# Data-driven delineation of geometallurgical domains in porphyry copper systems

by T. Mapupu[1,2], G.T. Nwaila[1,3]

**Affiliation:**
1 School of Geosciences, University of the Witwatersrand, South Africa
2 Sibanye-Stillwater Digital Mining Laboratory (DigiMine), Wits Mining Institute (WMI), University of the Witwatersrand, South Africa
3 African Research Centre for Ore Systems Science (CORES), School of Geosciences, University of the Witwatersrand, South Africa

**Correspondence to:**
T. Mapupu

**Email:**
1612442@students.wits.ac.za

**Dates:**
Received: 26 Mar. 2025
Revised: 29 Jun. 2025
Accepted: 30 Sep. 2026
Published: Oct. 2026

**How to cite:**
Mapupu T., Nwaila G.T. 2026. Data-driven delineation of geometallurgical domains in porphyry copper systems. *Journal of the Southern African Institute of Mining and Metallurgy*, vol. 126, no. 10, pp. 625 – 636

**DOI ID:**
https://doi.org/10.17159/2411-9717/3943/2026

**ORCiD:**
T. Mapupu
https://orcid.org/0000-0001-5903-2056
G.T. Nwaila
https://orcid.org/0000-0002-3974-9890

## Abstract

**Partitioning an orebody into spatially coherent domains supports stationarity and improves the reliability of resource estimates and metallurgical forecasts. Conventional domaining commonly relies on lithological or grade interpretations and can overlook subtler, yet economically important, variations in mineralogical, geochemical, and metallurgical attributes that affect recovery predictions. Unsupervised clustering offers a more data-driven means of defining such domains. This study presents a machine-learning workflow applied to a porphyry copper dataset comprising geochemical and processing variables. The variables were standardised and weighted using Bayesian optimisation to improve domain definition. Weighted dissimilarities were then represented in a lower-dimensional space using multidimensional scaling and clustered with the K-means algorithm to generate candidate domains. Validity indices guided domain selection, while principal component analysis within each domain assessed internal consistency and dominant compositional patterns. Cluster assignments were then mapped back into drillhole space and interpreted against established porphyry copper alteration zonation. The resulting domains show reduced internal variability while remaining geologically plausible and broadly consistent with known alteration patterns. Accurate delineation of such domains can improve geometallurgical modelling and operational planning because more consistent processing behaviour provides a clearer basis for anticipating milling response and recovery variability across the orebody. This reproducible workflow links orebody heterogeneity to processing behaviour and provides a practical, data-driven framework for domaining in complex deposits.**

## Keywords

**Geometallurgy, domaining, porphyry copper, unsupervised clustering, multidimensional scaling**

## Introduction

Resource estimation and mine planning depend on the assumption that grade and geometallurgical variables behave consistently enough within a modelling population for variograms, kriging, and conditional simulation to produce stable results (Deutsch et al., 2016). This assumption rarely holds across an entire orebody because geological controls introduce spatial trends, overprinting, and multiple statistical populations that weaken the basis for direct global modelling. Operations require reasonably consistent plant feed to support stable throughput, energy efficiency, and predictable metallurgical recovery; however, orebodies are inherently heterogeneous. Domaining partitions the deposit into smaller populations within which stationarity is more defensible and each population can support its own continuity model (Martin, Boisvert, 2020).

Conventional domaining largely relies on expert interpretation of lithology, alteration, and grade patterns. This conventional workflow remains widely used and often performs well where geological contacts are clear. Problems arise where geological structures change, and boundaries are transitional or where alteration assemblages overprint earlier mineralogical signatures. Data-driven domaining applies statistical and machine-learning methods to analyse patterns in orebody datasets and define domains that are more consistent with multivariate structure, spatial continuity, and processing response (Bhuiyan et al., 2019; Niquini et al., 2025). A persistent limitation of distance-based clustering on assay data is that variables with larger variance or scale can dominate similarity calculations, obscuring subtler yet geologically meaningful distinctions (Tsai, Chiu, 2008). Purely statistical clusters may also be difficult to reconcile with established alteration zonation and may therefore not be trusted by geologists and metallurgists responsible for operational decisions (Keeney, Walters, 2011; Montoya-Lopera, 2014).

# Data-driven delineation of geometallurgical domains in porphyry copper systems

Geometallurgical domains must reflect processing response as well as spatial continuity. Comminution performance, flotation behaviour, and concentrate grade depend on attributes such as mineral assemblage and alteration, all of which vary through space and may change over short distances. Geometallurgical programmes therefore seek to integrate geological and processing data so that material behaviour can be predicted and used for operational control (Dominy et al., 2018; Lishchuk et al., 2020). Porphyry copper systems provide a suitable setting for testing such a workflow because they are large-tonnage systems with marked geological and metallurgical heterogeneity.

This paper presents a data-driven workflow for delineating geometallurgical domains in a South American porphyry copper orebody using multi-element geochemistry and metallurgical testwork data. It shows that geochemical signatures can be used to define geologically plausible and operationally relevant domains for blending and geometallurgical forecasting, while also highlighting the value of spatial validation of clustering outputs in geoscientific applications.

## Geological context

Porphyry copper deposits are large hydrothermal systems that form mainly in magmatic arcs above subduction zones. They supply ~60% of global copper (Cu) and over 50% molybdenum (Mo), with gold (Au) and silver (Ag) commonly recovered as by-products (Sillitoe, 2010; John, Taylor, 2016). Mineralisation occurs as stockwork veinlets and disseminations of sulphide minerals distributed through large volumes of altered host rock. These systems may occupy tens to hundreds of cubic kilometres of the upper crust. Copper is primarily hosted in minerals such as chalcopyrite ($CuFeS_2$) and bornite ($Cu_5FeS_4$) (Seedorff et al., 2005; Sillitoe, 2010). Porphyry Cu deposits are characterised by concentric alteration shells, classically described by Lowell and Guilbert's (1970) model of outward zonation (Figure 1). At the core, proximal to the causative intrusion, is the potassic zone, characterised by secondary K-feldspar and biotite replacing primary minerals. The potassic core tends to host the highest-temperature mineralisation, typically chalcopyrite ± bornite ± molybdenite, with lesser amounts of pyrite. Outboard of, and locally overlapping with, the potassic domain is the phyllic zone, marked by pervasive quartz-sericite-pyrite alteration. It is commonly sulphur-rich because of pyrite enrichment and may also host elevated Cu where phyllic overprints affect earlier potassic zones (Sillitoe, 2010; Large, 2025). The system grades outward into propylitic alteration, characterised by chlorite–epidote–calcite assemblages. Propylitic zones typically carry only trace amounts of chalcopyrite and more abundant pyrite before grading into weakly altered or unaltered country rock. Locally, especially near the palaeosurface, an argillic overprint with clay minerals such as kaolinite and smectite may develop, commonly linked to late-stage magmatic-hydrothermal to meteoric fluid interaction along geological structures (Seedorff et al., 2005; Sillitoe, 2010). Many porphyry deposits also exhibit a secondary supergene enrichment profile. Circulating meteoric waters can leach copper from near-surface rocks to form a leached cap enriched in iron oxides and reprecipitate it at depth as secondary chalcocite ($Cu_2S$) – covellite (CuS) blankets (Sillitoe, 2010; Arabpour et al., 2021).

