**ASSESSMENT WORK REPORT**

**WWW AREA PROJECT**

**Spectral Analysis Study of the WWW Claim**

**Tenure#516512**

**EVENT #**
**4111034**

Alberni Mining Division
NTS 092F02E
UTM Zone 10 (NAD 83)
Northing: 5432034
Easting: 376849

(Associated Minfile No. 092F 141
ARIS No.s 02771 and 06865)

For

Julie P.McLelland

By

Auracle Geospatial Science Inc.
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January 10 2007

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**Executive Summary**

Auracle Geospatial Science Inc. was asked by Julie P. McLelland to carry out a Spectral Analysis program on the WWW mineral claims which had been staked for their precious metal potential.

Geologically this area consists of polymetalic quartz veins occurring within granodiorites and diorites (Corrigan Creek Plutonic rocks) intruding the Karmutsen Volcanic Basalts. This report outlines work done on the upper Corrigan Creek (WWW) area claims. Work was initiated in May 2006 and completed in November 2006. The program involved acquisition of satellite spectral data available from NASA,
reconfiguring this data into a workable format, geo-referencing to Trim map bases and extensive and rigorous classification of the data in search of indicators that might lead to the discovery of uranium mineralization. Although Spectral Analysis is still in its infancy, this work program was not intended to be a research project but rather to apply recently developed technology, methodologies and the latest computer software available for spectral analysis as a tool for mineral exploration.
This spectral work program was highly labour and computer intensive. Area files were subject to rigorous classification and analysis resulting in numerous spectral images for examination. These Classification results were examined for correlation to known structural and mineral occurrences. Spatial correlation to target mineralization was not conclusive however distinct alteration and surface rock type endmembers were identified and located. It is therefore advised that follow-up ground truthing and ground based PIMA Spectrometry.

Auracle Geospatial Science Inc.

## INTRODUCTION

In December 2003 the WWW mineral tenure was staked over the historic WWW mine site and newly discovered mineralization. This prospective ground hosts several known Au Ag mineralized quartz veins. The rising demand and price of gold on the World market was a further incentive for these acquisitions.

Julie McLelland asked Auracle Geospatial Science Inc. to undertake a technical exploration work program involving the use of Spectral Analysis to see if any quartz mineralization or other alteration signals associated with hosting structures could be identified on the WWW property.

Spectral Analysis is a newly developed and still evolving exploration tool. Dave McLelland of Auracle Geospatial Science Inc. has gained valuable experience in the use of Spectral data as part of his Post Graduate Diploma, Masters Degree program, and Industry certifications that he has completed.

Alteration mineral mapping by remote sensing has become an accepted tool in mineral exploration.

This work program has provided further insight into the surface mineral constitution of this claim and the surrounding area.

## LOCATION AND ACCESS (See Figure 1 - Location Map)

The WWW mineral tenure is located 28.6 Km southeast of The City of Port Alberni on the west coast of Vancouver Island British Columbia. Access to the area is via the Port Alberni-Bamfied Road proceeding 21 km. south to Corrigan Logging Main, and then South East 7.2 km to the WWW Corrigan Creek Bridge. The Main Roads are active logging roads and are generally cleared all season roads. Further logging and inactive mining roads access the mineral showings.

## PHYSIOGRAPHY

This prospect area is situated on the south side of the Corrigan Creek. Terrain is rugged and mountainous with elevations ranging from near sea level to 1300 metres.

Mountain sides are heavily covered by timber including Douglas Fir, Hemlock Balsam and Cedar. Much of the claim area has been logged. Some areas have grown back since early logging and recent logging has opened a number of areas allowing greater visibility for spectral image analysis.

## MINERAL CLAIM STATUS

This Claim held By Julie P. McLelland and is in good standing. This Mineral Tenure includes cells totalling 381.27 Hectares of coverage. Julie P. McLelland currently holds a 100% unencumbered interest to this claim. Julie also holds 5 of the 6 adjacent claims to this tenure.

**PREVIOUS WORK** (paraphrased from Minfile 092F 141 and MOM Annual Report 1922)

The WWW mineral Claims were originally staked in 1898 and crown granted in 1898. Underground development was undertaken from 1899 until 1935 with a production history of 116 non-metric tons "averaging 4.0 oz. gold 4.3 oz. silver per ton and 0.23% copper and 1.1% lead "- W.G.Stevenson 1970.

Further production was carried out in 1940 when 60 tonnes seem to have been shipped to recover: 8553g Au, 7745g Ag, 912 kg Pb and 171kg Cu. In 1941 10 tonnes were shipped to recover 871gAu, 871g Ag, 188kg Pb and 26kg Cu. In 1985 it is reported that 106tonnes were mined and 98 tonnes milled with recovery of 23,591g silver, 7,834g gold, 2,477kg zinc, 1,377kg Copper and 300Kg lead.

Work conducted by J.P McLelland consisted of prospecting and ground reconnaissance.

**GEOLOGY:**

(See attached map as figure 2)

According to a 1963 Gunnex Minerals report published as a report on Vancouver Island mineral occurrences by Hugo Laneela and referring to an earlier (1935) government report: "A complex group of igneous rocks is exposed in the various workings. Tongues of granodiorite alternate with masses of hybrid diorite with both types being cut by basic feldspar dykes which are older than the veins."

**MINERALIZATION:**

Mineralization consists of pyrite, sphalerite, and galena in north east trending quartz veins.

## 2006 TECHNICAL WORK PROGRAM

### Methodology

Remote sensing techniques and spatial data analysis through Geographic Information Systems (GIS) have been jointly applied in the mineral exploration context to identify mineral rich potential areas in a number of locations throughout the world including alteration zones. The Spectral Analysis work associated with this project is not intended to research and develop new spectral analysis methods or to develop new software. The aim is to utilize a combination of Spectral image data and sophisticated analysis software along with geological and other exploration data from the project target area as an exploration tool in search of mineral deposition, alteration, geological or other features which may result in the location of new locations of vein type mineralization. Any other mineralized deposits that may be identified as a result of this work will also be given due attention if time allows.

A wide range of Image analysis techniques were applied to spectral data from this project area. A good deal of effort went into a type of Multivariate Classification and Regionalization (grouping of like, statistically significant data) defined as Supervised Classification which was carried out to try to establish spectral characteristics for various geological models related to the project area. These “test areas”, or “training areas” as they are described in the literature, provided an opportunity for signature development of characteristics relevant to the styles of mineralization and related geological features that are present on the subject claims. Other methods used to try to extract useful spectral maps were the hard classification operators (Principal Components Analysis, Fisher or Linear Discriminant Analysis, Maximum Likelihood, Minimum Distance Parallelepiped, Canonical Components Analysis, and Neural Network Texture Classification) and the soft classification operators (Bayesian Analysis, Dempster-Shafer Weighting and Fuzzy Classification). These procedures although able to produce spectral images, the results often did not provide obvious or even subtle indications of a relation to underlying geology or mineralization. The procedure which did produce data that was most frequently considered to be co relatable to underlying geological features, although at times tenuous, was the technique called Unsupervised Classification. This procedure and related methodology is described in the following analytical steps.

**Analytical Steps:**

1. Compilation - The first step included an extensive geological, mineralogical and mineral deposit research and compilation from historical sources in search of features which could be used as spectral targets. These features, which are identified and described in the geology and mineralization sections of this report, were digitized where possible into map overlays.

2. Base Maps - Acquisition of Trim Maps for each area to form base maps.

3. Spectral Data Acquisition - Selection and acquisition of spectral image Granules for each area. Images can be chosen from a variety of satellite passes over a wide range of time.

4. Data Quality Assessment - The images selected were then checked to ensure they adequately covered the subject areas and were of suitable quality. For example if there was too much cloud cover or if the images were of poor resolution they were rejected and replaced with new granules.

5. Geo-referencing - Spectral Images were then linked or geo-referenced to the UTM grid system by overlaying on Trim Map bases then a Digital Elevation Model (DEM) and a Digital Terrain Model (DTM) were derived.

6. Spectral Data Noise Correction - Unwanted responses (noise) from features such as water, vegetation, topography, shade, cloud cover etc were filtered or screened out as part of the image analysis process. At times this spectral noise may still be present in the images used and must be recognized as such when making interpretations.

