LINEAR UNMIXING OF SIMULATED, NOISY SPECTRA: VEGETATION DETECTION LIMITS IN AREAS OF LOW COVER

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1. INTRODUCTION

Issues of global land use and land cover change are gaining importance as we strive to understand the impact of human activities on our planet. Remote sensing using current or anticipated technology is widely viewed as a time- and cost-efficient way to proceed with large-scale monitoring (Hall et al., 1995). Indeed, remote sensing techniques and technologies are likely to afford the best opportunities to proceed with regional- or global-scale environmental change detection. However, the low vegetation cover of arid regions poses a significant obstacle to the fulfillment of this goal. With high hopes for these technologies, it is important to understand their limits.

In this paper we probe the limits of spectral mixture analysis (SMA), a standard remote sensing analysis tool, in soil and vegetation parameter retrievals. The SMA method estimates the proportion of each ground pixel's area that belongs to different cover types (Drake et al., 1999; Settle and Drake, 1993). SMA is based on the assumption that the spectra of materials in an instrumental instantaneous field of view (IFOV) combine linearly, with proportions given by their relative abundances. A combined spectrum thus can be deconvolved into a linear mixture of its "spectral endmembers"—spectra of distinct materials in the IFOV. The weighting coefficients of each spectral endmember, which must sum to one, are then interpreted as the relative area occupied by each material in a pixel.

Previous published (Okin et al., 1998; Okin et al., 1999) and unpublished attempts by the current authors to retrieve vegetation type and cover from Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery met with only limited success. In order to determine the causes of our earlier difficulties, and to determine the intrinsic limitations of SMA in arid regions, the current study was undertaken. We find that SMA of hyperspectral data cannot retrieve vegetation type or vegetation covers reliably at low areal vegetation cover. Soil types may be mapped with greater reliably.

Early uses of SMA by other authors with multispectral data have met with some success. Smith *et al.* (1990) applied a mixing model that employed laboratory and field spectra to Landsat TM data from the Owens Valley, indicating that mixture modeling can facilitate mapping and monitoring of sparse vegetation cover while Cross *et al.* (1991) have used spectral mixture analysis of AVHRR data in subtropical forest areas to map forest cover.

SMA is particularly amenable to use with imaging spectroscopy data where the number of useful bands is much higher than the number of model endmembers, and solutions to the basic SMA equations are overdetermined. Roberts *et al.* (1998; 1997; 1993) have used linear mixture analysis of AVIRIS data to map green vegetation, nonphotosynthetic vegetation (NPV), and soils at the Jasper Ridge Biological Preserve and the Santa Monica Mountains, CA. García-Haro *et al.* (1996) have applied SMA to high resolution field spectroscopy, finding it to be less sensitive to soil background in the detection of vegetation than the normalized difference vegetation index (NDVI). Painter *et al.* (1998) have applied SMA of AVIRIS data acquired over snow-covered areas in the Sierra Nevada to estimate snow grain size. Most of these studies have used a constrained least squares approach to estimating the fraction of each ground pixel belonging to each endmember.

The unique capabilities of imaging spectrometers have proven useful for SMA in a variety of different land-cover types with significant plant cover. Despite these successes, the quantitative detection of sparse vegetation

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in remote sensing imagery, and hence in many arid and semiarid areas worldwide, remains problematic. Few investigators have examined the usefulness of hyperspectral data in the quantitative detection of vegetation at low covers (See for example, Chen et al., 1998; Elvidge et al., 1993).

The problem of quantitative retrieval of vegetation type, cover, biomass, or leaf area index (LAI) in areas of low cover arises from several factors:

1) A large soil background in many cases swamps out the spectral contribution of plants, especially in arid and semiarid regions where soils can be bright and mineralogically heterogeneous (Escafadel and Huete, 1991; Huete and Jackson, 1988; Huete et al., 1985; Smith et al., 1990).

2) Non-linear mixing is prevalent in areas of low cover where light rays reaching sensors from vegetation are often polluted by additional interactions with soils or other shrubs (Huete, 1988; Ray and Murray, 1996; Roberts et al., 1993).

