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The use of equant grain particles to validate analytical sample size in gold deposits – A case study

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ABSTRACT

The quest to sample and quantify a gold deposit depends on the ability to collect a representative sample and then maintain the lot's constitution throughout all sampling steps. Differences in ore type, grade, gold size, distribution, liberation and association are some variables which implies differences in procedures from one deposit to another. In a low-grade nugget environment, the final analysis depends more on the chance occurrence of a particle in the analytical aliquot rather than the actual concentration in the ore. A commonly used 30 g fire assay could result in bad exploration decisions and create a highly skewed database. The concept of equant grains simplifies particle size and distribution, and works with a uniform particle that represents the total content divided by the number of grains necessary to attain a certain precision. In this paper, we test this hypothesis in which 20 and 10 equant grains are used to simulate the grade values of six different analytical samples sizes, representing the smoky quartz of Lamego Mine. The results confirm that a 30 g final aliquot does not represent the rock and a 500 or 1000 g analytical sample is required to be assayed.

1. Introduction

Lode-gold deposits are known for having a strongly skewed grade distribution and a high nugget effect [1]. The nature of these deposits reflects the unique settings for the origin of a rich fluid, precipitation or remobilization [2]. Beyond the intrinsic complexity, gold sampling introduces new sources of variance, which can create misunderstanding and misinterpretation of the data [3].

By definition, a sample should represent the batch composition as closely as possible, by maintaining a constant ratio of the particles of interest in the parent throughout the entire sampling and sub-sampling process [4]. This task becomes challenging when the content of the mineral of interest drops under 1%, as is the case for gold.

A Poisson distribution is a limiting case for a binomial distribution, where the constituent of interest resides in low-frequency grains [5]. Its probability function can be described as:

$$P_n = \frac{e^{-Z} \cdot Z^n}{n!} \tag{1}$$

where Z is the average number of grains in a w-gram sample and P_n is the probability that n grains will appear in the sample. For a lot of known constitution, where in every 1000 g ($w = 1000\ g$) is one grain of interest, $Z = 1$. However, for the same lot, if $w = 250\ g$, $Z = 250/1000 = 0.25$. The probability value is rooted in the ability to represent the lot in the final stage of sampling. A shift from a Poisson to normal distribution is possible by increasing the number of gold particles to at least six in the sample. This is often implemented by using a larger analyte mass [3,6].

A larger analyte mass, collected using good sampling practices, improves probabilities of occurrence of particles and reduces variability. The limiting case is where everything is sampled and the unknown value is defined, as shown in Fig. 1.

For each sample, not only does the mass have an impact on grade variability, so does a series of other sampling errors, first discussed by Pierre Gy [4]. It is advisable to understand the mitigation of these errors and definition of optimum sample mass, which are beyond the scope of this paper. Papers by Gy [4], Pitard [7] and François-Bongarçon [8], are some literature in which the reader is referred for additional information.

Gold can be found in different sizes, forms and association through nature. A specific and challenging type of gold deposit is with free nuggetty gold. As noted by Pitard [7], any free gold deposit can be divided into two categories: a low grade, also called background, where gold is ultra-fine and sub-microscopic, and a high grade, associated with coarser grains, which accounts for most of the metal content. On this setting,

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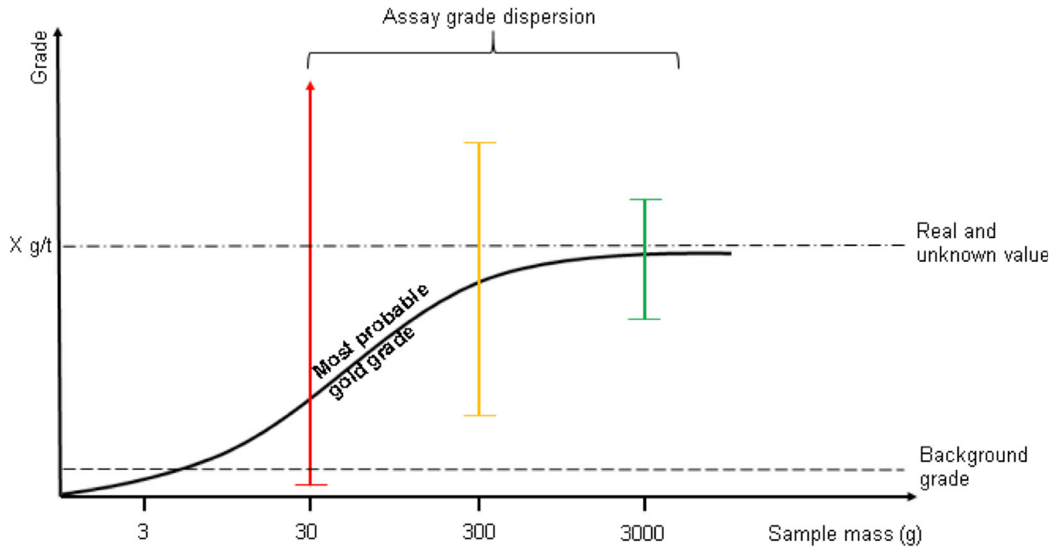


Font – modified Pitard [3]

Fig. 1. Grade distribution and most probable grade based on analytical mass.

studies based on Gy's Sampling Theory will focus on this coarser fraction. In addition, the controversy liberation factor is calculated disregarding the fine fraction of gold [7].

1.1. Equant grains

The concept of 'equant grains' is broadly used to correlate skewed data to nugget effects and sampling error [5,6,9]. Its use is effective to provide guidelines for sampling, although several important assumptions are made to simplify calculations. These assumption take part on interpretation, therefore they will be thoroughly explained for the reader's complete understanding.

