The novel application of continuous wavelet tessellation and data mosaic method to assess relationships between material fingerprints and time series plant response actuals at Tropicana gold mine

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Geochemical and mineralogical datasets collected from grade control drilling and blast hole samples at AngloGold Ashanti and Regis Resources' Tropicana Gold Mine in Australia were subjected to agglomerative hierarchical clustering to derive distinct material endmember 'fingerprints'. A forward simulator stockpile model, corrected for blending effects, was utilised to derive a temporal reconciliation of the crusher input feed composition (as time series) before a novel application of continuous wavelet tessellation and data mosaic method were applied to link crusher feed attributes to the actual plant performance (comminution and leaching). The resulting domains showed material variability at different scales and were used to analyse the corresponding metallurgical behaviour. Variability observed at strategic levels matched distinct modes of processing, whereas at the tactical resolution, this related to the minor scale variability in the processed blend composition. It was thus demonstrated that material fingerprints could be used to understand the impact of geological variability on metallurgical plant performance.

INTRODUCTION

The behaviour of mineral processing is a response to the complex interaction of primary rock attributes, such as chemical composition, mineralogy, texture, and fracturing (Dominy *et al.*, 2018; Guntoro, 2019; van Duijvenbode and Buxton, 2019). Optimisation of the mining beneficiation process is an important area for sustainable value creation and cost reduction across many mining operations (e.g., Hoal and Frenzel (2022); Mining Modular (2017)). To achieve this, mine sites require improvements in the ability to spatially characterise material as it moves through the reconciliation chain. This will enable them to effect process control in which geochemical, mineralogical, comminution, recovery and reagent consumption attributes are considered. However, the approach to unlocking full value using these geometallurgical considerations is complex and extensive, and no comprehensive method yet exists to effectively link separate geometallurgical components and datasets.

Machine performance optimisation in comminution circuits is increasingly important to mining companies since crushing and grinding units are among the most energy demanding machines whose high operating expense accounts for up to 4% of global energy consumption (de Bakker, 2013; Bortnowski *et al.*, 2021; Jeswiet and Szekeres, 2016). Concurrently, a non-optimal leach process will lower the extraction potential of gold and thus have a direct impact on the mine's revenue. Processing plants therefore require high yields, low operating costs and high efficiency to ensure profitability. Consequently, optimisation of the blend itself, as well as matching specific processing conditions becomes essential. To this end, it is important to first understand how geology impacts metallurgical plant performance. Logically, if variable geological behaviour becomes better understood, then machine performance can also be understood, controlled, and optimised.

There are many factors that can influence a plant's metallurgical performance. For instance, Both and Dimitrakopoulos (2021) showed evidence that for the Tropicana Gold Mine in Australia, processing typically harder material corresponds to a lower throughput while feeding softer material allows higher throughputs to be achieved. Other factors that may affect ore processing characteristics include volumes that are silicified, clay rich, sheared, and/or have internal dilution (Hoal and Frenzel, 2022). There are also many possible reasons for poor gold extraction by leaching, for instance, poor gold grain exposure due to insufficient grinding efficiency, variability in gold speciation, complex gangue mineralogy including cyanide and oxygen consumers (arsenic, sulphides), other deleterious minerals (clay) or coarse gold which requires longer retention times (Coetzee *et al*., 2011). Most of these factors are easily detectable pre-mining and early characterisation of material types that possess these, or similar attributes is definitely possible. However, relating defined material endmembers and/or blends to the complex mix of corresponding response variables measured at different scales, across a range of different processing steps is a non-trivial undertaking.

This paper briefly recaps various aspects of material type (fingerprints) characterisation but primarily focuses on how these fingerprints are actually linked with processing indicators. The paper presents a novel material tracking simulation model and application of a continuous wavelet tessellation (CWT) and data mosaic method. The tracking model is designed to replicate ore movements from the pit to the stockpile and crusher which facilitates discovery of relationships (using the CWT and data mosaic) that may exist between the crusher input feed, the mill and leach circuit processing responses. Results presented are based on data from the Tropicana Gold Mine, Australia.

TROPICANA GOLD MINE

The Tropicana Gold Mine (TGM) project is located 330 km east-northeast of Kalgoorlie-Boulder on the western edge of Western Australia's Great Victorian Desert (Figurea). The project is currently 70% owned by AngloGold Ashanti Australia Ltd and 30% by Regis Resources Ltd. As of December 2022, more than 4 Moz of Au have been produced and an estimated further 70.52 Mt grading 1.83 g/t Au for 4.15 Moz of gold remains as Exclusive Mineral Resource, while 36.70 Mt grading 1.78 g/t Au for 2.10 Moz remains as Mineral Reserve (AngloGold Ashanti Limited, 2023).

The Tropicana mineralisation extends over a total strike length of >7km, with a shallow dip (~30 °) to the SE and extends at least ~1.5 km down dip but remains open at depth. Initial open pit mining commenced in 2012 and has since transitioned to include underground mining at the Boston Shaker zone. Exploration for both potential openpitable and underground ore zones remains ongoing.

Within the processing plant, mineralised ore is reduced to ~75µm via a primary and secondary crushing circuit; equipped with high-pressure grinding rolls and a ball mill. The final slurry is thickened, and gold is extracted using a carbon-in-leach recovery circuit with a capacity of between 8-9 Mtpa (AngloGold Ashanti and Independence Group NL, 2010; Kent *et al*., 2014).

Geology

The TGM is situated in the Plumridge Terrane, a zone that separates the in situ eastern margins of the Archaean Yilgarn craton from the Albany-Fraser orogen (AFO), Western Australia, see Figure 1a (Crawford and Doyle, 2016). The AFO is a NE trending arcuate Neoarchaean – Mesoproterozoic orogenic belt and defines the SE extends of the West Australian Craton (Occhipinti *et al*., 2018). The AFO belt is divided into several fault-bound zones (Figure 1a), characterised by distinct lithologies and tectonic history.

