Evaluation of *casi* and SFSI Hyperspectral Data for Environmental and Geological Applications - Two Case Studies

K. Staenz[1], R.A. Neville[1], J. Lévesque[2], T. Szeredi[3], V. Singhroy[1], G.A. Borstad[4], and P. Hauff[5]

1) Canada Centre for Remote Sensing
588 Booth Street, Ottawa, Ontario, Canada K1A 0Y7
Phone: (613) 947-1250, Fax: (613) 947-1383, E-mail: karl.staenz@ccrs.nrcan.gc.ca

2) MIR Télédétection Inc.
2182 de la Province, Longueil, Québec, Canada, J4G 1R7

3) MacDonald Dettwiler and Associates Ltd.
13800 Commerce Parkway, Richmond, British Columbia, Canada V6V 2J3

4) G.A. Borstad Associates Ltd.
114 - 9865 West Saanich Rd., Sidney, British Columbia, Canada V8L 5Y8

5) Spectral International, Inc.
PO Box 1027, Arvada, Colorado, 80001, U.S.A.

ABSTRACT

The capabilities of two imaging spectrometers, the Compact Airborne Spectrographic Imager (*casi*) and the SWIR (Short-Wave Infra-Red) Full Spectrum Imager (SFSI), were evaluated for environmental and geological applications. Results from two case studies, one involving the identification of minerals at Cuprite, Nevada, the other an environmental characterization of a mine site and its rehabilitation near Sudbury, Ontario, are presented. SFSI SWIR II (2000 nm - 2400 nm) data were used for the mineral mapping study while *casi* visible and near infrared (VNIR) (450 nm - 900 nm) data were applied in the environmental study. The evaluation process included the retrieval of surface reflectances prior to the application of spectral unmixing for the identification of specific materials, and the subsequent validation of the extracted information. Results showed that the spectral features of the alteration minerals alunite, kaolinite, and buddingtonite could be clearly identified in the SFSI spectra and, hence, that these minerals could be mapped. Comparison of the mineral classification map and that retrieved from Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data showed generally good agreement. In addition, results derived from *casi* data demonstrated that vegetation, lime, oxidized tailings, fresh tailings, and water could be discriminated with spectral unmixing. Validation of the environment study results against field samples indicates good quantitative agreement with respect to the percent ground cover of lime and of vegetation; the latter is used as an indicator of the level of vegetation regrowth and hence rehabilitation of the mine site. In addition, a qualitative verification of the oxidized tailings indicates a good match between results derived from the remotely sensed data and field checks. In general, the *casi* and SFSI instruments provide useful information for environmental and geological mapping purposes.

1. **INTRODUCTION**

The usefulness of hyperspectral data for geological mapping has been demonstrated in the early development phase of imaging spectrometry by various experiments, as reported by Goetz *et al.* (1985), Huntington *et al.* (1986), and Kruse (1988), among others. Advances in imaging spectrometry or hyperspectral remote sensing related to instrumentation development and calibration, data preprocessing such as surface reflectance retrieval, and information extraction have led to the development of sophisticated techniques for identification and mapping of minerals (Clark *et al.*, 1990; Boardman and Huntington, 1996; Cloutis, 1996). Applications in areas such as environmental geology are not as well developed yet. However, recent work indicates that imaging spectrometry has the potential to play a significant role in the extraction of environmental information (Singhroy, 1996; Mueller *et al.*, 1997; Farrand and Harsanyi, 1997; Pearson *et al.*, 1997). In particular, the identification and monitoring of the surfaces of mine tailings sites are of interest. Baseline mapping and subsequent monitoring of the tailings sites are essential in documenting progress towards their rehabilitation as required by government regulations.

