Leaf Area Index Estimation Using MESMA Based on EO-1 Hyperion Satellite Imagery

Zhaoming Zhang, Guojin He, Qin Dai, and Hong Jiang

***Abstract*—Leaf area index (LAI) is an important surface biophysical parameter used by many process-oriented ecosystem models. Traditionally, remote sensing based techniques to estimate LAI have either been based on the empirical–statistical approach that relates ground-measured LAI to the spectral vegetation indices, or on a radiative transfer modeling approach. However, both approaches have their limitations. In recent years, much effort has been expended to develop new remote sensing based LAI estimation methods. Multiple endmember spectral mixture analysis (MESMA) is an important one in the newly developed LAI retrieval methods. The aim of this study is to test the effectiveness of MESMA in LAI retrieval of broad-leaf forest in Asian subtropical monsoon climate region. In this study, EO-1 hyperion hyper-spectral imagery acquired on May 22rd, 2012 was employed to carry out an experiment on the MESMA method to estimate LAI in the forested area of Yongan county, Fujian province, located in southeast of China. MESMA based LAI estimation model for broad-leaf forest in the study area were finally formulated. The result shows MESMA method can achieve a good LAI estimation result.**

***Index Terms*—Leaf area index, hyper-spectral satellite imagery, MESMA.**

I. Introduction

Leaf area index (LAI) is an important biophysical parameter, which is widely used in many fields, such as forestry, ecology, and global change studies. The most suitable way to acquire LAI is using remote sensing technology, especially for a large study area. Considerable effort has been made to develop remote sensing based LAI estimation methods in the past two decades. There are generally two ways to estimate LAI from remotely sensed imagery: the empirical–statistical approach or the radiative transfer modeling approach. The first method establishes LAI estimation models by statistically fitting ground-measured LAI to the corresponding spectral vegetation index or spectral reflectance. This method is simple and easy to implement, however, the major limitation of this approach is its lack of generality, which is dependent on different sites and vegetation types. The second method is based on the inversion of a physically based canopy reflectance model. The most advantage of this method is that it is physically based and independent of vegetation types [1]. However, the method suffers from the ill posed nature of model inversion [2], [3]. Due to the inevitable limitations of the aforementioned two methods, in the past years, great effort has been made to develop new remote sensing based LAI estimate approaches and various approaches has emerged, including reduced major axis (RMA) regression analysis [4], [5], the red edge inflection point (REIP) method based on hyperspectral remotely sensed imagery [6]-[8], and linear spectral mixture analysis (LSMA) [9], [10]. The LSMA approach has been demonstrated to be a promising way to map tree LAI in forest ecosystems [11], [12]. LSMA decomposes an image pixel into three-endmember (sunlit canopy, sunlit background, and shadow), and the number and spectrum of endmembers between different pixels are fixed not considering the spatial heterogeneity of endmembers. As an improved version of LSMA, Multiple endmember spectral mixture analysis (MESMA) takes into account the spectral variability within endmembers and optionally allows the number of endmembers to vary on a per-pixel basis to better meet the actual condition of natural surfaces. MESMA approach has been tested in ombrotrophic peatlands for tree and shrub LAI mapping, and satisfactory results were achieved [13]. Furthermore, LAI retrieval studies for broad leaf forest in Asian subtropical monsoon climate region using hyper-spectral remotely sensed satellite data were scarcely reported. It is of great importance to carry out such research. Therefore, the aim of this paper is to conduct a study on broad leaf forest LAI estimation using MESMA approach in yongan county, Fujian province, China, based on an EO-1 Hyperion hyper-spectral satellite imagery.

II. Datasets and Processing

Yong'an county, situated in central Fujian, is one of the 48 key forestry districts and counties (cities) in the south of China, with forest coverage reached 83.2%. Yong'an has a subtropical oceanic monsoon climate. Broad-leaf forest is a major forest type in Yong'an county and Fujian province, and the main aim of this study was to develop LAI retrieval models of the broad-leaf forest in yong'an county based on MESMA approach.