3) Evolutionary adaptations to the harsh desert environment make desert plants spectrally dissimilar to their humid counterparts, lacking in many cases a strong red edge, exhibiting reduced leaf absorption in the visible, and displaying strong wax absorptions around 1720 nm (Billings and Morris, 1951; Ehleringer, 1981; Ehleringer and Björkman, 1976; Ehleringer and Björkman, 1978; Ehleringer and Mooney, 1978; Gates et al., 1965; Mooney et al., 1977; Ray, 1995).

4) Spectral variability within shrubs of the same species can be high in arid and semiarid regions, as reported by Franklin *et al.* (1993) and Duncan *et al.* (1993). Rapid movement of many desert shrubs through phenological changes in response to small amounts of spatially-discontinuous precipitation can contribute to this effect.

5) Desert shrubs often display open canopies which contribute to poor correlations with LAI (Hurcom and Harrison, 1998). Roberts *et al.* (1990) have also suggested that canopy structure can affect plant reflectance, particularly in the near infrared.

The specific purpose of this study is to ascertain whether, and at what level, SMA of imaging spectrometer data obtained over regions with low vegetation covers (0 to 50%) could be expected to yield accurate estimates of vegetation type, vegetation cover, or soil type. We simulate noise-free and noisy AVIRIS spectra of various soil, vegetation cover, and vegetation type classes. Noise is modeled by reported 1998 AVIRIS signal-to-noise ratio (SNR) which is greater than any other imaging spectrometer currently or soon to be deployed, including Earth Observer-1 (EO-1) Hyperion, Australian Resource Information and Environment Satellite-1 (ARIES-1), and Naval EarthMap Observer (NEMO) Coastal Ocean Imaging Spectrometer (COIS) data. This approach comprises a realistic best-case scenario in which many typical problems with remote sensing in areas of low cover or desert areas are minimized. In particular, several real-world limitations on remote sensing are absent: intra-species spectral variability, nonlinear mixing, lighting and topographic effects, uncertainty related to apparent surface reflectance retrievals, and noise in field or image endmembers.

2. METHODS

2.1 Field Spectroscopy

Field reflectance spectra of soils and vegetation were collected in the Manix Basin on May 2, 1998, two days after an AVIRIS overflight. The Manix Basin is in the Mojave Desert, about 25 miles ENE of Barstow in southeastern California (centered around 34°56.5" N 116°41.5" W at an elevation of 600 m). Field spectra were collected from 350 nm to 2500 nm using an ASD Full Range portable spectroradiometer (Analytical Spectral Devices, Inc., Boulder, Colorado). Spectra were acquired from 0.25 to 0.5 meters (nadir-looking) above targets with an 8% field of view, and divided by the near-simultaneous (<2 minutes) spectrum of a 100% reflective Spectralon panel (Labsphere, North Sutton, New Hampshire) to yield reflectance. Reflectance spectra were collected of soils, individual shrubs of dominant species (*L. tridentata*, *A. dumosa*, and *A. polycarpa*) or over small areas for grasses and NPV (typically in an approximately 5-m radius circle). Ten spectra were averaged together for each shrub, NPV, grass, and soil. Averaged spectra were convolved to AVIRIS bands, and incorporated into a spectral library with 185 total spectra (54 vegetation/NPV spectra and 131 soil spectra). Spectra of soils from other dates were used to supplement this library.

2.2 Spectral Simulations

Representative field reflectance spectra of three abundant vegetation types in the Manix Basin (senesced *Schismus* grass, *A. polycarpa*, and L. *tridentata*) plus a spectrum of green lawn grass from the USGS Digital Spectral Library (Clark et al., 1993) were chosen as vegetation endmembers for spectral simulations. The lawn grass spectrum was chosen as it is representative of green vegetation, which is typically not found in the Mojave Desert. Representative spectra of three different common soil surface classes (blown quartz sand, armored deltaic deposits, and semi-armored soils from abandoned fields) were chosen as soil endmembers. The desert vegetation and soil spectra used as endmembers in spectral simulations were chosen from the spectral library using the method outlined by Gardner (1997) and Roberts *et al*. (1998) to determine their representation of the other spectra in their class. The endmember spectra used for spectral simulations are shown in Figure 1. The armored and field soils have very similar spectra due to their nearly identical surface appearance and related origins. The armored soil is a deflated deltaic deposit covered by a gravel lag, whereas the field soil is from an abandoned field located on deflated deltaic deposits where the deflationary lag has largely re-established since abandonment. The blown soil is from an area downwind of an abandoned field where sand, removed from the field by wind, has been deposited.