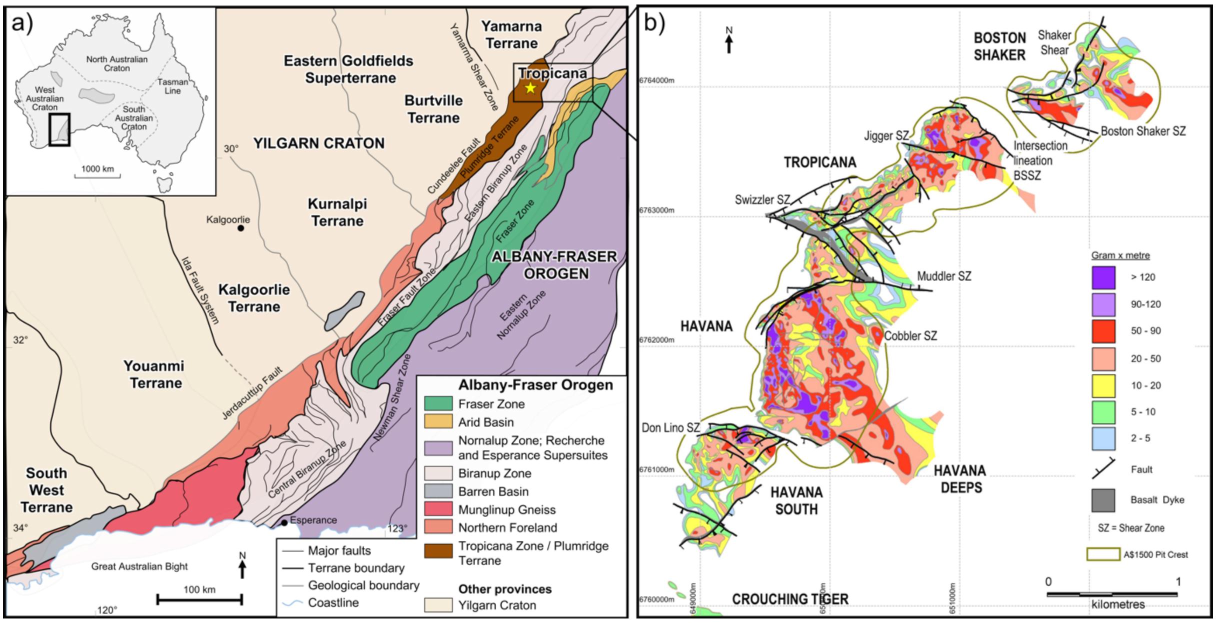

Figure 1. a) Geological map of the Albany-Fraser Orogen with respect to the eastern margin of the Yilgarn Craton, Western Australia, showing the location of the Tropicana gold deposit, modified after Spaggiari et al., *(2011); b) Structural domains and shear zones superimposed on a grade (g/t) x thickness (m) plot, modified after Blenkinsop and Doyle (2014).*

The Plumridge Terrane lithologies dominantly comprise Archaean crust (2.7 Ga) and is strongly modified by amphibolite- to granulite-facies grade metamorphism (Doyle *et al.*, 2015). These mineralised zones occur as one or two laterally extensive planar lenses with a moderate dip.

Most economic gold mineralisation occurs within high gold grade shoots, including the southeast plunging mineralised zones at Boston Shaker, Tropicana NE, Havana and Havana South (Figure 1b). The favourable host to mineralisation is a preferentially deformed feldspathic gneiss facies (Crawford and Doyle, 2016). Higher-grade mineralisation relates with a more perthitic K-feldspar lithology, whereas the more common plagioclase-rich feldspathic gneisses are associated with lower gold grades. The hanging wall is a predominantly thick and continuous garnet-bearing amphibolite unit with subordinate meta ferruginous chert. Post-mineralisation tholeiitic dolerite dykes typically crosscut and stope out the mineralisation (causing ore body dilution).

Additionally, some pre- to syn-mineralisation mafic alkaline intrusions occur in contact with mineralised horizons within Havana-Havana South (Roache, 2020). Both the gneissic lithologies and dykes have been overprinted by pervasive alteration and deformation, mainly related to biotite-pyrite rich shear zones, which occur sub-parallel to the regional gneissocity. The regional gneissic banding is typically observed in the core and is associated with the alignment of framework minerals (Blenkinsop and Doyle, 2014).

MATERIAL FINGERPRINTING

The material fingerprinting concept as advanced by the authors is fundamental to ultimately relating changes in material characteristics to processing response and has been detailed in several recent journal articles (van Duijvenbode *et al.*, 2020, 2022a, 2022b) and conference proceedings (van Duijvenbode *et al.*, 2019, 2021). The main approach follows a three-step process as outlined in Figure 2 and is briefly described in the following sections. The reader is also referred to the co-author's thesis (van Duijvenbode, J. R., 2023) for more information about each step.

