Mine environmental monitoring using CHRIS Proba imagery of the Dexing Copper Mine, China

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Abstract - Traditional ground based monitoring of mining activities are no longer acceptable or sometimes sufficient in terms of assessing sustainable business practices. Remote sensing is increasingly influencing the changing social and management processes of mineral extractions. This study focuses on the application of hyperspectral remote sensing to monitor water and vegetation pollutions at the Dexing Copper Mine (DCM), China. The 2007 CHRIS/Proba image was selected for this research. A focus of this study was the mapping of the tailings water body in addition to an assessment of the relative health of mine environment vegetation stress. This study critiques the use of advanced satellite based hyperspectral techniques in the monitoring of mineral resource extraction in accordance with the principles of sustainable development.

KEY WORDS: Environment, Hyperspectral, Pollution, Resources, Vegetation.

1 INTRODUCTION

Sustainable mining practices involve managing the environmental, economic, community, safety and resource efficiency dimensions (Laurence, 2011). Due to the toxicity of many mine site activities both in surface and underground operations have the potential to cause significant impacts not only on the environment but also on other dimensions of sustainable mining. The new generation of satellite platforms with their ability to capture data of higher spectral and spatial resolution has the capability to emerge as essential new tools for use in mine site monitoring. Although satellite remote sensing has provided significant contribution in construction, development and monitoring aspects of many projects in different industries, its use in mining industry is somewhat underutilised (Du *et al.*, 2003; McPherson, 2006). This study utilises hyperspectral image acquired from the Compact High Resolution Imaging Spectrometer (CHRIS) satellite (Barnsley *et al.*, 2004) to trial two pollutants tracking scenarios; one qualitative mapping of the mine tailings water, and another measurement of the relative health of the vegetation in the adjacent mine environment.

2 STUDY SITE

Dexing Copper Mine (DCM) situated in Jiangxi Province of China (Figure 1Figure 1. Location of the Dexing Copper Mine.) is one of the largest open pit copper mines in Asia. DCM underground mining was started in 1965, with the open pit operation commencing in 1971. Currently DCM produces around 36 million tonnes of copper ore annually. 600 million tonnes of overburden and waste rock, containing small quantities of copper and other metals have accumulated since the commercial production of the mine in the area (Wu *et al.*, 2009). This overburden and waste rock dumps are the source of acidic mine discharge in the area.

Many researchers have studied environmental pollution of the DCM area by ground based geochemical studies (He *et al.*, 1997, 1998; Teng *et al.*, 2009) as well as remote sensing based approach using Landsat (Wang *et al.*, 2003; Wang *et al.*, 2004; Yan *et al.*, 2004; Zhao *et al.*, 2003), ASTER (Cheng *et al.*, 2008) and Hyperion (Gan *et al.*, 2004) images.

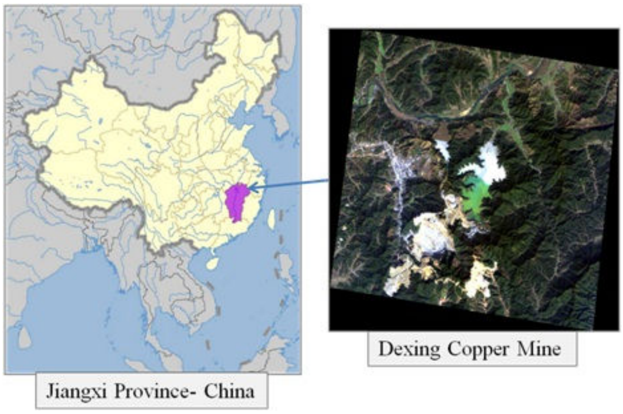

Figure 1. Location of the Dexing Copper Mine.

3 IMAGE ACQUISITION AND PRE PROCESSING

The CHRIS hyperspectral sensor is mounted on board the European Space Agency (ESA) small satellite platform PROBA (Project for On Board Autonomy) has multi-angular acquisition capabilities. CHRIS can acquire up to five consecutive images of a ground target in a single satellite overpass from different viewing angles (i.e. 0°, ±36°, and ±55°). Images selected for this study were selected from the nadir (0°) image acquisition acquired in Mode 3 on 31st December 2007. The dataset was pre-calibrated by using HDF Clean V2 (Cutter, 2006) followed by atmospheric correction of the image was performed using BEAM 4.8 (Brockmann Consult 2010), an open-source toolbox, together with CHRIS BOX 1.5.2. Multi-angular characteristic of CHRIS causes viewing distortions, especially for the first and last images with larger observation zenith angles. The image was geometrically rectified using BEAM to remove minor distortions. The image was then georeferenced through image to map registration tool of the software ENVI (ITT VIS, 2011). An extremely low RMS error of 0.140907 pixels was achieved during the image registration process.

