

Chapter 2

Leaf Area Index

Abstract This chapter briefly introduces the inversion algorithms used, discusses the product characteristics and validation results, and presents preliminary analyses and applications. The inversion algorithm was developed to estimate LAI from time-series remote sensing data using general regression neural networks (GRNNs). Unlike existing neural network methods that use remote sensing data acquired only at a specific time to retrieve LAI, the GRNNs used in this study are trained using the fused time-series LAI values from the MODIS and CYCLOPES LAI products and the reprocessed MODIS/AVHRR reflectance. The reprocessed time-series MODIS/AVHRR reflectance values from an entire year were input to the GRNNs to estimate the 1 year LAI profiles. This algorithm has been used to produce the GLASS LAI, one of the longest duration (1981–2012) LAI products in the world. Extensive validations for all biome types have been carried out, and it has been demonstrated that the GLASS LAI presents temporally continuous LAI profiles with much improved quality and accuracy compared with those of the current MODIS and CYCLOPES LAI products.

Keywords Leaf area index • General regression neural network • MODIS • AVHRR • Retrieval • Time series • GLASS

2.1 Background

Leaf area index (LAI) is defined as one half the total green leaf area per unit of horizontal ground surface area and is called *true LAI*. The true LAI multiplied by the clumping index is called *effective LAI*. LAI measures the amount of leaf material in an ecosystem, which imposes important controls on processes such as photosynthesis, respiration, and rain interception that link vegetation to climate. Hence, LAI appears as a key variable in many models that describe vegetation-atmosphere interactions, particularly with respect to the carbon and water cycles.

Models typically use satellite-based estimates of LAI in one of three ways: model forcing, validation of model output, and model assimilation. Buermann et al. (2001), using the National Center for Atmospheric Research (NCAR) Community Climate Model (CCM3) forced with an AVHRR-derived LAI, reported that the use of satellite derived fields revealed substantial warming and decreased precipitation over large parts of the Northern Hemisphere land areas during the boreal summer. This warming and drying reduced the discrepancies between simulated and observed near-surface temperature and precipitation fields.

The LAI user community includes the following categories (Myneni 2007): (a) scientific users: modelers of climate, primary production, ecology, hydrology, and crop production; (b) public users: meteorological organizations, deforestation and desertification monitoring organizations, rapid-response systems, pest-risk evaluation companies, governments involved in implementation of international treaties such as the Kyoto Protocol; and (c) private users: international agriculture and forestry companies, insurance companies, and traders.

The World Meteorology Organization (WMO) requirements shown in Tables 2.1 and 2.2 summarize the current global LAI products. Comparisons of these two tables indicate that current products do not meet user requirements.

Based on feedback from the user community and accumulated research experience, Myneni et al. (2007) proposed the following specifications for a global LAI product in a NASA Earth Science Data Record (ESDR) White paper:

Table 2.1 WMO observation requirements for LAI by space program. (<http://www.wmo-sat.info/db/variables/view/98>, updated June 3, 2012)

Application area	Uncertainty goal (%)	Uncertainty threshold (%)	Spatial resolution goal (km)	Spatial resolution threshold (km)	Temporal resolution goal	Temporal resolution threshold (days)
Global NWP	5	20	2	50	24 h	10
High-resolution NWP	5	20	1	40	12 h	2
Hydrology	5	20	0.01	10	7d	24
Agricultural meteorology	5	10	0.01	10	5d	7
Climate-TOPC	5	10	0.25	10	24 h	30

Table 2.2 Characteristics of current global LAI products

LAI products	LAI type	Spatial resolution	Temporal resolution (days)	Temporal range
MODIS	True	1 km	8	2000–present
CYCLOPES	Effective	1/112°	10	1999–2007
GLOBECARBON	True	1/11.2°	10	1998–2007
Geoland2	True	1 km, 0.05°	10	1999–2012
GLASS	True	1–5 km, 0.05°	8	1981–2012

- Accuracy of 0.5 LAI units to be achieved for corresponding global averages over individual biomes;
- Spatial resolution, depending on application from 250 m (local ecological studies) to 0.25 degree (global climate studies);
- Temporal frequency from 4 days to monthly;
- Length of recording starting from the beginning of AVHRR measurements (July 1981) and continuing into the future.

2.2 Algorithms

There are two methods for retrieving LAI from satellite data (Liang et al. 2012; Liang 2007): empirical methods and physical methods. The empirical methods are based on statistical relationships between LAI and spectral vegetation indices, which are calibrated for distinct vegetation types using field measurements of LAI and reflectance data recorded by a remote sensor or simulations with canopy radiation models. The physical methods are based on the inversion of canopy radiative transfer models through iterative minimization of a cost function, the look-up table (LUT) method, or various machine learning methods. Inversion techniques based on iterative minimization of a cost function require hundreds of runs of the canopy radiative transfer model for each pixel and are therefore computationally too demanding. For operational applications, LUT and artificial neural networks (ANN) methods are two popular inversion techniques that are based on a precomputed reflectance database. For example, MODIS and MISR LAI products are based on the LUT method (Myneni et al. 2002) and the CYCLOPES LAI product is based on the ANN method (Baret et al. 2007).

The GLASS LAI retrieval algorithm (Xiao et al. 2013) uses general regression neural networks (GRNNs) to retrieve LAI values from time-series MODIS/AVHRR reflectance data. The GRNNs are trained using fused LAI samples from MODIS and CYCLOPES LAI products and the reprocessed MODIS/AVHRR reflectance of the BELMANIP sites during the period from 2001 to 2004.

Two unique features of the GLASS LAI algorithm should be emphasized here. The first is that the LAI annual profile is estimated using annual observations. Unlike existing neural network methods that use remote sensing data acquired only at a specific time to retrieve LAI, the GRNNs used in the GLASS LAI production use the surface reflectance of an entire year as their input. The output is a 1 year LAI profile for each pixel. The second feature is that the GRNNs are training by integrating both MODIS and CYCLOPE LAI products. Training with representative samples is of critical importance in any ANN algorithms. Instead of using simulation data, the GRNNs are trained using fused time-series LAI values from MODIS and CYCLOPES LAI products and the reprocessed MODIS/AVHRR reflectance. A flow chart outlining this method is shown in Fig. 2.1.

A database was generated from the MODIS and CYCLOPES LAI products and the MODIS/AVHRR reflectance products at the BELMANIP sites from 2001 to

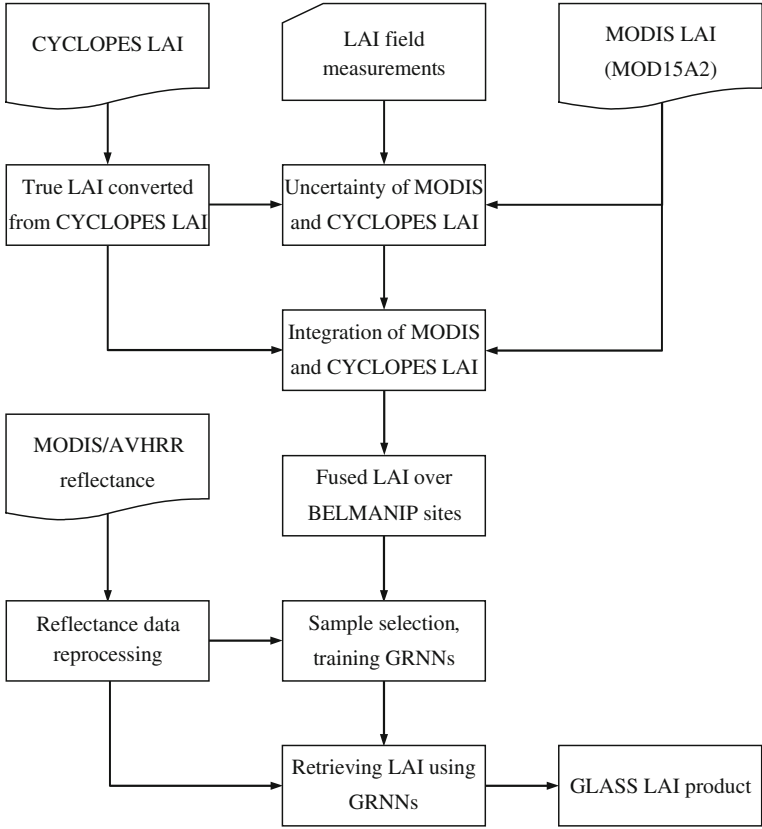


Fig. 2.1 Flow chart of LAI retrieval using general regression neural networks. (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

2004. The effective CYCLOPES LAI was first converted to true LAI and then combined with the MODIS LAI according to their uncertainties determined from the ground-measured true LAI values. The MODIS and AVHRR reflectance values were reprocessed to remove any remaining effects from cloud contamination and other factors. The GRNNs were then trained using the fused LAI and the reprocessed MODIS/AVHRR reflectance for each biome type. To retrieve LAI values from time-series remote sensing data, the reprocessed MODIS/AVHRR reflectance data from an entire year were input to estimate one-year LAI profiles using the GRNNs. A detailed description of the new algorithm is given in the following subsections.

2.2.1 General Regression Neural Networks

The GRNN, developed by Specht (1991), is a generalization of radial basis function networks (RBFNs) and probabilistic neural networks (PNNs). The advantage of this type of neural network is that it can approximate the map inherent in any sample data set. In addition, GRNNs possess a special property that these networks do not require iterative training. The functional estimate is computed directly from the training data. At present, GRNNs have been applied in a variety of fields, such as system identification, adaptive control, pattern recognition, and time series prediction (Leung et al. 2000).

