Impact of Competent Persons' judgements in Mineral Resources classification

by S.K.A. Owusu[1] and K. Dagdelen[1]

Affiliation:
[1]Mining Engineering Department, Colorado School of Mines, Golden, Colorado, USA

Correspondence to:
S.K.A. Owusu

Email:
oaksolo@yahoo.com

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ORCID:
S.K.A. Owusu
http://orcid.org/0000-0001-7709-578X
K. Dagdelen
http://orcid.org/0009-0003-6650-8616

Abstract

Uncertainty with regard to estimated grades and tonnages of a mineral deposit demands risk assessment in order to build investor confidence and attract the interest of other stakeholders in the success of a project. Uncertainties associated with Mineral Resource estimates can lead to unreliable production schedules and unpredictable cash flows. However, the techniques used in the mining industry to determine these uncertainties are inconsistent, because the important decisions taken in the process are solely dependent on the responsible Competent Person (CP), without limitations. This leads to disparities between different CPs' results, using data-sets from the same drill-holes. The various standard codes for public disclosure provide guidelines and recommendations for the classification of Mineral Resources and Reserves but do not provide details on, for example, the amount of geological and geostatistical information needed to qualify for each category of Resources and Reserves. The parameters used to generate the classification categories are subjectively assumed by the responsible CP. In this paper we investigate the impacts of different CPs' judgements on resource classification, using the same data-sets. The results underpin the need for the mining industry to develop a uniform Mineral Resources and Reserves classification framework that can minimize or avoid significant discrepancies that lead to potential misleading public disclosures.

Keywords

mineral resources, mineral reserves, classification, reporting codes, uncertainty

Introduction

Mineral Resource classification plays a key role in the economic assessment of mining projects, as investors typically make investment decisions based on the information used to generate the cash flow analysis. Due to inconsistencies in Mineral Resource reporting by various Competent Persons (CPs), it is crucial to investigate how different resource classification techniques are applied in the mining industry to categorize Mineral Resources as Measured, Indicated, and Inferred, based on the uncertainty assigned to each class. The Mineral Resources report should provide reliable information on the deposit under consideration and define the different Mineral Resource classes, based on the confidence levels assigned to the different blocks of the orebody model. The international standard reporting codes for Mineral Resources promote competence, materiality, and transparency in public disclosure (Shaw et al., 2006).

The principle of competence refers to a responsible, suitably qualified and experienced professional with at least 5 years of relevant experience, who is required to be a member of an organization recognized by the specific reporting code and capable of demonstrating competence among his or her peers. The principle of transparency requires that all available, accurate, and sufficient information is presented. Materiality requires the inclusion of all relevant and reasonable deposit information to enable investors and their advisors to make balanced judgements based on the information presented. To minimize or avoid misleading public disclosures, the standard reporting codes were established to encourage investor confidence in the exploration and mining business. Until the later part of 1980s, there were no industry standards for mineral asset reporting, and this led to doubtful and erroneous reports from individuals as well as companies.

The categorization of Resources and Reserves relies on the judgement of the CP in charge of a project, based on knowledge and experience, in conjunction with others if necessary. Each CP decides on the assumptions used and justifies the outcomes produced from each class of the Mineral Resources. The codes do not prescribe how CPs should conduct their assessments to classify Mineral Resources (Noppe 2014). The inconsistencies in the expected accuracy, precision, and confidence in the classifications can result in varying grades and tonnages of total Mineral Resources calculated by different CPs using the same drilling data. An effective estimate of Mineral Resources with a credible classification leads to reliable mine designs, efficient production schedules, robust business plans, and solid financial forecasts. The big question is; which CP produces a genuine (or not) Mineral Resources report? One common inaccuracy found in tonnage determination for a deposit is due to the application of an erroneous density or tonnage factor. Parrish (1993) stated that the most common error found when conducting Mineral Resources and Reserves audits is an error in the tonnage factor used to derive the tonnage of the orebody. The density used to convert volume to tons is crucial when determining the real in-situ tonnage and metal content of Mineral Resources, because an error of a few per cent in the bulk density can significantly alter the economic viability of a deposit. This is especially obvious in marginal projects, as the higher the tonnage factor, the lower the tonnage of a deposit, and vice versa. However, the methods used to determine the density considered in the estimation and classification of Mineral Resources are inconsistent.

The importance of bulk density is stressed in the various standard codes such as the Canadian Institute of Mining, Metallurgy and Petroleum (CIM) Mineral Exploration Best Practice Guidelines (CIM, 2018) and the Australasian Institute of Mining and Metallurgy (AusIMM) Guide to Good Practice (AusIMM, 2001). For some projects, there is insufficient data to adequately characterize the assigned density or tonnage factor of the waste and ore, while for others, there are good databases that contain well-documented density determinations. Some CPs in the mining industry assign different tonnage factors to ore and waste, while others assign an average tonnage factor to all rocks, depending on the nature of the deposit as well as their own judgement. Due to the subjectivity and dependency on the CP, the resources classified as Indicated by one CP may be classified as Inferred by another.

Misleading public reports and poor project outcomes

A deceptive Public Report on Mineral Resources due to erroneous estimation and classification assumptions can lead to poor production outcomes. For example, a publicly reported resource mistakenly classified as Indicated rather than Inferred can mislead investors and create future problems, including loss of investor confidence and lawsuits. There have been historical antecedents of some public announcements on Mineral Resources and Reserves where the expected risks and level of maturity of the projects were presented in incorrect contexts, thereby yielding undesired outcomes. A typical example of an estimation scandal that hit the mining industry is the Bre-X saga in 1997, where the company fraudulently claimed about 47 million ounces of gold in the Busang property in Indonesia (Groia, Bradley, and Jones, 2008).

In the 1980s, an investigation into 35 Australian gold mines showed that 68% failed to deliver the planned head grade (Burmeister, 1988). In North America, a review of about 50 projects found that only 10% achieved their commercial aims and 38% failed within a year (Harquail, 1991). An investigation into the start-up performance of a nine underground base metal mines In Australia established that only 50% achieved the designed production by the third year and 25% never achieved it at all (Ward and McCarthy, 1999). A study in the United States to compare the final feasibility study figure with the average sustained production rate from 60 steeply-dipping tabular deposits established that 35% of the mines were unable to achieve their planned production rates (Tatman, 2001). According to Noppe (2014), one partner in a coal deposit joint venture deal reported double the resource tonnage of the other JV partner, each using the same drill-hole data. This happened because the partner who produced the inflated estimate did not apply the likely mining parameters for the expected underground scenario.

