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Multi-scale standardized spectral mixture models

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ABSTRACT

Linear spectral mixture models can be standardized by using endmembers that span the global mixing space. By combining the benefits of location-specific mixture models with standardized spectral indices, standardized mixture models offer consistency, simplicity, inclusivity and applicability. We construct a globally representative mixing space using a spectrally diverse collection of 100 Landsat ETM+ (Thematic Mapper & Enhanced Thematic Mapper+) subscenes. Global composites of 100,000,000 Landsat spectra, constructed from both exoatmospheric reflectance and atmospherically corrected surface reflectance, represent the spectral diversity of a wide range of terrestrial environments. Principal Component (PC) Analysis of the global composite shows that 99% of the spectral variance can be represented in a 3-dimensional mixing space of the low order PCs. Within this 3D space 98% of spectra are contained within a tetrahedral hull bounded by a continuous plane of substrates, and well-defined apexes corresponding to vegetation and dark endmembers. Suites of individual substrate, vegetation and dark endmember spectra are used to derive mean endmembers and to quantify the effects of endmember variability on fractions estimated from a standardized Substrate, Vegetation, and Dark (SVD) linear mixture model. Maximum endmember variability introduces less than 0.05 difference in S, V, and D fractions for most SVD models constructed from individual pixel endmember spectra giving less than 0.05 model misfit for more than 97% of pixels in the global composite. The mean SVD endmembers define a standard global mixture model for Landsat spectra. These SVD endmembers can be used to model mixed reflectance spectra from other sensors with similar spectral responses to Landsat ETM+. Comparisons of endmember fractions estimated from coincident acquisitions of Landsat TM and ETM + and WorldView-2 imagery show strong linear scaling for vegetation and dark fractions. Substrate fractions do not scale as linearly for the urban validation sites because the Landsat substrate endmember does not accurately represent the impervious surfaces imaged by WorldView-2. Comparisons of Landsat and WorldView-2 unmixed with the same Visible-Near Infrared (VNIR) endmembers derived from the global Landsat endmembers are also strongly correlated but with reduced bias. This linear scaling suggests that the Landsat global endmembers may provide a basis for standardized mixture models for WorldView-2 and other broadband sensors with spectral response similar to Landsat TM and ETM+. Comparisons of vegetation fractions with vegetation indices for the global composite show strong linear correspondence for Tasseled Cap Greenness and Enhanced Vegetation Index, with some degree of saturation at high fractions for the Soil Adjusted Vegetation Index and a wide range of responses for the Normalized Difference Vegetation Index.

1. Introduction

The linear spectral mixture model represents radiance measurements as linear mixtures of endmember radiances reflected from different materials in the sensor's Instantaneous Field of View (IFOV). In cases of homogeneous target spectra, these endmembers are often considered "spectrally pure" but a more general criteria of "spectrally distinct" allows the mixture model to be used in situations where characteristic combinations of materials function as endmembers bounding continua of other spectral mixtures. Inverting the linear mixture model yields per pixel endmember fractions which can be interpreted as quantitative estimates of the areal abundance of specific land cover types (endmembers) contributing to the mixed pixel (Adams et al., 1986, 1993; Gillespie et al., 1990; Smith et al., 1990). By representing each pixel as a combination of endmembers, the resulting fraction images provide continuous field representations of the spectrally heterogeneous gradations in land cover that characterize much of the Earth surface. For many applications, such as physical models of land surface dynamics, a continuous field corresponding to a physical quantity (e.g., vegetation abundance) can more accurately represent land surface properties than a homogeneous thematic land cover class with discrete boundaries. In applications where distinct thematic classes are required, endmember fractions can be grouped into intervals to provide more physically consistent definitions of thematic classes than may be obtained from statistical classification methods.

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Linear mixture models are usually application-specific in the sense that the model is designed with spectral endmembers specific to the location or problem at hand. The number and choice of endmembers are the defining characteristics of the model. However, it is also possible to use the linear mixture model as a more general representation of land cover by using generic endmembers representative of common land cover types. We refer to a general linear mixture model, based on generic spectral endmembers, as a standardized spectral mixture model. A standardized spectral mixture model can offer many of the benefits of a spectral index (e.g., vegetation index) while providing a simple, physically-based representation of the abundance of different materials within the IFOV. The implicit assumption is that non-linear mixing (e.g., from multiple scattering) is negligible. In order to be generally applicable, the standardized spectral mixture model must represent the diversity of materials likely to be imaged at different locations and times. This means that the number and choice of generic endmembers that define the model must encompass the range of reflectances that can be distinguished by the sensor. The standardized spectral mixture model does not imply that the endmembers used are the only spectrally distinct (i.e., distinguishable) endmembers that exist. It merely represents the mixed reflectance measurement as the combination of generic endmember fractions that most closely matches the measurement. The standardized mixture model is not intended to replace location or problem-specific mixture models but rather to supplement them and to allow fractions to be compared consistently across locations and time.

