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ORIGINAL PAPER

Remote estimation of canopy leaf area index and chlorophyll content in Moso bamboo (*Phyllostachys edulis* (Carrière) J. Houz.) forest using MODIS reflectance data

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Abstract

• ***Key message*** **We estimated the leaf area index (LAI) and canopy chlorophyll content (CC) of Moso bamboo forest by using statistical models based on MODIS data and field measurements. Results showed that the statistical model driven by MODIS data has the potential to accurately estimate LAI and CC, while the structure of the calibration models varied between on- and off-years because of the different leaf change and bamboo shoot production characteristics between these types of years.**

• ***Context*** LAI and CC (gram per square meter of ground area) are important parameters for determining carbon exchange between Moso bamboo forest (*Phyllostachys edulis* (Carrière) J. Houz.) and the atmosphere.

• ***Aims*** This study evaluated the ability of a statistical model driven by MODIS data to accurately estimate the LAI and CC in Moso bamboo forest, and differences in the LAI and CC between on-years (years with great shoot production) and off-years (years with less shoot production) were analyzed.

• ***Methods*** The LAI and CC measurements were collected in Anji County, Zhejiang Province, China. Indicators of LAI and CC were calculated from MODIS data. Then, a regression analysis was used to build relationships between the LAI and CC and various indicators on the basis of leaf change and bamboo shoot production characteristics of Moso bamboo forest.

• ***Results*** LAI and CC were accurately estimated by using the regression analysis driven by MODIS-derived indicators with a relative root mean squared error (RMSEr) of 9.04 and 13.1%, respectively. The structure of the calibration models varied between on- and off-years. Long-term time series analysis from 2000 to 2015 showed that LAI and CC differed largely between on- and off-years.

• ***Conclusion*** This study demonstrates that LAI and CC of Moso bamboo forest can be estimated accurately by using a statistical model driven by MODIS-derived indicators, but attention should be paid to differences in the calibration models between on- and off-years.

Keywords Leaf area index · Canopy chlorophyll content · MODIS reflectance · Vegetation index · Moso bamboo

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1 Introduction

Leaf area index (LAI) and canopy chlorophyll content (CC, gram per square meter of ground area) are important indicators of the structural and biochemical characteristics of the canopy (Houborg et al. 2007). LAI, which is defined as half the total leaf area per unit ground surface area, is crucial in determining evapotranspiration and CO_2 exchange between the biosphere and the atmosphere (Running et al. 1989; Sellers 1997; Houborg et al. 2007; Maire et al. 2011; Olsoy et al. 2016). Changes in CC are related to vegetation senescence, photosynthetic capacity due to photosynthetically active radiation absorbed by CC, and effects of stress on destruction of CC (Datt 1999). Both parameters are important inputs in ecosystem models designed to quantify the spatial and temporal distributions of carbon, water, and energy fluxes (Gitelson et al. 2006; Wu et al. 2009).

LAI is routinely available from satellite-based Earth observation instruments, such as the Moderate Resolution Imaging Spectroradiometer (MODIS). The MODIS LAI estimates have been used widely and successfully in ecosystem models. However, many previous validation studies on MODIS-derived LAI have suggested that they contain considerable errors (Fang and Liang 2005; Leuning et al. 2005; Cohen et al. 2006; De Kauwe et al. 2011; Fang et al. 2012; Xu et al. 2016). Compared with in situ observations, MODIS LAI was often overestimated for broadleaf forest, needle-leaf forest, savannah, and woody vegetation (Fang and Liang 2005; Heinsch et al. 2006; Fang et al. 2012; Xu et al. 2016), but underestimates for cropland and bamboo forest (Meyers and Hollinger 2004; Li et al. 2014; Xu et al. 2016). For example, the Collection 4 MODIS LAI product for broadleaf forest and evergreen needle-leaf forest overestimates by around 2.0–3.0 and 0.9 m^2/m^2, respectively (Heinsch et al. 2006). Results from De Kauwe et al. (2011) suggest that the Collection 5 MODIS LAI underestimates the upper range of in situ LAI measurements. The relatively large uncertainties ($\pm$ 1.0 m^2/m^2) of the Collection 5 MODIS LAI product mean that it cannot satisfy the accuracy requirements of many systems used to observe global climate ($\pm$ 0.5 m^2/m^2) (Fang et al. 2012). The application of the Collection 5 MODIS LAI product to Moso bamboo (*Phyllostachys edulis* (Carrière) J. Houz.) forest resulted in underestimates with a larger degree of error than that for deciduous broadleaf forest and evergreen needle-leaf forest (Xu et al. 2016). Furthermore, errors in the LAI will propagate into CC results because LAI is a driver of CC.

Alternative and effective methods for the retrieval of LAI and CC data in Moso bamboo forest are necessary for the improvement of the MODIS LAI product. There are two common methods for estimating LAI and CC based on remote sensing techniques, namely, physically based models and empirical–statistical models (Coops et al. 2003; Houborg et al. 2007, 2009; Maire et al. 2011; Zhang et al. 2012). Physically based models can accurately explain the relationships between biophysical variables and canopy reflectance because they explicitly describe the transfer and interaction of radiation inside the canopy and external factors (Jacquemoud et al. 2000; Houborg et al. 2007). The main limitations of physically based models are the expenses associated with the computational requirements and the non-uniqueness of the solution (Jacquemoud et al. 2000; Houborg et al. 2007). Empirical–statistical models are commonly used for the remote estimation of LAI and CC, as they are based on the strong relationships between LAI and CC and remote sensing reflectance data. Their main advantage is the ease with which they can provide estimations of large-scale biophysical variables, i.e., they there are simple and computationally efficient. The main problem with empirical–statistical models is their lack of generality (Houborg et al. 2007). The structure of empirical–statistical models depends on site-, time-, and species-specific factors (Colombo et al. 2003; Houborg et al. 2007) that require representative field data for their calibration.

Bamboos are distributed naturally in tropical, subtropical, and temperate regions of all the continents (Grattani et al. 2008). The entire area of bamboo forest around the world is about 31.5 million ha and accounts for roughly 0.8% of the global forest area (FAO 2010). In China, the bamboo area is more than 6 million ha, 70% of which is covered by Moso bamboo forest (Song et al. 2016). Moso bamboo has a large carbon storage capacity (Chen et al. 2009; Komatsu et al. 2010, 2012; Yen and Lee 2011), and thus it is important to develop accurate estimates of LAI and CC for these forests despite the inaccuracy in the MODIS estimates (Xu et al. 2016). Precise determinations of the LAI and CC of Moso bamboo forest is needed for accurate estimations of the transpiration and carbon fluxes of Moso bamboo forests.

