MODIS Leaf Area Index Products: From Validation to Algorithm Improvement

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***Abstract*—Global products of vegetation green Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation absorbed by vegetation (FPAR) are being operationally produced from Terra and Aqua Moderate Resolution Imaging Spectroradiometers (MODIS) at 1-km resolution and eight-day frequency. This paper summarizes the experience of several collaborating investigators on validation of MODIS LAI products and demonstrates the close connection between product validation and algorithm refinement activities. The validation of moderate resolution LAI products includes three steps: 1) field sampling representative of LAI spatial distribution and dynamic range within each major land cover type at the validation site; 2) development of a transfer function between field LAI measurements and high resolution satellite data to generate a reference LAI map over an extended area; and 3) comparison of MODIS LAI with aggregated reference LAI map at patch (multipixel) scale in view of geo-location and pixel shift uncertainties. The MODIS LAI validation experiences, summarized here, suggest three key factors that influence the accuracy of LAI retrievals: 1) uncertainties in input land cover data, 2) uncertainties in input surface reflectances, and 3) uncertainties from the model used to build the look-up tables accompanying the algorithm. This strategy of validation efforts guiding algorithm refinements has led to progressively more accurate LAI products from the MODIS sensors aboard NASA's Terra and Aqua platforms.**

***Index Terms*—Fraction of Photosynthetically Active Radiation (FPAR) absorbed by vegetation, Leaf Area Index (LAI), Moderate Resolution Imaging Spectroradiometer (MODIS), validation.**

I. Introduction

THE MODERATE Resolution Imaging Spectroradiometer (MODIS) Land team is responsible for the development and validation of products which include vegetation green Leaf Area Index (LAI) and Fraction of Photosynthetically Active Radiation (FPAR) (400–700 nm) absorbed by vegetation (FPAR) [1]–[6]. The products are generated at 1 km spatial resolution daily and composited over an eight-day period based on the maximum FPAR value. MODIS product versions are called Collections. Collection 1 of Terra MODIS products covered the period from February 2000 to February 2001; Collection 3 from November 2000 to December 2002; and the latest version, Collection 4 from February 2000 to the present time. Collections 3 and 4 LAI/FPAR products have stage 1 validation status, i.e., product accuracy has been estimated using a small number of independent measurements obtained from selected locations and time periods and ground-truth/field program effort.

The objective of this paper is to summarize the experience of several collaborating investigators on LAI/FPAR validation and to demonstrate the close connection between product validation and algorithm refinement activities. At the present time, most of the field data are limited to LAI, and only a few FPAR measurements are available over select locations. Therefore, most of the material in this paper is focused on the LAI product.

This paper is organized as follows. Section II reviews the methodology for validation of moderate resolution LAI/FPAR products. Section III summarizes published results on the validation of these products over different vegetation types. Section IV demonstrates the feedback between validation and algorithm refinement activities. The concluding remarks are presented in Section V.

II. Validation Methodology

A direct comparison between ground measurements and corresponding MODIS products is not recommended because of scale-mismatch, geolocation errors and vegetation heterogeneity at the resolution of MODIS data. Thus, an intermediate step that involves a fine resolution map of the variable of interest is introduced. This map is generated with field data and high resolution satellite data (ETM+, SPOT, ASTER, etc.) When aggregated to the MODIS resolution, this map serves as the ground-truth [6]–[9]. Therefore, the validation of moderate resolution LAI products includes these steps (Fig. 1)—ground sampling of vegetation variables during field campaigns, generation of a fine resolution map of the variables and comparison of the aggregated fine resolution map with MODIS products. Validation results can be used to diagnose algorithm deficiencies and to develop refinements—this step is discussed in Section IV.

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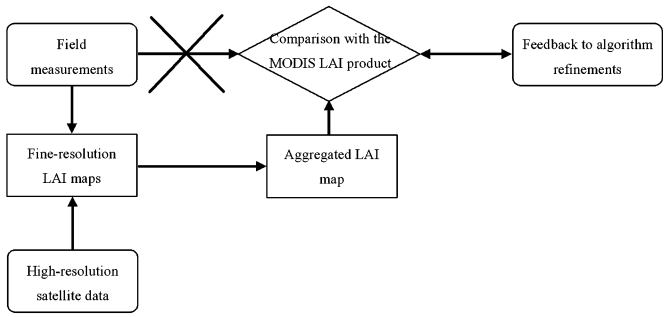

Fig. 1. Schematic representation of the validation procedure.

A. Ground Data Sampling

The selection of a particular site is restricted by several factors—availability of research facilities (laboratory, towers, and communication pathways), availability of scientific records for variables of interest from the past and also availability of ancillary data (such as fine resolution satellite data). In order to adequately represent the spatial distribution of LAI at the site with a minimum of sampling points, the spatial distribution of land cover types can be estimated by referencing existing land cover maps. For each land cover type, relatively homogeneous patches are defined in order to sample the natural range of the vegetation variables of interest. Patches can be identified by segmenting high resolution satellite data [6], [9]. Multiple LAI and GPS measurements are performed in each patch to reduce measurements errors. Measurements are also performed at multiple spatially distributed patches for each land cover class to sample the natural dynamic range of variation of the variable of interest.

LAI measurements can be performed by two methods: direct and/or indirect. Direct measurements through harvesting and litter traps are laborious and not practical for validation of moderate resolution satellite products. However, they can be used to calibrate indirect methods [10]. Most field campaigns utilize indirect measurements of LAI through allometric and optical methods. Optical measurements are performed with the LAI-2000 Plant Canopy Analyzer [WWW1], Tracing Radiation and Architecture of Canopies (TRAC) instrument [WWW2], and hemispherical fisheye photographs [WWW3]. Optical measurements of LAI could be biased. First, optical measurements do not account for clumping of vegetation elements (e.g., LAI-2000 measurements) or do it in a semi-empirical way (TRAC measurements). Ancillary information on structural properties of canopies is required to correct the retrievals for grouping of vegetation elements at shoot and crown levels [11]. Vegetation clumping and saturation of the optical signal reduce the accuracy of LAI measurements in high LAI stands (broadleaf forests). Second, automated processing of optical LAI measurements does not distinguish between green leaves and hardwood material. The removal of such effects can be tedious if it is done with manual processing of images from a fisheye camera or requires specific allometric relations to convent plant area index to LAI.

B. Generation of Fine-Resolution Maps

The validation procedure requires generation of a fine resolution map of the variable of interest from ground measurements and high resolution satellite imagery according to a specific algorithm, also called the transfer function. Three broad categories of transfer function exist: empirical methods, physical models, and hybrid approaches. Empirical methods are generally implemented with regressions or neural networks [6], [9], [12]–[14]. The correlation between various high resolution satellite data based vegetation indices (VI), such as Normalized Difference Vegetation Index (NDVI), Simple Ratio (SR), Reduced Simple Ratio (RSR), Canonical Correlation Analysis Index (CCA), and ground measurements of LAI is used to establish an empirical model. Empirical methods assume that variations in surface reflectances are due to variations in a single vegetation variable (LAI), and neglect the impact of variations in atmospheric conditions, view-illumination geometries, soil properties, etc. Such methods are relatively easy to implement and can provide optimal results when applied at the local scale of a validation site, where extensive ground measurements were performed.

The inversion of physical models is an alternative to empirical methods, if generation of a fine resolution LAI map is required over a large area [6], [15]. Generally, models based on the radiative transfer (RT) equation are used. The models solve the RT equation numerically to establish a relationship between LAI and surface reflectances for given patterns of soil reflectance, view-illumination conditions and optical properties of vegetation and other parameters. The solutions are stored in the form of a look-up table (LUT) and used to retrieve LAI from high resolution satellite surface reflectance data. In this approach ground data are mainly used to calibrate model parameters. The disadvantages of the method are: 1) some model parameters, such as information on canopy structure, may be laborious to collect; and 2) the inversion of a physical model does not have a unique solution [1].

