Defining Shaded Spectra by Model Inversion for Spectral Unmixing of Hyperspectral Datasets – Theory and Preliminary Application

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***Abstract* – The potential of using hyperspectral imagery of canopies to retrieve vegetation and soil information using spectral mixture analysis (SMA) techniques has been the focus of several recent studies. The SMA method estimates the proportion of pixel area that can be attributed to a cover type with a unique spectral profile. Shaded leaf, shaded residue, and shaded soil areas are generally ignored, or treated as equivalent.**

This paper presents a method of determining shaded spectral reflectance profiles for component cover types by determining the mean multi-scattering ratio (the ratio of shaded-to-sunlit reflectance) and applying that mean to measured sunlit component spectral reflectance. In this method, the multi-scattering ratio is determined by FLAIR model inversion. The resulting component shaded spectral reflectance can then be used as part of the SMA.

I. Introduction

Hyperspectral remote sensing of vegetative canopies provide high spectral resolution imagery of large areas. Such imagery however typically consists of mixed pixels, a result of each sensor element's instantaneous field-of-view (iFOV) imaging more than one land cover class. These sub-pixel contributors to the remotely sensed signal can include such things as edge pixels of a transition boundary with a different land cover class, background contributions through gaps in the overstorey, and shaded surfaces visible to the sensing element. The contributions of each will depend on the spatial scale of the imagery and the view/solar illumination geometry at the time the imagery is acquired.

II. Methods

A. Spectral Unmixing

Spectral unmixing is one technique often used to determined the fraction of canopy components contributing to the observed spectral reflectance for each image pixel [1][2][3]. This requires the selection of spectral signatures for each component (endmembers), which can be either measured in the field, or extracted from the image itself.

Spectral samples measured directly in the field are often disturbed in some way, removing the influence of the components' spatial distribution (leaf angle distribution, clumping index, etc.) and canopy multiple scattering contributions to the spectral intensity. These influences are especially important to shaded endmember apparent spectral reflectance characteristics. On the other hand, when extracted from the image it is often difficult to find "pure" endmembers [4], where the pixel spectral signature is the same as the canopy component to be unmixed. In face of these difficulties, shaded components are often ignored, or grouped together to form one endmember, regardless of the spectral differences between each endmember. It is thus not surprising that some variability in the results frequently remains unexplained [1].

Once determined, the endmembers can be used to unmix the pixels of a hyperspectral image into fractional component compositions. Constrained linear spectral unmixing is one method that often demonstrates correlation to field measurements of component compositions. In this technique, the spectral reflectance of a pixel (BRF_p) is expressed as a linear sum of N endmembers, with non-negative fractional composition ($0 \le f_i \le 1$) of each endmember with reflectance R_i in each pixel, and with the sum of the factional compositions per pixel totalling 1. Assuming that there are n canopy overstorey contributing components and m background contributing components, the pixel reflectance can be expressed as:

$$BRF_p = \sum_n \left(f_n R_n + f_{zn} R_{zn} \right) + \sum_m \left(f_m R_m + f_{zm} R_{zm} \right) \qquad (1)$$

where z refers to shaded fractional and reflectance characteristics. Component spectral reflectance is defined as the ratio of the nadir reflected radiance from the component at its location within the canopy to the nadir reflected radiance which would be reflected by a 100% reflecting Lambertian panel located at the top of the canopy, above the target component. Thus a shaded reflectance (R_{zx}) will have spectral characteristics dependent on the sunlit reflectance (R_x) of the same component and the multiple scattering characteristics where that component is located. Such a definition matches the use of remote sensing, where spectral reflectance imagery is produced using the downwelling irradiance at the top of the canopy and not the multiple scattering characteristics within the canopy.

