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Biophysical Parameter Estimations Using Multidirectional Spectral Measurements

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There has been a great deal of interest in estimation of terrestrial biophysical parameters such as vegetation with remotely sensed data. Quantitative estimation of vegetation properties with existing algorithms has been based on empirical relationships established by simple regression. The problem in applying these empirical relationships is that those coefficients proposed vary with vegetation type. To investigate the possible development of an algorithm to quantitatively estimate vegetation properties independent of vegetation type, a model-to-model approach is proposed. This approach first inverts a simple bidirectional reflectance distribution function (BRDF) model with limited data points and simulates multidirectional data. The simulated data are then used in the inversion of a physically based BRDF model to estimate vegetation optical properties (leaf reflectance and transmittance) and leaf area index (LAI). This approach is validated with data collected from three experiments conducted in cotton, alfalfa, wheat, and pecan fields. A sensitivity analysis and demonstration with multitemporal remote sensing data were performed, and the results show that estimated LAI values agree well with field observations and there is a potential in applying this approach on an operational basis in practice with multitemporal remote sensing data.

INTRODUCTION

Biophysical parameters have been identified as the most important physical properties of terrestrial surfaces due to their specific roles in geosphere–biosphere–atmosphere interactions, and vegetation is one of the most important biophysical parameters because of its unique role in global climate change studies. This parameter regulates the energy exchanges (including water) between the earth–atmosphere interface, and dominates the functioning of hydrological processes through modification of interception, infiltration, surface runoff, and its effects on surface albedo, roughness, evapotranspiration, and root system modification of soil properties. The vegetation amount controls the partitioning of incoming solar energy into sensible and latent heat fluxes, and consequently changes in vegetation amount will result in long-term changes in the local and global climates, which in turn will affect the vegetation growth as a feedback. In marginal ecosystems, this may result in persistent drought and desertification, with drastic impacts on the human populations of these regions through reduction in agricultural productivity, reduction in quantity and quality of water supply, and removal of land from human habitability.

Vegetation in arid regions is in itself a sensitive indicator of land degradation. Over the past several decades, substantial semiarid lands have become degraded to the point where their original biotic functions have been damaged, with subsequent reclamation being costly or in some cases impossible. The processes leading to degradation and the extent of the problem worldwide are only recently being understood. The continually increasing global population intensifies pressure on marginal lands, particularly in developing countries where population growth and poverty subvert efforts to introduce sustainable agricultural practices, leading to environmental problems such as soil erosion and deforestation. Assessment of the degree to which desertification is increasing is essential to decision-makers and others concerned with land degradation. Therefore, continuous monitoring of vegetation is absolutely indispensable and would certainly add much to our knowledge in understanding our living environment and its interactions with climate, and in predicting the future of our planet.

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Remote sensing techniques provide a powerful tool for obtaining such information. Radiometric measurements in the solar spectral domain contain useful information about vegetation. Analysis of remotely sensed data has revealed the possibility of using remote sensing techniques to characterize vegetation properties, and to estimate crop yields and total biomass productions. Consequently, there has been a great deal of interest in the estimation of vegetation properties via remote sensing means, among which leaf area index (LAI) is the key parameter. Several approaches have been made in relating remotely sensed data to LAI in the past decade (Asrar et al., 1985; Best and Harlan, 1985; Clevers, 1988; 1989; Current, 1983; Current et al., 1992; Hatfield et al., 1985; Holben et al., 1980; Price, 1993). These approaches can generally be classified into three categories: simple regression, vegetation index, and modeling approaches.

Simple Regression Approach

The simple regression approach is based on the fact that the reflectance in the red spectral region decreases while that in the near-infrared (NIR) region increases when the vegetation density (LAI) increases. By simple multiband regression to ground LAI measurements, a relationship between LAI and surface reflectance can be established, which can be used in LAI estimation with remote sensing data. There are several limitations in using this approach to estimate LAI values. The first limitation is that statistically a large number of LAI measurements are needed at the same site and same time as the spectral reflectances are collected (or a subset of a large data set) in order to establish a reliable relationship between LAI and spectral measurements. The second limitation is that the established reflectance–LAI relationship is vegetation type dependent, indicating that LAI sampling must be made at each vegetation type site in order that the relationship can be used for varying biomes. The third limitation is that this approach is very vulnerable to measurement noise such as soil substrate effect, atmospheric effect, and especially bidirectional properties of the vegetation. The soil substrate and atmospheric effects can be reduced by correcting for these factors (Huete et al., 1989; Kaufman, 1989), but the bidirectional effect remains difficult to resolve. Consequently, it is necessary to normalize the bidirectional effect in order to establish a viable reflectance–LAI relationship. This is not an easy task, however, because most natural land surfaces are non-Lambertian and the bidirectional reflectances made at off-nadir view angle can be substantially different from those made at nadir view angles (Kimes et al., 1985; Shibayama and Wiegand, 1985; Deering, 1989; Jackson et al., 1990; Qi et al., 1993). Furthermore, the bidirectional effect is vegetation-dependent, and even bare soil surfaces demonstrate significant bidirectional reflectance properties (Jackson et al., 1990). Variation in bidirectional reflectance measurements can be up to 50% due to view and sun angle differences between satellite and equivalent ground or aircraft measurements (Goward et al., 1991; Pinter et al., 1990). This approach works better with large data sets of constant view angles for a single vegetation type. For multidirectional remote sensing data of various types of biome, this simple regression approach needs further investigation with regard to the bidirectional effect as well as the regression coefficients of different types of biome.

Vegetation Index Approach

More than a dozen vegetation indices (VIs) have been developed by linearly combining or ratioing reflectances in the red and in the NIR spectral regions. The most commonly used VI is the normalized difference vegetation index (NDVI):