Considering the intensive capital funding and risks of mining projects, BHP Billiton's Olympic Dam project in Australia is a typical example (Valle, 2011). The project cost was estimated to be US$27 billion, hence huge sums of money would have been lost if the Mineral Resources and Reserves were wrongly classified and the mine failed to meet the production target. In the mining industry, little has been done in terms of investigating the impacts associated with different CP assumptions and judgements applied to classify resources. In this research, we provide quantitative analyses of different CP assumptions, using data-sets for copper and gold projects.

Mineral Resource classification methods

Although other techniques may be used to classify mineral deposits, the two basic methods used in the mining industry for Mineral Resource classification tasks are the geometric and geostatistical techniques. The geometric method considers the amount, proximity, and location of data available to classify resource blocks, while the geostatistical method uses model uncertainty and configuration of the neighbouring data to classify blocks. Figure 1 outlines the two classification techniques.

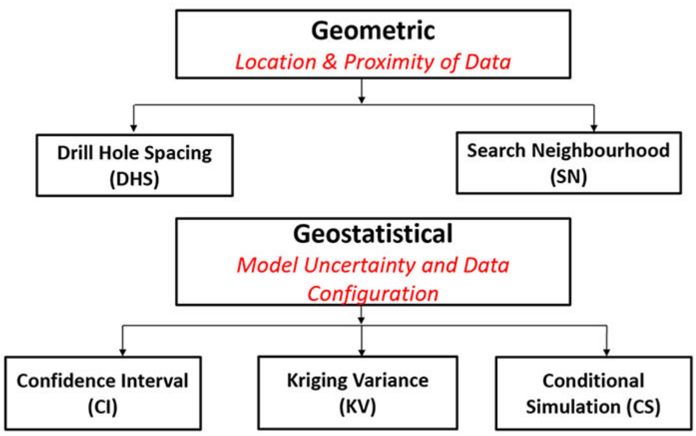


Figure 1—Mineral Resource classification methods and techniques applied in the mining industry

Table I

Summary of mineral resources classification from 45 SEDAR reports (Owusu and Dagdelen, 2019)

Classification Technique	Count	Persentage (%)
DHS	2	4.4
DNDH	2	4.4
NS + DNDH	2	4.4
DHS + NDH	3	6.7
NDH + ES	1	2.2
NDH +NS	2	4.4
NS + ES	3	6.7
NS + OS	3	6.7
DHS = CNDH	1	2.2
NDH+ CNDH	4	8.9
DHS + NDH + CNDH	1	2.2
DHS + NS+ OS	1	2.2
NDH + NS + OS	2	4.4
NDH + NS + CNDH	5	11.1
NDH + NS + OS	1	2.2
DHI + NS	6	13.3
KV + CNDH + NDH + NS	2	4.4
Unknown	4	8.9

A recent survey conducted on the different Mineral Resource classification techniques practiced in the gold mining industry showed that approximately 93% of CPs prefer the use of the geometric method, while 7% use the geostatistical method (Owusu and Dagdelen, 2019). The study was undertaken, using 45 NI 43-101 technical reports filed on the System for Electronic Document Analysis and Retrieval (SEDAR) website, to evaluate the state of practice concerning Mineral Resource classification techniques for gold deposits. Public Reports from 2006 to 2018 were compiled and another publicly available general classification reporting guideline from a major gold mining company in the United States was included. The review covered 20 junior, 20 mid-tier, and five major gold mining companies in North America, South America, Asia, and Africa. Different gold deposit types were covered, including gold-copper porphyries, orogenic gold, breccia pipe, carlin-type, lode and placer, epithermal high- and low-sulphidation, and greenstone belt.

After critical analysis of the classification guidelines used by the various companies, it was established that 43 of the reports applied geometric methods and two combined geostatistical and geometric methods. These included techniques such as drill-hole spacing (DHS), distance to nearest drill-hole (DNDH), number of samples (NS), number of drill-holes (NDH), ellipsoidal search (ES), octant search (OS), drill-hole intercept (DHI), and kriging variance (KV). In most cases, some of the CPs combined multiple techniques like NS and NDH (NS + NDH), DHS and NDH (DHS + NDH), NS and ES (NS + ES). Table I and Figure 2 represent the various classification techniques applied for gold deposits used in the research. In the pie chart, the percentages are rounded to their whole numbers. After evaluating the different reports, it was found that there is currently a lack of uniformity in resource classification reports due to the different assumptions made by individual CPs. Also, it was found that industry players prefer the the geometric method due to its time-saving and simplistic characteristics. Hence, there is a need to develop easier and quicker techniques for the geostatistical method to enhance its use in the resource classification process.

Silva and Boisvert (2014) conducted a similar survey from SEDAR and after reviewing a total of 281 technical reports, found only 120 had sufficient information to determine the techniques used for Mineral Resource classification. The information used for the evaluations included classification technique employed, the chosen criteria, and the drilling pattern. Silva and Boisvert did not provide detailed information in terms of the mineral commodity types, deposit types and locations, company categories, or parameters applied in the classification techniques, among others. According to the investigators, the most commonly used method was the geometric, representing about 80% of the reports. It included the NS technique which constituted approximately 50%, followed by DHS (30%) and KV (about 6%), with the remainder (14%) being unspecified. The techniques used by the various CPs were dependent on either regular or irregular drill-hole spacings.

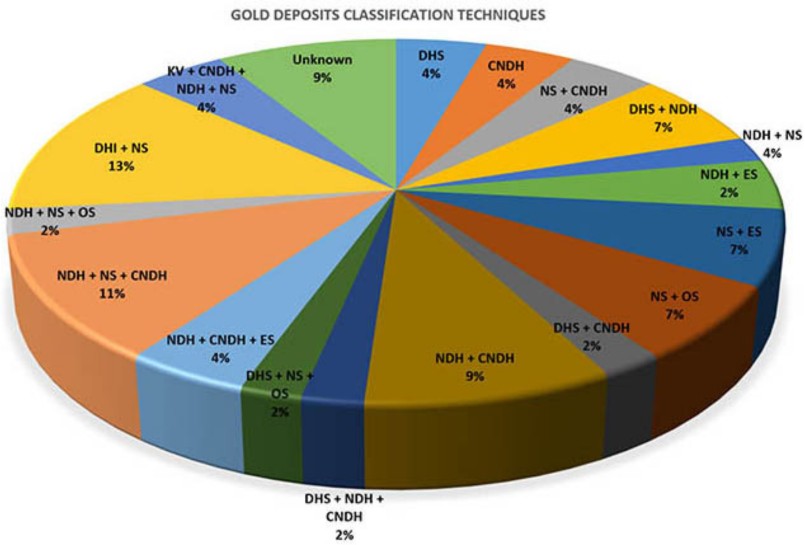


Figure 2—Summary of Mineral Resource classification techniques for 45 gold deposits from SEDAR (Owusu and Dagdelen, 2019)

In most reports, regularly spaced drill-hole data was used for the DHS technique, while NS was applied to irregularly spaced drill-hole data. Also, some industry professionals combined the different techniques to classify irregularly spaced data.

