A comparative analysis of implicit modelling and geostatistical methods for geometallurgical block modelling and resource estimation

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Accurate geometallurgical block modelling improves resource recovery, processing efficiency, and mine planning. This paper compares two modelling methods for geometallurgical block modelling. These are the fast radial basis function (FastRBF) implicit method and the ordinary kriging geostatistical method. The methods were applied to predict total cobalt, bond work index (BWI), and rock quality designation (RQD) in a cobalt deposit. Drillhole and geometallurgical data were composited into two-metre intervals and applied to a 10 × 10 × 10 m block model using Leapfrog Geo. Implicit method produced smoother grade distributions and gradual spatial transitions. This is useful in early-stage evaluations. Geostatistical method captured localised high-grade zones and better represented sharp geological boundaries, particularly for RQD. BWI estimates were similar in central tendency but showed higher variability under implicit method. These differences can influence project decisions. A model's ability to reflect local grade variation or broader spatial trends affects scheduling, energy forecasting, and process design. Model selection should align with data quality, geological context, and project stage. This work evaluated modelling outcomes for the two approaches. Future studies should incorporate detailed error metrics, such as RMSE, MAE, and R^2, and test these methods across varied deposits. Hybrid models may offer balanced solutions by combining the spatial precision of geostatistical methods with the trend continuity of Implicit methods.

Keywords: geometallurgical modelling, implicit methods, ordinary kriging, resource estimation, geostatistics methods, geometallurgical block modelling

INTRODUCTION

Geometallurgy is a field that combines geology with engineering, metallurgy, and environmental considerations (Bye 2011; Dominy *et al.*, 2018; Ehrig 2013). This integration supports mine planning and improves processing efficiency (Garrido *et al.*, 2018, 2020). Incorporating key metallurgical parameters into orebody models helps to overcome processing challenges and enhances resource extraction, contributing to project profitability (Coward and Dowd 2015). To support this integration, geometallurgical block models are used. A geometallurgical block model is a three-dimensional representation of a mineral deposit. It integrates geological characteristics with grades, as well as key metallurgical attributes such as ore hardness and recovery rates (Deutsch *et al.*, 2016). These models are typically developed using geostatistical estimation methods such as ordinary kriging (OK), implicit modelling, or hybrid approaches that combine machine learning with geostatistics (Abildin *et al.*, 2023). This enables the design of mine plans that optimise ore extraction, blending, and processing while managing technical and operational variability (Dominy *et al.*, 2018). It also helps mining operations identify and mitigate production risks, contributing to more stable economic outcomes (Khorram *et al.*, 2020).

However, there are many challenges associated with geometallurgical block modelling. It must capture the spatial variability of metallurgical and geotechnical features, which is often complex and non-linear (Hoffimann *et al.*, 2022). Many geometallurgical variables—such as recovery, comminution indices, mineral assemblages, and rock types—do not exhibit regular spatial patterns. Obtaining reliable parameter estimates and uncertainty measures is difficult when data is limited and uneven (Garrido *et al.*, 2020). More robust methods are needed to integrate diverse data types and model complex geological structures with greater confidence (Abildin *et al.*, 2023). Despite extensive research on traditional geostatistical, machine learning, and hybrid methods for geometallurgical block modelling, implicit modelling techniques remain comparatively underexplored. In particular, there is a lack of comparative analyses assessing the performance of fast radial basis function (FastRBF) relative to conventional geostatistical methods such as OK. This gap highlights the need for further research into the effectiveness of implicit modelling in accurately estimating critical parameters such as metallurgical recovery and rock quality.

This paper aims to provide practical insights by comparing FastRBF-based implicit modelling with OK for geometallurgical block modelling. FastRBF and OK were selected as representative methods from the implicit modelling and geostatistical categories, respectively. Each represents a single approach within its broader class. The comparison offers practical insights into how these specific methods perform when applied to geometallurgical block modelling. The study focuses on three operationally significant variables: total cobalt (TCo), bond work index (BWI), and rock quality designation (RQD). Model performance is assessed using statistical indicators, swath plots, grade-tonnage curves, and resource estimate tables. The paper also evaluates each method's ability to detect high-grade zones and represent spatial variability at broader scales. While this paper does not propose a new modelling approach, its findings may help practitioners and researchers select modelling strategies that align with geological context, data quality, and project objectives. The results may also inform future efforts to integrate geostatistical and implicit methods with machine learning to further improve the reliability and economic value of geometallurgical models.