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{NIR}} - \rho_{\mathrm{RED}}}{\rho_{\mathrm{NIR}} + \rho_{\mathrm{RED}}} \tag{1}$$

where ρ is reflectance in red or NIR spectral region. Most VIs are qualitatively related to the vegetation amount (LAI, % cover, for example) and have been used as an indicator of vegetation growth (Tucker, 1979; Choudhury, 1987; Clevers, 1989; Malingreau et al., 1989; Jackson and Huete, 1991; Baret and Guyot, 1991; Gutman, 1991; Cihlar et al., 1991; Wiegand et al., 1991; Danson et al., 1994). Some empirical or semiempirical quantitative relationships between VI and LAI have been developed (Asrar et al., 1985; Spanner et al., 1990; Price, 1993; Nemani et al., 1993). To establish a relationship between VI and LAI, vegetation index values are first calibrated to the ground LAI values to develop a fitting curve, and the fitting curve is used in estimating LAI values with remote sensing data. The advantage of this approach is its simplicity. The disadvantage of this approach is, however, the diversity of the established VI and LAI relationship. Some studies suggest a linear relationship between NDVI and LAI ($\mathrm{NDVI} = \alpha + \beta\,\mathrm{LAI}$), while others suggest an exponential relationship ($\mathrm{NDVI} = \alpha e^{\beta\,\mathrm{LAI}}$), whereas still others suggest a power relationship ($\mathrm{LAI} = \alpha + \beta\,\mathrm{LAI}^{x}$), where α, β, and x are empirical coefficients. Even within the linear relationship category, the proposed coefficients vary substantially from one vegetation type to another. No quantitative relationship has been generalized, because each study was done with a limited remote sensing data set and limited vegetation types. Another disadvantage is that this approach relies on the quality of vegetation indices. It assumes that a vegetation index normalizes most of the external noise (background substrate, atmosphere, and sun and view angle effects), which is unfortunately not always true. All vegetation indices developed so far (Baret and Guyot, 1991; Qi et al., 1994a;

Teillet et al., 1994) are subject to various effects as found in the reflectance measurements, especially bidirectional effects (Holben and Kimes, 1986; Deering, 1989; Deering et al., 1990; Jackson et al., 1990; Pinter et al., 1990; Qi et al., 1994b). When transformed from reflectance domain into vegetation index domain, the bidirectional effects could be reduced (Jackson et al., 1990; Huete et al., 1992), but could also be increased (Kimes et al., 1985; Epiphanio et al., 1994; Qi et al., 1994b), depending on vegetation types and solar zenith angles.

To demonstrate if the most commonly used NDVI will increase or decrease the bidirectional effect, an example is illustrated in Figure 1 using bidirectional spectral reflectance (ρ_λ) measurements made over a semiarid grassland at the USDA-ARS Walnut Gulch Experimental Watershed southeast of Tucson, Arizona on 4 August 1991 (Qi et al., 1994b). Data in Figure 1a are the normalized reflectance in NIR Region (ρ_{NIR}/ρ_{NIR0}), whereas data in Figure 1b are normalized NDVI ($NDVI/NDVI_0$). In the backscattering direction (negative view angles), the normalized NIR was larger than that in the forward direction (positive view angles). In contrast, the bidirectional effect on the normalized NDVI was much stronger in the forward direction (Fig. 1b).

In Figure 1c, another ratio $(NDVI/NDVI_0)/(\rho_{NIR}/\rho_{NIR0})$, was plotted as a function of the view angle. The significance of this ratio is to examine whether the NDVI would increase or decrease the bidirectional effects found in the NIR. If this ratio is greater than 1, it indicates that NDVI enhanced bidirectional effects found in the NIR. The bidirectional effect was indeed enhanced (ratio > 1.0) by the NDVI in the forward direction, but was reduced in the backscattering direction (ratio < 1.0). This indicates that use of NDVI in the forward direction will magnify the bidirectional effect and, therefore, it is better to use NIR rather than NDVI when bidirectional effect is the major concern. At two extreme view angles ($\pm 40°$), NDVI can reduce the view angle effect by 38% in the backscattering direction, but can increase the effect by 18% in the forward direction. Furthermore, the degree of reduction or enhancement of the bidirectional effect was a function of solar zenith angle, the effect being increased with larger solar zenith angles. Consequently, the bidirectional effect on vegetation indices must be quantified before a quantitative VI–LAI relationship can be used.

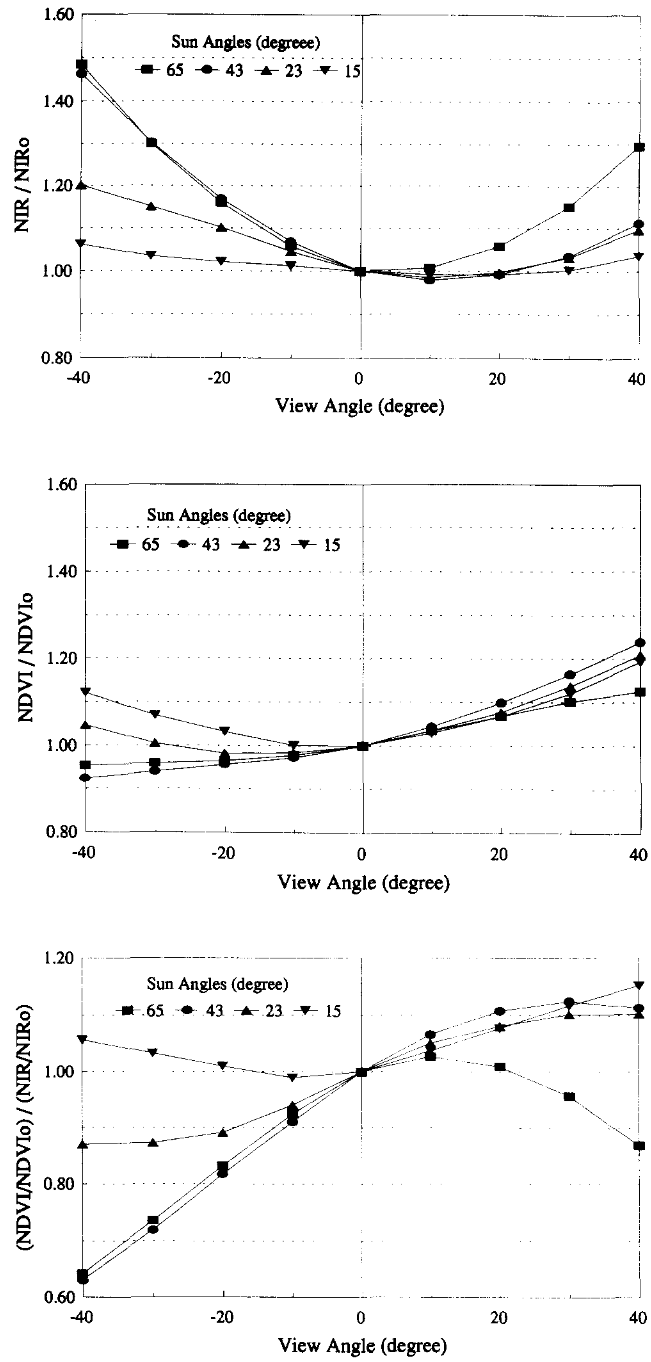


Figure 1. Bidirectional properties of the normalized (NIR/NIR_0) reflectances (a), corresponding normalized NDVI (b), and the ratio between the $NDVI/NDVI_0$ and NIR/NIR_0 (c). When the ratio is greater than 1, the NDVI increases the bidirectional effect found in NIR, and when the ratio is less than 1, the NDVI decreases the effect.