EO-1 satellite was launched on November 21, 2000 by the National Aeronautics and Space Administration (NASA) as part of a one-year technology validation and demonstration mission. Three primary instruments are aboard the EO-1 spacecraft; they are the Advanced Land Imager (ALI), the Hyperion, and the Linear Etalon Imaging Spectrometer Array (LEISA) Atmospheric Corrector (LAC). The Advanced Land

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Imager (ALI) instrument on EO-1 was used to validate and demonstrate technology for the Landsat Data Continuity Mission (LDCM)/Landsat 8, the eighth in the series of Landsat satellites, which was launched on February 11, 2013. Hyperion is a hyper-spectral sensor which offers data in 242 spectral bands. EO-1 Hyperion offers the highest available spectral resolution in the field of satellite-borne remote sensing systems.

The Hyperion, a high resolution hyper-spectral imager, covers 242 contiguous spectral bands (from 0.4 to 2.5 μm) with a spatial resolution of 30-meter, the same as the Landsat series. The instrument can provide a satellite image as large as 7.5 km by 100 km, in very fine spectral resolution and high radiometric accuracy. Table 1 lists the features of EO-1/ Hyperion.

The original EO-1 Mission was successfully accomplished in November 2001. Because of the outstanding features of EO-1 instruments, the remote sensing research and scientific communities expressed high interest in continued acquisition of EO-1 image data. In order to meet the need of the remote sensing research and scientific communities, an Extended Mission of EO-1 Program was approved by NASA and the United States Geological Survey (USGS) to continue acquisition of EO-1 data.The EO-1 Extended Mission is chartered to collect and distribute ALI multispectral and Hyperion hyper-spectral products in response to user Data Acquisition Requests (DARs). Under the Extended Mission provisions, image data acquired by EO-1 are archived and distributed by the USGS Center for Earth Resources Observation and Science (EROS) and placed in the public domain.

EO-1 Hyperion data employed in this study was acquired on May 22rd, 2012. In July of 2012, a field campaign was launched to collect ground LAI data, and a total of 24 sample plots were collected.

Ground LAI measurements were made using the instrument of Plant Canopy Analyzer (PCA), LAI-2000 [14] (LI-COR Inc., Lincoln, NE, USA). The LAI-2000 measures the gap fraction in five zenith angles, which ranges from 0 °to 75 °. Effective LAI (denoted as L_e) are finally got from the measured gap fraction data under the assumption of a random spatial distribution of leaves (equation 1), which is generally the truth for the broad-leaf forest in yong'an county, Fujian province.

TABLE I: FEATURES OF EO-1/HYPERION

Features	EO-1/ Hyperion
Spectral Range	0.4-2.5 microns
Visible Bands	35
Near Infrared Bands	35
Spectral Coverage	Continuous
Short Wave Infrared Bands	172
Spatial Resolution	30m
Swath Width	7.5km

Theoretically, the effective LAI (L_e) can be accurately obtained from formula (1) using the LAI-2000 instrument based on the Miller theory:

$$L_e = 2\int_0^{\pi/2} \ln\left[\frac{1}{P(\theta)}\right]\cos\theta\sin\theta d\theta \qquad (1)$$

where $P(\theta)$ is the measured canopy gap fraction at zenith angle θ, which is the best when averaged over the entire azimuthal angle range. In order to obtain L_e accurately, hemispherical $P(\theta)$ data must be known, which can be obtained by LAI-2000 instrument through sensing the diffuse radiation from the sky over the hemisphere.

A. Remotely Sensed Data Preprocessing and Reflectance Estimation

Radiometric calibration was firstly performed to the Hyperion Level 1 data to convert the digital numbers to spectral radiance by using the gains and offsets.

The atmosphere exerts an influence on the radiance values recorded by satellite sensors by scattering, absorbing and refracting light; when land surface reflectance is retrieved, atmospheric correction must be performed to compensate atmospheric effects in satellite scenes.

Considerable efforts have been made to develop atmospheric correction algorithms for remotely sensed satellite imagery. Most of the more sophisticated atmospheric correction methods make use of radiative transfer codes (such as Modtran and 6S). Studies have shown that these radiative transfer codes based atmospheric correction algorithms can accurately convert spectral radiances to land surface reflectances.

FLAASH (fast line-of-sight atmospheric analysis of spectral hypercubes) is a first-principles atmospheric correction tool that corrects wavelengths in the visible through near-infrared and shortwave infrared regions, up to 3 μm. Unlike many other atmospheric correction programs that interpolate radiation transfer properties from a pre-calculated database of modeling results, FLAASH incorporates the MODTRAN4 radiation transfer code. FLAASH also includes the following features: Correction for the adjacency effect (pixel mixing due to scattering of surface-reflected radiance); An option to compute a scene-average visibility (aerosol/haze amount). FLAASH uses the most advanced techniques for handling particularly stressing atmospheric conditions, such as the presence of clouds; Adjustable spectral polishing for artifact suppression.

