minerals

Article

Simulating Bulk Ore Sorting Performance of a Panel Cave Mine: A Comparison between Two Approaches

Mahir Can Cetin [1,*], Genzhuang Li [1], Bern Klein [1] and William Futcher [1,2]

[1] Norman B. Keevil Institute of Mining Engineering, University of British Columbia, 517-6350 Stores Road, Vancouver, BC V6T 1Z4, Canada; genzhuang.li@ubc.ca (G.L.); bklein@mining.ubc.ca (B.K.); william.futcher@newcrest.com.au (W.F.)
[2] Newcrest Mining Limited, Level 8, 600 St. Kilda Road, Melbourne, VIC 3004, Australia
* Correspondence: mcetin@mail.ubc.ca

Abstract: Conceptual bulk ore sorting studies are essential for determining a potential improvement in mine economics before undertaking on-site sensor trials. Two approaches, block modelling and drill core compositing, are applied to simulate the bulk ore sorting performance of mining operations. While one employs the grade data of a block model, the other approach utilizes composited drill core grades. This study aimed at comparing these two approaches by estimating in-situ grade heterogeneities and simulating the bulk ore sorting performances of the currently active caves of the Cadia East panel cave mine. The results show that block modelling tends to smooth the grade variability that initially exists in the drill core grade data. Particularly in the portions of the deposit where drilling is sparse or widely spaced compared to the selected block size, block modelling leads to lower grade heterogeneity and bulk ore sorting performance estimates. However, when the drill hole data is nonrepresentative of the area of interest, block modelling can predict more realistic bulk ore sorting performances compared to drill core grades. The assessments performed with the blocks and drill core composites of various sizes showed that grade heterogeneity was adversely affected by an increased sorting scale due to averaged metal grades.

Keywords: sensor-based ore sorting; bulk ore sorting; block caving; panel caving; in situ grade heterogeneity; bulk ore sorting potential; block modelling; drill core compositing

check for updates

Citation: Cetin, M.C.; Li, G.; Klein, B.; Futcher, W. Simulating Bulk Ore Sorting Performance of a Panel Cave Mine: A Comparison between Two Approaches. *Minerals* **2023**, *13*, 603. https://doi.org/10.3390/min13050603

Academic Editor: Chiharu Tokoro

Received: 16 February 2023
Revised: 2 April 2023
Accepted: 25 April 2023
Published: 27 April 2023

1. Introduction

Two recent trends challenge the mining industry while demand for metals grows: declining ore grades and the exhaustion of near-surface deposits. Block and panel caving are gaining attraction as they can be applied to low-grade and deeply situated orebodies. These methods are utilized primarily to mine low-grade porphyry copper deposits to produce copper, molybdenum, and significant amounts of gold, silver, and other metals [1].

Despite its many advantages, such as high production rates and low operating costs, cave mining inherently suffers from a lack of grade selectivity, leading to the extraction of below-cut-off grade material [2]. Sensor-based ore sorting technologies can potentially address the limited grade selectivity associated with cave mining methods by discriminating between ore grades or rock types [3]. The preconcentration of run-of-mine ore by sensor-based ore sorting provides an opportunity to improve mill feed grade, reduce milling costs, and increase the operation's overall economics. High throughput rates of bulk ore sorting, ranging from a few tonnes to several thousand tonnes per hour [4,5], make the technology suitable for large-scale block and panel caving operations. In addition to the standard application on production conveyor belts, bulk ore sorting sensors can also be integrated with mobile equipment such as shovels and loaders to improve the resolution at which grade control decisions are made.

Several factors determine the potential of applying bulk ore sorting: grade heterogeneity, the sensors' ability to capture the variability in grade, and sorting system efficiency [4,6,7]. Bulk ore sorting studies usually commence by estimating in situ grade heterogeneity since the distribution of recovered grades is a function of the spatial grade variability in an ore deposit [2,4,8,9]. The variability in the grade can then be translated into an economic evaluation to simulate the performance of bulk ore sorting. Such conceptual studies are essential for determining the potential improvement in mine economics before undertaking costly and logistically complicated on-site sensor trials [10].

Two approaches can be taken to simulate the performance of bulk ore sorting of a mining operation differ due to the type of data feeding the simulation. One of the approaches uses grade data of a block model, which is created using geostatistical interpolation techniques. The other approach, on the contrary, utilizes composited drill core grades as the source of the bulk ore sorting simulations. The terms block modelling and drill core compositing are used to refer to these two approaches in this study.

A block model is a simplified representation of an orebody with a stack of blocks. Block modelling utilizes geostatistical interpolation methods, such as inverse distance weighting and ordinary kriging, to estimate ore grades using raw or composited drill core samples obtained by exploration drilling. The grade data obtained by block modelling can be employed to assess the variability in grade spatially and the bulk ore sorting potential of an orebody at various selective mining units (SMU) [6,11]. In addition, blocks can be populated by sorter models to calculate the value associated with each block and evaluate the change in the mine economics [3]. It can be argued that block modelling smooths the grade profile of an ore deposit due to the geostatistical interpolation techniques employed in the process, thereby concealing the true variability in the grade [10,12–14].

As an alternative, drill core grades can also be utilized for simulating the bulk ore sorting performance [13,15]. This approach estimates the grade variability and bulk ore sorting potential using drill core grade data composited at different aggregation lengths representing various mining and sorting scales [16]. A notable shortcoming of this approach is its inability to assess the bulk ore sorting performance at unsampled portions of an orebody. In addition, drill core samples can represent variability only in one direction.

This study presented a comparison between block modelling and drill core compositing approaches in simulating bulk ore sorting potential at the Cadia East panel cave mine. The grade data sets required for the study were generated by the block modelling of the deposit at various SMUs and compositing the drill core samples at different length intervals. The grade heterogeneities of the active panel caves of the mine were estimated. The bulk ore sorting performances of the panel caves were simulated through an economic evaluation. The results reveal the limitations of the approaches and can aid in approach selection for similar types of mines, exploring the application of bulk ore sorting.

2. Overview of the Cadia East Panel Cave Mine

The Cadia East deposit, located in New South Wales, Australia, is one of the highest-grade gold-copper alkalic porphyries in the world [17]. The mineralized zone of the deposit has the following dimensions: 2.5 km in strike length, 600 m in width, and over 1900 m in vertical extent [18]. Two broad overlapping mineralization zones have been identified in the deposit. The copper-dominant upper zone has a core zone of disseminated chalcopyrite-bornite and is capped by chalcopyrite-pyrite mineralization. High molybdenite contents are usually associated with the upper zone. The deeper zone is gold-rich and localized around steeply dipping sheeted quartz-calcite-bornite-chalcopyrite-molybdenite-covellite-magnetite veins. The highest gold grades in this zone are associated with the widest bornite-bearing veins, which also contain native gold [19].

At the time of this study, three panel caves (PC1, PC2-West, and PC2-East) were in operation. A series of new caves will be developed to extend mine operations beyond 2060. The mining activities at Cadia East are typical of block caves mines. The caved ore is removed from the drawpoints located on the extraction levels of panel caves and is subsequently tipped into the coarse ore bins at the crushing stations by a load-haul dump (LHD) fleet. Jaw-gyratory crushers reduce the size of the caved ore. The main trunk belt transports the crushed ore to the surface at a rate of 4600 tonnes per hour. The ore is deposited onto a coarse ore stockpile before milling in two separate concentrators with processing capacities of 23 and 7 million tonnes per annum, respectively. Gravity concentration and flotation methods are utilized in the concentrators to produce gold doré and gold-rich copper concentrate [18].

Two sensor technologies, namely prompt gamma neutron activation analysis (PGNAA) and magnetic resonance (MR), were installed on the main trunk belt at Cadia East to monitor the quality of the caved ore. The mine also explores using these sensor technologies to bulk sort the ore. However, information regarding whether the Cadia East panel caves are amenable to sorting is lacking. As the first step of a comprehensive evaluation, this study compared the described approaches in estimating the bulk ore sorting performances of the panel caves for the ideal case.

3. Methodology

3.1. Data Description

An exploration drill hole data set consisting of 277 drill holes (totaling about 253 km of core samples) provided by the Cadia East metallurgy team was employed in this study. The data set included the grade, collar, and downhole survey information of the drill cores sampled at 2 m intervals. Figure 1 presents the locations and gold and copper grades of the drill holes.

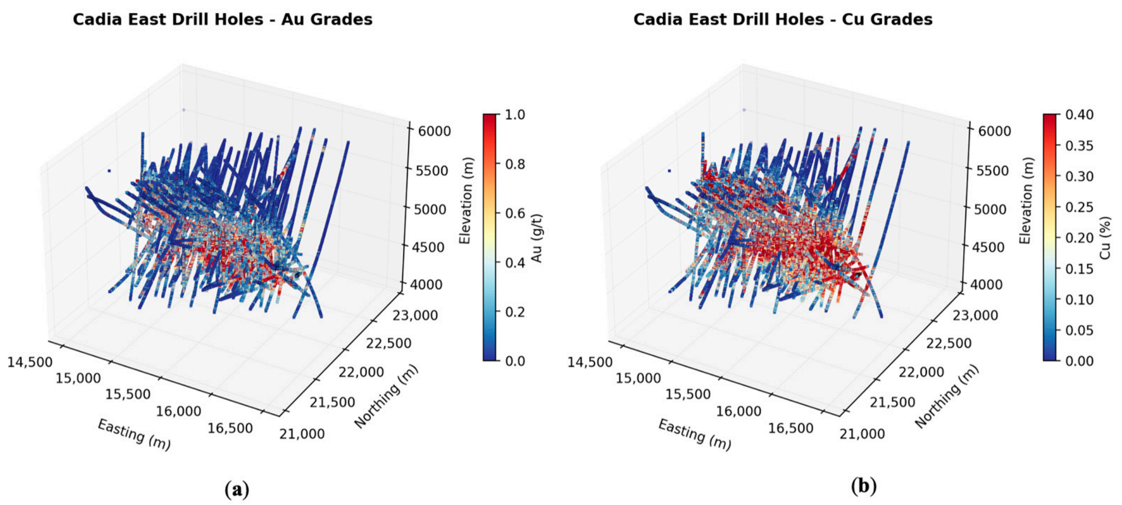


Figure 1. Cadia East drill holes: (**a**) Gold grades; (**b**) Copper grades.