A special characteristic of Moso bamboo forest is its ability to produce many bamboo shoots through an underground rhizome system. Unlike other vegetation types, a newly emerged bamboo shoot can reach its maximum height within 40 days (Yen 2016). According to the number of bamboo shoots, Moso bamboo forest can be classified as being in either an on-year or off-year state, i.e., years with great bamboo shoot production are known as on-years and years with less bamboo shoot production are known as off-years (Li et al. 1998; Zhou et al. 2011). The number of bamboo shoots in an on-year is considerably greater than that in an off-year during mid-March to mid-May. Moso bamboo forest commonly exists as an uneven-aged forest with one to 5-year-old culms in stands subjected to intensive management. Most of the culms in on-years have uneven-year ages (e.g., 1, 3, 5), while those in off-years have even-year ages (e.g., 2, 4). The leaf life span of Moso bamboo is 2 years, except for first-year shoots (Li et al. 1998). Leaves on culms of even-year ages are 1-year-old leaves, whereas those on culms of uneven-year ages are 2-

year-old leaves (Kleinhenz et al. 2001). Therefore, most of the leaves in on-years are 2-year-old leaves and those in off-years are 1-year-old leaves. Rates of photosynthesis between 1-year-old leaves and 2-year-old leaves are significantly different (Kleinhenz et al. 2001). Two-year-old leaves fall in spring and are replaced by 1-year-old leaves (Li et al. 1998). Hence, the seasonal dynamics of LAI and CC differ between on- and off-years. Besides, the frequency distribution of culms among the age classes and the aboveground carbon storage were found to be significantly different between Moso bamboo stands that were subjected to two different management strategies, namely, intensive management and extensive management (Yen 2015), which resulted in differences in the LAI and CC between the different stands. Therefore, significantly different leaf change and bamboo shoot production characteristics between on- and off-years and different management strategies may cause challenges in estimating the LAI and CC of Moso bamboo forest based on MODIS reflectance data.

In this study, relationships between four vegetation indices from the Terra MODIS 8-day composite reflectance product (MOD09A1) and in situ LAI and CC observations were analyzed. Then, empirical–statistical models were calibrated with a regression method and validated by a leave-one-out cross-validation method. LAI and CC of Moso bamboo forest in the study site from 2000 to 2015 were predicted and compared with the MODIS LAI product (MOD15A2), and corrected MODIS LAI data were produced by using the "upper-envelope" smoothing method (Gu et al. 2006; Xu et al. 2016). Finally, the differences in LAI and CC of Moso bamboo forest between on- and off-years were analyzed. The objectives were (1) to test the ability of simple empirical–statistical models to estimate LAI and CC of Moso bamboo forest accurately by using MODIS-derived indicators, (2) to discover differences in the structure of the calibration models between on- and off-years, and (3) to evaluate the uncertainties in the MODIS LAI estimates of Moso bamboo forest.

2 Material and methods

2.1 Study area

The study area is located in Anji County in Zhejiang Province, China (Fig. 1). Here, bamboo forest encompasses an area of 757 km^2, and it accounts for 56.47% of the forested area; of this, 79.30% is Moso bamboo. The canopy height of the Moso bamboo forest is approximately 11 m. The average annual precipitation is 1100–1900 mm, and the average annual temperature is 12.2–15.6 °C. Results from 55 sample plots showed that the mean diameter at breast height for the Moso bamboo in this study area is 9.3 cm (the range is between 6.9 and 11.3 cm) (Xu et al. 2013). The culm density is approximately 3235 culms per hectare (Xu et al. 2013). The average aboveground biomass of Moso bamboo in this study area was found to be 44.2 Mg/ha based on a point kriging interpolation method (Du et al. 2010). An eddy covariance (EC) tower (30.476° N, 119.673° E) was built in 2010 to measure the carbon fluxes of the Moso bamboo forest. The 1000 m × 1000 m area around the EC tower site comprises mainly Moso bamboo (86.1%) with small proportions of mixed forest (1.9%), cropland (8.6%), and buildings (3.4%). The EC system and its measurements are described in detail by Xu et al. (2013). In the study area, 2011 and 2015 were on-years and 2014 was off-years (Xu et al. 2013).

2.2 Canopy LAI and chlorophyll content

Twenty-five sample plots (Fig. 1) were selected within a 600 m × 600 m square around the EC tower to calculate the canopy LAI and leaf chlorophyll content (LCC). The size of each sample plot was 5 m × 5 m. We measured LCC and LAI once per month from April 2014 to December 2015. Furthermore, LAI data from April 2011 to July 2011 were also available.

A photograph of the canopy was taken at the center of each sample plot with a vegetation canopy analyzing system (WinSCANOPY2009a; Regent Instruments, Ste-Foy, Quebec, Canada). The canopy LAI was then calculated by using an LAI (2000G)-Log CI correction algorithm based on the photograph (Mao et al. 2017), which was taken as the measured LAI at the corresponding sample plot. The WinSCANOPY results processed by using the WinSCANOPY software with corrections for leaf clumping were close to the direct-harvest values for a tropical rain forest (Olivas et al. 2013).

Because most of the leaves on bamboo culms in on-years (except for new bamboo culms) or off-years are of the same age (Li et al. 1998), five leaves were randomly selected from each of three culms per sample plot and each of the 375 leaves was measured three times with a chlorophyll meter (CCM-200 plus; Opti-Sciences, Boston, USA). The average LCC was taken as representative ground truth data for the sample plot. A calibration equation was used to transform the values measured by the CCM-200 to the sum of the chlorophyll a and b per square meter of leaf (mg/cm^2) (Eq. (1), Fig. S1, Gu 2013). Then, CC was defined as the total amount of chlorophyll per unit land area (g/m^2), which was calculated by using product of the LAI and LCC (Gitelson et al. 2005).

$$\mathrm{LCC} = 0.0016 \times \mathrm{LCC}_{\mathrm{CCM\text{-}200}} + 0.0128 \qquad R^2 = 0.81 \quad p < 0.01 \tag{1}$$

where LCC is the sum of chlorophyll a and b per square meter of leaf (mg/cm^2), and $\mathrm{LCC}_{\mathrm{CCM\text{-}200}}$ is the value measured when using the CCM-200.

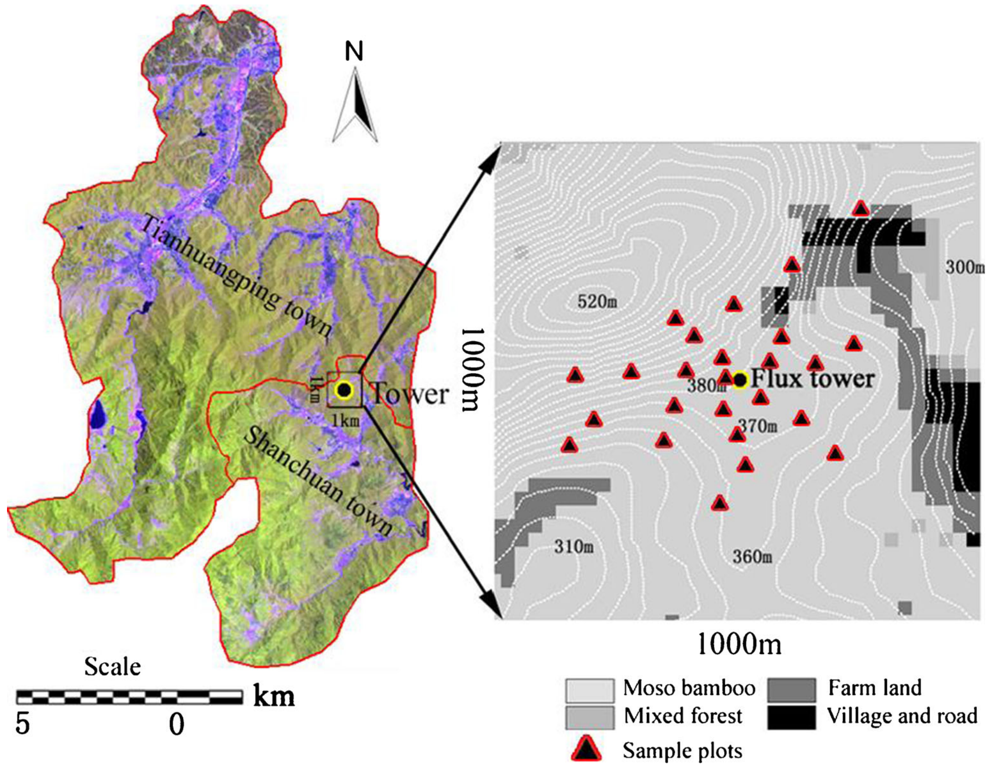


Fig. 1 The study area and distribution of sample plots in the town of Shanchuan, Anji County, Zhejiang Province, China. There are 25 sample plots (triangles) within a square with the center located in the eddy covariance (EC) flux tower site (circle). The GPS coordinates of the site are (30.476° N, 119.673° E)

In reference to Wu et al. (2008), the canopy LAI and CC collected from the 25 sample plots were averaged to represent ground truth data for the single 500-m-resolution pixel covering the 25 sample plots. Then, the relationships between the mean LAI and CC obtained from the 25 plots and the MODIS-derived indicators from the pixel with central coordinates closest to the location of the EC tower site were analyzed to build the statistical model for estimating LAI and CC. The variability in LAI and CC across sample plots was not taken into account in the statistical model.

