



Continuous observation of tree leaf area index at ecosystem scale using upward-pointing digital cameras

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ABSTRACT

Understanding the dynamics of leaf area index (LAI) at ecosystem scale is critical for evaluating and modeling the response of vegetation to environmental variability and change. We present an approach for quantifying daily ecosystem LAI that integrates automatic acquisition of a small number of reference photos, viewed towards the zenith, and a larger number of photos covering a spatially extensive area that were manually acquired during periodic field trips. We present an image archive spanning three years for an oak-savanna ecosystem in California to identify the timing of phenological and disturbance events, and to quantify the seasonal to interannual variability of tree LAI at ecosystem scale. The digital camera-derived LAI, corrected for clumping effects, agreed well ($r^2 = 0.94$, root mean square error = 0.05) with independent estimates of LAI from litterfall traps and the LAI-2000 Plant Canopy Analyzer. Using the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI product, which combined grass and tree LAI, we obtained realistic seasonal patterns of ecosystem LAI that corresponded with tree LAI from the digital cameras for the period when grass was dead. The digital camera method is an easy and inexpensive way to monitor LAI at ecosystem scale. This method can be used for testing and improving phenology models, evaluating remote-sensing-derived LAI products, and quantifying forest structures in rapidly changing environments.

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1. Introduction

Leaf area index (LAI) determines light interception by canopies (Anderson, 1966; Nilson, 1971; Ross, 1981), and participates in regulating carbon dioxide, water, and energy exchanges between plants and atmosphere (Baldocchi & Harley, 1995; Chase et al., 1996; Leuning et al., 1995; Ryu et al., 2011). In addition, LAI is a metric that quantifies the seasonal change of canopy development and phenology, which have been identified as integrative indicators of ecosystem response to climate change (Parmesan & Yohe, 2003; Peñuelas et al., 2009). Numerous direct and indirect methods to estimate LAI have been developed over the last few decades (Norman & Campbell, 1989), but most of these methods rarely provide continuous information for LAI in space and time. Thus, a major challenge is

how to observe LAI in the field continuously, accurately, inexpensively, and over multiple years.

In savanna ecosystems, the separation of LAI between trees and grass is very important to understand how trees and grass compete for scarce water resources, as well as how they respond to fire and grazing (Sankaran et al., 2004; Scholes & Archer, 1997). However, satellite-derived LAI products, which have spatial resolutions of approximately 1 km (e.g. MODIS and CYCLOPES), are unable to separate the LAI of trees from that of grasses when both are active. Therefore, in-situ observation of tree canopy LAI at an ecosystem scale could augment remote-sensing derived LAI, and enable the efficient estimation of LAI of both layers as well as detect important phenological events with high temporal resolution.

The most common direct and indirect methods to estimate LAI are as follows. Optical sensors, such as digital hemispheric photographs, LAI-2000 Plant Canopy Analyzer or its updated version LAI-2200 (LI-COR, Lincoln, NE, USA), can be used in regular field visits to measure LAI (Barr et al., 2004; Sprintsin et al., 2011). However, this approach is labor intensive and the possibly coarse temporal re-visit frequency (usually, bi-weekly to monthly) does not allow investigators to identify

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phenological and disturbance events with accuracy and precision. Furthermore, these sensors should be used under diffuse sky conditions, which results in logistical limitations for research.

Satellite remote sensing offers the opportunity to monitor LAI in space and time (Garrigues et al., 2008; Myneni et al., 2002). However, satellite remote sensing measurements are prone to contamination by atmospheric effects (e.g. aerosol, clouds) (Kobayashi & Dye, 2005), which can cause substantial data gaps ranging from days to months (Fang et al., 2008; Verger et al., 2011). For phenological studies, the 8 to 16 days interval of satellite-derived vegetation products such as those obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) sensors, requires using empirical curve-fitting methods to interpolate the coarse intervals to a daily time step (Zhang et al., 2003). Thus it is known that estimating the timing of spring leaf out is sensitive to the interpolation methods (Morissette et al., 2009; White et al., 2009).

