

# Spectral Mapping with Imaging Spectrometers

## Abstract

A technique for producing maps from reflectance-mode shortwave infrared airborne imaging spectrometer data is described. The reflectance signatures of hydrothermal alteration minerals are identified by the location and relative depth of absorption features in the 2.2- $\mu\text{m}$  region. The sensitivity of detection can be adjusted by changing the depth threshold criterion for absorption features. Correct classification rates are quantified using image subtraction of ground truth data, then optimized by varying the depth threshold. The technique is easily modified to identify other spectral features, such as emission features.

## Introduction

Producing geologic alteration maps from imaging spectrometer data requires rapid, automated identification and recognition of the spectral absorption features characteristic of hydrothermal alteration minerals. A spectral mapping technique is presented here that is based on matching the spectral features of pixel spectra to known spectral signatures. The data must be in reflectance mode; the technique cannot be used on absolute radiance data because spectral features due to ground reflectance are too subtle in raw radiance spectra.

Imaging spectrometers currently acquire data in one of two modes that are fundamentally different. Data from the NASA instruments (AIS-1, AIS-2, and AVIRIS) and from the Geophysical Environmental Research Imaging Spectrometer (GERIS) are acquired in absolute radiance mode, and must be processed using log-residuals or a related technique in order to obtain reflectance-mode data. Data from the Geoscan Advanced Multispectral Scanner Mark II (Geoscan) are acquired in relative radiance mode, and are similar to reflectance-mode data. Various techniques, briefly outlined below, have been devised to show spatial patterns of alteration minerals based on spectral signatures. However, these techniques have not, in general, utilized the standard methods of analyzing reflectance spectra.

The technique presented here is based on spectral analysis methods that are fundamentally related to an expert's judgment and knowledge of mineral chemistry and spectroscopy. It thus differs from most other techniques which are based primarily either on the statistics of a particular data set, or on generalized pattern matching algorithms that are unrelated to infrared reflectance spectroscopy.

The method was tested on data from the Yerington Mining District of west-central Nevada (Figure 1). The Yerington area was chosen because parts of it have already been mapped in detail (Dilles, 1983; Proffett and Dilles, 1984), and the extensive horizontal exposures of an originally vertical

hydrothermal system provide an excellent opportunity for mapping large-scale alteration zones using remote sensing. The area is characterized by a Jurassic porphyry copper system that has been tilted 70°W by Tertiary basin and range faulting. The sericitically altered parts of the hydrothermal system, which are well exposed in the Singatse Range and Blue Hills, have been mapped in detail (Dilles, 1983). There are, however, no published maps of alteration farther west in the Buckskin Range.

The image maps generated by this technique reproduce a traditional map of sericitic alteration. GERIS data (acquired in 1987) have higher spectral resolution, but were not as successful as Geoscan data (acquired in 1989) at reproducing Dilles' (1983) alteration map due to a lower signal-to-noise ratio. To optimize the spectral identification technique, mismatches between classified images and the traditional alteration map were quantified by subtracting a digitized version of the alteration map from the classified remote sensing data. A depth threshold producing the minimum total error rate in the previously mapped Singatse Range was determined, and then applied to similar data in the unmapped Buckskin Range. The resulting alteration map of the Buckskin Range shows an alteration zone with an alunite/pyrophyllite core surrounded by areas of sericitic alteration.

## Data Acquisition

### GERIS

GERIS is manufactured by GER of New York. It has three separate detector arrays that measure the wavelength ranges 0.499 to 1.083  $\mu\text{m}$  (24 channels), 1.080 to 1.800  $\mu\text{m}$  (7 channels), and 1.980 to 2.494  $\mu\text{m}$  (32 channels), all with 12-bit dynamic range (0 to 4095). Only data from array number three (1.980  $\mu\text{m}$  to 2.494  $\mu\text{m}$ ) were used in this study. The data were acquired in 1987. The instrument is designed so that "no gain and offset adjustment is necessary" (Collins and Chang, 1988). The dynamic range of the instrument encompasses the entire observed dynamic range of electromagnetic radiation from the Earth's surface between 0.5 and 2.5  $\mu\text{m}$  (Figure 2a).

