Comparing LAI Estimates of Corn and Soybean from Vegetation Indices of Multi-resolution Satellite Images

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Abstract : Leaf area index (LAI) is important in explaining the ability of the crop to intercept solar energy for biomass production and in understanding the impact of crop management practices. This paper describes a procedure for estimating LAI as a function of image-derived vegetation indices from temporal series of IKONOS, Landsat TM, and MODIS satellite images using empirical models and demonstrates its use with data collected at Missouri field sites. LAI data were obtained several times during the 2002 growing season at monitoring sites established in two central Missouri experimental fields, one planted to soybean (*Glycine max* L.) and the other planted to corn (*Zea mays* L.). Satellite images at varying spatial and spectral resolutions were acquired and the data were extracted to calculate normalized difference vegetation index (NDVI) after geometric and atmospheric correction. Linear, exponential, and expolinear models were developed to relate temporal NDVI to measured LAI data. Models using IKONOS NDVI estimated LAI of both soybean and corn better than those using Landsat TM or MODIS NDVI. Expolinear models provided more accurate results than linear or exponential models.

Key Words : leaf area index, NDVI, IKONOS, Landsat TM, MODIS, Missouri

1. Introduction

Leaf area index (LAI) was first introduced by Watson (1947) and defined as the ratio of leaf area to a given unit of land area, a ratio that is functionally linked to spectral reflectance. LAI is important in explaining the ability of the crop to intercept solar energy for biomass production and in understanding the impact of crop management practices. LAI

estimates in space and time from remotely sensed vegetation indices (VI) contribute to improve yield forecast.

VI's are dimensionless, radiometric measures that function as indicators of relative abundance and activity of green vegetation. A vegetation index should maximize sensitivity to plant biophysical parameters, normalize or model external effects such as sun angle, viewing angle, and the atmosphere, and

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normalize internal effects such as canopy background variations. In spectral signature analysis by remote sensing, vegetation indices that combine red and near-infrared bands are widely used for estimating the vitality and the productivity of vegetation. The cellular structure of leaf mesophyll strongly scatters and reflects near-infrared energy. In the visible region, vegetation looks dark on the imagery because of the high absorption of pigments such as chlorophylls (Jensen, 2000). Although these physical bases explain their function, vegetation indices are generally based on empirical evidence, not on basic biology, chemistry or physics.

Remote sensing estimation of LAI has been primarily based on the empirical relationship between the field-measured LAI and satellite image-based spectral signals (Curran *et al.*, 1992; Peddle *et al.*, 1999). As a single value to represent the remotely sensed spectral responses of vegetation, spectral vegetation indices, such as the normalized difference vegetation index (NDVI) as shown in Equation 1 or simple ratio, are frequently used to indirectly estimate LAI (Lee *et al.*, 2006; Baret and Guyot, 1991; Huete *et al.*, 1994; Potitthep *et al.*, 2010). Many previous studies investigated the relationship between LAI and NDVI, and developed empirical models based on that relationship (Turner *et al.*, 1999; Gonzalez-Sanpedro *et al.*, 2008; Zheng and Moskal, 2009; Kim and Lee, 2003). However, few studies compared LAI estimation based on data from various satellite sensors.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

ρ_{NIR} : Reflectance of near-infrared band

ρ_{RED} : Reflectance of red visible band

Many have attempted to develop relationships between LAI and vegetation indices for crop yield assessment and have discussed their potential and limitations (Baret and Guyot, 1991; Wiegand *et al.*,

1991; Thenkabail *et al.*, 2000; Hong *et al.*, 2004; Doraiswamy *et al.*, 2005). Jongschaap (2006) addressed LAI is often used for the crop growth model calibration leading to substantial improvement in the predictions. There is not a simple way to explain crop yield since it is influenced by many biotic and abiotic factors including weather condition and disease, Launay and Guerif (2005) reported spatial and temporal distribution of LAI estimates from remote sensing data was appealing to improve yield forecast. The objective of this study is to estimate LAI as a function of image-derived vegetation indices from temporal series of IKONOS, Landsat TM, and MODIS satellite data using empirical models and field data from Missouri field sites.

