Modeling Land-Cover Types Using Multiple Endmember Spectral Mixture Analysis in a Desert City

Soe W. Myint and Gregory S. Okin

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SOE W. MYINT ¥ and GREGORY S. OKIN §

¥ School of Geographical Sciences
Arizona State University
600 E. Orange St., SCOB Bldg Rm330
Tempe, AZ 85287-0104
Email: Soe.Myint@asu.edu
Phone: (480) 965-6514
Fax: (480) 965-8313

§ Department of Geography
1255 Bunche Hall
University of California
Los Angeles, CA 90095
E-mail: okin@ucla.edu
Phone: (310) 825-3426
Fax: (310) 206-5976
Abstract

Spectral mixture analysis is probably the most commonly used approach among sub-pixel analysis techniques. This method models pixel spectra as a linear combination of spectral signatures from two or more ground components. However, spectral mixture analysis does not account for the absence of one of the surface features or spectral variation within pure materials since it utilizes an invariable set of surface features. Multiple endmember spectral mixture analysis (MESMA), which addresses these issues by allowing endmembers to vary on a per pixel basis, was employed in this study to model Landsat ETM+ reflectance in the Phoenix metropolitan area. Image endmember spectra of vegetation, soils, and impervious surfaces were collected with the use of a fine resolution Quickbird image and the pixel purity index. This study employed 204 (=3x17x4) total four-endmember models for the urban subset and 96 (=6x6x2x4) total five-endmember models for the non-urban subset to identify fractions of soil, impervious surface, vegetation, and shade. The Pearson correlation between the fraction outputs from MESMA and reference data from Quickbird 60 cm resolution data for soil, impervious, and vegetation were 0.8030, 0.8632, and 0.8496 respectively. Results from this study suggest that the MESMA approach is effective in mapping urban land covers in desert cities at sub-pixel level.

Keywords: urban; impervious; multiple endmember spectral mixture analysis
1. Introduction

Urban development increases the amount of impervious surfaces in watersheds as farmland, forests, shrubs, rangeland, and meadows are converted into buildings, driveways, sidewalks, roads, and parking lots with virtually no ability to absorb storm water. The modification of the urban landscape influences the local (microscale), mesoscale, and even the macroscale climate (Brazel et al., 2000; Quattrochi et al., 2000; Voogt and Oke, 2003). It is well documented that urbanization results in increased amount of impervious surfaces (Brabec et al., 2002) that augment the intensity, volume, temperature, and duration of storm water runoff (Booth and Reinfelt, 1993; Schueler, 1994; U.S. EPA, 1997). Urban storm water runoff may cause or contribute to water quality degradation by changing natural hydrologic patterns (Driver and Troutman, 1989), accelerating natural stream flows (Booth and Jackson, 1997), increasing stream bank erosion (May et al., 1997), destroying aquatic habitat (Booth and Reinelt, 1993; Horner et al., 1997), degrading stream water quality (Schueler, 1994; Booth and Jackson, 1997; May et al., 1997), increasing temperature (Galli, 1990), and elevating pollutant concentrations and loadings (Brabec et al., 2002; Boyer et al., 2002; Roy et al., 2003).

Impervious surfaces, particularly tar roads and parking lots, are generally dark, and hence, they increase the temperature of runoff (Frazer, 2005) but impervious surfaces themselves have higher thermal conductivity than vegetated areas. Urbanization alters energy flow through the atmosphere, land, and aquatic systems (Lo and Quattrochi, 2003). For example, the temperature trend for Phoenix demonstrates a 5.5°C increase in the minimum temperatures from the late 1940s to present due to rapid expansion of urban areas (Balling and Brazel, 1987; Brazel et al., 2000). Another concern that is not yet well documented is the impacts of pollutants released into stormwater runoff by building and paving materials themselves. For example, asphalt contains coal tar pitch, a recognized human carcinogen, as well as polycyclic aromatic carbons including benzopyrene, another carcinogen. Another potential source of pollutants is wood used for building structures that is normally treated with chromated copper arsenate, pentachlorophenol, or creosote (Frazer, 2005). Impervious surfaces are one
of the key indicators of urban growth that can be directly quantified (Arnold and Gibbons, 1996; Brabec et al., 2002). With the advent of urban sprawl, impervious surfaces have become a key parameter to be considered in urban growth and sprawl management because of their impacts on habitat function and health (Arnold and Gibbons, 1996).

