Data driven approaches for estimating bulk ore sorting value[1]

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Abstract

ShovelSense is a robust shovel mounted X-ray fluorescence sensor that can measure multiple element grades of each bucket as it is dug at the mine face. The shovel sensor system allows for the bulk sorting of ore and waste at the mine face ensuring each truck is sent to its correct destination. Due to the previous inability of sorting at the truck scale there are not many established methods for predicting the bulk ore sorting value at a given deposit. The ShovelSense grade of the truck load is used to define its final destination, which can be different from the one defined by the short term plan, which is done at block resolution. In this paper, we present two approaches for quantifying the value of the truck reassignments based on the measured grade. First, truck loads within the block are assumed to follow a simple gamma distribution. The second method uses geostatistical simulation at point support to average the grades at truck or block resolution. Both distinct data driven methods predict the potential bulk ore sorting value based on the mine's current operating selectivity and natural variability drawn from blastholes or the short term block model. The bulk ore sorting value predictions are validated with ShovelSense truck diversions from a dispatch dataset of 28,418 trucks at a low-grade, high-tonnage homogeneous Cu porphyry deposit. In addition to the algorithms and workflows presented here, recommendations based on the potential and limitations of each method are given to practicioners seeking to evaluate the bulk ore sorting opportunity for any open pit operation.

1. Introduction

The natural variability linked to the mineralization of ore deposits and mining operational complexity make ore control challenging, resulting in the inevitable loss of ore and dilution of waste in the ore stream. The accurate sorting of material especially at ore-waste contacts is a significant challenge in the mining industry which scales with the deposit's variability (Amirá et al., 2019) and poor grade control practices (Vasylchuk and Deutsch, 2018). Routine grade control relies heavily on the measurement of element grades for samples from boreholes, estimation of blast movement, and constant monitoring with geologists at the mine face. Blastholes are drilled and sampled on a grid with a spacing that can range from 3 to 10 m depending on the material being blasted. These grades are used to estimate grades into a block model from which a dig plan is generated.

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The sparsity of grade measurements, the difficulty of accurately sampling a blasthole, smoothing introduced through estimation, and material displacement due to blast movement severely limit the performance of the current grade control processes (Rossi and Deutsch, 2013). Furthermore, all decisions based on this model are made at block support, which is usually much larger than the truckload support. This leads to the inevitable ore loss to waste and waste diluting the ore stream, reducing the efficiency of downstream processes.

ShovelSense is a shovel mounted robust X-ray fluorescence (XRF) based sensor which can predict elemental grades in each bucket as it is loaded before being dumped into a truck (Figure 1). This allows the mine to selectively exploit grade variations at a resolution that was not available before. Significant value can be achieved through bulk ore sorting by reducing the amount of ore loss to the waste stream and removing waste from material destined for processing. In a typical setup, the fleet management system (FMS) informs ShovelSense by identifying the buckets that were combined in a truck and the classification of that truck from the mine plan (e.g., ore or waste). ShovelSense aggregates the selected ShovelSense bucket grade predictions to the truck of interest and determines the material classification using the predicted grades. The predicted material classification is transmitted back to the FMS. If it is different from the original estimated material classification, the FMS can redirect the truck to the correct destination in a completely automated fashion requiring no action from the shovel operator or dispatcher.

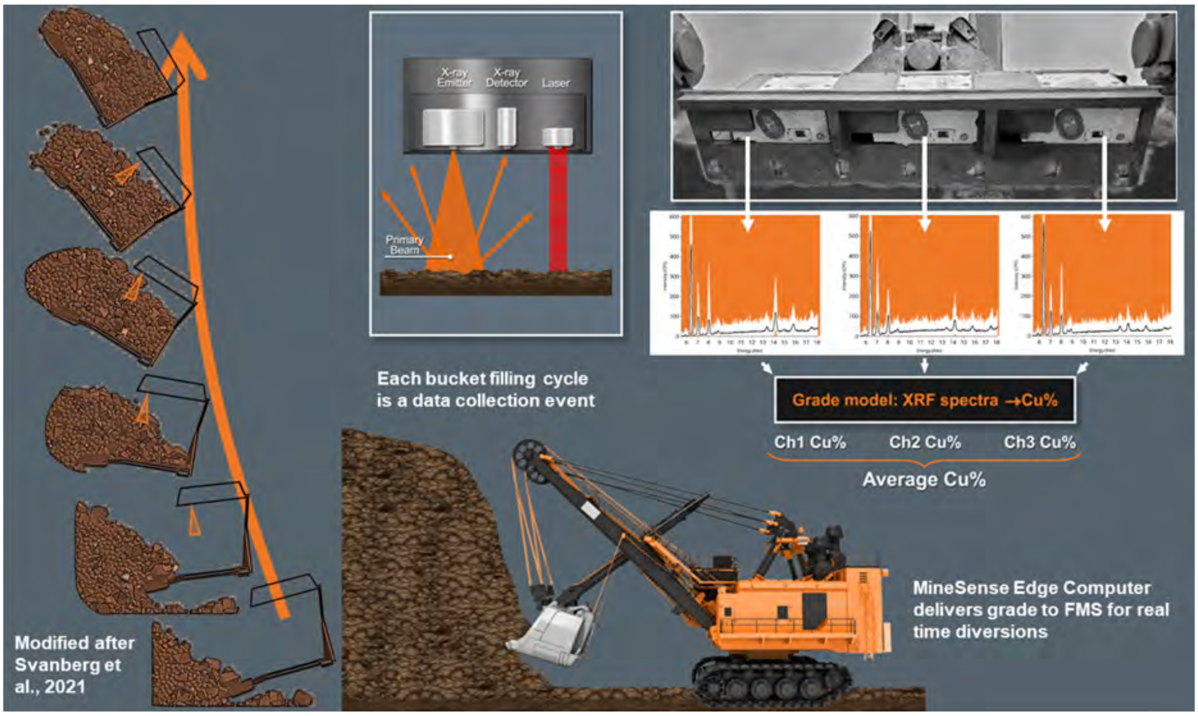


Figure 1: Schematic of the bucket filling and aggregate XRF spectra acquisition. Fill profile modified after Svanberg et al. (2021).

Numerous studies have identified the potential for bulk ore sorting revealing that the ore heterogeneity (Nadolski et al., 2016; Moss et al., 2018) and the mine's current ore control efforts (Sanhueza Passache, 2021) are key drivers in the sorting value in addition to other relevant variables such as the sorting efficiency, metal price, processing cost, and operation scale (Li et al., 2022). Bulk ore sorting evaluation methods will be critical as more mines consider implementing sensor-based ore sorting systems and decide which are the optimal loading units for sensor installations. Due to the previous inability of sorting at the truck scale, there are currently limited published studies quantifying and validating the potential bulk ore sorting value (Li et al., 2019, 2021). Proposed in this paper are two distinct methodologies for assessing the potential bulk ore sorting value based off truck scaled blasthole grades and variabilities within the selective mining unit (SMU). The validation of the bulk ore sorting predictions is done by comparing the inferred value with the value measured from ShovelSense truck diversions at a Cu porphyry mine.

2. Bulk Ore Sorting Value Prediction Workflows

Both bulk ore sorting value prediction approaches are based off the potential revenue generated from ore recovery and dilution reduction diversions resulting from the reduction of the mine's current SMU down to the truck level. The highest resolution ore control data available is used in a distinct way for each approach to estimate the grades and variability of grades within the current SMU and discretized to truck sized blocks. The two workflows are a simpler gamma distribution approach which is easily automated, and a geostatistical dense simulation approach requiring variogram modeling. Both methodologies start by using or creating an SMU block model with the ore control data available and discretizing it to truck sized blocks. Then the theoretical bulk ore sorting value resulting from the ore recovery and dilution reduction truck block diversions from the SMU block is quantified. Both workflows have the same steps when discretizing to truck sized blocks and quantifying the value but the grade and variability estimation which drives that value is distinct (Figure 2).

