APPLICATION OF WAVELET TRANSFORM ON HYPERSPECTRAL REFLECTANCE FOR SOYBEAN LAI ESTIMATION IN THE SONGNEN PLAIN, CHINA

Lu Dongmei[1], Kaishan Song[2], Zongming Wang[2], Jia Du[2], Lihong Zeng[2], Xiaochun Lei[2]*

[1]Computer Science and Engineering College, JLIAE, No. 1129, Hongqi Street, Changchun, China
[2]Northeast Institute of Geography and Agricultural Ecology,CAS, No. 3195, Gaoxin Road, Changchun, China
Email: songks@neigae.ac.cn; Tel:0431-85542364.

1. INTRODUCTION

Research has indicated that biochemical components, physical structure, water content have intimate relationship with spectral reflectance[1]. Numerous vegetation indices have been developed to detect environmental conditions of crops, usually by calculating ratios or linear combinations of two or more wavelengths within the visible and near-infrared (VNIR) region. Thought hyperspectral remotely sensed data can provide more information compared with multispectral remote sensing[2]. However, in practice, the data processing approaches that have so far been successfully applied to other multispectral data may not be effective for hyperspectral data processing. In the past two decades, wavelet transform (WT) has been developed as a powerful analytical tool of signal processing and is now being used in remote sensing applications and feature extraction[3]. Therefore, in this study, authors applied the WT techniques to automatically extract features from hyperspectral canopy reflectance data for estimation LAI; and compare the model prediction accuracy to those of spectral indices.

2. MATERIALS AND METHODOLOGY

Two years field works were conducted for this research during 2005-2006 over two agricultural sites in Songnen Plain representing a range of soybean cultivar and sites characteristics. The study area in 2005 is located in the rural area of Changchun (45°52′ N, 124°23′ E); and the second study area for 2006 is located in Hailun Agricultural Ecology Station (HAES). At the Changchun study site, four test fields, ranging in size from 0.3 to 0.6 ha, were chosen for ground sampling. Four soybean cultivars were planted, which represents different canopy structure and photosynthetic ability (the genotype are Jiyu47, Jinong10, Jilin28 and Tongnong11, respectively). For the HAES site, 23 sampling sites were chosen for ground measurements in 50 days after sowing. There were 16 sampling sites were planted with the same soybean genetic type for the comparative study induced by coupling effects of irrigation and fertilizer supply on harvest.

Hyperspectral data were obtained from the narrowband FieldSpec VNIR spectroradiometer from Analytical Spectral Devices (ASD) measuring spectra over a spectral range of 350–1050 nm. We measured soybean LAI using an *LAI-2000* Plant Canopy Analyzer (LI-COR Inc., Lincoln, NE, USA). The LAI measurement taken by the instrument is the ‘effective’ LAI[4]. The instructions for operating the LAI instrument were carefully followed to ensure that each LAI point was measured accurately. Each LAI measurement represents an average of 10 PCA readings taken along a specific transect in where canopy spectral reflectance collected.

In this paper, we selected the following vegetation ratio indices and briefly presented as: The Normalized Difference Vegetation Index (NDVI), as seen in Eq. (1):

$$NDVI = (R_{801} - R_{670})/(R_{801} + R_{670}) \tag{1}$$

The Soil-Adjusted Vegetation Index (SAVI) as shown in Eq. (2):

$$SAVI = (1+L)\times(R_{801} - R_{670})/(R_{801} + R_{670} + L) \tag{2}$$

And the Optimized SAVI (OSAVI) [see Eq. (3)]:

$$OSAVI = (1+0.16)\times(R_{801} - R_{670})/(R_{801} + R_{670} + 0.16) \tag{3}$$

The *MTVI2* [5] index as below:

$$MTVI2 = \frac{1.5\times\left[1.2\times(NIR-G) - 2.5\times(R-G)\right]}{\sqrt{(2\times NIR+1)^2 - (6\times NIR - 5\times\sqrt{R}) - 0.5}} \tag{4}$$

All the detail discussion on these spectral vegetation indices can be found in Haboudane et al [5].

