Advancing Process Understanding through Particle-Based Separation Modelling

Lucas Pereira

October, 2026

Abstract

Mineral beneficiation involves particle-specific processes, where performance is strongly influenced by the microstructural characteristics of individual particles. Ores currently being mined often exhibit high complexity, with fine-scale mineral intergrowths and diverse gangue associations that hinder separation. Within the field of process mineralogy, automated mineralogy has advanced the characterisation of such features, providing detailed particle-level data. However, these data are frequently summarised into bulk distributions (e.g., mineral composition, particle size, or liberation degree of the ore mineral), resulting in the loss of critical particulate information. Since particles are unique in size, shape, and mineral association, reliance on aggregated properties may oversimplify the relation between processing behaviour and ore microstructures, leading to incomplete or biased process interpretations.

This contribution highlights the use of data science techniques to exploit full-resolution particle datasets from automated mineralogy, namely particle-based separation models (PSMs). The usefulness of this technology, both for forecasting and for understanding separation processes, is illustrated on two case studies dealing with complex ores.

1 Introduction

Automated mineralogy, based on scanning electron microscopy (SEM) coupled with image analysis, routinely delivers full particle datasets: the size, shape, modal and surface composition, liberation and association of every particle in a sample [7, 4]. It has long been documented the impact of having such datasets for troubleshooting beneficiation plants [8, 6] – this is because minerals processing works as a function of particle properties 1 [16]. In practice, however, these rich data are typically reduced to a few bulk descriptors, such as the modal mineralogy, a single liberation number, or a d50 value. This reduction discards most of the particle-level information and can bias the interpretation of process behaviour. Within process mineralogy, such aggregation limits the ability to link processing performance to ore microstructures [12, 5] – a missed opportunity given the wealth of data that has already been collected.

The present contribution uses two case studies to demonstrate the power of this measured data when used at full resolution; particle-based separation models (PSMs) are taken as an example methodology that can be employed for this task, as already doccumented for several processing unit and ore types [15, 17, 14]. The first case study is the copper flotation circuit of the Kansanshi mine, where PSMs are used both to forecast metallurgical performance and to diagnose the recovery behaviour of individual mineral phases. The second case study concerns the recovery potential of a tailings storage facility (TSF). Reprocessing of TSFs has become a major interest in recent years, as these facilities may host considerable amounts of raw materials while also posing environmental threats [2]. Ideally, taking ore microstructures into consideration for decisions throughout the whole raw materials value chain is key to minimize the uncertainties of these decisions and better identify opportunities of increasing its overall efficiency [5].

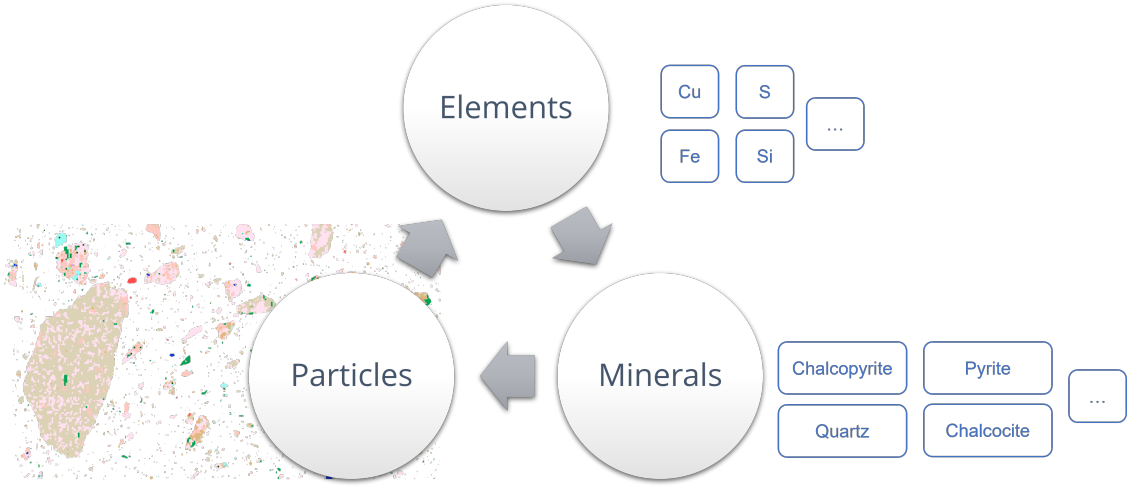

Figure 1: In minerals processing, elements are targeted, but processes are based on particles and their properties.

2 Case Study 1: The Kansanshi flotation circuit

Previously published as: Lucas Pereira et al. "A new approach to understanding how particle characteristics drive copper recovery at Kansanshi Mine." In: *Flotation 25*. Flotation 25. Cape Town, South Africa: MEI, 2025

The Kansanshi copper mine is an open pit mine in Solwezi, Zambia, with four circuits: sulphide (x2), mixed, and oxide. The mixed circuit, which is the focus of this study, has a highly variable feed mineralogy, and recovery models are based on total copper (TCu) and acid-soluble copper (ASCu) ratio proxies [11]; the feed copper grade is 0.8-1.5 wt.%. The ore is complex: multiple minerals carry copper – sulphides, carbonates, oxides, and silicates. Moreover, micro inclusions of copper-bearing minerals are observed within most gangue minerals. Operations already collect automated mineralogy information from the feed samples daily, using the Tescan Integrated Mineral Analyzer (TIMA), with weekly composites of the all output streams of the mixed circuit. It is known that Recovery trends follow sulphide grades, but this is not always sufficient for accurate predictions. While the complex copper deportment requires that all mineralogical information should be considered within this task, particle datasets are immense and can hardly be thoroughly used to guide daily plant operations. To better summarise the particle datasets, in a process-relevant manner, the noise must filtered out, without oversimplifying the data. For that, a clear link between recovery and particle size, shape, composition, and liberation, their microstructures, is required.

Thus, the aim of this work is to identify the most important mineralogical properties controlling copper grade and recovery in the Kansanshi deposit, which can then be used for later forecasting production KPIs in daily operations using particle-based separation models. The work has provided insight into particle properties of relevance for this operation, and should be understood/tackled to assure good process efficiency. Moreover, the power of these models to predict the processing outcome of individual particles in the Kansanshi circuit is demonstrated for several weeks of operation.

2.1 Methodology

The methodology is summarised in Figure 2. It started with the sampling of industrial operations: weekly composite samples of the final concentrate and final tailings streams were collected over six weeks in 2025, covering variations in ore properties and operating conditions. The samples were characterised with TIMA using long-standing analytical protocols. A particle-based separation model was trained per week, without simplification of the mineral list. The forecast results were then compared with the metallurgical key performance indicators (KPIs), and the recovery trends were evaluated to understand how the data can be

simplified. Finally, a single PSM has been trained with data from all weeks to evaluate the potential application of PSMs as a generalized tool to forecast the processing outcome of the Mixed Circuit in Kansanshi daily.

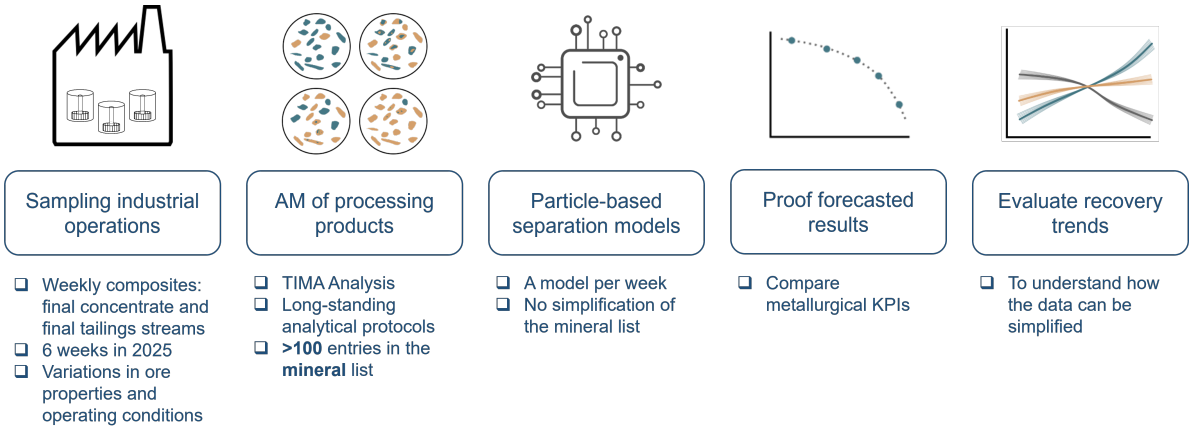

Figure 2: Overview of the methodology used for Case Study 1.