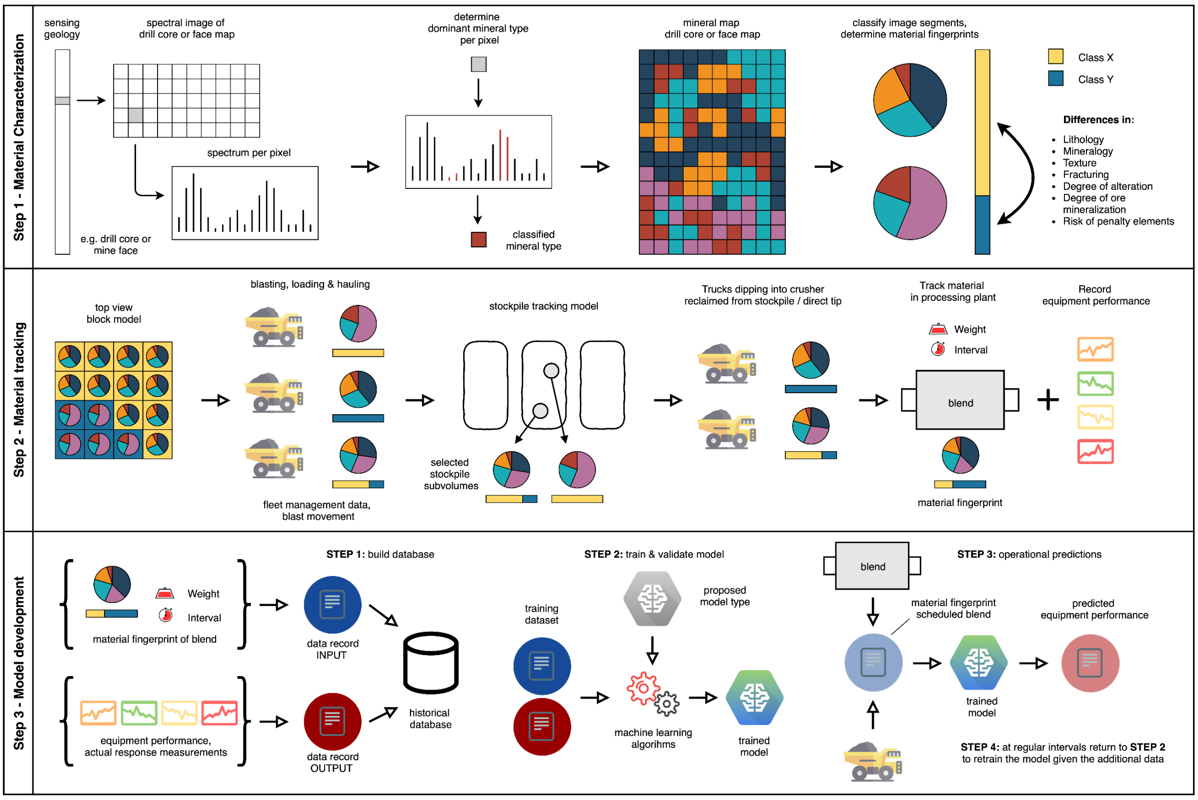

Figure 2. Material fingerprinting concept overview, after M. W. N. Buxton and T. Wambeke (pers. comm).

Material Characterisation

This first step relies on agglomerative hierarchical clustering of geochemical, mineralogical and (geo)physical datasets collected from grade control drilling and blast hole samples in order to derive distinct material endmember 'fingerprints'. As illustrated in Figure 3, distributed measurements of a range of material attributes, at a given time and location, serve to uniquely identify the material class or blended class proportions; as realistically, the fingerprint composition changes in each phase (dilution, blending, etc.).

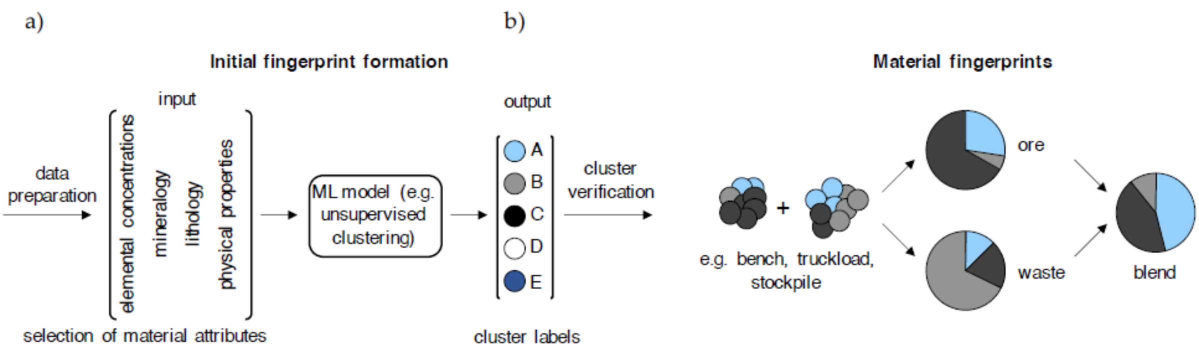

Figure 3. An example where initial fingerprint formation is done through unsupervised clustering. Clustering generates potential cluster or class labels and may act as training data input for another machine learning model, which can characterise new fingerprints from measured material attributes; b) An example where three (A, B, C) class outputs are used to explain proportionality of classes. The proportionality of classes allows the formation of fingerprints that characterise ore, wastes or blend types.

Aside from validating the resulting material classes against historical lithological discrimination (logging) which was found to effectively support the classification, several case studies (van Duijvenbode *et al*., 2022a, 2022b) were also presented to demonstrate that:

1) Although the clustering itself did not consider the Au concentration as a variable, the geochemical signatures of the resulting classes were distinct enough for economically mineralised and unmineralised material to be discriminated.
2) Material fingerprinting could be used to demonstrate a link between rapidly acquired geochemical, mineralogical and hardness data (BWi, Axb, Equotip and penetration rate) of various material types. The fingerprints function as proxies for the constitutive material hardness properties and provide a more comprehensive understanding of comminution behaviour.
3) Clustered material types may be used to study between and within material type variability attributed to the elevation/depletion of geochemical concentrations, absence/presence of minerals, spectral features, hardness proxies and spatial contextual relationships and reveal new insights regarding the effects of alteration on material attributes.

