Challenges of extreme grades in resource estimation: Spatial capping as an alternative to domain capping of outliers

by D. Fourie[1], P. le Roux[2], R. Minnitt[3]

Affiliation:
1 Harmony Central Services South, Harmony Gold Mining Co. LTD, Welkom, South Africa.
2 SRK Consulting South Africa Pty Ltd., South Africa.
3 School of Mining Engineering, University of the Witwatersrand, Johannesburg, South Africa.

Correspondence to:
R. Minnitt

Email:
Richard.Minnitt@wits.ac.za

Dates:
Received: 20 May 2025
Revised: 12 May. 2026
Accepted: 05 Jun. 2026
Published: June. 2026

How to cite:
Fourie, D., le Roux, P., Minnitt, R. 2026. Challenges of extreme grades in resource estimation: Spatial capping as an alternative to domain capping of outliers. *Journal of the Southern African Institute of Mining and Metallurgy*, vol. 126, no. 6, pp. 373 - 384

DOI ID:
https://doi.org/10.17159/2411-9717/3733/2026

ORCiD:
D. Fourie
http://orcid.org/0000-0001-9403-1008
P. le Roux
http://orcid.org/0000-0003-1143-8625
R. Minnitt
http://orcid.org/0000-0002-0267-8152

Abstract

This study proposes that the moving search neighbourhood used in ordinary kriging selects a subset of data surrounding each estimation block, and that this subset represents a local subpopulation of which the distributional parameters can be used to determine local, spatially-adaptive outlier capping values. This paper introduces a distance-weighted capping method applied within the kriging search ellipse after kriging weight calculation, transitioning from one-dimensional point estimation to two-dimensional block estimation for Witwatersrand-type gold deposits. Accurate ore grade estimation is essential for mine planning and economic evaluation, particularly in deep-level gold mines where extreme grade values (outliers) may distort resource assessments. Traditional capping methods, which apply a uniform threshold to outliers, often fail to account for spatial and geological variability, leading to biased estimates. A high-resolution simulation generates a synthetic 'ground truth' orebody, subsampled to mimic real-world data scarcity. A two-parameter lognormal distribution models grade variability, with capping values optimised by minimising the mean squared error between estimated and simulated block grades. Comparative analyses against traditional capping techniques demonstrate that the dynamic method improves regression fit, reduces conditional bias, and aligns more closely with production reconciliation data. Validation using swath plots, QQ-plots, and mine call factor comparisons confirms that the spatially adaptive capping technique mitigates over- and under-estimation, particularly in high-grade zones. Results indicate superior performance over conventional domain capping, with higher R^2 values and better alignment with actual production metrics. This approach offers a reproducible, scientifically rigorous framework for resource estimation, reducing reliance on rigid sub-domaining while enhancing decision-making in complex ore bodies. The study underscores the importance of integrating geological information with advanced geostatistics to optimise grade estimation and mine planning.

Keywords

Conditional bias, grade capping, outlier mitigation, geostatistics, resource estimation, kriging, Witwatersrand

Introduction

Accurately assessing ore grades is critical for mine planning and the economic evaluation of mineral deposits, particularly in deep-level gold mines in South Africa, where extreme grade values (outliers) can significantly distort resource estimates. Outliers in grade distributions can lead to overvaluation of low-grade regions and undervaluation of high-grade zones, negatively impacting the mine call factor (MCF), planning, and decision-making. While capping outliers is a common practice to limit their influence on overall grade estimates, traditional approaches—such as applying a single threshold to values above a fixed percentile—often fail to account for spatial variations and geological context, treating all outliers uniformly regardless of their location within the orebody. This study proposes capping the sample values within the search ellipse after calculating kriging weights as opposed to capping the input sample data used in estimation. Building on the work of Fourie, Morgan, and Minnitt (2019), the research refines capping methods by introducing a distance-weighted regime that considers both the grade and spatial relationship of outliers to estimation points. By balancing the treatment of outliers with geological understanding, this localised, and spatially sensitive approach aims to prevent the overestimation or smearing of extreme grades, ensuring more accurate and reliable resource models. The study highlights how integrating geological insights with advanced capping techniques can mitigate potential biases in grade estimation, enhance resource modelling, and support more informed mine planning and decision-making.

Challenges of extreme grades in resource estimation:

Objectives and significance

This study extends the mitigation of grade outliers from a one-dimensional point estimation, as developed by Fourie, Morgan, and Minnitt (2019), to a two-dimensional block estimation approach, addressing challenges in Witwatersrand-type deposits in South Africa. Block models are central to resource estimation in these deposits, where extreme grades can distort assessments, leading to inaccurate resource evaluations and flawed mine planning. This targeted approach incorporates distance-based weighting, which reduces the influence of extreme grades depending on their proximity to the point being estimated. By preserving geological context and spatial continuity, this method enhances the accuracy of resource assessments, particularly in heterogeneous ore bodies where grade variability is significant.

In addition to refining the capping process, the study builds on geostatistical best practices, including ordinary kriging, while ensuring compliance with the mineral resource reporting codes emphasising reproducibility and scientific rigor. The incorporation of sub-domaining allows for more nuanced handling of outliers, mitigating risks of over- or under-estimating resources, especially in high-grade zones, where the financial and operational implications are most critical. This localised approach aligns estimation practices with the deposit's geology, offering defendable and adaptable models that reduce the risk of overvaluing extreme grades. Practical implications include improved mine planning, financial forecasting, and risk management, particularly for complex ore bodies like those in South Africa's Witwatersrand Basin. By advancing outlier handling and enhancing the reliability of block models, this research addresses a critical gap in resource estimation, providing a scientifically grounded framework for optimising decision-making and resource management.

Literature review

The following is an overview of the development of robust statistical methods aimed at mitigating the influence of outliers on data analysis, with particular emphasis on geostatistical resource estimation. Outliers, observations inconsistent with the majority of data, can significantly distort variography, kriging weights, and block grade estimates. The review traces the evolution of outlier treatments from foundational robust statistics through to modern geostatistical and machine-learning-assisted approaches, culminating in the positioning of the present study.

The foundational robust statistics regarding outlier-resistant estimation approach was first formalised by Frank Hampel. He introduced the breakdown point, which measures the smallest proportion of outliers that can force an estimator to take arbitrarily large (or infinite) values. Hampel's work established the theoretical ceiling for any robust estimator. These ideas were extended by Peter Huber into regression analysis with M-estimators, which minimise a function of residuals, applying quadratic weighting to small residuals (like least squares) but down-weighting large residuals. Huber also introduced influence functions, quantifying how a single data point can affect an estimator. These contributions underpin later geostatistical robustification, including robust variography.

