Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments

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Abstract

Hyperspectral remote sensing is a promising tool for the analysis of vegetation and soils in remote sensing imagery. The purpose of this study is to ascertain how well hyperspectral remote sensing data can retrieve vegetation cover, vegetation type, and soil type in areas of low vegetation cover. We use multiple endmember spectral mixture analysis (MESMA), high-quality field spectra, and AVIRIS data to determine how well full-range spectral mixture analysis (SMA) techniques can retrieve vegetation and soil information. Using simulated AVIRIS-derived reflectance spectra, we find that, in areas of low vegetation cover, MESMA is not able to provide reliable retrievals of vegetation type when covers are less than at least 30%. Overestimations of vegetation are likely, but vegetation cover in many circumstances can be estimated reliably. Soil type retrievals are more than 90% reliable in discriminating dark-armored desert soils from blown sands. This simulation comprises a best-case scenario in which many typical problems with remote sensing in areas of low cover or desert areas are minimized. Our results have broad implications for the applicability of full-range SMA techniques in analysis of data from current and planned hyperspectral sensors. Several phenomena contribute to the unreliability of vegetation retrievals. Spectrally indeterminate vegetation types, characterized by low spectral contrast, are difficult to model correctly even at relatively high covers. Combinations of soil and vegetation spectra have the potential of generating mixtures that resemble an unmixed spectrum from different material, further confounding vegetation cover and soil type retrievals. Intraspecies spectral variability and nonlinear mixing produce uncertainties in spectral endmembers much larger than that only due to instrumental noise modeled here. Having established limits on linear spectral unmixing in areas of low cover through spectral simulations, we evaluate AVIRIS-derived reflectance data from the Mojave Desert, California. We show that MESMA is capable of mapping soil surface types even when vegetation type cannot be reasonable retrieved. © 2001 Elsevier Science Inc. All rights reserved.

1. Introduction

Concerns over global land use and land cover change are rising 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, Townshend, & Engman, 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 explore the limits of multiple endmember spectral mixture analysis (MESMA) in soil and vegetation parameter retrievals. MESMA is a modified spectral mixture analysis (SMA) approach in which many mixture models are calculated for each pixel in an image (Roberts, Gardner, Church, Ustin, & Green, 1997; Roberts et al., 1998). The basic SMA method estimates the proportion of each ground pixel’s area that belongs to different cover types (Adams, Smith, & Gillespie, 1993; Gillespie et al., 1990; Settle & Drake, 1993; Shimabukuro & Smith, 1991; Smith, Ustin, Adams, & Gillespie, 1990). SMA is based on the assumption that the spectra of materials in an 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.

SMA is particularly amenable for use with imaging spectrometry 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), Roberts, Green, and Adams (1997), and Roberts, Smith, and Adams (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 in the Santa Monica Mountains, California. Garcia-Haro, Gilabert, and Meliá (1996) have applied SMA to high spectral resolution field spectroscopy, finding it to be less sensitive to soil background in the detection of vegetation than the normalized difference vegetation index. Painter, Roberts, Green, and Dozier (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 least-squares approach to estimate 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. In contrast, the quantitative detection of sparse vegetation 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, Elvidge, & Groeneveld, 1998; Elvidge, Chen, & Groeneveld, 1993). Previous work by the current authors to retrieve vegetation type and cover from AVIRIS imagery met with only limited success (Okin, Okin, Roberts, & Murray, 1998; Okin, Okin, Roberts, & Murray, 1999). In order to determine the causes of our earlier difficulties, and to determine the limitations of SMA in arid regions, the current study was undertaken.

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 arid and semiarid regions where soils can be bright and mineralogically heterogeneous in many cases swamps out the spectral contribution of plants (Escañafadel & Huete, 1991; Huete & Jackson, 1988; Huete, Jackson, & Post, 1985; Smith et al., 1990).

2. There is the potential of nonlinear mixing in arid and semiarid regions due to multiple scattering of light rays (Huete, 1988; Ray & Murray, 1996; Roberts et al., 1993). Nonlinear mixing is likely to lead to an overestimation of green vegetation cover and an underestimation of shade.

3. Evolutionary adaptations to the harsh desert environment make desert plants spectrally dissimilar from 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 & Morris, 1951; Ehleringer, 1981; Ehleringer & Björkman, 1976, 1978; Ehleringer & Mooney, 1978; Gates, Keegan, Schleter, & Weidner, 1965; Mooney, Ehleringer, & Björkman, 1977; Ray, 1995).