In this paper, the capabilities of two Canadian hyperspectral airborne instruments are investigated to determine their potential for geological and environmental mapping. The two sensors evaluated are the Compact Airborne Imaging Spectrographic Imager (*casi*) and the SWIR (Short-Wave Infra-Red) Full Spectrum Imager (SFSI) (Neville *et al.*, 1995; Anger *et al.*, 1996). Both are pushbroom imagers utilizing two dimensional detector arrays. *casi* is a commercially available sensor operating in the visible and near-infrared (VNIR) from 400 nm to 1000 nm. A *casi* 72-band configuration covering the wavelength range from 407 nm to 944 nm was selected for this study. SFSI was developed by the Canada Centre for Remote Sensing as a research instrument to provide a SWIR capability in Canada. It provides 120 spectral bands covering a wavelength range between 1208 nm and 2445 nm.

The case studies selected to evaluate the capability of the two instruments include mineral identification and mapping in the Cuprite mining district of Nevada and an environmental assessment of mine tailings in vegetated terrain near Sudbury, Ontario. SFSI data were used for the mineral mapping case study while *casi* data were applied to map the mine tailings and their rehabilitation with respect to revegetation. Detailed examination of SFSI data was limited to the 2000 nm to 2400 nm region, which contains important absorption features of carbonate and hydroxyl minerals (Hunt, 1979; Goetz *et al.*, 1983; Huntington *et al.*, 1989). These absorption features due to overtone bending and stretching vibrations are distinct and can be used for mineral identification with proper spectral resolution. The *casi* VNIR wavelength range is sensitive mainly to changes in chlorophyll concentration and plant structure and, hence, provides the information necessary to map vegetation regrowth of the mine site. It further includes absorption features due to the charge transfer and crystal field effects of the transition element Fe (Huntington *et al.*, 1989; Goetz, 1992). This allows one to map the oxidized tailings.

The evaluation process included the retrieval of surface reflectance from calibrated at-sensor radiance. This enabled the comparison of image derived spectra with those acquired on the ground. In order to test the mapping capability of these sensors, spectral unmixing was applied to the data sets. The computed fractions were then mapped on a pixel-by-pixel basis and the resulting imagery compared to ground data at selected locations and classified imagery derived from data acquired by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (Vane *et al.*, 1993). The entire data processing was carried out on the Imaging Spectrometer Data Analysis System (ISDAS) of the Canada Centre for Remote Sensing (Staenz *et al.*, 1998).

2. SENSOR DESCRIPTION

The *casi* and SFSI instruments are pushbroom imagers based on two-dimensional detector arrays and as such use no moving parts in the imaging process (Anger *et al.*, 1994 and 1996; Neville *et al.*, 1995). Both sensors provide data with high spectral resolution of 10 nm or better in combination with spatial resolutions of up to 1 m. The characteristics of these sensors are summarized in Table 1.

casi

casi uses a two-dimensional Charge Coupled Device (CCD) array with 288 elements in the spectral direction and 612 pixels in the spatial direction of which 512 pixels are available for imaging. The 288 basic spectral bands have a band centre spacing of 1.9 nm, a bandwidth of 2.2 nm, and together span a range of 545 nm, which is selectable within the 400 nm to 1000 nm range. The signals from each of these bands are digitized to 12 bits. In the full spectral mode, all 288 basic bands are recorded, but the swath is limited to 39 pixels. In the full spatial mode, the full swath of 512 pixels is recorded for up to 20 preselected spectral bands. The sensor can also be operated in modes in which intermediate numbers of spectral bands and pixels are recorded. These bands can be formed of sums of up to 16 basic bands; their centre positions and bandwidths are programmable. For the present case study, 72 bands, each consisting of four contiguous basic bands summed together, were recorded. In this configuration, the swath consists of 406 pixels. The single pixel across-track instantaneous-field-of-view (IFOV) at nadir is 1.3 mrad. This gives a total field-of-view (FOV) of 29.6 degrees for the 406 pixel swath and 36.8 degrees for the full 512 pixel swath. The along-track IFOV is 1.2 mrad.

