

## Article

# How to Choose the Best Geometallurgical Strategy for Spatial Modeling of a Mineral Deposit

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## Abstract

Geometallurgical modeling is pivotal for optimizing mining projects, yet the selection of an appropriate modeling strategy often relies on empirical experience rather than a systematic methodology. This paper introduces a novel systems-theoretic framework that formalizes geometallurgical modeling as an information acquisition problem under cost and uncertainty constraints. We propose a taxonomy of four fundamental strategies ( $S_0$ – $S_3$ ) defined by their use of direct measurement, interpolation, and regression to populate the key target variable geometallurgical ore type in a spatial block model. A generalized decision algorithm is developed to select the optimal strategy by evaluating economic feasibility and predictive accuracy against system characteristics such as deposit complexity, cost structure, and internal variable correlations. The framework demonstrates that the proxy-based strategy ( $S_2$ ) generally offers the most robust balance between cost and accuracy for complex deposits. This work provides a scalable and generalizable approach applicable not only to geometallurgy but also to other domains involving spatial resource characterization under uncertainty, such as environmental monitoring and petroleum engineering.

**Keywords:** systems framework; mineral deposit; information acquisition; decision algorithm; geometallurgical modelling; strategies; formalization; strategic planning

## 1. Introduction

Modern mining enterprises represent complex socio–natural–technical systems where geological, technological, and economic subsystems interact in non-linear ways. The effective management of such systems requires integrated approaches that can balance multiple objectives under conditions of significant uncertainty and high information costs. The strategic planning of mine development particularly exemplifies this challenge, as decisions made during early exploration stages create path dependencies that persist throughout the project lifecycle [1–3].

Within this context, geometallurgical modeling emerges as a critical interdisciplinary field that connects geological characteristics with processing performance to maximize project value [1–9]. A geometallurgical model organizes “geological and metallurgical information into a spatial and predictive tool to be used in production planning and management in the mining industry” [10]. An effective geometallurgical model helps provide benefits in mining operations [11,12]. However, a core systemic challenge persists:



Academic Editors: Shaofeng Wang and Ming Li

Received: 2 December 2025

Revised: 4 February 2026

Accepted: 17 February 2026

Published: 2 March 2026

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the acquisition of high-fidelity process data through geometallurgical testing creates a fundamental trade-off between information cost and operational risk (Table 1).

**Table 1.** Comparison of the amount and cost of different samplings and testing obtained during geological exploration and the amount of data in the result expected, i.e., in the block model.

| Sampling Type       | Amount of Samples                       | Average Cost per Unit, 10 <sup>3</sup> Rubles * |
|---------------------|-----------------------------------------|-------------------------------------------------|
| Drilling, m         | -                                       | 30                                              |
| Routine geological  | 1000–50,000                             | 1                                               |
| Mineralogical       | 100–5000                                | 25                                              |
| Geometallurgical    | 10–100                                  | 650                                             |
| The result expected |                                         |                                                 |
| Block model         | 10 <sup>5</sup> –10 <sup>6</sup> blocks | 0.001                                           |

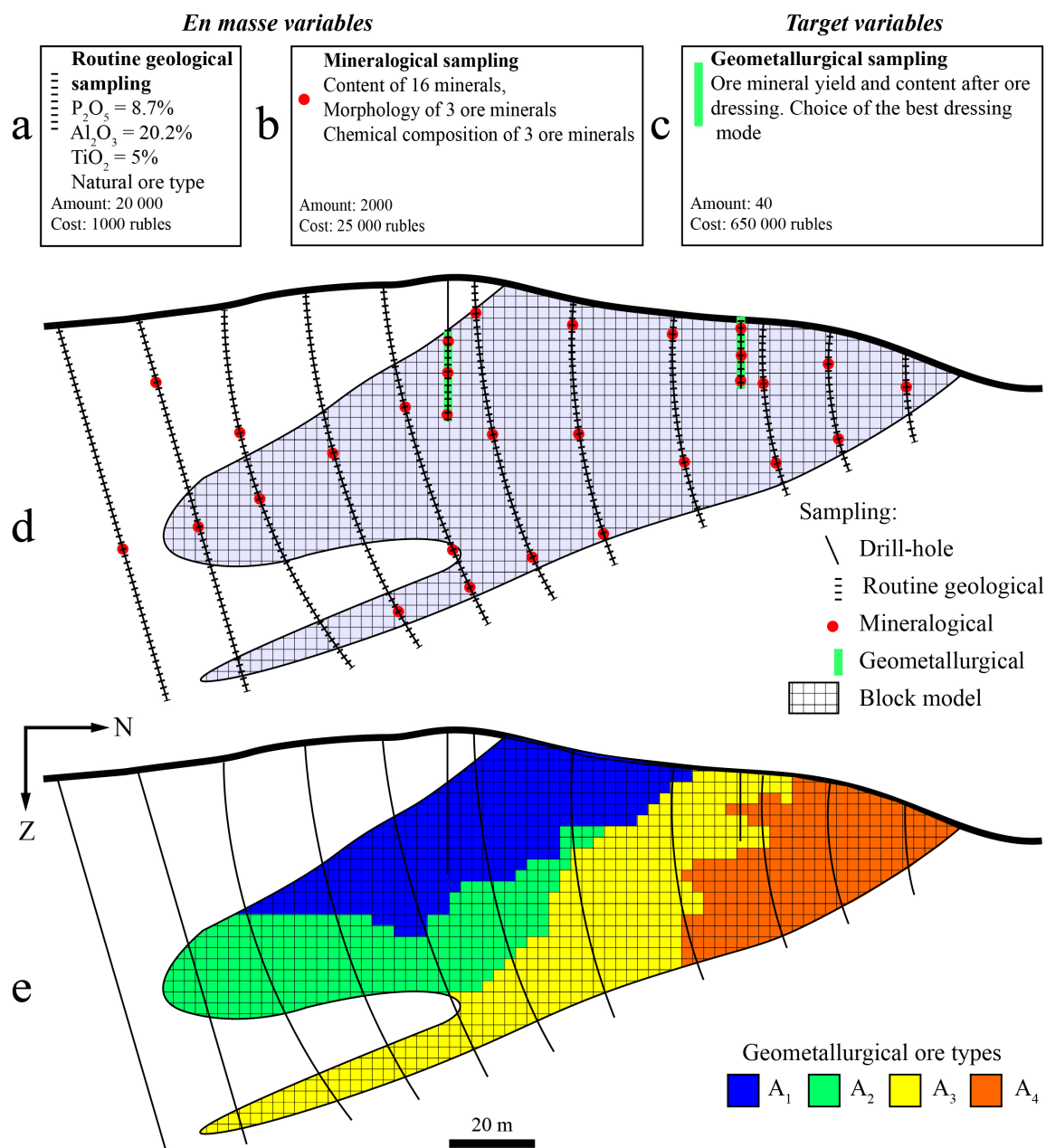
\* Prices are given for July 2025.