Research methodology

Classification is commonly performed on a block-by-block basis but the block volumes are chosen to be reasonably large and contiguous, because of the common perception that confidence in the grade should not change abruptly between adjacent blocks (Deutsch, Leuangthong, and Ortiz, 2016). To provide mining industry professionals with quantitative illustrations to demonstrate classification inconsistencies due to individual CP judgements and assumptions, we assessed data from a single bench at a copper deposit and from a gold deposit. Each case study included data validation, exploratory data analysis, geological modelling, variogram modelling, block modelling, grade estimation, model validation, and resource classification. Different assumptions made by different CPs in some of the SEDAR technical reports were applied to these two data-sets. The differences in the results indicate that the practice of applying individual CP assumptions without limitations creates discrepancies in the outcomes, because each CP has a strong influence on the parameters used to generate Mineral Resource classes.

Case study A: A single bench at a copper deposit

The bench is 90 m length × 90 m width × 15 m height. The data is considered as synthetic because much geological information is not provided, but it is useful for the purpose of the study. Thus, the research focuses on using the same data to analyse how different CP assumptions can produce varying outcomes. The data is from 36 irregularly spaced vertical drill-holes with a single sample from each hole.

The drill-hole information includes eastings, northings, elevations, and copper assay results. A block model of 7.5 m × 7.5 m × 15 m blocks was created for the data-set, in correspondence to the 15 m bench height. The available data from regularly spaced blast-holes 7.5 m × 7.5 m yields similar statistical results to the exploration data, hence the choice of block size.

Table II

Summary statistics of the one-bench copper deposit

Parameter	Composite Data	Declustered Date
Valid Data	36.00	36.00
Total Data	36.00	36.00
Missing Data	0.00	0.00
Invalid Data	0.00	0.00
Minimum Value	0.21	0.21
Maximum Value	1.27	1.27
Mean	0.50	0.48
Variance	0.05	0.04
Standard Deviation	0.20	0.19
Coefficient of Variation	0.40	0.40

Statistical and geostatistical analysis

The distribution of copper in the deposit was analysed using statistical and geostatistical techniques. Table II and Figure 3 show the summary statistics and the histograms of the original composite data and the declustered data respectively. All copper grade units are given as percentages (%Cu). Variogram modelling was generated from the data to determine the spatial continuity of the data points.

Considering the inadequacy of the data, good variograms and correlograms could not be created. The geostatistical parameters generated from the correlogram model are shown in Figure 4.

Block modelling and resource estimation

MineSight software was used to generate the block model and the applied interpolation technique was ordinary kriging (OK). For the purposes of this study, an arbitrary tonnage factor of 0.354 m^3/t (12.5 ft^3/t) was assigned to all rocks. For validation purposes, inverse distance squared (ID^2) and nearest neighbour (NN) estimation techniques were used to generate results for comparison. The three

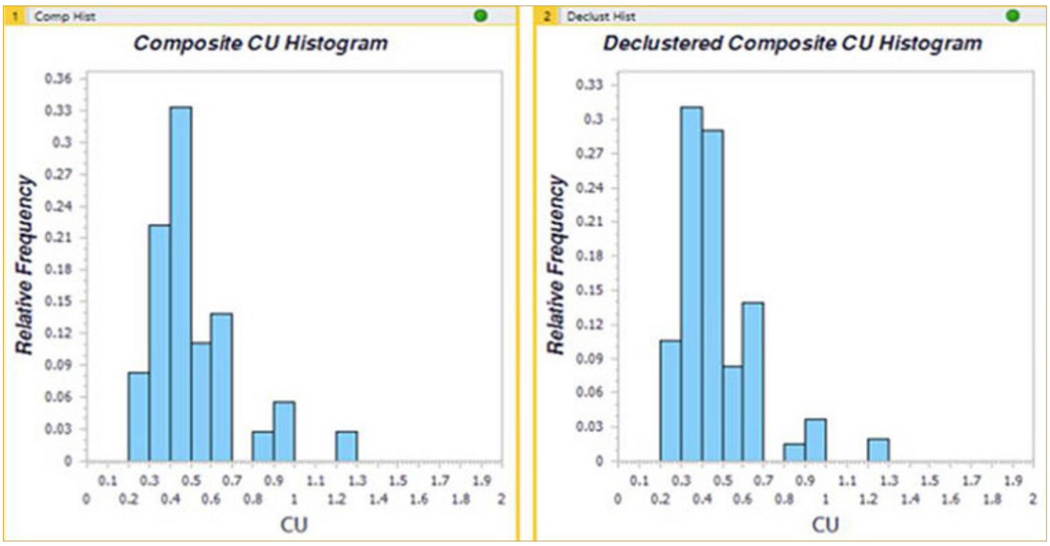


Figure 3—Histograms of the 2D copper composite data (left) and declustered data (right)

