Quantifying Impervious Surface, Vegetation, Soil, and Shade in the Phoenix Metropolitan Area Using Multiple Endmember Spectral Mixture Analysis

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Abstract

Urban land covers (e.g., cement parking lots, asphalt roads, shingle rooftops, grass, tress, exposed soil) can only be recorded as either present or absent in each pixel when using traditional per-pixel classifiers. Sub-pixel analysis approaches that can provide the relative fraction of surface covers within a pixel may be a potential solution to effectively identifying urban impervious areas. Spectral mixture analysis approach is probably the most commonly used approach that models image spectra as spatial average of spectral signatures from two or more surface features. 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) approach addresses these issues by allowing endmembers to vary on a per pixel basis. The MESMA technique was employed in this study to model Landsat ETM+ reflectance in the Phoenix metropolitan area. Field spectra of vegetation, soil, and impervious surface areas collected with the use of a fine resolution Quickbird image and pixel purity index tool in ENVI software were modeled as reference endmembers in addition to photometric shade that was incorporated in every model. This study employs thirty endmembers and six hundred and sixty spectral models to identify soil, impervious, vegetation, and shade in the Phoenix metropolitan area. The mean RMS error for the selected land use land cover classes range from 0.003 to 0.018. The Pearson correlation between the fraction outputs from MESMA and reference data from Quickbird 60 cm resolution data for soil, impervious, and vegetation were 0.7052, 0.7249, and 0.8184 respectively.

Figure 1. 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 2. A true color composite of Quickbird 2.4 meter resolution data over downtown Phoenix area by displaying channel 3 (0.63 – 0.69 µm), channel 2 (0.52 – 0.60 µm), and channel 1 (0.45 – 0.52 µm) in red, green, and blue respectively.

Data and study area

Primary Data (Figure 1)
Landsat Thematic Data (L1G product of path 37 and row 37) at 30 m spatial resolution with 6 channels ranging from blue (0.45 µm) to mid infrared portion of the spectrum (2.35 µm)

(1) Location: 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”)

(2) Date: April 19, 2000

Secondary Data for Accuracy Assessment (Figure 2)
Quickbird 2.4-meter spatial resolution multispectral image with 4 channels – blue (0.45 – 0.52 µm), green (0.52 – 0.60 µm), red (0.63 – 0.69 µm), and near infrared (0.76 – 0.90 µm) and 60 cm panchromatic image (0.45 – 0.90 µm)

(1) Location: Downtown Phoenix.

(2) Date: July 11, 2005

Sub-pixel Analysis

The traditional hard classifiers (e.g., minimum distance, Mahalanobis distance, maximum likelihood) can label each pixel only with one class. Information on the fractional amount of spatially mixed spectral signatures from different ground-cover features is not possible with the per-pixel classifiers (hard classifiers). Hence, the traditional classification of mixed pixels may lead to information loss, degradation of classification accuracy, and degradation of modeling quality in successive applications.

Sub-pixel analysis that can provide the relative abundance of surface materials within a pixel is a potential solution to per-pixel classifiers especially when dealing with medium to coarse spatial resolution satellite sensor images.

Linear Spectral Mixture Analysis (SMA)

Linear spectral mixture analysis (SMA) (Figure 3), which provides sub-pixel endmember abundance information, is probably the most commonly used approach of all subpixel analysis techniques. The approach is based on the assumption that the spectrum at each pixel is a linear combination of the spectra of all ground components within the pixel, and that the linear mixture coefficients are equal to the fractional area of each ground component in a pixel. The mathematical model of linear spectral mixture analysis can be defined as

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

where
Xi = Total spectral reflectance of band *i* of a pixel
k = number of endmembers
fk = fraction of an endmember *k* within a pixel
Xik = known spectral reflectance of endmember *k* within the pixel in band *i*
ei = error term for band *i*

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

$$RMS = \frac{\left(\sum_{i=1}^{m} (e_i)^2\right)^{0.5}}{m}$$

where *ei* are the error terms for each of the m spectral bands considered. The above constrained least-squares estimate assumes the followings.

$$\sum_{k=1}^{n} f_k = 1 \quad \text{and} \quad 0 \le f_k \le 1$$

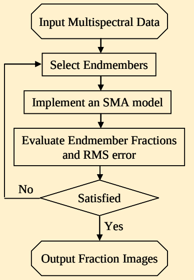

Figure 3. Standard linear SMA model

Limitations of Linear SMA

(1) linear spectral mixture classifier does not permit number of representative materials (endmembers) greater than the number of spectral bands.

(2) An invariable set of endmembers to model the spectra in all pixels. This assumption could potentially fail to account for the fact that the number and type of land cover components within each pixel are highly variable. The endmembers used in SMA are the same for each pixel, regardless of whether the materials represented by the endmembers are present in the pixel.

Multiple Endmember Spectral Mixture Analysis (MESMA) (Figure 4)

An extension of SMA approach that allows the number and type of endmembers to vary for each pixel within an image. MESMA has been proven to be effective in identifying different types of materials in a variety of environments. The algorithm produces the RMS error and the shade information in each pixel as separate layers.