There are many different types of wavelet mother functions. We tested most of wavelet families included in Wavelet Toolbox in Matlab that have proven to be especially useful. These include Daubechies family (‘dbN’), Biorthogonal family, Symlets (‘Sym’), Biorthogonal wavelets (‘Bior’), reverse biorthogonal wavelets (‘Rbio’), Discrete approximation of Meyer wavelet (‘dmey’), and Coiflets family (‘Coif’) as well. Based on correlation levels of results derived from different WTs with soybean LAI, we found correlation result generally fluctuated slightly derived from different WTs based upon various mother functions. Therefore, we performed a multilevel wavelet decomposition of a canopy spectral signal (n = 512) and implemented it with a Matlab function:

$$[C, L] = wavedec\,(s, p, 'motherwavelet') \tag{5}$$

where C is a vector that concatenates the wavelet coefficients of all the components of a p-level decomposition, that is, the pth-level approximation and the first p levels of details; vector L gives the lengths of each component; wavedec is a Matlab function of discrete multilevel wavelet decomposition; s is canopy spectral reflectance; and p is number of decomposition levels. After a set of DWT coefficients for each level or scale of a canopy spectrum is calculated by Eq. (6), the energy feature of the wavelet decomposition coefficients is computed at each scale for both approximation and details and is used to form an energy feature vector. The *1X* (p + 1) DWT energy feature vector = {Fj} is computed as

$$F_j = \sqrt{\frac{1}{K}\sum_{k=1}^{k} W_{jk}^2} \tag{6}$$

where K is number of coefficients at the decomposition level j, while W_{jk} is the kth coefficient at level j; p is the maximum number of decomposition levels; the length of the feature vector is $(p + 1)$ coming from p levels of detail coefficients and one level of final approximation coefficients

3. RESULT AND DISUCSSIONS

In this study, a program was compiled to find the optimal band combination for the empirical regression models based on spectral ratios. The best band combination pairs were applied with non-linear fitting methods, and the result were listed in Table.1. It can be seen from Table.1 that non-linear fitting method plays much better, and higher R^2 values can be obtained with those power, exponential regression models.

Table.1 The relationship between different spectral vegetation indices and LAI

		Model calibration (n = 100)		Model validation (n = 44)	
LAI	Regression model	R^2	$RMSE(m^2/m^2)$	R^2	$RMSE(m^2/m^2)$
NDVI	$y = 0.0214e^{5.658x}$	0.766	0.703	0.672	0.763
SAVI	$y = 0.1422e^{4.797x}$	0.925	0.363	0.897	0.434
OSAVI	$y = 0.4631e^{2.9023x}$	0.915	0.381	0.879	0.432
MTVI2	$y = 0.2597e^{3.337x}$	0.916	0.401	0.852	0.433
SUM_FDR	y = 6.6776x + 0.701	0.856	0.390	0.838	0.404

Table.2 The relationship between soybean canopy reflectance db3 wavelet transform and LAI

Wavelet energy coefficient	Model calibration Samples (n = 100)			Model validation Samples (n = 44)	
LAI	Regression model	R^2	$RMSE(m^2/m^2)$	R^2	$RMSE(m^2/m^2)$
First coef.	$y = 1.9088x - 3.0022$	0. 923	0.341	0.918	0.349
Second coef.	$y = 4.596x^{1.3503}$	0.938	0.343	0.927	0.357
Third coef.	$y = 9.739x^{1.4238}$	0.944	0.388	0.917	0.413
Fourth coef.	$y = 85.675x^{2.063}$	0.901	0.480	0.887	0.497
Fifth coef.	$y = 1423.9x^{2.324}$	0.757	0.652	0.725	0.680
Sixth coef.	$y = 22749x^{1.973}$	0. 857	0.481	0.831	0.507
Seventh coef.	$y = 140844x^{1.937}$	0.797	0.869	0.730	0.691
Eighth coef.	$y = 2334.6x + 0.0049$	0.302	1.090	0.228	1.109
Ninth coef.	$y = 4690x - 0.0857$	0.153	1.128	0.157	1.123

It can be found from Table.2 that the first to the seventh spectral wavelet coefficient have significant correlation with LAI, and still the determination coefficient derived from regression models based upon the second and the third produced higher R^2, which was 0.12 greater than that obtained from derivative reflectance derived from red edge region.