Material Tracking

This second step involves effective tracking of fingerprinted material using a combination of the mine's fleet management system (Caterpillar, 2020; Mining Modular, 2017) and a stockpile build/reclamation model. The model (Figure 4) tracks the flow of material through the stockpile and then enables the reconciliation of fingerprints throughout the unit operations of a mining cycle, thus informing on changes in the crusher feed composition and attributes over time.

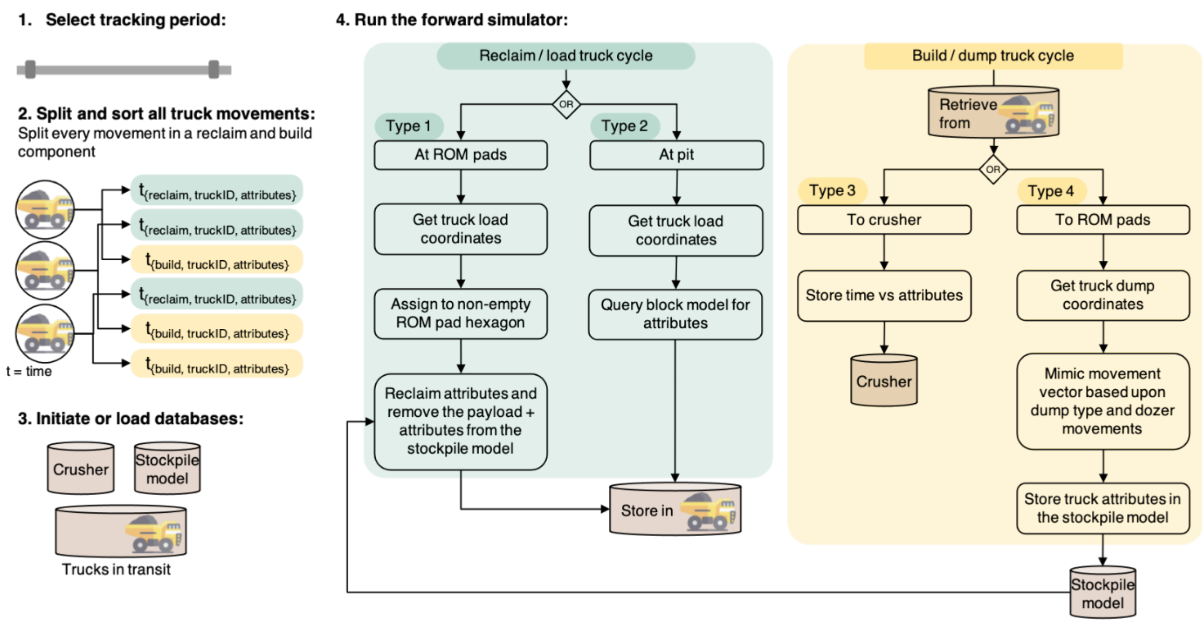

Figure 4. Schematic representation of the material tracking forward simulator. Only showing ore handling processes.

Using material tracking simulation, it was possible to identify and characterise all crusher dumps (stored in the crusher database). There were almost 295,000 crusher dumps in the six years considered. The crusher feed attributes are equal to the set of parameters tracked from the block models. Firstly, all dumps were grouped with a frequency of 12 hours and the observed payload, and its attributes, were adequately composited. A frequency of 12 hours was selected as this matched the resolution of the processing actuals. The total payload was the sum of all individual dumps; the density, geochemical attributes (Au, Al, Ca, Cr, Fe, K, Mn, Nb, Pb, S, Si, Sr, Ti, Zn and Zr) and mineralogical attributes (wAlOH, biotite abundance, wFeOH, w605) were expressed using a weighted average with the payload as weight; for the generic material attributes, including the penetration rate, Equotip hardness, BWi, Axb, recovery, lime consumption and NaCN consumption the median value was taken. Most of these attribute indices are non-additive in nature, and therefore the median was found more appropriate than the mean.

Secondly, the information contained in the 12-hour intervals was used to calculate a seven-day moving average of the crusher feed attributes to reduce noise in the time series dataset (Figure 5); values are rescaled with zero mean and standard deviation of one. This helps to identify periodical trends of higher and lower attribute values that are more likely linked to rock properties of the material processed. Each attribute is a moving average using fourteen consecutive 12-hour observations (seven days) calculated with a minimum of six observations (three days).

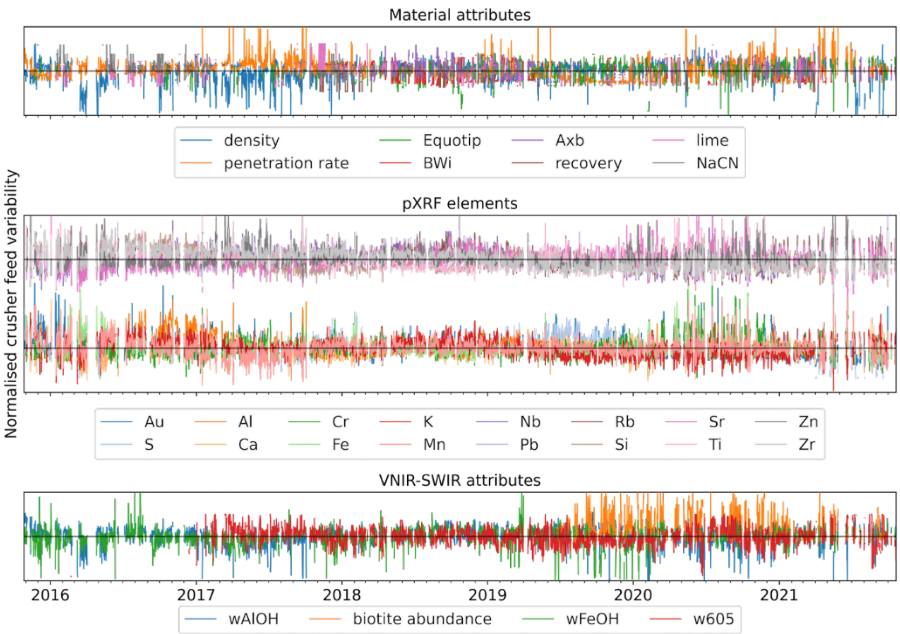

Figure 5. Time series data visualisation of the seven-day moving averages for each tracked crusher feed attribute.