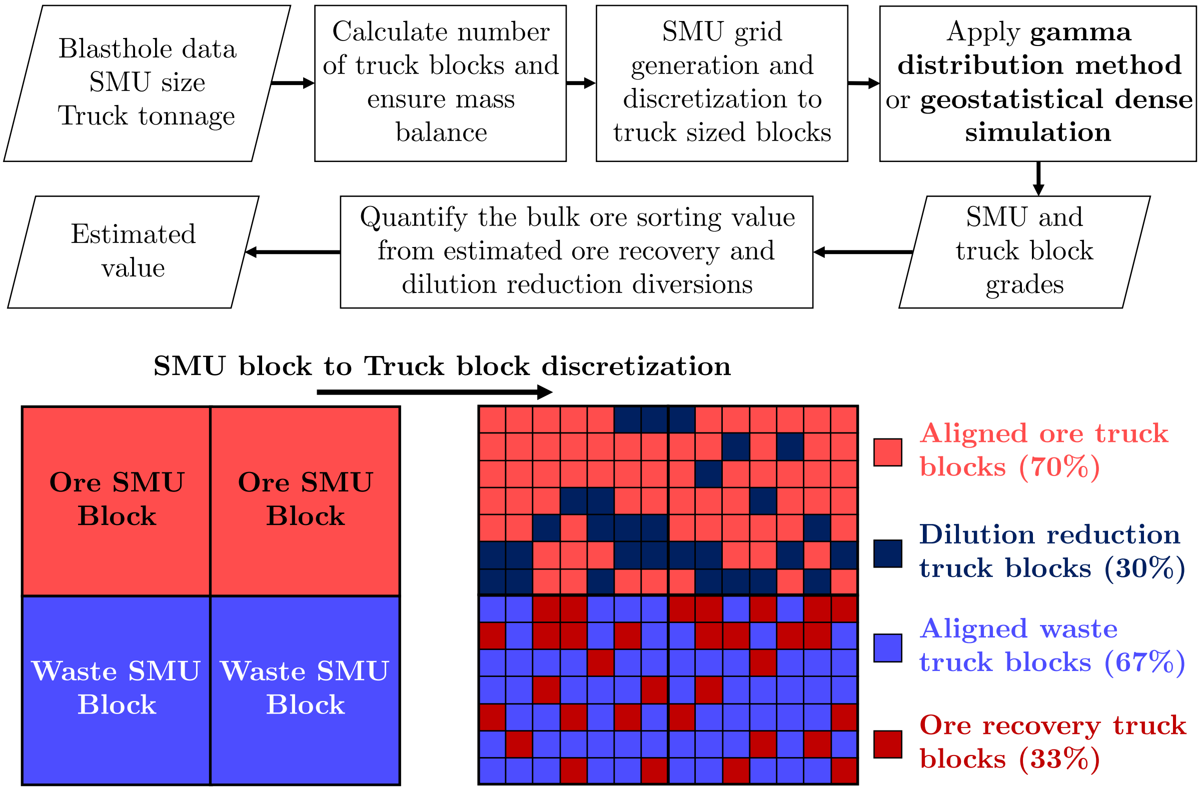


Figure 2: Overall methodology for predicting the bulk ore sorting value with either the simple gamma distribution or geostatistical dense simulation approach.

2.1. SMU Discretization to Truck Sized Blocks

The discretization of the SMU blocks to truck sized blocks needs to achieve a mass balance. The mass of each block is a function of density. For deposits with varying densities this variability needs to be accounted for. More truck blocks are thus assigned to regions of denser material as the tonnage is constrained by the truck type. The formula for calculating the number of truck blocks for each SMU is a simple function of the SMU dimensions, density, and truck capacity which is rounded to the nearest whole number:

$$\mathrm{T}_N = \mathrm{round}\left(\frac{\mathrm{SMU}_l * \mathrm{SMU}_w * \mathrm{SMU}_h * \mathrm{SMU}_\rho}{\mathrm{T}_C}\right), \tag{1}$$

where l, w, h, ρ are the SMU length, width, height, and density respectively and T_C is the truck capacity.

Figure 3 illustrates two extremely distinct cases where a 20x20x15 m SMU block is discretized to truck sized blocks for two different densities and truck capacities. Larger SMUs along with smaller truck capacities will result in more truck blocks for each SMU block and the increased selectivity will better separate ore and waste generating more value.

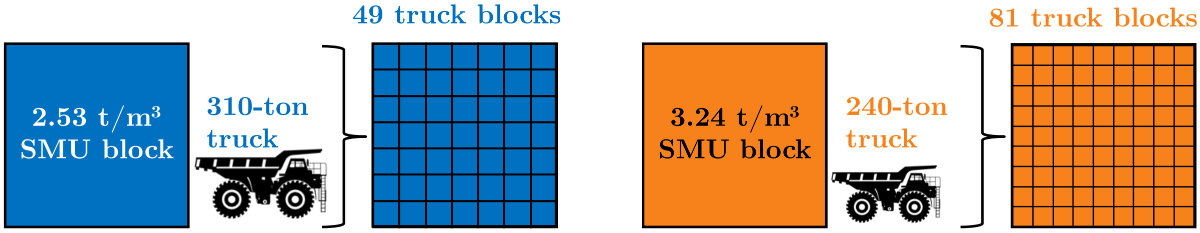


Figure 3: Schematic illustrating the discretization of a 20x20x15 m SMU block to truck blocks for distinct material densities and truck capacities.

When considering multiple payable or deleterious elements used in a net smelter return or similar value based cutoff, only the elements which the bulk ore sensing system can measure should be discretized. In cases where there is an element which cannot be measured by the shovel mounted sensor, the value of that element for all the truck blocks should be set equal to the corresponding SMU block. Generally, the more relevant elements the sensor can measure at a mine, the more valuable the bulk ore sorting tool will be as it provides the highest resolution information currently possible for ore control. Notice that the truckload volume extracted is approximated by a rectangular prism with the SMU height and a smaller area in the XY plane. This is not exactly the geometry of the volume extracted by the shovel to load a truck, but provides a good approximation of the selectivity associated to the truckloads.

2.2. Simple Gamma Distribution Approach

When the blasthole sampling at a given deposit is not preferential, it can be modeled using a theoretical distribution without the need for declustering (Chiles and Delfiner, 2012). In cases where the blasthole sampling is preferential, it must be declustered. Alternatively, the short-term block model can be used as the input source of grades as it is regularly gridded. Geochemical element concentrations of ore grades are always positive, have skewed distributions, and are typically modeled using lognormal distributions (Faraj and Ortiz, 2021) or gamma distributions (Pizarro Munizaga, 2011; Emery, 2012). For the purposes of estimating the Cu grade in a limited number of smaller blocks within an SMU, the gamma distribution is chosen as the longer tail of the lognormal distribution could complicate the SMU reconciliation, especially when the variance is high (Cadigan and Myers, 2001). When varying multiple elements different distributions could be chosen based on which best fit each element, and ideally accounting for their relationships. The probability density for the gamma distribution is given by

$$P(x) = \frac{x^{k-1} \mathrm{e}^{-\frac{x}{\theta}}}{\theta^k \Gamma(k)}, \tag{2}$$

where k is the shape parameter which controls the skewness, θ is the scale parameter which controls the spread of the distribution, and $\Gamma(k)$ is the Euler Gamma function. The shape and scale factor can be written as functions of the mean and variance

$$k = \frac{\sigma^2}{\mu}, \qquad \theta = \frac{\mu^2}{\sigma^2} \tag{3}$$

where μ is the mean and σ^2 is the variance.

The gamma distribution method is simple and based mainly off the blasthole data with another few parameter inputs as detailed in Algorithm 1 and illustrated in Figure 4. Aside from the blasthole data, SMU dimensions, and truck capacity, which are all fixed, the search radius is the only parameter which needs to be defined by the practitioner and could be set to 1.25 times the SMU horizontal length as done here. Squared inverse distance weighted estimates (IDW^2) within the search radius are used to assign the grade of each SMU block and the variance is taken from all the matched blastholes within the radius as well. Using this gamma distribution, the proportion of truckload blocks that are above and below the economic cutoff grade can be determined to quantify the quantity diverted from their original SMU assignment. The exact position within the SMU of these blocks is irrelevant, only their quantity is of significance.

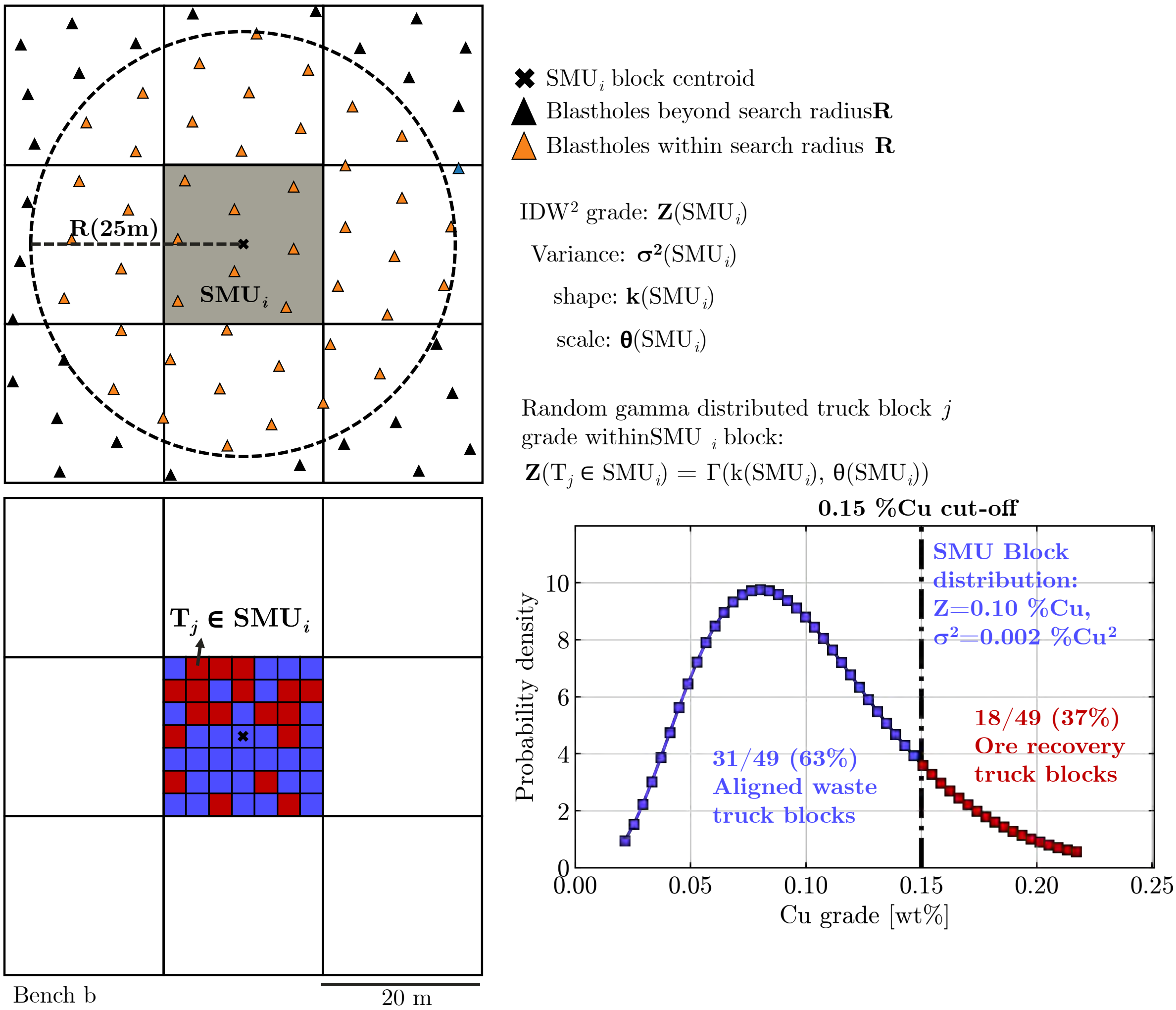


Figure 4: Methodology for assigning SMU and truck block grades with the simple gamma distribution approach with an example for a SMU block with a mean grade of 0.10 %Cu and variance of 0.002 %Cu^2.