SFSI

SFSI employs a two-dimensional platinum silicide Schottky barrier CCD array with 488 rows of 512 detector elements. In operation, a region of 480 lines by 496 columns is used; two adjacent lines are summed together on the detector array to yield an effective array of 240 by 496 detector elements. Following readout and digitization of these signals, adjacent bands are again summed together to reduce the output data rate. This gives 120 spectral bands with a wavelength coverage from 1208 nm to 2445 nm of which 115 bands covering 1219 nm to 2405 nm are used in practice. SFSI has 496 pixels in the across-track dimension and a fixed integration period of 20 ms. The band spacing and nominal bandwidth are 10.3 nm. (The sensor can now be flown with a band spacing of 5.2 nm). The data are digitized to 13 bits of which 8 bits are selected by the operator for recording. The across-track pixel IFOV is 0.33 mrad (1.16 mrad today), giving an across-track FOV of 9.4 degrees (32 degrees). The along-track IFOV is currently 1 mrad.

3. DATA ACQUISITION

casi

High spectral resolution *casi* data were acquired on August 24, 1996 over the Copper Cliff mine tailings site near Sudbury, Ontario, Canada. The *casi* was flown in the 72-band configuration (Table 1) at an altitude of 1.9 km above ground, resulting in a spatial resolution of 4.3 m along-track and 2.5 m across-track. Only wavelengths between 450 nm and 900 nm were used for the evaluation of the sensor's mapping capability because of the drop-off of the responsivity of the silicon detector at both ends of the casi wavelength range.

SFSI

The data used were collected on 21 June, 1995 over a site located in the Cuprite mining district of Nevada as part of a mission to test the capability of the sensor for mineral mapping (Hauff *et al.*, 1996). For this mission the sensor was flown at approximately 75 m s^{-1} and at an altitude of 3.3

km above ground level providing an approximate spatial resolution of 3.0 m along-track and 1.0 m across-track.

4. DATA PROCESSING

Data processing involved the removal of the most significant aircraft motion effects, surface reflectance retrieval, post-processing of the retrieved surface reflectance spectra, and spectral unmixing. An overview of the individual data processing steps is shown in Figure 1.

Aircraft Motion Effect

In assessing the data quality, it was noted that significant aircraft motion effects exist in the *casi* imagery. In order to correct for the most significant effect, the roll was removed using the navigation data to calculate the lateral pixel shifts for each line. These shifts were then applied to the entire image cube. Aircraft motion effects were minor in the SFSI data and, therefore, were not corrected.

Surface Reflectance Retrieval

In the next processing stage, surface reflectances were computed from calibrated at-sensor radiance data, compensating for atmospheric absorption and scattering effects. This procedure involves the use of the known geometric data acquisition parameters and a radiative transfer (RT) code with an appropriate atmospheric model to calculate look-up tables (LUTs), one each for a low and high reflectance spectrum (Staenz and Williams, 1997). This approach reduces significantly the number of RT code runs. The RT calculations yield computed radiances and are performed for only a few tunable values for each of the five input parameters: wavelength, pixel position, atmospheric water vapour, aerosol optical depth, and terrain elevation. The radiances for intermediate values of these parameters are calculated by multi-dimensional bi-linear interpolation; this results in several orders of magnitude savings in time and computing resources required to retrieve the desired at-target reflectances.

For the current case studies, the MODTRAN3 RT code (Berk *et al.*, 1989) was used to calculate the modelled at-sensor radiances for input target reflectance values. The parameters required as input to the MODTRAN3 RT calculations are listed in Table 2. For each case study, LUTs were created for all the MODTRAN3 wavelength grid values within the range of interest, for five pixel locations equally spaced across the swath, including nadir and the swath edges, and for single values of water vapour content and aerosol optical depth. The water vapour and CO_2 concentration were determined by applying the atmospheric correction process iteratively to sample scene spectra, while adjusting these atmospheric parameters, and selecting those values which best removed the corresponding absorption features. The aerosol optical depth was calculated from the horizontal visibility by the RT code. The LUT generation procedure was repeated for two spectrally flat target reflectance values, $\rho_1 = 5\%$ and $\rho_2 = 60\%$, which encompass the expected reflectance range. The net results are two LUTs (LUT_i, i = 1,2) between them containing four radiance values for each of the elements of the five dimensional matrix: the radiances reflected from the ground target L_{gi}, i = 1,2 , one for each of the two reflectance values, and the radiances, L_{oi}, i = 1,2 , from all other sources including atmospheric scattering, the adjacent pixels, and thermal radiation. The final step in the LUT generation is the convolution of these calculated output radiances with the sensor's spectral response profiles, and the resampling to the sensor's band centre wavelengths. The spectral response profiles for *casi* are approximated by a trapezoidal-shaped line spread function and for SFSI by a triangular-shaped line spread function.

