A Temporally Integrated Inversion Method for Estimating Leaf Area Index From MODIS Data

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Abstract—Multiple leaf area index (LAI) products have been generated from remote-sensing data. Among them, the Moderate-Resolution Imaging Spectroradiometer (MODIS) LAI product (MOD15A2) is now routinely derived from data acquired by MODIS sensors onboard Terra and Aqua satellite platforms. However, the MODIS LAI product is not spatially and temporally continuous and is inaccurate in many areas for some vegetation types. In this paper, a new algorithm is developed to estimate LAI from time-series MODIS reflectance data (MOD09A1). A radiative-transfer model is coupled with a double-logistic LAI temporal-profile model, and the shuffled complex evolution optimization method, developed at the University of Arizona, is used to estimate the parameters of the coupled model from the temporal signature in a given time window. Preliminary analysis using MODIS surface-reflectance data at flux sites was performed to validate this method. The results show that the new algorithm is able to construct a temporally continuous LAI product efficiently, and the accuracy has been significantly improved over the MODIS LAI product as compared to field-measured LAI data.

Index Terms—Dynamic model, leaf area index (LAI), Moderate-Resolution Imaging Spectroradiometer (MODIS), radiative transfer, retrieval.

I. INTRODUCTION

Leaf area index (LAI) is an important vegetation biophysical variable and has been widely applied to estimate crop yield, evapotranspiration, and net photosynthesis. As an important input or output parameter of several dynamic-process models, such as crop-growth and land-surface models, LAI functions as a bridge that connects dynamic-process models to remote-sensing radiative models. Therefore, it is important to accurately estimate LAI from satellite observations at the regional or global scale.

Currently, there are many methods to estimate LAI from remote-sensing data by taking advantage of the statistical relationship between LAI and spectral vegetation indexes [1]–[3] and using physical-model inversion [4], [5] or other non-parametric methods [6]–[8]. These methods have their own strengths and limitations. Since the model inversion methods are physically based and can be adjusted for a wide range of situations [9], radiative-transfer models are increasingly used in the inverse mode to estimate LAI from remotely sensed data [10], [12]. Several LAI products have been produced from data acquired by the Moderate-Resolution Imaging Spectroradiometer (MODIS) [13], Multiangle Imaging SpectroRadiometer (MISR) [14], Advanced Very High Resolution Radiometer [15], and VEGETATION [16]. Among them, the representative global LAI product is the MODIS LAI product (MOD15A2) which is now being routinely provided from data acquired by MODIS sensors onboard Terra and Aqua platforms as part of the National Aeronautics and Space Administration’s Earth-Observing System [17]. Since 2000, the use of MODIS-derived LAI in a variety of global and regional studies has steadily been increased.

However, there are at least two problems associated with the current MODIS standard LAI product. First, it is not spatially and temporally continuous, and there are coverage gaps due to instrument problems and persistent cloud cover in some areas. Second, it is inaccurate for some vegetation types in many areas [18]–[21]. Validation of the Collection 4 MODIS LAI product indicated that it significantly overestimated LAI for the Tapajós region, eastern Amazonia, by a factor of 1.18 [22], while in North China Plain cropland, the MODIS product noticeably underestimated LAI for the winter wheat in April 2004, although it resembles the general pattern of LAI seasonal variation [23]. The spatiotemporal discontinuity and inaccuracy of the MODIS standard LAI product limits its applications in crop-growth monitoring and yield estimation, land-surface process simulation, and global change research. To generate spatially and temporally continuous LAI products, many efforts have been made to fill the gaps and improve quality [24]. Chen et al. [25] developed a locally adjusted cubic-spline capping method to identify atmosphere-contaminated data points and replace them through temporal interpolation. Fang et al. [26] developed a temporal spatial filter method that integrates both the multiseasonal average trend and the seasonal observations to produce spatially and temporally complete LAI product. The product is derived from the highest quality MODIS LAI values. Both low-quality data and missing values are replaced by the new estimates from the highest quality data. Lu et al. [27] developed a wavelet-based method to reduce noise in MODIS normalized difference vegetation index (NDVI), LAI, and albedo time-series data. Nevertheless, these methods rely solely on the MODIS product itself to improve the accuracy without integrating prior information of the LAI changes and remote-sensing observations.