In addition, near-surface remote sensors such as webcams (Richardson et al., 2009; Sonnentag et al., 2012) or light emitting diodes (Ryu et al., 2010a) enable continuous observation of canopy status, specifically in terms of changes in the color or reflectance of vegetation. Although there might be some correlation between color index and structural variables (Sonnentag et al., 2011), it is evident that these sensors do not measure LAI directly. Recently, several studies have proposed the use of downward-looking digital cameras to monitor LAI in crops (Baret et al., 2010; Liu & Pattey, 2010) and other short vegetation (Macfarlane & Ogden, 2012). This approach is promising for short canopies with homogeneous and contrasting soil background spectral characteristics (i.e., spectrally different from the vegetation) to calculate gap fraction but is logistically complicated for tall forest canopies.

As an alternative, upward-pointing digital cameras with short-telephoto lenses have potential for monitoring the phenology of forest canopies because of the simplicity of the method (Macfarlane et al., 2007). Photos can be taken at the zenith direction and the pixels are classified as sky or vegetation in order to calculate the gap fraction, LAI and clumping index (Macfarlane, 2011). The clumping index indicates the degree of nonrandom distribution of foliage in space (Nilson, 1971). The main strengths of upward-pointing cameras include: 1) the capture of detailed canopy gaps in the photo; 2) the speed and ease of use; and 3) the estimation of LAI, rather than effective LAI, by correcting for foliage clumping. In addition, upward-pointing cameras do not require sensors to be mounted above tall forests, as with the LAI-2000. Furthermore, a multi-instrument and multi-model experiment showed that an upward-pointing camera offered the most reliable estimates of LAI and clumping index for open canopy (Ryu et al., 2010c). Several studies have used upward-pointing cameras to capture the spatial patterns of LAI or quantify spatially representative LAI (Fuentes et al., 2008; Macfarlane et al., 2007; Ryu et al., 2010c). Thus far, there have been no studies using upward-pointing cameras to monitor seasonal changes in LAI over multiple years continuously.

Estimates of gap fraction by optical sensors, such as LAI-2200 and upward-pointing cameras, usually involve contributions by leaves and plant woody elements. Thus, the incorporation of the gap fraction estimates into Beer's Law quantifies plant area index (PAI) instead of LAI. One widely-used approach to convert PAI to LAI is to subtract woody area index (WAI) observed in the leafless period from PAI observed in leafy period using optical sensors (i.e. $LAI = PAI - WAI$) (Chen et al., 1997). However, as Kucharik et al. (1998) noted, canopy woody elements are usually covered by leaves; therefore, the probability of a ray that hits woody elements is smaller for a full-leaf period than for a leafless period. Thus, care should be taken with the linear sum approach ($PAI = LAI + WAI$) to convert optical-sensor derived PAI to LAI.

The overarching goal of this study is to develop a method to monitor tree canopy LAI continuously at the ecosystem scale using upward-pointing digital cameras. Here we present data collected for

one 3-year period at an oak–grass savanna in California, USA to describe high temporal resolution (i.e., daily) LAI dynamics at the ecosystem scale. We address the following questions: 1) How to convert PAI from upward-pointing cameras to LAI? 2) Could continuous measurements of LAI detect important changes in the canopy (e.g., phenological transitions and responses to disturbance events)? 3) How can upward-pointing digital cameras be used to evaluate and augment the MODIS LAI product? Finally, we address the strengths and limitations of our method for continuous measurements of LAI using upward-pointing cameras, and propose improvements.

2. Methods

2.1. Site

The study site (Tonzi Ranch, latitude: 38.431°N; longitude: 120.966°W; altitude: 177 m) is located in the lower foothills of the Sierra Nevada Mountains, Lone, California, USA. The site is classified as oak–grass savanna woodland, characterized by open canopy (Baldocchi et al., 2004; Xu et al., 2004). The site is on a flat terrain (average slope: 1.5°) and experiences a Mediterranean-type climate with dry, hot summers and rainy, mild winters. The annual average temperature and precipitation are 16.9 °C and 565 mm, respectively (1949 to 2005 climate averages from Camp Pardee climate station; latitude: 38.25°N; longitude: 120.85°W). The overstorey consists of dominant blue oak trees (*Quercus douglasii*) with occasional (<10%) gray pine trees (*Pinus sabiniana*) (Baldocchi et al., 2004). Forest structural data was recently estimated using LiDAR and in-situ observation (Chen et al., 2008). The stem density was 144 ha⁻¹, the tree height was 9.4 ± 4.3 m (mean ± standard deviation), the trunk height (the height to the first live crown) was 1.8 ± 1.3 m, the diameter at breast height (DBH) was 0.26 ± 0.11 m, the mean crown radius was 2.9 ± 1.4 m, and the canopy cover was 0.48. Grass germinates around November when the rainfall starts, remains active during the wet period (December to May), and is dead during the dry summer and autumn after completing its annual life cycle (Ryu et al., 2008; Xu & Baldocchi, 2004). Blue oak trees start leaf-out in April and mostly shed their leaves in November. Active grasses and oak trees are typically co-dominant from April to May. More detailed site information can be found in previous studies (Baldocchi et al., 2004; Chen et al., 2008; Ma et al., 2007).