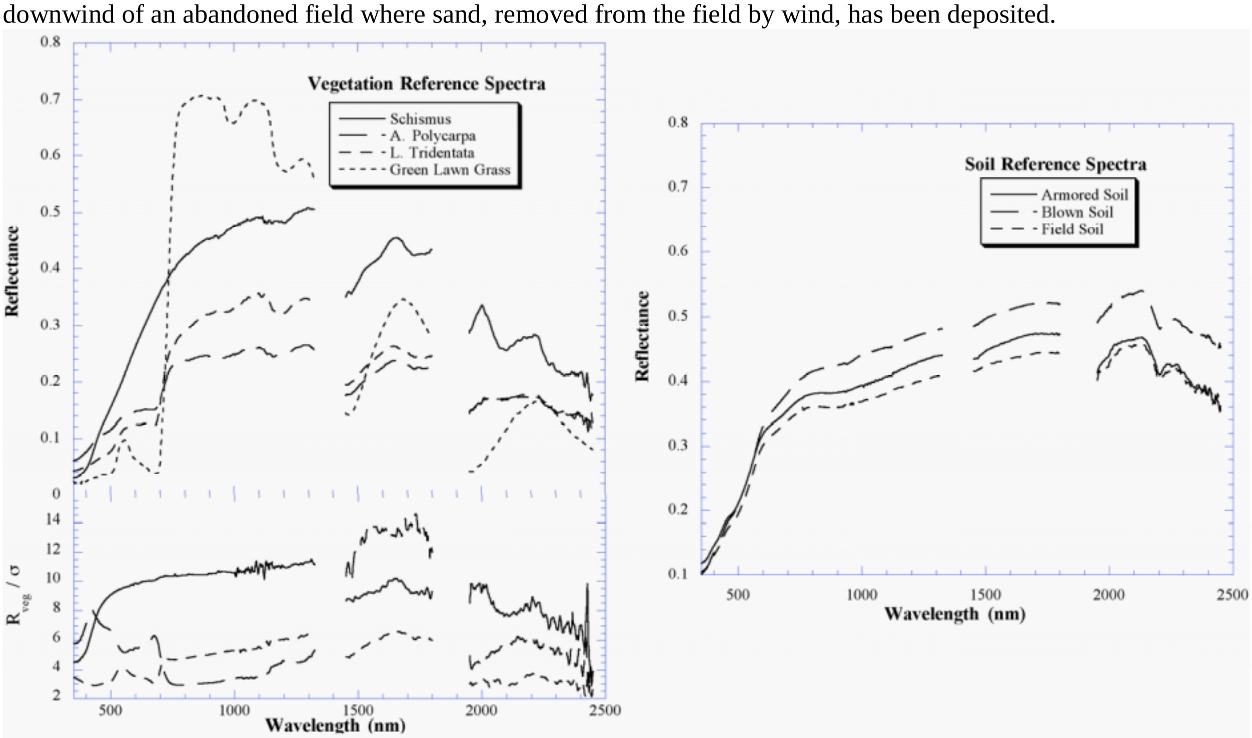


Figure 1. Field reflectance spectra of soils and vegetation collected in the Manix Basin on May 2, 1998. Each spectrum is the average of ten spectra. The quantity R_{veg}/σ is a signal-to-effect ratio which gives an indication of the intra-species spectral heterogeneity on the same scale as the signal-to-noise ratio.

The four vegetation endmember spectra were each combined linearly with each of the three soil endmember spectra in varying proportions (representing from 0% to 50% vegetation cover) according to the equation:

$$R_S(\lambda) = f_{veg} R_{veg}(\lambda) + (1 - f_{veg}) R_{soil}(\lambda)\,, \qquad (1)$$

where $R_s(\lambda)$ is the simulated spectrum, f_{veg} is the fraction of vegetation, $R_{veg}(\lambda)$ is the reflectance spectrum of the vegetation endmember, and $R_{soil}(\lambda)$ is the reflectance spectrum of the soil endmember. There were a total of 312 simulated spectra.