Hence, identification of the distribution, cover, and growth of impervious surfaces in an urban/suburban environment is an important step towards effective decision making for urban planning and smart growth. The urban heat island effect in relation to land use and vegetation cover is considered one of the most important challenges on the current environmental issue of Phoenix (Stabler et al., 2005; Brazel and Johnson, 1980) as it is surrounded by mountain ranges that trap warm air, and has experienced high degrees of conversion of natural to built materials (Gammage, 1999). It is important to note that the city is expanding at an alarming rate in a desert environment. Gober (2006) reports that Phoenix urban area is approximately half the size of Los Angeles, but Phoenix has a population (~3 million) one-quarter that of Los Angeles (~12 million).

Many of the fastest growing urban areas in the United States are in the Desert Southwest, including the Phoenix and Las Vegas areas (http://money.cnn.com/2006/03/15/real_estate/fastest_growing_US_counties/). The southwestern United States is expected to undergo significant aridification in the coming decades (Seager et al., 2007), which will have dramatic impacts on the water and energy balance in this region. Urbanization is already having impacts on some parts of the region comparable to those of climate change. The goal of this study is to examine and evaluate the potential of multiple endmember spectral mixture analysis (MESMA) to quantify fractional areas of impervious surface, shade, vegetation, and soil in the Phoenix metropolitan area using Landsat ETM+ data. This study is the first use of MESMA in a desert city to characterize urban land cover.

2. Sub-pixel Analysis
Since the traditional hard classifier can label each pixel only with one class, urban impervious surfaces (e.g., roads) can only be recorded as either present or absent. Information on the fractional amount of spatially mixed spectral signatures from different ground-cover features is not possible with hard classifiers. Hence, the traditional classification of mixed pixels may lead to information loss (Wang, 1990), degradation of classification accuracy, and degradation of modeling quality in successive applications (Ji and Jensen, 1996 and 1999).

Sub-pixel analysis provides the relative abundance of surface materials within a pixel and is thus preferable to hard classifiers especially when dealing with medium to coarse spatial resolution satellite sensor data (e.g., Landsat Thematic Mapper – Landsat TM; Moderate Resolution Imaging Spectroradiometer – MODIS; Advanced Very High Resolution Radiometer - AVHRR). There have been several methods to sub-pixel analysis – linear mixture models (Smith et al., 1990; Shimabukuro, 1991; Settle and Drake, 1993; Van der Meer, 1997; Wu and Murray, 2003; Rashed, et al., 2003), background removal spectral mixture analysis (Huguenin et al., 1997; Ji and Jensen, 1999; Myint, 2006), Bayesian probabilities (Wang, 1990a; Wang, 1990b; Foody et al., 1992; Eastman and Laney, 2002; Hung and Ridd, 2002; Song, 2006), neural network (Foody and Aurora, 1996; Zhang and Foody, 2001); fuzzy c-means methods (Fisher and Pathirana, 1990; Foody and Cox, 1994; Foody 2000), multivariate statistical analysis (Yang and Liu, 2005), regression tree (Xian, 2006) and fuzzy set possibilities (Eastman, 1999). However, under real-world condition, the success of the above sub-pixel classification techniques can be variable and the approaches need to be handled carefully with the awareness of the limitations and uncertainties (Myint, 2006).

2.1. Multiple Endmember Spectral Mixture Analysis

Linear spectral mixture analysis (SMA), which provides sub-pixel endmember fraction estimates, is probably the most commonly used technique of all subpixel analysis techniques. An
endmember is the spectrum of a pure ground component (e.g., vegetation, soil, water) and thus SMA endmember fractions are typically interpreted as ground component fractions. It has been recognized that spectral mixture of endmembers due to multiple scattering by vegetation canopies or vegetation and soil surfaces has the potential to become non-linear (Roberts et al., 1993; Borel and Gerstl, 1994; Ray and Murray, 1996). Inability to account for non-linear mixing is an acknowledged limitation of SMA (Adams et al., 1993). Although non-linear mixing can become significant in some applications, the effects of multiple scattering in majority of cases is assumed to be negligible.

