Method for improvement of MODIS leaf area index products based on pixel-to-pixel correlations

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Abstract
A new method, based on pixel-to-pixel correlations, was proposed to replace unreliable Moderate Resolution Imaging Spectroradiometer (MODIS) leaf area index (LAI) time series (termed the “pixel-to-pixel correction (PPC) method”). MODIS LAI products improved by the PPC method were compared to field-measured LAI data. Results show that the PPC method could reduce the error associated with MODIS LAI products in relation to the original MODIS LAI product, and provide a level of accuracy that meets the most reliable quality control level criterion (quality control = 0). The PPC method performed well at correcting unrealistically high and unreliable LAI values, and performed slightly better than the “upper envelope” smoothing method. The corrected data were also more continuous and smoother than the raw MODIS LAI products. Thus, the PPC method can successfully reduce the uncertainty and improve the accuracy of raw MODIS LAI products.

Keywords: MODIS LAI product, improvement, autocorrelation.

Introduction
The leaf area index (LAI) is an important parameter that describes vegetation structure and health [Bresciani et al., 2011; Ganguly et al., 2012], and LAI values have been widely used to quantitatively estimate the water, carbon, and energy cycles in terrestrial ecosystems. LAI data have also played important roles in a variety of studies including simulations of Earth’s surface processes, climate change modeling, and global change research [Demarty et al., 2007; De Kauwe et al., 2011; Gonsamo and Chen, 2014]. Many global LAI products based on satellite remote sensing data are available, for example, the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI, CYCLOPES LAI, and GLOBCARBON LAI. However, global LAI products often have relatively low accuracy because of (1) uncertainties in the input data, such as errors in remote sensing reflectance due to atmospheric effects and clouds; (2) model uncertainties and problems associated with ill-posed retrieval; and (3) errors in the ancillary information (e.g., land cover type) [Fang et al., 2013]. The use of these products has therefore been limited [Heinsch et al.,]
Heinsch et al. [2006] showed that the maximum differences between the MOD15A2 LAI product values and the measured LAI values were in the range of 1.0-5.2 m²/m², and the relative differences were 9.6-323.6%. Furthermore, Fang et al. [2012] concluded that there are relatively large uncertainties in current LAI products (±1 m²/m²), which cannot satisfy the accuracy requirements of many systems used to observe the global climate (±0.5 m²/m²).

Methods commonly used to correct MODIS LAI products [Chen et al., 2004; Zhao et al., 2005; Gu et al., 2006; Fang et al., 2008] can be grouped into three categories: (1) methods based on thresholds, for example, the best index slope extraction (BISE) algorithm; (2) methods based on Fourier fitting; and (3) methods that employ an asymmetric function fitting, for example, the asymmetric Gaussian function fitting approach and the weighted least-squares linear regression approach. These methods improve the accuracies of MODIS LAI products to a certain extent, and each has its own advantages and disadvantages in applications [Chen et al., 2004]. The BISE method is sensitive to the size of the sliding window. Specifically, large noise occurs when too small a window is used, but important variation information can be masked when using too large a window. The BISE method is highly subjective, and hence, the success of this approach depends on the experience and skills of the data analysts. Methods based on Fourier fitting depend critically on symmetric sine and cosine functions, and the results are sensitive to any pseudo values (high/low) in the LAI data from remote sensing. Relatively large errors are typically encountered when the data are distributed in an irregular or asymmetric pattern. When applying the asymmetric Gaussian function fitting approach, it is often difficult to identify a maximum and minimum for fitting function determination, especially for data without apparent seasonal changes. In addition, this method is very complicated and time-consuming. Gu et al. [2006] presented a three point “upper envelope” smoothing (UES) method to remove the noise in the MODIS LAI product. This method works well when the perturbations (errors) only occur in one data point, but the noise will not be removed as effectively for longer sequences of contaminated data [Gu et al., 2006]. A simple and effective linear interpolation method, which is based on the assumption that reliable values are accurate enough to be useful, has been proposed to replace contaminated MODIS LAI data [Zhao et al., 2005]. This method is advantageous in that many reliable values can eventually be obtained. However, if there are no reliable LAI values during a long time-series sequence, the filled-in values will be highly uncertain.