METHODOLOGY

Implicit method—Fast Radial Basis Function Review

The FastRBF method is part of a broader family of implicit modelling techniques. It is used for surface reconstruction in fields such as computer graphics and geology (Zhong and Wang 2020). The method was developed to address the computational limitations of traditional radial basis function (RBF) interpolation when applied to large datasets, particularly those exceeding 10,000 constraints (Zhong *et al.*, 2019). FastRBF improves efficiency through a domain decomposition strategy. It divides the dataset into smaller sections, which reduces computational demands. This segmentation also helps maintain or, in some cases, improve accuracy and numerical stability. The method involves selecting a suitable radial basis function from a predefined set of interpolants. The choice of kernel parameters plays a critical role, as it can significantly influence modelling outcomes. In practical applications, FastRBF has proven effective in modelling complex orebody geometries with high processing speeds. In Leapfrog Geo software, FastRBF-based implicit modelling builds on earlier work by Savchenko *et al.,* (1995) and Cowan *et al.,* (2003), who introduced the concept of volume functions. Geological boundaries are represented as volumetric surfaces that define distinct geological domains. These surfaces are constructed through the interpolation of a volume function (McLennan 2007; Rolo *et al.,* 2017). The modelling workflow includes several key steps. These are data validation, compositing, interpolation, and meshing. Morphological constraints are applied during interpolation to improve geological realism (Rolo *et al.*, 2017). The resulting three-dimensional models capture both geological structure and grade variability in a continuous and interpretable format.

Geostatistical Methods—Ordinary Kriging Review

OK is a popular geostatistical method for estimating values at unsampled sites in mineral resource models (Marwanza *et al.,* 2025). It is considered a statistically robust method that yields unbiased estimates with low variation. This is accomplished by using a spatial continuity model, represented by a semivariogram, to calculate interpolation weights (Tavares *et al.*, 2008). OK is used in a variety of applications, including mineral resource estimates, environmental contamination mapping, and soil management. One of its main advantages is its ability to offer solid geographical forecasts together with estimations of related uncertainty. However, OK has certain limits. It may be difficult to simulate non-linear or non-stationary geological phenomena seen in complicated ore deposits (Ibrahim *et al*., 2022). Interpolated findings are prone to smoothing effects, which often result in underestimating local high or low grades (Atalay 2024). This smoothing is inherent in the weighing process and the use of geographic averages. Furthermore, data density and geographical distribution have a significant impact on OK performance. Semivariogram modelling needs evenly distributed and representative data. In locations with low sampling or significant geological variety, OK may provide less trustworthy data, limiting its efficacy.

Description of the Drillhole and Geometallurgical Data

This research utilised drillhole data from Iverland Mining's cobalt exploration operation in the Democratic Republic of Congo. The data were initially reported by Mboyo (2018). The original data were collected under industry-standard exploration programmes. They were reported as having undergone appropriate quality assurance and quality control procedures. These included collar validation, downhole survey calibration, and assay verification, as detailed in the original studies. In this work, the secondary data were subject to additional format standardisation and validation before import into Leapfrog Geo. Automated checks were used to detect and correct depth inconsistencies, missing intervals, and data mismatches. Records that could not be reconciled were excluded to preserve the integrity of the modelling. To augment this dataset, geometallurgical data were gathered from the works of Dehaine *et al*., (2021) and (Mambwe *et al*., (2022). Laboratory collection of such data is both expensive and logistically challenging. The dataset contains spatial coordinates: Easting (mean, 530120.5), Northing (mean, 8714423.53), and Elevation (mean, 1330.6 m) (Table I). Drillhole depths vary from 77.0 to 287.0 m, with an average of 148.3 m. This research focuses on three key geometallurgical variables. TCo has a mean grade of 0.8%. The BWI has a mean value of 11.12 kilowatt-hours per tonne. RQD has a mean value of approximately 49.58%. The drillholes were bored with a mean azimuth of around 114° and a dip angle of 56°.

Table I. Statistical summary of drillhole and geometallurgical data

8,5	X (DD)	Y (DD)	Z (m)	Depth_max (m)	Depth_From (m)	Depth_To (m)	TCo (%)	BWI (kWh/t)	RQD (%)
count	66.0	66.0	66.0	66.0	4717.0	4717.0	4717.0	1122	1122
mean	530120.5	8714424	1330.6	148.3	80.9	81.6	0.8	11,12	49.58
Std	131.9	139.46	0.9	45.4	36.8	36.8	1.8	4,48	20.34
Min	529863.8	8714125.11	1328.9	77.0	2.0	2.4	0.0	0	0
25%	530027.7	8714329.56	1329.9	116.6	52.2	52.8	0.1	7	36.33
50%	530123.0	8714419.35	1330.6	144.8	79.5	80.4	0.2	12	54.74
75%	530218.6	8714518.54	1331.3	170.0	107.2	107.9	0.8	14,3	70
Max	530397.3	8714716.55	1332.6	287.0	197.5	198.5	25.4	19,6	72

Variogram Modelling

Variogram modelling was used to assess the spatial continuity and variability of geometallurgical parameters. The spatial modelling module in Leapfrog Geo was used to build initial variogram parameters, which were then improved, depending on the data's features. A spheroidal variogram model was chosen because it effectively captures the anisotropic spatial continuity seen in mineral deposits. The final model parameters were a nugget effect of 0.1781, a total sill of 1.081, and a significant range of 200 m. This variogram model was consistently used in both the implicit and geostatistical estimation procedures, allowing spatial analysis findings to be readily compared across all datasets.

