Geometallurgical Considerations: Processing Mineralogy vs Alteration Footprints

Cassady L. Harraden[1]*, Sam Scher[2], Cari Deyell-Wurst[1], Ronell Carey[1]

1. *Corescan Pty Ltd., 1/127 Grandstand Road, Ascot WA 6104, Australia*
2. *Corescan SpA, San Pablo 9900, Comuna de Pudahuel, Santiago de Chile*

ABSTRACT

Exploration for porphyry-style mineral deposits is enhanced by relatively well-developed models for metal deposition and alteration mineralogy. The interaction between magmatic-hydrothermal fluids and host rocks produces well-documented, zoned alteration patterns (Sillitoe, 2010). Consequently, geological alteration models focus on the distribution of 'primary' magmatic-hydrothermal minerals. While these models are successful in delineating ore bodies, they can impose bias in mine alteration mineralogy models and may have limited applications for mineralogical processing.

In a core logging setting, potassic alteration is typically characterised by hydrothermal K-feldspar and biotite, which commonly displays a 'shreddy' texture. Geologists are trained to 'interpret through' overprinting events to emphasise the ore-forming process to guide exploration. However, these minerals are often partially to completely altered post-ore deposition. Hydrothermal biotite is commonly altered to chlorite (Helgeson, 1970; Parry and Downey, 1982), while K-feldspar can be altered to white mica and/or montmorillonite (Helgeson, 1970). These overprinting phases are important in ore processing; for example, chlorite and montmorillonite can increase reagent consumption and change the viscosity in a flotation circuit, affecting liberation and recovery. Therefore, it is imperative to map the presence of these minerals, regardless of their implications, or lack thereof, to a genetic alteration footprint model.

Hyperspectral core imaging (HCI) analysis can be used to extract mineralogical information for both genetic alteration footprint modelling and geometallurgical sampling. This technology provides continuous downhole identification of minerals, which provides the exploration and processing teams with fit-for-purpose data to accurately model mineralogy for multiple applications. We utilised HCI data from a Chilean mine to demonstrate that, for geometallurgical sample selection, it is critical to understand the actual mineralogy regardless of magmatic-hydrothermal genetic considerations.

INTRODUCTION

Porphyry-style deposits display broad-scale, consistent mineralogical zonation patterns, so the alteration mineralogy of these deposits provides key information on the hydrothermal fluid pathways and the spatial relationship of these fluids to mineralisation (e.g., Sillitoe, 2010; Cooke et al., 2004). Using geologic alteration models as a guide, explorers can use the presence and absence of key alteration minerals as an indication of pressure, temperature, and pH conditions within the porphyry hydrothermal system.

Geometallurgical studies, on the other hand, aim to predict and model the variability of an ore deposit by correlating geology and mineralogy with metallurgical testwork data (Walters, 2009). These methods identify the minerals present, and subsequently geoscientists and geometallurgists can model how the mineralogy will affect processing behaviour. Information derived from geometallurgical models form the basis for mill, plant, and flowsheet optimisation and design on a mine site (Lotter, et al., 2010; Dominy et al., 2016). Specifically, minerals such as chlorite and montmorillonite can increase reagent consumption and change the viscosity in a flotation circuit, thereby affecting recovery (Leja, 2012).

A wholistic geometallurgical model is based on the integration of a deposit's alteration mineralogy model and metallurgical results. Thus, while geologic alteration models are extremely valuable for explorers, they often emphasise mineralogical information based on interpretation; not the mineralogy present. Hydrothermal biotite and K-feldspar are examples of two minerals that characterise potassic alteration in a genetic alteration model (identified using textural and visual observations), whereas in a quantitative alteration model these minerals are often a mixture of chlorite ± relict biotite and montmorillonite ± relict feldspar. It is important to note that the degree of alteration can vary from surficial, incomplete replacement to complete replacement of hydrothermal biotite by chlorite. The same applies to K-feldspar, whereby the primary feldspar can be variably replaced by montmorillonite. In the former case, a geologist can use visual information, such as a 'shreddy' texture to identify hydrothermal biotite, and in the latter use textural information such as montmorillonite replacing feldspar phenocrysts to 'see through' the post-ore deposition overprint and interpret the distribution or presence of hydrothermal potassic alteration. Because the presence of chlorite and montmorillonite can greatly impact processing behaviour, it is significant to the geometallurgist to note the presence of these minerals, and to map their distribution.