LAI that defines an important structural property of the plant canopy is time-dependent. It is this temporal variability that dynamic-process models (such as crop growth or forest...
Incorporating the inherent change rules of biophysical variables into estimation methods is essential to increase the accuracy of biophysical-variable retrievals.

This paper aims at developing a new LAI inversion algorithm by coupling a radiative-transfer model and an empirical LAI temporal-profile model. The shuffled complex evolution (SCE) method developed at the University of Arizona (SCE-UA) is an optimization method that is used to adjust the values of control variables of the coupled model. The algorithm is tested using MODIS data at some flux sites and validated using ground LAI measurements.

II. METHODOLOGY AND DATA

The general process of the new method is shown in Fig. 1. MODIS time-series NDVI are used to determine the number of growing seasons and the start and end of the seasons. The time from the start to the end is designated as a time window, and the MODIS time-series reflectance data of good quality in these time windows are selected to estimate control variables of the coupled model. The MODIS LAI multiyear mean is fitted by the LAI temporal-profile model to determine the values of the model parameters which are used as prior information. Surface reflectance over time are simulated by the coupled model. The method tunes control variables of the coupled model until the temporal behavior of modeled surface reflectances reaches the best agreement with the multitemporal remotely sensed measurements. Then, LAI profiles can be reconstructed by the LAI temporal-profile model according to the values of the coupled-model control variables.

A. Determination of the Number of Growing Seasons

The TIMESAT program, developed by Jonsson and Eklundh [28], presents three different least squares methods for processing time-series of satellite sensor data, and the resulting smoothed curves are used for extracting seasonal parameters related to the growing seasons. Because of the high level of noise, it is often difficult to determine the number of annual growing seasons based on data for only one year. In TIMESAT, the data from surrounding years are included to reduce the effect of noise on determinations.

Suppose \( I(t_i), i = 1, 2, \ldots, K, \) is a set of data values for three years, and a model function shown in (1) is fitted to the time-series

\[
f(t) = c_1 + c_2 t + c_3 t^2 + c_4 \sin(\omega t) + c_5 \cos(\omega t) + c_6 \sin(2\omega t) + c_7 \cos(2\omega t) + c_8 \sin(3\omega t) + c_9 \cos(3\omega t)
\]  

where \( \omega = 6\pi/K \). In fact, (1) consists of a combined polynomial and harmonic bases. The combined polynomial basis determines the base level and the interannual trend, while the combined harmonic basis represents one, two, and three annual vegetational seasons, respectively, which correspond to three maxima of the smoothed curve. If the amplitude of the secondary maxima exceeds a certain fraction of the amplitude of the primary maxima, we determine two annual seasons. For cases where the amplitude of the secondary maxima is low, the number of annual seasons is set to one. Fig. 2 shows the fitted MODIS NDVI temporal profiles with different annual vegetational seasons. (a) Fitted NDVI temporal profiles with the start and end of a single season, (b) Fitted NDVI temporal profiles with the starts and ends of double seasons. In Fig. 2(a), the amplitude of the secondary maxima is small, and the number of seasons is set to one, while in Fig. 2(b), the amplitude of the secondary maxima is comparatively large, so the number of annual seasons is set to two.
Then, the start and end of the seasons are computed according to the combined harmonic basis. In TIMESAT, the beginning of a season is defined from the fitted functions as the point in time for which the value has increased by a certain number of the distance between the left minimum level and the maximum, and the end of the season is defined similarly. In this paper, we just determine the start and end of the seasons roughly to fit the growing season using the double-logistic function. Therefore, the left minimum value and right minimum value of the season are defined as the start and end of the season marked by circles, as shown in Fig. 2.

