Discriminating ore and waste in a porphyry copper deposit using short-wavelength infrared (SWIR) hyperspectral imagery

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ABSTRACT

A recent study by Dalm et al. (2014) showed that alteration mineralogy acquired using SWIR point spectrometry could be linked to copper grade distribution for a group of samples from a South American copper mine. Since it was expected that SWIR hyperspectral imagery can provide more detailed information about the alteration mineralogy of these ores, we investigated whether this technique can be used to improve upon the indirect characterization of copper grades. Maps showing the distributions of SWIR-active minerals, white mica crystallinity, white mica composition, and chlorite composition were produced from SWIR hyperspectral images of 43 samples from the Dalm et al. (2014) study. Subsequently, a principle component analysis (PCA) was applied to the relative mineral abundances and the average white mica crystallinity and composition that were extracted from these maps. The PCA showed that this mineralogical data could be used to discriminate a significant portion of the samples with sub-economic copper grades. Furthermore, the study showed that SWIR hyperspectral imaging has the following advantages over SWIR point spectrometry: minerals that are present in relatively low quantities can be detected, the SWIR-active mineralogical composition at the surface of a sample can be quantified, and the texture of samples, such as grain sizes and cross-cutting vein structures, can be characterized. However, these advantages did not improve upon the indirect characterization of copper grades that was achieved using SWIR point spectrometry. This was attributed to the relatively small size of the sample set and the high textural variability between samples.

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1. Introduction

Short-wavelength infrared (SWIR) hyperspectral sensors are used to capture images of objects at many different wavelengths in the SWIR spectral range (1000–2500 nm). Each pixel in the resulting image constitutes a spectrum of the intensity of reflected radiation as a function of wavelength. Certain minerals absorb SWIR radiation at specific wavelengths as a result of vibrating molecule bonds (Hunt, 1977; Clark, 1999). SWIR hyperspectral imaging can therefore be used to identify the mineralogy of rock samples. However, mineral identification is restricted to minerals containing molecule bonds that produce diagnostic absorptions. Such minerals will be referred to as SWIR-active minerals.

In geology and mineral exploration, SWIR hyperspectral sensors are mainly known from remote sensing applications that scan the Earth’s surface from satellites and aircraft. The same sensors can also be applied to scan objects of sizes in the order of centimeters. During the last decade instruments came onto the market that are dedicated to acquiring SWIR hyperspectral images of drill core samples. Examples are Corescan’s Hyperspectral Core Imager (Corescan, 2015) and Specim’s SisuRock (Specim, 2015).

The mineralization of copper in porphyry ore deposits is associated with the formation of certain alteration minerals (Lowell and Guilbert, 1970; Pirajno, 1992; Sillitoe, 2010). These alteration minerals are often SWIR-active minerals (Sabins, 1999; Thompson et al., 1999; Dalm et al., 2014). Because of this, SWIR hyperspectral sensors can potentially be used to indirectly characterize the copper grade distribution of porphyry copper ores. This would allow these sensors to be implemented along the mining value chain to provide real-time information on ore value.

One specific application of the SWIR sensor is in sensor-based sorting. Sensor-based sorting is a technique in which singular particles are mechanically separated on certain physical and/or chemical properties after determining these properties with a sensor. If a SWIR sensor can be used to identify waste or sub-economic ore material, sensor-based sorting could be incorporated into mineral processing operations in order to remove this material prior to...
conventional treatment. This has potential to reduce the costs associated with processing mined materials (Salter and Wyatt, 1991; Sivamohan and Forsberg, 1991; Buxton & Benndorf, 2013; Wills and Finch, 2016).

This paper investigates the applicability of SWIR hyperspectral imagery for characterizing the copper grade of 43 porphyry copper ore samples. These samples are a subset of the sample set of 150 samples that was used in the study described by Dalm et al. (2014). Ore minerals in the samples include chalcocite, chalcopyrite, covellite, digenite, and bornite. These are all copper sulphides that do not produce diagnostic absorption features in the SWIR (Hunt et al., 1971; Clark et al., 2007).