3.2. Compositing Drill Core Samples and Block Modelling

For the drill core compositing approach, the drill core grades were composited down the hole using an algorithm developed in Python. The algorithm consisted of functions that could compute the drill hole geometry, aggregate the lengths of drill core samples, and produce the composited grade data. Composite lengths of 5 m, 10 m, and 20 m were selected to reveal the grade heterogeneity at various scales.

Block models of the Cadia East ore deposit were built using undisclosed resource modelling software at various mining scales. The software utilized inverse distance weighting (IDW) to populate the ore blocks with gold and copper grade estimates. The block models with block sizes of $5 \times 5 \times 5$ m^3, $10 \times 10 \times 10$ m^3 and $20 \times 20 \times 20$ m^3 were built. Block modelling was carried out using the composited drill core grades. This was to ensure that the impact of geostatistical interpolation on grade heterogeneity could be disclosed without a bias in the input data scale. Figure 2 shows a comparison between the described approaches.

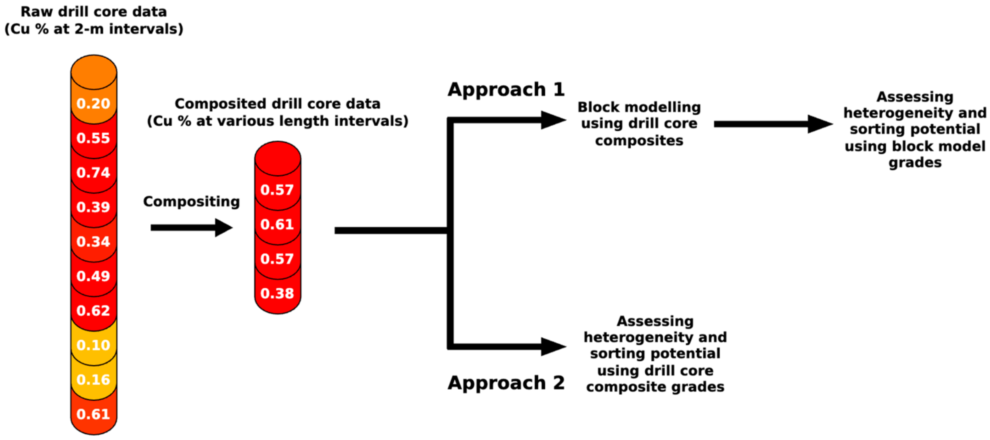


Figure 2. A schematic of block modelling and drill core compositing approaches.

3.3. Determining Cave Footprints and Locating Data Points

An algorithm called "ConvexHull" in SciPy (an open-source Python library) was used to locate the data points (blocks and drill core composites) within the footprints of the panel caves. This algorithm computed the convex hull–the smallest polygon that covers all the given data points–in n-dimensional space using the "Quickhull" method [20].

The main objectives of creating a convex hull for each cave were to locate the data points accurately considering the drawpoint coordinates and to exclude the uneconomic portions of the orebody based on the best height of draw (BHOD) information provided for the drawpoints. Involving the uneconomical portions of the deposit would otherwise indicate unrealistic sorting potential estimations.

Figure 3 presents the procedure for creating the convex hulls of the caves and locating the data points. Table 1 summarizes the number of data points located by the ConvexHull algorithm and the average gold and copper grades of the caves estimated by the blocks and drill core composites.

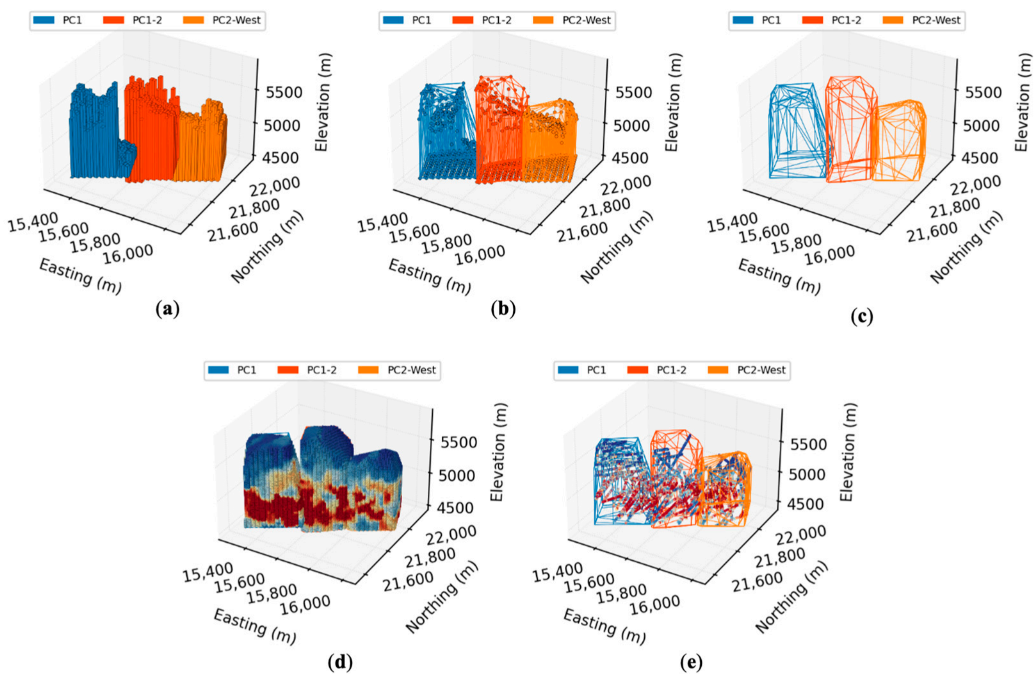


Figure 3. Creating convex hulls for panel caves and locating data points: (**a**) Cave drawpoints with BHOD; (**b**) Constructing convex hulls for panel caves; (**c**) Simplifying shapes of convex hulls before data selection; (**d**) Locating blocks within convex hulls; (**e**) Locating drill core composites within convex hulls.

Table 1. Number of grade data points located and average gold and copper grades of panel caves.

Approach 1: Block Modelling				
Block Size	**Panel Cave**	**Number of Blocks**	**Au Grade (g/t)**	**Cu Grade (%)**
$5 \times 5 \times 5$ m^3	PC1	482,080	0.59	0.32
	PC2-West	388,183	0.74	0.27
	PC2-East	388,766	0.64	0.33
$10 \times 10 \times 10$ m^3	PC1	60,424	0.69	0.33
	PC2-West	48,691	0.72	0.29
	PC2-East	50,320	0.69	0.35
$20 \times 20 \times 20$ m^3	PC1	7525	0.68	0.33
	PC2-West	6078	0.73	0.30
	PC2-East	6441	0.69	0.35
Approach 2: Drill Core Compositing				
Composite Length	**Panel Cave**	**Number of Drill Core Composites**	**Au Grade (g/t)**	**Cu Grade (%)**
5 m	PC1	3426	0.84	0.34
	PC2-West	3138	0.99	0.34
	PC2-East	3798	0.84	0.40
10 m	PC1	1711	0.84	0.34
	PC2-West	1575	0.99	0.34
	PC2-East	1908	0.84	0.40
20 m	PC1	853	0.84	0.34
	PC2-West	800	0.99	0.34
	PC2-East	957	0.83	0.40

3.4. Estimating In Situ Heterogeneity and Simulating Bulk Ore Sorting Performance

Distribution heterogeneity (DH), often referred to as spatial heterogeneity, is a concept developed by Gy [21]. DH can be calculated by Equation (1), where N_u is the number of units that make up the ore lot, a_i and M_i are the grade and mass of a unit within the lot, and a_L and M_L are the average grades and total mass of the entire lot. DH is employed in bulk ore sorting studies to quantify variations in the contents of certain components of units that constitute an ore lot [4,22]. These units can be blocks or drill core samples when the in situ grade heterogeneity of an ore deposit is assessed. Alternately, units can be batches of material (whether on a conveyor or in a bucket of an excavator) when on-site sensor trials are conducted. DH is a dimensionless indicator that essentially measures the variation in the grade product, i.e., grade multiplied by mass. Higher DH values denote a higher potential for bulk ore sorting. The DH equation was used to calculate the in situ gold and copper heterogeneities of the panel caves.

$$DH = N_u \sum_i \left[\frac{(a_i - a_L)M_i}{a_L M_L} \right]^2 \quad (1)$$

In addition to the grade heterogeneity, determining the degree of upgrading and mass rejection rates through grade-recovery versus mass yield curves is essential for assessing the bulk ore sorting potential of an ore deposit. To produce the curves, grades are sorted from high to low, and the cumulative recovery (or distribution) and mass values, and the average concentrate grades are calculated. DH is positively correlated with the theoretical recovery at a given mass yield rate. For instance, a heterogeneity assessment for a block cave mine showed a drill hole with 1.96 DH, 40% of the mass, which contained about 90% of the total copper. In contrast, for a drill hole with a comparably low DH value (0.56), the same mass amount contained around 70% of the total copper in that drill hole [12].

