

Article

A Proactive Reconciliation System at the Cuiabá Mine: Quantification of Random Errors in Gold Grade Determination Across the Production Chain

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Abstract

Establishing a proactive reconciliation chain is essential for understanding the gold production system from the geological model to the final product. Monitoring this chain enables the identification of process deviations and sources of variation, providing a robust management tool for quality control. Although the major process steps are well known, the sources and magnitudes of measurement errors are often unknown. Quantifying errors at each node of the reconciliation system allows estimation of the statistical confidence of each dataset and its impact across the entire chain. This study presents the reconciliation chain implemented at the Cuiabá Mine, owned and operated by AngloGold Ashanti, identifies the principal random errors, as defined by geostatistics and Pierre Gy's Theory of Sampling (TOS), and quantifies the statistical reliability of the data at key stages. This work provides one of the first quantitative integrations of TOS-based sampling errors and geostatistical uncertainty across a full industrial reconciliation chain. Results show that sampling-related uncertainties are dominated by the Fundamental Sampling Error, reaching 24.84% in channel samples and 22.24% in plant feed samples, whereas the Heterogeneity Fluctuation Error contributes 2.96%, and the geological model uncertainty reaches 5.80%. These results highlight the critical influence of sampling protocols on reconciliation performance and demonstrate the value of integrating statistical error quantification into mine production management and decision-making.

Keywords: reconciliation; Cuiabá mine; gold; random error quantification; mine call factor; theory of sampling

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1. Introduction

Mining operations are complex systems comprising multiple stages that lead to the final product. Due to the involvement of distinct disciplines, specialized knowledge, and intricate processes, the entire value chain must be monitored and controlled, from orebody modeling to mineral processing. In this context, proactive reconciliation practices [1] compare data acquired at each stage of the mining process, aiming to identify discrepancies and address each one individually. At AngloGold Ashanti (AGA), the

reconciliation process highlights the main variations in tonnage, grade, and metal content by structuring the production chain into stages (nodes), i.e., key control points at which data are evaluated against historical benchmarks for each mining stage.

Following Morrison [2], identifying and analyzing errors at each stage is crucial for a holistic understanding of the system, allowing targeted adjustments and improved process control. Accordingly, in addition to building a proactive reconciliation system, one must determine which measurement points exert the greatest leverage on controls and develop techniques to measure or estimate the error associated with each stage.

However, identifying problems and implementing ad hoc fixes alone does not address the underlying causes of variation. A complete mapping of the production chain is required, pinpointing the main sources of discrepancy between reconciliation stages and unraveling all nodes as predefined in the corporate guideline. Such mapping is essential to identify operational risks and opportunities, determine realistic factors for long- to short-term production planning, and improve the traceability, including the detection of possible fraud throughout the process.

Sampling is a mass-reduction process in which the sample, a representative portion of a physical lot made of particulate material, is collected. It is fundamental in mining for estimating the metal content of mineral resources. Collecting and analyzing samples provides a dataset of grade, density, moisture, particle-size distribution, and other variables for processing the material. However, sampling inherently introduces errors, and Pierre Gy's Theory of Sampling (TOS) explains the origin of such errors, how to reduce or eliminate them, and how to estimate the residual error. Table 1 presents the sampling errors proposed in the TOS [3–8]; [9] apud [10].

Table 1. Sampling errors and their notation [8], [9] apud [10].

Error Name	Notation
Overall Estimation Error	OEE
Total Sampling Error	TSE
Fundamental Sampling Error	FSE
Grouping and Segregation Error	GSE
Heterogeneity Fluctuation Error	HFE
Quality Fluctuation Error	QFE
Increment Weighting Error	IWE
Increment Materialization Error	IME
Increment Delimitation Error	IDE
Increment Extraction Error	IEE
Increment Preparation Error	IPE
In Situ Nugget Effect	INE

Beyond sampling errors, geological models also introduce errors in the reconciliation process. In geostatistical workflows, data uncertainty, especially in sparsely sampled areas, can lead to estimates that do not reflect the true grade of the deposit. Conditional simulation methods, grounded in Monte Carlo methods [11], provide a way to quantify this uncertainty by analyzing variability among multiple equiprobable realizations.

Systematic errors are generated by biased samples, impacting the representativeness (accuracy) of the data of the lot. Random errors, in turn, affect data precision, affecting the variability of the values obtained during the repeated process. Statistically, according to Chieregati and Pitard [10], random errors have a mean equal to zero and a non-zero variance, while systematic errors have a non-zero mean and a zero variance when compared to the reference value. Although the errors involved in the process occur separately, their effect on the sampling result is cumulative.

With the objective of preserving, quantifying, and ensuring sample representativeness, Quality Assurance and Quality Control (QA/QC) programs are established to monitor the correct implementation of sampling protocols, as well as the controls applied at each stage of the collection, preparation, and analytical processes. Dominguez [12] defines the concept of Quality Management (QM) as the precursor for appropriate corrective actions to close gaps determined by the execution of a quality program with the aim of proactively determining control performance deviation and thus proactively rectifying the source of deviation.

Despite the widespread application of reconciliation practices in mining, few studies have quantitatively integrated sampling-derived uncertainties and geostatistical estimation errors across a complete industrial reconciliation chain. This study addresses this gap by combining TOS-based error quantification with SGS-based estimation uncertainty in a fully operational mining context.

This study aims to evaluate and expand the proactive reconciliation system applied at the Cuiabá Mine in accordance with the company's guidelines. The goal is to detail the methodology and the steps for sample/data collection and the QM program, identify potential sources of deviation, and define improvement actions and best practices to ensure the quality of data. In parallel, a statistical analysis of each data node is performed to quantify the variance of the main random errors at each reconciliation node.

Although the study includes elements of mineral processing, its primary focus is the quantification of uncertainty across the mining reconciliation chain, integrating geological modeling, sampling practices, and data quality management.

2. Reconciliation Process at the Cuiabá Mine

2.1. Cuiabá Mine Operation

AGA is a global gold mining company with a diversified, high-quality portfolio of operations, projects, and exploration activities across 10 countries on four continents. In Brazil, the AGA Mineração (Figure 1), located in the state of Minas Gerais, comprises the Cuiabá and Lamego underground mines, as well as the Cuiabá and Queiroz metallurgical plants.



Figure 1. AGA's footprint in Brazil. Source: Adapted from AGA Operational profiles [13].

The Cuiabá gold deposit is situated in the northern portion of the Quadrilátero Ferrífero (QF), within a Brazilian Archean greenstone belt province. It is hosted within the Nova Lima Group and consists of a metavolcano-sedimentary sequence metamorphosed under greenschist facies conditions. Multiple mineralization styles have been identified, including stratabound replacement in banded iron formations, disseminated sulfide mineralization along shear zones, and gold-bearing quartz–carbonate veins. These mineralization styles are primarily controlled by Archean deformation associated with the Rio das Velhas Orogeny.