4. Spectral variability within shrubs of the same species can be high in arid and semiarid regions, as reported by Duncan, Stow, Franklin, and Hope (1993) and Franklin, Duncan, and Turner (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 & Harrison, 1998). Roberts, Adams, and Smith (1990) have also suggested that canopy structure can affect plant reflectance, particularly in the near infrared.

In this study, we have ascertained whether, and at what level, MESMA of AVIRIS-derived reflectance from regions with low vegetation covers (0% to 50%) can be expected to yield accurate estimates of vegetation type, vegetation cover, or soil surface type. In order to do this, we simulate noise-free and noise-degraded AVIRIS spectra of various soil, vegetation cover, and vegetation type classes, and neglect many other sources of error in real applications. 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: intraspecies spectral variability, nonlinear mixing, lighting and topographic effects, uncertainty related to apparent surface reflectance retrievals, and noise in field or image endmembers. We find that MESMA of full range (350 to 2500 nm) reflectance derived from hyperspectral remote sensing data cannot retrieve vegetation type reliably at the low areal vegetation cover that normally characterize arid regions. Vegetation cover and soil types may be mapped with greater reliably however.

Having established limits on linear spectral unmixing in areas of low cover through spectral simulations, we evaluate real AVIRIS data from the Mojave Desert, California. We find that MESMA of AVIRIS-derived apparent surface reflectance is capable of mapping soil surface types even when vegetation parameters cannot be reasonably retrieved.
2. Methods

2.1. Study site description

The Manix Basin is in the Mojave Desert, about 40 km ENE of Barstow in southeastern California (centered around 34°56.5′N, 116°41.5′W at an elevation of 600 m). Much of the basin is filled with lacustrine, fluvial, and deltaic sediments capped by weak armoring (Meek, 1990). There are two modern playas in the basin. Fig. 1 depicts the surface geology of the northern lobe of the Manix Basin (after Meek, 1990).

The vegetation in undisturbed areas of the basin is dominated by an association of *Larrea tridentata* and *Ambrosia dumosa* with minor occurrence of *Atriplex polycarpa*, *Atriplex hymenelytra*, *Atriplex canescens*, *Ephedra californica*, and *Opuntia* spp. A species of *Schismus* is the dominant annual grass in the basin, and can high cover temporarily in years of high winter/spring precipitation.

There has been extensive human activity in the Manix Basin with several phases of agricultural activity utilizing groundwater recharged by the Mojave River, which carries runoff from the San Bernardino Mountains to the south–southwest (Tugel & Woodruff, 1978). Establishment and subsequent abandonment of agricultural lands in the Manix Basin has been associated with indirect disturbance of adjacent, downwind areas by sand blown off of the areas of direct disturbance (Okin, Schlesinger, & Murray, 2001; Ray, 1995). This has led to decreased shrub density, increased soil albedo, and changes in soil texture in these areas. The abandoned fields themselves are either usually dominated by *At. polycarpa* with total

![Fig. 1. The surface geology of the northern (Coyote) lobe of the Manix Basin (after Meek, 1990). The outlined area is the location of the AVIRIS flight used in this study (flight 980430, run 10, scene 3).](image-url)
cover greater than that in undisturbed desert, or bare of perennial shrub cover altogether.

2.2. Field spectroscopy

Field reflectance spectra of soils and vegetation were collected in the Manix Basin on May 2, 1998, 2 days after an AVIRIS overflight. Field spectra were collected from 350 to 2500 nm using an ASD full-range portable spectroradiometer (Analytical Spectral Devices, Boulder, CO). Spectra were acquired from 0.25 to 0.5 m (nadir-looking) above targets with an 8% field of view, and divided by the near-simultaneous (<2 min) spectrum of a 100% reflective Spectralon panel (Labsphere, North Sutton, NH) to yield reflectance. Reflectance spectra were collected of soils, individual shrubs of dominant species (L. tridentata, A. dumosa, and At. polycarpa) or over small areas for grasses and NPV (typically in an approximately 5-m radius circle). Ten individual spectra were averaged together for each shrub, NPV, grass, and soil-averaged spectra. Spectra of soils from other dates were used to supplement the spectral database. Averaged spectra were convolved to AVIRIS bands, and incorporated into a spectral library with 185 total averaged spectra (54 vegetation/NPV spectra and 131 soil spectra) from six sites. Representative spectra are shown in Fig. 1.