The first assumption is that gold variability is random with no systematic variation across the ore body. This ideal is unreal to a certain extent, since gold is concentrated in specific geological features (distinct layers, hinge zones of folds, veins or faults). By dividing the deposit or domaining it in similar styles or mineralizations, this risk could be reduced [9].

Second, the sample is treated as a binary composition of two mineral, gold and gangue. Gold can be found associated or in contact with many minerals and rarely it would be in a setting with only one gangue mineral. Sulphides, silicates, micas and carbonates are a few common ones, with a diverse spectrum of specific gravity and concentrations [10]. A realistic assumption is to use a composition of gold and the most abundant gangue mineral, quartz.

Third, gold particles are assumed to be of uniform mass, not necessarily the same shape and gangue minerals have uniform mass, but not the same as gold particles. This ground rule cascade through different steps: definition of precision of the assays, directly associated with the number of particles; sample weight requirement to guarantee the defined number of particles; and estimation of the equant grain size [9].

The statistical analysis is simplified by a couple assumptions. If the number of particles in the sample is greater than 10^3 (i.e. a lot of 1000 particles of quartz with 800 μm in diameter, yields approximately 0.7 g) and deposit's grade is below 0.001, as usual for gold deposits, the following equation based on a binomial distribution can be resumed to:

$$E_C^{\pm} = X^{-1/2}\left[\frac{Z_{1-1/2\alpha}^2}{2}\cdot X^{-1/2} \pm Z_{1-1/2\alpha}\right] \quad (2)$$

Where E_C^- and E_C^+ are the negative and positive errors at a confidence limit, $-Z_{1-1/2\alpha}$ and $+Z_{1-1/2\alpha}$, which are read from a table of cumulative normal distribution and X is the number of gold particles. Being the expected relative error`at a given percent confidence a function of only one variable, the number of gold particles in a sample, independent of grade. As the example given by Clifton [9], for 20 particles in the sample, with a 95% confidence level, the expected relative errors are:

$$E_{95}^- = 20^{-1/2}\left[1.921\cdot 20^{-1/2} - 1.960\right] = -0.34 \quad (3)$$

$$E_{95}^+ = 20^{-1/2}\left[1.921\cdot 20^{-1/2} + 1.960\right] = 0.54 \quad (4)$$

As noted, a higher precision will require more gold grains in the sample. Based on the number of gold particles, the following step is to determine the mass in which is more likely to contain it.

The number of gold particles per weight depends on the grade, grain size and its size distribution. The later is a source of error, especially because gold particles are not restricted to a narrow range of size. This issue is diminished by assuming that gold particles have uniform mass larger than the average mass per gold particle in the sample. By definition, average mass per gold particle means the total mass of gold in the sample divided by the number of gold particles on it [9].

On Fig. 2, the relationship between gold grain size and distribution is highlighted using an example of four different hypothetical deposits yielding the same grade.

After all simplifications and assumptions, the equant grain size will be chosen from the total mass of gold in the sample, a direct correlation between sample mass and average grade, and the number of gold particles necessary for the required precision. For example, a sample with one kilogram and gold grade of 7.18 g/t, has a total gold mass of 0.00718 grams. This gold mass can be represented by a diverse range of particle sizes related to the required precision (Table 1).

The equant grain approach, assuming that gold is in a unique size as large or larger than the coarsest, and the sum of all particles yields the total gold content in the sample, can be used as a safe guide to obtain adequate sample size and a representative sample [9]. Thus, it allows one to test the effects of nuggets in final aliquots of diverse masses.

The foundation of the equant grains approach relies on a binomial distribution, where the number of gold particles is more than 5 ($Z = 5$). Since this fact is directly associated with sample mass, it cannot represent low mass samples where there is not enough particles, especially low-grade deposits with coarse grains. However, based on a deposit's historical data, average grade and particle characteristics, one could