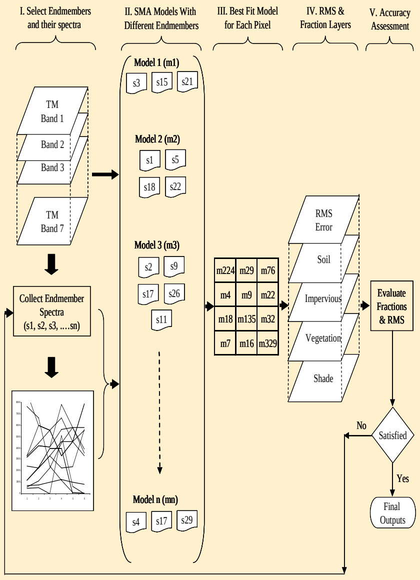

Figure 4. MESMA approach

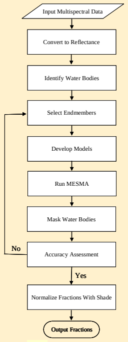

Figure 5. Flow Chart (Research Design)

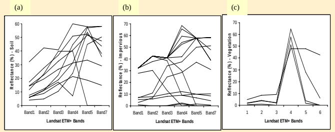

Figure 6. Spectra from urban materials: (a) Soil, (b) Impervious, (c) Soil.

Table 1. Mean fraction values of soil, impervious, vegetation, shade, and RMS error of the selected land use land cover classes

Land Use Land Cover Class	Mean fraction values (Original)				RMS Error
	Soil	Impervious	Vegetation	Shade	(Mean)
Agriculture (Active)	0.024	0.015	0.796	0.078	0.018
Agriculture (Inactive)	0.560	0.144	0.061	0.148	0.008
Airport	0.158	0.384	0.009	0.362	0.010
Commercial	0.227	0.338	0.047	0.302	0.016
Exposed soil	0.517	0.170	0.085	0.151	0.008
Forest	0.146	0.047	0.312	0.409	0.003
Golf course	0.078	0.041	0.675	0.119	0.009
Residential (Crown closure-Low)	0.261	0.279	0.092	0.281	0.007
Residential (Crown closure-Medium)	0.260	0.183	0.148	0.363	0.005
Residential (Crown closure-High)	0.213	0.100	0.194	0.326	0.005
Rugged terrain	0.254	0.096	0.080	0.524	0.004

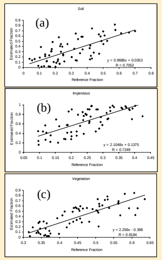

Figure 7. Pearson correlation between the fraction outputs produced by MESMA and reference data from Quickbird 60 cm resolution data: (a) Soil, (b) Impervious, and (c) Vegetation. Note: Outputs are not normalized with shade information.

Conclusion

Results from this study demonstrated that the MESMA approach is reliable and the sub-pixel processor picked out the signatures effectively. It should be noted that a careful selection of endmembers that represent all land covers under study play an important role in the MESMA approach. It was noticed that there is some signature confusion between dry exposed soil/sand bars vs. bright impervious surface and water vs. tar roads/parking lots. We recommend that all possible models (combinations of all surface materials) be considered in the analysis. It is also important to note that number of surface features and all possible combinations of endmember models are increased and generate fraction layers repeatedly until a satisfactory result is received. The MESMA approach not only allows unlimited endmembers regardless of the number of spectral bands but also allows the number and type of endmember to vary for each pixel within an image. One of the key advantages of using the MESMA 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.

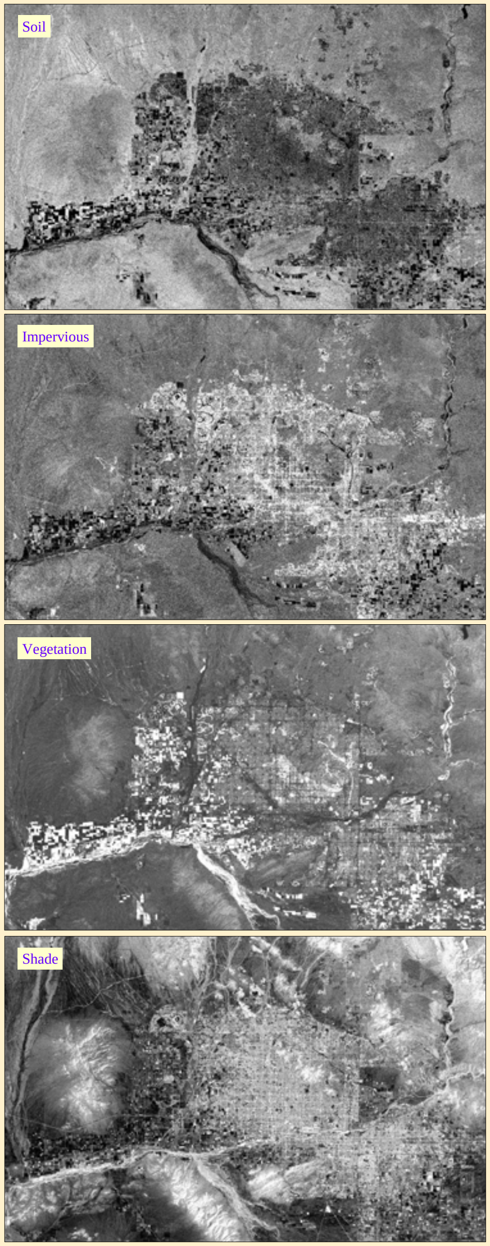

Figure 8. Output Faction Images. Note: White = 100%; Black = 0%