2.2. Theory

Plant area index is calculated by an inversion of Beer's Law:

$$PAI = \frac{-CC \times \log(CP)}{k} \quad (1)$$

where CC is the fraction of crown cover, CP is the crown porosity and k is the light extinction coefficient at zenith ($k(0) = G(0)/\cos(0)$) where G is the projection coefficient of unit foliage area on a plane perpendicular to the view direction). Eq. (1) applies Beer's law only within crowns where clumping effects are marginal in the case of broadleaf trees (Nilson, 1971, 1999), calculates PAI within crowns, and then multiplies the result by CC. In this study, k was determined as 0.5, being the mean of k values at zenith ($G(0)/\cos(0) = 0.45$) and 32° ($G(32)/\cos(32) = 0.55$) of view zenith angles. The G -function was quantified based on the in-situ leaf inclination angle observations using a digital camera (Ryu et al., 2010c). The 32 degree of view zenith angle was adopted based on the field of view in the digital camera (see Section 2.3).

Fraction of crown cover (CC) is the fraction of pixels that do not lie in between-crown gaps:

$$CC = 1 - \frac{N_L}{N_T} \quad (2)$$

where N_T is the total number of pixels in the image, and N_L is the total number of pixels located in the large gaps. We determined large gaps as being gaps larger than 1.3% of the total image area (Macfarlane et al., 2007). The classification of the photos into sky and vegetation pixels is described in Section 2.4.

Crown porosity (CP) is the gap fraction within crowns:

$$CP = 1 - \frac{(1-GF)}{CC} \quad (3)$$

where GF is the gap fraction in the image:

$$GF = \exp(-PAI \times \Omega \times k). \quad (4)$$

By combining Eqs. (1), (3), and (4), the clumping index (Ω) can be derived:

$$\Omega = \frac{(1-CP) \log(GF)}{\log(CP)(1-GF)}. \quad (5)$$

2.3. Data collection

Three identical consumer grade point-and-shoot digital cameras (PowerShot A570IS, Canon, Japan) were used to quantify LAI continuously (Fig. 1). We leveled the cameras at a height of 1 m with the lens pointed towards the zenith. In 2009, two cameras were installed on the day of year (DOY) 133, and a third was installed on DOY161. The cameras were approximately 50 m apart. The cameras were set to: maximum wide angle (focal length of 5.8 mm), automatic exposure, aperture priority mode and minimum aperture (F/2.6) (Macfarlane et al., 2007). These settings yielded a view zenith angle from 0 to 32° diagonally. The cameras' power buttons were removed and leads were soldered to the button contacts, so that the camera could be turned on and off by a relay (TSC-112C3H, Tyco Electronics Corp., China). The Canon Hack Development Kit (CHDK) (CHDK Project, <http://chdk.wikia.com>) was installed on the cameras' flash memory cards to extend the cameras' capabilities, including digital repeat photography through a simple script written in uBasic (Sonnentag et al., 2012). The cameras were turned on and off with data loggers (CR200, CR10X, Campbell Scientific Inc., USA). Photos were taken with the highest resolution [3072 × 2304 pixels] hourly from 1500hh and 1900hh until DOY266 in 2011. This setting was changed as 2.5, 2, 1.5, 1, and 0.5 h before sunset after DOY266 in 2011 to take photos under similar solar zenith angles for the various seasons. We

selected one photo per day when the solar zenith angle was closest to 80° to avoid over saturation from the direct beam.