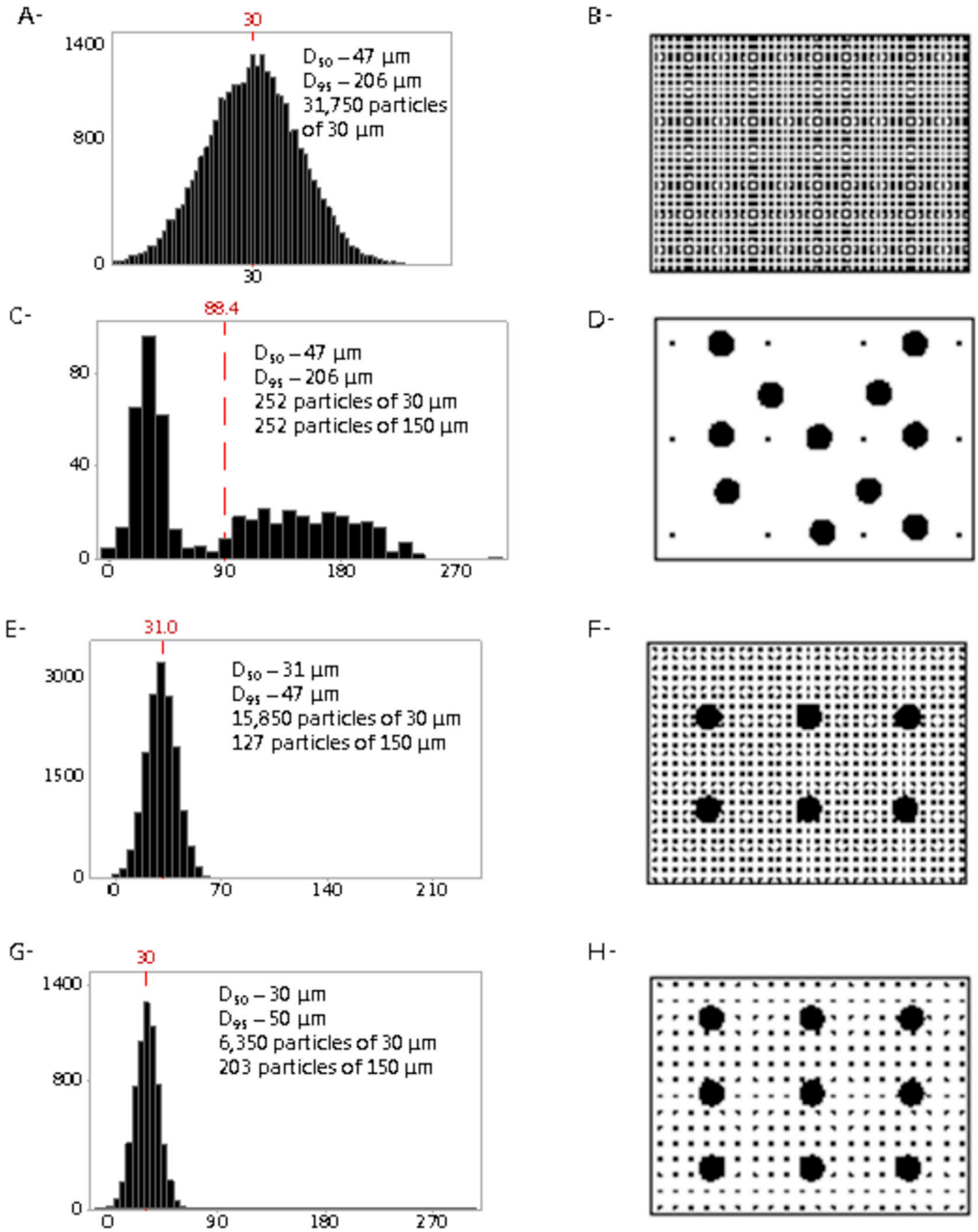


Fig. 2. Comparison between one kilogram samples in different types of gold deposits with the same average grade. A- Fine particle distribution, 30 μm with 10 μm standard deviation; B— graphical representation of A, each dot is a gold particle in the sample; C— half of the particles are fine and the other half is medium, 150 μm with 45 μm standard deviation; D-graphical representation of C, small dots are 30 μm, large dots are 150 μm; E–half of the grade comes from fine particles and the other half comes from medium particles; F— representation of E, small dots are 30 μm, large dots are 150 μm; G- 80% of the grade comes from medium particles, and 20% from fine particles; H— representation of G, small dots are 30 μm, large dots are 150 μm.

correlate it to number of grains on its analyte samples and number of particles to produce that precision.

1.2. Geological setting

Lamego mine, is a quartz-hosted gold deposit in an Archean greenstone belt sequence, located on the north border of the Iron Quadrangle in Minas Gerais, Brazil. The gold is hosted erratically in smoky quartz (MCH), which cross-cuts and/or overlies banded-iron formations (BIF) sealed by carbonaceous schists on top of the sequence. The width of this mineralized rock type varies from a few centimeters when cross-cutting the BIF, up to 8 meters when saddled by both contact rocks [10]. Gold grade averages are 7 g/t in the MCH, where there is no distinct geological feature to domain it and 3 g/t in BIF, mostly associated with sulphides, mainly pyrite and arseno-pyrite. The mine has a yearly production of 450,000 tons with 3.5 g/t and since 2009, has produced approximately 500,000 ounces.

The Iron Quadrangle has gold mineralization in different stratigraphic depths and nonetheless yields a background grade of 0.20 g/t, which is found in most rocks. This gold is ultra-fine, from 2 μm particles to invisible sub-microscopic gold. This class accounts for 23% of the assay results in Lamego, as depicted in Fig. 2. The fine nature of the gold makes

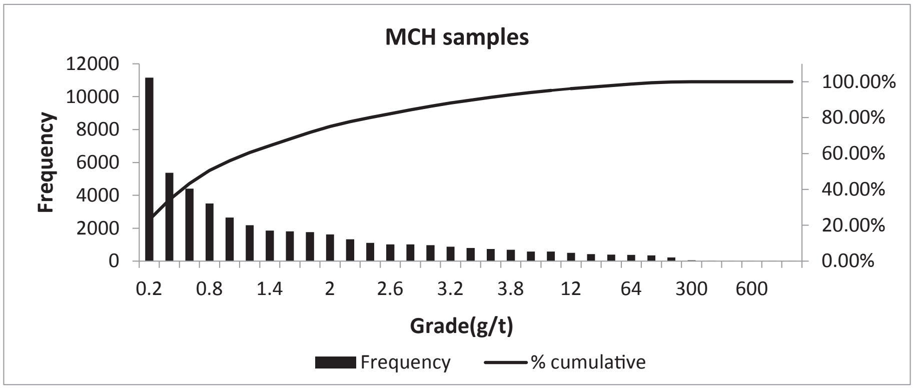


Fig. 3. Frequency distribution of MCH samples.

Table 1
Samples with same grade and mass, yielding different grain size based on the relative precision.

Gold grade (g/t)	Sample mass (kg)	N° of particles	Relative precision	Equant grain size (μm)
7.18	1	10	−0.42 + 0.81	440
7.18	1	20	−0.34 + 0.53	350
7.18	1	40	−0.26 + 0.36	277

it straightforward to sample and a 30 g fire assay aliquot is more than enough to represent it [7]. Gold distribution in the MCH have 17.8% above 2016's cut-off grade of 2.6 g/t, having 3.6% of these values (0.64% of all samples) higher than 100 g/t.