B. Hyperspectral inversion

Although seldom referred to in this manner, inversion of observed spectral reflectance using a semi-empirical model of canopy radiative transfer provides another technique to unmix an image and provide component spectral reflectance and fractional composition. In this case, the bidirectional reflectance factor of a canopy (BRF_c), the reflectance as a function of the view/illumination geometry, is modelled. Inversion refers to the process of using BRF_p from a canopy scene, taken over a range of view and/or solar geometries, as model input and extracting canopy parameters, such as component reflectance and effective leaf area index (*eLAI*).

Such a technique can be computationally difficult, often requiring approximations to various aspects of the radiative transfer problem to simplify the model [5][6]. This is especially true when attempting to model the reflectance characteristics of several scene components at once. What is often done instead is to assume that BRF_c can be described with a minimal number of mean component contributions.

One such model, FLAIR (**F**our-Scale **L**inear Model for **A**n**I**sotropic **R**eflectance) [6][7], has been developed for inversion of *BRF* data. Given a set of *BRF* data with a range of view/illumination geometries, FLAIR inversion provides coefficients which may be used to normalize given data to a set view/illumination geometry. These coefficients have also been successfully related to canopy *eLAI* and mean overstorey (R_t) and background (R_g) sunlit reflectance factors for boreal forest canopies [7]. Having been recently modified for inverting hyperspectral data [8], a multi-band FLAIR has been implemented in the Imaging Spectrometer Data Analysis System (ISDAS) [9] developed at the Natural Resources Canada – Canada Centre for Remote Sensing.

In short, FLAIR inversion models the *BRF* as consisting of four component contributors. In order to model the shaded contributions to the observed canopy reflectance, FLAIR (as with most canopy radiative transfer models) incorporates a description of the overstorey distribution and density over an area of several plant radius. *BRF*'s of several pixels spatially distributed in the imagery over the canopy of interest, and with a range of view/illumination geometry, are then used as input to the inversion. Inversion results are thus related to the canopy scene, and not to individual pixels within that scene. Thus a canopy reflectance is modelled as:

$$BRF_c = R_{zt} \times k_{zt} + R_{zg} \times k_{zg} + R_t \times k_t + R_g \times k_g \qquad (2)$$

where R_x are the four scene component mean reflectance factors. The four scene components are shaded overstorey (*zt*); shaded background (*zg*); directly sunlit overstorey (*t*); and directly sunlit background (*g*). k_j are the viewed proportions of the four scene components, functions of the view/illumination geometry and mean canopy *eLAI*.

III. Relating Spectral Unmixing And Inversion – Preliminary Directions

While constrained linear spectral unmixing focuses on sub-pixel fractional composition, and hyperspectral inversion focuses on sub-scene (multiple pixel) composition, there exists the potential of a synergic use of both.

One difficulty of endmember selection is the ability to determine the shaded endmember spectral reflectance. A method of obtaining this spectral signature is to first determine the spectral irradiance within the canopy due to multiple scattering and the diffuse sky. This can be accomplished through inversion to determine overstorey and background multi-scattering factors (MS_t and MS_g), where:

$$MS_t = R_{zt}/R_t \quad \text{and} \quad MS_g = R_{zg}/R_g \qquad (3)$$

Once derived, these multi-scattering factors can be applied to the pre-determined sunlit endmember spectral signatures and used as shaded endmembers during unmixing.

IV. Applying Multi-Scattering Factors To Endmember Spectral Signatures – A Test Case

As part of an agricultural study near Clinton, Ontario, airborne Probe-1 hyperspectral nadir imagery was obtained in conjunction with detailed ground surveys [1][4]. This included two overflights of a corn field taken mid- and late-morning, approximately 45 minutes apart, with a resulting change of solar zenith angle (θ_i) from 43° to 35°. BRF values were extracted from this imagery, with view zenith (θ_v) and azimuth angles determined for each image pixel, with θ_v ranging from nadir up to ~15°. Inversion of this data set was then performed.