Copper was used as the proxy element for gold to determine the degree of upgrading and mass rejection rates of the Cadia East panel caves. The selection of copper as the proxy was based on two factors: (1) challenges in detecting gold accurately by sensor technologies and (2) the strong correlation between gold and copper in the Cadia East deposit [23]. The sorting cut-off grade was assigned to be 0.1% Cu.

A density of 2.76 t/m^3 [18] was used to calculate the masses of drill core composites based on their lengths and diameters. As discussed previously, a limitation of using drill core composites for bulk ore sorting evaluations is that they only represent a small volume and grade variation in the vertical direction. However, it was assumed that the mass yield rates estimated using the drill core composite masses might represent the mass yield rates, which can be typically achieved when the ore is subjected to bulk sorting.

The density of 2.76 t/m^3 was also assigned to convert the block volumes to masses. The selected block sizes correspond to 345, 2760, and 22,080 tonnes of ore. Considering the capacity of the main production conveyor at Cadia (4600 tph), the block model with the finest resolution ($5 \times 5 \times 5$ m^3) would equal bulk sorting the ore every four and a half minutes using a diverter on the conveyor belt.

After obtaining the degree of upgrading and mass rejection rates, the bulk ore sorting performances of the caves were estimated by calculating the change in the Net Smelter Return (NSR) of the ore. Net Smelter Return (NSR) is the net revenue a mine receives from selling metal or non-metal concentrates less mining-and-processing-related costs. The main benefit of ore sorting is that the below cut-off material can be discarded as waste and is not processed in the concentrators, thereby increasing the net revenue received from the ore. In addition, higher recoveries are usually obtained in the concentrators due to the improvement in the quality of the feed material by sorting.

Table 2 shows the cost and price assumptions and plant recovery models used to calculate NSR. The assumptions and recovery models were determined from the technical report on the Cadia Valley operations [18]. The cost assumptions were converted from AUD to USD using an exchange rate of 1:0.8. The rationale behind using the plant recovery models was to incorporate the impact of grade uplifting by sorting.

Table 2. Cost and price assumptions.

Assumptions		Unit	With Bulk Ore Sorting		Without Bulk Ore Sorting
			Concentrate	Reject	
Cost	Mine operating cost	USD/t	4.25	4.25	4.25
	Mine sustaining capital cost	USD/t	0.63	0.63	0.63
	Mineralization treatment operating cost	USD/t	6.64	0.00	6.64
	Mineralization treatment sustaining capital cost	USD/t	0.71	0.00	0.71
	Tailings dam sustaining capital cost	USD/t	0.60	0.00	0.60
	General and administration cost	USD/t	2.14	2.14	2.14
	Sorting cost	USD/t	0.4	0.4	0
		Total	15.37	7.42	14.97
Price	Au	USD/oz	1300		
	Cu	USD/lb	3.40		
Plant recovery models		Cave	Model		
	Au	PC1	Recovery (%) $= 80.65 + 2.88\ln(\text{Au})$		
		PC2-West and PC2-East	Recovery (%) $= 79.76 + 3.52\ln(\text{Au})$		
	Cu	All caves	Recovery (%) $= -50.64(\text{Cu})^2 + 47.91(\text{Cu}) + 76.27$		

The sorting cost was nominated to be USD0.4 per ton of sorter feed [24]. In cave mining, many mixing events that occur within caved ore result in lower grade variability and bulk ore sorting potential [9]. The impact of mixing that would occur in the caves during mining and along the material handling system was not incorporated in the NSR estimations, and the sorting efficiency was assumed to be 100%. This was due to the study, which was aimed at comparing the differences between the presented approaches to estimate the maximum theoretical benefit that could be gained instead of calculating the actual value of bulk ore sorting for the mine. The change in NSR was calculated using the following equation:

$$\text{Change in NSR (USD/t)} = \text{NSR with sorting} - \text{NSR without sorting} \quad (2)$$

4. Results and Discussion

4.1. In Situ Grade Heterogeneity Estimations

Figure 4 presents a comparison of the in situ gold and copper grade distribution heterogeneities of the panel caves estimated by both approaches. Higher gold DH values of all the caves showed that gold was more heterogeneously distributed within the deposit than copper. For ore deposits where the economy is driven by multiple commodities and the use of a proxy element is inevitable, bulk ore sorting potential depends on the grade heterogeneity of the proxy and the extent of correlation that it has with other target elements. Since copper was decided to be the proxy element for gold in this study, the variability in copper grades and its relationship with gold were the main factors determining the bulk ore sorting performances of the Cadia panel caves.

Figure 4 also reveals the adverse impact of scale on grade variability. The smallest size blocks ($5 \times 5 \times 5$ m^3) and drill core composites (5 m) yielded the highest gold and copper DH values. As shown in Table 3, on average, the DH values decreased by 27 and 38% for gold and 31 and 44% for copper when the block size was increased to $10 \times 10 \times 10$ and $20 \times 20 \times 20$ m^3. Similarly, when the composite length was increased from 5 m to 10 and 20 m, the Au DH values dropped by 16 and 27%, and the Cu DH values decreased by 15 and 27%, on average.

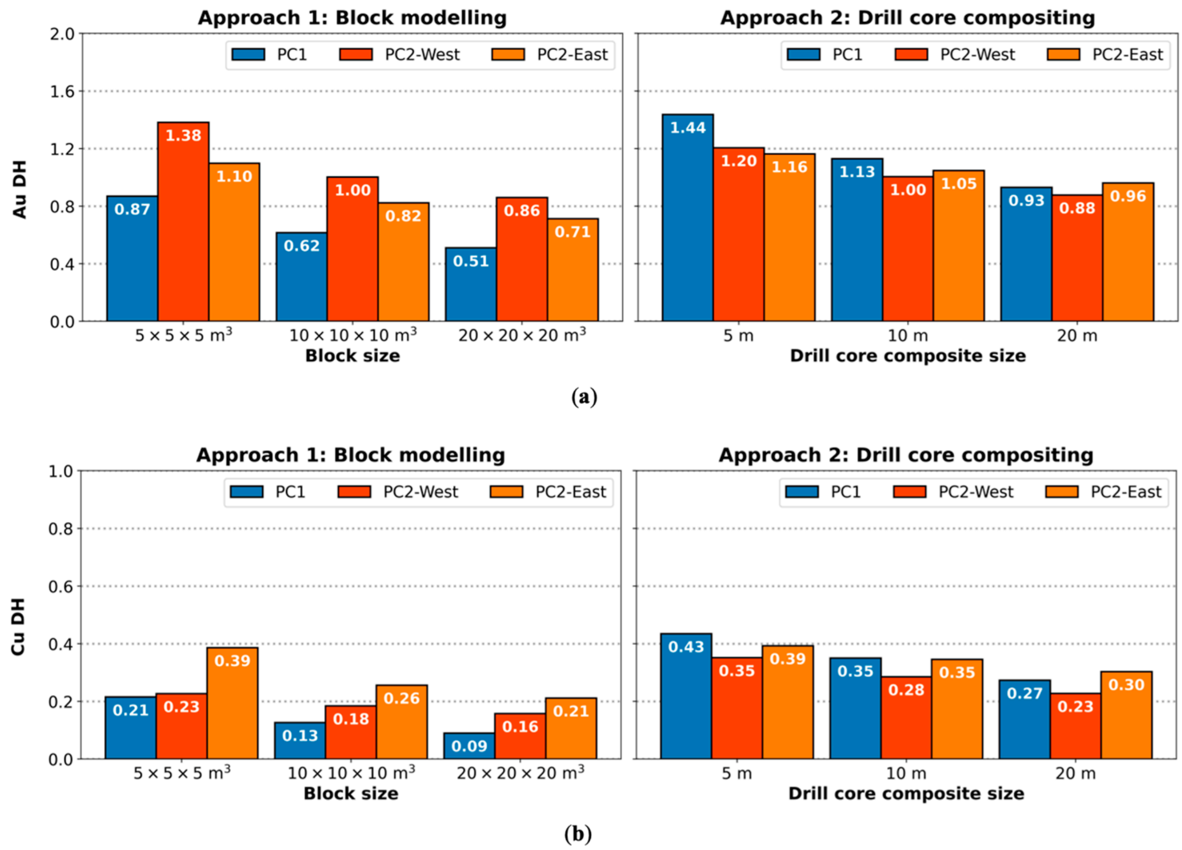


Figure 4. In situ gold and copper grade heterogeneities of panel caves estimated by block modelling and drill hole grade data sets: (**a**) Gold heterogeneity; (**b**) Copper heterogeneity.

