

# A GLOBAL ANALYSIS OF URBAN REFLECTANCE

Christopher SMALL

*Lamont Doherty Earth Observatory  
Columbia University  
Palisades, NY 10964 USA  
[small@LDEO.columbia.edu](mailto:small@LDEO.columbia.edu)*

## ABSTRACT

Spectral characterization of urban reflectance is necessary for discrimination of human settlements from other types of land cover. The 10 to 20 m scale of urban land cover elements results in a preponderance of spectrally mixed pixels when imaged with moderate resolution optical sensors like Landsat. The overall reflectance of the urban mosaic is determined by the spectral reflectance of surface materials and shadows and their spatial distribution. Building materials dominate net reflectance in most cities but in many cases vegetation also has a very strong influence on urban reflectance. A comparative analysis of Landsat imagery for a set of 28 cities worldwide provides a basis for a general spectral characterization of urban reflectance. The results of the analysis indicate that the reflectance of these cities can be described as linear combinations of high albedo, low albedo and vegetation spectral endmembers within a 2 dimensional mixing space. The primary two dimensions of the full six dimensional mixing space consistently contain over 90% of observed variance. The relative proportions of the endmembers vary considerably among different cities and within individual cities. The most consistent characteristic of the urban mosaic is spectral heterogeneity. At scales of 10 to 30 meters, urban areas are considerably more heterogeneous than other land cover types investigated. Spectral characterization of urban land cover on the basis of heterogeneity could provide a basis for mapping the spatial extent of human settlements with satellite imagery collected over the past 30 years.

## 1 Introduction

Moderate resolution optical sensors provide a 30 year record of urban evolution worldwide. Although urban areas occupy a relatively small fraction of Earth's surface area, their extent, distribution and evolution have enormous impact on environmental and socioeconomic dynamics world wide. Despite its fundamental importance, urban land cover has not been characterized to the same extent that other land cover types have. In order to quantify the extent and evolution of urban areas with optical sensors it is necessary to understand the physical characteristics that distinguish developed urban areas from other types of human modified land surfaces and from undeveloped land surfaces. A systematic physical characterization of optical reflectance properties of urban areas would facilitate global mapping of urban extent. Such a characterization of urban land cover would also benefit understanding of energy flux and micro and mesoscale meteorological processes controlling urban environmental conditions.

One of the primary obstacles to urban land cover classification is the diversity and spectral heterogeneity of urban reflectance. Unlike many other land cover types, urban reflectance is extremely variable at a variety of spatial scales. Spectral heterogeneity at scales comparable to the Ground Instantaneous Field Of View (GIFOV) of an optical sensor results in a preponderance of spectrally mixed pixels. Mixed pixels are problematic for conventional classification methods because most algorithms are predicated on the assumption of spectral homogeneity within a particular type of land cover. The diversity of land cover types at different spatial scales in the

urban mosaic therefore results in high rates of misclassification between urban and other land cover classes.

The objective of this study is to develop a quantitative physical characterization of the reflectance properties of the urban mosaic. This task is complicated by two distinct types of variability in urban reflectance. Intraurban spatial variability is a result of the diversity of building materials and land covers present in the urban mosaic at different spatial scales. Characterizing scale dependent reflectance properties requires higher spatial resolution than is provided by moderate resolution sensors like Landsat. Interurban variations in urban reflectance are a result of socioeconomic, cultural, historical and environmental differences among cities. Factors such as building materials, physical environment, urban planning constraints and historical evolution influence differences in overall reflectance patterns observed in cities worldwide. This study uses the concepts of spectral mixture analysis to provide self consistent physical descriptions of a variety of cities in order to determine what, if any, reflectance characteristics can be used to distinguish urban land cover in moderate resolution optical imagery.