Figure 2.2 shows a GRNN with a multi-input–multi-output architecture. It includes four layers: the input layer, the pattern layer, the summation layer, and the output layer. The input layer provides all the measurement variables to all the neurons in the pattern layer; each neuron represents a training pattern, and the output of each neuron is a measure of the distance of the input from the stored patterns. The summation layer consists of two types of summation neurons: one type computes the summation of the weighted outputs of the pattern layer, where the weight for the i th neuron in the pattern layer is the target output value corresponding to the i th input pattern, and the other type calculates the unweighted outputs of the pattern neurons. Finally, the output layer performs a normalization step to compute the GRNN-predicted value of the output variable.

If the kernel function of the GRNN is Gaussian, the fundamental formulation of the GRNN can be deduced as follows:

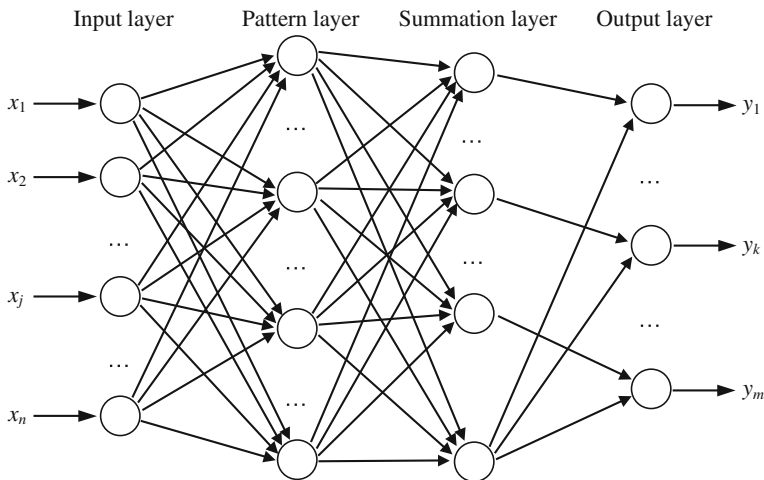


Fig. 2.2 GRNN with a multi-input–multi-output architecture. (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

$$Y'(X) = \frac{\sum_{i=1}^n Y^i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^n \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}, \quad (2.1)$$

where $D_i^2 = (X - X^i)^T (X - X^i)$ represents the squared Euclidean distance between the input vector $\mathbf{X}$ and the i th training input vector $\mathbf{X}^i$, Y^i is the output vector corresponding to the vector $\mathbf{X}^i$, $Y'(X)$ is the estimate corresponding to the vector $\mathbf{X}$, n is the number of samples, and σ is a smoothing parameter that controls the size of the receptive region. As σ becomes larger, the GRNN output approaches the mean of the training set outputs. As σ becomes smaller, the GRNN output approaches the output pattern of the training set. Equation (2.1) shows that the estimate $Y'(X)$, given an input vector $\mathbf{X}$, is the weighted average of all the sample observations Y^i , where the weight for each observation is proportional to the Euclidean distance between the vector $\mathbf{X}$ and the training input vector $\mathbf{X}^i$.

The input vector $\mathbf{X}$ of the GRNNs used to retrieve LAI includes the reprocessed MODIS/AVHRR time-series reflectance values in the red (R) and near-infrared (NIR) bands (for a one-year period); that is, $X = (R_1, R_2, \dots, R_{46}, \text{NIR}_1, \text{NIR}_2, \dots, \text{NIR}_{46})^T$ and contains 92 components. The output vector $\mathbf{Y}' = (\text{LAI}_1, \text{LAI}_2, \dots, \text{LAI}_{46})^T$ is the corresponding LAI time series for the year and contains 46 components.

2.2.2 Generating the Training Database

To generate LAI products at the regional to global scale using GRNNs, the training database should be globally representative of surface types and conditions. The BELMANIP network, which includes 402 sites, aims to provide a good sampling of biome types and conditions throughout the world (Baret et al. 2006). For each BELMANIP site, a 3×3 subset of the MODIS and CYCLOPES LAI products and the MODIS reflectance products for 2001–2004 was extracted.

The MODIS LAI product represents a true LAI, while the CYCLOPES LAI product represents an effective LAI. Therefore, there is a great need for a conversion relationship between effective and true LAI for use when integrating multiple LAI products.

Chen et al. (1996) demonstrated that the effective LAI (LAI_e) can be determined as the product of the true LAI (LAI_t) and the clumping index (Ω) as follows:

$$\text{LAI}_e = \Omega \times \text{LAI}_t \quad (2.2)$$

Based on the linear relationship between the clumping index and the normalized difference between hotspot and darkspot (NDHD) indices, Chen et al. (2005) derived the first global clumping index map using multiangular POLDER 1 satellite data from ADEOS-1. Pisek et al. (2010) expanded the global mapping of

the clumping index by integrating new, complete, year-round observations from POLDER 3. The across-biome difference in the topographical effect was removed in the new global clumping index map. The spatial resolution of the global clumping index map is 6 km.

Global average of the clumping index values for different biome types were derived according to the MODIS land cover product. For each land cover class, the pixels in the global clumping index map were selected to calculate the global average if at least 85 % of the pixels were covered with a single MODIS land cover type. In this case, the CYCLOPES LAI for different vegetation types can be converted to the true LAI using Eq. (2.2).

After the CYCLOPES LAI was converted to true LAI, the true CYCLOPES and MODIS LAI values were combined according to their uncertainties as determined from the ground-measured true LAI.

The fused LAI was generated as follows:

$$\text{LAI}_{\text{modcyc}} = w_{\text{mod}}\text{LAI}_{\text{mod}} + w_{\text{cyc}}\text{LAI}_{\text{cyc}}^*, \quad (2.3)$$

where $\text{LAI}_{\text{modcyc}}$ is a combined estimate of LAI, LAI_{mod} is the smoothed and gap-filled MODIS LAI resulting from the multistep Savitzky-Golay filtering procedure (Xiao et al. 2011), $\text{LAI}_{\text{cyc}}^*$ is the true LAI converted from the CYCLOPES LAI using the method described above, and w_{mod} and w_{cyc} are the normalized weights for the MODIS LAI and the true CYCLOPES LAI, respectively, the sum of these weights being equal to one.

By this method, the fused LAI can be obtained using Eq. (2.3) if the weights are known. Figure 2.3 shows the fused LAI time series for four different biome types. For convenient comparison, the MODIS and CYCLOPES LAIs and their corresponding weights are also shown in Fig. 2.3. Because the true CYCLOPES LAI is more consistent with the ground-measured LAI than is the MODIS LAI, the CYCLOPES weights are larger than the MODIS weights during the growing season.

The MODIS and AVHRR reflectance values were then processed further. The quality of MODIS reflectance is affected by many factors such as clouds, aerosols, water vapor, and ozone. Although many of these effects can be removed through atmospheric corrections, the remaining effects can sometimes be very large and require further processing (Chen et al. 2006). Much effort has been devoted to the development of reprocessing methods to remove residual atmospheric contamination from the reflectance. In this study, the method developed by Tang et al. (2013) was used for MODIS reflectance reprocessing. Data contaminated by undetected and fallout clouds were identified in the MODIS reflectance data using MODIS snow and cloud mask data, the spectral characteristics of temporal and spatial continuity and correlation, and other auxiliary information. Then, the cloud-contaminated data were removed using temporal-spatial filtering algorithms, and the missing data were filled in using an optimum interpolation algorithm to obtain smooth continuous surface reflectance values. Detailed information on this reprocessing method for MODIS reflectance is given by Tang et al. (2013).

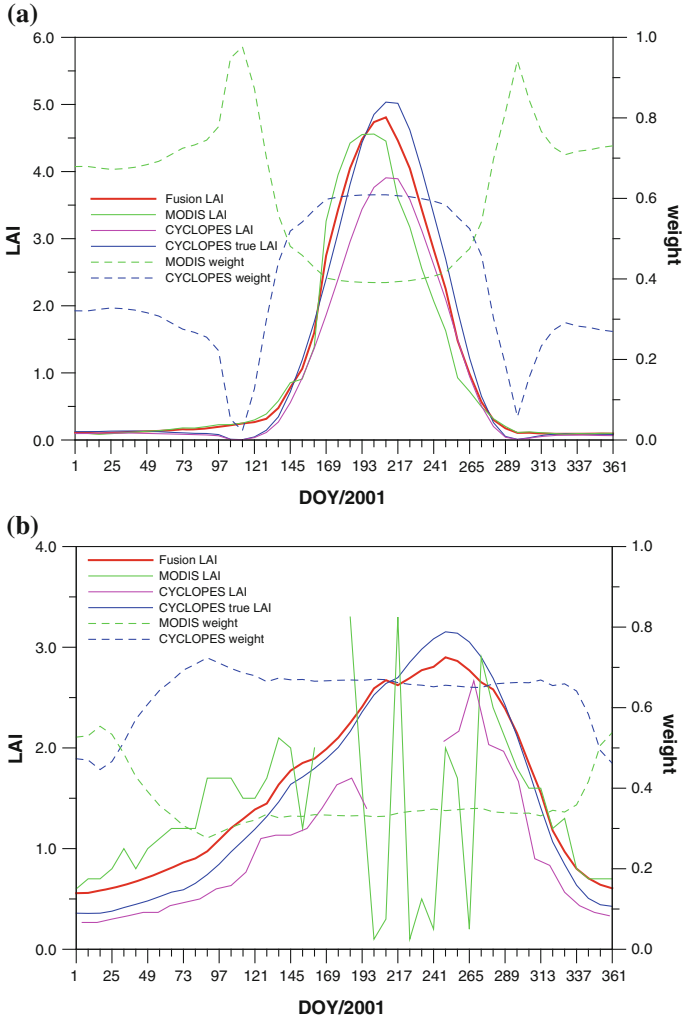


Fig. 2.3 Fused LAI time series from MODIS and CYCLOPES LAI values for different vegetation types: **a** crops, **b** grasses, **c** broadleaf forests, and **d** coniferous forests. (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

Figure 2.4 shows the reprocessed reflectance in the red (R) and near-infrared (NIR) bands at the Bondville site. It can be observed that the reprocessed reflectance is relatively smooth compared to the original MODIS reflectance. The fused time-series LAI and the reprocessed MODIS reflectance values were then used to train the GRNNs.