The problem at hand, the calculation of the target reflectances given the at-sensor radiances, is the inverse of the above process. To accomplish this, the radiances L_{gi} and L_{oi} are parameterized as follows (Staenz and Williams, 1997):

$$L_{gi} = A \frac{\rho_i}{1 - \rho_i S}, \qquad i = 1,2 \tag{1}$$

and

$$L_{oi} = B \frac{\rho_i}{1 - \rho_i S} + L_a \ , \qquad i = 1{,}2 \tag{2}$$

where A and B are coefficients depending on geometric and atmospheric conditions, S is the spherical albedo of the atmosphere, and L_a is the radiance backscattered from the atmosphere. In this system of four equations, A, B, S, and L_a are the unknowns, while ρ_i, L_{gi} and L_{oi} are the known quantities: $\rho_1 = 5\%$ and $\rho_2 = 60\%$, and the L_{gi} and L_{oi} are found from the LUTs for each pixel in the scene by multi-dimensional bi-linear interpolation (Press *et al.*, 1992). By substituting the values for A, B, S, and L_a resulting from the solution of the Equations 1 and 2 into Equation 3, one can calculate, for each pixel in the scene, the surface reflectance

$$\rho = \frac{L - L_a}{A + B + S\,(L - L_a)} \ , \tag{3}$$

where L is the at-sensor radiance provided by the calibrated image cube.

Post-processing

The next stage of processing performs an empirical correction for irregularities in the reflectance data that may have originated in the sensor, or that may have resulted from the approximations made in the atmospheric modeling, and the selection of the RT code input parameters. This involves the calculation of correction gains and offsets using spectrally flat target pixels using a technique similar to the one described in Boardman and Huntington (1996). The underlying assumption in this technique is that there are a number of pixels whose true reflectance spectra are flat, or nearly flat, and whose brightnesses range over a major portion of the full range is covered by all the pixels in the scene. In this procedure, a second-order polynomial fit to the reflectance spectra, along with a goodness of fit measure (Π-squared), is computed on a pixel-by-pixel basis. A scatter plot is generated by plotting for each pixel the Π-squared value versus the average, calculated over spectral bands, of the corresponding reflectance spectrum. The pixels which, for a given spectrum average, have the smallest Π-squared values are selected as the ‘spectrally flat’ target pixels. For this set of spectrally flat pixels and for each spectral band separately, a scatter plot is generated in which the second-order polynomial model value for the given band is plotted versus the measured value. Linear fits performed on a band-by-band basis give slopes and offsets which are used as gain and offset corrections to the reflectance data. In the case of the SFSI image cube, the “flat” spectra are assumed only to be slowly varying, not spectrally flat. *casi* data were not corrected, since the irregularities in reflectance were minor between 450 nm and 900 nm.

Selection and Mapping of Materials of Interest

The endmember spectra were chosen from the image cubes themselves. A principal component analysis was performed on the reflectance cube and scatter plots of pairs of principal components were created. The endmembers were chosen from averages of those pixels occurring in the extremities of the scatter plots. These pixels are often referred to as the “purest pixels” (Boardman, 1993). The subsequent mapping of the materials represented by the endmembers was done using a constrained linear unmixing procedure. This method attempts to express the reflectance spectrum of an image pixel at location (x, y) as a linear sum of N endmember spectra as follows (Adams *et al.*, 1986; Shimabukuru and Smith, 1991; Boardman, 1995):

$$\vec{r}_k^{\,(x,y)} = \left(\sum_{e=1}^{N} f_e^{(x,y)} \vec{S}_{ek} \right) + \vec{r}_k^{\,(x,y)} \quad , \ k = 1, 2, ..., M \qquad (4)$$