In addition to the three reference cameras, we manually collected many more spatially representative photos on DOY 182, 218, 254, and 294 in 2009 and DOY 11, 63, and 88 in 2010. The scale of heterogeneity determined through semivariogram analysis using an IKONOS image (5.4 km × 7.9 km) of the study site was c.a. 300 m by 300 m (Kim et al., 2006). Within the 300 m by 300 m plot, Ryu et al. (2010c) showed that 35 samples (i.e. photos) were sufficient to obtain the 95% of the variation for a mean GF at the zenith (0–30° range of zenith angle). In the current study, we used three 300 m long transects 30 m apart, and collected zenith direction photos every 30 m interval, which yielded 33 samples for each sampling date. The same make and model of camera, and camera settings, were used as for the reference images.

2.4. Data processing

To classify pixels as sky or vegetation, we followed an automated procedure proposed by Macfarlane (2011). First, we extracted the blue channel of each photo and made a histogram. To identify pixels that are unambiguously either sky or canopy, we used the corner-detection method (Rosin, 2001) to identify two digital numbers (DN_L and DN_U) located at the maximum curvature on the L shaped curves to the right of the lower maxima (DN_L) and to the left of the upper maxima (DN_U) in the histogram (Macfarlane, 2011). The pixels located between DN_L and DN_U in the histogram are considered “mixed pixels” and appear around edges between the canopy and the sky. To separate the mixed pixels into sky and canopy, we used a variation of the dual binary threshold method (Macfarlane, 2011). Pixels that were unambiguously canopy ($DN < DN_L$) were initially classified as such and gaps smaller than 0.01% of the image size were included in the canopy. To minimize the loss of small gaps due to lower light intensity within the canopy, a 25% threshold (i.e. $DN_L + (DN_U - DN_L) \times 0.25$) was used in these vegetated pixels. The classification of the pixels in the remainder of the image was sensitive to sky light conditions. Thus, we calculated a sky blueness index (i.e., $B/(R+G)$) for only the sky pixels, and classified images as containing overcast sky if the index was less than 0.65. Otherwise, the sky condition was classified as clear (blue sky). For overcast sky conditions, we used a 50% threshold (i.e. $DN_L + (DN_U - DN_L) \times 0.5$) whereas for clear sky conditions, we used a 75% threshold (i.e. $DN_L + (DN_U - DN_L) \times 0.75$) to minimize the loss of leaves located in the bright region.

To extrapolate PAI from the three reference cameras to ecosystem scale, we calculated the mean PAI from those three cameras (i.e., reference PAI) and the mean PAI from the 33 spatial samples for each of the sampling dates (i.e., ecosystem PAI). Then we developed a linear regression between ecosystem PAI and reference PAI, and applied it (i.e., multiply the slope estimate) to the whole observation period of the three cameras. We calculated the mean reference PAI using

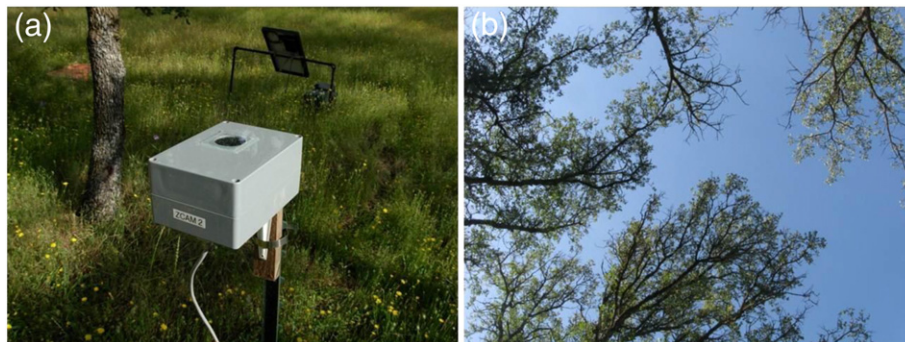


Fig. 1. (a) An upward-pointing digital camera installed at our study site and (b) a photo taken from one of the three cameras.

$\log(\overline{CP})$ instead of $\log(\overline{CP})$ to incorporate clumping effects in Eq. (1) (Lang & Xiang, 1986; Ryu et al., 2010b). The scaling relationship was only applied on dates when all three cameras were operational. Occasional system failures resulted from water drops on the glass windows (see Fig. 1) and power loss. Photos with water drops on the glass windows were identified by a file size of less than 80% of a 10-day moving window average time series of file sizes. The resulting data gaps were filled using a linear interpolation method.