The Cuiabá deposit has a cumulative production exceeding 7 Moz [13], classifying it as a world-class deposit. The mine is currently developed at Level 24 (>1500 m depth), with an annual production of approximately 230 koz Au. It is one of the most important underground gold mines worldwide, with reported reserves of 1.86 Moz [13].

2.2. Reconciliation Chain

In alignment with AGA’s global reconciliation guideline, the policy at Cuiabá aims to ensure a consistent approach to accounting for grade, tonnage, and metal content. Its primary objectives are to:

- (i) identify value opportunities and inefficiencies along the mining chain;
- (ii) identify short-term operational risks and opportunities;
- (iii) determine realistic factors for planning across timescales;
- (iv) optimize the mining efficiency; and
- (v) improve the detectability of precious-metal losses or possible fraud.

The current reconciliation process at the unit is based on the chain shown in Figure 2. Grade and tonnage must be measured or estimated at each stage of the reconciliation chain.

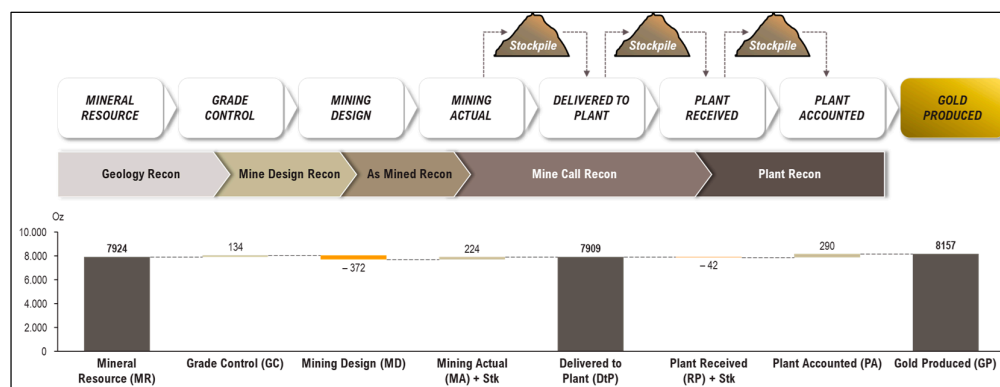


Figure 2. Idealized production reconciliation chain adopted at the Cuiabá Mine. Source: AGA Internal Guideline [14].

The principal stages are:

- Mineral Resource (MR)—Represents the official geological model, which is used for the long-term mining plan. Data reported at this stage correspond to the reconciled volume at the operational cut-off grade.
- Grade Control (GC)—Represents the mining blocks in the short-term plan. Data reported at this stage correspond to the reconciled short-term volume at the operational cut-off grade.
- Mining Design (MD)—Represents the mining blocks in the short-term plan and includes the planned dilution of the mining stope, as well as possible ore loss due to operational factors that may influence the mine design.

- Mining Actual (MA)—Represents the scanned topographic survey of the excavated mining area for the period, and the grade obtained for the excavated blocks by applying the Grade Control model.
- Delivered to Plant (DtP)—Represents the Run of Mine (ROM) of the Cuiabá Mine delivered to the plant. Tonnage is measured using a fixed industrial weighing system, and grade is determined by the application of the Grade Control model.
- Plant Received (PR)—Represents the ROM excluding intraplant stockpiles, for which the grade is measured using an automatic cross-stream sampler, and the tonnage using a fixed scale, both at the plant feed point of entry.
- Plant Accounted (PA)—Represents the total tons processed by the plant, the metallic content corresponding to the gold produced, the gold inventoried in the process, and the gold destined for the tailings.
- Gold Produced (GP)—Gold produced at the end of the beneficiation process.

2.3. Random Errors of the Measurement Steps

The Theory of Sampling defines random errors as those associated with heterogeneities in the composition and distribution of the lot. Such errors cannot be eliminated, but they must be minimized by optimizing sampling protocols and guaranteeing that standard deviations are within acceptable limits. The random errors described in Gy's TOS are the Fundamental Sampling Error (FSE), the In Situ Nugget Effect (INE), the Grouping and Segregation Error (GSE), and the Heterogeneity Fluctuation Error (HFE).

- Fundamental Sampling Error (FSE)—This error is a function of constitutional heterogeneity, which refers to the compositional differences of the fragments when compared individually. Adhering to the definition of correct probabilistic selection, when randomly collecting a sample of mass M_s from a lot of mass M_L , a sampling error arises between the content of the selected sample and the real and unknown content of the lot. The relative variance of the sample content can be determined using Gy's Formula (1):

$$s^2_{FSE} = c f g l d^3 \left(\frac{1}{M_s} - \frac{1}{M_L} \right) \quad (1)$$

where s^2_{FSE} is the relative variance of the FSE, d is the nominal sieve size that retains 5% of the fragments (top size, d_{95}), and c , f , g , and l are, respectively, the mineralogical, shape, size distribution, and liberation factors, which are experimentally obtained or calculated.

- In Situ Nugget Effect (INE)—The TOS, originally developed for particulate materials, does not explicitly address the uncertainty associated with the selection of a given sample mass from in situ material obtained through channel sampling on the walls of ore drive galleries. Under these conditions, the main source of random error in the sampling process is attributed to the INE (S^2_{INE}), which is intrinsically related to the geological component of the deposit. This effect corresponds to the variance of the intrinsic heterogeneity of the material [10]. According to Pitard [8], for gold deposits, the variance of the INE can be estimated using the following Equation (2):

$$S^2_{INE} = \frac{0.8 d_{Au}^3}{a_L M_s} \quad (2)$$

where d_{Au} is defined as the sieve aperture that retains 5% of the gold particles or the equivalent of gold particles occurring in clusters, a_L is the lot grade, and M_s is the sample mass.

- Grouping and Segregation Error (GSE)—Knowing that in sampling protocols, samples are not generated from increments of individually selected fragments but from random groups of fragments, sample reproducibility also becomes sensitive to distributional heterogeneity. The GSE is a function of the variability added by this

segregation and grouping of the lot. Chierigati & Pitard [10] state that the greater the constitutional difference between the samples that make up the lot (composition, shape, size, density, etc.), the greater the possibility of segregation. One way to reduce this additional variance would be to add a greater number of increments to the sample. According to Pitard [7], the GSE will be less than or equal to the FSE if the sample is composed of at least 10 random increments.

- iv. **Heterogeneity Fluctuation Error (HFE)**—This error characterizes the one-dimensional heterogeneity of the lot, since industrial activities require sampling of continuous material flows, such as conveyor belts, slurry pipelines, or elongated piles. This error can be estimated using a time-based variogram, or chronovariogram. The HFE can be divided into three components: short-term or small-scale, long-term or large-scale (non-periodic), periodic heterogeneity or large-scale periodic, and its value is given by the sum of these components. Plotting the chronovariogram scale allows visualization of all components of the HFE, and its value reaches its maximum at the variogram sill, at which the samples no longer show correlation [7].