The raw data from GERIS have the general appearance of the solar irradiance spectrum at the Earth's surface (Figure 2a), and must be processed to obtain reflectance-mode data. Log residuals (Green and Craig, 1985) were used to convert raw data to reflectance-mode data; other techniques include internal average reflectance normalization (Crowley *et al.*, 1988; Kruse, 1988), reflectance regression (Lyon *et al.*, 1975; Marsh, 1979; Abrams *et al.*, 1988; Gardiner *et al.*, 1988; Kierlein-Young and Kruse, 1989; Lyon and Honey, 1989b), flat field correction (Goetz and Srivastava, 1985; Hutsinpilller and Taranik, 1986; Feldman and Taranik, 1986; Feldman and

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Taranik, 1988; Carrere, 1989), and atmospheric modeling (Conel *et al.*, 1986; Conel *et al.*, 1988; van den Bosch and Alley, 1990).

Wavelength calibration was verified by comparing the positions of absorption features in training sets from areas of known ground mineralogy to published spectra of the minerals sericite, alunite, and pyrophyllite (Lee and Raines, 1984). There was a one-channel offset between published absorption wavelengths and the nominal wavelength of the channel with observed absorption. To correct for this offset, the wavelength calibration for detector array number three (channels 32 to 63) was shifted by one channel. Kierein-Young and Kruse (1989) discovered a similar one-channel offset in a different GERIS dataset during calibration to atmospheric CO<sub>2</sub> absorptions.

**Geoscan**

Geoscan is produced by Geoscan Pty. Ltd., a division of Aston Mining in Perth, West Australia. Geoscan records 24 wavelength bands during flight. The bands recorded at Yerington in 1989 include ten between 0.522 and 0.955 μm (Visible and Near InfraRed, or VNIR), eight between 2.044 and 2.352 μm (Short-Wave InfraRed, or SWIR), and six between 8.64 and 11.28 μm (Thermal InfraRed, or TIR). Only the eight shortwave infrared (SWIR) bands were used in this study. These data have an 8-bit dynamic range (0 to 255).

The Geoscan instrument uses a very different approach to obtaining reflectance-mode data remotely. Rather than measuring absolute radiance, as GERIS and the NASA instruments do, the detector gains and offsets in Geoscan are adjusted to measure relative radiance, which approximates reflectance. Figure 2b shows the gain settings for Geoscan. Instead of measuring absolute radiance and then removing the effects of solar illumination and atmospheric filtering with post-acquisition processing, the Geoscan acquisition mode measures relative radiance by adjusting the channel gains and offsets immediately before data acquisition. These adjustments remove the spectral pattern of solar irradiation and atmospheric filtering during acquisition, and for most purposes, the data need no further processing to be treated as reflectance data.

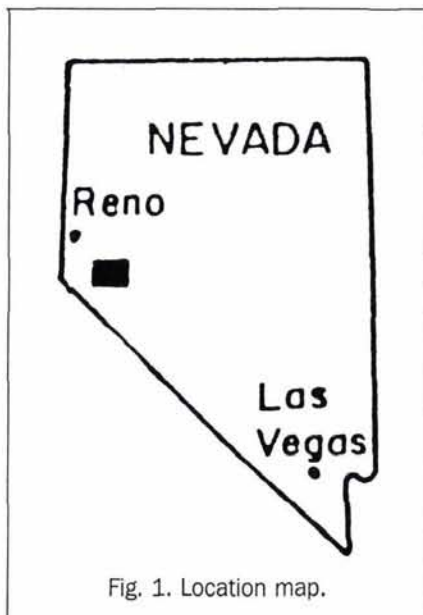


Fig. 1. Location map.

The wavelength calibration supplied by Geoscan was verified with field data and was used without modification.

**Methods for Airborne Spectral Mapping**

**Previous Work in Spectral Processing**

A variety of techniques have been developed for extracting mineralogic information from spectral data. The techniques can be divided into two categories: the multivariate approaches, where spectra are treated as multidimensional data, and knowledge-based approaches, where specific knowledge of mineral spectroscopy is utilized.

