

## Chapter 2

# Green Leaf Area and Fraction of Photosynthetically Active Radiation Absorbed by Vegetation

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**Abstract** Leaf Area Index (LAI), the area of leaves per unit ground area, and the Fraction of Photosynthetically Active Radiation (FPAR; 400–700 nm) absorbed by vegetation are important biophysical variables for quantifying the cycling of water, carbon and nutrients through ecosystems. The LAI/FPAR products from the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor and the Système Pour l’Observation de la Terre (SPOT) sensor have a large Earth science community user base and the ease of access, provision of pixel quality and validation information have greatly aided the use of these products. Recent research efforts focusing on inter-sensor product consistencies have developed a foundation upon which mature algorithms and a validation framework can act synergistically to further refine the accuracy and precision of these existing long-term products. This chapter provides a brief

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overview of the recent progresses in LAI/FPAR estimation algorithms and resulting biophysical products from the AVHRR, MODIS, SPOT and Landsat data.

## 2.1 Introduction

Leaf Area Index (LAI), the one-sided green leaf area per unit ground area, and the Fraction of Photosynthetically Active Radiation (FPAR; 400–700 nm) absorbed by vegetation are important biophysical variables for quantifying the cycling of water, carbon and nutrients through ecosystems (Demarty et al. 2007; Sellers et al. 1996; Tian et al. 2004). LAI characterizes the functioning surface area of a vegetation canopy (Myneni et al. 2002). The interactions between the vegetation surface and the atmosphere, for example, radiation exchange, transpiration rates, precipitation interception, momentum and gas exchange, is predominantly determined by leaf area (Monteith and Unsworth 1990). An increase in leaf area, for example, increases the uptake of CO<sub>2</sub> from the atmosphere due to greater sunlight absorption and hence results in increased canopy conductance and transpiration rates (Field and Mooney 1983). Field measurements of LAI include hemispherical photography and optical instruments like TRAC, LAI-2000 or LI-3000C (Chen et al. 1997; Weiss et al. 2004). Satellite remote sensing enables retrieval of LAI globally at different spatial resolutions and temporal frequency with algorithms based on the physics of radiative transfer. Another parameter that characterizes the energy absorption capacity of a vegetation canopy is FPAR, defined as the fraction of photosynthetically active radiation (0.4–0.7  $\mu\text{m}$ ) absorbed by the vegetation canopy. FPAR depends on the incident radiation field, architecture and absorption, reflectance and transmission spectra of the canopy as well as the reflectance of the soil and/or understory background. FPAR is well related to NDVI and usually increases with fractional canopy cover and plant leaf area (Myneni and Williams 1994). It is one of the fundamental parameters used to estimate net primary production and for modeling of terrestrial carbon processes (Knorr and Kattge 2005; Pitman 2003; Sellers et al. 1986). Similar to LAI, FPAR has also been identified as one of the fundamental terrestrial state variables in the context of global change studies (GCOS 2006).

The LAI/FPAR products from the Advanced Very High Resolution Radiometer (AVHRR), the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor and the Système Pour l'Observation de la Terre (SPOT) sensor have a large Earth science community user base and the ease of access, provision of pixel quality and validation information have greatly aided the use of these products. Recent research efforts focusing on inter-sensor product consistencies have developed a foundation upon which mature algorithms and a validation framework can act synergistically to further refine the accuracy and precision of these existing long-term products (Brown et al. 2006; Ganguly et al. 2008b; Tarnavsky et al. 2008;

Van Leeuwen et al. 2006). Multi-decadal, validated, consistent global and regional data sets of LAI/FPAR from the AVHRR, MODIS, and the SPOT-VGT sensors are now available at resolutions of 1 km to 1° in service of several national and international initiatives (Chen 2002; Fernandes and Butson 2003; Ganguly et al. 2008a; Myneni et al. 2002). Long-term records of LAI and FPAR are required by various terrestrial biosphere models, like the Terrestrial Ecosystem Model (TEM) (Melillo et al. 1993), Biome-BGC (Running and Gower 1991), Simple Biospheric Model (SiB) (Sellers et al. 1986), Integrated Biosphere Simulated Model (IBIS) (Foley et al. 1996), Lund-Potsdam-Jena (LPJ) dynamic global vegetation model in Land Surface Model (LSM) (Bonan et al. 2003) and the Atmospheric-Vegetation Interactive Model (AVIM) (Jinjun 1995), for the investigation of the response of ecosystems to the changes in climate, carbon cycle, land cover and land use. The Landsat series of sensors also provides a unique opportunity to characterize terrestrial ecosystem processes at a spatial scale at which most natural resources management decisions are made. Although regional- to continental-scale multi-temporal mosaics of Landsat data have been constructed for pilot studies of national land use change monitoring and disturbance mapping (Chander et al. 2009; Hansen et al. 2008; Wulder et al. 2002), the Landsat archive has not yet been exploited to derive long-term biophysical products. This chapter provides a brief overview of the recent progresses in some of the key LAI/FPAR estimation algorithms and resulting biophysical products from the AVHRR, MODIS, SPOT and Landsat data at global to continental scales.