Minerals suitable for hyperspectral analysis exhibit distinctive absorption patterns and spectrum profiles over different wavelength positions of the electromagnetic spectrum (Thompson et al., 1999). Montmorillonite, chlorite, and biotite have unique spectral features and can be distinguished and mapped by VNIR-SWIR hyperspectral analysis (Figure 1). The mineral class 'aspectral' (often associated with anhydrous quartz or feldspar as logged visually by geologists) includes spectra with a consistent, negative slope and indistinguishable absorption features (Figure 1). Feldspar is not infrared-active and therefore does not produce distinct absorption features in the VNIR-SWIR.

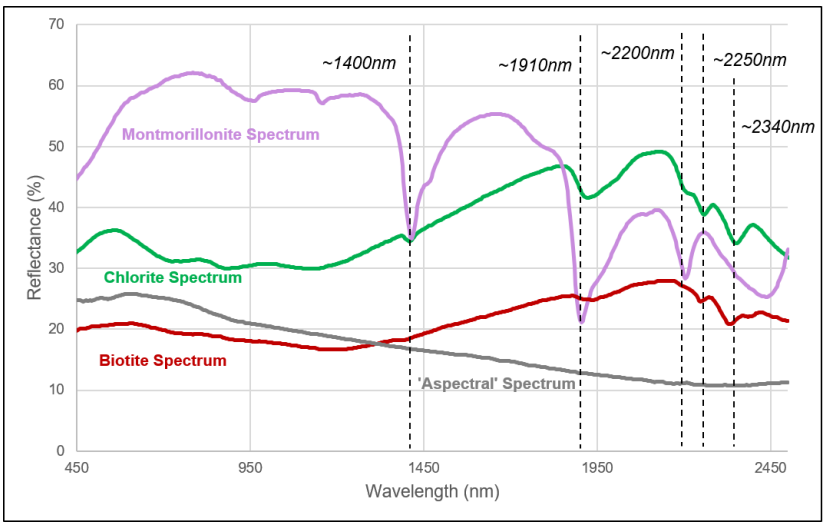

Figure 1 Typical montmorillonite, chlorite, biotite, and 'aspectral' VNIR-SWIR spectra (from Corescan reference library); wavelength positions (nm) of major absorption features are shown

Recent technological developments have resulted in a new generation of high-speed hyperspectral core imaging (HCI) systems that incorporate a number of sensors to collect core photography, core topography and hyperspectral-based mineralogical information. In this paper, we present a case study demonstrating the opportunities for using an HCI system to determine mineralogy in an effort to supplement current geometallurgical testwork design. We compare the mineralogical results interpreted from a hyperspectral imaging cube with those logged by the site geology team. To accomplish this, we present two mineralogical models of a Chilean porphyry deposit: (1) a geological alteration model based on the genetic-model mineralogy (2) an alteration mineralogy model based on the physical mineralogy present in the drill core as detected by HCI and interpreted using a combination of numerical outputs and the hyperspectral imagery to better understand the presence and paragenetic relationships amongst the minerals.

METHODOLOGY

The continuous, downhole hyperspectral data for this study (approximately 8,500 meters of drill core through two cross-sections from an operating porphyry copper deposit located in Chile) was scanned using the Corescan Hyperspectral Core Imager Mark-III (HCI-3) system. This system collects high resolution, true color photography, laser height profiles, and high-resolution VNIR- SWIR spectra (Martini et al., 2017). The photography is collected at a resolution of 50 μm per pixel while the laser profile data is collected at a pixel size of 200 μm with a vertical resolution of 15 μm. VNIR-SWIR spectra between 450 nm and 2500 nm is collected at an average 3.84 nm spectral resolution with a 500 μm pixel size (Martini et al., 2017).

Using the alteration mapping data provided by the Chilean mine, a simplified 3D geologic alteration model was created (Figure 2). Argillic (A), chlorite (CL), hydrothermal biotite (KB), hydrothermal K-feldspar (KF), and quartz-sericite (QS) alteration types were identified by the mine geologists.