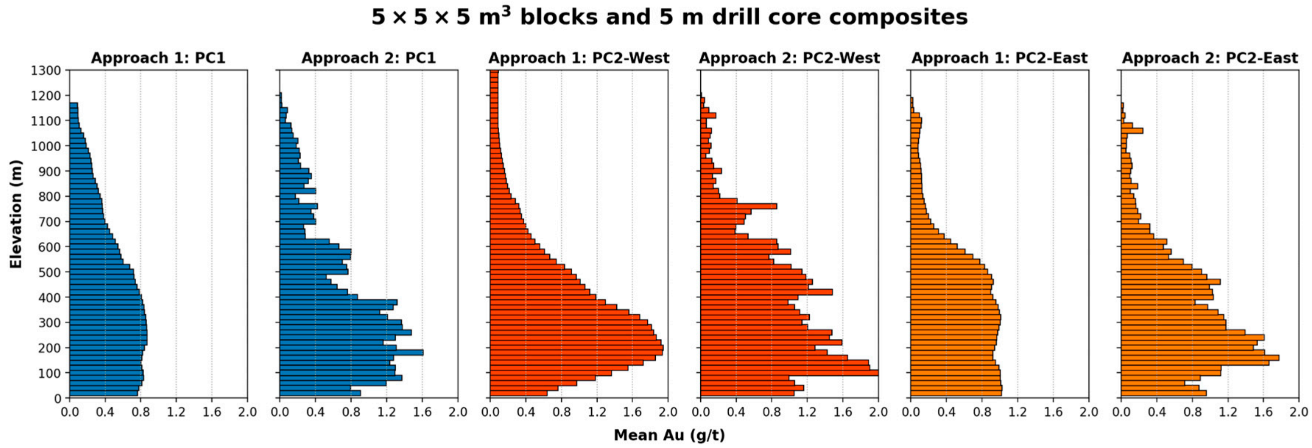
Table 3. Relative change in DH of panel caves with scale.

Variable	Mean Relative Change (%) in DH (Reference: DH of the Smallest Scale)			
	Approach 1: Block Model Grade Data		Approach 2: Drill Hole Grade Data	
	Block Size	Change (%)	Composite Size	Change (%)
Au	$5 \times 5 \times 5$ m^3	0	5 m	0
	$10 \times 10 \times 10$ m^3	−27	10 m	−16
	$20 \times 20 \times 20$ m^3	−38	20 m	−27
Cu	$5 \times 5 \times 5$ m^3	0	5 m	0
	$10 \times 10 \times 10$ m^3	−31	10 m	−15
	$20 \times 20 \times 20$ m^3	−44	20 m	−27

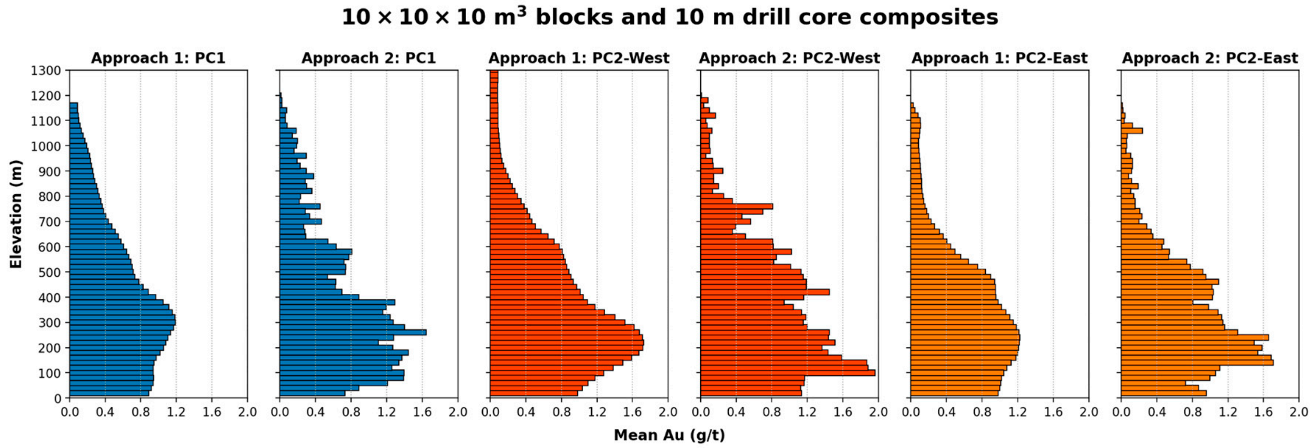
When a comparison is made between the results presented in Figure 4, it can be observed that the gold and copper DH values estimated by the block modelling approach were usually lower than the ones calculated by the drill core compositing approach. These lower grade heterogeneity estimates are due to block modelling smoothing out the metal grades and decreasing the variance of the metal grade distributions. Figures 5 and 6 show the gold and copper grade profiles of the caves along the *z*-axis at different scales. Block modelling reduces the grade variability that was initially existent in the drill core data, thus leading to smoother grade profiles and lower DH estimates.

The only exception where block modelling did not lead to comparably lower DH estimates was the PC-2 West cave. As shown in Figure 4, a higher Au DH was obtained with block modelling at the smallest scale for PC2-West (at $5 \times 5 \times 5$ m^3 block size: 1.38 vs. at 5 m composite length: 1.20). The block model grades also yielded very similar Au DH values to the drill core grades at the other two scales ($10 \times 10 \times 10$ and $20 \times 20 \times 20$ m^3 block sizes: 1.00 and 0.86 vs. at 10 and 20 m composite lengths: 1.00 and 0.88). This could be due to the fact that block modelling produced a high percentage of data points (blocks) with low gold grades for PC2-West. As shown in Figure 7, there was a significant difference between PC2-West's mean and median block model (mean: 0.71 and median: 0.33 g/t) and drill core (mean: 0.99 and median: 0.61 g/t) gold grades. Such changes in grade distribution profiles can stem from nonrepresentative drilling, i.e., the available samples over a domain may not be representative of that domain due to spatial clustering [14]. During block modelling, geostatistical interpolation methods utilize all the drill holes found within a specified search distance to carry out grade estimations. In cases where drilling is not entirely representative of the area of interest, block modelling can yield grade distribution dissimilar to those produced by drill core samples. As evident by the substantial increase in the share of the below 0.3 g/t data points, for PC2-West, the gold grade distribution obtained with the block model grades was not similar to that obtained with the drill core grades (Figure 7). Despite the grade smoothing effect of geostatistical interpolation, spatial clustering could be suggested as a factor leading to high heterogeneity estimates with block modelling.

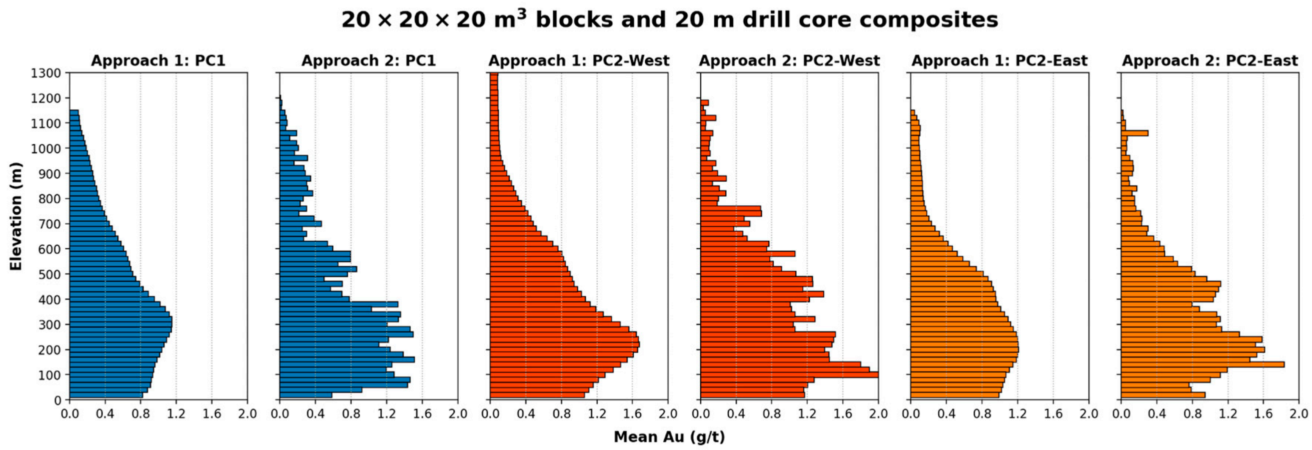
The discrepancy between the heterogeneity estimates of approaches is the highest for the PC1 cave. The gold and copper heterogeneities estimated using the drill core composite grades were nearly twice as high as those obtained by the block model grades. The grade distributions presented in Figures 7 and 8 reveal that the approaches predict similar median grades for PC1. However, block modelling predicts lower mean gold and copper grades than the drill compositing approach for the same cave. When drilling is sparse or widely spaced compared to the selected block size, block modelling artificially smooths out the grade variability, as small adjacent blocks receive about the same grade if the same drill hole grade data are used to populate them [25,26]. Although PC1 possesses the most extensive footprint of all the caves, it has the lowest ratio of the number of drill core samples to the number of blocks at all scales, as shown in Table 4. In other words, PC1 is the cave with the sparsest drilling data. As a result, block modelling produces significant amounts of similar-grade blocks around a lower mean, thus yielding remarkably lower DH estimates for PC1. While the PC1 cave is estimated to be the most heterogeneous cave by the drill core compositing approach, the block modelling approach suggests the opposite (Figure 4).



