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Insights on Prioritization Methods for Mining Exploration Areas: A Case Study of the Tiltil Mining District, Chile

Claudio Sebastián Molina [1], Carlos Jorge Marquardt [1,2,*], José Joaquín Jara [1] and Patricio Ignacio Faúndez [3]

[1] Departamento de Ingeniería de Minería, Pontificia Universidad Católica de Chile, Santiago 7820436, Chile; cbmolina@uc.cl (C.S.M.); jjjara@uc.cl (J.J.J.)
[2] Departamento de Ingeniería Estructural y Geotécnica, Pontificia Universidad Católica de Chile, Santiago 7820436, Chile
[3] Independent Mining Consultant, Santiago 7590943, Chile; pfaundez@gem-mc.com
* Correspondence: cmarquardt@uc.cl

Abstract: This study proposes a simple and replicable methodology to prioritize mining exploration projects based on their geoscientific characteristics and contextual factors, which can be adapted to different mining contexts. Using the Tiltil Mining District in Central Chile as a case study, where over 100 small and medium-sized Au and Cu prospects exist, this research outlines three key stages: (1) collection of relevant data; (2) selection of the most appropriate multi-criteria decision-making methods (MCDMs); and (3) the application, analysis, and comparison of these methods. This study identifies AHP and PROMETHEE II as the most suitable MCDM for the case study. The application of these methods consistently ranked El Huracán, San Aurelio, and La Despreciada as the top three exploration priorities. The AHP's weight assignment highlights economic, geological, and social factors as the most critical variables in determining project viability.

Keywords: early exploration; resource ranking; geoscientific evaluation; multi-criteria decision-making methods (MCDMs); AHP; PROMETHEE II

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1. Introduction

Mineral exploration, the initial stage in the mining life cycle, involves high-risk, long-term investments and significant geological uncertainty. To manage these challenges, prioritization tools are essential for identifying the most promising prospects for exploration programs [1–7].

Multi-criteria decision-making methods (MCDMs) are valuable tools in this context, allowing for the analysis of complex problems by evaluating various alternatives, outcomes, and uncertainties [8–11]. MCDMs are widely used across industries such as natural resource management, chemical engineering, environmental studies, civil engineering, and mining, where they have proven effective in solving multi-criteria problems [8,12–19]. Their application in mineral exploration includes tasks such as prospectivity mapping and target selection, which are critical for determining the best areas to focus exploration efforts [8,20–25].

Despite the extensive application of MCDMs, selecting the most suitable method for a specific problem remains a challenge in the literature [26–29]. This challenge is particularly acute in small and medium-scale mining operations [22,30], where budget constraints often necessitate a direct transition from exploration to exploitation [31].

This study aims to (i) propose a simple and replicable methodology for prioritizing prospects in a mining district with small and medium-sized deposits, based on geoscientific and contextual parameters, and (ii) apply this methodology and suitable MCDMs to the Tiltil Mining District in Central Chile. The proposed three-stage process draws on previous works by Guarini et al. [26,27], Jara et al. [21], and Faúndez et al. [31], and includes the following stages:

Characterization of the mining district based on geoscientific parameters.
Development of a methodology for selecting the most appropriate MCDM methods.
Prioritization of mining prospects using the selected MCDM methods.

This paper is structured as follows: Section 2 provides the background of the research; Section 3 details the methodology, data collection, and its application in the Tiltil Mining District; Section 4 presents the results; and Sections 5 and 6 offer the discussion and conclusions.

2. Methodological Developments

2.1. Introduction to Multivariate Decision-Making Methods

To effectively apply MCDM selection, it is important to briefly introduce the key methods used. The Analytic Hierarchy Process (AHP), developed by Saaty [32], is a widely recognized method that organizes complex decision-making problems into a hierarchical structure of objectives, criteria, sub-criteria, and alternatives [33]. Its extension, the Analytic Network Process (ANP), includes the interactions and dependencies among these elements, making it suitable for more complex, non-hierarchical problems [34].

Multi-attribute Utility Theory (MAUT) provides a systematic approach to decision-making by building a multi-attribute utility function that integrates individual utilities [35]. The MACBETH method, meanwhile, uses linguistic and numerical values to evaluate options based on qualitative opinions of variations in attractiveness in decision-making [36].

The Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE), introduced by Brans [37], ranks alternatives based on a preference function that quantifies the differences between options. It has been widely adapted for various MCDM challenges [38]. Similarly, the ELimination Et Choice Translating Reality (ELECTRE) method, developed in the 1960s [39,40], focuses on binary dominance between options and has evolved into several variants tailored to different problem types [41].

Finally, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), developed by Hwang and Yoon [42], identifies the alternative closest to the ideal solution by calculating the geometric distance to both the ideal and negative ideal solutions [42,43].

2.2. Methodology for the Selection of MCDMs

The selection of the most suitable MCDM method for a specific application remains unresolved, despite numerous studies offering various approaches and comparisons to address this challenge [28,29,44–48]. This research follows the methodology proposed by Guarini et al. [44], which focuses on constructing a taxonomy of endogenous and exogenous variables inherent in different MCDM methods. The goal is to identify the method that best aligns with the specific problem requirements and the available information [26,44]. Endogenous variables depend on the attributes of each MCDM method, such as whether the decision-making problem involves sorting alternatives, ranking options, or describing issues. Exogenous variables, on the other hand, are linked directly to the problem under study, such as whether the criteria used in the MCDM process are quantitative, qualitative, or a combination of both [26,44].

After identifying the endogenous and exogenous variables (Vn), their qualifications (Qn) are specified, which reflect the alternatives available in the problem's context. The weights (Wn) assigned to these variables indicate their importance in the decision-making process. Typically, these weights are assigned through the Delphi method, where a panel of experts assigns values between zero (0) and one (1) to each variable [26,49]. This method, as used by Guarini et al. [26,44], involves the same expert panel that initially defined the endogenous and exogenous variables.

Finally, the general suitability index (ISW) is calculated to determine each MCDM's ability to address the problem [26,44]. To calculate the ISW, a binary matrix Tn is established to link each variable Vn with the qualifications (Qn) that the MCDMs can address. This structured approach ensures that the selected MCDM aligns closely with the specific needs of the problem being studied.

The next stage of prioritization is based on a comparison of the characteristics of the MCDMs with the expected *Ep* properties. Before the *ISW* index can be obtained, the weighted suitability score (*SRW*) must be calculated. This value is obtained from Equation (1), which multiplies the weight associated with each variable (*Wn*), the expected property value (*Ep*), and the binary matrix (*Tn*). There is an *SRW* for each variable associated with each MCDM.

$$SRW = Wn \cdot Tn \cdot Ep \tag{1}$$

Finally, for each method, all the *SRW* values associated with each classification are added and divided by the number of variables considered in the analysis ($N*Vn$), giving the *ISW* value, as Equation (2) shows. After this, it is possible to rank the MCDMs from the highest *ISW* to the lowest [26,44].

$$ISW = \frac{\sum_{i=0}^{n} SRW_i}{N \cdot Vn} \tag{2}$$

2.3. AHP Method

The AHP method simplifies complex multi-criteria decision problems by breaking them down into smaller, more manageable subproblems within a hierarchical structure [21]. Generally, the application of the AHP involves three main stages [49,50]:

The first stage, hierarchical structuring, is pivotal in the AHP. It involves dissecting the problem into its fundamental components, defining the objective, and identifying the criteria that will influence achieving this objective. This process results in a hierarchical tree that graphically represents the problem, showing the relationship between the objective, criteria, sub-criteria, and alternatives [48].

The second stage involves the paired comparisons technique, developed by Saaty [32], and is widely used in various research fields and MCDMs [21,51,52]. This stage requires constructing a comparison matrix **A** of mxm dimensions, where m corresponds to the number of criteria involved in the problem. Each a_{jk} value of the matrix represents the relative importance of criterion j with respect to criterion k. The elements of this pairwise comparison matrix are the numerical values obtained from the comparisons. These values vary between 1 and 9, and their descriptive meaning in terms of relative importance is shown in Appendix A.1.

$$\mathbf{A} = \begin{pmatrix} 1 & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & 1 \end{pmatrix} \tag{3}$$

There are several ways to assign the values in matrix **A**, such as the Delphi method used by Pazand et al. [49], or the approach applied by Jara et al. [21] using a group of 10 experts, each conducting pairwise comparisons independently. After obtaining the matrix **A**, it is normalized by using the sum of the values in each column C_i of the matrix [21,33]:

$$_{jk} = \frac{a_{jk}}{\sum_{j=1}^{m} a_{jk}} \tag{4}$$

$$\mathbf{A}_{\text{norm}} = \begin{pmatrix} 1/C_1 & \cdots & \frac{a_{1m}}{C_m} \\ \vdots & \ddots & \vdots \\ \frac{a_{m1}}{C_1} & \cdots & \frac{1}{C_m} \end{pmatrix} = \begin{pmatrix} _{11} & \cdots & _{1m} \\ \vdots & \ddots & \vdots \\ _{m1} & \cdots & _{mm} \end{pmatrix} \tag{5}$$

Once the normalized matrix has been calculated, the vector of criterion weights **w** is obtained by calculating the average of each row of the normalized matrix $\mathbf{A}_{\text{norm}}$ (Equation (6)) [21,33]:

$$\mathbf{w} = \begin{pmatrix} w_1 \\ \vdots \\ w_j \\ \vdots \\ w_m \end{pmatrix} = \begin{pmatrix} \frac{\sum_{k=1}^{m} {}_{1k}}{m} \\ \vdots \\ \frac{\sum_{k=1}^{m} {}_{jk}}{m} \\ \vdots \\ \frac{\sum_{k=1}^{m} {}_{mk}}{m} \end{pmatrix} \tag{6}$$