To convert from ecosystem PAI to LAI, we conducted the following procedures: 1) determine leaf-out, complete leaf-off and peak PAI dates for each year using the time series of ecosystem PAI; 2) set PAI to be 0.08 between DOY 1 and leaf-out dates, and between complete leaf-off dates and DOY 365; 3) linearly rescale PAI values between leaf-out and peak PAI dates; and 4) linearly rescale PAI values between leaf senescence dates and complete leaf-off dates. The leaf-out dates were determined from the curvature change rate of a sigmoidal curve fitted to the daily PAI data (Zhang et al., 2003). The complete leaf-off dates were determined visually. The leaf senescence dates were defined as the date when daily PAI fell to 60% of the range in seasonal PAI (i.e., maximum PAI minus minimum PAI) (see Section 3.1). The 0.08 of LAI during the leafless period for the oak trees represents the pine trees' LAI, which was determined by multiplying the basal area ratio of the pine trees to all of the trees (10%, Ryu et al., 2010c) and the ecosystem LAI (0.8, Ryu et al., 2010c).

2.5. Ancillary data

We visited the site every one to two weeks during the phenological transition periods. Based on visual observation, two developmental stages were recorded for the oak trees: (1) the date of oak leaf-out and (2) the date of foliage senescence. The onset and ending dates of each phenological stage were defined when 60% of the plants showed the same phenology. Mean absolute errors in the phenology observations were approximately ± 3 days (Ma et al., 2007).

We deployed two different sets of litterfall traps to obtain spatially representative LAI (25 traps) and the seasonality in LAI near one digital camera location (6 traps). For the former purpose, litter was collected three times during 2009 from the 25 traps with the last collection timed soon after the last leaf fall in 2009 (Ryu et al., 2010c). For the latter purpose, six traps were deployed on DOY 217 in 2009, and litter was collected on DOY 254, 275, 293, 329, and 356. Litter was separated into leaves, twigs and seeds. We summed the biomass from these sequential collections to calculate total leaf biomass per litter trap. Specific leaf area (SLA) was determined for a subset ($n=480$) of oak leaves obtained during the three collection times from the 25 litter traps. We measured the one-sided area of fresh flat oak leaves ($n=480$) using the LI-3100C Area Meter (LI-COR, Lincoln, NE, USA). These samples were then oven dried at 65 °C for 48 h to achieve a constant weight. Based on these measurements, the mean SLA for blue oak leaves was $91.8 \text{ cm}^2 \text{ g}^{-1}$ (standard error = $8.09 \text{ cm}^2 \text{ g}^{-1}$). LAI per litter trap was calculated as leaf biomass per litter trap $\times$ SLA and then the means of these 25 and 6 values were taken as the best measure of litterfall LAI.

LAI of the tree canopy was measured using two LAI-2000 sensors. A reference sensor was placed at the top of a micrometeorological tower (20 m height) to log blue diffuse light over the canopy at 15 second intervals. The other sensor measured light transmission under the canopy along the three 300 m transects. All of the samples were collected just before sunset to avoid direct beams (Welles & Norman, 1991). The operator always stood between the sensor and the sun, and a 180° view cap was used on both sensors to shield the sensors from both the operator and block any remaining direct light. The LAI-2000 data were collected on DOY 154 and 218 in 2009 and DOY 120 and 148 in 2010. The GF for all five rings of the LAI-2000 were used as input to a forest gap fraction model (Nilson,

1999; Nilson & Kuusk, 2004) and actual LAI was quantified. For details, see Ryu et al. (2010c).

2.6. Remotely sensed LAI

We obtained 1 km pixel resolution MODIS LAI data (MOD15A2 collection 5) (Myneni et al., 2002) for the study site from MODIS Land Subsets provided by Oak Ridge National Lab (<http://daac.ornl.gov/MODIS/>). We only used data classified as “Significant clouds NOT present” and either “Main (RT) method used, best result possible (no saturation)” or “Main (RT) method used with saturation. Good, very usable” in the quality flags. We selected nine pixels (3×3) from each image centered on the study site as suggested by Tan et al. (2006). If LAI data of at least six of the nine pixels passed the quality check then we averaged the LAI of those pixels to calculate LAI for that date. The LAI value for seven dates between DOY 161 in 2009 and DOY 41 in 2012, that failed quality checks, was filled by linear interpolation.