In the 1980s, robust statistics expanded to include multivariate data and high-breakdown methods. Beckman and Cook (1983) extended Huber's concepts using Mahalanobis distance and influence diagnostics. Rousseeuw and Croux (1993) proposed the median absolute deviation (MAD) and the more efficient Sn and Qn scale estimators. These tools remain foundational for outlier detection in geochemical and assay datasets.

Outliers in geostatistical resource estimation

Barnett and Lewis (1994) emphasised that outliers in mining datasets—particularly gold—can inflate resource estimates by orders of magnitude if not handled appropriately. Traditional methods such as lognormal kriging, disjunctive kriging, and indicator kriging were developed partly to reduce outlier influence, each with limitations.

Indicator kriging (Journel, 1983) transforms continuous grades into binary indicators at multiple thresholds, thereby limiting the influence of extreme values. However, it requires careful threshold selection and can lose information on within-class grade magnitude.

Multigaussian kriging (Verly, 1984) applies a normal score transform to the data, estimates at the Gaussian scale, and back-transforms. While effective for many deposits, it assumes a multivariate Gaussian distribution after transformation—a condition often violated in the presence of extreme outliers.

Top-cut models (Rivoirard et al., 2013) explicitly model the tail of the grade distribution as a separate population (often Pareto or lognormal) above a cutoff. This method preserves total metal while reducing the influence of individual extreme samples. The present study's localised capping shares conceptual similarities but applies capping at the estimation (block) level rather than globally.

Robust variography and kriging

Cressie and Hawkins (1980) developed robust variogram estimators resistant to outliers. Hawkins and Cressie (1984) proposed robust kriging, which uses a weighted combination of robustly estimated sample values. However, robust kriging can be computationally intensive and sensitive to initial parameter choices.

Krige and Magri (1982) demonstrated that logarithmic transformation followed by careful outlier elimination could improve variogram modelling in gold deposits. Journel and Arik (1988) provided early case studies on outlier management in precious metals.

Restricted kriging and post-processing approaches

Pan and Arik (1993) introduced restricted kriging, which imposes constraints on kriging weights to limit the propagation of extreme grades. This method directly influences the estimation equations, unlike the present study's post-weight capping approach, which leaves the kriging system unchanged.

Fourie, Morgan, and Minnitt (2019) proposed a post-processing method that nonlinearly transforms positively skewed data into Gaussian categorical bins, calculating restriction factors that limit the influence of extreme data points in the kriging process. Their 2021 follow-up introduced spatial sub-domaining to apply capping limits specific to an outlier's range of influence rather than a uniform value. The present study extends this work from one-dimensional point estimation to two-dimensional block estimation, incorporating distance-weighting within the search ellipse.

Simulation-based calibration of capping

Chiquini and Deutsch (2017) suggested using simulation to calibrate capping levels, estimating the expected metal content in volumes affected by outliers. The present study adopts a similar philosophy but applies it at the block level, using a high-resolution synthetic "ground truth" to optimise capping via mean squared error (MSE) minimisation.

Modern and machine-learning-assisted approaches (2022 – 2025)

Recent literature has seen the integration of machine learning (ML) with geostatistical outlier handling (Anvari et al., 2025; Fouedjio, Arya, 2024; Leung et al., 2021). These recent works confirm that the field is moving toward local, adaptive, and spatially aware outlier treatments—exactly the direction taken by the present study. However, none of the above combine (a) post-kriging-weight capping, (b) block-level optimisation via MSE against synthetic truth, and (c) full reconciliation with production data (mine call factor). This gap defines the contribution of this paper.

Industry compliance and reporting codes

Mineral resource reporting codes (JORC, SAMREC, NI 43-101) require that estimation methods be reproducible, defensible, and appropriately handle high-grade outliers. The SAMREC Code (2016) supports this requirement directly: its guidance to Clauses 24 and 35 specifies that any adjustment made to the data for the purpose of a Mineral Resource or Mineral Reserve estimate—including the cutting or capping of grades—must be clearly described in the Public Report. This obligation to disclose and justify capping decisions sits alongside the Code's overarching principles of Transparency and Competency (Clause 4), which require that a Competent Person provide sufficient information for a reader to understand, and not be misled by, the methods used to derive an estimate.

The present study's localised, distance-weighted capping method explicitly meets these requirements: it provides a reproducible, data-driven optimisation (MSE minimisation), documents the capping basis per block, and preserves geological context through the kriging search ellipse.

In conclusion, the evolution from Hampel's breakdown point to modern ML-assisted spatial capping shows a clear trajectory: outlier treatment must become local, adaptive, and geologically informed. The present study advances this trajectory by integrating distance-weighted capping into the ordinary kriging workflow, with rigorous validation against both synthetic truth and production data. It offers a reproducible, code-compliant alternative to domain capping, particularly suited to high-variance gold deposits such as those of the Witwatersrand Basin.

Research problem and methodology

This article presents a method for resource estimation that refines existing capping techniques by incorporating the identification and mitigation of extreme values within estimated blocks. High-grade outliers may result in the smearing of high grades within the estimates, leading to overestimation of resources in areas surrounding and informed by, high-grade outliers. This approach minimises their impact, improving estimation accuracy, block classification, and decision-making in resource planning and extraction. The methodology is reproducible, defensible, and aligned with industry standards.

The experiment involves generating a 'ground truth' orebody through a high-resolution simulation of the original sampling data within a defined domain. This simulated orebody is then subsampled, and the estimates derived from these subsamples, using the methodology outlined here, are compared to the ground truth. The workflow starts by addressing high-grade outliers in selected blocks (each block corresponding to a subsample set) through capping. Experimental analysis identifies the optimal capping value based on the grade distribution. While there are various ways to define distribution shapes, this method uses the two-parameter lognormal distribution for grade modelling (after confirming that the three-parameter threshold is negligible), incorporating Rendu's formula (1979; 1981) to estimate distribution shape parameters from quantiles. Comparisons with historical techniques and mine production data confirm the validity of this approach, providing a systematic and scientifically grounded solution to extreme grade challenges in resource estimation. Additionally, the methodology includes a comparative study of contemporary capping techniques to ensure best practices are followed and to benchmark effectiveness.

The proposed method determines the optimal local capping value by minimising the mean squared error (MSE) in simulated block distributions. The capping quantile is determined by minimising the MSE of the subsample estimates for the simulated orebody. Block values calculated using ordinary kriging with traditional domain-capped data are compared with those derived by local dynamic capping which refines the estimates and reduces the conditional bias. This approach is validated using the mean squared error, swath plots, and mine production reconciliation.

Key steps in the workflow include capping high-grade outliers per block within the search ellipse to reduce their distorting effect, recalculating block values with the capped grades to improve accuracy and evaluating the impact of localised capping on block estimates. An optimal capping value is identified through experimental analysis to reflect the actual grade distribution within the simulated resource. We are then in a position to compare the entire simulated orebody to the estimate derived from the subsampled data set. The ultimate objective is to develop a reproducible approach for localising capping values, improving block classification, and reducing bias in resource estimation workflows. This refined model enhances accuracy and precision of resource models. It aligns with industry standards, providing valuable insights into outlier management in resource estimation and a comprehensive framework for enhancing resource estimation workflows.