## 2.2 Algorithmic Theoretical Basis

There is considerable literature on the estimation of LAI from vegetation indices like the Normalized Difference Vegetation Index (NDVI), Simple Ratio and Reduced Simple Ratio (RSR) (Asrar et al. 1984; Chen and Cihlar 1996; Stenberg et al. 2004; Brown et al. 2000). In particular, (Sellers et al. 1996) introduced an empirical algorithm that calculated FPAR as a function of the simple ratio. Lu and Shuttleworth (2002) used this definition of FPAR and approximated the relationship between LAI and FPAR to be exponential (Monteith and Unsworth 1990) for evenly distributed vegetation. Strong positive correlations were found between LAI and NDVI for various vegetation types (Myneni et al. 1997), as well as with simple ratio in coniferous forests (Chen and Cihlar 1996). Site-specific NDVI/RSR-LAI empirical relationships have been used in various ecosystems (Colombo et al. 2003; Fassnacht et al. 1997; Stenberg et al. 2004), but with limited success when applied across sites and vegetation classes.

The sensitivity of NDVI or RSR to LAI is controlled by the relationship between NDVI/RSR and fractional vegetation cover when LAI is in the range of about 2–4 (Carlson and Ripley 1997; Stenberg et al. 2004). Steltzer and Welker (2006) incorporated fractional cover of photosynthetic vegetation for multiple species into the exponential NDVI-LAI model for a regional scale analysis, and

suggested that species composition affects the NDVI-LAI relationship through leaf-level properties (leaf optics, leaf structure and orientation) and canopy-level structural properties that influence the vertical and horizontal distribution of leaf area within a canopy. Relationships between RSR and LAI in closed canopy regimes suggest that the inclusion of the short-wave band decreases the effect of understory reflectance on the retrieval of LAI below a certain threshold value of crown-closure (Nemani et al. 1993; Rautiainen 2005). It is evident that NDVI/RSR-LAI empirical relationships do vary across different species and are sensitive to canopy structure and fractional ground cover. These empirical relationships can also vary both seasonally and inter-annually with respect to phenological development of the vegetation. Thus, a relationship established between LAI and NDVI in a particular year may not be applicable in other years (Wang 2004). Consequently, the empirical relationships will be site-, time-, and species-specific, and, therefore, poorly suited for large-scale operational use (Houborg et al. 2007).

An alternate approach is to use physically based models that describe the interaction of radiation inside a canopy based on physical principles and provide an explicit connection between biophysical variables and canopy reflectance (Combal et al. 2002). The physical models of radiation transfer and interaction in vegetation canopies are usually categorized into four broad types: (1) radiative transfer models (Knyazikhin et al. 1998; Myneni et al. 1989), (2) geometrical optical models (Li and Strahler 1992), (3) hybrid models that incorporate both radiative transfer as well as geometric optics (Welles and Norman 1991), and (4) Monte-Carlo simulation models (Lewis 1999; Ross and Marshak 1988). In Sects. 2.1 and 2.2, we describe in brief two state-of-the-art physical algorithms in retrieving LAI and FPAR that have evolved over time.

## 2.3 Modis LAI/FPAR Algorithm: Scaling to AVHRR and Landsat

The MODIS LAI/FPAR algorithm retrieves LAI and FPAR values given sun and view directions, Bidirectional Reflectance Factor (BRF) for each MODIS spectral band, uncertainties in input BRFs, and land cover classes based on a 8-biome classification map (Myneni et al. 2002; Yang et al. 2006). The retrieval technique compares observed and modeled BRFs stored in a Look\_Up\_Table (LUT) for a suite of canbiome-opy structures and soil patterns that represent an expected range of typical conditions for a given biome type. The modeled BRFs are simulated using a canopy 3D stochastic radiative transfer model. All canopy/soil patterns for which modeled and observed BRFs differ within a specified uncertainty level are considered acceptable solutions. The mean values of LAI averaged over all acceptable solutions and the dispersion are reported as the output of the algorithm (Knyazikhin et al. 1998). The algorithm currently requires: (a) atmospherically corrected surface reflectances at Red and NIR bands, and (b) an 8-biome Land

Cover classification map distinguishing the following biomes types: (1) grasses and cereal crops, (2) shrubs, (3) broadleaf crops, (4) savannas, (5) evergreen broadleaf forests, (6) deciduous broadleaf forests, (7) evergreen needle leaf forests, (8) deciduous needle leaf forests. The biome map reduces the number of unknowns of the inverse problem through the use of simplifying assumptions (e.g., biome-specific models of leaf orientation distributions; Knyazikhin et al. 1998) and standard constants (e.g., biome-specific leaf and soil optical properties at given wavelengths). Over 11 years of Terra MODIS and about 10 years of Aqua MODIS LAI/FPAR products have been generated with this algorithm. Figure 2.1 shows global fields of annual average LAI and FPAR derived from 10 years of Terra MODIS Collection 5 data.