2. Materials and Methods

1) Study areas and monitoring sites

Data were collected on two fields (Field A, 36 ha and Field B, 13 ha) located within 3 km of each other near Centralia, in central Missouri (39.2 N, 92.1 W), USA as shown in Fig. 1. The soils found at these sites are classified as Aqualfs and are commonly referred to claypan soils. They are poorly drained and have a restrictive, high-clay layer (the claypan) occurring below the topsoil. Because of extensive weathering, the claypan soil is usually low in natural fertility and pH. Plant available water capacity is low because a large portion of the stored water is retained with the clay at the wilting point. Topsoil depth and landscape position influence water holding capacity and water flow within the fields, having a direct impact on crop yield (Kitchen *et al.*, 1999).

The selection of within-field monitoring sites for this study was based on existing topography, topsoil depth, and historic yield information (Fraisie *et al.*,

Fig. 1. Locations of Field A and Field B in Centralia, Missouri, USA.

Fig. 2. Crop monitoring sites in the Field A for soybean and Field B for corn in 2002.

Fig. 2. Continued

2001). The main goal was to select and properly place enough sites to adequately characterize the yield variability measured in the fields. Seven monitoring sites were selected in Field A (Sites 101-107) and five were selected in Field B (Sites 201-205) as shown in Fig. 2.

Data for this study were collected in 2002. Field A was planted to soybean on June 1 and June 3 (76 cm row spacing, 408,000 seeds/ha) and Field B was planted to corn on April 18 and April 19 (76 cm row spacing, 69,000 seeds/ha). Field A was managed with minimum tillage, while Field B was managed with no-tillage. Harvest was on October 1, 2, and 8 for Field A and September 23 and 24 for Field B. Destructive crop sampling for LAI was carried out with a 1-m row section for corn and three 1-meter row sections for soybean. Corn measurements were obtained on 05/09, 05/21, 06/04, 06/13, 06/20, 06/25, 07/03, 07/10, 07/23, and 08/12, while soybean measurements were obtained on 06/20, 06/25, 07/03, 07/10, 07/23, 08/01, 08/12, 08/21, 08/31, and 09/16. Leaf area was measured with a LI-COR1) leaf area meter (LI-3100), where the projected image of a leaf sample traveling under a fluorescent light source is reflected by a system of mirrors to a solid-state

scanning camera. Hatfield *et al.* (1976) reported that measurement error with this type of area meter is generally less than 2%. Growth stages for soybean and corn were also surveyed at each sampling date according to the handbook of 'How a Soybean Plant Develops (Iowa State University, 1997a)' and 'How a Corn Plant Develops (Iowa State University, 1997b)'.

2) Image data used and image processing

Multi-sensor optical data from IKONOS (4 m), Landsat TM (30 m), and MODIS (250 m) satellites were acquired for Field A and Field B on multiple dates from May to September during the 2002 cropping season (Table 1). Areas for extracting NDVI from the images were selected to be coincident with the hand-harvested areas for estimating LAI. Field measurement data were interpolated using two adjacent dates to match the dates for images and paired with the image data value extracted from the one coincident pixel of the Landsat TM and MODIS images for data analysis. The one exception was for sites 106 and 107, which were located within the same MODIS image pixel. The LAI value corresponding to this pixel was determined by

Table 1. Multi-sensor optical image data acquired in 2002

Sensor	Date	Resolution	Processing level	Area used for extracting NDVI
IKONOS	06/21 07/21 09/03	4 m	Standard (Geometric Correction, Dial G. <i>et al.</i> , 2003)	3 × 3 pixels The following image data were excluded from analysis because of clouds or shadows: #103 (07/21), #104 (06/21), #106 (07/21), #107 (07/21), #203(06/21), and #204 (06/21).
Landsat TM (Path-Row: 25-33)	06/16 08/03 09/04	30 m	Level 1G (Systematic Correction, Chander <i>et al.</i> , 2007)	1 pixel
MODIS	05/09~05/24(05/17) 05/25~06/09(06/02) 06/10~06/25(06/18) 06/26~07/11(07/04) 07/12~07/27(07/20) 07/28~08/12(08/05) 08/13~08/28(08/21) 08/29~09/13(09/06) 09/14~09/29(09/22)	250 m	MOD13 (16-day NDVI, Huete <i>et al.</i> , 2002)	1 pixel See exception for points #106 and #107 described in the text.