**B. Model Coupling**

There are two main methods for integrating remotely sensed data into dynamic-process models [1]. The first approach uses canopy state variables (such as LAI and soil moisture) derived from remote-sensing observations, to force or recalibrate a few well-identified dynamic-model parameters. The second approach assimilates the direct observations (such as reflectance and temperature) in which the whole process, from control variables to radiometric signals, is considered by coupling a dynamic-process model with an appropriate radiative-transfer model. The coupled model is, thus, directly recalibrated to provide the best agreement between simulations and satellite measurements. In this paper, the second approach is used to assimilate MODIS time-series reflectance data.

Radiative-transfer models describe the relationship between canopy characteristics and reflectance, and many of them have been developed to obtain land-surface biophysical parameters [29]–[32]. In our parameter retrieval, the Markov chain reflectance model (MCRM) developed by Kuusk [33], [34] is selected as the forward model to simulate the canopy reflectance. This model incorporates the Markov properties of stand geometry into an analytical multispectral canopy-reflectance model, which makes the model more flexible and more applicable [35]. The MCRM can calculate the angular distribution of the canopy reflectance (ranging spectrally from 400 to 2500 nm) for a given solar direction [33].

Many mechanical or semimechanical models were proposed to describe LAI dynamics [36], [37]. In this paper, an empirical statistical model which, was first used to describe the temporal NDVI profile of agricultural crops [38], [39], is utilized to describe the seasonal LAI trajectory. The model, named after a double-logistic function, is

$$LAI(t) = vb + \frac{k}{1 + \exp(-c(t-p))} - \frac{k + vb - ve}{1 + \exp(-d(t-q))} \quad (2)$$

where the variable $t$ represents the day of the year, and January 1 is set to zero, the variable $k$ represents the asymptotic value of LAI, the variables $c$ and $d$ represent the slopes at the first and second inflection points, the variables $p$ and $q$ represent the date of these two points, the variables $vb$ and $ve$ represent the LAI values at the beginning and the end of the growing season, respectively, and the vector $\theta$ represents the parameter set of the double-logistic function. In order to determine the prior information of these parameters, the double-logistic function is fit to the MODIS LAI profile. Noting that the MODIS LAI product is discontinuous both spatially and temporally, existing spatial and temporal gaps are first filled with the multiyear averages of the same day before fitting the MODIS LAI. If the values are missing over all years, the pixel is filled with the spatial averages of the same vegetation type within the site area. Then, the Levenberg–Marquardt optimization algorithm [40] is used to determine the parameters of the double-logistic function according to the average values of multiyear MODIS LAI. Fig. 3 shows the fitted curves using the fitted parameters for the vegetation type of crop and forest at pixel level. Obviously, the double-logistic function can effectively describe the LAI profiles for these vegetation types.

In our algorithm, the double-logistic function was coupled to the Kuusk model. As shown in (2), LAI is the only output of the double-logistic function. At the same time, LAI is an important input variable of the Kuusk model. Therefore, LAI is used as a bridge to couple the double-logistic function with the Kuusk model. The coupled model is then used to simulate surface reflectances at each observation time corresponding to the MODIS observation in the growing season. The input parameters of the coupled model are summarized in Table I.

**C. Cost Function and Optimization Method**

Radiative-transfer model inversion consists in adjusting the values of input canopy biophysical variables, such that the surface reflectance simulated with the radiative-transfer model optimally matches the reflectance measured by the sensor. This
In this paper, a temporally integrated inversion method is applied to estimate LAI from time-series remote-sensing observations. The coupled model is used to simulate surface reflectances at each observation time corresponding to the MODIS observation in the growing season. An optimization method seeks a model trajectory that best fits a set of observations, i.e., to minimize the following functional:

$$J_2(x) = \frac{1}{2}(x - x_b)^T B^{-1}(x - x_b) + \frac{1}{2} \sum_{i=1}^{n}(y_i - H_i(\alpha, \text{LAI}_i(\theta)))^T R_i^{-1}(y_i - H_i(\alpha, \text{LAI}_i(\theta)))$$