Similarly, to the MODIS surface reflectance data, the AVHRR reflectance data were also reprocessed to remove cloud-contaminated data and fill in the missing data using the method developed by Tang et al. (2013). In addition, the maximum

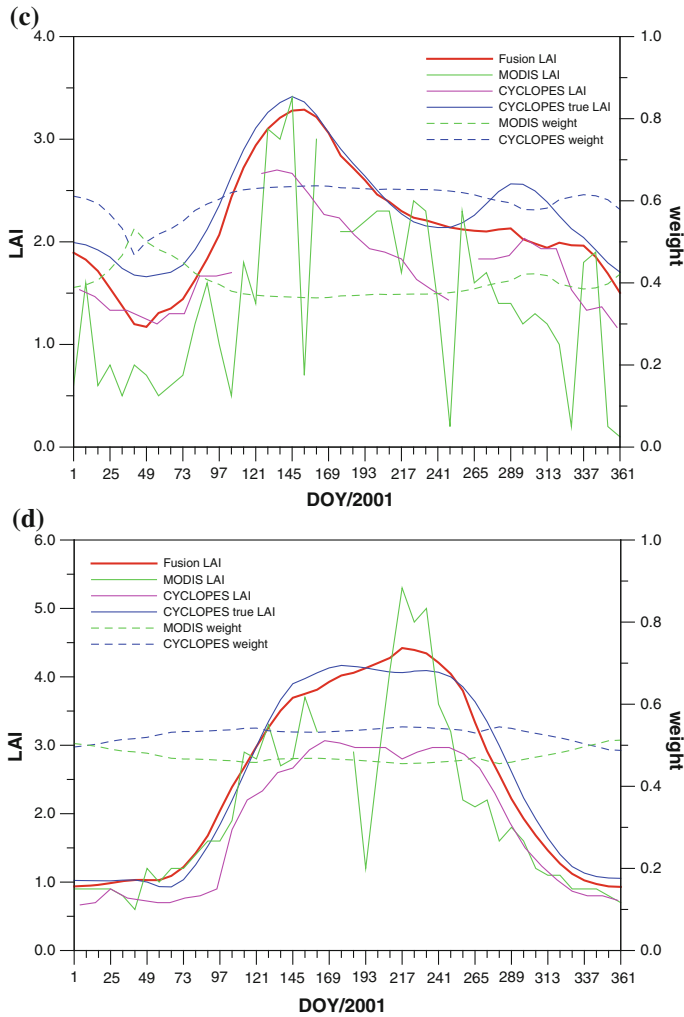


Fig. 2.3 continued

value composite approach (MVC) was used to combine the daily surface reflectance data into composites of eight-day intervals to maintain a consistent time resolution with MODIS surface reflectance data (Liang et al. 2012). The MVC method selects the AVHRR reflectance data with the highest normalized difference vegetation index (NDVI) over each eight-day time interval. To generate training database of the GRNNs for retrieval of LAI from time series AVHRR reflectance data, the fused LAI values at the BELMANIP sites calculated from MODIS, and CYCLOPES LAI products for 2003–2004 were transformed to the geographic projection and aggregated to 0.05° resolution using a spatial average sampling

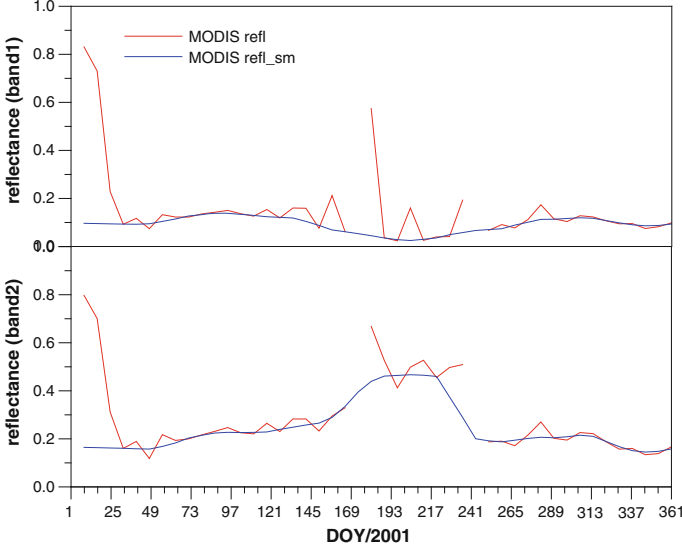


Fig. 2.4 Reprocessed reflectance (MODIS refl_sm) and original MODIS reflectance (MODIS refl) in the R and NIR bands. (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

method. Then, the fused time-series LAI values were used to train GRNNs with the corresponding reprocessed AVHRR reflectance values.

To achieve better performance and convergence, the values of the training inputs and outputs were normalized according to Eq. (2.4) before training the GRNNs:

$$X_{\text{norm}} = 2.0 \times (X - X_{\min}) / (X_{\max} - X_{\min}) - 1, \quad (2.4)$$

where $X_{\max}$ and $X_{\min}$ are the maximum and minimum values, for variable X , and X_{norm} is the normalized value corresponding to the training inputs or outputs X .

2.2.3 Training of the GRNNs

Unlike back-propagation neural networks, which are iteratively trained to determine the weights, the architecture and weights of GRNNs are determined when the input to the GRNN is given. The smoothing parameter σ is the only free parameter in the GRNN formulation. Therefore, training of a GRNN is essentially optimization of the smoothing parameter. The value of the smoothing parameter significantly affects the accuracy of the GRNN predictions. Therefore, the magnitude of σ must be chosen carefully.

Specht (1991) suggested the use of the holdout method to find a suitable σ . For a particular value of σ , the holdout method consists of removing one sample at a time from the training dataset and constructing a GRNN based on all the other training samples. The GRNN is then used to estimate Y for the removed sample. By repeating this process for each sample and storing each estimate, the mean squared error between the actual sample values $\mathbf{Y}^i$ and the estimates can be evaluated. The value of σ giving the smallest error should be used in the final GRNN. In fact, for the GRNNs in this study, the learning period was completed when the minimum of the following cost function of the smoothing parameter was reached:

$$f(\sigma) = \frac{1}{n} \sum_{i=1}^n [\hat{Y}_i(X_i) - Y_i]^2, \quad (2.5)$$

where $\hat{Y}_i(X_i)$ is the estimate corresponding to X_i using the GRNN trained over all the training samples except the i th sample.

A variety of optimization methods are currently available to find the optimal smoothing parameter in Eq. (2.5). The most commonly used methods are the hill-climbing method and the conjugate gradient method. However, these are prone to become caught in local minima, and they can produce false minima. Hansen and Meservy (1996) used a genetic algorithm to optimize the smoothing factor to find the optimal GRNN regression surface for global optimization. In this study, the shuffled complex evolution method developed at the University of Arizona (SCE-UA) was used to obtain the optimal smoothing parameter for the GRNN; this algorithm does not require the derivatives of the function, and is not susceptible to being trapped by small pits and bumps on the function surface (Duan et al. 1992). It has been extensively used in our recent studies (Xiao et al. 2009, 2012).

Using the MODIS land cover product, a dedicated GRNN was constructed for each biome type. Then, the trained GRNNs were used to retrieve LAI for the corresponding biome types from the reprocessed MODIS and AVHRR reflectance values.