7. Purified - Through an iterative process (5000 to 20000 iterations) data are projected repeatedly onto a random vector. Pixels that exceed an imposed threshold are collected as extreme and therefore representative of the data set.

8. n-Dimensional Visualization

9. Data Classification - This data is then subjected to a number of analytical techniques designed to isolate the target minerals and/or their pathfinders, associations or emmittances. Spectral libraries were selected for suitability and imported. Comparative analysis was performed against these spectral library signatures established for known minerals, rock types and expected alteration products of the various rock units. The comparative analysis was done using the following classification methods:

   - Spectral Angle Mapping (SAM)
   - Spectral Unmixing
   - Mixture Matched Filtering

10. Output - Spectral Classifications were then displayed for visual analysis as:

   • Greyscale Quantification Images - When displayed in grayscale for specific classifications, the system identifies relative abundances of specified end members (e.g. minerals or rocktypes). These concentrations normally show up in white (light grey) when there is high co-relation and in dark grey to black if there is a low coefficient of co relation (i.e. when none of the specific components are present). False color composite images can then be used to highlight specific minerals and mineral assemblages representing classifications or groups with vector data layers. Spectral comparison tests were then made using the one of the material suites listed below selected from the various spectral libraries.

a) Metamorphic Rock Types
b) Intrusive Rock Types
c) Minerals
d) Vegetation
e) Soils

However one must use some caution in accepting these classifications. Just because a given pixel is classified as a specific mineral doesn't make it so. Classifications are a measure of similarity and not necessarily definitive identifiers. Ground truthing is important to check and test the apparent results. RGB – Some of the data were also subject to RGB (Red-Green-Blue) analysis. This is a very simplified chromatic expression of spectral relationships. Pure colors in these images represent areas where the mineralogy is relatively pure. Mixed colors indicate spectral mixing, with the resultant colors indicating how much mixing is taking place and the relative contributions of each endmember.

11. Post Processing - Classified images require post-processing to evaluate classification accuracy and to generalize classes for export to image-maps and vector GIS. Greyscale, false colour and colour symbology responses were overlayed along with the base geological features gathered in Step 1 and were reviewed visually to see if any spectral anomalies, e.g. bright or dark spots overlying these features could be identified or colour patterns reflecting underlying geology could be found. A selection of the resulting spectral signatures which most closely reflected real or apparent underlying geological features were then displayed as color coded maps.

**Results**

The primary objective of this analysis in the WWW area was to explore for signal correlation and to work toward developing a recognizable spectral signature. The Spectral Analysis was done on a portion of one spectral data granule. This is an area where there is appropriate satellite spectral coverage. The image used in this analysis covers the entire claim and adjoining claims held by the same owner. Several iterations of this process were done starting with the broader geological features, typically rock types including igneous and metamorphic suites and finally classifications were done for specific minerals. Matching results were identified, often including several duplicate responses. Duplicates were either displayed collectively or left out if no additional useful information was evident by their inclusion. The results of the classification procedure were viewed as spectral maps. These classifications have generally been identified by the name of the “mineral” or “rock type” that shows the greatest proportion of positive co relation or if not the greatest, is the identity which more reasonably fits the geological picture. These IDs may however only reflect an apparent co-relation and should not be relied upon to infer any direct relationship. Spectral data management specialists always recommend using local experience and if possible ground truthing as a check on what is really being spectrally measured. Results of the spectral plot reviews are discussed in the figure descriptions following. A tabulation of the files used in preparation of the output is displayed in Appendix III. Digital Elevation and Terrain models have been created and are included in the digital database provided with this submission but are not reproduced as part of this report as they do not add anything to the specific results displayed.

The rocks in the area are predominantly of igneous volcanic and intrusive origin. Metal sulphide quartz vein mineralization in the area is of hydrothermal origin. A suite of igneous rocks and minerals and associated alteration products should produce the most likely and detectable spectral association. These rocks and associated minerals have strong signal responses in areas of road cuts, recent logging and sparse vegetation, as well as waste dumps and old mine sites. Pyrite distribution, Diabase recognition and sulphide recognition correlate to known outcrop. A key alteration mineral buddingtonite is also included with a high matching score. Buddingtonite is not detectable using conventional means and as an alteration indicator may disclose areas of hydrothermal event history. It is suggested that a program of ground truthing and ground based PIMA spectrometry be planned to follow up this analysis.

## REFERENCES

### Area Specific References


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2) **B.C. Ministry of Energy, Mines and Petroleum Resources,**
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**Minfile Report –** 092F 141

3) Spectral Analysis References

a) **Krause, Fred A, 2003**; Advances in Hyperspectral Remote Sensing for Geologic Mapping and Exploration : Analytical Imaging and Geophysics; Boulder, CO

b) **MicroImages, Inc**; An Introduction to Hyperspectral Imaging: http://www.microimages.com/getstart/pdf/hyprspec.pdf

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d) **Clark, R.N., G.A. Swayze, A.J. Gallagher, T.V.V. King, and W.M. Calvin, 1993**; The U. S. Geological Survey, Digital Spectral Library: Version 1: 0.2 to 3.0 microns, *U.S. Geological Survey Open File Report 93-592*, 1340 pages, http://speclab.cr.usgs.gov.

e) **King, T.V.V., Clark, R.N., Ager, C., and Swayze, G.A., 1995**; Remote mineral mapping using AVIRIS data at Summitville, Colorado and the adjacent San Juan Mountains. *Proceedings: Summitville Forum '95,* H.H. Posey, J.A. Pendelton, and D. Van Zyl Eds. Colorado Geological Survey Special Publication 38, p. 59-63

f) **The Provincial Government of Saskatchewan, Canada**: Remote Sensing of Uranium Biogeochemical Anomalies, Wollaston Lake, Saskatchewan : Saskatchewan Ministry of Industry and Resources Open File (based on the use of Spectral Analysis in Uranium Exploration) http://www.publications.gov.sk.ca/details.cfm?p=4923

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Young Geologists Conference on Mineralogy, Petrology and Geochemistry, Guiyang, China. Proceedings of the 5th China Conference of Genesis of Ore Deposits, Geology Press (in Chinese).
i) **Ranjbar, Hojjatollah and Shahriari, Hadi and Honarmand, Mehdi, 2003;** Integration of ASTER and Airborne Geophysical Data for Exploration of Copper Mineralization, a Case Study of Sar Cheshmeh Area: Department of Mining Engineering, Department of Geology, Faculty of Science, Shahid Bahonar University of Kerman, Kerman, Iran.

**FIGURES**



APPENDIX I-Project Cost Report

- Total Assessment work applicable to this project………………..….$6000.00
- Total Work on this project took place in accordance with the following table