At the mine, there are two sources of samples that are used on the estimation and evaluation of blocks, diamond drill cores and channel/chip samples. The former, are designed in regular mesh distances that will progressively reduce to the final grade control grid of 15 m by 15 m, on the plunge and strike of the orebody. The latter, is systematically marked with 3 meters spacing on strike and the samples are taken perpendicular to bedding or foliation, respecting the lithology. Both drill core and channel samples have on average 80 cm and weigh around 2.5 kg.

After collection, the protocol followed by the company to assay gold consists of: a) collection of the entire 80 cm sample from diamond drill core or the entire channel sample, weighting 2.5 kg, b) primary crushing of the entire mass until 80% are below 2 mm, c) selection of 500 g, using a riffle splitter, d) pulverization of the entire 500 g mass until 80% are below 75 μm and e) collection of six increments with a flat spatula making a 30 g aliquot, for fire assay. The lab provides results with a lower detection limit of 0.05 g/t.

This protocol has two steps in non-compliance to TOS, namely c and e. Split with a riffle splitter (c) is done passing the sample twice through the riffle, where systematically the same drawer is chosen for the next split. Ignoring the equal probability that is regarded for any sub-sampling step. On step e, the selection is sensitive to the operator. The protocol requires to place the 500 g in a paper bag, put it on the horizontal position, introduce the flat spatula all the way to the bottom of the bag, take a “scoop” and fill the crucible; repeat it five times. Again, non-compliance by the operator will introduce errors of grouping and segregation, delimitation, extraction and the result will be non-probabilistic and incorrect, introducing bias to the result.

The sampling protocol of Lamego is the subject of work by Villanova [11], and fire assay was defined as the least reliable assay method for the nature of the mineralization, with gold nuggets. Pitard and Stevens [12] suggest the use of different assay methods depending on particle size and distribution. Emphasizing that for visible gold, cyanidation using bottle-roll or LeachWell of 500–1000 g, followed by fire assay of the residue, would provide reliable results.

This study will use a hypothetical sample of an isotropic deposit with the same characteristics of the smoky-quartz in Lamego, to correlate the impact of low analyte sample mass to errors and its ravelling outcomes on the estimation process.

2. Material and methods

All grade calculations in this paper disregard any gold contribution from a different source than gold particles itself. We also interpret gold as a perfect sphere of specific gravity (ρ) of 16 g/cm^3 (gold-silver alloy). Based on the example at Table 1, the definition of the equant grain size (2r) or the number of particles can be written as the equation below:

$$\frac{Gold\ content}{N^{\circ}\ Particles} = \rho \cdot \frac{4\pi r^3}{3} \tag{5}$$

With this concept, to understand the impact of the analytical sample size on the grade, a simulation was done as follows:

a) Two different cases were tested based on a hypothetical 1 kg lot with average grade of 7.18 g/t, similar to Lamego's smoky-quartz. The first sample is represented by a mass of 1 kg with 20 equant grains, and the second sample has also a mass of 1 kg, but 10 equant grains (see Table 2).
b) Although minor sulphides and silicates could be present in the sample, the present trial accounts for a mixture of two minerals only. Gold and quartz will represent the entire lot.
c) Simulation is done in a single Poisson distribution, meaning that the hypothetical mass selected will not be sub-sampled.
d) A sample with 1 kg truly represents the lot containing 20 or 10 particles. Any aliquot below 1 kg will have less gold particles, and based on Z definition for Equation (1), we calculate the probability of the occurrence of a or any particle in each sample mass.
e) Since the number of equant grains determines gold content and they yield discrete values, the grade obtained for each estimation will not be continuous.
f) The only error associated to this hypothetical simulation will be due to the number of gold particles in the sample mass. There is no sub-sampling stages, preparation and analysis errors are zeroed to simplify the conclusions.

The simulation was done based on the Poisson probability function (Equation (1)) for n, number of particles, starting at 0.5 and going up by

Table 2
Size and number of equant grains.

Grain size (μm)	N° EGS	Grade (g/t)
350	20	7.18
441	10	7.18

integer numbers until the probability of occurrence of a n number of particles dropped below 1%. Aliquots weighing 30, 50, 100, 250, 500 and 1000 grams were simulated with the respective value of Z determined by the number of particles pre-defined. Grades for $P_{0.5}$ were randomly selected from 0.05 to 0.20 g/t, based on the grades of the lower detection limit and the background. For the probabilities with at least one grain ($n \geq 1$), the grade value was determined by the correspondent number of grains in the hypothetical sample (Fig. 4).

Using the MCH average grade, as real grade, the background content as the Iron Quadrangle value of 0.20 g/t and the standard deviation from the simulated results, Ingamells' [5] equation provides the most probable result for each final aliquot mass:

$$Y = K - \frac{K - L}{2Z^{*} + 1} \tag{6}$$

Where K is the real grade value, L is the background value and Z^* is defined in Equation (3), where s is the standard deviation.

$$Z^{*} \approx \frac{(K - L)^{2}}{s^{2}} \tag{7}$$

Therefore, the most probable result is a function of the analyte size or Z^* [6]. As the sample size increases, the number of particles rise and consequently the standard deviation decreases [3,5,9]. A higher Z^* means that the fraction on Equation (6) will contribute with lower values, and the most probable results will be closer to the real grade (K). This is notion schematically represented on Fig. 1.

3. Results and discussion

One hundred simulations were done for each of the six aliquot sizes and for 20 equant grain (EGS-20) and 10 (EGS-10), yielding the total of 1200 simulations. A summary of the results is graphically presented in Figs. 5 and 6.

The grade distribution data for the 30–100 g samples in Figs. 5 and 6 is discrete. As the name of the method describes, each grain selected will have a uniform size and therefore a unique grade. When Z is below 1.5, the probability of having more than three grains in the sample is greatly reduced. Nonetheless, when a particle is selected in a low mass sample, the result is substantially overestimated, represented on the graphs by the large gaps and misleading high values.