A hybrid approach that combines physical and empirical methods can be used to generate fine resolution LAI maps [14]. A training data set is generated by the physical model and is used to train a neural network or to calibrate a regression. The trained empirical method can be applied to predict LAI values. This method uses a physical model in a forward mode. The disadvantage of the hybrid approach, common to all methods that involve the use of a physical model, is that some parameters required by the model may not be available.

Irrespective of the method used, uncertainties in field measurements and satellite data ultimately limit the accuracy of fine resolution LAI maps. The estimation of LAI from spectral surface reflectances (inverse calculations) is an ill-posed problem, while the prediction of the radiation field given LAI values (forward calculations) is a well-posed problem [6]. The forward mode is stable, i.e., small variations in LAI and other model parameters result in limited variations in modeled spectral surface reflectances, while, inverse calculations result in unstable solutions, namely, small variations in surface reflectance result in large variations in retrieved LAI values and/or in destabilization of the retrieval process [5], [6].

C. Comparison of Aggregated Fine-Resolution Map and MODIS Product

The last step in the validation procedure requires aggregation of the fine resolution LAI map to moderate resolution through

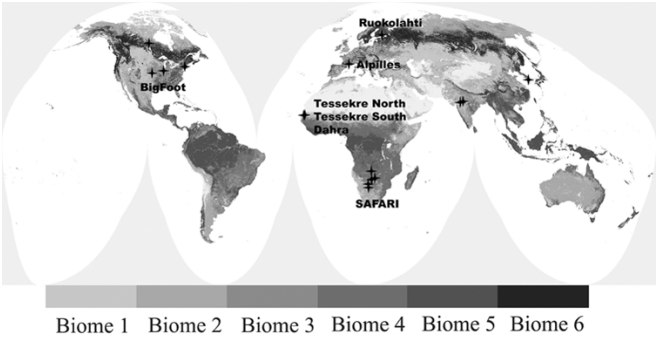

Fig. 2. Spatial distribution of MODIS LAI validation sites overlaid with Collection 4 six biome map used by the algorithm. Table I provides a description of the validation efforts associated with these sites. BigFoot sites include KONZ and other sites in North America, while SAFARI sites include Okwa and other sites in south part of Africa.

averaging or some other procedure. The comparison between these two fields provides a quantitative accuracy assessment of the moderate resolution LAI products. However, a pixel-by-pixel comparison might not be appropriate for two reasons, although it may be the desirable option. First, the actual spatial location of the corresponding pixels in the two LAI maps may not match well because of geolocation uncertainties and pixel-shift errors due to point spread function. Second, the LAI algorithm is not designed to retrieve a deterministic LAI value, but instead generates a mean LAI value from all possible solutions within a specified level of input satellite data and model uncertainties [1], [6]. Therefore, the retrieved LAI value for a single pixel may be unreliable, but the mean LAI of multiple similar pixels may be valid [9]. Thus, we felt it more appropriate to perform comparison at the multipixel (patch) scale, where the LAI product is statistically stable.

III. Validation Results

Table I summarizes published MODIS LAI/FPAR product validation efforts by multiple international teams. The LAI product was validated over the six biomes referenced by the LAI/FPAR algorithm (Fig. 2). Two of these validation exercises are detailed below to highlight the implementation of the ideas discussed in Section II, followed by a brief summary of related validation efforts.

A. Validation at a Cropland Site in France

A field campaign over a 3×3 km agricultural area near Alpilles in France (43.810°N, 4.750°E) was performed from February 26, 2001 to March 15, 2001 [6]. This area is one of the Validation of Land European Remote Sensing Instruments (VALERI) network [26]. More than 95% of this site was composed of young and mature wheat and grasses on a flat terrain. LAI was measured with a LAI-2000 Plant Canopy Analyzer at 49 distinct locations, 34 of which were concentrated near the center of the site and the remaining 15 scattered throughout the site to better sample the spatial variability of LAI in fully grown and young wheat [Fig. 3(a)]. Measurements at the 15 scattered locations were performed at 4-m intervals on two 20-m lines which formed a regularly shaped cross. The average of 12 measurements was assigned as the LAI value at each

TABLE I
Summary of MODIS LAI/FPAR Field Campaigns

Site	Lat/Lon	Biome Type	Date	Meas.	Ref.
KONZ	39.089°N/ 96.571°W	Grasses/ Cereal Crops	Jun 2000 Jul 2001	LAI	[13]
Alpilles	43.810°N/ 4.750°E	Grasses/ Cereal Crops	Feb 26- Mar 15, 2001	LAI	[6]
Okwa	22.409°S/ 21.713°E	Shrubs	Mar 3-18, 2000	LAI	[7] [19]
Mongu	15.438°S/ 23.253°E	Shrubland/ Woodland	Apr 20, 2000 Sep 02, 2000	LAI	[19]
			Oct 2000- Apr 2002	LAI/FPAR	[21]
AGRO	40.007°N/ 88.292°W	Broadleaf Crops	Jul, Aug 2000	LAI	[13]
Indore	22.880°N/ 75.950°E	Broadleaf Crops	Dec 2, 2001 Dec 27, 2001 Jan 21, 2002	LAI	[27]
Bhopal	23.170°N/ 77.470°E	Broadleaf Crops	Dec 24, 2001 Jan 18, 2001 Feb12, 2002	LAI	[27]
Tshane	24.164°S/ 21.893°E	Savannas	Mar 3-18, 2000	LAI	[7] [19]
Dahra	15.350°N/ 15.480°W	Grasses/Savannas	Aug-Sep 2001 Aug-Sep 2002	LAI/FPAR	[20]
Tessekre North Tessekre South	15.817°N/ 15.070°W	Grasses/Savannas	Jul-Sep 2002	LAI/FPAR	[20]
Pandamatenga	18.655°S/ 25.500°E	Savannas	Mar 3-18, 2000	LAI	[7] [19]
Maun	19.923°S/ 23.594°E	Savannas	Mar 3-18, 2000	LAI	[7] [19]
Kataba	15.439°S/ 23.253°E	Shrubland/Woodland	Feb 29, 2000 Aug 2000	LAI	[28]
HARV	42.529°N/ 72.173°W	Broadleaf Forests	Jul 2000 Jul 2001	LAI	[13]
NOBS	55.885°N/ 98.477°W	Needle Leaf Forests	Jul 2000 Jul 2001	LAI	[13]
Ruokolahti	61.320°N/ 28.430°E	Needle Leaf Forests	Jun 14-21, 2000	LAI	[9]
Fundulea	44.410°N/ 26.570°E	Broadleaf Crops	May 2, 2003	LAI	[29]
Concepcion	37.470°S/ 73.470°W	Broadleaf Forests	Jan 10, 2003	LAI	[29]
Larose	45.380°N/ 75.220°W	Needleleaf Forests	Aug 8, 2003	LAI	[29]
Haouz	31.660°N/ 7.600°W	Grasses	Mar 11, 2003	LAI	[29]
Turco	18.240°S/ 68.200°W	Grasses	Apr 16, 2003	LAI	[29]
Barrax	39.060°N/ 2.100°W	Broadleaf Crops	Jul 11, 2003	LAI	[29]
Hirsikangas	62.520°N/ 27.030°E	Needleleaf Forests	Aug 13, 2003	LAI	[29]
Wisconsin	45.804°N/ 90.080°W	Broadleaf Forests	May-Jun, 2002	LAI	[24]