Implicit Modelling
The previously described variogram model was implemented in Leapfrog Geo, which was used in this work for both implicit and geostatistical estimates, as well as block modelling. The software was chosen because it provides a good implementation of the FastRBF for implicit modelling, alongside classic geostatistical methods such as OK, allowing for a uniform methodological comparison. The drillhole data entered into Leapfrog Geo contained collar coordinates, survey data (azimuth and dip), assay data, and geometallurgical parameters. During the import procedure, the software automatically detected possible issues such as anomalies in collar depth, missing intervals, and mismatched Hole ID values. Any discovered faults were addressed inside the software to assure the accuracy of future modelling. Data that could not be changed were removed to ensure data integrity. Assay and geometallurgical interval data were composited into 2 m intervals, which roughly matched the original mean sample length. Intervals less than this limit were discarded. A minimum interval coverage of 50% was used to address missing data and reduce possible compositing bias. Geometallurgical parameter estimation was performed using the implicit modelling method in Leapfrog Geo, using the variogram model mentioned before. The interpolation contained a drift component, with each parameter's mean value given correspondingly; for example, RQD's mean was 52.5%. An interpolant accuracy of 0.3 was used, and data values were clipped within set upper and lower ranges to reduce the possibility of overestimation or underestimation.

Geostatistical Method
Geostatistical methods were used in Leapfrog Geo to estimate geometallurgical parameters. The previously established variogram model was used, with parameters maintained consistently throughout both estimate methods to guarantee comparability. Negative estimated values were adjusted to zero to ensure geological validity. Leapfrog Geo automatically set discretisation with cell dimensions of X-5, Y-5, and Z-2, hence improving estimate accuracy inside the block model. Value clipping was used during interpolation, using predetermined minimum and maximum thresholds to restrict extreme estimations. The anisotropic ellipsoid parameters used in the OK process were synchronised with those applied in the implicit modelling workflow, guaranteeing uniform handling of spatial continuity in both methodologies. The final outputs included the estimated geometallurgical parameter values and their associated status indicators, used for further assessment and comparison.

Block modelling of Geometallurgical Data
To facilitate the evaluation of the estimated geometallurgical parameters, a three-dimensional block model was constructed in Leapfrog Geo, balancing computational efficiency with the size of the dataset. The model used a block size of 10 m × 10 m × 10 m, a measurement often chosen to correspond with practical factors like bench heights in open-pit mining or stope dimensions in underground mining. The block model was established at a reference position of (529843.20, 8714064.00, 1382.80), with dimensions of 640 m along the X-axis, 680 m along the Y-axis, and 350 m along the Z-axis. The implicit method and geostatistical methods estimators were used on this block model to get comparative estimates of the geometallurgical parameters. The use of a common block model framework guaranteed that any discrepancies noted between the two methods were due to the estimating methodologies, not to variances in model geometry or resolution.

RESULTS

Comparison of Block Models of Total Cobalt Generated through Implicit and Geostatistical Methods
The statistical analysis of the TCo estimations generated by the implicit and geostatistical methods indicated variations in central tendency, variability, and dispersion (Table II). The geostatistical method yielded a mean TCo of 1.04%. It also had a higher standard deviation and variability, indicating a broader range of anticipated grades within the model. This trend was further shown by a bigger coefficient of variation, underscoring increased relative dispersion of TCo values. The implicit method produced the highest individual TCo estimate at 8.78%, surpassing the maximum value of 6.92% achieved by the geostatistical method. These results underscore the significant disparities in how each method represents grade variability and extreme values inside the block model.

Table II. Statistical comparison between Implicit and Geostatistical methods for the TCo-based block models

Name	Implicit TCo (%)	Geostatistical TCo (%)
Block Count	6 416	6 416
Volume	6 416 000 m³	6 416 000 m³
Mean	0.99	1.04
Standard deviation	0.71	0.85
Coefficient of variation	0.71	0.81
Variance	0.49	0.72
Minimum	0	-0.02
Median	0.79	0.76
Maximum	8.79	6.92

Swath plots were used to compare TCo estimates derived from the geostatistical (blue) and implicit (red) methodologies (Figure 1). The geostatistical method exhibited increased variability, characterised by a broader spectrum of TCo values and more significant peaks and troughs across the model. The implicit method yielded a slower trend, marked by a consistent rise in TCo values interspersed with sporadic declines. In low-grade zones (Swath Numbers 0–20 and 50–60), both methodologies exhibited a generally similar pattern. However, the geostatistical method demonstrated more localised variations. In high-grade areas (Swath Numbers 20–50), the geostatistical method yielded more pronounced amplitude responses and deeper troughs, whereas the implicit method attenuated these fluctuations, resulting in a more uniform grade profile. The geostatistical method demonstrated more sensitivity to local spatial structure and data connection, whilst the implicit method offered a more comprehensive and generalised perspective on grade distribution.