The effect of increasing the number of particles in the analyte proves the transition from a Poisson distribution to a normal one as mentioned by various authors [3,5,6,9]. The major reduction in the coefficient of variation (standard deviation divided by the mean) from the 30 g to the 1000 g aliquot is an indication of this change in distribution. The mean, being sensitive to extreme values, fluctuates between 6.70 and 7.22 g/t, having a small increase (1%) from the 30 g aliquot to the 1000 g for the EGS-20. For the second case, EGS-10, the average grade was more dispersed and ranged from 6.32 to 7.19 g/t. As opposed to the EGS-20 case, it experienced a significant 13% increase in the mean grade from the 30 g to the 1000 g aliquot.

The median of EGS-20 is 0.19 g/t only for the 30 g aliquot, where Z is 0.6. When Z becomes an integer, the median shifts to 7.18 g/t and this value is unchanged as samples become larger. In contrast, the same parameter for EGS-10 starts as 0.15 g/t, increases to 7.19 g/t for the 100 g aliquot, drops to 5.75 g/t for the 250 g sample, then stabilizes at 7.14 g/t. This difference is rather related to the size of the equant grain, which is coarser for EGS-10, affecting the results to a greater extent. The improvement in the median from the lightest to the heaviest sample was a 38-fold for EGS-20 and 48-fold for EGS-10.

One could be tempted to validate mass size use by the median, using the weight in which the median is approximated to the expected value as the optimum sample weight. However, for the EGS-20, 50 g sample, the standard deviation is still high. In this case, the assumption would yield a poor relative precision of ±98% or ±7.06 g/t.

When using the EGS methodology, it is extremely important to take into account the value used for the average grade and where it came from. For example, what is the coefficient of variation for this variable? Does it represent an average of all samples or an area of high/low grade? What is the sample size used? What is the particle size?

The first question is to assess the behaviour of the variable. If the coefficient of variation (CV) if it is more than 0.5, there is a high probability that the samples will not behave as a normal distribution. A CV of 0.5 can be correlated with a limit case calculated by Equation (2), where four particles retrieve a relative precision of −0.50 and + 1.46, with 95 percent confidence. This is a sign of low sample mass, where there are not enough particles to represent the variable and therefore, understates grade [13].

Upon selecting the area, which will determine the EGS, one should be cautions of the non-stationarity of the grades. Usually low-grades will be

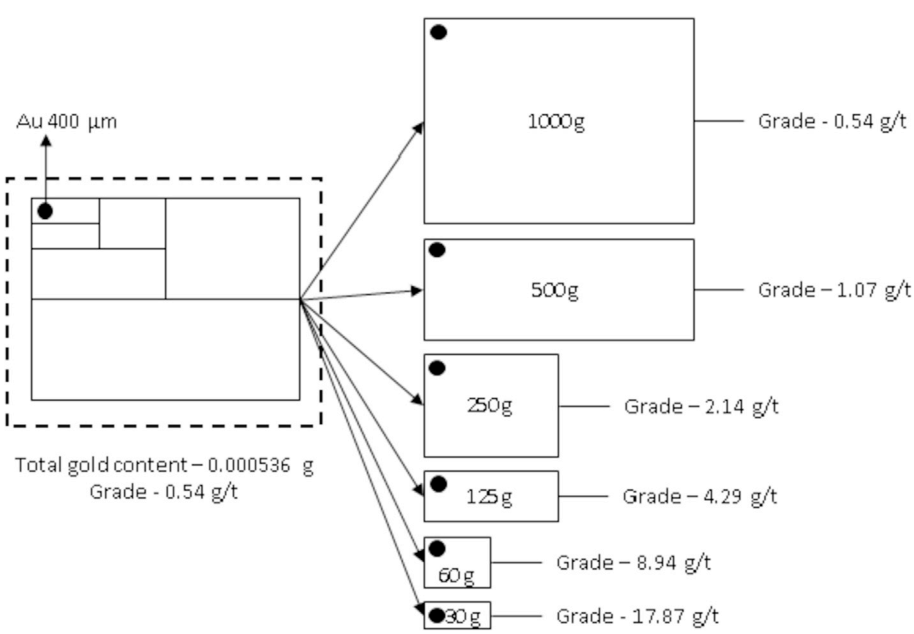


Fig. 4. One gold particle in different aliquots sizes yielding significant discrepancies in grade.