WWW

Assessment Work Cost Report

Property/Claim Name: WWW Tenure 516512

| Cost Categories | | Units | Rate | Qty | No Units | Cost |
|---|---|---|---|---|---|---|
| Labour Costs | | | | | | |
| | Project Manager | $/Day (8 hr) | $650.00 | | | |
| | Technical Manager (Spectral Analysis) | $/Day (8 hr) | $550.00 | 10 | 1 | $5,500.00 |
| | Technician | $/Day (8 hr) | $350.00 | 2 | 1 | $700.00 |
| | Consulting Geologist | $/Day (8 hr) | $500.00 | | | $0.00 |
| | Other Consultants | | | | | |
| Travel | | | | | | |
| | Lodging | Cost | $100.00 | | | |
| | Meals | Cost | | | | inc |
| | Vehicle | $/Km | $0.51 | 2 | | |
| | Airfare | | | | | |
| Materials and Supplies | | Cost | | | | |
| Communications | | | | | | |
| | Telephone | Cost | | | | |
| | Internet | $/Mo | | | | |
| Field Equipment Rental | | | | | | |
| | 4X4 Truck | $/Day | $200.00 | 1 | 1 | $200.00 |
| | ATV | $/Day | $100.00 | 2 | | |
| | Aircraft | | | | | |
| Technical Equipment Rental | | | | | | |
| | Photospectrometer | | | | | |
| | Base Computer | $/Day | $50.00 | | | |
| | Portable Computer | $/Day | $25.00 | | | |
| | Printer | $/Day | $10.00 | | | |
| | GPS | $/Day | $20.00 | | 1 | $20.00 |
| Freight | | | | | | |
| Sample Analyses | | | | | | |
| | Rock Sample Preparation | $/Sample | $6.00 | | | |
| | Soil/Silt Sample Preparation | $/Sample | | | | |
| | Rock Samples Analyses | $/Sample | $21.00 | | | |
| | Soil Samples Analyses | $/Sample | | | | |
| | Stream Sediment Sample Analyses | $/Sample | | | | |
| Technical Work Costs | | | | | | |
| | Spectral Analysis Preparation | | | | | |
| | Spectral Data Acquistion Costs | | | | 2 | $180.00 |
| | Software Rental | $/Day | | | | |
| | Software Purchase | Cost +10% | | | | |
| | Computer Processing | $/Hr | | | | |
| Map & Report Preparation | | | | | | |
| | Mapping Contractor | Cost +10% | | | | |
| | Printing & Copying | Cost +10% | | | | $150.00 |
| Total Assessment Work Applicable Costs | | | | | | $6,750.00 |
| Assessment Work Filing Fees | | | | | | |
| | Assessment Filing Fees | $/Unit | | | | |
| | Grouping Fees | $/Group | | | | |
| Total Non Assessment Work Applicable Costs | | | | | | |

6750.00 reduced to $6000.00 budget

## Appendix II

### Statement of Qualification

**I David J. McLelland** do hereby certify that:

**1**. I am employed as a Geospatial and Geospectral Analyst by:
Auracle Geospatial Science Inc.,
325 Dorset Road Qualicum Beach,
British Columbia, Canada V9K 1H.5
**2.** I am a post graduate student of Geographic Science and have completed the postgraduate certificate in applied and theoretical GIScience at Simon Fraser University, and have completed the academic component of the MSc. GIS and Remote Sensing program requirement at MMU. I have also received application specific training and am RSI certified.
**3**. I have completed the B.C.I.T. B.C.Y.C.M. Mineral Exploration program, and Completed the B.C.I.T. and B.C.Y.C.M. Advanced field School.
4. I am the Spectral Analysis Manager and I am responsible for the management of data and execution of analysis.
**5.** This report was prepared on behalf of Auracle Geospatial Science Inc. who has been engaged by Julie. P. McLelland to complete a work program on this property.
**6.** I have no material or financial interest in the subject property or the companies that own them.
**7.** This report has been prepared in accordance with generally accepted Scientific Principles and is based upon the best information available at the time of preparation. I am not aware of any material fact or material change with respect to the subject matter of the report that is not reflected in the report and therefore the omission of which makes this report misleading.

Signed______________ Date: January 10 2007
David McLelland

Qualicum Beach, British Columbia

## Appendix III

Spectral Image Classification Data Key:

Classification 2- USGS library match: .871Hematite and .824 Buddingtonite
Classification 4- JPL library1 Magnesiochromite .559, Arsenopyrite .478
JHU library Diabase.731
Classification 5- USGS library Howelite .655 Pyrite .618
Classification 7- JPL library 1 Ferroaxinite .706, Arsenopyrite.475
Classification 10- USGS library Hematite .811 JPL library1 Pyrite .767

Note: These classifications represent results of spectral endmember matching against appropriate spectral libraries which are widely accepted from:
Johns' Hopkins University (11 separate libraries used)
Jet Propulsion Laboratory (3 separate libraries used)
United States Geological Survey (1 mineral library used)
And IGCP (5 libraries used)
So that all retrieved endmember spectra were tried against all 20 libraries by 4 methodologies.

**APPENDIX IV**

SPECTRAL IMAGE ANALYSIS – TECHNICAL DISCUSSION

## APPENDIX IV

SPECTRAL IMAGE ANALYSIS - TECHNICAL DISCUSSION

**i )Remote Sensing Overview**

Remote Sensing is the science and art of acquiring information (spectral, spatial, and temporal) about material objects, area, or phenomenon, without coming into physical contact with the objects, or area, or phenomenon under investigation. Without direct contact, some means of transferring information through space must be utilized. In remote sensing, information transfer is accomplished by use of electromagnetic radiation (EMR). EMR is a form of energy that reveals its presence by the observable effects it produces when it strikes the matter. Types of EMR response with respect to type of energy sources and with respect to wavelengths are as follows:

1. in respect to the type of Energy Resources:
   - Passive Remote Sensing: Makes use of sensors that detect the reflected or emitted electro-magnetic radiation from natural sources.
   - Active remote Sensing: Makes use of sensors that detect reflected responses from objects that are irradiated from artificially-generated energy sources, such as radar.
2. In respect to the wavelength, Remote Sensing is classified into three types:
   - Visible and Reflective Infrared
   - Thermal Infrared
   - Microwave

Spectroscopy is the study of light that is emitted by or reflected from materials and its variation in energy with wavelength. As applied to the field of optical remote sensing, spectroscopy deals with the spectrum of sunlight that is diffusely reflected (scattered) by materials at the earth’s surface. Instruments called spectrometers (or spectroradiometers) are used to make ground-based or laboratory measurements of the light reflected from a test material. An optical dispersing element such as a grating or prism in the spectrometer splits this light into many narrow, adjacent wavelength bands and the energy in each band is measured by a separate detector. By using hundreds or even thousands of detectors, spectrometers can make spectral measurements of bands as narrow as 0.01 micrometers over a wide wavelength range, typically at least 0.4 to 2.4 micrometers (visible through middle infrared wavelength ranges).

Remote imagers are designed to focus and measure the light reflected from many adjacent areas on the earth’s surface. In many digital imagers, sequential measurements of small areas are made in a consistent geometric pattern as the sensor platform moves and subsequent processing is required to assemble them into an image. Until recently, imagers were restricted to one or a few relatively broad wavelength bands by limitations of detector designs and the requirements of data storage, transmission, and processing. Recent advances in these areas have allowed the design of imagers that have spectral ranges and resolutions comparable to ground-based spectrometers.

In reflected-light spectroscopy the fundamental property that we want to obtain is spectral reflectance: the ratio of reflected energy to incident energy as a function of wavelength. Reflectance varies with wavelength for most materials because energy at certain wavelengths is scattered or absorbed to different degrees. These reflectance variations are displayed as spectral reflectance curves (plots of reflectance versus wavelength) for different materials. The overall shape of a spectral curve and the position and strength of absorption bands in many cases can be used to identify and discriminate different materials. For example, vegetation has higher reflectance in the near infrared range and lower reflectance of red light than soils. The configuration of spectral reflectance curves provides insight into the characteristics of an object and has a strong influence on the choice of wavelength region(s) in which remote sensing data are acquired for a particular application.

Multispectral remote sensors such as the Landsat Thematic Mapper produce images with a few relatively broad wavelength bands and consequently drastically under sample the information content available from a reflectance spectrum by making only a few measurements in spectral bands up to several hundred nanometers wide. Hyperspectral remote sensors, on the other hand, collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands. These measurements make it possible to derive a continuous spectrum for each image cell. After adjustments for sensor, atmospheric, and terrain effects are applied, these image spectra can be compared with field or laboratory reflectance spectra in order to recognize and map surface materials such as particular types of vegetation or rock types or diagnostic minerals associated with ore deposits.

Imaging spectrometers or Hyperspectral Sensors collect unique data that are both a set of spatially contiguous spectra and a set of spectrally contiguous images. These data have been available since 1983 however they are just now achieving widespread use, primarily due to a number of complicating factors related to the maturity of the field. Issues that have slowed acceptance and use of Hyperspectral data include: lack of high quality data sets for most areas of interest, inadequate correction for sensor and atmospheric effects, availability and suitability of specific analysis software, and the relative paucity of well trained scientists to analyze the data.

High-quality Hyperspectral data is now available from aircraft systems, as well as global coverage from satellite systems. Data is now readily available for most areas of the planet. Most modern image processing systems can handle the high number of spectral bands however new algorithms are under development which will dramatically improve speed and quality of output. Publicly available atmospheric correction software makes it possible to use these data without a priori knowledge and finally sophisticated analysis software allows even scientists new to Hyperspectral analysis to derive useful information from this data.