Particle-based separation models were trained using the mineralogical data collected routinely by the mineralogy team. Data were exported from the TIMA in sqlite format and imported into the HIF particle simulation platform, where each particle is treated individually. For each particle the following information is considered:

- Modal content: the weight of each mineral within a particle. This vector is closed before being used in the model.
- Surface exposure: the area of each mineral on the surface of a particle. This vector is closed before being used in the model.
- Equivalent circle diameter (ECD): a measure of particle size. This value is log-transformed before being used in the model. Additionally, the squared log-transformed ECD is added as an extra variable to allow for capturing a non-linear relation between particle size and recovery.
- Aspect ratio: a measure of particle elongation. This value is log-transformed before being used in the model.
- "Main mineral": a categorical variable indicating the dominant mineral, per weight, in a particle. This value is used within the logistic regression as an analysis of covariance framework with the size and shape variables.

A LASSO-regularised logistic regression model was trained with the output samples of each week: final concentrate and tailings. The model estimates the importance of each particle property for its probability of recovery and eliminates irrelevant or correlated variables to avoid overfitting. The metallurgical results, grade and recoveries, observed with the TIMA are then compared to those predicted by the models. Once the prediction errors are confirmed to be low, model results are used to understand the recovery behaviour of individual particles.

2.2 Forecast using a series of PSMs trained for each individual week

The prediction errors of the weekly-PSMs are presented as Halbich plots for elements of interest: copper, silica, and sulphur (Figure 3). The reason for presenting errors as a function of elements instead of minerals is twofold. First, smelter contracts are signed in terms of elemental grades and it is thus meaningful to be able to forecast this KPI. Second, this ore contains numerous minerals containing each of these target elements – the prediction of elemental grades and recoveries can thus only be correct if that of all of these minerals is correct. This strategy then allows for a summarised evaluation of the prediction errors of multiple minerals at a time.

The confidence intervals of predicted and observed results almost always overlap, which is consistent with a good accuracy of the models. The predictions are excellent, which means we can move forward and use the models to evaluate recovery trends.

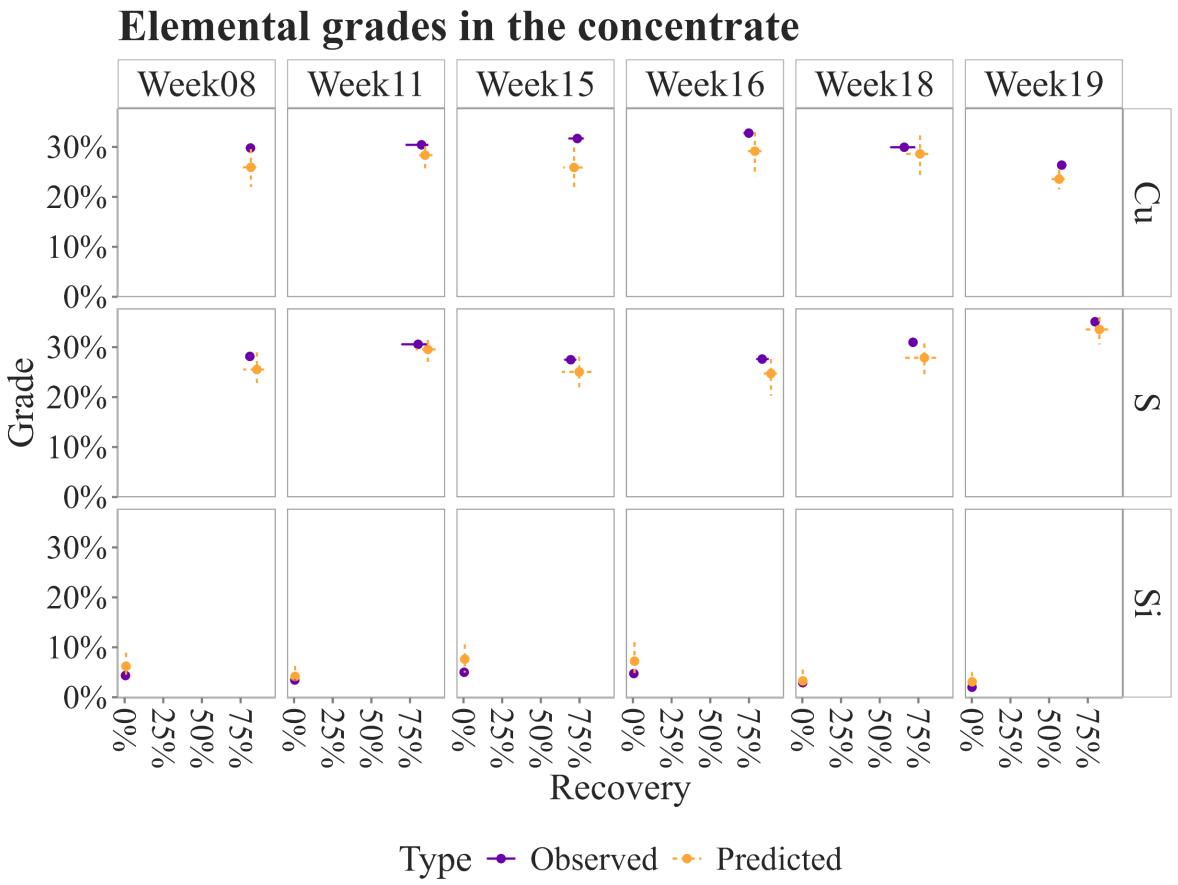

Figure 3: Predicted versus observed metallurgical results for the sampled weeks (per-week models).

2.3 Recovery trends

The recovery trends of liberated particles for minerals of interest are discussed next. The aim is to understand the recovery behaviour of each of these minerals – and recovery is displayed as a function of particle size. The focus on liberated particles assures an analysis of the recovery behaviour of each mineral individually, without the influence of associated phases. Stereological bias must be kept in mind – these phases can be influenced by liberation issues not visible in this 2D analysis. Here it is also important to highlight that no detailed mineral chemistry study has been conducted to understand the phase speciation depicted by the mineral list. Thus, results for non-stoichiometric phases should be interpreted as an indication that multiple species of a given mineral may exist, be it due to substitution in the mineral structure or microinclusions that have not been resolved in the TIMA analysis, and that they might lead to variations in process responses.

2.3.1 Chalcopyrite

For chalcopyrite ($CuFeS_2$), the recovery of liberated particles is generally high, mostly above 80%, and is lowest in weeks 15 and 18, especially for particles finer than 20 µm (Figure 4).

The influence of particle size changes from week to week. Particle size has a weaker influence in weeks 11 and 16 than in the other weeks; elsewhere the recovery of particles below 20 µm is slightly lower, while no drop is observed for coarser particles.

The lower recovery of non-stoichiometric phases (Chalcopyrite_mixed spec, Chalcopyrite_surfdef, Chalcopyrite_lowS, Chalcopyrite_CC) helps shedding light on the effect of long-term stockpile storage to the recovery of this mineral; such phases generally occur at finer particle sizes and show lower recoveries than standard chalcopyrite, with the exception of Chalcopyrite_lowS in weeks 11 and 18.

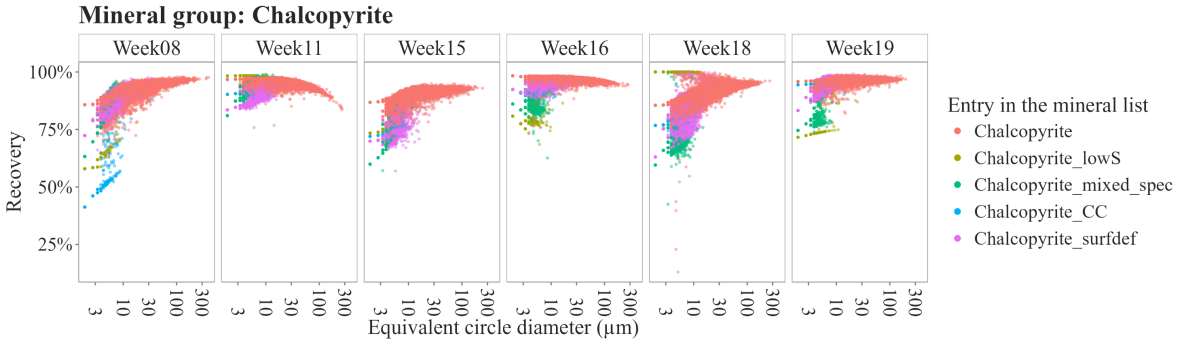

Figure 4: Recovery trends of liberated chalcopyrite particles as a function of particle size, per week.

2.3.2 Malachite

For malachite ($Cu_2CO_3(OH)_2$), the recovery of liberated particles is highly variable between weeks, ranging between 50 and 100% (Figure 5). Pure malachite generally shows higher recovery than "Malachite_mixed spectra". The influence of particle size is strong in Week 8 for pure malachite, but not in the other weeks.

These trends is probably caused by variations in the operating conditions of the controlled sulphidisation units of the circuit. Yet, the discussion about an influence of operating conditions in this study is out of the scope of this contribution.

