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Global cross-calibration of Landsat spectral mixture models

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ABSTRACT

Data continuity for the Landsat program relies on accurate cross-calibration among sensors. The Landsat 8 Operational Land Imager (OLI) has been shown to exhibit superior performance to the sensors on Landsats 4–7 with respect to radiometric calibration, signal to noise, and geolocation. However, improvements to the positioning of the spectral response functions on the OLI have resulted in known biases for commonly used spectral indices because the new band responses integrate absorption features differently from previous Landsat sensors. The objective of this analysis is to quantify the impact of these changes on linear spectral mixture models that use imagery collected by different Landsat sensors. The 2013 underflight of Landsat 7 and Landsat 8 provides an opportunity to cross calibrate the spectral mixing spaces of the ETM+ and OLI sensors using near-simultaneous acquisitions of radiance measurements from a wide variety of land cover types worldwide. We use 80,910,343 pairs of OLI and ETM+ spectra to characterize the Landsat 8 OLI spectral mixing space and perform a cross-calibration with Landsat 7 ETM+. This new global collection of Landsat spectra spans a greater spectral diversity than those used in prior studies and the resulting Substrate, Vegetation, and Dark (SVD) spectral endmembers (EMs) supplant prior global Landsat EMs. We find only minor ($-0.01 < \mu < 0.01$) differences between SVD fractions for coregistered pairs of spectra unmixed using the new sensor-specific endmembers identified in this analysis. Root mean square (RMS) misfit fractions are also shown to be small (<98% of pixels with <5% RMS), in accord with previous studies using standardized global endmembers. Finally, vegetation is used as an example to illustrate the empirical and theoretical relationship between commonly used spectral indices and subpixel fractions. We include the new global ETM+ and OLI EMs as Supplementary Materials. SVD fractions unmixed using global EMs thus provide easily computable, linearly scalable, physically based measures of subpixel land cover area which can be compared accurately across the entire Landsat 4–8 archive without introducing any additional cross-sensor corrections.

1. Introduction

The Landsat program provides the longest continuous record of satellite imaging of the Earth available to the scientific community (Wulder et al., 2016). One great strength of this record lies in data continuity provided by the generally excellent cross-calibration between the sensors on board the different satellites (Markham and Helder, 2012). To extend this continuity into the future, the Operational Land Imager (OLI) onboard Landsat 8 must be intercalibrated with the rest of the archive. Over the 3+ years since launch, the OLI has been shown to exhibit superior performance to previous Landsat sensors with respect to radiometric calibration (Mishra et al., 2016; Morfitt et al., 2015), signal to noise (Knight and Kvaran, 2014; Morfitt et al., 2015; Schott et al., 2016), and geolocation (Storey et al., 2014).

One of the applications enabled by such a deep archive of high quality Earth observation data is multitemporal analysis to study long-baseline changes (Vogelmann et al., 2016). However, concern has recently emerged over the direct intermixing of data collected by both the OLI and older TM/ETM+ instruments onboard Landsats 4–7 because of the changes in band placement introduced with Landsat 8 (Holden and Woodcock, 2016). Statistical corrections and corresponding transfer functions have been introduced to correct for these differences (Roy et al., 2016). Considerable work has been done to examine the effect of these discrepancies and corrections in the context of spectral indices. The implications of these changes for spectral mixture analysis (SMA) are different than for spectral indices. The implications for multi-sensor and multitemporal SMA have been investigated on the regional scale by (Flood, 2014), but, to our knowledge, no attempt has been made to address these implications for globally standardized spectral mixture models.

The purpose of this study is to characterize the global Landsat 8 OLI spectral mixing space and cross-calibrate it with the Landsat 4–7 TM/ETM+ spectral mixing space. Previous work has shown the TM and ETM+ sensors to provide globally consistent results for Substrate, Vegetation, and Dark (SVD) subpixel fraction estimates using SMA (Small, 2004; Small and Milesi, 2013). Extending this cross-calibration to

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include imagery from the OLI onboard Landsat 8 could thus extend this consistency across the entire 30+ year archive of Landsat 4–8 imagery. In order to develop a cross calibration suitable for multi-sensor SMA, it is necessary to compare spectral mixing spaces for both sensors and identify comparable spectral endmembers that span both spaces. Under ideal circumstances, this would require spectrally diverse collections of TM/ETM+ and OLI spectra where both sensors image the same targets simultaneously.

Before Landsat 8 was placed into its final orbit, it was maneuvered into underflight configuration below Landsat 7 for one day: March 30 (Julian Day 89) 2013. While the two satellites were positioned in this way, they imaged a diversity of land cover spanning a wide range of spectral reflectance signatures. Each pair of ETM+/OLI images was collected approximately 2–5 min apart. The short temporal baseline between image pairs minimizes changes in solar illumination, surface processes and atmospheric effects. The underflight imagery thus provides a rare, nearly ideal opportunity for cross-calibration of the OLI and ETM+ sensors.

However, while the underflight dataset is nearly ideal for this purpose in many ways, there are some caveats. Standard LaSRC surface reflectance is not available for the OLI underflight data, so this analysis is limited to exoatmospheric reflectance with no atmospheric correction attempted. Furthermore, this analysis is both retrospective and global in extent, limiting the results of this study to that of an intercomparison and cross-calibration, but not a full field validation. We suggest that the unique, near-synchronous imaging geometry of the underflight data provides valuable information that is worth exploring despite these limitations.