4 MAPPING MINE TAILINGS LEACHATE

The ENVI (ITT VIS, 2011) hourglass processing flow was used to define hyperspectral endmembers to identify the most spectrally pure or unique pixels within the dataset and map their locations and sub-pixel abundances. The initial processing incorporates polished apparent reflectance data as the input for further spectral reduction through the Minimum Noise Fraction (MNF) transformation as modified from Green *et al*. (1988). As there are no field-derived spectra available for this study, all 18 MNF bands were selected for further processing to preserve full data dimensionality. The Pixel Purity Index (PPI) (J. W. Boardman *et al.*, 1995) was used to find the most spectrally pure or extreme pixels in the data. A threshold value 2.5 was set to define the pixels as extreme ends of the projected vector. The automated clustering method was used to retrieve all possible endmembers. The method yields n^{+1} endmembers where n in the number of input MNF bands. The automated clustering therefore defined 19 class endmembers. The hyperspectral image was classified using Spectral Angle Mapper (SAM) method (Center for the Study of Earth from Space -CSES, 1992; Kruse *et al.*, 1993) with these 19 endmembers. The tailings water body was defined as a separate region of interests (ROI) from hourglass processing and SAM rules images. Each rule image was enhanced through linear contrast stretching of the histograms. The minimum and maximum stretching value was used as the threshold constraints for the respective rule image to further define water ROI. The pixels defining water ROIs were then integrated to *n*-D Visualiser (J. W. Boardman, 1993; J. W. Boardman & Kruse, 1994) to further define clusters of pure endmember pixels in 18-dimensional space. Mean spectra of water ROIs were included in a spectral library for classification.

The SAM classification has effectively highlighted target pixels with smaller SAM angles (closer match). The lowest value of the histogram of the classified rule image displayed as a flat line represents significant matches for the given target spectra. Figure 2 shows values ranging from 0.023 to 0.543 which were stretched to form the output rule image display range of 0 to 255.

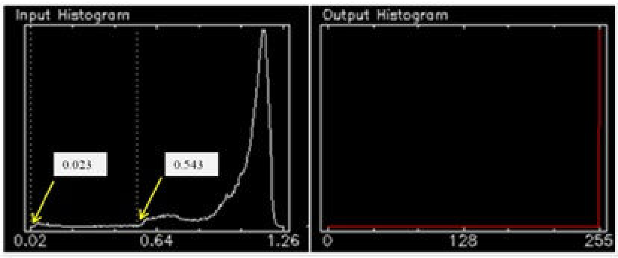

Figure 2. Histogram of the rule image of the classified water.

The resultant stretched rule image is shown in Figure 3 using the standard ENVI rainbow colour scheme where the spectral matches for water targets decreases across red (highest match) to blue colours (moderate-high match).