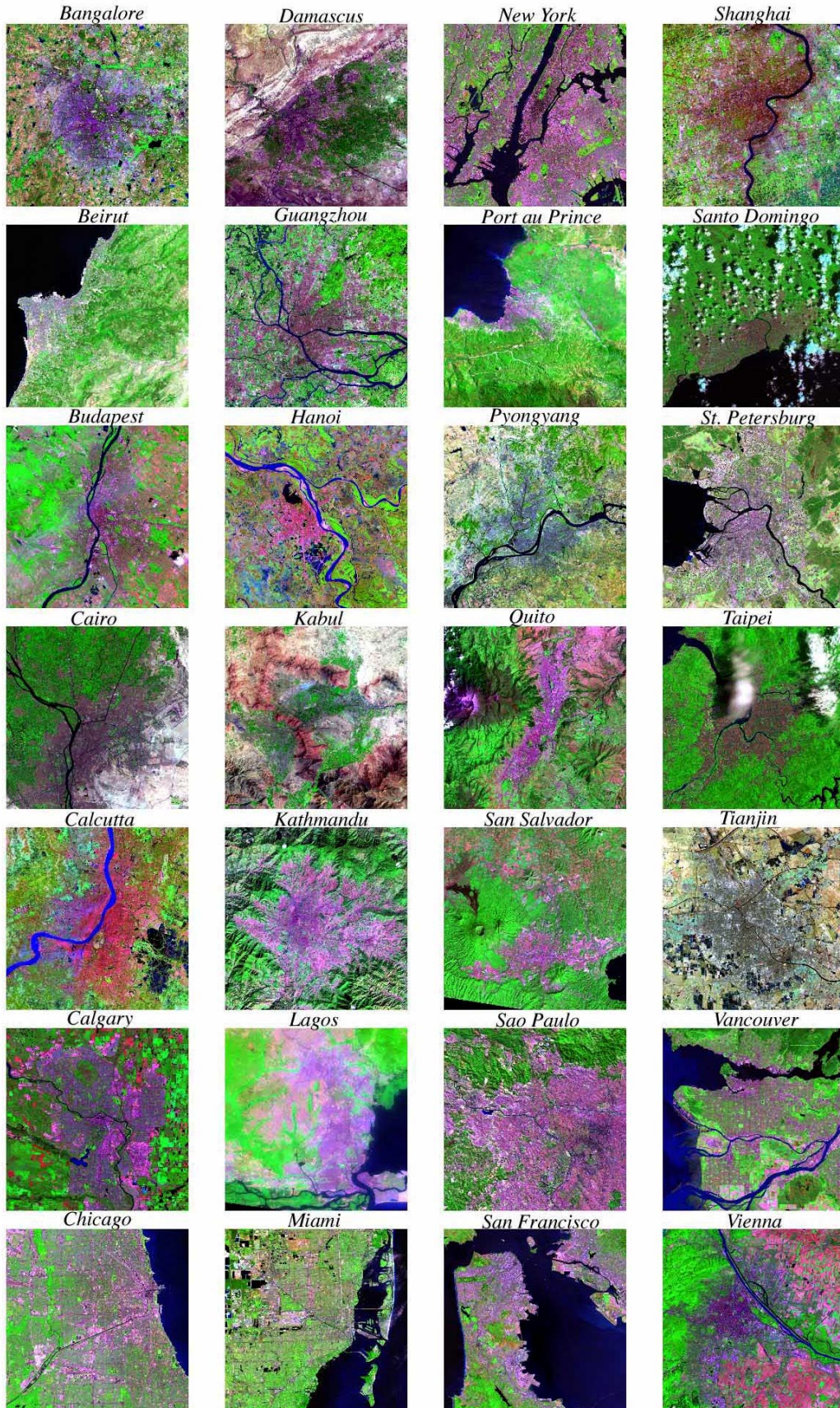
## 2 Reflectance Scale and Spectral Mixing

The characteristic spatial scale of surface reflectance patterns in the built environment is comparable to the GIFOV of most operational multispectral sensors in use today. Two dimensional spatial autocorrelation of 1 m Ikonos imagery in 14 cities of varying size and setting indicates that the characteristic spatial scale on which Visible/Near Infrared reflectance decorrelates is 10 to 20 meters (*Small, 2002*). This explains the preponderance of mixed pixels observed in Landsat imagery of urban areas. This spectral mixing within the urban mosaic is what prevents hard classification algorithms from producing accurate results. In order to characterize urban reflectance in a physically meaningful and sufficiently robust way, it is necessary to accommodate the fact that moderate resolution sensors will generally image a combination of discrete surface reflectances and represent the upwelling radiance field in the form of a mixed pixel.