Signal-chain noise was modeled in the resulting spectra by adding to each band the reported 1998 AVIRIS signal-to-noise (Green et al., 2000) times a standard-normal random number:

$$R_{SN}(\lambda) = R_S(\lambda)\left(1 + \frac{N(0,1)}{SNR(\lambda)}\right), \quad (2)$$

where $R_{SN}(\lambda)$ is the simulated, noisy spectrum, SNR(λ) is the signal-to-noise ratio, and N(0,1) is a random number generated from a standard normal distribution with a mean of zero and a standard deviation of one. A total of 16 complete sets of noisy spectra were generated so that each spectrum in each set had its own unique noise vector.

2.3 Spectral Mixture Analysis of Simulated Spectra

Each of the noisy simulated spectra was modeled by each of the non-noisy simulated spectra by minimizing root-mean-squared error (RMS) for a simplified SMA equation:

$$R_{SN}(\lambda) = f_m R_S(\lambda) + \varepsilon(\lambda) \quad (3)$$

where $-0.01 \le f_m \le 1.01$ and $\varepsilon(\lambda)$ is an error term. RMS is given by:

$$RMS = \frac{\left(\sum_{j=1}^{m} (\varepsilon_j)^2\right)^{0.5}}{m}, \quad (4)$$

where ε_j are the error terms for each of the m spectral bands considered. In this study, we used a reduced set of 197 of the AVIRIS bands. Bands that span the deep atmospheric water absorptions at approximately 1400 nm and 1900 nm were not used.

In many cases, a noisy spectrum was equally modeled by two or more spectra. The spectra, $R_S(\lambda)$, which modeled each noisy spectrum, $R_{SN}(\lambda)$, with the lowest RMS were recorded. Cases in which RMS was greater than 2.5% or in which residuals deviated from zero in the same direction for more than seven consecutive bands were not considered.

The simulations carried out here represent a best-case scenario in which confusions due to intra-species spectral variability, nonlinear mixing, lighting and topographic effects, uncertainty related to apparent surface reflectance retrievals, and noise in field or image reference endmembers are absent. How would these other sources of variability affect the success of modeling vegetation under low-cover conditions? In order to probe this question, we modeled each noisy simulated spectrum in a set by all other noisy spectra in a set. Although this approach does not directly address issues like non-linear mixing and intra-species or intra-soil spectral variability, it roughly simulates the effect of adding a modest amount of uncertainty to a spectral library. In truth, many types of uncertainty cannot be treated mathematically in the same way as instrumental noise. However, by adding noise to both the modeled spectra and the spectral endmembers, we can determine the magnitude of effect expected from other sources of variability. If the addition of this modest amount of error compromises the ability to retrieve relevant information using SMA of hyperspectral data, much larger sources of uncertainty can certainly be expected to do so as well.

How does this uncertainty compare quantitatively to others? The quantity R_{veg}/σ plotted in Figure 1 gives an indication of the intra-species spectral heterogeneity. R_{veg}/σ varies between 2 and 14, while the 1998 AVIRIS SNR varies between 300 and 1200 except in the deep atmospheric water bands. R_{veg}/σ is a signal-to-effect ratio (SER) analogous to SNR, where here the "noise" is not instrument noise but intra-species spectral variability. Asner *et al* (1998) have reported intra-species spectral variability in reflectance spectra of many plants and litter types with SER values on order 10 for visible and near-infrared multispectral channels. Results from Asner's (1998) canopy-scale radiative transfer models of vegetation suggest that small changes in LAI, stem-area index, leaf angle, and the ratio of living material to litter can contribute to inter-canopy variability and therefore intra-species variability. For example, a 10% decrease in living material in a plant with 100% living material can increase NIR reflectance from approximately 0.25 to approximately 0.30, a SER of 5. It is important to note that the change in these spectra is wavelength-dependent and nonlinear: the reflectance spectrum of a canopy with 90% living material cannot simply be expressed as the reflectance spectrum of a canopy with 100% living material times a scalar. Intra-species variability has a magnitude much greater than instrumental noise and therefore is more likely to confound linear spectral mixture analysis.

Ray and Murray (1996) have reported that the effect of nonlinear mixing in *L. tridentata* canopies in the visible and near-infrared can be one-half the reflectance spectrum. The resulting SER is approximately 2, which is an effect larger than intra-species variability and more than two orders of magnitude larger than the 1998 AVIRIS SNR. Clearly, confusion due to intra-species variability and nonlinear mixing in vegetation is much more likely than that due to instrumental noise.