Figure 1 shows a conditional section of a mineral deposit, for which several types of sampling and testing were carried out. Such sampling and testing are inevitably performed for any mineral deposit in the deposit exploration stage. Routine geological sampling (Figure 1a) in this example includes the determination of three chemical components and the natural ore/rock type. As Table 1 presents, it is the cheapest type of sampling and gives the greatest value, but its results usually have the lowest value for the final result. Mineralogical sampling (Figure 1b) includes the quantitative determination of the mineral composition and petrographic description. It is more expensive and usually provides an order of magnitude smaller values than routine geological sampling. Geometallurgical sampling and testing (Figure 1c) directly determine the geometallurgical ore type. It typically requires 250 kg of core for each sampling and is expensive and usually performed in critically important points of a deposit, thus it is done in very small volumes (2–3 orders of magnitude smaller than routine geological sampling). Obtaining and studying geometallurgical samples is the most expensive and the most valuable at this stage of deposit exploration (see Table 1). Geometallurgical ore types are crucial for the development of the ore blending and processing streams at an ore dressing plant (e.g., [13–16]).

The explanation above contains the terms “natural” and “geometallurgical” ore type. A natural ore type is assigned based on routine geological sampling data and expert decisions. Expert decisions are based on international and/or local rock classification (for example, the classification of igneous rocks by the IUGS [17]) and a system of geological knowledge. Furthermore, information on the geometallurgical ore type is obtained during the geometallurgical testing of each natural ore type. The geometallurgical ore type is the explicitly indicated method of processing of a given natural ore type: blending, crushing, dressing, metallurgical processing, etc.

As one can see from Figure 1 and Table 1, there are several types of sampling and testing. Some of them are easy to obtain and cheap but not valuable, while the target variable—geometallurgical ore type—is very expensive to obtain for each deposit block. The economic and practical infeasibility of exhaustive direct sampling exemplifies the “iron triangle” trade-off (“Good, fast, cheap. Choose two.”) [18]. In exploration, a balance must be struck between data quality (through dense drilling and testing) and project cost/time. So the general idea of this paper is how to find this balance.

Currently, the mining industry relies on several established geometallurgical modeling strategies often categorized as traditional, mineralogical, and proxy-based approaches [19–24].



**Figure 1.** A conditional section of a mineral deposit. (a–c) Different types of samplings during geological exploration and their graphical images, example of geological exploration (d), and result of geometallurgical studies (e), i.e., the block model of the deposit with the attribution of geometallurgical ore type to each block.

(1) Identification of natural and geometallurgical ore types (the so-called traditional approach). Each block of the deposit model is assigned a natural ore type. Each block is assigned a geometallurgical ore type based on its natural type.

(2) Direct interpolation of mineralogical properties (the so-called mineralogical approach). The strategy is based on the idea that the geometallurgical ore type depends on the characteristics of its constituent minerals and their relationships. The characteristics may include the proportion of their content in the rock, mineral chemistry, grain size, texture (for example, [14,22,23,25]), etc. First, mineralogical sampling of the deposit is carried out in a volume comparable to the volume of routine geological sampling. The volume of routine geological sampling is calculated from the need to calculate reserves and average content for a given exploration category. Then the mineralogical data are interpolated into

a block model of the deposit. Knowing the values of mineralogical variables for each block and their impact on ore dressing, the geometallurgical ore type is calculated. At present, this strategy is considered the most progressive one [19,21]. However, in its pure form it is quite time- and cost-consuming [24]. Moreover, obtaining ore dressing parameters from the mineralogical properties of a specific ore is a non-trivial task that currently has no general solution.

(3) Indirect (regression, proxy) approach (the so-called proxy-based approach). The essence of this strategy is to calculate geometallurgical ore types using regression functions from mineralogical and/or routine geological sampling data. An example of the strategy is realized for rare-metal granite [26].

The above-described types of strategies arose as an attempt to classify all possible approaches to geometallurgical modeling. The explicit presentation of a geometallurgical model has been presented in the literature before by Sola et al. [27], Lund et al. [28], Keeney et al. [29], Newton et al. [30], Lishchuk et al. [22] and Lang et al. [31]. For example, the authors of [32] believe that deposits fit into throughput-dominated or metallurgy-dominated. The geometallurgy plan for the first type of deposit must have comprehensive ore hardness characterization, while the geometallurgy plan for the second type will strongly focus on the variable mineralogy, mineral associations, and liberation size of the key minerals. All approaches arose empirically, as a response to production needs, and the following questions remain: Are other strategies possible? How are existing strategies related to each other? How can we choose them?

While these strategies are well documented in case studies, their selection is predominantly based on empirical experience and heuristic knowledge rather than a systematic framework. This ad hoc approach fails to formally account for the systemic variables of a deposit, such as its inherent geological complexity, spatial variability, and the economic trade-offs between different information sources.

We propose a systems-theoretic approach that formalizes the selection of a geometallurgical strategy as an optimization problem. Our framework models the deposit as an information system and introduces a novel taxonomy of four fundamental strategies ( $S_0$ – $S_3$ ) defined by their pathways for data acquisition (direct measurement, interpolation, regression). This enables the development of a general algorithm that selects the optimal strategy based on system characteristics and economic constraints.

The primary contributions of this work are as follows:

- A formal systems framework for geometallurgical modeling that explicitly represents information flows, dependencies, and constraints.
- A novel taxonomy of strategies ( $S_0$ – $S_3$ ) based on fundamental approaches to information management in complex systems.
- A decision algorithm that enables systematic strategy selection based on system characteristics (deposit complexity, cost structure, accuracy requirements).
- Quantitative analysis of boundary conditions where each strategy provides optimal system performance.

By adopting this systems perspective, we aim to transform geometallurgical strategy selection from an art based on experience to a science based on systematic optimization principles.

## 2. Economic Framework and Problem Formalization

### 2.1. Geometallurgical Block Model as an Information System

The core entity in geometallurgical modeling is a spatially explicit block model of the deposit [28,32]. As illustrated in Figure 1, the entire ore body is discretized into a set of homogeneous unit blocks  $I = \{b^{\bar{x}}\}$ , where  $\bar{x} = (x, y, z)$  represents the spatial coordinates of each block  $b^{\bar{x}}$ . This model synthesizes diverse data from geological exploration, including

routine geological sampling, mineralogical analyses, and critical but costly metallurgical tests [27].

The primary objective is to populate this model with its most important attribute: the geometallurgical ore type for each block. This target variable  $a_1$  is determined by the ore's behavior in specific processes (e.g., grinding, flotation) and is crucial for planning processing streams and ore blending [1,3]. Figure 1 demonstrates the journey from raw data acquisition (a–c) to the final, attributed block model (e), which serves as a predictive tool for mine planning and management [10].