Modeling Approach

This approach includes radiative transfer and empirical models. Empirical models are simple but the parameters, when inverted, infer little information about vegetation. The radiative transfer model approach characterizes light interactions with vegetation canopies and predicts the bidirectional reflectance distribution function (BRDF) as a function of the observation geometry (Suits, 1972; Verhoef, 1984; Deering et al., 1990; Choudhury, 1987; Verstraete et al., 1990; Pinty et al., 1992; Strahler, 1994). Although most models were developed for the purpose of normalizing the bidirectional effects, some models can be potentially inverted to infer vegetation physical properties. Among them, Verhoef (1984) developed the

SAIL (scattering by arbitrarily inclined leaves) model, as a function of solar position and sensor's viewing geometry. This model assumes that the vegetation or plant canopy is uniformly distributed in a single layer and the leaves are randomly oriented. The model requires such parameters as reflectances of the underneath soils, LAI, leaf reflectance, and leaf transmittance. Inversion of this model with remote sensing data, therefore, can be used to estimate LAI and it has been proved to be feasible (Goel and Deering, 1985).

In another more complicated, physically based model by Verstraete et al. (1990) and Pinty et al. (1990), vegetation is characterized with such parameters as average single scattering albedo, asymmetry factors, leaf orientation, and interception cross section of the canopy. Although these parameters are not as intuitive as LAI, they indicate some physical properties of the vegetation such as leaf orientation, distribution, and optical properties (Pinty et al., 1990). The parameters inverted from this model, however, are difficult to relate directly to any vegetation properties because these parameters are usually difficult or even impossible to measure in the field. Rahman et al. (1993a,b) further modified this model with parameters that characterize the bidirectional properties and reduced the number of input parameters to three (mean level of reflectance and two anisotropy factors). Due to simplifications, direct links between the inverted parameters and vegetation physical properties are difficult.

So far, more than a dozen BRDF models have been developed for various types of surfaces such as crop land, grassland, and bare soil surfaces (see Strahler, 1994), and most are being used for the purpose of normalizing bidirectional effect. When used in estimation of vegetation properties, some are mathematically invertable and some are not. Even for those invertable models, there are several limitations. The first limitation is the lack of knowledge about those required input parameters, because inverted parameters have no direct link to physical properties of vegetation and, therefore, cannot be measured directly from field experiments. The second limitation is the requirement of multiple simultaneous multidirectional measurements. If a model requires a set of N input parameters, actual measurements needed for inversion must be at least $N+1$ if statistically meaningful results are expected. In practice, multiple simultaneous multidirectional measurements over the same targets are usually not possible due to remote sensors' capabilities and economic considerations.

All of the three LAI estimation approaches, simple regression, vegetation index, and modeling, have advantages as well as disadvantages. The first two approaches are simple and easy to compute, but require substantial ground LAI sampling virtually for every biome type. In addition, they are also very sensitive to bidirectional effects. Although some work on normalization of sun/

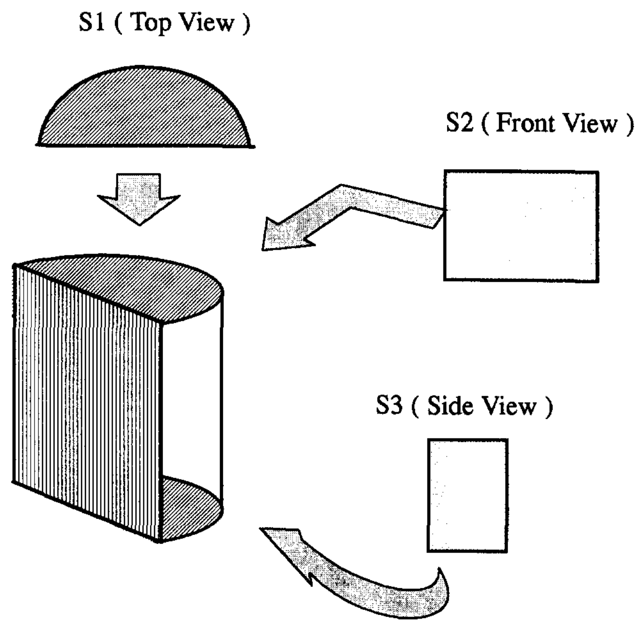


Figure 2. A schematic illustration of an object sensed by three sensors of different viewing direction to illustrate the bias each sensor may result in when looking at only one single direction.

view angle effects (Huete et al., 1992; Qi et al., 1995) with vegetation indices has been made, the bidirectional effects is till the major obstacle to overcome. The third approach has three major advantages over the simple regression and vegetation index approaches, although it may not be as simple as the previous two and maybe more time-consuming. The first advantage of this modeling approach is the utilization of information content contained in multidirectional remote sensing measurements. Multidirectional measurements can provide complementary information that nadir view measurements alone cannot (Strahler, 1994). A single nadir-view measurement obtains information about the surface as if the surface had no vertical structures, which is usually not the case in practice, while off-nadir view measurements reveal different aspects of the vertical structures such as vegetation height. An example is illustrated in Figure 2, where an object (a cut cylinder having a height equal to the diameter) is viewed by three sensors (S1, S2, and S2). Looking from the top, sensor S1 sees a semicircle, viewing at the front, sensor S2 sees a square, and viewing from aside, sensor S3 sees a rectangle. As a consequence, the reflectances as measured with these three sensors would be different. In any case, the object is biased by all of the three sensors, since each of them only views one aspect of the object, which is usually the case in remote sensing. Consequently, to objectively characterize vegetation status, spectral reflectances or derived vegetation indices at a single viewing geometry (e.g., nadir) may be insufficient. The bidirectional property of natural land surface is a direct consequence of surface anisotropy resulting from such factors as the scattering process within the canopy layer, leaf angle distribution and orientation, thickness and the size of single leaves, crowns and their spatial distribution, as well as the underlying soil properties such as roughness, color, and organic matter content. When multidirectional measurements are used, more information about the object will be obtained and a more realistic description of the target will be achieved. It is based on such bidirectional properties of natural land surface that most radiative transfer models are developed and, therefore, by inversion of these models, surface physical properties can be more objectively inferred.

The second advantage of the modeling approach is the physical basis that links the biophysical properties of vegetation to model-inverted parameters such as LAI. Radiative transfer models were developed based on light interactions with vegetation. The optical properties of an individual leaf are characterized by such parameters as leaf reflectance, transmittance, absorptance, and single scattering albedo, and the physical properties are usually characterized with parameters such as LAI, height, and cross-section area that intercept light (e.g., Pinty et al., 1990). Given those optical and physical properties, BRDF models can predict bidirectional reflectances in different viewing directions and with different illumination conditions. Inversion of these BRDF models, when multidirectional measurements are available, will result in parameters of optical and physical properties of target vegetation, provided that these models are mathematically invertable.