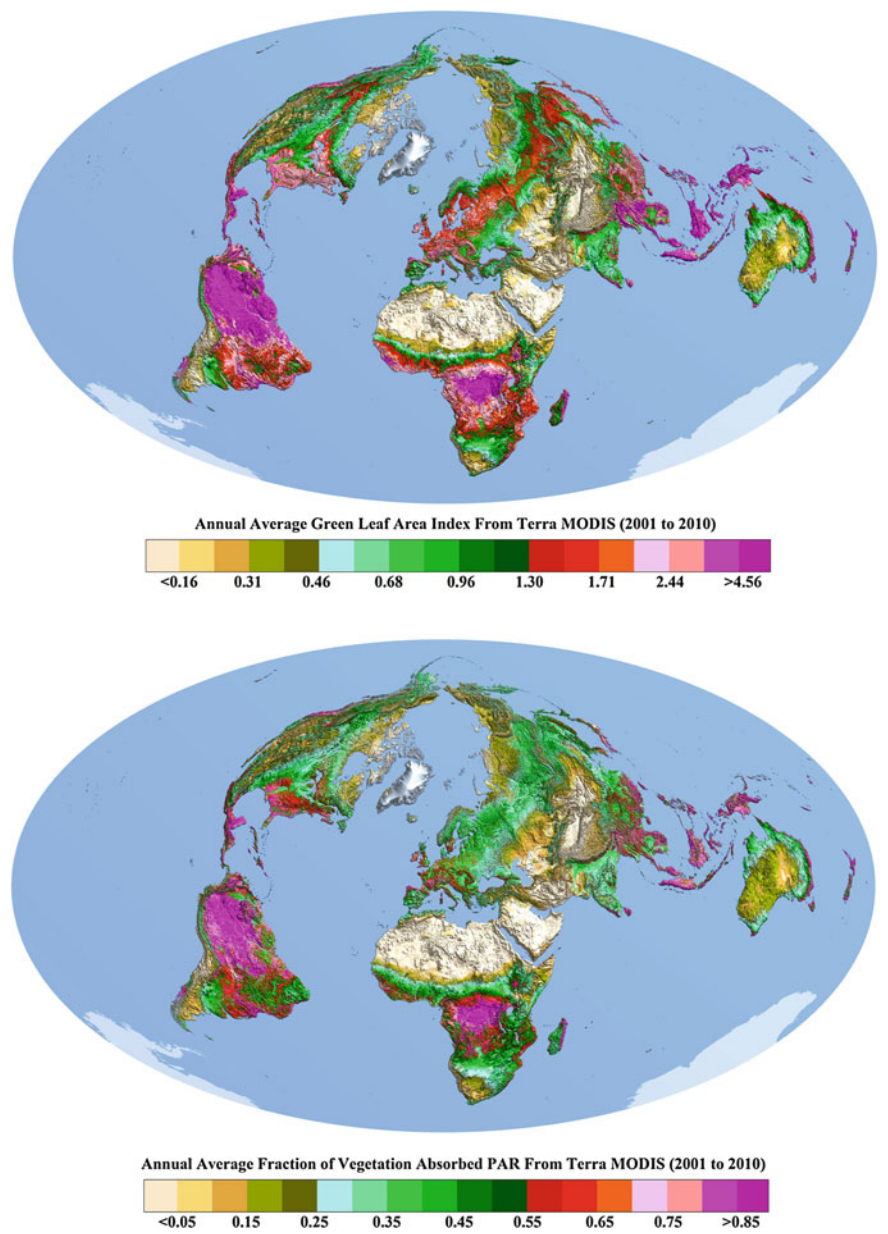
A consistent retrieval of LAI/FPAR from different sensors depends on the parameterization of the physically-based algorithm by adjusting for sensor-specific features of the BRF measurements (spatial resolution, bandwidth, calibration, atmospheric correction, information content, etc.). The theory of canopy spectral invariants provides the required BRF parameterization via a small set of well-defined measurable variables that specify the relationship between the spectral response of vegetation canopy bounded by biome-specific canopy architecture low by a non-reflecting surface to the incident radiation at the leaf and canopy scales (Huang et al. 2007; Yuri Knyazikhin et al. 2011; Lewis and Disney 2007; Smolander and Stenberg 2005). The core theory provides a more easy and efficient way of simulating wavelength dependent BRFs as a function of biome-specific canopy structural attributes. The first order approximation of the BRF for a vegetation canopy bounded below by a non-reflecting surface (Ganguly et al. 2008b; Huang et al. 2007) is approximated as:

$$BRF_{BS,\lambda}(\Omega) = \omega_{\lambda}R_1(\Omega) + \frac{\omega_{\lambda}^2}{1 - p\omega_{\lambda}}R_2(\Omega), \quad (2.1)$$

where  $\omega_{\lambda}$  is the leaf single scattering albedo,  $R_1$  and  $R_2$  are escape probabilities expressed relative to the number of incident photons and  $p$  refers to the recollision probability, which is defined as the probability that a photon scattered by a foliage element in the canopy will interact within the canopy again. The spectral absorptance,  $a_{BS,\lambda}$  of the vegetation canopy with non-reflecting background can be expressed as:

$$a_{BS,\lambda} = \frac{1 - \omega_{\lambda}}{1 - p\omega_{\lambda}}i_0, \quad (2.2)$$

where  $i_0$  is the probability of initial collisions, or canopy interception, defined as the portion of photons from the incident beam that are intercepted, i.e., collide with phytoelements for the first time. The FPAR is a weighted integral of Eq. (2.2) over the photosynthetically active radiation (PAR) spectral region (Knyazikhin et al. 1998). The formulation in Eq. (2.1) permits decoupling of the structural and radiometric components of any optical sensor signal, and requires a set of sensor-specific values of configurable parameters, namely the “single scattering albedo”