The next action is to check the consistency of the expert's judgments. The consistency of the expert's answers in pairwise comparisons is measured by the consistency index *CI* [21,33]:

$$CI = \frac{\lambda_{max} - N}{N - 1} \tag{7}$$

The value of λ_{max} is obtained by multiplying the matrix **A** by vector **w,** resulting in a column vector. Subsequently, each component of this column vector is divided by the components of vector **w**, generating a new column vector formed by the eigenvalues of the matrix **A**. Finally, these values are averaged and λ_{max} is obtained, as shown in Equations (8)–(10) [21,33]:

$$\mathbf{A} * \mathbf{w} = \widetilde{\mathbf{w}} = \begin{pmatrix} \widetilde{w}_1 \\ \vdots \\ \widetilde{w}_j \\ \vdots \\ \widetilde{w}_m \end{pmatrix} \tag{8}$$

$$\frac{\widetilde{\mathbf{w}}}{\mathbf{w}} = \begin{pmatrix} \widetilde{w}_1 / w_1 \\ \vdots \\ \widetilde{w}_j / w_j \\ \vdots \\ \widetilde{w}_m / w_m \end{pmatrix} \tag{9}$$

$$\lambda_{max} = \frac{\sum_{i=1}^{m} \widetilde{w}_i / w_i}{M} \tag{10}$$

To calculate the consistency index (*CI*), the obtained value of λ_{max} and the number N of comparison criteria applied in Equation (7) are used. The *CI* is then compared with the random consistency index (*AI*), defined by Saaty [32], which represents the average *CI* from randomly generated matrices. The consistency ratio (*CR*) is determined by dividing *CI* by *AI*. A *CR* below 0.1 indicates acceptable consistency; if it exceeds 0.1, the inconsistency is deemed unacceptable, requiring further adjustments [21,33]. After confirming consistency, the final eigenvectors are used to calculate the percentages for alternatives, criteria, and sub-criteria. Finally, the last stage of AHP involves calculating the final weighting vectors for each alternative, criterion, and sub-criterion using these eigenvectors [21,33].

Let $\boldsymbol{x_{ij}} = \left(x_{1j}, .., x_{nj}\right)$ be the criteria vector of panel member i for criterion j, where there are m alternatives. Consequently, the matrix composed of n weighting vectors is formed as [21,33]:

$$\mathbf{X} = \begin{pmatrix} x_{1,1} & \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ x_{j,1} & \cdots & x_{jn} \end{pmatrix} \tag{11}$$

The weighted geometric mean is used to calculate the relative weight of each i alternative for criterion j and based on the general weight or $\propto$. Using $\propto$, the vector of aggregate priorities obtained via the geometric mean for each criterion, sub-criterion, or alternative is established using Equation (12) [21,33]:

$$\bar{x} = \left(\prod_{j=1}^{n} x_{ij}{}^{\alpha_i}\right) = \begin{pmatrix} \tilde{x}_1 \\ \vdots \\ \tilde{x}_j \\ \vdots \\ \tilde{x}_m \end{pmatrix} \tag{12}$$

Then, the vector of final weights is constructed based on the vector of aggregated priorities. The results are normalized to obtain the vector of final weights $\check{\mathbf{x}}$ [21,33]:

$$\check{\mathbf{x}} = \begin{pmatrix} \tilde{x}_1 / \sum_{i=1}^{m} \tilde{x}_i \\ \vdots \\ \tilde{x}_j / \sum_{i=1}^{m} \tilde{x}_i \\ \vdots \\ \tilde{x}_m / \sum_{i=1}^{m} \tilde{x}_i \end{pmatrix} \tag{13}$$

The AHP method provides the weights for criteria, which are then used to calculate the weight vector for sub-criteria relative to their superior criteria. Once the multi-expert weighting vector is established, the performance matrix is calculated by multiplying the weight of each criterion by the vector of alternatives, representing the set of groups to be evaluated (e.g., prospects or mines). Also, it is necessary to define $\mathbf{c_i}$ as the vectors that shows the alternatives for each sub-criterion and $\mathbf{P_i}$ for each group as a binary matrix that represent which of these alternatives is present or absent:

$$\mathbf{a} = \begin{pmatrix} a_1 \\ \vdots \\ a_n \end{pmatrix} \tag{14}$$

$$\mathbf{c}_1 = \begin{pmatrix} c_1 \\ \vdots \\ c_m \end{pmatrix}; \ldots ..; \boldsymbol{c_n} = \begin{pmatrix} c_1 \\ \vdots \\ c_k \end{pmatrix} \tag{15}$$

Then, to obtain the performance matrix of alternatives, the following procedure is carried out for each sub-criterion C_j associated with group a_k:

$$C_j * P_{jk} = c_1 * p_1 + \cdots + c_m * p_m = m_{jk} \tag{16}$$

Thorough Equation (16), the matrix F is obtained as shown Equation (17) [21,33]:

$$\mathbf{F} = \begin{pmatrix} m_{1,1} & \ldots & m_{1,n} \\ \vdots & \ddots & \vdots \\ m_{m,1} & \ldots & m_{mn} \end{pmatrix} = \begin{pmatrix} f_{1,1} & \ldots & f_{1,n} \\ \vdots & \ddots & \vdots \\ f_{m,1} & \ldots & f_{mn} \end{pmatrix} \tag{17}$$

To ensure comparability, matrix **F** values are normalized, resulting in matrix **S**.

With the normalized performance matrix (**S**) and the criteria weight vector $\check{\mathbf{x}}$ (Equation (13)), the final step is to compute the global scores vector **v** through the following operation:

$$\mathbf{v} = \mathbf{S} * \check{\mathbf{x}} \tag{18}$$

The resulting scores in **v** are then ordered to rank the alternatives from highest to lowest, completing the AHP process.

2.4. PROMETHEE II Method

The PROMETHEE II also uses pairwise comparisons, considering the difference in value between two alternatives for a given criterion. Unlike other MCDMs, it includes a preference function that assigns relative weights, reflecting the importance of each factor and their interrelationships. Initially, the performance matrix **F** (Equation (17)) is used without normalization [37,38,53]. Then, the difference between two alternatives for a criterion is calculated, indicating the distinction between evaluations of alternatives a and b for criterion C_j. The above is defined as follows [37,38,53,54]:

$$d_j(a,b) = h_j(a) - h_j(b) \tag{19}$$

$$P_j(a,b) = F_j[d_j(a,b)\big] \quad j = 1,..k \;\; \& \;\; \forall\, a,\, b\, \in A \tag{20}$$

For criteria that must be minimized, the preference function is rewritten as follows:

$$P_j(a,b) = F_j[-d_j(a,b)\big] \quad j = 1,..k \;\; \& \;\; \forall\, a,\, b\, \in A \tag{21}$$

After obtaining the preference function, it is necessary to define the aggregate preference index, which is determined using the following equation [37,38,53,54]:

$$\pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j \quad j = 1,..k \;\; \& \;\; \forall\, a,\, b\, \in A \tag{22}$$

where $\pi(a,b)$ represents the level of preference that a has on b considering all criteria. The PROMETHEE II method is based on the calculation of positive (φ^+) and negative (φ^-) flows for each alternative according to the given weight for each criterion. With the aggregate preference index (Equation (22)), the outranking flows for each alternative are calculated. The equations are as follows [37,38,53,54]

$$\varphi^+(a) = \frac{1}{n-1} \sum_{x\,\epsilon\,A} \pi(a,x) \tag{23}$$

$$\varphi^-(b) = \frac{1}{n-1} \sum_{x\,\epsilon\,A} \pi(x,a) \tag{24}$$

Equation (23) indicates how relevant is alternative a compared to the rest, i.e., the higher or the better the alternative it is. Meanwhile, Equation (24) shows the weakness or how it is dominated by the rest of the alternatives. Finally, the net relevance flow is calculated, which is expressed as follows in Equation (25):

$$\varphi(a) = \varphi^+(a) - \varphi^-(a) \text{ for each alternative } a. \tag{25}$$

The obtained values by Equation (25) are ordered by preference rank, thus completing the PROMETHEE II method and determining a ranking of the best to the worst alternatives in relationship with the objective of the MCDM problem to be solved [37,38,53,54].

3. Methodology and Data

3.1. Characterization of the Study Area: The Tiltil Mining District

The geological and structural evolution of mining districts plays a pivotal role in mineral exploration, as evidenced by the La Huifa Ore Deposit in Central Chile, where detailed geoscientific analyses have provided key insights into resource distribution [55]. The Tiltil Mining District is located 60 km northwest of Santiago, on the eastern flank of the Coastal Cordillera of Central Chile and along the western slope of the Tiltil Estuary (Figure 1). The district follows a north–south direction, with elevations ranging from 600 to 2000 m above sea level and covers an area of approximately 230 km^2. In this district, small mining projects have been developed since pre-Hispanic times, focusing on placer gold, gold–copper, and copper–silver veins, as well as breccia-hosted and strata-bound copper deposits [56–60].