Algorithm 1: Gamma Distribution Grade Assignment

Input: Blasthole data ($\mathbf{BH}$), SMU data ($\mathbf{SMU}$), truck block data ($\mathbf{T}$)

Input: Benches (b), Search radius (R), Blasthole positions ($P(\mathbf{BH})$), and grades ($Z(\mathbf{BH})$)

Input: Centroids for each **SMU** block i ($P(\mathbf{SMU}_i)$), and truck blocks j within each **SMU** block i ($T_j \in \mathbf{SMU}_i$)

Output: **SMU** block grades, variance, and gamma distributed grade for each truck block

for *each bench b* **do**

`/*` Filter blastholes, SMU blocks, and truck blocks to bench b `*/`

$$P(\mathbf{BH}), P(\mathbf{SMU}_i) \in b$$

for *each **SMU** block i* **do**

`/*` Search for all matched blastholes ($\mathtt{BH}'$) where the distance d of $P(\mathtt{BH})$ and $P(\mathtt{SMU}_i)$ is within R `*/`

$$\mathbf{BH}' = \{\mathbf{BH} | d(\mathbf{BH} - \mathbf{SMU}_i) \leq R\}$$

`/*` Assign IDW^2 SMU grade ($Z(\mathtt{SMU}_i)$) and variance ($\sigma^2(\mathtt{SMU}_i)$) from the matched blasthole grades ($Z(\mathtt{BH}')$), average grade ($\overline{Z}(\mathtt{BH}')$), and distances ($d(\mathtt{BH}')$) `*/`

$$Z(\mathbf{SMU}_i) = \sum_{n=1}^{N} \frac{Z(\mathbf{BH}'_n)}{d(\mathbf{BH}'_n)^2} \div \sum_{n=1}^{N} \frac{1}{d(\mathbf{BH}'_n)^2}$$

$$\sigma^2(\mathbf{SMU}_i) = \frac{1}{N} \sum_{n=1}^{N} \Big(Z(\mathbf{BH}'_n) - \overline{Z}(\mathbf{BH}'_n) \Big)^2$$

`/*` Calculate the SMU shape ($k(\mathtt{SMU}_i)$) and scale ($\theta(\mathtt{SMU}_i)$) `*/`

$$k(\mathbf{SMU}_i) = \frac{Z(\mathbf{SMU}_i)^2}{\sigma^2(\mathbf{SMU}_i)}, \quad \theta(\mathbf{SMU}_i) = \frac{\sigma^2(\mathbf{SMU}_i)}{Z(\mathbf{SMU}_i)}$$

`/*` For each of the truck block j draw random gamma distributed grade ($\Gamma(k, \theta)$) and scale the truck block grades ($Z_j(\mathtt{T})$) with the SMU grade ($Z(\mathtt{SMU}_i)$) divided by the average truck block grade ($\overline{Z(\mathtt{T})}$) `*/`

$$Z_j(\mathbf{T}) \sim \Gamma(k(\mathbf{SMU}_i), \theta(\mathbf{SMU}_i)), \quad Z_j(\mathbf{T}) = Z_j(\mathbf{T}) \frac{Z(\mathbf{SMU}_i)}{\overline{Z(\mathbf{T})}}$$

end

end

2.3. Geostatistical Dense Simulation Approach

The use of geostatistical simulations in mining operations is on the rise to quantify heterogeneity and transfer uncertainty and variability into risk for decision making. A major benefit of simulations is the ability to quantify the risk associated with the estimation by assessing the spatial variability (Vann et al., 2002; Rendu, 2002). Here, densely gridded simulations are used to estimate grades at a truck scale for predicting the potential bulk ore sorting value. Densely gridded simulations have previously been used to develop high resolution mining models of mineral grades (Charifo et al., 2013), which have been used for many applications such as informing mining decisions through the mine value chain (Altinpinar et al., 2020).

The geostatistical dense simulation approach requires only the blasthole data, SMU blocks, and discretized truck block definitions. First, domains must be established if there is domaining information available. Then, for each domain, normal score variogram models are developed and used to generate a number of point support realizations (100 sequential gaussian simulations were used in our case) in a dense grid defined by the practitioner such as 1 by 1 m in each bench. The dense grid is averaged to the truck blocks, and then the truck blocks are also averaged to each SMU block as illustrated in Figure 5. The gaussian simulations proposed serve as an adequate baseline for typical homogeneous porphyry deposits. However for more geologically complex deposits which exhibit a high degree of nonlinear features such as veins, channels or folds the simulations could incorporate locally varying anisotropy (Boisvert and Deutsch, 2011) or different continuity for different grade ranges through an indicator approach, since standard gaussian simulations have been shown to miss complex geological structures (Lee et al., 2007).

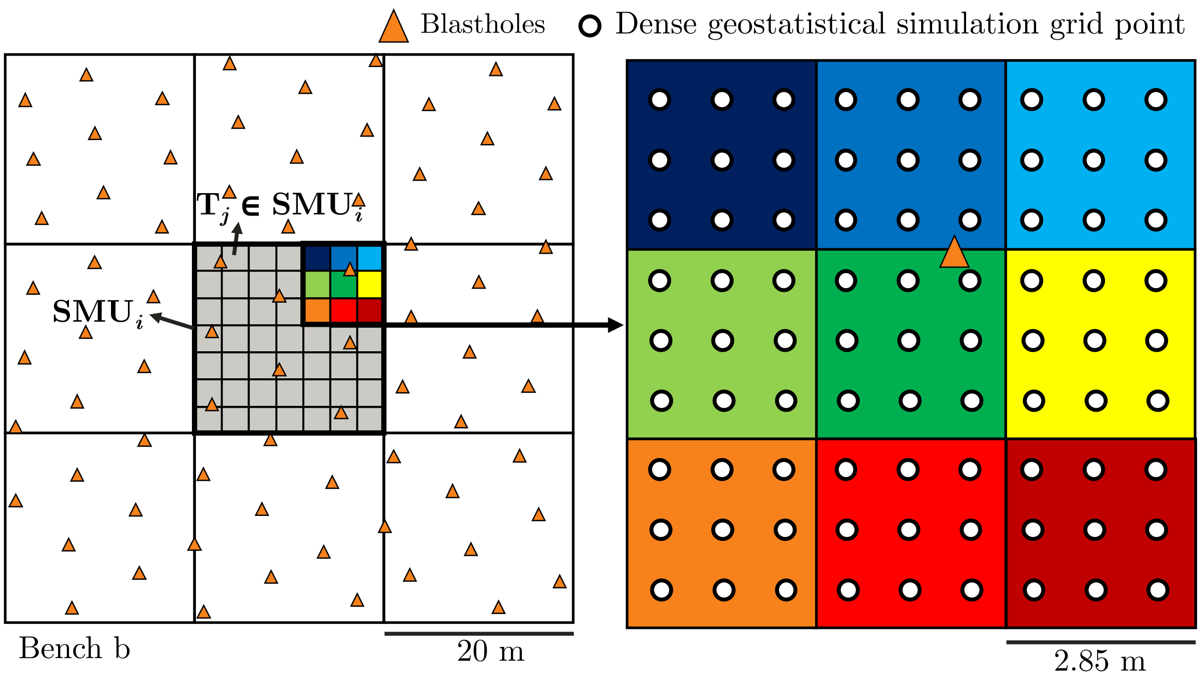
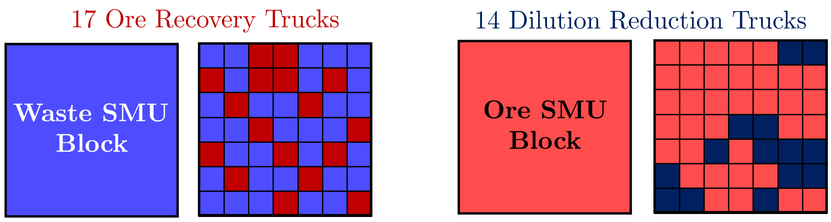


Figure 5: Methodology for assigning SMU and truck block grades with the geostatistical dense simulation approach.