Spectral mixture analysis provides a systematic way to quantify spectrally heterogeneous urban reflectance. Spectral Mixture Analysis (SMA) is based on the observation that, in some situations, radiances from surfaces with different "endmember" reflectances mix linearly within the IFOV (*Nash and Conel, 1974; Singer and McCord, 1979; Singer, 1981; Johnson et al, 1983*). This observation has made possible the development of a systematic methodology for Spectral Mixture Analysis (*Adams et al, 1986, 1989; Smith et al, 1990; Gillespie et al, 1990*) that has proven successful for a variety of quantitative applications with multispectral imagery (e.g. *Adams et al, 1995; Pech et. al., 1986; Smith et al, 1990; Elmore et al, 2000; Roberts et al, 1998*). If a limited number of distinct spectral endmembers are known it is possible to define a "mixing space" within which mixed pixels can be described by linear mixtures of the endmembers. Given sufficient spectral resolution, a system of linear mixing equations may be defined and the best fitting combination of endmember fractions can be estimated for the observed reflectance spectra. The strength of the SMA approach lies in the fact that it explicitly takes into account the physical processes responsible for the observed radiances and therefore accommodates the existence of mixed pixels.

**Figure 1** (Next Page) Visible/Infrared false color composites of urban Landsat 7 imagery. ETM+ bands 7, 4 and 2 (RGB) emphasize contrast between soil, vegetation, high albedo and low albedo landcovers at 30 m spatial scales. The most heavily built up areas are near the center of each 30 x 30 km subscene. A full resolution color version of this figure is available online at: [www.LDEO.columbia.edu/~small/Urban.html](http://www.LDEO.columbia.edu/~small/Urban.html)





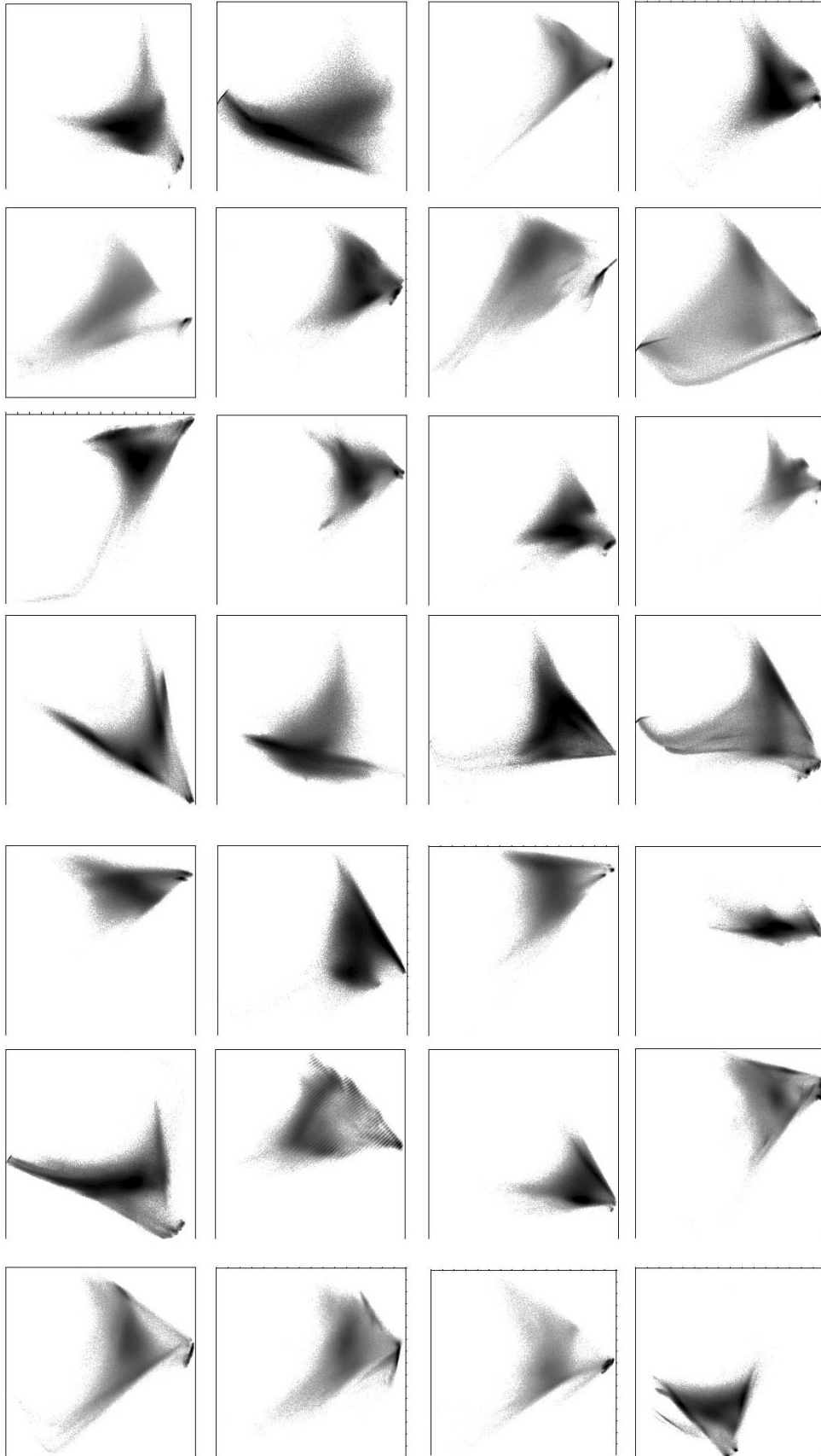
This analysis is based on a diverse collection of cities spanning a range of environmental, cultural and socioeconomic settings. The analyses are conducted on a set of 28 Landsat 7 ETM+ images acquired between 1999 and 2001. This quasi-random selection was gleaned from the Landsat 7 archive at the University of Maryland's Global Land Cover Facility (*glcf.umiacs.umd.edu*). The cities were chosen on the basis of area, diversity and image quality. All analyses were conducted on calibrated exoatmospheric reflectance. For each city, a 30 x 30 km image was chosen to represent the urban area and as wide a variety of surrounding land covers as possible. In most cases, the 900 km<sup>2</sup> image contained all of the built up area and varying amounts of surrounding land covers. In only two cases (New York and Sao Paulo) was the built up area too large to be contained in the subscene. In these cases, the scene was chosen to cover the city center as well as some land cover representative of the surrounding areas.