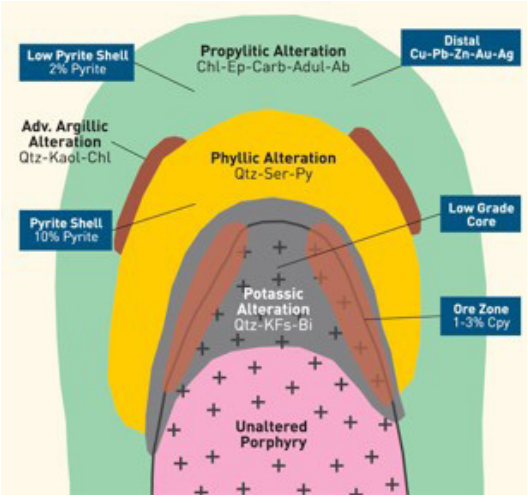


**Figure 1—Generalised alteration-zonation schematic of a porphyry copper (Cu) system, showing potassic, phyllic, propylitic, and advanced argillic alteration zones, pyrite shells, ore zone, and distal polymetallic mineralisation. Abbreviations: Qtz = quartz; Kaol = kaolinite; Chl = chlorite; Ep = epidote; Carb = carbonate; Adul = adularia; Ab = albite; Ser = sericite; Py = pyrite; Kfs = potassium feldspar; Bi = biotite; Cpy = chalcopyrite; Pb = lead; Zn = zinc; Au = gold; Ag = silver (adapted from Sillitoe, 2010)**

## Data and methods

The study integrates three nested datasets extracted from a South American porphyry Cu mine. The base dataset comprises 2,000 drill-core samples with assays for 18 major and trace elements, which provide the multivariate geochemical input for geological domaining. Two smaller embedded subsets comprise 60 comminution-test samples and 53 flotation-test samples (Table 1 and Figure 2). The comminution subset includes Graphite C, which was not part of the base assay dataset. The assay, comminution, and flotation tables were imported and aligned to a common schema. No additional compositing was applied before clustering; the exported assay records were analysed as provided because interval-length fields were not retained in the raw dataset. Variable names and units were standardised, numeric types were enforced, duplicate records were removed, and missing numeric values were imputed using the column mean. The clustering inputs were elemental assay variables; oxide variables were not used.

Feature engineering involved deriving the drop weight test (DWT) parameter and Bond work index (BWI) from the measured comminution variables (Table 1). Together, these indices describe complementary aspects of ore hardness. The DWT captures impact breakage behaviour and how the rock responds to sudden impact

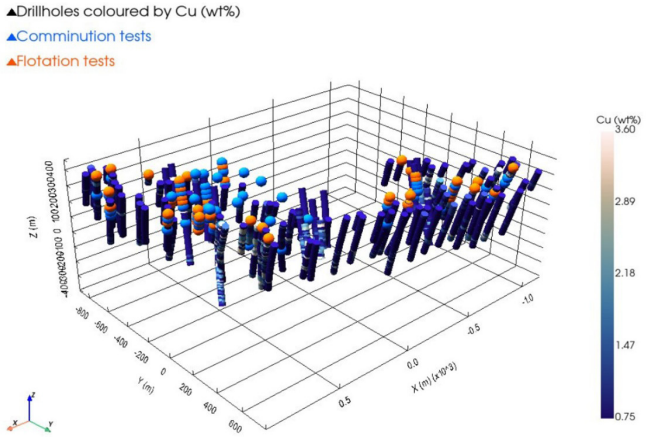


**Figure 2—Spatial distribution of the raw combined porphyry Cu dataset, showing drillholes coloured by Cu, with comminution and flotation testwork samples overlain**

in the mill. In the Julius Kruttschnitt drop weight test (JKDWT), the relationship between breakage response and specific energy is expressed as (Morrell, 2004; Mwanga et al., 2015):

$$t_{10} = A\left(1 - e^{-bE_j}\right), \quad [1]$$

where $t_{10}$ is the percentage passing one-tenth of the original particle size, and A and b are ore-dependent impact breakage parameters. Ej is the specific input energy at the three standard energy levels j=1,2,3 used in the test. The measured responses were first normalised as:

$$\tilde{t}_{10,j} = \frac{th_j}{\max(th_j)}, \quad [2]$$

where $th_j$ is the measured breakage response at energy level j. The parameters $A$ and $b$ were then estimated for each sample by minimising:

$$\min_{A,b} \sum_{j=1}^{3} \left[\tilde{t}_{10,j} - A\left(1 - e^{-bEj}\right)\right]^2. \quad [3]$$

The impact breakage parameter used in the analysis was then calculated as:

$$DWT = A \times b. \quad [4]$$

BWI explains the overall grindability and provides a measure of how much energy is needed to reach the target product size. BWI was computed from the laboratory variables as follows (Bond, 1961; Nikolić et al., 2024):

$$BWI = \frac{49.0}{P_c{}^{0.23} M^{0.82} \left(\frac{10}{\sqrt{P_{80}}} - \frac{10}{\sqrt{F_{80}}}\right)}, \quad [5]$$

where $F_{80}$ and $P_{80}$ denote feed and product 80% passing sizes in µm, $M$ denotes the grindability index in grammes per revolution, and $P_c$ denotes the closing screen size in µm.