As an alternative to the individual crusher feed attributes (Figure 5), it was also possible to directly express the feed composition as proportions of the clustered material types (Figure 6). For this, the proportion of each material type within the geometallurgical domains was defined and applied to each truck payload leaving a specific domain. Then, the proportion of each material type's payload defines the new input fingerprint and should reflect mining of different domains, different blends and thus resulting in different crusher feed compositions. These material type proportions also function as data input as used in the next section.

Validation of the tracking model was done using the actual logged crusher tonnes and visual inspection of the stockpile attribute maps. Spatial-temporal modelling and visualisations of the tracking data (Figure 7) show realistic geological variability and spatial cohesion and enable its temporal reconciliation.

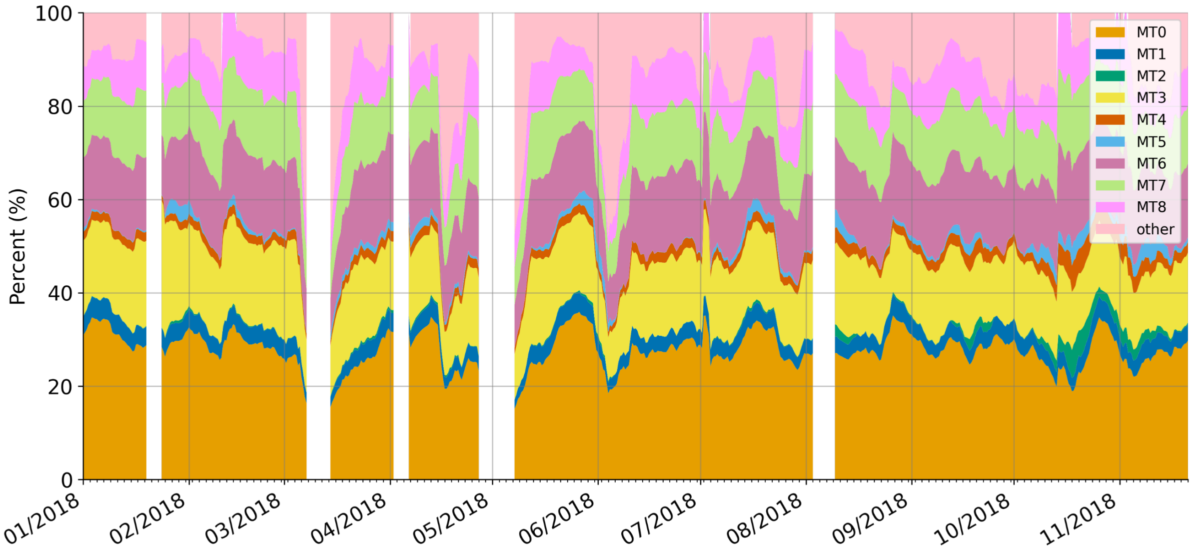

Figure 6. Material type (MT) proportions as a function of the crusher feed over time.

Furthermore, it is observed that there is a minor difference in the tracked payload and visual configuration of the actual and modelled stockpiles. The model captured truck movements with great detail, indicated by the variability observed in the material attributes distribution and the observed material attribute variability can reliably be traced back to the source location.

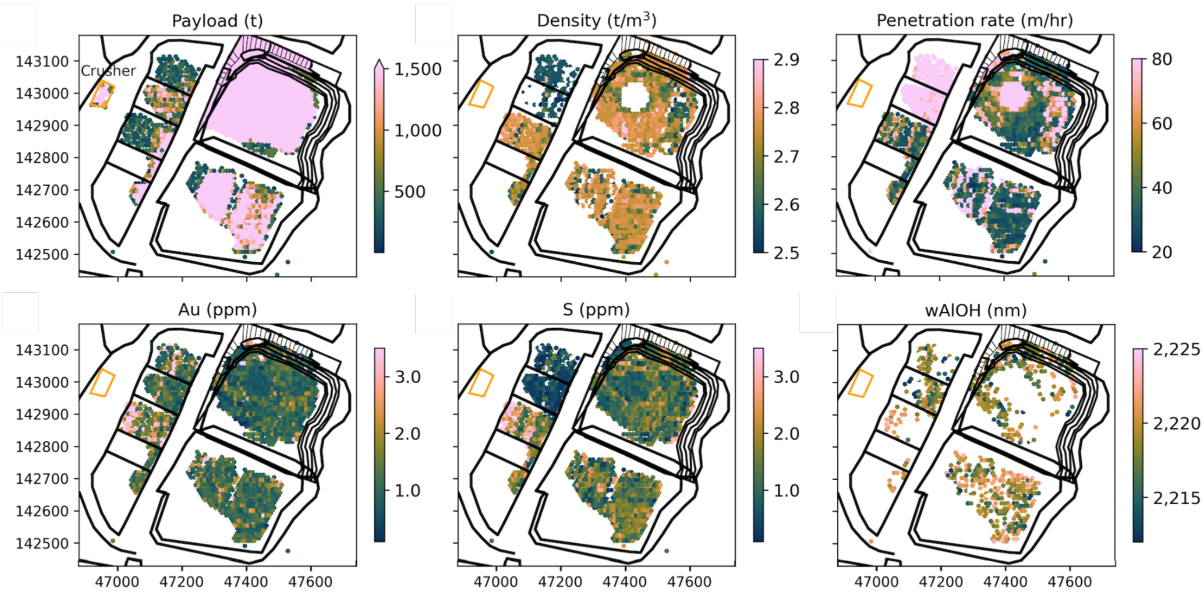

Figure 7. ROM pad overview showing selected physical (payload, density, penetration rate), geochemical (Au, S) and mineralogical (wAlOH) variables; stockpiles state at 07-03-2019 (local mine grid coordinates).