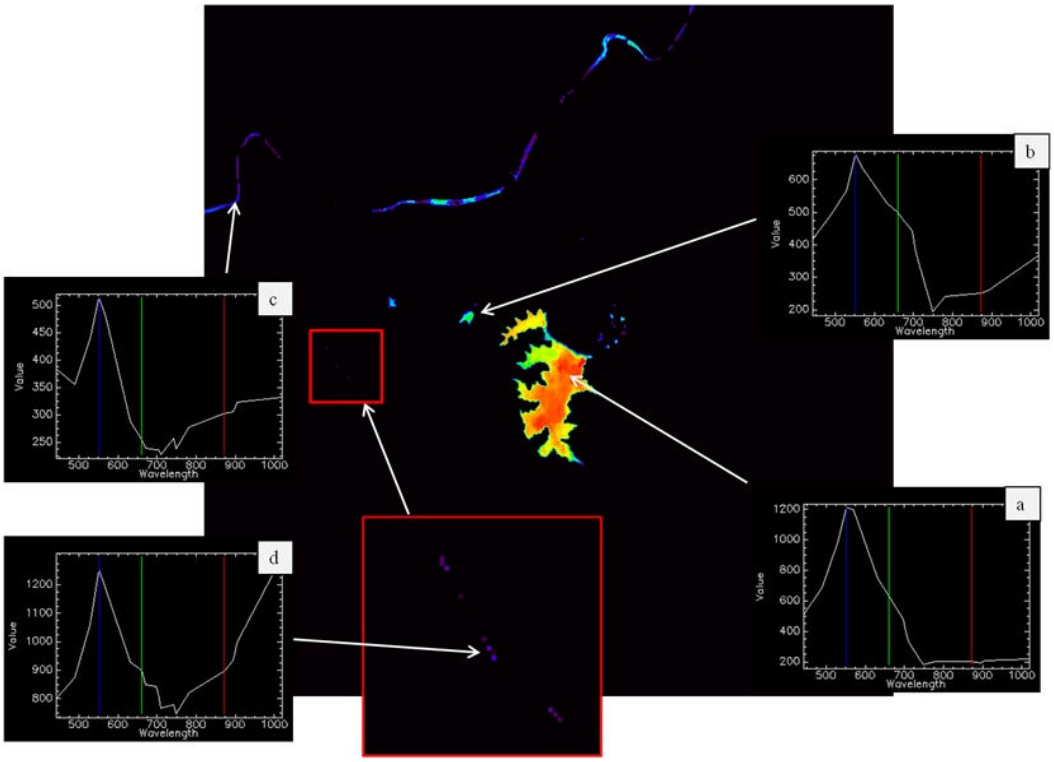

Figure 3. The rule image of the water showing spectral signatures at (a) Mine tailings No.4 (b) Mine tailings No. 2 (c) the Le'an River (d) the Dawu River.

The water spectra at mine tailings no. 4 (Figure 3a) maps alkaline water corresponding to pH~11 (Gan, *et al.*, 2004). A decreasing trend in apparent pH is highlighted from the centre towards the periphery of tailings deposits. This trend is also evident in tailings no. 2 (Figure 3b), however this could be influenced by the depth and turbidity of water. The spectra of the Le'an River and Dawu River shows characteristic of both acidic and alkaline water, which could be attributed to acidic runoff from mining waste dumps.

Similar trends can be identified in the surrounding mine areas, clearly indicating the potential for further qualitatively mapping of mine leachate in surrounding water bodies with hyperspectral imagery.

5 MAPPING MINE ENVIRONMENT VEGETATION

Vegetation Indices (VIs) are simple numerical indicators that reduce multispectral or hyperspectral data to a single variable for the accurate measurement, monitoring, and modelling of terrestrial ecosystems at a range of spatial scales (Merton, 1998). Based on the wavelength range of 18 spectral bands of the CHRIS image, 14 vegetation indices were analysed resulting in three selected to map the relative health of the vegetation adjacent to the mine environment. VI's trialled included:

(i) The Modified Red Edge Normalized Difference Vegetation Index ($mNDVI_{705}$) as a narrowband greenness vegetation index.

(ii) The Anthocyanin Reflectance Index 1 (ARI1) as a leaf pigment vegetation index.

(iii) The Structure Insensitive Pigment Index (SIPI) as a light use efficiency index.

The nadir spectrally polished georeferenced image was used to create a spatial map highlighting patterns of overall vegetation health and vigour in the adjacent mine environment. Figure 4 maps healthy vegetation as responding to lower apparent stress VI values, whereas classes mapped as vegetation under apparent stress may be associated with more toxic environments resulting from increased airborne or leachate derived mine pollutants. Spectral signatures clearly show signs of partial or total senescence of these vegetated area and down-regulation of photosynthesis. The nadir image was divided into nine classes from the most stressed vegetation (class 1) to the healthiest vegetation (class 9) as shown in Figure 4.