### *Multidimensional scaling and clustering*

Each variable was standardised using the StandardScaler transformation prior to clustering and assigned a continuous weight. These weights were tuned using Bayesian optimisation to maximise the mean silhouette score (Rousseeuw, 1987; Snoek et al., 2012). The rationale is that not all variables should contribute equally to similarity. Feature weighting is a well-established way to improve partitioning quality in high-dimensional clustering by emphasising discriminative variables while suppressing irrelevant or redundant features (Tsai, Chiu, 2008).

The optimised weights were used to compute a weighted Euclidean dissimilarity matrix on the standardised variables, where pairwise distance was calculated as the square root of the weighted sum of squared variable differences. These dissimilarities were embedded into a two-dimensional representation using multidimensional scaling (MDS), which seeks a configuration that best preserves the original distance relationships in fewer dimensions (Hout et al., 2013). The variable weights were optimised with Optuna by assigning one continuous weight per variable and searching each weight over the interval 0.001–1.000 for 15 trials. A 15-trial optimisation was used as a computationally efficient tuning step, and the resulting partition was then checked using validity indices and reseeding runs. The optimisation objective was the mean silhouette score of K-means solutions in the MDS space. K-means clustering was then applied in the embedded space to delineate domains. The final number of clusters was selected by evaluating the silhouette score (Rousseeuw, 1987), Calinski–Harabasz (Caliński, Harabasz, 1974), and Davies–Bouldin (Davies, Bouldin, 1979) indices across the candidate K values. A stability test was performed by rerunning clustering 100 times with different random seeds and quantifying reassignment as a simple check on partition robustness (Hennig, 2007), as illustrated in Figure 3.

Clusters were mapped spatially and interpreted against established porphyry alteration assemblages and zonation models. Principal component analysis (PCA) was used as an internal validation step to assess whether each domain was internally coherent and to identify the dominant elemental associations that define it. Processing-response domaining was then performed on the comminution and flotation subsets using the same unsupervised clustering workflow to identify internally similar metallurgical behaviours. Finally, the geological and metallurgical domains were combined into integrated geometallurgical domains that can be translated into ore-routing and blending rules.

*Table 1*

**Attribute table for porphyry Cu database**

| Variable | Description |
|---|---|
| BHID | Borehole ID |
| X | Easting coordinate |
| Y | Northing coordinate |
| Z | Vertical coordinate |
| **Geochemistry fields** | |
| Ag, Al, Au, C, Ca, Cl, Cu, F, Fe, K, Mg, Mn, Na, P, Pb, S, Th, U | Whole-rock assay geochemistry |
| Graphite C | Graphitic carbon |
| **Comminution fields** | |
| th1, th2, th3 | $T_{10}$ values |
| $F_{80}$ | Feed size at 80% passing |
| $P_{80}$ | Product size at 80% passing |
| M | Grindability index |
| $P_c$ | Closing screen size |
| **Flotation fields** | |
| fr | Rougher mass pull |
| xr | Rougher concentrate grade |
| LCT | Locked-cycle test recovery |

## Results and analysis

Pearson correlation analysis of the whole-rock geochemistry revealed that Cu correlates positively with S and other

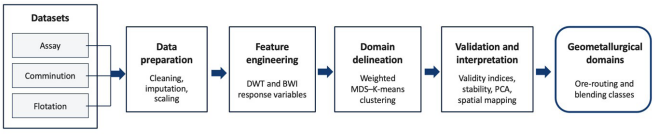


**Figure 3—Data-driven geometallurgical domain delineation workflow**

transitional metals such as Fe, Ag, and Au, consistent with copper mineralisation being hosted mainly in Cu–Fe sulphides such as chalcopyrite and bornite (Figure 4). Alkali and alkaline earth elements group together and oppose the chalcophile suite, reflecting alteration-related mass transfer across the system (Seedorff et al., 2005; Sillitoe, 2010). The spatial distribution of copper grades across drillholes, as per Figure 2, shows a coherent pattern of higher-grade intercepts surrounded by lower-grade zones, and the positions of comminution and flotation samples span this range. This supports the representativeness of the geology and testwork subsets for subsequent domain interpretation.

## Geological domains

Initial runs of the standard K-means algorithm on the geochemical data yielded some separation of the deposit but struggled to produce geologically meaningful clusters, as shown in Figure 5a. As a result, the initial K-means partition did not align well with the expected porphyry zonation because it merged the ore zone with parts of the alteration halo and produced only two domains. Applying MDS before clustering improved domain delineation. The transformation reduced the influence of variables that dominated the initial structure and allowed other geochemically informative features to contribute more effectively to domain separation (Figure 5b). Cu and S emerged as influential variables for domain separation, whereas Ca, Pb, and U were down-weighted. The MDS-based workflow delineated four geological domains, indicating that the transformed space captured the internal structure of the system more effectively than the standard approach.

Clustering validity metrics confirmed the choice of four geological clusters. All three indices, namely the silhouette, Caliński–Harabasz (CH), and Davies–Bouldin (DB) scores, identified K = 4 as the optimal number of clusters (Figure 6). The mean silhouette coefficient peaks at four clusters, CH reaches a maximum at four, and DB reaches a minimum at four clusters. Beyond four clusters, the silhouette values decline, indicating that over-partitioning would create smaller or less coherent clusters. Likewise, fewer than four clusters would underfit the deposit's complexity. The chosen four-cluster MDS–K-means model was tested for stability by rerunning the algorithm with different initial seeds; fewer than 5% of samples changed cluster assignment upon reseeding, indicating that the partition is stable.

The four geological domains can be characterised as an outward-to-inward sequence of alteration facies, consistent with the classic porphyry Cu model. Domain 0 is enriched in Ca, Na, and Mg relative to the other clusters, while being comparatively depleted in Cu, S, and precious metals. Domain 0 has the lowest mean Cu (0.37 wt%), S (0.14 wt%) and Au-Ag of all clusters, but the highest combined Na+Ca content. It also contains elevated Th-U. Its PCA plot (Figure 7a) shows that Ca and Mg load heavily on the first principal component, whereas Cu and S form a minor component; this indicates that variation within domain 0 is dominated by plagioclase–epidote alteration mineralogy, with only minor introduction of sulphides. Figures 7b and c provide the average grades for each element, reinforcing the domain's depletion in Cu–S. These traits collectively point to an outer propylitic alteration zone, which is the low-grade zone of the porphyry system.