In addition to random errors associated with sampling, the nodes of the reconciliation chain that show grades from estimated block models incorporate a geostatistical random error component, related to the uncertainty of the estimated value at a position x_0 . Several methodologies can be used to quantify this variance. Among them, conditional simulations provide a more realistic spatial characterization of uncertainty, being particularly relevant in contexts of mineralization with a high nugget effect [15].

Sequential Gaussian Simulation (SGS) is a conditional simulation method based on a Gaussian distribution [16,17]. This method uses data transformed to a Gaussian distribution with zero mean and unitary variance (Gaussian anamorphosis), which are then used to simulate the spatial distribution of the variable of interest. SGS is applied to continuous and regionalized variables that follow a multivariate normal distribution [18], and generates N equiprobable realizations of the geological model, respecting the sampled data and the geostatistical characteristics of the deposit.

The workflow of SGS (Figure 3) follows the standard geostatistical framework described by Goovaerts [16], including data transformation to Gaussian space, variogram modeling, sequential simulation using kriging, and back-transformation of results. These simulations are then used to quantify the uncertainty associated with the estimate through statistical analysis of the variability between the different simulations, and can be obtained by Equation (3).

$$s^2(x_0) = \frac{1}{N-1} \sum_{j=1}^N [z_j(x_0) - \bar{z}(x_0)]^2 \quad (3)$$

where,

$z_j(x_0)$ is the value of the j th simulation at location x_0 ;

$\bar{z}(x_0)$ is the mean of the simulated values;

N is the number of simulations.

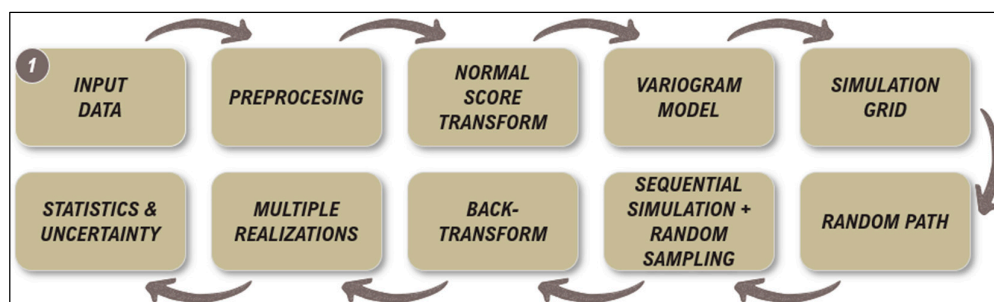


Figure 3. Workflow of SGS applied to the geological model.

In turn, the variance s_{SGS}^2 associated with the mean grade of a set of simulated blocks can be expressed by Equation (4), where s_i^2 is the variance among simulations for block i and n is the number of blocks included in the accumulated production volume.

$$s_{SGS}^2 = \frac{1}{n^2} \sum_{i=1}^n s_i^2 \quad (4)$$

3. Quality Management

Assay data are numerical values obtained from samples considered representative of their source and are essential inputs for various activities carried out by geoscience, mine planning, operations, and processing teams. Consequently, a significant portion of business decisions across the mining value chain relies directly on the quality of these data, which also underpin the metrics used to evaluate the “health of the mining value chain”, such as in Reconciliation. In this context, sample representativity is critical to ensure reliable interpretations and actions.

Dominguez [12] defines the concept of Quality Management and describes the key technical requirements for sampling and assay practices designed to proactively quantify and monitor the representativity and quality of the data generated.

The process adopts a pragmatic and operational approach, focusing on quantifying the quality of key areas within the process in which a sample becomes data (including sources of bias and variability) within a continuous improvement framework. Its main objectives are:

- (i) Ensuring that samples and assays are representative of the in situ material and guarantee the quality of the final assay data;
- (ii) Proactively monitoring and quantifying information quality;
- (iii) Identifying gaps and issues within sampling and analytical processes;
- (iv) Quantifying business risk (and/or opportunity cost) in terms of financial impact.

Thus, QM refers to the proactive and reliable detection of “anomalous trends” in results over time or within a given statistic, as well as the process of interpreting, communicating, and correcting such trends [12]. This approach is essential to ensure representativity and eliminate systematic errors associated with sampling stages throughout the mining process.

4. Materials and Methods

The methodology applied in this work includes three main pillars: (1) detailing the reconciliation chain adopted at the Cuiabá Mine; (2) defining actions and best practices for obtaining data with the greatest impact on the process and quality control; and (3) obtaining the variance of the main random errors at each stage of the proactive reconciliation system.

The production reconciliation process is a comparison between an estimate and a measurement, but resource and grade control models should not simply be evaluated based on the product. In fact, each stage of the operation must be examined sequentially for continuous evaluation, correction, and improvement of resource estimates, production plans, and operational processes of the mineral project. To achieve this, it was necessary to conduct a complete and detailed mapping of the entire production chain, identifying the main sources of discrepancies between the reconciliation stages and uncovering all the nodes already identified in the company’s guidelines.

Figure 4 shows a simplified map of the Cuiabá Mine’s operational processes. For each stage, tonnage and grade are obtained, either by measurement or estimation/accounting.

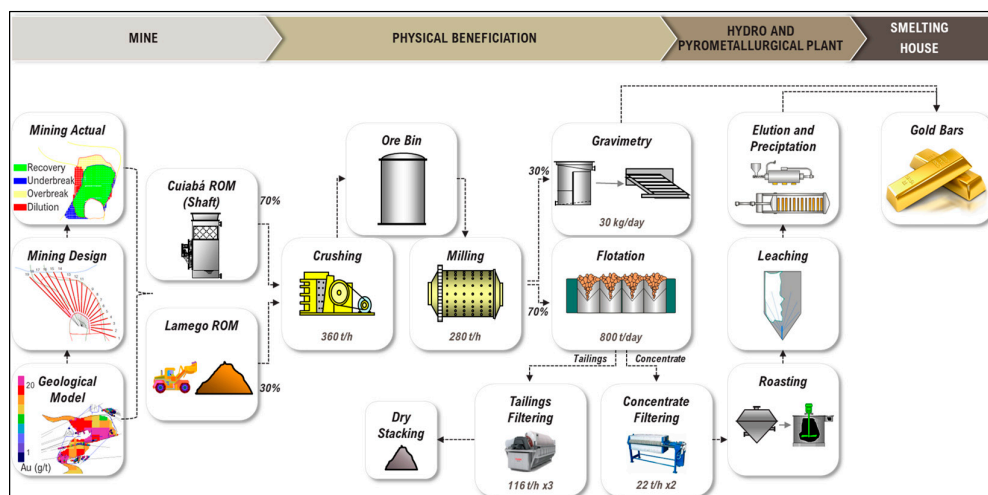


Figure 4. Simplified process map of the Cuiabá Mine's production.