## 2.2. Economic Block Value: The Foundation for Optimization

The economic rationale for building a detailed geometallurgical model lies in assigning a value to each of these model units. The value  $Block_{value}^x$  of the  $x$  block can be fundamentally expressed as [20]

$$Block_{value}^x = D^x - (T^x + P^x)$$

where  $D^x$  is the revenue from the sale of components extracted from the block,  $T^x$  is the mine cost, and  $P^x$  is the cost of its processing. There are other approaches to block value assessment. For example, in [33] a formula has the same idea, but it is more detailed and adjusted for the timing of mining and block scheduling. In [34] time and cash flow, as well as CAPEX, are assumed in an explicit form for a whole deposit, not for each block. Nonetheless, the formula in [20] is the most generalized among others. There are different methods for risk hedging evaluation in the mining industry [16,33], but here we believe that its cost can be determined with enough accuracy (i.e., the problem can be solved).

However, this classical formula omits a crucial component for geometallurgical optimization: the cost of information acquisition ( $C^{\bar{x}}$ ). To account for this, we extend the economic model to form the basis of our framework:

$$Block_{value} = D^{\bar{x}} - (T^{\bar{x}} + P^{\bar{x}} + H^{\bar{x}} + C^{\bar{x}}) \quad (1)$$

where  $H^{\bar{x}}$  represents the cost of risk hedging and  $C^{\bar{x}}$  is the cost of obtaining the geometallurgical information itself (e.g., drilling, sampling, geometallurgical testing). The core challenge formalized in this paper is the optimization of this  $C^{\bar{x}}$  term—finding the strategy that minimizes information costs while achieving the required reliability in predicting the geometallurgical ore type across the entire block model. In actual fact, the formula should be much more complex (like Equation (1) in [1]); however Equation (2) does not consider time or focus on spatial modeling. Thus, Equation (2) does not include discount rate and other economic parameters depending on time.

While Equation (2) provides a foundational spatial optimization model, we acknowledge that a comprehensive economic analysis would incorporate temporal factors such as discount rates, which are beyond the scope of this spatial modeling framework.

## 2.3. Formalization of the Geometallurgical Modeling Problem

Our formalization is based on two key assumptions:

**Assumption 1.** *The set of possible geometallurgical ore types and their corresponding processing modes is predefined. The selection and optimization of these modes are considered an external task for metallurgists and process engineers.*

**Assumption 2.** *The economic parameters of deposit development (e.g.,  $T^{\bar{x}}$ ,  $P^{\bar{x}}$ ) are treated as known inputs. While these are typically refined iteratively during exploration, their precise determination is exogenous to our modeling strategy selection problem.*

### Model Description

The formal model is constructed as follows:

1. **Spatial Discretization:** The deposit is divided into a set of unit blocks  $I = \{b^{\bar{x}}\}$ , with  $\bar{x} = (x, y, z)$  representing spatial coordinates.
2. **Block Properties:** Each block is described by a consistent set of variables  $a_1, a_2, \dots, a_r$ , where each variable represents a specific geological or technological property.
3. **Target Variable:** One variable, denoted  $a_1$ , is the target (e.g., geometallurgical ore type). Determining its value for all blocks is the ultimate goal.
4. **Block Homogeneity:** Each block is considered homogeneous; all variable values are constant within a block.
5. **Data Availability:** The values of variables in any given block may be known or unknown.
6. **Variable Dependencies:**
  - 6.1 **Internal (Regression):** the value of a variable in a block  $b^{\bar{x}}$  may depend on other variables within the same block:

$$a_i^{\bar{x}} = f(a_1^{\bar{x}}, a_2^{\bar{x}}, \dots, a_{i-1}^{\bar{x}}, a_{i+1}^{\bar{x}}, \dots, a_r^{\bar{x}}).$$

- 6.2 **External (Interpolation):** the value of a variable may depend on its values in a subset of surrounding blocks  $V$ :

$$a_i^{\bar{x}} = g(a_i^V).$$

Determining the subset  $V$  is a separate task addressed by geostatistics and interpolation theory.

The objective is to determine the target variable  $a_1$  for all blocks, subject to two constraints:

- (a) **Cost constraint:** the total cost  $C$  of obtaining information must not exceed a fraction of the potential revenue:

$$C \leq (1 - \rho) \sum_I [D^{\bar{x}} - (T^{\bar{x}} + P^{\bar{x}} + H^{\bar{x}})], \quad (2)$$

where  $\rho \in [0; 1]$  is the planned revenue fraction. Thus,  $(1 - \rho)$  represents the fraction of revenue the operator is prepared to spend on information acquisition. It is assumed that all quantities on the right-hand side of the inequality are known, and  $C$  depends on the choice of calculation strategy.

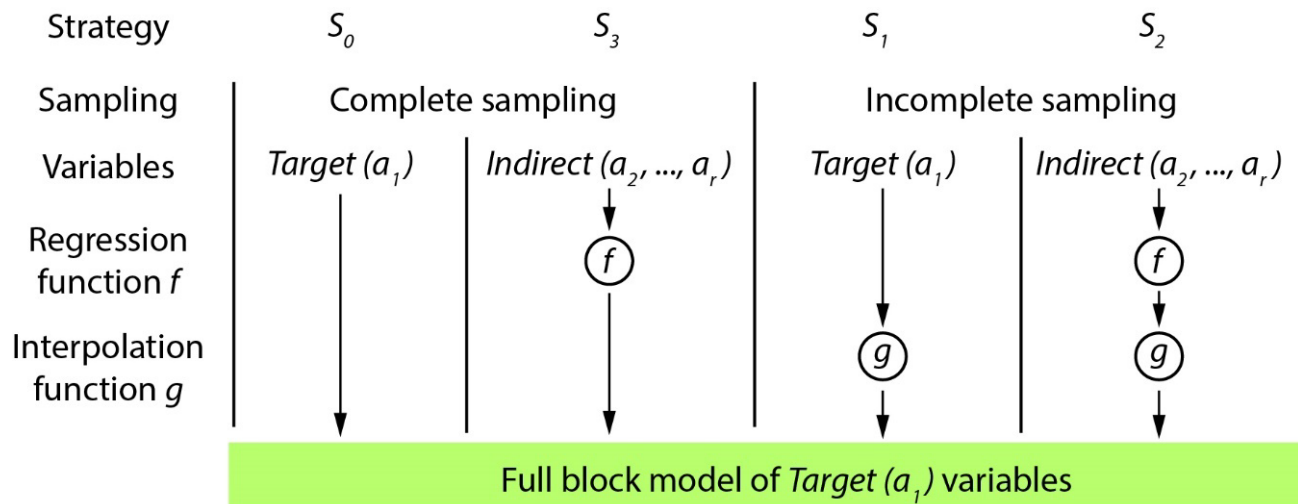
- (b) **Accuracy constraint:** the model error for the target variable  $\hat{a}_1$  must remain below a regulator-defined (e.g., the relative root mean square error prescribed by the Russian State Reserves Committee [35]).