2.3 MODIS reflectance data and vegetation indices

Surface reflectance data were acquired from the Terra MODIS 8-day composite reflectance product (MOD09A1) at a 500-m resolution and were downloaded directly from the website of the Oak Ridge National Laboratory Distributed Active Archive Center. The MOD09A1 product includes the following seven bands: band 1 (red, 620–670 nm), band 2 (near infrared, NIR, 841–876 nm), band 3 (blue, 459–479 nm), band 4 (green, 545–565 nm), band 5 (mid-infrared, mid-IR, 1230–1250 nm), band 6 (mid-IR, 1628–1652 nm), and band 7 (mid-IR, 2105–2155 nm). There are uncertainties in MODIS reflectance data as a result of atmospheric effects, clouds, and snow. Outliers of band 3 reflectance above 0.05 were removed. Then, other band reflectance data were defined as bad if the blue band 3 reflectance data were bad.

Based on MOD09A1 reflectance data, four important vegetation indices were calculated. The Normalized Difference Vegetation Index (NDVI) is a good indicator for the estimation of canopy LAI because it combines the NIR band 2 and red band 1 reflectance data (Houborg et al. 2007). A non-linear transformation of NDVI, called the Wide Dynamic Range Vegetation Index (WDRVI), was also tested because WDRVI is linearly related to green LAI data (Gitelson et al. 2007; Guindin-Garcia et al. 2012). The simple ratio (SR) index was calculated by dividing the reflectance of band 2 by the reflectance of band 1, and it is highly sensitive to the LAI and CC (Chen and Cihlar 1996; Zhang et al. 2008). The Gitelson Green Index (GI) was also used because it is sensitive to changes in CC (Gitelson et al. 2005; Wu et al. 2009). The four indices can be calculated as follows:

$$\mathrm{NDVI} = {(R_{\mathrm{NIR}}-R_{\mathrm{red}})} \Big/ {(R_{\mathrm{NIR}}+R_{\mathrm{red}})} \tag{2}$$

$$\mathrm{WDRVI} = {(\alpha\times R_{\mathrm{NIR}}-R_{\mathrm{red}})} \Big/ {(\alpha\times R_{\mathrm{NIR}}+R_{\mathrm{red}})} \tag{3}$$

$$\mathrm{SR} = {R_{\mathrm{NIR}}}/{R_{\mathrm{red}}}-1 \tag{4}$$

$$\mathrm{GI} = {R_{\mathrm{NIR}}}/{R_{\mathrm{green}}}-1 \tag{5}$$

where R_{NIR}, R_{red}, and R_{green} are reflectance data in the NIR band 2, red band 1, and green band 4, respectively. α is equal to 0.1 (Guindin-Garcia et al. 2012).

2.4 Statistical analysis

The day of year (DOY) of the ground-measured biophysical parameters was not the same as the DOY of the MODIS 8-day reflectance data. Therefore, to ensure good correspondence between the ground-measured biophysical parameters and the MODIS 8-day reflectance data, the ground-measured biophysical parameters measured closest to the MODIS 8-day reflectance data in terms of DOY were paired and used for the relationship analysis. The relationships between LAI and CC in Moso bamboo forest and MODIS 8-day reflectance data were analyzed by using the correlation analysis method of the SPSS13.0 statistical software. Linear or non-linear regression models were built to estimate the LAI and CC in Moso bamboo forest. The data sets used in this study are presented in Table 1.

A data set from 3 years (2011, 2014, and 2015) was used for developing the regression models for the estimations of LAI and CC. A leave-one-out cross-validation method was used for the validation of the prediction accuracy of the regression models. The goodness of fit of the regression models was measured by calculating the coefficient of determination (R^2), root mean squared error (RMSE), and relative RMSE (RMSEr) for the calibration and validation sets. Eight-day synthesized Collection 5 MODIS LAI (MOD15A2) data with a 1-km spatial resolution were compared with the LAI estimates. The time series of the remote sensing data and the biophysical parameters shown in Table 1 were used in this study.

Data availability statement The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

3 Results

3.1 Relationship between the LAI and CC

Relationships between CC and LAI differed between on-years (2011 and 2015) and off-years (Fig. 2). The relationship between LAI and CC in the off-year ($R^2 = 0.62$) was weak relative to that during on-years ($R^2 = 0.91$). CC during DOY 97 to DOY 137 in the off-year was obviously smaller than that in the on-years (Fig. 3a), but differences in the LAI in the same period between the off- and on-years were relatively small (Fig. 3b). Thus, the difference in CC was caused by the different change trends of the LCC between the off- and on-years during the period of DOY 97 to DOY 153 (Fig. 3c). The differences in CC between off- and on-years were also well represented by the visible red band 1 (Fig. 4). The reflectance of visible red band 1 in the off-year during DOY 65 to DOY 129 was greater than the reflectance in the on-years, which indirectly implies that there was a smaller CC in the off-year than that in the on-years. However, the reflectance of visible red band 1 in the off-year decreased earlier during DOY 129 to DOY 153 when CC in the off-year was still smaller than that in the on-years. Therefore, separation of sample points into on- and off-years is necessary for analyses of the relationships between LAI and CC and the vegetation indices.

3.2 Correlations of vegetation indices with the LAI and CC

The results in Figs. 5 and 6 show the relationships between the vegetation indices and the LAI and CC. The WDRVI, SR, and NDVI displayed significant linear relationships with the LAI and CC in on-years, with R^2 values of over 0.7 ($p < 0.01$), thus implying that they are good indicators for the estimation of LAI in on-years (Figs. 5 and 6). The relationships between the vegetation indices and the LAI and CC in the off-year tended to be exponential. The slopes of the relationships between vegetation indices and CC were very different between on- and off-years, so for the same vegetation indices, CC in on- and off-years were different. Different relationships of LAI and CC to vegetation indices between on- and off-years were caused by the different change trends of the LAI and CC between the on- and off-year (Fig. 2). The WDRVI and SR ($p < 0.01$) were slightly accurate than the NDVI ($p < 0.05$) for estimating the LAI in the off-year. The GI had the weakest

Table 1 Descriptions of the remote sensing data and biophysical parameters used in this study