Long-term models are built from a database containing rotary diamond drilling data processed by an implicit modeling software. Samples are generated from the collection of all material recovered from non-destructive drilling in the zone of interest. Short-term or grade control models include infill drilling and channel samples collected along the ore drive galleries.

The topographical scanner survey of the excavations provides the mining quality indicators of recovery, dilution, overbreak, and underbreak. The grades of the mining blocks can be obtained from the geological model, and the tonnage moved is estimated based on the average load and the number of trips per truck model. This mass is measured on a fixed industrial weighing system only when the material is hoisted via a shaft to the surface and delivered to the plant. The average moisture content of the material from routine measurements is set at 3%.

At the plant feed, the material is then weighed on a Siemens Milltronics MSI belt scale, and the grade is obtained from the sample generated by an automatic bottom dump cross-stream sampler with a cut every 15 min. Throughout the beneficiation process, there are two additional automatic material sampling points, which are linear cross-stream samplers at the flotation circuit feed and at the flotation tailings. All products generated at the three primary sampling points pass through a Vezin-type secondary sampler.

At the end of all data collection steps, the following can be measured:

- The effectiveness of the long-term modeling and estimation compared to the grade control model;
- The selectivity and sustainability of the production plan;
- The efficiency of the ore extraction process;
- The difference between the estimated and predicted grades and tons compared to those measured at the plant;
- The efficiency of the processing plant.

To obtain the random errors of the measurement steps, FSE, INE, GSE, and HFE must be measured, in addition to the estimated variance by SGS, which corresponds to the random component of the estimated errors.

4.1. Standard Heterogeneity Test

The FSE is generated at each sampling stage and can be measured by running the Standard Heterogeneity Test (HT). This test calibrates the intrinsic heterogeneity parameters of the ore described in Gy's formula to obtain the error variance (s_{FSE}^2). It was

conducted in 2021 by an external consultancy company, MinPro Solutions [19], for a representative mass of approximately 500 kg of ore fed to the Cuiabá Plant, according to the following protocol:

- i. Selection of a representative sample of the ore fed to the plant;
- ii. Drying, crushing, and screening of all material into four size fractions;
- iii. Division of the mass of each particle size fraction into two parts (one for the HT and one for the SSFA) using a riffle splitter;
- iv. Spreading one part of each particle size fraction over the test cells (Figure 5);
- v. Selection, for each particle size fraction, of 50 groups of at least 50 fragments each, collected one by one randomly;
- vi. Chemical analysis of the 200 (4×50) samples generated;
- vii. Determination of the masses and contents of each group of fragments;
- viii. Calculation of the average masses and the weighted average contents;
- ix. Calculation of the estimated intrinsic heterogeneity of the lot (IH_L) for each particle size fraction.



Figure 5. Material from the $-12.7 + 6.35$ mm fraction spread for the HT. Source: AGA Internal Report [19].

For further details and theoretical basis on the HT, it is recommended to read Pitard [7,20].

4.2. Simplified Segregation-Free Analysis

Another way to calibrate the constants of Gy's formula is the experiment known as Simplified Segregation-Free Analysis (SSFA), proposed by Chieragati et al. [21], or Duplicate Series Analysis (DSA), proposed by François-Bongarçon [22]. Pitard and François-Bongarçon [23] state that DSA results reflect the sum of the FSE and the GSE. The reader is advised to consult the referenced literature for more detailed information.

The 250 kg of material selected for testing was half of that sent for the HT. The SSFA was performed according to the following protocol:

- i. Selection of a representative sample of the ore fed to the plant;
- ii. Drying, crushing, and screening of all material into five size fractions;
- iii. Division, using a riffle splitter, of each particle size fraction into two parts, one for the HT and one for the SSFA;
- iv. Division, using a riffle splitter, of one part of each size fraction into 32 subsamples of approximately equal mass;
- v. Chemical analysis of the 160 (5×32) samples generated.

4.3. Variographic Test of the Plant Feed

The HFE is generated by collecting sample increments along a conveyor belt at defined time intervals. This error characterizes the one-dimensional heterogeneity of particulate material flows and can be defined as the difference between the actual lot content and the content of samples collected at a given time interval [24]. The HFE can be determined from a variographic test, where the experimental variogram function is defined from Equation (5), which determines the difference in grades as a function of time between two points located on an axis.

$$v(j) = \frac{1}{2N} \sum_q (t_{q+j} - t_q)^2 \quad (5)$$

where j is the time interval separating two increments, $v(j)$ is the variogram function for time interval j , t_q is the grade of increment q , and t_{q+j} is the grade of the increment separated by j from increment q . Note that there are several pairs of values separated by time j , and N represents the number of such pairs.

The variance of the HFE can be defined from Equation (6), which represents the variance obtained from the point-by-point calculation of the auxiliary functions and the error generation function (W_i) as a function of the total number of increments (Q) collected for a given time interval (i):

$$s_{HFE}^2 = \frac{W(i)}{Q} \quad (6)$$

The variographic test was conducted by MinPro Solutions [25], collecting 50 sequential samples. For each of the 50 samples generated in the variographic campaign, two gold grade determinations were performed by fire assay.

4.4. Variance Estimation by Sequential Gaussian Simulation

SGS is a stochastic method that generates multiple equiprobable realizations of a spatial variable, preserving its statistical distribution and spatial continuity. The variability among realizations is used to quantify the uncertainty of grade estimates.

To obtain the variance estimate data using SGS, 100 equiprobable simulations were performed on $5 \times 5 \times 5$ m blocks using a database with over 60,000 entries, whose geological model was constructed based on implicit modeling of the host rock's grade shell. The simulations were performed using the same variogram model and parameters adopted in the resource estimation model, ensuring consistency between the estimation and simulation frameworks. A convergence analysis was performed to evaluate the stability of the estimation variance (s_{SGS}^2) as a function of the number of realizations.

Uncertainty quantification followed AGA's resource classification guidelines, in which the definition of the resource category is conditioned by the uncertainty associated with the average grade of a representative mass corresponding to three months of production. Considering a stationary data domain, the variance estimate was calculated based on the ROM excavated from stopes at the Cuiabá Mine, accumulating the simulated volumes until the average monthly production tonnage was reached.

5. Results

5.1. Standard Heterogeneity Test and Simplified Segregation-Free Analysis

The 360 samples generated by the two tests, 200 in the Standard Heterogeneity Test and 160 in the Simplified Segregation-Free Analysis, were prepared and analyzed by AGA's internal laboratory. The graph in Figure 6 shows the correlation between the estimated intrinsic heterogeneity of the lot (IH_L) and the nominal fragment size, using the HT results.