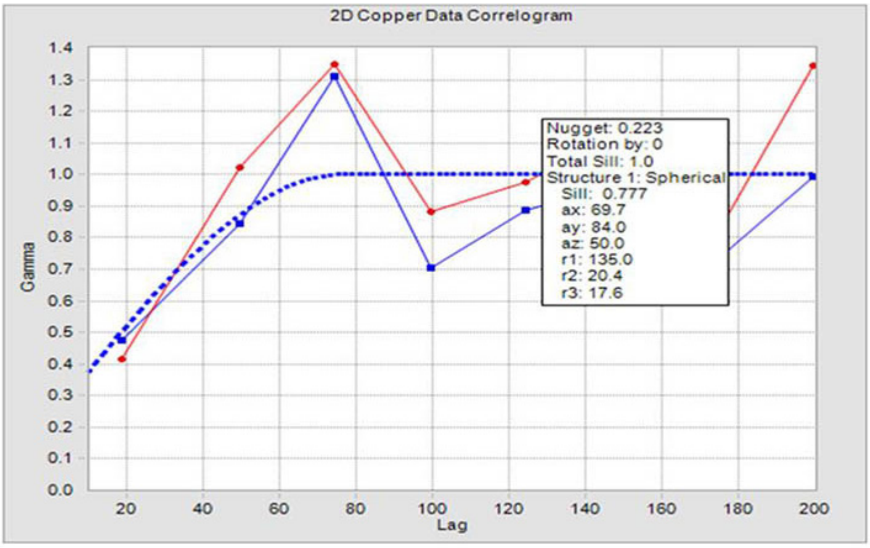


Figure 4—Correlogram modelling of the 15 m bench at a copper deposit

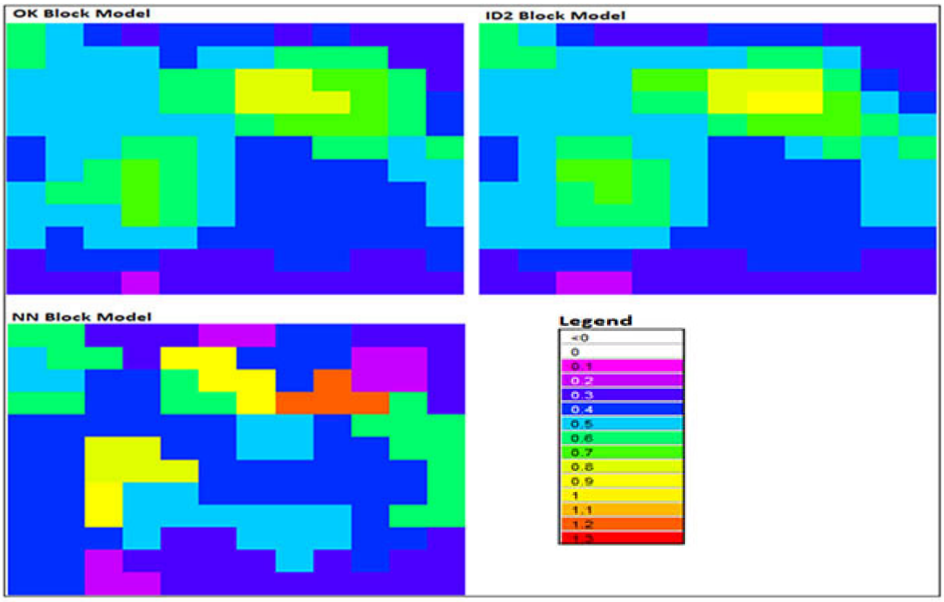


Figure 5— OK (top left), ID^2 (top right), and NN (bottom left) block models

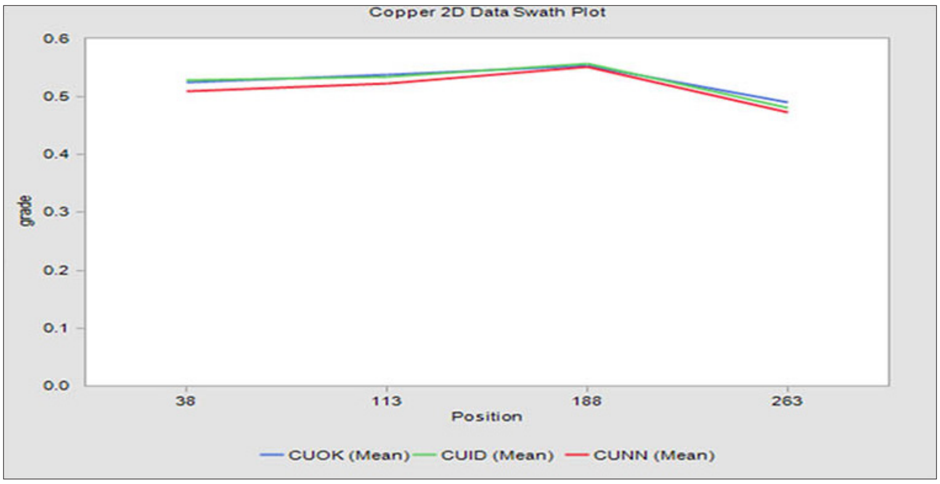


Figure 6—Swath plots for OK, ID^2, and NN block models

Table III

Grades and tonnages from the three scenarios at different cutoff grades

Cutoff (1 (%Cu)	Ordinary Kriging (OK)			Inverse Distance (ID2)			Nearest Neighbour (NN)		
	Tonnage (t)	Grade (%Cu)	Cu (lb)	Tonnage (t)	Grade (%Cu)	Cu (lb)	Tonnage (t)	Grade (%Cu)	Cu (lb)
0.00	360 000	0.53	4 205 232	360 000	0.53	4 205 232	360 000	0.52	4 086 216
0.20	360 000	0.53	4 205 232	360 000	0.53	4 205 232	360 000	0.52	4 086 216
0.40	297 500	0.56	3 671 864	292 500	0.57	3 674 619	267 500	0.58	3 425 402
0.60	97 500	0.68	1 461 252	87 500	0.71	1 369 235	77 500	0.81	1 376 729
0.80	10 000	0.88	193 952	15 000	0.88	291 589	30 000	1.01	666 490

Table IV

Classification parameters for the three scenarios of the copper deposit

Scenario	Search distance description	Search Distance (m)	NC	NDH
1	Measured: 1/3 of sill range Indicated: 1/2 of sill range Inferred: 1 – 1.5% of sill range	8.5 12.8 34.4	≥3 ≥2 ≥1	≥3 ≥2 ≥1
2	Measured: 60% of sill range Indicated: 75% 75% of sill range Inferred: 90% of sill range	15.4 19.2 23.0	≥3 ≥2 ≥1	≥3 ≥2 ≥1
3	Measured: 40% of sill range Indicated: 80% of sill range Inferred: 100 – 200% of sill range	10.2 20.5 51.2	≥3 ≥2 ≥1	≥3 ≥2 ≥1

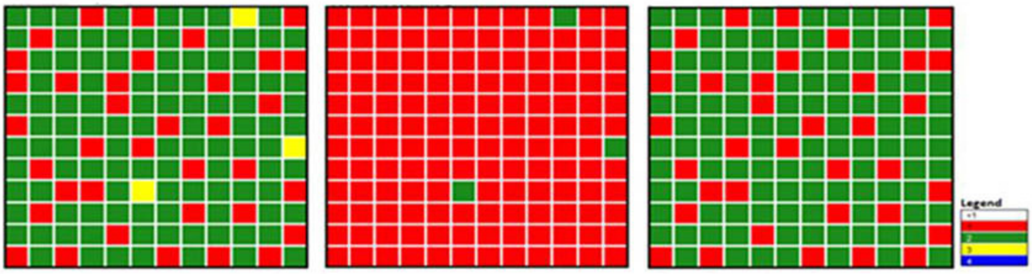


Figure 7—Classification blocks for scenarios 1 (left), 2 (middle), and 3 (right)

models are displayed in Figure 5. The swath plot is another tool used to validate block models, as it shows the moving window mean plots of block grades at different locations. Figure 6 shows how the results from the three estimation techniques were represented well on the swath plot. Table III summarizes the tonnages and grades generated from the three models at different cutoff grades.