Mathematically, SMA is expressed as

\[ X_i = \sum_{k=1}^{n} f_k X_{ik} + e_i \]

where

- \( X_i \) = Spectral reflectance of band \( i \) of a pixel
- \( n \) = number of endmembers
- \( f_k \) = fraction of an endmember \( k \) within a pixel
- \( X_{ik} \) = known spectral reflectance of endmember \( k \) within the pixel in band \( i \)
- \( e_i \) = error term for band \( i \)

The root mean square (RMS) error is given by:

\[ RMS = \left[ \frac{\sum_{j=1}^{m} (e_j)^2}{m} \right]^{0.5} \]
where \( e_i \) are the error terms for each of the \( m \) spectral bands considered. The application of SMA to remote sensing imagery typically also adds the additional constraints that

\[
\sum_{k=1}^{n} f_k = 1 \quad \text{and} \quad 0 \leq f_k \leq 1.
\]

Because finding \( f_k \) requires solving a system of \( m \) or \( m+1 \) (when the sum of fractions is forced to be 1) equations, the number of endmembers cannot exceed the number of bands, \( m \). This is a major limitation in modeling urban land covers with SMA technique when dealing with commonly used satellite sensor images such as IKONOS, SPOT, IRS, ASTER, Landsat TM since they normally contain fewer than or equal to seven bands and urban features are composed of many spectrally diverse materials concentrated in a small area (e.g., plastic, metal, rubber, glass, tar, cement, wood, shingle, sand, gravel, brick, stone, soil, grass, trees, shrubs, water) (Myint et al., 2004). Another limitation is that a standard SMA approach as presented in Figure 1 employs an invariable set of endmembers to model all pixels. This assumption could potentially fail to account for the fact that the number and type of land cover components are highly variable. The endmembers used in SMA are the same for each pixel, regardless of whether the ground components represented by the endmembers are present in the pixel. Uncommon materials, which may not merit their own endmember, may be poorly modeled by SMA. In addition, because SMA allows only one endmember per material it does not account for the same material with different spectral responses.

Roberts et al. (1998) introduced multiple endmember spectral mixture analysis (MESMA), an extension of SMA approach that allows the number and type of endmembers to vary for each pixel within an image. Hence, we employed MESMA to quantify impervious, soil, vegetation, and shade in the Phoenix metropolitan area in this study. MESMA allows more than one endmember in the scene per ground component, and has proven to be effective in identifying different types of materials in a variety of environments: vegetation species and land cover type in Southern California chaparral.
(Dennison et al., 2000; Roberts et al., 2003); urban environments (Rashed et al., 2003; Powell et al., 2007); snow grain size in the Sierra Nevada of California (Painter et al., 1998 and 2003); lunar surface composition (Li and Mustard, 2003); soils and vegetation in arid environments in California (Okin et al., 2001).

Our approach is based initially on a simplification proposed by Ridd (1995) that land cover in an urban environment is a linear combination of three land-cover types (i.e., impervious surfaces, soil, vegetation). Our use of MESMA starts with the selection of a set of endmembers that represent pure spectra of the target materials in the scene (Figure 2). SMA models consisting of representatives from the major spectral categories (i.e., impervious surfaces, soil, vegetation) are created, and the best-fit fraction for each model are determined using a modified Gram-Schmidt orthogonalization and a subsequent least-squares unmixing (Roberts et al., 1998). Performance of all models for each pixel is evaluated by selecting the model with the lowest RMS error, with the proviso that the RMS error of the best-fit model may not exceed some user-defined threshold. For the best-fit model for each pixel, the fraction values for each endmember, and the identity of those endmembers are recorded.