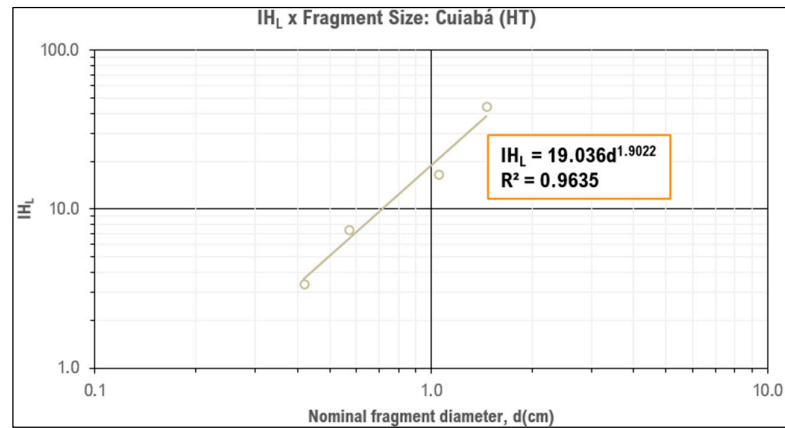


Figure 6. Correlation between IHL and fragment size for the HT. Source: AGA Internal Report [19].

The graph in Figure 7 shows the correlation between the estimated intrinsic heterogeneity of the lot (IHL) and the nominal fragment size, constructed from the SSFA results.

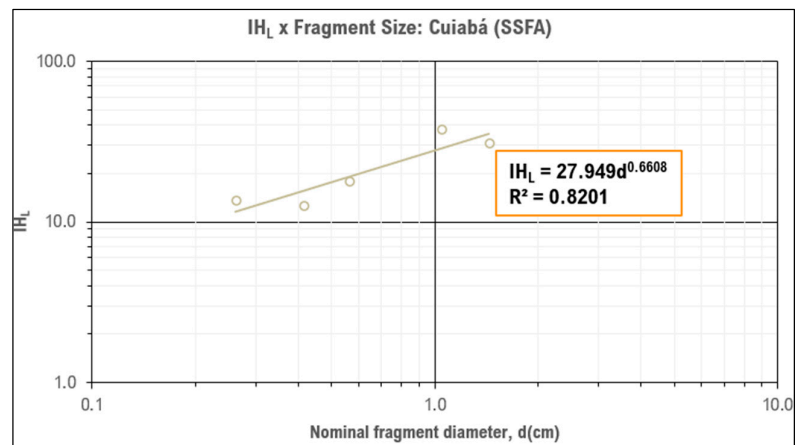


Figure 7. Correlation between IHL and fragment size for the SSFA, excluding outliers. Source: AGA Internal Report [19].

These tests calibrate the intrinsic heterogeneity parameters of the ore, K and α , where $K = c f g l$ and α is the calibrated power of the maximum fragment diameter d (equal to 3 in Gy's formula), thus, $IHL = K d^\alpha$. It can be observed from the regression line equations that the heterogeneity parameter K calibrated by the HT was smaller than that calibrated by the SSFA. This was expected, since the SSFA includes the GSE in its results. On the other hand, the heterogeneity parameter α calibrated by the HT was larger than that calibrated by the SSFA. The generated heterogeneity parameter values can be used to calculate the FSE and the GSE in the case of SSFA, at each stage of the sampling protocols for the reconciliation chain phases.

5.1.1. Error Calculation Associated with the Grade Control Sample Preparation Protocol

The Cuiabá Mine's grade control models have a sampling support consisting of 15×15 m diamond core drill holes and 1 m-long samples in a channel, collected every 4 m along the production development gallery. Since channel samples have the highest FSE and INE in the model construction stage (due to their larger particle size), their protocol was considered for calculating the FSE and INE. The channel samples are prepared according to the following protocol:

1. Collection of approximately 3.0 kg of primary sample with a diameter of about 5 cm;
2. Receiving and drying the sample, with an approximate mass of 3 kg;
3. Crushing the entire sample to 95% passing 2.00 mm;
4. Splitting in the Rocklabs combo (crusher and rotary splitter) to an approximate mass of 300 g;
5. Pulverizing the 300 g sample to 95% passing 200#;
6. Selecting a 30 g analytical sample for fire assay.

Figure 8 shows the channel sample preparation protocol.

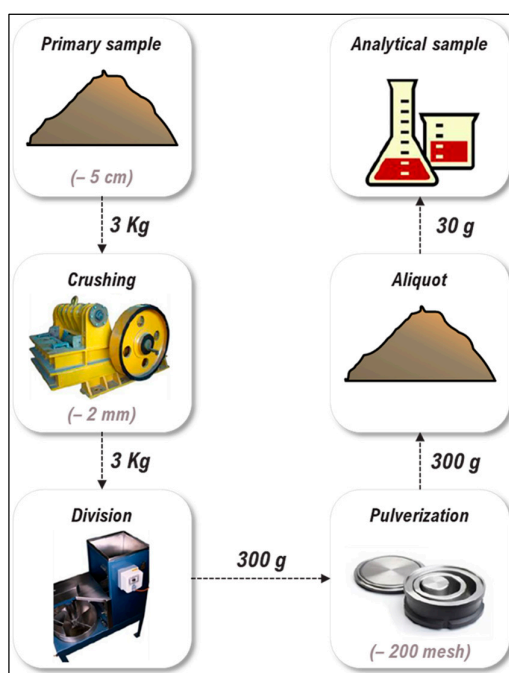


Figure 8. Channel sample preparation protocol.

Based on the heterogeneity parameters calibrated by the HT and SSFA tests, Tables 2 and 3 present the calculations of the relative variance of the FSE (s^2_{FSE}) for the channel sample preparation protocol.

Table 2. Variance and standard deviation of the FSE for the channel sampling protocol according to the HT.

Stage		Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1.	Crushing	3000	3000	0.2000	0.89	0.000000	0.00%
2.	Division	3000	300	0.2000	0.89	0.002674	5.17%
3.	Pulverization	300	300	0.0074	0.00	0.000000	0.00%
4.	Selection of analytical sample	300	30	0.0074	0.00	0.000051	0.71%
Total s^2_{FSE}		-	-	-	-	0.002724	5.22%

Table 3. Variance and standard deviation of the FSE for the channel sampling protocol according to the SSFA.

Stage		Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1.	Crushing	3000	3000	0.2000	9.65	0.000000	0.00%
2.	Division	3000	300	0.2000	9.65	0.028947	17.01%

3.	Pulverization	300	300	0.0074	1.09	0.000000	0.00%
4.	Selection of analytical sample	300	30	0.0074	1.09	0.032770	18.10%
Total s^2_{FSE}		-	-	-	-	0.061717	24.84%

The first stage of the channel sampling process in underground galleries corresponds to the collection of the primary (in situ) sample. At this stage, the INE is introduced, representing the variability associated with the intrinsic heterogeneity of the material at the sampling location. Based on the granulometric characterization of gold from the Cuiabá deposit, as well as the average lot grade and the collected sample mass, it is possible to estimate the variance of the INE (s^2_{INE}) associated with this stage of the process.