Mineral Resource classification

Mineral Resource classification was performed to determine the Measured, Indicated, and Inferred classes. Search distances for the scenarios were calculated from different percentages of the variogram range, while the same number of composites and number of drill-holes were assigned to each category in each scenario. Table IV presents the details of the classification parameters for each resource class, using a sill range of 25.6 m (84 ft), number of composite (NC) samples used, and number of drill-holes (NDH) used.

The different classes generated using MineSight are shown in Figure 7. Measured, Indicated, and Inferred Resources are indicated by red, green, and yellow respectively. The different classification results for each scenario in terms of grade, tonnage, and metal content are presented in Table V.

Discussion – case study A

Table V shows the inconsistencies in Mineral Resource classification after the application of different parameters based on different CP assumptions and judgements. As seen in Figure 7, scenario 1 produced few blocks of Inferred class, while scenarios 2 and 3 did not produce any Inferred blocks. Also, scenario 2 produced Measured blocks for the entire deposit, with three blocks of Indicated class. Finally, scenario 3 generated more Indicated blocks than Measured blocks. Although the sample population of the single-bench data is small, the results from each of the three scenarios were generated by considering assumptions used by

CPs in technical reports. This has shown that there can be overly or insufficiently assumed parameters, which can be applied by individual CPs to classify Mineral Resources.

Case study B: Gold deposit in California

The gold deposit, discovered in 1978, is located in California. The deposit consists of a large but low-grade set of veins, 1829 m (6000 ft) wide and 305 m (1000 ft) deep, in a fault zone. It was formed in a shallow epithermal and hot spring environment with gold and silver as the primary mineral commodities. Other associated minerals in the deposit include mercury, lead, iron, copper, thallium, arsenic, antimony, and zinc (Homestake Mining, Western Mining History, 2019). This case study considers the gold mineralization in the southern portion of the deposit (6600N – 10500N). This portion generally strikes north-northwest (NNW) and the dip varies depending on the orientation of the vein set.

Table V

Tonnage, grade and metal content of the three scenarios at 0.405 cutoff grade

CP Assumptions	Scenario 1	Scenario 2	Scenario 3
Class	**Tonnage (t)**		
Measured	60 000	275 000	60 000
Indicated	215 000	5 000	222 500
Measured & Indicated	275 000	280 000	282 500
Inferred	7 000		
Class	**Grade (%Cu)**		
Measured	0.59	0.57	0.59
Indicated	0.56	0.52	0.56
Measured & Indicated	0.57	0.57	0.57
Inferred0.48	0.00	0.00	
Class	**Metal Content (kg)**		
Measured	353 900	1 567 057	353 900
Indicated	1 203 660	25 993	1 245 648
Measured & Indicated	1 557 560	1 593 050	1 599 548
Inferred	35 990		

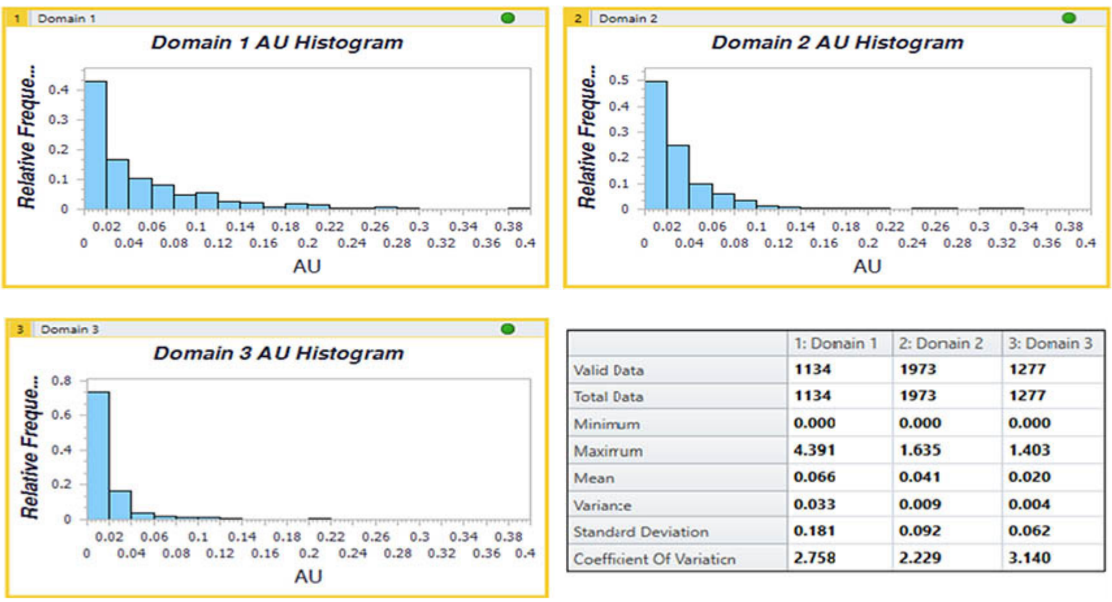
Statistical and geostatistical analysis of data

Three estimation domains were generated after the statistical and geostatistical analyses of the data, as shown in Figure 8. The original axis range values were in feet (ft) and later changed to metres (m) for the purposes of international readership. The variogram models for each estimation domain are shown in Figure 9 and the parameters generated from each variogram are presented in Table VI. The classification parameters of the three different scenarios used for this investigation were created from the assumptions made by the CPs of three companies in the 45 technical reports compiled from SEDAR.

The classification parameters that were used by the CPs included percentage of variogram range for search radius, minimum number of composites, maximum number of composites, number of drill-holes, and number of composites per hole. Table VII shows the resource classification parameters for the three geometric scenarios. Brief descriptions of the scenarios are as follows.

Scenario 1 represents the 2018 resource classification parameters used for Coeur Mining, Wharf Mine site technical report in the USA (Jimmerson et al., 2018). Based on the NI 43-101 technical report, OK was used for the estimation and the sample search distance for each class was determined based on a certain percentage of the sill range of the major continuity direction of the variogram. Three classification passes were used to categorize the deposit into Measured, Indicated, and Inferred classes.

Scenario 2 represents the 2008 resource classification parameters used for the technical report of Kinross Gold, Cerro Casale Project in Chile (Henderson et al., 2008). The report shows that the CPs applied ID^2 for the estimation interpolation and the search distance for each class was determined based on a percentage of the sill range of the omnidirectional correlogram. There were six classification passes for the three resource classes.