Fang et al. [2008] proposed a time-space filtering method that comprehensively takes into account the temporal and spatial characteristics of different types of vegetation to make corrections and interpolations for MODIS LAI products. This method performs better than the Savitzky-Golay filtering method. On the basis of the time-space filtering method, Xiao et al. [2008] proposed an improved time-space filtering algorithm and developed a MODIS LAI product with higher continuity in space and time. Notably, a given type of vegetation within a small region will retain similar physiological and ecological characteristics in both time and space. Thus, despite differences in absolute numerical values, canopy LAI data will share similar temporal and spatial variation trends for a given type of vegetation under the same geographical and environmental conditions. For this type of data, there are frequently significant similarities among the LAI values for different pixels [Fang et al., 2008].
Building upon the above work and knowledge, the objective of this study is to propose a new correction method for LAI products based on inter-pixel autocorrelations; this method is referred to herein as the pixel-to-pixel correction (PPC) method. Specifically, this method uses reliable LAI data for one pixel to correct unreliable LAI data for other pixels to solve the UES problem, i.e., the problem of achieving good performance in cases where a large number of unreliable data points emerge continuously. To test the validity of the proposed method, field-measured data from sampling plots were used to evaluate the accuracy of the corrected results, and the temporal and spatial continuities of the corrected MODIS LAI data were analyzed. Ultimately, the authors hope that this study will provide researchers with an effective tool to improve the accuracy of MODIS LAI products.

**Data and methods**

**Data sources**
The field-measured LAI data came from four flux observation sites (US-Ha1, US-MMS, US-SP1, and US-Ne1) in the AmeriFlux network of North and South America, and one flux observation site (AnJi-Moso) in the Moso bamboo (*Phyllostachys edulis*) forest of Anji, Zhejiang Province, China (Tab. 1). Site US-Ha1 was established in 1991 for deciduous forests, and the majority of trees at the site are red oak and red maple. Site US-MMS was established in 1999 for secondary deciduous broadleaf forests, and the majority of trees at the site are maple and beech. Site US-Ne1 was established in 2001 for croplands. Site US-SP1 was established in 2000 for evergreen needle-leaf forests, and the majority of trees at the site are *Pinus palustris* (longleaf pine) and *Pinus elliottii*. AnJi-Moso was established in 2010 for bamboo forests, and this site mainly consists of Moso bamboo (*Phyllostachys edulis*). The LAI data for the four AmeriFlux sites were downloaded from the FLUXNET website (http://www.fluxdata.org/DataInfo/ default.aspx). The data from the FLUXNET website can be used for the verification of MODIS products [Fang et al., 2012].

| Site ID | Land cover | Latitude | Longitude | Number of samples | Period    |
|---------|------------|----------|-----------|-------------------|-----------|
| US-Ha1  | DBF        | 42.5378° | -72.1715° | 41                | 2005-2008 |
| US-MMS  | DBF        | 39.3231° | -86.4131° | 95                | 2003-2006 |
| US-SP1  | ENF        | 29.7381° | -82.2188° | 46                | 2003-2006 |
| US-Ne1  | CRO        | 41.1651° | -96.4766° | 43                | 2004-2007 |
| AnJi-Moso| Moso      | 30.4773° | 119.6720° | 14                | 2011      |

*DBF: deciduous broadleaf forest, ENF: evergreen needle-leaf forest, CRO: croplands, Moso: Moso bamboo forest.
Taking US-Ha1 as an example, 33 sample plots were first selected within the surrounding area of the flux tower. Five sampling points for each sample plot were then selected, with one subplot at the center and four subplots to the east, south, west, and north of the sample plot. The distance between subplots was 2 m. The LAI was measured with an LAI-2000 device, and the final LAI of each sample plot was taken as the average LAI value of the five subplots. Finally, the average LAI of the 33 sample plots was given by the field-measured LAI value for the observation site. The LAI data at AnJi-Moso were acquired using a vegetation canopy analyzing system (WinSCANOPY). A 30 m × 30 m sample spot centered on the flux tower was established. Five observation sites were then selected, one at the center and four at the corners of the plot. Three photographs were taken at each site and an LAI (2000G)-Log CI correction algorithm was used to calculate the LAI. The average value of the three photographs was taken as the measured LAI at the corresponding observation site, and the average LAI of the five observation sites in each plot gave the final LAI of the plot.