FLAASH supports hyperspectral (A term used to describe data sets typically composed of 100 to 200 (or more) spectral bands of relatively narrow, contiguous, bands (5 to 10 nm). Hyperspectral imaging creates a large number of images from contiguous regions of the electromagnetic spectrum. This increases sampling of the spectrum (versus multispectral data) and greatly increases the amount of information available to a researcher.) sensors (HyMAP, AVIRIS, HYDICE, HYPERION, Probe-1, CASI, and AISA) and multispectral sensors (ASTERA, AVHRR, GeoEye-1, IKONOS, IRS, Landsat, QuickBird, RapidEye, SPOT, and WorldView-2). Water vapor and aerosol retrieval are only

possible when the image contains bands in appropriate wavelength positions. In addition, FLAASH can correct images collected in either vertical (nadir, The point on the ground that lies vertically beneath the perspective center of the aerial camera lens or satellite sensor.) or slant-viewing geometries.

Atmospheric correction was finally conducted to convert the Hyperion radiance values into land surface reflectance with the FLAASH module in ENVI software. Input parameters of FLAASH model for the Hyperion image are as follows: Sensor altitude:705km; ground elevation: 0.6km; pixel size: 30m; flight date: May 22nd, 2012; flight time: 02:19:30; atmospheric model: Mid-latitude-summer; aerosol model: rural; water retrievel: Yes; aerosol retrieval: 2-Band(K-T); initial visibility:40km; aerosol scale height:2km; co_2 mixing ratio: 390ppm; modtran resolution: 5/cm; modtran multiscatter model: Scaled DISORT; number of DISORT streams:8.

III. LAI Retrieval with the Mesma Approach

The Hyperion sensor on board EO-1 provides a new class of Earth observation data for improved Earth surface characterization. Unlike the most other imaging spectrometers, Hyperion capabilities provide a spectral resolution of earth surface properties into 220 spectral bands. Through these spectral bands, complex land eco-systems can be mapped and accurately interpreted in the finest spectral resolution.

There are a total of 242 unique spectral channels collected with a complete spectrum covering from 357 - 2576 nm. The Level 1 Radiometric product stores 242 bands but only 198 bands are calibrated. Because of an overlap between the VNIR (Visible and Near Infrared) and SWIR (Short Wave Infrared) focal planes, there are only 196 unique channels. Calibrated channels are 8-57 for the VNIR, and 77-224 for the SWIR. The reason for not calibrating all 242 channels is mainly due to the detectors' low responsivity. The bands that are not calibrated are set to value of one in those channels.

Linear spectral mixture decomposition was accomplished with VIPER Tools developed at the Department of Geography at University of California Santa Barbara as an add-on for the ENVI software package (http://www.vipertools.org). A spectral mixing technique called Multiple Endmember Spectral Mixture Analysis (MESMA) is at the core of VIPER Tools. MESMA is an extension of simple Spectral Mixture Analysis (SMA). In simple SMA, a spectrum is modeled as the sum of “pure spectra” called endmembers, each weighted by the fraction of an endmember required to produce the mixture. SAM fails to account for variability of endmember number and types within a pixel, which must be considered, especially for heterogeneous land surfaces. MESMA improves SMA by allowing the number and types of endmembers to vary on a per-pixel basis.