Data		Years	Temporal scale	DOY of data
Remote sensing data	MOD09A1	2000–2015	8-day	All data except for bad data
	NDVI, WDRVI, GI, SR	2000–2015	8-day	All data except for bad data
Biophysical parameters	CC	2011 ($n = 7$)	Daily	118, 127, 134, 141, 148, 177, 192
		2014 ($n = 7$)	Daily	106, 133, 156, 211, 269, 317, 358
		2015 ($n = 10$)	Daily	23, 71, 103, 142, 181, 196, 218, 290, 330, 364
	LAI	2011 ($n = 9$)	Daily	118, 127, 134, 141, 148, 177, 183, 192, 206
		2014 ($n = 7$)	Daily	106, 133, 156, 211, 269, 317, 358
		2015 ($n = 10$)	Daily	23, 71, 103, 142, 181, 196, 218, 290, 330, 364

n the number of sample data, *DOY* the day of year

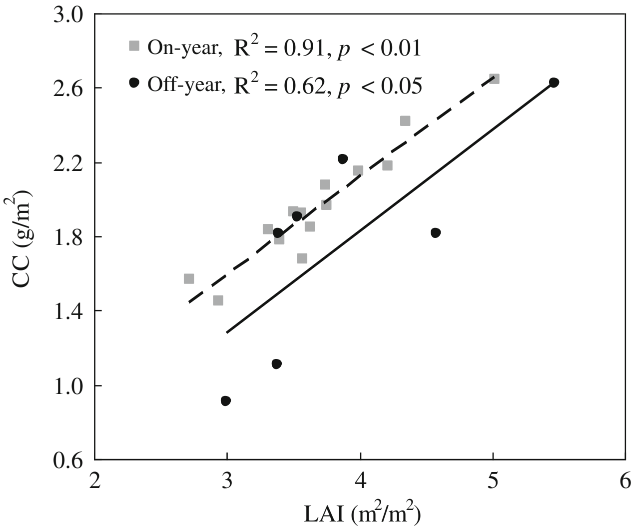


Fig. 2 Relationships between leaf area index (LAI) and canopy chlorophyll content (CC) in the on-years and off-year. The gray squares and dashed line represent the LAI and CC of the on-years in 2011 and 2015. Data for 2011 were collected on DOY 118, 127, 134, 141, 148, 177, and 192. Data for 2015 were collected on DOY 23, 71, 103, 142, 181, 196, 218, 290, 330, and 364. The black circles and solid line represent the LAI and CC of the off-year in 2014. Data for 2014 were collected on DOY 106, 133, 156, 211, 269, 317, and 358

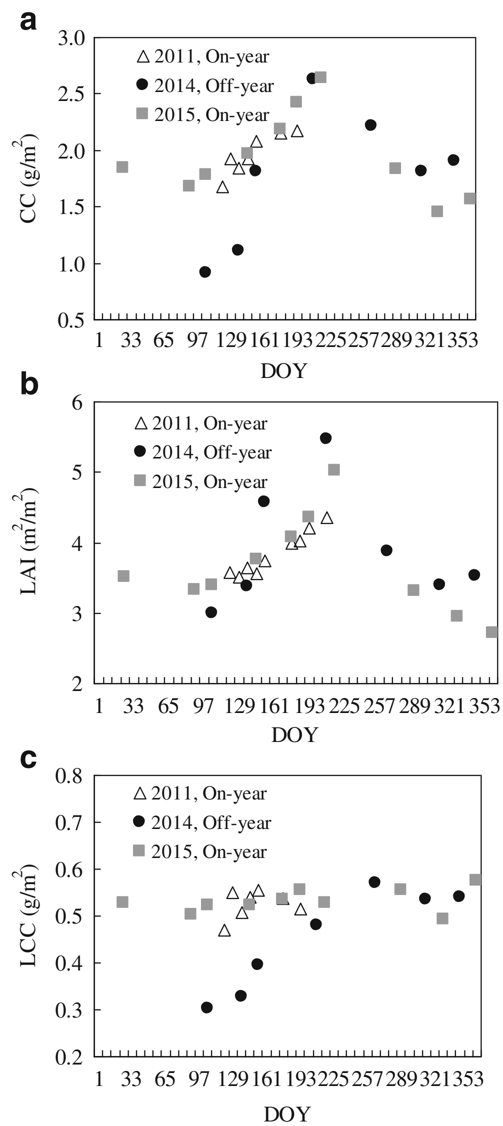


Fig. 3 Annual time course for **a** canopy chlorophyll content (CC), **b** leaf area index (LAI), and **c** leaf chlorophyll content (LCC) in on-years (2011 and 2015) and off-year (2014). White triangles represent LAI, CC, and LCC collected in 2011. Black circles represent LAI, CC, and LCC collected in 2014. Gray squares represent the LAI, CC, and LCC collected in 2015

relationship with the LAI (Fig. 5d), whereas it had the strongest relationship with CC in the off-year (Fig. 6d).

3.3 Calibration and validation of the LAI and CC estimation models

Because the same capacity was exhibited by the WDRVI ($\alpha = 0.1$) and SR for explaining the LAI and CC (Fig. 5), we chose the WDRVI ($\alpha = 0.1$) to build a linear regression model for the estimation of the LAI in on-years and an exponential model for estimating the LAI in off-years by using the 21 sample data points collected in 2011, 2014, and 2015. Additionally, the WDRVI ($\alpha = 0.1$) was used for the estimation of CC in on-years and the GI was used for the estimation of CC in off-years. The algorithm equations used for the estimations of LAI and CC were as follows:

$$\mathrm{LAI} = \begin{cases} 4.1349 \times \mathrm{WDRVI}(\alpha = 0.1) + 4.0657 & \text{on-year} \\ 4.1929 \times e^{1.4324 \times \mathrm{WDRVI}(\alpha = 0.1)} & \text{off-year} \end{cases} \quad (6)$$

$$\mathrm{CC} = \begin{cases} 2.186 \times \mathrm{WDRVI}(\alpha = 0.1) + 2.165 & \text{on-year} \\ 0.3406 \times e^{0.3339 \times \mathrm{GI}} & \text{off-year} \end{cases} \quad (7)$$

Equation (6) yielded the following accuracy values for the LAI estimation: RMSE = 0.28 m^2/m^2 and RMSEr = 7.40% in on-years and RMSE = 0.24 m^2/m^2 and RMSEr = 6.04% in off-years. Equation (7) yielded the following accuracy values for the CC estimation: RMSE = 0.15 g/m^2 and RMSEr = 7.42% in on-years and RMSE = 0.25 g/m^2 and RMSEr = 14.29% in off-years. A leave-one-out cross-validation method was used to test the robustness and prediction accuracy of the equations. The values of R^2, RMSE, and RMSEr are given in Table 2. The high R^2 and low RMSEr values between the predicted data and measured data show the good predictive ability of the models for both on- and off-years. There were no obvious differences in the predictive ability between on- and off-years for the estimation of the LAI. However, the predictive ability for CC in off-years was slightly poorer than that in on-years. The models were able to estimate the LAI with accuracy values amounting to an RMSE = 0.34 m^2/m^2 and RMSEr = 9.04% and to estimate the CC with accuracy values amounting to an RMSE = 0.25 g/m^2 and RMSEr = 13.09%. These validation results confirmed that accurate LAI and CC