**Fig. 2.1** Global *color-coded* maps of Terra MODIS Collection 5 annual average LAI and FPAR. These maps were generated from nearly 10 years of Terra MODIS data (January 2001 to December 2010). Leaf area index (LAI) is defined as the one-sided *green leaf* area per unit ground area in broadleaf canopies and as one-half the total needle surface area per unit ground area in coniferous canopies. FPAR is defined as the fraction of incident photosynthetically active radiation (400–700 nm) absorbed by the green elements of a vegetation canopy. Both quantities are dimensionless

and “uncertainties in surface reflectances” that allow to maintain consistency in the retrieved LAI (Ganguly et al. 2008b). The analytical expressions for the total BRF formulation (e.g. contributions from understory and canopy that are related to reflectance, transmittance and absorptance simulations) are documented in (Ganguly et al. 2012) and are not provided here for the sake of brevity.

To achieve accurate retrievals from a particular sensor like Landsat, the *simulated* surface reflectances making up the LUT should be adjusted to be consistent with the expected range of *measured* surface reflectances. The simulated surface reflectances are highly sensitive to leaf single scattering albedo for medium-to-high LAI and to soil reflectances for low LAI. The single scattering albedo is a function of spatial resolution and accounts for the variation in BRF with sensor spatial resolution and spectral bandwidth (c.f. Sects. 4 and 5 of Ganguly et al. 2008b). The theoretical scaling of the algorithm has been demonstrated by (Ganguly et al. 2008a) to derive LAI from the AVHRR dataset that is consistent with LAI products from other sensors such as MODIS and SPOT. In essence, the BRF can be computed for the sensor-specific resolution and spectral bands by adjusting the single scattering albedo. For Landsat, the initial set of single scattering albedos for the red, NIR and SWIR bands are calculated for each biome as the mean single scattering albedo, such that

$$\overline{\omega} = \int_{\alpha}^{\beta} \omega_{\lambda} f(\lambda) d\lambda \quad (2.3)$$

where  $f(\lambda)$  is the relative spectral response function for the Landsat spectral bands.  $\alpha$  and  $\beta$  represents the lower and upper bounds for wavelengths in the red and NIR bands and  $\omega_{\lambda}$  for different biomes is obtained from field measured leaf spectral measurements (Tian et al. 2004).  $\overline{\omega}$  is further tuned to achieve the best possible overlap of simulated BRFs with Landsat observed surface reflectances over a suite of biomes (Ganguly et al. 2012). The dominant factors in classifying the biomes, based on RED, NIR, and SWIR bands, are soil reflectances and single scattering albedos in the respective bands.

The LAI retrieval algorithm exploits the location information in the reflectance cross planes by attributing each point in the spectral space to a specific physical state that is characterized by a background brightness and LAI (Knyazikhin et al. 1998). A pixel can have a background ranging from dark to bright depending on the type of soil, and the LAI can vary over a range for each specific instance of background brightness. Given a Landsat pixel with a reflectance triplet (RED, NIR, SWIR), a merit function is used to select the set of acceptable solutions such that

$$\Delta^2 = \frac{BRF_{NIR} - BRF_{NIR,sim}}{\sigma_{NIR}^2} + \frac{BRF_{RED} - BRF_{RED,sim}}{\sigma_{RED}^2} + \frac{BRF_{SW} - BRF_{SW,sim}}{\sigma_{SW}^2} + \quad (2.4)$$