Several multivariate approaches have been designed to enhance differences between pixel spectra, but not to identify the pixel spectra. Principal components analysis has been used since the first days of Landsat MSS data (e.g., Taylor, 1974), and has been followed by other techniques such

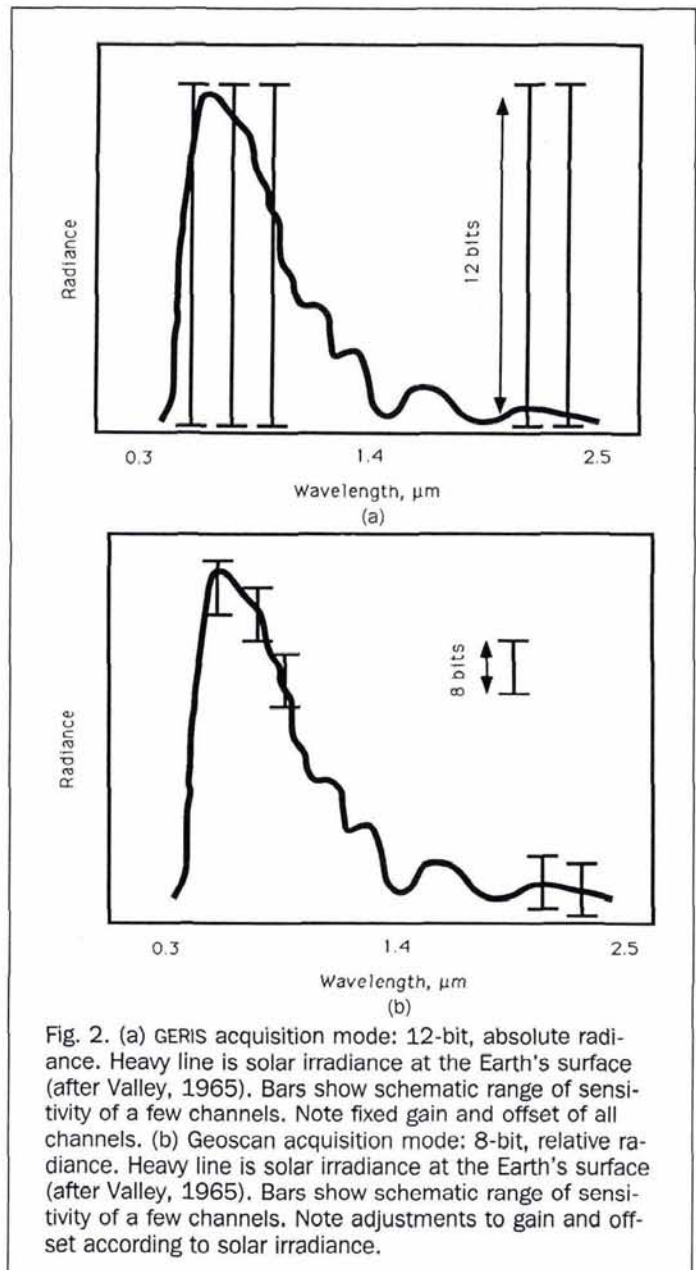


Fig. 2. (a) GERIS acquisition mode: 12-bit, absolute radiance. Heavy line is solar irradiance at the Earth's surface (after Valley, 1965). Bars show schematic range of sensitivity of a few channels. Note fixed gain and offset of all channels. (b) Geoscan acquisition mode: 8-bit, relative radiance. Heavy line is solar irradiance at the Earth's surface (after Valley, 1965). Bars show schematic range of sensitivity of a few channels. Note adjustments to gain and offset according to solar irradiance.



as band moment analysis (Rundquist and Di, 1989) and Chebyshev polynomial fitting (Chiu and Collins, 1978). The meaning of the patterns and colors in the images produced by these techniques is not known without detailed correlation to a map. These approaches can often *discriminate*, but not *identify*, different geologic units.

The most commonly used technique for identifying spectra in imaging spectrometer data is binary encoding, well described by Mazer *et al.* (1988) and used by Hutsinpilller and Taranik (1986), Feldman and Taranik (1988), Kierein-Young and Kruse (1989), Kruse *et al.* (1990), and others. A related approach utilizes least-squares residuals to match spectral characteristics (Fraser *et al.*, 1986; Kierein-Young and Kruse, 1989; Kruse *et al.*, 1990), while Taranik and Kruse (1989) code the slope of adjacent spectral points to match the more subtle spectral shapes of iron oxides. These techniques match patterns in binary codes of pixel spectra to patterns in a library of known spectra.