Determination of population parameters

The first step in determining the local capping value is to establish the population parameters of the initial dataset distribution. While a three-parameter lognormal distribution is often used for grade data with a lower threshold (Rendu, 1981), analysis of our dataset showed the threshold parameter β (Equation 1) to be effectively zero for the grade ranges of interest (i.e., the distribution is well-approximated by a standard two-parameter lognormal). Rendu's formula for β is:

$$\beta = \frac{m^2-(q_h \cdot q_l)}{q_h+q_l-2m} \qquad [1]$$

where:

- m = 50th percentile
- q_h = n^{th} percentile (e.g., 95th)
- q_l = (100 - n)th percentile (e.g., 5th)

For our data, β consistently calculated to values < 0.01 cm.g/t across all quantile pairs tested, confirming that the two-parameter model is appropriate. We therefore use the computationally simpler two-parameter lognormal model throughout, with the understanding that $\beta = 0$ in all subsequent equations. For deposits requiring a three-parameter model, replace Z with $(Z - \beta)$ in Equations 2 to 4 and modify Equation 5 to $Z_h = \beta + \exp(\omega + \phi\text{-}1(h)\tau)$.

The shape of the distribution is not a primary factor as one could use the same capping methodology even if the distribution is not lognormal.

Calculation of block parameters

Block parameters are derived using the log mean calculated from the log estimate of samples within the search ellipse (Equation 2), while the log variance (Equation 3) and standard deviation is determined using the population coefficient of variation (CV) and the block mean (Equation 4). These calculations ensure the block parameters reflect the adjusted population distribution, enhancing accuracy in the estimation process.

$$\omega = \ln(Z) - \frac{\tau^2}{2} \quad [2]$$

$$\tau^2 = \ln\left(\left(\frac{\sigma}{Z}\right)^2 + 1\right) \quad [3]$$

$$\sigma = \varepsilon Z \quad [4]$$

Where

- ω = log mean
- τ = log standard deviation
- ε = coefficient of variation
- Z = block mean
- σ = standard deviation

A note on the estimation of local block parameters: The block mean Z used in Equation 4 is calculated as the simple arithmetic mean of sample values within the search ellipse. This does not account for spatial clustering of samples (e.g., multiple closely-spaced samples from a high-grade shoot). Sensitivity testing showed that using kriging-weighted means changed capping values by less than 5% for > 90% of blocks. For irregularly sampled datasets, declustering weights (Deutsch, Journel, 1998) should be used.

Calculation of quantile values

The quantile value is calculated using the block parameters to calculate the value at a given quantile Z_(h)_ using Equation 5:

$$Z_h = e^{\omega + \phi^{-1}(h)\tau} \quad [5]$$

Where

- ϕ = normal cumulative distribution function
- ω = log mean
- τ = log standard deviation
- h = quantile fraction
- e= Euler's number (base of natural logarithm,≈2.71828)

Determining capping value from experimental data

Consider a block estimate with thirty-five samples and calculated kriging weights within the search ellipse, as shown in Table 1.

A population coefficient of variation of 1.6 has been calculated for all the samples in the entire domain. The uncapped estimate for the block is the sum-product of the sample values and kriging weights, in this case, 189. From the block sample data, the arithmetic mean is calculated as 498. Using the population coefficient of variation, a standard deviation is calculated as σ = CV × $\bar{x}$, which calculates as 1.6 × 498 = 797 (rounded).

For a block with a mean of 498 and standard deviation of 797, the log variance (Equation 3) is:

$$\tau^2 = \ln\left(\left(\frac{797}{498}\right)^2 + 1\right) = 1.27$$

and the log mean (Equation 2) is:

$$\omega = \ln(498) - \frac{1.27}{2} = 5.58$$

In this case, the 95th percentile is chosen simply as an example capping value for this block (Equation 5):

$$Z_h = e^{\omega + \phi^{-1}(h)\tau} = e^{5.58 + 1.64 \times \sqrt{1.27}} = 1687$$

Consequently, all the sample values in Table 1 larger than 1687 (2500 and 2192) are replaced with 1687, and the new block estimate becomes 177.

Simulation of high-resolution block distributions

The first step was to select a domain with appropriate face sampling values (the initial selected dataset), typically carried out at 5 m intervals on mining faces which have 5 m – 10 m sampling coverage. These data were then used to simulate exactly the same sample distribution, but at a much higher 1 m × 1 m resolution, and for the purposes of this research, the simulated distribution is considered to be the actual truth. A comparison of the cumulative distribution frequency for both the input data and the simulated data are shown in Figure 1, indicating a high degree of correspondence between the two sets of data.

The subsampling methodology involves creating a high-resolution, non-conditional simulation using population parameters to generate a synthetic representation of the distribution, which is then treated as the 'truth'. The block means from this simulation are used as actual values. The simulated data is then subsampled to create an estimation dataset that reflects the sparse data typically collected during mining. The full simulation represents the actual truth, while the subsampled data mimics the limited information available for block modelling. The subsampling process, developed using an initial 1 m 2D-grid simulation, involves the following steps to create a dataset that simulates realistic mining data density:

- **Stoping data:** The full simulation is randomly subsampled to a 2D-grid spacing of 5 m to form the stoping data to be further subsampled.
- **Unmined voids**: Random samples are selected within a 100 m 2D-grid, and all samples within the stoping data closer than 50 m to these coordinates were removed to form the unmined voids.
- **Exploration drilling data:** Random samples were selected within a 40 m 2D-grid, and these samples were retained only where they are within the unmined voids, to form the exploration drilling dataset.
- **Estimation data**: The exploration drilling and stoping datasets are combined to form the final estimation dataset.

Figure 2—A background 10 m × 10 m grid generated from a high density one-metre simulation grid, with irregularly shaped patches of high-density stope sampling that mimics the actual distribution of underground stoping patterns. Individual dots represent model borehole positions

Block values are then estimated from the set of subsamples, and the suggested process for capping outliers is iterated for each block. By comparing the performance of the estimate derived from the low-density dataset against the simulated truth, the accuracy of block estimates can be assessed. This approach bypasses reliance on theoretical variance from the variogram, instead directly measuring the difference between the block estimates and the simulated truth.