2.3. Spectral simulations

Representative field reflectance spectra of three abundant vegetation types in the Manix Basin (senesced Schismus grass, At. polycarpa, and L. tridentata) plus a reflectance spectrum of green lawn grass from the USGS Digital Spectral Library (Clark, Swayze, Gallagher, King, & Calvin, 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 deltic deposits, and semiarmored 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 endmembers used for spectral simulations are shown in Fig. 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 deltic deposit covered by a gravel lag, whereas the field soil is from an abandoned field located on deflated deltic deposits where the deflationary lag has largely reestablished 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.

The four vegetation endmembers were each combined linearly with each of the three soil endmembers in varying proportions (representing from 0% to 50% vegetation cover in 2% increments) according to Eq. (1):

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

where \( R_S(\lambda) \) is the simulated reflectance spectrum of a given with specified cover on a given soil, \( f_{veg} \) 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 312 simulated spectra.

Signal-chain noise was modeled in the resulting spectra by adding to each band the reported 1998 AVIRIS signal-to-noise (Fig. 2) (Green, Pavri, Faust, & Williams, 1999) multiplied by a standard-normal random number (Eq. (2)):

\[ R_{SN}(\lambda) = R_S(\lambda) \left( 1 + \frac{N(0,1)}{SNR(\lambda)} \right), \]

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

2.4. Spectral mixture analysis of simulated spectra

Each of the noise-degraded simulated spectra was modeled by each of the nondegraded simulated spectra by minimizing root-mean-squared error (RMS) for a simplified SMA equation (Eq. (3)):

\[ R_{SN}(\lambda) = f_{model}R_S(\lambda) + \varepsilon(\lambda) \]

where \(-0.01 \leq f_{model} \leq 1.01 \) and \( \varepsilon(\lambda) \) is an error term. Interval limits slightly less than zero and slightly greater than one were used to accommodate a small amount of noise in the modeling; RMS is given by:

\[ RMS = \left( \frac{1}{m} \sum_{j=1}^{m} (\varepsilon_j)^2 \right)^{0.5}, \]

where \( \varepsilon_j \) is the error term for each of the \( m \) spectral bands considered. In this study, we used a reduced set of 197 of the AVIRIS bands that covered the full AVIRIS spectral range. The full AVIRIS range was used in this study in order to allow simultaneous retrieval of vegetation and soil parameters. Bands that span the deep atmospheric water absorptions at approximately 1400 and 1900 nm were not used.

In many cases, a noise-degraded spectrum was equally well modeled by two or more spectra. The spectra, \( R_{SN}(\lambda) \), which best modeled each noise-degraded spectrum, \( R_{SN}(\lambda) \), with the lowest RMS was 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 maximum error cutoff used was 2.5% RMS error because the vast majority of spectra were modeled by at least one model within this limit.

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

Since the spectra, genesis, and surface appearance of the armored soil and the field soil (Fig. 1) were so similar, an additional category was considered:

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 was 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. For example, consider the case where all simulated spectra with 22% to 30% Schismus were modeled a total of 100 times by spectra other than themselves. If only 25 of the spectra that modeled the Schismus spectra were themselves Schismus spectra (with other soils or other covers), then the error probability would be 75%.

The simulations carried out here represent a best-case scenario in which confusions due to intraspecies 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.

In order to explore the effects of these other sources of variability on modeling success, we modeled each noise-degraded simulated spectrum in a set by all other noise-degraded spectra in a set. Although this approach does not directly address issues like nonlinear mixing and intraspecies or intrasoil spectral variability, it roughly simulates the effect of adding a modest amount of uncertainty to a spectral library. In practice, 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 uncertainty 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.