The most important of the multivariate approaches is spectral mixture modeling, because essentially all pixels comprise spectra from multiple materials. Early work by Hapke (1981) on microscopic mixing was modified by Johnson *et al.* (1983), Clark (1983), and Clark and Roush (1984), and was more fully developed by Mustard and Pieters (1986; 1987a; 1987b; 1988). In using spectral mixing to analyze remotely sensed spectra, each pixel spectrum is assumed to be composed of a combination of different end-member spectra (e.g., Smith and Adams, 1985; Adams and Smith, 1986; Boardman, 1989). The pixel spectrum is deconvolved into proportions of end-member spectra, but knowledge about reflectance spectroscopy is used only to develop a mixing model, not to analyze and identify the spectra of individual minerals. Crowley and Virgo (1988) found that mixed-layer clays have the same spectral signature as physical mixtures of the two end-members.

Imaging spectrometer data can be richer in information if analyzed with a knowledge of mineral reflectance spectroscopy than if analyzed only as  $n$ -dimensional multivariate data. The virtue of general knowledge-based approaches is their more complete utilization of high resolution data as infrared *reflectance* data, rather than simply as multidimensional data or as a collection of a few individual absorption features. There are several approaches to using knowledge of reflectance signatures.

Kruse (1988) developed the simplest technique utilizing the spectral absorption parameters of depth, position, and shape to produce a colored image, although the technique is non-specific in that it does not identify any particular absorption feature or mineral. A number of techniques have been devised that are sensitive to one aspect of a particular absorption feature or mineral. Most of these use the difference or ratio of two or more bands to identify the relative depth of a particular absorption feature. Honey and Daniels (1986) and Feldman and Taranik (1988) use band ratios, (i.e., channel  $x$  / channel  $y$ ) and Lyon and Honey (1990) use band differences to identify particular absorption features. Relative Band Depth (RBD) images developed by Crowley *et al.* (1988; 1989), Crowley and Podwysocki (1989), and Kingston and Crowley (1989) utilize differences between groups of bands to identify a particular absorption feature, and are more robust in noisy spectra. These techniques are limited to observing three differences, hence three absorption features, at one time. More than three band differences can be assessed by using principal components analysis in a technique known as directed or selected principal components, described by Fraser *et al.* (1986), Crowley *et al.* (1988), and Hutsinpilller (1988).

Several "expert systems" have been developed that are

designed to mimic a human expert's style of spectral analysis. Goetting and Lyon (1986), and Yamaguchi and Lyon (1986) developed an expert system for laboratory spectra based on feature-coding and code-matching that is the basis for the technique presented here for imaging spectrometer data (Rubin, 1989). Lyon and Zhu (1989) extended the system to utilize absorption feature shape. Kruse, Taranik, and Kierein-Young (1988), and Kruse, Calvin, and Seznec (1988) developed a rule-based expert system for identifying spectra. Ali *et al.* (1989) developed a knowledge-based expert system based on characteristic features in infrared spectra.

#### A New Method for Spectral Mapping Using Imaging Spectrometer Data

The infrared reflectance spectrum of a mineral is determined by its physical chemistry, and can be characterized by the position, depth, and shape of absorption features caused by molecular constituents in particular crystallographic locations (Hunt and Salisbury, 1970; Hunt, 1977). To more fully utilize the infrared reflectance data from imaging spectrometers, a new method for automated mapping was developed with the following goals:

- It should be based on fundamental knowledge of reflectance spectra of minerals and other ground targets, not prior knowledge of a particular field area (e.g., training areas), or other purely statistical properties of multivariate data.
- It should be sensitive to a wide range of absorption features, and not limited to a few particular features.
- It should identify specific minerals and/or alteration zones on output images with individual colors that have specific and defined meanings, similar to a geologic map, rather than a continuous range of colors that require qualitative interpretation. Historically, remote sensing images have often been more visually appealing than informative because colors have often not had specific, definable meanings.
- The system should be relatively fast, and able to handle the large data transfer rates of future spaceborne imaging spectrometers.