	1: Domain 1	2: Domain 2	3: Domain 3
Valid Data	1134	1973	1277
Total Data	1134	1973	1277
Minimum	0.000	0.000	0.000
Maximum	4.391	1.635	1.403
Mean	0.066	0.041	0.020
Variance	0.033	0.009	0.004
Standard Deviation	0.181	0.092	0.062
Coefficient Of Variation	2.758	2.229	3.140

Figure 8—20 ft composite data histograms for domains 1 (top left), 2 (top right), and 3 (bottom left)

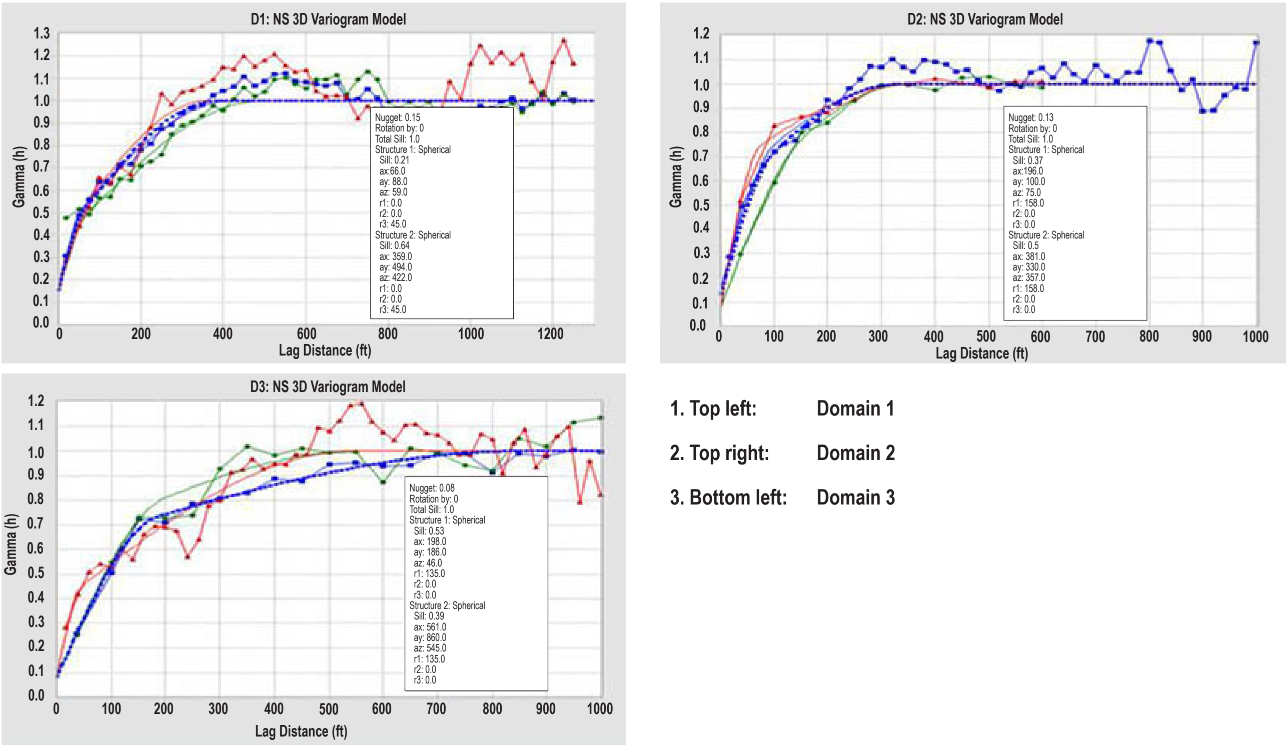


Figure 9—Variograms for domains 1 (top left), 2 (top right), and 3 (bottom left)

Table VI

Variogram parameters for each estimation domain of the gold deposit

Parameters	**Domain 1**		**Domain 2**		**Domain 3**	
Structure	**Structure 1**	**Structure 2**	**Structure 1**	**Structure 2**	**Structure 1**	**Structure 2**
Total sill	1.00	1.00	1.00	1.00	1.00	1.00
Nugget	0.15	0.15	0.13	0.13	0.08	0.08
Sill	0.21	0.64	0.37	0.50	0.53	0.39
Major axis range (m)	27	151	196	60	60	262
Minor axis range (m)	20	109	100	30	57	171
Vertical axis range (m)	18	129	75	23	14	166
Major axis azimuth (°)	0	0	158	158	135	135
Minor axis azimuth (°)	90	90	68	68	45	45
Plunge (°)	0	0	0	0	0	0
Dip (°)	45	45	0	0	0	0

Scenario 3 represents the 2017 resource classification parameters applied in the technical report for Barrick Gold, Goldstrike Mine in the USA (Krutzelmann et al., 2017). The report shows that the CPs used ID² for the estimation interpolation and the search distance for each class was determined based on a certain percentage of the sill range of the major continuity direction of the correlogram. For the Measured class estimation pass, a box search of 12 m × 12 m × 6 m (40 ft × 40 ft × 20 ft) was used to include only composites found within each evaluated block. Thus, blocks without samples did not qualify for a Measured category. There were five classification passes for the Measured, Indicated, and Inferred classification categories.

At cutoff grades from 0.283 g/t to 1.417 g/t (0.010 to 0.050 oz/t), the different mineral resource assumptions applied on each estimation domain from the different scenarios produced different results. Again, this substantiates the discrepancies in Mineral Resource reports in public disclosures due to the application of different CP judgements in the estimation and classification

Table VII

Classification parameters for the three geometric method scenarios

Estimation Pass #	Resource Classification	Search Dist (m)		Max Dist (m)	Min Comp	Max Comp	Number of Holes	Max Comp / Holes	Comment
		Sill Range (a)	Search Value						
Scenario 1: 2018 resource classification parameters for Coeur Wharf Mine, South Dakota, USA (sill Range, a = 44m)									
1	Measured	70% *a	31	44	2	6	Default	3	Range: Major continuity range of correlogram
2	Indicated	80% * a	35	50	2	4	Default	2	
3	Inferred	95% * a	42	63	2	2	Default	2	
Scenario 2: 2008 resource classification parameters for Kinross Cerro Casale Project, Chile (sill Range, a = 40m)									
1	Measured	60% *a	24	39	1	5	1	5	Range: Omnidirectional range of correlogram
2	Measured	80% * a	32	49	1	5	2	3	
3	Indicated	80% * a	32	49	1	5	1	5	
4	Indicated	90% * a	36	55	1	5	2	3	
5	Inferred	90% * a	36	55	1	5	1	5	
6	Inferred	100% * a	40	60	1	5	2	3	
Scenario 3: 2017 resource classification parameters for Barrick Goldstrike Mine, Nevada, USA (sill Range, a = 44m)									
1	Measured	Box 40 x 40	12	26	1	99	1	99	Range: Major confinuity range of correlogram
2	Indicated	80% * a	35	53	2	3	2	1	
3	Indicated	80% * a * 0.5	18	32	1	3	3	1	
4	Inferred	90% * a	40	60	2	3	2	1	
5	Inferred	90% * a * 0.5	20	35	1	3	3	1	