VIPER Tools provides a set of key analysis tools for creating and managing spectral libraries, selecting optimal endmembers for SMA/MESMA, calculating SMA and MESMA fractions, and post-processing of SMA/MESMA outputs (VIPER Tools provides the option to shade normalize or apply an empirically-based terrain correction of SMA/MESMA results when topography and solar geometry are known. The current version (version 1.5) of VIPER Tools includes 12 main processing options: 1. Spectral Library Development Tools (Create Spectral Library from ROIs, Create Metadata for Spectral Library, View Spectral Library (*BETA*), Manage Spectral Libraries, and Convert Library to Image (*BETA*)); VIPER Tools provides several tools for creating, describing and managing spectral libraries. Generate spectral libraries using image spectra extracted from one or more Regions of Interest (ROIs) in an image. Take advantage of VIPER Tools' open and flexible format for spectral library metadata to more effectively manage spectral libraries. Utilize new tools for merging, scaling and sorting spectral libraries.Starting with version 1.3, VIPER Tools contains a new Spectral Library Viewer that allows users to display spectra while simultaneously exploring the associated metadata and viewing field photographs, if available. The Spectral Library Viewer provides an intuitive interface for viewing, sorting, and subsetting spectral libraries based on their spectral properties or their metadata. 2. Optimum Endmember Selection Tools (Create Square Array, Calculate EAR/MASA/CoB (EMC), View EMC File, and CRES); Four techniques used for identifying optimal endmembers from a spectral library are included in VIPER Tools:Count-based Endmember Selection(CoB), Endmember Average RMSE (EAR), Minimum Average Spectral Angle (MASA) and Constrained Reference Endmember Selection (CRES).3. Spectral Mixing Tools (Run SMA/MESMA, Shade Normalize SMA Results, and Terrain Correct SMA Results). Calculate SMA Fractions and Determine Best-fit Models - The SMA module is the core of VIPER Tools and allows for flexible and robust implementation of SMA and MESMA with an optional range of constraints, numbers and types of endmembers, models and more.

An important step in MESMA is endmember spectra extraction. Four approaches are commonly used in endmember spectra selection. 1) Obtain the endmember spectra from a spectrum library. 2) Derive the endmember spectra from the pure pixels of the image itself. 3) Automatically obtain endmember spectra using factor analysis. 4) Automatically construct endmember spectra using convex geometry [10]. For lack of field observations, the endmember spectra were extracted from the image itself by use of the VIPER Tools. Fig. 1- Fig. 3 demonstrate the derived endmember spectra of sunlit canopy, sunlit background, and shadow.

Fractions of the three endmembers (sunlit canopy, sunlit background, and shadow) were finally derived with the VIPER Tools. Each fraction was correlated to the corresponding ground–measured LAI to establish an empirical–statistical relationship. It was found that the sunlit canopy fraction exhibits the strongest correlation with field-measured LAI. The regression relationship between sunlit canopy fraction (SCF) and LAI is expressed as follows:

$$\mathrm{LAI} = 2.779e^{0.374SCF} \qquad (R^2=0.37) \qquad (2)$$

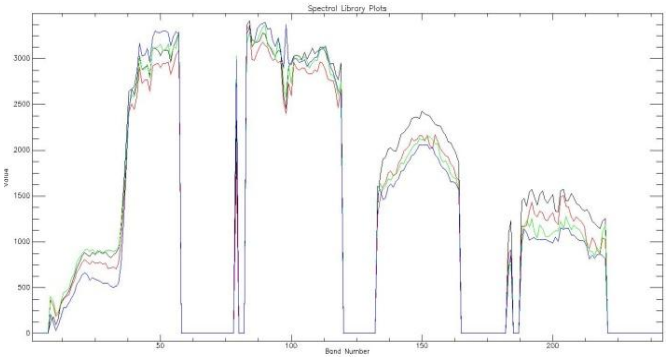

Fig. 1. Spectra of sunlit background.

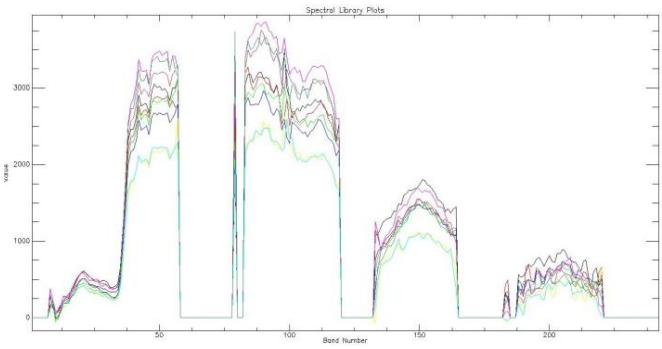

Fig. 2. Spectra of sunlit canopy.

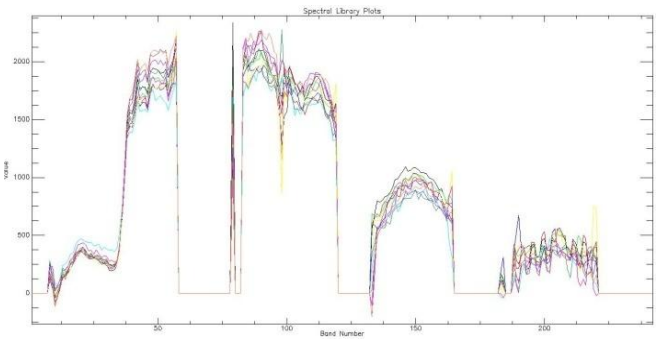

Fig. 3. Spectra of shadow.