(a)

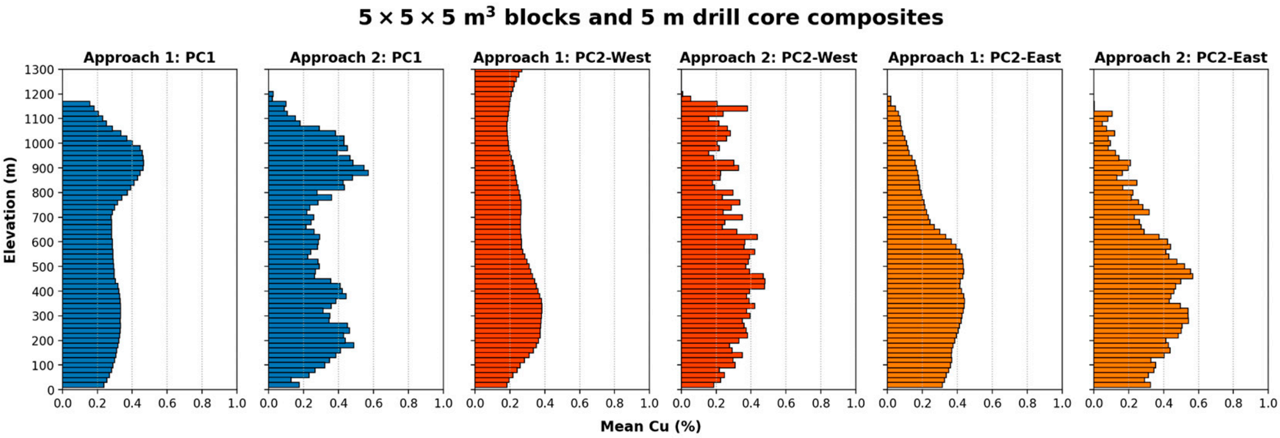


(b)

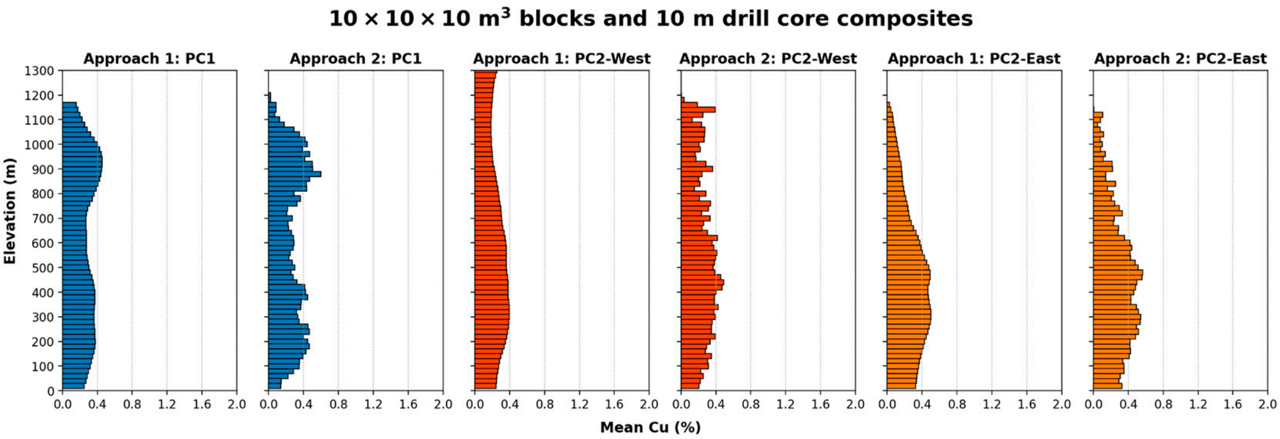


(c)

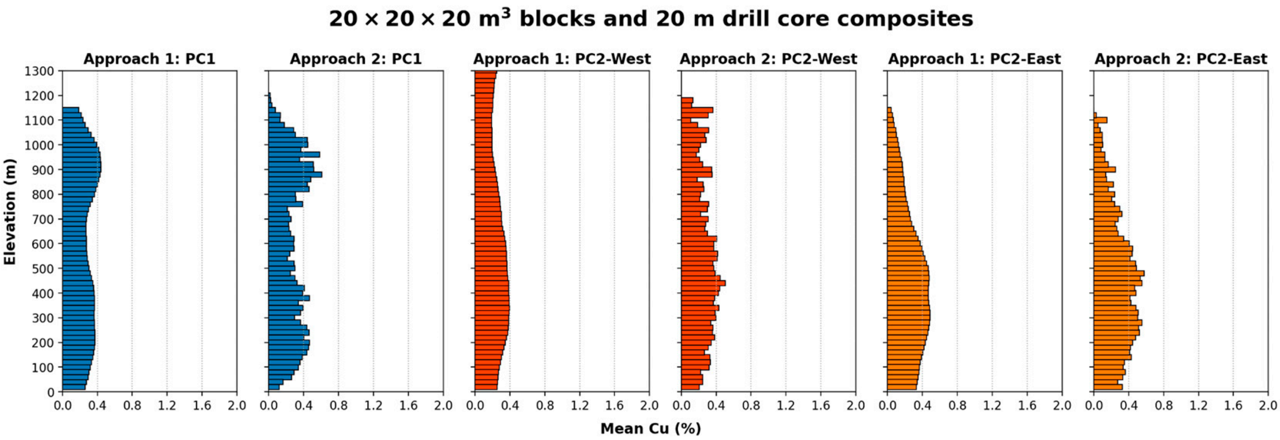
Figure 5. Change in gold grades of caves with elevation: (**a**) $5 \times 5 \times 5$ m^3 blocks and 5 m drill core composites; (**b**) $10 \times 10 \times 10$ m^3 blocks and 10 m drill core composites; (**c**) $20 \times 20 \times 20$ m^3 blocks and 20 m drill core composites.



(a)



(b)



(c)

Figure 6. Change in copper grades of caves with elevation: (**a**) 5 × 5 × 5 m^3 blocks and 5 m drill core composites; (**b**) 10 × 10 × 10 m^3 blocks and 10 m drill core composites; (**c**) 20 × 20 × 20 m^3 blocks and 20 m drill core composites.

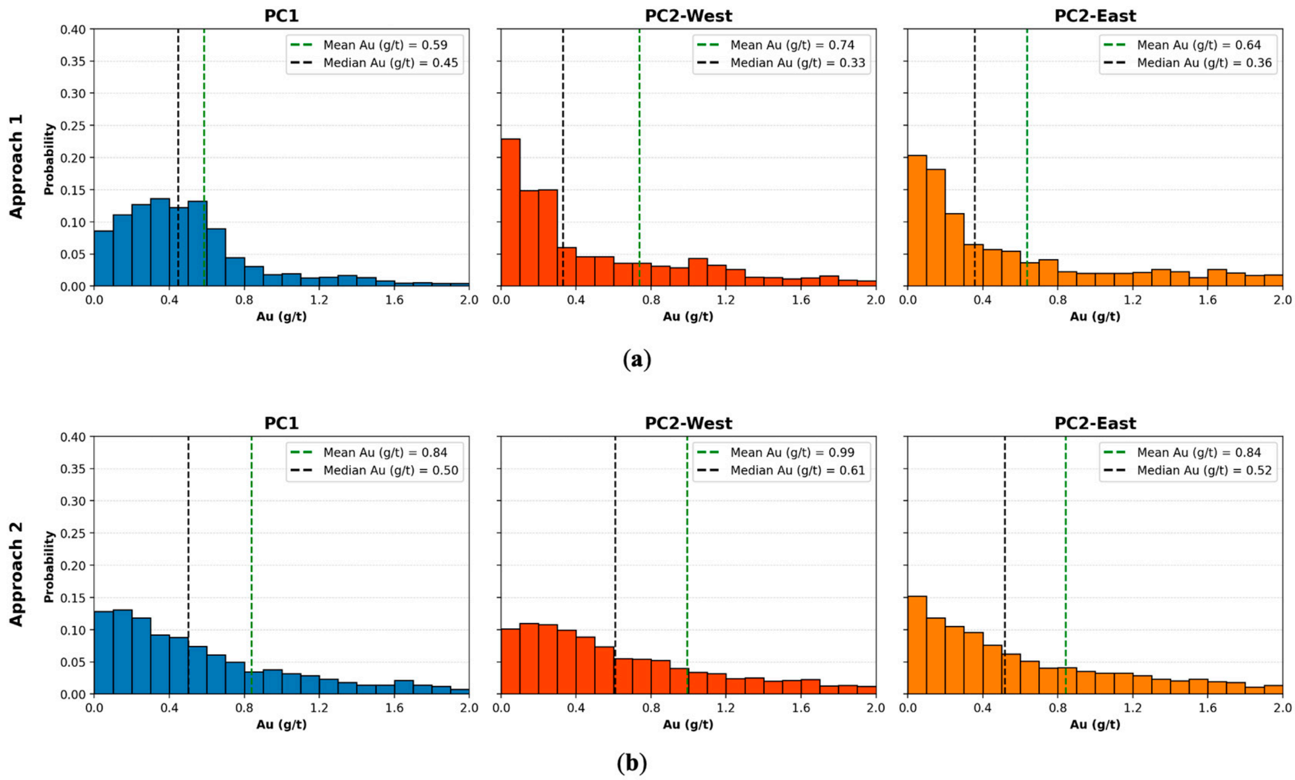


Figure 7. Gold grade distributions of data sets: (**a**) Approach 1—grade data of 5 × 5 × 5 m^3 blocks; (**b**) Approach 2—grade data 5 m drill core composites.