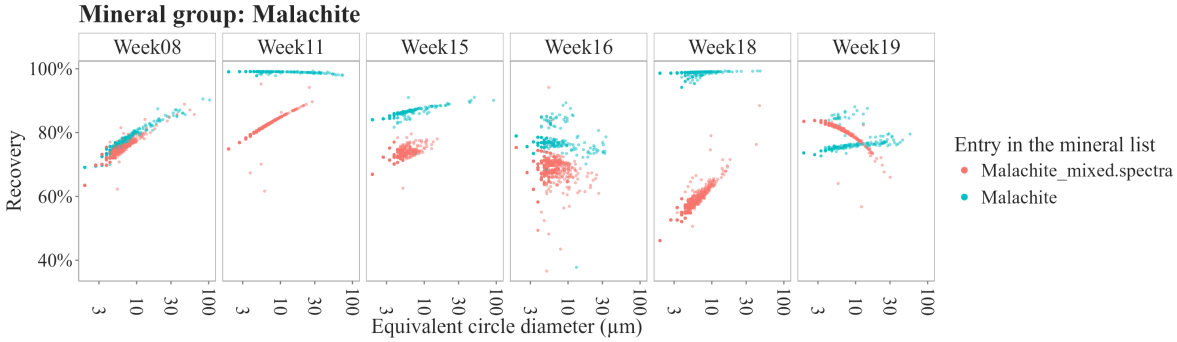

Figure 5: Recovery trends of liberated malachite particles as a function of particle size, per week.

2.3.3 Pyrite

Pyrite (FeS_2) shows a moderate to high recovery (mostly 50 to 100%), being lowest in weeks 11 and 15; coarse particles (>30 µm) recover best, and "Pyrite_6Cu" is mostly recovered whereas "Pyrite_mixed spectra" typically recovers less than standard pyrite (Figure 6).

There is a strong influence of trace copper on the recovery of pyrite, together with a strong influence of particle size, which points to possible improvements in the reagent regime.

2.3.4 Gangue minerals and copper-bearing inclusions

Among the gangue minerals, a representative silicate and carbonate mineral are used to highlight the influence of tiny inclusions of copper-bearing minerals on their recovery behaviour. Standard albite

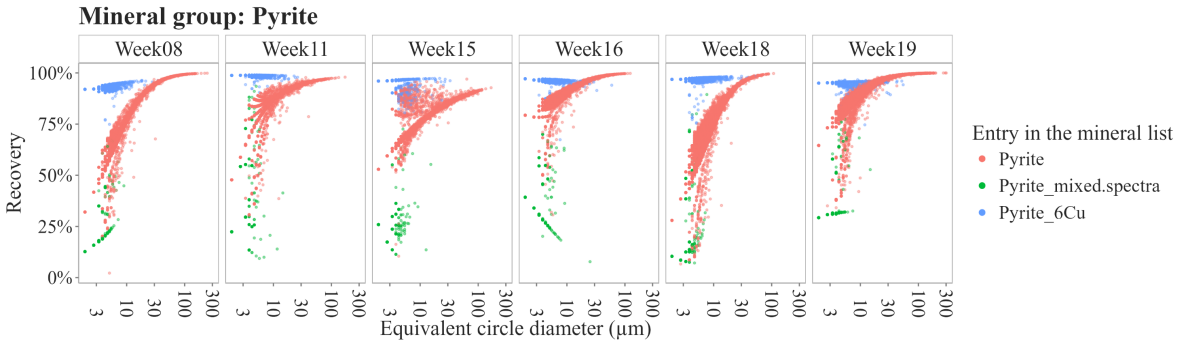

Figure 6: Recovery trends of liberated pyrite particles as a function of particle size; the highlighted series distinguish pyrite with trace copper.

($NaAlSi_3O_8$) and standard calcite ($CaCO_3$) both recover close to 0% with no size dependence, whereas the corresponding copper-bearing entries recover well above this – "Albite_1.7Cu" mostly below 20% and "Calcite_chalcocite_mixed spectra" mostly below 40% – both increasing above 3 µm (Figures 7 & 8, respectively). It is clear that silicates and carbonates that would not be expected to float become recoverable once copper inclusions are present. While this trend applies to all weeks investigated, it is more expressive for calcite on Week 08, and for albite on Week 16.

Avoiding to group all entries of a specific mineral in the mineral list is thus important wherever copper has been mobilised – any grouping here would have masked the clear influence of these tiny inclusions, and convergence to the mean would have hidden these phenomena. Automated mineralogy is expensive, so it should be used thoroughly.

These copper-bearing entries within gangue minerals in the mineral list are more likely to be tiny exposed intergrowths of copper-bearing minerals at the surface of gangue particles than copper substituting within the mineral structure. The practical implication is that even a minute copper-bearing-mineral occurrence at the surface of gangue mineral particles – including inclusions smaller than 3 µm, both in carbonates and in silicates – can be sufficient to make these floatable. This effect is essentially invisible in bulk descriptors but becomes directly quantifiable when the full particle data are used. It is nevertheless important to point out that this study has not investigated the role of entrainment of fine particles in these recovery figures. Besides, further work in revisiting the mineral list to evaluate the occurrence modi of these copper-bearing mineral inclusions on gangue minerals is advised.

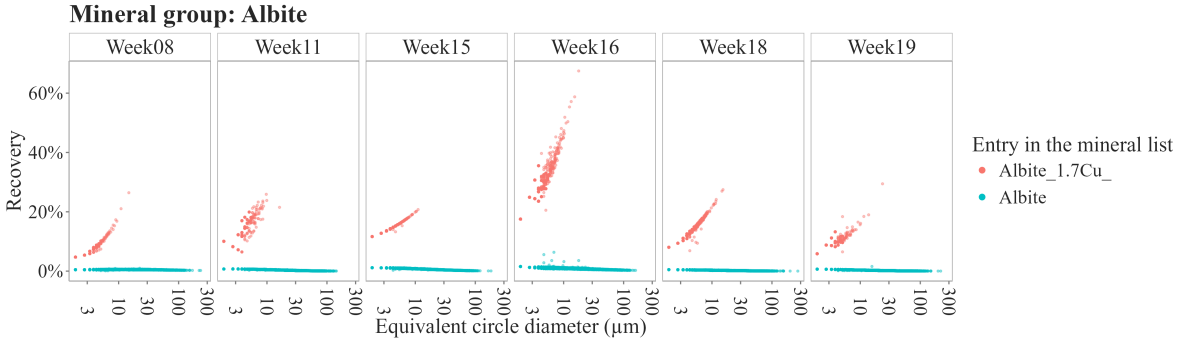

Figure 7: Recovery trends of albite as a function of particle size, per week.

2.4 A single PSM for daily operations

Ideally, a model to be used in daily operations should be able to forecast the copper grade and recovery of the final concentrate. For that, the recoverability of the many copper-bearing minerals must be predicted,

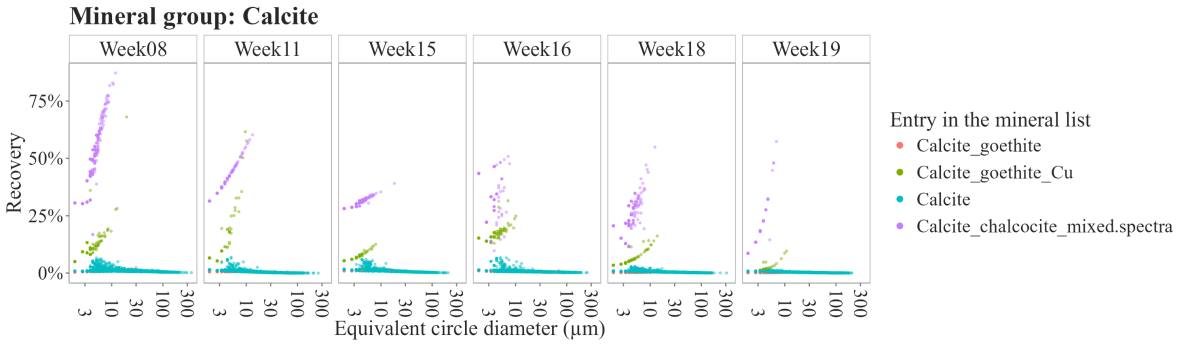

Figure 8: Recovery trends of calcite highlighting the effect of copper inclusions.

also considering the type of particles in which they are encountered.

In this exploratory exercise, we evaluate the accuracy of using a single particle-based separation model to forecast the grade and recovery of different minerals for all the weekly data available for the study. For that, the single PSM was trained using all particle data collected for the study. Its accuracy was compared to the model trained with the particle data of the said week itself (itself), which theoretically should yield the most accurate predictions, as well as the model that had been trained for Week 08, which had a relatively low prediction error amongst all weeks tested (Figure 3). In general, the accuracy of using a single PSM, especially with the strategy in which all samples are used, is comparable to the PSM trained with the samples of the week itself (Figure 9). These results demonstrate the potential of using a global PSM in daily operations to predict the recovery of every new incoming feed.

These preliminary results are positive. Whether a single PSM outperforms the simpler TCu and ASCu proxy models is still to be confirmed with long-term testing; if it does not, it can at least be used to identify and confirm the importance of the key mineralogical KPIs to track. In this case, the proxy models could be parsimoniously updated with key particle microstructural information.