As can be seen from equation 2, the R^2 (coefficient of determination) reaches 0.37, not very high. Possible reasons may be in this study, the endmember spectra were extracted from the image itself. The precision can be improved if field-measured endmember spectra were used.

IV. Conclusion

EO-1 hyperion hyper-spectral satellite imagery acquired on May 22rd, 2012 was employed in this study to test the effectiveness of a newly proposed LAI estimation approach, named MESMA, in the forested area of Yongan county, Fujian province. The result shows MESMA based LAI estimation method can achieve satisfactory accuracy despite lack of field measured data.

References

[1] Z. M. Zhang, G. J. He, X. Q. Wang, and J. Hong, "Leaf area index estimation of bamboo forest in Fujian province based on IRS P6 LISS3 imagery," *International Journal of Remote Sensing*, vol. 32, pp. 5365-5379, 2011.

[2] B. Combal, F. Baret, M. Weiss, A. Trubuil, D. Mace, A. Pragnere, R. Myneni, Y. Knyazikhin, and L. Wang, "Retrieval of canopy biophysical variables from bidirectional reflectance: using prior information to solve the ill-posed inverse problem," *Remote Sensing of Environment*, vol. 84, pp. 1−15, 2002.

[3] C. Atzberger, "Object-based retrieval of biophysical canopy variables using artificial neural nets and radiative transfer models," *Remote Sensing of Environment*, vol. 93, pp. 53-67, 2004.

[4] P. Curran and A. Hay, "The importance of measurement error for certain procedures in remote sensing at optical wavelengths," *Photogrammetric Engineering and Remote Sensing*, vol. 52, pp. 229–241, 1986.

[5] W. B. Cohen, T. K. Maiersperger, S. T. Gower, and D. P. Turner,"An improved strategy for regression of biophysical variables and Landsat ETM+ data," *Remote Sensing of Environment*, vol. 84, pp. 561−571, 2003.

[6] R. Pu, P. Gong, G. S. Biging, and M. R. Larrieu, "Extraction of red edge optical parameters from Hyperion data for estimation of forest leaf area index," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 41, pp. 916-921, 2003.

[7] R. Darvishzadeh, C. Atzberger, A. K. Skidmore, and A. A. Abkar, "Leaf area index derivation from hyperspectral vegetation indices and the red edge position," *International Journal of Remote Sensing*, vol.30, pp. 6199-6218, 2009.

[8] Z. M. Zhang, G. J. He, and J. Hong, "Leaf area index retrieval using red edge parameters based on hyperion hyper-spectral imagery," *Journal of Theoretical and Applied Information Technology*, vol. 48, pp. 957-960, 2013.

[9] D. R. Peddle, F. G. Hall, and E. F. Ledrew, "Spectral mixture analysis and geometric-optical reflectance modeling of boreal forest biophysical structure," *Remote Sensing of Environment*, vol. 67, pp. 288−297, 1999.

[10] B. Hu, J. R. Miller, J. M. Chen, and A. Hollinger, "Retrieval of canopy leaf area index in the BOREAS flux tower sites using linear spectral mixture analysis," *Remote Sensing of Environment*, vol. 89, pp. 176−188, 2004.

[11] F. G. Hall, Y. E. Shimabukuro, and K. F. Huemmerich, "Remote sensing of forest biophysical structure using mixture decomposition and geometric reflectance models," *Ecological Applications*, vol. 5, pp. 993−1013, 1995.

[12] R. J. Hall, D. P. Davidson, and D. R. Peddle, "Ground and remote sensing of leaf area index Rocky Mountain forest stands, Kananaskis, Alberta," *Canadian Journal of Remote Sensing*, vol. 29, pp. 411− 427, 2003.

[13] O. Sonnentag, J. Chen, and D. A. Roberts, "Mapping tree and shrub leaf area indices in an ombrotrophic peatland through multiple endmember spectral unmixing," *Remote Sensing of Environment*, vol. 109, pp. 342-360, 2007.

[14] J. M. Welles and J. M. Norman, "Instrument for indirect measurement of canopy architecture," *Agronomy Journal*, vol. 83, pp. 818–825, 1991.

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