Eight-day synthesized Collection 5 MODIS LAI (MOD15A2) data with 1-km spatial resolution were obtained from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC, http://daac.ornl.gov/MODIS/modis.shtml). There were 46 sets of time-series LAI data for each year. MOD15A2 was used to provide LAI quality control (QC) information for each pixel: “QC < 32” indicates good quality data, “32 ≤ QC < 64” indicates a saturation issue in the main algorithm, “64 ≤ QC < 96” indicates that the main algorithm failed because of a geometrical problem, “96 ≤ QC < 128” indicates that the main algorithm failed because of other problems, and “128 ≤ QC” means there was no access to data. The QC values of LAI data represented the major criteria used to determine the reliability of MODIS LAI data. In this paper, we defined the points where the LAI data had a QC value smaller than 32 as reliable values, while all others were classified as unreliable values. The reliable values were used to correct the unreliable values in this study.

**PPC-based LAI optimization method**

Here, we describe the PPC method. This method assumes that vegetation of a given type will have similar physiological and ecological characteristics in similar geographical and environmental conditions [Fang et al., 2008]. Hence, the absolute LAI values may vary for different pixels, but should show close correlations in terms of their variations over time. Consequently, a correlation model between pixels can be established. With such a model, reliable values for pixels can then be used to correct for unreliable values of other pixels within the same time series. The specific calculation procedures are as follows (Fig. 1):

1. For a moving window around pixel \( P_{ij} \) with a given size \((m \times m, 20 \times 20 \text{ pixels in this study})\), calculate the correlation coefficient \( C_{ij} \) of the time-series LAI data between pixel \( P_{ij} \) and other pixels in the window. The LAI data used to calculate the correlation coefficient of each pair of pixels must satisfy the following conditions: (1) QC < 32, (2) the serial numbers of the time series are the same for each pair, and (3) the valid sample number is > 6;
2) Pixels \( P_c \) are defined as those pixels with a correlation coefficient with pixel \( P_{ij} \) of \( > 0.7 \) and a significance level of \( p < 0.05 \). Regression equations are established with the LAI of pixel \( P_{ij} \) serving as the dependent variable and the LAI of \( P_c \) serving as the independent variable. After the slope \( A \) and intercept \( B \) are obtained, Equations [1] and [2] (shown below) are applied to correct the unreliable points within \( P_{ij} \) and \( P_c \), respectively, i.e., reliable LAI values in \( P_{ij} \) are used to correct unreliable LAI values in \( P_c \) and vice versa. The points obtained after correction are considered to be reliable points (QC = 0). The original \( m \times m \) image data are then updated as follows:

\[
\begin{align*}
\text{Eq. (1)} & : \quad P_i' = A P_i + B \\
\text{Eq. (2)} & : \quad P_c' = A P_c + B
\end{align*}
\]
\[ LAI_{P_c} = A \times LAI_{P_c} + B \] \[ \text{[1]} \]

\[ LAI'_{P_c} = \frac{LAI'_{P_{ij}} - B}{A} \] \[ \text{[2]} \]

where \( LAI_{P_c} \) is a reliable LAI value at pixel \( P_c \) where the LAI value at pixel \( P_{ij} \) (for the same time series) is unreliable; thus, the LAI for the unreliable pixel \( P_{ij} \) can be corrected using the reliable LAI at pixel \( P_c \). \( LAI'_{P_{ij}} \) is a reliable LAI value at pixel \( P_{ij} \) where the LAI of pixel \( P_c \) (for the same time series) is unreliable; thus, the LAI for the unreliable pixel \( P_c \) can be corrected using the reliable LAI at pixel \( P_{ij} \).

3) All the pixels in the window are examined according to Step (1) and Step (2);

4) Apply the UES method to the results from Step (3), as shown in Equation [3] [Gu et al., 2006] below:

\[ LAI_s(t) = \text{MAX}[LAI(t), (0.5 \times LAI(t) + 0.25 \times (LAI(t - 1) + LAI(t + 1)))] \] \[ \text{[3]} \]

where \( LAI_s(t) \) is the smoothed MODIS LAI at time \( t \); \( LAI(t) \) is the original MODIS LAI at time \( t \); \( LAI(t - 1) \) is the original MODIS LAI at time \( t - 1 \); and \( LAI(t + 1) \) is the original MODIS LAI at time \( t + 1 \).