Fig. 3. Flow chart of the image processing and analysis procedures used in this study.

averaging the data values from two sites. Because IKONOS pixels were much smaller, the effect of different averaging windows (1×1 , 3×3 , and 5×5 pixels) was evaluated. Because IKONOS NDVI from the 3×3 pixel window size had the highest correlation to LAI (data not shown), those data were used for further data analysis. Some IKONOS data were excluded from the analysis because of clouds or shadows as shown in Table 1.

Fig. 3 shows a flow chart of the image processing and analysis steps used in this study. Image data were first standardized for sensor comparison. The MODIS products (MOD13) used in this study were pre-processed atmospherically and geometrically by the image provider (Huete *et al.*, 2002). Pre-processed MODIS images were reprojected from sinusoidal to UTM projection with zone 15 using the MODIS Reprojection Tool provided by the National Aeronautics and Space Administration (NASA, USA).

Atmospheric correction, which is a process to reduce atmospheric effects and more accurately estimate surface reflectance, was applied to the IKONOS and Landsat TM images using the COST model (Chavez, 1996). Based on Equation 2, Landsat TM and IKONOS digital numbers were converted to radiance values using radiometric calibration coefficients for each band as shown in Table 2. Radiometric calibration coefficients for Landsat TM were obtained from the metadata file of the image. Radiometric calibration coefficients developed by the NASA calibration team (Pagnutti *et al.*, 2003) were

Table 2. Radiometric calibration coefficients for Landsat TM and IKONOS images

Band	Landsat TM		IKONOS	
	Gain	Offset ($\text{W/m}^2/\text{sr}/\mu\text{m}$)	Gain	Offset ($\text{W/m}^2/\text{sr}/\mu\text{m}$)
Band 3	0.806	-1.2	0.119	0.00
Band 4	0.816	-1.5	0.134	0.00

used for IKONOS images.

$$L_i = \text{gain}_i \times \text{DN}_i + \text{offset}_i \quad (2)$$

The COST model is an image-based atmospheric correction method. Radiance images calculated from Equation 2 are converted to reflectance images based on Equation 3. The COST model uses the cosine of the sun zenith angle for approximating the effects of absorption by the atmosphere. In Equation 4, path radiance due to haze ($L_{\text{haze},i}$) can be calculated by subtracting $L_{1\%}$ from the at-satellite radiance of hazy objects as shown in Equation 5. The basic assumption is that dark objects comprise 1 percent minimum reflectance (Chavez, 1996). By correcting haze effects, the images are corrected band by band for atmospheric and radiometric noise (Chavez, 1996).

$$\rho_i = \frac{\pi d^2 (L_i - L_{\text{haze},i})}{ESUN_i \cos \theta^2} \quad (3)$$

$$\text{where, } L_{\text{haze},i} = L_{\text{min}} - L_{1\%} \quad (4)$$

$$L_{1\%} = \frac{0.01 \times ESUN_i \cos \theta^2}{\pi d^2} \quad (5)$$

ρ : spectral reflectance of the surface

θ : solar zenith angle

$ESUN$: top of the atmospheric solar irradiance

d : distance between sun and earth

L_i : at-sensor radiance for each band i

$L_{\text{haze},i}$: path radiance due to haze for each band i

$L_{1\%}$: radiance of an absolutely dark object when it is haze-free

L_{min} : minimum radiance of each band i

Linear, exponential, and expolinear models (Anderson *et al.*, 2004) as shown in Table 3 were used to estimate image-based LAI and compared with observed LAI. Although the linear model is simple to apply, performance of this model is poor during periods of Maximum LAI (Wang *et al.*, 2005). For deciduous forest, the exponential model was more effective than the linear model (Tagesson, 2006). The expolinear model, which combined both linear and exponential functions, was used for modelling crop

Table 3. Models used for estimating LAI from satellite NDVI values

Model	Equations
Linear	$LAI = a \times NDVI + b$
Exponential	$LAI = a \times \exp^{(b \times NDVI)}$
Exponential	$LAI = (a \times NDVI + b) \times (1 + c \times \exp^{(d \times NDVI)})$

growth and provided consistency between retrieved biophysical properties (Lee *et al.*, 2003; Anderson *et al.*, 2004). For the comparison of three models, coefficient of determination (r^2) and root mean square error (RMSE) were used.