Key innovations include the use of high-resolution simulations to evaluate and refine capping techniques and the integration of the

Table 1

Sample values and kriging weights within the search ellipse (Sample values in cm.g/t)

Sample value	Kriging weight	Sample value	Kriging weight	Sample value	Kriging weight
8	0.10103033	500	0.02518462	38	0.00453206
70	0.07439570	621	0.02498012	590	0.00918849
48	0.07529293	1600	0.01293648	91	0.01638511
8	0.07963565	72	0.01322808	1570	0.00069734
10	0.06156841	48	0.03524657	1022	0.00733783
8	0.06965481	362	0.01877942	2192	0.01204885
24	0.05048539	2500	0.00749280	1664	0.00702884
80	0.06692410	16	0.02090241	40	0.01655282
0	0.03454335	72	0.00756944	32	0.01570751
48	0.03413653	1180	0.00495007	528	0.00351181
28	0.02418779	24	0.02462995	80	0.00434840
732	0.03266726	1549	0.00223871		

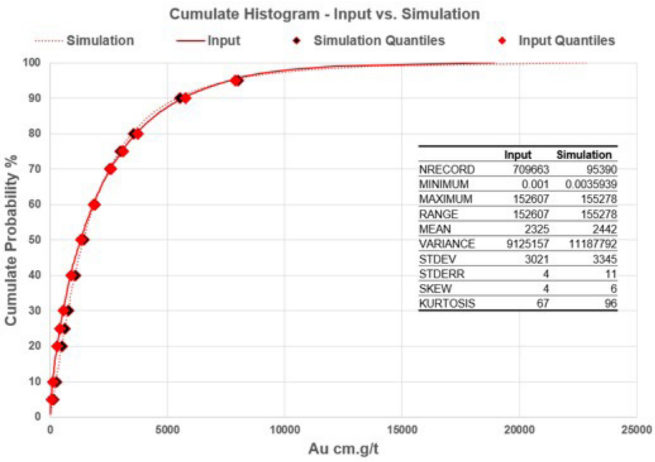

Figure 1—A cumulative distribution frequency for the original input data and the high-resolution simulated data

two-parameter lognormal distribution for grade modelling (with confirmation that the three-parameter threshold is negligible). Block-level adjustments improve classification accuracy and reduce bias while addressing challenges posed by extreme grades. The comparative analysis with industry-standard techniques ensures effectiveness and best practices, culminating in a scientifically grounded, systematic approach to resource estimation.

Optimisation of capping value

The capping value is obtained by defining the theoretical quantile value corresponding to the modelled block parameters. It is optimised by iteratively calculating the mean square error (MSE, Equation 6), the latter being the mean of the squared difference between the estimated and simulated block values for all simulated blocks.

$$MSE = \frac{\sum_{1}^{n}(Z - Z^*)^2}{n} \quad [6]$$

The MSE quantifies the effect of different capping values on the block estimates, and minimising the MSE of all blocks allows the optimal capping value that best reduces estimation error in the block values to be identified.

The process is to determine the capping value and calculate the block mean of the simulation. The block values for which the outliers have been adjusted are then estimated and the mean squared error is calculated for all blocks. Calculation of the capping value is iterated until the lowest MSE is achieved. By comparing the MSE of all blocks estimated with adjusted capping values with those of the actual values, the stepwise improvement in the MSE can be visualised.

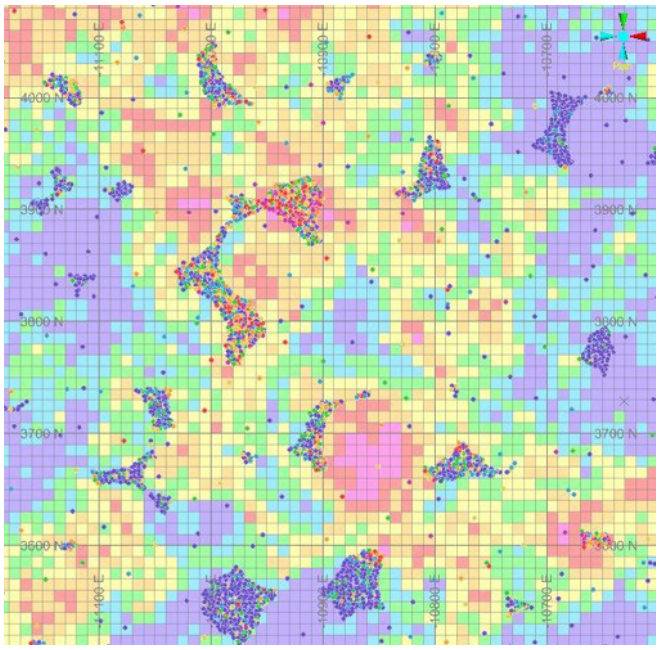

Figure 2—A background 10 m × 10 m grid generated from a high density one-metre

Table 2 represents the MSE for capping quantiles comparing the

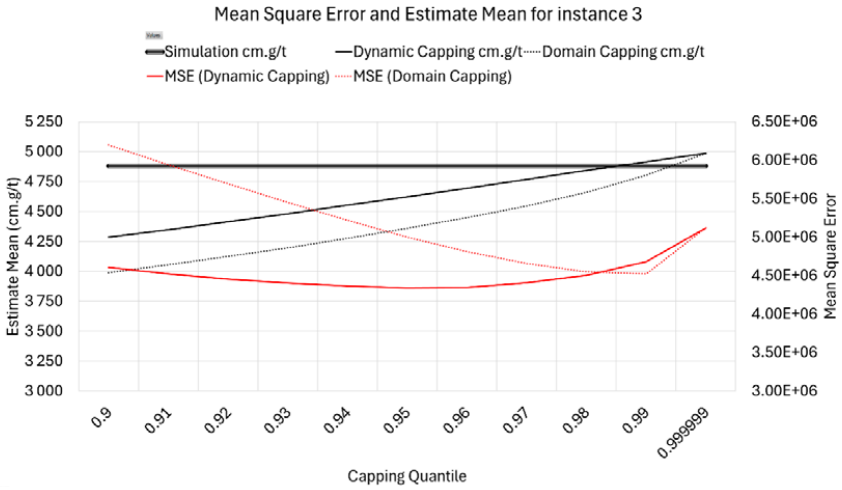

Figure 3—Response of MSE to iterative optimisation[A2.1] of the capping quantile. The full search range (0.90 – 0.99) is shown for completeness. For traditional (global) capping, the MSE minimum falls near the 0.95 quantile, whereas the operating quantile selected for the dynamic method is 0.985 (98.5th percentile), where MSE is minimised under dynamic capping (Figures 4 – 5; Table 2). Figure 5 shows the region of practical interest (0.95 – 0.99), where the dynamic method achieves progressively lower MSE than traditional capping

