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Mapping northern land cover fractions using Landsat ETM+

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Abstract

The goal of fractional mapping is to obtain land cover fraction estimates within each pixel over a region. Using field, Ikonos and Landsat data at three sites in northern Canada, we evaluate a physical unmixing method against two modeling approaches to map five land cover fractions that include bare, grass, deciduous shrub, conifer, and water along an 1100 km north–south transect crossing the tree-line of northern Canada. Error analyses are presented to assess factors that affect fractional mapping results, including modeling method (linear least squares inversion (LLSI) vs. linear regression vs. regression trees), number of Landsat spectral bands (3 vs. 5), local and distant fraction estimation using locally and globally calibrated models, and spatial resolution (30 m vs. 90 m). The ultimate purpose of this study is to determine if reliable land cover fractions can be obtained for biophysical modeling over northern Canada from a three band, resampled 90 m Landsat ETM+ mosaic north of the tree-line. Of the three modeling methods tested, linear regression and regression trees with five spectral bands produced the best local fraction estimates, while LLSI produced comparable results when unmixing was sufficiently determined. However, distant fraction estimation using both locally and globally calibrated models was most accurate using the three spectral bands available in the Landsat mosaic of northern Canada at 30 m resolution, and only slightly worse at 90 m resolution. While local calibrations produced more accurate fractions than global calibrations, application of local calibration models requires stratification of areas where local endmembers and models are representative. In the absence of such information, globally calibrated linear regression and regression trees to estimate separate fractions is an acceptable alternative, producing similar root mean square error, and an average absolute bias of less than 2%.

Keywords: Landsat ETM+; Spectral unmixing; Arctic; Vegetation; Land cover; Fractions; Ikonos

1. Background

Conventional satellite remote sensing land cover maps are based on hard classifiers, where pixels are assigned a single land cover label. In areas that are relatively homogeneous at the level of the minimum mapping unit (MMU) of moderate resolution sensors, single land cover labels may be appropriate. However, depending on the size of objects relative to the MMU and their spatial distribution, pixels may be composed of more than one object type, producing mixed pixels. Land cover legends used to generate a hard classification deal with the mixed pixel problem by including mixed land cover classes. For example, most land cover legends include a mixed forest class composed of both conifer and deciduous land cover classes. Hard classifiers can map forested areas well due to the fact that trees are large objects relative to the MMU, and often occur in stands that are relatively homogeneous at that scale. In tundra environments north of the tree line, objects such as shrubs are small relative to the MMU and their distribution tends to be governed by microclimate and microtopography, generally leading to mixed pixels.

Tundra land cover classes in many legends such as the Circumpolar Arctic Vegetation Map (CAVM) legend (Walker et al., 2002) and the modified Federal Geographic Data Committee National Vegetation Classification System (FGDC-NVCS) legend (Cihlar et al., 2003) contain many classes that are composed of several vegetation types mixed with bare soil or rock, and are described by the relative fraction each occupies in descending order. These legends do not provide quantitative fraction thresholds in the label descriptions to differentiate among classes. Rather, they are intended to be used in a more

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qualitative manner, which is in contrast to forest land cover classes that are often based on quantitative descriptions of percent tree type and cover. Describing the percentage occurrence of relatively pure land cover fractions that comprise pixels provides a quantitative land cover description. Mapping land cover fractions has the added benefit of allowing subtle spatial or temporal changes to be detected, and facilitates scaling land cover information to coarser resolutions through summation of finer scale fractions within the coarse scale pixel. Hard classifiers present difficulties doing this when several fine scale land cover types combine to produce a different land cover class within the coarse resolution pixel. For example, deciduous and coniferous fine scale forest pixels combine to produce a mixed forest pixel at a coarser resolution.

Physical linear mixture modeling is based on the energy conservation law in physics, which proposes that pixels can be represented by the linear combination of areal fractions of pure endmember signatures within the pixel instantaneous field of view (IFOV) (Drake et al., 1999). Pure reference spectral signatures are referred to as endmembers (EM) because they represent the case where 100% of the sensor's field of view is occupied by a single cover type (Lillesand & Kiefer, 2000). Strictly speaking, EMs are located at the extreme ends of a multidimensional scatter plot, but when determined in this manner, they sometimes do not represent a single meaningful cover type. In the current study, EMs are selected based on the definition by Lillesand and Kiefer (2000) as single, meaningful land cover types.