The gold particles from the Cuiabá Mine are classified as very fine, based on the 2023 Gold Department analysis and according to the semi-quantitative classification scale based on AMIRA's project P420B. For this deposit, the sieve aperture retaining 5% of the gold particles is approximately 40 μm . Considering a sampled mass of 3.0 kg and an average grade of 3.67 g/t for the samples collected for the HT, Equation (2) allows the determination of the relative variance and the relative standard deviation associated with the INE, assuming negligible values.

5.1.2. Error Calculation Associated with the Feed Grade Sample Preparation

The plant feed samples from the Cuiabá Mine processing plant are prepared according to the following protocol:

1. Receiving and drying the sample, with an approximate mass of 25 kg;
2. Mass reduction using a riffle splitter to approximately 18 kg;
3. Crushing the entire sample to 95% passing 2.00 mm;
4. Splitting in the Rocklabs combo (crusher and rotary splitter) to an approximate mass of 700 g;
5. Pulverizing the 700 g sample to 95% passing 200#;
6. Screening at 200#;
7. Assay to extinction of the gold in the retained fraction;
8. Selecting three 30 g determinations for chemical analysis by fire assay for the passing fraction.

Figure 9 presents the plant feed sampling protocol.

Based on the heterogeneity parameters calibrated by the HT and SSFA tests, Tables 4 and 5 present the calculations of the relative variance of the FSE (s^2_{FSE}) for the feed grade sample preparation protocol.

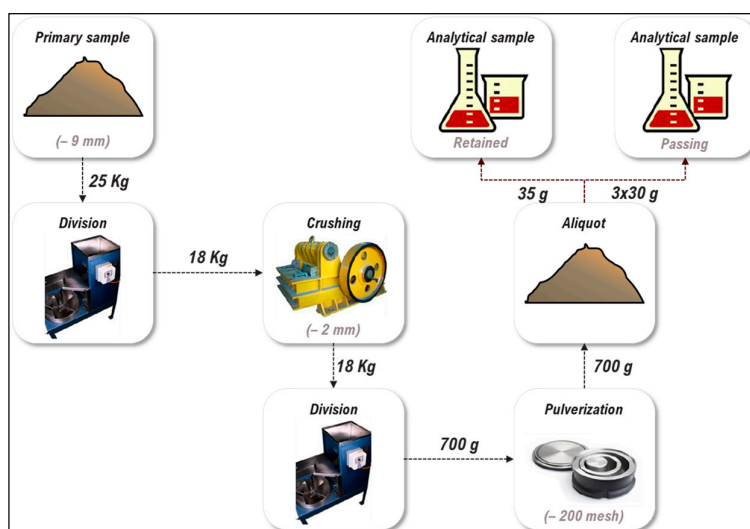


Figure 9. Sample preparation protocol for the plant feed samples.

Table 4. Variance and standard deviation of the FSE for the plant feed sampling protocol according to the HT.

Stage	Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1. Primary sampling	2,000,000,000	25,000	0.9000	15.58	0.000623	2.50%
2. Division	25,000	18,000	0.9000	15.58	0.000242	1.56%
3. Crushing	18,000	18,000	0.2000	0.89	0.000000	0.00%
4. Division	18,000	700	0.2000	0.89	0.001224	3.50%
5. Pulverization	700	700	0.0074	0.00	0.000000	0.00%
6. Extinction of the retained fraction	35	35	0.0074	0.00	0.000000	0.00%
7. Selection of analytical sample	665	30	0.0074	0.00	0.000054	0.73%
Total s^2_{FSE}	-	-	-	-	0.002143	4.63%

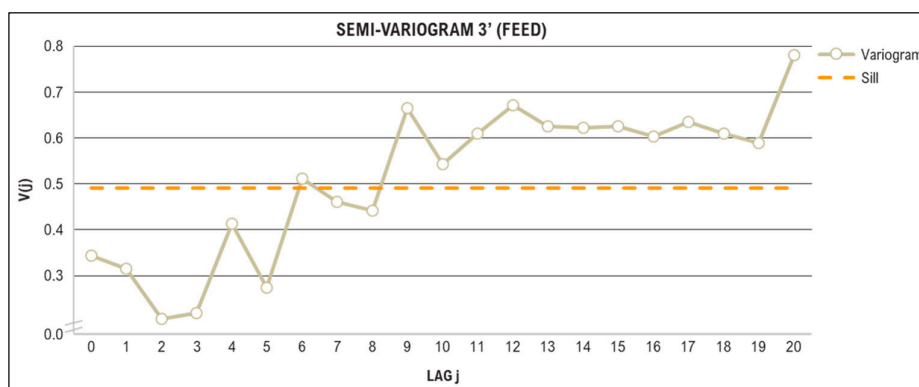
Table 5. Variance and standard deviation of the FSE for the plant feed sampling protocol according to the SSFA.

Stage	Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1. Primary sampling	2,000,000,000	25,000	0.9000	26.07	0.001043	3.23%
2. Division	25,000	18,000	0.9000	26.07	0.000406	2.01%
3. Crushing	18,000	18,000	0.2000	9.65	0.000000	0.00%
4. Division	18,000	700	0.2000	9.65	0.013248	11.51%
5. Pulverization	700	700	0.0074	1.09	0.000000	0.00%
6. Extinction of the retained fraction	35	35	0.0074	1.09	0.000000	0.00%
7. Selection of analytical sample	665	30	0.0074	1.09	0.034768	18.65%
Total s^2_{FSE}	-	-	-	-	0.049465	22.24%

5.2. Variographic Test

The 50 samples collected sequentially from the mill feed conveyor belt were analyzed in AGA's internal laboratory. The calculation of the variograms was based on the results of the averages of the two gold assay determinations for each sample, and the experimental variograms can be observed in Figure 10.

Table 6 shows the results of the calculations of the HFE variances for the 3-min cut intervals, considering different time intervals j , where $v(j)$ is the variogram function for the time interval j , s_{HFE} is the standard deviation of the error, and $s_{HFE(68\%)}$ represents the 68% confidence interval, assuming that the errors follow a normal distribution.

**Figure 10.** Experimental variogram of the mill feed for a 3-min interval. Source: AGA Internal Report [25].

Considering that the sampling interval of the mill feed for Cuiabá Mine production is 15 min, the variographic analysis indicates a variance of the HFE of 0.01078 and a relative standard deviation of 2.96%, considering the variogram for a 3-min sampling interval.

Table 6. Variance of the HFE of the mill feed for a 3-min cut interval. Source: AGA Internal Report [25].