Hyperspectral images contain a wealth of data, but interpreting them requires an understanding of exactly what properties of ground materials we are trying to measure, and how they relate to measurements actually made by the sensors.

**ii) Spectral Image Noise Effects**

Atmospheric Effects - Even a relatively clear atmosphere interacts with incoming and reflected solar energy. For certain wavelengths these interactions reduce the amount of incoming energy reaching the ground and further reduce the amount of reflected energy reaching an airborne or satellite sensor. The transmittance of the atmosphere is reduced by absorption by certain gases and by scattering by gas molecules and particulates. These effects combine to produce the transmittance curve. The pronounced absorption features near 1.4 and 1.9 μm, caused by water vapor and carbon dioxide, reduce incident and reflected energy almost completely, so little useful information can be obtained from image bands in these regions. This curve does not however show the effect of light scattered upward by the atmosphere. This scattered light adds to the radiance measured by the sensor in the visible and near-infrared wavelengths, and is called path radiance. Atmospheric effects may also differ between areas in a single scene if atmospheric conditions are spatially variable or if there are significant ground elevation differences that vary the path length of radiation through the atmosphere. Many atmospheric correction algorithms are now available to handle this "noise effect" and the corrections are virtually invisible to the user as they are done before receipt of spectral data packages.

Sensor Effects & Data Noise - A sensor converts detected radiance in each wavelength channel to an electric signal which is scaled and quantized into discrete integer values that represent encoded radiance values. Variations between detectors within an array, as well as temporal changes in detectors, may require that raw measurements be scaled and/or offset to produce comparable values. Data noise management includes making periodic comparisons with original data to ensure integrity and completeness after manipulations and modifications.

**iii) Spectral Data Libraries**

Several libraries of reflectance spectra of natural and man-made materials are available for public use. These libraries provide a source of reference spectra that can aid the interpretation of Hyperspectral and Multispectral images. Each library is composed of a series of sub-libraries that list spectral data for a variety of materials that has be produced by various techniques and sorted into equivalent groupings. Each library needs to be reviewed to determine which data matches characteristics of the material (minerals or rocks) that are being sought or expected in the target areas and which are comparable to the type of spectral response reproduced in the images being used. Some of the libraries used in this work program are listed below.

ASTER Spectral Library - This library has been made available by NASA as part of the Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) imaging instrument program. It includes spectral compilations from NASA's Jet Propulsion Laboratory (JPL), Johns Hopkins University (JHU), and the United States Geological Survey.

The ASTER spectral library currently contains nearly 2000 spectra, including minerals, rocks, soils, man-made materials, water, and snow. Many of the spectra cover the entire wavelength region from 0.4 to 25μm. You can search for spectra by category, view a spectral plot for any of the retrieved spectra, and download the data for individual spectra.

USGS Spectral Library - The United States Geological Survey Spectroscopy Lab in Denver, Colorado has compiled a library of over 800 reflectance spectra that covers the ultraviolet to near-infrared region of the electromagnetic spectrum over the wavelength range from 0.2 to 3.0 μm. Along with sample documentation, the library includes spectral responses of minerals, rocks, soils, physically constructed as well as mathematically computed mixtures, vegetation, micro-organisms, and man-made materials. The samples and spectra collected were assembled for the purpose of using spectral features for the remote detection of these and similar materials. Johns Hopkins University (JHU) Spectral Index Database – This library contains additional spectral image data to that available in the libraries listed above and the I.C.G.P. (Institute for Chemistry and Geosphere Dynamics) spectral library. Collectively these libraries include approximately 25 sub-libraries of spectral data which contain approximately 625,000 individual spectra for use in comparison with and classification of spectra derived from satellite images.

**iv) Spectral Analysis Data Extraction, Signature Determination and Spectral Matching Methods**

Analysis of imaging spectrometer data allows extraction of a detailed spectrum for each picture element (pixel) of the image. High spectral resolution reflectance spectra collected by imaging spectrometers allow direct identification (and in some instances, abundance determinations) of individual materials based upon their reflectance characteristics including minerals, atmospheric constituent gases, vegetation, snow and ice, and dissolved and suspended constituents and water quality in lakes and other water bodies and the near-shore environment The critical step in most imaging spectrometer data analysis strategies is to convert the data to reflectance so that individual spectra can be compared directly with laboratory or field data for identification. This requires that accurate wavelength calibration be performed. Laboratory measurements made before and after data acquisition usually provide the initial wavelength calibration. An additional check on the wavelength calibration can be made by comparing the positions of known atmospheric absorption features to their locations in the imaging spectrometer data. Atmospheric carbon dioxide absorption bands located at 2.005, and 2.055 μm are useful for wavelength-calibration of the data in the shortwave infrared. In the visible and near infrared portion of the spectrum, narrow atmospheric water bands at 0.69, 0.72, and 0.76 μm can be used to calibrate wavelengths.

**v) Spectral matching methodologies**

In order to directly compare Hyperspectral image spectra with reference reflectance spectra, the encoded radiance values in the image must be converted to reflectance. A comprehensive conversion must account for the solar source spectrum, lighting effects due to sun angle and topography, atmospheric transmission, and sensor gain. In mathematical terms, the ground reflectance spectrum is multiplied (on a wavelength per wavelength basis) by these effects to produce the measured radiance spectrum. Methods for detecting a target spectrum against a background of unknown spectra are often referred to as matched filters, a term borrowed from radio signal processing.

Various matched filtering algorithms have been developed, including orthogonal subspace projection and constrained energy minimization. All of these approaches perform a mathematical transformation of the image spectra to accentuate the contribution of the target spectrum while minimizing the background. In a geometric sense, matched filter methods find a projection of the n-dimensional spectral space that shows the full range of abundance of the target spectrum but hides the variability of the background. In most instances the spectra that contribute to the background are unknown, so most matched filters use statistical methods to estimate the composite background signature from the image itself. Some methods only work well when the target material is rare and does not contribute significantly to the background signature. A modified version of matched filtering uses derivatives of the spectra rather than the spectra themselves, which improves the matching of spectra with differing overall brightness. Some Hyperspectral image applications do not require finding the fractional abundance of all endmember components in the scene. Instead the objective may be to detect the presence and abundance of a single target material. In this case a complete spectral unmixing is unnecessary. Each pixel can be treated as a potential mixture of the target spectral signature and a composite signature representing all other materials in the scene. Finding the abundance of the target component is then essentially a partial Unmixing problem. The shape of a reflectance spectrum can usually be broken down into two components: broad, smoothly changing regions that define the general shape of the spectrum and narrow, trough-like absorption features. This distinction leads to two different approaches to matching image spectra with reference spectra. Many pure materials, such as minerals, can be recognized by the position, strength (depth), and shape of their absorption features. One common matching strategy attempts to match only the absorption features in each candidate reference spectrum and ignores other parts of the spectrum. A unique set of wavelength regions is therefore examined for each reference candidate, determined by the locations of its absorption features. The local position and slope of the spectrum can affect the strength and shape of an absorption feature, so these parameters are usually determined relative to the continuum: the upper limit of the spectrum's general shape.

The continuum is computed for each wavelength subset and removed by dividing the reflectance at each spectral channel by its corresponding continuum value. Absorption features can then be matched using a set of derived values (including depth and the width at half-depth), or by using the complete shape of the feature. These types of procedures have been organized into an expert system by researchers at the U.S. Geological Survey Spectroscopy Lab. Many other materials, such as rocks and soils, may lack distinctive absorption features. These spectra must be characterized by the overall shape of their spectral curve. Matching procedures utilize full spectra (omitting noisy image bands severely affected by atmospheric absorption) or a uniform wavelength subset for all candidate materials. One approach to matching seeks the spectrum with the minimum difference in reflectance (band per band) from the image spectrum (quantified by the square root of the sum of the squared errors). Another approach treats each spectrum as a vector in spectral space and finds the reference spectrum making the smallest angle with the observed image spectrum.