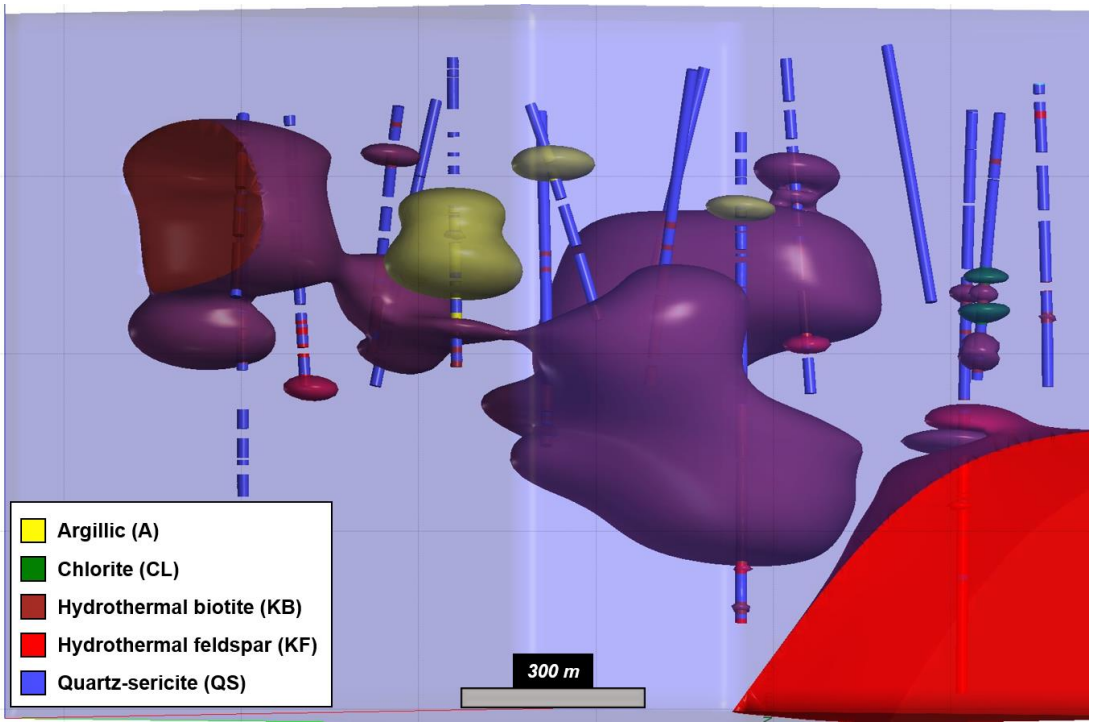

Figure 2 Simplified geological alteration model created from logged alteration domains; note large volumes of QS and KF/KB alteration with only minor volumes of CL and A alteration

The 3D alteration mineralogy model was then created using HCI data, which integrated numerical log data and paragenetic information from textural relationships observed in the HCI imagery (Figure 3). The numerical log data was investigated with statistical software to define hyperspectral domains of biotite, chlorite, alunite, kaolinite, montmorillonite, and muscovite (Figure 4). These mineral domains were verified spatially and subsequently modelled as alteration domains, applying a 10-meter smoothing filter (Figure 5).

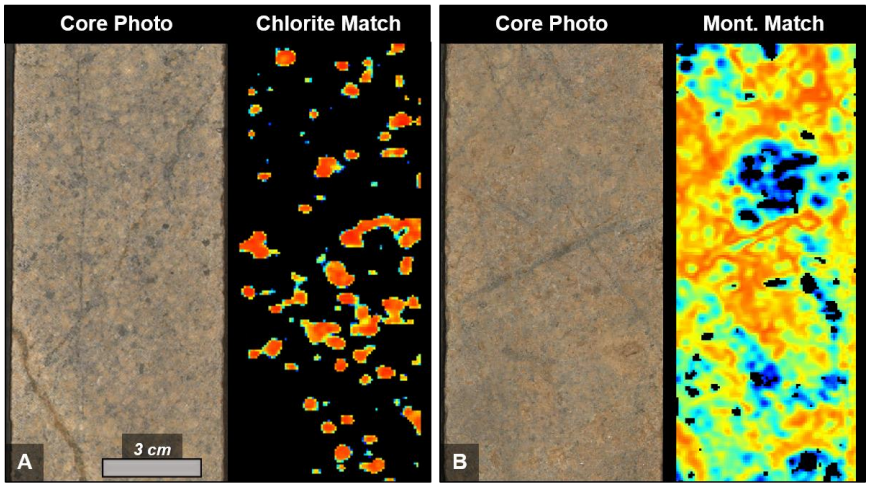

Figure 3 Chilean porphyry samples with core photography and HCI mineral match images for post-ore minerals: chlorite replacing hydrothermal biotite (A) and montmorillonite replacing potassic feldspar (B)