In this study, we use 80,910,343 unsaturated broadband spectra imaged nearly simultaneously by Landsat 7 and Landsat 8 while flown in underflight configuration to address the following question: How reliably can subpixel Substrate, Vegetation and Dark (SVD) fractions be used interchangeably between ETM+ and OLI?

We find that the subscenes chosen for this analysis span an even greater range of the Landsat spectral mixing space than previous (Small, 2004; Small and Milesi, 2013) studies. We suggest that endmembers (EMs) generated for this study can thus effectively replace previous global EMs. While the new Dark (D) EM does not differ substantially from previous EMs, small differences in the Vegetation (V) EM and larger differences in the Substrate (S) EM are apparent. The overall behavior of the model is consistent with the findings of (Flood, 2014). The differences in the Vegetation EM are consistent with the findings of (Holden and Woodcock, 2016; Roy et al., 2016) as being a result of band placement. The differences in the Substrate EM are likely due to the wider range of global substrates present in this study than in any previous global study and constitute an improvement upon previous global models.

As a result, we find that subpixel estimates of SVD fractions for Landsat 8 using the old and new EMs display strong linear relations, with estimates of subpixel V fraction essentially unchanged and with easily correctible biases for S and D. When compared with the new EMs, all three SVD fractions scale linearly between the sensors with minimal ($\mu = -0.01$ to 0.01) bias. Root-mean-square (RMS) misfit to the SVD model for both the old and the new EMs is generally small, with >98% of all pixels showing <5% error.

Finally, we use vegetation as an example to show the relationship between commonly used spectral indices and subpixel EM fractions produced by SMA of Landsat 8. We suggest that fractions estimated by SMA from global EMs provide easily computable, linearly scalable, physically based measures of subpixel land cover which can be compared accurately across the entire Landsat 4–8 archive without introducing any additional cross-sensor corrections.

2. Background

a. *Implications of spectral band positioning*

The spectral response function of a sensor quantitatively defines its sensitivity to different wavelengths of light. The radiometric design of the Landsat 8 OLI featured an improvement on the previous TM/ETM+ sensors by modifying its spectral response function to narrow and slightly relocate several of the spectral bands. This has the effect of reducing the impact of common atmospheric absorptions which impede imaging the land surface (Mishra et al., 2016). However, it also has the effect of subtly changing the broadband spectrum imaged by OLI for any object which is not spectrally flat over the wavelengths for which the spectral response function was modified.

Fig. 1 shows the effect of the different spectral responses of the OLI and ETM+ sensors. Four sample green vegetation spectra (column 1) are shown, as well as four sample mineral spectra (column 3) from the USGS spectral library. The response functions of the two Landsat sensors are plotted as well to demonstrate the portions of the spectrum over which they are sensitive. The narrowing and slight adjustment to the position of the NIR and SWIR bands (black, cyan, and gold) are evident. Superimposed on each of these spectra are simulated Landsat 7 and 8 broadband spectra computed by convolving the reflectance spectra with the response functions of the sensors as described above.

Column 2 shows the difference between the OLI and ETM+ reflectances derived from the laboratory spectra. The essential shape and fundamental characteristics of the spectra are all very similar, but perceptible differences in the spectra are detectible. While the differences in aggregate are generally <0.01 reflectance units (<5%), the differences can approach 0.02 reflectance units (10%) for individual bands in some cases.

b. *Spectral mixture models and linear spectral unmixing*

At the scale of the 30 m Landsat pixel, most landscapes are spectrally heterogeneous. As a result, most pixels imaged by Landsat sensors are spectral mixtures of different materials (e.g. soils, vegetation, water, etc) with varying amounts of subpixel shadow. The continuum of aggregate radiance spectra imaged by a sensor forms a spectral mixing space in which each pixel occupies a location determined by the relative abundance of material reflectances imaged in the Ground Instantaneous Field Of View (GIFOV) of the pixel. In situations where multiple scattering among subpixel targets is small compared to single scattering from each subpixel target to the sensor, the aggregate response of the sensor often varies in proportion to the relative abundance of the spectrally distinct materials (Singer and McCord, 1979).

The topology of the full space of radiance (or equivalently reflectance) spectra reveals the linearity of mixing and the composition of the spectral endmembers and mixtures that bound the space of all other observed spectral mixtures (Boardman, 1993). In the case of decameter resolution sensors like those on the Landsat satellites, the combination of spatial and spectral resolution, and positioning of the spectral bands, resolves characteristics of reflectance spectra that distinguish the most spectrally distinct materials commonly found in landscapes. Ice, snow, rock and soil substrates, vegetation, and water each represent a general class of reflectance spectra that are clearly distinguishable with broadband sensors at decameter spatial scales (Small, 2004). Of these, the aggregate broadband reflectances of most landscapes can be represented accurately as linear mixtures of substrate (S), vegetation (V) and dark (D) endmembers. The dark endmember corresponds to either absorptive, transmissive or non-illuminated surfaces and typically represents either shadow or water. As a result, linear combinations of these three spectral endmembers can represent the aggregate reflectance of a very wide range of landscapes at meter to decameter scales (Small and Milesi, 2013).

By identifying the SVD endmember spectra that bound the spectral mixing space, it is possible to use these endmembers together with a linear spectral mixture model to project the 6D feature space of the Landsat sensors onto a simpler 3D mixing space bounded by spectrally and functionally distinct components of a wide range of landscapes (Adams et al., 1986). Inverting a simple three endmember linear spectral mixture model using the SVD endmembers yields estimates of