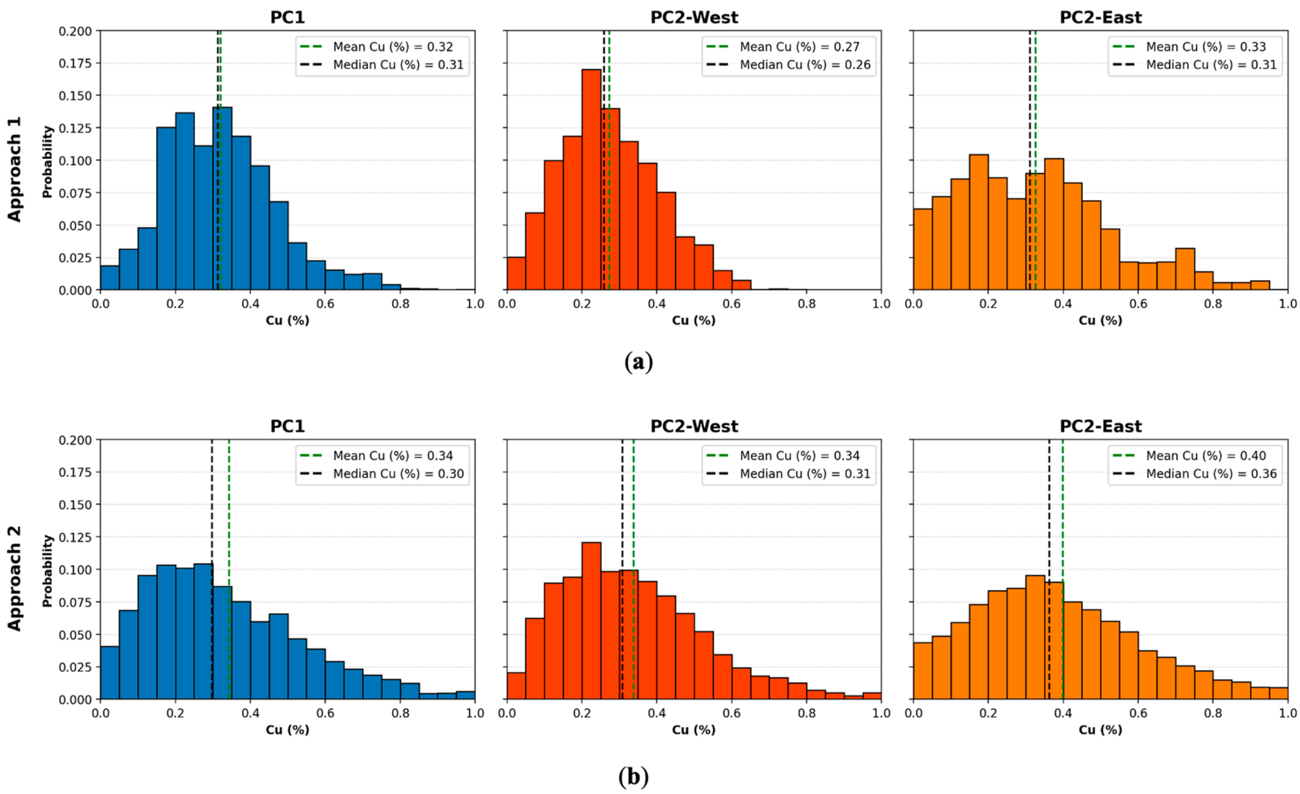


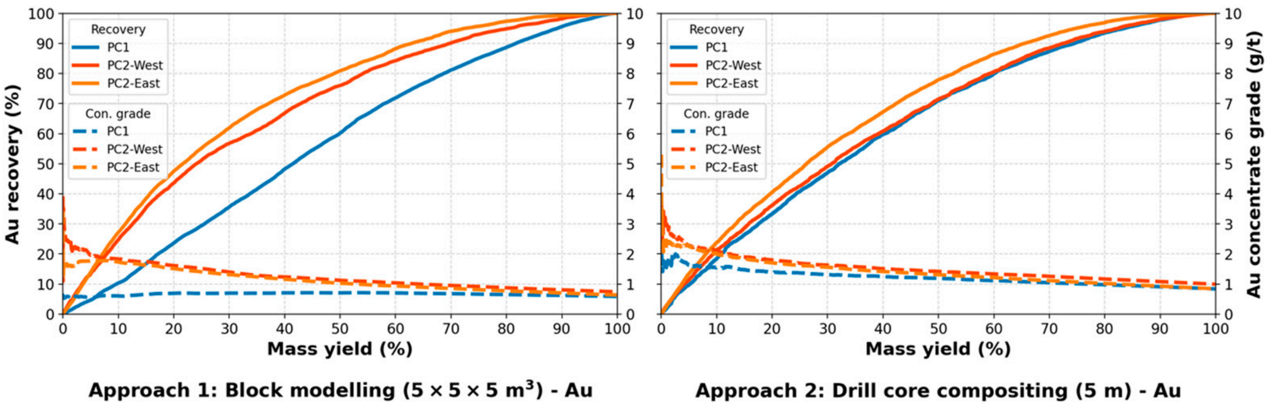
Figure 8. Copper grade distributions of data sets: (**a**) Approach 1—grade data of 5 × 5 × 5 m^3 blocks; (**b**) Approach 2—grade data 5 m drill core composites.

Table 4. Ratio of the number of drill core composites and the number of blocks identified in cave footprints.

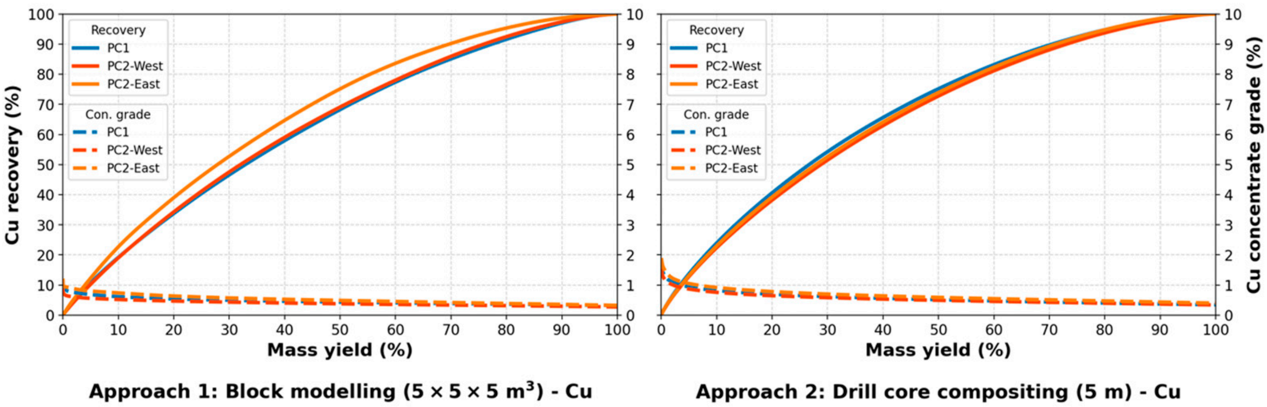
Block Size vs. Composite Length	Panel Cave	Number of Core Samples/Blocks Identified in Cave Footprints (%)
$5 \times 5 \times 5$ m^3 vs. 5 m	PC1	0.71
	PC2-West	0.81
	PC2-East	0.98
$10 \times 10 \times 10$ m^3 vs. 10 m	PC1	2.83
	PC2-West	3.23
	PC2-East	3.79
$20 \times 20 \times 20$ m^3 vs. 20 m	PC1	11.34
	PC2-West	13.16
	PC2-East	14.86

4.2. Simulating Bulk Ore Sorting Performance

The data obtained from the recovery-grade curves shown in Figures 9–11 are presented in Table 5. The table shows a drop in the degree of upgrading and mass rejection rates for each cave with the scale. This is because the grades of blocks and drill core composites converged to average values as the scale increased. The highest-grade uplift and sorting rejection rates were achieved when the block size or composite length was the smallest.



(**a**)



(**b**)

Figure 9. Grade-recovery curves obtained by Approach 1: grade data of $5 \times 5 \times 5$ m^3 blocks and Approach 2: grade data of 5 m drill core composites: (**a**) Gold; (**b**) Copper.