Linear unmixing is an alternative approach to simple spectral matching. Its underlying premise is that a scene includes a relatively small number of common materials with more or less constant spectral properties. Furthermore, much of the spectral variability in a scene can be attributed to spatial mixing, in varying proportions, of these common endmember components. If we can identify the endmember spectra, we can mathematically unmix each pixels spectrum to identify the relative abundance of each endmember material. The unmixing procedure models each image spectrum as the sum of the fractional abundances of the endmember spectra, with the further constraint that the fractions should sum to 1.0. The best-fitting set of fractions is found using the same spectral-matching procedure as described previously. A fraction image for each endmember distills the abundance information into a form that is readily interpreted and manipulated. An image showing the residual error for each pixel helps identify parts of the scene that are not adequately modeled by the selected set of endmembers. The challenge in linear unmixing is to identify a set of spectral endmembers that correspond to actual physical components on the surface. Endmembers can be defined directly from the image using field information or an empirical selection technique. Alternatively, endmember reflectance spectra can be selected from a reference library, but this approach requires that the image has been accurately converted to reflectance. Variations in lighting can be included directly in the mixing model by defining a shade endmember that can mix with the actual material spectra. A shade spectrum can be obtained directly from a deeply shadowed portion of the image. In the absence of deep shadows, the spectrum of a dark asphalt surface or a deep water body can approximate the shade spectrum.

**vi) Spectral Data Classification**

Organizing spectral data into useful bits of information requires a sorting or “classification” system. There are two types of classification, Unsupervised and Supervised.

In an *Unsupervised Classification*, the objective is to group multiband spectral response patterns into clusters that are statistically separable. The pixels in an image are examined by the computer and grouped into spectral classes. This grouping is based solely on the numerical information in the data and the spectral classes are later matched by the analyst to information classes. In order to create an Unsupervised Classification the analyst typically determines the number of spectral classes to identify and a computer algorithm will find pixels with similar spectral properties and group them accordingly. Each of the spectral classes in an image are assigned a gray tone value ranging from black to white, with intermediate shades of gray. Programs, called clustering algorithms, are used to determine the statistical groupings in the data. Usually, the analyst specifies how the initial classification should proceed. In addition to specifying the desired number of classes, the analyst may specify parameters to determine how close pixels' digital numbers (DNs – see definition below) must be to be considered in the same class. Once the clustering process has run, the analyst may want to combine or further break down some clusters. Thus, unlike its name suggests, an unsupervised classification often requires interaction with an analyst.

*Supervised Classification* is essentially the opposite of Unsupervised Classification in that the interpreter knows beforehand what classes are present and where each is in one or more locations within the scene. These are located on the image and then areas containing examples of the class are circumscribed making them Training Sites (see definition below). The determination of training sites is based on the analyst's knowledge of the geographical region and the surface cover types present in the image. Once the training sites have been established, the numerical information in the entire image's spectral bands are used to define the spectral "signature" of each class. Once the computer has determined the signatures for each class, it will compare every pixel to the signatures and label it as the class that it is mathematically closest to. Instead of clusters then, one has class groupings with appropriate discriminant functions that distinguish each (it is possible that more than one class will have similar spectral values but unlikely when more than 3 bands are used because different classes or materials seldom have similar responses over a wide range of wavelengths). All pixels in the image lying outside training sites are then compared with the class discriminants, with each being assigned to the class it is closest to. This makes a map of established classes with a few pixels usually remaining unknown.

Various classification or comparison methods are available to determine if a specific pixel qualifies as a class member including Parallelepiped, Maximum Likelihood, Minimum Distance, Mahalanobis Distance, Binary Encoding, and Spectral Angle Mapper are available to sort the data. In the analysis done for this project Maximum Likelihood, Spectral Angle Mapper (SAM), Spectral Unmixing and Mixture Matched Filtering were most commonly used techniques.

*Maximum Likelihood* classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless a probability threshold is selected, all pixels are classified. Each pixel is assigned to the class that has the highest probability (i.e., the "maximum likelihood").

The *Spectral Angle Mapper (SAM)* is a physically-based spectral classification that uses the n-dimensional angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra, treating them as vectors in a space with dimensionality equal to the number of bands.

Small angles between the two spectrums indicate high similarity and high angles indicate low similarity. Spectral Angle Mapping (SAM) - This algorithm takes as input a number of "training classes" or reference spectra from ASCII files, ROIs (Regions of Interest), or spectral libraries. It calculates the angular distance between each spectrum in the image and the reference spectra or "endmembers" in n-dimensions (see definition below). The result is a classification image showing the best SAM match at each pixel and a "rule" image for each endmember showing the actual angular distance in radians between each spectrum in the image and the reference spectrum. Darker pixels in the rule images represent smaller spectral angles, and thus spectra that are more similar to the reference spectrum. The rule images can be used for subsequent classifications using different thresholds to decide which pixels are included in the SAM classification image.

S*pectral Unmixing* weighs membership in classifications against imposed constraints. Geologic surfaces are rarely composed of a single uniform material, thus it is necessary to use mixture modeling to determine what materials cause a particular spectral “signature” in imaging spectrometer data. In order to determine the abundances, we must first determine what materials are mixing together to give us the spectral signature measured by the instrument. Selection of “endmembers” is the most difficult part of linear spectral unmixing. The ideal spectral library used for unmixing consists of endmembers that when linearly combined can form all other observed spectra. The endmember library defined using the n-dimensional visualization procedure is used in the unmixing process and abundance estimates were made for each mineral. *Mixture Matched Filtering* creates and measures statistical covariance in pure pixel populations. It provides a rapid means of detecting specific minerals based on matches to specific library or image endmember spectra. This technique produces images similar to the unmixing as described above, but with significantly less computation. Matched filter results are presented as gray-scale images with values from 0 to 1.0, which provide a means of estimating relative degree of match to the reference spectrum (where 1.0 is a perfect match)

*Supervised classification* is much more accurate for mapping classes, but depends heavily on the cognition and skills of the image specialist. The strategy is simple: the specialist must recognize conventional classes (real and familiar) or meaningful (but somewhat artificial) classes in a scene from prior knowledge, such as, personal experience with the region, by experience with thematic maps, or by on-site visits. This familiarity allows the specialist to choose and set up discrete classes (thus supervising the selection) and then assign them category names. Thus, in a supervised classification, the analyst starts with information classes and uses these to define spectral classes. Each pixel in the image is then assigned to the class which it most closely resembles.

*Training sites* are areas representing each known land cover category that appear fairly homogeneous on the image (as determined by similarity in tone or color within shapes delineating the category). Specialists locate and circumscribe them with polygonal boundaries drawn on the image display. For each class thus outlined, mean values and variances of the DNs (See definition below) for each band used to classify them are calculated from all the pixels enclosed in the site. More than one polygon can be established for any class. *Digital Number* (DN) or spectral vector is a value assigned to a pixel in a digital image. It is a mathematically calculated measure of light intensity or electromagnetic radiance from the pixel. When DNs are plotted as a function of the band sequence (increasing with wavelength), the result is a *spectral signature* or spectral response curve for that class. In reality the spectral signature is for all of the materials within the site that interact with the incoming radiation.

*n-Dimensional Visualization* - Spectra can be thought of as points in an n-dimensional scatterplot, where n is the number of bands. The coordinates of the points in n-space consist of “n” values that are simply the spectral reflectance values in each band for a given pixel. The distribution of these points in n-space can be used to estimate the number of spectral endmembers and their pure spectral signatures, and provides an intuitive means to understand the spectral characteristics of materials. In two dimensions, if only two endmembers mix, then the mixed pixels will fall in a line in the histogram. The pure endmembers will fall at the two ends of the mixing line. If three endmembers mix, then the mixed pixels will fall inside a triangle, four inside a tetrahedron, and so on. Mixtures of endmembers "fill in" between the endmembers. All mixed spectra are "interior" to the pure endmembers, inside the simplex formed by the endmember vertices, because all the abundances are positive and sum to unity. This "convex set" of mixed pixels can be used to determine how many endmembers are present and to estimate their spectra.
Classification now proceeds by statistical processing in which every pixel is compared with the various signatures and assigned to the class whose signature comes closest. A few pixels in a scene do not match and remain unclassified, because these may belong to a class not recognized or defined. In fact at this level there is an overlap between Supervised and Unsupervised classifications. Spectra determined by Unsupervised classifications are now compared to selected spectra as determined by the analyst and thus become effectively Supervised.