### 3. A Decision Support Framework for Geometallurgical Strategy Selection

This section presents a systematic framework for selecting the optimal geometallurgical modeling strategy. The core of this framework is an algorithm that evaluates the four strategies ( $S_0$ – $S_3$ ) against the economic and accuracy constraints defined in Section 2.3. The algorithm conceptualizes the deposit as an information system with three fundamental methods for populating the target variable  $a_1$  in the block model:

- I. Direct Measurement.
- II. Interpolation ( $g$ ): Estimating a value based on known values in surrounding blocks.
- III. Regression ( $f$ ): Calculating a value from other, cheaper variables within the same block.

The combinations of these methods form the basis of our strategy taxonomy (Figure 2) and guide the selection algorithm, the flowchart of which will be discussed in Section 3.3.



**Figure 2.** Combinations of ways for obtaining the target variable.  $S_0$ – $S_3$  are strategies for obtaining a complete block model of the target variable. For the formalization definition, see Section 2.

According to Figure 2,  $S_0$  is a strategy where geometallurgical ore type is determined via geometallurgical testing and sampling for each block directly. The  $S_3$  strategy means that indirect variables (the results of routine geological and mineral sampling) are obtained in each block and the direct variable (geometallurgical ore type) is obtained in each block via regression.  $S_1$  means that geometallurgical ore type is determined via geometallurgical testing and sampling for some blocks, and this data is interpolated into the whole deposit model.  $S_2$  means that indirect variables (the results of routine geological and mineral sampling) are obtained in some blocks, the direct variable (geometallurgical ore type) is obtained in these blocks via regression, and then the data is interpolated into the whole deposit model.

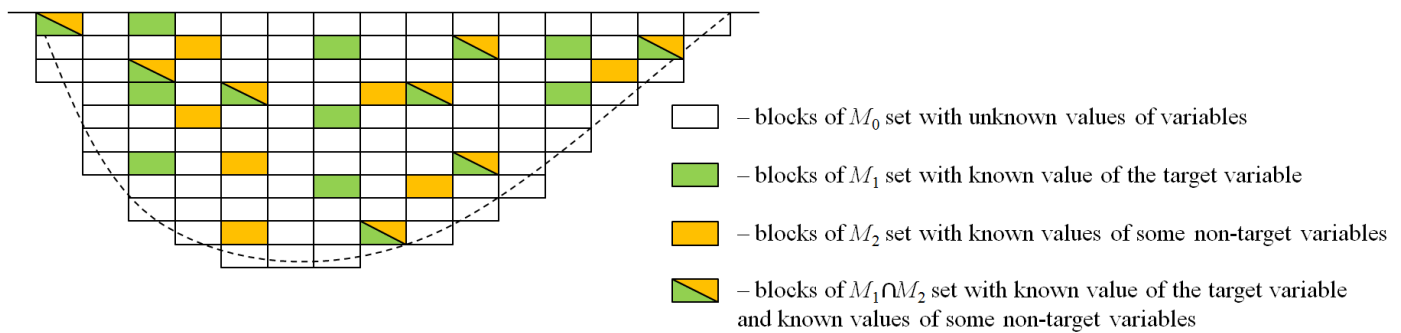
### 3.1. Algorithm Inputs and Initial Data

The algorithm requires the following initial state of the block model (as illustrated in Figure 3):

- $M_0$ : Blocks with unknown values for all variables.
- $M_1$ : Blocks with a known value of the target variable  $a_1$  (e.g., from geometallurgical tests).
- $M_2$ : Blocks with known values of one or more non-target variables  $a_2, a_3, \dots, a_r$  (e.g., from routine geological or mineralogical sampling).

The sets  $M_1$  and  $M_2$  may overlap. The goal is to determine  $a_1$  for all blocks in  $M_0 \cup M_2$ .

An object divided into blocks is provided as the initial data for the algorithm for searching for a geometallurgical modeling strategy. For a certain set of blocks  $M_1$ , the values of the target variable are known, and for a certain set of blocks  $M_2$ , the values of some non-target variables are known. In this case, the sets  $M_1$  and  $M_2$  can intersect in common blocks. Blocks with unknown values of all variables form a set  $M_0$  (Figure 3).



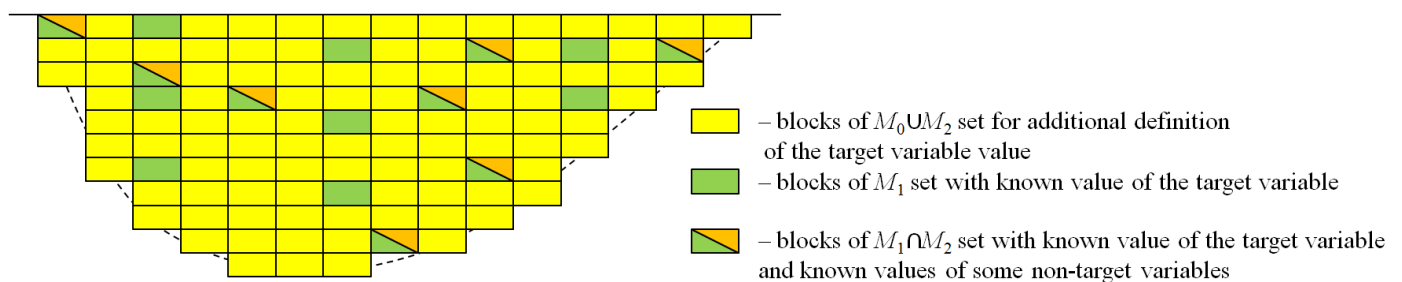
**Figure 3.** An example of the initial data of the algorithm for searching for a geometallurgical modeling strategy: white—blocks of  $M_0$  set with unknown values of variables, green—blocks of  $M_1$  set with known value of target variable, and orange—blocks of  $M_2$  set with known values of some non-target variables.