### 3 Urban Mixing Spaces

The diversity of landcovers present in the urban mosaic determines the spectral dimensionality of the image collected by a sensor. The limited spatial and spectral resolution of the ETM+ sensor results in a projection of a high dimensional mixing space onto a lower dimensional representation constrained by the ability of the sensor to discriminate different surface reflectances at GIFOV scales. Analyses of AVIRIS hyperspectral imagery suggest that some urban areas have as many as 30 to 50 spectral dimensions (*Green and Boardman, 1999; Small, 2001*) but the TM and ETM+ sensors can resolve only 6 of these dimensions at most. A central question of this analysis is whether these six dimensions provide an adequate basis for a systematic characterization of urban reflectance. Is the information content provided by the Landsat sensors sufficient to discriminate between urban areas and other land cover types in a consistent manner? The fact that an experienced interpreter can recognize urban areas in Landsat imagery suggests that this is the case but visual interpretation is based on a complex combination of spectral and textural cues that have proven extremely difficult to simulate with machine-based algorithms.

The basis of the spectral mixture analysis is the variance partition and mixing space characterization provided by a principal component transformation of the multispectral imagery. The eigenvalue distribution provides a quantitative estimate of the variance partition between the signal and noise dominated principal components of the image. This partition and the number of signal dominated components forms the basis of the dimensionality estimate of the image. The multidimensional feature space of the low order principal components represents the spectral mixing space that can be used to describe the spectral mixtures as combinations of spectral endmembers (*Johnson et al, 1985; Boardman, 1993*). In this analysis, a Minimum Noise Fraction (MNF) principal component transformation is used. The MNF transformation implemented in ENVI is analogous to the Maximum Noise Transformation described by Green et al (1988) but differs in ordering of the principal components from high to low signal variance (*RSI, 2000*). With Landsat imagery, the MNF transformation usually produces principal components similar to those resulting from a traditional covariance-based PC rotation but offers the added benefit of normalizing the eigenvalues relative to the variance of the sensor noise estimate. For this analysis, all MNF transformations were applied using noise covariance statistics derived from a June 2000 ETM+ image of a large, clear lake at 3400 m elevation in the Peruvian Andes. Normalized eigenvalue distributions quantify the partition of variance among the principal components indicating how many spectral dimensions are required to represent the information content in the image. The larger eigenvalues are associated with the low order principal components representing the dominant reflectance patterns while the smaller eigenvalues are associated with the higher order principal components associated with the pixel scale variance commonly assumed to be noise.