where $\vec{r}_k^{\,(x,y)}$ is the reflectance in band k of the spectrum under pixel (x, y), $\vec{S}_{ek}$ is the reflectance in band k of the eth endmember spectrum $\vec{S}_e = \left(S_{e1}, S_{e2}, ... S_{eM}\right)$, $f_e^{(x,y)}$ is the fraction of endmember e contributing to the spectrum $\vec{\rho}^{\,(x,y)}$ of pixel (x, y), M is the total number of bands in the spectrum, and $\vec{r}$ is the error term. In constrained unmixing, the conditions that the fractions are positive and that the sum of the fractions under pixel (x, y) equal 1 are imposed:

$$\sum_{e=1}^{N} f_e^{(x, y)} = 1 \text{ and } f_e > 0 \quad , \qquad e = 1, 2, \ldots\ldots, N. \tag{5}$$

5. CASE STUDY I - Mine Site Characterization

Background

Environmental restoration of sulphide mine tailings is a growing concern for many mine operators. Complex chemical weathering reactions initiated when tailings are exposed to air and water lead to the production of sulphuric acid (acid mine drainage), which is capable of liberating the heavy metals present in large amounts within the tailings (Kelley and Tuovinien, 1988). It is difficult to revegetate such sites because of their high level of contamination in heavy metals and other toxic substances related to mining exploitation. One technique used at the Copper Cliff mine to reduce the acidity level of the tailings, thereby aiding revegetation, is the spreading of lime prior to seeding (Peters, 1988). This allows certain tolerant species to initiate the revegetation process. Long term quantitative measurements are required to monitor progress from year to year.

Results

Endmembers were selected from the image cube using the first three principal components, which account for 99% of the variability in the data. The following five endmembers were identified: green vegetation, lime, oxidized tailings, and water 1 and 2 (Figure 2). Water 1 located in the active tailings area is contaminated with fresh tailings while water 2 in the inactive tailings area is highly contaminated by sewage, tailings, and lime (Figure 3a). The endmembers were identified using field reference information in combination with ground-based spectral measurements collected with a GER 3700 field spectroradiometer (GER 3700, 1997). The endmember and ground-based spectra are compared in Figure 4 for lime and oxidized tailings. Overall scale differences in the reflectance domain, apparent in Figure 4, can result when the target has texture that will produce shadowing, even at the microscopic level. This shadowing is dependent upon the solar illumination and sensor viewing angles. The geometrical differences between the ground-based and airborne measurements tend to bias ground-based results to higher reflectance values. The ground-based measurements were acquired from sunlit, pure targets. This selectivity was made possible by the small IFOV and the flexibility of the field instrument. By contrast, this selective sampling process is not possible with the airborne instrument because of the much larger IFOV and the fixed viewing directions.

The results of the constrained unmixing are presented in Figure 3. An examination of the error images revealed no significant errors and hence, one can be confident all major endmembers have been found and the endmembers span the data space. A colour composite providing an overview of the study area is shown in Figure 3a. The upper part of the image is the inactive tailings area where revegetation work is being done. The lower part is an active tailings area where fresh tailings are being deposited. Figures 3b, 3c, and 3d show the three endmember fraction images of green vegetation, lime, and oxidized tailings obtained from the linear constrained spectral unmixing analysis. Since the mine tailings and their various stages of rehabilitation were the targets of primary interest of this study, the unmixing results presented concentrate on the three endmembers green vegetation, lime, and oxidized tailings.