2.4. Value Quantification and Validation Methodology

There are multiple ways to calculate the ore recovery and dilution reduction value from the estimated truck diversions. The optimal way to calculate these will vary from mine to mine. Some mines ideally use a net smelter return to incorporate additional variables and give an accurate evaluation. In contrast others may just work based off the Cu content. We propose a generic method to estimate the ore recovery and dilution reduction value which is applied to both approaches and the dispatch validation data (Figure 6). For the purposes of comparing the predicted value to dispatch data for validation, the assumptions and calculations done to quantify the value are not critical as the same methodology is applied to each. For this deposit, the recovery, recovered value factor, processing cost, and Cu price are taken as 85%, 85%, 5 USD/t, and 3.50 USD/lb respectively.



$$\textbf{Value} = \sum \textbf{OreRecoveryValue} + \sum \textbf{DilutionReductionValue}$$

$$\textbf{Value} = \sum RD*Z*T*R*RVF*P\text{-}T*Pr + \sum DD*T*Pr$$

RD – Recovery Diversion
Z – Truck Cu proportion
T – Truck tonnage (t)
R – Recovery
RVF – Recovered value factor
P – Cu price ($/t)
Pr – Processing cost ($/t)

DD – Dilution Diversion
T – Truck tonnage (t)
Pr – Processing cost ($/t)

Figure 6: Bulk ore sorting value estimation methodology.

3. Bulk Ore Sorting Value Predictions at a Cu Porphyry Mine

Both the gamma distribution and dense geostatistical simulation approach were applied on a blasthole dataset from a low-grade, high tonnage Cu porphyry mine. The data spans six benches from which ShovelSense truck data was also collected during several months. There are 23,192 blastholes and 28,418 trucks with ShovelSense grades which are used to validate the bulk ore sorting value predictions. Figure 7 shows the blastholes and ShovelSense truck Cu grades throughout the six benches. The Cu porphyry mine has a cutoff grade of 0.15 %Cu and SMU of 20x20x15 m.

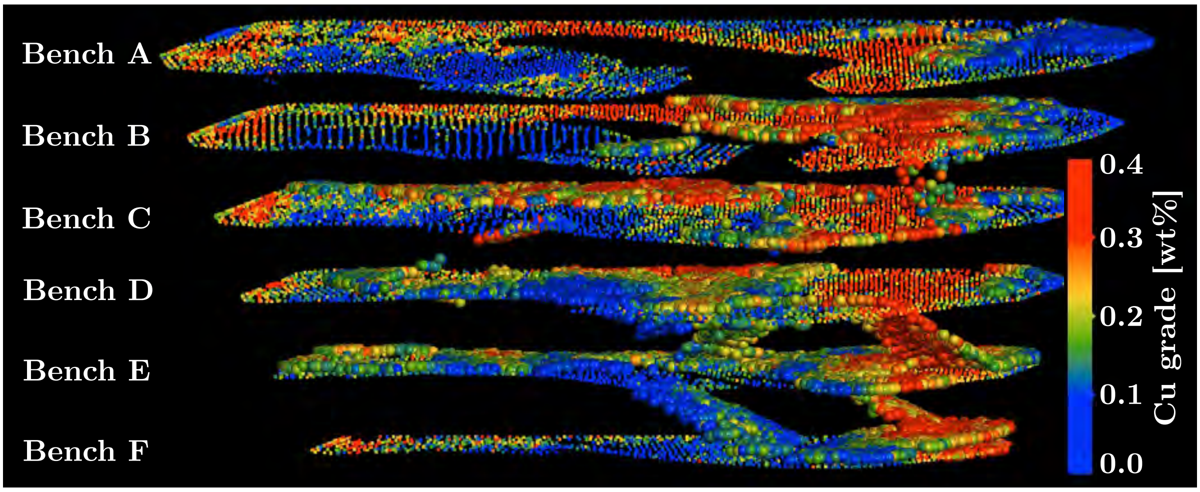


Figure 7: The low-grade, high tonnage Cu porphyry dataset used showing the blastholes and ShovelSense truck grades for each of the six benches. The vertical scale is four times the horizontal scale.

3.1. Discretization Integrity for Tonnage and Metal Balance

With the mine's pit density of 2.54 t/m^3 there will be 49 truck blocks for each SMU block to achieve a tonnage balance as outlined in Table 1. From the 23,192 blasthole data, 2,911 SMU blocks were generated with a corresponding 142,639 truck blocks after filtering out SMU blocks with less than 10 blastholes in the 25 m radius as these represent blocks along the edges without sufficient data to be properly evaluated. In addition to achieving a mass balance, the truck block grades averaged to the corresponding SMU block must also match in metal content. The error metrics tabulated in Table 1 demonstrate that their is no significant metal mismatch. The discretization integrity for tonnage and metal content should always be checked for all considered elements as significant differences could cause errors in the final bulk ore sorting value estimate.

Table 1: Parameters and summary statistics of the SMU to truck block discretization for the tonnage and metal balance.

SMU and Truck Block Tonnage Balance		
Parameter	SMU Block	Truck Block
Width [m]	20	2.857
Length [m]	20	2.857
Height [m]	15	15
Volume [m^3]	6000	122
Density [t/m^3]	2.54	2.54
Tonnage [t]	15,240	310
SMU and Truck Block Metal Balance		
Parameter	GammaDistribution - SMU	GeostatsSimulations - SMU
Count	2911	2911
Min [%Cu]	-9.99e-16	-5.55e-16
Mean [%Cu]	1.46e-18	1.22e-18
Max [%Cu]	8.32e-16	5.55e-16
St Dev [%Cu]	8.53e-17	1.37e-16

For comparing the predicted bulk ore sorting value to the ShovelSense dispatch dataset, the SMU and truck block data was further filtered to only include blocks within 15 m of a dispatched truck. This filter was applied to improve the comparison by roughly matching the SMU and truck block data to the actual material dug. There will still be some expected noise and errors in the comparison because there were other shovels without ShovelSense installed working in the same area but not far enough to filter out.

3.2. Truck Block Grades and Classification

The truck block grades for the gamma distribution were randomly assigned to each block within the SMU block. The spatial aspect of each truck block is not relevant for the purpose of bulk ore sorting value predictions. The dense simulation accounts for the spatial distribution of the data and the continuity is based on the normal score spherical variogram models developed for the three principal directions of anisotropy given by

$$\gamma(h) = \begin{cases} 0 & \text{for } h = 0 \\ C_0 + C_1 \left[\frac{3}{2}\frac{h}{a} - \frac{1}{2}\left(\frac{h}{a}\right)^3 \right] & \text{for } 0 < h \leq a \\ C_0 + C_1 & \text{for } h > a \end{cases} , \tag{4}$$

where C_0 is the nugget of 0.20, C_1 is the sill contribution of the spherical structure, equal to 0.80, h is the lag distance, a is the range of 250 m, 140 m, and 80 m for the three directions respectively.

The gamma distributed truck block grades show much higher spatial variability than the dense geostatistical simulation which drives the difference in the theoretical ore recovery and dilution reduction from the SMU. A zoomed in section on the SMU block model in Figure 8 highlights the difference in the spatial distribution of grades for each truck block within the SMU blocks. There are even many blastholes with different classification from their host SMU block which is also captured by the gamma distributed grades but not by the dense geostatistical simulation throughout this variable zone. This is explained because, even for the truck blocks, the geostatistical simulation takes into account the change of support, that is, the fact that the truckload is much larger in volume than the blasthole.