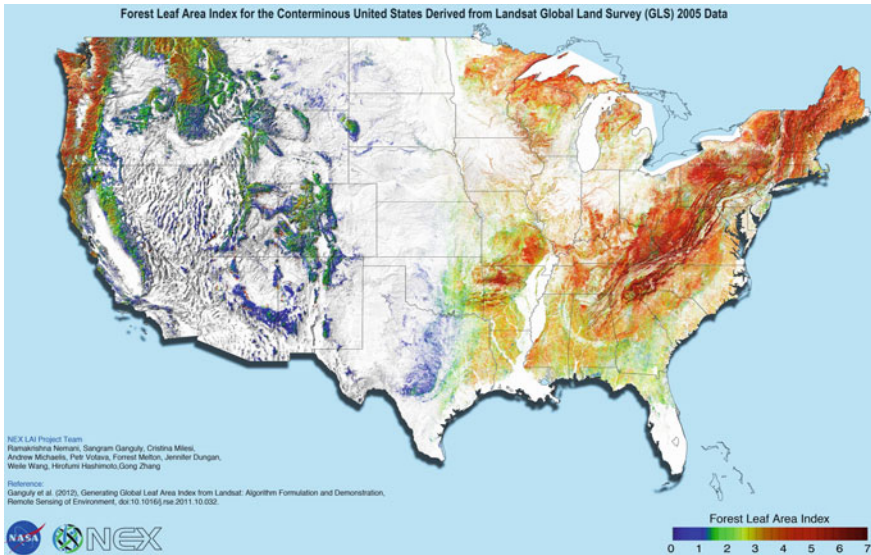


Here,  $BRF_{NIR}$ ,  $BRF_{RED}$  and  $BRF_{SW}$  denote values of measured surface reflectances in the NIR, Red and SWIR spectral bands, while  $BRF_{NIR,sim}$ ,  $BRF_{RED,sim}$  and  $BRF_{SW,sim}$  correspond to respective simulated reflectances from the LUT. The dispersions  $\sigma_{NIR}^2$ ,  $\sigma_{RED}^2$  and  $\sigma_{SW}^2$  quantify combined model and observational uncertainties in NIR, RED and SWIR spectral bands and are configurable parameters in the retrieval approach (Wang et al. 2001). The dispersions are represented as  $\sigma_{NIR} = \varepsilon_{NIR} \cdot NIR$ ,  $\sigma_{RED} = \varepsilon_{RED} \cdot RED$ , and  $\sigma_{SWIR} = \varepsilon_{SWIR} \cdot SWIR$ , where  $\varepsilon_{NIR}$ ,  $\varepsilon_{RED}$ , and  $\varepsilon_{SWIR}$  are the corresponding relative uncertainties (Wang et al. 2001). The optimum values of relative uncertainties used in this study (Ganguly et al. 2008a) are those that result in maximizing the retrieval index without loss of information content. The variable  $\Delta^2$ , characterizing how close the measured surface reflectances are to the simulated ones, has a Chi square distribution with three degrees of freedom. A value of  $\Delta^2 \leq 3$  (3-band inversion) indicates good proximity between observations and simulations. All LAI and soil reflectance values satisfying this criterion constitute the set of acceptable solutions for a particular Landsat observation (NIR, RED and SWIR). In the situation in which  $\Delta^2 \leq 3$  fails to localize a solution set, Eq. (2.4) limits to a two band based merit function (excluding SWIR and  $\Delta^2 \leq 2$ ). If the reflectance based inversion fails, an empirical relationship between Simple Ratio and LAI is used to retrieve LAIs. (Ganguly et al. 2012) shows the implementation of the algorithm to derive LAI from Landsat derived surface reflectances. Figure 2.2 shows a 30 m forest LAI for the Conterminous United States derived from the Landsat Global Land Survey (GLS) 2005 dataset.

## 2.4 Spot GEOV2 LAI/FPAR Algorithm

The GEOV2 LAI and FPAR products derive from the past experience gained in the development of GEOV1 products from the SPOT VEGETATION (GEOV1/VGT) instrument (Baret et al. 2010, 2013) and AVHRR (GEOV1/AVHRR) (A Verger et al. 2012). The theoretical framework for GEOV1/VGT capitalizes on the MODIS and CYCLOPES products development. A database of sites representative at the global scale was populated with MODIS (Myneni et al. 2002; Shabanov et al. 2005) and CYCLOPES (Baret et al. 2007) products that were combined to retain the advantages while minimizing their deficiencies shown in few validation exercises (Garrigues et al. 2008; Weiss et al. 2007; McCallum et al. 2010). The resulting LAI or FPAR products values were used to train a neural network with VEGETATION derived top of the canopy directionally normalized reflectance values as inputs. This approach provided improved performances as compared to both MODIS and CYCLOPES products as demonstrated by few validation exercises (Camacho et al. 2012). However, these GEOV1/VGT products did not improve the continuity of the original MODIS and CYCLOPES products. Further, the pre-processing steps used to normalize the directional effects was based on a 30 days compositing window, making at least a 15 days delay between the actual date of the product and its delivery. Several operational applications require real