Field work, if logistically possible, before and after computer-based classification of an image, is the key to selecting and then checking class locations. Thus it is the best insurance for achieving a quality product. But, if an on-site visit is not feasible, a skilled interpreter can develop a fairly reasonable classification based mainly on his/her abilities in recognizing obvious ground features in the scene.

**vii) Geological Application of Spectral Analysis**

Classical geologic mapping and mineral exploration utilize physical characteristics of rocks and soils such as mineralogy, weathering characteristics, geochemical signatures, and landforms to determine the nature and distribution of geologic units and to determine exploration targets for metals and industrial minerals. Subtle mineralogical differences, often important for making distinctions between rock formations, or for defining barren ground versus potential economic ore, are often difficult to map in the field. Multi-band, multi-sensor Multi Spectral Imaging (MSI) has been available for some years. More recently Hyperspectral remote sensing, the measurement of the Earth's surface in up to hundreds of spectral images, has provided a unique means of remotely mapping mineralogy. A wide variety of Hyperspectral data are now available, along with operational methods for quantitatively analyzing the data and producing mineral maps. The key to the search for minerals however is in the use of the Short Wave Infra Red (SWIR) part of the spectrum as minerals are best detected at these levels. Remote-sensing displays, whether they are aerial photos or space-acquired images, show the surface distribution of the multiple formations usually present and, under appropriate conditions, the type(s) of rocks in the formations. Experienced geologists can recognize some rock types just by their appearance in the photo/image. They are now also beginning to identify geological features, rocks and minerals from their spectral signatures.

A common way of mapping formation distribution is to rely on training sites at locations within the photo/image. Geologists identify the rocks by consulting area maps or by visiting specific sites in the field. They then extrapolate the rocks' appearance photographically or by their spectral properties across the photo or image to locate the units in the areas beyond the site (in effect, the supervised classification approach). In doing geologic mapping from imagery, we know that rock formations are not necessarily exposed everywhere. Instead they may be covered with soil or vegetation. In drawing a map, a geologist learns to extrapolate surface exposures underneath covered areas, making logical deductions as to which hidden units are likely to occur below the surface. In working with imagery alone, these deductions may prove difficult and are a source of potential error. Also, rock ages or rock types/composition are not directly determined from spectral data, so that identifying a particular characteristic requires some independent information such as knowledge of a region's rock types and their sequence, alteration features and distribution.

Spectral data derived from confused sources can also be handled using *Fuzzy Set* theory for mineral exploration. Some spectral data can be very clearly organized into groups based on their spectral properties. The boundary of each group is quite sharp because each training site is a region that contains a known material (e.g. basaltic rock). One of the main assumptions in the traditional classification methods is that the training sites represent pure samples of the classes they represent. But this is rarely the case with the geological materials. With fuzzy classification it is assumed that the boundaries are transitional.

A Fuzzy set is characterized by a fuzzy membership grade (also called a possibility) that ranges from 0.0 to 1.0, indicating a continuous increase from non membership to complete membership in the group. For example, if a pixel is covered by 60% altered and 40% by unaltered rocks, it would be considered to have a fuzzy membership grade of 0.60 in the class of altered and a membership grade of 0.40 in the unaltered class. Wang (1990) has developed a method of classification of remotely sensed data by using fuzzy logic. The same method is used to classify remote sensing and geophysical data sets. Geological information and data interpretations used in mineral exploration are inherently ambiguous. The quantitave precision of expressions like "relatively high", high", "fair", "low", and "relatively low" or "fairly favourable" for the mineral occurrence, as well as grey areas between these expressions, is difficult to define. Fuzzy set theory provides a mathematical framework to represent the linguistic and data ambiguities frequently encountered in mineral exploration, geological information analysis and interpretation.

Idrisi has produced a software module called FUZCLASS, a so called soft classifier, to handle this type of interpretation.

Other Methods used in the spectral unmixing process included: Principle Component Analysis, Bayesian Analysis, Dempster-Shafer, Fisher and other Linear and Non-linear statistical classification and assignment operations.

*Principal Components Analysis* (PCA) is a statistically based procedure for transforming a set of correlated variables into a new set of uncorrelated variables. This transformation is a rotation of the original axes to new orientations that are orthogonal to each other and therefore there is no correlation between variables. PCA is a decorrelation procedure which reorganizes by statistical means the DN values from as many of the spectral bands as we choose to include in the analysis. In producing these values, we used all seven bands and requested that all seven components be generated (the number of components is fixed by the number of bands, because they must be equal). Color composites made from images representing individual components often show information not evident in other enhancement products

A variant of PCA is known as *Canonical Analysis* (CA). Whereas PCA uses all pixels regardless of identity or class to derive the components, in CA one limits the pixels involved to those associated with pre-identified features/classes. This requires that those features can be recognized (by photo interpretation) in an image display (single band or color composite) in one to several areas within the scene. These pixels are "blocked out" as training sites. Their multiband values (within the site areas) are then processed in the manner of PCA. This selective approach is designed to optimize recognition and location of the same features elsewhere in the scene.

**viii) Data Sources and Software**

The following is a list of material sources and software used for this project.

• ASTER (Advanced Space borne Thermal Emission and Reflection Radiometer) is an imaging instrument flying on Terra, a satellite launched in December 1999 as part of NASA's Earth Observing System. ASTER is a cooperative effort between NASA, Japan’s Ministry of Economy, Trade and Industry (METI) and Japan's Earth Remote Sensing Data Analysis Center.

ASTER has been designed to acquire land surface temperature, emissivity, reflectance, and elevation data. An ASTER scene covers an area of approximately 60 km by 60 km and data is acquired simultaneously at three resolutions. The images are georeferenced to the WGS84 datum and Universal Transverse Mercator (UTM) projection. A complete ASTER scene consists of 14 bands of data, with one additional band pointing backwards to create parallax. The three bands in the visible and near infrared (VNIR) part of the spectrum have a 15m resolution and an 8-bit unsigned integer data type. This file also features a second near infrared backward-scanning band labelled Band 3B. This is used to create a stereo view of the earth to develop elevation information. The six bands in the short wave infra-red (SWIR) have a 30m resolution and also have an 8-bit unsigned integer data type. Finally there are five thermal bands (TIR) with a 90m resolution and have a 16-bit unsigned integer data type.

• ASTER Granules - The basic unit of Hyperspectral Satellite data coverage is defined as *Granules*. Each granule represents area on average about 60km x 60km.

ASTER satellite data granules were acquired from NASA's LPDAAC facility for the various mineral claim areas.

• IDRISI GIS is a powerful raster-based GIS system produced by Clark Labs, an off-shoot of Clark University. The current version of Idrisi used for this project is ANDES, plus extensions.

• IDRISI Kilimanjaro - Image format conversion and spectral signature development was performed using Clarke University's "Kilimanjaro" Image Analyst software coupled with a spectral scan for indicator minerals and rock types. Resulting spectra are then compared by Principal Components Analysis to Spectral Library data.

• ENVI – "Environment for Visualizing Images" is image processing software produced by Research System (RSI). This software provides tools for traditional image processing tasks and is supported by import filter, classification, multi- and hyperspectral processing, data-transformation, registration, calibration, filtering, radar, topographic and mapping modules.

• Hyperspectral Data Libraries are used for matching spectral plots from exploratory data with known spectral responses from specific minerals, rocks and other features

- NASA's Jet Propulsion Laboratory ASTER Index
- USGS Spectral Library
- Johns Hopkins University Spectral Index Database

• ATMOC is software supplied with the IDRISI package that is used to screen atmospheric and topologic noise.

• Clark Labs IDRISI Cartalinx - This is a database development and topological editing software package. These data are then typically exported to a GIS either as entire coverage or as a series of map layers.

• FUZCLASS - Supervised Fuzzy Classification procedure (described earlier) was performed using this soft classifier available in IDRISI image processing software.

• MYSQL – Microsoft ACCESS relational database management system.