The technique is patterned after the expert system for analysis of laboratory spectra developed by Yamaguchi and Lyon (1986). It is suitable for any wavelength-calibrated data in reflectance form, but not for data in raw radiance form. In raw (absolute) radiance form, the effects of solar irradiation and atmospheric filtering dominate the smaller effects of ground reflectance. The technique is outlined below, and described in greater detail by Rubin (1989; 1991).

The technique is a distinctive expert system because it allows the user to vary the spectral analysis criteria in terms of both judgment (in the form of the depth threshold) and knowledge (in the form of the code database, or "knowledge-base").

#### FEATURE EXTRACTION

Deviation from the spectrum average is used to define absorption features. The pixel average is a useful reference because it accounts for pixels that have different overall brightness due to shading. A channel is determined to be an absorption if it (1) is a local minimum and (2) falls more than a given threshold (D) below the spectrum average. Figure 3 illustrates the determination of absorption depth in a typical log residual GERIS spectrum from an area with sericitic alteration. The sensitivity of absorption feature detection, and hence image classification, can be adjusted by changing the depth threshold. The result of feature extraction is a list of the minima in each pixel spectrum. The system could be easily modified to identify features such as emission peaks, slopes, inflection points, or any other attribute of spectra.

#### FEATURE CODING

The presence or absence of absorption features (or other spectral attributes) in one or more diagnostic wavelength



boxes can be summarized in a simple code. Each wavelength box is labeled with a single-digit number (using hexadecimal notation for numbers greater than nine). If an absorption falls within one of the wavelength boxes, the number of that wavelength box is entered into the code for the spectrum. The code for a spectrum consists of a list of the numbers corresponding to those wavelength boxes where absorption features occur. The codes are arranged in order of decreasing absorption depth. Absorptions which occur outside of the wavelength boxes are not recorded in the code.

#### CONSTRUCTING A CODE DATABASE

The codes of known or predicted spectra are entered into a database. The spectra can be obtained from laboratory or field measurements, or from training sets of known ground surface mineralogy in imaging spectrometer data. By selecting which codes to include in the database, the user can vary the knowledge component of classification decisions. The user can also specify whether a group of codes (corresponding to either multiple spectra, or spectra that are ambiguous due to noisy data) are to be placed into a single class.

#### CODE MATCHING

The code for each pixel in an image is matched against the codes in the database by a simple character-by-character string match. If the code for a pixel matches one of the codes in the database, the pixel is assigned the color code corresponding to that mineral or alteration type. If there is no match for the pixel, the pixel is not assigned a color. The resulting image consists of pixels color-coded for specific alteration zones.

#### Results

Figure 4 is an example of a classified Geoscan image. In the area shown in this image, the mineral sericite is the only mineral detectable remotely in significant quantities; hence, the image is essentially a map of the distribution of sericite. The sensitivity of the classification can be adjusted by changing the depth threshold of the feature extraction algorithm. The section below describes a method for optimizing the accuracy of classification by changing the depth threshold.

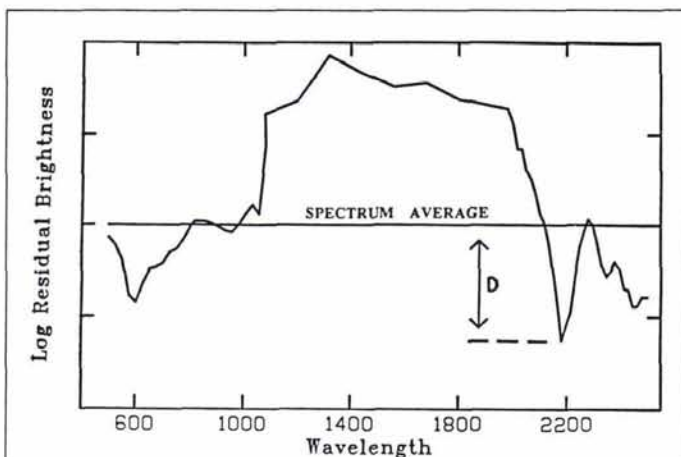


Fig. 3. Absorption features are identified as local minima a threshold depth  $D$  below the spectrum average.