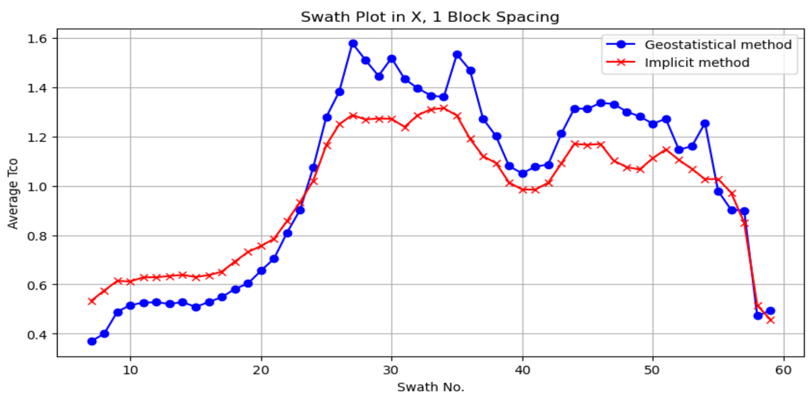

Figure 1. Comparison of swath plots between implicit and geostatistical methods for the TCo-based block models

Figures 2a and 2b illustrate the geographical distribution of TCo) throughout the two geometallurgical block models. Both models exhibit comparable proportions of high- and medium-grade TCo; however, they significantly diverge in local variability and spatial continuity. The implicit model (Figure 2a) has increased total TCo variability, characterised by more gradual transitions across the deposit. The geostatistical model (Figure 2b) generates more defined grade boundaries, especially in the middle area of the model, where significant transitions between high- and moderate-grade zones are apparent. The implicit method is well-suited for deposits exhibiting gradual geological variability, providing a continuous depiction of mineralisation patterns. The geostatistical method, in comparison, delineates localised grade variations more clearly, which may be significant in deposits with intricate geological formations.

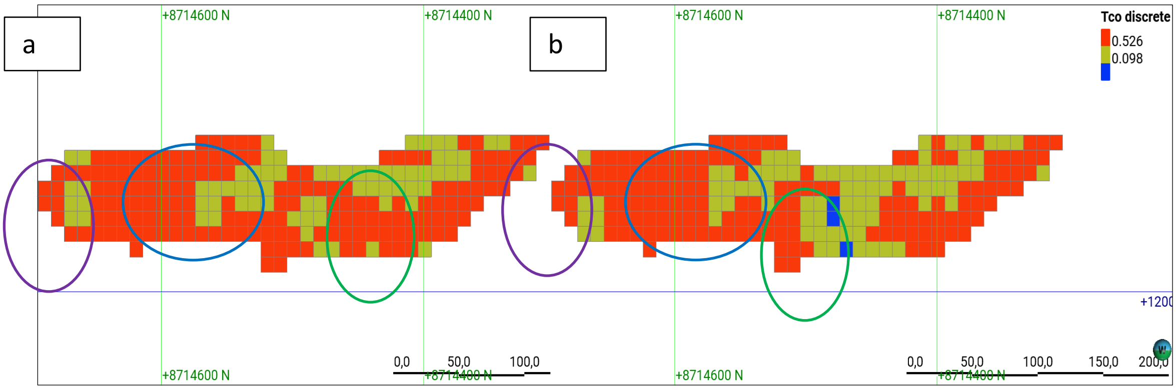

Figure 2. Visual comparison between a) Implicit method and b) Geostatistical method for the TCo-based block models.

Comparison of Block Models of Bond work Index Generated through Implicit and Geostatistical Methods

The statistical comparison of BWI estimations generated by the implicit and geostatistical methods indicates slight discrepancies in central values, accompanied by some variance in distribution features (Table III). The implicit method yielded a mean BWI of 12.79 kWh/t, somewhat lower than the 12.82 kWh/t mean obtained by the geostatistical method. The standard deviation for the implicit method was 2.02 kWh/t, slightly above the 1.95 kWh/t recorded for the geostatistical method, indicating somewhat more uncertainty in the implicit estimator. The coefficient of variation for the implicit method (0.16) was somewhat greater than that of the geostatistical method (0.15), indicating a relatively broader dispersion of BWI values. The implicit method yielded a lower minimum BWI of 6.49 kWh/t, in comparison to 7.00 kWh/t obtained by the geostatistical method. Although both methodologies generated comparable mean estimates, the geostatistical method demonstrated somewhat greater consistency, exhibiting less variability and a more confined range of values. The noted discrepancies probably indicate the responsiveness of each method to localised modifications in the dataset.