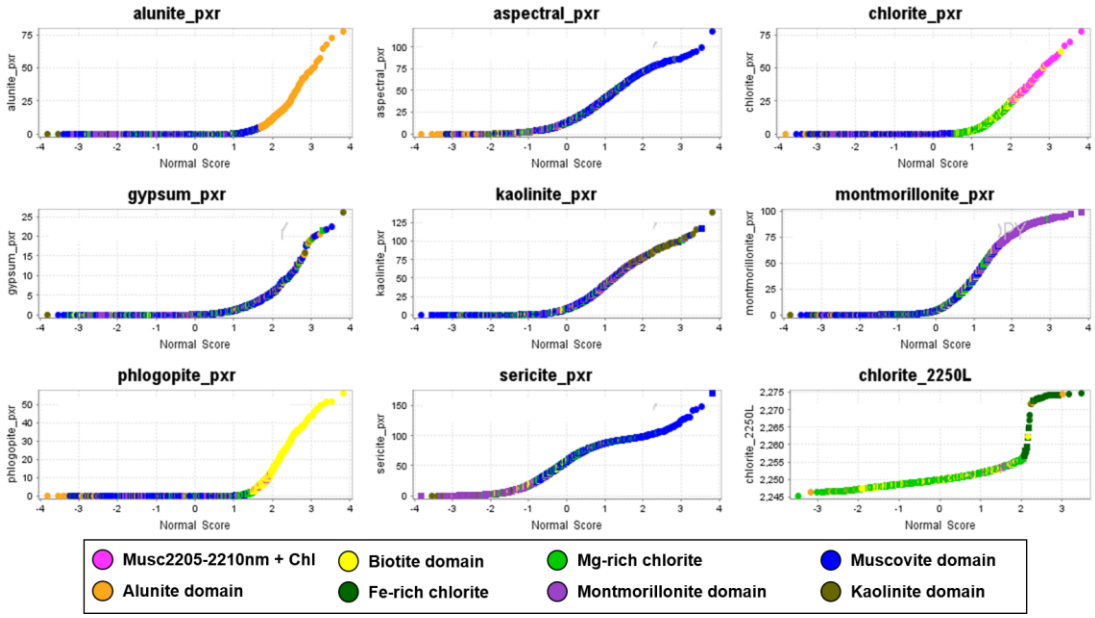

Figure 4 Probability plots used to define alteration domains; note mineral occurrence > 5% is used to define each interval; most domains report more than one mineral