**ix) Data Presentation and Storage**

Spectral data map presentations in digital format are provided as a series of separate digital data base layers and overlays. A selection, or in some cases all, of the layers noted below may be included in the image displayed. Hard copy presentations and assessment report .PDF files will normally show combined layers on a single sheet for each classification map presented in this report.

- Base map satellite photo coverage layer
- Base spectral image in greyscale
- Classified spectral image layer
- UTM grid layer
- DEM or DTM layer
- Geology and mineral showing information layers

Data transformations and digitization methods and data formats are disclosed together with analysis results in a metadata file for future use. This information has been provided separately as a set of CD's to accompany this assessment report submission.

**x) Computer Hardware Requirements**

The massive quantities of data that need to be analyzed require significant computing power. Two AMD Athelon 64 systems powered with dual core processors and with 500 gig hard disks and 500 gigabyte auxiliary external storage were required to handle the heavy duty processing and data storage requirements of this project.

**xi) Conclusions**

Spectral Images may become representative of mineralization or host geology, in much the same way as these features may be detected using airborne geophysical techniques. These spectral representations form a statistical pattern that is distinct from the surroundings (or anomalous with respect to surroundings) and can therefore be considered to indicate the possible presence of a geological unit or mineralized body. With the advent of space imagery, geoscientists now can now improve and extend the geologic exploration process in three important ways: 1) The advantage of large area or synoptic coverage allows them to examine in single scenes (or in mosaics) the geological portrayal of Earth on a regional basis 2) The ability to analyze Multispectral bands quantitatively in terms of numbers (DNs) permits them to apply special computer processing routines to discern and enhance certain compositional properties of Earth materials. 3) The capability of merging different types of remote sensing products (e.g., reflectance images with radar or with thermal imagery) or combining these with topographic elevation data and with other kinds of information bases (e.g., thematic maps; geophysical measurements and chemical sampling surveys) provides an opportunity to improve exploration success.

Most spectral studies to date have been focused on relatively barren and flat terrain with moderate to extensive rock exposures. However with the advent of radar spectral detection methods research has shown that spectral signatures of underlying host rocks and alteration types beneath a partial canopy of vegetation and even beneath partial surficial cover can also be detected in less than barren locations.