3. Data and Study Area

Landsat ETM+ image data (L1G product of path 37 and row 37) at 30 m spatial resolution with six channels ranging from blue to short-wave infrared portion of the spectrum was used in this study. The thermal channel was excluded. The image data was acquired over the Phoenix metropolitan area under cloud-free conditions on April 19, 2000. The original image was subset to extract the Phoenix metropolitan area (upper left longitude 112° 47’ 10.96” and latitude 33° 49’ 59.62”, lower right longitude 111° 34’ 18.56” and latitude 33° 12’ 09.81”).

The study area is shown in Figure 3 and covers common urban/suburban land-use and land-cover classes: high-density residential, low-density residential, commercial, wild grass, woodlands,
man-made grass, riparian vegetation, agriculture, cement roads, tar roads, cement/tar parking, river, lakes, sandbars, and exposed soil. To assess the accuracy MESMA-derived fractions of impervious, soil, vegetation, and shade endmembers, a Quickbird image acquired over downtown Phoenix on June 11, 2005 was used (Figure 4). Quickbird and Landsat ETM+ data were orthorectified and co-registered. Field verification was also carried out to supplement the identification of endmember classes accurately. Several field trips were conducted to identify uncertain features and classes. We performed field verifications in areas that were believed to be no significant changes between 2005 (Quickbird) and 2006 (field verification).

The differences in the dates of the acquisition of Landsat TM (i.e., 2000) and Quickbird (i.e., 2005) could be considered a limitation in accurately performing the correlation and regression analysis. This uncertainty is minimized by the fact that we selected only the areas that were identified as no changes or at least negligible changes between 2000 and 2005. This was accomplished by visual comparison of the overlapping areas of the images on a monitor using interactive display and geographic link function. We believe that there is no significant difference in green vegetation cover in metropolitan Phoenix in April and June because it is a desert environment, and both images were taken during the summer period when vegetation in the area exhibits negligible phenological change.

4. Methods

4.1. Preprocessing

The Landsat ETM+ data were converted to apparent surface reflectance using an atmospheric correction method known as the Cos(t) model (Chavez, 1996). This model incorporates all of the elements of the dark object subtraction model (for haze removal) and a procedure for estimating the effects of absorption by atmospheric gases and Rayleigh scattering. Even though data import, image
layer stacking, qualitative analysis, and image subset were performed in ERDAS Imagine, conversion from DN values to reflectance was performed one band at a time using ATMOSC module in IDRISI software package. The reflectance data were imported back to ERDAS Imagine for layer stacking. The layer stacked image data was multiplied by 10,000 and kept as 16 bit integer data for easy computation and comparison.

We employed a wavelet resolution merge function in ERDAS Imagine to pansharpen Quickbird 1 meter multispectral data using its 60 cm panchromatic data. The ERDAS Imagine wavelet resolution merge algorithm is a modification of the work of King and Wang (King et al., 2001). Aside from traditional Pan-Multispectral image sharpening, this algorithm can be used to merge any two images. Fusing information from different remotely sensed data into one composite image with fine resolution can take place on four levels; signal, pixel, feature, and symbolic. The wavelet function in ERDAS Imagine works at the pixel level (Erdas Field Guide, 2003). Since Quickbird panchromatic image is a 60 cm resolution data, the final composite image with 4 multispectral bands has 60 cm.

4.2. Selection of Endmembers

The selection of appropriate endmembers plays a vital role in any SMA method. Even though the use of laboratory-based measurement of pure signatures would be the optimal approach to sub-pixel classifiers (Wu and Murray, 2003), a common technique for determining pure signatures is to select representative pixels from homogeneous land covers from satellite sensor images (Rashed et. al., 2003; Small, 2001; Eastman and Laney, 2002; Hung and Ridd, 2002; Wu and Murray, 2003). One advantage of image endmembers is that they contain the same systematic errors due to atmospheric correction as the image to be unmixed (Settle and Drake, 1993). Another advantage of using image endmembers is that they represent responses from the selected material at the same scale as the original image. In addition, the absence of a suitable library of field or laboratory spectra of ground components may require the use of image endmembers. The selection of image endmembers can be
effectively done through the use of Pixel Purity Index (PPI) (Boardman, et al., 1995) available in the ENVI software package. The PPI method calculates for each pixel a score based on the number of times it is found to occupy a near-vertex position in the repeated projections of the n-dimensional data onto a randomly oriented vector passing through the mean of the data cloud. The output scores help identify image endmembers because those pixels that hold pure spectra often display high PPI scores. We selected endmembers manually by visualizing the PPI results of spectrally pure pixels identified using the PPI in an N-dimensional visualizer with ENVI. We geographically linked the PPI image to the original image and high resolution Quickbird image to identify the image endmembers. We also conducted field trips to confirm land cover features before finalizing the endmember spectra. Selected endmembers were grouped into three classes: impervious surfaces (e.g., tar roads, cement roads, different types of rooftops, swimming pool, parking lots), vegetation (e.g., grass, shrubs, desert scrub, trees), and soil (e.g., exposed soil, sand bars, inactive agriculture, recently plough fields, cleared ground for construction).

