Classification of Remote Sensing Images having High Spectral Resolution[1]

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Abstract

A method for classifying remote sensing data with high spectral dimensionality that combines the techniques of chemical spectroscopy and pattern recognition is described in this paper. The technique uses an atmospheric adjustment to allow a human operator to identify and label training pixels by visually comparing the remotely sensed spectra to laboratory reflectance spectra. Training pixels for materials without easily identifiable spectra are labeled by traditional means.

Linear combinations of the original radiance data are computed that maximize the separability of the classes and classified by a maximum likelihood classifier. No adjustment for the atmosphere or other scene variables is made to the data before classification. This technique is applied to Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data taken over Cuprite, Nevada in 1992, and the results are compared to an existing geologic map. This technique performed well even for classes with similar spectral features and for classes without absorption features.

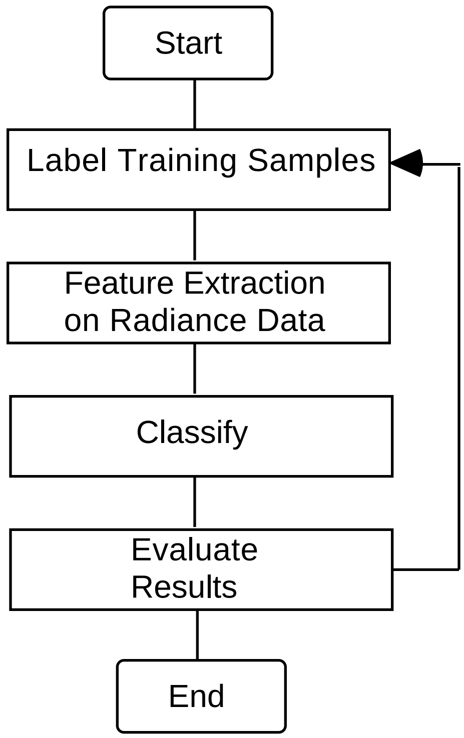


Figure 1. Flowchart of Classification Technique

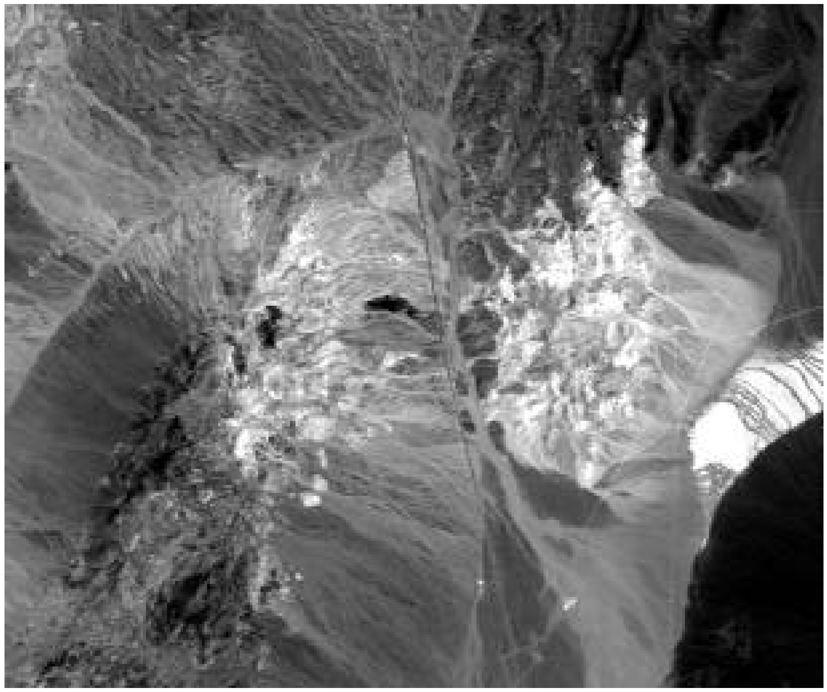


Figure 2. The 1.20 µm band from the Cuprite site.