### 2.5. AVIRIS image preprocessing

AVIRIS data were acquired over the Manix Basin on April 30, 1998. AVIRIS measures the total upwelling spectral radiance in 224 band from 400 to 2500 nm in...
20-m ground pixels from a NASA ER-2 aircraft flying at 20-km altitude. The northern lobe of the Manix Basin (Fig. 3) is the focus of this study and is covered by flight 980430, run 10, scene 3. The data were radiometrically calibrated at the AVIRIS data facility (Jet Propulsion Laboratory, Pasadena, CA). Apparent surface reflectance was retrieved using a technique developed by Green et al. (Green, Conel, & Roberts, 1993; Green, Roberts, & Conel, 1996; Roberts et al., 1998; Roberts, Green, et al., 1997). The reflectance spectrum from a gravel parking lot in the AVIRIS scene was used to calibrate the apparent surface reflectance spectra of the entire scene. The AVIRIS image and its products were rectified using a nearest-neighbor triangulation method that employed 107 ground-control points chosen in the image and in a series of 1-m-resolution USGS digital orthophotos.

2.6. Multiple endmember spectral mixture analysis

How well do spectral simulation results represent the use of SMA with real-imaging spectrometer data? In order to probe this question, we applied an SMA technique to AVIRIS data acquired over the Manix Basin, a Mojave Desert shrubland.

The basic SMA equations are (Eqs. (5) and (6)):

\[ R_p(\lambda) = \sum_{i=1}^{n} f_i R_i(\lambda) + \varepsilon(\lambda), \]  

\[ \sum_{i=1}^{n} f_i = 1, \tag{6} \]

and 
\(-0.1 \leq f_i \leq 1.01\), where \(\varepsilon(\lambda)\) is the difference between the actual and modeled reflectance, \(R_p(\lambda)\) is the apparent surface reflectance of a pixel in an image, \(R_i(\lambda)\) are the reflectance spectra of spectral endmembers in an \(n\)-endmember model, and \(f_i\) are weighting coefficients, interpreted as fractions of the pixel made up of endmembers \(i = 1, 2 \ldots n\). RMS error is given by Eq. (4).

MESMA is simply an SMA approach in which many mixture models are analyzed in order to produce the best fit (Gardner, 1997; Roberts, Gardner, et al., 1997; Roberts et al., 1998). In the MESMA approach, a spectral library is defined that contains spectra of plausible ground components. A set of mixture models with \(n\) \((n \geq 2)\) endmembers from the library is defined, with shade always present as one endmember in the model.

Each model is fit to every pixel in a remote sensing image, and a valid fit is restricted to a maximum preset RMS error and an additional constraint that not more than seven contiguous bands in the residual spectrum may deviate from zero in the same direction. In this study, 2.5% maximum RMS error was used because the vast majority of pixels were modeled by at least one model within these limits. Increasing the maximum RMS had little impact on the number of unmodeled pixels in the image. The model that fits each pixel with the lowest RMS is recorded along with the endmember fractions for that model.

MESMA requires an extensive library of field, laboratory, and/or image spectra, where each plausible ground component is represented at least once. Including more than one spectrum of a ground component allows for the spectral variability often found in desert vegetation, thus partially overcoming a difficulty problem that is prevalent in arid region remote sensing (this study and Franklin et al., 1993). However, there is a trade-off between having a small enough library that all models may be run on a standard computer in a reasonable amount of time, and having a library large enough to incorporate sufficient spectral variability in ground targets. Indeed, incorporating sufficient intra- and interspecies spectral variability in the spectral library to enable retrieval of vegetation type may be impossible given finite field and computation time. Furthermore, MESMA is a linear SMA technique and therefore not capable of dealing with nonlinear mixing effects other than those captured by the spectral library.

This study employs MESMA to retrieve soil type only because vegetation covers in the Manix Basin are lower than can be expected to yield reliable vegetation type and cover retrievals. Nonetheless, vegetation spectra must be present in mixing models because the absence of the vegetation’s contribution, even when subtle, can confound soil type identification. In solving the mixing equations for each pixel and for each model, vegetation type and cover are always estimated, but these results should be considered unreliable. Soil retrievals, on the other hand, have much lower error probabilities and therefore can be considered reliable.

A total of 1656 four-endmember models were used in MESMA modeling of apparent surface reflectance derived from the April 30, 1998 AVIRIS Manix Basin scene. The Supercomputing Visualization Workbench was used for planning and calculation of these model runs. Of these models, the one that modeled each pixel with the lowest RMS was chosen as the optimal model. Each

![Graph](image-url)
A four-endmember model consisted of shade + soil + shrub + grass or shade + soil + shrub1 + shrub2 spectra. Four-endmember models were chosen because in any given 20-m square in the Manix Basin, there will be at least two dominant types of vegetation (two shrub species or, more likely, a shrub species and a grass), soil, and shade. From ground observations, there are very few places in the basin that are bare soil (a two-endmember model). Because shrubs cover most of the basin, and high rainfall in the winter of 1998 promoted the growth of annual grasses, three-endmember (soil plus a single type of vegetation) areas are also rare. Five-endmember models and higher were excluded from consideration because they are computationally very expensive and they simply allow greater variability in vegetation, which is not the purpose of this study. Instead, our intent is to use MESMA of AVIRIS data to map soil surface categories in the basin.