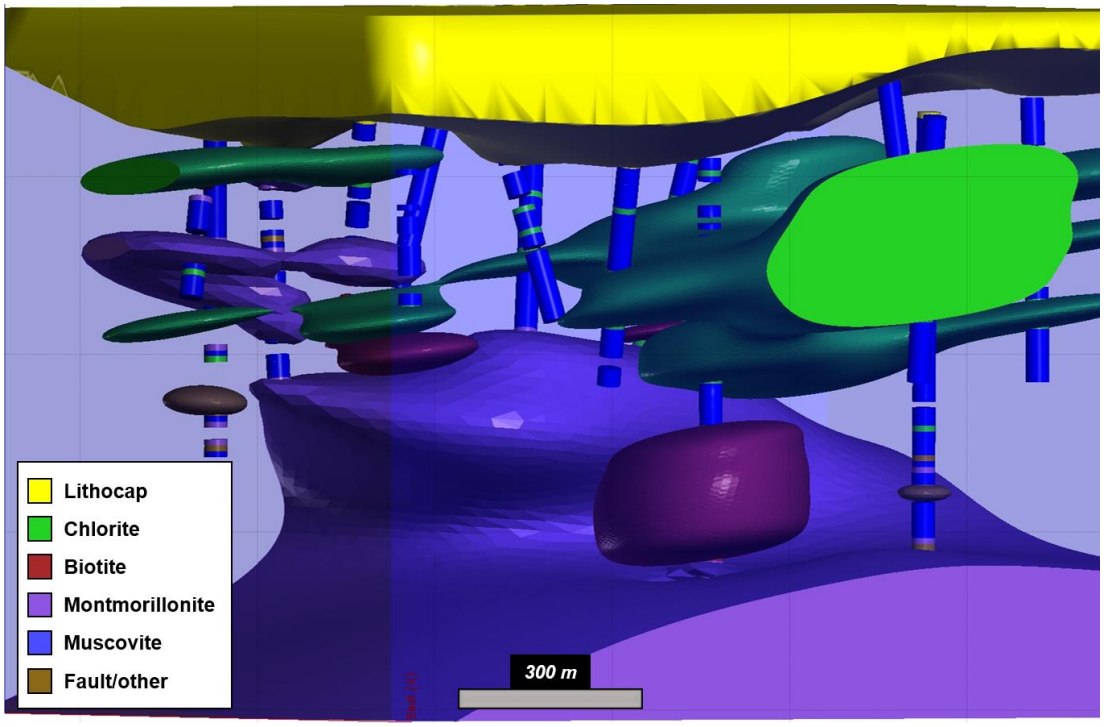

Figure 5 Alteration mineralogy model constructed using the domains defined by the mineralogy from the hyperspectral data and using the probability plots shown in Figure 3

Montmorillonite is abundant and spatially continuous in the HCI dataset. Based on variations in the aspectral mineral class, montmorillonite-bearing results were further subdivided into a K-feldspar-rich domain and a quartz-rich domain (Figure 6). These domains were modelled separately after applying a 10-meter smoothing filter (Figure 7).

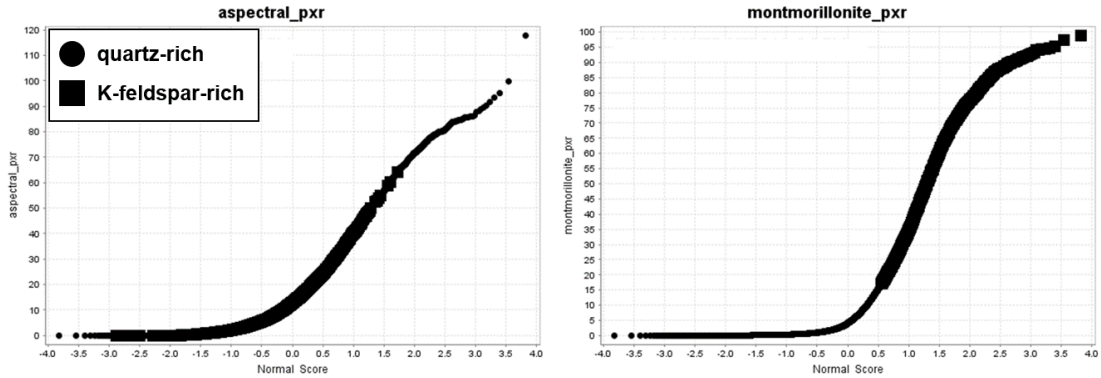

Figure 6 Probability plots used to divide the aspectral class into feldspar- and silica-dominated domains; divided using the presence of montmorillonite to delineate feldspar-dominance