2.3 Product Characteristics and Quality Control

2.3.1 GLASS LAI Product Characteristics

The GLASS LAI product, archived in the HDF-EOS format, has a temporal resolution of 8 days and is available from 1981 to 2012. From 2000 to 2012, the LAI product is derived from MODIS reflectance. It is provided in an Integerized Sinusoidal (ISIN) projection at a resolution of 1 km for each of the 289 land tiles (each representing 1200×1200 pixels) on the Earth. From 1981 to 1999, the LAI

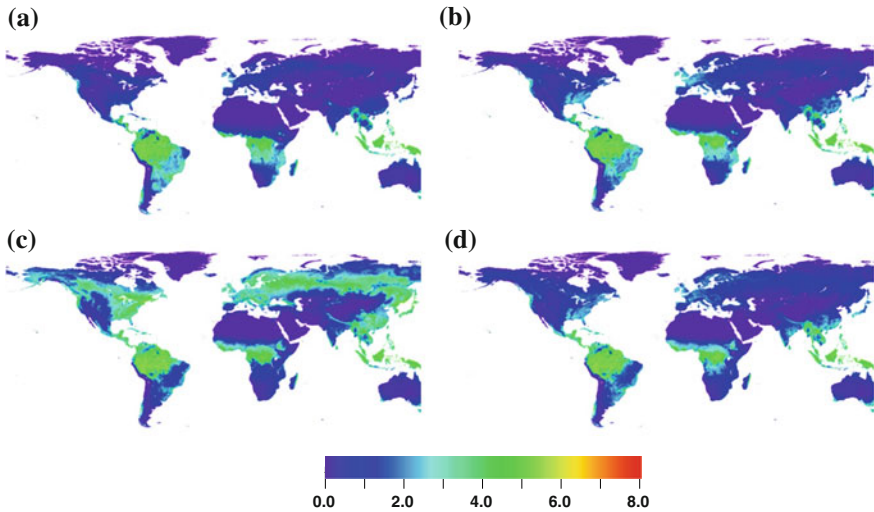


Fig. 2.5 GLASS LAI maps for January (a), April (b), July (c), and October (d) 2005. Geographic projection, 0.05° resolution for display purposes

product was generated from AVHRR reflectance. It is provided in a geographic projection at a resolution of 0.05° .

Four examples of the GLASS LAI global product for January, April, July, and October 2005 (Fig. 2.5) show a coherent global spatial distribution of the GLASS LAI product, presenting the highest values over equatorial forest, and zero values in desert areas.

The GLASS LAI product is spatially complete, and no gaps are present even if the MODIS/AVHRR surface reflectance is contaminated due to cloud or missing due to sensor failure.

Using the basic data product described above, 0.05° and 1° spatial resolution products were produced from 1981 to 2012 in the geographic projection of the Climate Modeling Grid (CMG) to meet the needs of global change and climate studies. The CMG products are also available for distribution.

2.3.2 *Quality Control*

Every scene of the GLASS LAI products has been subjected to a strict quality control (QC) procedure. Quality control was carried out both automatically and with human involvement. Automatic QC refers mainly to the generation of a QC flag that can be used to estimate the uncertainty in the GLASS LAI products. The quality check with human involvement is a computer-aided visual inspection of the spatial and temporal variations in the LAI product before its final release.

Table 2.3 Quality control flags of the GLASS LAI product

Bit	Bit combination	Meaning
0–1	00	LAI value with high quality
	01	LAI value with good quality
	10	Fill value
2–3	00	LAI value is retrieved using GRNNs
	01	Fill value
4	0	Non-water
	1	Water
5	0	Non-snow
	1	Snow
6	0	Non-cloud
	1	Cloud
7	0	The cloud has not been processed, and original value is retained
	1	The cloud has been processed

The term “LAI” is referred to an LAI value stored in an eight-bit signed integer data type. Valid product values range from 0 to 100, and the scale factor that converts the digital number to an LAI value is 0.1. The pixels representing water are filled with a digital number of 255. “QC” is the quality control flag, which gives a pixel-wise description of the data processing parameters as well as an indication of credibility of the result. The flag is an eight-bit unsigned integer data type provided for each pixel. The bitwise interpretation of the QC flags for the GLASS LAI product is given in Table 2.3.

2.4 Product Validation

To evaluate the accuracy of the GLASS LAI product, its results were first compared with those from other global LAI products, in addition, a direct validation was also performed (Xiang et al. 2013).

2.4.1 Cross-Comparison of GLASS LAI with Other Global LAI Products

A cross-comparison and validation of the GLASS, MODIS, and CYCLOPES LAI products was performed. The MODIS LAI product has been produced since 2000 at a 1-km spatial resolution and an 8-day time step. The MODIS LAI retrieval algorithm includes a main algorithm and a backup algorithm. The main algorithm is based on LUTs simulated from a three-dimensional radiative transfer model for eight main biome classes. When the main algorithm fails, the backup algorithm is used to estimate LAI from biome-specific LAI-NDVI relationships (Knyazikhin

et al. 1998). The CYCLOPES LAI product, with a spatial resolution of $1/112^\circ$ and a 10-day temporal sampling interval, was generated from SPOT/VEGETATION sensor data for 1999–2003 (Weiss et al. 2007). The algorithm used to estimate LAI was based on training neural networks with PROSPECT + SAIL radiative transfer model simulations (Weiss et al. 2007). The CYCLOPES LAI product was projected in *plate carrée*. Because of the different projection systems used for the GLASS, MODIS, and CYCLOPES LAI products, the CYCLOPES LAI values were reprojected into the MODIS projection system using the General Cartographic Transformation Package (GCTP) map projections library (U.S. Geological Survey 1993), and resampled to exhibit a 1 km spatial resolution using a bilinear interpolation technique.

2.4.1.1 Spatial Consistency

Results from global comparisons of the GLASS, MODIS, and CYCLOPES LAI products on DOY 25 and 217 in 2003 are presented in this section. Figure 2.6 shows the spatial patterns of these LAI products at a global scale. It can be observed that the GLASS LAI was consistent with the MODIS and CYCLOPES LAI products and in rough agreement as to magnitude. The highest LAI values and the relatively large differences between products were observed at latitudes 15°S – 15°N , close to the Equator, and near 50°N in Russia and Canada. The CYCLOPES LAI maintained the lowest values and was never greater than 4 on DOY 217 in most regions of South America close to the Equator. In the same area, the GLASS and MODIS LAI values were between 4 and 6.

Better spatial completeness was achieved by GLASS and MODIS than by CYCLOPES. High-latitude regions in the Northern Hemisphere were blank due to the effects of snow on DOY 25. On DOY 217, as shown in the right-hand column in Fig. 2.6, GLASS and MODIS had almost no fill values anywhere in the world.

All the products followed the seasonality effect, which shows opposite properties in the two hemispheres. In the Northern Hemisphere (NH), the LAI values in the right-hand column (summer) were much higher than those in the left-hand column (winter). In fact, in the left-hand column, the LAI values for the Northern Hemisphere were between 0 and 1, and the spatial variation was very low globally. There were many missing data points, represented by blanks, at high latitudes due to snow in winter. In the right-hand column, the Northern Hemisphere showed large spatial variations, with high LAI values in Canada and Russia. Similarly, in the Southern Hemisphere (SH), the LAI values in summer were larger than in winter. The spatial inconsistency in the SH was greater than in the NH.

To analyze more deeply the differences between GLASS and other LAI products, maps of their frequency distributions of differences were produced (see Fig. 2.7). The GLASS LAI values were in good agreement with the MODIS LAI values with the best possible quality ($QC < 32$). When the QC of the MODIS LAI values was greater than 32, large discrepancies were observed between the GLASS LAI values and the MODIS LAI values. The properties of the differences between

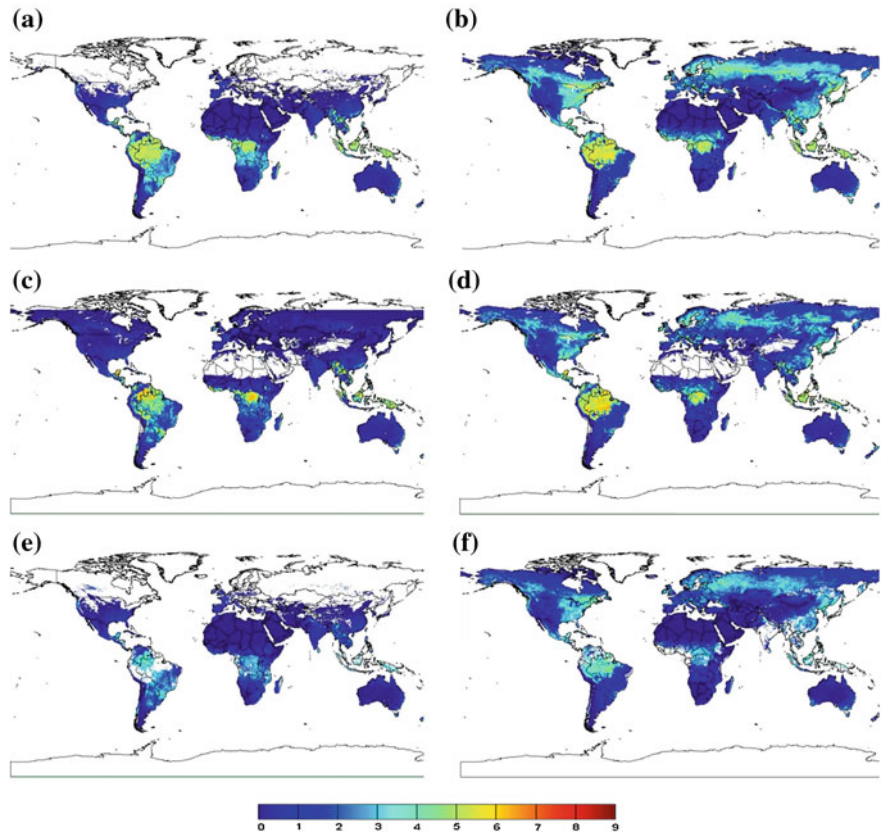


Fig. 2.6 Spatial patterns of the GLASS, MODIS, CYCLOPES, and CCRS LAI products on DOY 25 and 217 of 2003. Fill values are set to blanks. **a** GLASS LAI, DOY 25, 2003, **b** GLASS LAI, DOY 217, 2003, **c** MODIS LAI, DOY 25, 2003, **d** MODIS LAI, DOY 217, 2003, **e** CYCLOPES LAI, DOY 25, 2003, **f** CYCLOPES LAI, DOY 217, 2003

GLASS and MODIS described above suggest that the GLASS LAI has improved upon the unrealistically high or low values of the MODIS LAI when the QC is poor, especially for forest.