### 3.2. Strategy Evaluation Workflow

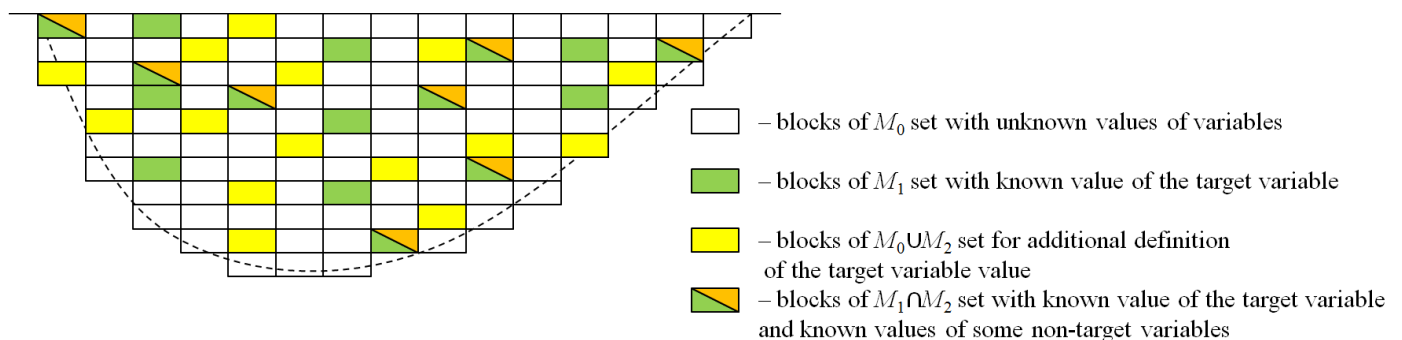
The algorithm proceeds by evaluating each strategy in order of increasing complexity.

- Step 1: evaluate strategy  $S_0$  (Complete Direct Measurement)  
The algorithm first checks the feasibility of directly determining  $a_1$  in all blocks of  $M_0 \cup M_2$  (Figure 4). It calculates the total cost  $C$  and checks it against the cost constraint (Equation (3)). If feasible,  $S_0$  is added to the list of viable strategies. This strategy guarantees the highest accuracy but is typically cost-prohibitive.
- Step 2: evaluate strategy  $S_1$  (Incomplete Direct Measurement + Interpolation)  
The algorithm determines a minimal set of additional blocks  $M'$  where  $a_1$  must be directly measured to enable reliable interpolation across the entire model (Figure 5). The cost of measuring  $a_1$  in  $M'$  is evaluated against Equation (3). If feasible, the values in all other blocks are estimated using the interpolation function  $g$ , and  $S_1$  is added to the list of viable strategies.
- Step 3: evaluate strategy  $S_2$  (Proxy-Based + Regression + Interpolation)  
This step leverages internal dependencies (regressions) to reduce costs. For a given set of non-target variables:
  1. Regression building: Using blocks in  $M_1 \cap M_2$ , the algorithm constructs a regression function  $a_1^{\bar{x}} = f(a_2^{\bar{x}}, a_3^{\bar{x}}, \dots, a_r^{\bar{x}})$ .
  2. Accuracy check: The error of the regression model is validated. If unsatisfactory, the strategy for this variable set is discarded.
  3. Cost evaluation: If accurate, the algorithm calculates the cost of directly measuring the required non-target variables in blocks  $M'$  and applies the regression  $f$  to obtain  $\hat{a}_1$  for these blocks. Finally, interpolation  $g$  is used to propagate these calculated values throughout the model, as described in Equation (5). The total cost is checked, and if feasible,  $S_2$  is added to the list.
- Step 4: evaluate strategy  $S_3$  (Complete Indirect + Regression)  
This strategy involves directly measuring all non-target variables in the entire block model and then applying the regression function  $f$  to every block to obtain  $a_1$ . While theoretically present in our taxonomy (Figure 2), this strategy is often uneconomical due to the high cost of exhaustive sampling of non-target variables, but it is evaluated for completeness.

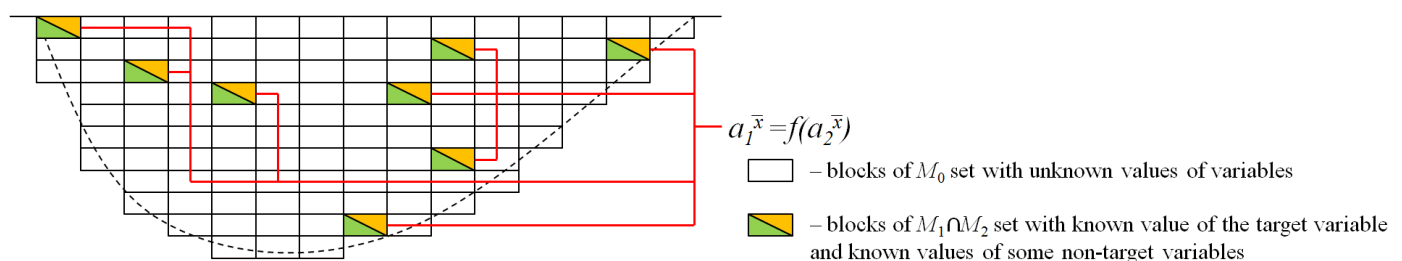
Interpolation ( $g$  function) is assumed to be a good method if it provides enough data under a given accuracy limit in the white blocks based on knowledge in the yellow, green and orange blocks, Figures 3–6. The interpolation is built according to the competence and experience of the geologist. The interpolation (propagating geometallurgical parameters into a block model) can be performed by different methods, e.g., nearest-neighbor method, piecewise linear, inverse distance weighted, spline interpolation, kriging, conditional stochastic simulation [29,36], etc. Obtaining exact deposit interpolation is a separate non-trivial task, which is not supposed to be solved here. This paper is aimed at building the general model and sets that the  $g$  explicit form is already given. However, some details of the possibilities to build good enough interpolation are discussed in the hypothetical example. In general, interpolation accuracy depends on the deposit complexity.



**Figure 4.** Example of an object diagram for a strategy  $S_0$ : yellow—blocks of  $M_0 \cup M_2$  set for additional definition of the target variable value; green and orange—as on Figure 3.



**Figure 5.** Example of an object diagram for a strategy  $S_1$ : yellow—blocks of  $M'$  set for additional definition of the target variable value; white, green, and orange—as on Figure 3.



**Figure 6.** Example of an object diagram for a proxy-strategy  $S_2$ , using one non-target variable  $a_2$ : white, green, and orange—as on Figure 3.

Also, it is believed that the  $f$  regression function is already built by the geometallurgical modeling stage. The details of accuracy, possibility and variability are given in the hypothetical example.

The block size of the deposit block model is also determined by the value of ore variability in each ore body or, in other words, deposit complexity. The complexity of a mineral deposit can be evaluated according to criteria provided in JORC Code, from simple to highly complex. In complex deposits, it may be very difficult to ensure that the bulk samples taken are truly representative of the whole deposit. The lack of direct bulk sampling and the uncertainty in demonstrating the spatial continuity of size and price relationships should be persuasive in determining the appropriate resource category [37]. So, if the complexity is high, it is necessary to take samples more often in order to determine the distribution of the target variable in the volume with a given accuracy. If it is low, then less frequent drilling and sampling is sufficient. It should be noted that the precise definition of the drilling grid geometry is a separate science task (see e.g., [38–42]) and is beyond the scope of this article.

