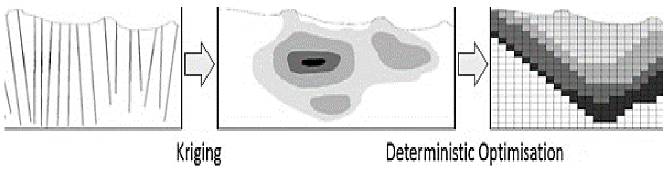

Figure 17. Kriging and optimization in mining planning

In contrast, current stochastic approaches produce more adaptive mining plans as shown in Figure 18, increasing the expected NPV of mining operations by more than 20%, which can correspond to millions of dollars.

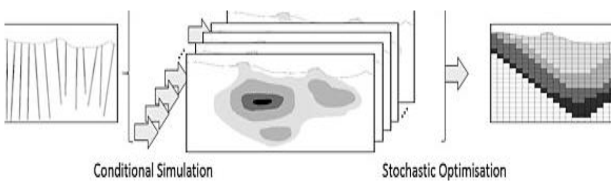

Figure 18. Stochastic optimization and conditional simulation in long-term mine planning

3.2.3 Implementation of innovation techniques in the mining industry

In the future, mineral deposits will be more complex and, In the future, mineral deposits will be more complex and challenging, in this context, geometallurgy is a crucial tool to integrate uncertainty, variability and external factors that will be crucial in evaluating the profitability and sustainability of mining projects [20].

Prediction of metallurgical [19] and environmental parameters can have a profound impact on the final economic, social and environmental outcomes of mine exploration, operation and closure. For example, in the early stages of the business, geometallurgy can allow better estimation of the value of a project, particularly for deposits with complex mineralogy, where, for example, for an acceptable grade of a valuable species, recovery may be difficult. This type of information can improve the design of the mine extraction plan, the circuits and equipment of the concentrator plant.

Technological innovation in mining helps to improve efficiency, sustainability and productivity in the mining sector, as seen in Figure 19. In these terms, the advance of the digital era and the implementation of artificial intelligence allows the generation of more advanced geometallurgical models, allowing us to anticipate possible problems that the mineral entering the plant may have [20].

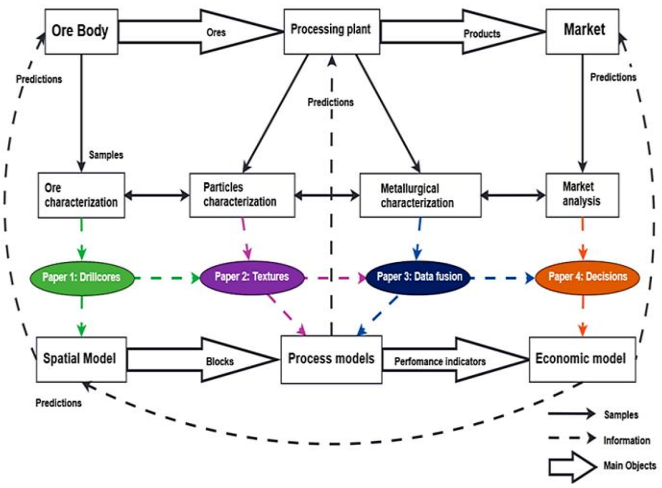

Figure 19. Computational methods and strategies for geometallurgy complete workflow in geometallurgy [20]

4. CONCLUSIONS

- Geometallurgy is a comprehensive and multidisciplinary approach that plays a crucial role in the modern mining industry, addressing the intrinsic variability of mineral deposits and its influence on the quality of the material processed in the plant.
- Mineralogical and metallurgical characterization, together with geostatistical studies and the application of machine learning, allow the management and analysis of quantitative and descriptive data, which adds significant value to the planning and management of mining resources.
- The implementation of geometallurgical domains, based on mineralogical composition and other properties, is essential to optimize mineral processing and reduce variability in production. The analysis of geometallurgical [24]. data in the field of mining is of utmost importance, because it allows generating behavior patterns that can result in trends that benefit the mining-metallurgical business.
- Geometallurgical planning can be applied at all stages of the mining operation, from pre-project exploration to processing plant configuration, helping to optimize production and reduce environmental impact. Of course, the great challenge is integration by applying geostatistics and machine learning, according to data and digital mining.

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NOMENCLATURE

SWIR	Shortwave Infrared Spectrometry
XRF	X-ray Fluorescence
ICP-OES	Inductively Coupled Plasma Optical Emission Spectrometry