4.3. Masking

Because we did not wish to consider areas of open water in this study, we identified water bodies in the scene so that we could mask these areas out. We employed an unsupervised classification algorithm, namely iterative self organizing data analysis (ISODATA), to identify 50 clusters using 20 iterations and 0.97 convergence threshold in the study area. We determined the clusters that belong to water bodies by interactively displaying one cluster at a time. There was some signature confusion among water, tar roads, and shade in mountainous areas. We used a USGS 30 meter digital elevation model to exclude shade in mountainous areas. We manually corrected tar roads and other dark objects that were mistakenly identified as water in the residential and commercial area. We masked out water pixels from the original image before employing MESMA to produce fraction images.
Built-up areas (urban) and non-urban areas (the complement of urban areas) were digitized by hand to allow separate spectral mixture analysis of these two disparate landscapes. Figures 5 and 6 present urban and non-urban areas of the study area respectively.

4.4. Development of MESMA Models

Creation of spectral mixture models for MESMA followed the suggestion of Ridd (1995) that land cover in an urban environment consists of a combination of three land-cover types (i.e., impervious surfaces, soil, vegetation). Shade is typically also present all but the flattest pixels. Thus we employed four-endmember models to model urban areas in this study. Each model contained one representative from each class of our image endmember library: impervious materials, soils, and vegetation. In non-urban areas, five-endmember models were used. Each model for non-urban areas contained one representative from each of the following classes: impervious materials, bright soils, dark soils, and vegetation. In this study, photogrammetric shade was used as a final endmember in all models. We employed all possible combinations of endmembers in the non-shade categories.

The separate modeling of urban and non-urban areas is justified by the fact that non-urban areas may not have impervious surfaces and, in the presence of a bright and dark soil surface in a pixel, the impervious surface that provides the best approximation of one of these will be chosen by the MESMA algorithm. This approach is similar to an approach called variable MESMA (VMESMA) reported by Camacho-de Coca et al. (2003) and García-Haro et al. (2005). Thus, the use of four endmember models in which each contains an impervious endmember can artificially increase the abundance of impervious surfaces in areas where they are, in fact absent. We noticed this effect when we applied four-endmember models to areas known to not have impervious surfaces. We believe that using only one set of models for urban areas (which nearly always have impervious surfaces at the scale of a Landsat ETM+ image) and non-urban areas (which may or may not have impervious
surfaces at the scale of a Landsat ETM+ image) may not be very effective in accurately quantifying the three major land cover materials for both urban and non-urban areas.

We used more impervious endmembers for urban areas and more bright soil endmembers that are suitable for non-urban areas. We were not concerned with vegetation endmembers since there was no signature confusion between vegetation and impervious or vegetation and soil. Spectra from urban and non-urban materials from the different land cover classes of endmembers (i.e., impervious, vegetation, soil) are presented in Figure 7. The impervious material category for urban subset contained 17 endmember spectra (e.g., tar, cement, pool, shingle, metal). The soil category contained 3 spectrally distinct soil endmembers. The vegetation category was comprised of 4 vegetation types. The set of MESMA models for non-urban areas were constructed from 12 soil endmembers, 2 impervious endmembers, and 4 vegetation endmembers. We used 2 different soil major categories (i.e., dark soil, bright soil) to force each pixel in non-urban area to be modeled with soil so that there will be a higher chance of being identified as soil in the area. This procedure was based on the assumption that a bright soil and dark soil covers may coexist in a pixel (i.e., 30x30 m). Since we employed all possible combinations of endmembers in these categories, there were 204 (=3x17x4) total four-endmember models for the urban subset and 96 (=6x6x2x4) total five-endmember models for the non-urban subset. The final soil fraction images for the five-endmember models were calculated as the sum of the two bright- and dark soil fractions.