**Figure 2** (Previous Page) Spectral mixing spaces of the 28 urban areas and their surroundings shown in Figure 1. Each 2D mixing space is represented by a density shaded scatter plot of the two low order principal components of the corresponding image in Figure 1. The pixels near the apexes of the scatter plot represent spectral endmembers while the darker interior regions represent a greater number of mixed pixels. The mixing spaces generally have a triangular form in the two primary dimensions (except some images w/ clouds). The pixels at the apexes consistently correspond to High Albedo, Low Albedo and Vegetation endmembers. The small, dark clusters (generally at right-most apex) correspond to low albedo water and deep shadow.

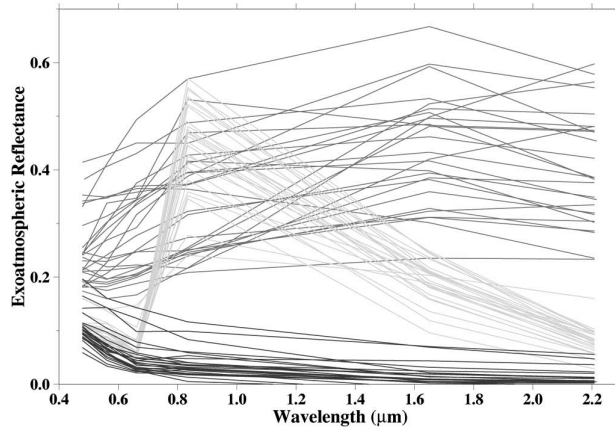
Spectral mixing spaces provide a self-consistent basis for comparison of urban reflectance characteristics. The similarity of the triangular mixing spaces shown in Figure 2 indicates that all 28 of the urban areas in this study show a consistent mixing space topology. Although the distributions of mixed pixels within the mixing spaces vary considerably, the overall form is consistent. The apexes of the mixing space corresponding to the spectral endmembers are generally well defined and the edges between the apexes are generally straight or concave. This suggests that the mixing among the endmembers is primarily linear. The spectra of the endmembers (Figure 3) are also remarkably consistent. This suggests that a three component linear mixing model may provide a consistent and accurate way to represent urban reflectances.