Domain 1 marks a gradational zone between the barren propylitic halo and the high-grade core. It is characterised by elevated Al (5.3 wt%) and Fe (22.5 wt%) relative to domain 0, together with moderate Cu (0.6 wt%) and S (~0.2 wt%). K is moderate (~1.2 wt%), while Ca and Na are strongly depleted compared to domain 0. This geochemical signature is consistent with a phyllic domain with possible argillic overprint. Plagioclase has been replaced by clay-sericite assemblages, and the moderate K content suggests that sericite is present, but less strongly developed than in a potassic zone (Seedorff et al., 2005; Sillitoe, 2010). The PCA for domain 1 (Figure 8a) shows a split: one subgroup trends toward the Cl-Na-K direction, whereas another subset trends toward the Cu-Fe-S vector, indicating incipient mineralisation. Domain 1 is therefore interpreted as a transitional argillic to early

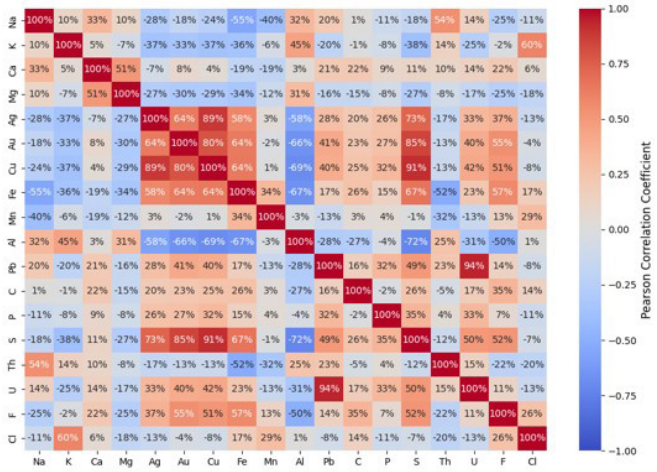


Figure 4—Pearson correlation matrix for the elemental assays

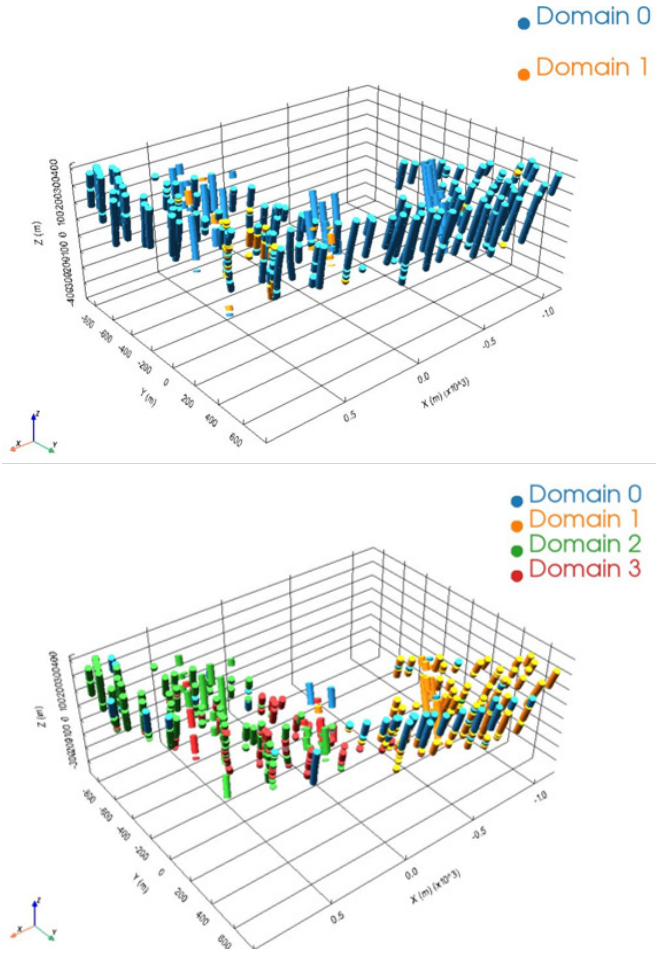


Figure 5—Geological domains as classified by the a. standard K-means versus b. MDS K-means workflow

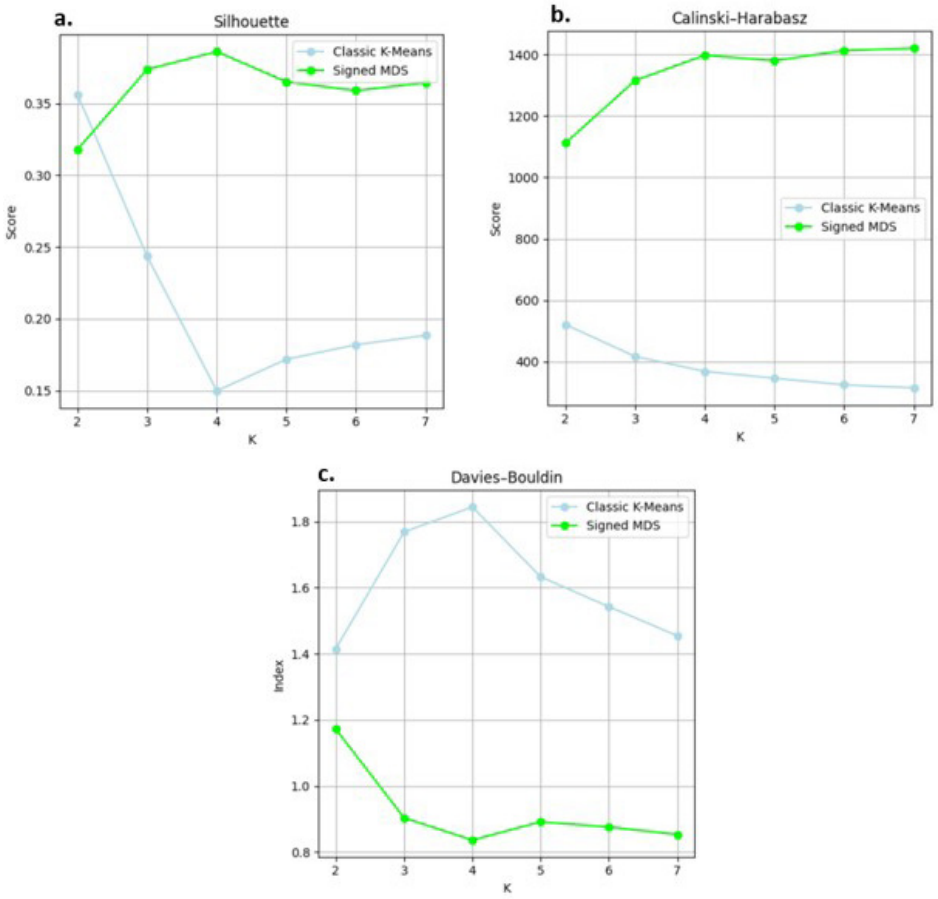


**Figure 6—Validity indices indicating the optimal clusters (K) for the dataset, comparing the standard and MDS K-means workflow**