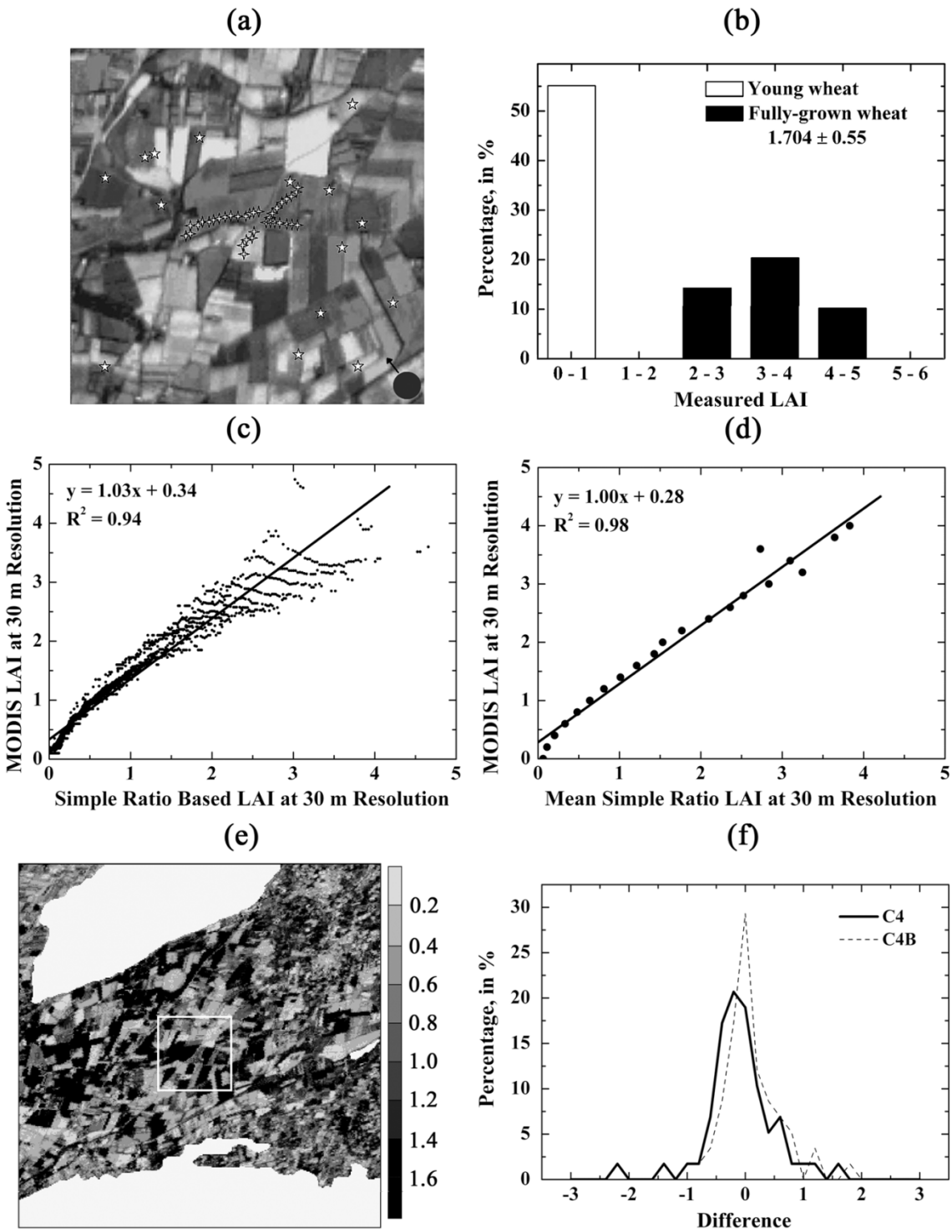

Fig. 3. Validation of Collection 4 MODIS LAI product by Tan *et al.* [6] at the Alpilles site in France (croplands). Panel (a): Location of measurements (stars) at the 3 × 3 km site. Panel (b): Distribution of LAI measurements from young wheat and fully-grown wheat. Panel (c): LAI retrievals from the fine resolution MODIS LAI/FPAR algorithm versus retrievals by the simple ratio based algorithm. Panel (d): Same as in panel (c), but retrievals from the simple ratio based algorithm were averaged at each LAI values retrieved by the fine resolution MODIS algorithm. Panel (e): Fine resolution LAI map over the 10 × 10 km centered at the Alpilles site (white rectangle). Panel (f): Histograms of deviations of the Collection 4 LAI product (C4) and LAI product generated with the correct biome map (C4B) from the reference map.

of these locations. The values of standard deviation (STD) for these 15 sampling locations were taken as the precision of field measured LAI. The distribution of measured LAI at all 49 locations is shown in Fig. 3(b).

A subset of an ETM+ image from March 15, 2001 (path 196, row 90) containing the Alpilles site was selected for the purpose of generating a fine resolution LAI map of the site. The image was atmospherically corrected using the 6S radiative transfer code [16]. The fine resolution MODIS algorithm and the SR relationship ($\mathrm{LAI} = 0.2\mathrm{SR}\text{-}0.22, \mathrm{R}^2 = 0.85$) derived from field measured LAI and atmospherically corrected ETM+ image were used to produce 30-m LAI maps of a 10 × 10 km

area centered on the Alpilles site. The fine resolution algorithm differs from the algorithm used to generate the MODIS LAI/FPAR product in that it uses fine resolution (30 m) LUTs corresponding to the ETM+ spatial resolution (30 m). This algorithm was then run with ETM+ red and near-infrared reflectances. The correlation between LAI retrieved with the fine resolution algorithm and the SR regression is shown in Fig. 3(c). Note that at any given value of LAI retrieved by the fine resolution algorithm, the SR method results in a range of LAI values. This is because the empirical SR approach is sensitive to the precision of fine resolution satellite observations which is about 13%–20% in this example. The MODIS LAI/FPAR algorithm, however, explicitly accounts for input data uncertainty, and, therefore, the retrievals are stable, i.e., do not vary with noise. Variations in surface reflectance due to observation uncertainties, therefore, cause horizontal trends seen in Fig. 3(c). The SR-based LAI retrievals should, therefore, be averaged over "indistinguishable" surface reflectances (i.e., reflectances equal within the observation precision) to account for input reflectance uncertainties. The correct LAI values, thus, obtained with the SR method agree well with the LAI values retrieved by the fine resolution algorithm [Fig. 3(d)].

A fine resolution LAI map was derived with both the SR and fine resolution algorithms [6], reprojected into the sinusoidal projection [Fig. 3(a)] and then degraded to 1-km resolution. This map was taken as a reference. Reference LAI values of cropland and grass 1-km pixels in the 10×10 km were compared with the Collection 4 MODIS LAI product. Their difference is shown in Fig. 3(f) (legend C4). Note that most of the selected reference LAIs fell in the interval 1 ± 0.3 and formed a relatively homogeneous patch [6]. The MODIS product is an overestimate compared to the reference values. This is because most of the pixels in this region were misclassified as broadleaf crops (biome 3) in the biome map used by the Terra MODIS algorithm. A re-calculation of the MODIS LAI product with the correct biome map shows a better agreement with the reference values [Fig. 3(f), C4B].