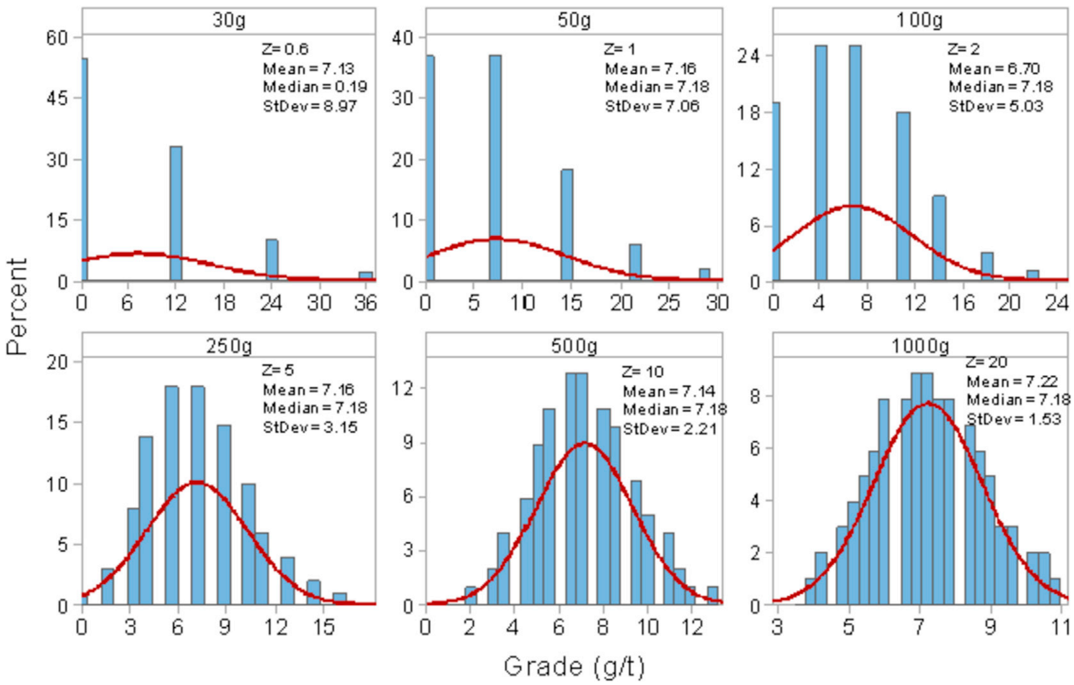


Fig. 5. Grade distributions for different analytical masses for EGS-20.

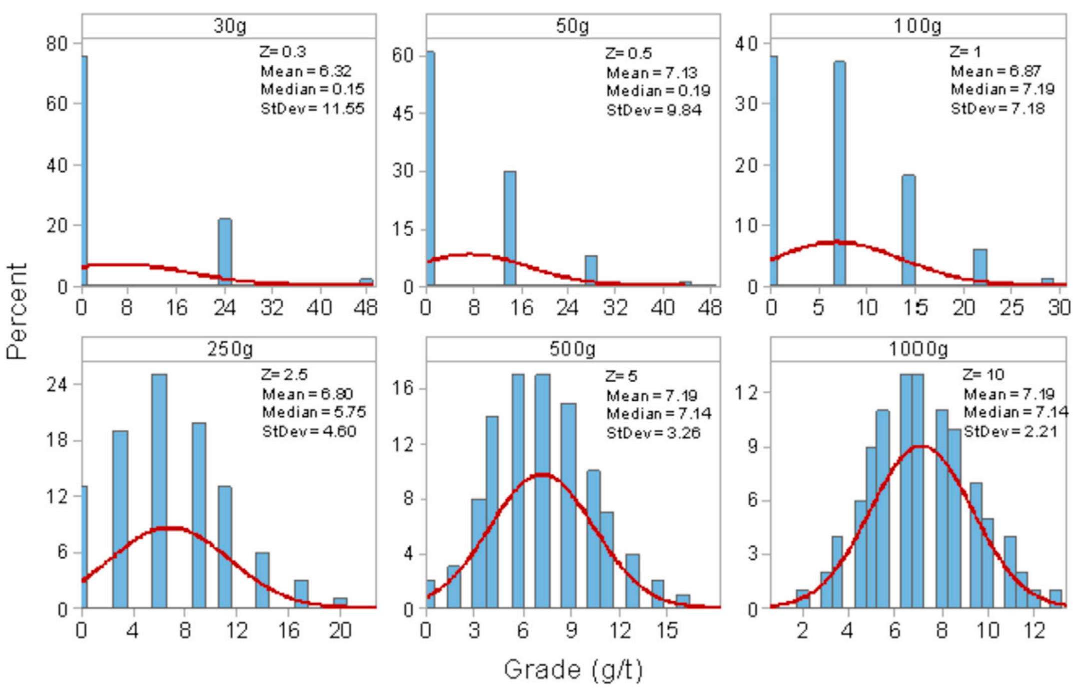


Fig. 6. Grade distributions for different analytical masses for EGS-10.

associated with small particles and higher grades with coarser, locally defining different averages [6]. However, in a counter-intuitive way, low-grade areas could yield poorer precision or higher standard deviation, than high-grade domains. The main issues to create this phenomenon relates to the mass of the analyte and particle size (Table 3).

The definition of the equant grain size, based solely on the total content divided by the number of particles necessary for the required precision works well when the EGS is larger than the average particle size. This will occur when the characteristics of the lot are already represented throughout all sampling phases and many particles are found in the final aliquot.

However, there is no rule-of-thumb to guarantee the lot's constitution during the sampling steps. Gold deposit's constitution, even in an environment of coarse particles and low-grade, such as placers, can be respected through all phases of sampling. The problem is a matter of scale. While in fine particles, as the low grade example in Table 3, is accordingly represented in a 30 grams aliquot, a placer with the same average grade and particles of 300 μm, would require 20 kg to provide the same relative precision.

A final analyte with small mass is prone to yield extreme values by the presence of nuggets, as demonstrated in both 30 g simulations (Figs. 5 and 6). In a poor area, a low average grade could mask the presence of

Table 3
Implications of gold characteristic of disseminated ore for 20 equant grains in a 30 grams final aliquot.