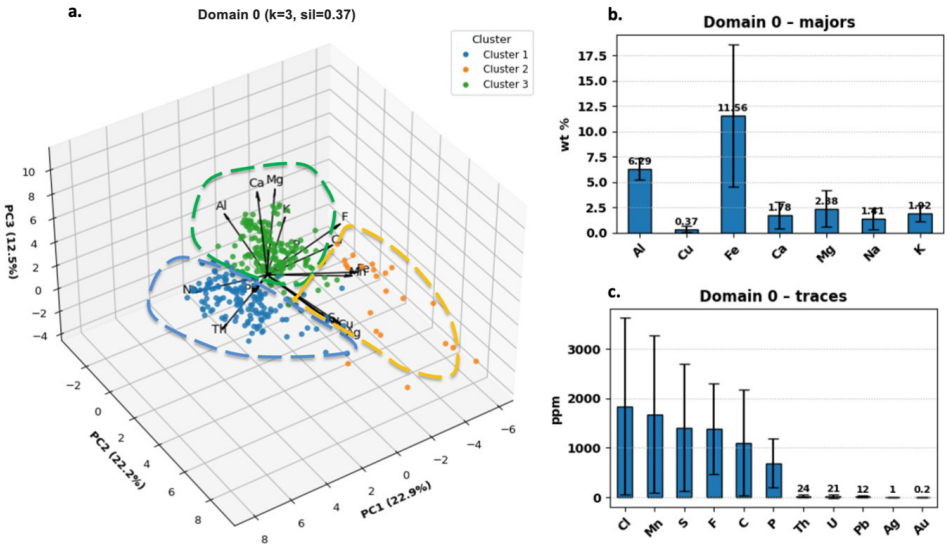


**Figure 7—Elemental associations within domain 0 analysed by a. PCA and mean b. major and c. trace element statistics**

phyllic zone, likely forming a shell around the core mineralisation.

Domain 2 is the most mineralised cluster. It contains the highest average Cu (~1.1 wt%) and S (~0.4 wt%) of the four domains, as well as the highest average Au (0.8 ppm) and Ag (2.5 ppm). It is markedly low in Na and depleted in feldspar-related elements, consistent with intense hydrolytic alteration and a well-defined high-sulphide signature, likely with abundant chalcopyrite and pyrite. The PCA for domain 2 (Figure 9a) shows Cu, S, and Au clustering together as the dominant component within this domain. Domain 2 therefore represents a sulphide-rich phyllic domain in the inner mineralised part of the orebody, rather than the potassic core itself. The abundance of sulphides in sericite-altered host rock explains its high Fe, Cu, and S, and likely contributes to its elevated Au (Sillitoe, 2010; Large, 2025).

Domain 3 is characterised by elevated K (~1.6 wt% on average) and high Fe (~28 wt%), along with the second-highest Cu (~0.68