3. RESULTS AND DISCUSSION

Several categories of modeling errors were considered for the analysis of spectral simulation results:

1) Was each spectrum modeled by other spectra with the same vegetation type?

2) Was each spectrum modeled by other spectra within 10% of the modeled spectra, regardless of vegetation type?

3) Was each spectrum modeled by other spectra with the same soil type?

Since the spectra, genesis, and surface appearance of the armored soil and the field soil (Figure 1) were so similar, two additional categories were considered:

4) Was each spectrum modeled by other spectra with the same or similar soil type?

The total number of times all spectra were modeled correctly according to each of the categories above was recorded. Spectra were also divided into vegetation cover classes (2-10%, 12-20%, 22-30%, 32-40%, and 42-50%) and the total number of times spectra in each cover class were modeled was recorded. These were then divided by the total number of times all spectra were modeled and result was subtracted from one. The resulting metrics are interpreted as error probabilities and are shown in Figure 2.

Figure 3 gives error probabilities when noisy spectra are modeled by other noisy spectra. These error probabilities are higher compared to those in Figure 2. Thus, there is a dramatic effect in introducing even modest uncertainty to spectral endmembers.

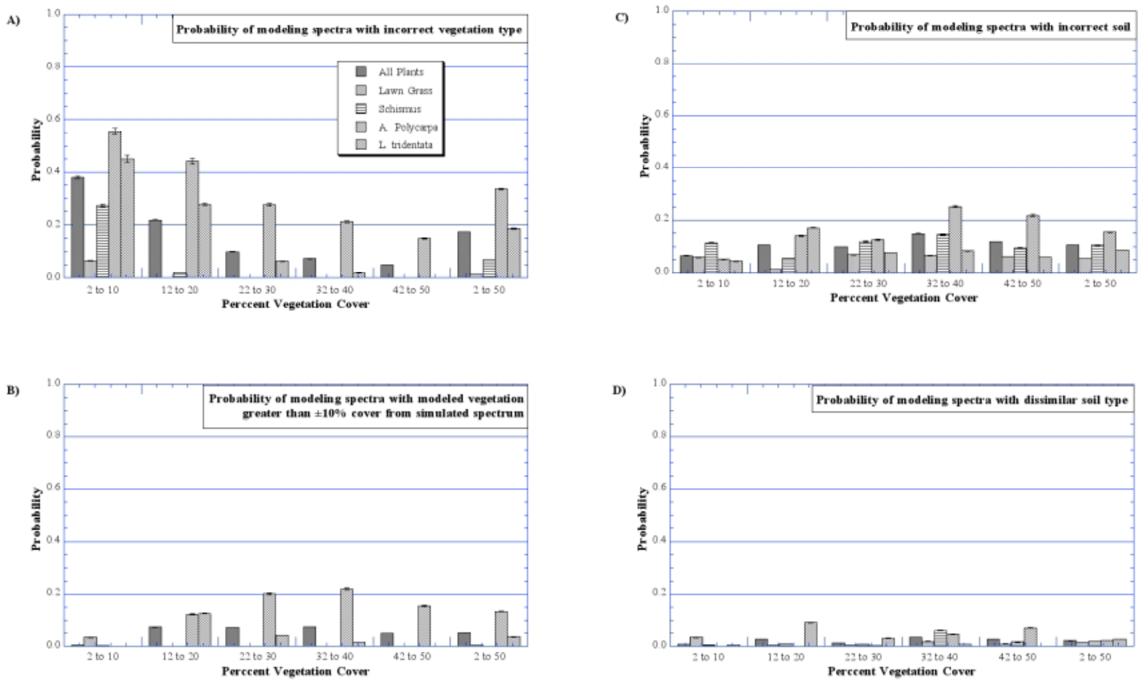
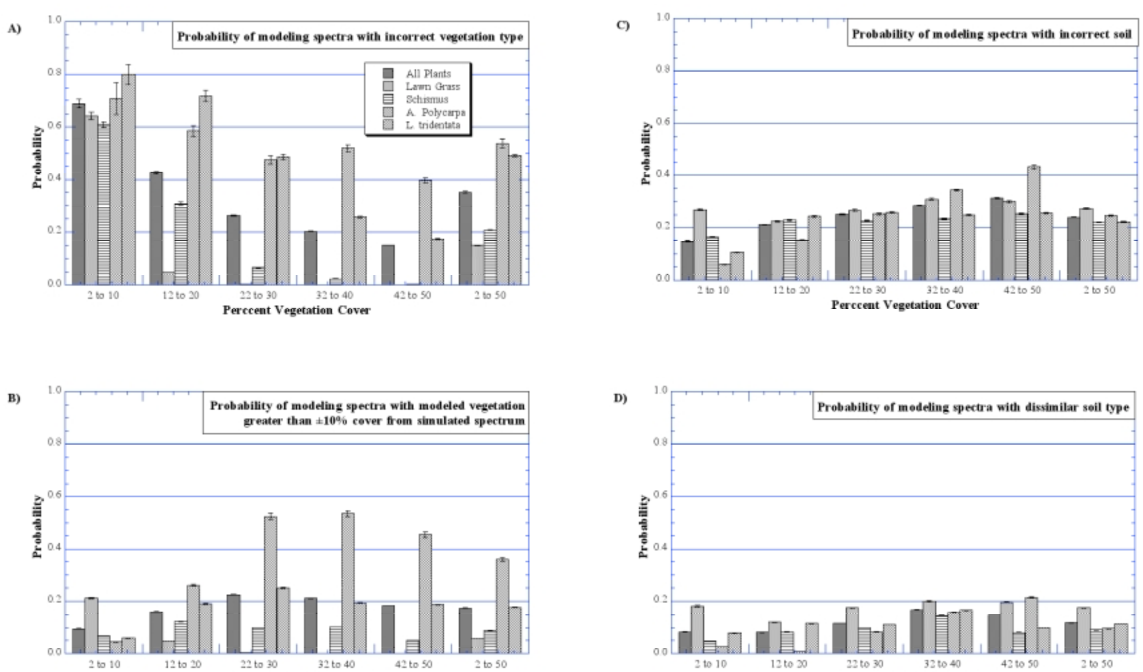