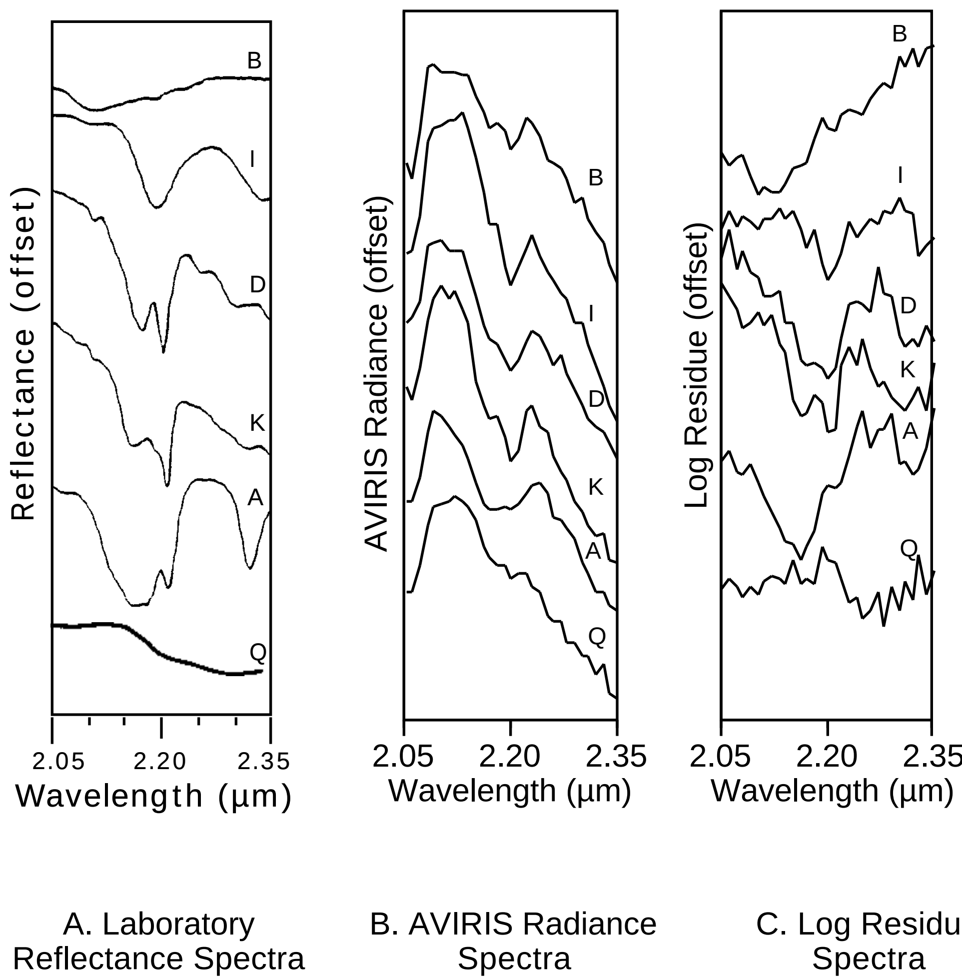
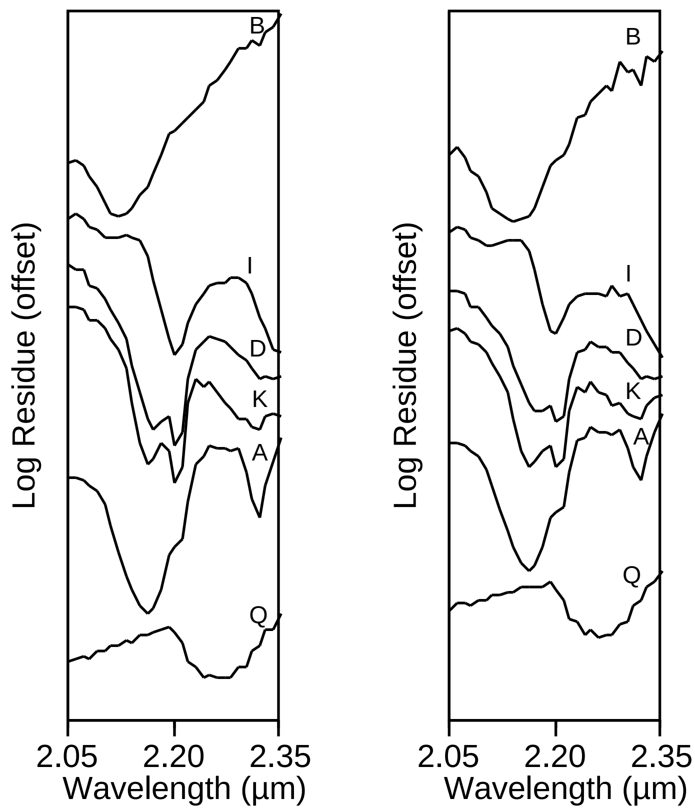