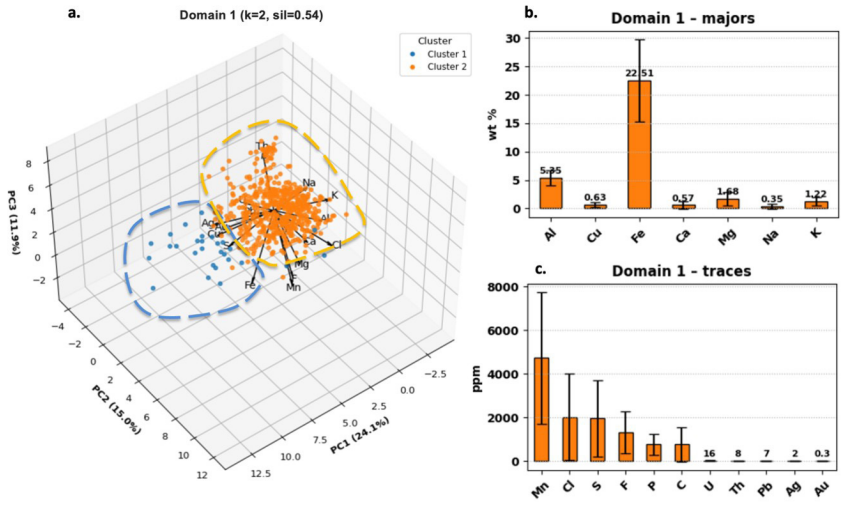


**Figure 8—Elemental associations within domain 1 analysed by a. PCA and mean b. major and c. trace element statistics**

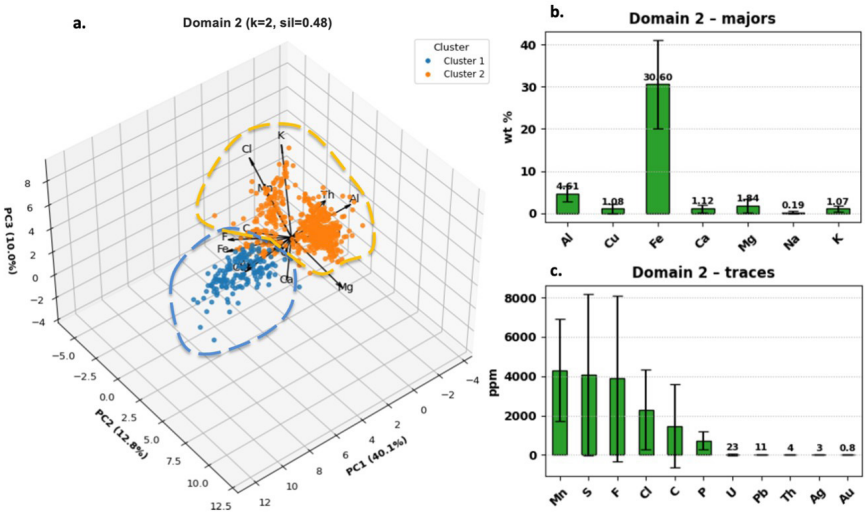


**Figure 9—Elemental associations within domain 2 analysed by a. PCA and mean b. major and c. trace element statistics**

wt%) and S (0.24 wt%) grades. These attributes point to a potassic alteration domain, generally associated with the inner part of the porphyry system. Potassic alteration introduces abundant K, and it can host substantial Cu mineralisation. Domain 3's PCA (Figure 10a) reveals notable internal variability: one subset of samples loads strongly on Al, K, F, and Cl, indicative of biotite-rich potassic rock, while another subset trends toward the Cu-Fe-S direction, indicating that some domain 3 samples are transitional and share characteristics with the high-sulphide domain 2. Domain 3 therefore represents the potassic core of the system, likely including both strongly potassic-altered rock and potassic-phyllic transitional zones. It contains a substantial portion of the deposit's copper resource, enveloped by domain 2 and grading outward to domains 1 and 0.

In addition to the bulk assay dataset, the comminution and flotation testwork samples were examined in the context of these geological domains. The results confirmed that the testwork samples span the previously defined domains. One noteworthy observation is localised graphitic enrichment: a small cluster of comminution samples plots distinctly because of higher graphitic carbon content, with ~688 ppm graphite C and elevated Cu (~0.8 wt%) and Fe (~27 wt%). This carbonaceous enrichment did not form a standalone geological domain in the deposit-scale clustering because it was identified only within the smaller comminution subset and did not show sufficient spatial continuity in the main geological domain model. It is, however, identifiable within the 60 comminution samples and may represent graphite-enriched material within the phyllic domain, highlighting the value of sub-domain analysis because even minor lithological variants can be isolated when focused subsets are examined.

### *Comminution domains*

Clustering was next applied to the comminution response variables to define comminution domains, thereby grouping samples with similar breakage and grinding behaviour. Using the MDS–K-means workflow on the comminution variables separated the 60 samples into two clear clusters. These two comminution domains can be described as "hard" and "soft" ore. Domain 0 (comminution) comprises 47 samples and has a notably higher BWI than domain 1 (comminution), indicating that domain 0 contains more competent rock that is harder to grind (Figure 11). The distribution of BWI values for domain 0 averages 20.6 kWh/t with a standard deviation

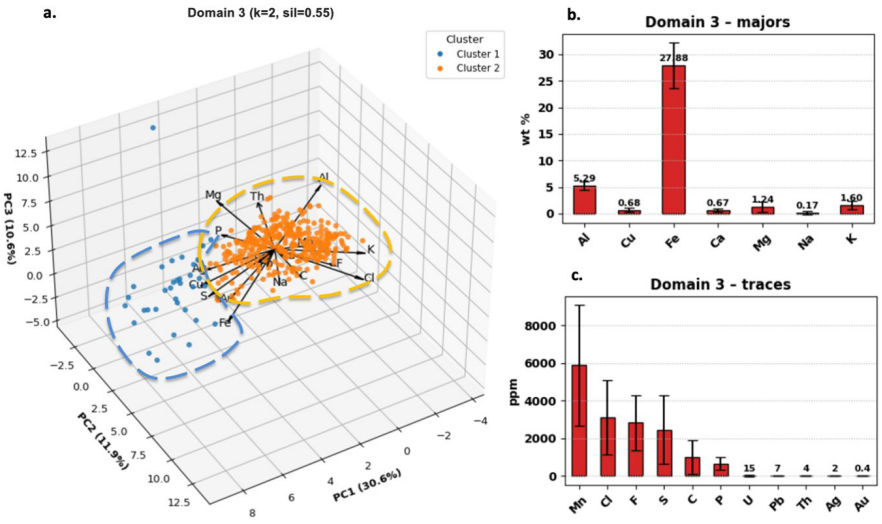


**Figure 10—Elemental associations within domain 3 analysed by a. PCA and mean b. major and c. trace element statistics**

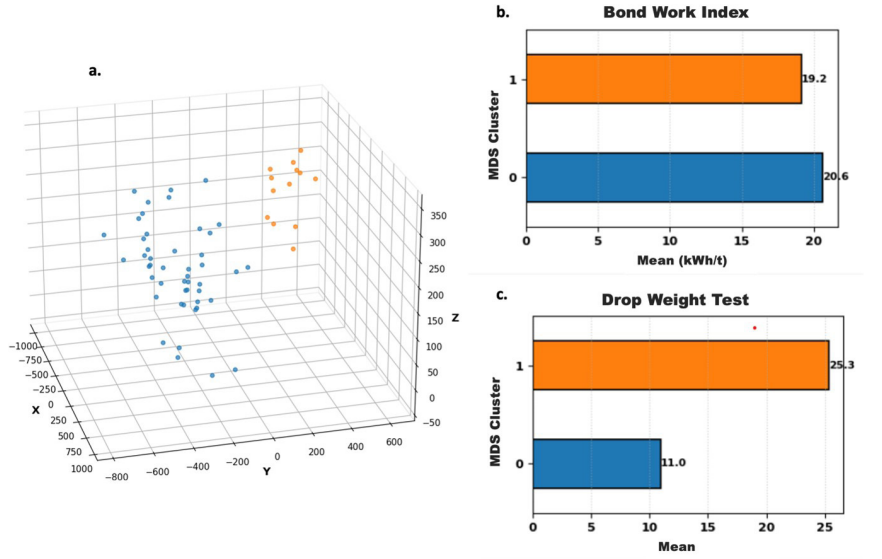


**Figure 11—Metallurgical domains for comminution, showing the a. MDS K-means clusters, and a comparison of the b. BWI and c. DWT statistics per domain**

(SD) of 2.6 kWh/t; this is about 1.5 kWh/t higher than domain 1, which averages 19.1 kWh/t (SD 1.4 kWh/t). Domain 0 samples also have lower DWT values, indicating harder, more competent rock. Domain 1, by contrast, shows greater breakage response and lower BWI. The assigned comminution domains correlate strongly with the geological domains defined earlier. The harder domain 0 (comminution) is dominated by samples from the propylitic, transitional argillic-phyllic, and potassic geological domains. In contrast, the softer domain 1 (comminution) draws mainly from the high-sulphide phyllic domain and samples characterised by graphitic enrichment.