The third advantage of the modeling approach is its potential for operational applications with multidirectional measurements available or to be available. As global change is becoming a major environmental issue, more and more remote sensors will be launched that have the capabilities of acquiring multidirectional data at high temporal frequencies. Examples of these types of sensors are Advanced Very High Resolution Radiometer (AVHRR) on NOAA satellite series, Moderate-Resolution Imaging Spectrometer (MODIS) and Multiangle Imaging Spectral Radiometer (MISR) to be launched on the Earth Observing System (EOS) platforms, the VEGETATION sensor to be on board the French SPOT 4 satellite, and the Advanced Visible and Near-Infrared (AVNIR) to be on board the Japanese Advanced Earth Observing Satellite (ADEOS). Once atmospheric effects are corrected for, data acquired with these sensors will be ideal for surface physical property estimation with BRDF modeling effort.

Consequently, the modeling approach is a more reliable method in estimating vegetation biophysical properties through inversion. There are, however, some practical limitations in operational use of this approach. The first limitation is that inversion of a BRDF model of N parameters requires at least $N+1$ simultaneous multidirectional measurements available, which is usually not possible from a single sensor in practice. The second limitation is that acquiring multiple simultaneous multidirectional measurements is not always possible and not economic. For these reasons, those models that require fewer input parameters, therefore fewer multidirectional measurements to invert, are consequently preferred. Parameters estimated by inversion of these models, however, have little or no direct link to vegetation biophysical properties. To estimate parameters that have a direct link to surface biophysical properties, inversion of those physically based models is therefore preferred, though this requires a substantially large number of simultaneous multidirectional measurements. Consequently, an optimistic approach should be investigated to overcome these controversial problems. The objective of this article is, therefore, to investigate approaches that utilize a limited number of multidirectional measurements (maybe fewer than required by physically based BRDF models) to invert those physically based models that require more data than available, for estimation of biophysical properties such as LAI.

APPROACH

Multidirectional reflectance measurements provide complementary information about surface characteristics, while physically based BRDF models provide a direct link between the measurements and physical vegetation parameters. Therefore, multidirectional reflectance measurements can be combined with BRDF models to infer vegetation properties. However, physically based BRDF models require a large number of simultaneous multidirectional measurements than are usually available in inversion processes. Empirical or semiempirical models require fewer input parameters and are easily inverted, but the physical link between the parameters inverted from models and vegetation properties is weak. To overcome this problem, we propose a model-to-model approach that combines physically and empirically based BRDF models to predict vegetation parameters with a limited number of multidirectional measurements.

A Model-to-Model Approach

To use a limited number of remote sensing measurements in the inversion of physically based BRDF models that may require more than the number of measurements available, we combine a simple BRDF model requiring fewer input parameters (N_1) and a physically-based model (requiring N_2 parameters) from which vegetation parameters can be estimated. The simple model will be used in inversion and simulation before the physically based model is inverted. This approach is referred to as the model-to-model approach and is illustrated in

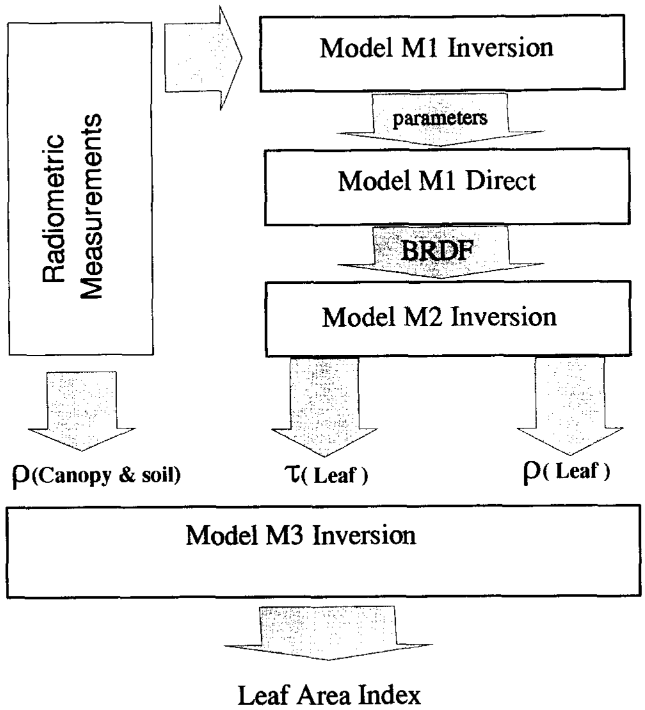


Figure 3. A schematic description of the model-to-model approach in LAI estimation using multidirectional remote sensing measurements and bidirectional reflectance distribution function (BRDF) models.

Figure 3. First, with a limited number (N) of multidirectional spectral reflectance measurements (ρ_τ), a simple empirical or semiempirical model (M1) that requires that N_1 parameter ($N_1 < N$) is inverted to obtain a set of N_1 parameters. These estimated parameters are then used in the simple model itself to simulate multidirectional reflectances of different geometric direction by varying the solar zenith, solar azimuth, view zenith, and view azimuth angle, resulting in a larger data set ($>> N_2$) than required by the physically based model (M2). The simulated data are then used in the inversion of a physically based model (M2), from which some parameters characterizing vegetation properties can be estimated. In this study, we attempted to estimate leaf reflectance ($\rho_{\tau L}$) and transmittance ($\tau_{\tau L}$) from model M2 which are then used as inputs to a third BRDF model (M3) to predict leaf area index (LAI).

Selected BRDF Models

In this study, a semiempirical model proposed by Rahman et al. (1993a,b) was selected in the first step (M1):

$$\rho_s(\theta_1,\varphi_1,\theta_2,\varphi_2) = \rho_0 \frac{\cos^{k-1}\theta_1 \cos^{k-1}\theta_2}{(\cos\theta_1 + \cos\theta_2)^{1-\kappa}} P(g)\,[1 + R(G)], \quad (2)$$

where

$$P(g) = \frac{1 - \Theta^2}{[1 + \Theta^2 - 2\Theta\cos(\pi - g)]^{3/2}} \quad (3)$$

$$R(G) = \frac{1 - \rho_0}{1 + G} \quad (4)$$

$$G = \sqrt{\tan^2\theta_1 + \tan^2\theta_2 - 2\tan\theta_1\tan\theta_2\cos(\varphi_2 - \varphi_1)}, \quad (5)$$

$$\cos g = \cos\theta_1\cos\theta_2 + \sin\theta_1\sin\theta_2\cos(\varphi_2 - \varphi_1), \quad (6)$$