Correlation with Processing Performance

In the final step, the crusher feed attributes, defined in the previous step, were linked to the actual plant performance to identify which and in which manner specific geological features affect the comminution and leach behaviour. The continuous wavelet tessellation and data mosaic method (Figure 8), as implemented for the interpretation of down-hole univariate and multivariate data by Hill *et al.*, (2020), was identified as a suitable means since this method applies a multiscale and multivariate analysis that transforms the time series signals into continuous temporal domains consisting of samples of similar fingerprints.

The wavelet transform is based upon the idea that a particular wavelet shape will capture the signal variation by applying a wavelet scaling and shifting approach. The scaling will stretch or shrink the signal in time by the scaling factor, where the stretched wavelets capture slow changes and shrunken wavelets capture abrupt changes in the signal. Then, the shifting translates the differently-scaled wavelets from the beginning to the end of the signal (Cooper and Cowan, 2009; Hill *et al.*, 2021; Torrence and Compo, 1998; Witkin, 1983). The benefit of using the CWT is that it provides multiscale results by effectively smoothing the signal to simulate larger time frames as the wavelet scale increases (Hill *et al.*, 2021). Boundary strength is used as a measure of scale in the multiscale domains and the location of the zero contour on the CWT at the smallest scale is used to estimate the depth of the boundary. The strength and depth are combined to form domains which can be coloured by the signal median or mean value from the samples within the domain (Hill *et al.*, 2021).

Mosaic plots and pseudo-logs (horizontal slices) are generated as part of the final analysis of these results. Domains are grouped together using agglomerative hierarchical clustering, which groups domains with similar input signal characteristics and allows for comparison of the metallurgical plant response to corresponding fingerprints. The data visualisation provided by the classified mosaic plots also offers an intuitive display of multiscale analysis and variability that can be evaluated at different scales aligned to various strategic and tactical geometallurgical objectives.

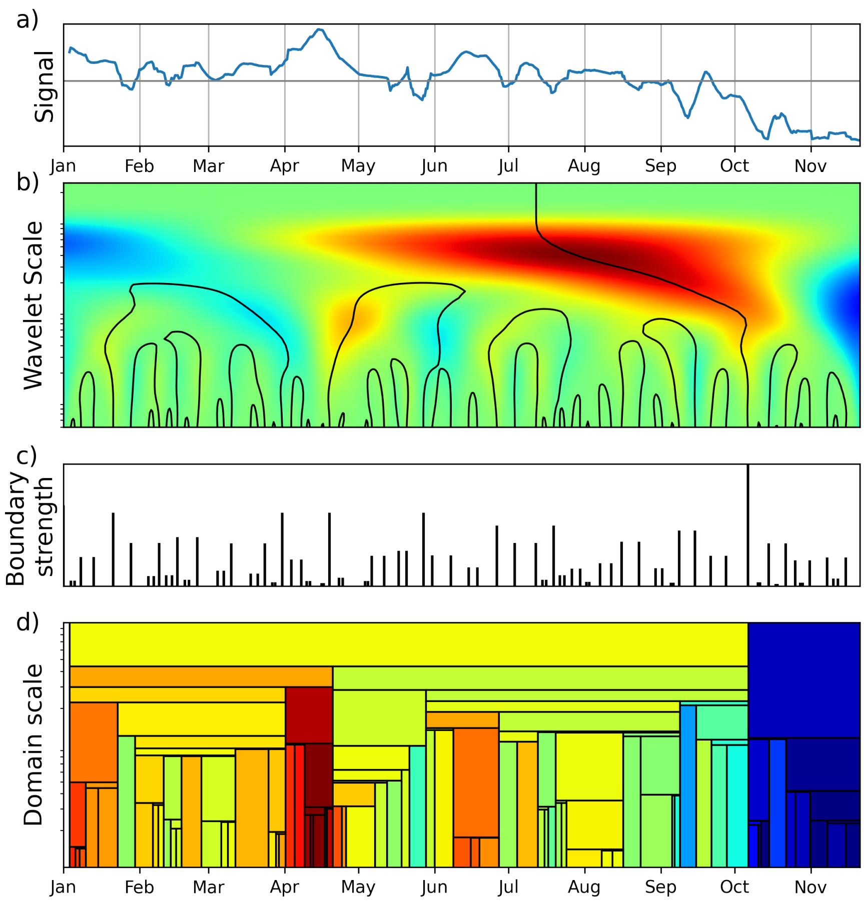

Figure 8. Workflow for tessellation and data mosaic for a time series signal: a) input signal; b) continuous wavelet transform, colours are first derivative wavelet coefficients (blue, low; red, high), black lines are zero contours of the second derivative; c) time-corrected boundaries from CWT; and d) tessellation the boundary location and strengths. The colours are the mean values of the samples in the domain (blue, low; red, high).

Pseudo-logs taken at different domain scales can be used to determine whether the observed variability is deterministic for strategic or tactical decision-making and inform on targeted variability/optimisation opportunities. These different scales might even be considered in establishing aspirational targets for either strategic or tactical optimisation initiatives and could also serve to inform on the required scale at which subsequent optimisation models should be developed.