#### 4 Spectral Endmembers and Linear Mixture Models

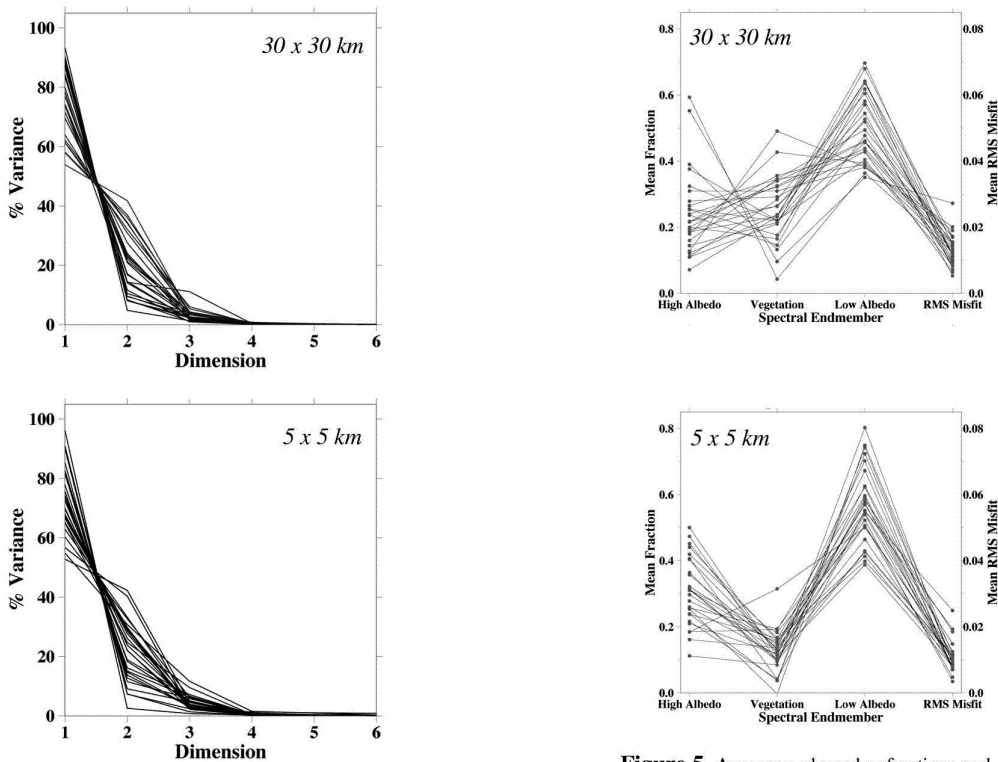
The consistency in the topology of the urban mixing spaces is reflected in the consistency of the spectral endmembers. Figure 3 shows exoatmospheric reflectance profiles for the three primary endmembers associated with the apexes of the triangular two dimensional mixing space. The Low Albedo and Vegetation endmembers are remarkably consistent. The High Albedo endmember is variable in amplitude but is generally convex upward with a peak at SWIR wavelengths.

The low albedo endmember generally corresponds to deep shadow or clear water. In many cases, several different water bodies of differing reflectance can be resolved as distinct clusters near the low albedo apex of the mixing space. In these cases, the Low Albedo endmember was chosen to correspond to clear water or deep shadow areas. These Low Albedo reflectances represent the atmospheric path radiance component that is present in every pixel. The fraction of Low Albedo provides an indication of the net albedo of a mixed pixel because it represents the complement of overall surface reflectance. The fraction of High Albedo endmember does not provide an accurate estimate of the overall albedo because of the nonlinearity and dispersion of most mixing spaces near the high albedo apex. The high intra and interurban variability of the High Albedo endmember suggests that a single endmember could not accurately represent the wide variety (but low areal abundance) of high albedo reflectances observed. For the same reason, the similarity of the Low Albedo endmember suggests that it provides a more consistent metric of inverse urban albedo (darkness). Eigenvalue distributions provide concise estimates of urban spectral dimensionality. Consistency in the topology of spectral mixing spaces is reflected in the consistency in variance partition and spectral dimensionality seen in eigenvalue distributions (Figure 4). Analysis of AVIRIS hyperspectral imagery indicates that urban spectral dimensionality can be scale dependent as larger areas can contain a wider variety of spectral endmembers (Small, 2001b). Because surrounding areas may be more spectrally diverse than the built up area, mixture analyses were also conducted for 5 x 5 km areas around the city centers. Eigenvalue distributions for these areas also indicate that the mixing space is essentially two dimensional.

Simple three endmember mixing models are well posed for most of the urban areas investigated in this study. Some areas could be represented more accurately with four



**Figure 3** Spectral endmember reflectance vectors. Exoatmospheric reflectances correspond to pixels at the apexes of the mixing spaces shown in Figure 2. Even without radiometric rectification or atmospheric correction, the Low Albedo (dark curves) and Vegetation (light gray) endmembers are remarkably consistent in shape while variable in amplitude. The High Albedo (medium gray) endmembers are quite variable in amplitude but generally show a convex upward shape with peak reflectance at SWIR wavelengths.



**Figure 4** Spectral dimensionality and spatial scale. Normalized eigenvalue distributions show the partition of variance among the principal components for each urban area and for 5 x 5 km subscenes from the city centers. The two low order principal components generally account for more than 90% of scene variance indicating that the mixing spaces are primarily two dimensional. The larger 30 km images generally have a slightly greater percentage of variance in the first dimension as a result of the albedo contrast between the built up areas and surrounding landcover.