2.5 Conclusion

Case Study 1 demonstrated that particle-based separation models can both forecast and explain copper flotation performance in the complex, highly variable feed of the Kansanshi mixed circuit. Per-week PSMs, trained without simplifying the mineral list, predicted copper, silica, and sulphur grades and recoveries with errors within the confidence intervals of the observations, and a single PSM trained across all weeks performed comparably to models trained on each week individually, supporting its use in daily operations – although whether it outperforms the existing TCu and ASCu proxy models remains to be confirmed by long-term testing. The recovery trends observed for different minerals indicate possible particle binning that could be done without masking any recovery trends. Liberated chalcopyrite recovers mostly above 80%, lowest in weeks 15 and 18 for particles finer than 20 µm, with non-stoichiometric phases generally recovering less than standard chalcopyrite, an impact to be considered when using long-term stockpile storage; Malachite recovery is variable (50-100%), likely reflecting the controlled sulphidisation operating conditions; Pyrite recovers moderately to highly (50-100%), with coarse particles recovering best and trace copper and particle size both exerting a strong influence, pointing to necessary reagent-regime improvements. Most notably, gangue minerals that would not be expected to float recover close to 0% when pure (albite, calcite) but become floatable once copper-bearing inclusions are present (reaching up to 40% for calcite, both increasing above 3 µm), an effect that can most likely be attributed to tiny exposed intergrowths at the particle surface rather than substitution in the mineral structure. This effect is invisible in bulk descriptors but directly quantifiable from full particle data, so mineral list entries should not be grouped before understanding the processing behaviour of individual phases. The same applies to any sort of particle binning.

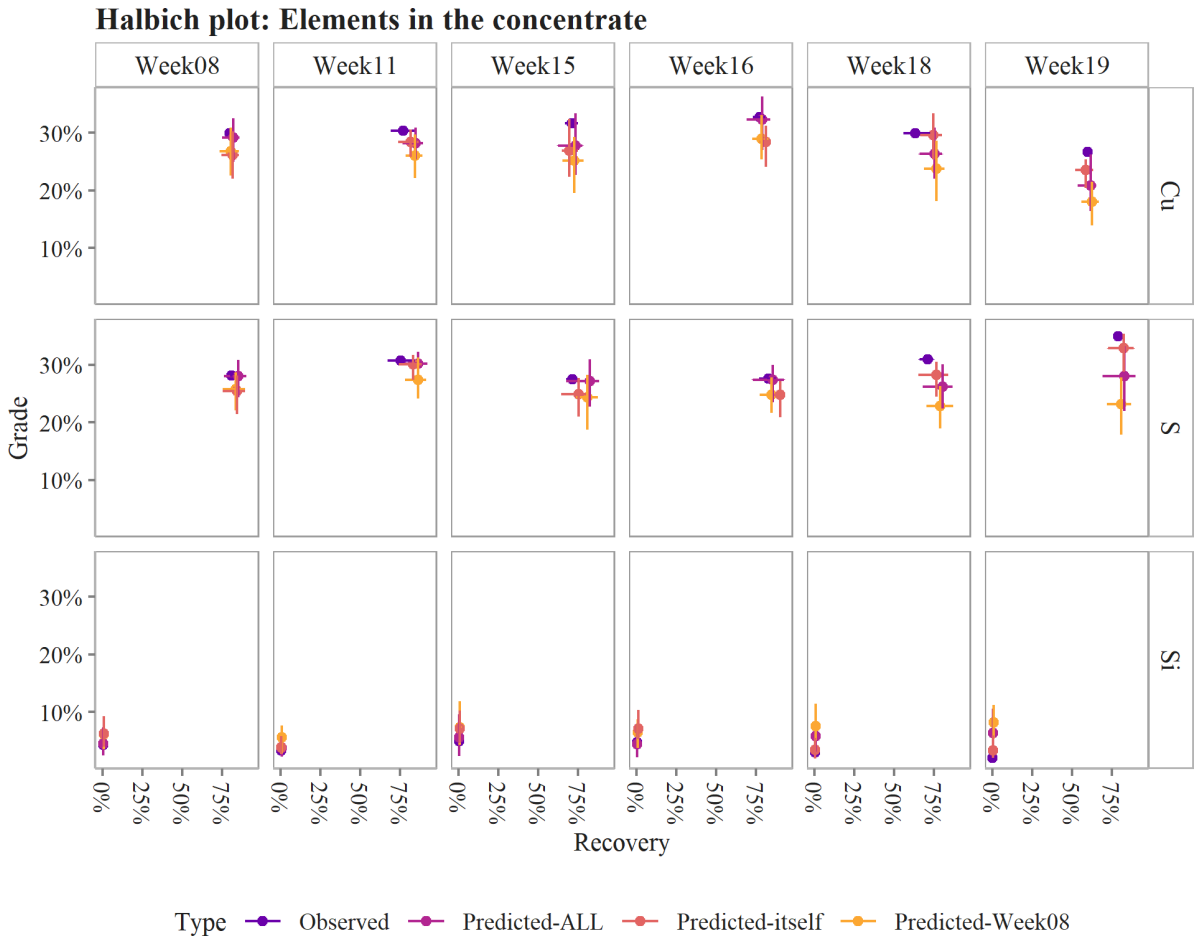

Figure 9: Comparison between predicted and observed results using a single PSM across all weeks.

3 Case Study 2: Forecasting the recovery potential of the Davidschacht TSF

Previously published as: Lucas Pereira et al. "Forecasting the Recovery Potential of a Tailings Storage Facility with Particle-Based Separation Models". In: *Int. Miner. Process. Congr.* International Mineral Processing Congress. Washington, DC: International Mineral Processing Council, 2024

Tailings storage facilities (TSFs) may host considerable amounts of raw materials while also being potential environmental threats; reprocessing them could minimise environmental issues while recovering marketable metals [1, 10]. This is made difficult by the fact that the metals of interest are often carried by fine and non-liberated particles – the reason they were lost to the tailings in the first place – so that new processing strategies and better techniques for understanding and forecasting operations are required. The particle-based separation models (PSMs) introduced by Pereira et al. [15] enable the use of all relevant particle data collected with automated mineralogy, yielding the recovery of all individual particles in a sample based on their size, shape, and composition, both in terms of liberation and association.

In the broader context of predictive geometallurgy, models and consequently decisions should be based on particle microstructures – the *de facto* meaningful information controlling beneficiation processes. Particle-based methods for understanding separation processes are already available, whereas equivalente models for particle breakage are still under development (Figure 10). Tailings offer an important opportunity to test such a predictive geometallurgy concept as they may not require comminution.

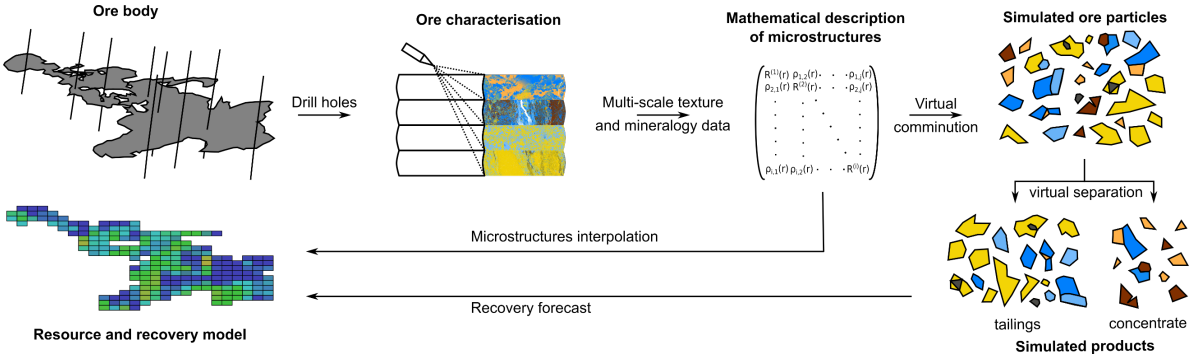

Figure 10: The predictive geometallurgy concept of the Helmholtz Institute Freiberg for Resource Technology: it is all about particles.

This study aims to combine PSMs and geostatistical tools into a methodology to estimate the recovery potential of TSFs with only a few processing experiments. The objective is to be able to forecast the recovery of every particle in the system – which allows to estimate the full composition and particle size properties of all product to be generated as well as the remaining material to be re-deposited in the TSF. As a case study, we evaluate the potential of minimising the environmental impact of a historical TSF in Germany with bulk sulphide flotation, aiming at its desulphidization.

3.1 Methodology

The workflow (Figure 11) started a detailed sampling campaign [2], conducted on the shallow zone (<3 m) of a historical TSF in Freiberg, Germany. All 68 samples were characterised with X-ray fluorescence (XRF) and a subset of 36 samples also with the Mineral Liberation Analyser (MLA). Samples were clustered based on the XRF results, dividing the TSF into four regions. Composite samples of each region and a global composite were used for flotation tests aimed at bulk sulphide recovery. The processing products were characterised with XRF and MLA, and the MLA data from the products of the global composite were used to train a PSM that estimates the potential sulphide recovery of all MLA-analysed samples. A recovery model of the TSF was then computed by interpolating sulphide recovery throughout the TSF with ordinary kriging. The necessary information on each of these steps is given below.