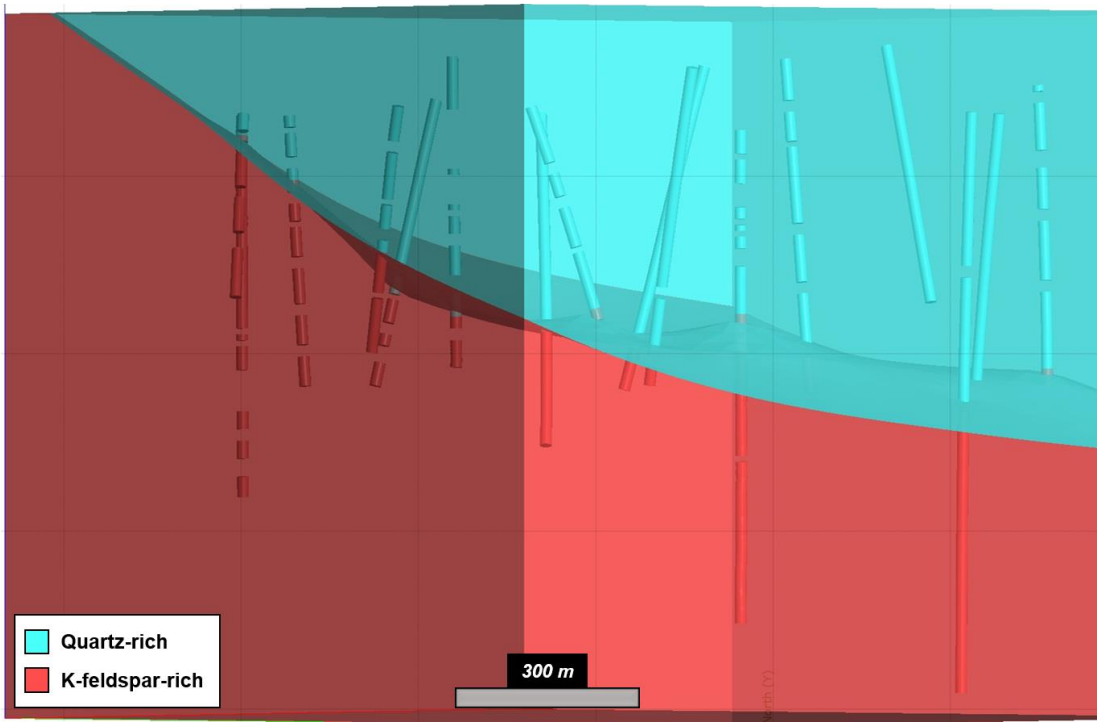

Figure 7 Model of feldspar- and quartz-dominated domains using mineralogy domains derived from the hyperspectral data and the probability plots shown in Figure 6

The end-product model (Figure 8) was created by combining the geological alteration model with the HCI data-derived alteration domains to create an integrated, alteration mineralogy model. This resulting model contains biotite-, chlorite-, kaolinite-, alunite-, montmorillonite, and muscovite-rich domains that are further subdivided into 'potassic' (i.e. K-feldspar-rich) or 'non-potassic ' (i.e. quartz-rich) alteration domains.