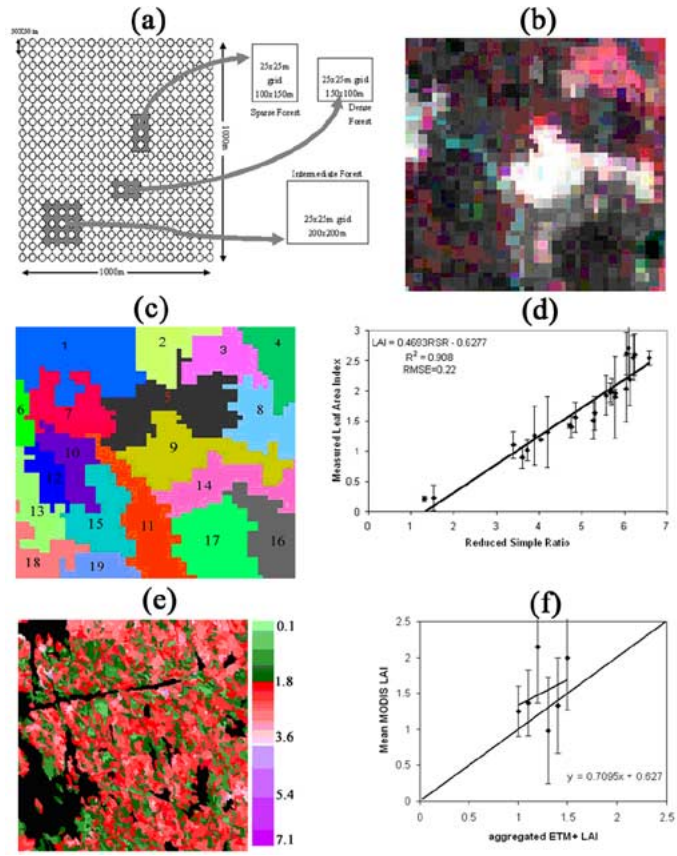

Fig. 4. Validation of Collection 4 MODIS LAI product by Wang *et al.* [9] at the Ruokolahti site in Finland (needle leaf forests). Panel (a): LAI sampling at the site. Panel (b): 1×1 km ETM+ image of the Ruokolahti site (false color). Panel (c): Segmentation of the 1×1 km ETM+ image. Panel (d): Relationship between field measured LAI and reduce simple ratio at the patch scale. Panel (e): Fine resolution LAI map over the 10×10 km region centered on Ruokolahti campaign site (white rectangle). Panel (f): Patch-by-patch comparison of the aggregated fine resolution LAI map and the Collection 4 MODIS LAI product $(\mathrm{RMSE} = 0.48)$.

B. Validation at a Coniferous Forest Site in Finland

A field campaign over an 1×1 km area near Ruokolahti, Finland (61.320°N, 28.430°E), was performed from June 14, 2000 to June 21, 2000 [9]. This site is a managed needle leaf forest dominated by Scots pine (*Pinus sylvestris*) with Norway spruce (*Pices abies*) as a subdominant species. The site has a well developed understorey of a mixture of re-growing small pine and spruce trees (less than 1.3 m in height), dwarf shrubs, mosses, lichens, and occasionally a few grasses. The tree canopy LAI values were measured with a LAI-2000 Plant Canopy Analyzer, positioned at breast height. The LAI of the understorey was not measured. The 1×1 km site was divided into 20 parallel rows and 20 parallel columns, for a total of 400 grid points, i.e., the points were 50 m apart from each other [Fig. 4(a)]. Additionally, intensive measurements were performed over three subgrids, corresponding to sparse, dense and intermediate forests, where sampling was performed at 25-m intervals. An ETM+ image acquired on June 10, 2000 was used to generate the fine resolution LAI map in this study. The image was atmospherically corrected using the Simplified Method for Atmospheric Correction (SMAC) algorithm [17].

Comparison at patch scale was assumed to be a reasonable approach considering the uncertainties in ground measurements of LAI, uncertainties in ETM+ surface reflectances and geolocation errors. The size and number of patches is limited by these considerations: 1) patches should be large enough to ensure a sufficient amount of field samples in each patch and to reduce geolocation errors; 2) patches should be small enough to preserve patch homogeneity and to ensure a sufficient number of patches over the natural range of LAI variation. The 1×1 km site area in the ETM+ image [Fig. 4(b)] was segmented into 19 patches [Fig. 4(c)]—the reader is referred to of Wang *et al.* [9] for details on the segmentation procedure. The reflectances show low variation within each patch—the coefficients of variation (STD/mean) did not exceed 10^{-2}. The coefficient of variation for LAI within each patch is significantly higher, but generally did not exceed 0.2.

The Simple Ratio (SR) and the Normalized Difference Vegetation Index (NDVI) were found to be not suitable for the generation of fine resolution LAI map because of the understorey.

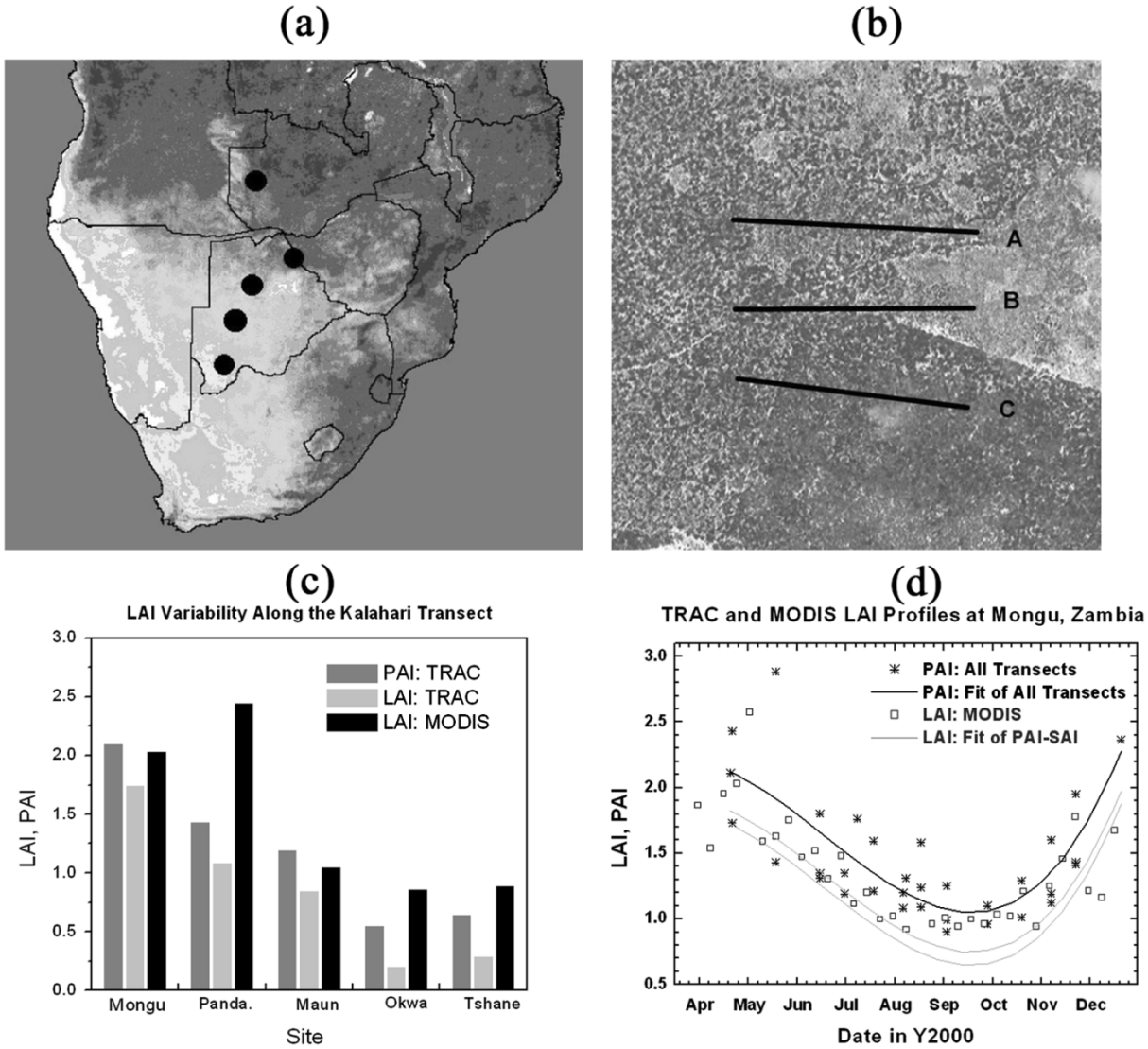

Fig. 5. Validation of Collection 4 MODIS LAI product by Privette *et al.* [19] along the IGBP Kalahari transect in South Africa. Panel (a): Location of the four sites along the transect (from North to South)—Mongu, Zambia; Pandamatenga, Botswana; Maun, Botswana; Okwa River Crossing, Botswana; and Tshane, Botswana. Panel (b): LAI sampling at the sites along three east-west transects, each 750 m long and 250 m apart. Panel (c): Mean TRAC plant area index (PAI), TRAC-derived LAI, and Collection 4 MODIS LAI for the five sites along the transect. The PAI at Pandamatenga site ranged from 1.01 to 1.56. The LAI value estimated from allometry is about 1.68. However, the measured area was adjacent to a fertilized cropland. This may perhaps explain the large discrepancy between MODIS and field measurements. Panel (d): Comparison of annual course of LAI from field measurements and Collection 4 MODIS product for the Mongu site. Note that the original figure in Privette *et al.* [19] showed Collection 1 MODIS LAI product validation—this figure is, thus, an update with Collection 4 MODIS LAI product.