Table VIII

Domain 1 comparison of the tonnage (t) and grade (g/t) of the three geometric scenarios at different cutoff grades

Class	Cutoff (g/t)	Scenario 1		Scenario 2		Scenario 3	
		Tonnage	Grade	Tonnage	Grade	Tonnage	Grade
Measured	0.28	11 473 920	1.96	10 150 400	1.06	3 870 720	2.33
	0.57	9 047 040	2.38	8 099 840	2.38	3 079 680	2.83
	0.85	7 321 600	2.81	6 656 000	2.75	2 490 880	3.37
	1.13	6 131 200	3.20	5 521 920	3.15	2 145 280	3.80
	1.42	4 940 800	3.69	4 677 120	3.52	1 907 200	4.11
Indicated	0.28	1 098 240	1.15	2 150 400	1.47	3 758 080	1.76
	0.57	721 920	2.04	1 571 840	1.90	2 721 280	2.32
	0.85	483 840	2.78	1 113 600	2.44	2 096 640	2.86
	1.13	368 640	3.38	814 080	3.03	1 715 200	3.29
	1.42	273,920	4.17	665 600	3.46	1 482 240	3.63
Inferred	0.28	258 560	0.77	811 520	1.08	1 845 760	1.53
	0.57	133 120	1.22	506 880	1.56	1 331 200	2.01
	0.85	94 720	1.50	360 960	1.96	975 360	2.52
	1.13	58 880	1.90	248 320	2.44	775 680	2.98
	1.42	38 400	2.30	212 480	2.67	581 120	3.57

Table IX

Domain 2 comparison of the tonnage (t) and grade (g/t) of the three geometric scenarios at different cutoff grades

Class	Cutoff (g/t)	Scenario 1		Scenario 2		Scenario 3	
		Tonnage	Grade	Tonnage	Grade	Tonnage	Grade
Measured	0.28	30 284 800	1.16	31 086 080	1.16	5 870 080	1.42
	0.57	22 336 000	1.47	23 559 680	1.45	4 505 600	1.76
	0.85	15 050 240	1.90	16 307 200	1.81	3 246 080	2.21
	1.13	9 784 320	2.47	10 728 960	2.32	2 240 000	2.83
	1.42	7 121 920	2.98	7 728 640	2.78	1 597 440	3.52
Indicated	0.28	4 275 200	0.91	5 507 040	0.79	12 938 240	0.04
	0.57	2 800 640	1.22	3 348 480	1.08	9 758 720	0.05
	0.85	1 792 000	1.59	2 035 200	1.42	6 428 160	0.07
	1.13	1 103 360	2.07	1 085 440	1.93	4 180 480	0.09
	1.42	724 480	2.55	762 880	2.24	2 954 240	0.12
Inferred	0.28	217,600	0.99	1 728 000	0.74	5 885 440	0.04
	0.57	168,960	1.19	980 480	1.11	4 195 840	0.05
	0.85	110,080	1.50	550 400	1.50	2 744 320	0.06
	1.13	66 560	1.93	322 560	1.96	1 674 240	0.09
	1.42	61 440	2.01	225 280	2.32	1 116 160	0.11

Table X

Domain 3 comparison of the tonnage (t) and grade (g/t) of the three geometric scenarios at different cutoff grades

Class	Cutoff (g/t)	Scenario 1		Scenario 2		Scenario 3	
		Tonnage	Grade	Tonnage	Grade	Tonnage	Grade
Measured	0.28	14 960 640	0.82	17 456 640	0.77	2 350 080	0.85
	0.57	7 290 880	1.39	8 030 720	1.30	1 256 960	1.33
	0.85	4 456 960	1.90	4 887 040	1.79	721 920	1.90
	1.13	2 887 680	2.49	3 171 840	2.30	422 400	2.64
	1.42	2 150 400	2.95	2 227 200	2.81	286 720	3.37
Indicated	0.28	1 559 040	0.74	2,506 240	0.65	7 843 840	0.79
	0.57	611 840	1.47	857 600	1.36	3 919 360	1.28
	0.85	427 520	1.87	599 040	1.70	2 273 280	1.81
	1.13	317 440	2.21	396 800	2.15	1 362 920	2.47
	1.42	248 320	2.52	302 080	2.47	962 560	3.01
Inferred	0.28	248 160	0.57	1 128 960	0.54	2 199 040	0.82
	0.57	97 280	1.11	307 200	1.28	1 031 680	1.42
	0.85	66 560	1.36	240 800	1.62	647 680	1.96
	1.13	53 760	1.50	138 240	1.98	419 840	2.52
	1.42	28 160	1.84	107 520	2.24	307 200	3.06

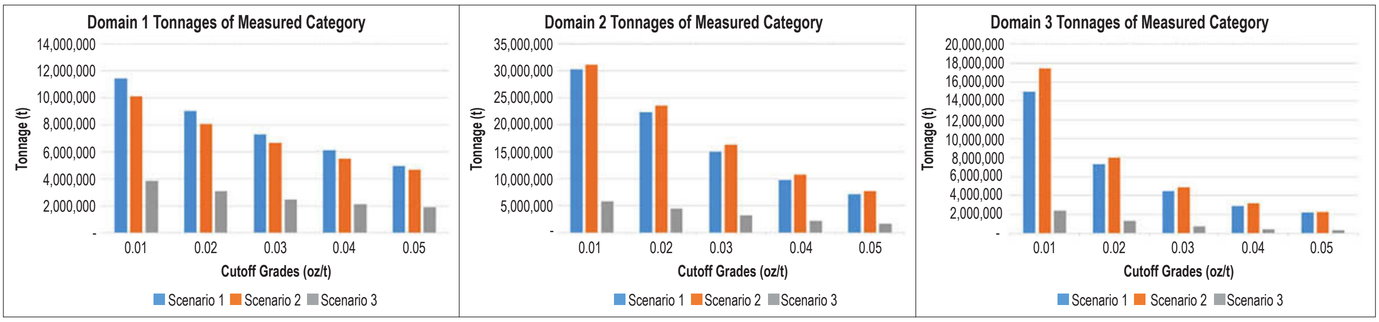


Figure 10—Tonnages for Measured Resources at different cutoff grades from the three scenarios for domains 1 (left), 2 (middle), and 3 (right)