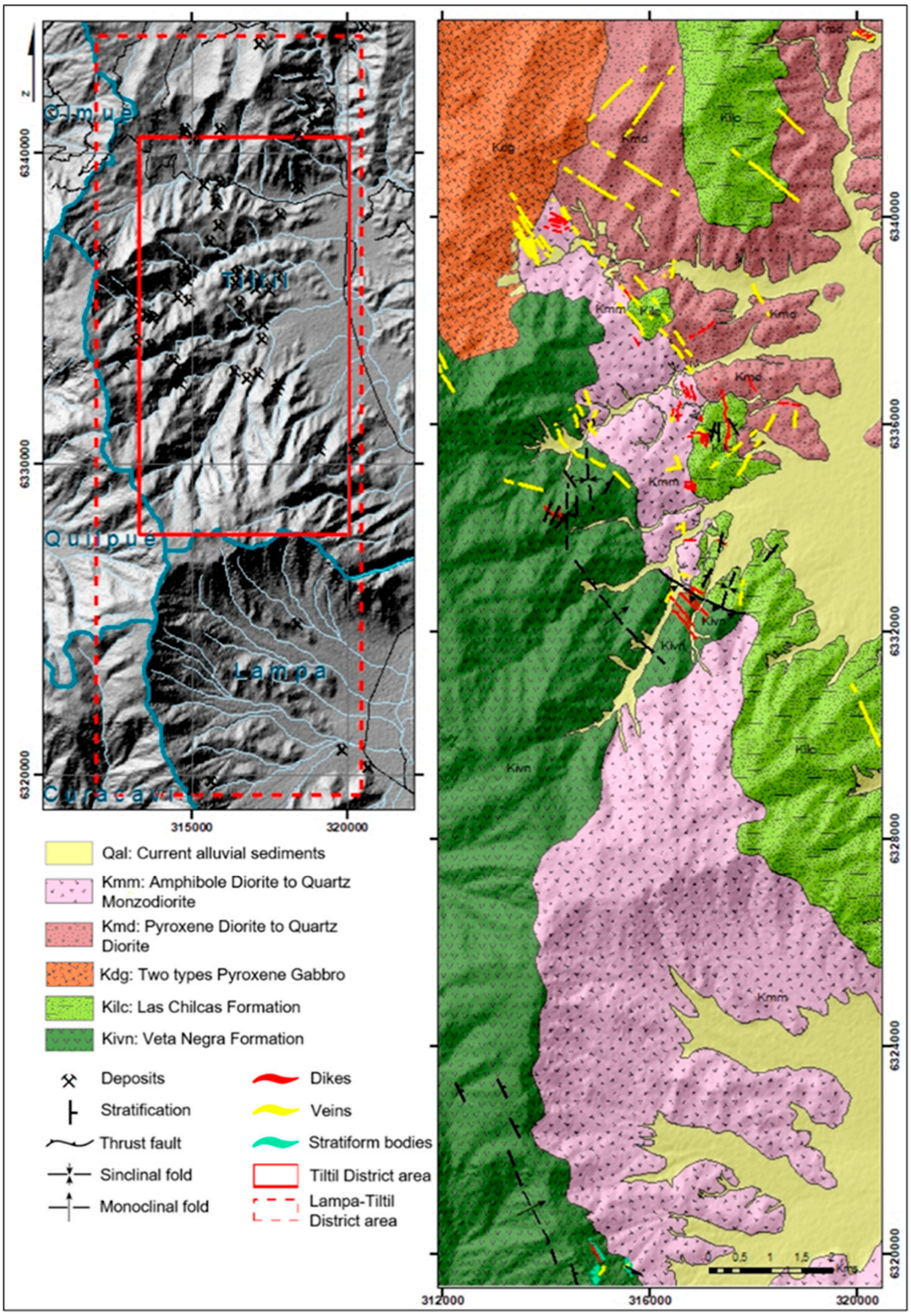

Figure 1. Location (**left**) and geological map (**right**) of the Tiltil Mining District, Central Chile. Modified from Faúndez et al., 2020 [31].

In the district, volcanic and sedimentary sequences from the Lower Cretaceous, specifically the Veta Negra and Las Chilcas Formations, are exposed and intruded by the Middle Cretaceous Caleu Pluton, which dates to between 100 and 94 million years ago [61–63]. The dominant structural features in the district are subvertical fault systems with NNE-SSW, NNW-SSE, NS, and EW directions, characterized by minor strike-slip displacements [64]. Several of these faults are associated with hydrothermal or mesothermal gold and gold–

copper vein systems, which exhibit orientations similar to those of the primary fault systems [38,60,65].

To establish a comprehensive database for prioritizing mining projects in the Tiltil Mining District, a detailed cadaster was compiled for each project, focusing on its geoscientific characteristics. This effort expanded upon the cadaster developed by Faúndez et al. [31] to include additional mine sites and further data for each location. This database is crucial for defining the hierarchical structure necessary for prioritizing exploration areas using MCDMs [31].

The compilation process began with an extensive review of existing reports, many of which were sourced from the archives of the National Geological and Mining Service of Chile (SERNAGEOMIN) and the National Mining Society of Chile (SONAMI). A subsequent field survey was conducted to gather missing or complementary data. The technical sheet used during fieldwork is provided in Appendix A.2.

The database incorporates the following parameters for each project: (1) general information (location, access, and goods and services), (2) lithology, (3) mineralization, (4) alteration, (5) exploration and/or production information, (6) main ore and copper equivalent grade, (7) secondary ore, (8) rock element and sediment anomalies, (9) geophysics and geochemistry information, (10) water resources, (11) geography and weather, (12) flora and fauna information, (13) land use and local communities, and (14) other resources. A summary of the database used in the case study using the AHP and PROMETHEE II methods is presented in Appendix A.3.

3.2. Inputs for the Selection of MCDMs

For this case study, the context was framed within a district characterized by small and medium-sized Cu and Au deposits and mine sites. The first step involved the creation of the first panel of experts (Panel of Experts N°1), composed of three interdisciplinary experts with extensive experience in mining, engineering, and geology. This panel's primary objective was to define and evaluate the variables, criteria, and weightings necessary for selecting the most appropriate MCDMs to rank exploration prospects within the district. Each expert was selected based on their expertise in MCDM methodologies, geological sciences, and mining optimization, ensuring a well-rounded approach to the problem.

The experts began by identifying the characteristics of the variables (Vn) that best represent the factors most used in the literature to evaluate the exploratory potential of a prospect, distinguishing between exogenous and endogenous variables. The work of Guarini et al. [26,27,44] provided a well-known set of variables that were adapted to fit the specific context of this study. The selected variables, as detailed in Appendices A.4 and A.5, were chosen based on their relevance and applicability to the problem at hand.

In the second stage, the weights associated with each variable were involved in the MCDM process (W_n). While there are numerous methods to assign these weights, in this instance, the same panel of experts determined the values. To maintain objectivity and avoid potential biases stemming from the experts' individual experiences, a uniform weight of $W_n = 1$ was assigned to each variable, following the simplification used by Guarini et al. [26,27,44]. This approach was intended to generate a result that is as generic as possible, focusing on the type of problem rather than its specific details.

The third stage of the process involved considering the expected properties of each MCDM in prioritizing small and medium-sized prospects within the district. Panel of Experts N°1 was responsible for defining these properties, guided by recommendations from the existing literature [32–34,48,66,67]. The final stage compared the expected properties with the capabilities of the MCDMs, ultimately determining the suitability of each method for addressing the problem. The ISW indicator was calculated to rank the MCDMs from most to least suited.

3.3. Inputs for the Prioritization of Mining Prospects

Before applying the best-ranked methods, it is essential to establish the hierarchical structure, determine the weights for each criterion, and define the performance matrix for the exploration prospects [21]. These foundational elements ensure that the selected MCDMs provide reliable and consistent results.

The objective of the performance matrix is to represent the presence or absence of key characteristics for each project concerning the selected criteria. Several approaches can be used to develop this matrix. In the context of the Tiltil Mining District, the matrix was constructed by Panel of Experts N°1. This panel leveraged the characteristics and properties documented in the mining cadaster, as detailed in Section 3.1, to accurately populate the matrix.

To calculate vector v using the PROMETHEE II method, the same inputs as in the AHP are used, which are the weights of the criteria and sub-criteria x (Equation (13)) and performance matrix of non-normalized alternatives F (Equation (17)). This approach was chosen to maintain consistency across the comparison of both MCDMs and to facilitate the integration of results. This methodology is supported by the work of Bogdanovic et al. [65], who successfully applied AHP for assigning criteria and sub-criteria weights in mining method selection and used PROMETHEE II to rank the available alternatives. For this study, a usual-type criterion preference function was selected for PROMETHEE II. Specifically, if the difference between the alternatives for each criterion exceeds 0, a value of 1 is assigned to the function; otherwise, a value of 0 is assigned.

Following this, the prioritization methodology incorporated a second, larger panel of experts (Panel of Experts N°2), consisting of 13 professionals. This panel was tasked with defining the hierarchical structure of the problem to be solved, including establishing the goal at the first hierarchical level and determining the weights for applying the selected MCDMs in this case study. The weights were assigned using pairwise comparisons, a method well suited for capturing the relative importance of various criteria.

Experts for the second panel were chosen for their extensive experience and diverse expertise in mineral exploration, mining development, and related technical fields, following the selection approach used in studies by Jara et al. [21] and Faundez et al. [31]. This multidisciplinary panel consisted of 10 senior experts, typically aged 45–65, with advanced degrees and over 15 years of industry experience, alongside 3 junior professionals aged 25–35 with strong academic backgrounds. The panel's diversity in age and regional representation ensured a broad perspective, crucial for accurately defining the hierarchical structure, selecting MCDMs, and applying them to the case study of the Tiltil Mining District.

To further refine the analysis, the process of identifying endogenous and exogenous variables was guided by the methodology proposed by Guarini et al. [26,27,44]. This approach ensures that the variables are appropriately categorized and weighted, enhancing the robustness and applicability of the MCDMs in various contexts.

4. Results

4.1. Characterization of the Study Area and Database for the Prioritization Processes

One hundred and thirteen prospects or mining areas are identified in the Tiltil Mining District. These include different types of orebodies and mine sites. The data gathered for these mining areas are as follows: location, access, geology (lithology, alteration, and ore mineralogy), evidence of mining activities, type of exploitation (underground or open pit), and current mining status (active, sporadic, or abandoned), among other information (Appendix A.3).