Lag j	Time	v(j)	Q	S ² HFE	SHFE	SFSE(68%)
0	00:00:00	0.343	-	-	-	-
1	00:03:00	0.315	29	0.01181	0.1087	3.11%
2	00:06:00	0.206	28	0.01235	0.1111	3.16%
3	00:09:00	0.218	27	0.01248	0.1117	3.16%
4	00:12:00	0.412	26	0.01170	0.1082	3.06%
5	00:15:00	0.273	25	0.01078	0.1038	2.96%
6	00:18:00	0.511	24	0.01016	0.1008	2.86%
7	00:21:00	0.460	23	0.01023	0.1011	2.91%
8	00:24:00	0.441	22	0.01133	0.1065	3.06%
9	00:27:00	0.665	21	0.01240	0.1114	3.16%
10	00:30:00	0.542	20	0.01259	0.1122	3.21%
11	00:33:00	0.609	19	0.01300	0.1140	3.27%
12	00:36:00	0.670	18	0.01448	0.1203	3.42%
13	00:39:00	0.624	17	0.01633	0.1278	3.62%
14	00:42:00	0.621	16	0.01796	0.1340	3.83%
15	00:45:00	0.625	15	0.01951	0.1397	3.98%
16	00:48:00	0.602	14	0.02110	0.1453	4.13%
17	00:51:00	0.634	13	0.02335	0.1528	4.34%
18	00:54:00	0.609	12	0.02691	0.1640	4.69%
19	00:57:00	0.589	11	0.03115	0.1765	5.05%
20	01:00:00	0.780	10	0.03538	0.1881	5.36%

5.3. Estimation Variance by Sequential Gaussian Simulation

The SGS was applied to preserve both the statistical properties of the input data and the spatial structure defined by the variogram model, as it enables the quantification of estimation uncertainty not only at the block scale, but also over larger volumes or production domains. To ensure data representativeness, the SGS interpolation variance was determined based on the accumulated mass corresponding to one month of production at the Cuiabá Mine, with the reported value obtained as the mean of the variances from all monthly production periods since 2021. Figure 11 presents the simulated model for the Fonte Grande Sul (FGS) and Serrotonho (SER) orebodies, along with the statistics of the generated data.

Based on the proposed data, the grade control geological model indicates a mean gold grade (m) of 11.94 g/t for the resource, with an absolute estimation variance $s^2_{SGS} = 0.4800$ and an absolute standard deviation of $s_{SGS} = 0.6928$. The relative standard deviation for the dataset can be defined according to Equation (7).

$$s_{SGS\ Rel} = \frac{s_{SGS}}{m} \quad (7)$$

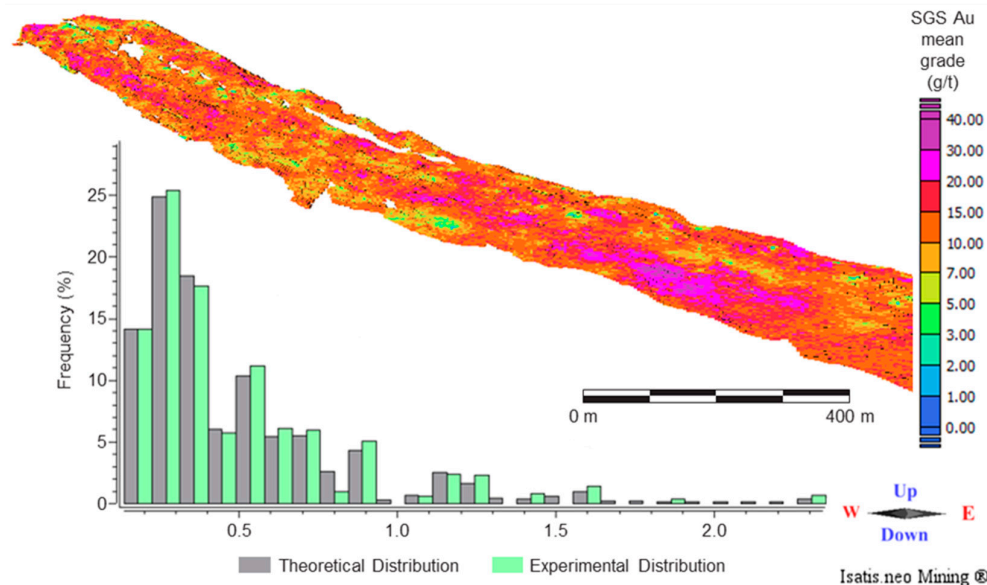


Figure 11. Mean of 100 SGS for FGS and SER orebodies and comparative histogram.

5.4. Identification of Random Error for the Cuiabá Mine Reconciliation Chain

The practice of proactive reconciliation, beyond detailing and identifying inefficiencies throughout the production process, seeks to validate resource model estimates by comparing the grades delivered to the plant with those sampled at the plant feed.

It is known that the quality of reconciliation results depends on the reliability of the input data, that is, the estimated and measured values at each stage of the process. All these measurements contain associated errors, whether random or systematic. Whenever possible, such errors should be eliminated or minimized [26]. Assuming an ideal condition in which all systematic errors have been eliminated in the reconciliation chain, and the data are therefore unbiased, it is possible to quantify the random errors at each reconciliation node, as illustrated in Figure 12.

According to Pitard [27], random errors generated at different points in a multi-stage process should be treated as statistically independent. This statistical independence allows the individual variances of the random errors to be summed to obtain the total variance of the process.

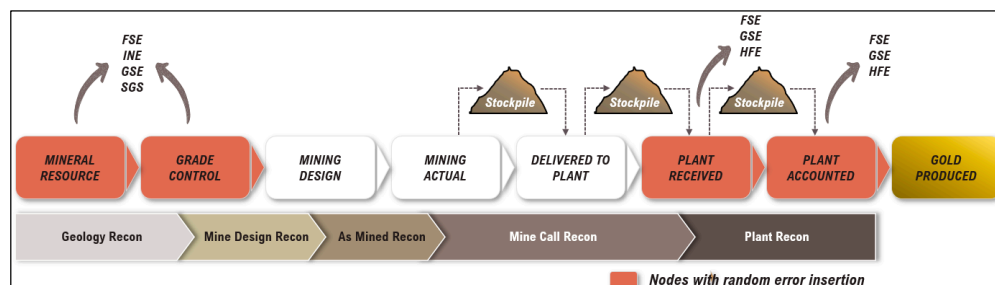


Figure 12. Reconciliation chain from Cuiabá Mine and random errors in each node.

For the stages involving sampling and geological modeling processes, the random errors are the Fundamental Sampling Error, the In Situ Nugget Effect, the Grouping and Segregation Error, and the Sequential Gaussian Simulation. Considering that the number of increments in the sampling processes for these stages exceeds 10, the GSE can be disregarded [7].