(4)

where the variable $i$ represents the time index, vector $y_i$ represents the surface reflectance obtained by MODIS at time step $i$, vector $H_i(\cdot)$ represents the time-dependent radiative-transfer model, LAI$_i(\cdot)$ stands for the empirical statistical model shown in (2), matrices $B$ and $R_i$ represent the background error covariance and the observation error covariance, respectively. The control vector $x$ depicts the parameter set to be estimated, and the vector $x_b$ represents the a priori information of the control vector. In this paper, the control vector includes two parts, namely, the starred variables of the Kuusk model denoted by the vector $\alpha$ and the starred variables of the double-logistic function in Table I. In consideration of some factors affecting the quality of MODIS observation data or some spectral bands of the observation data, the quality-control information from the MODIS reflectance data are used to reject the contaminated data before parameter retrieval.

To minimize the objective function $J_2(x)$, the SCE-UA algorithm is used to obtain the optimal control vector, which does not require the derivatives of the function and can avoid being trapped by small pits and bumps on the function surface. The SCE search routine is a global optimization strategy that combines the strength of the simplex method with the concept of a controlled random search, competitive evolution, and the strategy of complex shuffling. The synthesis of the four concepts makes the SCE-UA method more effective, robust, flexible and efficient, and less sensitive to initial values of parameters than the simplex method [42].

### D. Data

To compare retrieved LAI to ground-measured LAI, some flux sites where there are time-series of LAI field measurements were selected. Such comparison is used to validate the new algorithm. The attributes of the chosen flux sites are given in Table II. One year’s data were processed for each site, and the specific year used for a comparison is not the same for all sites, since years were picked based on availability of both measured LAI and MODIS satellite data.

The Bondville site is an agricultural site in the midwestern part of the U.S. (near Champaign, IL) which is part of the network of eddy covariance flux towers associated with AmeriFlux and Core Validation Sites affiliated with the MODIS Land Team [43], [44]. The site was established in 1996, with the long-term goal of obtaining the in situ information required.
to test and improve the representation of land-surface processes in soil–vegetative–atmosphere transfer models. The field at the Bondville site was continuous no-till with alternating years of soybean and maize crops [45]. In 2001, the crop was maize with a maximum LAI of 4.38 and a corresponding height of 2.4 m.

The Mead rain-fed maize–soybean rotation site is one of three sites located at the University of Nebraska Agricultural Research and Development Center near Mead, NE. While the other two sites are equipped with irrigation systems, this site relies on rainfall. The field in this site has been under no-till with alternating years of maize and soybean crops, since 2001. In 2004, the crop was soybean with a maximum LAI of 4.5 and an associated height of 0.9 m.

The Tonzi Ranch site is located on a privately owned (Mr. Russell Tonzi) ranch in California, U.S., and is subject to grazing. It possesses two distinct layers with blue oak trees in the overstory and annual grasses in the understory. The oak trees are deciduous and dormant in the winter-wet season with an average canopy height of 7.1 m and a maximum LAI of 0.6. The grass understory is active only during the winter/spring-wet season, usually from the end of October to the middle of May in the next year. The maximum LAI of the grass is around 1.0 [46].

Located in the North China Plain (an alluvial plain in the lower reaches of the Yellow River), the Yuchen site is in an irrigated agricultural field. This site was chosen for analysis because it practices double cropping. After harvesting a wheat crop by early summer, the farmers in this region plant corn on that acreage for harvest in the fall. This site is part of the largest agricultural area of wheat and corn production in China.

Located on the northern slope of Changbai Mountain in northeastern China, the Changbaishan site is characterized by temperate broadleaf-conifer-mixed forest.