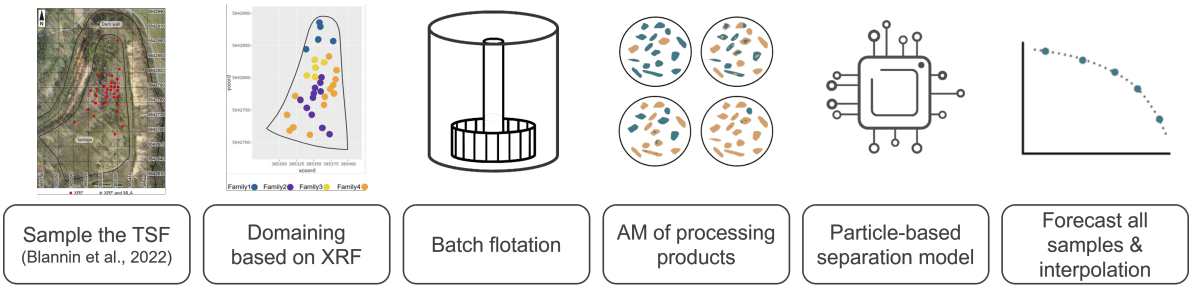

Figure 11: The overall methodology used in case study 2.

Sampling and clustering

- The sampling protocol and analytical scheme followed Blannin et al. [2].
- The shallow zone (<3 m) was sampled on a 30 m grid, with nested grids of about 15 and 7.5 m, plus random and twin samples, limited to the region with restricted human activity after closure.
- A 1-3 m blend sample was produced at each point by drying, homogenising, and splitting the 1-2 m and 2-3 m intervals to 100-250 g aliquots and mixing equal splits.
- The 68 samples were analysed as pressed pellets (Ø40 mm) with a PANalytical Axiosmax Minerals wavelength-dispersive XRF at the Helmholtz Institute Freiberg for Resource Technology (HIF).
- A hierarchical clustering method with Euclidean distance was applied to all XRF data to group samples of similar chemical composition.
- The TSF was split into four regions: Region 1 in the very north, regions 2 and 3 in the centre and partially the south, and region 4 mostly on the east and west borders.
- Composites of each region were prepared by mixing 500 g of six randomly selected samples.
- Two aliquots of each region composite were used for the region flotation tests, while the remaining aliquots were combined into the 8 kg global composite, which was split into 500 g aliquots for flotation tests.

Flotation test work and product characterisation

- Flotation was used to produce a sulphide-rich concentrate and sulphide-poor tailings (process optimisation is beyond the scope of this study).
- A Magotteaux® bench-scale flotation device with a 2 L cell was used.
- All tests used the same parameters:
  - 500 g of feed,
  - 450 rpm impeller speed,
  - 5 L/min air flow rate,
  - 50 g/t potassium amyl xanthate (PAX) as collector,
  - and 20 g/t methyl isobutyl carbinol (MIBC) as frother.
  - Five concentrates were collected over 0-30, 30-90, 90-210, 210-390, and 390-630 s.
- Products were dried overnight at 60 ºC and split into 1-2 g samples.
- Samples were prepared as B-section grain mounts [9] for MLA analysis in a FEI Quanta 650F SEM equipped with two Bruker Quantax X-Flash 5030 EDS detectors and MLA Suite 3.1.4.
- Grain-based X-ray mapping used 1 µm pixel size, 6 µm X-ray spacing, 25 kV, and a minimum particle area of 2 pixels.

Particle-based models

- A particle-based model [15] was trained with the processing products of the global composite to act as a general recovery model for the TSF.
- Data treatment and model training protocols are the same described for case study 1. Yet, it is important to highlight that particle data are compiled into a training dataset with the same number of particles per process stream. Following, model intercepts are adjusted to reflect the actual particle balance of the process (prior adjustment).

- For model validation, a bootstrap approach is used. It resamples the validation particle dataset with replacement, predicts individual particle recovery probabilities, assigns particles to streams, and computes the bulk mass and composition of each stream for comparison with observed values; this is repeated 1000 times to capture model and sampling uncertainties.
- Uncertainties of observed stream compositions are captured by resampling the particle dataset, as proposed by Blannin et al. [3].
- All four concentrates are represented as a single flotation product to simplify the analysis, and the model is validated with each of the five composite samples.
- The modeling approach used here follows the assumption that PSMs are accurate as long as they are presented with the different particle types found in a deposit, being all of these available in the global composite sample. Besides, PSMs assume that the recovery of a particle depends only on its microstructural properties, i.e. particle-particle interactions are not considered. It is important to mention that Pereira et al. [19] demonstrated that PSMs can be accurate despite variations in feed composition for magnetic separation, which is sufficient for the objective of an overall framework to model the recovery potential of a TSF.

Recovery interpolation

- With the global PSM, the samples collected throughout the TSF and analysed with the MLA were virtually-processed to forecast the mass pulls of each mineral to concentrates and tailings, applying the prior adjustment corresponding to the particle balance of each sample's composite region.
- Because the aim was to recover sulphides, all minerals were pooled into two groups: sulphides and gangue.
- This gives, for each sample, four predicted numbers:
  - the proportions of the sulphide mass in the feed that reports to the concentrate (M_s^C),
  - the proportions of the sulphide mass in the feed that reports to the tailings (M_s^T),
  - the proportions of the gangue mass in the feed that reports to the concentrate (M_g^C),
  - the proportions of the gangue mass in the feed that reports to the tailings (M_g^T),
- From these four numbers, grades and recoveries follow directly, and the results can be summarised as grade-recovery curves, for example:
  - Recovery of sulfides in the concentrate (R_s^C): $R_s^C = \frac{M_s^C}{M_s^C + M_s^T}$
  - Recovery of gangue in the tailings (R_g^T): $R_g^T = \frac{M_g^T}{M_s^C + M_g^T}$
  - Grade of sulfides in the concentrate (G_s^C): $G_s^C = \frac{M_s^C}{M_s^C + M_g^C}$
  - Grade of gangue in the tailings (G_g^T): $G_g^T = \frac{M_g^T}{M_s^T + M_g^T}$
- These four numbers are almost always strictly positive and sum to one (the mass balance closure), which allows them to be treated geostatistically with compositional data analysis (CoDa) [20].
- A preliminary log-ratio transformation is applied before computing empirical variograms, which describe the spatial dependence structure of the target variables between any two locations within the study area. Direct variograms measure the loss of dependence of a variable as locations move apart, and cross variograms do the same for the co-dependence between two variables.
- Estimating this function requires assuming some form of stationarity – that the dependence structure depends on geographic distance rather than on the actual sample locations. This assumption is highly questionable in a TSF, but necessary here in the absence of a better model.
- A model was fitted from the class of power variogram models, known to account for the non-stationarities expected here. The parameters were chosen as those giving the highest correlations between observed and estimated values in a leave-one-out cross-validation routine.
- With this variogram and the available data, kriging interpolates the log ratios on a dense grid within the TSF.
- Because the transformation is invertible, the corresponding mass pulls, grades, and recoveries are computed at each grid point.
- The pipeline just described – sampling, clustering, flotation, PSM training, and geostatistical interpolation – is generic.

3.2 Results

3.2.1 Ore characterisation

In summary, Region 1, in the north of the TSF (Figure 12-a), is characterised by coarser particles and a lower sulphide grade, whereas Region 3 is characterised by finer particles and a sulphide higher grade (Figure 12-bc)

The modal composition of the composite samples, as bulk and per size class, shows that pyrite and arsenopyrite – the two most abundant sulphide minerals in all composites – have their lowest and highest grades in Region 1 (1.3 and 0.3 wt.%) and Region 3 (7.0 and 1.4 wt.%), respectively. Sphalerite, chalcopyrite, and galena are minor in all samples (<0.5 wt.%). Silicates and micas are the most important gangue minerals in all composites. While the modal composition of the different size fractions is similar among composites, the content of each size fraction differs: in Region 3, arsenopyrite and sphalerite are more abundant below 36 µm (~45%) than in the other composites (~10-20%), whereas sulphates are almost entirely above 75 µm [18].

3.2.2 Flotation behaviour by region

Flotation results are presented as mass vs. water pull curves in Figure 12-e and the selectivity of different pyrite against the silicate gangue in Figure 12-d. The recovery behaviour is rather different for each region: Region 1 shows a low mass pull with high selectivity, whereas Region 3 shows a high mass pull with low selectivity. The mass pull of Region 1 (~3 wt.%) is five times smaller than the average for the other composites (~15 wt.%), and Region 1 shows a less laden froth (lower mass pull per unit water pull). Region 3 yielded the highest mass pull and the most loaded froth (Figure **??**).

The flotation behaviour of minerals differs between Region 1 and the other composites: an selective behaviour is seen for all sulphides against silicates in Region 1. In all other regions, sphalerite is the only sulphide with selective concentration against silicates.