### *Flotation domains*

The same unsupervised approach was applied to the flotation testwork data. This yielded two distinct flotation response domains (Figure 12). Domain 0 (flotation) comprises 35 samples and represents the higher-performance class, with an LCT recovery of ~88.7% (SD 4.4%), compared with ~86.3% (SD 6.5%) for domain 1. Domain 1 material comprises 18 samples and has a slightly higher rougher mass pull (Fr ~25.7% vs. 24.3%), meaning that more material is floated in the first stage for domain 1 samples. The lower recoveries in domain 1 suggest the presence of flotation-penalty material, most plausibly clays or graphitic carbon. Cross-checking the geological compositions confirms that domain 1 (flotation) corresponds mostly to the high-sulphide phyllic and carbonaceous samples, whereas domain 0 (flotation) corresponds mainly to cleaner ore from the propylitic, transitional argillic-phyllic, and potassic zones. Domain 1 therefore captures penalty ore that yields sub-optimal metallurgical response. Domain 0, by contrast, represents ore that floats more efficiently and produces higher recovery. Identifying these two flotation domains early is important because a ~2.4% difference in Cu recoveries is substantial in a production context. Operators can anticipate lower recoveries when a larger proportion of domain 1 material is fed and can thus adjust reagent schemes or blending accordingly (Morales et al., 2019; Saavedra et al., 2025).

### *Geometallurgical domains*

Combining the geological and metallurgical perspectives, geometallurgical domains can be defined for the deposit (Table 2

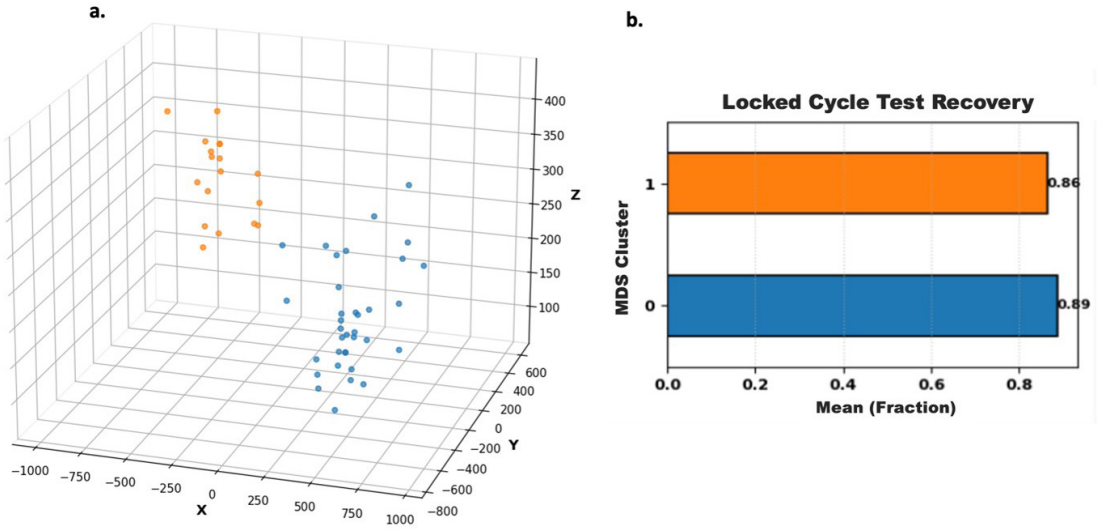


**Figure 12—Metallurgical domains for flotation, showing the a. MDS K-means clusters, and a comparison of the b. LCT recovery per domain**

*Table 2 Geo*
**metallurgical domains**

| Geomet domain | Geological domain | Facies | Net processing behaviour |
|---|---|---|---|
| I – hard/high recovery | Argillic phyllic | Sericite-clay halo | Breakage similar to propylitic rock, acceptable Cu recovery. |
| | Potassic | K silicate core | Hard rock, reliable Cu recovery; useful for blending. |
| | Propylitic | Outer halo | Harder to break; Cu grades too low to influence plant performance. |
| II – soft/low recovery | Graphitic enrichment | Carbonaceous lens | Very soft; can dilute the concentrate grade. |
| | Phyllic | High sulphide core | Breaks easily but loses Cu during flotation. |

and Figure 13). The findings indicate two main geometallurgical domains that capture the contrast in processing behaviour: (I) a hard, high-recovery domain and (II) a soft, lower-recovery domain. The hard, high-recovery domain comprises rocks from the propylitic, potassic, and transitional argillic-phyllic portions of the orebody; these are relatively competent, with higher BWI and less deleterious carbonaceous or clay-rich materials. Although they may require more grinding energy, they deliver better flotation performance and therefore higher Cu recovery. The soft, lower-recovery domain corresponds to the high-sulphide phyllic zones and associated graphitic enrichment. This material grinds more easily, often supporting higher mill throughput, but tends to suffer roughly 2% lower Cu recovery. In effect, domain 1 classes in comminution and flotation broadly represent the same altered and carbonaceous material population. The complementary set of samples, domain 0 in both comminution and flotation, corresponds to cleaner lithologies that, despite being harder to grind, yield better recoveries.

## Discussion

Clustering analysis identified distinct geochemical populations in the porphyry Cu dataset, and the domaining workflow refined these into operationally interpretable classes. Four geological domains were delineated from assay data, reflecting the natural alteration zoning of the porphyry system without manual facies labelling during clustering. This indicates that multi-element geochemistry contains sufficient signal to delineate alteration-related material classes objectively when clustering data is stabilised and made less sensitive to the dominance of high-variance variables. The geological domains were found to drive differences in comminution hardness and flotation response. The comminution results show that phyllic and carbonaceous material is generally softer than propylitic and potassic material. The magnitude of the observed BWI separation should not be interpreted as trivial, because even a moderate difference in hardness can translate into operational consequences. A 1.5 kWh/t gap corresponds to roughly 10% variation in SAG-mill throughput at constant power, consistent with operational observations (Keeney, Walters, 2011).