RESULTS

Material type (fingerprint) proportions, for a given period (here Period 1 – 2018, similar to Figure 6), were used as input for boundary detection via the multiscale wavelet tessellation method. Material type proportions were interpolated at periods without data. These domains correspond to shutdown periods and can thus be ignored. The resultant mosaic plot, produced using wavelet tessellation, is shown in Figure 9, where each domain corresponds to a period in which a particular material composition was processed. At high domain scales from ~10 to 100, a pseudo-log (a horizontal slice) shows the longer-term variability that may correspond to different mining domains. Whereas at the lower domain scale, pseudo-logs indicate the shorter-term variability that typically corresponds to material variability from different stockpiles or within a mining bench.

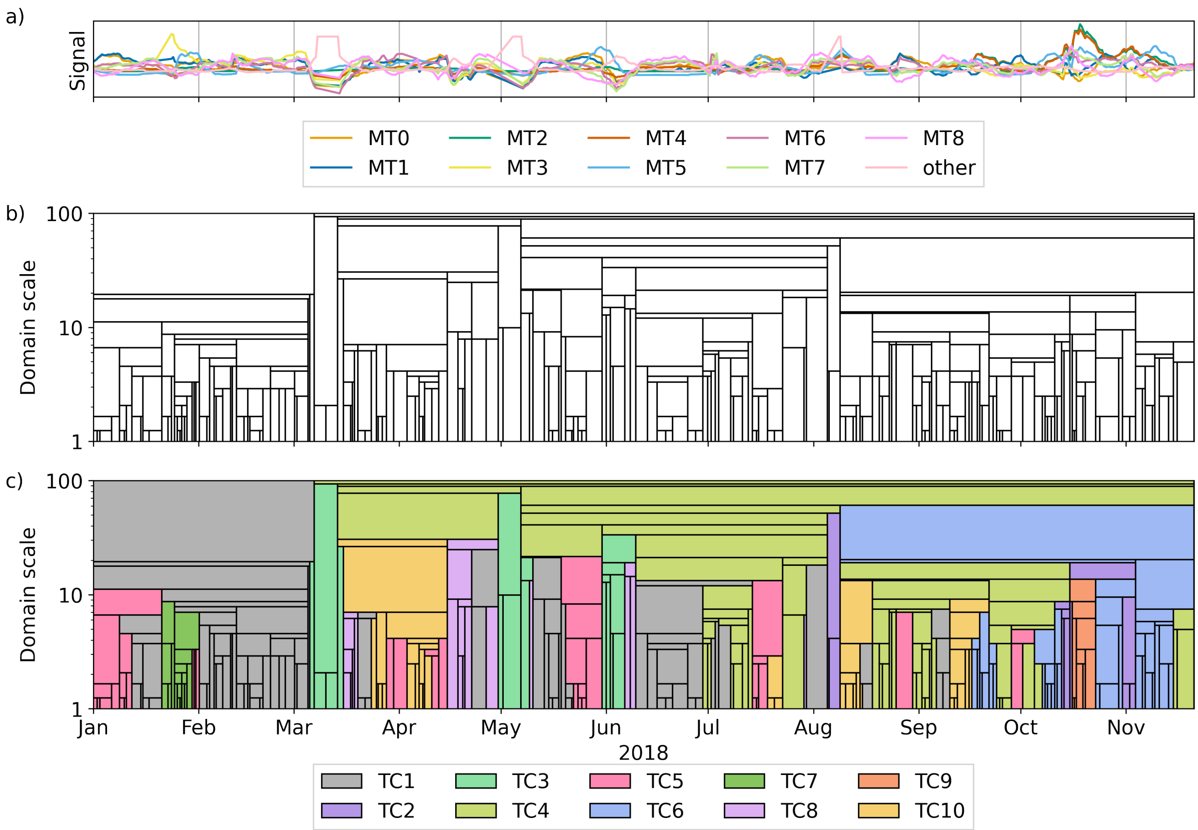

Figure 9. Tessellation results from the material fingerprint crusher feed proportion for Period 1; a) input signals from the material type proportions; b) multiscale mosaic plot; c) classified mosaic plot by tessellation clustering class).

Visual comparison between the mosaic plot (Figure 9b) and the input signals (Figure 9a, similar to the signals in Figure 6) indicates how closely the boundary locations are related to the material fingerprints of the tessellation. Boundaries of the periods were controlled by the strength of the signal change, which corresponds to a change in material composition. For example, the most abrupt changes in the signals gave a stronger boundary and thus extended/persisted to a higher domain scale (>30). Material fingerprints from these periods are thus different from those of the previous period and should therefore correspond with an observable change in the processing performance.

Subsequent analysis linked classes and domains to the corresponding average processing performance, for sets of measured response parameters related to different processing functions (crushing, grinding, leaching etc.), making a direct link to the processed material fingerprints. Here, the period from each domain is linked to the corresponding seven-day rolling mean signals of the processing actuals (Figure 10). The example in Figure 10 shows the resulting domains coloured by the average ball mill throughput (t/h), BWi (kWh/t) and grind size (P_{80}). The changes can mostly be explained by looking at the feed material class proportions and their source locations. A clear example is in late August/early September, when a pure blend comes from the NE part of Tropicana. This is a relatively soft material which is easier to grind (low BWi, P_{80}) and can be processed with high throughputs.

Overall, the derived domains constrained material variability at different scales and were used to analyse the corresponding metallurgical plant performance (comminution and leaching). The geological variability observed at strategic levels matched the distinct modes of processing, whereas the minor scale variability in the processed blend composition reflects changes observed at a tactical level.