Spectra used in four-endmember models were chosen from the library of field reflectance spectra to minimize computation time and to maximize spectral variability using the method outlined by Gardner (1997) and Roberts et al. (1998). In this library analysis, each spectrum in the spectral library is modeled by every other spectrum in the library, coupled with shade, and constrained by the constraints that will be used in the final analysis. This approach allows spectra to be compared with one another, and redundant or unique spectra to be identified. Spectra were chosen that (1) modeled other spectra of the same type, (2) were not modeled by other spectra of the same type, and (3) were not confused with spectra of other types.

Thirty-six field spectra were chosen to be included in four-endmember models for this study. This includes 2 senesced Schismus grass spectra and one spectra of dead, herbaceous annuals (NPV), 9 shrub spectra (two A. dumosa, two At. polycarpa, and five L. tridentata), and 23 soil spectra (13 armored soil, 6 blown sand, and 2 soil spectra from abandoned fields in addition to two spectra from a nearby alluvial fan). The blown sand is spectrally bright, and has smaller surface particle size than the other two soils.

3. Results and discussion

3.1. Spectral simulations

The error probabilities when noise-degraded spectra are modeled by other noise-degraded spectra (Fig. 5) are higher compared to those when noise-degraded spectra are modeled by nondegraded spectra (Fig. 4). Thus, there is a dramatic effect in introducing even modest uncertainty to spectral endmembers.

How does this uncertainty compare quantitatively to others? The quantity $R_{\text{veg}}/\sigma$ where $\sigma$ is the standard deviation of the 10 spectra averaged to produce $R_{\text{veg}}$, plotted in Fig. 1 gives an indication of the intraspecies spectral heterogeneity. Standard deviation is highly dependent on the samples that are used to calculate it and may not be representative of the population. The $\sigma$ represented here do not represent a comprehensive survey of the plant spectra for an entire population, but do provide a clear indication of the magnitude of $R_{\text{veg}}/\sigma$. $R_{\text{veg}}/\sigma$ is a signal-to-effect ratio (SER) analogous to SNR, where here the "noise" is not instrument noise but intraspecies spectral variability. $R_{\text{veg}}/\sigma$ varies between 2 and 14, while the 1998 AVIRIS SNR varies between 300 and 1200 except in the deep atmospheric water bands (Fig. 2). Asner, Wessman, Schimel, and Archer (1998) have reported intraspecies 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 intercanopy variability and therefore intraspecies 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, an SER of 5 where the effect is not $\sigma$ but potential intraspecies variability given by a change in living material. 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. Intraspecies variability has a magnitude much greater than instrumental noise and therefore is more likely to confound linear SMA.

Nonlinear mixing is likely to further complicate the analysis if the spectra used in the library are collected under conditions where the substrate in the image varies markedly from what was present when the library spectra were collected. For example, based on observations by Ray and Murray (1996), in the extreme case that L. tridentata canopies occurred on a bright background, yet the library spectra were collected on a black background, the multiple scattering effect can result in one half the reflectance spectrum, equivalent to an SER of approximately 2. While this extreme is unlikely to occur, it illustrates that intraspecific and multiple scattering effects are likely to be larger than the effects of instrumental noise.

Clearly, confusion due to intraspecies variability and nonlinear mixing in vegetation is much more likely than that due to instrumental noise. Hence, we consider the calculated error probabilities for cases where noisy spectra are modeled by noisy endmembers to yield a lower bound on the reliability of spectral unmixing of hyperspectral reflectance data by full-range field reflectance spectra.

3.1.1. Vegetation retrievals

Error probabilities in Fig. 4 clearly indicate that even in the best case 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 (Fig. 4A). Errors were made in modeling green lawn grass less than 10% of the time and only for covers less than 10% while errors were made in modeling At. polycarpa no less than 15% of the time.