**Results**

**Accuracy evaluation**

The measured LAI data from the five flux observation sites were used to evaluate the accuracy of the original MODIS LAI and the LAI corrected using the PPC and UES methods. The frequencies of LAI measurements at the flux observation sites were irregular. Hence, in order to ensure good correspondence between the ground-measured LAI and the MODIS LAI products, LAI data measured closest to the MODIS LAI product in time (with a time difference of less than 4 days between the two) were used for the accuracy evaluation. A comparative analysis of the accuracy of the MODIS LAI raw values and those corrected using the PPC method indicated that the PPC method provided better estimations (Fig. 2). The PPC method increased correlation coefficients (\( r \)) between estimated values and observed values compared with the MODIS LAI product, except at the US-NE1 site. Low and unreliable MODIS LAI raw values were improved using the PPC and UES methods for the US-HA1, US-MMS, US-SP1, and AnJi-Moso sites (Fig. 2a, b, c, and e). Moreover, high and unreliable MODIS LAI raw values were improved using the PPC method for the US-SP1 site, but the UES method failed to correct the high and unreliable MODIS LAI raw values at this site (Fig. 2c). Such data were not encountered at the other sites. The unreliable LAI values corrected using the PPC method were closer to the observed values than the raw data. This implies that the PPC method can improve both high and low unreliable LAI values. Compared with the original MODIS LAI data, the MODIS LAI data corrected with the PPC method showed decreased discrepancies from the measurement data. The
root mean square errors (RMSEs) for the five observation sites US-Ha1, US-MMS, US-SP1, US-Ne1, and AnJi-Moso were reduced by 29.6%, 21.7%, 50.5%, 2.2%, and 14.9%, respectively, using the PPC method (Tab. 2). The PPC method performed slightly better than the UES method. The reduction of RMSEs varied among different vegetation types. Negligible improvement was observed for cropland (US-Ne1, Fig. 2d and Tab. 2), but marked improvements were observed at the forested sites. This indicates that the PPC method for the MODIS LAI product can improve the accuracy of LAI data to a certain extent, and its correction performance depends on the type of vegetation and the quality of the original MODIS LAI data.

Figure 2 - A comparison of the relationships between observed and estimated LAI values from the MODIS LAI product and values corrected using the PPC and UES methods for the following sites: (a) US-Ha1, (b) US-MMS, (c) US-SP1, (d) US-Ne1, and (e) AnJi-Moso.
Table 2 - Root mean square error of raw MODIS leaf area index (LAI) data, UES-corrected LAI data, and LAI data corrected using the pixel-to-pixel correction method.

| Method                        | US-Ha1 (DBF) | US-MMS (DBF) | US-SP1 (ENF) | US-Ne1 (CRO) | AnJi-Moso (Moso) |
|-------------------------------|--------------|--------------|--------------|--------------|-----------------|
| Raw data                      | 1.35         | 1.52         | 2.00         | 2.28         | 2.75            |
| UES                           | 1.00         | 1.30         | 1.78         | 2.23         | 2.52            |
| Pixel-to-pixel correction     | 0.95         | 1.19         | 0.99         | 2.23         | 2.34            |

Temporal-spatial variation analysis

The temporal trends in the measured LAIs, the original MODIS LAIs, and the MODIS LAIs corrected using the PPC and UES methods were compared. Results indicate that both correction methods improved abnormalities in the MODIS LAI data caused by clouds and atmospheric aerosols, and this in turn enhanced the continuity of the trends over time. For the US-SP1 site, the trend in the corrected data from the PPC method was more closely correlated with the observed data trend than the UES-corrected data trend. Although the PPC method eliminates abnormalities in the MODIS LAI product, the corrected data still showed relatively large fluctuations (Fig. 3). Compared with measured LAI data, the corrected LAI data for deciduous broadleaf forests (US-Ha1 and US-MMS) in the growing season were overestimated (Fig. 3a and b), while the corrected LAI data for cropland (US-Ne1) and Moso bamboo forest (AnJi-Moso) in the growing season were significantly underestimated (Fig. 3d and e).