Figure 2 shows that mining activity in the district is scarce and sporadic, while 55% of the registered mining areas are abandoned and only 2% are active at the time of fieldwork. In addition, the results of the cadaster show that 33 mining areas have gold as primary production, 23 have copper oxides, 9 have copper sulfides, 15 have copper oxides and sulfides, and only 2 have non-metallic ores. The remaining mines do not have available information about their main product objective due to complete resource depletion, inaccessible orebodies, or other information restrictions.

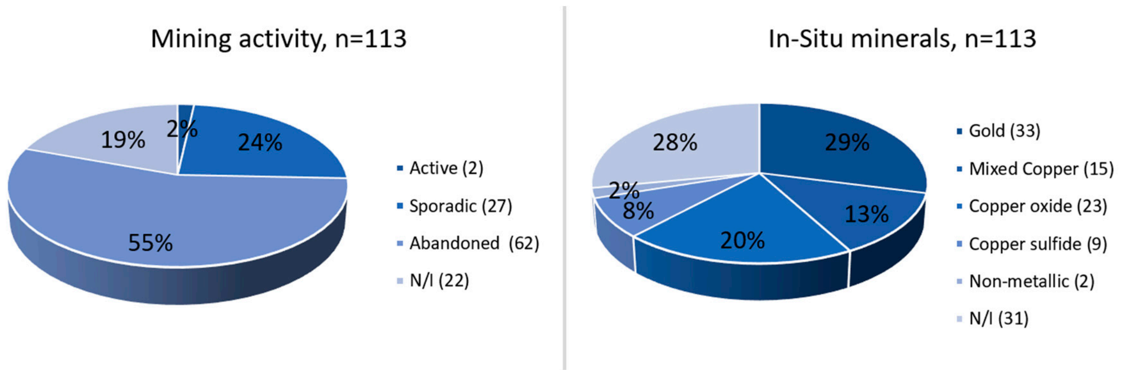

Figure 2. Mining activity (**left**) and in situ minerals (**right**) in the Tiltil Mining District, Central Chile.

The cadaster also showed that only 11 mining areas have sufficient quantity and quality information to carry out a proper prioritization analysis. These projects have both old exploitation signals and rudimentary production. Therefore, they have fresh rock outcrops that can be used for field description and subsequent laboratory analyses. The 11 prospects or mining areas subject to prioritization are (1) San Aurelio, (2) Valdi, (3) Lophan-Lujan, (4) La Poza, (5) San Jorge, (6) Los Guindos, (7) Mogote, (8) La Vaca, (9) El Huracán, (10) Condor, and (11) La Despreciada.

4.2. Selection of MCDMs

The complete results obtained by the first panel of experts are shown in the binary matrix *Tn* in Appendix A.6. Owing to space restrictions and for simplicity, only one example of the results is presented in the main text. Table 1 shows that for the variable "number of elements under evaluation", only the ELECTRE method has the capacity to solve problems with a "limited number of criteria and sub-criteria and a small number of alternatives". Thus, it is assigned a value of 1 in a particular row of the *Tn* matrix. The binary matrix is defined for every variable considered relevant to the problem and for all MCDMs included in the analysis.

Table 1. An example of a section of the binary matrix *Tn* used to determine the classification *Qn* for each multivariate decision-making method (MCDM) in terms of the variable "number of elements under evaluation". More information in Appendix A.6.

Variables (*Vn*)	Qualification of Variables (*Qn*)	Binary Matrix (*Tn*)						
		ELECTRE	MAUT	ANP	MACBETH	AHP	TOPSIS	PROMETHEE II
Number of elements under evaluation	Limited number of criteria and sub-criteria and a small number of alternatives	1	0	0	0	0	0	0
	Limited number of criteria and sub-criteria and many alternatives.	0	1	0	0	0	0	0
	Large number of criteria and sub-criteria and a small number of alternatives.	0	0	1	0	1	0	0
	Large number of criteria and sub-criteria and many alternatives	0	0	0	1	0	1	1

Once matrix Tn is obtained, the weighted suitability score (*SRW*) is calculated by multiplying this matrix with the weights of each variable *Wn* and the expected property values Ep. Table 2 shows the results for the endogenous variable "type of decision-making problem", with three possible qualifications of alternatives: sorting, description, and ranking/choice; and with expected property values of zero for the first two alternatives and one for the last one since the specific problem in this case is a prioritization process. The results for all the variables considered in the analysis are presented in Appendix A.7.

Table 2. An example of a section of the information used to determine the weighted suitability score SRW for each multivariate decision-making method (MCDM) in terms of the endogenous variable "type of decision-making problems". More information in Appendix A.7.

Type of vs	Weight (Wn)	Variables (Vn)	Qualification of Variables (Qn)	Properties in Relation to Decision-Making Problem (Ep)	Properties of the MCDA Tool in Binary System (SRW = EP × T × Wn)						
					ELECTRE	MAUT	ANP	MACBETH	AHP	TOPSIS	PROMETHEE
Endogenous	1	Type of decision-making problems	Sorting	0	0	0	0	0	0	0	0
			Description	0	0	0	0	0	0	0	0
			Ranking/Choice	1	1	1	1	1	1	1	1

Finally, the general suitability index *ISW* was obtained through the sum of the *SRW* values for each individual MCDM method and divided by the number of variables considered in the analysis. The results of the application of the methodology to the case study are presented in Table 3 in descending order of suitability.

Table 3. Suitability ranking of the seven multivariate decision-making methods (MCDMs) for the case study applied.

MCDM	ISW	Ranking
AHP	0.91	1
PROMETHEE II	0.91	1
MACBETH	0.91	1
ANP	0.82	4
MAUT	0.73	5
ELECTRE	0.64	6
TOPSIS	0.55	7

As shown in Table 3, AHP and PROMETHEE II were identified as the most suitable MCDMs for addressing the problem in this case study. Although the MACBETH tool received an identical *ISW* score, its application was excluded due to the necessity of specialized proprietary software [36]. Consequently, the AHP and PROMETHEE II methods were employed to generate the ranking and prioritize exploration projects within the Tiltil Mining District.

4.3. Hierarchical Structure and Performance Matrix for the Prioritization of Exploration Projects

The aim of the problem to be solved (first hierarchical level) is to rank exploration projects within a district of small and medium-sized Cu and Au mining deposits according to their "technical, economic, social, and environmental feasibility of exploitation". The defined objective should seek to improve the existing situation through a process or methodology and must be aligned with the goals and characteristics of the problem.

The second hierarchical level—the identification of criteria and sub-criteria, both quantitative and qualitative—considers structures commonly designed for mining exploration, as well as specific characteristics of the Tiltil Mining District. Geological, geochemical, and geophysical criteria have been extensively used in frameworks devised for prioritizing mineral exploration areas [51,68]. However, references to criteria associated with the characteristics of mining districts are less common. It is now widely recognized that environmental, social, and economic variables, such as the presence of fauna and flora, climate, accessibility, and available infrastructure, are crucial when evaluating the feasibility of mining projects [21].

The last hierarchical level involves identifying alternatives [33,69]. These alternatives represent the various approaches through which the overall objective can be achieved, each possessing both positive and negative characteristics. The hierarchical structure for prioritizing exploration projects in small and medium-sized Cu and Au mining districts is illustrated in Figure 3, showing the first and second hierarchical levels.

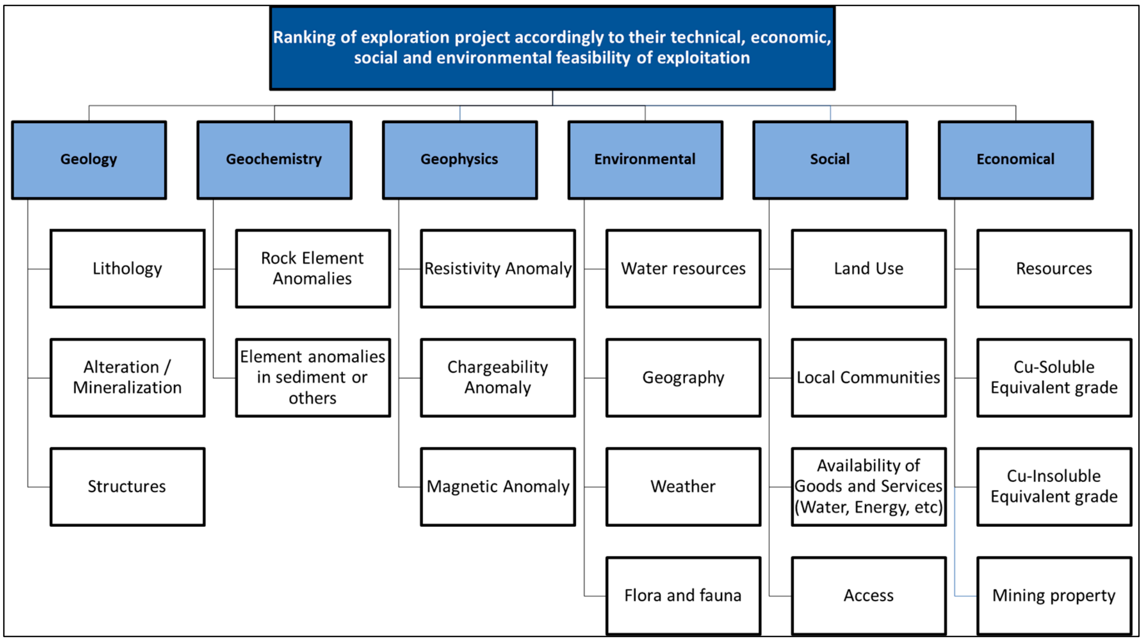

Figure 3. Hierarchical structure for ranking exploration projects in districts of small and medium-sized Cu and Au mineral deposits in the case of the Tiltil Mining District, Central Chile.