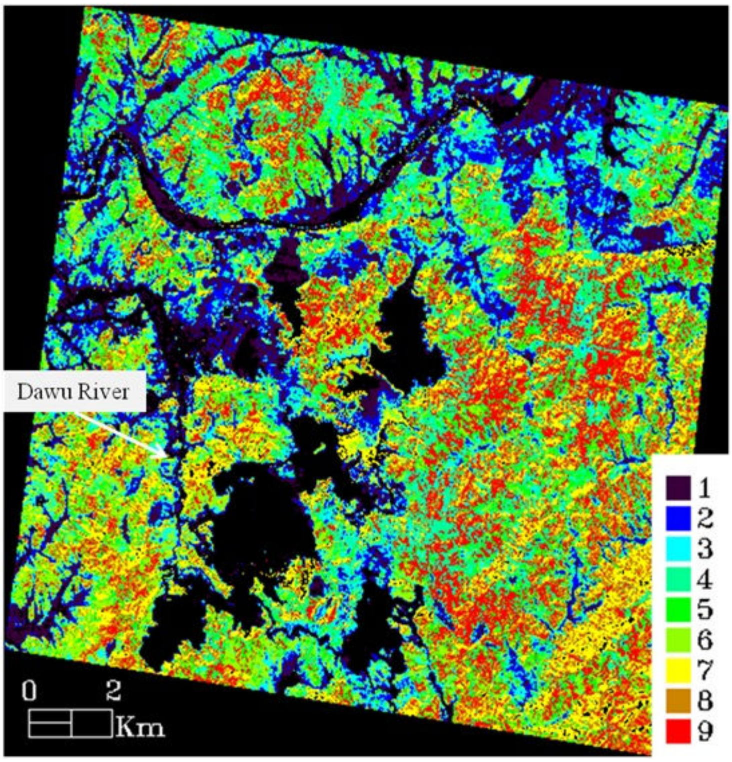

Figure 4. Relative health of the vegetation in DCM area.

The black areas represents pixels containing no vegetation ($mNDVI_{705} \leq 0.2$) within the mine and adjacent areas. Importantly, vegetation immediately adjacent to the Dawu River is classified as high stress, possibly associated with high mining leachate concentrations. The area surrounding the Dawu River was overlain with the SRTM DEM topography dataset to highlight the effects of stress in elevated terrain. All areas up slope from the drainage system containing high leachate concentration mapped as lower apparent stress with this index as shown in Figure 5.

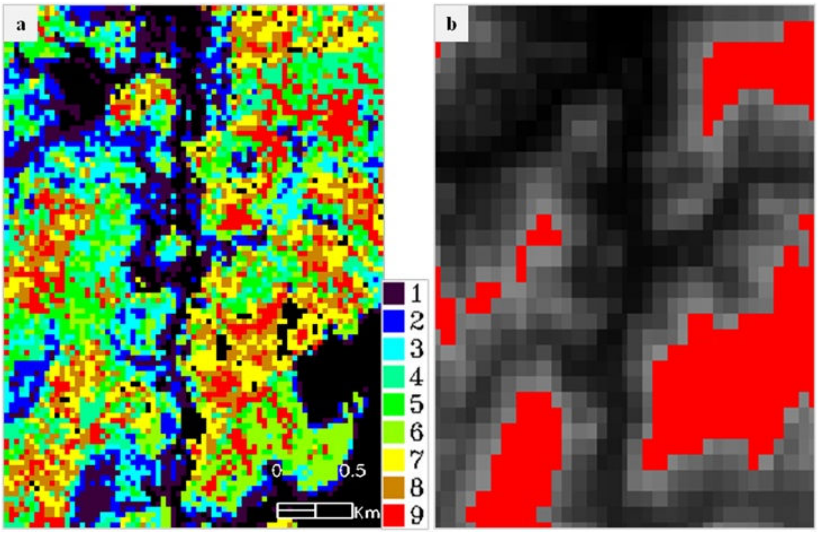

Figure 5. (a) Relative health of the vegetation (b) The red area represents more elevated terrain.

It is observed that there is a stronger relationship between areas with higher elevation exhibiting more vigorous vegetation health values. Vegetation on the tops of hills away from moisture sources normally exhibits the opposite trend due to the reduced availability of soil water. Importantly, high stressed vegetation in low elevation areas, although in a moister environment, is more likely to be influenced by the adverse effects of mining leachate.

6 CONCLUSION

Orbital hyperspectral remote sensing provides a new tool for the monitoring of environments adjacent to mine sites. Field spectra could have further validated these results however access to these data was restricted. Satellite remote sensing is still largely rated by the mining sector as an interesting research tool with great potential. However, it will take some time for this sector to fully integrate this new tool with traditional ground based surveying and monitoring methods. An increased number of satellites now provide an economic means to collect or validate environmental patterns resulting from mine waste. Furthermore, image analysis software is rapidly developing which further improves the accuracy and adoptability of this technology. Environmental scientists and engineers within the mining sector are increasingly adopting remote sensing technology to further understanding of the needs, cultural context, and organizational environment of mines.

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ACKNOWLEDGEMENT

Authors would like to acknowledge the Surrey Satellite Technology Ltd. & ESA for providing the CHRIS/Proba data for this study.