As has been suggested by Sabol, Adams, and Smith (1992) for soils in a shade–vegetation mixture, the spectral contrast of endmembers 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 At. 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 & 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 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 & Morris, 1951; Mooney et al., 1977). Thus, vegetation remote sensing in arid and semiarid regions is faced with an inherent difficulty due to the low spectral contrast common in arid zone vegetation.

When noise-degraded spectra are modeled by other noise-degraded spectra, errors in vegetation type retrievals for all desert plants remain above 30% at less than 20% cover, and error probabilities for At. polycarpa and L. tridentata type retrievals are greater than 25% at less than 40% cover (Fig. 5A).

The increase in the error probabilities in Fig. 4A over Fig. 5A indicates that adding even modest uncertainty to endmembers will influence how well vegetation type is modeled. If we assume that a 30% rate of species misidentification is unacceptable, we can express our ability to identify species relative to vegetation cover and spectral contrast. For example, using this value of 30% error as a 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 At. 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. Note also that other sources of uncertainty in real-world applications of mixture analysis to hyperspectral data are much larger, and may further reduce the reliability of vegetation retrievals.

The probability of modeling errors in the retrieval of vegetation cover are significantly lower than those for retrieval of vegetation type (Fig. 4B). With the exception of At. polycarpa, the probability of error in modeling vegetation cover within 10% of the modeled vegetation
cover is lower than 10% and decreases 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 *At. polycarpa*, error probabilities of modeling spectra with greater than a 10% difference in cover remain below 25%. However, vegetation cover estimates are likely to be as vulnerable to additional sources of uncertainty and variability as vegetation type retrievals.

Thus, in arid and semiarid regions with covers below at least 30%, SMA is unable to reliably model vegetation type. Total surface cover was retrieved to within 10% of the correct value, but only under the near-optimal conditions of the simulations. This result is consistent with the findings of Elmore, Mustard, Manning, and Lobell (2000). Spectrally determinate vegetation may be reliably retrieved at lower covers and areas of relatively high cover may be modeled correctly regardless of vegetation type. 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, all vegetation type retrievals must be treated with care.

### 3.1.2. 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 (Fig. 4C). 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 (Fig. 4D). When noise-degraded spectra are modeled by other noise-degraded spectra, errors in the retrieval of the same or similar soil types (Fig. 5C and D) increase, but remain low compared to vegetation type retrievals of desert plants.

In cases where *At. polycarpa* is mixed with soils, error probabilities exhibit a countereintuitive increase in errors of both percent cover and soil type retrieval. This effect is not present in Fig. 4D where the armored and field soils are classed together. The field soil spectrum is the darkest soil spectrum at all wavelengths. Since $f_{\text{mode}}$ is constrained to be less than 1.01, the field soil cannot model the armored soil. Thus, the presence of *At. polycarpa* must be leading to confusion between the armored and field soils by allowing *At. polycarpa* field soil spectra to be modeled by armored soil spectra with lower covers.

Thus, we conclude that the spectrum of *At. polycarpa* “couples” with the spectrum of the field soil to appear more like the armored soil spectrum without vegetation. The spectrum of *At. polycarpa* lacks strong water absorption bands near 940 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 *At. polycarpa* look more like the soil spectra than any other vegetation spectrum considered here. It also has lower reflectance in
SWIR2 relative to SWIR1. Thus, the *At. 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 SMA 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 classify 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 pixel reflectance, 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 to 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 SMA in arid 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 to inform accuracy assessment once minimum-RMS SMA has been employed.

### 3.2. MESMA of AVIRIS data

As a real-world application of the spectral simulation results, we used MESMA of AVIRIS data acquired over an arid shrubland to highlight the limitations and opportunities in arid region applications of SMA. MESMA results are depicted in Fig. 6A–C.