Gold characteristics	Average grade (g/t)	Size of equant grain (μm)	Interpretation
Fine (30 μm)	0.20	33	Equant grain coarser than actual grains, a 30 g sample has 26 fine particles. Final mass is adequate
Medium (150 μm)	0.20	33	Equant grain smaller than actual grains. Database with several results with lower detection limit and rare higher results, when one or more particles are selected in a sample. Displays a high standard deviation. It is necessary to increase final mass
Fine (30 μm)	2.00	71	Equant grain coarser than actual grains, a 30 g sample has 265 fine particles. Final aliquot could be reduced to 3 grams
Medium (150 μm)	2.00	71	Two medium particles yield the average grade. Dispersed results, less erratic than when average grade was 0.20 g/t. Final mass needs to increase
Coarse (300 μm)	2.00	71	Similar situation of Medium particles in a low-grade area. Several results at the low detection limit and rare results displays extreme values. One particle yields a 7.54 g/t grade. Final mass must be larger
Fine (30 μm)	10.00	121	Equant grain coarser than actual grains, a 30 g sample has 1326 fine particles. Final aliquot could be greatly reduced to 0.5 grams
Medium (150 μm)	10.00	121	A sample has ten particles, results demonstrate a relative precision of −0.42 + 0.81. In order to reach the required precision, sample size must increase.
Coarse (300 μm)	10.00	121	Each sample will have one particle and less often more than one, yielding higher results than average. Sample mass must increase

isolated coarse particles. Depending on the number of data, an “outlier” found in a background area (0.20 g/t) could increase the standard deviation in many folds. For a 30 g sample, this “outlier” could be a unique 300 μm nugget that would return a grade of 7.54 g/t.

In addition, according to Ingamels [5], the most probable results of relative small masses will return lower results than the real and unknown value (Fig. 1). We must emphasize the term “relative small”, because it is not only a function of grade, but also of particle size. A relative small mass translates in a limited number of particles in the final analyte, which has a direct impact on the average grade and standard deviation of the results. Furthermore, the underestimation of total gold content divided by, the required but not practiced, number of particles will estimate an EGS smaller than the average particle. In short, it will define a smaller final aliquot than necessary.

Ingamells' method [5] highlights the impact of small samples on average grade. Based on Equations (6) and (7), results for the most probable value *Y,* using the simulated data are shown on Table 4:

As stated previously, the increase on sample mass is followed by an increase of the most probable result, affecting the average grade in a lesser extent. The difference between the most probable result and the median shown in Figs. 5 and 6, relies on the fact that this method accounts for the standard deviation when defining Z^*, while Z used on Clifton's approach [9] depends only on the mass of sample. It is noted that the most probable result for EGS-10 in a 30 g sample, 0.86 g/t, correlates with the median of all MCH values shown on Fig. 3, an evidence that sample mass used for Lamego ore is not optimum.

In conclusion, the best approach to define sample mass is to do a thorough analysis of the data, associated with mineralogical characterization. By knowing the average size of the particles, one could estimate how much mass is required to obtain the actual average grade when the defined number of particles, EGS, are present in the final aliquot (Fig. 7).

As depicted on Fig. 7, an EGS determined in a low-grade area will not define sufficient mass for a high-grade in a coarse gold domain. On the contrary, an EGS based on a limited high-grade area could determine larger sample masses that if used in indiscriminated, becomes an inefficient action cost-wise.

Distinct geological features can be used for domaining the deposit. A thorough study to assess the average grade in these divisions should be done. An option of assay samples to extinction improves the understanding of grade variation and the unknown real value.

3.1. Simulations

The simulated data allows the use of a couple of examples to demonstrate the impact of sample mass on decision-making. Disregarding any spatial distribution and using each one of the simulated result to represent a $5 \times 5 \times 5$ m block yielding 337.5 tons, the hypothetical dataset can be evaluated for its gold content (Fig. 8). All comparisons will have the 1000 g sample as the real result or expected value.

Example 1. Evaluation of gold content using the average grade of all samples.

For EGS-20, the 30 g results would provide an estimation, which would undermine the gold content by 96 ounces, a variation of only 1%. Analyzing all mass sizes, the 100 g results would provide the estimate with least ounces, 556 less than expected, a 7% variation. The same comparison using EGS-10 30 g results would report a content depleted in 891 ounces, or 12% less than the total content. Apart of the 30 g difference, all other block estimations in different masses would vary between an overestimation of 0.03% to an underestimation of 5%.

Example 2. Evaluation of gold content after the application of a cut-off grade of 2.6 g/t.

Frequently a decision will be made over a certain cut-off grade and this value depends on a series of variables that produce the total cost. Applying a cut-off value of 2.6 g/t on the 30 g results of EGS-20 reduces data from 100 to 45 results and the calculated gold content is 7665 ounces. This value drastically contrasts when the same 45 blocks are estimated with the 1000 g results. The real value for these blocks is 4198 ounces, and the 30 g results overstates it by 44%. For EGS-10, even more results are excluded by the lower cut. In this setting, a total of 24 results would estimate a gold content of 6756 ounces, while it should be 2,620, a surplus of 53%.

The estimation process was simplified to create comparable situations. The highest grades on the 30 g sample would be compared with its pairs on the 1000 g aliquot. While, in reality, what could happen is an overestimated high grade in a low-grade area or the contrary. These “outliers” will increase the local variability and depending on estimation method, could influence a wide area with its anomalous grade.

It is important to emphasize that after the assay results are received, there is limited action for the geologist to control the variance on the system. Practices of de-clusterization and capping are usually done prior to estimation, assigning different weights to data preferentially sampled and putting a ceiling value to control anomalous results, respectively. The selection of the geostatistical method will depend on the nature and quality of the data.

Simple examples, as described above, demonstrate the misleading impacts of poor sampling with regards to analyte mass. Even when selecting a robust geostatistical method, all estimates are obtained from samples and its quality could create completely wrong definitions of ore and waste units.

Table 4
Most probable result for EGS-20, EGS-10 and their final aliquot size. *K* is the real grade value, *L* is the background value and *Z** is defined the square difference of *K* and *L* divided by the square of the standard deviation and Y is the most probable result.