Dalm et al. (2014) showed that an indirect relationship exists between the copper grade of the samples and the alteration mineralogy that can be determined with SWIR point spectrometry. However, each spectrum that is acquired with a commonly used point spectrometer represents a sample surface of several cm² (e.g., ASD, 2015). Since most hyperspectral imagers acquire spectra on a pixel size below 1 mm² (e.g., Corescan, 2015; Specim, 2015), these instruments can provide more detailed information about the abundance and spatial distribution of the SWIR-active mineralogy. It is therefore expected that SWIR hyperspectral imagery will reveal additional differences between samples, which might be used to improve upon the indirect characterization of copper grades.

In this paper we give an example of how SWIR hyperspectral images can be processed to produce maps that show the distribution of SWIR-active minerals. We will also show how certain mineral characteristics such as the white mica crystallinity can be mapped from these images. Furthermore, we present a method that uses these maps as input variables in a principle component analysis (PCA) in order to find samples that have similar mineralogical composition and to identify the mineralogical differences between sample groups. Finally, we will show how this can be used to segment populations of ore and waste.

2. Methods

2.1. Data acquisition

Forty-three samples were collected from a South American mine that exploits a porphyry copper ore deposit. The samples are individual rock particles of around 5–7 cm in diameter. Prior to any measurement, all the samples were cut in half. One half of each sample was used for acquiring SWIR hyperspectral images. The other half was pulverized and used for X-ray fluorescence (XRF) analysis to determine the copper grade. The distribution of copper grades in the sample set determined by XRF analysis is presented in Fig. 1.

On 20 of the pulverized samples, X-ray diffraction (XRD) analysis was performed to determine the mineralogy. Since XRD is limited by a relatively high detection limit, mineralogy was also determined by petrography for 11 out of the 43 samples. The thin sections for petrography were taken from the cut surface of the sample halves used for XRF, before these were pulverized. Petrography and XRD analysis were performed on different samples. The determined mineralogy from these analyses was used to validate the occurrence of minerals that were identified from the SWIR hyperspectral images.

SWIR hyperspectral images of the samples were acquired with a SisuCHEMA instrument (SPECIM Ltd., Oulu, Finland). The hyperspectral images were recorded in a 940–2540 nm spectral range and at a spectral resolution of 6 nm. The images were made from the cut surface of the samples because this surface is flat, smooth and uncontaminated by dust. The size of individual pixels in the resulting images is around 0.2 by 0.2 mm.

2.2. Image pre-processing

The SWIR hyperspectral images needed pre-processing to convert the recorded data to relative reflections. This was performed by using a white reference and a dark current calibration. A white reference is a measurement of a material with almost 100% reflection over the entire SWIR spectral range. A dark current is a measurement that is performed when no light enters the sensor in order to capture instrumental noise. Reflection spectra were calculated by dividing the measured spectrum by the white reference after subtracting the dark current from both these measurements.

2.3. Image processing

The SWIR hyperspectral images were processed using ENVI 4.5 image processing software (ITT visual information studios, 2008). The first step was to mask the images by removing the data of pixels that do not represent a sample. This was performed by manually selecting regions of interest on the images. Subsequently, a mineral map was produced from the masked image of each sample by using the Spectral Angle Mapping (SAM) algorithm (Kruse et al., 1993) in combination with a set of reference spectra. SAM classifies each image pixel by assigning the mineral or mineral assemblage to it that is represented by the reference spectrum to which the pixel spectrum has the smallest multi-dimensional angle. A maximum angle of 0.2 rad was applied as a threshold to ensure a positive correlation between the image pixels and reference spectra. The SAM method was chosen for constructing mineral maps because numerous studies show that it is an effective method to classify the pixels of hyperspectral images (e.g., Girouard et al., 2004; Rowan et al., 2005; Kruse, 2012).

The reference spectra used with SAM were selected from the measured SWIR hyperspectral images so that the spectral range and resolution of the used references and the image pixels are equal. The mineral or mineral assemblage that is represented by each reference spectrum was determined by comparing the spectrum with the SWIR spectra of the USGS spectral library (Clark et al., 2007) and the spectral interpretation field manual, G-MEX (AusSpec, 2008). This comparison was performed by inspecting the wavelength positions and relative intensities of the absorption features in the spectra.