The flotation results similarly align with established mechanisms, as potassic alteration is commonly associated with harder rock and comparatively cleaner copper mineralogy, whereas clay-rich alteration is typically softer but more deleterious to

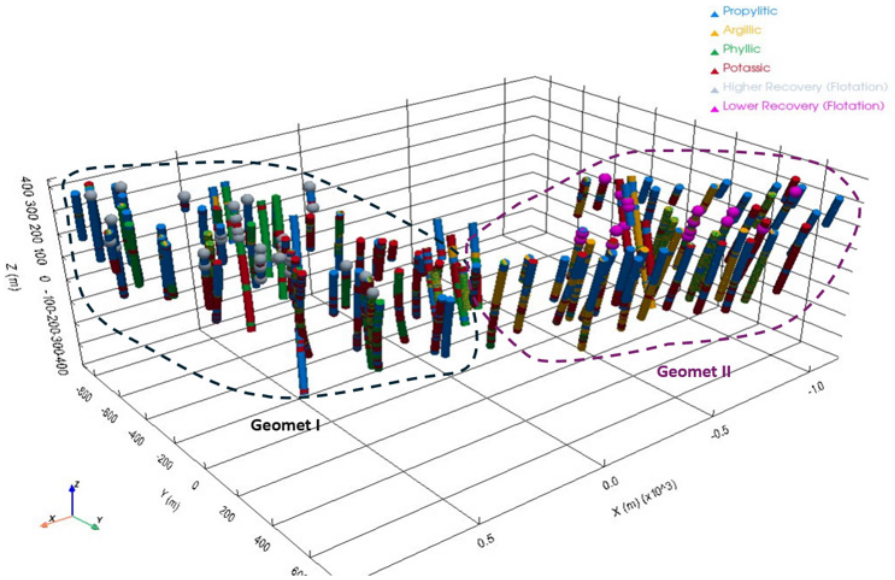


**Figure 13—Final geometallurgical domains for the porphyry Cu database**

flotation (Sillitoe, 2010; Yildirim et al., 2014). Higher rougher mass pull paired with reduced LCT recovery is consistent with increased entrainment and reduced selectivity, especially when fine gangue and clay minerals are present. Clay minerals reduce flotation performance through rheology effects, slime coatings, and altered froth behaviour, and this has been demonstrated in copper ore deposits (Uribe et al., 2016; Jeldres et al., 2019; Taner, Onen, 2021; Pan et al., 2022). At 100,000 t/d and 0.5% Cu feed, a 2% recovery deficit would equate to the loss of approximately 10 t Cu per day; depending on copper price and operating assumptions, this could translate into a substantial annual revenue penalty. Explicit flagging of such material is therefore warranted, even where it does not form a deposit-scale geological cluster.

## Machine learning for geoscientific data

Equal-weight clustering assumes that all variables contribute equally to meaningful similarity. This assumption is rarely valid because geoscientific data differ in variance, scale, and measurement distribution. In this study, Bayesian optimisation efficiently tuned continuous weights under a defined objective function, avoiding manual trial-and-error and using a well-established framework for optimisation in complex parameter spaces (Tsai, Chiu, 2008; Snoek et al., 2012). Clustering outputs mapped back into drillhole space allow the resulting domains to be assessed for geological plausibility, reducing the risk of retaining purely statistical classes that are difficult to model and mine (Martin, Boisvert, 2020; Mohammadi et al., 2022). MDS helps visualise domain structure in a form that can be communicated across geoscience and processing teams. Stable domains, reflected here by low reassignment under reseeding, matter because unstable material codes undermine forecasting and reconciliation. A persistent constraint in geometallurgy is that metallurgical testwork is costly and sparse relative to drillhole geochemistry. Data-driven techniques can help address this by using more abundant proxy information, such as geochemistry, drilling-derived variables, or lithological classes, to define or predict processing-related classes and then calibrate them against limited comminution and flotation measurements (Van Duijvenbode et al., 2022; Niquini et al., 2025).

## Operational use

The integrated geometallurgical domains make the relationship between throughput and recovery explicit in a spatial model. Such a model can be used to forecast periods of throughput increase or recovery penalty, design blending strategies that limit variability, and adjust reagent schemes when lower-quality material is scheduled (Dominy et al., 2018; Morales et al., 2019; Lishchuk et al., 2020). Geometallurgical models are specifically used to link ore variability to production planning and process response, while blending is widely used to manage feed variability and stabilise downstream performance. The results suggest three feed categories for planning. First, propylitic and potassic domains form a hard, competent ore that requires more grinding energy yet still yields high Cu recovery once processed. Second, the argillic-phyllic material falls in the mid-range for both hardness and recovery and is therefore well suited to smoothing daily variation in mill load and metal output (Both, Dimitrakopoulos, 2021). Third, high-S phyllic and graphite-enriched intervals form a softer feed that produces a lower-grade concentrate. Blending this softer, lower-recovery ore with the more competent, higher-recovery feed can help stabilise SAG-mill throughput and sustain overall copper production (JKTech, 2024). The domain model (Figure 13) therefore provides a clear, geologically grounded basis for ore scheduling and process optimisation.

## Conclusion

The data-driven workflow combining multidimensional scaling and K-means clustering delineated four spatially coherent geological domains in a porphyry copper deposit. These were then consolidated into two geometallurgical groupings representing hard, higher-recovery material and soft, lower-recovery material, which provide a practical basis for feed classification and planning. The domains align with established alteration zonation and explain differences in comminution and flotation response, demonstrating a direct link between orebody heterogeneity and plant behaviour. Even moderate differences in hardness (~1.5 kWh/t) and recovery (~2%) are operationally meaningful because they influence grinding energy, throughput, and metal recovery. The resulting framework supports scheduling, blending, and recovery planning while reducing reliance on subjective domaining decisions. The workflow

uses standard geoscientific databases and open-source software, making it readily transferable to other porphyry copper deposits where heterogeneity and non-stationarity complicate resource modelling and process forecasting.

## Acknowledgements

This work was funded by the Sibanye-Stillwater Digital Mining Laboratory (DigiMine), hosted at the Wits Mining Institute at the University of the Witwatersrand. Additional support was provided by the Julian Baring Scholarship Fund.

## CRediT author statement

TM: Conceptualisation, methodology, writing – original draft, visualisation, validation; GN: Writing – review and editing, methodology, conceptualisation, supervision, resources, funding acquisition.

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