4.5 Quantification and Normalization of Fraction Images

We estimated soil, impervious, vegetation and shade fraction in urban and non-urban areas separately using two different sets of MESMA models. We normalized non-shade information by dividing each endmember by the total percent cover of all non-shade endmembers (1-shade fraction) in each pixel. This suppresses the shade fraction so that we obtain more information on the relative abundance of non-shade endmembers (i.e., soil, impervious, vegetation). This process also allows us to
compare fractional cover estimates from Quickbird in which shade was considered part of other land
cover elements, and shade fractions were not determined. Finally, because shade changes quickly
during the day as well as throughout the year, suppression of shade fractions is required to compare
images taken at different times of the day or year. However, it should be noted that shade information
is considered important in many urban issues including urban heat island, urban planning, and smart
growth applications since shade provides cooling and shelter from the sun. For the above reason we
also keep the original output fraction layers with shade information. After normalization was
performed, output fraction layers were later merged to produce the final output layers for the whole
study area. Figure 8 (a) to (d) present final soil, impervious, vegetation, and shade fraction images
respectively. Since the model number is available for each pixel, it is also possible to trace which
impervious spectra (e.g., tar), vegetation spectra (e.g., grass), or soil cover spectra (e.g., sand bar)
provided the best fit in each pixel if necessary.

4.6. Validation of Fraction Images

To validate the MESMA-derived fractions, we created a reference dataset using an
unsupervised classification algorithm (i.e., ISODATA) of the Quickbird image using 20 iterations and
0.97 convergence threshold. 100 classes were identified, and each class was assigned to a class type
(i.e., soil, impervious, vegetation) by interactively observing one class at a time using opacity function
in the raster attribute table that blocks other classes and shows one class at a time on the original
satellite image. Field verification was also carried out to attribute ambiguous classes. From this
reference image, we were able to determine the fractional cover of each class type in 60 x 60 m areas
(100 x 100 pixels) by assigning a value of one for a particular class type and zero for other class types
and summing over all 10,000 pixels to compute the percentage of that class at the coarser resolution.
The aggregation of Quickbird class types into an image with 60 m resolution was chosen, instead of
Landsat ETM+’s 30-m resolution, to minimize errors due to misregistration of the Quickbird and ETM+ images. The resolution of the MESMA fraction maps were also degraded to 60 m resolution.

A regression analysis was performed to determine the correlation between endmember fractions of the reference and MESMA-derived fraction images (Smith, et. al., 1990; Foody and Cox, 1994; Bastin, 1997; Small, 2001; Hung and Ridd, 2002). The shade-normalized MESMA-derived fractions were used in this analysis due to the difficulty associated with comparing shade fraction in the Quickbird and ETM+ images. A subset of about 62 samples were selected from each image to conduct a regression between MESMA-derived results and the reference dataset. A \( n \) of ~62 allows the maintenance of some statistical power when dealing with large overlapping remote sensing dataset. In choosing the samples, we avoided areas and pixels that had changed between 2000 and 2005. A diagram illustrating the research design employed in this study is presented in Figure 9. This diagram explains a step by step procedure of how we conducted our research to produce fraction images.

5. Results and Discussions

The correlation coefficient between MESMA-derived fractions and fractions derived from our Quickbird reference image were significant at the 99% confidence level (Figure 10). The regression between the two datasets for all fractions gave slopes of near 1 and y-intercepts of near 0, suggesting that the MESMA-derived fractions are an accurate depiction of fractional cover of impervious surfaces, soils, and vegetation in the Phoenix area.