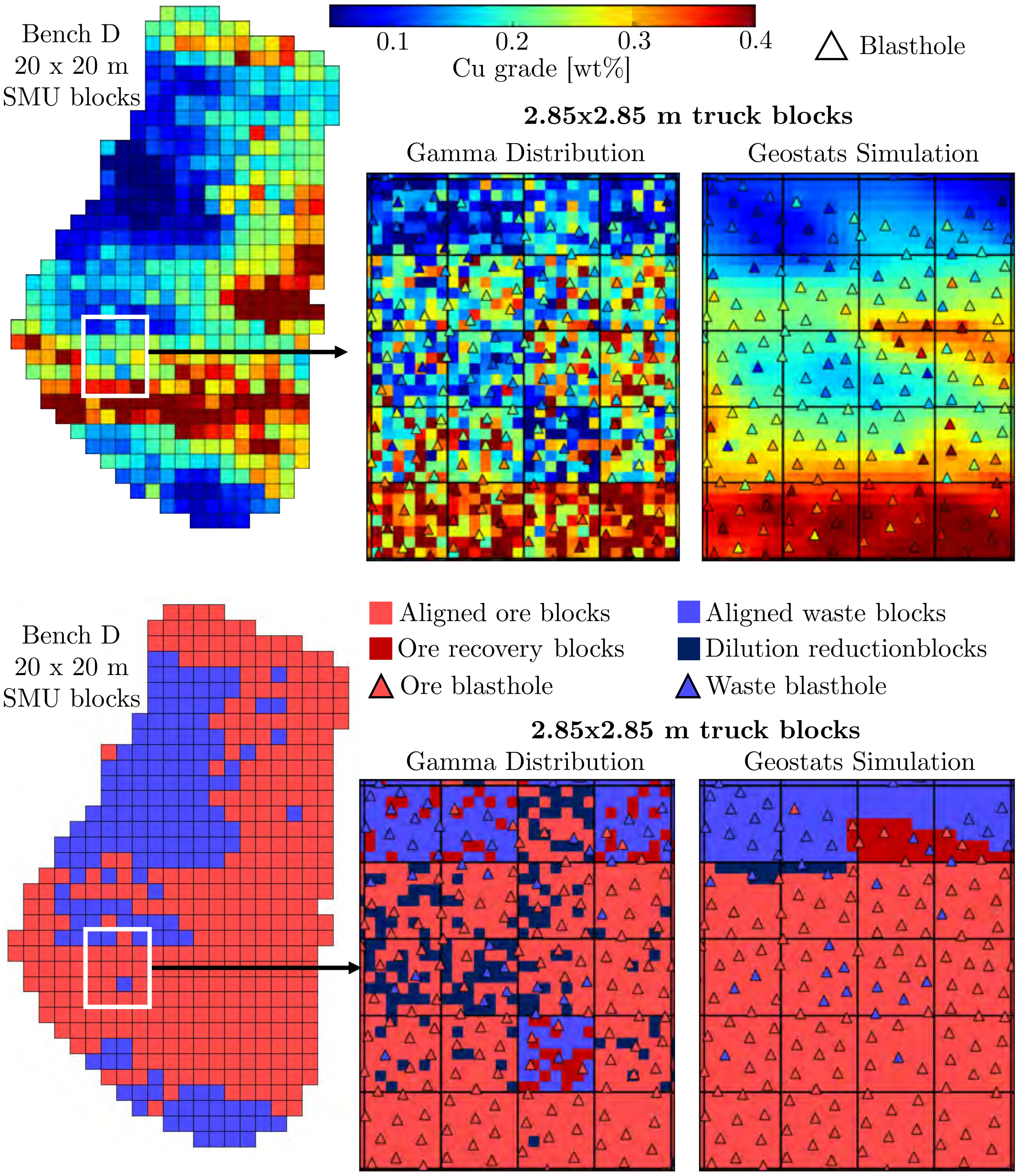


Figure 8: Spatial plots comparing the SMU and truck block grades and classifications for the gamma distribution and geostats simulation within a variable section.

The SMU grade and variability has the biggest influence on the proportion of truck blocks classified differently than the SMU blocks. Figure 9 shows that most of the difference in material classifications occur with more variable SMU blocks near the cut-off of 0.15 %Cu. Even highly variable blocks don't result in many theoretical diversions if the SMU grade is significantly higher or lower than the cut-off. Compared to the ShovelSense truck grades, the gamma distribution was more variable while the geostatistical simulation was less variable (Figure 10). Despite applying the 15 m filter, the ShovelSense data still represents less than half of the predicted tonnages and could have dug more homogeneous areas.

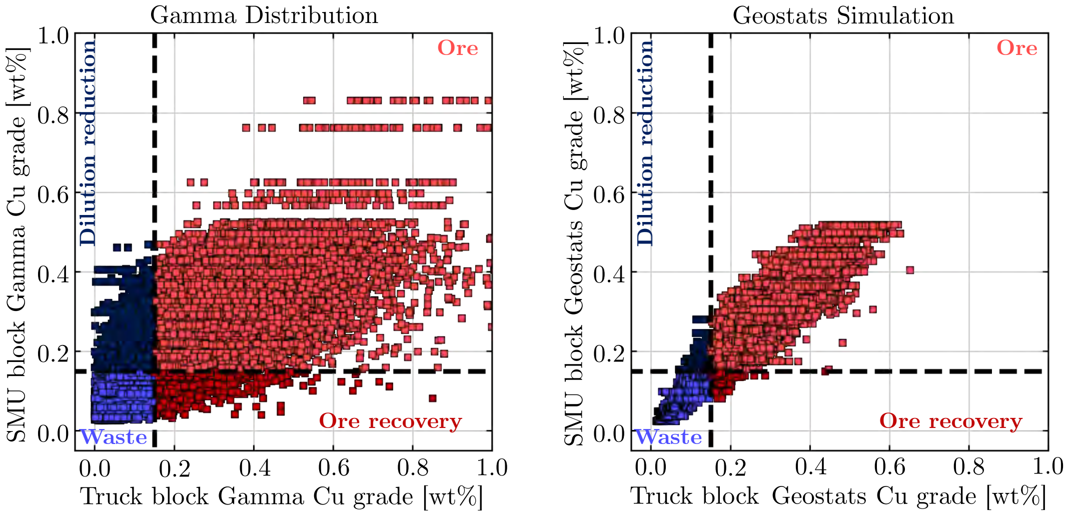


Figure 9: Scatter plots of the truck block grades against their respective SMU block grade for the gamma distribution and geostats dense simulation approaches with a black dashed line highlighting the 0.15 %Cu cut-off.

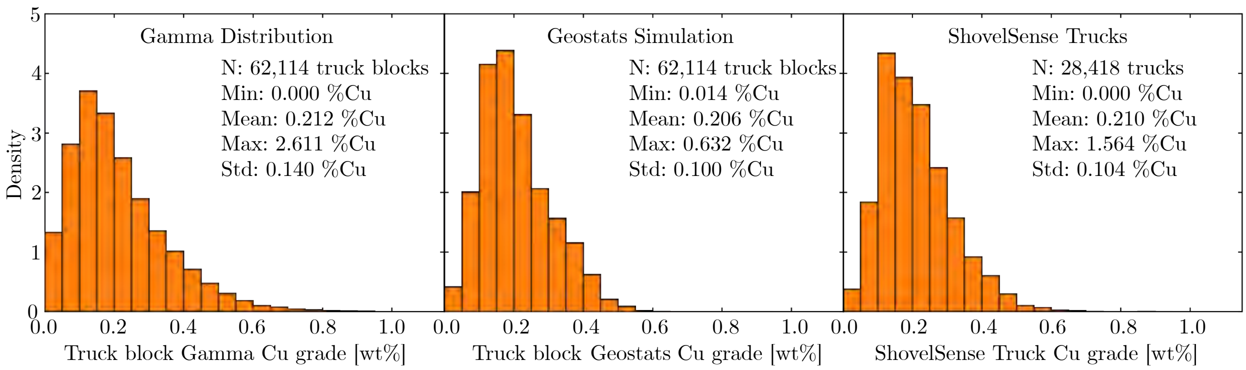


Figure 10: Histograms showing the distribution of Cu grades for the gamma distribution, geostats simulation, and ShovelSense trucks.

The material classification predictions as either ore or waste varied significantly between the predictions and ShovelSense dispatch diversions (Figure 11). The gamma distribution approach predicted a total of 20.1% diversions which is similar to the 22.7% measured by the ShovelSense dispatch data but the predictions resulted in much more dilution reduction than ore recovery which is opposite of the ShovelSense dispatch data. The geostats simulation significantly underpredicted the diversions at only 6.1%. The main discrepancy between the deviation types of the gamma distribution and ShovelSense dispatch data is due to a cut-off change and short term blending campaigns carried out during the study period without the data being available to account for it. Nevertheless the diversions are high due to the majority of the grades being close to the cut-off which is expected of a homogeneous, low-grade, and high-tonnage Cu porphyry deposit.

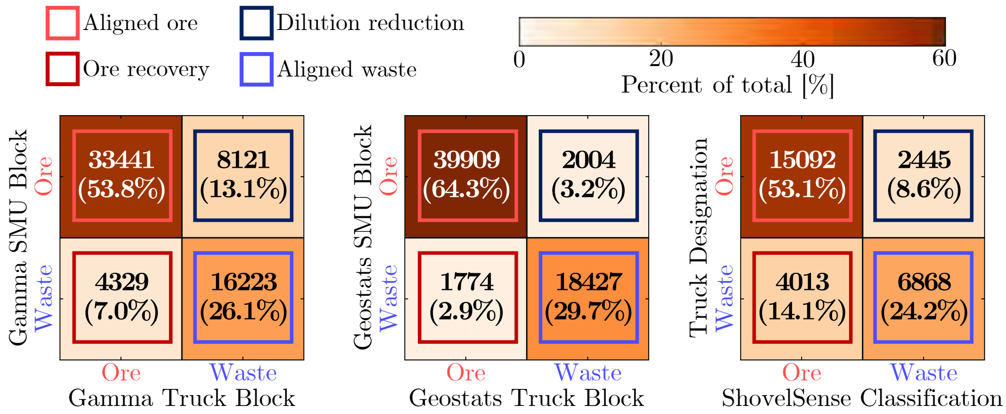


Figure 11: Confusion matrices showing the distinct material classifications of the gamma distribution and geostatistical simulation predictions as well as ShovelSense compared to the dispatch classification.

3.3. Comparing the Predicted and ShovelSense Diversion Value

Since the ShovelSense installed shovel did not dig the entirety of the six benches, there will be predicted volumes not present in the validation data even after applying the filter to only include blocks within 15 m of a ShovelSense truck. In order to make a fair comparison it is important to normalize the predicted value by the tonnage. The weighted average bulk ore sorting value per ton mined for the ShovelSense diversion data is 1.04 USD/t which was best predicted by the gamma distribution at 0.94 USD/t while the geostats simulation predicted a lower value at 0.22 USD/t (Table 2). Interestingly, the gamma method value predictions for benches which did not include data containing ramps lined up with the ShovelSense diversion data by a weighted average of about 9.3% which is 6.6% better than those with ramps at 15.9%. Despite the best efforts some noise such as the effect from the ramps is always to be expected with the comparison of two distinct spatial datasets, especially when considering that the blastholes are fixed in space and the shovel with ShovelSense measures material in situ after having been displaced and mixed by blast movement.