Figure 2. Error probabilities by vegetation type and cover class when noisy spectra were modeled by noise-free endmember spectra. (A) Probability of modeling spectra with incorrect vegetation type. (B) Probability of modeling spectra with endmember cover greater than ±10% from that of the modeled spectrum. (C) Probability of modeling spectrum with incorrect soil. (D) Probability of modeling spectra with dissimilar soil type.



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Vegetation Retrievals

Error probabilities in Figure 2 clearly indicate that even in a best case scenario the probability of incorrectly modeling vegetation types can be high (>50%) and are highly dependent on vegetation type as well as the amount of cover (Figure 2-A). Errors are made in modeling green lawn grass less than 10% of the time and only for covers less than 10% while errors are made in modeling *A. polycarpa* no less than 15% of the time.

As has been suggested by Sabol *et al.* (1992) for soils in a shade-vegetation mixture, the spectral contrast of endmember spectra has a major influence on their detectability. The vegetation considered here may be grouped into two categories based on this insight and on our modeling results. Green lawn grass and senesced *Schismus* grass are "spectrally determinate" vegetation, while *A. polycarpa* and *L. tridentata* are "spectrally indeterminate" vegetation. The spectrally determinate vegetation both have high spectral contrast. The green lawn grass spectrum has a strong red edge and deep absorption bands due to water (Gao and Goetz, 1990). Unlike the green lawn grass spectrum, the spectrum of senesced *Schismus* grass has no red-edge, but does have strong absorption bands due to cellulose and lignin in the SWIR1 and SWIR2 regions (Elvidge, 1990). The spectrally indeterminate vegetation, on the other hand, lack deep chlorophyll absorptions around 420 nm and 680 nm (Gates et al., 1965), a strong red edge, deep water absorption bands in the near-infrared, and the clear cellulose and lignin absorption bands in SWIR1 and SWIR2. These spectrally indeterminate vegetation display the same lack of spectral contrast shown by many other desert shrubs even during the growing season (Billings and Morris, 1951; Mooney et al., 1977). Thus, vegetation remote sensing in arid and semiarid regions is faced with an inherent difficulty.

When noisy spectra are modeled by other noisy spectra, errors in vegetation type retrievals for all desert plants remain above 30% at less than 20% cover, and error probabilities for *A. polycarpa* and *L. tridentata* type retrievals are greater than 25% at less than 40% cover (Figure 3-A).