A standardized spectral mixture model can be thought of as an alternative coordinate system within which a continuum of spectral mixtures can be represented in terms of a small number of canonical endmembers representing the most spectrally distinct land cover components that the sensor can resolve (Small, 2004b). These canonical endmembers are analogous to the “universal endmembers” discussed by Adams and Gillespie (2006) for specific types of scenes — but are further generalized to represent the diversity of spectral mixtures that can be resolved by a given sensor over the full range of landscapes found on Earth. An important benefit of this alternative coordinate system is potentially a lower dimensionality than that defined by the (possibly redundant) bands of the sensor. Another benefit is the ability to represent landscapes as continuous fields of fundamental land cover components. The standardized spectral mixture model has its conceptual origin in the Kauth–Thomas model of spectral evolution of agricultural landscapes (Kauth & Thomas, 1976) but includes all landscapes for which the important components can be resolved by the sensor being used. Despite the conceptual similarity in their origins, there are important distinctions between the standardized linear spectral mixture model and the Kauth–Thomas Tasseled Cap Transformation (TCT) as explained in the Discussion below.

This depiction of a standardized linear spectral mixture model, and its distinction from the underlying physical concept of spectral mixing in the radiance field raises two complementary points. 1) The image endmembers that a particular sensor can distinguish do not necessarily encompass all spectrally distinct materials that might be considered endmembers for a different sensor capable of distinguishing more or different spectra. In this sense, the mixture model is sensor-specific. 2) Different sensors with similar spectral responses can represent the same target reflectance similarly. This suggests that generic endmembers derived from one sensor may provide a basis (literally and mathematically) for linear mixture models of spectra measured by other sensors with similar spectral responses. In this sense, the mixture model and its canonical endmembers may be portable from one sensor to another.

The objectives of this study are 1) to characterize the topology and spectral dimensionality of the Landsat ETM+ spectral mixing space, 2) to identify spectral endmembers that span the space, 3) to quantify image endmember variability and its effect on the distribution of misfit to the standardized mixture model, 4) to quantify the linearity of spatial scaling of fractions derived from the generic mixture model and 5) to compare vegetation fractions from the standardized mixture model with other standardized vegetation metrics over a wide range of different environments. As the basis for the analysis we use a global composite of 100 spectrally diverse subscenes collected by Landsat 5 and Landsat 7. We use the abbreviation ETM+ to refer to intercalibrated imagery collected by either the TM or ETM + sensor. The images are calibrated to both exoatmospheric reflectance (Chander et al., 2009) and surface reflectance (Masek et al., 2006) to yield endmembers for each type of calibration. To accomplish these objectives we first construct a global composite from the 100 subscenes and select suites of Substrate, Vegetation, and Dark (SVD) endmembers spanning its 3D mixing space. We use these endmember suites to quantify the effect of endmember variability on the SVD endmember fractions estimated for the global Landsat composite. We investigate the linearity of spatial scaling by comparing endmember fractions derived from Landsat with fractions derived from near simultaneous acquisitions of WorldView-2. Finally, we compare vegetation fractions estimated with the generic endmembers to Tasseled Cap greenness and three vegetation indices for the global composite to illustrate the relationships between them in a wide variety of environments.

This study uses the analysis of Small (2004b) as a starting point and extends the analysis in five ways. 1) The original set of 30 subscenes is expanded to a larger, more geographically diverse collection of 100 subscenes of both Landsat 5 TM and Landsat 7 ETM+. 2) Parallel analyses are conducted using both exoatmospheric (top of atmosphere) and atmospherically corrected surface reflectance. 3) Effects of endmember variability on fraction distributions are quantified. 4) Linearity of spatial scaling of endmember fractions from 2 m to 30 m is demonstrated. 5) Vegetation fraction estimates from the standardized model are compared to other standardized vegetation metrics for the diverse range of environments in the global Landsat composite.

2. Data

A spectrally diverse collection of 100 subscenes from 67 unique Level 1 terrain corrected (L1T) Landsat ETM+ scenes was selected on the basis of diversity of land cover and diversity of biomes (Fig. 1). The global collection spans all terrestrial biomes as determined by mean annual temperature and precipitation (Houghton et al., 1996) in approximate proportion to land area (Small, 2004a). The DNs are calibrated to exoatmospheric reflectance using the calibration approach and coefficients given by Chander et al. (2009). We also convert the data to surface reflectance correcting for atmospheric effects by means of the 6S code implementation in the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) atmospheric correction method (Masek et al., 2006), which is currently used by the United States Geological Survey to distribute surface reflectance Landsat data. Ice sheets and open marine environments are not well represented in the collection because the atmospheric correction is known to be problematic over these surfaces. In each scene we strive to use cloud-free imagery to the extent possible. The atmospheric correction reduces the perturbations caused by the Rayleigh scattering and the absorption of the mixing atmospheric molecules and aerosols (Vermote et al., 1997). In the analyzed dataset, the LEDAPS correction (ledapsSrc.20111121) acts primarily on reducing the effects of Rayleigh scattering at low reflectances of the visible bands and increasing the reflectance in the SWIR, which is otherwise reduced by aerosols and other gas molecules absorption (Ju et al., 2012). In our study the atmospheric correction has the effect of eliminating some of the random variations in the fractions that would otherwise appear from unmixing exoatmospheric reflectances. A comparison of the atmospherically corrected reflectances to the exoatmospheric reflectances shows the two variables to be strongly collinear with absolute differences less than 0.07 for more than 98% of pixels in all bands, indicating a reasonable performance of the LEDAPS code. For each of the 67 Landsat scenes used, one to four 30 × 30 km subscenes were chosen on the basis