3.2.3 Accuracy of the particle-based separation models

The composition and mass of the flotation concentrate observed for each composite region are compared to those predicted by using the PSM trained solely with the global composite. PSM predictions are very close to experimental values for both products of all composites except the concentrate of Region 1: pyrite grades predicted (~6 wt.%) there are five times smaller than observed (~30 wt.%), while silicate and mica grades are overestimated.

Discrepancies are thus rather low, with the major errors observed for Region 1, which is attributed to its rather different flotation behaviour: the selectivity trends for sulphide recovery in Region 1 differ strongly from those of the other regions (Figure 13).

Product masses are predicted very close to observed values for all composites, indicating the suitability of the prior adjustment strategy.

3.2.4 Recovery interpolation in the TSF

The quality of mass pull predictions is good for both mineral groups in both products, indicating the suitability of the chosen strategy and variogram models (Figure 14). Predictions of sulphide grade in the tailings and of sulphide recovery to the concentrate are slightly less accurate, particularly in the northernmost part of the TSF – Region 1, as expected due to the innacuracy of PSMs for this region. Interpolations also show somewhat lower variability than the original data, because kriging smooths the data; this discrepancy is larger in the north (Region 1), suggesting that errors derive from the differences in flotation behaviour among composites. In the resulting recovery map(Figure 15), the intricate recovery patterns observed for each domain can be captured.

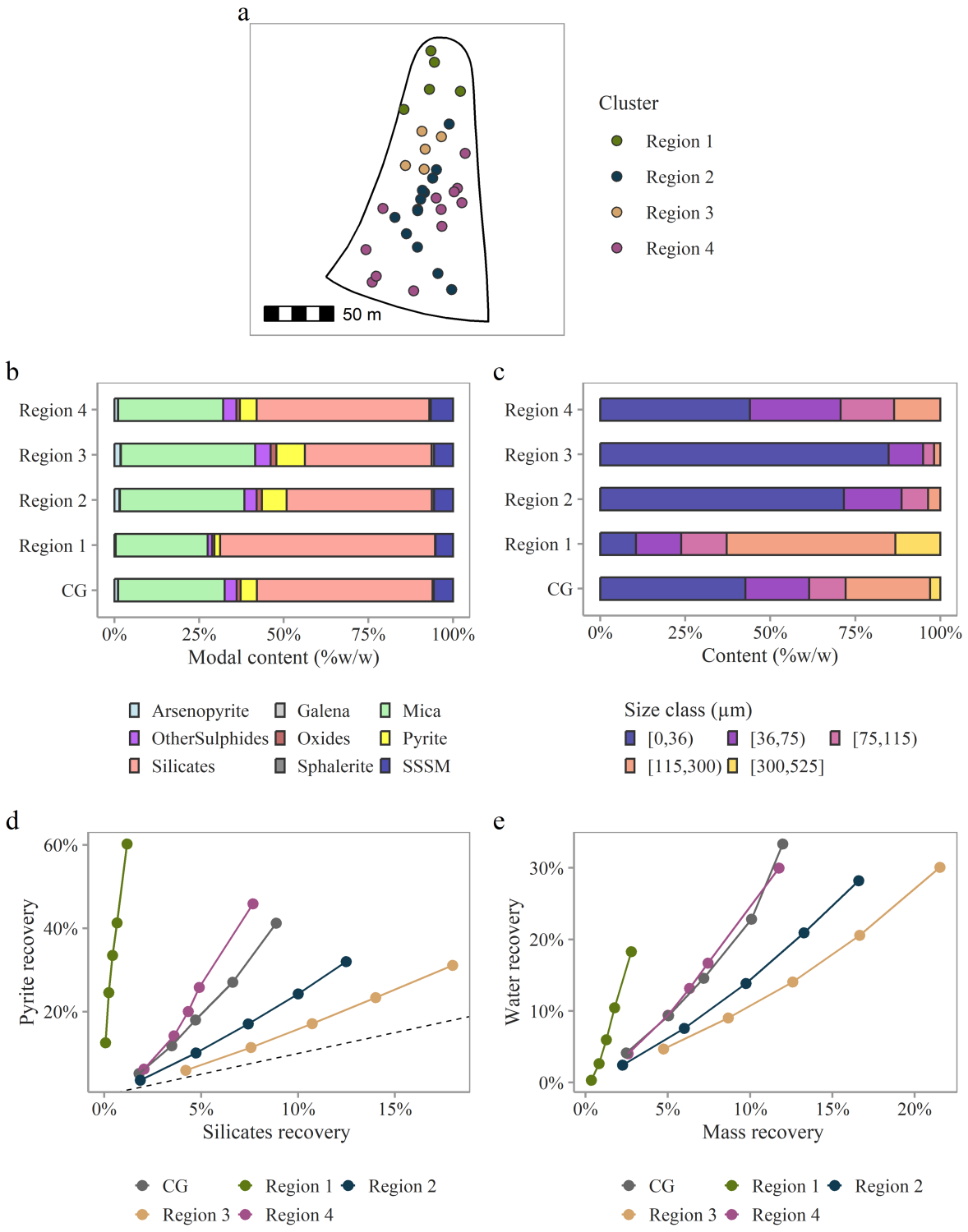

Figure 12: (a) Results of the hierarchical clusters displayed on the area of the TSF. For each region: the modal mineralogy (b), mass distribution of size fractions, obtained from MLA (c), Fuesternau plots between the recovery of pyrite and silicates (d), and the relation between water and mass recovery (e). SSSM stands for semi-soluble salt-type minerals..

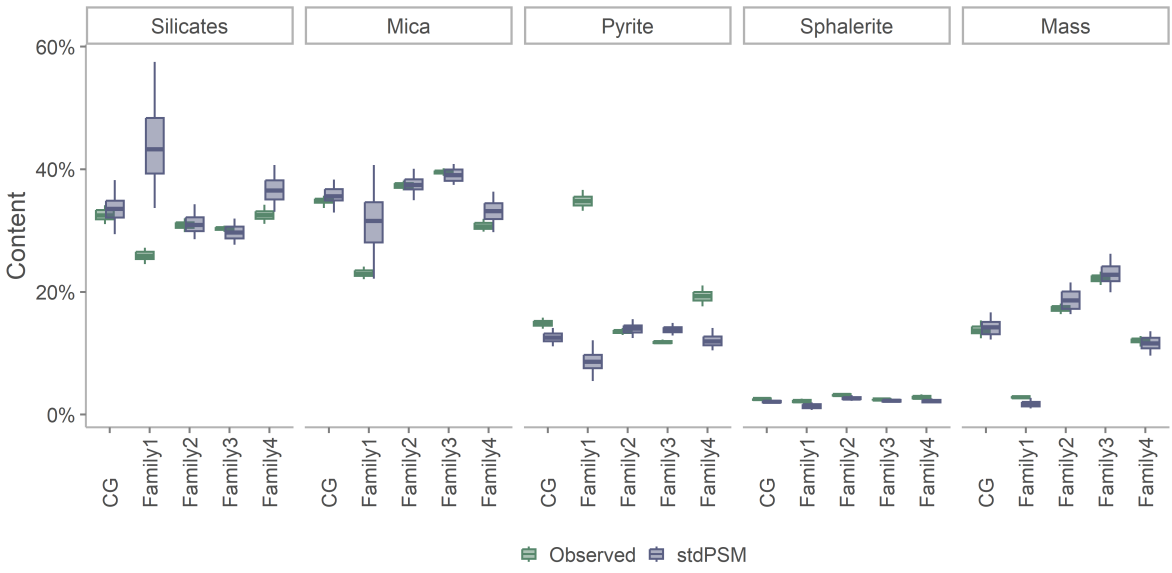

Figure 13: Accuracy of the particle-based separation models: comparison between observed and predicted composition and mass of the flotation concentrates and tailings, per region.

3.3 Geometallurgy outlook

The implementation of a recovery model for a TSF based on particle microstructures was successful: despite local incongruences, global patterns can be captured. Because the same measured particle properties feed the model, the framework can in principle be applied to any particle property of interest and not only recovery, so that a single characterisation campaign could produce a family of spatially resolved property models for the TSF. As an example, if one is concerned with the stability of a tailings storage facility, this approach could be used to forecast the particle size distribution of the remaining tailings material to be re-deposited in the body after its processing. The next step is the refinement of particle-based models to tackle issues related to variations in process mechanisms for the different regions caused by their bulk ore properties.