Figure 3. Reflectance, Radiance, and Log Residue Spectra (B - Buddingtonite, I - Illite, D - Dickite, K - Kaolinite, A - Alunite, Q - Quartz)



A. Log Residue of the Mean of Training Pixels

B. Log Residue of the Mean of Classified Pixels

Figure 4. Mean Log Residue Spectra of Training Pixels and Classified Pixels (B - Buddingtonite, I - Illite, D - Dickite, K - Kaolinite, A - Alunite, Q - Quartz)

Figure 5. A Likelihood Map. Dark areas indicate low likelihood of membership in the class to which they have been assigned, while light areas indicate high likelihood.

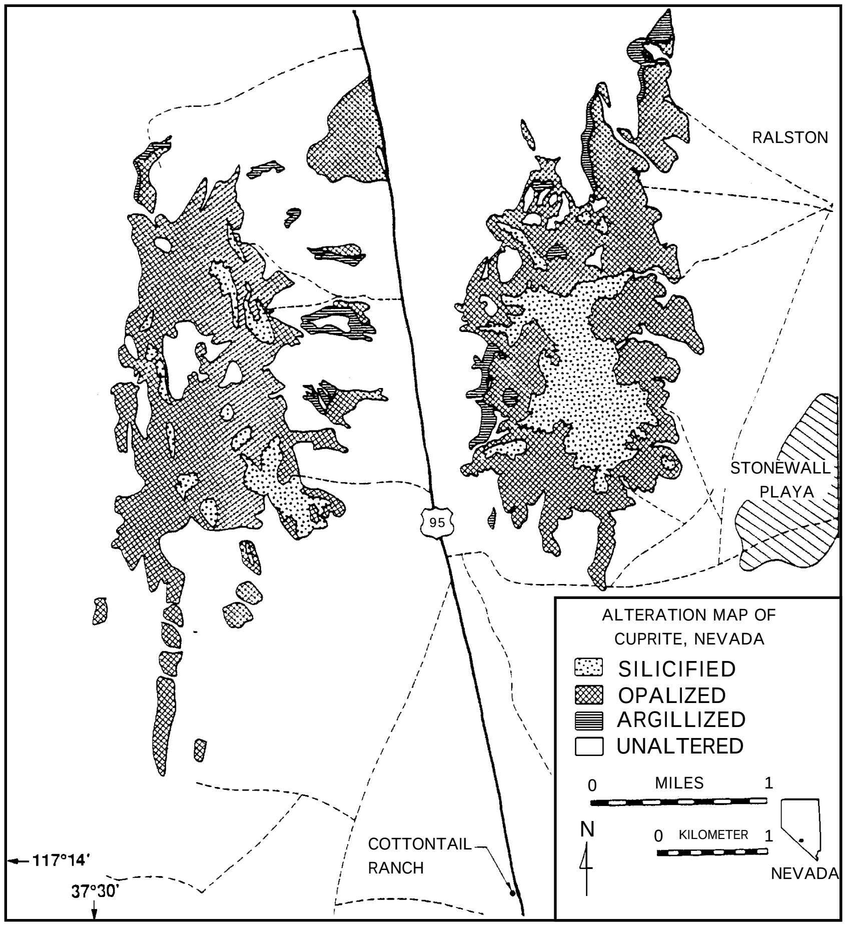
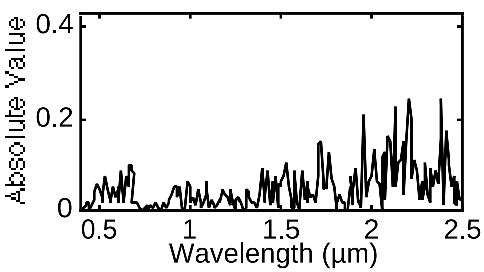
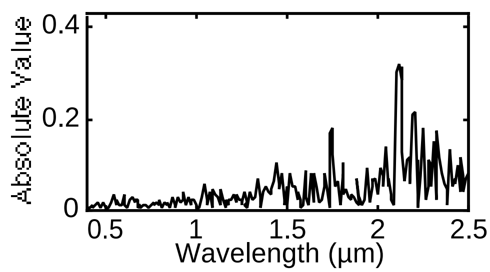


Figure 6. Geological map from Hook, et al., 1992.