Table 2: Normalized bulk ore sorting value for the two approaches compared to the ShovelSense dispatch data, the average is multiplied to a total using the 8.81 Mt from the 28,418 ShovelSense trucks.

	Bulk Ore Sorting Value per ton mined		
Bench	Gamma Distribution	Geostats Simulation	ShovelSense Dispatch
Bench A [USD/t]	0.80	0.25	0.69
Bench B [USD/t]	0.99	0.22	1.03
Bench C [USD/t]	0.94	0.23	1.09
Bench D* [USD/t]	0.97	0.20	1.13
Bench E* [USD/t]	0.93	0.20	1.2
Bench F* [USD/t]	0.90	0.26	0.83
Weighted average [USD/t]	0.94	0.22	1.04
Total from 8.81 Mt [MUSD]	8.28	1.94	9.16

*Includes a ramp connecting two distinct benches introducing noise in the ShovelSense dispatch data

4. Discussion

4.1. Discrepancies and Alignment in Ore Recovery and Dilution Reduction Estimates

While the value predictions roughly aligned for the gamma distribution approach, there was a 6% average discrepancy in the diversion predictions. The mine labels were assigned based on the mine plan at the time of mining, during which the cutoff changed and there were short term blending campaigns adding inconsistencies to the originally assigned material type compared to the fixed 0.15 %Cu cut-off applied to the ShovelSense truck grades. The effects of changing the cut-off or any kind of special campaigning could be prevented by using the historical ShovelSense classifications at the time of digging but this data was not available. In order to allow for a more fair comparison the gamma distribution method was compared to the ShovelSense diversions based on inverse distance weighted estimates of the blasthole Cu grade to each truck. When compared to the blasthole classifications, the average discrepancy in diversions reduced to an impressive 0.6%. After exluding ramp data, a bench by bench analysis of the diversion predictions with the gamma method correlated to the ShovelSense diversions from blasthole classifications with a pearson correlation coefficient of 0.80 (Figure 12). The weighted average bulk ore sorting value per ton mined estimate based off ShovelSense diversions from the blasthole estimates is 0.90 USD/t which deviates by only 4% from the gamma distribution estimate of 0.94 USD/t.

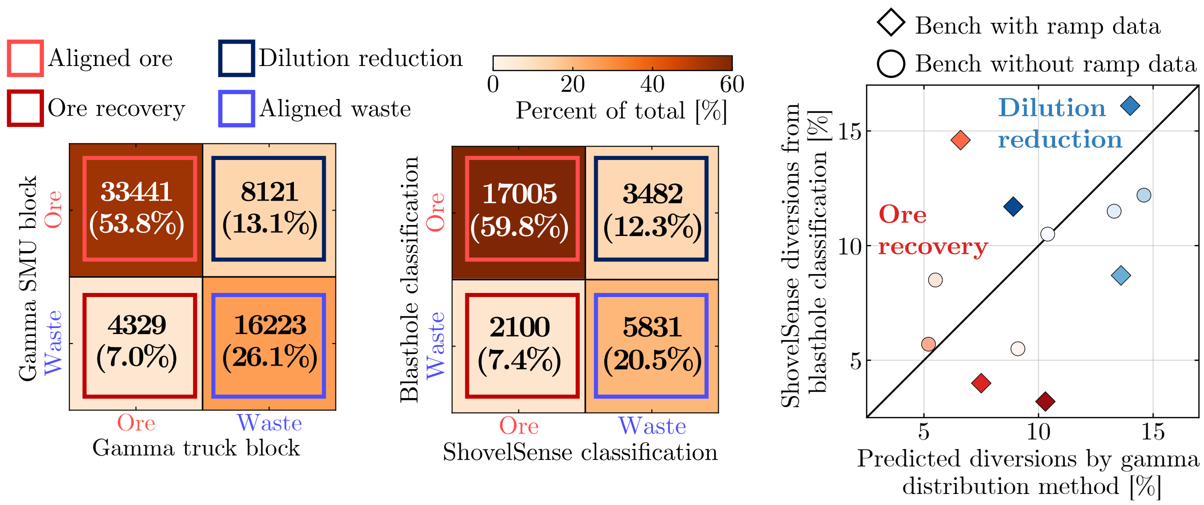


Figure 12: Confusion matrices showing the distinct material classifications of the gamma distribution predictions and ShovelSense compared to a blasthole classification. Also shown a scatter plot of the predicted diversions and the ShovelSense diversions from the blasthole classification for ore recovery and dilution reduction with the different shades representing distinct benches.

In addition to predicting the bulk ore sorting value from diversions, the additional Cu metal and reduced waste processed by the mill can be calculated. The mine plan based on blasthole classifications would have produced 14,607 t Cu metal and generated 2.5 Mt of waste. With ShovelSense the Cu production increases by 9% to 15,990 t Cu metal and generates 2.9 Mt waste which is a 14% reduction in the 0.4 Mt of waste processed by the mill. This compares well to what the mine plan would be based on the gamma distribution method with the SMU blocks normalized to the same 28,418 truck tonnage which would have produced 14,756 t Cu metal and 2.9 Mt waste.

The predicted truck block diversions from the SMU blocks would increase Cu metal by 6% at 15,583 t Cu metal and the waste generated would have been 3.4 Mt waste, an 18% decrease in the 0.5 Mt of waste processed by the mill. The gamma distribution method predictions of Cu metal increase and processed waste reduction align within 4% of the ShovelSense truck diversions from the blasthole classifications.

4.2. Potential and Limitations of the Geostatistical Dense Simulation and Gamma Distribution Approach

The simplicity of the gamma distribution method likely influenced its effectiveness at predicting the bulk ore sorting value over the dense geostats simulation due the little information available for the study. To make the geostatistical simulation approach more robust, domaining information would have been required as treating the entire dataset as a single domain likely had an over smoothing effect (Lee et al., 2007). Despite the simply defined simulation parameters and single domain simulation, the resulting geostats simulation distribution matched the ShovelSense truck grades much better than the gamma distribution. Interestingly the higher variability of the gamma distribution may have influenced why its predicted value better matched the ShovelSense dispatch data since the higher in situ variability replicates the effect of blast movement and mixing which is not accounted for in the static block models. The gamma distribution algorithm could also be fine tuned by capping the max grade or shifting the median grade to match the mean SMU grade depending on the input data for a given deposit.

The theoretical standard deviation at truck support was estimated to be 1.20 %Cu based on the blasthole data using the normal score variogram. Sensitivities were made of the nugget effect to calibrate this truck block variance with the ShovelSense data. The standard deviation for the gamma distribution method was 0.140 %Cu which is 0.020 %Cu higher while ShovelSense was 0.104 %Cu which is 0.016 %Cu lower. Despite the 15 m filter applied, the discrepancy in the variance may have still been influenced by the ShovelSense not capturing more variable areas while the gamma method did evaluate some of the more variable areas where the shovel did not dig. Furthermore the variance in the gamma distribution approach could have been scaled to better fit the deposit. Ultimately the variance of Cu grades depends on the type of deposit (Gerst, 2008) and if the optimal distribution is uncertain, the gamma or lognormal distributions are adequate options for most base metal deposits (Journel, 1980).

When using the proposed, or any bulk ore sorting value estimation tool, it is crucial to consider the data being used. Many mines have shovels which work exclusively in waste where there is no potential for bulk ore sorting and thus using an entire dataset from the mine may lead to inaccurate results. To better predict the value a shovel would unlock with a bulk ore sorting sensor representative data should be used from the pit, phase, or area where it is working. Predictions could even be made for different phases of the mine to determine a sequence for shovel sensor installations based on which would maximize the net present value.

When validating bulk ore sorting predictions as done here there are many variables which are important to consider. The presence of ramps could add noise to the analysis as truck loads by the shovel will need to be assigned to either the bench above or below. Also assuming a fixed cut-off grade could be troublesome if the mine changed their cut-off or had some kind of blending campaigns during the time period being analyzed, these factors could be incorporated if that information is available.

4.3. Influence of Selectivity and Deposit Heterogeneity on the Bulk Ore Sorting Value

The larger SMUs will have a greater bulk ore sorting value when decreasing the selectivity down to the truck scale. The bulk ore sorting benefit correlates with the remnant uncertainty within a mining block which depends on the geological variations and sampling but scales with increasing block size (Chiquini and Deutsch, 2020). Efforts have been made to quantifying the recoverable reserves from exploration drill hole data to the SMU scale (Boisvert et al., 2008) and studies have investigated the benefits and downsides to mining with varying smaller block sizes (Jara et al., 2006). With ShovelSense the selectivity is down to the truck scale and the gamma distribution bulk ore sorting tool can be run with varying SMU sizes and truck capacities to quantify the bulk ore sorting value at a truck scale selectivity.

For the 42.84 Mt mined through six benches in the low-grade, high tonnage Cu porphyry deposit studied here, the gamma distribution bulk ore sorting value prediction tool was run with several distinct SMUs and truck capacities used in the industry for large open pit mines. The SMU was varied from 10x10x15 m to 30x30x15 m and the trucks from 205 t to 400 t. As expected, the most benefit is achieved when reducing a larger SMU to the smallest truck available, however there is no consideration for the significant negative impact the more selective mining would have on production costs. However note that the potential limitation of the current approach is that the support effect is not properly handled. The current data compares sample information taken at point support and averaged over each shovel load with a discretized simulated truckload block. This requires further investigation to ensure the smoothing due to the change of support (from ”point” blasthole data to block data) is properly accounted.