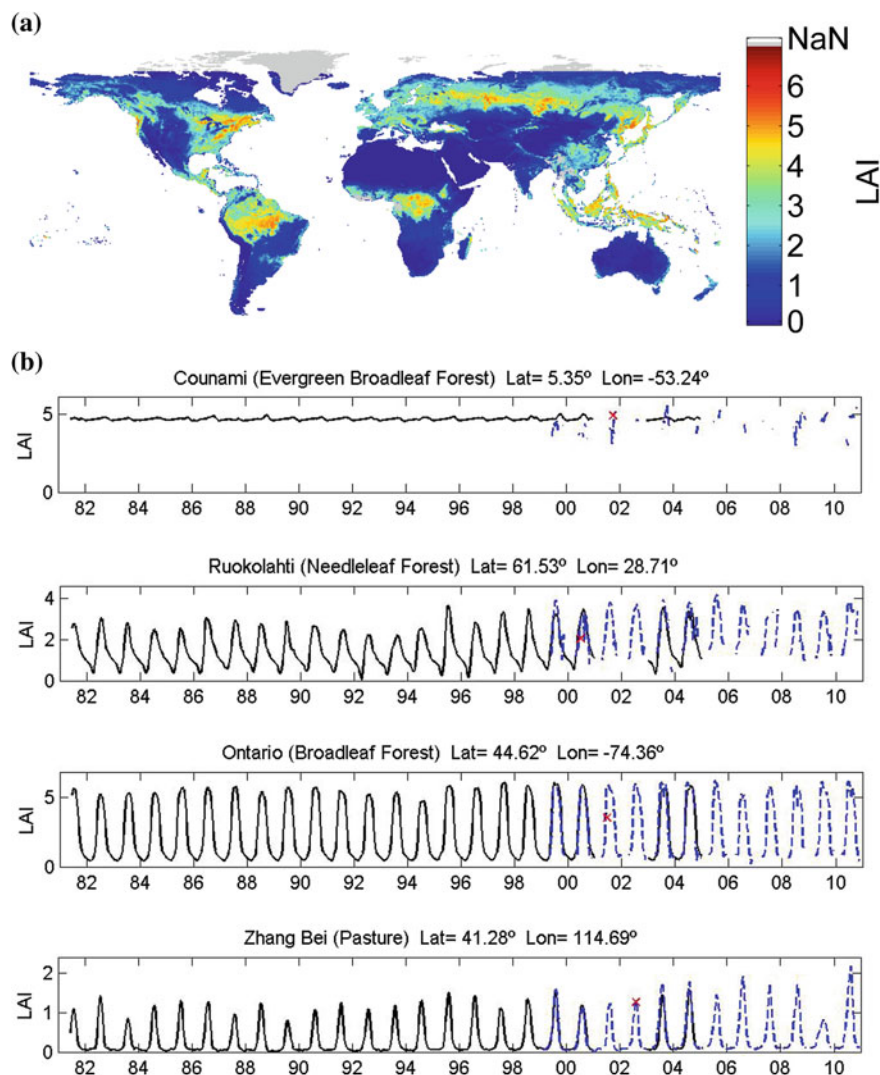




**Fig. 2.2** A 30 m Forest LAI for the Conterminous United States derived from the Landsat Global Land Survey (GLS) 2005 dataset. Most of the GLS Landsat scenes are acquired during the peak of growing season. The forested pixels are delineated from the National Land Cover Dataset (NLCD 2006) classification map. The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) framework is used to convert the GLS Landsat data to surface reflectances at the *Red*, NIR and Shortwave Infrared (SWIR) bands. Following the approach as detailed in Ganguly et al. (2012), a radiative transfer based inversion methodology was implemented to retrieve LAI for each pixel given the surface reflectances at the *Red*, NIR and SWIR bands

time delivery of the products and the 15 days delay was clearly a limitation for these users. Finally, the VEGETATION observations were starting only from 1998, while several applications require long time series.

The AVHRR archive was consequently exploited to derive the GEOV1/AVHRR products that extend the GEOV1/VGT products back to 1981. For this purpose, the 1999–2000 years where both VEGETATION and AVHRR overlap were used to train a neural network with GEOV1/VGT products as output and AVHRR reflectance as inputs. The AVHRR LTDR reflectance products (Devadiga et al. 2007) were used here. They correspond to atmospherically corrected and directionally normalized daily values. The corresponding daily LAI and FPAR products were smoothed using TSGF algorithm (Verger et al. 2011) and gap filled using the climatology as background information when limited observations are available. The GEOV1/AVHRR products have been demonstrated to be highly consistent with the GEOV1/VGT product values while improving largely the continuity, with almost no gaps (Verger et al. 2012). Figure 2.3a shows a global map of the GEOV1/VGT LAI product for the first dekade of May 2002 and Fig. 2.3b demonstrates the consistency between the GEOV1/VGT and GEOV1/AVHRR products for the overlapping time period.



**Fig. 2.3** **a** GEOV1/VGT LAI global map for the first dekad of May 2002. **b** Typical temporal profiles derived from GEOV1/AVHRR (black) and GEOV1/VGT (blue). The overlap period in 1999–2000 shows good consistency between both products. The red crosses correspond to available ground measurements of LAI

The GEOV2/VGT products were later developed to improve the continuity of GEOV1/VGT as well as to provide real time estimates of the products. The MODIS and CYCLOPES products were first combined similarly as what was achieved with GEOV1/VGT over a globally representative data set. Then the daily VEGETATION reflectances were used as input to train a neural network to estimate the LAI and FPAR computed from the combination of MODIS and

CYCLOPES products. The resulting daily LAI and FPAR estimates were gap filled and smoothed with the time series-processing algorithm developed previously for GEOV1/AVHRR. The use of the background climatology information on LAI and FPAR values, as well as the smoothing algorithm allowed for short-term projections required for deriving real time estimates of the products. The resulting GEOV2/VGT products were demonstrated to be highly consistent with GEOV1/VGT values with a large improvement in the continuity of the data (Baret et al. 2013). GEOV2/VGT is also fairly consistent with GEOV1/AVHRR and provides thus a time series of more than 32 years of LAI and FPAR products. The GEOV series of products are shown below in Table 2.1.