#### Misclassification Assessment Using Image Subtraction

The classified Geoscan image of the Ann-Mason area shows a close resemblance to Dilles' (1983) Younger Alteration Map of sericite-bearing mineral assemblages. (To facilitate comparison with spectral data sensitive to sericite, Dilles' map was simplified to combine all sericite-bearing mineral assemblages into one unit of "sericitic" rock.) The older GERIS image of the same area also showed clear similarities, but was more ambiguous than the Geoscan image due to lower spatial resolution and noise in the spectra. The better spectral signal-to-noise ratio and higher spatial resolution of Geoscan data allow a more detailed comparison of classification results to Dilles' alteration map.

The simplified version of Dilles' "sericite" map was prepared in a digital format and geometrically registered to the Geoscan image maps for comparison (Figure 5). By digitally subtracting the map from the image, the differences and similarities of the classification results could be quantified. A classification was considered a correct positive if both the classified image and Dilles' map show the area as altered (i.e., a pixel that is white in both Figure 4 and Figure 5). A correct negative was an area that both the classified image and Dilles' map show as unaltered (i.e., a pixel that is greyscale in Figure 4 and black in Figure 5). A false positive was a pixel classified as altered in an area Dilles mapped as unaltered (i.e., white in Figure 4 and black in Figure 5). A false negative was a pixel classified as unaltered in an area that Dilles mapped as altered (i.e., a pixel that is greyscale in Figure 4 but white in Figure 5).

As the depth threshold was changed, the relative rates of "correct" and "incorrect" classification changed. For example, because a smaller depth threshold allowed more pixels to be classified as altered, the number of false positives increased and the number of false negatives decreased. Conversely, a stringent depth threshold criterion caused very few pixels to be classified, which resulted in fewer false positives but more false negatives. Figure 6 shows the relationship between the depth threshold and the degree of mismatch between Dilles' map and the classified images.

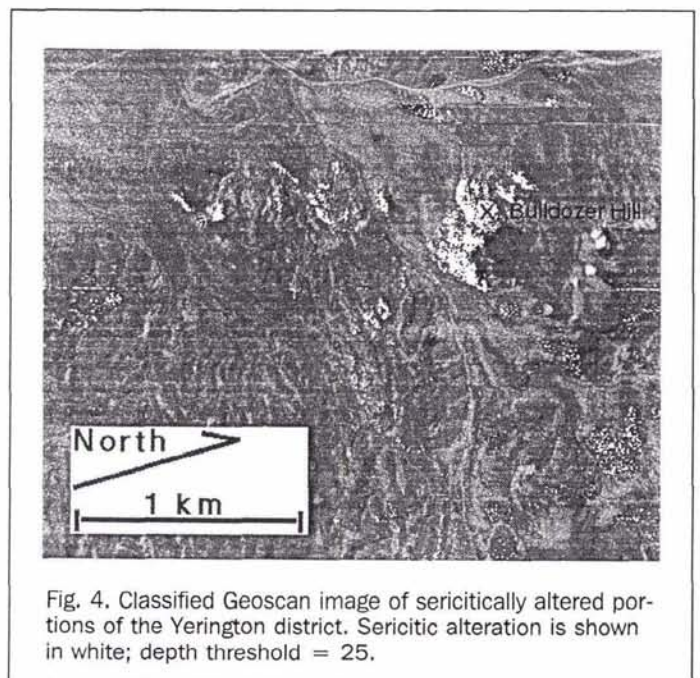


Fig. 4. Classified Geoscan image of sericitically altered portions of the Yerington district. Sericitic alteration is shown in white; depth threshold = 25.