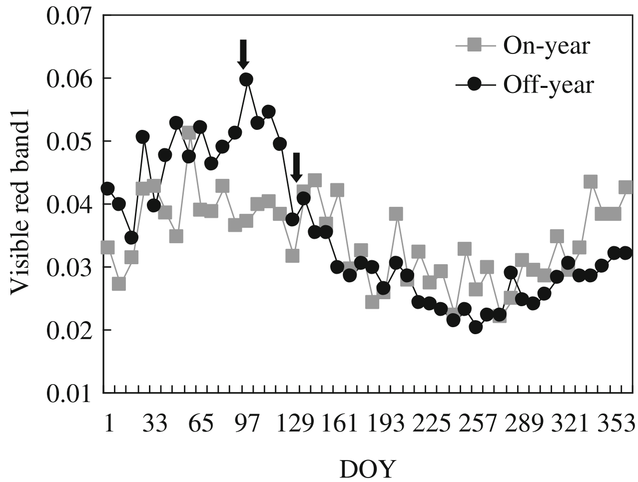


Fig. 4 Annual time course for the visible red band 1 average in on-years (odd-numbered years) and off-years (even-numbered years) from 2000 to 2015. Gray squares represent on-year data. Black circles represent off-year data. Arrows represent the period during DOY 65 to 129 when the canopy chlorophyll content (CC) in off-years was greater than that in on-years

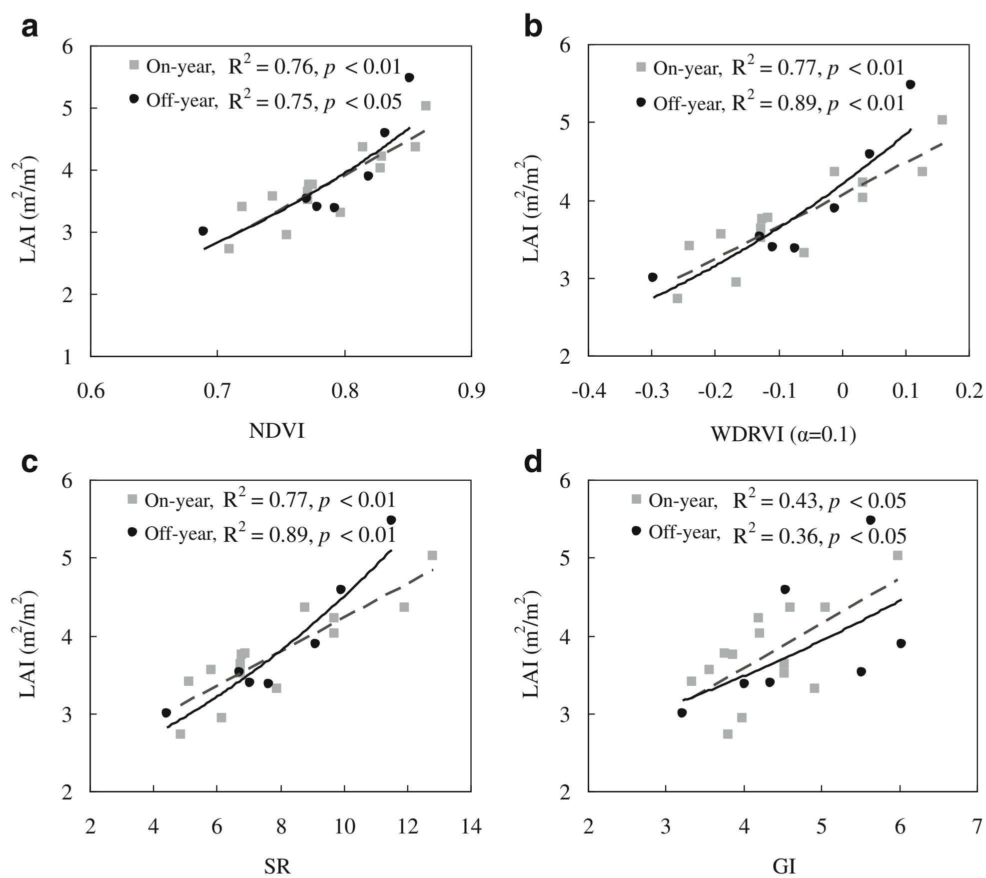
estimates of Moso bamboo forest can be obtained based on simple relationships between the LAI and CC and vegetation indices from MODIS reflectance data.

3.4 Comparison of the LAI estimates with the MODIS LAI product

The relationship between the validation results for the LAI and ground-measured LAI was close to the 1:1 line, thus implying that there is no problem with underestimation and overestimation (Fig. 7a). Compared with ground-measured LAI, the LAI of Moso bamboo forest from the MODIS LAI product (MOD15A2) had serious problems with underestimation and significant errors were encountered (RMSEr = 58.76%) (Fig. 7). The relationship between the measured LAI and the MODIS LAI corrected by using the "upper-envelope" smoothing method showed improvements, but the corrected MODIS LAI remained underestimated, i.e., RMSEr = 37.90% (Fig. 7c). Therefore, the LAI of Moso bamboo forest derived from the simple regression model (Eq. (6)) is more accurate than both the MODIS LAI product (MOD15A2) and the corrected MODIS LAI.

Variations in the 8-day LAI average from 2000 to 2015 showed that LAI estimates from this study ranged between 1.9 and 5.9 m^2/m^2 and MODIS LAI estimates of Moso bamboo forest ranged between 0.7 and 6.5 m^2/m^2 (Fig. 8a). Although the MODIS LAI time series can also capture the growing phases typical of Moso bamboo forest, the data

Fig. 5 **a** Normalized Difference Vegetation Index (NDVI), **b** Wide Dynamic Range Vegetation Index (WDRVI, $\alpha = 0.1$), **c** simple ratio (SR), and (**d**) Gitelson Green Index (GI) derived from the MODIS reflectance data versus leaf area index (LAI) relationship for Moso bamboo forest in the on-years and off-year. The gray squares and dashed line represent the LAI of on-years in 2011 and 2015. The black circles and solid line represent the LAI of the off-year in 2014