where the θ's are solar (θ_1) and sensor (θ_2) zenith angles and the φ's are the corresponding azimuth angles. This model is simple and requires only three input parameters (ρ_0, k, and Θ). The first parameter, ρ_0 ($0 \leqslant \rho_0 \leqslant 1$), is an arbitrary parameter that characterizes the intensity of surface reflectance. The second parameter, k ($0 \leqslant k \leqslant 1$) is an indicator of the vegetation anisotropy. When $k = 1$, the surface anisotropy characteristics is controlled solely by the third parameter Θ ($-1 \leqslant \Theta \leqslant +1$). The Θ parameter controls the relative contributions of the forward scattering ($0 \leqslant \Theta \leqslant +1$) and backscattering ($-1 \leqslant \Theta \leqslant 0$) and, therefore, is an indicator of the vegetation structures. These parameters are not directly measurable because of the way they were defined (Rahman et al., 1993a,b), and there is no one-to-one relationship with any surface physical parameters. Other existing BRDF models can be used for the purpose of this study, but a general study by Cabot et al. (1994) on the validity of existing BRDF models using ground and airborne remote sensing data indicated that Rahman's model was as good as other more-complex BRDF models in predicting reflectances and is simple and easy for inversion.

The second model (M2) used is from Pinty et al. (1990) and Verstraete et al. (1990):

$$\rho(\theta_1,\varphi_1,\theta_2,\varphi_2) = \frac{\omega}{4}\frac{\kappa_1}{\kappa_1\mu_2 + \kappa_2\mu_1}\left[P_v(g)P(g) + H\!\left(\frac{\mu_1}{\kappa_1}\right)H\!\left(\frac{\mu_2}{\kappa_2}\right) - 1\right], \quad (7)$$

where

$$\mu_1 = \cos\theta_1,\ \mu_2 = \cos\theta_2,\ H(x) = \frac{1 + x}{1 + (1 - \rho)^{1/2}x}, \quad (8)$$

$$P_v(g) \approx 1 + \frac{1}{1 + V_p(g)} \text{ and } V_p(g) = 4\left(1 - \frac{4}{3\pi}\right)\frac{G\mu_2}{2r\Lambda\,\kappa_2}. \quad (9)$$

The $P_v(g)$ is a function that counts for the joint transmission of the incoming and outgoing radiation as well as hot spot effect, ω is the average single-scattering albedo of the particular particles making up the surface, Θ is asymmetry factor as defined in Rahman's model, χ defines leaf orientation, $2r\Lambda$ defines interception cross section of the canopy, and κ is a parameter that is a function of leaf angle distribution (see Pinty et al., 1990). By integrating the average single-scattering albedo (ω) and asymmetry factor (Θ), leaf reflectance and transmittance can be inferred, provided that the leaf angle distribution is quasiuniform and the asymmetry parameter is close to zero (Pinty, 1995, personal communication).

The third model (M3) used in this study is the SAIL model (Verhoef, 1984), which involves a set of radiative transfer equation as proposed by Suits (1972):

$$dE_S/dx = kE_S \quad (10a)$$

$$dE_-/dx = -s\,E_S + aE_- - \sigma E_+, \quad (10b)$$

$$dE_+/dx = s'E_S + \sigma E_- - aE_+, \quad (10c)$$

$$dE_o/dx = wE_S + vE_- + uE_+ - KE_o, \quad (10)$$

where E_s is direct solar flux, E_- and E_+ are diffuse downward and upward flux, E_o is total solar irradiance, K is the extinction coefficient, and k, s, s', a, and σ are coefficients defined by Bunnik (1978). In the SAIL model, Verhoef (1984) characterized vegetation by a leaf inclination distribution function (LIDF), leaf reflectance ($\rho_{\lambda L}$), transmittance ($\tau_{\lambda L}$), and leaf area index (LAI), and a soil substrate by its reflectance ρ_s. With these vegetation parameters he derived k, s, s', a, and σ coefficients and predicted bidirectional reflectance as a function of angular parameters of the sun and sensors (Verhoef, 1984; Bunnik, 1978; Suits, 1972). Because this model requires an LAI parameter as input, inversion of this model allows one to obtain LAI values (Goel and Deering, 1985).

Model Inversion

Parameters in all three models are wavelength (λ) dependent, and we selected spectral wavelengths in the blue, green, red and NIR spectral regions in this study, which corresponded to the Landsat TM bands and three SPOT HRV spectral bands. In the inversion and simulation processes, all four spectral bands were used, and the inversion was performed in such a way that the estimated value would result in a least squared fit for all spectral bands.

EXPERIMENT

Remote Sensing Data Description

In order to validate the proposed model-to-model approach in estimation of LAI, a total of four remote sensing data sets were obtained over alfalfa, cotton, wheat, and pecan canopies from three field experiments. The first experiment, which is referred to as the *wheat* experiment, was conducted at Phoenix, Arizona from day of year (DOY) 13 to DOY 146 (13 January–26 May) in 1983 in a spring wheat field of north–south row direction with spacing of 0.81 m. Spectral reflectances were collected on all clear days with a Modular Multiband Radiometer (MMR) which has spectral bands similar to the TM sensors. The radiometer was mounted onto a yoke and was carried across the previously designed target (size = 1 m × 3 m), acquiring at a 0.25 m interval with a resolution of ~0.5 m. The resulting 12 measurements were then combined to obtain an average reflectance of the wheat canopy.

The second experiment was conducted at The University of Arizona Maricopa Agricultural Center, near Phoenix, Arizona, 1990, and is referred to as the *MAC VI* experiment. Two data sets were collected during this experiment with two sensors. The first data set consisted of the spectral reflectances acquired with the ASAS sensor at 5000 m above ground level on DOYs 250 and 251 (7 and 8 September, respectively) in 1990 at the Maricopa Agricultural Center (MAC) near Phoenix, Arizona. The ASAS data consisted of spectral reflectances in 29 spectral bands from 465 nm to 871 nm, with ~15 nm bandwidth, and the spatial resolution was ~5 m × 2.3 m. A total of three different types of surfaces was selected in this study, which included recently harvested alfalfa, pecan orchards (60–80% cover), and cotton canopy (~80% cover). The data were first corrected for the atmospheric effect using the Herman and Browning (1965) algorithm for scattering and the 5S radiative transfer model (Tanré et al., 1990) for gas absorption [see Moran et al. (1995) for a detailed description]. To overcome spatial differences within each selected target, a window of about 40 × 40 m^2 was extracted from each of the ASAS images for the LAI estimation. The high spectral reflectances were integrated into the same spectral bandwidth as the TM Band 1 and three SPOT HRV spectral bands for easy model inversion. The integrated spectral reflectances were compared with the ground reflectance measurements by Moran et al. (1995), and a good correlation ($R^2 = 0.98$) was found between the ASAS and ground measurements, suggesting that the atmospheric effect was properly removed.