Our correlations between MESMA-derived fractions and fractions from the Quickbird-derived reference dataset are, nonetheless, not as high as those reported by Powell et al. (2007) for Manaus, Brazil for impervious surfaces and vegetation, though we get better correlations and more realistic regression statistics for bare soil. There is a major difference between the accuracy assessment of our approach and that of Powell et al. (2007). Our accuracy assessment was based on the fractional cover of each class type in 60 x 60 m areas, whereas Powell et al. (2007) used 270 x 270 m areas. It was
reported that the correlation between reference and modeled fractions was low for all land-cover
categories when the sampling unit corresponds to a single pixel (i.e. 30x30 m area), and larger sample
units (larger areas) increased the correlation; i.e. both the slope and R-squared value of the relationship
approached 1.0 for all fractions. There are two other factors that we believe likely contribute to the
differences between this study and that of Powell et al. (2007). First, there was a five-year difference
between the dates of acquisition of the Landsat ETM+ image on which MESMA analysis was
performed (2000) and the Quickbird image from which reference data were calculated (2005).
Although attempts were made to avoid points that appeared to have changed in the five year period
between these images, subtle changes could have resulted in the slight reduction in precision in our
study.

In addition, environmental differences could contribute to differences in the use of MESMA for
the derivation of ground cover fraction. The Phoenix metropolitan area is located in the northern
Sonoran Desert. Desert soils, particularly on flats used most commonly for urban/suburban
development and agriculture, are typically bright. This causes spectral confusion with bright
impervious surfaces such as concrete. Moreover, vegetation cover in deserts is typically low, and
desert vegetation is typically brighter throughout the reflected optical spectrum than vegetation from
more mesic areas (Okin et al., 2001). Thus, vegetation and soil in the Phoenix metropolitan area is
considerably different from that in Manaus, Brazil. Our experience in the Phoenix area was that
confusion between bright soil and impervious surfaces was a significant source of error that
necessitated division of the study area into urban areas, which were almost guaranteed to have some
impervious surface cover in every pixel, and non-urban areas, which may have limited impervious
surfaces in each pixel but which can have multiple soil types. Confusion between bright soils and
impervious areas was reduced in this study by using a five-endmember model and a more extensive set
of soil endmembers in non-urban areas and by using a more extensive library of impervious
endmembers spectra in the urban area. This methodological difference, which was demanded by
difficulties inherent in the discrimination of soils and impervious surfaces in deserts, may explain our improved precision, as well as accuracy, in the derivation of soil fractions relative to that of Powell et al. (2007) for Manaus, Brazil. On the other hand, easier discrimination of vegetation from both soils and impervious surfaces in Manaus could easily explain the better precision and accuracy of from that city relative to our study of Phoenix. Okin et al. (2001), for instance, has shown that desert vegetation, which can have low water and chlorophyll content, and can be spectrally similar to soils, resulting in difficulty discriminating between vegetation types in desert regions with cover < 30%.

6. Conclusion

MESMA-derived fractions of soil, vegetation, and impervious surfaces for the Phoenix metropolitan area are reliable with differences between this study and previous studies from more mesic areas attributable to marked differences in soil and vegetation spectral characteristics in the respective study areas. Using these fractions, we calculate that there were 5639.02 sq km of exposed soil (71.32%), 1160.76 sq km of impervious area (14.68%), and 1107.06 sq km of vegetation cover (14.00%) in metropolitan Phoenix in 2000. Total urban areas and non-urban areas were found to be 2866.75 sq km and 5040.08 sq km respectively. Detailed information on the area and percent coverage of soil, impervious, and vegetation in urban areas and non-urban areas in the Phoenix metropolitan area is presented in Table 1.

This study shows that MESMA may be used to derive fractions cover of major ground cover types in desert cities. It thus extends the applicability of MESMA for urban studies outside that of more mesic regions like those studied by Powell et al. (2007) and Rashed et al. (2003). However, we would like to acknowledge that a careful selection of endmembers that represent all land covers under study plays an important role in the MESMA approach. It was noticed that there is some signature confusion between water vs. tar roads/parking lots and dry exposed soil/sand bars vs. bright impervious surface. The signature confusion between water and tar surfaces can be minimized by
identify water bodies first and masking these areas out. We discovered that the only way to solve the latter problem is to split urban and non-urban areas of the study area and employ different models using different endmembers separately. Results from this study suggest that all possible models (combinations of all surface materials) be considered in the analysis. One important issue to be considered in MESMA is that there is a possibility that there may be more than one endmember of the same major land cover type in a pixel. This could be a potential problem for all sub-pixel approaches since all approaches take one endmember of a major land cover (e.g., soil, vegetation, impervious). Here, we show that two endmembers of one land cover type (soil) can be profitably used to improve model performance.