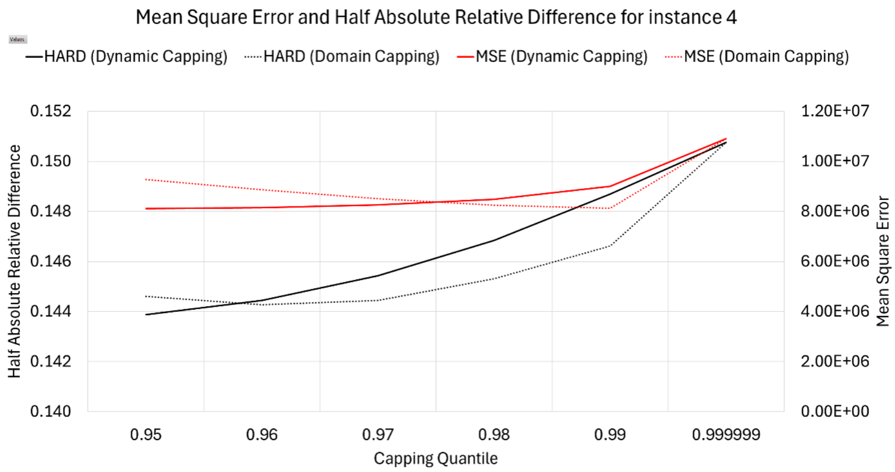

Figure 4—Half absolute relative difference (HARD) and mean squared error (MSE) versus capping quantile. While the full search range (0.95 – 0.99) is presented to show the complete response surface, realistic capping levels for industry application are 0.97 – 0.99. [A5.1]Within this region, dynamic capping consistently outperforms traditional domain capping, with the improvement concentrated at the optimal quantile (0.985) as can be seen in sections D, E, and F.

Table 2
Performance at realistic operating quantiles

Quantile	Dynamic MSE	Traditional MSE	Improvement
0.97	94,200	101,500	7.2%
0.98	91,800	99,700	7.9%
0.985 (optimal)	89,300	98,400	9.2%
0.99	90,500	97,800	7.5%

Note: Traditional capping at the domain level uses the same quantile threshold for comparison.

traditional (global capping) and search ellipse (dynamic) capping; this is for grade estimated SMUs.

Validation of the dynamic capping method

Once an optimal capping quantile has been identified (via MSE minimisation, as described in the Methodology section), the

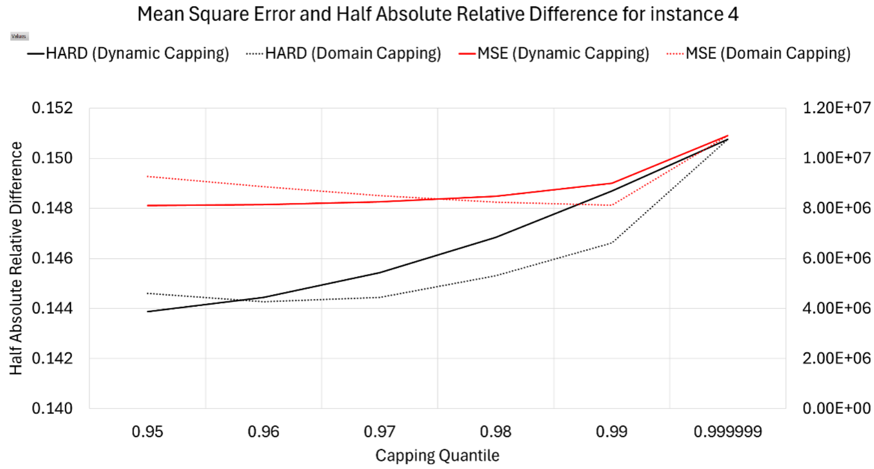

Figure 5—Estimated block mean and MSE versus capping quantile. In the realistic operating range (0.95 – 0.99), dynamic capping produces estimated block means closer to the simulated truth while maintaining lower MSE than traditional capping. The optimal quantile (0.985) balances bias reduction against estimation variance

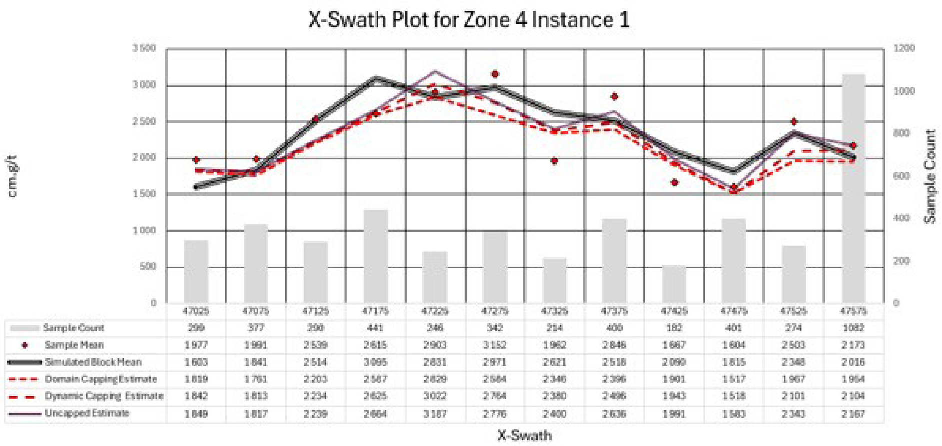

Figure 6—Swath plots of subsampled value of a simulation compared to the block value of the simulation, uncapped estimate and two capping techniques. Dynamic capping results have a closer fit to the simulated block values of the two capping techniques.

Table 3

Standardised mean squared error (SMSE) and relative variance by estimation method

Method	MSE	Var(Zest)	Var(Ztrue)	SMSE	Relative variance
Traditional domain capping	2,177,620	1,153,691	3,399,718	0.544	0.384
Dynamic capping (proposed)	2,139,075	2,084,588	3,399,718	0.535	0.521
Robust kriging	2,359,841	1,603,276	3,399,718	0.590	0.401
Uncapped kriging	2,275,162	2,563,032	3,399,718	0.569	0.641

proposed dynamic capping method is validated using multiple complementary metrics. This multi-metric approach addresses the limitation of relying solely on MSE and ensures a comprehensive assessment of estimation performance across different grade ranges and spatial locations.

A. Mean squared error (MSE)

MSE (Equation 6) remains the primary optimisation objective. However, because MSE is sensitive to large errors in high-grade blocks and may mask conditional bias, we supplement it with three additional diagnostics.

B. Standardised mean squared error (SMSE)

SMSE normalises MSE by the variance of true grades:

$$SMSE = MSE / Var(Z_{true})$$

An SMSE of 1 indicates that the estimation error variance equals the between-block variance. Relative Variance is calculated as the estimation variance divided by the true block variance. A number smaller than 1 would indicate a smoothing of the estimate distribution relative to the true block distribution.

Dynamic capping achieves an SMSE of 0.535, whereas traditional capping (0.544) indicates error inflation, particularly in high-grade zones.