In the green vegetation fraction image of Figure 3b, the red colour indicates forested areas and grass areas appear in tones of blue, green, yellow, and orange, which represent fractions ranging from 0.0 to 0.4. This result indicates that revegetation is well on the way in the inactive tailings area. Label A indicates a grass area where seeding and liming was performed in previous years. This area is a mixture of dry and green grass containing less than 10 % exposed oxidized tailings (Figure 3d). The area labelled B had been limed and seeded with grass a few months prior to the airborne data acquisition. Here, oxidized tailings can still be seen through the grass. In Figure 3c, label C points to a lime pile where lime is stored for future spreading. Note the absence of green vegetation (Figure 3b) on the lime pile and the presence of oxidized tailings (Figure 3d) on its east side where the loading area for trucks is located . Oxidized tailings appear primarily in the inactive tailings area as depicted in Figure 3d. The different colours indicate the fractions of exposed tailings. Label D indicates an area of fresh deposited tailings where fractions of oxidized tailings are very low (0.01 to 0.03). Accordingly, fresh tailings are not represented by this endmember. Instead the fresh tailings spectrum resembles more closely the water 1 endmember (fractions from 0.7 to 0.8). This may be due in part to the fact that the fresh non-oxidized tailings in the study area are wet, since approximately 65% of the discharged slurry is water (Peters, 1988).

Validation

The unmixing results were validated by correlating the image endmember fractions to the fractions visually assessed on the ground at 34 known pixel locations. Visual estimations of the fractions of lime and green vegetation were performed at these sample sites, which varied in size from 10 m by 10 m to 20 m by 20 m. Image endmember fractions (percent ground cover) were averaged over the pixels corresponding to the sample areas. The relationship between image-based endmember fractions and ground-based visually assessed fractions (percent ground cover) is illustrated in Figures 5a and b, respectively, for the green vegetation and lime endmembers. The root mean square deviation from the x = y line is 0.04 for the green vegetation and 0.05 for the lime. These validation results indicate that the endmember fractions of green vegetation and lime agree with visual estimates of ground cover accurate to within 5%, two thirds of the time, for these constituents. Errors at these low levels could easily be attributed to uncertainties in the visual estimations or other sources such as natural variability of the target material spectra.

The presence of oxidized tailings as mapped in Figure 4d has been validated visually on a qualitative basis at specific locations. However, it was not possible to perform a quantitative assessment of the degree of oxidation. Tailings composition and therefore oxidizing potential depend on the nature of the ore being mined at the time the tailings were produced and discharged (Peters, 1988). This has resulted in high spatial variability of the tailings composition with no supporting documentation. Although this variation in composition produced a corresponding variation in the airborne and ground-based reflectance spectra, no ground estimates were available for a validation of the oxidized tailings endmember fraction image.

6. CASE STUDY II - Mineral Identification/Mapping

Background

Airborne imaging spectrometry is being used increasingly for mapping surface alterations in arid and semi-arid areas. This is because numerous recent results have shown that spectral analysis of both field and airborne imaging spectrometer data can provide useful mineralogical and geochemical information for geological mapping and exploration. In addition, the image processing techniques developed to facilitate surface compositional mapping using data compression and spectral unmixing techniques are now more robust (Boardman and Kruse, 1994). Clay and carbonate minerals indicative of hydrothermal alterations were mapped from both field spectra and AVIRIS data by many investigators (Rowan *et al.*, 1995; Boardman and Huntington, 1997; and others). Recently, Kruse and Boardman (1997) interpreted AVIRIS data to identify illite and calcite associated with the serpentization and carbonization of deeply weathered kimberlites. Our investigation builds on the existing knowledge of surface mineral identification techniques, with specific reference to SFSI.

Results

The endmembers were chosen from the SFSI image cube using the scatter plots in the first three principal components, which contain 99% percent of the variability in the data. Six endmembers were obtained for the Cuprite image: alunite, kaolinite, buddingtonite, silica, 'class 8 clay', and shadow. The identification was done by comparing these endmember spectra to ground reference spectra obtained at the Cuprite site and nearby sites with the Portable Infrared Mineral Analyser (PIMA), a field spectrometer (Hauff and Cocks, 1995). The three endmembers identified as alunite, kaolinite, and buddingtonite are plotted in Figure 6. By comparing these with the PIMA spectra in Figure 7, one can see the very strong spectral similarities between the SFSI and PIMA spectra. As for the previous case study, there are overall scale differences between the remote and in-situ measurements. These can result from different illumination conditions and different mineral grain sizes; for this study both are likely to apply. The PIMA instrument uses an internal light source to illuminate the ground samples, thereby avoiding shadows and atmospheric effects. In addition, the PIMA samples very small areas (20 mm^2) compared to the SFSI pixel size (approximately 3 m^2).