The second data set collected during the *MAC VI* experiment consisted of coincident aircraft measurements of seven view angles over the same targets as the ASAS data but acquired with an Exotech radiometer. The radiometer had one filter similar to the first spectral band of the TM and three filters similar to the SPOT HRV spectral bands. The aircraft was flown at 150 m above ground level, resulting in a nominal spatial resolution of 40 m. The atmospheric effect on the aircraft data was assumed negligible because of its low altitude (150 m) and, therefore, the data were calibrated to surface reflectances with ground reference panel measurements. Comparison of the aircraft data with ground measurements, as well as with the ASAS data indicated that the assumption was valid [see Fig. 3 and 4 in Moran et al. (1995)].

The third experiment, referred to as *mini-alfalfa* experiment, was conducted at the University of Arizona Campus Agricultural Center in Tucson, Arizona from DOY 251 to DOY 284 (9 September–11 October) in 1994 in a small growing alfalfa field (~10 m × 10 m). Bidirectional reflectance factor (BRF) measurements were made with an Exotech radiometer (similar to the one used on aircraft measurements during the *MAC VI* experiment) mounted on a portable BRF apparatus, which can be adjusted according to canopy height. Attached to the apparatus was also a clinometer that recorded exact view angles of the sensor. The Exotech sensor was aligned in the SPOT HRV scanning direction, and the view angle varied from $-55°$ in the backscattering to $+55°$ in the forward scattering directions. Daily BRF measurements were made at different times (from 9:00 a.m. to 12:00 p.m. local time) on all clear days at three different solar zenith angles (ranging from 28° to 56°) in the morning. This data set was used in simulation of the AVHRR sensor overpass geometry later in this study.

Ground LAI Measurements

During the *wheat* experiment, a total of 12 plants were destructively sampled at random in the field, and the green leaf area index (LAI) was measured with an optically integrating lead area meter on a three median-sized plant subsample. Then LAI values were obtained by taking the average of the three measurements.

At the time of the *MAC VI* experiment, LAI measurements were made in cotton and pecan fields. The corresponding LAI measurements in the cotton were made with LAI-3000 leaf area meter. Cotton leaves were collected within randomly selected areas of 31 cm × 41 cm and were put through a portable leaf area meter (LAI-3000A) to obtain the LAI values (3.9 m^2/m^2). At the time of the experiment, the cotton field was uniform and the cotton cover was about 80%. The LAI measurements in the pecan field were made at 17 locations selected at random. The measurements were made with Li-Cor LAI-2000 canopy analyzer, which recorded incoming and intercepted light by the canopy. Although the pecan field was generally uniform, missing trees were observed in the surroundings of some selected locations, resulting in a variation of LAI values from 0.87 to 2.48 from location to location. The alfalfa field was recently harvested and the LAI values were estimated to be near zero, although some litter could be seen at the time of measurement.

During the *mini-alfalfa* experiment, no corresponding LAI measurements were made due to the size of the experiment plots as well as due to the fact that BRF apparatus was kept at the same site for all days in order to monitor the alfalfa growth.

RESULTS

Leaf Area Index Estimation

The estimated LAI values using the ASAS and the aircraft data from the *MAC VI* experiment are depicted in Figure 4 for the three targets: harvested alfalfa, cotton, and pecan. The LAI values for the harvested alfalfa field were estimated to be 0.0 and the calculated LAI value was 0.1. For the pecan trees, the estimated LAI values were consistently lower than the measured values. The variation in estimated LAI from DOY 250 to DOY 251 was less than 10% for the pecan site. Considering the variations among the LAI measurements of

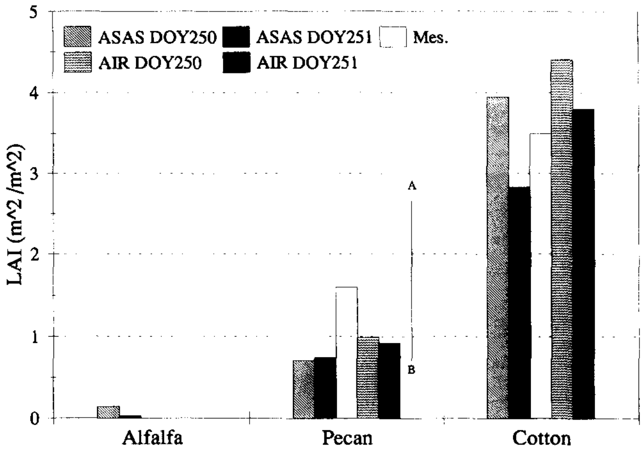


Figure 4. Estimated and measured LAI values for the three selected biome types using data acquired by ASAS and aircraft sensors from the *MAC VI* experiment. The vertical bar AB indicates the range (maximum and minimum) of LAI measurements in the pecan orchards.

the pecan orchards as indicated by the line AB, the estimated LAI is a reasonable approximation of the actual LAI values. There were also some differences in estimated LAI values between the two days, but the variation was less than 10% for the pecan site.

The estimated LAI values for the cotton field on DOY 250 (3.9 m^2/m^2 using ASAS data and 4.4 m^2/m^2 using aircraft data) were higher than the measured LAI (3.5 m^2/m^2), but lower on the next day (2.8 m^2/m^2 using ASAS, and 3.8 m^2/m^2 using aircraft data), with ~10% errors. These errors were within the range of the measurement uncertainties in determining LAI and, therefore, the estimated LAI values were considered to be good estimates. The differences in estimated LAI values of the cotton field between the two consecutive days were ~25% with the ASAS data and ~14% with the aircraft data.