Figure 2.8 shows a histogram of the discrepancy map of the GLASS and CYCLOPES LAI values on DOY 217 in 2003. Because of the mismatch between the projections used in the GLASS and CYCLOPES products, the projection of the CYCLOPES LAI was converted into sinusoidal form using the GCTP library. Then the difference values were computed by subtracting the reprojected CYCLOPES LAI from the GLASS LAI. Better consistency was achieved between the GLASS and CYCLOPES products than between GLASS and MODIS products. The GLASS LAI was larger than the CYCLOPES LAI by approximately -0.5 to 0.5 over most of the study regions. The histogram had only one peak near zero, and the percentage at the zero value was 27 %. More than 70 % of the difference

Fig. 2.7 Histograms of the discrepancies between GLASS and MODIS LAI

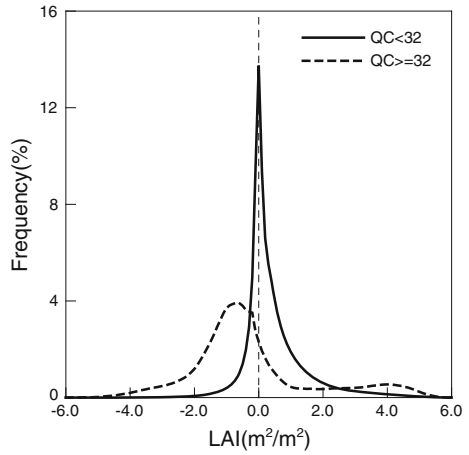
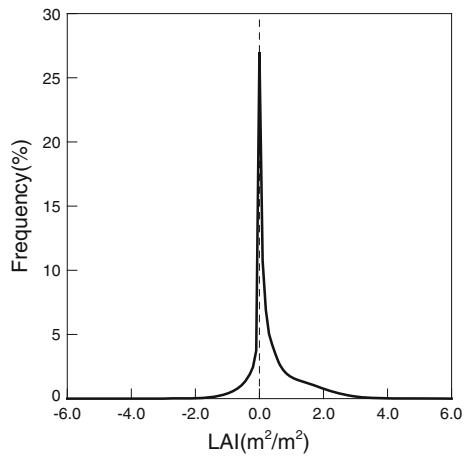


Fig. 2.8 Histogram of differences between GLASS and CYCLOPES LAI values on DOY 217 in 2003



values were between -0.5 and 0.5 . The number of positive discrepancies was far greater than the number of the negative discrepancies because of underestimation by the CYCLOPES algorithm. Moreover, larger discrepancy values, between 0.5 and 3 , were observed near the Equator and in the higher latitudes of the Northern Hemisphere. These large discrepancies occurred because of underestimation by the CYCLOPES LAI in forest areas, due to early saturation of the CYCLOPES LAI (values are never larger than 4) and the lack of a clumping representation (Weiss et al. 2007).

Table 2.4 Characteristics of the validation sites (total 19)

Site	Country	Latitude (°)	Longitude (°)	DOY	Year	Mean LAI
Alpilles	France	43.8104	4.7146	204	2002	1.69
Camerons	Australia	−32.5983	116.2542	63	2004	2.13
Demmin	Germany	53.8921	13.2072	164	2004	4.15
Donga	Benin	9.7701	1.7784	172	2005	1.85
Fundulea	Romania	44.4058	26.5849	144	2002	1.53
Gilching	Germany	48.0819	11.3205	199	2002	5.39
Gngangara	Australia	−31.5339	115.8824	61	2004	1.01
Larose	Canada	45.3805	−75.2170	219	2003	5.87
Larzac	France	43.9375	3.1230	183	2002	0.81
Nezer	France	44.5680	−1.0382	107	2002	2.38
Plan-de-Dieu	France	44.1987	4.9481	189	2004	1.13
Puechabon	France	43.7246	3.6519	164	2001	2.85
Sonian	Belgium	50.7682	4.4111	174	2004	5.66
Sud-Ouest	France	43.5063	1.2375	189	2002	1.96
Wankama	Niger	13.6450	2.6353	174	2005	0.14
Zhangbei	China	41.2787	114.6878	221	2002	1.26
Counami	French Guyana	5.3435	−53.2368	269	2001	4.93
Laprida	Argentina	−36.9904	−60.5527	286	2002	4.37
				311	2001	5.82
				292	2002	2.81
Turco	Bolivia	−18.2350	−68.1836	208	2001	0.31
				240	2002	0.04

2.4.1.2 Temporal Consistency

The LAI temporal profiles of the central pixel at various sites in Table 2.4 are depicted in Figs. 2.9–2.13. To enable better evaluation of the quality of the GLASS LAI values, the temporal profiles of CYCLOPES LAI values, MODIS LAI values, and ground measurements are also shown for each selected site.

Figure 2.9 shows the temporal LAI trajectories over the Alpilles site for 2002. The biome type is broadleaf crops according to the MODIS land cover map. The GLASS, and CYCLOPES LAI values are in very good agreement for the entire year, while the MODIS LAI profile maintains lower LAI values. Comparatively speaking, the GLASS LAI values are the closest to the ground-based measurements. The MODIS data are very noisy, while all other LAI profiles are relatively smooth. Similar phenomena can also be observed in the other figures below. This is mainly due to the high sensitivity of the MODIS algorithm to surface reflectance uncertainties, especially at large LAI (Shabanov et al. 2005).

Figure 2.10 shows the temporal LAI trajectories for 2001–2002 at the Fundulea site with grass and cereal crop biome types according to the MODIS land cover map. The Fundulea site presents more interannual variability than other sites because its crops and cereals change from year to year. Although a good

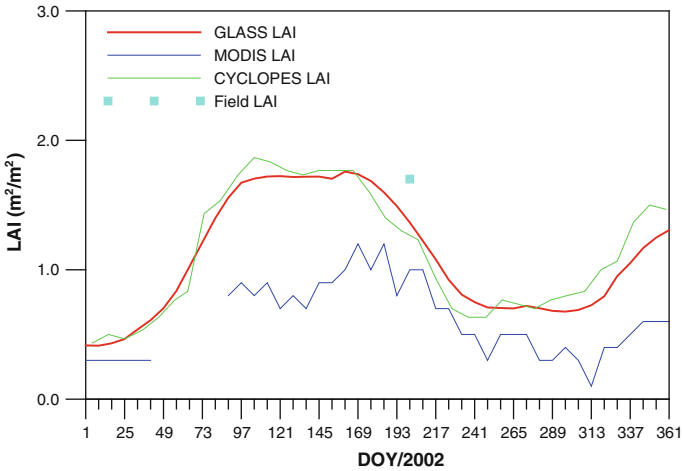


Fig. 2.9 Temporal profiles of GLASS, CYCLOPES, and MODIS LAI values for the Alpilles site for 2002. From Xiao et al. (2013), Copyright © 2003 reproduced with permission of IEEE

seasonality agreement is achieved among the GLASS, CYCLOPES, and MODIS LAI values, they are all underestimates in comparison with the BELMANIP mean LAI data at this site in 2001.

Figure 2.11 shows the temporal LAI trajectories for the Larose and Nezer sites with the conifer forest biome type according to the MODIS land cover map. The LAI products generally exhibit similar temporal trajectories, although with differences in magnitude. The strongest agreement is achieved between the GLASS and MODIS LAI values, aside from some fluctuations in the MODIS LAI values, while the CYCLOPES LAI values are significant underestimates throughout the entire growing season. The GLASS LAI values are in very good agreement with the BELMANIP mean LAI data at both sites.

As for broadleaf forests, the LAI temporal profiles at the Puechabon and Counami sites are illustrated in Fig. 2.12. The Puechabon site is largely dominated by trees of the species *Quercus ilex*, and is classified as an evergreen broadleaf forest according to the MODIS land cover map. Large discrepancies between products can be observed in the LAI magnitudes for 2001. The CYCLOPES LAI values exhibit an almost flat profile throughout the entire year. The GLASS and MODIS LAI values exhibit similar temporal trajectories, but with substantial differences in magnitude. The MODIS LAI values, except for dramatic fluctuations, are much larger than either the GLASS LAI values or the mean BELMANIP LAI values. However, the GLASS LAI values follow a smooth trajectory, and the GLASS LAI values outperform the other LAI products in terms of accuracy compared to the mean BELMANIP LAI data at this site. At the Counami site, visual inspection of the temporal profiles confirmed that the MODIS product values are extremely dubious, and most of the CYCLOPES LAI estimates are missing; in fact, there are only five CYCLOPES LAI values for the entire year.