Table II: Site Information for FLUXNET Sites Selected for Testing the Method

<table>
<thead>
<tr>
<th>Site Name</th>
<th>Latitude (°)</th>
<th>Longitude (°)</th>
<th>Year of Data Used</th>
<th>Land Cover Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bondville</td>
<td>40.0061</td>
<td>-88.2919</td>
<td>2001</td>
<td>Croplands (maize)</td>
</tr>
<tr>
<td>Mead: rainfed maize–soybean rotation site</td>
<td>41.1797</td>
<td>-96.4396</td>
<td>2004</td>
<td>Croplands (soybean)</td>
</tr>
<tr>
<td>Tonzi Ranch</td>
<td>38.4316</td>
<td>-120.966</td>
<td>2001–2002</td>
<td>Oak savanna, grazed grassland Broadleaf conifer mixed forest</td>
</tr>
<tr>
<td>Changbaishan</td>
<td>42.4025</td>
<td>128.0958</td>
<td>2002</td>
<td>Croplands (wheat, corn)</td>
</tr>
<tr>
<td>Yuchen</td>
<td>36.95</td>
<td>116.60</td>
<td>2002</td>
<td></td>
</tr>
</tbody>
</table>

To test the new methods, the input data include multiyear MODIS LAI (MOD15A2), time-series of MODIS reflectance (MOD09A1), and time-series of MODIS NDVI (MOD13Q1). All products are from the latest version (Collection 5). For each site, a 49-km² region around the tower or field site is extracted, so there are 7 × 7 subsets from the MODIS LAI product with a spatial resolution of 1 km, 14 × 14 subsets from the MODIS reflectance product with a spatial resolution of 500 m, and 28 × 28 subsets from the MODIS NDVI product with a spatial resolution of 250 m.

III. RESULTS ANALYSIS

A. Results for Different Vegetation Types

To assess the temporally integrated inversion method, comparisons between the routine method [retrieval of biophysical parameters by minimizing the cost function described in (3)] and the new method were carried out over several flux sites for three primary vegetation types (crops, grasslands, and forests) at pixel level. To better compare and analyze the retrieved results, both the routine method and the temporally integrated inversion method used the SCE-UA algorithm to minimize $J_1(x)$ and $J_2(x)$, respectively. For clarification, the LAI values derived by the new method are denoted by LAI-TS, while the LAI values derived by the routine method are denoted by LAI-SP.

At the same time, we note that regardless of the method (either routine or new) used to estimate the control vector, how to specify the background error covariance and the observation error covariance is an important issue because it determines the balance between measurements and prior information. In our experiments, we use diagonal error-covariance matrices, and they are set up according to the statistical analysis of field measurements.

Fig. 4 shows the retrieved LAI time-series for crops at the center pixel of the Bondville site. The MODIS NDVI (MOD13Q1) data are first fitted to determine the number of seasons and the start and end of the seasons. From Fig. 4(a),
the secondary maxima is small, so there is only one annual season in the area of Bondville, and the start (Julian day 97) and end (Julian day 289) of the season are also shown in Fig. 4(a). The MODIS surface-reflectance data between the start and end of the season are used to estimate the control variables of the coupled model, and the LAI time-series computed using the double-logistic function by inputting the newly estimated control-variable values is shown in Fig. 4(b). MODIS LAI values and LAI time-series retrieved by the routine method are also shown in Fig. 4(b). Clearly, the MODIS LAI values at this pixel have markedly underestimated field measurements in the crop growing season. Fluctuations, particularly during the crop growing season, result from the difficulty of acquiring cloud-free images in this time period due to the high humidity in the atmosphere. For days 169 and 177, MODIS LAI values are missing. The LAI time-series retrieved by both the routine and new methods are much closer to the field-measured LAI data, but the routine method’s time-series retains unrealistic fluctuations, as shown in Fig. 6(b). Obviously, the temporally integrated inversion method performs better.