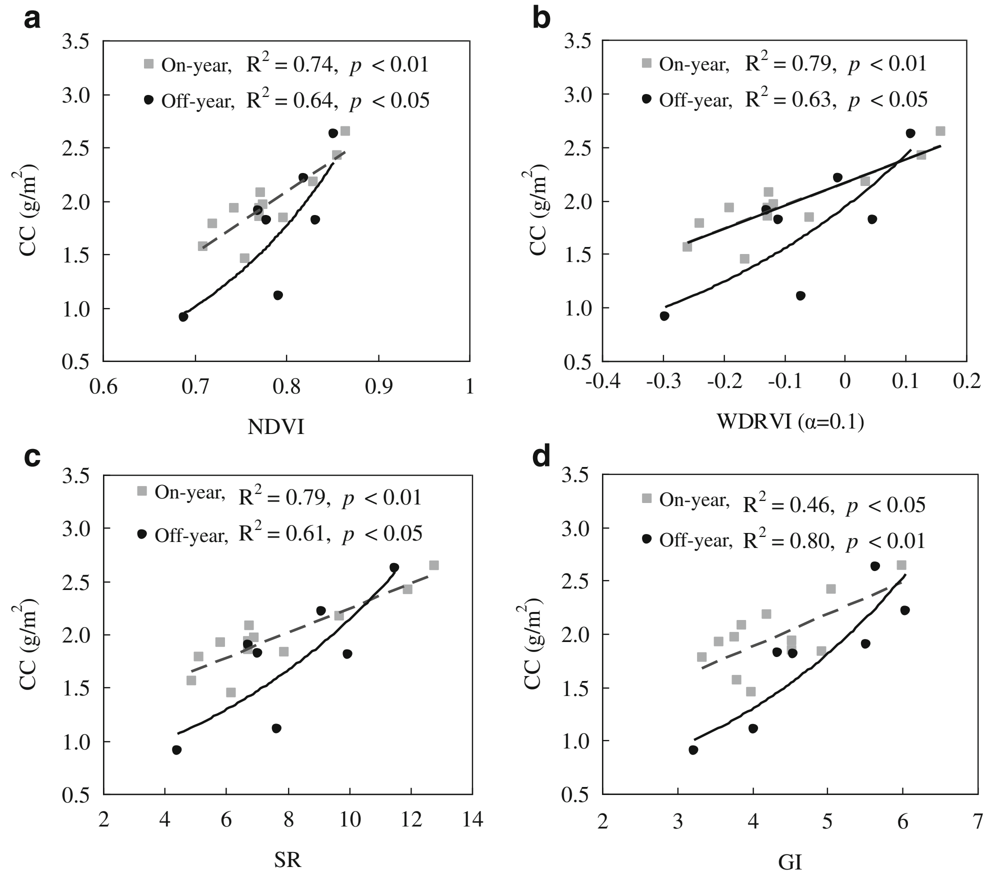


Fig. 6 **a** Normalized Difference Vegetation Index (NDVI), **b** Wide Dynamic Range Vegetation Index (WDRVI, $\alpha = 0.1$), **c** simple ratio (SR), and (**d**) Gitelson Green Index (GI) derived from the MODIS reflectance data versus canopy chlorophyll content (CC) relationship for Moso bamboo forest in the on-years and off-year. The gray squares and dashed line represent the CC of on-years in 2011 and 2015. Black circles and solid line represent CC of the off-year in 2014

tended to increase early, display a relatively short steady period during June–August, and then decrease rapidly after reaching the maximum value compared with the LAI estimates from this study (Fig. 8a). The LAI estimates from this study were significantly greater than the MODIS LAI products in the winter season ($p < 0.01$), thus implying that there is a large amount of underestimation in the MODIS LAI estimates of Moso bamboo forest. The relative difference (RD) between the LAI estimates from this study and the MODIS LAI estimates was very large (i.e., $> 30\%$) for the periods extending from DOY 1 to DOY 129 (about May 10) and from DOY 257 (about September 15) to DOY 365 (Fig. 8b).

Table 2 Accuracy evaluation of leaf area index (LAI) and canopy chlorophyll content (CC) estimates based on the leave-one-out cross-validation method

Biophysical parameters	Data	R^2	RMSE	RMSEr (%)
LAI	On-year	0.69	0.33	8.67
	Off-year	0.79	0.38	9.69
	All data	0.74	0.34	9.04
CC	On-year	0.72	0.17	8.55
	Off-year	0.63	0.34	19.46
	All data	0.67	0.25	13.09

3.5 Differences in the LAI and CC between on- and off-years

Variations in the 8-day average LAI from 2000 to 2015 showed that the LAI in off-years was slightly smaller than that in on-years during DOY 1 to DOY 121 (end of April), whereas the LAI in off-years was about 12% ($p < 0.01$) larger than that in on-years during DOY 121 (beginning of May) to DOY 241 (end of August) (Fig. 9a). The LAI values remained stable in the on-years and only slightly decreased from DOY 1 to DOY 113 (mid-April). From DOY 113 (mid-April) to DOY 169 (mid-June), the LAI increased rapidly from 2.4 to 4.7 m^2/m^2 in the off-years because of the spread of new leaves, and the LAI increased rapidly from 2.6 to 4.1 m^2/m^2 in the on-years because of the spread of leaves of the bamboo shoots (Fig. 9a). The increase in LAI due to the flushing of new leaves on old bamboo in off-years was greater than that due to the flushing of leaves of the bamboo shoots in the on-years. After the new leaves and leaves of the bamboo shoots stopped spreading in mid-June, the LAI values reached their highest level and remained stable during DOY 169 (mid-June) to DOY 241 (end of August). The LAI decreased at the beginning of September for both the on- and off-years. Variations in the 8-day average of CC in the on- and off-years (Fig. 9b) showed that CC in the off-years was about 50% ($p < 0.01$)

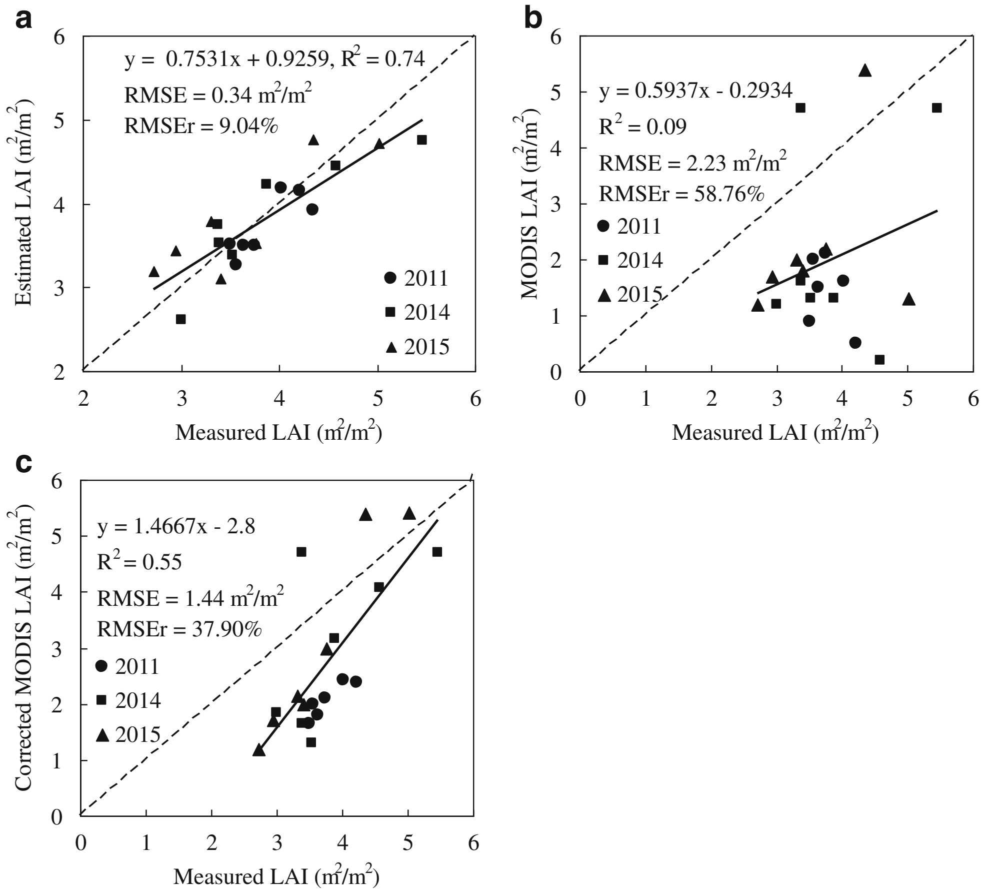


Fig. 7 Scatter plots for the measured leaf area index (LAI) and the **a** estimated LAI derived by using Eq. (6), **b** raw MODIS LAI, and **c** corrected MODIS LAI derived by using the "upper-envelope" smoothing method according to Gu et al. (2006). Circles represent LAI in 2011. Squares represent the LAI in 2014. Triangles represent the LAI in 2015. See Table 1 for the day of year (DOY) data. The solid line represents the regression line between the measured LAI and estimated LAI. The dashed line represents the 1:1 line

smaller than that in the on-years during DOY 1 to DOY 113 (mid-April). The CC in the off-years increased steeply after DOY 113 (mid-April), which is when new leaves were spreading, and it was comparable to the CC in the on-years after DOY 169 (mid-June), which is when the growth of new leaves had finished.