Linear spectral mixture analysis, a usual technique for mixed pixel classification, does not permit a number of representative materials greater than the number of spectral bands. The MESMA approach not only allows a large number of endmembers regardless of the number of spectral bands but also allows the number and type of endmembers to vary for each pixel within an image. We consider this to be a major advantage recommending the use of MESMA in urban areas where different land covers tend to occur as complex features in a small area. A further key advantage of using the MESMA in urban areas is that a particular type of endmember (e.g., shingle roof under impervious surface or grass under vegetation endmember) could easily be identified by tracing the number of model identified in each pixel. The algorithm also produces shade information for each pixel that could be used in the study of urban structure or heat balance.

The applicability of MESMA analysis of Landsat ETM+ data for desert cities provides an important tool in the study of urbanization, energy and water balances, and climate change in sensitive desert environments. In addition to having some of the fastest growing cities in the U.S. the desert Southwest is also predicted to be especially prone to climatic change (Seager et al. 2007). Thus there is likely to be increasing conflict between a growing population’s need for environmental goods and
services and the natural environment’s inability to provide those goods and services. This conflict will take place in the most densely populated areas. The availability of a remote sensing tool for the study of the physical structure of desert cities is vital for making balanced land management decisions in booming desert counties.
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Table 1. Soil, impervious, and vegetation coverage of the Phoenix metropolitan area in 2000.

<table>
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<th></th>
<th>Urban</th>
<th>Non-Urban</th>
<th>Entire Study Area</th>
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<tr>
<td>Soil Area (%)</td>
<td>43.41</td>
<td>87.19</td>
<td>71.32</td>
</tr>
<tr>
<td>Impervious Area (%)</td>
<td>34.62</td>
<td>3.34</td>
<td>14.68</td>
</tr>
<tr>
<td>Vegetation Area (%)</td>
<td>21.98</td>
<td>9.47</td>
<td>14.00</td>
</tr>
<tr>
<td>Soil Area (sq km)</td>
<td>1244.39</td>
<td>4394.62</td>
<td>5639.02</td>
</tr>
<tr>
<td>Impervious Area (sq km)</td>
<td>992.36</td>
<td>168.40</td>
<td>1160.76</td>
</tr>
<tr>
<td>Vegetation Area (sq km)</td>
<td>630.00</td>
<td>477.06</td>
<td>1107.06</td>
</tr>
<tr>
<td>Total (sq km)</td>
<td>2866.75</td>
<td>5040.08</td>
<td>7906.84</td>
</tr>
</tbody>
</table>
Figure 1. Standard linear SMA model.
Figure 2. MESMA approach (modified from Rashed et al., 2003).
Figure 3. A false color composite of Landsat ETM+ 30 meter resolution data over Phoenix metropolitan area by displaying channel 4 (0.750 – 0.900 µm), channel 3 (0.630 – 0.690 µm), and channel 2 (0.525 – 0.605 µm) in red, green, and blue respectively.
Figure 4. Quickbird multispectral image displayed over the digitized urban coverage.
Figure 5. Urban subset of the study area.
Figure 6. Non-urban subset of the study area.
Figure 7. Spectra from urban and non-urban materials: (a) Soil, (b) Impervious, (c) Vegetation.
Figure 8. Final fraction layers after merging output layers from urban and non-urban subsets: (a) Soil, (b) Impervious, (c) Vegetation, (d) Shade. Note: White = 100%; Black = 0%.
Figure 9. Research design.
(a) Soil

(b) Impervious
Figure 10. Correlation between the fraction outputs produced by MESMA and reference data from Quickbird 60 cm resolution data: (a) Soil, (b) Impervious, and (c) Vegetation.