The FSE associated with the channel sampling protocol was considered, since the larger particle fragment sizes collected in this process result in the highest FSE among all sampling stages used in constructing the geological model. The uncertainty of the FSE estimated for a channel sample corresponding to a development ore drive blast is $_{SFSE} = 24.84\%$. Furthermore, the relative standard deviation corresponding to the uncertainty associated with the SGS is $_{SSGS} = 5.80\%$. Considering that the gold grain size is very fine and the mass collected in the primary sample is about 3 kg, the INE can be disregarded.

In the sampling stages of the processing plant, and assuming the Increment Weighting Error (IWE) is negligible [27], the relevant random errors are the FSE, the GSE, and the HFE. Considering that the SSFA test captures the combined effects of FSE and GSE, the relative standard deviation associated with the uncertainty of these errors for the plant feed samples is $_{SFSE} = 22.24\%$. In turn, the relative standard deviation associated with the HFE, obtained from the variographic test, is $_{SHFE} = 2.96\%$.

6. Discussion

A robust and well-structured proactive reconciliation chain is essential for understanding the mine production process. Detailing each stage, with a methodological description of data acquisition, allows for the definition of actions to improve the quality of information and identify potential sources of errors.

Based on the tests conducted for the Cuiabá ore, it was possible to measure the random errors associated with the sampling process, as well as the error associated with the geological model estimation process.

The magnitude of the sampling-related uncertainties observed in this study is consistent with previous findings reported in the literature. Studies based on Pierre Gy's Theory of Sampling [21,27] have demonstrated that coarse particle size and insufficient sample mass are the main contributors to elevated FSE, as also observed in the channel sampling protocols analyzed here.

Similarly, the estimation uncertainty obtained through SGS aligns with results from applied geostatistical studies, which indicate that uncertainty at the production scale is typically lower than sampling-induced variability [15,16]. This behavior reinforces the importance of prioritizing sampling optimization over model refinement in improving reconciliation performance.

Regarding the heterogeneity tests, the sampling constants, K and α , showed different calibrated values in both tests, which was expected, as the SSFA includes a portion of the GSE in its results.

The sampling and sample preparation protocols were evaluated based on the calculation of the relative standard deviation of the FSE and presented values higher than the maximum deviations recommended by Pitard [28]. Following Pitard's recommendations and considering the SSFA results for channel sampling, it is recommended to pulverize 650 g of the sample and send 140 g for Fire Assay analysis. The optimized protocol would reduce the total relative standard deviation of the FSE to 13.32%, as shown in Table 7. In turn, for plant feed sampling, it is recommended to pulverize 800 g of material and send 140 g for the Screen Fire Assay. In this scenario, the optimized protocol would reduce the total relative standard deviation of the FSE to 13.91%, as shown in Table 8.

Table 7. Variance and standard deviation of the FSE for the channel sampling optimized protocol according to the SSFA.

Stage		Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1.	Crushing	3000	3000	0.2000	9.65	0.000000	0.00%
2.	Division	3000	650	0.2000	9.65	0.011628	10.78%
3.	Pulverization	650	650	0.0074	1.09	0.000000	0.00%
4.	Selection of analytical sample	650	140	0.0074	1.09	0.006122	7.82%
Total s^2_{FSE}		-	-	-	-	0.017750	13.32%

Table 8. Variance and standard deviation of the FSE for the plant feed sampling optimized protocol according to the SSFA.

Stage		Initial Mass (g)	Final Mass (g)	d (cm)	IHL	Rel Val (s^2_{FSE})	Rel Dev (s_{FSE})
1.	Primary sampling	2,000,000,000	25,000	0.9000	26.07	0.001043	3.23%
2.	Division	25,000	18,000	0.9000	26.07	0.000406	2.01%
3.	Crushing	18,000	18,000	0.2000	9.65	0.000000	0.00%
4.	Division	18,000	800	0.2000	9.65	0.011525	10.74%
5.	Pulverization	800	800	0.0074	1.09	0.000000	0.00%
6.	Extinction of the retained fraction	40	40	0.0074	1.09	0.000000	0.00%
7.	Selection of analytical sample	760	140	0.0074	1.09	0.006365	7.98%
Total s^2_{FSE}		-	-	-	-	0.019339	13.91%

Due to the one-dimensional heterogeneity of the plant feed, the variographic analysis indicated a relative standard deviation of the HFE associated with the current cut interval for mill feed sampling—15 min—of 2.96%. It is not recommended to decrease the current cut interval of the primary plant feed sampler, as the standard deviation of the HFE would not decrease substantially.

The Estimation Variance parameter s^2_{SGS} for the geological model in the block mined per month over the last 36 months of production indicated a relative standard deviation of 5.80%, demonstrating low uncertainty in the data estimation and, consequently, high reliability of the geological model.

7. Conclusions

By continuously monitoring sources of bias and variability, Quality Management is essential for ensuring sample representativity and mitigating systematic errors throughout the data-generation process. Disregarding systematic errors and considering only the random errors involved in the process, this study detailed the proactive reconciliation system at the Cuiabá Mine, identifying the MR and GC as the lowest-quality nodes due to higher FSE and SGS error, and quantifying the standard deviation of the principal random errors in certain stages of the production chain. Through uncertainty identification, the variance at certain steps of the reconciliation process was estimated.

Considering that channel sampling errors (FSE) and estimation uncertainty derived from Sequential Gaussian Simulation are independent and unbiased, their variances can be summed provided they refer to the same decision support. The FSE associated with individual channel samples (24.84%) was scaled to a monthly production period, resulting in a relative standard deviation of 0.64%. The SGS-derived uncertainty for the same production period corresponds to a relative standard deviation of 5.80%. The combined relative uncertainty for the RM and GC nodes is therefore obtained by summing variances, resulting in a total relative standard deviation of approximately 5.83%.

The errors determined from the feed conveyor belt samples used in the variographic and SSFA tests correspond to a single production shift, equivalent to approximately 2 kt

of material. When this uncertainty is scaled up to the monthly production period of roughly 150 kt, the resulting relative standard deviations for the FSE and HFE decrease to $_{SFSE} = 2.57\%$ and $_{SHFE} = 0.34\%$, respectively. Assuming statistical independence between these error components, the sum of their variances yields a combined relative standard deviation of approximately 2.59%.

Optimizing channel and plant-feed sampling protocols can reduce the total relative uncertainty, improving the reliability of the reconciliation process throughout the production chain.

This study contributes theoretically by integrating sampling theory and geostatistical uncertainty within a unified reconciliation framework. From a practical perspective, it provides a methodology to quantify and prioritize sources of variability along the mining production chain, supporting decision-making and process optimization in mining operations.

This study is limited by the assumption of statistical independence between error components and by the application to a single mining operation. In addition, systematic errors were not explicitly quantified, as the focus was on random error components. Future research should focus on integrating systematic errors into reconciliation frameworks, extending the methodology to different types of deposits, and evaluating the economic impact of reducing uncertainty across the production chain.

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