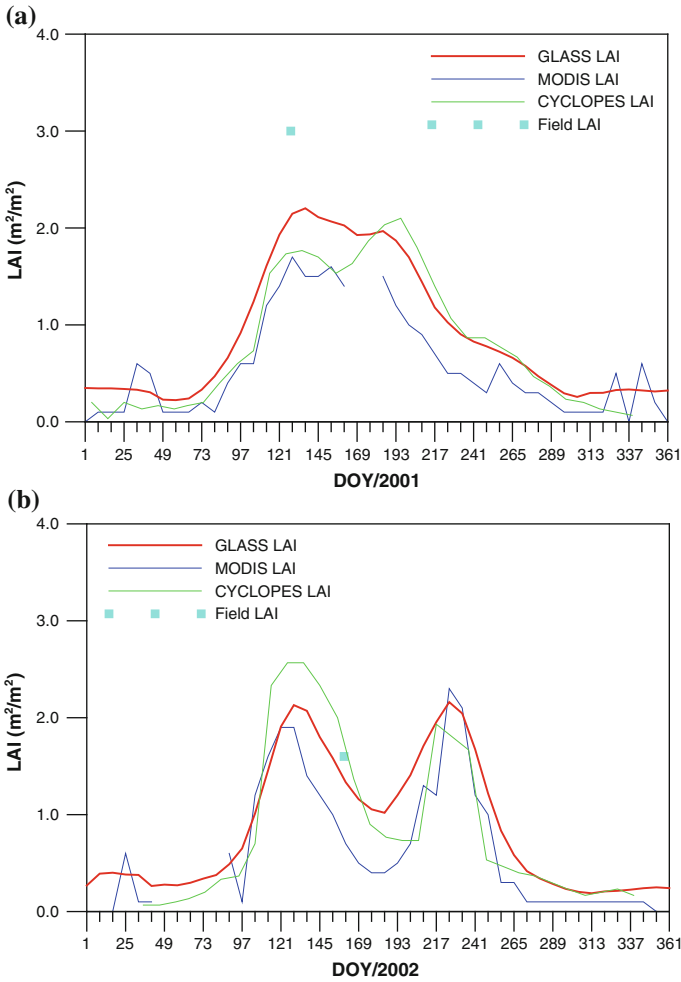


Fig. 2.10 Temporal profiles of GLASS, CYCLOPES, and MODIS LAI values for the Fundulea site for 2001 (a) and 2002 (b). (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

Meanwhile, the GLASS LAI values are relatively smooth and close to the mean BELMANIP LAI values.

The temporal profiles of the GLASS, MODIS, and CYCLOPES LAI values at the Laprida and Larzac sites, which are of the savannah biome type, are provided in Fig. 2.13. At the Laprida site, the LAI temporal profiles were generally in very good agreement at the beginning of the growing season (Fig. 2.13a). However, during the peak of the growing season, the MODIS LAI values became underestimates and the CYCLOPES LAI values became overestimates in comparison with the mean BELMANIP LAI data at this site, while excellent agreement was

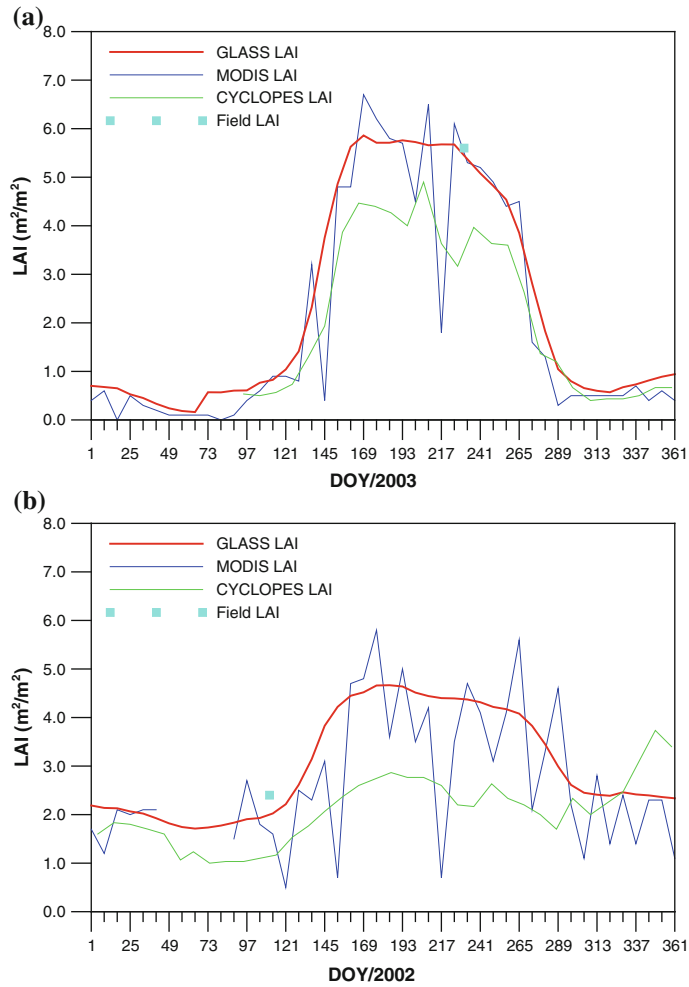


Fig. 2.11 Temporal profiles of GLASS, CYCLOPES, and MODIS LAI values at (a) the Larose site in 2003 and (b) the Nezer site in 2002. (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

achieved between the GLASS LAI values and the ground measurements. At the Larzac site (Fig. 2.13b), the GLASS, MODIS, and CYCLOPES LAI values showed similar temporal trajectories, although with differences in magnitude. The strongest agreement was achieved between the GLASS and MODIS LAI values, although the MODIS LAI profile showed dramatic fluctuations; CYCLOPES maintained lower LAI values throughout the year. Figure 2.13b also shows that the GLASS, MODIS, and CYCLOPES LAI values were all overestimates when compared to the ground-based LAI values.

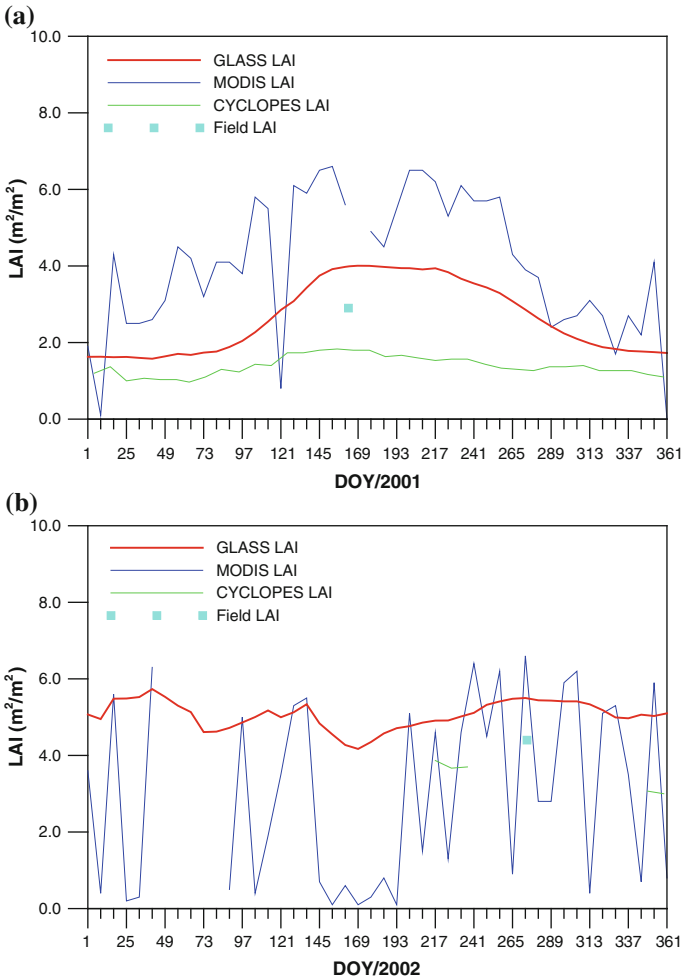


Fig. 2.12 Temporal profiles of GLASS, CYCLOPES, and MODIS LAI values at the Puechabon site for 2001 (a) and the Counami site for 2002 (b). (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

To analyze the temporal consistency of the GLASS, MODIS, and CYCLOPES LAI products, the General Cartographic Transformation Package (GCTP) map projections library (U.S. Geological Survey 1993) was used to reproject the GLASS LAI values derived from MODIS surface reflectance and the MODIS and CYCLOPES LAI values into the geographic Lat/Lon projection, used in the GLASS LAI derived from AVHRR surface reflectance, and to resample them to exhibit a 0.05° spatial resolution using a spatial average sampling technique. To reduce potential co-registration errors, the average of all pixels in a 3×3 window, centered on the study sites, was used to compare the LAI time series. Figure 2.14

