

Temporal Variation in Spectral Detection Thresholds of Substrate and Vegetation in AVIRIS Images

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The ability to map changes over large surface areas over time is one of the advantages in using remote sensing as a monitoring tool. Temporal changes in the surface may be gradual, making them difficult to detect in the short-term, and because they commonly occur at the subpixel scale, they may be difficult to detect in the long-term as well. Also, subtle changes may be real or merely an artifact of image noise. It is, therefore, necessary to understand the factors that limit the detection of surface materials in evaluating temporal data. In this study, we evaluated and compared the spectral detectability of vegetation and soil in the 1990 July and October AVIRIS data of Jasper Ridge, CA.

The spectral detectability of subpixel material in an image depends upon its spectral contrast with background materials, its relative abundance, instrumental noise, and local atmospheric/topographic effects (Sabol et al. 1992). Spectral mixture analysis was used in this study to identify spectral endmembers and determine their spectral fractions for each image pixel. The minimal requirements for potentially physically meaningful fractions are: 1) the fractions are between 0 and 1, and 2) the residuals are low (within the level of system noise) (Smith et al., 1985; Adams et al., 1989). However, Smith et al. [1990] noted that the band residuals decrease as the number of endmembers increases, even when the additional endmembers are not actually present in the image. In this case, the endmember fractions may or may not be realistic, depending on the spectra involved. Additionally, Sabol et al. [1992] noted that the spectral detectability of targets generally decreases as the number of endmembers increases. Therefore, fractions are more physically meaningful, and detectability is enhanced, when the image is modeled using the minimal number of endmembers that result in realistic fractions and low residuals.

In past applications of spectral mixture analysis, only a few endmembers (usually fewer than five) have been used to model a large scene to preclude inclusion of extraneous endmembers. This, however, does not take into account the spectral variability of the surface components that each endmember represents. For example, earlier images of Jasper Ridge have been modeled as mixtures of a soil, green vegetation, senescent vegetation, and shade endmembers (Roberts et al. [1990, 1991], Sabol et al. [1991]). These endmembers, in fact, are "representative" of a type of surface component. In this study, to allow for spectral variability of the components in the scene, a number of spectra representing the range of spectral variation of each component were included in the spectral library and organized as classes. The library (466 spectra) included a green vegetation class, as well as soil, senescent vegetation and shade classes. To find the appropriate endmembers, each pixel was modeled as mixtures of 2 and 3 components, allowing a maximum of one spectrum from each class. The endmembers for each pixel were indicated when the fewest number of endmembers was needed to have realistic fractions and low residuals.

The resultant endmembers were then used to determine the best-case detection threshold of each component (excluding shade). A general outline of the analysis follows:

- 1) the images were calibrated to reflectance using the methods described by Roberts et al. [1991],

- 2) the images were modeled as mixtures of endmember groups (described above),
- 3) the signal-to-noise ratios for each image were determined using the method described by Sabol et al.[1991],
- 4) the detection thresholds for the different soil and vegetation spectra in the grasslands were determined for each combination of endmembers using the methods described Sabol et al.[1990, 1992].
- 5) the fractions and detection thresholds from the two data sets were then compared to ascertain actual changes in surface composition and changes due to other effects such as the change in solar illumination angle.

Two general types of shade were found in the image: photometric shade and vegetation shade. Photometric shade, spectrally flat (near zero reflectance) at all but the lower wavelengths, typically occurred in areas where the fraction of green vegetation was minimal (i.e. senescent grasslands, roads, lakes), while vegetation shade, spectrally similar to green vegetation, but with greatly reduced reflectance (maximum reflectance of ~30 %), was a prominent endmember in areas containing significant fractions of green vegetation. Roberts et al. (1991) showed that vegetation-shade is caused by the transmission and scattering of incident radiation through the leaves, and by solving for the shade component, the spectral signature of vegetation-shade for a given area can be determined. To get a more appropriate shade spectrum and to account for the non-linearities in spectral mixing due to green vegetation, we used the methods described by Roberts et al. [1991] to determine the vegetation-shade endmember for the several areas in the image. These spectra were incorporated into the detectability analysis.

A preliminary analysis indicates that for much of the July and October images, 2 image-endmember combinations yielded the most reasonable models. Although the fractions and endmembers are similar between the two images, some subtle differences were observed. For example, a portion of the grasslands at the crest of Jasper Ridge were modeled as a mixture of vegetation shade and senescent vegetation in the July image. This is interpreted as short, shadowed green grass among the taller dry grass. In the October image, the same area was modeled as a mixture of photometric shade and senescent vegetation, indicating that the green grass in the July image had senesced. The spectral signature of the exposed soil in this area was not included as an endmember because it was mimicked by mixtures of the endmembers. Therefore, band residuals were still necessary for detection of materials that were spectrally unique at only a few bands.

By allowing each pixel to be modeled by the most appropriate endmembers in the spectral library, the spectral variability of each surface component throughout an image can be more closely approximated in image analysis. The detectability of any endmember in a pixel, therefore, varied across the image. Soil, for example, which can be represented by a different spectrum in other image pixels, had a different detection threshold from pixel to pixel due to: 1) varying fractions, and 2) varying background endmembers. This data, when combined with spectral mixture analysis in evaluating temporal data, provides a methodology for separating actual changes in surface composition from uncertainties due to system noise and local temporal changes, such as change in the angle of solar illumination.

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