Taking the data from US-SP1 as an example, an image of a 61 km × 61 km area centered on this site was selected and the data on the 177th day in 2006 were used for analysis. This MODIS LAI image was processed using the PPC method, and the spatial changes in the corrected image were then evaluated. For the US-SP1 site, the distribution maps of land use and cover (Fig. 4a) and the QC map of the MODIS LAI (Fig. 4b) demonstrate that the LAI values in the eastern section were more reliable (QC = 0) than those in the western section. In contrast, the MODIS LAI map corrected using the UES and PPC methods showed a distribution pattern that was more realistic and consistent with the corresponding vegetation types. As shown in Figure 4, after correction, the LAI values increased from 1-3 m²/m² to 5-6 m²/m² for the deciduous broadleaf forest shown in the figure in Area 1, from 2-4 m²/m² to 5-6 m²/m² for the deciduous broadleaf forest and mixed forest shown in Area 2, and from 1-2 m²/m² to 4-6 m²/m for the deciduous broadleaf forest and mixed forest shown in Area 3. After these changes, the LAI values for a given type of vegetation became more consistent between the eastern and western areas (Fig. 4c, d and e). For the spatial distribution pattern, there are no obvious differences between the UES method and PPC method (Fig. 4d and e). Fig. 5 shows the mean LAI values after correction by the UES and PPC methods for the main land cover types within the study area, and both sets of corrected LAI values were smoother than the MODIS LAI raw data. However, the mean LAI values from the UES method were higher than values from the PPC method (Fig. 5a), which is consistent with result of Figure 3c. Moreover, the coefficient of variation (CV) values for the LAI data corrected using the UES and PPC methods were lower than the CV values of the MODIS LAI raw data for the main land cover types within the study area. This implies that, after
the UES and PPC methods were applied, the spatial distribution of MODIS LAI values became more continuous for all land cover types. There was no obvious difference in the CV value between the results from the UES method and from the PPC method. Therefore, the PPC method improved the quality and reliability of the original MODIS LAI product, particularly at points with unreliable data in the western section of the US-SP1 site (QC > 0), and the continuity of the spatial distribution data was also improved.

Figure 3 - Temporal trends in the raw MODIS leaf area index (LAI) data and the LAI data from the PPC and UES methods for the following sites: (a) US-Ha1, (b) US-MMS, (c) US-SP1, (d) US-Ne1, and (e) AnJi-Moso. DOY indicates the “day of year”.
Figure 4 - (a) Land use and cover map, (b) quality check value map, (c) MODIS leaf area index (LAI) map, (d) MODIS LAI map improved by the USE method, and (e) MODIS LAI map improved by the PPC method for a 61 km × 61 km area around the center of station US-SP1.
Figure 5 - Mean LAI values and coefficients of variation (CVs) for MODIS LAI raw data and for data corrected with the UES and PPC methods for the main land cover types within the study area: (a) evergreen broadleaf forest, (b) mixed forests, and (c) wood savannas.
Discussion

The proposed PPC approach is based on the assumption that a given type of vegetation in similar geographical and environmental conditions will have similar physiological and ecological characteristics. Because this method can sufficiently reflect the effects of biological and environmental factors on LAI values, the corrected results have biological significance, and they should therefore be more reasonable and realistic than the MODIS LAI raw values. In contrast, the UES method, which is an alternative technique for improving LAI data, is based on statistical methods, and the derived results using this method lack biological significance. The UES method does show a relatively good correction performance when there is only a single point of unreliable data, but it cannot effectively remove noise and achieve good performance in cases where a large number of points with unreliable data emerge continuously [Gu et al., 2006]. When using the PPC method, a regression model can be established between pixels that show the most similar LAI trends, and unreliable data pixels can be corrected using the reliable data. Through this approach, the number of continuously unreliable data points can be reduced before applying a data correction using the UES method, thus avoiding the disadvantages of using the UES method alone. Notably, the UES method uses the highest LAI value among three continuous data points to correct the lower points without considering their QC values; this may lead to overestimated corrected data because the high LAI value may be unreliable [Zhao et al., 2005]. This problem is not encountered when using the PPC method. However, the PPC method is much more time consuming than the UES method. With the PPC method, the size of the window needs to be adjusted according to different research areas and subjects. Too large a window will increase the amount of calculations, while too small a window will result in too few reliable data for model construction and unreliable data correction procedures. For research areas with few land cover types, the window size can be small. Geostatistical analysis, whereby the range parameter of LAI is calculated, may be a good way to determine the optimal window size.