The unmixing results are displayed in Figure 8 along with a three-band colour image of the site

(Figure 8a). As in the previous case study, the error image showed no significant errors. This indicates that all major endmembers have been found. In Figure 8b the calculated fraction of alunite for each image pixel is indicated by colour, with blue representing a low value, red a high value. The same is done for kaolinite and buddingtonite in Figures 8c and 8d, respectively. The areas of high surface abundance for buddingtonite occur in the south-west quadrant, with alunite in the neighbouring south-central region, and kaolinite in the south-east as well as in the far north-west corner of the imaged area.

Validation

There are seven sites in the SFSI image at which PIMA samples were acquired. However, these were insufficient to determine the validity of the mineral fraction maps. On the other hand, these PIMA sample spectra, along with others obtained from neighbouring sites in the Cuprite area, served to identify the minerals common to the area and to provide spectra for comparison with the SFSI endmember spectra. The similarity between the SFSI and PIMA spectra is striking (Figures 6 and 7), especially when the differences in measurement methods are taken into consideration. This similarity provides a degree of assurance that the remote sensing approach is a valid one. As well, the mineral distribution as indicated in Figure 8 was compatible with the known mineralogy of the area.

In addition to the above checks against the PIMA data, the SFSI endmember maps were compared to a mineral map derived from AVIRIS data. The SFSI image in Figure 8a was subsampled using nearest neighbour resampling to a four-metre grid and georeferenced to a topographic map; the result is shown in Figure 9a. In Figure 9b the georeferenced SFSI image has been used as a background upon which thresholded versions of the alunite, kaolinite, and buddingtonite endmember fraction images have been superimposed in red, yellow, and pink, respectively. In addition, the endmember fraction image for the fourth endmember, tentatively identified as silica, is added in white. In Figure 9c, the results of the classification of an AVIRIS image acquired in June of 1995 and analysed using a different process (Tricorder v3.3) (Clark and Swayze, 1995 and 1997) are superimposed on the same georeferenced SFSI image using nearest neighbour resampling. For the AVIRIS image, the white area has been classified as chalcedony and the blue area as Na-montmorillonite. Simple visual assessment indicates that agreement between the two classifications is generally good for alunite, kaolinite, and buddingtonite. There are localised differences, specifically in the spatial distribution of kaolinite in the upper left corner of the image, in the extent of the buddingtonite in the lower third of the image, and in the presence of alunite along the right edge. In addition, it would appear that the SFSI class 'silica' coincides with the two AVIRIS classes 'chalcedony' and 'Na-montmorillonite'.

Most of these variances can be explained by differences in acquisition conditions, sensor parameters, processing methods, and possible errors in the registration of the two images. The AVIRIS data were collected at a higher solar elevation angle (70 degrees) than was the SFSI image (38 degrees); hence, shadowed areas were mostly absent in the AVIRIS image. Some of the regions classified in the AVIRIS image coincide with the shaded areas of the SFSI image and were consequently classed as shadow in the latter image. For these data sets, the AVIRIS spatial resolution is 17 m by 17 m while the SFSI spatial resolution is 1 m by 3 m; this contributed to the increased spatial distribution of SFSI pixels classified as one of the endmember minerals, as compared to the classified AVIRIS image. The AVIRIS classification was performed using a spectral matching procedure, Tricorder 3.3, while the SFSI image was analysed using spectral unmixing. The former method permits matching against any number of mineral spectra and has yielded more classes for this image; the risk is that it may have misidentified a mixture of two minerals as a third. There is not sufficient ground reference data available to determine which is correct in this instance. Both analysis techniques have used thresholding to arrive at their respective classified images and the spatial extent of the classes depends upon these thresholds. A rigorous quantitative analysis of the relative performance of the two sensors would require that both data sets be acquired under the same conditions, that both be processed using the same analysis technique, and subsequently co-registered to sub-pixel accuracy.