**Figure 5** Average endmember fractions and RMS misfits. The diversity of urban areas shows varying fractions of High Albedo and Vegetation components with consistently higher fractions of Low Albedo components. City centers contain fewer types of landcover than surrounding areas so their endmember fraction distributions are more similar. Average vegetation fractions are less than 0.2 for built up city centers. At both scales RMS misfits are generally less than 0.02, suggesting that the three component linear mixing model provides good fit to the observed reflectances.

endmember models but, in general, the RMS misfits to the three endmember models were quite small ( $>0.02$  in Figure 5). Small misfit is a necessary but not sufficient verification of the three endmember model. Large misfits would indicate that the model did not provide an accurate description of the mixed reflectances but small misfit does not guarantee that the estimates are accurate. It would be necessary to validate the fraction estimates with independent field measurements to determine the level of accuracy (e.g. Small, 2001). Nonetheless, the low misfits do suggest that the three endmember model can account for most of the observed variance.

The most consistent spectral characteristic of urban reflectance at 30 m scale is spectral heterogeneity. Despite the consistency of the 2D mixing spaces and the similarity of the bounding spectral endmembers, a wide variety of endmember fraction abundances characterize the built up areas of the cities shown in Figure 2. Non-urban land covers generally correspond to distinct mixing fractions nearer the apexes of the mixing spaces. This suggests that a measure of spectral heterogeneity at GIFOV scales may be an effective indicator of urban land cover.

## REFERENCES

- Adams, J.B. et al., 1986. Spectral Mixture Modeling: a New Analysis of Rock and Soil Types at the Viking Lander 1 Site. *Journal of Geophysical Research*, 91, pp.8089-8122.
- Boardman, J.W., 1989. Automating Spectral Unmixing of AVIRIS data using Convex Geometry Concepts, *Proceedings Third JPL Airborne Earth Science Workshop*, Pasadena, CA, 1993
- Green, A. A., M. Berman, P. Switzer, and M. D. Craig, 1988, A transformation for ordering multispectral data in terms of image quality with implications for noise removal, *I.E.E.E. Transactions on Geoscience and Remote Sensing*, 26, 1, 65-74.
- Green, R. O., and J. Boardman, 2000, Exploration of the relationship between information content and signal/noise ratio and spatial resolution in AVIRIS data, edited by R.O. Green, *Proceedings of the Ninth JPL Airborne Earth Science Workshop*, Pasadena, CA, 195-206.
- Johnson, P. E., M. O. Smith, and J. B. Adams., 1985, Quantitative analysis of planetary reflectance spectra with principal components analysis, *J. Geophys. Res.*, 90, C805-C810.
- Johnson, P. E., M. O. Smith, S. Taylor-George, and J. B. Adams, 1983, A semiempirical method for analysis of the reflectance spectra fo binary mineral mixtures, *J. Geophys. Res.*, 1983, 88, 3557-3561.
- Kauth, R.J. and Thomas, G.S., 1976. The Tasseled Cap – a Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by Landsat. *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data*, pp.4041-4051.
- Singer, R.B. and McCord, T.B., 1979. Large Scale Mixing of Bright and Dark Surface Materials and Implications for Analysis of Spectral Reflectance. *Journal of Geophysical Research*, pp.1835-1848.
- Small C., 2001a. Estimation of Urban Vegetation Abundance by Spectral Mixture Analysis. *International Journal of Remote Sensing*, 22(7), pp.1305-1334.
- Small C., 2001b. Multiresolution Analysis of Urban Reflectance. *Proceedings of the IEEE Workshop on Remote Sensing and Data Fusion Urban Areas*, 8-9 Nov. 2001, Rome, Italy.
- Small, C., 2002, High Resolution Spectral Mixture Analysis of Urban Ikonos Imagery, *Remote Sensing of Environment*, Submitted 5/2002.
- Smith, M. O., P. E. Johnson, and J. B. Adams, 1985, Quantitative determination of mineral types and abundances from reflectance spectra using principal component analysis, *J. Geophys. Res.*, 90, 792-804.
- Smith, M. O., S. L. Ustin, J. B. Adams, and A. R. Gillespie, 1990, Vegetation in deserts: I. A measure of abundance from multispectral images, *Remote Sensing of Environment*, 31, 1-26.