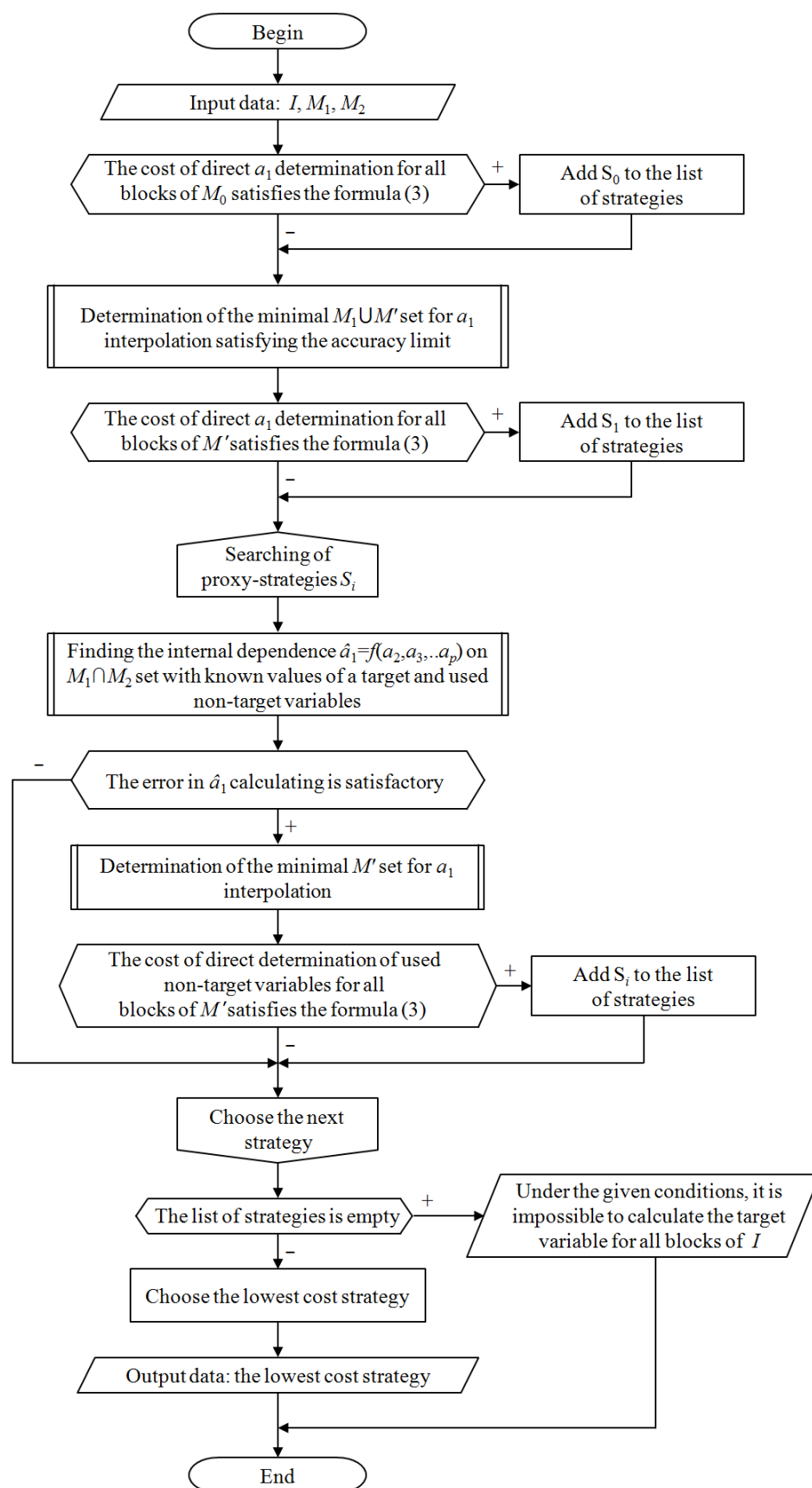
The use of strategy  $S_2$  is quite common, for example, sometimes the geometallurgical ore type is uniquely determined by the natural ore type or the content of the target component. For deposits with a high cut-off value, this is almost always the case. In more complex cases, several non-target variables are used to find the internal dependence. This is usually a non-trivial task. Currently, finding ways to solve it is at the cutting edge of modern geometallurgical research. The problem is solved, among other things, by machine learning methods [43–47]. The solution to this problem is usually associated with the exploration and development of complex, small deposits that have currently been recognized as profitable. Ultimately, the result depends on the skill of the researcher and the general development of mathematical methods for solving regression problems.

### 3.3. Strategy Selection and Implementation

The final stage is the selection of the optimal strategy from the list of viable candidates generated by the workflow in Figure 7.

- If the list is empty, the deposit cannot be modeled profitably under the given constraints, signaling a need to renegotiate economic parameters or technological capabilities.
- If the list contains one or more strategies, the algorithm selects the one with the lowest total cost.
- The output is a definitive implementation plan, specifying the chosen strategy ( $S_0$ ,  $S_1$ ,  $S_2$ , or  $S_3$ ), the required sampling campaign ( $M'$ ), and the mathematical models ( $f$ ,  $g$ ) to be deployed.

For example, we can search for technologies that reduce the cost of operations, identify tools that allow working with increased risk values, develop technologies that allow increasing the cost of extracted components, etc. Otherwise, the list of strategies is ordered by increasing their cost and the cheapest strategy is adopted for implementation. The flowchart of the above-described algorithm for searching for the optimal strategy is shown in Figure 7. The result of the algorithm is a decision on choosing the best strategy for the geometallurgical exploration of the deposit.



**Figure 7.** Algorithm for searching and selecting strategies for determining the target variable of geometallurgical modeling.

## 4. Discussion

### 4.1. The Systems-Theoretic Interpretation of Strategy Performance

Our analysis reveals that the optimal geometallurgical strategy is not intrinsically the “best” but emerges from the interaction between a deposit’s system characteristics and economic constraints. The performance of each strategy can be interpreted through the lens of systems theory as follows:

- Strategy  $S_0$  (Complete Direct Measurement) represents a brute-force approach to eliminating systemic uncertainty. While it achieves maximum accuracy, it functions as a closed system with minimal information processing, making it economically inefficient for all but the smallest, highest-value deposits. Its prohibitively high cost, as shown in Table 2, underscores a fundamental systems principle: the marginal cost of perfect information often exceeds its marginal benefit.
- Strategy  $S_1$  (Interpolation-Based) transforms the deposit into an information-sparse system reliant on spatial continuity. Its viability is entirely dependent on the external dependency  $g$ . This strategy fails in geologically complex systems where spatial correlations break down, demonstrating how structural complexity within a system can invalidate simpler predictive models.
- Strategy  $S_2$  (Proxy-Based) embodies the concept of a complex adaptive system. It leverages internal dependencies ( $f$ ) to create a more efficient and resilient information network. By using cheaper proxy variables, it effectively creates a model of the system that is far less costly to observe and monitor. Its dominance in our hypothetical scenarios (Table 2) highlights a core tenet of systems engineering: the power of indirect observation and inference in managing complex systems.
- Strategy  $S_3$  (Complete Indirect) represents a theoretical extreme where the system is fully described through its component relationships. Its current impracticality underscores the real-world constraints of data acquisition costs, even for proxy variables.