As shown in the time-series map for the MODIS LAI data (Fig. 3), the quality of the LAI data for different vegetation types varied in terms of reliability. Deciduous broadleaf forest and evergreen needle-leaf forest had the highest proportions of unreliable data, and these data were mainly from the growing season. This finding is consistent with results from Fang et al. [2012]. The accuracy evaluation of the original MODIS LAI product that used field measurements demonstrated that the MODIS LAI values for deciduous broadleaf forest and evergreen needle-leaf forest were overestimated. Our conclusion is consistent with results from Heinsch et al. [2006], who showed that the Collection 4 MODIS LAI for broadleaf forest overestimated the measured data by 2.0-3.0 m$^2$/m$^2$, and the annual average MODIS LAI for evergreen needle-leaf forest overestimated the measured data by 0.9 m$^2$/m$^2$; the LAI of woody vegetation was also overestimated. These overestimations were mainly due to defects in the algorithm, particularly in the empirical back-up method [Fang and Liang, 2005; Shabanov et al., 2005; Fang et al., 2013]. For example, the empirical back-up method generally overestimates LAI values compared with the radiative transfer method [Fang and Liang, 2005]. Furthermore, the vegetation indices method has problems associated with the saturation of reflectances in the various spectral bands at high LAI values [Deng et al., 2006]. Thus, the uncertainties in input surface reflectances, and in the models used to generate the look-up table, limit the quality of LAI retrievals [Myneni et al., 2002]. The
RMSEs of MODIS LAI values for deciduous broadleaf forest and evergreen needle-leaf forest were 1.35-2.00 m²/m², higher than the results for broadleaf forest and needle-leaf forest reported by Fang et al. [2012], who found RMSEs for MODIS LAI values (QC = 0) of 1.11-1.35 m²/m². The LAI data corrected by the PPC method had RMSE values (0.95-1.19 m²/m²) lower than those from the original LAI product, indicating that the accuracy of the data from the PPC method met the criterion for the most reliable quality level (QC = 0) in relation to the original MODIS LAI product. The LAI of the Moso bamboo forest was underestimated and had a RMSE value that was higher than for deciduous broadleaf forest and evergreen needle-leaf forest. Misclassification of land cover can play an important role in the uncertainty of MODIS LAI products because this can potentially lead to the incorrect selection of values from look-up tables and the use of inappropriate radiative transfer models and estimation algorithms [Fang et al., 2013]. Some variables, such as soil and leaf optical properties, which vary with biome types, are important input data for the MODIS look-up table method [Fang and Liang, 2005]. Therefore, errors in classifying the land cover type may also lead to LAI uncertainties during the parameter retrieval process [Fang et al., 2013]. For example, underestimation will occur when an evergreen needle-leaf forest is misclassified as a broadleaf forest [Gonsamo and Chen, 2011; Fang et al., 2013]. The land cover types in MODIS (MOD12Q1) do not include Moso bamboo forest, which is classified as mixed forest. Therefore, in this study, the MODIS LAI for Moso bamboo forest was determined using a look-up table that was established based on the parameters of mixed forest, which might have contributed to the underestimation of Moso bamboo forest LAI values at the Anji-Moso site in the MODIS LAI product. The MODIS LAI for cropland was significantly underestimated, which is consistent with the findings for the central pixel at the Bondville site in the Midwestern USA [Meyers and Hollinger, 2004; Li et al., 2014]. An annual rotation system of beans and corn was implemented at this site. The peak value of the LAI during the crop growing season may reach 5.0 m²/m², while the MODIS LAI was only approximately 3.5 m²/m², showing a clear underestimation [Meyers and Hollinger, 2004; Li et al., 2014]. Global 30-m resolution land-cover maps with the land-cover classification system crosswalked to the International Geosphere-Biosphere Programme (IGBP) system have been produced using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data, and the maps are associated with an overall classification accuracy of over 80% [Gong et al., 2013; Chen et al., 2015]. Therefore, global land-cover maps may be a viable alternative to the use of the MODIS standard land cover as ancillary information in the MODIS LAI retrieval algorithm and the PPC method proposed in this study; use of such data has the potential to further increase the accuracy of LAI values.

Conclusions
A relatively large amount of uncertainty is associated with time-series data derived from MODIS LAI products, and error rates vary among different vegetation types. The original MODIS LAI products evaluated in this study overestimated the LAI of deciduous broadleaf forest and evergreen needle-leaf forest during the growing season, and underestimated that of cropland and Moso bamboo forest. A PPC method was proposed to reduce uncertainty in MODIS LAI data. Specifically, the proposed method can eliminate apparently abnormal values in the MODIS LAI product to a certain extent, and improve the temporal-spatial
continuity of the data distribution. The performance of the PPC method was slightly superior to that of the UES method, and the PPC method was able to correct high and unreliable MODIS LAI raw values. When using MODIS LAI products to simulate Earth’s surface processes and study global changes, it will be necessary to employ field-measured LAI data to assimilate the MODIS LAI product in order to minimize the overestimation- or underestimation-related uncertainty in MODIS LAI data.

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