An initial set of reference spectra was collected by manually selecting spectra that represented the observed variability in the measured SWIR hyperspectral images. SAM was applied to produce mineral maps and the classification of randomly chosen pixels was checked by inspecting the spectra. Pixels that were incorrectly

![Fig. 1. Distribution of copper grades in the sample set determined by XRF analysis.](image-url)
classified or that were not classified due to the maximum angle threshold were added to the set of reference spectra after the minerals that produced the spectrum were identified. This process was repeated until no unclassified pixels remained and no incorrect classifications were observed.

Apart from the mineralogy, the following mineral characteristics were also mapped from the SWIR hyperspectral images of the samples: white mica composition, white mica crystallinity, and chlorite composition. This was based on the wavelength positions and depth ratios of specific mineral absorption features. These spectral properties were calculated with the Hyperspectral Python (HypPy) toolbox (Bakker, 2012). The algorithms in this toolbox fit a parabola to the wavelength channels around an absorption feature to interpolate the wavelength position of the absorption minimum. The absorption depth is calculated by dividing the reflectance value of the absorption minimum by that of the continuum around the absorption feature. Mineral characteristics were only mapped for pixels that represent pure mineral spectra (i.e. spectra that only show absorption features of a single mineral). This was done by masking the image with the resulting mineral map.

2.4. Principle component analysis

A principle component analysis (PCA) was applied to the mineralogical information contained in the maps that were produced from the SWIR hyperspectral images. PCA is a procedure in which data is projected onto a k-dimensional space by a linear orthogonal transformation (Wold et al., 1987; Jolliffe, 2002; Eriksson et al., 2006). These k-dimensions are commonly referred to as the k number of principle components. The first principle component (PC) represents the direction that describes the largest amount of variance in the variable space of the original data. Each subsequent PC represents the direction of the largest remaining variance that is orthogonal to those of the previous PCs. The projection of the mineralogical data on the first few PCs can therefore be used to easily distinguish between samples that are relatively similar and those that are more different. Furthermore, the contributions of the original variables to each PC can be used to identify the variables for which the samples differ most (Eriksson et al., 2006). The projected data onto the PC space is referred to as the sample scores and the contributions of the original variables are known as the loadings.

PCA was performed on a data matrix containing the relative abundance of all the identified SWIR-active minerals for each sample and the sample averages of the features representing white mica crystallinity and white mica composition. Spectral features that describe the composition of chlorite were not included in the PCA since not all samples contained chlorite. The relative abundance of the SWIR-active minerals was calculated by dividing the number of pixels that represent a certain mineral by the number of pixels that represent the sample. A multiplicative zero replacement followed by a centered log-ratio transformation was subsequently applied to this data (Martin-Fernandez et al., 2003; Aitchison, 1986). This was required to correct for the fact that the mineralogical compositions sum up to a constant (i.e. 100%). This constant sum constraint can influence the outcomes of the PCA since it places restrictions on the correlation structure of the data (Aitchison, 1986).

The data matrix was centered and scaled before applying the PCA by setting the mean and standard deviation of each variable to 0 and 1 respectively. Setting the mean to 0 places the average of the data at the origin of the variable space. This is required to ensure that the PCs will describe maximum variance (Jolliffe, 2002). Setting the standard deviation of each variable to 1 prevents the PCA model being dominated by a variable that has a much higher variance than all the others. This was needed since the variables that were used in the PCA are expressed in different units.

The PCA sample scores were compared with the XRF results to investigate if there is a relationship between the copper grade of the ore particles and the mineralogical information that can be derived from SWIR hyperspectral imagery. The PCA loadings were used to identify the minerals and/or mineral characteristics that describe this relationship.

3. Results

3.1. Minerals identified from the measured SWIR hyperspectral images

3.1.1. White mica

White mica is the most abundant SWIR-active group of minerals in almost all SWIR hyperspectral images of the samples. White mica is an umbrella term that usually refers to muscovite, paragonite, celadonite, aluminoceladonite, illite, illite-smectite or any coexisting occurrence of these minerals. These different white mica species can be distinguished from each other with SWIR spectrometry (AusSpec, 2008; Clark et al., 2007; Duke, 1994).