## 2.5 Availability of Data Products

The LAI/FPAR products as described above are available to use by the scientific research community. The standard MODIS Collection 5 LAI/FPAR products are available via the Reverb/ECHO web service at <http://reverb.echo.nasa.gov/reverb/>. The standard MODIS products from 2000 till present are available at a spatial resolution of 1 km and at 8 day temporal frequency. The long-term multi-year (1981 till present) monthly AVHRR LAI/FPAR dataset based on a scaled version of the MODIS algorithm is available upon request at the Climate and Vegetation Research Group at <http://cliveg.bu.edu/modismisr/index.html>. The GEOV2 LAI/FPAR products can be downloaded freely from the GEOLAND2 web portal located at <http://www.geoland2.eu/portal/>. They are available at the dekadal time step with 0.05° and 0.0089° spatial sampling interval in lat-lon geographic projection system. The MODIS LAI products at a spatial resolution of 250 m is also available upon request via the NASA Earth Exchange (NEX) web portal located at <https://c3.nasa.gov/nex/>. NEX in collaboration with USGS EROS is also currently making Landsat derived LAI available to research community on demand basis.

## 2.6 Validation Efforts

There has been an extensive effort since the inception of the NASA EOS era to validate biophysical products. Validation campaigns from existing network of sites like the BigFoot, AERONET, FLUXNET, EOS Land Validation Core Sites, and Valeri with sustained efforts from several research teams across the globe have provided the necessary platform to validate these biophysical products (Garrigues et al. 2008; Morisette et al. 2006; Pisek and Chen 2007). Both the MODIS and SPOT derived LAI/FPAR products have been extensively validated over a suite of vegetation types and climatic regimes. It is to be noted that “validation” refers to both (a) direct and (b) indirect validation, where the former refers to comparing satellite derived measures with ground truth while the later refers to an exercise

**Table 2.1** Table showing the different GEOV products

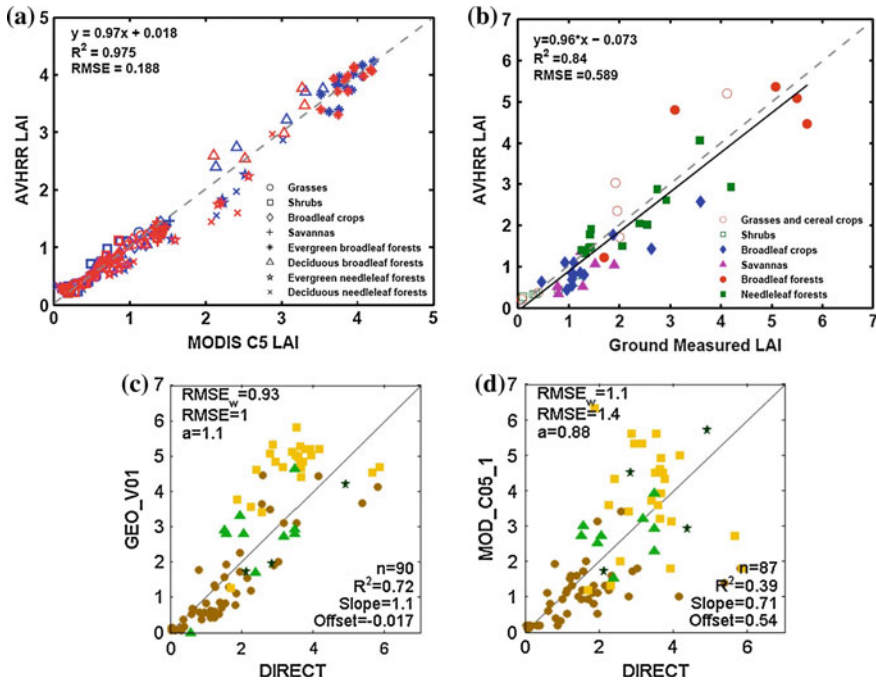
	GEOV1/VGT	GEOV1/AVHRR	GEOV2/VGT
Sensors	Vegetation	AVHRR	Vegetation
Period	1999-present	1981–1998	1999-present
Spatial sampling	0.0089°	0.05°	0.0089°
Temporal sampling	10 days	10 days	10 days
Near real time	No	No	Yes
Products used for training	MODIS and CYCLOPES	GEOV1/VGT	MODIS and CYCLOPES
Input reflectance	Composited ToC normalized reflectance (CYCLOPES L3a)	Daily ToC directionally normalized	Daily ToA i original view configuration
Output products	LAI, FPAR, FCOVER	LAI, FPAR, FCOVER	LAI, FPAR, FCOVER
Gap filling	No	Yes (using climatology)	Yes (using climatology)
Smoothing	Using BRDF model (30 days window)	Using TSGF and CACAO (variable window)	Using TSGF and CACAO (variable window)
Uncertainties	Based on training data set	Based on local differences with daily estimates	Based on local differences with daily estimates
Definition domain	Yes	Yes	Yes

intercomparing products from different sensor systems to test consistency. Both direct and indirect validation provides a comprehensive knowledge about the accuracy of these products and level of uncertainties that may results due to input data and modeling errors.