The lack of information about the understorey LAI made the fine resolution MODIS algorithm unfeasible to derive the reference map [9]. However, several studies suggested the use of shortwave infrared (SWIR) reflectance and Reduced Simple Ratio (RSR) to account for the impact of background reflectances [18]. Our analysis shows that the RSR has the best correlation with field measurements—R^2 is 0.82 (pixel scale) and increases to 0.91 (patch scale) [Fig. 4(d)]. The regression model at the patch level was selected to generate the fine resolution LAI map of the 10×10 km study area [Fig. 4(e)]. The map was then reprojected into the Sinusoidal projection and degraded to 1-km resolution by averaging all fine resolution LAI values within each MODIS pixel. A 5×5 km region centered on the validation site was used to compare Collection 4 Terra MODIS LAI product with the aggregated fine resolution LAI values. Fig. 4(f) shows the patch-by-patch comparison between the MODIS LAI and the reference values. With the exception of one retrieved value, the Collection 4 MODIS LAI product was found to be within an accuracy of 0.5 LAI.

C. Related Validation Studies

An early spatial and temporal validation of Collection 1 MODIS LAI product was performed by Privette *et al.* [19] in southern Africa along the International Geosphere Biosphere Programme's Kalahari Transect. This large-scale transect incorporates five sites [Fig. 5(a)]—Mongu, Zambia (15.438°S, 23.253°E); Pandamatenga, Botswana (18.655°S, 25.500°E); Maun, Botswana (19.92S, 23.59E); Okwa River Crossing, Botswana (22.409°S, 21.713°E); and Tshane, Botswana (24.164°S, 21.893°E). From north to south, the sites represent a decreasing annual precipitation trend, decreasing vegetation productivity, and land cover changes from shrubland/woodland

in Mongu, open woodland in Pandamatenga to open savanna in Tshane. Field data were collected during March 2000 at four sites in Botswana, and from March through December 2000 at the remaining site in Zambia. At each site, TRAC instruments were used to sample the vegetation overstorey LAI along three 750-m transects separated by a distance of 250 m [Fig. 5(b)]. The direct outcome of TRAC, plant area index (PAI), was adjusted with ancillary stem area index data to estimate the LAI. The results indicate that the MODIS LAI products correctly captured the spatially decreasing LAI trend from Mongu, Zambia ($\mathrm{LAI} \sim 1.7$) through Tshane, Botswana ($\mathrm{LAI} < 0.5$) in the wet season [Fig. 5(c)], and the temporal phenology in Mongu [Fig. 5(d)] including the peak during wet season, senescence, peak dry season, and green-up.

Fensholt *et al.* [20] performed validation of the seasonal profiles of Collection 4 MODIS LAI and FPAR products at three sites in Senegal (the western Sudano-Sahelian zone) during years 2001 and 2002. All sites are closely located: Dahra (15.350°N, 15.480,°W), Tessekre North and South (15.817°N, 15.070°W). The land cover types at the sites were similar—dry grasslands with scattered trees and shrubs. A comparison of the seasonal profiles of the in-situ and the MODIS LAI data is shown in Fig. 6(a) for Dahra, in Fig. 6(b) for Tessekre North, and in Fig. 6(c) for Tessekre South. The results show that the seasonal dynamics of *in situ* LAI were captured well by the MODIS LAI, but that the MODIS LAI is a 2%–25% overestimate generally and in instances of low LAI, the overestimation to be as large as 75%. Similar results for FPAR can be found in Fensholt *et al.* [20].

The seasonal profiles of Collection 3 MODIS LAI products were validated with two-year (2000–2002) times series of monthly ground measurements by Huemmrich *et al.* [21] near the flux tower at the Kataba Local Forest, in western Zambia (15.439°S, 23.253°E). The land cover type at the site is a Miombo woodland on Kalahari Sand (woody savanna). Comparison of the seasonal profile of the Collection 3 MODIS LAI product and the corresponding ground measurements demonstrated some agreement [Fig. 7(a)–(b)].

IV. Algorithm Refinement

Validation activities are an integral part of product assessment efforts which feed into algorithm refinement. This idea is demonstrated here utilizing the validation results from Cohen *et al.* [13] and consequent algorithm refinements. Cohen *et al.* performed validation of Collections 3 and 4 LAI products at four sites in North America—AGRO, a cropland site in Illinois (40.007°N, 88.292°W); KONZ, a prairie grassland site in Kansas, (39.089°N, 96.571°w); NOBS, a boreal needle leaf forest site in Manitoba, Canada (55.885°N, 98.477°w); and HARV, a temperate mixed forest site in Massachusetts (42.529°N, 72.173°w). Their results indicated the Collection 3 LAI product to be an overestimate at all four sites. Samples of Collection 4 LAI products were examined and found to consist of improved LAI predictions for KONZ and to some extent for the AGRO sites. These validation results motivated a detailed investigation of algorithm performance with respect to input data quality and the LUT entries accompanying the algorithm.

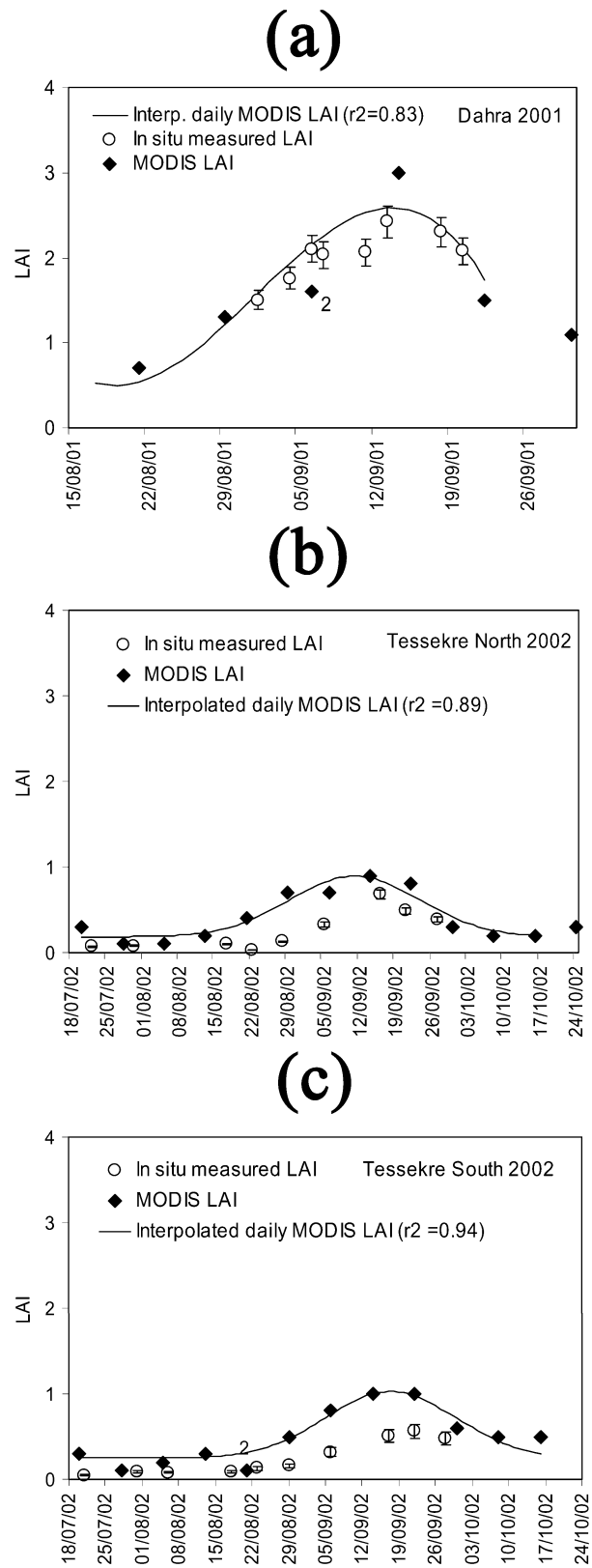

Fig. 6. Validation of the seasonal profiles of the Collection 4 MODIS LAI products by Fensholt *et al.* [20] at three sites in Africa: Dahra [panel (a)], Tessekre North [panel (b)], and Tessekre South [panels (c)].