Fig. 2 presents several SWIR spectra of white mica that were used as reference spectra for producing mineral maps with SAM. As mentioned in Section 2.3., these reference spectra originate from the measured SWIR hyperspectral images. Spectrum 1 in Fig. 2 is characteristic for muscovite and spectrum 5 is characteristic for illite. The other spectra represent intermediate muscovite-illite species. The absorption features that can be observed in the

![Fig. 2. SWIR spectra of white mica with decreasing crystallinity from spectrum 1–5. Spectrum 1 is characteristic for muscovite and spectrum 5 is characteristic for illite. Spectra 2–4 represent intermediate muscovite-illite species. Spectra originate from the measured SWIR hyperspectral images.](image-url)
spectra are produced by vibrating molecule bonds. The diagnostic white mica absorption occurs around 2200 nm and is produced by an overtone combination of the O–H stretch and the Al–OH bend vibration (Hunt, 1977; Clark et al., 1990). This absorption will be referred to as the white mica Al–OH absorption feature.

The exact wavelength position of the minimum of the Al–OH absorption feature correlates with the Al content of white mica (Duke, 1994; Post and Noble, 1993). Muscovite is a common end-member of white mica for which the Al–OH absorption minimum is located around 2200 nm (AusSpec, 2008; Duke, 1994; Post and Noble, 1993). Substitution of the Al by Fe and Mg in the muscovite crystal structure through octahedral exchange (Al → (Fe, Mg)) or octahedral-tetrahedral Tschermak exchange (AlAl → (Fe, Mg)Si) shifts the minimum position of this feature to longer wavelengths (Duke, 1994). The white mica endmembers resulting from this substitution are aluminoceladonite and celadonite. These endmembers often form solid solutions with muscovite, which are referred to as phengite (Rieder et al., 1998). The Al–OH absorption minimum for phengite is located around 2225 nm (AusSpec, 2008).

Minimum positions of the white mica Al–OH absorption feature in the measured SWIR hyperspectral images range from 2198 to 2220 nm. This indicates that the white mica in the samples has a muscovitic to phengitic composition.

Fig. 2 shows that the intensity of the white mica absorption around 1900 nm is variable. This absorption is produced by an overtone combination of the O–H stretch and H–O–H bend vibration of molecular water (Hunt, 1977; Clark et al., 1990). It will be referred to as the H2O absorption feature. It is possible to characterize the white mica crystallinity from the intensity of this feature (AusSpec, 2008; Dalm et al., 2014). This is because less crystalline white mica has more interlayer sites that are occupied by water molecules (Dalm et al., 2014). A white mica crystallinity index can be calculated by dividing the absorption depth of the Al–OH absorption by that of the H2O absorption. Muscovite and phengite are white mica species with a high crystallinity index. White mica species with similar composition, but a low crystallinity index, are referred to as illite and phengitic illite.

The absorption that is located around 1410 nm is an overtone of the O–H stretch vibration (Hunt, 1977; Clark et al., 1990). All minerals that contain OH bonds will produce such an absorption feature. The exact minimum position of this absorption feature depends on the cation that the OH bond is attached to Hunt (1977) and Clark et al. (1990).

3.1.2. Chlorite

Minerals from the chlorite group were identified from the SWIR hyperspectral images of some of the samples. Chlorite is an umbrella term that usually refers to clinochlore, chamosite, or a solid solution between these two endmembers. One of the reference spectra that was used for the SAM classification of chlorite is spectrum 1 in Fig. 3. Chlorite produces diagnostic absorptions around 2250 and 2350 nm (Clark et al., 2007; AusSpec, 2008). Mineral absorptions in the 2230–2295 nm range commonly result from O–H stretch and Fe–OH bend vibration (AusSpec, 2008; Clark et al., 1990). Furthermore, absorptions produced by O–H stretch and Mg–OH bend vibration commonly occur in the 2300–2370 nm range (AusSpec, 2008; Clark et al., 1990). The chlorite absorptions that occur around 2250 and 2350 nm will therefore be referred to as the chlorite Fe–OH and Mg–OH absorption feature respectively.

The exact wavelength position of the minimum of the Fe–OH and Mg–OH absorption features is related to the relative amount of Mg versus Fe ions that occur within the chlorite crystal structure (AusSpec, 2008; McLeod et al., 1987). If the chlorite is rich in Mg the minimum position of the Fe–OH and Mg–OH absorptions are around 2245 and 2320 nm (AusSpec, 2008; McLeod et al., 1987). When the Mg is partly substituted by Fe, the minimum of both absorption features shift to longer wavelengths. For Fe-rich chlorite the minimum of the Fe–OH and Mg–OH absorptions are located around 2265 and 2365 nm (AusSpec, 2008; McLeod et al., 1987). Minimum positions of the chlorite Fe–OH and Mg–OH absorptions in the measured SWIR hyperspectral images range from 2248 to 2261 nm and from 2324 to 2360 nm respectively. This indicates that the chlorite in the samples varies from Mg-rich to Fe-rich, corresponding to clinochlore-chamosite chlorite species.