Fig. 6A and B depicts vegetation type and vegetation cover retrievals, respectively. Lessons may be learned from these results. In Fig. 6A, the largest area is modeled by “nonphotosynthetic vegetation,” which is a mixture of NPV and senesced *Schismus* grass. While these two components are ubiquitous in the basin, *L. tridentata* is the dominant perennial and should have modeled more of the image when mixed with senesced *Schismus* grass. Our spectral library incorporated more *L. tridentata* spectra than any other shrub in order to capture its spectral variability and increase its chances of being correctly modeled. This approach clearly only met with limited success. Furthermore, nowhere in the image is *A. dumosa* dominant, though it models a large proportion of the image. In particular, the pixels in the northern part of the image, which are modeled by *A. dumosa*, are largely the pixels modeled by the sandy soil. This could be an example of spectral coupling where the spectrum of the soil and vegetation in this area mix within the pixel to create a combined spectrum that appears as a different shrub altogether. Finally, *At. polycarpa* is the dominant perennial shrub only in areas that have been dramatically disturbed by human activity. The area of *At. polycarpa* modeled on the southeastern fan is, therefore, inaccurate.

Our vegetation modeling results were not without some success, however. Abandoned fields tend to have either high covers of *At. polycarpa* (as much as 30%) or an absence of perennial vegetation and moderate covers of annual grasses in wet years. The high covers of *At. polycarpa* are above the rough 30% vegetation cover threshold for reliability and are modeled correctly. The fields without perennial vegetation cover are also modeled correctly, possibly because of their spectral simplicity. The mixed success of vegetation type retrievals from AVIRIS imagery illustrates a principal pitfall in SMA of hyperspectral reflectance data from arid regions. Some areas, due to their cover or vegetation type, will be modeled correctly while others will not. As before, without detailed a priori knowledge of the spatial arrangement of vegetation cover and type, all vegetation type retrievals must be considered ambiguous. With detailed a priori knowledge of the spatial arrangement of vegetation cover and type, the application of remote sensing to determine these parameters is redundant.

Vegetation cover estimates in Fig. 6B were more successful than vegetation type retrievals. These results highlight the greater vegetation cover found on abandoned fields and disturbed areas covered with *At. polycarpa*. However, they also suggest higher vegetation cover on abandoned fields that are known from field observations to lack perennial shrub cover. While these fields do have some annual grass cover, it is likely less than the 60% to 70% cover retrieved by spectral unmixing.

By and large, the vegetation cover estimates from MESMA (Fig. 6B) are greater than the perennial shrub cover in Table 1. This may be due to the fact that no attempt was made in field estimates to incorporate annually, and the winter of 1998 was a very wet El Niño year. The 20% to 40% covers estimated in some undisturbed areas and the
60% to 80% cover in abandoned fields are high but realistic for a wet year with relatively high grass covers.

Vegetation type retrievals may be used to place bounds on the confidence in interpreting vegetation cover retrievals. If there is sufficient spectral contrast between vegetation types and soil, vegetation cover can be reliably estimated. Spectral simulations presented here allow estimation of a threshold below which the presence of spectrally determinate vegetation cannot be estimated reliably. For green vegetation, this threshold is about 10%. For spectrally indeterminate vegetation types, cover cannot be estimated reliably at covers below 50%. In an image, one type of spectrally indeterminate vegetation is likely to be modeled as some other spectrally indeterminate vegetation type. Therefore, areas of high uncertainty can be identified in an image. Cases in which there is very low cover for a spectrally determinate plant or relatively higher cover for a spectrally indeterminate plant are truly ambiguous.

In contrast to vegetation type retrievals, Fig. 6C gives an accurate description of surface soil types at the time that this AVIRIS image was acquired. Comparison of the northern half of the image with the surficial geology (Fig. 3) shows that we were able to accurately map the sand and sandy-beach deposits using MESMA. The areas modeled as “sandy/blown soil” in the southern part of the image have a different origin. These are areas downwind of abandoned agricultural fields, roads, housing developments, and other anthropogenic disturbances where sand has blown off the areas of direct disturbance onto adjacent, undisturbed areas.

Modeling of soil surfaces in Fig. 6C was not perfect. For example, one area in the middle of the image remained unmodeled. Ground observations indicate that this area should have modeled as sandy/blown soil. This area is the brightest area in the entire image, however, and the soil present here likely has reflectance higher than that of any of the blown soils in our spectral library. Since fractions greater
than one were not allowed in the modeling of these spectra, a slightly darker soil cannot model a brighter soil, even if they could be expressed as scalar multiples of each other. One of the small playas in the northern part of the image failed to be modeled, which is unsurprising, as there were no spectra of this soil in our library. Other small playas on the northeastern edge of the image were modeled, but as armored soils. The alluvial fans in the image, which are located on the northeastern and southeastern edges of the image, were also mismodeled as armored soil. Despite these modeling errors (< 10% of the modeled image) we conclude that MESMA is able to provide a reliable map of armored and sandy areas within the Manix Basin. Improvements in accuracy could be obtained by incorporating missing spectra — such as the bright sand and spectra from the small playas — into the library.