The model-to-model approach was further applied to the remote sensing data from the *wheat* experiment, which consisted of nadir view angle measurements acquired at different solar positions. Ten measurements during the peak growing season from DOY 90 to DOY 100 were used to obtain leaf reflectance and transmittance, which were assumed to be constant throughout the whole growing season. The reflectance measurement at the beginning of the season was used as the soil reflectance for the entire growing season. The results were plotted in Figure 5 as a function of DOY. The circles are the estimated LAI while the solid line is the observed LAI. In the early growing season, the estimated and the measured LAI values matched very well until DOY 80. Between DOY 90 and 100 there was a divergence between the observed and the estimated LAI values. The variations found with the measurements seemed unrealistic since the LAI (vegetation

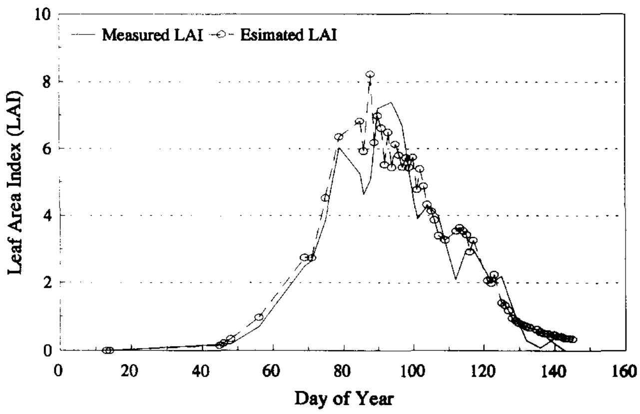
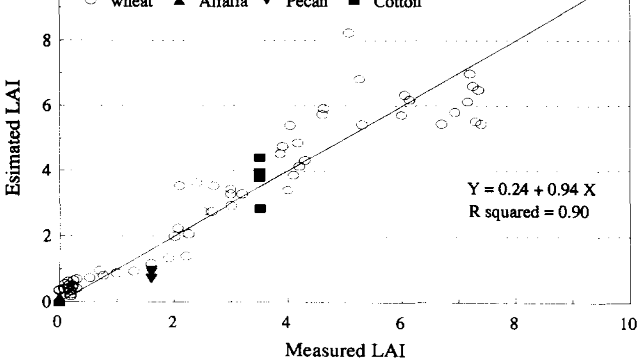


Figure 5. Temporal variation of the estimated and measured LAI values of the wheat canopy using data from the *wheat* experiment as function of growing time (day of year).

density) should be a steady function of time. The noise in the measurements could be due to the sampling schemes and the measurement errors. The model estimated LAI, however, appeared to be less noisy, especially in the early and late parts of the growing seasons. The rapid increase in the estimated LAI from DOY 86 to DOY 88 seemed to be unrealistic since LAI could not increase by 2 (m^2/m^2) within such short time period (2 days). One possible explanation might be the sensitivity of the approach to the spectral reflectances. Reflectance measurement errors may have been amplified by this approach (see sensitivity analysis section).

In Figure 6, the estimated LAI was plotted against the measurements using all data from the *MAC VI* and *wheat* experiments. Statistically, there was little difference between the estimated and measured LAI values, with the correlation coefficient (R^2) of 0.90, indicating the capability of the model-to-model approach by predicting LAI. The estimated LAI values with these data sets were within the range of LAI values

Figure 6. Estimated LAI plotted against the measurements using all data acquired from the *MAC VI* and the *wheat* experiments for different vegetation types: (O) wheat, (▲) harvested alfalfa, (▼) pecan, (■) cotton.



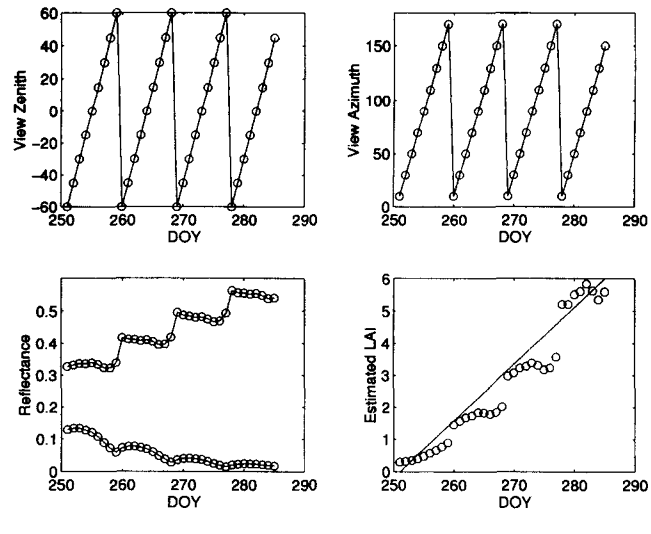


Figure 7. Demonstration of using multitemporal remote sensing data for estimation of LAI with the simulated data from the *mini-alfalfa* experiment: a) sensor's view zenith angles; b) sensor's view azimuth angles; c) simulated temporal red and NIR reflectances; d) estimated temporal LAI.

from field measurements. Notice that the data from the *wheat* experiment consisted of only nadir view angle measurements, but at different solar zenith angles. The good agreement between estimated LAI with the field measurements using this data set suggests that if no simultaneous *multidirectional* measurements are available, *multitemporal* data can be equivalently used in this approach.

Applications with Multitemporal Remote Sensing Data

To demonstrate the potential use of this model-to-model approach in practice using multitemporal remote sensing data, the data collected during the *mini-alfalfa* experiment were used to simulate the observations by the AVHRR sensor, which can provide daily coverage over most areas of the globe. The multitemporal BRF data over the growing alfalfa canopy from the *mini-alfalfa* experiment were first interpolated to different view and then to different solar angles. From the interpolated data, a subset was selected by choosing those daily measurements that have the same geometric configurations as the AVHRR sensor. Figures 7a and 7b show the sensor's geometric configuration, while Figure 7c shows the simulated red and NIR reflectances for a total of four AVHRR generic revisit cycles (a total of 36 days). In the inversion processes, the mean leaf reflectance and transmittance obtained with DOY 278 data were used. The soil reflectance was measured on DOY 251 (before alfalfa emerged). The temporal LAI values estimated with the model-to-model approach are illustrated in Figure 7d. Though there were no ground LAI data available, the estimated LAI values appear reasonable

Table 1. Sensitivities of Leaf Reflectance, Transmittance, and Estimated LAI Values to Measurement Noise in Remote Sensing Measurements

Leaf	*Noise in Reflectance Data*	*Blue (%)*	*Green (%)*	*Red (%)*	*NIR (%)*	*LAI (%)*
Reflectance	30%	15	11	10	0.6	2–40
Transmittance	30%	11	14	14	2	2–40

for the alfalfa canopy. The variation found in the temporal LAI estimates were most likely to due to the fact that the SAIL model does not taken into account the soil bidirectional properties.