The studies indicated three key factors to influence the accuracy of LAI retrievals: 1) uncertainties in input land cover (biome) data, as in the case of KONZ site, 2) uncertainties in input

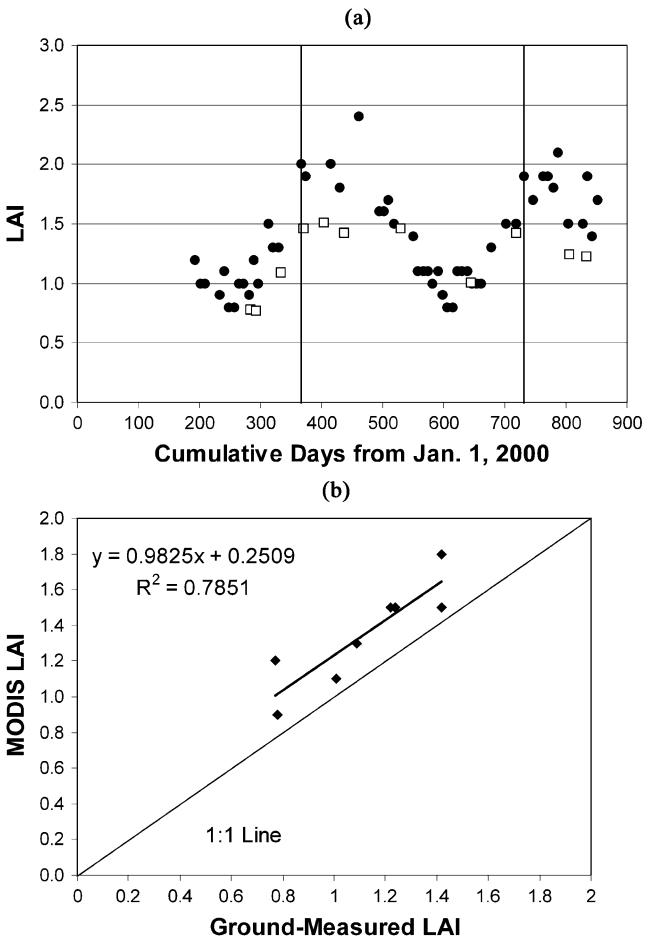

Fig. 7. Validation of the seasonal profiles of Collection 4 LAI products by Huemmrich *et al.* [21] at the Mongu site in South Africa. In panel (a), LAI data from ground measurements are shown with open squares and those derived from MODIS observations are shown with fill circle.

surface reflectances, as in the case of AGRO site, and 3) uncertainties from the model used to build the LUTs accompanying the algorithm, as in the case of HARV site. Example results are provided below.

The MODIS LAI/FPAR algorithm references a biome map to select vegetation variables required for LAI retrievals. Biome misclassification may have a two-fold effect—directly whereby a misclassification may result in the selection of a wrong LUT during the retrieval and indirectly through the algorithm calibration procedure when the LUTs are developed. For example, consider the six biome map for the MODIS tile h10v05 containing the grassland site, KONZ. The Collection 3 algorithm referenced the at-launch biome map based on AVHRR data, the accuracy of which was unknown [Fig. 8(a)], while the Collection 4 algorithm referenced a validated biome map based on one year of MODIS data [Fig. 8(b)]. The at-launch map has significant misclassification between grasses (biome 1) and broadleaf crops (biome 3) both at the site and tile scales and this clearly impacted the retrievals. The retrievals from the correctly classified grassland pixels in the vicinity of the validation site compared favorably to field measurements [22] [see also Fig. 9(a) and (b)].

The precision of the surface reflectance product depends on the extent to which atmospheric correction successfully removes the impact of clouds and aerosols on the measurements. While the LAI algorithm was designed to account for uncertainties in the surface reflectance product, the algorithm cannot retrieve LAI values with more precision than its inputs. Input precision can be evaluated with data from invariant targets. Successive and repetitive reflectance measurements from these surfaces accumulated over several days under identical illumination and observation conditions can be used to characterize the mean, variance and precision expressed by the coefficient of variation. If the instrument and the atmospheric correction are stable, temporal variation should be minimal because the target itself is not changing. The mean, variance and the precision of corresponding LAI values can be quantified in a similar manner. Fig. 8(c) shows a regression curve of the LAI precision with respect to the precision of the MODIS surface reflectance derived from tile h11v04 containing the AGRO site for the period July 20–27, 2001. Retrieval precision is stable and low when surface reflectance precision is lower than the threshold used by the algorithm. However, when these exceed the threshold, LAI and surface reflectance precisions are linearly related. This example illustrates the connection between the quality of algorithm inputs and outputs. The retrievals from the main RT algorithm obtained with high quality surface reflectance data compared well to field measurements at the AGRO site [23] [see also Fig. 9(c) and (d)].

Finally, we consider the third type of uncertainties—mismatch between algorithm simulated reflectances and measured MODIS reflectances which results in either an inaccurate LAI retrieval or failure of the main radiative transfer (RT) algorithm [1]. This is illustrated using retrievals from tile h12v04 containing the Harvard forest validation site in Massachusetts [Fig. 8(d)]. The main algorithm mostly fails during the summer period (Julian days 150–250) which is due to the mismatch between simulated and MODIS surface reflectances [Fig. 8(e)]. This figure demonstrates the retrieval domain of the main RT algorithm and the backup NDVI-based algorithm in the Red-NIR spectral space and overlaid with a contour plot of MODIS data density. Collection 4 main algorithm can not simulate a range of observed BRF values in red and near-infrared spectral bands over broadleaf forests, and, hence, the rather low retrieval rate of the main RT algorithm. Further improvements in LAI and FPAR retrieval coverage and quality will require a better overlap of the observational space in the red—near-infrared plane by simulated reflectances in the LUTs of the algorithm.

Thus, the observed anomalies in Collection 3 LAI/FPAR products can be traced to these three sources of uncertainties acting either uniquely or in concert. LAI/FPAR products have been incrementally improved from Collections 3 through 4 (the present) and 5 (expected from 2006). Collection 4 includes the following modifications to the algorithm and its inputs: 1) the at-launch AVHRR-based biome map was replaced with a MODIS-based map; 2) atmospheric correction of surface reflectances incorporated improved cloud screening and compositing algorithms; 3) the algorithm was optimized to better simulate features of MODIS surface reflectances for herbaceous vegetation (biomes 1–4). Similar improvements to the algorithm for woody vegetation (biomes 5–6) have been implemented in Collection 5 processing [2].