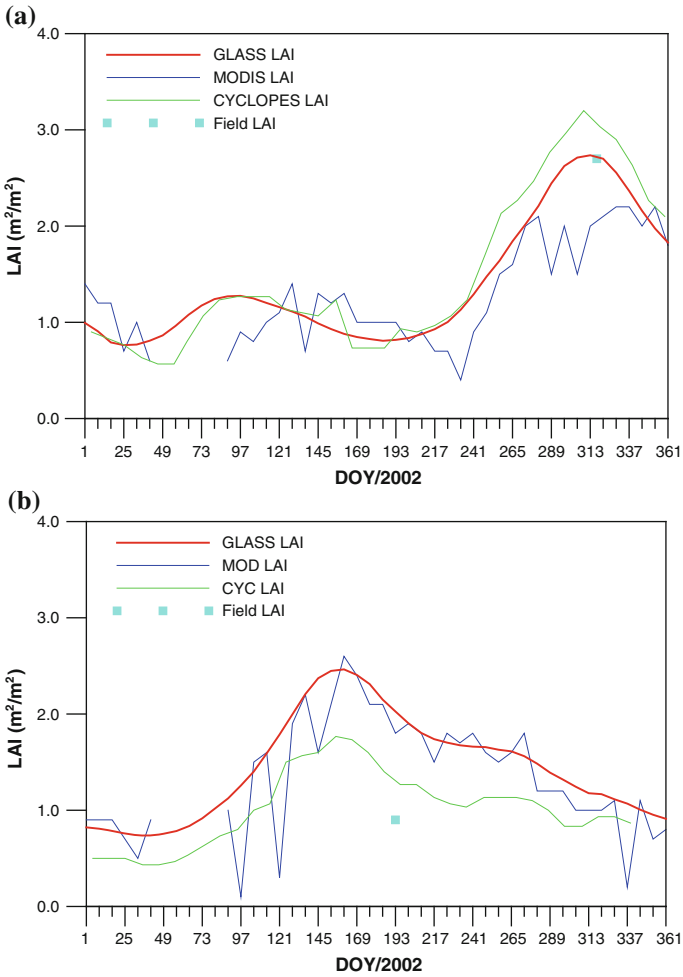


Fig. 2.13 Temporal profiles of GLASS, CYCLOPES, and MODIS LAI values at the Laprida site for 2002 (a) and the Larzac site for 2002 (b). (Xiao et al. 2013), Copyright © 2003 reproduced with permission of IEEE

shows the GLASS, CYCLOPES, and MODIS LAI profiles from 1982 to 2012 over the Bondville and NOBS—BOREAS sites.

The Bondville site (40.01°N, 88.29°W) is an agricultural site in the mid-western United States near Champaign, Illinois. The fields at this site were continuous no-till, with alternating years of soybean and maize crops (Meyers and Hollinger 2004). The NOBS—BOREAS site is located in the BOREAS Northern Study Area (NSA) at 55.89°N, 98.48°W and is surrounded by a black spruce-dominated forest of varying statures. The plots in Fig. 2.14 show that the GLASS LAI values retrieved from AVHRR and MODIS reflectance exhibit good time consistency,

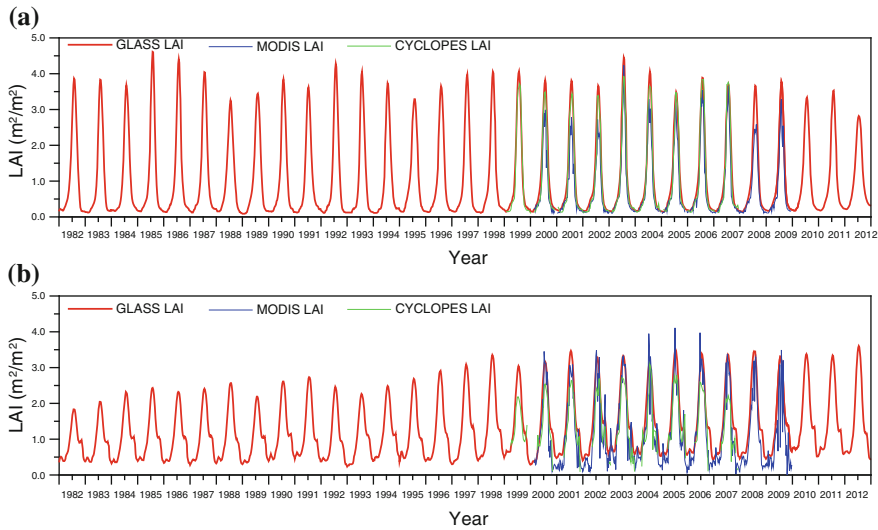


Fig. 2.14 Time profiles of LAI values from the GLASS, CYCLOPES and MODIS products at the Bondville (a) and NOBS-BOREAS (b) sites

and that all three LAI products are able to capture the seasonal change properties of vegetation to a similar degree, although the LAI peak value during the growing season may be different. Moreover, the GLASS and CYCLOPES LAI profiles are relatively smoother, while the MODIS LAI profiles fluctuate especially during the growing season.

In a separate study, Fang et al. (2013) compared five major global LAI products (MODIS, GEOV1, GLASS, GLOBMAP, and JRC-TIP) by examining their climatological and uncertainty information for different biome types. The results demonstrated that MODIS, GEOV1, GLASS, and GLOBMAP are generally consistent and show strong linear relationships between the products ($R^2 > 0.74$), with typical deviations of <0.5 for non-forest and <1.0 for forest biomes, and that the GEOV1 and GLASS products showed improvement over the earlier CYCLOPES and GLOBCARBON products in terms of spatial and temporal consistency and similarity to MODIS (Fang et al. 2013).

2.4.2 Direct Validation

The Validation of Land European Remote Sensing Instruments (VALERI) project has developed a globally distributed network of sites and a standard method to measure biogeophysical variables of interest directly at the proper spatial and temporal scales. This network contains 33 sites and 52 LAI reference maps. The LAI reference maps were derived by determining the transfer function between the

reflectance values of high-spatial-resolution SPOT images and LAI ground measurements. The SPOT images were acquired by HRVIR1 on SPOT4 during or just before or after the ground campaign using the UTM projection. The ground measurements consisted mainly of gap-fraction measurements obtained using LAI-2000 measurements or hemispherical photographs. For each Elementary Sampling Unit (ESU), the hemispherical images were processed using the CANEYE software (Version 3.6) developed at INRA-CSE. Among the 52 LAI reference maps, only 22 LAI reference maps provide true LAI values from 2000 to 2004. These true LAI maps were aggregated to produce a moderate resolution and used to compare and evaluate the GLASS LAI products. Characteristics of the validation sites are shown in Table 2.4.

The GLASS, MODIS, and CYCLOPES LAI products were compared directly with the same set of LAI reference maps. Figure 2.15 presents the accuracy of each product as quantified by the regression function, R-squared, and RMSE. Each

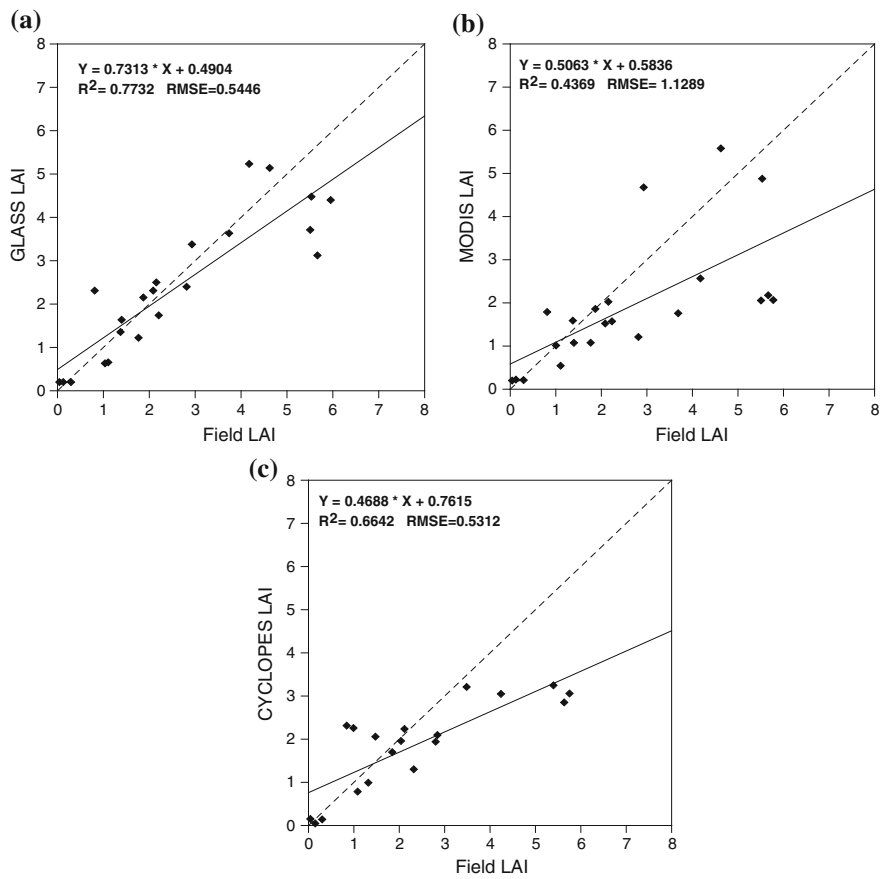


Fig. 2.15 GLASS (a), MODIS (b), and CYCLOPES (c) LAI products versus LAI reference map scatterplots for direct validation

scatter diagram has 22 plots corresponding to the 22 LAI maps, except for CYCLOPES. Because there are two fill values of the CYCLOPES LAI corresponding to two of the LAI reference maps, only 20 plots are shown in Fig. 2.15c. The best agreement was achieved by the GLASS LAI ($R^2 = 0.77$, RMSE = 0.54), followed by the CYCLOPES LAI ($R^2 = 0.66$, RMSE = 0.53), and the MODIS LAI ($R^2 = 0.44$, RMSE = 1.13). It can be concluded that the GLASS LAI has better consistency with ground measurement data than the other two products.