Table III. Statistical comparison between Implicit and Geostatistical methods for the BWI-based block models

Name	Implicit BWI (kWh/t)	Geostatistical BWI (kWh/t)
Block Count	6 416	6 416
Volume	6 416 000 m^3	6 416 000 m^3
Mean	12.79 kWh/t	12.82 kWh/t
Standard deviation	2.02 kWh/t	1.95 kWh/t
Coefficient of variation	0.16 kWh/t	0.15 kWh/t
Variance	4.09 kWh/t	3.78 kWh/t
Minimum	6.49 kWh/t	7 kWh/t
Median	13.16 kWh/t	13.17 kWh/t
Maximum	19.97 kWh/t	19.42 kWh/t

The swath plot compares the geostatistical and implicit methods in estimating the average BWI along the X-axis (Figure 3). Both methods display regional differences, with the geostatistical method producing a smoother and more stable profile in certain sections of the model. The implicit method shows minor discrepancies, particularly around local peaks and troughs, where small fluctuations are more apparent. Despite these differences, the two methods produced consistent results at the overall model scale, with limited variation in key areas. The comparison indicates that both methods are suitable for modelling BWI at a general scale, though differences in handling localised variations remain evident, especially when representing finer-scale features of the deposit.

Figure 3. Comparison of swath plots between Implicit and Geostatistical methods for the BWI-based block models.

Figures 4a and 4b compare BWI estimates generated using the implicit and geostatistical methods within the geometallurgical block model. Both models display a broadly consistent pattern, with widespread intermediate BWI values (yellow), centred around approximately 13.2 kWh/t. Localised differences appear in areas of higher (blue) and lower (red) BWI values. The two methods differ in their representation of spatial continuity and the distribution of hardness values. The implicit model (Figure 4a) shows more fragmented zones of high BWI (blue), particularly on the left and central portions of the section. The geostatistical model (Figure 4b) produces more continuous zones of both high and low BWI, with sharper transitions between different BWI classes. These variations in model behaviour may reflect differences in how each method handles local estimation and spatial smoothing. Such differences can influence mine planning and energy optimisation. Variations in estimated rock hardness affect decisions related to grinding circuit design, energy forecasting, and throughput expectations.

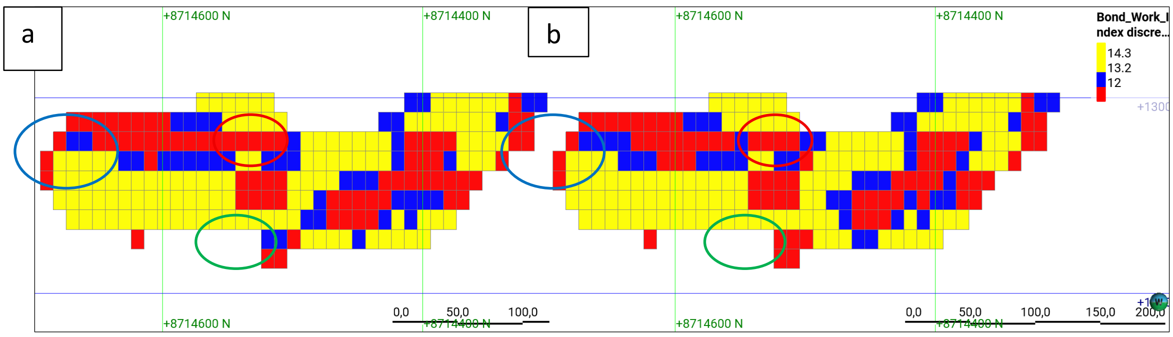

Figure 4. Visual comparison between a) Implicit method and b) Geostatistical method for the BWI-based block models.

Comparison of Block Model for Rock Quality Designation Index Generated through Implicit and Geostatistical Methods

Statistical analysis of the RQD block model, comparing the implicit and geostatistical methods, shows that the geostatistical method produces a slightly higher mean RQD value. This is accompanied by a standard deviation of 10.41% and a variance of 100.81%. The geostatistical model also exhibits reduced variability around the mean compared to the implicit model. Its minimum estimated RQD is 15.03%, and the maximum reaches 75.85%. The results indicate that the geostatistical method produces a more uniform distribution of RQD values, with a narrower range of estimates across the model.