Direct validation results for the MODIS LAI/FPAR over vegetation types representative of all the major biome types suggest that the product provides reasonable estimates of LAI for most cover types and land use types (Garrigues et al. 2008; Huang et al. 2006; Kauwe et al. 2011; Pisek and Chen 2007; Sea et al. 2011; Tan et al. 2005; Yang et al. 2006). The MODIS LAI/FPAR products are categorized as a Stage 2 land validated product (<http://landval.gsfc.nasa.gov/ProductStatus.php?ProductID=MOD15>) that have the following characteristics: (a) LAI accuracy of 0.5 LAI units (uncertainty of 0.66 LAI), FPAR accuracy of 0.1; (b) spatial resolution from 500 m to 1 km; (c) temporal frequency from 4 days to monthly (Yang et al. 2006). Direct validation of the GEOV-1 products also shows a satisfactory agreement with field observations. An indirect validation implementing a scaled version of the MODIS algorithm to derive an LAI dataset from AVHRR shows satisfactory agreement with the MODIS and CYCLOPES LAI products at a range of spatial resolutions and field data (Ganguly et al. 2008a). The Landsat based LAI products are not rigorously validated, however an indirect validation with MODIS shows comparable results (Ganguly et al. 2012). Figure 2.4 briefly demonstrates the results obtained from validation exercises performed with the AVHRR, MODIS and GEOV suite of LAI products.

## 2.7 Concluding Remarks

Current scientific research and application studies have demonstrated the usefulness of physically derived LAI/FPAR products at local-to-regional scales; however, there are certain limitations in physically based approaches. First, data measurement uncertainties from different sensors can impact the retrieval of a biophysical product. Data uncertainties mostly result from calibration ambiguities, current state of the atmospheric correction algorithm and other effects introduced by solar/view angle corrections. Second, global retrievals of LAI/FPAR products utilize land cover classification maps. Classification inaccuracies are a critical source of error in the LAI retrieval process, especially for those regions undergoing dynamic land cover change (e.g. changes from herbaceous to woody biomes). There are intrinsic limitations in the retrieval algorithms that mostly include (1) accurately modeling the uncertainty of the input reflectances and incorporating the variability in model and input uncertainties with biome types; (2) incorporating a better understory reflectance characterization in simulating the soil reflectance behavior and (3) using constrained definitions of leaf spectral properties as defined by the broad biome types. Finally, a global validation of coarse-to-fine resolution



**Fig. 2.4** Validation of global LAI/FPAR products. Panel **a** shows comparison between MODIS Collection 5 and AVHRR LAI product from Ganguly et al. (2008b) for the year 2001 (blue color) and 2002 (red color) for different vegetation classes. The LAI values are globally averaged values for the respective vegetation pixels. Panel **b** shows a comparison of AVHRR LAI as in **a** with field measurements for the six major vegetation classes. Altogether 44 field data values were used (Table B2 of Appendix B in Ganguly et al. 2008b). Panel **c** shows comparison between GEOV1 (GEO\_V01 on y-axis) LAI product and ground measurements (DIRECT on x-axis). All ground measurements for the period January, 1999 till August, 2012 are used. Panel **d** shows a similar comparison as in **c** but with MODIS Collection 5 LAI product. Reprinted from Remote Sensing of Environment, 112, Ganguly, S., Samanta, A., Schull, M. A., Shabanov, N. V., Milesi, C., Nemani, R. R., Knyazikhin, Y., Myneni, R.B., Generating vegetation leaf area index Earth system data record from multiple sensors. Part 2: Implementation, analysis and validation, 4318–4332, Copyright (2008), with permission from Elsevier

LAI/FPAR products with ground measurements is a complicated task because of issues with aggregation of plot-level measurements to sensor resolution, limited temporal and spatial sampling of the ground data, field instrument calibrations, sampling errors, etc.

Future research on LAI/FPAR product development will continue along the following directions:

- (a) Implementation of physical algorithms to derive high-resolution LAI/FPAR products—this will involve characterizing land cover types at a sufficiently high resolution.

- (b) Continued validation of coarse-to-high resolution LAI/FPAR products with available and future acquisitions of field measurements in enhancing the accuracy of the satellite-derived products. Field measurements that provide synoptic knowledge about biome-specific spectral characteristics, will be an integral part of product assessment efforts that feed into algorithm refinement.
- (c) Utilization of high-resolution LAI products for estimating above ground biomass and Net Primary Productivity (NPP) estimates. Current algorithms in fusing Landsat derived LAI and canopy height estimates from the ICESat GLAS instrument have shown significant potential in estimating biomass over forested regions.
- (d) Enhancing the MODIS experience to Landsat LAI/FPAR products to monitor long-term changes and trends in land surface characteristics due to climatic variability and human-induced changes.

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