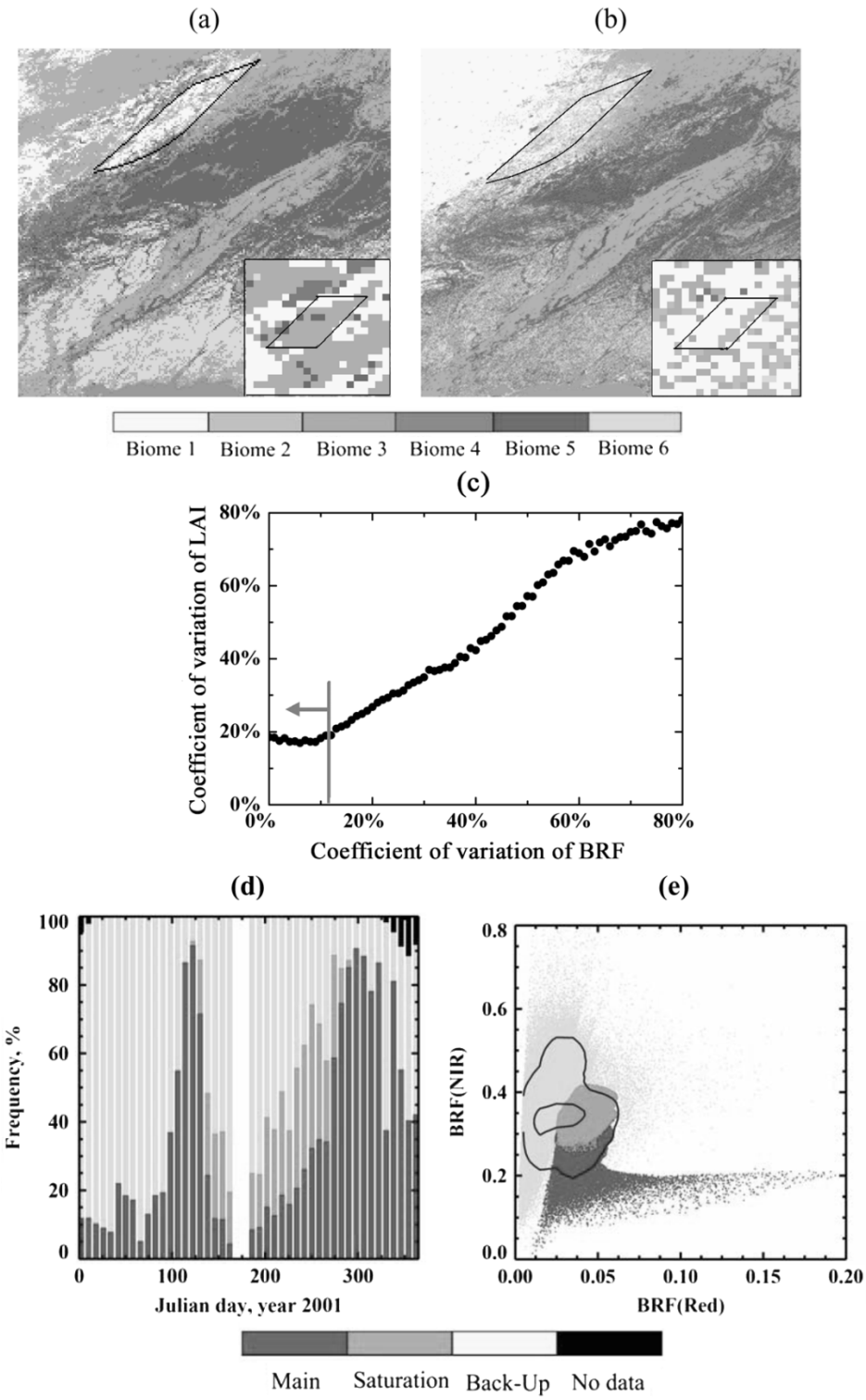

Fig. 8. Impact of model and input uncertainties on LAI retrievals. The at-launch AVHRR-based biome map (panel a) and the MODIS-based biome map (panel b) are compared at the tile scale—1200 × 1200 km. The KONZ validation site is marked as a rectangle in this tile (h10v05). The inset shows the biome distribution in a 20 × 20 km area centered on the site. Panel (c) shows the relationship between precision in surface reflectances and LAI from tile h11v01 containing the AGRO site for the composite period July 20–27, 2001. Panels (d) and (e) demonstrate the impact of model uncertainties on LAI retrievals for broadleaf forests pixels in MODIS tile h12v04, containing HARV validation site. Panel (d) shows the annual course of main and backup (yellow bars) algorithm retrievals for year 2001. Retrievals from the main algorithm are broken down into "best retrievals" (red bars) and "LAI values retrieved under a condition of saturation" (green bars). Panel (e) shows the retrieval domain of the main radiative transfer algorithm and the backup NDVI-based algorithm in the red and near-infrared spectral space, overlaid with high density contours of MODIS surface reflectance data for the period July 20–27, 2001. The inner and outer contours contain 30% and 50% of observed MODIS BRFs, respectively. The color scheme is the same as in Panel (d).

Fig. 9. shows enhancements to product quality based on the above mentioned refinements. For the grassland and cropland sites—LAI overestimation and proportion of main RT algorithm retrievals was resolved in Collection 4

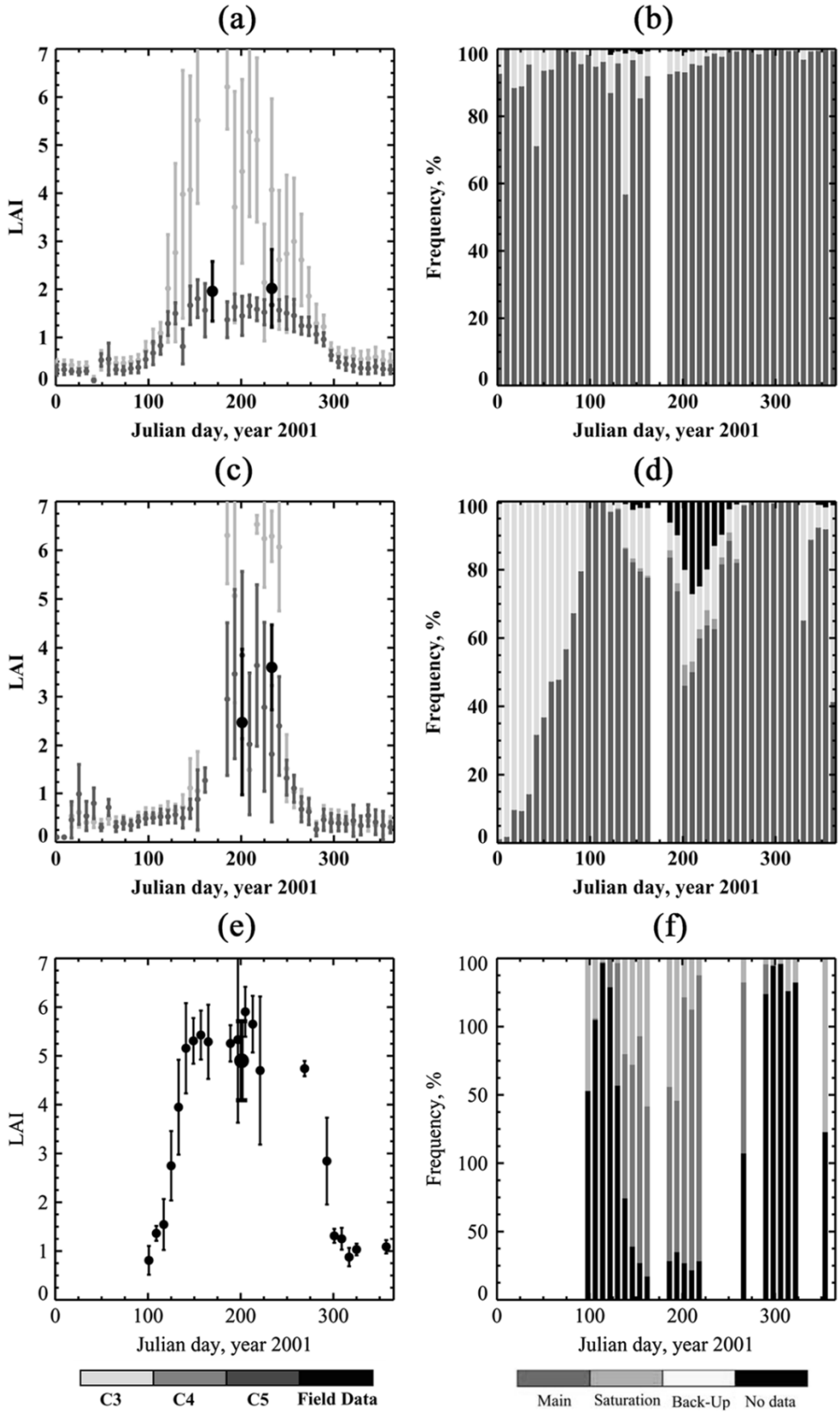

Fig. 9. MODIS LAI product for the three BigFoot validation sites: KONZ (panels a and b), AGRO (panels c and d), and HARV (panels e and f). Panels on the left show the annual course of MODIS LAI product (Collection 3 in green, Collection 4 in red, and prototype of Collection 5 in blue) averaged over a 7 × 7 km area centered about the site and the corresponding BigFoot measurements (in black). Panels on the right show the annual course of relative proportion of main and backup algorithm retrievals (Collection 4 for KONZ and AGRO, and prototype of Collection 5 for HARV), evaluated over the tile where the corresponding site is located.