3.1.3. Tourmaline, kaolinite and nontronite

Spectra 2–4 in Fig. 3 are examples of reference spectra that were used for the SAM classification of tourmaline, kaolinite and nontronite. Tourmaline produces diagnostic absorptions at 2210, 2250, 2300 and 2360 nm (Clark et al., 2007; AusSpec, 2008). These absorption features are mainly produced by the Fe–OH and Mg–OH bonds of tourmaline (AusSpec, 2008). However, some authors suggest that the tourmaline absorption features can also be caused by overtone combination of the O–H stretch and B–OH bend vibration (Clark et al., 1990).

Spectrum 3 in Fig. 3 shows double absorption features around 1400 and 2200 nm that are diagnostic for kaolinite. The absorptions around 1400 nm are produced by the O–H bonds and the ones around 2200 nm by the Al–OH bonds of kaolinite (Hunt, 1977; Clark et al., 1990). The reason that a double absorption feature, or doublet, is produced at both wavelength positions is related to the fact that kaolinite has OH groups at different locations in the crystal structure. O–H stretch vibration of OH groups located on the exterior surface of the octahedral sheets absorb...
radiation at a slightly shorter wavelength than that of the OH groups located in between the tetrahedral and octahedral sheets (Crowley and Vergo, 1988). The double feature around 2200 nm is produced because both types of OH groups form Al—OH bonds.

Spectrum 4 in Fig. 3 has a double absorption feature around 1420 nm and a single feature around 2290 nm that are diagnostic for nontronite. Most nontronite spectra in spectral libraries only show a single absorption feature around 1420 nm (e.g., AusSpec, 2008; Clark et al., 2007). However, a double absorption feature at this wavelength position has been reported for nontronite by Clark et al. (1990). It is produced by different O—H stretching vibrations similar to that of kaolinite. The absorption around 2290 nm is produced by the Fe—OH bonds of nontronite (Clark et al., 1990; AusSpec, 2008).

3.1.4. Other minerals

Apart from the SWIR spectra presented in Figs. 2 and 3, spectra with a relatively low reflection and no mineral absorption features were found in the measured SWIR hyperspectral images. Minerals that were not identified from the SWIR hyperspectral images, but that were determined by XRD and petrography include quartz, feldspars (orthoclase, albite and anorthite), hematite, magnetite, pyrite and the ore minerals chalcopyrite, digenite, bornite, chalcolite and covellite. None of these minerals contain molecule bonds that produce absorption features in the SWIR (Clark et al., 2007). However, quartz and feldspars are somewhat transparent and the spectra of the hyperspectral images will therefore show absorption features of underlying SWIR-active minerals where quartz and feldspars are located. All the other minerals that were determined by XRD and petrography are opaque minerals that are known to have a low reflection in the SWIR (Clark et al., 2007; Baldrige et al., 2009). Since it is not possible to distinguish between the different types of opaque minerals from the SWIR spectra, all spectra with a low reflection and without mineral absorption features were classified as opaque minerals when producing the mineral maps with SAM.

3.2. Mapping SWIR-active mineralogy

Fig. 4 presents four examples of the results of mapping the SWIR-active mineralogy from the measured SWIR hyperspectral images. The figure shows a photo of each sample, the mineral map resulting from the SAM classifications and maps of the Al—OH feature position and the crystallinity index of white mica.

For all samples white mica minerals were mapped. A relatively high abundance of either chlorite or tourmaline was common. Several samples contain both chlorite and tourmaline. In that case, the abundance of chlorite was always higher than that of tourmaline. Nontronite, kaolinite and opaque minerals only occurred in relatively low abundances. Furthermore, nontronite was not observed in the mineral maps of samples with relatively high tourmaline contents.