**Table 2.** Comparison of strategy application costs for a deposit with a volume of ~10 million m<sup>3</sup>.

| Strategy | Application Conditions                                                    | Summary Drilling Length, m | Drilling Cost, Thousand Rubles | Sample Number | Analyses Type | Analyses Cost, Thousand Rubles | Total Cost, Thousand Rubles |
|----------|---------------------------------------------------------------------------|----------------------------|--------------------------------|---------------|---------------|--------------------------------|-----------------------------|
| $S_0$    | Small blocks (3 m × 3 m × 3 m), high complexity                           | 3,600,000                  | 108,000,000                    | 1,200,000     | Geomet.       | 780,000,000                    | 888,000,000                 |
|          | Large blocks (30 m × 12 m × 12 m), low complexity                         | 225,000                    | 6,750,000                      | 7500          | Geomet.       | 4,875,000                      | 11,625,000                  |
| $S_1$    | Low deposit complexity                                                    | 3000                       | 90,000                         | 60            | Geomet.       | 39,000                         | 129,000                     |
|          | High deposit complexity                                                   | 30,000                     | 900,000                        | 600           | Geomet.       | 390,000                        | 1,290,000                   |
| $S_2$    | Complexity of a deposit is low; good regression                           | 3000                       | 90,000                         | 600           | Routine       | 600                            | 90,600                      |
|          | Complexity of a deposit is high; good regression                          | 20,000                     | 600,000                        | 2000          | Routine       | 2000                           | 602,000                     |
|          | Complexity of a deposit is low; regression requires additional variables  | 3000                       | 90,000                         | 600           | Routine + Min | 15,600                         | 105,600                     |
|          | Complexity of a deposit is high; regression requires additional variables | 20,000                     | 600,000                        | 2000          | Routine + Min | 52,000                         | 652,000                     |
| $S_3$    | Small blocks (3 m × 3 m × 3 m); good regression                           | 3,600,000                  | 108,000,000                    | 1,200,000     | Routine       | 1,200,000                      | 109,200,000                 |
|          | Large blocks (30 m × 12 m × 12 m); good regression                        | 225,000                    | 6,750,000                      | 7500          | Routine       | 7500                           | 6,757,500                   |

Table 2. Cont.

| Strategy | Application Conditions                                                      | Summary Drilling Length, m | Drilling Cost, Thousand Rubles | Sample Number | Analyses Type | Analyses Cost, Thousand Rubles | Total Cost, Thousand Rubles |
|----------|-----------------------------------------------------------------------------|----------------------------|--------------------------------|---------------|---------------|--------------------------------|-----------------------------|
| $S_3$    | Small blocks (3 m × 3 m × 3 m); regression requires additional variables    | 3,600,000                  | 108,000,000                    | 1,200,000     | Routine + Min | 31,200,000                     | 139,200,000                 |
|          | Large blocks (30 m × 12 m × 12 m); regression requires additional variables | 225,000                    | 6,750,000                      | 7500          | Routine + Min | 195,000                        | 6,945,000                   |

Geomet.—geomettallurgical testing. Min—mineralogical analyses. Routine—routine geological sampling.

#### 4.2. Comparative Analysis of Strategy Performance and System Trade-Offs

The systematic evaluation of strategies  $S_0$ – $S_3$  reveals fundamental trade-offs between cost, accuracy, and implementation complexity inherent to the geomettallurgical system. These trade-offs are synthesized in Table 3, which serves as a decision-making guide for system designers.

**Table 3.** Advantages and disadvantages of geomettallurgical modeling strategies  $S_0$ – $S_3$  from a systems perspective.

| Strategy | Disadvantages                                                                                                           | Advantages                                                                                     | Ideal Application Context                                                                           |
|----------|-------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| $S_0$    | Highest cost (informationally “closed” system); inefficient resource use.                                               | Maximum accuracy; eliminates model uncertainty.                                                | Small, very high-value deposits; final feasibility study stage.                                     |
| $S_1$    | Accuracy limited by spatial structure (fails in complex systems); requires reliable interpolation model $g$ .           | Cost-effective for systems with high spatial continuity.                                       | Large, geologically homogeneous deposits with clear zonation.                                       |
| $S_2$    | Accuracy depends on discoverability of robust proxy relationships $f$ ; requires technical expertise in model building. | Optimal balance of cost and accuracy for complex systems; leverages system internal structure. | Most real-world deposits, especially those with correlated geological and metallurgical parameters. |
| $S_3$    | High cost of exhaustive proxy data collection; accuracy is capped by regression model $f$ .                             | More cost-effective than $S_0$ ; provides full spatial data on proxy variables.                | Theoretically possible, but rarely optimal; could be used if proxy data is already available.       |

As synthesized in Table 3, the framework reveals how each strategy manages the fundamental system trade-off between information cost and predictive accuracy differently. This transforms strategy selection from a matter of convention into a quintessential systems engineering optimization problem, involving trade-offs between the cost of information and the value derived from reduced uncertainty.

The analysis clearly positions strategy  $S_2$  (Proxy-Based) as the most systemically robust approach for the majority of scenarios. Its core advantage lies in its ability to leverage the internal structure of the system (the regression  $f$ ) to create information efficiency. This transforms the deposit from a “black box” requiring expensive interrogation ( $S_0$ ) into a “gray box” whose behavior can be predicted through intelligent, indirect observation.

Conversely, the viability of strategy  $S_1$  is entirely contingent upon the external structure of the system (the interpolation  $g$ ). Its failure in conditions of high geological complexity is a direct consequence of broken spatial correlations, a classic limitation of systems reliant on spatial inference.

Ultimately, Table 3 provides a diagnostic tool. By assessing a deposit’s key system characteristics—such as its internal correlation strength (potential for  $f$ ) and spatial ho-

mogeneity (potential for  $g$ )—a planner can immediately narrow down the set of viable strategies before engaging in detailed costing.

#### 4.3. Managerial and Operational Implications as a Control System

From a managerial perspective, our framework re-frames geometallurgical planning from a one-off study to a dynamic control system for a mining enterprise.