3.4 Conclusion

This case study introduced a new methodology to forecast the recovery potential of a tailings storage facility, combining TSF sampling, sample clustering into regions, flotation test work, automated mineralogy, PSMs, and geostatistical interpolation – a chain in which uncertainties accumulate. Errors up to the PSM step are low and indicate that a single PSM for the entire TSF is successful for all but one composite sample, extending the findings of Pereira et al. [19] on the generalisation performance of PSMs: PSMs can predict the process outcome of samples not used in training even for flotation, where particle-particle interactions are expected, as long as flotation mechanisms are not extremely different. Here, bulk sample properties seem to control the overall flotation behaviour, with selectivity negatively correlated with the content of fine particles; informing PSMs with bulk sample properties could help overcome this limitation. Interpolation errors are also low for all regions but the northernmost one, although these cannot be validated experimentally as the TSF is not being remined. The methodology can thus forecast the recovery potential of a TSF with a minimal number of tests, although testing each region is currently required for the prior adjustment; a single prior adjustment would reduce this to the global composite alone. More broadly, the recovery model was implemented successfully from particle microstructures, global patterns were captured despite local incongruences, and the approach can be extended to the recovery of particles of any type and, in principle, to any particle property of interest.

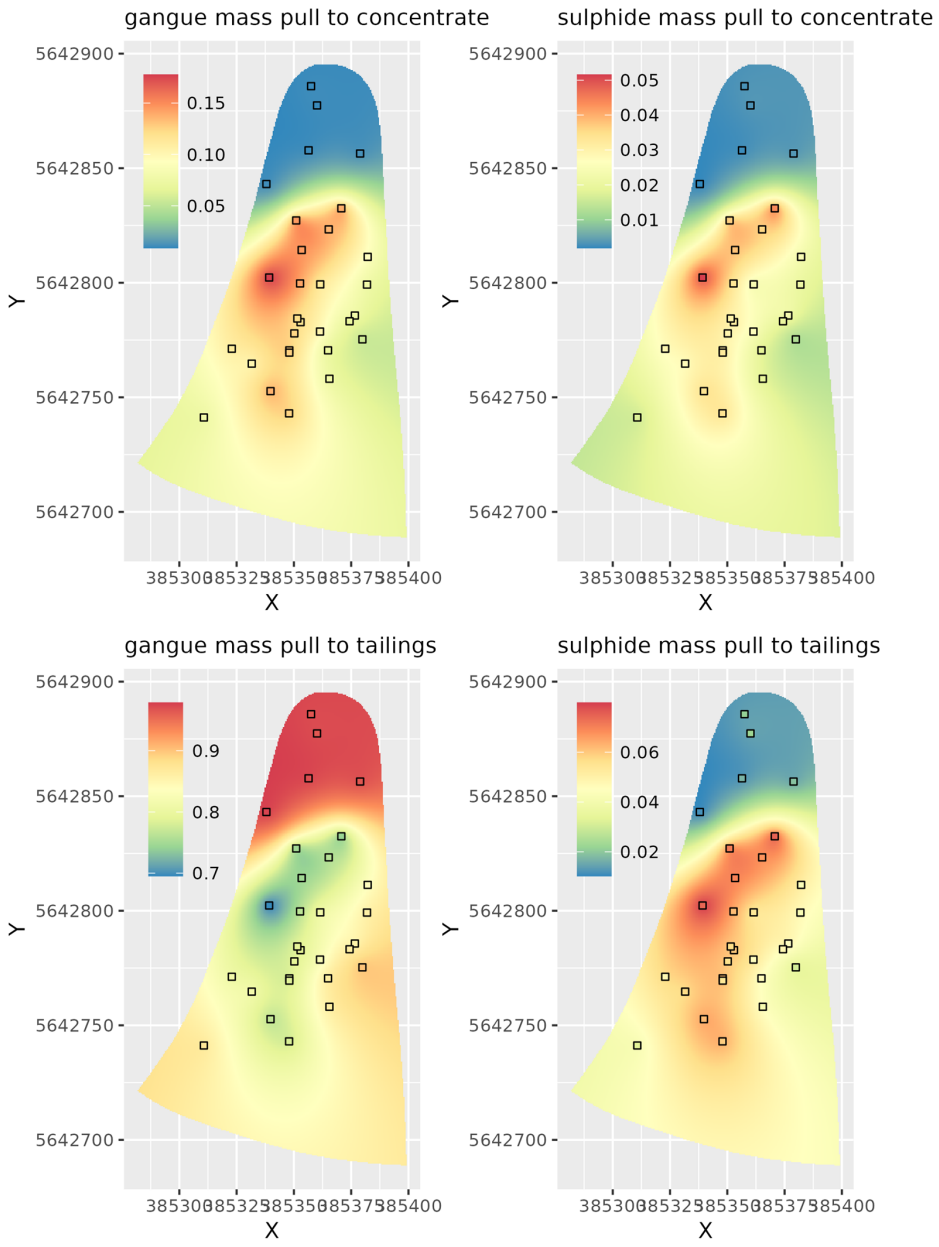

Figure 14: Predictions of the mass pulls of sulfides and gangue to concentrates and tailings throughout the TSF. Colored squares represent the values quantified with the particle-based separation models for each sample

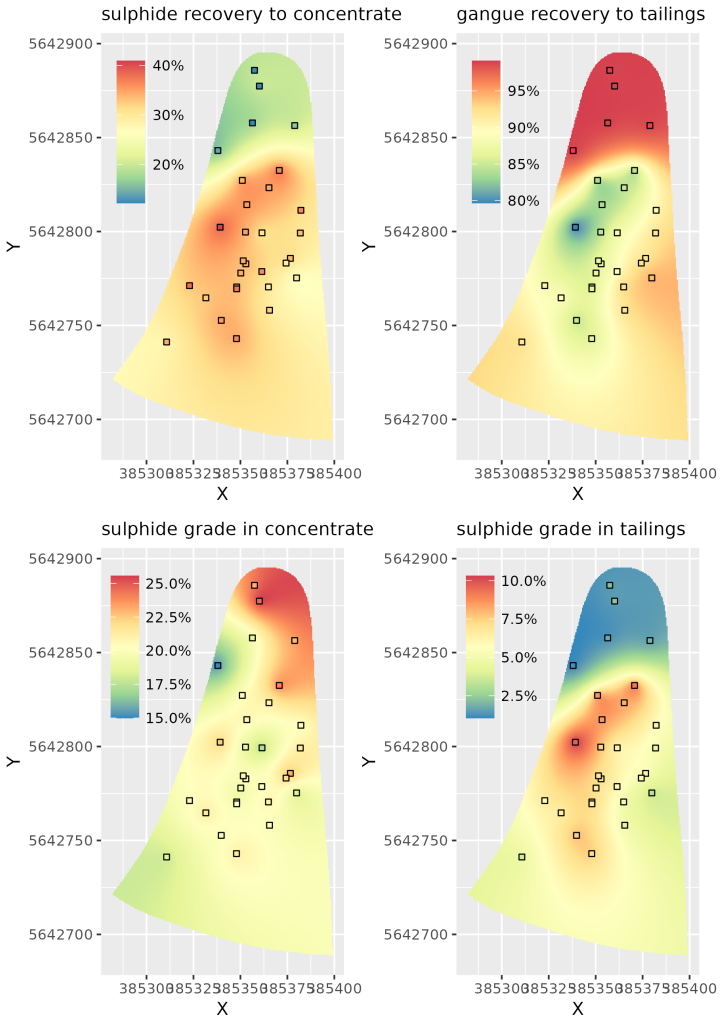

Figure 15: Predictions of sulfides and gangue grades in the concentrates and tailings throughout the TSF. Colored squares represent the values quantified with the particle-based separation models for each sample.

4 Discussion and Conclusion

The two case studies were chosen to showcase the following proposition: automated mineralogy already provides, at routine cost, the full-resolution particle information needed to predict and explain how mineral processing behaves, and that most of this value is discarded when the data are reduced to bulk descriptors. Both studies support this proposition, and together they show that the benefit is not confined to a particular commodity, circuit, or problem.

At Kansanshi, PSMs trained on the routinely collected TIMA data reproduced the mixed circuit's copper, silica, and sulphur grades and recoveries within the confidence intervals of the observations, and a single model pooled across all weeks performed comparably to models trained on each week separately, supporting deployment in daily operations. Beyond forecasting, the same full particle data exposed the complex recovery behaviour of different minerals: the reduced recovery of non-stoichiometric phases relevant to long-term stockpile storage, and the ability of minute copper-bearing inclusions to render otherwise barren silicate and carbonate particles floatable. That last result points out to rethinking automated mineralogy routines: when mineral phases are grouped, or when only bulk liberation is reported, the small copper hosts that decide whether a particle floats disappear from the analysis, and with that the convergence to the mean masks meaningful plant troubleshooting guides.

At Davidschacht, the same principle was taken a step further, from forecasting a single product stream to forecasting an entire deposit. A single PSM, trained on the products of one global composite, was coupled with geostatistics to produce a spatially resolved recovery model of a historical TSF from a handful of bench tests. The accuracy was good for all but one region, and that exception should be used to rethink routines for geometallurgical modelling – an unique flotation mechanism was observed due to variations in bulk ore properties in a minute region of the deposit. If flotation trials were only performed on the global composite, or on the *most representative samples* of the deposit, this behaviour and the consequent modelling limitation would have been masked.