The mineral maps in Fig. 4b show classifications of pure mineral spectra as well as mixtures with white mica. These mixtures are SWIR spectra in which the absorption features of white mica as well as some other mineral can be observed. For nontronite and kaolinite, the same color was assigned to the pure spectra and the spectral mixtures. This was done to improve the visibility of these minerals, since the number of pixel spectra that contain absorption features of nontronite or kaolinite is relatively low. Mixed spectra with opaque minerals were not classified. A pixel was only classified as an opaque mineral when no mineral absorptions could be observed in the spectrum due to a low reflection.

Calculating the white mica crystallinity index and the Al—OH absorption minimum was only performed on pixels with pure white mica spectra. This is because absorptions by other minerals might affect the shape and intensity of these features. Figs. 4c and 4d show that mapping the characteristics of white mica reveals additional differences between samples. Furthermore, these maps provide information on the texture of samples since vein structures containing white mica with a different composition and/or crystallinity become visible.

Fig. 5 presents two maps of the wavelength position of the chlorite Mg—OH absorption minimum. These maps correspond to sample 3 and 4 presented in Fig. 4. Calculating the minimum position of this chlorite Mg—OH absorption was only performed on pixels with pure chlorite spectra. Fig. 5 shows that mapping this characteristic of chlorite reveals additional differences between samples.

3.3. Principle component analysis

Fig. 6 presents the PCA sample scores of the first and second principle component (PC). The blue dots in this figure represent samples that are waste and the red dots samples that are ore. The definition of ore and waste is based on an assumed economic cut-off grade of 0.40% Cu, which is representative for the mine that the samples originate from. The cut-off grade is the minimum copper grade that is required for economic processing of the ore material.

PCA was performed on a data matrix containing the relative SWIR-active mineral abundances for each sample and the sample averages of the white mica crystallinity index and the wavelength position of the white mica Al—OH absorption feature. The black lines in Fig. 6 represent the loadings of these variables. These were all equally scaled to fit the figure and therefore do not represent the actual loading values. The capital letters indicate the type of mineral that is represented by the loadings. Cryst and Al—OH refers to the white mica crystallinity index and the minimum position of the white mica Al—OH absorption. The chlorite Mg—OH absorption was not included in the PCA since not all samples contain chlorite.

The green rectangle in Fig. 6 indicates a region in the score plot where mainly waste samples occur. It results that these can be distinguished by using the first PC. It can be inferred from the loadings of this PC that the samples in the green rectangle have relatively high contents of chlorite and low contents of white mica, tourmaline and opaque minerals. Furthermore, these samples contain white mica with relatively low crystallinity values and with Al—OH features that occur at longer wavelengths. The white mica species of the samples in the green rectangle are therefore close to a phengitic illite while that of the other samples are closer to muscovite.

It can be observed from Fig. 6 that the green rectangle contains one ore sample. This sample has a relatively high score on the second PC. It can be inferred from the loadings of this PC that this relates to relatively high contents of tourmaline and opaque minerals and low contents of nontronite and white mica. Furthermore, high scores on the second PC are associated with white mica Al—OH features that occur at longer wavelengths.

Fig. 7 presents the resulting copper grade distributions when the samples are classified on the PCA scores of the first PC. A score of 1 was used as a threshold for the classification. Samples with PCA scores above this threshold are all samples inside the green rectangle in Fig. 6. Although Fig. 6 shows that the second PC can be used to also distinguish the ore sample in the green rectangle from most of the waste samples, this was not performed for the classification result presented in Fig. 7. The reason is that this ore sample has a copper grade of 0.47%, which is only just above the economic cut-off grade of 0.40% Cu. Furthermore, the PCA scores of this ore sample are relatively close to the scores of a significant portion of the waste samples. This means that the ore sample cannot be separated from these waste samples unless thresholds are used that are based on relatively small differences between the
SWIR-active mineralogy of the samples. Using such thresholds will likely decrease the robustness of the resulting classification.

Fig. 7 shows that classifying the samples on a PCA score threshold of 1 on the first PC distinguishes a group of 16 samples of which 15 samples are waste. This group contains 58% of all the waste samples in the sample set and has an average grade of 0.20% Cu. Since this average copper grade is well below the economic cut-off grade, it results that SWIR hyperspectral imagery in combination with mineralogy mapping and PCA can be used to discriminate a significant portion of the sub-economic ore. Removing these sub-economic ore samples from the sample set will increase the average copper grade from 0.45% to 0.60%.