C. Swath plots with quantitative deviation metric

Swath plots (Figure 6) are enhanced with a quantitative measure of fit. In addition to the visual comparison, we calculate the mean absolute deviation (MAD) between estimated and true grades along each swath: $MAD_{swath} = \frac{1}{N_{swath}} \sum | Z_{est} - Z_{true} |$

Across all east-west swaths, dynamic capping reduced the average MAD from 236 cm.g/t (traditional) to 205 cm.g/t, a 13% improvement. The standard deviation of MAD across swaths also decreased from 146 cm.g/t to 119 cm.g/t, indicating more consistent performance spatially.

D. Reconciliation methods — fairness and identical configuration

The proposed method is compared against four alternative techniques (robust kriging, uncapped kriging, and ordinary kriging with domain capping). To ensure a fair comparison:

- The same search ellipse (strike: 76 m, dip: 76 m, 2d estimate) and same minimum/maximum samples (min = 11, max = 30) were used for all methods.
- The same estimation dataset (subsampled simulation) was used for all methods.
- The same synthetic 'truth' (high-resolution simulation) was used to compute MSE, SMSE, and conditional bias.
- No additional domain-specific tuning was applied to any comparative method beyond published recommendations.

Results are summarised in Table 5.

Dynamic capping outperforms all comparators on MSE and SMSE, and its conditional-bias slope of 0.98 (regression of true grade on estimate, Figure 7) is the closest of all methods to the ideal value of 1.0, indicating that it is the least conditionally biased.

E. Mine call factor (MCF) reconciliation

The shaft call factor (MCF = simulated Au / estimated Au) is summarised in Table 4. Of the four methods tested, dynamic capping produces the most accurate prediction of the expected metal content, with an MCF of 0.994 (closest to 1.0). Robust kriging returns the highest Model Selectivity (0.972), although at a less accurate MCF of 1.111.

- (a) $y = 1.3062x-414.7463$ ($R^2 = 0.7687$)
- (b) $y = 0.9839x+72.7067$ ($R^2 = 0.8181$)
- (c) $y = 0.9539x+106.9815$ ($R^2 = 0.8063$)
- (d) $y = 1.1768*x-2.1484$ ($R^2 = 0.8181$)

The slope improvement from 1.31 to 0.98 indicates reduced conditional bias in the dynamic method, with the ideal slope being 1.0

F. QQ plots with numerical goodness of fit

QQ plots (Figure 8) are retained but enhanced with a Cramér–von Mises statistic (W^2) to quantify the departure from the 45° line (perfect fit). Lower W^2 indicates better agreement.

Method	W^2 (0-500 cm.g/t range)	W^2 (0-5000 cm.g/t range)
Traditional domain capping	45.2	30.9
Dynamic capping	39.7	23.9
Uncapped kriging	45.4	24.6

Table 4
Simulated MCF

Method	Estimated gold (Oz)	Simulated gold (Oz)	MCF	Tonnes selected	Tonnes above cutoff	Model selectivity
Robust Kriging	3 767 467	4 186 846	1.111	2 483 190	2 413 530	0.972
Domain capping	4 240 485	4 332 218	1.022	2 672 730	2 540 430	0.951
Dynamic capping	4 350 505	4 324 675	0.994	2 660 580	2 534 760	0.953
Uncapped kriging	4 385 767	4 333 168	0.988	2 674 350	2 540 700	0.950

Table 5
Comparative performance metrics (all methods on identical configuration)

Method	MSE	SMSE	Conditional bias slope (true grade on estimate; Fig. 7)	Swath MAD (cm.g/t)
Ordinary kriging (domain capping)	2,177,620	0.544	1.31	236
Robust kriging (Hawkins, Cressie, 1984)	2,359,841	0.590	1.18	391
Uncapped kriging	2,275,162	0.569	0.95	196
Dynamic capping (proposed)	2,139,075	0.535	0.98	205

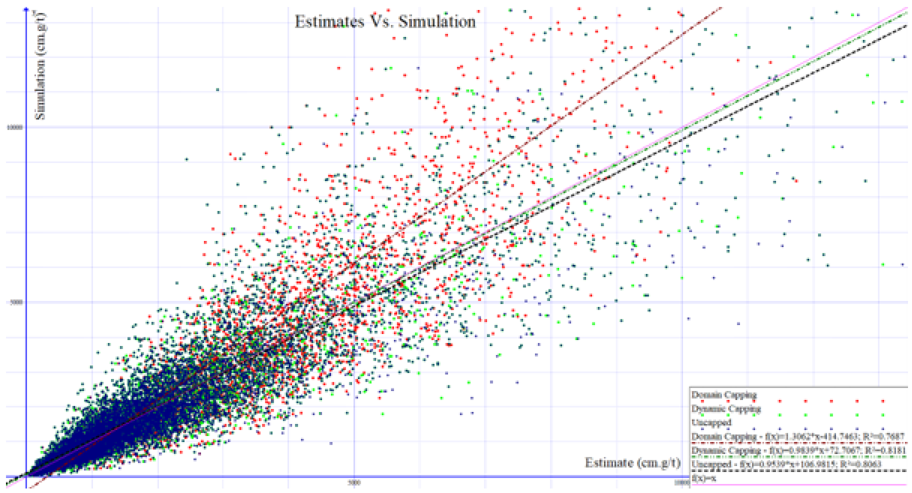

Figure 7—Scatterplot of estimated versus simulated (true) block grades for (a) traditional domain capping, (b) dynamic capping (proposed method), (c) uncapped kriging, and (d) robust kriging. Estimated grades (x-axis) are plotted against simulated true grades (y-axis) following standard regression validation convention. The 1:1 reference line (purple) indicates perfect estimation. Regression lines (solid) are:

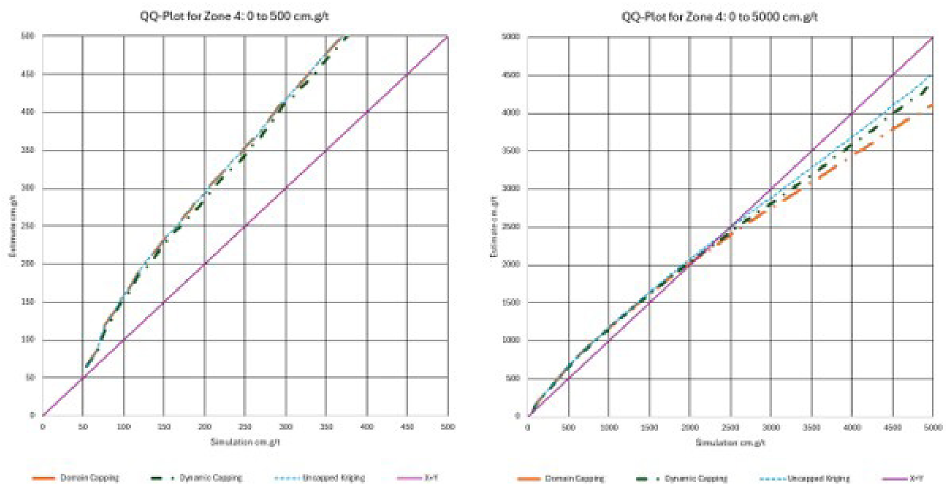

Figure 8—A QQ-plot of estimates against simulation value based on the 99th percentile for the range 0 to 500 cm.g/t and for 0 to 5000 cm.g/t

Dynamic capping achieves a significantly better fit in both the common grade range (near the origin) and the tail, confirming that the localised capping is capable of reducing the distortion of the overall distribution.