With this small variation of θ_v and θ_i, initial inversion of this data set resulted in multiple possible results. Constraints were then applied, with the sunlit background reflectance parameter limited to the sunlit soil reflectance value extracted from the image, located where a vegetation-free patch of ground was prepared prior to the overflights. Inversion was then repeated using this constraint.

Resulting coefficients from the FLAIR inversion of this data set provided spectral multi-scattering factor coefficients for the canopy overstorey (mature corn crop) and background (soil). Sunlit overstorey spectral reflectance derived by inversion was larger in magnitude than that obtained image extraction using targets of dense patches of corn. Spectral signatures of corn from image extraction may be somewhat contaminated by contributions from background soil and shaded surfaces.

To examine the potential use of applying derived multi-scattering factors in linear spectral unmixing, the sunlit spectral reflectance factors used in the original study were multiplied by the appropriate spectral multi-scattering factors determined by FLAIR inversion to produce shaded endmembers for unmixing. As the corn overstorey spectral reflectance was obtained by image extraction, this spectra was not adjusted for this preliminary study, and was used as a combined sunlit/shaded vegetation spectra. Soil spectral

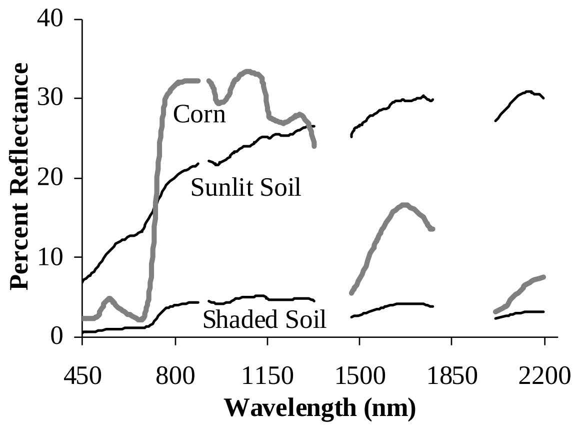

Fig. 1. Reflectance signatures used for linear unmixing of the corn field. Corn and Sunlit Soil spectral reflectance extracted from imagery, Shaded Soil spectral reflectance obtained using multi-scattering determined from scene BRF inversion with mFLAIR.

reflectance however was adjusted by the derived background multi-scattering factor to produce a shaded soil spectral reflectance. The corn field was then unmixed using these three endmembers (vegetation, sunlit soil, and shaded soil). The endmember spectral signatures are provided in Fig. 1.

Results of unmixing these endmembers resulted in a decrease of vegetation fraction and an increase of soil fraction compared to the initial unmixing. Table 1 shows how the endmember fractions changed at five sample sites within the field. Note how the new endmember fractions are more comparable to the in-field measurements taken during the Clinton study [1].

TABLE 1.
Endmember fractions from spectral linear unmixing of the corn field from sample plot locations.

	From Vertical Photographs		From Image Endmember Extraction		From Image Endmember Extraction and Multiple Scattering Contributions		
Site ID	Soil	Corn	Soil	Corn	Sunlit Soil	Shade Soil	Corn
377-38	0.19	0.81	0.03	0.97	0.00	0.18	0.82
362-57	0.22	0.78	0.02	0.98	0.00	0.09	0.91
343-80	0.14	0.86	0.01	0.99	0.00	0.11	0.89
331-95	0.13	0.87	0.02	0.98	0.00	0.14	0.86
315-101	0.21	0.79	0.06	0.94	0.02	0.21	0.77
Scene Average	0.18	0.82	0.03	0.97	0.01	0.14	0.85

V. Discussion – Conclusion

This preliminary study has demonstrated that scene inversion with a BRDF model such as FLAIR can be successfully used to help define shaded endmember spectral signatures for spectral linear unmixing efforts. This assumes that the scene being investigated is uniform in species composition and density. More detailed investigation with corn and other agricultural crops, as well as boreal forest canopies, are planned.

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