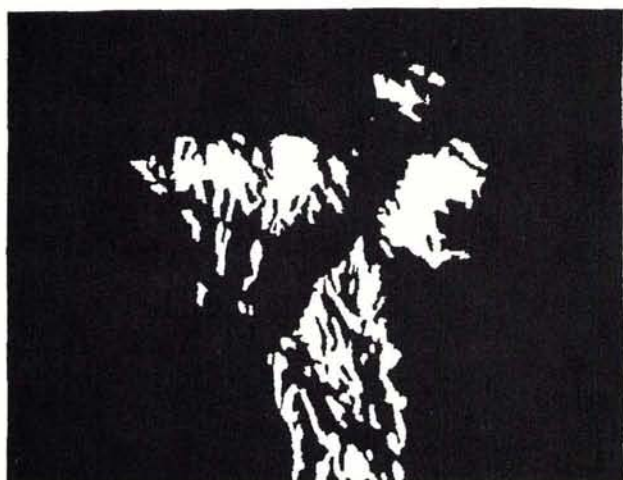


Fig. 5. Digitized form of simplified version of Dilles' (1983) Younger Alteration map. Geometrically registered to Geoscan imagery.

The choice of an optimal depth threshold depends on the desired results of classification. The best threshold may be considered one that produces equal probability of a false positive or a false negative ( $D = 21$  in Figure 6). Alternatively, the best threshold might be one that produces the lowest total mismatch of false negatives plus false positives ( $D = 25$  in Figure 6). It should be noted that the threshold for the lowest total mismatch produces an image where misclassified pixels have a strong bias toward false negative classification. A more complex decision might be based on a loss function that describes the costs of a false negative or a false positive misclassification, then finds the threshold producing the minimum loss.

The degree of mismatch between spectral mapping and Dilles' alteration map is a function of both the difference in support size, and the difference between detection of minerals versus mapping of alteration assemblages. The support size of "ground truth" is different for spectral mapping at a scale of 6-metre Geoscan pixels and 20-metre GERIS pixels, and different again for a geologic map. Additionally, imaging spectrometry is able to detect minerals with objective measurements, while a geologic map is a mixture of objective observation and subjective interpretation. The mismatch is an error only if one technique is used to indicate or approximate the results of another technique. Mismatch is thus not necessarily equivalent to error.

## Conclusions

The spectral mapping technique presented here, based on fundamental principles of infrared spectroscopy, successfully reproduced a traditional geologic map with a low degree of misclassification. Image subtraction of ground truth data allowed quantitative optimization of classification criteria, and extension to a new area that did not have previously available ground data. By incorporating expert spectroscopic knowledge and decision criteria, the technique is superior to others that rely only on multivariate statistics or prior knowledge of the area.

The signal-to-noise characteristics of the input data were found to be extremely important in determining their value

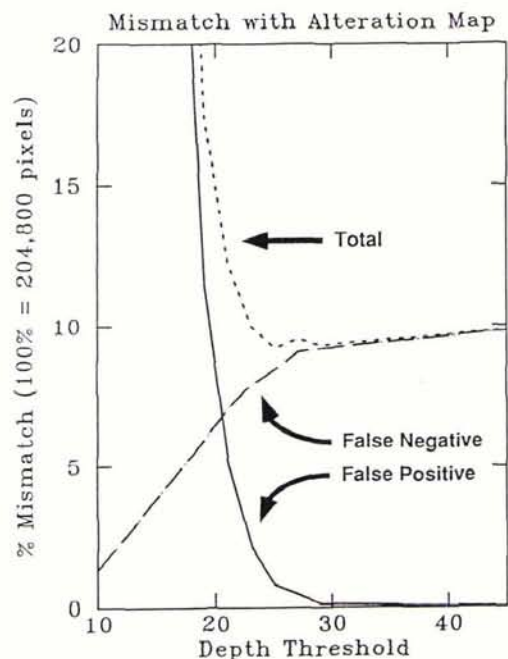


Fig. 6. Relationship between depth threshold and rate of mismatch between alteration map and classified Geoscan imagery.

for use in classification. The 1987 GERIS data for the study area had much more noise (estimated  $S/N = 5:1$ ) than the 1989 Geoscan data ( $S/N = 20:1$ ; Lyon, 1989a). In spite of the increased spectral resolution, the GERIS data were not as useful as the Geoscan data. In fact, the wavelength bands used for feature coding effectively decreased the spectral resolution of the GERIS data. The bandpasses of the Geoscan instrument, though wider than those of GERIS, were selected for alteration mapping, and the resulting data are very useful. These results indicate that, within reason, signal-to-noise should not be sacrificed at the expense of spectral resolution.

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