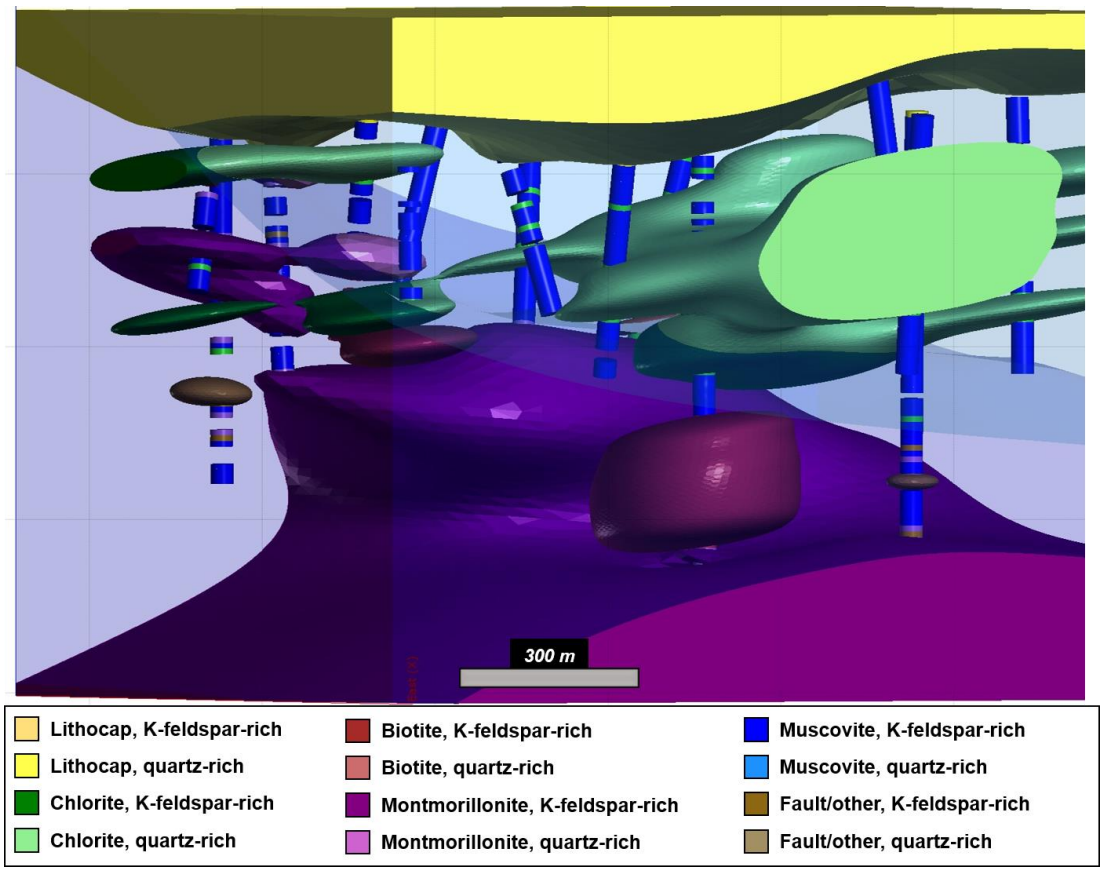

Figure 8 Combined alteration mineralogy model (hyperspectral + logged data) showing improved mineralogical domains and better deposit variability for mineral processing

RESULTS AND DISCUSSION

The two 3D models constructed for this study illustrate similar porphyry-related alteration domains, however with different end-results applications (Figures 2 and 8). The primary differences between these two models are: (1) a strong reliance on textures (i.e. hydrothermal biotite and feldspar) in the exploration model compared to the detection of present mineralogy in drill core, and (2) an underestimation of post-ore deposition mineral phases in the exploration model. If geometallurgical samples were selected using the geological mineralogy model alone, the variability of this deposit would not be captured as chlorite, muscovite and montmorillonite, but rather as K-feldspar and biotite. The relative volumetric differences in chlorite and montmorillonite between the two models is upwards of 200% (Table 1). Both chlorite and montmorillonite can increase reagent consumption and change the viscosity in a flotation circuit, affecting recovery. The difference between the two models highlights the importance of using integrated, fit-for-purpose mineralogical data when developing geometallurgical models and testwork programs. Ultimately, the application of HCI data

can enhance geometallurgical models and increase the ability to select metallurgical samples which will adequately represent the mineralogical variability of a deposit.

Table 1 Comparison of volumes (in km^3) for the 3D geological and mineralogical alteration models

Alteration Logged on Site	HCI Mineral Assemblage	Geological Model Vol.*	Mineralogy Model Vol.*	Rel. Difference (%)
Argillic (A)	Lithocap	6,192.8	319,560.0	98%
Chlorite (CL)	Chlorite	219.8	135,670.0	100%
Biotite (KB)	Biotite	131,980.0	38,751.0	241%
K-feldspar (KF)	Montmorillonite	186,170.0	690,310.0	73%
Quartz-sericite (QS)	Muscovite	2,326,100.0	1,465,400.0	59%
Not included	Fault/other	-	960.8	100%

CONCLUSION

Exploration geology and processing mineralogy require mineralogical information for different purposes, thus the information used in either application must be fit-for-purpose. The case study presented here highlights the fundamental difference between alteration footprints and processing mineralogy and the challenges associated with using these different datasets for geometallurgical applications. The integration of hyperspectral mineralogical data into geometallurgical models allows for the mineralogy to be adequately represented without imposing genetic information on the model. It is recommended that future studies investigate the differences between exploration models and mineralogical models, and how these differences may impact goemetallurgical modelling of a deposit and, ultimately, processing and recovery behaviour. Ultimately, it is critical to understand the actual mineralogy (and variability of that mineralogy) within a deposit, regardless of magmatic-hydrothermal genetic considerations.

ACKNOWLEDGEMENTS

This work represents a culmination of years of work by the Corescan team in conjunction with a number of our clients – we would like to express sincere gratitude to everyone involved over the years. We would also like to thank two unnamed reviewers whose feedback was very helpful in compiling the final paper, as well as Brigette A. Martini (Corescan Pty Ltd) and Brian McNulty (University of Tasmania) for providing meaningful edits in previous versions.

NOMENCLATURE

SWIR short-wave infrared
VNIR visible near-infrared

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