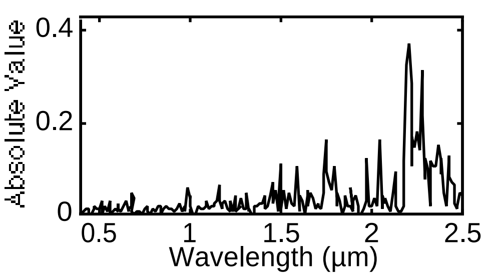
Figure 8. Likelihood Map for Final Classification.



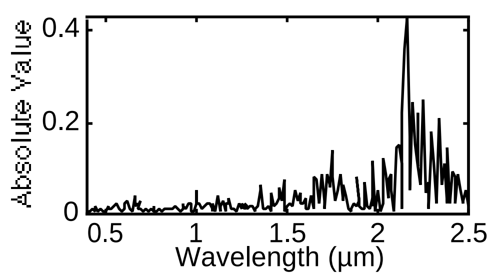
A. First Discriminant Feature



B. Second Discriminant Feature



C. Third Discriminant Feature



D. Fourth Discriminant Feature

Figure 9. First Four Discriminant Features

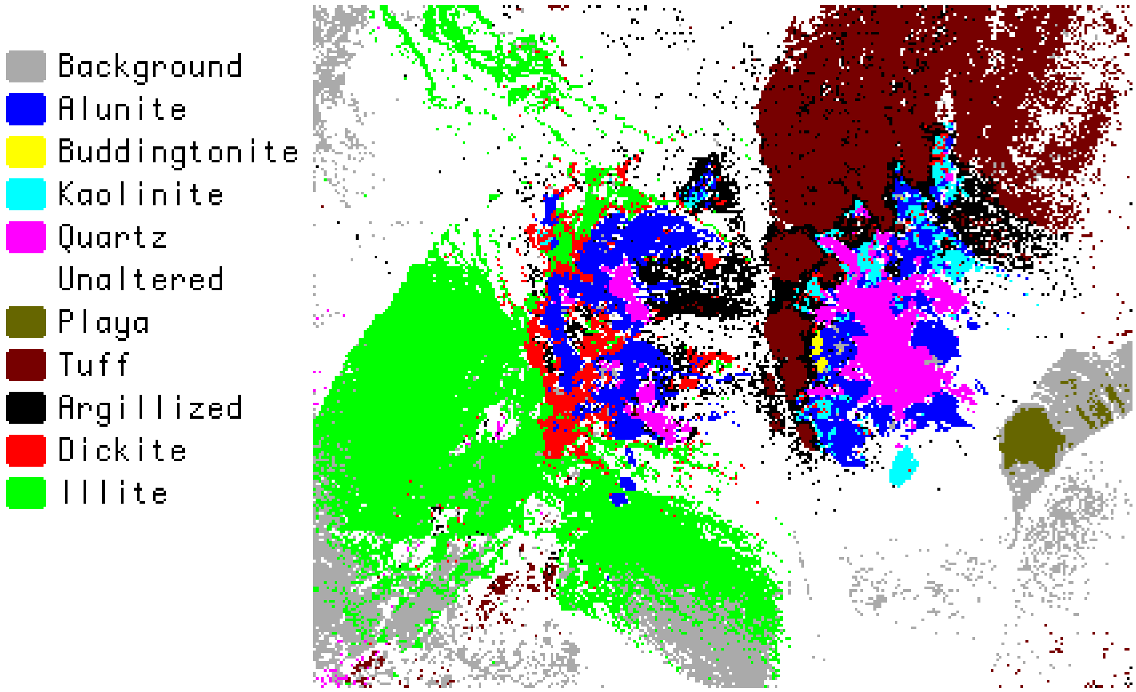


Figure 7. Classification of 1992 AVIRIS data.