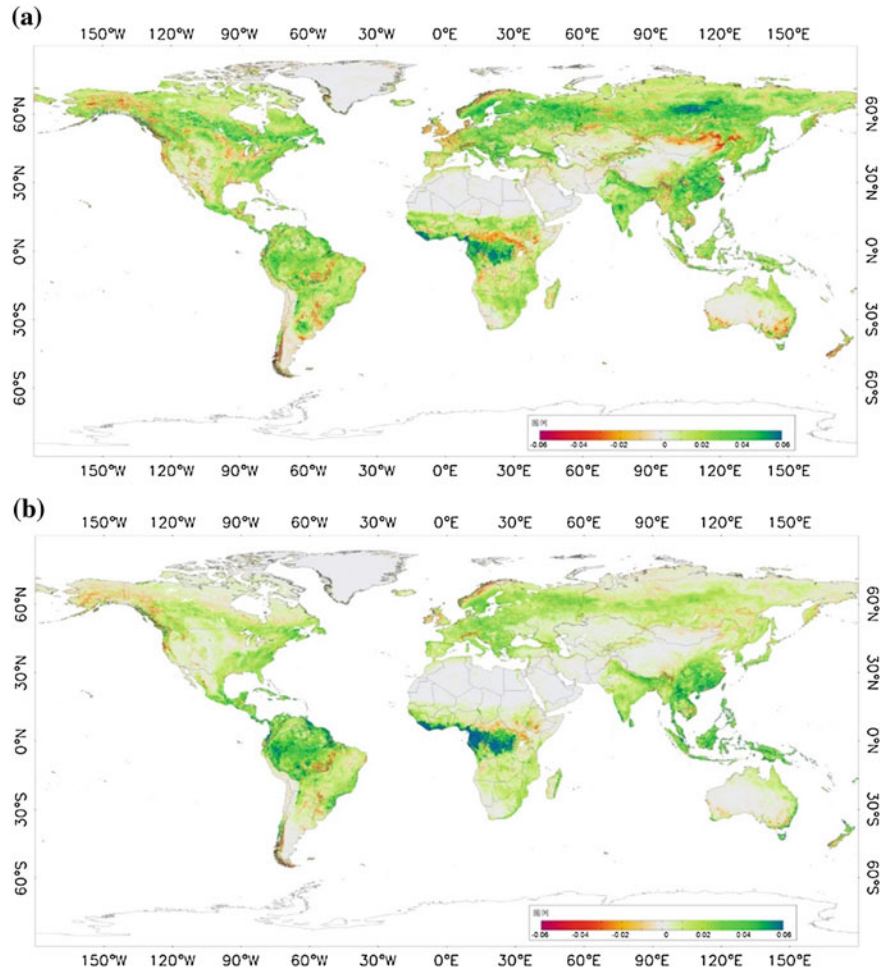


Fig. 2.16 Linear trend based upon annual maximum LAI (a) and annual average LAI (b) for 1982–2011

2.5 Preliminary Analysis and Applications

2.5.1 Spatial and Temporal Variation of Global LAI

The GLASS LAI product for 1982–2011 was used to analyze the global temporal and spatial variations of vegetation for periods of 30 years. For each pixel, a least-squares fit was applied to the annual maximum LAI and annual average LAI from 1982 through 2011, to determine the slope coefficients of the linear regressions that represent annual trends (shown in Fig. 2.16).

The linear trends based upon the annual maximum LAI (Fig. 2.16a) shows a significantly decreasing trend of vegetation growth on the Europe’s Atlantic coast, in Alaska, in the northeastern part of the Mongolian Plateau, and along the northern margin of the African rainforest. On the other hand, a significantly increasing trend of vegetation growth was found in Central Siberia, the Gulf of Guinea along the west coast of Africa, and the Congo Basin.

The linear trends based on the annual average LAI (Fig. 2.16b) shows a significantly increasing trend of vegetation growth in the African countries along the Gulf of Guinea, such as Liberia, Ivory Coast, Ghana, Cameroon, Equatorial Guinea, Gabon, Congo-Kinshasa, and Congo-Brazzaville, and a significantly decreasing trend of vegetation growth in northern Mongolia, eastern Inner Mongolia in China, the Central African Republic, Central Nigeria, northern Cameroon, southern South Sudan, northern Uganda, southern Ethiopia, Alaska, western Canada, southeastern and western Paraguay, northern Chile, northern Argentina, the southeastern margin of the Amazon plains, and south-central, and southwestern Australia.

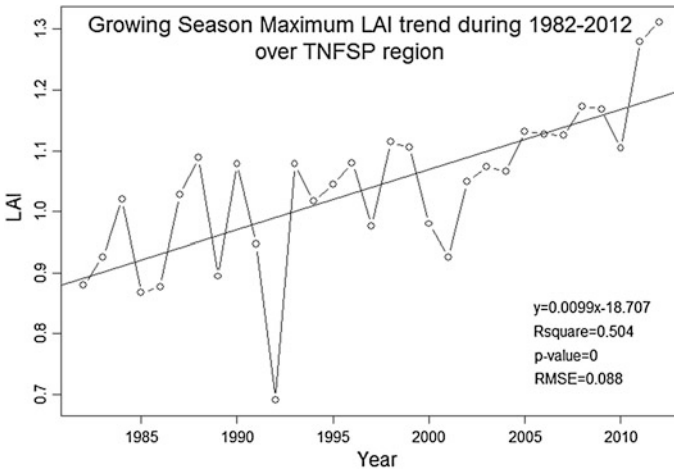


Fig. 2.17 Average values of annual maximum LAI over the three-north China area during 1982–2012

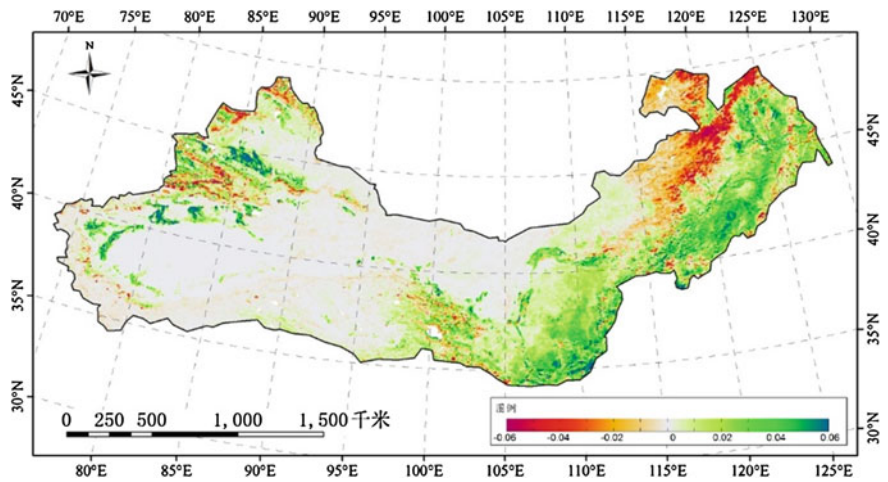


Fig. 2.18 Linear trend based on annual maximum LAI over the Three-North China area for 1982–2012

2.5.2 Three-North China Afforestation

The Three-North Forest Shelterbelt Program has been carried out in northeastern China, northern China, and northwestern China since 1978. Other ecological restoration programs have also been carried out in these regions. These programs have greatly improved the ecological status of the Three-North Forest Shelterbelt region, making it one of the most significant areas of positive vegetation change in China over the past 30 years. Figure 2.17 shows the average of the annual maximum LAI over the area during 1982–2012, and it is interesting to note an overall increasing trend.

The linear trend based on the annual maximum LAI over the Three-North Forest Shelterbelt region is demonstrated in Fig. 2.18. In addition to the eastern region of Inner Mongolia, all other Three-North project areas show a significantly increasing trend for 1982–2012 (Fig. 2.18).

2.6 Summary

The GLASS LAI product has been generated using GRNNs for 1981–2012 from time-series MODIS and AVHRR reflectance data. The GRNNs were trained using fused LAI values calculated from the MODIS and CYCLOPES LAI products and the corresponding reprocessed MODIS/AVHRR reflectance values. The input to the GRNNs was the time-series reprocessed MODIS/AVHRR reflectance values for an entire year, and the output of the GRNNs was the LAI profile for 1 year.

By computing the RMSE and R-squared values of each product over the LAI reference maps at various validation sites, it has been demonstrated that the accuracy of the GLASS LAI product is clearly better than that of MODIS and CYCLOPES. Moreover, the GLASS LAI is more temporally continuous and spatially complete than the other products tested. The spatial patterns generated by GLASS are reasonable and consistent with good quality MODIS and CYCLOPES LAI values. The GLASS and CYCLOPES LAI products have smoother trajectories compared to the erratic fluctuations of the MODIS LAI. The GLASS LAI has more realistic and reasonable trajectories representing seasonal variations, especially for forest.

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Global LAnd Surface Satellite (GLASS) Products

Algorithms, Validation and Analysis

Liang, S.; Zhang, X.; Xiao, Z.; Cheng, J.; Liu, Q.; Zhao, X.

2014, IX, 167 p. 93 illus., 73 illus. in color., Softcover

ISBN: 978-3-319-02587-2