Spectral unmixing has frequently been performed to estimate a small number of sub-pixel EM fractions from Landsat imagery. The number and type of fractions are often determined based on limitations related to both unmixing method and inherent dimensionality of the spectral data. These constraints sometimes do not allow unmixing of the number or type of EMs required to model biophysical attributes on a landscape. In the current study, we make a distinction between spectral unmixing as the use of spectral endmembers input into a physical mixture model, as opposed to fractional mapping, whereby fractions may be derived through a number of modeling methods.

Numerous studies have applied linear spectral unmixing to characterize land cover as a mixture of a few, simple EM types related to the dimensionality of Landsat data. Kauth and Thomas (1976) estimated the dimensionality of Landsat multispectral imagery in developing the Kauth–Thomas Tasseled Cap transformation to derive wetness, brightness and greenness indices. In an analysis of Landsat ETM+ mixing space across a broad range of spectrally diverse land cover types using Principal Components Analysis (PCA), Small (2004) showed that more than 98% of the variance contained in the 6 reflectance channels of Landsat can be represented by the first three principal components explaining the variance in substrate, vegetation and dark surface EMs, but that all six components may contain spatially coherent information. Unmixing studies using Landsat imagery have also converged on a similar number and set of EMs related to the dimensionality of the data and methods used to unmix. Radeloff et al. (1999) applied linear unmixing to detect budworm defoliation using a three EM model consisting of shade, nonphotosynthethic vegetation and green vegetation. Ridd (1995) produced a linear unmixing model consisting of vegetation, impervious surface, and soil, which was later modified by Wu and Murray (2005) by including low and high albedo surfaces to account for variability of the impervious EM. The 3–4 general EMs normally unmixed from Landsat are limiting when attempting to characterize and map biophysical parameters across a landscape. An accurate biophysical description requires the vegetation EM to be broken down further into vegetation type.

Most image unmixing applications in the literature assume stable EM representation for all parts of the image. This assumption is not easily met, as EMs can vary from pixel to pixel within a scene (Song, 2005) or between scenes due to poor inter-scene calibration. Methods have been developed to deal with EM variability on a per-pixel basis, including the Multiple Endmember Spectral Mixture Analysis (MESMA) and the Carnegie Landsat Analysis System (CLAS). Both methods are similar in that they generate a large number of linear unmixing models using candidate EM signatures from field and image data, and select among them on a per-pixel basis to meet certain predefined error criteria. MESMA was developed in Roberts et al. (1998) and has been applied to map chaparral communities in Southern California to manage fire hazard. CLAS is an entire processing system that includes automatic atmospheric correction and spectral unmixing and has been used to map selective logging in the Amazon (Asner et al., 2005).

In an examination of EM variability in an urban environment, Song (2005) determined that mean EM signatures from the sampled distribution produce best vegetation unmixing results. In another study examining the effects of EM variability in predicting land cover from coarse (1 km) resolution data, Kerdiles and Grondona (1995) took NOAA-AVHRR land cover signatures from each of four windows and applied them using linear unmixing to the remaining three. They determined that the accuracy of fraction estimation decreased when signatures extracted from one window were applied to estimate fractions in another. Averaged land cover signatures from all four windows were found to improve overall fraction estimates. Thus, EM bias between regions implies that a local calibration is needed to achieve good local unmixing results. However, application of a locally calibrated unmixing model also requires knowledge of the area over which EMs are representative. In the absence of such information, global calibration using EM means sampled from all locations can produce acceptable global unmixing results.

A study by Fernandes et al. (2004) also considered the application of local EM signatures to unmix distant fractions. They compared 1 km fractional land cover and continuous field vegetation characteristic estimates from four different algorithms and validated using both proximate (<100 km) and distant (>400 km) Landsat land cover datasets. The four algorithms they compared included linear least-squares inversion (LLSI), a look-up table approach, artificial neural network, and linear regression calibration. Fractional land cover estimation was similar for the four methods for the proximate validation dataset, producing average root mean square errors (RMSE) in the range of 10–15% of Landsat land cover fractions. However, the distant treatment produced average RMSEs of 19–