Table IV. Statistical comparison between Implicit and Geostatistical methods for the RQD-based block models

Name	Implicit RQD (%)	Geostatistical RQD (%)
Block Count	6 416	6 416
Volume	6 416 000 m³	6 416 000 m³
Mean	56.49%	56.62%
Standard deviation	10.41 %	10.04 %
Coefficient of variation	0.18 %	0.18 %
Variance	108.43 %	100.81 %
Minimum	15.03 %	16.99 %
Median	56.52 %	56.52 %
Maximum	75.85 %	71.31 %

The swath plot in Figure 5 shows that average RQD values estimated by the geostatistical method range from 50.03% to 60.63%, while those produced by the implicit method range from 48.53% to 58.56%. In some swath intervals, the two methods produce closely aligned RQD values, indicating similar results in those areas. In other intervals, the differences between the methods are more pronounced. At Swath Number 13, for example, the geostatistical method produced an average RQD of 59.29%, compared with 58.54% from the implicit method. At Swath Number 47, the geostatistical estimate was 55.91%, while the implicit method produced 56.38%. These differences reflect local variations in how each method models the spatial continuity of RQD within the block model.

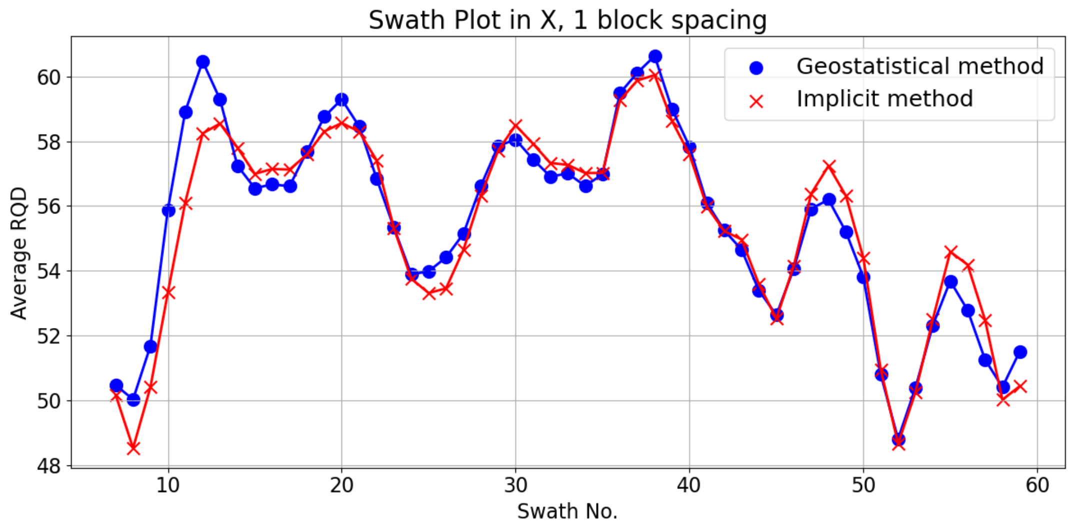

Figure 5. Comparison of swath plots between Implicit and Geostatistical methods for the RQD-based block models.

Figures 6a and 6b compares implicit modelling (Figure 6a) and geostatistical methods (Figure 6b) for the estimation of RQ within the geometallurgical block model. Both models exhibit similar overall spatial patterns, with dominant trends in the central high-RQD zone (red). Differences emerge in how the two methods represent spatial continuity and local variability. The implicit model shows more gradual transitions across the deposit, while the geostatistical model displays more pronounced oscillations in RQD values. A region marked with a black circle highlight one such difference. The implicit model predicts more fragmented zones with frequent extremes in RQD values, whereas the geostatistical model produces a smoother and more continuous representation of spatial variability. Such differences can influence how each method supports geotechnical interpretations and informs mine planning decisions.

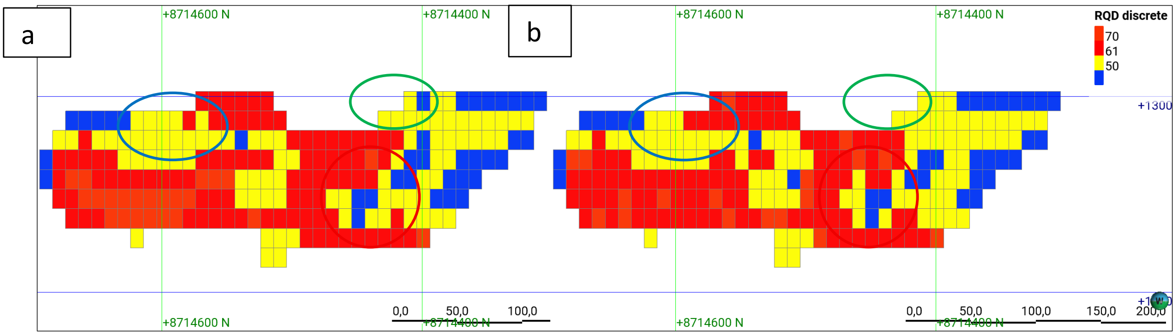

Figure 6. Visual comparison between a) Implicit method and b) Geostatistical method for the RQD-based block models.