The hierarchical structure was defined using 6 criteria and 20 sub-criteria (Figure 3). The alternatives defined for the qualitative sub-criteria by the experts are presented in Appendix A.8, and those for the quantitative sub-criteria are presented in Table 4.

Table 4. Quantitative variables and their alternatives for prioritizing exploration projects in districts of small and medium-sized Cu-Au mineral deposits. For areas with economic gold grades (%), the conversion to equivalent copper grades is carried out using the procedure in Ballantyne et al. [70].

Criteria	Extremely Important (9)	Very Important (7)	Important (5)	Moderately Important (3)	Equally Important (1)
Resources	More than 3 Mton	Between 1 and 3 Mton	Between 100 kton and 1 Mton	No information	Less than 100 kton
Cu soluble grades	More than 12%	4.2–12% Cu	2.5–4.2% of Cu	No information	Less than 2.5% Cu
Cu-eq grades	More than 12%	4.2–12% Cu	2.5–4.2% Cu	No information	Less than 2.5% Cu

Additionally, and prior to prioritizing using AHP and PROMETHEE II methods, the weights of the criteria and sub-criteria x (Equation (13)) and performance matrix of non-normalized alternatives F (Equation (17)) were obtained through the judgements of the first panel of experts. The results of this process are summarized in the performance matrix of the exploration projects to be ranked (Appendix A.9).

4.4. Prioritization Using AHP and PROMETHEE II

The results of applying the AHP method to obtain the weights of the criteria in the Tiltil Mining District are shown in Figure 4. The figure presents the weights of the criteria determined by each panel member, and the final vector that is obtained by weighting the answers of the 10 senior experts and the three junior experts in a 90/10 percent relationship.

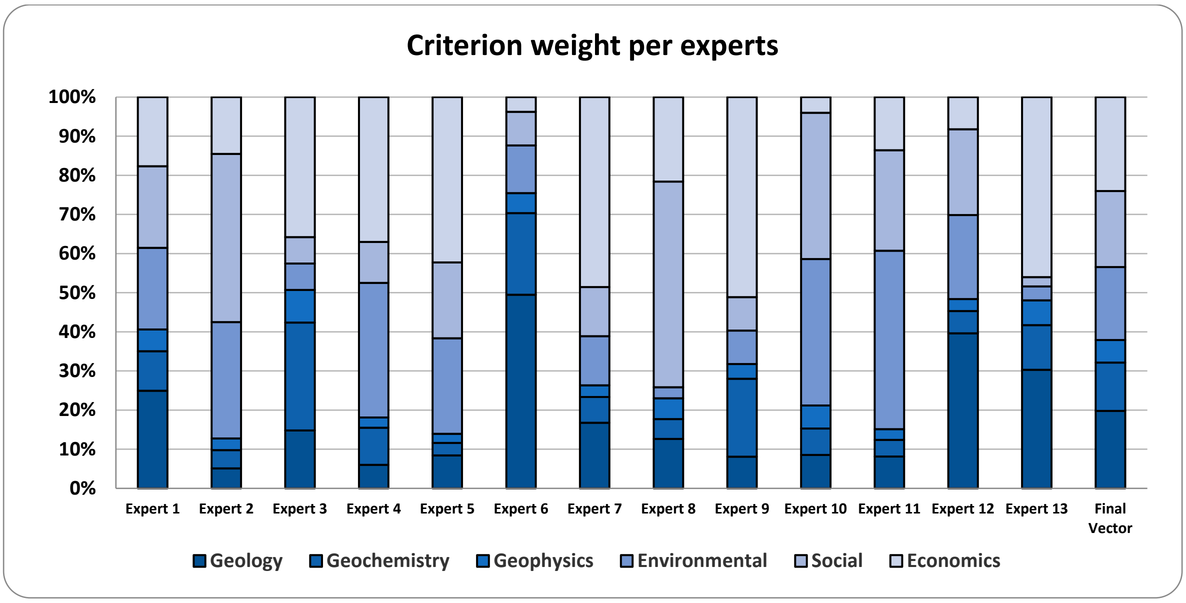

Figure 4. Weights (percentage unit) for criteria groups determined by each expert for ranking exploration areas in the Tiltil Mining District, Central Chile.

The final weights correspond to 24% for economic, 19.8% for geology, 19.4% for social, 12.4% for geochemistry, and 5.8% for geophysical criteria. Appendix A.10 shows the weights obtained for each sub-criterion.

The application of the cadaster shows that only 11 exploration areas have sufficient information in terms of quality and quantity to carry out prioritization analysis. The final ranking resulting from applying AHP for these mining projects is presented in Table 5.

Table 5. Ranking of exploration areas obtained by applying the AHP method in the Tiltil Mining District, Central Chile.

Exploration Project	AHP Value	AHP Ranking
El Huracán mine	0.97	1
La Despreciada mine	0.90	2
San Aurelio mine	0.90	2
La Vaca mine	0.89	4
La Poza mine	0.89	4
Cóndor mine	0.86	6
San Jorge mine	0.85	7
Los Guindos mine	0.85	7
Valdi mine	0.83	9
Lophan-Lujan mine	0.83	9
Mogote mine	0.81	11

In the case of the application of the PROMETHEE II method, the preference function used is the so called "usual" one, as previously stated. The preference indices were calculated using this functional form, and the input and output flows associated with each of the exploration projects were obtained. Finally, the net flows were calculated, and the exploration projects were ranked accordingly, as shown in Table 6.

Table 6. Flows and ranking of exploration areas obtained by applying the PROMETHEE II method in the Tiltil Mining District, Central Chile.

Exploration Project	Inflow +	Outflow −	PROMETHEE II Value	PROMETHEE II Ranking
El Huracán mine	0.23	0.02	0.21	1
La Despreciada mine	0.17	0.07	0.10	2
San Aurelio mine	0.15	0.06	0.08	3
La Vaca mine	0.10	0.08	0.02	4
La Poza mine	0.08	0.10	−0.01	5
Cóndor mine	0.08	0.12	−0.03	6
Lophan-Lujan mine	0.09	0.15	−0.06	7
Los Guindos mine	0.05	0.11	−0.06	7
San Jorge mine	0.05	0.11	−0.06	7
Valdi mine	0.06	0.16	−0.10	10
Mogote mine	0.09	0.19	−0.10	10

5. Discussion

5.1. Correlation between Results from Different MCDMs

In the context of multi-criteria decision-making methods (MCDMs), it is crucial to acknowledge that different methods can yield varying outcomes, making it essential to consider the use of aggregation techniques or the combination of complementary methods such as AHP and PROMETHEE II. These methods, while distinct in their approach, can enhance the reliability and robustness of decision-making when used together. This study's approach, which involved employing multiple MCDMs alongside a smaller expert panel, highlights the careful consideration required when selecting methodologies.

Larger expert panels typically provide a broader range of perspectives, potentially leading to more balanced results. However, a smaller, highly specialized panel, as utilized in this study, allows for more focused and in-depth analysis. This approach aligns with existing research, such as that by Jara et al. [21], which demonstrates the effectiveness of smaller, expert-driven evaluations in complex decision-making contexts. Despite the advantages of this method, future research could explore the use of larger expert panels in the initial stages of MCDM selection. By comparing the outcomes derived from larger versus smaller panels, it would be possible to assess any differences in results and the potential benefits of broader expertise in the decision-making process.

After applying the AHP and PROMETHEE II methods for ranking exploration areas in the Tiltil Mining District, the prioritizations obtained from both methods are compared in Table 7. The methods are highly consistent, with a correlation coefficient of 96% between their numerical results. The use of both methods in parallel allows for clearer discrimination when one method cannot distinctly differentiate between individual mine sites. For example, the AHP shows no preference between certain pairs of mines, while PROMETHEE II can identify a preferred alternative. Conversely, in other instances, PROMETHEE II struggles to make distinctions, which AHP resolves.

Table 7. Comparative results from applying AHP and PROMETHEE II methods in ranking exploration areas in the Tiltil Mining District, Central Chile.

Exploration Project	AHP Value	AHP Value	PROMETHEE II Ranking	PROMETHEE II Value
El Huracán mine	1	0.97	1	0.21
La Despreciada mine	2	0.90	2	0.10
San Aurelio mine	2	0.90	3	0.08
La Vaca mine	4	0.89	4	0.02
La Poza mine	4	0.89	5	−0.01
Cóndor mine	6	0.86	6	−0.03
San Jorge mine	7	0.85	7	−0.06
Los Guindos mine	7	0.85	7	−0.06
Lophan-Lujan mine	9	0.83	7	−0.06
Valdi mine	9	0.83	10	−0.10
Mogote mine	11	0.81	10	−0.10

The integration of GIS and MCDMs has proven effective in various resource management scenarios, including the identification of groundwater potential zones [71]. This highlights the versatility of MCDM approaches in addressing diverse geoscientific challenges. In fact, recent studies continue to underscore the efficacy of combining the AHP with GIS for assessing environmental risks and resource management, as demonstrated in flood susceptibility mapping in Bangladesh [72]. The integration of GIS with MCDMs can be instrumental in managing natural resources more effectively, ensuring that exploration efforts are both efficient and environmentally sustainable.

The findings of this study offer several recommendations that could be valuable for the global mining industry. First, the dual application of AHP and PROMETHEE II provides a robust framework for prioritizing exploration projects. This approach can be adopted globally, particularly in regions with similar geological settings, to enhance the reliability of decision-making processes in mineral exploration.