Sensitivity Analysis

To investigate the sensitivity of the model-to-model approach to noise from the input radiometric measurements, randomly generated noise of up to 30% was added to the reflectance data collected over the growing alfalfa canopy on DOY 278 during the *mini-alfalfa* experiment when the canopy just reached its full cover. The noisy data (after adding up to 30% noise to the original data) were used to first estimate the leaf properties and then the LAI values. In Figure 8, the estimated leaf reflectance, transmittance, and absorptance were plotted as a function of the spectral wavelength, with the vertical bars being errors due to introduced noise in the reflectance data. It appeared that the leaf transmittance was more sensitive to the noise than the leaf reflectance. The uncertainties in leaf reflectance and transmittance due to the introduced noise in reflectance data are listed in Table 1. The introduced noise was further examined in the LAI estimation using the multitemporal alfalfa data set from the *mini-alfalfa* experiment by running the model-to-model approach with leaf optical properties estimated with noisy data. The estimated LAI values were plotted in Figure 9, where the x-axis is the LAI values estimated with the mean reflectance and transmittance, while the y-axis is the LAI values estimated with noisy leaf reflectance and transmittance. The LAI estimation was clearly sensitive to the noise in leaf reflectance and transmittance, which in turn was a function of the noise levels in the reflectance measurements. At low vegetation densities, where the soil substrate is the dominant radiance contributor, the LAI was less sensitive to noise effect than at high vegetation densities. The noise in LAI estimates can be up to 40% when the remote sensing measurements contain up to 30% uncertainty at LAI value of ~ 6.0.

CONCLUDING REMARKS

Fairly good agreement was found between model-estimated LAI and field measurements, suggesting the validity of the model-to-model approach. Some differences between the measured and estimated LAI values were found, due partially to the errors inherent in field

Figure 8. Sensitivities of the estimated leaf reflectance, transmittance, and absorptance as a function of wavelength (nm) to the noise in spectral reflectance measurements. The vertical bars are the corresponding uncertainties using data from the *mini-alfalfa* experiment.

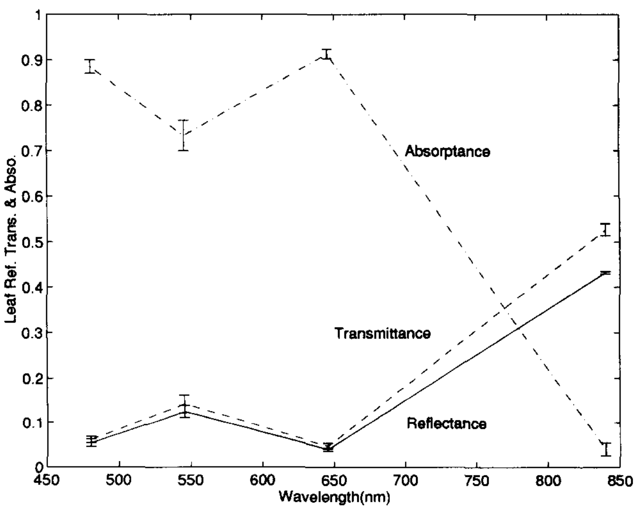
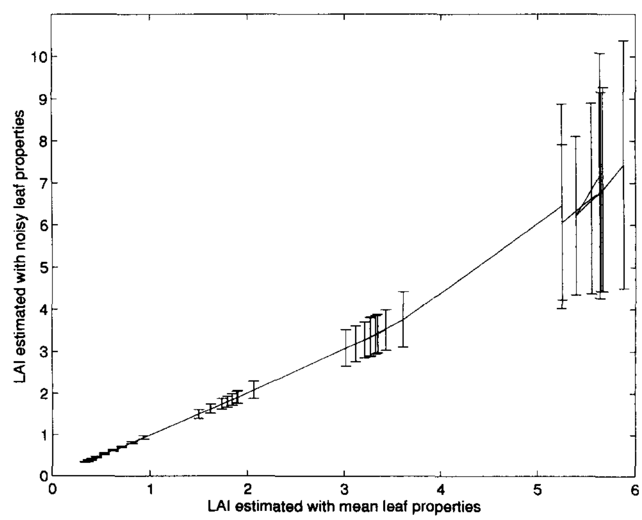


Figure 9. Sensitivity of LAI estimation to the noise in the spectral reflectance measurements. The vertical bars are the uncertainties in LAI estimation using data from the *mini-alfalfa* experiment.



measurements and partially to the errors induced by the modeling approach. The random-sampling schemes for LAI measurements in both wheat and cotton data might be the major cause for variations in the measured LAI, while the uncertainty in reflectances measurements and some degree of inaccuracy in the BRDF models used may account for the variations in estimated LAI. The noise in reflectance measurements certainly influenced the prediction of the vegetation optical properties and, therefore, LAI estimation. When the noise is limited within 30% in the reflectance domain, the optical properties can vary up to 15%, which leads to an error of up to 40% in LAI estimation. The uncertainty in the LAI estimation, however, was shown to be dependent on the stage of the vegetation growth. The denser the canopy (larger LAI values), the larger is the uncertainty in LAI estimation.

The model-to-model approach requires multiple simultaneous multidirectional remote sensing measurements theoretically. Since satellite remote sensors normally cannot provide simultaneous multidirectional measurements over the same pixel or target, there exists a limitation on extending this approach to an operational vegetation monitoring. It was shown, however, that multitemporal remote sensing data could be potentially used with this approach. Within the multitemporal measurement period, a time window (e.g., 1 week) may be located when the vegetation growth is not fast enough to change its spectral properties substantially. The multitemporal data collected within this time window may, therefore, be treated as if they were collected at the same time but different geometric configurations. This was demonstrated to be promising with the *wheat* experiment data as well as with data from the *mini-alfalfa* experiment. Another alternative may be to use data acquired with multiple sensors, which is possible from a practical point of view (Moran et al., 1995). However, when using data collected with different sensors, differences in spectral resolution, spatial scales, and radiometric calibration should be taken into account.

Although potentially this approach can be used in an operational mode to predict LAI with satellite remote sensing data such as those acquired with AVHRR or future MODIS, the atmospheric effect must be sufficiently corrected for, because the atmosphere cannot only introduce substantial noise, which will transform into uncertainties in estimation of vegetation optical properties and the LAI, but also change the bidirectional properties of the radiometric measurements. In either cases the atmospheric effects may result in errors in estimation of vegetation optical properties and the LAI. Consequently, to adapt this approach for operational uses, it may be necessary to incorporate an atmospheric model in this approach or perform atmospheric corrections before applications.

The accuracy of predicting LAI with this approach would certainly be dependent on the accuracy of the BRDF models. Some models were developed for tall vegetation while others were for sparsely vegetated surfaces (see Strahler, 1994; Cabot et al., 1994). Selection of different BRDF models would influence the results of this approach. Different BRDF models should be evaluated. Those models that require fewer input parameters (therefore fewer bidirectional measurements required in inversion) but result in good accuracy are preferred and should be identified. The models used here were satisfactory in predicting LAI for wheat, cotton, pecan, and alfalfa. Application to other vegetation parameter and types of vegetation needs further investigation. Finally, the spatial scaling effect should also be investigated because spatial scales not only influence bidirectional reflectance properties but also the heterogeneity of land surfaces (Moran et al., 1994) and, therefore, affect the interpretation of the results.

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