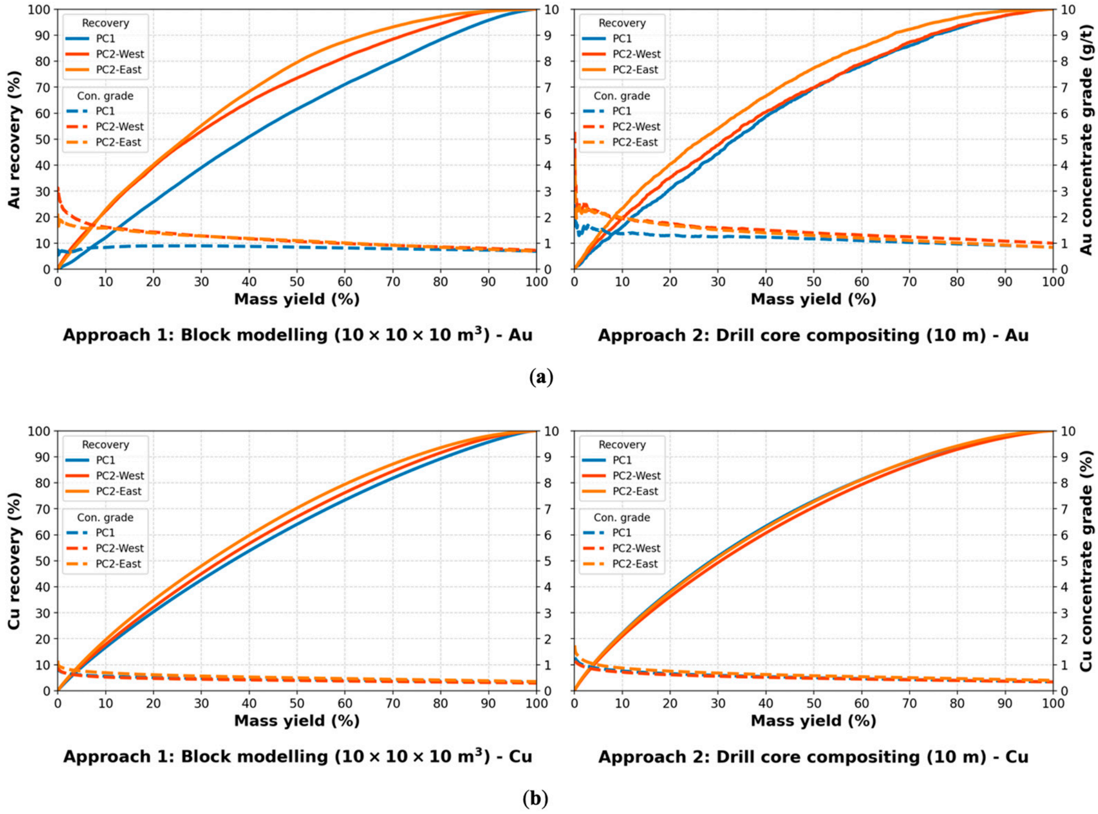


Figure 10. Grade-recovery curves obtained by Approach 1: grade data of 10 × 10 × 10 m^3 blocks and Approach 2: grade data of 10 m drill core composites: (**a**) Gold; (**b**) Copper.

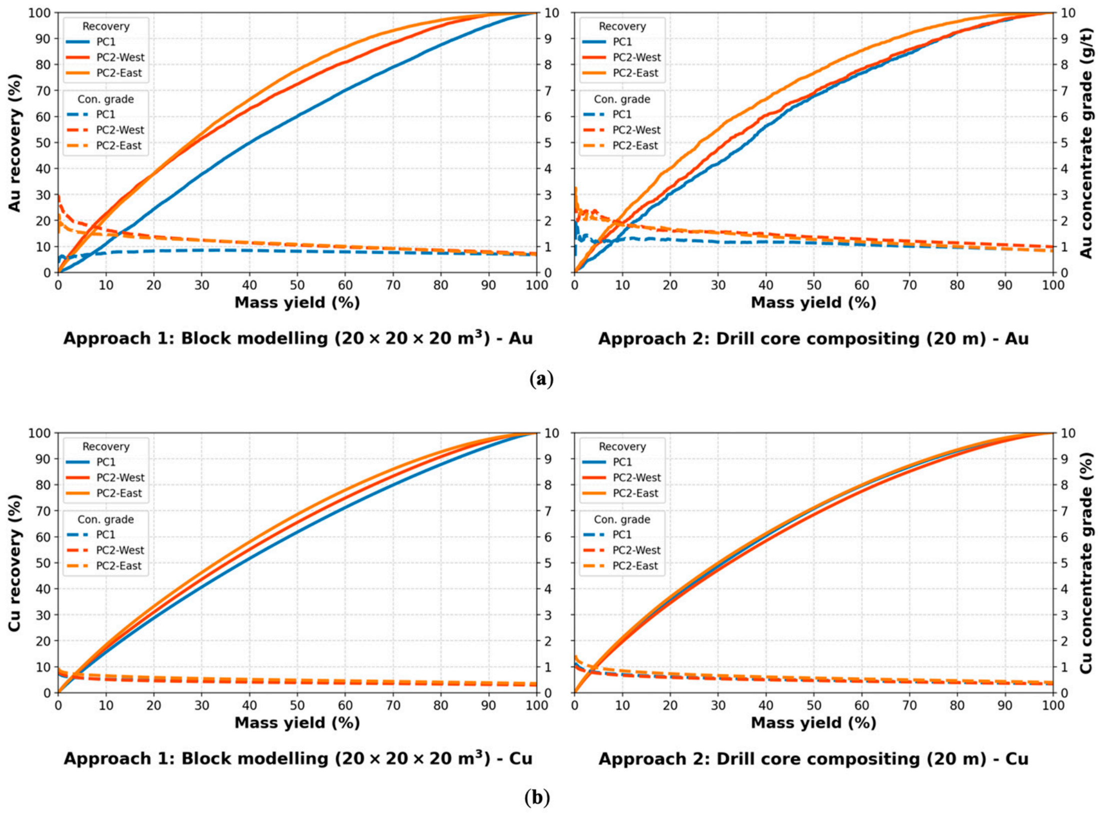


Figure 11. Grade-recovery curves obtained by Approach 1: grade data of 20 × 20 × 20 m^3 blocks and Approach 2: grade data of 20 m drill core composites: (**a**) Gold; (**b**) Copper.

Table 5. Comparison of recovery, upgrading, mass yield, and mass rejection rates of panel caves.

Approach 1: Block Modelling		**Recovery (%)**		**Concentrate Grade**		**Reject Grade**		**Upgrading (%)**		**Mass Rejection (%)**
Block Size	**Panel Cave**	**Au**	**Cu**	**Au (g/t)**	**Cu (%)**	**Au (g/t)**	**Cu (%)**	**Au**	**Cu**	
$5 \times 5 \times 5$ m^3	PC1	98.14	99.04	0.61	0.33	0.22	0.06	103.32	104.27	5.02
	PC2-West	98.74	97.99	0.80	0.29	0.11	0.06	107.84	107.03	8.45
	PC2-East	98.91	97.74	0.73	0.37	0.05	0.05	114.28	112.93	13.45
$10 \times 10 \times 10$ m^3	PC1	99.61	99.66	0.70	0.34	0.15	0.06	101.48	101.53	1.84
	PC2-West	99.64	98.55	0.77	0.31	0.04	0.06	106.83	105.66	6.73
	PC2-East	99.36	98.50	0.75	0.38	0.05	0.06	108.61	107.67	8.52
$20 \times 20 \times 20$ m^3	PC1	99.77	99.80	0.68	0.34	0.17	0.07	100.70	100.73	0.92
	PC2-West	99.75	98.96	0.76	0.31	0.04	0.06	105.11	104.28	5.10
	PC2-East	99.48	98.73	0.74	0.37	0.06	0.07	106.33	105.53	6.44
Approach 2: Drill Core Compositing		**Recovery (%)**		**Concentrate Grade**		**Reject Grade**		**Upgrading (%)**		**Mass Rejection(%)**
Composite Size	**Panel Cave**	**Au**	**Cu**	**Au (g/t)**	**Cu (%)**	**Au (g/t)**	**Cu (%)**	**Au**	**Cu**	
5 m	PC1	97.43	98.12	0.92	0.38	0.20	0.06	109.20	109.97	10.77
	PC2-West	98.49	98.38	1.07	0.36	0.18	0.07	107.35	107.23	8.25
	PC2-East	99.36	98.77	0.92	0.43	0.06	0.05	109.22	108.57	9.03
10 m	PC1	98.13	98.54	0.90	0.37	0.19	0.06	107.14	107.59	8.42
	PC2-West	98.94	98.96	1.04	0.35	0.19	0.06	104.58	104.61	5.40
	PC2-East	99.49	98.88	0.90	0.43	0.05	0.06	108.04	107.38	7.91
20 m	PC1	98.53	98.86	0.88	0.36	0.19	0.06	105.32	105.67	6.45
	PC2-West	99.30	99.34	1.01	0.35	0.19	0.06	102.90	102.95	3.50
	PC2-East	99.54	98.95	0.89	0.42	0.05	0.06	106.91	106.28	6.90

A summary of the NSR return calculations simulating the bulk ore sorting performances of the caves is shown in Table 6. The PC2-East cave was identified as the only cave for which there was potential for bulk ore sorting. The same cave was assessed to have the highest copper grade variability, degree of upgrading, and mass rejection rates by the block modelling approach (Table 5). An increase in the NSR of PC2-East of USD0.22 per ton was estimated if the sorting application was conducted at a scale of $5 \times 5 \times 5$ m^3 blocks. The cave lost its bulk ore sorting potential when the scale increased to the block sizes of $10 \times 10 \times 10$ and $20 \times 20 \times 20$ m^3. The drill core compositing approach was unable to produce any NSR estimates that would favour the bulk ore sorting application at PC2-East. The low mass rejection rates predicted by the drill core compositing approach are insufficient to offset the metal losses and the sorting cost.

The PC1 cave is predicted to have the lowest bulk ore sorting performance, as demonstrated by the decrease in its NSR estimated by both approaches. Table 5 shows that significant amounts of gold were lost to the sorting waste (around 0.2 g/t Au in the material rejected at 0.1% Cu cut-off grade), making PC1 unsuitable for bulk ore sorting. The generation of similar-grade blocks (generally above the sorting cut-off) with block modelling due to the drill hole data sparsity drops the mass rejection rates of the PC1 cave, which causes a significant decline in its NSR estimates. Although PC1 was assessed to possess the highest gold and copper grade heterogeneities by the drill core compositing approach, the calculations show that the cave is not amenable to bulk ore sorting. The NSR calculations of the PC1 cave show the importance of carrying out economic evaluations rather than sticking only with grade heterogeneity estimations in order to estimate the actual value associated with bulk ore sorting.

The NSR values estimated for PC2-West show that the application of bulk ore sorting is not economically feasible for the cave at any scale. For PC2-West, block modelling produced more promising NSR values than drill core compositing. This difference was due to the higher-grade uplift and mass rejection rates obtained by the block modelling approach.