For the broader global mining industry, adopting a combination of MCDMs could facilitate more objective and transparent decision-making. This is particularly important in regions where resource allocation and prioritization are critical, such as during the allocation of public funds or securing private investment. By applying these methods, mining projects can be prioritized based on a clear and replicable methodology, improving the credibility and justification for funding decisions. In parallel, applying case studies further enhances the methodology and theoretical purpose, improving research and providing validation for approaches as demonstrated by various investigations [73,74].

5.2. Sensitivity Analysis for Expert Weights

Although this study proposes an expert-based approach for prioritizing exploration projects, the methodology is designed to be adaptable, allowing for modifications that align with specific objectives, hierarchical structures, criteria, and sub-criteria relevant to various contexts. The methodology offers a general framework for structuring the prioritization process in early-stage mineral exploration, particularly within districts characterized by small to medium-sized Cu–Au deposits. Importantly, while the endogenous variables are inherently tied to the characteristics of MCDMs and therefore remain constant, exogenous variables can be tailored to address the unique challenges and data availability of different projects.

An important factor in the prioritization process is the number of experts involved. While similar studies typically do not use an expert panel to decide the MCDM, this study incorporated them and then, use the second panel with 10 senior and three junior professionals, that is used in various research [21,31,51,75,76]. The differentiated relevance of the responses was accounted for by incorporating a weighting factor (α_i) ensuring that the influence of senior experts was proportionately higher.

Therefore, a sensibility analysis can be performed by varying α_i between 0 to 100%. Doing this, the geophysical and geochemical criteria are not greatly affected and remain within a limited range of values, which implies good concordance between the views and answers of senior and junior professionals. On the other hand, the geological and economic aspects are the most sensitive to variations in the weighting assignment: senior experts give much more relevance to geological aspects than economic and other contextual considerations, in contrast to younger participants (Figure 5). This result is in accordance with the results of Jara et al. [21], who found that younger and diverse professionals (not mining engineers or geologists) weighed higher aspects related to economic, environmental, and social viability of mining projects.

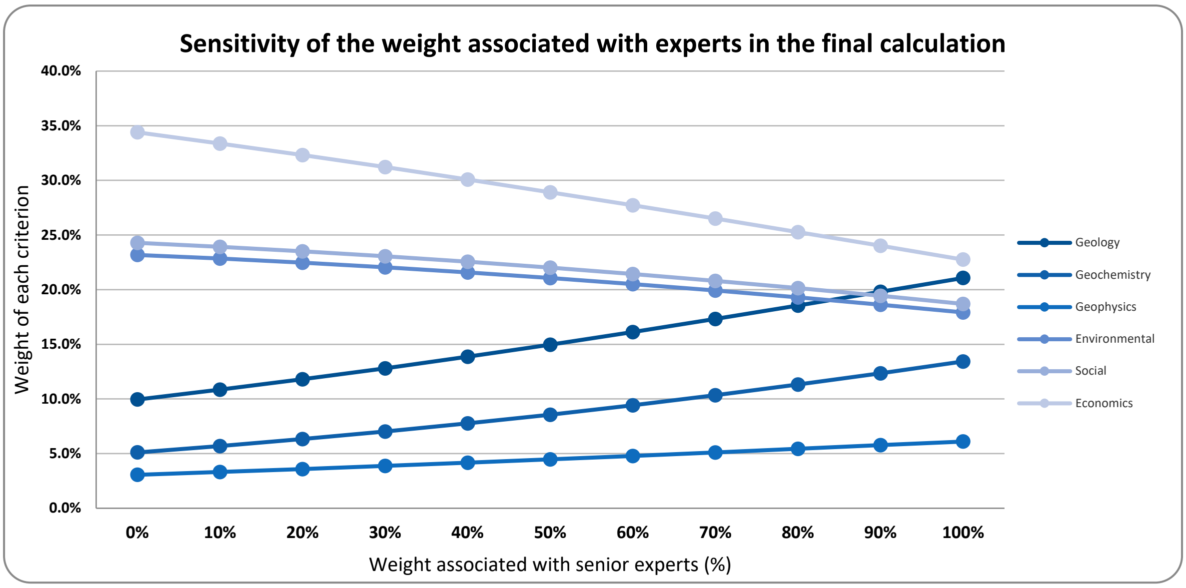

Figure 5. Variation in weights (percentage unit) for criteria groups determined by the two groups of experts (senior and junior) for ranking exploration areas in the Tiltil Mining District, Central Chile.

Selecting the appropriate MCDM is crucial for accurately evaluating the correlation between AHP and PROMETHEE II. If the methodological structure is not rigorously followed, or if the chosen MCDM is unsuitable for the specific context, the results may show a correlation between the methods but fail to provide valid insights for the decision-making process.

The methodology developed in this study is highly replicable and consistent, making it suitable for application in various global contexts. However, its effectiveness can be challenged in regions experiencing significant political, economic, or social instability, such as high inflation, political unrest, or conflict. In such settings, the reliability of data and the consistency of expert judgments may be compromised, complicating the prioritization process.

Despite these challenges, with appropriate adjustments and consideration of local conditions, the methodology can still offer valuable insights and support decision-making in diverse environments. By tailoring the approach to account for regional variability, particularly in unstable areas, the mining industry can benefit from a structured framework for prioritizing exploration projects. This, in turn, enhances the efficiency and effectiveness of exploration efforts on a global scale, particularly in more stable regions where the methodology can be applied with greater confidence.

6. Conclusions

The prioritization of areas for mining exploration and development, particularly in small and medium-sized Cu and Au mining districts, is inherently complex, involving a multitude of geoscientific, economic, environmental, and social factors. Existing methodologies often fall short in fully addressing these diverse aspects. In response, this study introduces a robust two-step methodology designed to prioritize projects within such districts, effectively integrating geological, geophysical, geochemical, environmental, social, and economic considerations. By leveraging MCDMs, particularly AHP and PROMETHEE II, our approach provides a more holistic and reliable framework for prioritizing mining exploration projects.

In the Tiltil Mining District case study, we evaluated seven different MCDMs, ultimately applying the AHP and PROMETHEE II to rank and prioritize the most promising exploration areas. This approach not only ensures better resource allocation but also enhances decision-making transparency and consistency. The survey of 113 mines within the district revealed that only 11 projects had sufficient data for prioritization, highlighting the critical importance of comprehensive data collection. The analysis underscored the significance of economic, geological, and social factors in determining project viability, with the El Huracán, San Aurelio, and La Despreciada mines consistently emerging as top priorities.

The high correlation between the results of the AHP and PROMETHEE II further validates the reliability of our methodology, suggesting that employing multiple MCDMs in tandem can significantly enhance the robustness of decision-making processes. This study's primary contribution lies in offering a replicable and objective methodology, crucial for making informed decisions during the high-risk, high-uncertainty phase of early mining exploration. This approach is particularly valuable for small and medium-sized mining operations, enabling the maximization of resources through a justified and impartial decision-making process.

While this methodology has proven effective in the context of the Tiltil Mining District, its adaptability to other geological settings and global contexts is noteworthy. However, challenges may arise in regions with significant political, economic, or social instability, where data reliability and expert consensus may be compromised. Future research could explore the application of this methodology in diverse global contexts, potentially integrating more modern MCDMs and expanding expert panels to further refine and validate the approach.

As a final conclusion, by providing a structured and adaptable framework for prioritizing exploration projects, this study not only contributes to the field of mineral exploration but also sets the stage for more efficient and effective resource management in the global mining industry. As the industry continues to evolve, this methodology offers a valuable tool for guiding investment decisions, ensuring that exploration efforts are both strategic and sustainable.

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Conflicts of Interest: The authors declare no competing interests regarding the development and publication of this article.

Appendix A

Appendix A.1. Fundamental Scale of Comparison between Pairs [32]

Importance Index	
Value	**Meaning**
1	j and k are equally important
3	j is slightly more important than k
5	j is more important than k
7	j is considerably more important than k
9	j is much more important than k
2,4,6,8	Intermediate values

Appendix A.2. Type Sheet Used to Collect Information

New "Geomining" Strategies for the Development and Improvement of Skills of Small Mining
Information
Name:
Owner name:
Mines and/or mining property:
Phone:
Email:
Do you consider that you have relevant information for the project (indicate which ones):
Additional comments on exploitation and/or mining exploration of your mining property:

Appendix A.3. Cadaster of Mines

Mine	San Aurelio	El Huracán	Lophan-Lujan	Condor	La Poza	La Despreciada	Valdi	San Jorge	Mogote	La Vaca	Los Guindos
WGS 284-East	316,977	320,101	316,748	314,978	316,749	315,610	316,531	314,821	317,734	314,241	315,771
WGS 284-North	6,336,158	6,343,596	6,332,811	6,319,635	6,334,856	6,319,831	6,336,270	6,336,439	6,332,487	6,335,825	6,338,582
WGS 284-AMSL	784	653	857	1594	820	1211	860	963	925	1093	913
Lithology	Amphibole Diorite to Quartzite Monzodiorite	Amphibole Granodiorite to Quartziferous Monzonite	Veta Negra Formation and dacitic porphyry dikes	Veta Negra Formation	Las Chilcas Formation	Veta Negra Formation and Amphibole Diorite to Quartzite Monzodiorite	Amphibole Diorite to Quartzite Monzodiorite	Amphibole Monzonite	Las Chilcas Formation	Veta Negra Formation	Las Chilcas Formation and Amphibole Diorite to Quartzite Monzodiorite
Mineralization	Cu Sulphides and Oxides	Au and Cu Sulphides and Oxides	Cu Sulphides and Oxides	Cu Sulphides and Oxides	Cu Sulphides and Oxides	Au and Cu Sulphides and Oxides	Cu Sulphides and Oxides	Au and Cu Sulphides and Oxides	Cu Sulphides and Oxides	Au and Cu Sulphides and Oxides	Au and Cu Sulphides and Oxides
Alteration	Potassic and Sericitic	Potassic and Sericitic	Potassic, Sericitic and Propylitic	Propylitic	Sericitic and Propylitic	Potassic and Propylitic	Sericitic and Propylitic	Sericitic and Propylitic	Propylitic	Sericitic and Propylitic	Sericitic and Propylitic
Activity	Sporadic	Sporadic	Sporadic	Sporadic	Sporadic	Sporadic	Inactive	Sporadic	Inactive	Inactive	Sporadic
Method	Open Pit-Underground	Underground	Open Pit	Underground	Open Pit-Underground	Underground	Open Pit-Underground	Underground	Underground	Underground	Underground
Main Ore	Cu Oxide and Sulphides	Gold	Cu Oxide and Sulphides	Cu Oxide	Cu Oxide and Sulphides	Cu Oxide and Sulphides	Cu Oxide	Gold	Cu Sulphides	Gold	Gold
Secondary Ore	Gold-Silver	Copper-Silver	-	-	-	Gold	-	Copper	-	Copper	Copper
Rock Element Anomalies	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization	With economic anomaly and without penalization
Element anomalies in sediment o others	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample	No Sample
Resistivity Anomaly	Weak anomaly	Weak anomaly	No information	Weak anomaly	No information	No information	No information	No information	No information	No information	No information