4 Discussion

4.1 Effect of various factors on the accuracy of LAI and CC estimations

The relationships of canopy reflectance to LAI and CC were likely confounded by other factors such as the understory component, canopy architecture, and sun/view angle, which are known to contribute to the reduction of accuracy in empirical models (Zhang et al. 2008). The main factor focused on here was the different leaf change and bamboo shoot production characteristics of Moso bamboo forest between on- and off-years, which caused the relationships between vegetation indices and CC were very different between on- and off-years. Furthermore, the factor caused the differences in the calibration model results between on- and off-years. For example, the relationships between vegetation indices and LAI and CC in the on-years were linear, whereas those relationships were exponential in the off-year that was evaluated in detail (Figs. 5 and 6). The reflectance of visible red band 1 decreased earlier in the off-year during DOY 129 to DOY 153 which also caused the structure of the calibration models varied between on- and off-years. The NDVI increased earlier than the CC in Amazon forests was also reported (Hilker et al. 2017). The GI showed a higher sensitivity than the other vegetation indices to the CC in the off-year. The reason for this is that reflectance at 550 nm (central wavelength of the green band) might be highly sensitive to CC in some types of leaves, e.g., uniformly young leaves (Datt 1999).

The retrieval of LAI data from remote sensing imagery can be hindered by the effect of the understory component on the relationships between the LAI and remote sensing reflectance data (De Kauwe et al. 2011; Qi et al. 2014). Leaf change in off-year will increase the effect of the understory component on the relationships between biophysical parameters and vegetation indices and bring about greater uncertainties in the models for estimating the LAI and CC in off-years compared to on-years (Table 2).

In this study, it is hard to assess whether the obtained calibration models are robust because the sample data sets used for the

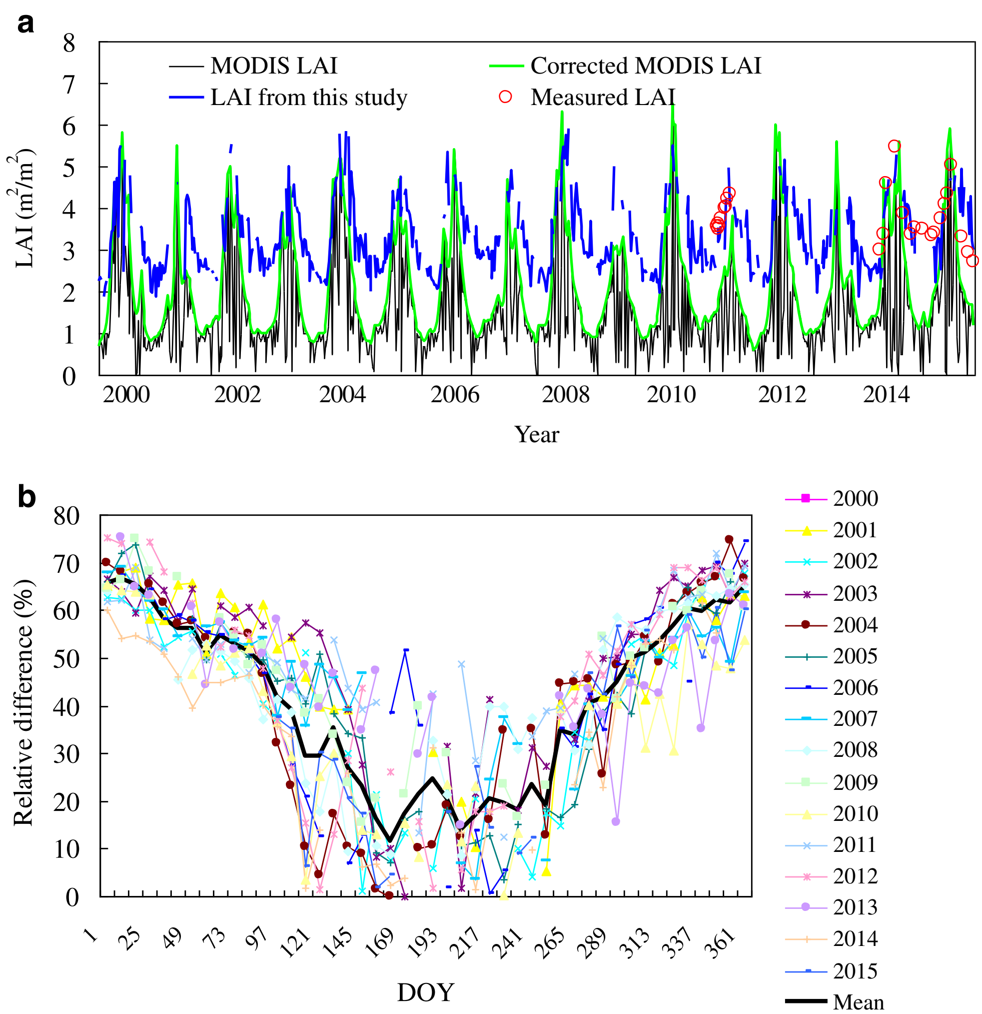


Fig. 8 **a** Seasonal variations of 8-day leaf area index (LAI) estimates from this study derived by using Eq. (6) in the text and MODIS LAI from 2000 to 2015 and **b** relative difference between the LAI from this study and the corrected MODIS LAI derived by using the "upper-envelope" smoothing method. In **a**, the black line represents the raw MODIS LAI, the green line represents the corrected MODIS LAI derived by using the "upper-envelope" smoothing method according to Gu et al. (2006), and the blue line represents the LAI estimates derived by using Eq. (6) in the text. Red circles represent the measured LAI. In **b**, the black line represents the mean relative difference for data from 2000 to 2015

model calibration was limited in spatial variability. Five pixels randomly and spatially distributed in Anji County were selected. The LAI for the five pixels were calculated using the obtained calibration models (Fig. S2). Good relationships between the estimated LAI and MODIS LAI estimates were found and the MODIS LAI estimates were smaller than the estimated LAI in most of the pixels, which indirectly showed the ability of the obtained calibration models in explaining spatial variation of LAI. Many in situ measurements are required to assess accuracy of the obtained calibration models in estimating spatial variation of LAI in the future.

4.2 Comparison of the LAI estimates with the MODIS LAI product

The LAI estimates of Moso bamboo forest from this study were more accurate than the MODIS LAI product. Our findings suggest that the LAI of Moso bamboo forest was underestimated by the MODIS LAI product. The main causes of unrealistic MODIS LAI values can be attributed to cloud contamination in the surface reflectance input data, the MODIS LAI algorithm itself, and misclassifications (De Kauwe et al. 2011; Fang et al. 2013). In the latest MODIS LAI algorithm, land surfaces are classified into eight biomes, which is an insufficient number to describe actual vegetation types. For example, Moso bamboo forest is not included in the MODIS land cover type product (MOD12Q1); it is classified as mixed forest instead (Xu et al. 2016). There are obvious differences between mixed forest and Moso bamboo forest, which can be attributed to the special growth characteristics of Moso bamboo. The rapid growth from shoots to bamboo within 40 days (Yen 2016) and the changing leaf period are accompanied by changes in the LAI and CC. Therefore, the probable reason for the uncertainties in the MODIS LAI of Moso bamboo forest is that some parameters of mixed forest, such as the soil and leaf optical properties, are not suitable for estimating the LAI of Moso bamboo forest based on the look-up table method (Xu et al. 2016).