Grade-Tonnage Curve for Implicit and Geostatistical Methods

The grade-tonnage curve illustrates the relationship between estimated ore tonnage and grade across varying cut-off grades. It provides insight into the quantity and quality of material that could be extracted under different economic scenarios. Figure 7 compares the grade-tonnage results obtained using the implicit and geostatistical methods. At a cut-off grade of 0.5%, the implicit method estimates a total ore tonnage of 11.29 million tonnes (Mt), with an average grade of 1.12% and an estimated commodity recovery of 90.83%. In comparison, the geostatistical method estimates a slightly higher ore tonnage of 11.36 Mt, with a higher mean grade of 1.34%, while 90.50% of the contained metal remains unmined. While the curves produced by both methods are similar in overall shape, minor differences appear in the estimated grades and recoverable tonnages. These variations reflect differences in how each modelling method represents grade distribution across the deposit.

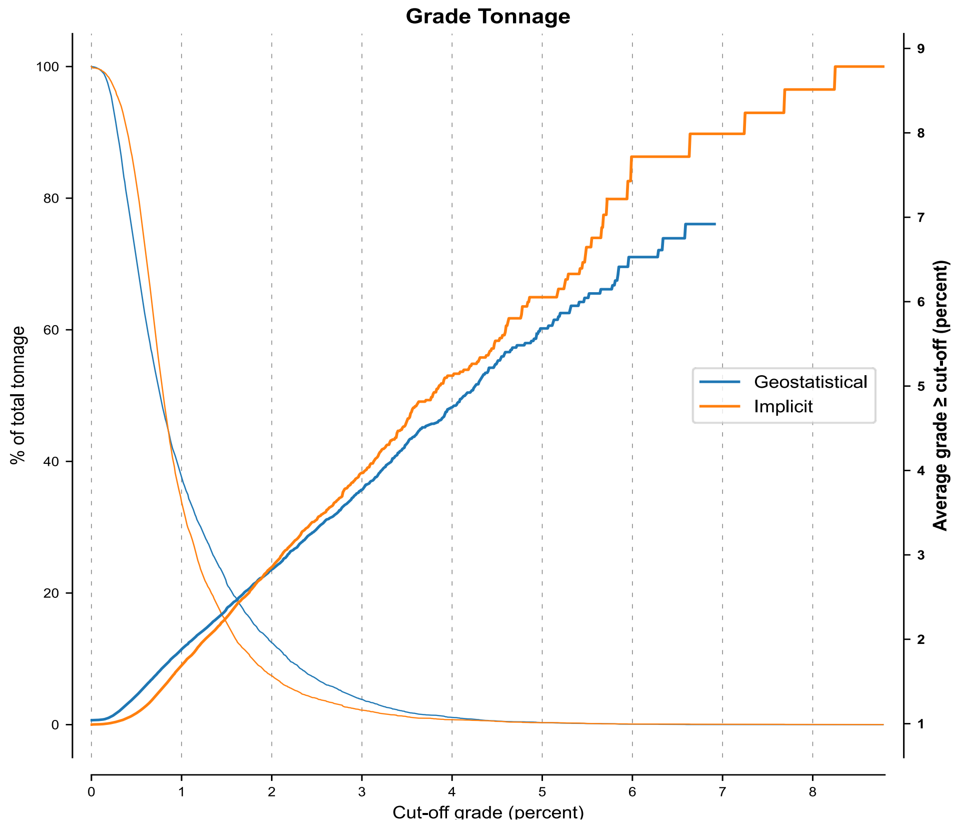

Figure 7. Comparison of grade tonnage curves generated using Implicit and Geostatistical methods.

Resource Estimation

The resource estimation results highlight differences between the implicit and geostatistical methods in the classification of ore, as well as in the estimated values of TCo, BWI, and RQD (Tables V and VI). The implicit method classified 253,000 cubic metres of high-grade ore, with an average grade of 3.04% TCo, a BWI of 13.83 kWh/t, and an RQD of 54.37%. The geostatistical method identified a smaller volume of 142,000 cubic metres of high-grade ore, but with a higher average grade of 3.78% TCo, a BWI of 14.04 kWh/t, and an RQD of 52.35%. For medium-grade material, the implicit model is estimated to be 2,147,000 cubic metres, with average values of 1.39% TCo, 13.02 kWh/t BWI, and 56.75% RQD. The geostatistical model produced a medium-grade volume of 2,049,000 cubic metres, with a higher average TCo of 1.72% a comparable BWI of 13.12 kWh/t, and an RQD of 56.89%. In the low-grade category, the implicit method assigned 2,145,000 cubic metres, with average values of 0.77% TCo, 12.70 kWh/t BWI, and 57.71% RQD.