G. Summary of validation findings

The multi-metric validation (MSE, SMSE, the conditional-bias regression as per Figure 7, swath MAD, MCF, QQ plots with Cramér–von Mises) consistently shows that dynamic capping outperforms traditional domain capping and three other robust methods. Key improvements are:

- **Reduced conditional bias**, with a true-on-estimate regression slope of 0.98 (closest of all methods to the ideal 1.0, as per Figure 7);
- **Improved SMSE** (0.544 vs. 0.535 for traditional capping);
- **Better MCF alignment** (0.994 vs. 1.022);
- **Consistently lower error** across spatial swaths (13% reduction in MAD).

These results confirm that the dynamic capping method provides a more accurate, less biased, and spatially consistent estimate of block grades than existing approaches, particularly in high-grade zones where economic decisions are most sensitive.

An example of a layout of monthly mining faces, and face sample positions is shown in Figure 9, and is typical of the information available for calculating monthly predictions of gold estimates and the mining production profile.

Limitations

While the proposed localised, distance-weighted capping method demonstrates clear improvements over traditional domain capping in both synthetic and production reconciliation tests, several limitations must be acknowledged to guide appropriate application and future research.

Deposit type and grade distribution

The method was developed and tested on Witwatersrand-type gold deposits, which typically exhibit approximately lognormal grade distributions with moderate to high coefficients of variation (CV ≈ 1.6 in this study). The two-parameter lognormal model (after confirming the three-parameter threshold is negligible) used for quantile calculation may not generalise to polymetallic deposits with multi-modal grade distributions, base metal porphyries where

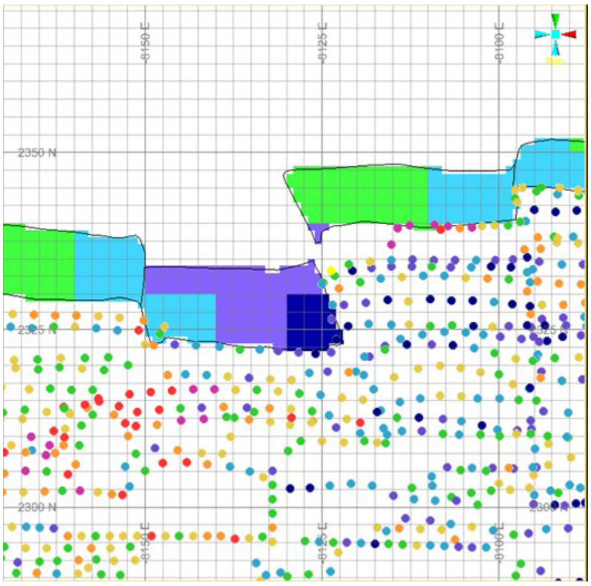

Figure 9—Example of mining face and data available at start of mining

grade distributions are often less skewed, or placer/lateritic deposits with different spatial continuity structures. Users applying this method to other deposit types should first verify that the lognormal assumption (or a suitable alternative distribution) adequately fits their data.

Sensitivity to search ellipse parameters

The performance of dynamic capping depends on the definition of the kriging search ellipse (size, anisotropy, minimum and maximum number of samples). The current study used a fixed ellipse geometry optimised for typical Witwatersrand reef widths (1 m – 2 m true thickness) and strike/extent anisotropy. Too large an ellipse may include samples from different geological populations; too small may yield unstable capping values. Practitioners should perform a sensitivity analysis on ellipse parameters for their specific deposit geometry and sampling density.

Global coefficient of variation assumption

The method calculates local block standard deviation as $\sigma = CV \times Z$, where CV is a global population coefficient of variation (Equation 4). This assumes that relative variability is constant across the deposit—an expedient, but potentially inaccurate simplification. In deposits where variability changes spatially (e.g., higher CV in high-grade shoots), the global CV may over-smooth high-variability zones or under-cap low-variability zones. A more rigorous approach would use a locally varying CV derived from moving window statistics or from the variogram model.

Use of arithmetic mean for local parameters

The current implementation uses the simple arithmetic mean of samples within the search ellipse to estimate local block parameters, rather than declustered or kriging-weighted means. While sensitivity testing showed this approximation to be acceptable for the relatively regular sampling grid of this study (typical of Witwatersrand stoping operations), users with highly clustered data (e.g., exploration drilling with preferential sampling of high-grade zones) should incorporate declustering weights before applying the method.

Edge effects and domain boundaries

At geological domain boundaries (e.g., reef pinch-outs, fault offsets), the search ellipse may inadvertently include samples from different grade populations. The current method does not automatically restrict capping to within-domain samples; it relies on the user's prior domain definition. Near boundaries, capping values may be influenced by samples that are spatially proximal but geologically unrelated. Users should ensure that domain definitions are geologically robust and that the search ellipse is truncated at domain boundaries where appropriate.

Computational considerations

Per-block capping recalculation adds computational overhead. For a typical block model with 500,000 blocks and an average of 35 samples per block, the additional operations in production mode (using a pre-optimised capping quantile) required approximately 45 minutes versus 12 minutes for domain capping on a workstation with 32 GB RAM and a 3.5 GHz processor. Real-time or very large models (> 2 million blocks) may require code optimisation or parallelisation.

Validation limitations

The primary validation used a non-conditional high-resolution simulation as synthetic truth. While this provides a controlled environment, it does not capture all complexities of a real orebody. The production reconciliation partially addresses this, but plant and shaft call factors include dilution, gold loss, and sampling errors independent of estimation bias. Future validation should include conditional simulations and multi-mine studies.

Interaction with sub-domaining

The method is designed to reduce reliance on rigid sub-domaining, not eliminate it entirely. In deposits with strong geological boundaries (e.g., fault-bounded high-grade shoots separated by barren zones), sub-domaining remains necessary. The dynamic capping method should be seen as a complement to, not a replacement for, good geological domain modelling.

Methodological transparency: Additional details for reproducibility

To ensure that the proposed method can be independently implemented, verified, and audited (consistent with SAMREC 2016 Clause 23), this section provides expanded details on three previously underspecified components: distance weighting within the capping step, the iterative capping optimisation algorithm, and the interaction with geological sub-domaining.