The increase in the error probabilities in Figure 2-A over Figure 3-A indicates that adding uncertainty to endmember spectra will influence how well vegetation type is modeled. For most applications, mismodeling vegetation type in 30% of the pixels in a remote sensing image would, we believe, be unacceptable. Using this value of 30% error as a liberal cut-off for acceptability, green lawn grass cannot be mapped at covers below 10%, senesced *Schismus* grass, below 20% cover, *L. tridentata*, below 30% cover, and *A. polycarpa*, below 40% cover. Thus, the ability to retrieve vegetation type information using SMA of hyperspectral data at low covers is compromised by modest amounts of uncertainty. Other sources of uncertainty in real-world applications of mixture analysis to hyperspectral data are much larger, and will further reduce the reliability of vegetation retrievals.

The probability of modeling errors in the retrieval of vegetation cover are lower than those for retrieval of vegetation type (Figure 2-B). With the exception of *A. polycarpa*, the probability of error in modeling vegetation cover within 10% of the modeled vegetation cover is lower than 10% and is seen to decrease with increasing cover. Overestimations of vegetation cover are nearly two times more likely than underestimations.

Cover estimations also suffer from the additional uncertainty of modeling noisy spectra with noisy endmembers. With the exception of *A. polycarpa*, error probabilities of modeling spectra with greater than a 10% difference in cover remain below 30%. However, vegetation cover estimates are likely to be as vulnerable to additional sources of uncertainty, including intra-species spectral variability, as vegetation type retrievals. So, although Figure 3-B indicates that vegetation cover may be retrieved in most cases within a total cover difference of 10%, we conclude that vegetation cover estimates must also be treated with skepticism.

Thus, in arid and semi-arid regions with covers below at least 30%, spectral mixture analysis is unable to reliably model vegetation type and cover. Spectrally determinate vegetation may be reliably retrieved at lower covers and areas of relatively high cover may be modeled correctly. However, in an image with both spectrally determinate and indeterminate vegetation and a variety of vegetation covers, some of the data will be reliably modeled, while the rest will not. Without *a priori* knowledge of which is which, the all vegetation type and cover retrievals must be treated with suspicion.

Soil Retrievals

In contrast to the errors in modeling vegetation type, errors in modeling soil type are much less likely, with error probabilities lower than 20% for most cases (Figure 2-C). The probability of modeling a spectrum with the wrong soil type increases with increasing vegetation cover. This is due to the decreasing dominance of the soil spectrum. When the similarity of two of the soils—armored soil and field soil—is considered, the probability of modeling spectra with a dissimilar soil type drops even further (Figure 2-D). When noisy spectra are modeled by other noisy spectra, errors in the retrieval of the same or similar soil types (Figures 3-C and 3-D) also increase, but remain low compared to vegetation type retrievals of desert plants.

In cases where *A. polycarpa* is mixed with soils error probabilities exhibit a counterintuitive increase in errors of both percent cover and soil type retrieval. This effect is not present in Figure 2-D where the armored and field soils are classed together. The field soil spectrum is the darkest soil spectrum at all wavelengths. Since f_m is constrained to be less than 1.01, the field soil cannot model the armored soil. Thus, the presence of *A. polycarpa* must be leading to confusion between the armored and field soils by allowing *A. polycarpa*-field soil spectra to be modeled by armored soil spectra with lower covers.

Thus, we conclude that the spectrum of *A. polycarpa* "couples" with the spectrum of the field soil to appear more like the armored soil spectrum without vegetation. The spectrum of *A. polycarpa* lacks strong water absorption bands near 940 nm and 1140 nm, is relatively flat in the NIR and SWIR2 regions, and has the smallest red-edge of all the spectra used in this study with high reflectance in the visible. These features make the spectrum of *A. polycarpa* look more like the soil spectra than any other vegetation spectrum. It also has lower reflectance in SWIR2 relative to SWIR1. Thus, the *A. polycarpa* spectrum, when mixed with the field soil to represent moderate covers, decreases the SWIR2 reflectance of the combined spectrum at a rate greater than the decrease in the SWIR1 reflectance. The result is a spectral curve similar to that of the armored soil, but with a reduced reflectance at all wavelengths. Spectral coupling is also seen, to lesser degrees with the senesced *Schismus* grass.