Placed side by side, the studies delineate what the full use of particle data can achieve. First, it unifies forecasting and diagnosis within one framework: the same model that predicts a metallurgical key performance indicator also attributes recovery and loss to specific particle types. Second, it makes the particle – not the element, the mineral, or the sample – the unit of analysis, which matches the reality that beneficiation processes operate on particles and their properties (Figure 1) [16]. Third, because the model is expressed in terms of measured particle properties, its logic is extendable. The same pipeline can be re-targeted to another particle property of interest – for instance the particle size distribution of the material to be re-deposited in a TSF – and not only to the recovery of a single target mineral/element. Together, these properties describe predictive geometallurgy in which decisions, from daily circuit control to facility-scale remining appraisal, rest on particle microstructures rather than on averages [5].

It is also important to discuss the limits to outline the work to be done in the near future. The current implementation of PSMs assume that a particle's fate depends only on its own microstructural properties and do not represent particle-particle interactions, so they remain reliable only while the governing process mechanisms do not change. Besides, in order to change into more predictive rather than reactive plant operations, PSMs should incorporate processing parameters in their structure – finally allowing for process optimization as a function of the unique microstuctures of each ore type. In conclusion, automated mineralogy is a key characterisation tool for predictive and diagnostic geometallurgy as long as its full particle datasets are exploited.

Acknowledgements

The author thanks the Kansanshi, Erzlabor, and Helmholtz Institute Freiberg for Resource Technology (HIF) teams for their collaboration and support. The Kansanshi study was carried out with Charles Chunda, Michele Giorno, and Lucy Little, while the Davidschacht TSF study was carried out with Silum Ghebreyesus, Max Frenzel, Duong H. Hoang, Martin Rudolph, Gerald van den Boogaart, Jens Gutzmer, and Raimon Tolosana-Delgado – their contributions are gratefully acknowledged. The author also thanks the German Fed-

eral Ministry of Research, Technology and Space for funding the PURE Project (Grant number 03G0948A) under the EGARoh_Junior funding scheme – the funding was fundamental for this contribution.

References

[1] Natalia Araya, Andrzej Kraslawski, and Luis A. Cisternas. "Towards Mine Tailings Valorization: Recovery of Critical Materials from Chilean Mine Tailings". In: *Journal of Cleaner Production* 263 (Aug. 1, 2020), p. 121555. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2020.121555. URL: https://www.sciencedirect.com/science/article/pii/S0959652620316024 (visited on 01/28/2024).

[2] Rosie Blannin et al. "Towards a Sampling Protocol for the Resource Assessment of Critical Raw Materials in Tailings Storage Facilities". In: *Journal of Geochemical Exploration* 236 (May 1, 2022), p. 106974. ISSN: 0375-6742. DOI: 10.1016/j.gexplo.2022.106974. URL: https://www.sciencedirect.com/science/article/pii/S0375674222000322 (visited on 01/15/2024).

[3] Rosie Blannin et al. "Uncertainties in Quantitative Mineralogical Studies Using Scanning Electron Microscope-Based Image Analysis". In: *Minerals Engineering* 167 (June 15, 2021), p. 106836. ISSN: 0892-6875. DOI: 10.1016/j.mineng.2021.106836. URL: https://www.sciencedirect.com/science/article/pii/S0892687521000650 (visited on 01/07/2024).

[4] Rolf Fandrich et al. "Modern SEM-Based Mineral Liberation Analysis". In: *International Journal of Mineral Processing* 84.1–4 (Oct. 2007), pp. 310–320. ISSN: 03017516. DOI: 10.1016/j.minpro.2006.07.018. URL: https://linkinghub.elsevier.com/retrieve/pii/S0301751606001621 (visited on 11/01/2021).

[5] Max Frenzel et al. "Geometallurgy: Present and Future". In: *Elements* 19.6 (Dec. 1, 2023), pp. 345–351. ISSN: 1811-5217, 1811-5209. DOI: 10.2138/gselements.19.6.345. URL: https://pubs.geoscienceworld.org/elements/article/19/6/345/632498/Geometallurgy-Present-and-Future (visited on 01/07/2026).

[6] Paul Gottlieb. "The Revolutionary Impact of Automated Mineralogy on Min- Ing and Mineral Processing". In: (), p. 10.

[7] Ying Gu. "Automated Scanning Electron Microscope Based Mineral Liberation Analysis An Introduction to JKMRC/FEI Mineral Liberation Analyser". In: *JMMCE* 02.01 (2003), pp. 33–41. ISSN: 2327-4077, 2327-4085. DOI: 10.4236/jmmce.2003.21003. URL: http://www.scirp.org/journal/PaperDownload.aspx?DOI=10.4236/jmmce.2003.21003 (visited on 11/01/2021).

[8] Ying Gu, Robert P. Schouwstra, and Chris Rule. "The Value of Automated Mineralogy". In: *Minerals Engineering* 58 (Apr. 2014), pp. 100–103. ISSN: 08926875. DOI: 10.1016/j.mineng.2014.01.020. URL: https://linkinghub.elsevier.com/retrieve/pii/S0892687514000302 (visited on 11/01/2021).

[9] T Heinig et al. "Monitoring Gravitational and Particle Shape Settling Effects on MLA Sampling Preparation". In: *IAMG Conf. 2015*. 2015, pp. 200–206. ISBN: 978-3-00-050337-5.

[10] Päivi H. -M. Kinnunen and Anna H. Kaksonen. "Towards Circular Economy in Mining: Opportunities and Bottlenecks for Tailings Valorization". In: *Journal of Cleaner Production* 228 (Aug. 10, 2019), pp. 153–160. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2019.04.171. URL: https://www.sciencedirect.com/science/article/pii/S0959652619312508 (visited on 01/28/2024).

[11] L. Little et al. "Relationship between Ore Mineralogy and Copper Recovery across Different Processing Circuits at Kansanshi Mine". In: *Journal of the Southern African Institute of Mining and Metallurgy* 118.11 (2018), pp. 1155–1162. ISSN: 2225-6253. DOI: 10.17159/2411-9717/2018/v118n11a5. URL: https://www.scielo.org.za/scielo.php?pid=S2225-62532018001100007&script=sci_abstract.

[12] Norman O. Lotter. "Modern Process Mineralogy: An Integrated Multi-Disciplined Approach to Flowsheeting". In: *Minerals Engineering*. Special Issue : Process Mineralogy 24.12 (Oct. 1, 2011), pp. 1229–1237. ISSN: 0892-6875. DOI: 10.1016/j.mineng.2011.03.004. URL: https://www.sciencedirect.com/science/article/pii/S0892687511000938 (visited on 01/07/2024).

[13] Lucas Pereira et al. "A new approach to understanding how particle characteristics drive copper recovery at Kansanshi Mine." In: *Flotation 25*. Flotation 25. Cape Town, South Africa: MEI, 2025.

[14] Lucas Pereira et al. "A New Particle-Based Approach to Process Modelling and Diagnostics". In: Procemin-Geomet. Santiago, Chile, 2019, p. 9.

[15] Lucas Pereira et al. "A Self-Adaptive Particle-Tracking Method for Minerals Processing". In: *Journal of Cleaner Production* 279 (Jan. 2021), p. 123711. ISSN: 09596526. DOI: 10.1016/j.jclepro.2020.123711. URL: https://linkinghub.elsevier.com/retrieve/pii/S0959652620337562 (visited on 10/26/2021).

[16] Lucas Pereira et al. “All About Particles: Modelling Ore Behaviour in Mineral Processing”. In: *Elements* 19.6 (Dec. 1, 2023), pp. 359–364. ISSN: 1811-5209. DOI: 10.2138/gselements.19.6.359. URL: https://doi.org/10.2138/gselements.19.6.359 (visited on 08/21/2025).

[17] Lucas Pereira et al. “Computing Single-Particle Flotation Kinetics Using Automated Mineralogy Data and Machine Learning”. In: *Minerals Engineering* 170 (Aug. 2021), p. 107054. ISSN: 08926875. DOI: 10.1016/j.mineng.2021.107054. URL: https://linkinghub.elsevier.com/retrieve/pii/S0892687521002831 (visited on 10/26/2021).

[18] Lucas Pereira et al. “Forecasting the Recovery Potential of a Tailings Storage Facility with Particle-Based Separation Models”. In: *Int. Miner. Process. Congr.* International Mineral Processing Congress. Washington, DC: International Mineral Processing Council, 2024.

[19] Lucas Pereira et al. “Testing the Robustness of Particle-Based Separation Models for the Magnetic Separation of a Complex Skarn Ore”. In: *Int. J. Min. Sci. Technol.* (2022). ISSN: 2095-2686. DOI: 10.1016/j.ijmst.2022.01.008. URL: https://www.sciencedirect.com/science/article/pii/S2095268622000088.

[20] Raimon Tolosana-Delgado, Ute Mueller, and K. Gerald van den Boogaart. “Geostatistics for Compositional Data: An Overview”. In: *Math Geosci* 51.4 (May 1, 2019), pp. 485–526. ISSN: 1874-8953. DOI: 10.1007/s11004-018-9769-3. URL: https://doi.org/10.1007/s11004-018-9769-3 (visited on 06/12/2023).