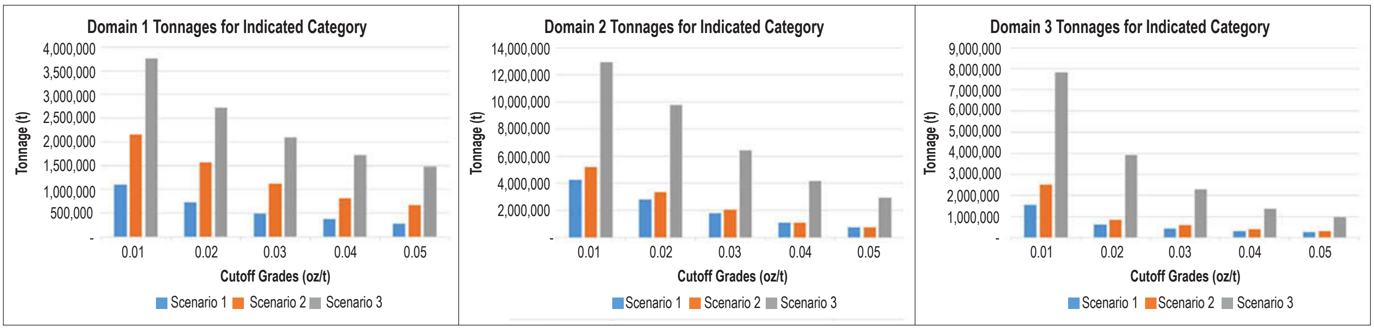


Figure 11—Tonnages for Indicated Resources at different cutoff grades from the three scenarios for domains 1 (left), 2 (middle), and 3 (right)

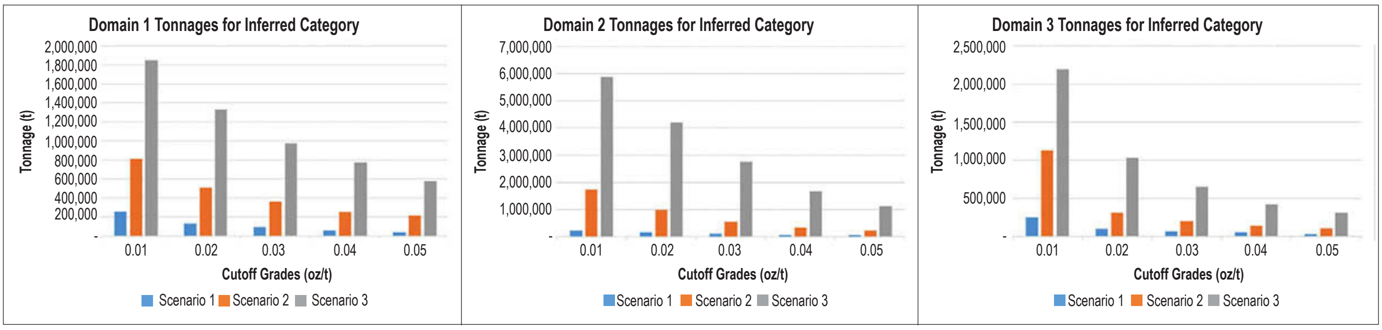


Figure 12—Tonnages for Inferred Resources at different cutoff grades from the three scenarios for domains 1 (left), 2 (middle), and 3 (right)

processes. Tables VIII to X show each scenario's tonnages and grades generated from domains 1, 2, and 3 respectively at different cutoff grades.

Discussion case study B

The tonnages produced from the three different scenarios in the three domains are shown in Figures 10, 11, and 12 for Measured, Indicated, and Inferred classes respectively.

Measured category

Scenario 3 produced far less tonnage in the Measured class than the other two scenarios in all three domains. In domain 1, scenario 1 generated more tonnage than scenario number 2 at all the cutoff grades. Considering domain 2, scenario 2 produced more tonnage than scenario 1.

Indicated category

Scenario 3 produced far greater tonnage in the Indicated class than the other two scenarios in all the three domains. In domains 1 and 3, scenario 2 generated more tonnage than scenario 1 at all the cutoff grades. Domain 2 produced more tonnage in scenario 2 than scenario 1 at cutoff grades of 0.28 g/t to 0.85 g/t. At cutoffs of 1.13 g/t and 1.42 g/t, scenarios 1 and 2 produced almost equal tonnages.

Inferred category

Scenario 3 produced the greatest tonnage in the Inferred class in all the domains and at all the cutoff grades. Scenario 2 generated more tonnage than scenario 1 in all three domains.

The figures clearly display the differences in tonnages produced from the three CP assumptions applied to the same gold deposit. Converting the Mineral Resources into Mineral Reserves for this deposit after applying modifying factors, including technical, economic marketing, and governmental factors would also produce different results. The differences in the Measured and Indicated Resources shown in Tables VIII–X can have significant impacts on investment, development, and mining production decisions. This is a clear indication of resource classification inconsistencies, since the mining industry lacks a uniform classification framework. Diligent analysis of the classification results produced from the same data-sets corroborates the conclusions of Owusu and Dagdelen (2019) from their review of 45 technical reports on SEDAR. Considering the three scenarios applied on the same data and the corresponding outcomes, it is difficult to distinguish the right results from the wrong, since each CP followed the CIM best practice guidelines.

Conclusions

Mineral Resource classification is a critical factor in the success of a mining business, as it provides the confidence level that can be ascribed to a project. In spite of its importance, the techniques used to determine the uncertainties are applied inconsistently in the mining industry because the parameters utilized in the process are subjectively determined by the responsible CP. We have presented quantitative illustrations of the impacts of different CP assumptions and judgements to demonstrate that varying grades, tonnages, and metal contents can be generated from the same drill-hole data, leading to discrepancies in classification reports. In the 45 technical reports from SEDAR used for this work, the responsible CPs provided reasons for choosing their classification parameters and each report was assumed to be acceptable as per the CIM best practice guidelines for public disclosures.

This work has shown that the practice of applying individual CP assumptions without limitation can cause misleading public disclosures and affect future project outcomes. It underpins the need for a standard or uniform resource classification framework, with particular emphasis on an acceptable range of parameters to be applied per each deposit type, based on the available geological and geometallurgical information. An effective and acceptable uniform framework will help minimize the effects of individual CPs' assumptions on the Mineral Resource classification process and thus, enhance investor confidence in mineral projects.

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