Mine	**San Aurelio**	**El Huracán**	**Lophan-Lujan**	**Condor**	**La Poza**	**La Despreciada**	**Valdi**	**San Jorge**	**Mogote**	**La Vaca**	**Los Guindos**
Chargeability Anomaly	Weak anomaly	Weak anomaly	No information	Weak anomaly	No information	No information	No information	No information	No information	No information	No information
Magnetic Anomaly	Weak anomaly	No information	No information	No information	No information	No information	No information	No information	No information	No information	No information
Water resources	Underground water	Without Water	No information	Underground water	Without Water	Underground water	Without Water	Underground water	No information	No information	Underground water
Geography	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside	Hillside
Weather	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean	Mediterranean
Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna	Unprotected Flora and Fauna
Land Use	Mining	Mining	Mining	Mining	Mining	Mining	Mining	Mining	Mining	Mining	Mining
Local Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities	Nearby Mixed Communities

Mine	**San Aurelio**	**El Huracán**	**Lophan-Lujan**	**Condor**	**La Poza**	**La Despreciada**	**Valdi**	**San Jorge**	**Mogote**	**La Vaca**	**Los Guindos**
Availability of Goods and Services (Water, Energy)	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services	Availability of Goods and Services
Access	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements	With Accesses and Easements
Resources	No information	100 kTon–1 Mton	No information	No information	No information	No information	No information	No information	No information	No information	No information
Cu- Soluble Equivalent grade	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	Less than 2.5% of Cu-eq	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	Less than 2.5% of Cu-eq	2.5–4.2% of Cu-eq	No information	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq
Cu-Insoluble Equivalent grade	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	No information	No information	No information	2.5–4.2% of Cu-eq	No information	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq	2.5–4.2% of Cu-eq
Mining Property	Owner Company	Owner Company	Owner Company	Tenant Company	Tenant Company	Owner Company	Tenant Company	Tenant Company	Non-Owner Company	Tenant Company	Tenant Company

Appendix A.4. Features of Endogenous Variables (from Guarini et al. [26,27,44])

Type of Decision-Making Problems	Solution Approach	Implementation Procedure	Input Level	Output Typology	Decision Problem Solution	Tool
Sorting/Description	Outranking approach	Preference thresholds, indifference thresholds, veto thresholds	Medium	Partial ordering obtained by expressing pairwise preferences degrees	n categories of alternatives of equal score but different behavior	ELECTRE
Ranking/Choice	Full aggregation approach	Utility function	High	Full ordering obtained by considering the scores	Alternative with the higher global score	MAUT
		Pairwise comparison on rational scale and interdependencies	High	Full ordering obtained by considering the scores	Alternative with the higher global score	ANP
		Pairwise comparison on interval scale	High	Full ordering obtained by considering the scores	Alternative with the higher global score	MACBETH
		Pairwise comparison on rational scale	Low	Full ordering obtained by considering the scores	Alternative with the higher global score	AHP
	Goal, aspiration, or reference level approach	Ideal option and anti-ideal option	Low	Full ordering with score closest to the aim assumed	Alternative with the closest score to the ideal solution	TOPSIS
	Outranking approach	Preference thresholds, indifference thresholds, veto thresholds	Medium	Partial ordering obtained by expressing pairwise preference degrees	n categories of alternatives of equal score but different behavior	ELECTRE
		Preference thresholds, indifference thresholds, veto thresholds		Total ordering obtained by expressing pairwise preferences degrees	Alternative with the higher global score	
		Preference thresholds, indifference thresholds	Medium	Partial ordering obtained by expressing pairwise preferences degrees	n categories of alternatives of equal score but different behavior	PROMETHEE
		Preference thresholds, indifference thresholds		Total ordering obtained by expressing pairwise preferences degrees	Alternative with the higher global score	

Appendix A.5. Features of Exogenous Variables (from Guarini et al. [26,27,44])

Technical Support of A Specialist	Number of Evaluation Elements	Typology of Indicators	Expected Solution	Stakeholders to Be Included in the Decision Process	Tool
Yes	Limited number of criteria and sub-criteria and a small number of alternatives	Quantitative	Definition of n alternatives valid in relation to the objectives	Participatory process not activated	ELECTRE
	Limited number of criteria and sub-criteria and a large number of alternatives	Qualitative	A better overall alternative definition for the purpose. The ideal alternative definition closest to the lens	Participatory process activated with a limited and specialized number of stakeholders	MAUT
No	Large number of criteria and sub-criteria and a small number of alternatives	Mixed	A better overall alternative definition for the purpose. The ideal alternative definition closest to the lens	Participatory process activated with a significant number of stakeholders, preferably organized in categories	AHP; ANP
	Large number of criteria and sub-criteria and a large number of alternatives				MACBETH; PROMETHEE; TOPSIS

Appendix A.6. Binary Matrix (Tn)

Type of Variables	Variables	Qualification of Variables	Properties of MCDA Tools in Binary System (P)						
			ELECTRE	**MAUT**	**ANP**	**MACBETH**	**AHP**	**TOPSIS**	**PROMETHEE II**
Exogenous	Number of evaluation elements	Limited number of criteria and sub-criteria and a small number of alternatives	1	0	0	0	0	0	0
		Limited number of criteria and sub-criteria and a large number of alternatives	0	1	0	0	0	0	0
		Large number of criteria and sub-criteria and a small number of alternatives	0	0	1	0	1	0	0
		Large number of criteria and sub-criteria and a large number of alternatives	0	0	0	1	0	1	1
	Typology of indicators	Quantitative	1	1	1	1	1	1	1
		Qualitative	1	0	1	1	1	1	1
		Mixed	1	0	1	1	1	1	1
	Stakeholders to be included in the decision process	Participatory process not activated	1	1	1	1	1	1	1
		Participatory process with a limited and specialized number of stakeholders	1	1	1	1	1	1	1
		Participatory process with a significant number of stakeholders preferably organized in categories	1	1	1	1	1	1	1
	Expected solution	Definition of n alternatives valid in relation to objectives	1	0	0	0	0	1	0
		A better overall alternative definition for the purpose	0	1	1	1	1	0	1
		The ideal alternative definition closest to the lens	0	0	0	0	0	1	0
	Technical support of a decision aid specialist	Yes (advisable)	1	1	1	1	0	0	0
		No (not necessary)	0	0	0	0	1	1	1

Type of Variables	Variables	Qualification of Variables	Properties of MCDA Tools in Binary System (P)						
			ELECTRE	**MAUT**	**ANP**	**MACBETH**	**AHP**	**TOPSIS**	**PROMETHEE II**
Endogenous	Type of decision-making problems	Sorting	1	0	0	0	0	0	0
		Description	1	0	0	0	0	0	0
		Ranking/Choice	1	1	1	1	1	1	1
	Solution approach	Outranking approach	1	0	0	0	0	0	1
		Full aggregation approach	0	1	1	1	1	0	0
		Goal, aspiration, or reference level Approach	0	0	0	0	0	1	0
	Implementation procedure	Preference thresholds, indifference thresholds, veto thresholds	1	0	0	0	0	0	0
		Preference thresholds, indifference thresholds	0	0	0	0	0	0	1
		Utility function	0	1	0	0	0	0	0
		Pairwise comparison on rational scale and interdependencies	0	0	1	0	0	0	0
		Pairwise comparison on interval scale	0	0	0	1	0	0	0
		Pairwise comparison on rational scale	0	0	0	0	1	0	0
		Ideal option and anti-ideal option	0	0	0	0	0	1	0
	Input level	High	0	1	1	1	1	0	0
		Medium	1	0	0	0	0	0	1
		Low	0	0	0	0	0	1	0
	Output typology	Partial ordering obtained by expressing pairwise preferences degrees	1	0	0	0	0	0	1
		Total ordering obtained by expressing pairwise preferences degrees	1	0	0	0	0	0	1
		Full ordering obtained by considering the scores	0	1	1	1	1	0	0
		Full ordering with score closest to the aim assumed	0	0	0	0	0	1	0
	Decision problem solution	n categories of alternatives of equal score but different behavior	1	0	0	0	0	0	1
		Alternative with the higher global score	0	1	1	1	1	0	0
		Alternative with the closest score to the ideal solution	0	0	0	0	0	1	0