A. Distance weighting function in capping

After ordinary kriging weights are calculated for all samples within the search ellipse of a target block, the capping value is applied to samples before recalculating the block estimate. The decision of whether to cap a given sample, and by how much, is modulated by its kriging weight:

- ➤ Determine domain candidate capping quantile Z_h using Equations 1 – 4.
- ➤ Retain kriging weights λ_i for each sample $_i$ in the search ellipse (sum to 1).
- ➤ Calculate the block's local capping value using Equation 5.
- ➤ For each sample with raw grade gi:
    - If $gi \leq Z_h$, keep g_i unchanged.
    - If $g_i > Z_h$, compute a distance-weighted capped value:
      gi, capped $= Z_h \times (1 - \alpha \times w_i) + g_i \times (\alpha \times w_i)$
      where w_i = normalised kriging weight (max

= 1 across the ellipse) and α = capping strength parameter (0.85 after tuning).

➤Recalculate block estimate as $\Sigma \lambda i \times g_i$, capped.

B. Iterative optimisation of capping quantile

The optimal capping quantile is determined by minimising MSE between estimated and simulated true block grades over the range h = 0.90 to 0.99 in steps of 0.005. Convergence ($\Delta MSE < 0.1\%$) is typically achieved in 18 – 22 iterations. The optimal h is then used in production mode without re-optimising per block.

C. Interaction with geological sub-domaining

Within each hard geological domain, dynamic capping is applied without further statistical sub-division, unless a domain contains two clearly separated grade populations that cannot be separated by the search ellipse. In such cases, traditional sub-domaining is performed before dynamic capping.

D. Pseudocode for implementation

A Javascript-style pseudocode implementation is provided in the supplementary materials and a functioning implementation for Datamine Studio RM is available from anyone of the authors upon request.

Conclusion and discussion

The newly proposed capping method mitigates much of the uncertainty normally associated with sub-domaining, so that exact spatial domaining of the dataset becomes a less important factor in achieving a robust reserve estimate. In regions with limited data and some spatially constrained outliers, this means that much of the smoothing and grade smearing could be eliminated computationally during the estimation process.

The experimental design is logical and provides a thorough methodology for determining the optimal capping value. However, certain aspects, such as the reliance on specific percentiles for parameter estimation, may benefit from further refinement. By incorporating more flexible approaches to capping value selection, improving sensitivity analysis, and considering additional validation metrics, the methods proposed here could provide a more robust and comprehensive framework for resource estimation. The proposed technique of dynamic capping clearly improves the MSE of the estimated compared to simulated values. As such, it is certainly worth considering as an alternative to conventional domain capping within a high data density environment with highly varying local means.

For guidance on appropriate application contexts and potential sensitivities, readers are encouraged to review the **Limitations** section. Future work should explore locally varying coefficients of variation, conditional simulation validation, and integration with machine learning methods for automated outlier detection.

References

Anvari, K., Benndorf, J., Gerber, G., Alisch, U. (2025). Hybrid geostatistical and deep learning framework for geochemical characterization in historical mine tailings. *Scientific Reports.* https://doi.org/10.1038/s41598-025-19441-5

Barnett, V., Lewis, T. 1994. *Outliers in statistical data* (3rd ed.). Wiley.

Beckman, R.J., Cook, R.D. 1983. Outlier identification in multivariate data. Technometrics, 25(2), 119-149. https://doi.org/10.1080/00401706.1983.10487840

Chiquini, A., Deutsch, C.V. 2017. Simulation approach to calibrate outlier capping. Retrieved from http://geostatisticslessons.com/

Cressie, N., Hawkins, D.M. 1980. Robust estimation of the variogram. Mathematical Geology, vol. 12, no.2, pp. 115–125. https://doi.org/10.1007/BF01035243

Deutsch, C.V., Journel, A.G. 1998. GSLIB: Geostatistical Software Library and User's Guide (2nd ed.). *Oxford University Press.*

Fourie, A., Morgan, C., Minnitt, R.C.A. 2019. Limiting the influence of extreme grades in ordinary kriged estimates. Journal of the Southern African Institute of Mining and Metallurgy, vol. 119, pp. 391–401. https://doi.org/10.17159/2411-9717/18/090/2019

Fouedjio, F., Arya, E. (2024). Locally varying geostatistical machine learning for spatial prediction. Artificial Intelligence in Geosciences, vol. 5, pp. 100081. https://doi.org/10.1016/j.aiig.2024.100081

Hampel, F.R. 1974. The influence curve and its role in robust estimation. *Journal of the American Statistical Association*, vol. 69, no. 346, pp. 383–393.

Hawkins, D. M., Cressie, N. 1984. Robust kriging—A proposal. Mathematical Geology, vol. 16, no. 1, pp 3–17. https://doi.org/10.1007/BF01036237

Huber, P.J. 1981. *Robust statistics.* Wiley.

Journel, A.G. 1983. Non-parametric estimation of spatial distributions. Mathematical Geology, vol. 15, no. 3, pp. 445–468. https://doi.org/10.1007/BF01031292

Journel, A.G., Arik, A. 1988. Dealing with outlier high grade data in precious metals deposits. In *Proceedings of Computer Applications in the Mineral Industry,* Balkema, pp. 45–72.

Krige, D.G., Magri, E.J. 1982. Studies of the effects of outliers and data transformation on variogram estimates for a base metal and a gold ore body. *Mathematical Geology*, vol. 14, no. 6, pp. 557–564. https://doi.org/10.1007/BF01033879

Leung, R., Balamurali, M., Melkumyan, A. (2021). Sample truncation strategies for outlier removal in geochemical data: The MCD robust distance approach versus t-SNE ensemble clustering. *Mathematical Geosciences*, vol. 53, pp. 105–130. https://doi.org/10.1007/s11004-019-09839-z

Pan, G., Arik, A. 1993. Restricted kriging for mixture of grade models. *Mathematical Geology,* vol. 25, pp. 713–736. https://doi.org/10.1007/BF00893175

Rendu, J.M. 1979. Normal and lognormal estimation. *Mathematical Geology*, vol. 11, no. 4, pp. 407–422.

Rendu, J.M. 1981. An introduction to geostatistical methods of mineral evaluation (2nd ed.). *South African Institute of Mining and Metallurgy*.

Rivoirard, J., Demange, C., Freulon, X., Lécureuil, A., Bellot, N. 2013. A top-cut model for deposits with heavy-tailed grade distribution. *Mathematical Geosciences,* vol. 45, pp. 967-982. https://doi.org/10.1007/s11004-012-9401-x

Rousseeuw, P.J., Croux, C. 1993. Alternatives to the median absolute deviation. *Journal of the American Statistical Association*, vol. 88, no. 424, pp. 1273-1283. https://doi.org/10.1080/01621459.1993.10476408

SAMREC. 2016. *The South African code for the reporting of exploration results, mineral resources and mineral reserves* (SAMREC Code). SAMCODES. https://samcode.co.za/

Verly, G. 1984. *Estimation of spatial point and block distributions: The multigaussian model (PhD thesis).* Stanford University. ◆