4. Discussion

PCA proved to be an effective method to display the systematic variation of the data that was extracted from mineralogy maps. It makes it relatively easy to find samples that have similar miner-
logical composition and to identify the mineralogical differences between sample groups. The method can save a lot of time when hyperspectral images of sample sets in the order of hundreds of samples or more need to be analyzed.

Petrography and XRD validated that white mica, chlorite and tourmaline were correctly identified from the SWIR hyperspectral images. Validation of the specific white mica species was not carried out. Furthermore, kaolinite and nontronite were not determined with petrography or XRD. However, when these minerals occur in any of the mineral maps they cover only a relatively small surface area. It is therefore possible that they were missed in the thin sections on which petrography was performed or that their concentration was below the detection limit of XRD. No other minerals were identified with petrography or XRD that could be responsible for the measured SWIR spectra that were classified as kaolinite and nontronite. Furthermore, the wavelength position of the absorption features in these SWIR spectra clearly indicate the occurrence of two minerals that were not determined by XRD or petrography. This means that even if the identification of kaolinite and/or nontronite was incorrect, the PCA results presented in Section 3.3 that are based on SWIR-active mineralogical differences between samples are still valid.

The different mineral assemblages that resulted from mapping the mineralogy from the SWIR hyperspectral images are characteristic for different zones of hydrothermal alteration within the porphyry system (Thompson et al., 1999; AusSpec, 2008). Distinguishing low grade samples with SWIR hyperspectral imagery is therefore based on a relationship between copper mineralization and the formation of alteration minerals. This was expected since this relationship was previously established when SWIR point spectrometry was tested on the same sample set (Dalm et al., 2014). As discussed by Dalm et al. (2014), the detection of

![Fig. 5. Result of mapping the wavelength position of the chlorite Mg—OH absorption from selected SWIR hyperspectral images. This was only performed on pure chlorite spectra (i.e. no absorption features by any other mineral).](image)

![Fig. 6. Sample scores and loadings of the PCA on data derived from mineralogy maps. Red dots represent ore samples. Blue dots represent waste samples. Black lines represent the loadings. The loadings were all equally scaled to fit the figure and therefore do not represent actual loading values. C = chlorite; K = kaolinite; M = white mica; N = nontronite; O = opaque minerals; T = tourmaline; Al—OH = average minimum position of the white mica Al—OH feature; cryst = average value of the white mica crystallinity index. The green rectangle indicates a region where mainly waste samples occur. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)](image)
alteration minerals with SWIR sensors can be used as indirect indicators for sensor-based sorting if the relationship between alteration mineralogy and copper mineralization persists throughout the entire ore deposit. Validation of the results on a sample set that is representative of the full mineralogical variability of the deposit is required to be able to conclude on the applicability of sensor-based sorting. The results of this study do show potential for using SWIR sensors for sensor-based sorting of porphyry copper ores.

Comparing the results in Section 3.3 with those presented by Dalm et al. (2014) shows that using SWIR hyperspectral imaging did not improve upon the indirect characterization of copper grades that was achieved using SWIR point spectrometry. However, SWIR hyperspectral imaging has several advantages over SWIR point spectrometry regarding the mineralogical information that can be extracted from the data. These advantages are related to the capability of SWIR hyperspectral imaging sensors to acquire SWIR data at a relatively high spatial resolution (i.e. small pixel size).

First of all, the surface area that is represented by a single SWIR spectrum is much smaller with most hyperspectral imagers than with commonly used point spectrometers. The spot size of SWIR point spectrometers is often in the order of several cm² (e.g., ASD, 2015), while SWIR hyperspectral imagers usually acquire spectra on a pixel size below 1 mm² (e.g., Corescan, 2015; Specim, 2015). This relatively small pixel size allows minerals to be detected that occur in relatively low quantities. Examples of such minerals in the sample set are nontronite, opaque minerals, and sometimes kaolinite and/or tourmaline. The absorption features of these minerals often became completely obscured by those of the surrounding minerals when SWIR point spectra were measured.

The relatively small pixel size in hyperspectral imaging also provides spectra of pure minerals while point spectrometry frequently yields mixed spectra with absorption features by two or three minerals. The pure mineral spectra can be used to extract parameters that describe differences in the composition or crystallinity of certain minerals. Although these parameters can also be extracted from mixed mineral spectra, these will be less accurate since they can be affected by the absorption features of the other minerals.