Table 6. Change in net smelter returns of panel caves with bulk ore sorting.

Approach 1: Block Modelling			
Block Size	**Panel Cave**	**Change in NSR (USD/t)**	**Comment on Sortability**
$5 \times 5 \times 5$ m^3	PC1	−0.49	Not sortable
	PC2-West	−0.23	Not sortable
	PC2-East	0.22	Sortable
$10 \times 10 \times 10$ m^3	PC1	−0.39	Not sortable
	PC2-West	−0.09	Not sortable
	PC2-East	−0.05	Not sortable
$20 \times 20 \times 20$ m^3	PC1	−0.41	Not sortable
	PC2-West	−0.15	Not sortable
	PC2-East	−0.18	Not sortable
Approach 2: Drill Core Compositing			
Composite Size	**Panel Cave**	**Change in NSR (USD/t)**	**Comment on Sortability**
5 m	PC1	−0.50	Not sortable
	PC2-West	−0.42	Not sortable
	PC2-East	−0.02	Not sortable
10 m	PC1	−0.44	Not sortable
	PC2-West	−0.44	Not sortable
	PC2-East	−0.06	Not sortable
20 m	PC1	−0.44	Not sortable
	PC2-West	−0.42	Not sortable
	PC2-East	−0.12	Not sortable

5. Conclusions

The comparison between block modelling and drill core compositing shows that the approaches are prone to producing varying in situ grade heterogeneity and sorting performance estimates.

The results reveal that the block modelling of an ore deposit tends to smooth the grade variability in the drill core data. In particular, the grade-smoothing effect of block modelling can be observed in the portions of the deposit where the drill hole data is sparse or widely spaced. The ore blocks in those portions are populated with similar grade estimates by the geostatistical interpolation method used. As a result, block modelling yields lower grade heterogeneity and bulk ore sorting performance estimates. When assessing the potential to apply bulk ore sorting using the block modelling approach, the scale should be selected according to drill hole spacing to avoid artificially smoothing out the grade variability of an ore deposit.

In cases where the drill hole data is not representative of the area of interest due to spatial clustering, the block modelling approach can produce more realistic bulk ore and sorting performance estimates than the drill core compositing approach. Since preferential drilling is generally concentrated in high-grade portions of an ore deposit, the drill core compositing approach is more likely to yield lower-grade uplift and mass rejection rates due to lacking low-grade data points. Such bias in the drill core data leads to more discouraging bulk ore sorting potential estimates by the drill core compositing approach.

The sorting scale impacts the grade heterogeneity estimates obtained by both approaches similarly. An increase in the sizes of blocks and the lengths of drill core samples reduces the grade variability due to the averaged metal grades.

The approaches compared in this study were limited to simulating the bulk ore sorting performances of the caves for the ideal case. A further investigation where the simulation results and the actual production data are compared is required to assess the impact of mixing that occurs during mining and material handling. The aim of the study is not to justify one approach over another but to compare their principal and practical advantages and limitations.

Author Contributions: Conceptualization, M.C.C.; Methodology, M.C.C., G.L. and B.K.; Software, M.C.C. and G.L.; Validation, M.C.C., G.L. and B.K.; Formal analysis, M.C.C.; Investigation, M.C.C.; Resources, B.K. and W.F.; Data curation, M.C.C.; Writing—original draft, M.C.C.; Writing—review & editing, M.C.C., G.L., B.K. and W.F.; Visualization, M.C.C.; Supervision, B.K.; Project administration, B.K.; Funding acquisition, B.K. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Mitacs Accelerate Program.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank Newcrest Mining Limited for supporting this research project.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Weston, A.J. The Evolution of Block Caving Technology. In Proceedings of the Seventh International Conference and Exhibition on Mass Mining, Sydney, NSW, Australia, 9–11 May 2016.
2. Moss, A.; Klein, B.; Nadolski, S. Cave to mill: Improving value of caving operations. In Proceedings of the Caving 2018: Proceedings of the Fourth International Symposium on Block and Sublevel Caving, Vancouver, BC, Canada, 15–17 October 2018.
3. Nadolski, S.; Samuels, M.; Klein, B.; Hart, C.J.R. Evaluation of bulk and particle sensor-based sorting systems for the New Afton block caving operation. *Miner. Eng.* **2018**, *121*, 169–179. [CrossRef]
4. Klein, B.; Bamber, A. Mineral Sorting. In *Mineral Processing and Extractive Metallurgy Handbook*; Society for Mining, Metallurgy & Exploration (SME): Englewood, CO, USA, 2019; pp. 763–786.
5. Scott, M.; Amini, E. Quantifying economic and environmental impacts of preconcentration. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
6. Scott, M.; Rutter, J.; Plessis, J.D.; Alexander, D. Operational deployment of sensor technologies for bulk ore sorting at Mogalakwena PGE Mine. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
7. Li, G.; Klein, B.; Sun, C.; Kou, J. Investigation on influential factors of bulk ore sortability based on fractal modelling. *Miner. Eng.* **2021**, *177*, 107362. [CrossRef]
8. Duffy, K.; Valery, W.; Jankovic, A.; Holtham, P.; Valle, R. In search of the Holy Grail—Bulk ore sorting. In Proceedings of the Austmine 2015—Transforming Mining, Technology and Innovation, Brisbane, QLD, Australia, 19–20 May 2015.
9. Nadolski, S.; Klein, B.; Elmo, D.; Scoble, M.; Liu, Y.; Scholar, J. Investigation into the Implementation of Sensor-based Ore Sorting Systems at a Block Caving Operation. In Proceedings of the Seventh International Conference & Exhibition on Mass Mining, Sydney, NSW, Australia, 9–11 May 2016.
10. Ballantyne, G.; Pyle, M.; Foggiatto, B.; Vizcarra, T. Assessing the value of bulk ore sorting with drill core data. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
11. Revell, P.A.; Wilkie, G.J. An integrated and balanced approach to developing pre-concentration technologies across the mining value chain. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
12. Klein, B.; Erdenebat, E.; Nadolski, S.; Samuels, M. Assessing Ore Heterogeneity for Bulk Sorting at the New Afton Copper Mine. In Proceedings of the 8th Sensor-Based Sorting & Control Conference, Aachen, Germany, 6–7 March 2018.
13. Noble, G.; Ferguson, S. Understanding ore heterogeneity and effective bulk ore sorting using PGNAA/PFTNA. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
14. Rutter, J.; Dunham, S. Heterogeneity and bulk ore sorting—Methods to estimate ore sorting performance. In Proceedings of the Preconcentration Digital Conference, Online, 10–11, 17–18 November 2020.
15. McCarthy, R.J. *Is Bigger Better?—An Analysis Orebody Heterogeneity and Mining Scale*; SRK Consulting: Vancouver, BC, Canada, 2018.
16. McCarthy, R.J. Exploiting heterogeneity: Improving head grade and project value. In Proceedings of the World Gold Conference, Perth, WA, Australia, 11–13 September 2019.
17. Cooke, D.R.; Wilson, A.J.; House, M.J.; Wolfe, R.C.; Walshe, J.L.; Lickfold, V.; Crawford, A.J. Alkalic porphyry Au-Cu and associated mineral deposits of the Ordovician to Early Silurian Macquarie Arc, New South Wales. *Aust. J. Earth Sci.* **2007**, *54*, 445–463. [CrossRef]
18. Gleeson, K.; Newcombe, G.; Griffin, P.; Stephenson, P. *Cadia Operations New South Wales, Australia NI 43-101 Technical Report*; Newcrest Mining Limited: Melbourne, VIC, Australia, 2020.
19. Holliday, J.R.; Wilson, A.J.; Blevin, P.L.; Tedder, I.J.; Dunham, P.D.; Pfitzner, M. Porphyry gold-copper mineralisation in the Cadia district, eastern Lachlan Fold Belt, New South Wales, and its relationship to shoshonitic magmatism. *Miner. Depos.* **2002**, *37*, 100–116. [CrossRef]

20. Barber, C.B.; Dobkin, D.P.; Huhdanpaa, H.T. The quickhull algorithm for convex hulls. *ACM Trans. Math. Softw.* **1996**, *22*, 469–483. [CrossRef]
21. Gy, P.M. Introduction to the theory of sampling I. Heterogeneity of a population of uncorrelated units. *Trends Anal. Chem.* **1995**, *14*, 67–76. [CrossRef]
22. Nadolski, S. Cave-To-Mill: Mine and Mill Integration for Block Cave Mines. Ph.D. Thesis, University of British Columbia, Vancouver, BC, Canada, 2018.
23. Bonnici, N.K. The Mineralogical and Textural Characteristics of Copper-Gold Deposits Related to Mineral Processing Attributes. Ph.D. Thesis, University of Tasmania, Hobart, Tasmania, 2012.
24. Li, G.; Klein, B.; Sun, C.; Kou, J. Insight in ore grade heterogeneity and potential of bulk ore sorting application for block cave mining. *Miner. Eng.* **2021**, *170*, 106999. [CrossRef]
25. Rossi, M.E.; Deutsch, C.V. *Mineral Resource Estimation*; Springer: Dordrecht, The Netherlands, 2014.
26. Boisvert, J.B.; Ortiz, J.M.; Deutsch, C.V. Local recoverable reserves prediction with block LU simulation. *Int. J. Min. Miner. Eng.* **2008**, *1*, 3–21. [CrossRef]