The proposed empirical models in this study have a greater ability than the MODIS LAI algorithm to capture the dynamic changes of the LAI of Moso bamboo forest. The MODIS LAI of Moso bamboo forest tends to rise early and to decrease

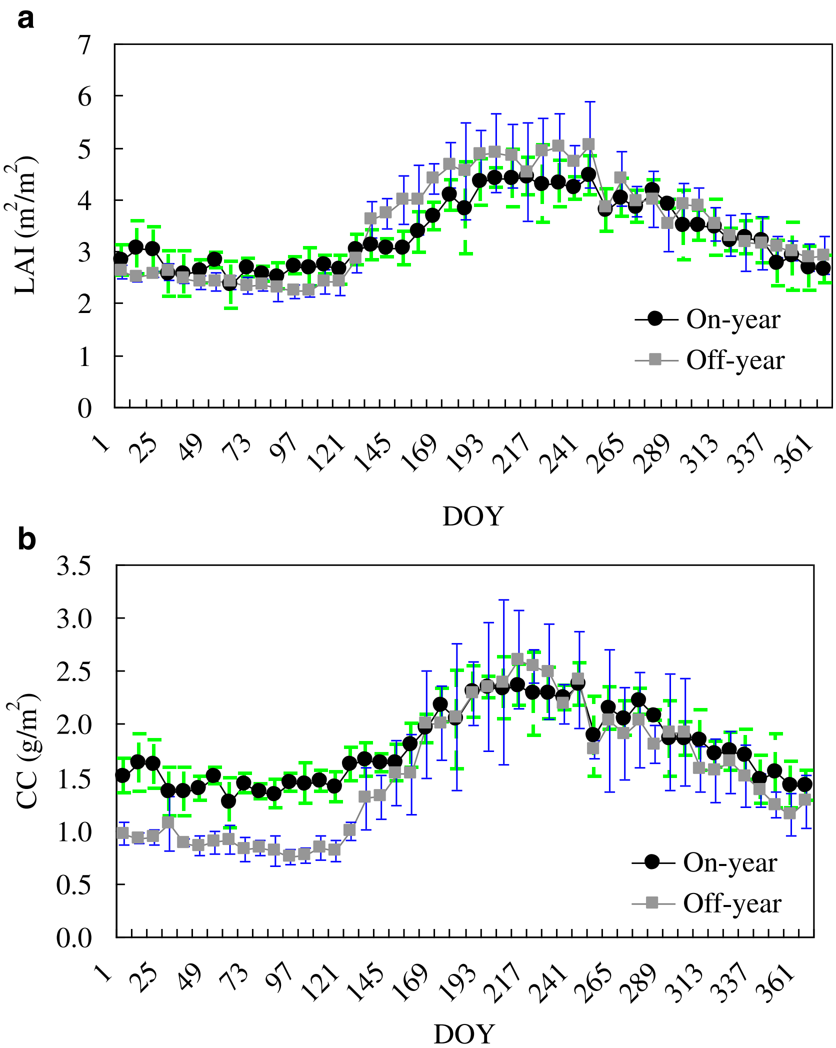


Fig. 9 Variations in the 8-day average **a** leaf area index (LAI) estimates according to Eq. (6) in the text and **b** canopy chlorophyll content (CC) estimates according to Eq. (7) in the text averaged from 2000 to 2015. Black circles represent the LAI and CC in on-years. Gray squares represent the LAI and CC in off-years. The green vertical bars represent the ± 1 standard deviation for the on-years, and the blue vertical bars represent the ± 1 standard deviation for the off-years

quickly after a short constant period, which is a trend that also has been found in the MODIS LAI of deciduous broadleaf forest (Wang et al. 2005). The MODIS LAI product is used as a key variable for the MODIS gross primary productivity/net primary productivity (GPP/NPP) product, and therefore, errors in LAI will lead to uncertainty in the MODIS GPP/NPP product (Heinsch et al. 2006; De Kauwe et al. 2011; Qi et al. 2014). An underestimation of the MODIS GPP product for Moso bamboo forest compared with observations from the flux tower has been confirmed (Xu et al. 2013), and it might be strongly related to the underestimation of the MODIS LAI product. The LAI estimates from this study had higher accuracies and agreed better with the temporal and dynamic trends of observations than the MODIS LAI, thus implying that they are superior for capturing the important and special phenological phases of Moso bamboo forest and can be used for estimating the GPP of Moso bamboo forest.

4.3 Differences in LAI and CC between on- and off-years

There were obvious differences in LAI and CC between on-years and off-years, especially for CC data from DOY 1 to DOY 169. Previous studies have shown that the LAI increases rapidly as new leaf flushing starts in May and ends in June, and thereafter, it remains stable from July onward (Grattani et al. 2008; Jin et al. 2010). During the leaf flushing period, leaf area increases considerably from 270 to 835 mm^2 (Jin et al. 2010). The mechanisms for new leaf flushing in the on- and off-years are different. New leaf flushing in the on-years is due to growth of the bamboo shoots, whereas that in the off-years results from 2-year-old leaf defoliation and other changes. Thus, changes in LAI from DOY 113 (mid-April) to DOY 241 (end of August) between the on- and off-years were different (Fig. 9a).

Leaves of old bamboo turn yellow after the flushing of new shoots in March during on-years because the growth of bamboo shoots consumes considerable quantities of carbohydrates and nutrients (Qiu 1984; Hu 2011; Song et al. 2016). Furthermore, the LCC in on-years will remain stable throughout the whole year (see Fig. 3c) as the increases in CC due to leaves of new bamboo becoming dark green compensate for the decreases in CC due to leaves of old bamboo becoming yellow. The LCC in off-years is relatively small and stable during DOY 1 to DOY 137 (mid-April) when the leaf changing process occurs (Grattani et al. 2008). It increases rapidly from DOY 137 (mid-April) to DOY 169 (mid-June) as the leaf growth process occurs and remains stable from DOY 169 (mid-June) to DOY 241 (end of August) as leaf color turns dark green (Grattani et al. 2008; Song et al. 2016). The leaf color turns yellow in November because of leaf senescence, which results in obvious decreases in the LAI and CC in both on-years and off-years.

5 Conclusions

Previous studies have revealed underestimates in the MODIS LAI and GPP products of Moso bamboo forest. In order to obtain estimates of biophysical parameters that are more accurate, simplified empirical–statistical models were developed based on an analysis of the relationships between vegetation indices and in situ LAI and CC observations. The calibration models for estimating LAI and CC between on- and off-years were different because of different leaf change and bamboo shoot production characteristics. This implies that it is necessary to build separate models for on- and off-years, which will improve the potential for retrieving accurate LAI and CC estimates. A relationship analysis between vegetation indices and LAI and CC showed that the WDRVI was a good indicator for estimations of LAI in on- and off-years and CC in off-years. The GI was the vegetation index most sensitive to CC in off-years. The models presented in this study produced better estimates of LAI than the MODIS LAI product (MOD15 A2). It was identified that the MODIS LAI time series has a problem with rising early, having a short constant period, and decreasing soon after reaching the maximum value. Therefore, caution must be observed when analyzing the phenological characteristics of Moso bamboo forest directly with the MODIS LAI product. The different variations in LAI and CC between on- and off-years were first discussed based on the LAI and CC estimates from this study. This study then presented simple methods to estimate the LAI and CC accurately from MODIS reflectance data based on the knowledge of complicated leaf change and bamboo shoot production characteristics of Moso bamboo forest between on- and off-years, and it was concluded that the statistical model driven by MODIS data had the potential to accurately estimate the LAI and CC. This study also identified superior biophysical parameters for both assessing the growth and health status of Moso bamboo forest and for estimating the amount of carbon fixation within Moso bamboo forest.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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