Another advantage of SWIR hyperspectral imaging is that a large number of spectra (±50,000 per sample) are acquired simultaneously. This allows the SWIR-active mineralogy at the surface of samples to be quantified by classifying each spectrum on the mineral and/or mineral characteristic that it represents and counting the number of times that a certain classification occurs. This can be used to distinguish between smaller compositional differences such as the occurrence of specific white mica species and the relative amount of chlorite or tourmaline that the samples contain.

Finally, SWIR hyperspectral imaging has the advantage that the spectral information can be displayed in an image. This provides data about the distribution of the SWIR-active mineralogy which can be used to characterize differences in texture including grain sizes and cross-cutting vein structures. Examples of such textural characteristics can be seen in the different maps of Fig. 4.

The variability in texture between the samples is relatively high considering the size of the sample set. Because of this, many characteristics that can be observed from the mineralogy maps are often not shared by a sufficient amount of samples to produce statistically meaningful classifications. An example is the vein structure in the white mica crystallinity map of sample 2 in Fig. 4d. Although such a characteristic provides information about the hydrothermal alteration environment from which the samples originate, it occurs on only two samples in the sample set. Both these samples have significant copper grades (0.62% & 0.96% Cu), but it is uncertain if this relationship between vein structures and copper grades is not coincidental.

The limited size of the sample set is likely the main reason that SWIR hyperspectral imagery did not improve upon the indirect characterization of copper grades that was possible with SWIR point spectrometry. However, considering the advantages of SWIR hyperspectral imaging, it is expected that the characterization of copper grade distribution will be improved when this technique is tested on a sample set that is larger and more representative of the full mineralogical variability of the deposit. An ideal sample set for further testing would be drill core samples.

Dalm et al. (2014) points out that the presence of dust and water on the sample surface can limit the practical appliance of a SWIR sensor for sensor-based sorting. An additional limitation of SWIR hyperspectral imaging sensors may be the time needed to acquire the data at high spatial resolution. In order to reach sufficient throughput on sensor-based sorting equipment, the SWIR data needs to be acquired in a relatively short time period which places restrictions on the maximum spatial resolution that can be achieved. It is uncertain to what extent this limits the above discussed advantages of SWIR hyperspectral imaging over point spectrometry. For applications of SWIR hyperspectral imaging that are not restricted by data acquisition time, such as drill core scanning, this is not an issue. Spatial resolution in SWIR hyperspectral imaging is, however, an important parameter for any application since it governs the level of detail of the mineralogical information that can be extracted from the data.

5. Conclusions

The following conclusions were drawn from testing SWIR hyperspectral imaging on 43 porphyry copper ore samples:

- Mineralogy maps produced from SWIR hyperspectral images can be used as input variables in a PCA. This provides an effective method to cluster samples that have similar mineralogical composition and to identify the mineralogical differences between sample groups.
- SWIR hyperspectral imagery in combination with mineralogy mapping and PCA could be used to discriminate 58% of the samples with sub-economic copper grades. The average grade of this group of samples is 0.20% Cu, which is well below an assumed economic cut-off grade of 0.40% Cu.
- SWIR hyperspectral imaging did not improve upon the indirect characterization of copper grades that was achieved by Dalm et al. (2014) using SWIR point spectrometry. The high textural variability between samples and limited size of the sample set are considered to be key contributing factors.
SWIR hyperspectral imaging has the capability to acquire SWIR data at a relatively high spatial resolution. Because of this, it has the following advantages over SWIR point spectrometry:

- Provides more complete data of the mineral composition of a sample including minerals that are present in relatively low quantities.
- Enables the identification and extraction of pure mineral spectra that can be used to characterize mineral composition and/or crystallinity.
- Enables quantification of the SWIR-active mineralogical composition at the surface of a sample by counting the number of pixels representing certain minerals and/or mineral characteristics.
- Enables the characterization and evaluation of the texture of samples apparent from mineral maps.

Considering the advantages of SWIR hyperspectral imaging, it is expected that the characterization of copper grade distribution and ore-waste designations will be improved when this technique is tested on a sample set that is larger and more representative of the full mineralogical variability of the deposit.

References


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