Similar results are shown in Fig. 5 at the Mead rain-fed maize–soybean rotation site. Because LAI products from Collection 5 MODIS reprocessing in 2004 are not yet available, Fig. 5(b) shows the multiyear averages of LAI, which also noticeably underestimate the field measurements in the crop growing season. The time-series of LAI retrieved by the routine method show abrupt rises or drops in the crop growing season, while the temporally integrated inversion method produces a smoothed LAI profile with improved accuracy of retrieved LAI. Fig. 6 shows the retrieved LAI time-series for the grass type at the center pixel of the Tonzi Ranch site from Julian day 241 of 2001 to Julian day 233 of 2002. There is only one season at this site according to the MODIS NDVI profile, with the beginning and end of the season marked by circles, as shown in Fig. 6(a). From Fig. 6(b), the MODIS LAI values at this pixel have markedly overestimated field measurements of LAI. Fluctuating values during the grassland growing season are evident, with abrupt drops at day 361 of 2001 and day 1 of 2002. The MODIS LAI value for day 81 of 2002 is missing. The time-series of LAI retrieved by both the routine and new methods are much closer to the field-measured LAI data as compared to the MODIS LAI product, but the routine method’s time-series retains unrealistic fluctuations, as shown in Fig. 6(b). Obviously, the temporally integrated inversion method performs better.
Fig. 7. Fitted NDVI temporal profiles with different annual vegetational seasons. (a) Fitted NDVI temporal profiles with the start and end of a single season. (b) Fitted NDVI temporal profiles with the starts and ends of double seasons.

Fig. 7 shows the retrieved LAI time-series for broadleaf-conifer-mixed forest at the center pixel of the Changbaishan site. From Fig. 7(b), both the MODIS LAI profile and the LAI time-series retrieved by the routine method show several dramatic spikes and dips. The MODIS LAI values at this pixel are obviously greater than the basic retrieved LAI values particularly during the forest growing season. The temporally integrated inversion method produced a smoothed LAI profile; however, there is no field-measured LAI with which to compare the accuracy of the LAI retrievals.

B. Results for Multiple Cropping

For some areas, there is only one annual vegetation-growth season, but for other areas, there may be two or even three annual vegetation growth seasons. Accordingly, the profiles of the NDVI or LAI time-series are unimodal, bimodal, or trimodal. Fortunately, the method described in Section III-C can determine the number of annual growing seasons and their approximate timing. In this section, the results to retrieve LAI for the multiple annual vegetation seasons are described.

Because the double-logistic function can only fit a unimodal profile, it is necessary to separate the two or three annual vegetation seasons into multiple unimodal profiles according to the beginning and end of the seasons. The LAI profiles are then retrieved for each separate, but sequential, vegetation season. The profiles from all the seasons then are merged into an overall annual LAI profile.

Fig. 8 shows the retrieved LAI time-series with double annual vegetation seasons at the center pixel of the Yuchen site. From Fig. 8(a), the fitted NDVI profile shows that there are two annual vegetation seasons, for which the beginning and end of the seasons are marked by circles. The MODIS LAI values at this pixel are obviously greater than the basic retrieved LAI values particularly during the forest growing season. The temporally integrated inversion method produced a smoothed LAI profile; however, there is no field-measured LAI with which to compare the accuracy of the LAI retrievals.

C. Regional Application

To further confirm the algorithm’s validity, we apply the temporally integrated inversion method to retrieve LAI on the regional scale. A 7 km × 7 km area around the flux tower at Bondville was selected, and the regional LAI mapping results from the MODIS reflectance data acquired over this area in 2001 with the spatial resolution of 500 m are shown in Fig. 9.
As shown, temporal variation of the LAI values in this region is reasonable.

To document the spatial variability of the Bondville site, the MODIS NDVI data at 250-m resolution over the area on day 193 of 2001 are shown in Fig. 10. Although cropland is the sole designated land-cover type in this 49-km² region (according to the MODIS land-cover product MOD12Q1), some degree of heterogeneity is evident. A comparison of the LAI mapping results with the MODIS NDVI image for day 193 of 2001 illustrates that the LAI and NDVI maps show very consistent spatial patterns, which gives good confidence in the retrieval performances.