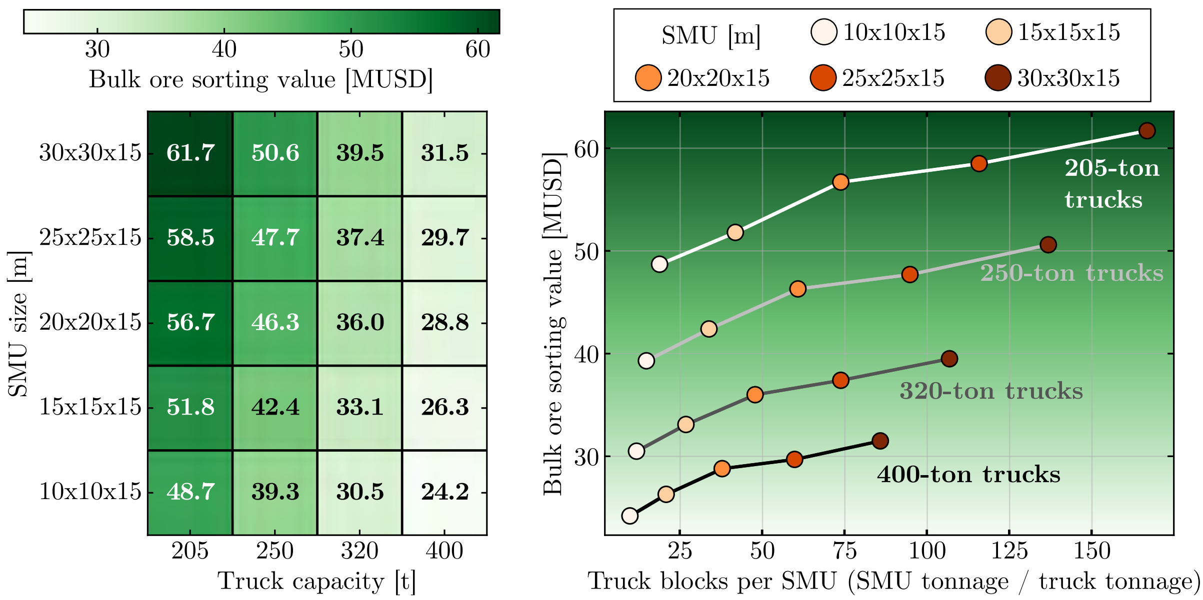


Figure 13: Gamma distribution bulk ore sorting value when digging through 42.84 Mt in six benches varying the SMU and truck capacity to standard values for large open pit mines.

Another important key driver in the bulk ore sorting value is the natural variability of the deposit. The schematic in Figure 14 illustrates how the ore recovery value scales with the SMU grade variance in four distinct deposits based off the authors' experience. The gamma distribution bulk ore sorting tool from the Cu porphyry data used in this study achieved a strong pearson correlation coefficient of 0.85 when comparing the SMU grade variance to the ore recovery value (Figure 14). The relationship between the grade variability and ore recovery value is expected to scale with more variable deposits. Cu porphyries typically represent some of the more homogeneous deposits which still present significant opportunities for bulk ore sorting when considering the truck scale.

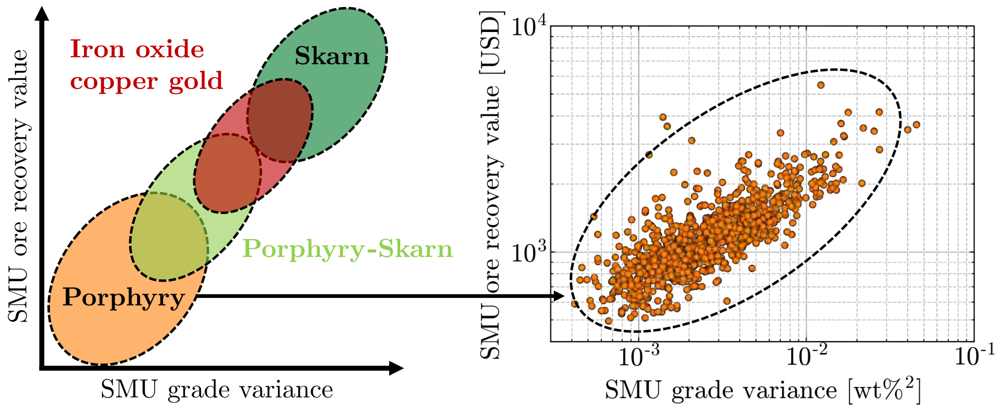


Figure 14: Schematic showing how increasingly heterogeneous deposits generate higher ore recovery value with real data from the gamma distribution bulk ore sorting tool shown for the homogeneous low grade high tonnage Cu porphyry deposit.

As a deposit's heterogeneity increases the mine will benefit more from increasing its selectivity with a bulk ore sorting system. While a system like ShovelSense has a negligible impact on mining, the use of a smaller trucks will likely have a negative impact on production and costs. If the operational complexity can be handled, extremely heterogeneous areas could even justify the use of smaller shovels and bucket level sorting by using two trucks side by side to solely load each one with either ore or waste separately. There is room for optimizing the selectivity and productivity to maximimize the net present value as illustrated in Figure 15. Areas with lower variability will benefit more from a more productive mining method while areas with higher variability will generate additional value with an increased selectivity.

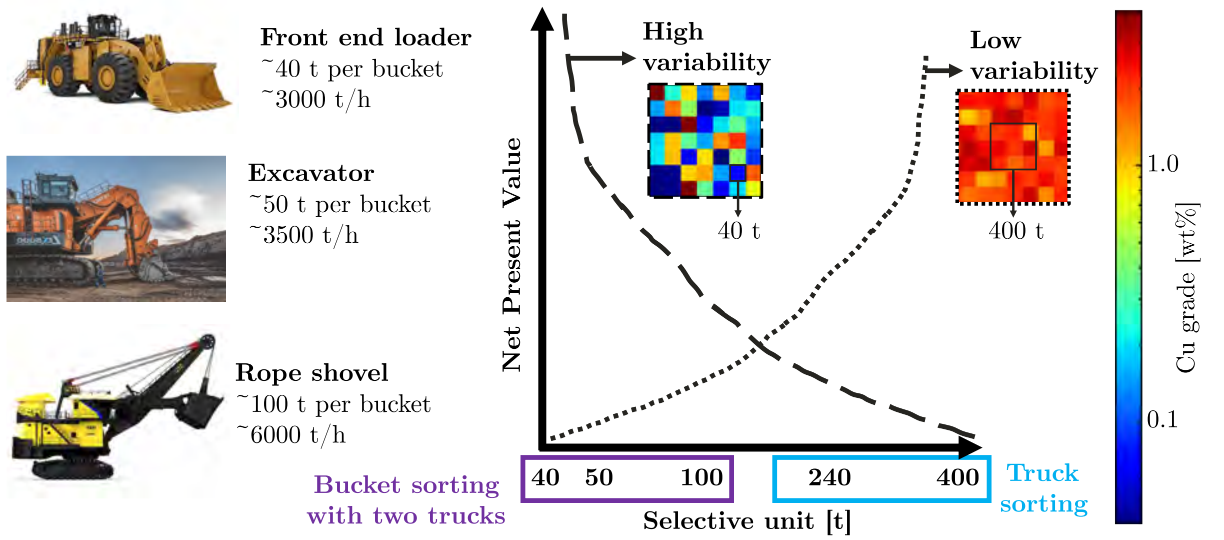


Figure 15: Schematic representing how the maximum net present value is achieved by optimizing the production rate and selectivity based on the loading and haulage systems available. Front end loader picture from Caterpillar (2022), excavator picture from Hitachi (2022), and rope shovel picture from Komatsu (2019).

The gamma distribution bulk ore sorting value prediction tool could even be used by mines which already have ShovelSense installed. Assuming the mine has mining equipment with distinct selectivity and productivity, the predicted bulk ore sorting value can be used to optimize where to send each available unit in the fleet. For example considering the bench shown in Figure 16 more selective loading and hauling units can be sent to dark green areas with high predicted sorting value while bigger, less selective units are sent to more homogeneous areas where the sorting value is predicted to be low as these would benefit more from the increased production rate.

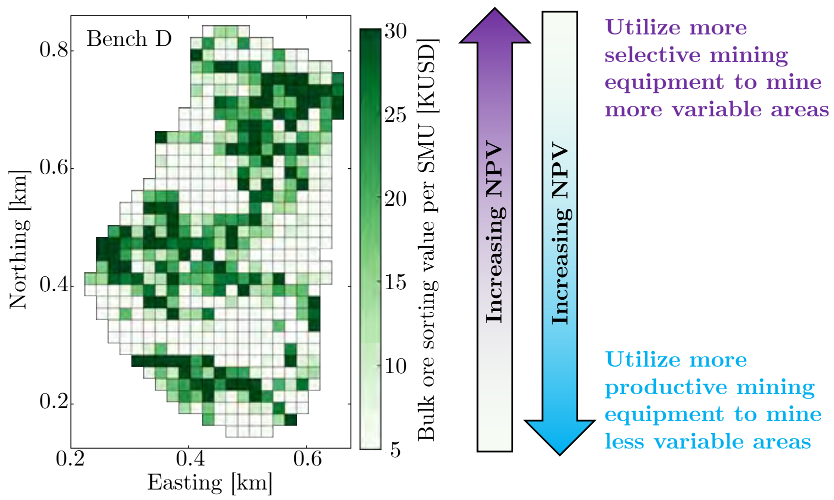


Figure 16: Map showing the bulk ore sorting value prediction for a bench indicating areas which would benefit from either more selectivity or a higher productivity.

