An ASABE Meeting Presentation

Paper Number: 072013

Relationship between LAI and Landsat TM Spectral Vegetation Indices in the Texas Panhandle

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Written for presentation at the
2007 ASABE Annual International Meeting
Sponsored by ASABE
Minneapolis Convention Center
Minneapolis, Minnesota
17 - 20 June 2007

Abstract: *Mapping and monitoring leaf area index (LAI) is important for spatially distributed modeling of surface energy balance, evapotranspiration and vegetation productivity. Remote sensing can facilitate the rapid collection of LAI information on individual fields over large areas in a time and cost-effective manner. However, there are no LAI models available for the major summer crops in the Texas Panhandle. The main objective of this study was to develop statistical relationship between LAI and Landsat Thematic Mapper (TM) based spectral vegetation indices (SVI) for major crops in the Texas Panhandle. LAI was measured in 48 randomly selected commercial fields in Moore and Ochiltree counties. Data collection was made to coincide with Landsat 5 satellite overpasses on the study area. Numerous derivations of SVIs were examined for estimating LAI using ordinary least square regression models such as linear, quadratic, power and exponential models. The R^2 values for the selected models varied from 0.76 to 0.84 with the power function model based on the normalized difference between TM bands 4 and 3 (NDVI) producing the best results. Analysis of the results indicated that the SVI-LAI models based on the simple ratio i.e. the ratio of TM bands 4 and 3, and NDVI are most sensitive to LAI.*

Keywords: Semi-arid, Ogallala Aquifer Region, ET modeling, Texas Panhandle

INTRODUCTION

Leaf area index (LAI) is a measure of foliage density that plays a major role in photosynthesis, groundwater-surface water interactions through evapotranspiration (ET) (Sumner and Jacobs, 2004), atmospheric gas exchange (Burkart et al., 2004), nutrient uptake (Leonard et al., 1987) and crop productivity (Thenkabail et al., 1994). Obviously, it is one of the sensitive input parameters to plant growth, atmospheric circulation (Sellers et al., 1997; Ruimy et al., 1994), energy balance (Bonan, 1995), and water quality simulation models (Gowda et al., 1999) at field to landscape to global scales. Accurate estimates of LAI are also useful in estimating soil water content from microwave remote sensing data by subtracting the effects of crop water content on reflectance (Anderson et al., 2004).

Traditional in-situ techniques to measure LAI involve destructive sampling of leaves and are time intensive. However, in recent years, numerous indirect in-situ methods have been developed to measure LAI including the scanner method (Yang et al., 2002; Kang et al., 2005), electronic leaf area meter (Delta-T Devices Ltd, Cambridge[1], UK; Rouphael and Colla, 2005) and LAI-2000, Plant Canopy Analyzer[1] (Welles and Norman, 1991). Although these in-situ techniques can be accurate, it is not practical to use them to monitor LAI spatially and temporally over large geographic areas. One approach is to employ satellite remote sensing techniques to estimate LAI. The use of satellite data is a practical alternative to in-situ measurements, provided that suitable spectral vegetation indices (SVI) can be developed.

In the last three decades, numerous SVIs have been developed to estimate LAI from Landsat Multi-Spectral Scanner (MSS) (Wiegand et al., 1979 for winter wheat), Thematic Mapper (TM) (Thenkabail et al., 1994 for corn and soybean) and Enhanced Thematic Mapper Plus (ETM+) (Xavier and Vettorazzi, 2004 for mixed crops mainly sugarcane; Walthall et al., 2004 for corn and soybean) sensors. Table 1 presents spatial and spectral resolutions of the Landsat 5 TM data.

Table 1. Landsat 5 Thematic Mapper(TM) sensor specifications.

Band	**Wavelength Region (μm)**[†]	**Spatial Resolution (m)**
1	0.45 – 0.52 (Blue)	30
2	0.52 – 0.60 (Green)	30
3	0.63 – 0.69 (Red)	30
4	0.76 – 0.90 (NIR)	30
5	1.55 – 0.75 (MIR)	30
6	10.4 – 12.5 (TIR)	120
7	2.08 – 2.35 (MIR)	30

[†]NIR – Near Infrared, MIR – Mid Infrared, TIR – Thermal Infrared.

[1] Mention of trade or manufacturer names in this article is made for information only and does not imply an endorsement, recommendation, or exclusion by the United States Department of Agriculture – Agricultural Research Service.