3. Results and Discussion

1) Atmospheric correction effect on IKONOS and Landsat TM images

NDVI values of IKONOS and Landsat TM atmospherically corrected using the COST model were compared with the NDVI values calculated from digital numbers of original images (Fig. 4). The relationship between NDVI values before and after atmospheric correction followed a strong linear

relationship as shown in Fig. 4, which reflects linear equation of COST model algorithm. NDVI values of IKONOS and Landsat TM after atmospheric correction were approximately 0.2 to 0.3 higher than those values from digital numbers of original images. Minimum radiance (L_{min}) of red band had generally higher values than that of near infrared band because of higher scattering in the visible band than in the near infrared band meanwhile radiance of an absolutely dark object when it is haze-free ($L_{1\%}$) are the same in the red and near infrared bands. This resulted in higher spectral reflectance (ρ) of near infrared band and then higher NDVI values after atmospheric correction. Two sensor's NDVIs using atmospheric corrected reflectance could be objectively compared as absolute value removed atmospheric effect. The range of IKONOS and

Fig. 4. Comparison of NDVI values before and after atmospheric correction of Landsat TM and IKONOS images in soybean and corn fields.

Fig. 4. Continued

Fig. 5. LAI change of soybean (a) and corn (b) during the 2002 growing season.

Landsat TM NDVI values was wider in soybean than in corn. The NDVI range of IKONOS was larger than that of Landsat TM, which is because high spatial resolution of IKONOS image provides more detail spatial variability than Landsat TM does.

2) Crop growth and NDVI change

The LAI of soybean and corn at all monitoring sites increased to about 3~4 until the maturing stage(R4) at the end of August for soybean and until

the grain filling stage(R3) in mid-July for corn, and then decreased as shown in Fig. 5. Time difference for LAI peak for soybean and corn was about a month. Within-field LAI variability was found at both fields, with higher LAI variability among monitoring sites before the reproductive stages.

Soybean NDVI values calculated from IKONOS, Landsat TM, and MODIS at the sampling sites increased to about 0.9 until early September as shown in Fig. 6. Corn NDVI values increased to about 0.7 to

Fig. 6. NDVI calculated from IKONOS (a), Landsat TM (b), and MODIS (c) images at soybean (#101~#107) and corn (#201~#205) monitoring sites during growing period in 2002.

0.8 in late July or early August and then decreased everywhere except site 202. Site 202 was located in a highly eroded sloped area. Low topsoil depth and low

water-holding capacity at this site, coupled with low precipitation in July and August (Jung *et al.*, 2005), led to poor corn growth.

It was not easy to estimate the time of peak NDVI using IKONOS or Landsat TM data because only three images were obtained from each satellite during the 2002 crop growth season. Although timely acquisition of satellite imagery was known as one of limitations of remote sensing, IKONOS can be obtained more frequently because of shorter revisiting time. Landsat TM has a fixed temporal resolution as 16 days, which gives harder time to get time-series images during crop growing season. MODIS images are obtained each day but their coarse spatial resolution has a limitation to characterize field-level crop properties.

3) LAI estimation using NDVI values

Linear, exponential, and expolinear models were applied to estimate LAI using NDVI values from IKONOS, Landsat TM, and MODIS images as shown in Table 4. Expolinear models showed higher r^2 than linear and exponential models for corn LAI estimation. Anderson *et al.* (2004) indicated "One functional advantage to the expolinear regression form is that the linear section (at low VI) extrapolates to bare soil conditions at reasonable values of VI". For soybean, expolinear model showed the highest r^2 value from IKONOS-derived models for LAI estimation but linear and exponential models showed the highest r^2 value from Landsat TM- and MODIS-derived models, respectively.

All IKONOS-derived models for LAI estimation had higher r^2 values than Landsat TM- or MODIS-derived models, which implied satellite images with higher spatial resolution were more useful for estimating within-field LAI variability than those with coarser spatial resolution such as Landsat TM and MODIS (Table 4).

Table 4. LAI prediction models using IKONOS, Landsat TM, and MODIS NDVI values for soybean and corn