5. Conclusion

The discretization of SMU blocks to theoretical truck blocks was proven to be an adequate method for simulating truck grades based on the average grade and variance of blastholes surrounding the SMU blocks. Various bulk ore sorting value parameters based on ShovelSense diversions from their blasthole classification were successfully predicted by the simple gamma distibution method (Table 3). The minor discrepancies between the gamma distribution method predictions and ShovelSense truck data is likely due to a slight overprediction of the variance due to the high degree of homogeneity within the studied deposit. The dense geostats simulation did not compare well with the ShovelSense truck data likely due to poor domain definition and likely a discrepancy in assessing the support effect. A better understanding of the post blast grade variability at the truck scale could also serve to inform and improve the bulk ore sorting value predictions.

Table 3: Summary of the various gamma distribution method predicted parameters compared to the ShovelSense diversions from blasthole classifications.

Parameter	Gamma Distribution Method	ShovelSense/Blasthole diversions	Difference
Ore recovery diversions	7.0%	7.4%	-0.4%
Dilution reduction diversions	13.1%	12.3%	0.8%
Cu metal increase	6%	9%	-3%
Dilution decrease	18%	14%	4%
Sorting value from 8.81 Mt	8.28 MUSD	7.93 MUSD	0.35 MUSD

Here the bulk ore sorting value was estimated for a low-grade, high tonnage Cu porphyry mine. Future work should consider comparing deposits with distinct natural variability as the deposit's heterogeneity likely has the strongest impact on the bulk ore sorting value. While increasingly variable deposits will reap more benefits from bulk ore sorting, even the more homogeneous Cu porphyry mines as the one discussed here present various opportunities to reroute trucks to their correct destinations. Ultimately, when working with a selectivity at the truck scale most magmatic base metal deposits will present various opportunities for bulk ore sorting.

The value presented here only include the immediate benefits from recovering additional ore and reducing dilution. The calculation of these immediate benefits will vary from mine to mine but the most precise information available should be used to get most accurate estimates. There is still a big need to better understand the impact bulk ore sorting has downstream. A few examples include increasing the grade and reducing the variability in the mill feed which could improve recovery (Kurth, 2021), the environmental benefits reducing the tons of CO_2 emitted per ton of concentrate (Sturla-Zerene et al., 2020), or the savings on the operational costs such as pneumatic maintenance, fuel, or electricity on transportation equipment (de Werk et al., 2017), and the liner or steel balls of the SAG mills for comminution equipment (Avalos et al., 2020; Yahyaei et al., 2009).

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7. Bibliography

Altinpinar, M., Sari, Y.A., Ortiz, J.M., 2020. Synthetic high-resolution ore deposit model and mine plan. Predictive Geometallurgy and Geostatistics Lab 2020-09, 147–169.

Amirá, R., Morales, N., Cáceres, A., 2019. Analysis of the impact of the dilution on the planning of open-pit mines for highly structural veined-shaped bodies, in: Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection-MPES 2018, Springer. pp. 187–196.

Avalos, S., Kracht, W., Ortiz, J.M., 2020. Machine learning and deep learning methods in mining operations: A data-driven sag mill energy consumption prediction application. Mining, Metallurgy & Exploration 37, 1197–1212.

Boisvert, J.B., Deutsch, C.V., 2011. Programs for kriging and sequential gaussian simulation with locally varying anisotropy using non-euclidean distances. Computers & Geosciences 37, 495–510.

Boisvert, J.B., Ortiz, J.M., Deutsch, C.V., 2008. Local recoverable reserves prediction with block lu simulation. International Journal of Mining and Mineral Engineering 1, 3–21.

Cadigan, N.G., Myers, R.A., 2001. A comparison of gamma and lognormal maximum likelihood estimators in a sequential population analysis. Canadian Journal of Fisheries and Aquatic Sciences 58, 560–567.

Caterpillar, 2022. Large wheel loaders 994k. https://www.cat.com/en_US/products/new/equipment/wheel-loaders/large-wheel-loaders/1000001147.html. Accessed: 2022-09-11.

Charifo, G., Almeida, J.A., Ferreira, A., 2013. Managing borehole samples of unequal lengths to construct a high-resolution mining model of mineral grades zoned by geological units. Journal of Geochemical Exploration 132, 209–223.

Chiles, J., Delfiner, P., 2012. Geostatistics: Modeling Spatial Uncertainty. 2-nd ed.-NewYork, Toronto,-JohnWiley'Sons. Inc.

Chiquini, A., Deutsch, C.V., 2020. Mineral resources evaluation with mining selectivity and information effect. Mining, Metallurgy & Exploration 37, 965–979.

Emery, X., 2012. Co-simulating total and soluble copper grades in an oxide ore deposit. Mathematical Geosciences 44, 27–46.

Faraj, F., Ortiz, J.M., 2021. A simple unsupervised classification workflow for defining geological domains using multivariate data. Mining, Metallurgy & Exploration 38, 1609–1623.

Gerst, M.D., 2008. Revisiting the cumulative grade-tonnage relationship for major copper ore types. Economic Geology 103, 615–628.

Hitachi, 2022. Ex5600-7b, t4f mining excavator. https://www.hitachicm.us/products/excavators/ex5600-7b/. Accessed: 2022-09-11.

Jara, R., Couble, A., Emery, X., Magri, E., Ortiz, J., 2006. Block size selection and its impact on open-pit design and mine planning. Journal of the Southern African Institute of Mining and Metallurgy 106, 205–211.

Journel, A., 1980. The lognormal approach to predicting local distributions of selective mining unit grades. Journal of the International Association for Mathematical Geology 12, 285–303.

Komatsu, 2019. Electric rope shovels p&h 4100xpc. https://mining.komatsu/es/product-details/p-h-4100xpc. Accessed: 2022-09-11.

Kurth, H., 2021. Digitalisation of ore composition and its benefits. https://www.ausimm.com/bulletin/bulletin-articles/digitalisation-of-ore-composition-and-its-benefits/. Accessed: 2022-09-11.

Lee, S.Y., Carle, S.F., Fogg, G.E., 2007. Geologic heterogeneity and a comparison of two geostatistical models: Sequential gaussian and transition probability-based geostatistical simulation. Advances in water resources 30, 1914–1932.

Li, G., Klein, B., He, C., Yan, Z., Sun, C., Kou, J., 2021. Development of a bulk ore sorting model for ore sortability assessment—part ii: Model validation and optimisation. Minerals Engineering 172, 107143.

Li, G., Klein, B., Sun, C., Kou, J., 2022. Investigation on influential factors of bulk ore sortability based on fractal modelling. Minerals Engineering 177, 107362.

Li, G., Klein, B., Sun, C., Kou, J., Yu, L., 2019. Development of a bulk ore sorting model for sortability assessment. Minerals Engineering 141, 105856.

Moss, A., Klein, B., Nadolski, S., 2018. Cave to mill: improving value of caving operations, in: Caving 2018: Proceedings of the Fourth International Symposium on Block and Sublevel Caving, Australian Centre for Geomechanics. pp. 119–132.

Nadolski, S., Klein, B., Elmo, D., Scoble, M., Liu, Y., Scholar, J., 2016. Investigation into the implementation of sensor-based ore sorting systems at a block caving operation. Proceedings of MassMin 2016 , 393–399.

Pizarro Munizaga, S.H.A., 2011. Modelamiento geoestadistico de leyes de cobre total y soluble. Master's thesis. Universidad de Chile.

Rendu, J.M., 2002. Geostatistical simulations for risk assessment and decision making: the mining industry perspective. International Journal of Surface Mining, Reclamation and Environment 16, 122–133.

Rossi, M.E., Deutsch, C.V., 2013. Mineral resource estimation. Springer Science & Business Media.

Sanhueza Passache, A.R., 2021. Evaluación económica de técnicas de selectividad de mineral (Ore Sorting) para su aplicación en Collahuasi. Master's thesis. Universidad de Chile.

Sturla-Zerene, G., Figueroa, E., Sturla, M., 2020. Reducing ghg global emissions from copper refining and sea shipping of chile's mining exports: A world win-win policy. Resources Policy 65, 101565.

Svanberg, A., Larsson, S., Mäki, R., Jonsén, P., 2021. Full-scale simulation and validation of bucket filling for a mining rope shovel by using a combined rigid fe-dem granular material model. Computational Particle Mechanics 8, 825–843.

Vann, J., Bertoli, O., Jackson, S., 2002. An overview of geostatistical simulation for quantifying risk, in: Proceedings of Geostatistical Association of Australasia Symposium" Quantifying Risk and Error, Citeseer. p. 1.

Vasylchuk, Y., Deutsch, C., 2018. Improved grade control in open pit mines. Mining Technology 127, 84–91.

de Werk, M., Ozdemir, B., Ragoub, B., Dunbrack, T., Kumral, M., 2017. Cost analysis of material handling systems in open pit mining: Case study on an iron ore prefeasibility study. The Engineering Economist 62, 369–386.

Yahyaei, M., Banisi, S., Hadizadeh, M., 2009. Modification of sag mill liner shape based on 3-d liner wear profile measurements. International Journal of Mineral Processing 91, 111–115.