These studies and others have shown that there is a strong contrasting relationship between spectral reflectance measurements of canopy cover in red and infrared wavelengths. Consequently, a simple ratio (SR), normalized difference vegetation index (NDVI), and soil adjusted vegetation index (SAVI) (Huete et al., 1994) are the three most commonly used SVIs to estimate LAI. All three use ratios of red (R) and near-infrared (NIR) reflectance: SR = NIR/R; NDVI = (NIR-R)/(NIR+R) and SAVI = (1+L) (NIR – R)/(NIR+R+L) where L is a coefficient introduced to reduce variation in background (soil and crop residue) reflectance and its value varies from 0 to 1. However, these indices are not sensitive at LAI values greater than 3.0 m^2 m^{-2}. The normalized difference water index (NDWI; Anderson et al., 2004) uses normalized difference between NIR and shortwave infrared (SWIR) reflectance and the green index (GI; Gitleson et al., 2003) that uses green in place of red reflectance appear to be remain sensitive for LAI values between 3.0 and 6.0 (Walthall et al., 2004). The GI is given as: GI = (NIR / G)-1 where G is the spectral reflectance in green wavelength. Most of LAI-SVI statistical relationships reported in the literature are based on ordinary least square regression (SAS Institute Inc., 2003) and follow one or more of the following models: (1) linear; $LAI = a + bX$; (2) exponential; $LAI = a\ e^{bX}$; (3) power or logarithmic; $LAI = aX^b$; and quadratic; $LAI = aX^2 + bX + c$; where, X is either SVIs or reflectance/raw digital number derived from remote sensing data.

While satellite remote sensing based SVIs have been used for mapping and monitoring LAI, the strengths and transferability of empirical LAI-SVI relationships to other regions may potentially be affected by exogenous factors such as sun-surface sensor geometry, background reflectance, and atmosphere-induced variations on canopy reflectance (Turner et al., 1999; Chen and Cihlar, 1996; Jacquemond et al., 1995; Meyer et al., 1993). There have been few tests to compensate for exogenous effects factors on LAI-SVI relationships and results are mixed. Further, most studies in the past considered one vegetation type. Moreover, comparisons across studies have been limited by differences in sensor characteristics and image processing methods (Turner et al., 1999).

Overall, canopy cover reflectance is a multiple function of many variables that are different over time and space. Therefore, it may not be a viable option to develop a single SVI-based LAI model for one region and apply it to different regions. Further, spectrally based LAI models for agricultural crops in semi-arid regions are scarce and, currently, there are no such models available for the Texas Panhandle. Development of region-specific SVI indices will minimize errors in estimating LAI for use in as input to groundwater (to predict evapotranspiration), agronomic, ecological and climatic models. The main objective of this study is to develop a set of Landsat TM-based SVIs to estimate LAI for major agricultural crops in the Texas Panhandle.

METHODS AND MATERIALS

Study Area: This study was conducted with LAI data collected from 48 commercially operated farms (24 each in Ochiltree and Moore counties) in the Texas Panhandle underlain by the Ogallala aquifer (Fig. 1), which is being depleted by excessive pumping for irrigation. Moore County is in the north-central part of the Panhandle and has a total area of 236,826 ha. Two-thirds of the land is in the nearly level, smooth uplands of the High Plains (USDA-SCS, 1975) and most of it under row crop production. Corn, sorghum, cotton and soybean are the major summer crops in both Ochiltree and Moore counties. In 2004, it ranked fifth in corn production in Texas and accounted for about 5.7 percent of total corn produced in the state (NASS, 2005).

The area of Ochiltree County is 234,911 ha with more than 45 percent of the land in 2004 under row crop production. In 2004, the Ochiltree County ranked eighth in Texas for sorghum production and accounted for about 2.4 percent of the total sorghum produced in the state (NASS, 2005). Annual average precipitation is about 481 and 562 mm for Moore and Ochiltree counties, respectively. Crop water needs are supplemented with groundwater from the underlying Ogallala aquifer. Nearly level to gently sloping fields with clay loam soils of the Sherm series occupy nearly all of the crop land in both Moore and Ochiltree counties.