Mass	Type	*K*	*Z*	*L*	*Y*	Type	*K*	*Z*	*L*	*Y*
30 g	EGS-20	7.18	0.09	0.2	**1.23**	EGS-10	7.18	0.05	0.2	**0.86**
50 g	EGS-20	7.18	0.14	0.2	**1.73**	EGS-10	7.18	0.07	0.2	**1.08**
100 g	EGS-20	7.18	0.28	0.2	**2.68**	EGS-10	7.18	0.14	0.2	**1.69**
250 g	EGS-20	7.18	0.70	0.2	**4.28**	EGS-10	7.18	0.33	0.2	**2.97**
500 g	EGS-20	7.18	1.43	0.2	**5.37**	EGS-10	7.18	0.66	0.2	**4.16**
1000 g	EGS-20	7.18	2.98	0.2	**6.18**	EGS-10	7.18	1.43	0.2	**5.37**

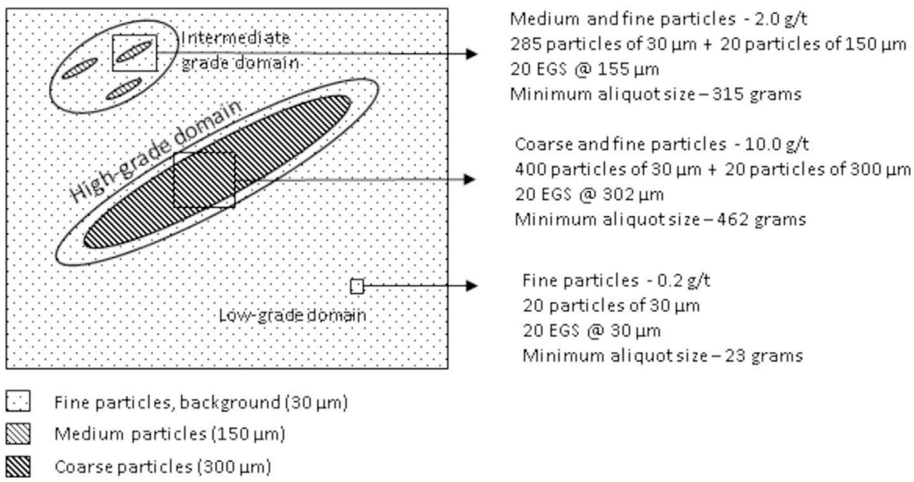
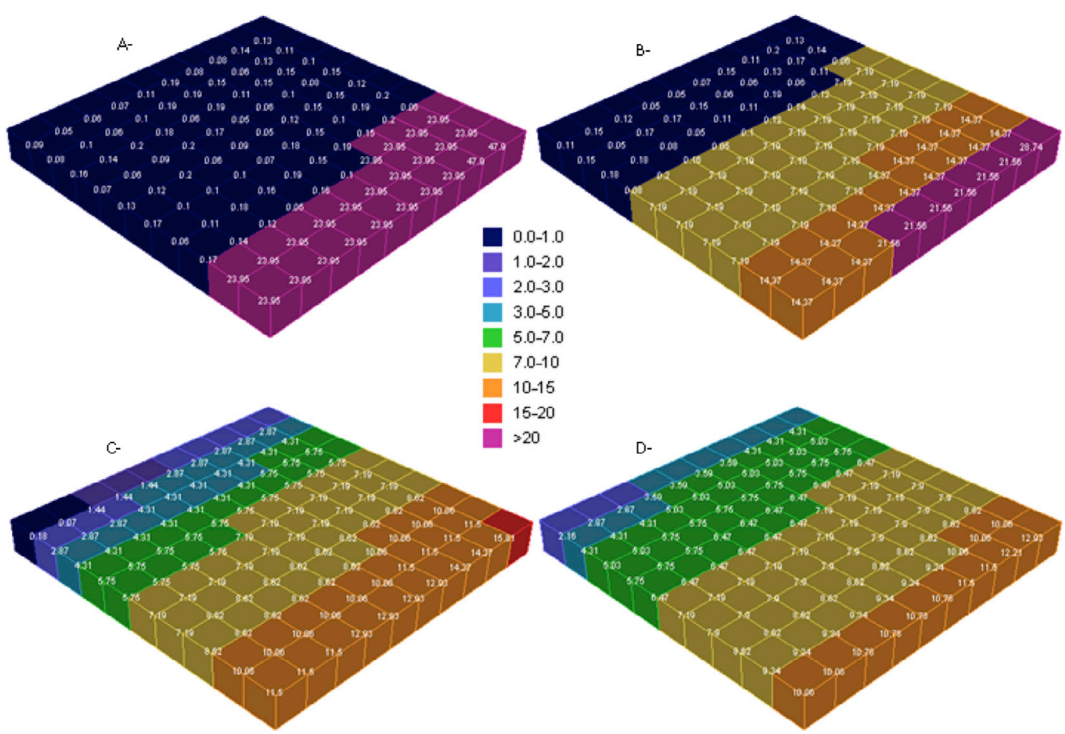


Fig. 7. Sample mass definition in different domains, with different grades and particles sizes.



Font - modified Ingamells [5]

Fig. 8. Block representation showing five random selected values from EGS-10 of the final aliquots 30 g (A), 100 g (B), 500 g (C) and 1000 g (D).

4. Conclusions

The use of EGS methodology from Clifton [9] and Ingamells [6] equations proved to be extremely useful to determine the analyte sample size and to numerically demonstrate possible losses. A 30 g final aliquot proved to be too small to represent the MCH at Lamego Mine, and thus a larger size must be used, such as 500 g or 1000 g. A comparison between the current MCH grade distribution and the most probable results puts a spotlight on the underestimation nature of Lamego's protocol, which is under review.

A future study will be conducted to compare how sampling errors can play a major role on the spatial distribution of grade, using 30 g fire assay and 500 g cyanide leaching.

Conflicts of interest

None.

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