[Fig. 9(a)–(d)]. For the Harvard forest site—analysis of a Collection 5 prototype indicates substantial increase in main RT algorithm retrievals and agreement with field measurements [Fig. 9(e) and (f)].

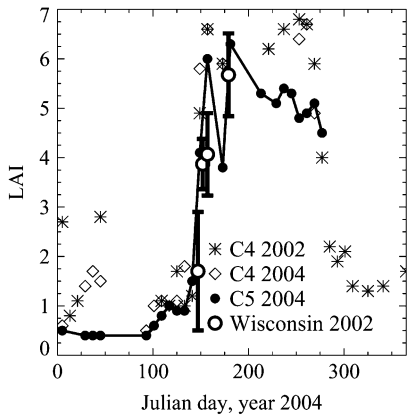

Fig. 10. Comparison of the Collection 4 and prototype Collection 5 MODIS LAI products with field measurements over a deciduous broadleaf forest in Wisconsin. Field data over 540 × 540 m grid at the northern Wisconsin site (45.804 167°N, 90.079 853° W MODIS tile h11v04, $\mathrm{line} = 503, \mathrm{sample} = 864$) were collected by Ahl *et al.* [24]. Panel (a) compares annual course of the Collection 4 and prototype Collection 5 MODIS LAI.

Ahl *et al.* [24] measured spring phenology in a deciduous broadleaf forest on Julian days 147 (May 26), 152 (June 1), 157 (June 6), and 179 (June 28) in year 2002 over a 540 × 540 m area of the northern Wisconsin validation site. The prototype Collection 5 LAI product was generated for year 2004. The Collection 5 LAI and mean field LAI for the above dates are as follows: $1.5(1.7\pm1.2), 4.1(3.9\pm0.5), 6.0(4.1\pm0.8)$, and $6.3(5.7\pm0.8)$. Average LAI for the growing season decreased from 6.2 (Collection 4) to 5.2 (Collection 5) (Fig. 10). Similar to the Harvard forest site, winter time LAI decreased from about 2 to <0.5. The success rate of the main algorithm increased by more than 40% during the growing season. The few nonzero LAI values during the winter are likely due to the presence of evergreen samplings in the understorey. These results presented here illustrate the importance of feedback from validation studies for algorithm refinement activities.

V. Concluding Remarks

This paper summarizes the experience of several collaborating investigators on validation of MODIS LAI products and demonstrates the close connection between product validation and algorithm refinement activities. The validation of moderate resolution (1 km) LAI products includes three steps: 1) sampling of LAI and ancillary data in field campaigns, 2) generation of a fine resolution reference LAI map based on field data, and 3) comparison of MODIS LAI product with aggregated reference LAI map.

An ideal field sampling of LAI must adequately represent its spatial distribution and cover the natural dynamic range within each major land cover type at the site. Therefore, the validation site must be segmented into spectrally homogeneous patches for sampling by utilizing high resolution imagery and existing land cover maps. It is necessary to characterize the uncertainty of the fine resolution LAI map, irrespective of the transfer function used, because of the ill-posed nature of the inverse problem, i.e., generating LAI from reflectance data. A pixel-by-pixel comparison between MODIS and reference LAI values is not recommended for two reasons—first, the actual spatial location of the corresponding pixels in the two maps may not match because of geo-location and pixel-shift errors [25]; second, the LAI algorithm is not designed to retrieve a deterministic LAI value, but instead generates a mean value from all possible solutions within a specified level of input satellite data and model uncertainties [1]. Therefore, the retrieved LAI value for a single pixel may be unreliable, but the mean LAI of multiple similar pixels may be valid [9]. Therefore, it is preferable to perform this comparison at the patch (multipixel) scale.

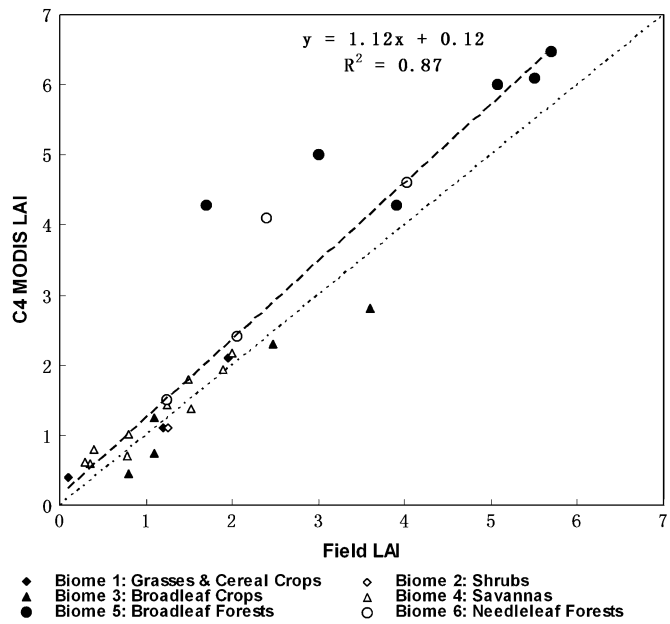

Fig. 11. Comparison of Collection 4 MODIS LAI with field measurements in all six biomes referenced by the algorithm. Altogether 29 values are used—the site information, measurement time and source reference are listed in Table I. The MODIS LAI product is an overestimate by about 12% $(\mathrm{RMSE} = 0.66)$ when all six biomes are taken in account.

Validation activities are an integral part of product assessment efforts that help diagnose algorithm deficiencies, thus resulting in refined/revised algorithms which then are used to derive the next generation of products. A summary figure showing comparison of MODIS LAI product with field measurements in all the six biomes referenced by the LAI/FPAR algorithm indicates that the product is an overestimate by about 12% $(\mathrm{RMSE} = 0.66)$ when all six biomes are taken in account (Fig. 11). This, then, represents the current status of MODIS LAI product validation efforts.

The MODIS LAI validation experience suggests three key factors to influence the accuracy of LAI retrievals: 1) uncertainties in input land cover (biome) data, 2) uncertainties in input surface reflectances, and 3) uncertainties from the model used to build the LUTs accompanying the algorithm. This strategy of validation efforts guiding algorithm refinements has led to progressively more accurate LAI products from the MODIS sensors aboard NASA's Terra and Aqua platforms.

Appendix
WWW Sites

WWW1: LAI-2000 plant canopy analyzer from LI-COR, http://www.licor.com/env/Products/AreaMeters/lai2000/2000_intro.jsp

WWW2: Tracing Radiation and Architecture of Canopies (TRAC) instrument from 3-D, Wave Technologies, http://www.ccrs.nrcan.gc.ca/ccrs/rd/apps/landcov/beps/trac_e.html

WWW3: Hemispherical fisheye system from Regent, http://www.regent.qc.ca/products/Scanopy/Scanopy.html

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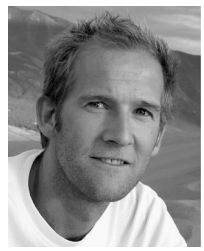

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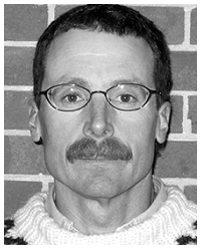

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