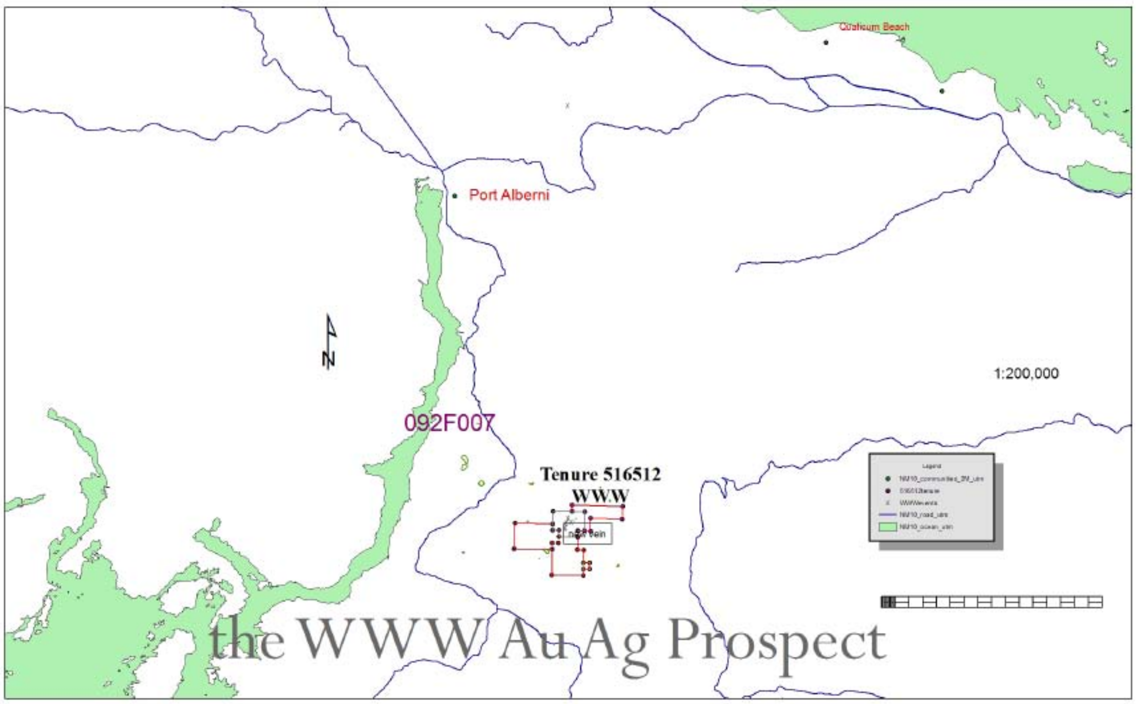


Figure 1 General location

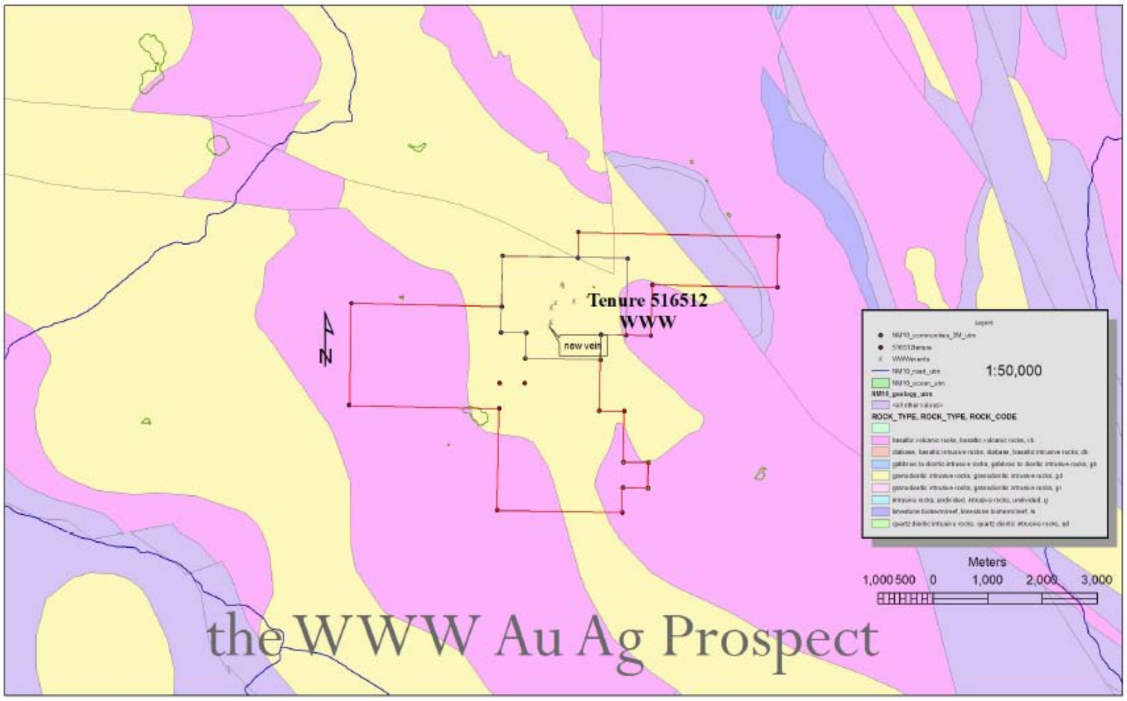


Figure2 Geology

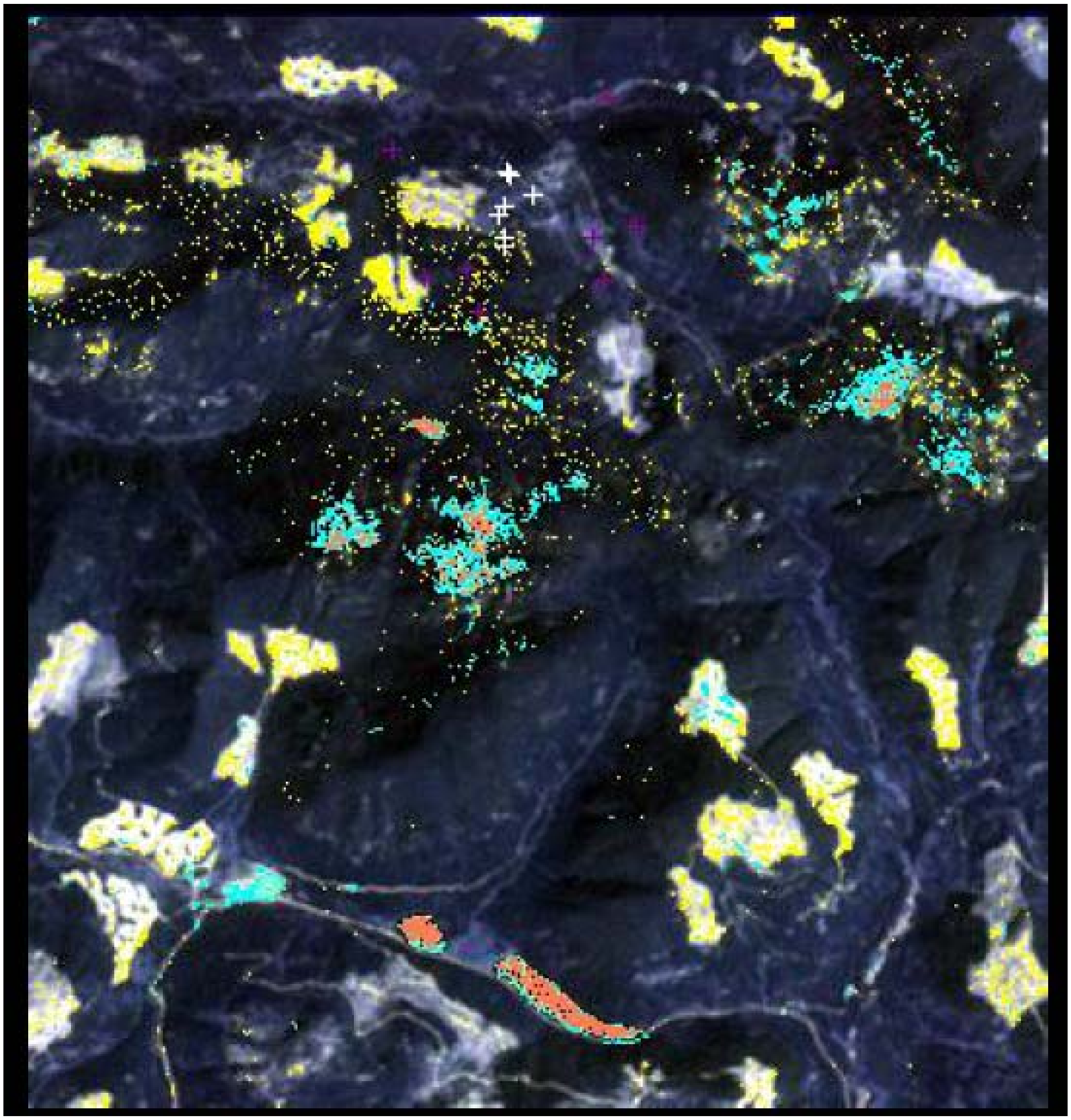

Figure4

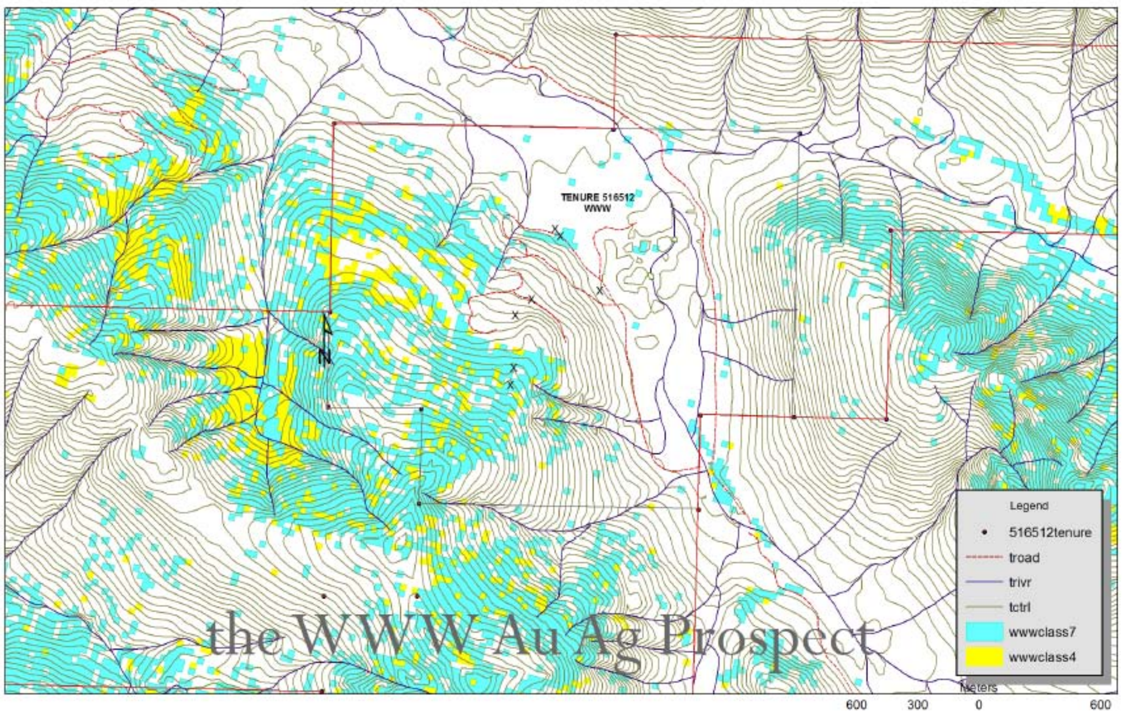
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Figure 5

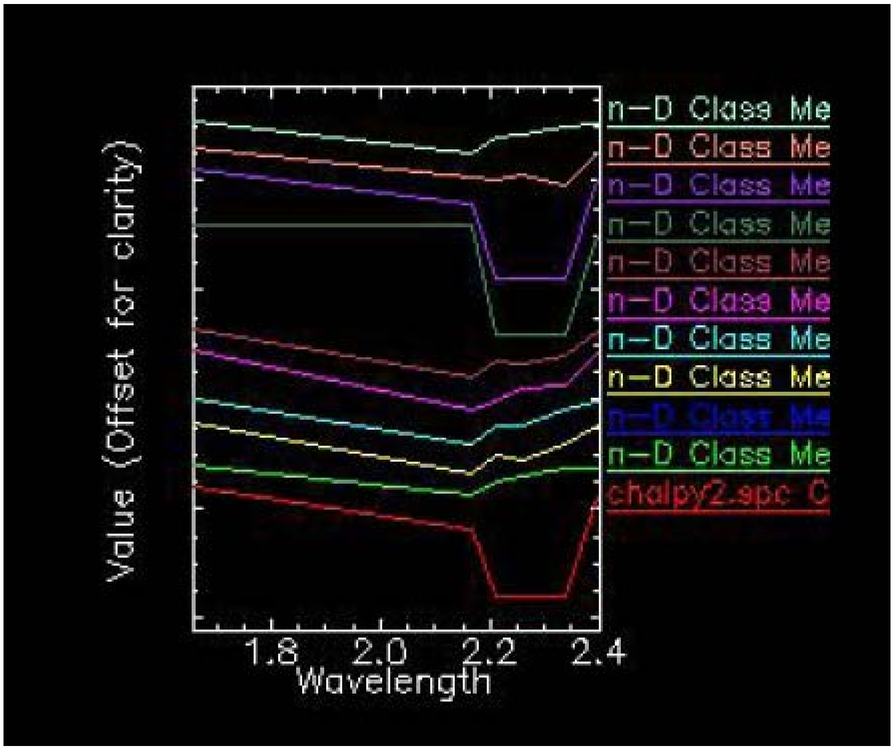
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Figure 6