- Resource allocation: The algorithm provides a quantitative basis for allocating exploration budgets, shifting the decision from “how much data can we afford?” to “what is the optimal data acquisition strategy to maximize project net present value?”
- Risk management: Strategies  $S_1$  and  $S_2$  explicitly quantify the trade-off between information cost and model uncertainty, allowing managers to make informed decisions under uncertainty—a classic challenge in systems management.
- Adaptive planning: The framework enables adaptive planning through iterative deployment. For instance, an initial low-cost  $S_2$  campaign could identify spatial domains where proxy relationships weaken, guiding a subsequent targeted  $S_1$  drilling campaign to resolve these uncertainties. This creates a closed-loop control system that dynamically optimizes information value over the project lifecycle.

#### 4.4. Limitations and Boundary Conditions of the Framework

While general, our framework has inherent boundary conditions set by its assumptions.

- Regression quality: The efficacy of the most potent strategy,  $S_2$ , is wholly dependent on the discoverability and robustness of the regression function  $f$ . In deposits where ore behavior is governed by poorly understood or non-linear mineralogical factors (e.g., complex textures), establishing a reliable  $f$  may be the primary scientific challenge.
- Static economic parameters: The model uses a static economic snapshot. In reality, metal prices and costs fluctuate, making the cost constraint  $C$  a dynamic variable. Future work could integrate real options analysis or stochastic optimization to address this temporal dimension.
- Data quality: The framework assumes that input data ( $M_1, M_2$ ) is representative and reliable. Biased or non-representative sampling in early stages can lead to a cascade of errors in the chosen strategy, a manifestation of systemic error propagation.

#### 4.5. Generalizability and Applications Beyond Geometallurgy

The core principles of our framework—classifying information acquisition strategies and selecting them via cost–accuracy optimization—are transferable to other domains involving spatial resource characterization under uncertainty.

- Environmental management: optimizing monitoring network design for groundwater contamination, where direct sampling ( $S_0$ ) is expensive, but proxy measurements from geophysics ( $S_2$ ) could be highly efficient.
- Oil and gas geology: characterizing reservoir properties where core samples ( $S_0$ ) are limited, and strategies based on well log correlations ( $S_2$ ) or seismic data interpolation ( $S_1$ ) are commonplace.
- Agricultural land management: prescribing soil treatments based on a combination of direct soil tests ( $S_0$ ) and remote sensing data ( $S_2$ ).

This demonstrable generalizability confirms that our contribution extends beyond geometallurgy. We have developed a systems-based meta-model for information strategy selection under uncertainty—a methodological framework that can be instantiated across multiple domains where spatial resource characterization faces similar cost–accuracy trade-offs.

## 5. Conclusions

This study has introduced a systems-theoretic framework that fundamentally re-frames geometallurgical strategy selection from an empirical approach into a systematic engineering approach. The primary contributions of this work are fourfold:

First, we have developed a formal systems framework for geometallurgical modeling that explicitly represents information flows, dependencies, and constraints. By extending the conventional block value model to include information acquisition costs (Equation (2)), we have established an economic foundation for detailing geometallurgical investments.

Second, we have proposed a novel taxonomy of four fundamental strategies ( $S_0$ – $S_3$ ) based on their approach to information management in complex systems. This taxonomy reveals that strategy performance emerges from the interaction between a deposit's inherent characteristics and economic constraints, rather than being intrinsically superior.

Third, we have created a generalizable decision algorithm that enables systematic strategy selection based on system characteristics. As the boundary conditions demonstrated, the algorithm identifies strategy  $S_2$  (Proxy-Based) as the most systemically robust approach for most real-world scenarios, achieving an optimal balance between cost and accuracy through intelligent information leveraging.

Fourth, our quantitative analysis of boundary conditions provides practical insights into how deposit size, complexity, and internal parameter correlations determine optimal strategy choice. The analysis reveals that systems with high internal correlation strength favor  $S_2$  strategies, while spatially homogeneous systems may benefit from simpler  $S_1$  approaches.

The broader implication of our research extends beyond geometallurgy. We have demonstrated that the fundamental problem of information strategy selection under uncertainty—with its inherent trade-offs between direct measurement, interpolation, and regression—permeates numerous domains involving spatial resource characterization. The proposed framework offers a systems-based meta-model applicable to environmental monitoring, reservoir engineering, and agricultural management.

Future research should focus on integrating temporal dynamics into the framework, including price volatility and discount rates through real options analysis. Additionally, machine learning methods could enhance the discovery of robust proxy relationships (regression function  $f$ ), particularly for deposits with complex, non-linear mineralogical characteristics.

**Author Contributions:** Conceptualization, A.O.K. and D.V.M.; methodology, A.O.K., D.V.M. and D.G.S.; research, A.O.K. and D.V.M.; validation, A.O.K., D.V.M. and D.G.S.; writing—original draft preparation, A.O.K., D.V.M. and D.G.S.; writing—review and editing, A.O.K., D.V.M. and D.G.S.; visualization, A.O.K., D.V.M. and D.G.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** A.O.K. and D.G.S. was supported by Kola Science Centre RAS, project FMEZ-2024-0008; D.V.M. was supported by Kola Science Centre RAS, project FMEZ-2025-0055.

**Data Availability Statement:** Data is provided within the manuscript and will be available from the corresponding author upon reasonable request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following notations are used in this manuscript:

|               |                                                                                                                     |
|---------------|---------------------------------------------------------------------------------------------------------------------|
| $a_i$         | Variable characterizing the properties of a block $b$ . $i = 1, 2, \dots, r$                                        |
| $\hat{a}_i$   | Calculated value of variable $a_i$                                                                                  |
| $b^{\bar{x}}$ | Block model block with coordinates represented by a vector $\bar{x}$                                                |
| $C$           | Cost of additional testing of blocks of the set $M$                                                                 |
| $D^{\bar{x}}$ | Revenue received from the sale of all products extracted from the block $b^{\bar{x}}$                               |
| $f$           | Internal dependence of one variable on others (including regression function)                                       |
| $g$           | External dependence of one variable on its values in the surrounding blocks of the set $V$ (interpolation function) |
| $H^{\bar{x}}$ | Cost of hedging block risks                                                                                         |
| $I$           | All blocks of the object                                                                                            |
| $M_1$         | Set of blocks in which the value of the target variable is known                                                    |
| $M_2$         | Set of blocks in which the values of some non-target variables are known                                            |
| $M'$          | Set of blocks in which it is planned to define the values of variables                                              |
| $p^{\bar{x}}$ | Cost of the block dressing                                                                                          |
| $S_i$         | Strategy of geometallurgical exploration of the deposit                                                             |
| $T^{\bar{x}}$ | Cost of extracting and transporting the block                                                                       |
| $V$           | Multiple blocks for interpolation                                                                                   |
| $\rho$        | Planned revenue fracture                                                                                            |
| $x, y, z$     | Coordinates of the block $b^{\bar{x}}$ (or decomposition of the vector $\bar{x}$ into components)                   |

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