Sensor	Model type	Crops	
		Soybean	Corn
IKONOS	Linear	$LAI = 5.472 \times NDVI - 1.597$ $r^2 = 0.952, RMSE = 0.315$	$LAI = 7.670 \times NDVI - 2.541$ $r^2 = 0.924, RMSE = 0.229$
	Exponential	$LAI = 0.009 \times e^{7.093 \times NDVI}$ $r^2 = 0.890, RMSE = 0.764$	$LAI = 0.239 \times e^{3.489 \times NDVI}$ $r^2 = 0.955, RMSE = 0.230$
	Expolinear	$LAI = (11.653 \times NDVI - 3.156) \times (1 - 0.836 \times e^{-0.510 \times NDVI})$ $r^2 = 0.954, RMSE = 0.293$	$LAI = (2.076 \times NDVI - 0.479) \times (1 + 0.670 \times e^{1.465 \times NDVI})$ $r^2 = 0.929, RMSE = 0.222$
Landsat TM	Linear	$LAI = 5.702 \times NDVI - 1.881$ $r^2 = 0.516, RMSE = 0.576$	$LAI = 11.521 \times NDVI - 5.635$ $r^2 = 0.770, RMSE = 0.375$
	Exponential	$LAI = 0.375 \times e^{2.3915 \times NDVI}$ $r^2 = 0.549, RMSE = 0.595$	$LAI = 0.023 \times e^{6.608 \times NDVI}$ $r^2 = 0.788, RMSE = 0.337$
	Expolinear	$LAI = (6.376 \times NDVI - 2.122) \times (1 - 0.087 \times e^{0.376 \times NDVI})$ $r^2 = 0.488, RMSE = 0.585$	$LAI = (65.650 \times NDVI - 24.902) \times (1 - 1.139 \times e^{-0.363 \times NDVI})$ $r^2 = 0.835, RMSE = 0.349$
MODIS	Linear	$LAI = 6.410 \times NDVI - 1.908$ $r^2 = 0.474, RMSE = 1.110$	$LAI = 5.899 \times NDVI - 1.462$ $r^2 = 0.584, RMSE = 0.919$
	Exponential	$LAI = 0.032 \times e^{5.809 \times NDVI}$ $r^2 = 0.567, RMSE = 1.380$	$LAI = 0.040 \times e^{5.653 \times NDVI}$ $r^2 = 0.506, RMSE = 1.196$
	Expolinear	$LAI = (5.040 \times NDVI - 1.785) \times (1 + 2.787 \times e^{-2.354 \times NDVI})$ $r^2 = 0.484, RMSE = 1.102$	$LAI = (0.369 \times NDVI - 0.131) \times (1 + 146.117 \times e^{-2.653 \times NDVI})$ $r^2 = 0.660, RMSE = 0.827$

Fig. 7. Comparison between measured and estimated LAI with linear, exponential, and expolinear equations from satellite NDVI values for soybean (top) and corn (bottom).

Differences between IKONOS-derived LAI and measured LAI were lower than for Landsat TM-derived or MODIS-derived LAI for both soybean and corn (Fig. 7). The expolinear models generally provided better results, as shown both by higher r^2 values and lower RMSE than linear or exponential models. The RMSE for corn LAI estimation, in general, was lower than for soybean LAI estimation (Table 4).

The reason that NDVI-based expolinear model performed better for LAI estimation than linear or exponential models can be explained that expolinear model is closer to crop growth pattern, which combines linear and exponential curves at the same time during the growing period (Anderson *et al.*, 2004; Lee *et al.*, 2003). Although recent studies used time-series MODIS NDVI data to monitor crop LAI and growth (Breuning *et al.*, 2011; Wardlow *et al.*, 2007), NDVI from satellite images with higher spatial resolution such as IKONOS were more useful for estimating within-field LAI or crop growth variability than those with coarser spatial resolution including Landsat TM and MODIS in this study

4. Conclusions

LAI is important in explaining the ability of the crop to intercept solar energy for biomass production and in understanding the impact of crop management practices. For improved efficiency of measurement, soybean and corn LAI was estimated using IKONOS, Landsat TM, and MODIS NDVI values. After geometric and atmospheric correction, field-measured LAI was modelled as a function of NDVI using linear, exponential, and expolinear regression models. Soybean NDVI values calculated from IKONOS, Landsat TM, and MODIS increased to about 0.9 until early September and corn NDVI

values increased to about 0.7~0.8 until late July or early August. The IKONOS-derived models for provided higher r^2 values than Landsat TM- or MODIS-derived models, which implied satellite images with higher spatial resolution were more useful for estimating within-field LAI variability than those with coarser spatial resolution. Based on RMSE, the expolinear model generally fit the data better than linear or exponential models for both soybean and corn. We suggest remote sensing estimates of LAI from satellite images with high spatial resolution can provide estimates of spatial variability in LAI, which is of use in modelling of crop growth and yield.

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