Appendix A.7. Assigning the Properties of the MCDMs

Type of Variable	Weight (Wn)	Variables (Vn)	Qualification of Variables (Qn)	Properties in Relation to Decision-Making Problem (Ep)	Properties of the MCDA Tool in Binary System (SRW = EP × Tn × Wn)						
					ELECTRE	MAUT	ANP	MACBETH	AHP	TOPSIS	PROMETHEE
Exogenous	1.00	Number of evaluation elements	Limited number of criteria and sub-criteria and a small number of alternatives	0	0	0	0	0	0	0	0
			Limited number of criteria and sub-criteria and a large number of alternatives	0	0	0	0	0	0	0	0
			Large number of criteria and sub-criteria and a small number of alternatives	0	0	0	0	0	0	0	0
			Large number of criteria and sub-criteria and a large number of alternatives	1	0	0	0	1	0	1	1
	1.00	Typology of indicators	Quantitative	0	0	0	0	0	0	0	0
			Qualitative	0	0	0	0	0	0	0	0
			Mixed	1	1	0	1	1	1	1	1
	1.00	Stakeholders to be included in the decision process	Participatory process not activated	0	0	0	0	0	0	0	0
			Participatory process with a limited and specialized number of stakeholders	1	1	1	1	1	1	1	1
			Participatory process with a significant number of stakeholders preferably organized in categories	0	0	0	0	0	0	0	0
	1.00	Expected solution	Definition of n alternatives valid in relation to objectives	1	1	0	0	0	0	1	0
			A better overall alternative definition for the purpose	1	0	1	1	1	1	0	1
			The ideal alternative definition closest to the lens	0	0	0	0	0	0	0	0
	1.00	Technical support of a decision aid specialist	Yes (advisable)	0	0	0	0	0	0	0	0
			No (not necessary)	1	0	0	0	0	1	1	1

Type of Variable	Weight (Wn)	Variables (Vn)	Qualification of Variables (Qn)	Properties in Relation to Decision-Making Problem (Ep)	Properties of the MCDA Tool in Binary System (SRW = EP × Tn × Wn)						
					ELECTRE	MAUT	ANP	MACBETH	AHP	TOPSIS	PROMETHEE
Endogenous	1.00	Type of decision-making problems	Sorting	0	0	0	0	0	0	0	0
			Description	0	0	0	0	0	0	0	0
			Ranking/Choice	1	1	1	1	1	1	1	1
	1.00	Solution approach	Outranking approach	1	1	0	0	0	0	0	1
			Full aggregation approach	1	0	1	1	1	1	0	0
			Goal, aspiration, or reference level approach	0	0	0	0	0	0	0	0
	1.00	Implementation procedure	Preference thresholds, indifference thresholds, veto thresholds	0	0	0	0	0	0	0	0
			Preference thresholds, indifference thresholds	1	0	0	0	0	0	0	1
			Utility function	1	0	1	0	0	0	0	0
			Pairwise comparison on rational scale and interdependencies	1	0	0	1	0	0	0	0
			Pairwise comparison on interval scale	1	0	0	0	1	0	0	0
			Pairwise comparison on rational scale	1	0	0	0	0	1	0	0
			Ideal option and anti-ideal option	0	0	0	0	0	0	0	0
	1.00	Input level	High	1	0	1	1	1	1	0	0
			Medium	0	0	0	0	0	0	0	0
			Low	0	0	0	0	0	0	0	0
	1.00	Output typology	Partial ordering obtained by expressing pairwise preferences degrees	1	1	0	0	0	0	0	1
			Total ordering obtained by expressing pairwise preferences degrees	1	1	0	0	0	0	0	1
			Full ordering obtained by considering the scores	1	0	1	1	1	1	0	0
			Full ordering with score closest to the aim assumed	0	0	0	0	0	0	0	0
	1.00	Decision problem solution	n categories of alternatives of equal score but different behavior	0	0	0	0	0	0	0	0
			Alternative with the higher global score	1	0	1	1	1	1	0	0
			Alternative with the closest score to the ideal solution	0	0	0	0	0	0	0	0

Appendix A.8. Ranges Assigned to Qualitative Variables

Variable	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6	Alternative 7	Alternative 8
Lithology	Covered Area (without outcrops) with Unknown Power	Covered Area (without outcrops) with less potential resource at critical depth	Covered Area (without outcrops) with higher potential resource at critical depth	Uncovered or partially uncovered area (with outcrops) with unfavorable main rock	Uncovered or partially uncovered area (with outcrops) with favorable main rock	Uncovered or partially uncovered area (with outcrops) with main rock and unfavorable intrusive	Uncovered or partially uncovered area (with outcrops) with favorable main rock and intrusive	
Alteration/Mineralization	No evidence of alteration or mineralization	No alteration or mineralization	Small to moderate areas with magmatic-hydrothermal alteration and without mineralization	Small to moderate zones with magmatic-hydrothermal and mineralized alteration	Large areas with magmatic-hydrothermal alteration and without mineralization	Large areas with magmatic-hydrothermal alteration and without mineralization		
Structures	No evidence of structures	Without Structures	Small to moderate structures without alteration or mineralization	Small to moderate structure with alteration and without mineralization	Small to moderate structure with alteration and mineralization	Large structures without alteration or mineralization	Large structures with alteration and without mineralization	Large structures with alteration and mineralization
Rock elemental anomaly	No Sample	No anomaly	With economic anomaly	With economic and penalized anomaly	With main element anomaly			
Anomaly of elements in sediment or others	No Sample	No anomaly	With economic anomaly	With economic and penalized anomaly	With main element anomaly			
Resistivity anomaly	No information	Does not present anomaly	Weak anomaly	Strong anomaly				
Chargeability anomaly	No information	Does not present anomaly	Weak anomaly	Strong anomaly				
Magnetic anomaly	No information	Does not present anomaly	Weak anomaly	Strong anomaly				
Water resources	No Information	No Water	Groundwater	Surface and Groundwater				
Geography	Flat surface	River valley	Glacier valley	Hillside	Mountain hillside	Beach shore		
Weather	Arid-semiarid	Mediterranean	Temperate-rainy cold	Steppe to tundra	Mountain			
Flora and fauna	Unprotected flora and fauna	Flora protected	Fauna protected	Flora and fauna protected				
Land use	Mining	Agricultural-Livestock-Forestry	Fiscal land	Residential land	Protected area			
Local communities	On-site communities	Nearby mining communities	Nearby mixed communities	Nearby non-mining communities	It has no nearby communities			

Variable	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6	Alternative 7	Alternative 8
Availability of goods/services (water, energy, roads, etc.)	Availability of goods and services	Availability of goods	Availability of services	Unavailable				
Access	Without access	With access	With access and easement					
Mining property	Owner company	Leasing company	Non-owner company	Not incorporated (free)				

Appendix A.9. Performance Matrix Valued for Exploration Projects

cd	Sub Criteria	El Huracán Mine	Valdi Mine	San Aurelio Mine	Los Guindos Mine	San Jorge Mine	La Vaca Mine	La Poza Mine	Mogote Mine	Lophan-Lujan Mine	Cóndor Mine	La Despreciada Mine
Geology	Lithology	1	1	1	1	1	7	1	7	1	7	1
	Alteration/Mineralization	6	6	6	6	6	6	6	6	6	6	6
	Structures	8	8	8	8	8	8	8	8	8	8	9
Geochemistry	Rock Element Anomalies	9	9	9	9	9	9	9	9	9	9	9
	Element anomalies in sediment or others	5	5	5	5	5	5	5	5	5	5	5
Geophysics	Resistivity Anomaly	5	4	5	4	4	4	4	4	4	5	4
	Chargeability Anomaly	5	4	5	4	4	4	4	4	4	5	4
	Magnetic Anomaly	4	4	5	4	4	4	4	4	4	4	4
Environmental	Water Resources	9	9	2	2	2	4	9	4	4	2	2
	Geography	9	9	9	9	9	9	9	9	9	9	9
	Weather	9	9	9	9	9	9	9	9	9	9	9
	Flora and Fauna	9	9	9	9	9	9	9	9	9	9	9
Social	Land Uses	9	9	9	9	9	9	9	9	9	9	9
	Local communities	5	5	5	5	5	5	5	5	5	5	5
	Availability of Goods and Services (Water, Energy, etc.)	9	9	9	9	9	9	9	9	9	9	9
	Access	9	9	9	9	9	9	9	9	9	9	9
Economical	Resources	5	3	3	3	3	3	3	3	3	3	3
	Cu Soluble grades	5	1	5	5	5	5	5	3	1	5	5
	Cu-eq Insoluble grades	5	3	5	5	5	5	3	5	3	3	5
	Mining Property	9	5	9	5	5	5	5	0	9	5	9

Appendix A.10. Weights of the Criteria and Sub-Criteria of the Tiltil Mining District Using AHP

Criteria	Criteria Weight (%)	Sub Criteria	Global Weights (%)
Geology	19.8%	Lithology	2.5%
		Alteration/Mineralization	9.9%
		Structures	7.4%
Geochemistry	12.4%	Rock Element Anomalies	9.3%
		Element anomalies in sediment or others	3.1%
Geophysics	5.8%	Resistivity Anomaly	1.6%
		Chargeability Anomaly	2.7%
		Magnetic Anomaly	1.5%
Environmental	18.6%	Water Resources	6.9%
		Geography	3.1%
		Weather	2.1%
		Flora and Fauna	6.6%
Social	19.4%	Land Uses	4.4%
		Local communities	9.2%
		Availability of Goods and Services (Water, Energy, etc.)	3.3%
		Access	2.5%
Economical	24.0%	Resources	4.3%
		Cu Soluble grades	7.1%
		Cu-Eq Insoluble grades	4.4%
		Mining property	8.2%

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