Field Data Collection: Two Landsat TM scenes were acquired, one on June 27, 2005 for Ochiltree County and the other on July 4, 2005 for Moore County, for developing the Landsat TM-based LAI models. Developing the LAI models consist of three steps: 1) ground-truth data collection, 2) atmospheric correction of Landsat TM imagery for deriving surface reflectance values for ground-truth location, and 3) development of SVI-LAI statistical relationships using the ordinary least square technique. On the day of the Landsat 5 satellite overpass, ground-truth data were collected from 48 randomly selected commercial fields (24 each in Ochiltree and Moore counties) in the study area. Ground-truth data included geographic coordinates using a handheld Global Positioning System (GARMIN GPSMAP 76, Garmin Ltd), plant type and density, width of plant rows and extraction of one representative plant for LAI measurement in the laboratory. The LAI was measured using the electronic leaf area meter (Delta-T Devices Ltd, Cambridge, UK; Rouphael and Colla, 2005).

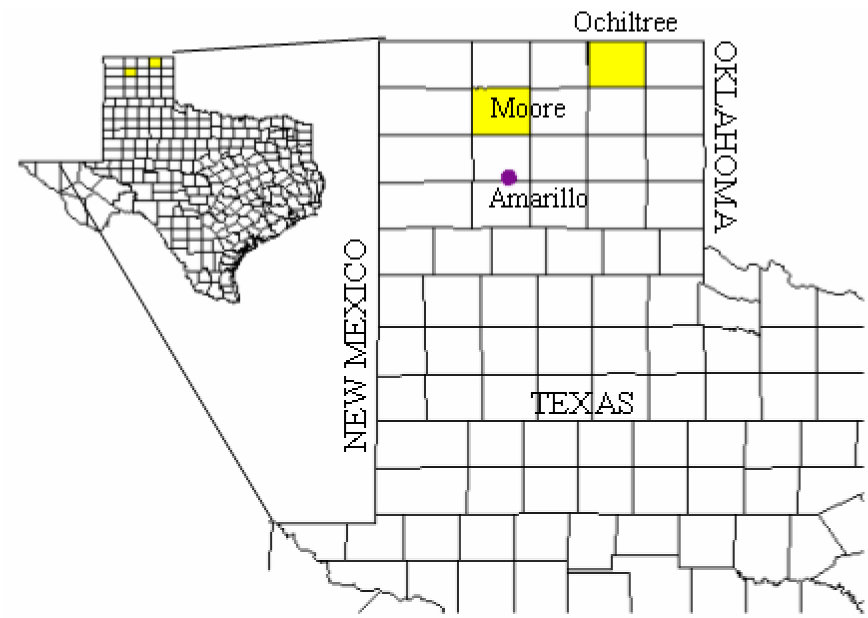

Figure 1. Location of Moore and Ochiltree counties in the Texas Panhandle, USA.

Each pixel in the Landsat 5 image has a spatial resolution of 30 m after resampling. Ground truth pixel locations on the image were identified using the GPS coordinates. For model development, mean reflectance data from 9-pixels (ground-truth pixel and surrounding 8 pixels) were used, as it was difficult to precisely identify the ground truth location in the field. Atmospherically corrected surface reflectance (ρ_{SUR}) for each TM band was used to develop SVIs. As a first step to compute ρ_{SUR}, the digital numbers in each TM band image except thermal band 6 were converted into spectral radiance (L_b), using the equation: L_b = Gain x DN + Bias, where Gain and Bias were extracted from the image header files from the satellite data provider. The top-of-the-atmosphere reflectance (ρ_{TOA}) was calculated for each pixel in the image using the procedure outlined in Chander and Markham (2003). In this procedure, the ρ_{TOA} for each pixel was calculated by dividing spectral radiance by the incoming energy (radiance) in the same short-wave band. The incoming radiance is a function of mean solar exo-atmospheric irradiance, solar incidence angle, and square of the relative earth-to-sun distance (Thenkabail, 2003). The ρ_{SUR} was computed after applying atmospheric interference corrections for short-wave absorption and scattering using narrow band transmittance calibrated for each band with the MODTRAN, a radiative transfer model (Berk et al., 2003).

The LAI-SVI relationships were evaluated using ordinary least square regression analysis with measured LAI as the independent variable. A set of SVIs evaluated to develop LAI-SVI statistical relationships included difference indices, sum indices, product indices, ratio indices, and normalized difference indices. The least square regression models used to evaluate each of the SVIs were linear, exponential, power, and quadratic. Finally, the most significant models were identified and reported for the study area. The cutoff R^2 value of 0.75 was used to identify the most significant models.

RESULTS AND DISCUSSION

LAI measurements were made in 16 commercial fields that planted to corn, 11 fields each to cotton and sorghum, and 8 fields to soybean, respectively. The measured LAI values varied from 0.09 to 6.21 m^2 m^{-2} with a standard deviation of 1.91 m^2 m^{-2}. High variability in the LAI measurements was due to presence of different crops at different growth stages.