The geostatistical method classified 3,101,000 cubic metres as low grade, with an average TCo of 0.71%, a BWI of 12.68 kWh/t, and an RQD of 57.07%. The two methods also differed in their estimation of waste material. The geostatistical model identified 1,124,000 cubic metres of waste, compared to 1,871,000 cubic metres in the implicit model. Waste exhibited similar average BWI and RQD values in both models, though the higher waste tonnage estimated by the implicit model may affect dilution considerations during mine planning. Across the entire resource model, the geostatistical method produced a higher overall mean TCo (1.05%) compared to the implicit model (0.99%). Mean BWI values were nearly identical: 12.82 kWh/t (geostatistical) and 12.79 kWh/t (implicit). Mean RQD values were also very close, at 56.62% for the geostatistical model and 56.49% for the implicit model. These variations in classification and estimated values are likely to influence mine planning decisions, particularly regarding processing circuit design and the management of operational risks associated with ore hardness and rock quality.

Table V. Resource estimation using Implicit method

				Average Value		
Class	Volume	Density	Mass	TCo	Bond_Work_Index	RQD
	m^3	g/cm^3	t	%	kWh/t	%
High	253 000.00	2.7	683 100.00	3.04	13.83	54.37
Low	2 145 000.00	2.7	5 791 500.00	0.77	12.7	57.71
Medium	2 147 000.00	2.7	5 796 900.00	1.39	13.02	56.75
Waste	1 871 000.00	2.7	5 051 700.00	0.51	12.5	55.07
Total	6 416 000.00	2.7	17 323 200.00	0.99	12.79	56.49

Table VI. Resource estimation using the Geostatistical method

				Average Value		
Class	Volume	Density	Mass	TCo	Bond_Work _Index	RQD
	m^3	g/cm^3	t	%	kWh/t	%
High	142 000.00	2.7	383 400.00	3.78	14.04	52.35
Medium	2 049 000.00	2.7	5 532 300.00	1.72	13.12	56.89
Low	3 101 000.00	2.7	8 372 700.00	0.71	12.68	57.07
Waste	1 124 000.00	2.7	3 034 800.00	0.37	12.52	55.43
Total	6 416 000.00	2.7	17 323 200.00	1.05	12.82	56.62

DISCUSSION AND CONCLUSION

In addition to evaluating technical performance, this paper examined the potential economic implications of using implicit modelling and geostatistical methods to estimate TCo, BWI and RQD in a geometallurgical block model. The results show that the geostatistical method produced slightly higher mean TCo values and captured more localised high-grade zones. This supports its use in selective mining and short-term production planning. The implicit method produced a smoother spatial profile. This makes it better suited to early-stage project evaluation and understanding broader mineralisation trends. For BWI, both methods provided similar mean estimates. The implicit model, however, showed greater variability. This could affect comminution circuit design and energy forecasts. RQD estimates were closely aligned across both models. The geostatistical method demonstrated lower variability, improving its ability to capture rock mass quality variations.

These modelling differences can influence key economic outcomes. Variations in high-grade ore estimation affect projected revenue and guide cut-off grade optimisation, which impacts project net present value. The broader distribution of BWI values in the implicit model introduces more uncertainty in energy consumption. This could influence grinding circuit sizing and operating costs. Differences in waste classification also affect mine scheduling and ore dilution, with downstream effects on processing efficiency and economic returns. A more conservative waste estimate from the geostatistical model may improve net smelter return by reducing dilution. The broader classification in the implicit model may provide greater flexibility in production planning but could introduce risk if marginal material underperforms. Choosing a modelling method should align with the project stage and economic priorities. Geostatistical modelling may be better suited to feasibility studies and investment decisions, where detailed estimation of grade variability and processing parameters is required. Implicit modelling, with its smoother spatial trends, is valuable in exploration and conceptual resource studies focused on identifying broader patterns and development opportunities.

Both methods offer distinct advantages. Combining the local precision of geostatistics with the continuity modelling of implicit methods could provide balanced solutions for a range of mining applications. Further research should focus on developing such hybrid frameworks. While this study concentrated on comparative modelling behaviour and practical implications, a detailed error analysis was beyond its scope. Future work should incorporate such analyses to strengthen understanding of model accuracy and precision. Method performance should also be evaluated across different geological settings and larger datasets. Improving the quality of geometallurgical block models supports better resource estimation, risk management, and economic decision-making. Aligning the modelling approach with geological context, data quality, and project objectives is critical to achieving sound technical and financial outcomes. This study compared one implicit modelling technique (FastRBF) and one geostatistical method (OK). The findings reflect the performance of these specific approaches and should not be generalised to all methods within each category. Future work could expand this comparison by including additional techniques to further inform method selection.

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