It is interesting to note that the abandoned fields in the image were modeled as armored soils and not by the spectra of field soils that were in the spectral library. These spectra are quite similar, suggesting that the deflationary armor that has been reestablished on the abandoned fields makes these soil surfaces indistinguishable from their undisturbed cousins.

Our MESMA results highlight the inaccuracy of vegetation type retrievals under low-cover conditions. In light of our spectral simulation results, the inability of MESMA to reliably map vegetation type in the Manix Basin arid shrubland with low cover is hardly surprising. This failure results from fundamental limitations of the basic SMA approach when the soil dominates the reflectance and when vegetation does not display typical green vegetation spectra. The dominance of the soil signature, on the other hand, provides an opportunity to map soil surface characteristics with MESMA of hyperspectral data.

Vegetation cover is modeled more reliably than vegetation type in arid regions, with the threshold of reliability lower for spectrally determine vegetation than for spectrally indeterminate vegetation. Unlike simple SMA approaches, MESMA estimates shrub and grass cover, not the cover of green vegetation. Since shrubs in arid regions are spectrally dissimilar to green vegetation and are also spectrally dissimilar to one another, MESMA is better suited for estimation of vegetation cover in arid and semiarid regions than simple unmixing where the soil, shade, NPV, and green vegetation are used as endmembers.

The MESMA approach to mixture analysis is simply an extension of the simple SMA approach with many models calculated for each pixel of an image instead of just one. Thus, the inability of MESMA to reliably identify vegetation type in areas of low cover strongly implies that the basic SMA approach will also be unreliable. The effectiveness of MESMA in obtaining reasonable estimates of vegetation cover and soil surface type, on the other hand, suggests that the basic SMA approach to obtaining these parameters will be significantly more reliable. In using SMA for vegetation cover retrievals in arid and semiarid environments, however, it is of the utmost importance to use vegetation spectra from arid regions. Since vegetation in the world’s deserts is spectrally dissimilar to typical green vegetation, mixture modeling using only green vegetation spectra will lead to significant underestimations of cover.

4. Conclusions and implications

In areas of low vegetation cover, MESMA of imaging spectrometer data using full-range field reflectance spectra is not able to provide reliable retrievals of vegetation type, when covers are below at least 30%. For spectrally determinate vegetation, cover may be estimated with high reliability while spectrally indeterminate vegetation may yield very unreliable estimates. 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 MESMA to hyperspectral data, and therefore have important consequences for the use of current and planned imaging spectrometers for arid regions. The principal import of our results is that the use of MESMA with hyperspectral reflectance data leads to unreliable vegetation type retrievals in arid areas, and the potential for slight vegetation cover overestimations.

This study has highlighted sources of ambiguity in hyperspectral data not currently recognized. Several phenomena contribute to low reliability in vegetation type 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 soil type retrievals. In practice, intraspecies 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 including many spectra of the same vegetation or soil type into MESMA mixture models. Albedo effects may be eliminated by normalizing spectra or using their derivatives.

It is the landscape and vegetation structures themselves that contribute to the difficulty of hyperspectral remote sensing in arid regions. Arid environments are characterized by low cover globally. In addition, the ecological adaptations that make desert plants able to survive high heat and low water availability can make them spectrally indeterminate. Thus, the results of this study indicate that hyperspectral remote sensing is not a panacea for effective global monitoring of arid regions. Indeed, in contrast to the authors’ original expectations that the plant signature in hyperspectral remote sensing would be the telltale sign of
land degradation, we have found that the vegetation signature is by and large too faint amid a dominant, bright soil background to yield reliable and useful information. Changes in the spectral signature of the soil associated with land degradation, however, is identifiable with hyperspectral data and may serve as a fingerprint of desertification in low cover arid areas.

Given the limitations of SMA of hyperspectral data in the retrieval of vegetation cover and type, it is 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 that 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 that 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. For example, Drake, Mackin, and Settle (1999) have suggested that mixture modeling is much more susceptible to noise than spectral matching.

The author will gladly make the data used in this study available for investigators wishing to evaluate other methods for vegetation mapping in an arid shrubland.

References