Both vegetation cover estimates and soil type retrievals are sensitive to spectral coupling. Thus, while vegetation cover estimates from spectral mixture analysis of hyperspectral data are more reliable than vegetation type retrievals and are not in error more than 25% of the time, they must be treated with care. The effect of coupling on soil type determinations is also strong, though error probabilities are low over all. If similarities in soil types are considered in order to class them into broader soil categories, these errors in soil type retrievals are minimized, and coupling effects are negated.

It is important to note that the accuracy of soil type retrievals is dependent on vegetation type, independent of coupling effects. This suggests that retrievals of soil type must still consider vegetation type and cover in mixing models. The absence of the vegetation's contribution to a real image spectrum, even when subtle, could confound correct soil type identification.

Soil type retrievals, while adversely affected by the addition of greater uncertainty to the models, appear robust in cases where soil spectra are significantly different. While spectral variability within a soil type will play a role in reducing the accuracy of soil type retrievals, this effect will be smaller than it is for vegetation type retrievals. Soils within a given type and geographic area typically have smaller relative variations than vegetation types. This is due the facts that soils do not undergo phenological change and the spectra of soil surfaces are not affected by canopy-scale effects (leaf-size, geometry, canopy structure, *etc*.). Thus, we conclude that soil type retrievals may be considered reliable in most cases where vegetation is at least less than 50%. The determination of soil surface properties is the proper domain for spectral mixture analysis in areas of low cover.

Each application of SMA results will have its own accuracy requirements. The results presented here may be used as guidelines for decisions on which analytical technique is to be used depending on information and accuracy requirements, or for accuracy assessment once minimum-RMS spectral mixture analysis has been employed.

4. CONCLUSIONS

In areas of low vegetation cover, spectral mixture analysis of imaging spectrometer data is not able to provide reliable retrievals of vegetation type and cover, when covers are below at least 30%. However, low vegetation covers provide for the dominance of the soil spectral signature, providing an opportunity to retrieve soil type from spectral mixture models. These results circumscribe the applicability of SMA to hyperspectral data, and therefore have dramatic consequences for the use of current and planned imaging spectrometers.

Several phenomena contribute to low reliability in vegetation type and cover retrievals. Spectrally indeterminate vegetation types, characterized by low spectral contrast and common in arid and semiarid regions, are difficult to model correctly, even at relatively high covers. Coupling of vegetation and soil spectra to cause confusion with other spectra can confound vegetation cover and soil type retrievals. In practice, intra-species spectral variability and nonlinear mixing can account for uncertainties in spectral endmembers much larger than that due to instrumental noise modeled here. There are methods for partially compensating for these sources of uncertainty. Uncertainties of soil surface type may be reduced by classing similar soil types together. Spectral variability may be partially accommodated by using multiple-endmember spectral mixture analysis (MESMA) (Gardner, 1997; Roberts et al., 1998) and including many spectra of the same vegetation or soil type in mixture models.

Remote sensing remains likely to afford the best opportunities to proceed with regional- or global-scale environmental change detection. Given the limitations of SMA of hyperspectral data in the retrieval of vegetation cover and type, we find it difficult to see how subtle vegetation biophysical and foliar chemistry parameters can reasonably be retrieved in low cover areas. We believe that no technique will be able to sufficiently compensate for all of the wide range of instrumental, atmospheric, and natural sources of uncertainty in order to fulfill this goal in arid regions. Noise will always be present in remotely sensed data. Reflectance retrievals from imaging spectrometer data are not perfect. Spectral variability and nonlinear mixing are a fact of life in arid and semiarid remote sensing. Some arid vegetation types are spectrally indeterminate. The reflectance of an entire pixel is the composites of the spectra of its constituent parts which may couple, thus causing confusion.

Remote sensing techniques and technologies have serious practical limits based on fundamental properties of instrumentation and the ubiquitous heterogeneity and vagaries of nature. New technologies and techniques need to be developed which address these limits in a realistic manner and applications of presently-available tools must be interpreted in line with their limitations. Although other classification techniques will also have to contend with sources of error intrinsic in remote sensing of arid regions, it is possible that another technique will be more robust under low-cover conditions than SMA.

The ability to retrieve vegetation information from remote sensing data remains a valuable goal. Reliable remotely-derived vegetation information has great application in environmental change detection studies of arid and semiarid environments. We invite other investigators to use the data from this study to retrieve vegetation type and cover using a different method.

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