The AVIRIS data, while they do not in any way constitute 'ground truth', have been checked against ground samples distributed (sparsely) over a 25 km^2 area containing the site under discussion. In addition, AVIRIS is a known sensor, one which has undergone considerable testing and calibration over a number of years, and which has become an accepted norm in the hyperspectral airborne remote sensing arena. While the Tricorder method used to process the

AVIRIS data is not universally accepted, it is currently considered one of the best of the spectral matching procedures and is in competition with spectral unmixing for widespread acceptance as the preferred analysis technique. That the two classification maps agree as well as they do, given all the aforementioned differences in the data sources and in the analysis methods, is noteworthy and is a result that cannot readily be discounted as merely coincidental.

7. CONCLUSIONS

The results based on the two case studies, mine site characterization and mineral identification and mapping, indicate that *casi* and SFSI hyperspectral data have strong potential for environmental and geological application. The linear constrained spectral unmixing techniques have been demonstrated to be useful for extracting information from hyperspectral data sets.

The VNIR *casi* data were successfully used to assess the mine site in terms of fresh and oxidized tailings and levels of revegetation. Validation of the classification results against ground reference information showed that the fractions of the endmember 'vegetation' can be related to visual estimates of percent ground cover. The same was found for the endmember 'lime', which aids revegetation through a reduction of acidity. These relationships between endmember fractions and percent ground cover allow the interpretation of the classification results on a quantitative basis and, therefore, make spectral unmixing a powerful tool for assessing and monitoring revegetation of mine sites.

The SWIR results show that the alteration minerals alunite, kaolinite, and buddingtonite can be identified using SFSI data. The capability of SFSI to resolve the distinct absorption features of these minerals in the 2100 nm to 2250 nm region allowed the mapping of these minerals using spectral unmixing. Comparison of the resulting fraction images and corresponding classification retrieved from AVIRIS data showed generally good agreement. While the endmember fractions can be interpreted as mineral abundances for each pixel, the validation required to substantiate this interpretation is extremely difficult and needs large sets of intensive ground reference data. For many practical applications, a map showing the spatial distribution, as opposed to the absolute abundance, of a given exposed mineral is sufficient. That SFSI has the spectral and spatial characteristics necessary to identify alteration minerals has been demonstrated.

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Table 1: *casi* and SFSI characteristics. The casi characteristics are given for the nominal sensor configuration set-up in spectral data acquisition mode. (FWHM = Full Width at Half Maximum.)

Sensor	***casi***	**SFSI**
Basic design	2D array	2D array
Detector array size	288 x 612	488 x 512
Spectral coverage	407 nm - 944 nm	1208 nm - 2445 nm
Number of bands	72	120
Spectral sampling interval	7.6 nm	10.3 nm
Bandwidth at FWHM	7.9 nm	10.0 nm
Field-of-View (FOV)	29.6º	9.4º
Swath	406 pixels	496 pixels
Instantaneous FOV - across track - along track	 1.3 mrad 1.2 mrad	 0.33 mrad 1.00 mrad
Digitization	12 bits	13 bits

Table 2: Input parameters for MODTRAN3 code runs.

Sensor	***casi***	**SFSI**
Atmospheric model	Mid-latitude Summer	Mid-latitude Summer
Aerosol model	Continental	Continental
Wave number interval	1 cm^{-1}	1 cm^{-1}
Date of overflight	August 24, 1996	June 21, 1995
Solar zenith angle	31.5º	52.4º
Solar azimuth angle	176º	272.4º
Sensor zenith angle	variable	variable
Sensor azimuth angle	variable	variable
Terrain elevation above sea level	0.3 km	1.554 km
Sensor altitude above sea level	2.21 km	4.877 km
Water vapour content	2.35 g/cm^2	0.6 g /cm^2
Ozone column	as per model	as per model
CO_2 mixing ratio	as per model	200 ppm
Horizontal visibility	50 km	50 km