Fig. 11 shows the MODIS LAI product with a spatial resolution of 1 km over the same region in 2001. Obviously, the MODIS LAI product is discontinuous in space and time, particularly in the crop growing season. On days 169 and 177, there are no LAI values over the region due to instrument problems. The MODIS LAI does not display an obvious seasonal trajectory as can be seen, comparatively speaking, with the continuous LAI retrieved by the temporally integrated inversion method. Although there may be some possible scaling biases with the LAI-TS, the ranges of LAI values are more reasonable and realistic than those of the MODIS LAI product.

IV. CONCLUSION AND DISCUSSIONS

At present, scientists in a variety of disciplines using models to estimate crop yields, monitor crop growth, simulate land-surface processes, and research global change scenarios are limited by deficiencies in data representing LAI, an important biophysical parameter. The MODIS LAI product is discontinuous in both time and space. Additionally, the MODIS product systematically underestimates LAI for some vegetation types in one region and overestimates LAI for some vegetation types in other regions. In this paper, a temporally integrated inversion method was designed to produce spatially and temporally continuous LAI products with relatively higher quality. Two advantages of the method are that it integrates the inherent change rules of biophysical variables into the retrieval methods and uses multitemporal remote-sensing data to retrieve parameters of the coupled model. Another advantage of the method is that it allows a significant reduction in computation time by using the retrieved parameters of the empirical statistical model to compute a temporal profile of LAI, as compared to the radiative-transfer model inversion which is replicated over all dates using the cost function described in (3).

Results as described in this paper have shown that the new algorithm is able to produce a continuous LAI product efficiently, and the validation of the retrieved LAI against field measurements shows that the retrieved LAI precisely reconstructs the seasonal variation patterns of remote-sensing biophysical variables.

The temporally integrated inversion method can remove abrupt spikes and dips and generate a smoothed LAI profile. On the downside, the relatively fixed shape of the LAI empirical statistical model precludes description of more local (in time) impacts of stresses such as temperature and precipitation changes or disturbances such as fire, disease, and insect damage. Perturbations caused by these various stresses could
be responsible for abrupt fluctuations in observed and routine-retrieved LAI. For example, in Fig. 4, MODIS LAI and LAI-SP show sudden drops at day 201. The ground-measured LAI also shows a decrease (although less than that of MODIS LAI) at day 198. Fig. 12 shows crop height in the 2001 growing season. Note that from days 184 to 191 and from days 198 to 205, the crop grows quickly, while from days 191 to 198, crop height grows only 18 cm, and the LAI is reduced from 4.39 to 3.72 during this period. Fig. 4(b) shows that the LAI profiles reconstructed by the LAI empirical statistical model fail to describe these local changes. Consequently, an important future-research priority is to improve the performance of the dynamic model. More complex models based on the physical and biological processes of ecosystems will be employed.

Currently, although an understanding of the LAI dynamics described by the empirical statistical model is integrated into the retrieval method, the structural and optical properties of leaves and background are specified as constant with time. In fact, many biophysical variables used in the radiative-transfer model, such as the leaf chlorophyll content, may also possess inherent temporal change rules as a function of canopy phenomena. Integrating more information about other biophysical variables into the retrieval method may further improve the accuracy of the retrieved LAI.

In addition, with observational information restricted to data from a single satellite with limited observational frequency, the retrieved control variables of the coupled model are, in turn, less than ideal. In the near future, we hope to carry out more extensive validation for all cover types and plan to further improve upon the quality of the MODIS LAI product by integrating multisensor [MISR, VEGETATION, and synthetic aperture radar] data and extending the retrieval effort on the regional scale.

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REFERENCES


R. Myneni, Y. Knyazikhin, and L. Wang, “Retrieval of canopy biophysical
Int. J. Remote Sens.
[37x589]Authorized licensed use limited to: Univ of Calif Berkeley. Downloaded on January 6, 2010 at 03:37 from IEEE Xplore.  Restrictions apply.