Table 2 presents a set of significant LAI-SVI models and associated R^2, adjusted R^2, root mean square error (RMSE), and F statistic for major summer crops in the Panhandle of Texas. Adjusted R^2 measures the improvement in the performance of the model by adding another independent variable to the least square regression model.

Seven out of 13 reported models (Table 2) use either SR (*R43*=TM band 4/ TM band 3) or NDVI i.e. normalized difference of TM bands 4 and 3. The remaining models use SVI that derived using either TM band 3 (R) or 4 (NIR) in combination with other TM bands such as 1, 2 or 7. This indicates that the R and NIR bandwidths are sensitive to the LAI and is consistent with previous reports (Thenkabail et al., 1994; Huete et al., 1994; Walthall et al., 2004). Chlorophyll pigments in plant leaf absorb energy in the red band of the electromagnetic spectrum resulting in relatively low red reflectance and transmittance while lignin in plant cell walls cause scattering of near-infrared energy resulting in relatively high near-infrared reflectance and transmittance (Gates et al., 1965).

Based on the RMSE and F statistic, exponential and power models (Table 2) based on the normalized difference between the TM bands 4 and 3 were found to be the best models for estimating LAI. The power model that uses NDVI43 accounted for 84 percent of the variability in the measured LAI data with a relatively small RMSE of 0.50.

Table 2. Landsat 5 Thematic Mapper (TM) based Leaf area index (LAI) models for major crops in the Texas Panhandle.

No.	Model[1]	R^2	Adj. R^2	RMSE	F
Linear					
1	LAI = -5.789 + 11.848 * *R13*	0.76		0.96	138.00
2	LAI = -1.296 + 0.437 * *R41*	0.76		0.95	138.15
3	LAI = -0.301 + 0.425 * *R43*	0.77		0.93	147.53
4	LAI = -0.306 + 0.811 * *R47*	0.79		0.90	160.77
5	LAI = -3.488 + 9.291 * *NDVI43*	0.77		0.94	142.92
Quadratic					
6	$LAI = -2.581 + 0.777 * R41 – 0.018 * (R13)^2$	0.77	0.76	0.94	72.95
7	$LAI = -3.143 + 1.365 * R42 – 0.055 * (R42)^2$	0.80	0.79	0.89	83.51
8	$LAI = -1.195 + 0.775 * R43 -0.023 * (R43)^2$	0.80	0.79	0.89	83.12
9	$LAI = -1.095 + 1.412 * R47 – 0.076 * (R47)^2$	0.80	0.79	0.88	86.19
10	$LAI = 1.066 – 6.973 * NDVI43 + 13.277 * (NDVI43)^2$	0.79	0.78	0.89	82.88
Exponential					
11	$LAI = 0.029\ e^{6.137 * NDVI43}$	0.81		0.55	182.41
Power					
12	$LAI = 0.099 * (R43)^{1.632}$	0.75		0.63	129.75
13	$LAI = 8.768 * (NDVI43)^{3.616}$	0.84		0.50	228.10

[1] R13, R41, R42, R43, and R47 = Ratio of bands 1 and 3, 4 and 1, 4 and 2, 4 and 3, and 4 and 7, respectively; NDVI43 = normalized difference between bands 4 and 3.

CONCLUSIONS

Leaf area index (LAI) is important for spatially distributed modeling of surface energy balance, evapotranspiration and vegetation productivity. The Landsat 5 Thematic Mapper (TM)-based spectral vegetation indices (SVIs) were evaluated using the ordinary least regression technique for their ability to estimate LAI for major crops in the Panhandle of Texas. A set of most significant SVI-LAI models was identified. The R^2 values for the selected models varied from 0.76 to 0.84 with the power model based on the NDVI producing the best agreement with field-measured LAI. Analysis of the results indicated that SR and NDVI were sensitive to LAI, which is consistent with the literature. Overall, the remote sensing approach is promising for the rapid collection of LAI information on individual fields over large areas in the Northern High Plains of Texas in a time and cost-effective manner.

ACKNOWLEDGEMENTS

We extend our appreciation to Mr. Leon New, Professor/extension specialist, Texas Cooperative Extension, Texas A&M University System, Amarillo, Texas; Mr. Timothy Trimble and Mr. Scott Strawn, both County Extension Agents, Texas Cooperative Extension, Dumas, Texas and Perryton, Texas, respectively, for their logistical support to conduct field campaigns in Moore and Ochiltree counties.

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