Different wavelet mother functions are applied in study for wavelet transform analysis, correlation between wavelet transform coefficients and LAI are conducted, and regression models are established by the selected highest correlative wavelet transform coefficient (Table.3). It can be seen from Table.3 that most wavelet mother functions are suitable for spectral reflectance feature extraction for regression models. The determination coefficient ranges 0.91 to 0.95.

Table.3 The relationship between various wavelet transform coefficient and LAI

Various mother wavelet functions	Model calibration (n = 100)			Model validation (n = 44)	
LAI	Regression model	R^2	$RMSE(m^2/m^2)$	R^2	$RMSE(m^2/m^2)$
db2	$y = 4.3897x^{1.38}$	0.950	0.341	0.934	0.406
db4	$y = 9.7391x^{1.424}$	0.944	0.355	0.921	0.387
db6	$y = 30.588x^{1.578}$	0.943	0.367	0.924	0.372
db8	$y = 5.5656x^{1.263}$	0.947	0.354	0.918	0.405
bior33	$y = 1.9088x - 3.0022$	0.923	0.341	0.927	0.381
bior68	$y = 18.256x^{1.445}$	0.948	0.353	0.931	0.379
rbior33	$y = 18.256x^{1.445}$	0.947	0.354	0.927	0.383
ciof5	$y = 13.101x^{1.263}$	0.948	0.350	0.925	0.396
dmey	$y = 388.87x^{1.655}$	0.924	0.428	0.913	0.431
sym8	$y = 1.910x - 3.012$	0.923	0.341	0.921	0.347

We investigated and measured soybean canopy reflectance in two study sites in the blacksoil belt of Songnen Plain, China, 144 samples were collected in 2005 and 2006 during 13 times of field works in the whole soybean growing stages. This investigation of wavelets transform has revealed that this technique can produce results that comparable with, and in some extent superior to, existing spectral approaches (including vegetation index) to LAI estimation from spectral reflectance data. Work still need be done to refine the wavelets transform technique by developing automated approaches for the selection of appropriate wavelet mother functions, application of the technique to mathematical transformed spectral reflectance (e.g. log (R), log (1/R), and spectral derivatives) for quantifying other vegetation parameters.

4. REFERENCES

[1]I.B. Strachan, E. Pattey, and J.B. Boisvert, “Impact of nitrogen and environmental conditions on corn as detected by hyperspectral reflectance,” *Remote Sensing of Environment*, Vol. 80, pp. 213-224, 2002.

[2]F. Baret, G. Guyot, and D. Major, “TSAVI: a vegetation index which minimizes soil brightness effects on LAI and APAR estimation,” *Proceedings of 12th Canadian Symposium on Remote Sensing and IGARSS’89*, Vancouver, Canada, pp. 1355– 1358,1989.

[3]S. Pittner, S.V. Kamarthi, “Feature extraction from wavelet coefficients for pattern recognition tasks,” *IEEE transactions on Pattern Analysis and Machine Intelligence*, Vol. 21, pp. 83– 88, 1999.

[4]J. Chen, J. Cihlar, “Retrieving leaf area index of boreal conifer forests using Landsat TM images,”*Remote Sensing of Environment*, Vol.55, pp.153– 162, 1996.

[5]D. Haboudane, J.R. Miller, E. Pattey, P.J. ZarcoTejada, and I.Strachan, “Hyperspectral vegetation indices and novel algorithms for predicting green LAI of crop canopies: modeling and validation in the context of precision agriculture,” *Remote sensing of environment*, Vol.90, pp. 337-352, 2004.