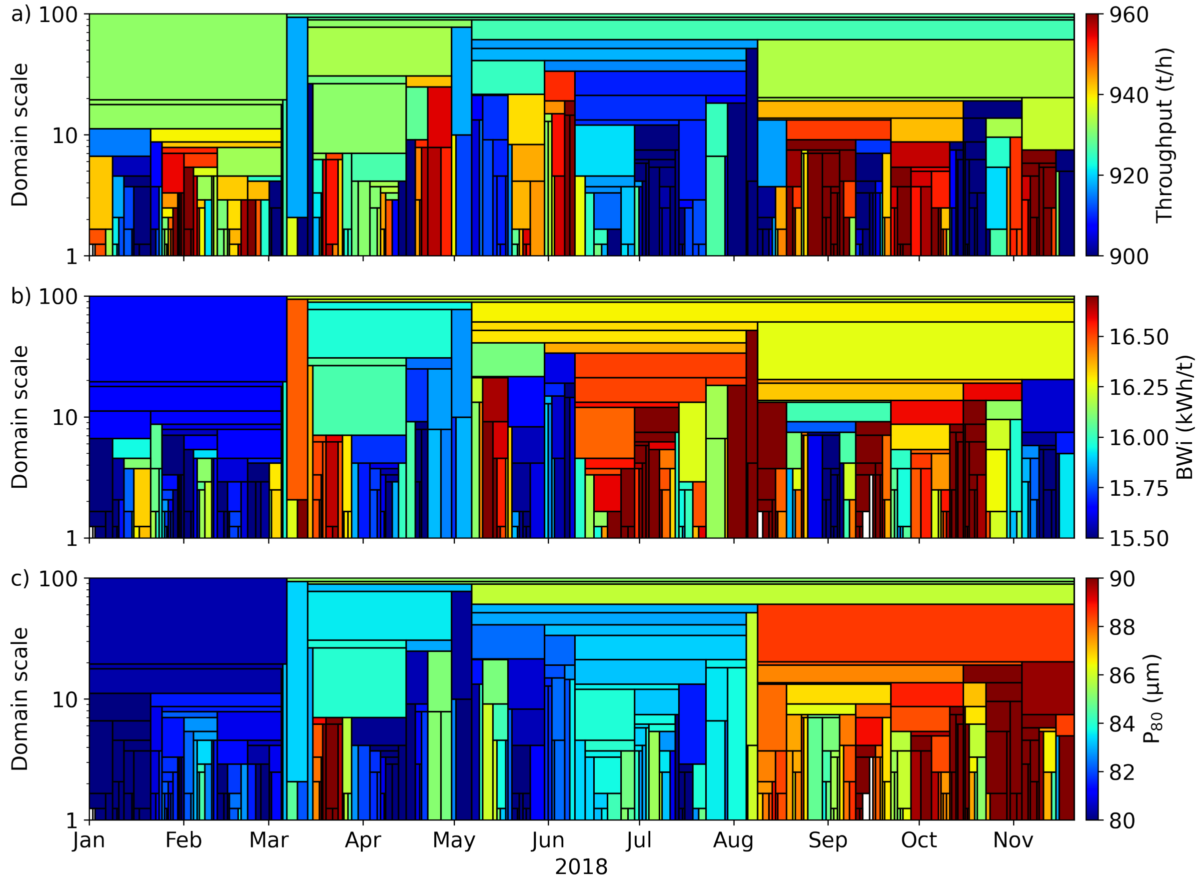

Figure 10. Data mosaic from Period 1 coloured by comminution actuals: a) ball mill throughput (t/h); b) ball mill BWi (kWh/t), and c) P80 μm.

Three case study examples, focused on 1) crushing circuit recirculation, 2) recovery and reagent use, and 3) the effects of long-term stockpiling of material, were developed to further elucidate the usefulness of this approach. Figures 9 and 10 above provide a high-level depiction of the first case study results, where the ability to directly correlate specific changes (such as clay- and sulphide content or alteration mineralogy), associated with specific material types or blends, to specific processing outcomes (ball mill BWi, throughput, and grind size) served to unlock a greater understanding of the underlying performance drivers and allowed optimisation opportunities to be identified. Case studies 2 and 3 followed similar logic but applied to different measures.

CONCLUSION

The material tracking simulation model provided a direct link between the crusher feed material attributes and the actual plant performance. Then, combining the time series material blend tessellation and processing actuals made it possible to link geology with metallurgical plant performance. This is because: 1) the mosaic domains were limited by the temporal geological variability, which was shown in the proportion of material types and then grouped into classes by the clustering; and 2) adding the processing performance to the domains and taking the temporal changes into account further revealed the root causes. Insights from the presented approach open the door to identifying processing drivers more proactively and can thus serve to inform and prioritise future modelling initiatives, resulting in fit for purpose models with a higher likelihood of being relevant, accepted, and actioned.

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Louis holds a MSc. in Geology from the University of Johannesburg and has served in the gold mining and exploration industry for the past eighteen years.

He started his career in the Witwatersrand, more specifically AngloGoldAshanti’s Vaal River Region mines, where he held various underground production geology roles including Senior Geologist and Geosciences Technical Assistant.

Louis spent the next six years as Senior Specialist Project Geologist and Specialist Geochemist supporting projects across Continental Africa, before joining AngloGold Ashanti’s International Specialists team in a dedicated Geometallurgy-focused role in 2017.

As Principal Geometallurgist, Louis is responsible for coordinating geometallurgical projects and growing the geometallurgy discipline across AngloGoldAshanti’s global portfolio.

Aside from geometallurgy Louis’ skills and experience include geochemistry, project geology, underground production geology, Green- and Brownfields exploration as well as technical project evaluation and business improvement.