3. Results

3.1. Comparison of PAI from digital cameras and LAI from litterfall

To determine the contribution of wood to LAI estimated from upward-pointing cameras, we compared PAI and LAI derived from one upward-pointing digital camera and periodically collected litterfall in 2009. Both the camera and litterfall showed similar PAI and LAI values (~ 1.1) on DOY 216. The PAI and LAI started to diverge around DOY 253, and this discrepancy increased with time. On DOY 355, litterfall-derived LAI was zero, whereas camera-derived PAI was 0.54, which we interpreted as the woody area index (WAI) for this specific camera location. PAI and LAI started to diverge on DOY 253 at about 60% of the PAI range (i.e., maximum minus minimum PAI over the year). Based on this information, we determined leaf senescence dates at 60% of the range in the camera-derived LAI.

3.2. Time series of gap fraction, clumping index and plant area index

The GF, Ω and PAI from the three reference cameras varied greatly seasonally (Fig. 3). GF and PAI were inversely correlated; Ω decreased as PAI increased indicating increased foliage clumping as the crowns thickened. The pattern of canopy development was similar for all three cameras between leaf-out and full canopy development. However, the patterns of crown senescence differed between the three cameras, in particular during 2009 (Fig. 3c). Some data was lost owing to water drops on the glass windows (see Fig. 1) and power loss. During the study period, missing data were 17%, 17% and 14% for cameras 1, 2 and 3, respectively.

3.3. Scaling of PAI from the reference cameras to the ecosystem

A regression equation was developed to calculate ecosystem PAI from reference camera PAI, based on the seven dates when photos were manually collected along transects. There was a strong linear relationship between ecosystem PAI and the mean PAI from the reference locations (Eq. (6), $r^2 = 0.97$, $p < 0.001$, 95% confidence interval of the slope: 0.53 ± 0.03 , linear regression was forced through the origin). PAI of the reference locations was about twice that of ecosystem PAI.

$$PAI_{\text{ecosystem}} = 0.53 PAI_{\text{reference}} \quad (6)$$

From the mean reference PAI (Fig. 3c) and Eq. (6) (Fig. 4a) we constructed a daily time series of ecosystem PAI (Fig. 4b). The uncertainty of ecosystem PAI caused by uncertainty in the slope of Eq. (6) (0.53 ± 0.03) was 0.1 for peak canopy development ($PAI = 0.9$). The

time series of ecosystem PAI captured the dates of leaf-out and the windstorm events that decreased PAI abruptly, and the inter-annual variability of canopy development and senescence. The mean PAI value during the winter was 0.38. Based on the LAI estimate for pine trees of 0.08 (see Section 2.4), we calculated that WAI at ecosystem scale was 0.3 (0.38–0.08).

3.4. Converting ecosystem PAI to ecosystem LAI

The ecosystem LAI time series (Fig. 5a) was identical to the ecosystem PAI time series (Fig. 4b) between the peak LAI dates and the senescence dates. The LAI and PAI time series differed only in winter, from the leaf-out dates to the peak LAI dates, and from the senescence dates to the complete leaf-off dates.

The ecosystem LAI was evaluated against two independent LAI estimates, which included litterfall collection and LAI-2000 corrected for clumping effects and woody element contribution (Nilson & Kuusk, 2004). The ecosystem LAI derived from upward-pointing cameras was in good agreement with the independent LAI estimates ($r^2=0.94$, root mean squared error (RMSE)=0.05, 95% CI of the slope: 1 ± 0.07 , the linear regression was forced to pass the origin).

3.5. Phenology

Phenological events determined from upward-pointing cameras were compared against in-situ observed phenological records. The leaf-out dates identified from the curvature change rate method (Zhang et al., 2003) were DOY 78, 93 and 90 for 2010, 2011, and 2012, respectively (Fig. 4b). These dates agreed well with the in-situ observer's record, which presented the leaf-out dates as DOY 75, 89, and 82 for 2010, 2011, and 2012, respectively (mean bias: 5 day, RMSE: 5.4 day). The leaf senescence dates determined from 60% of the range in PAI time series for each year were DOY 280, 295, and 314 for 2009, 2010, and 2011, respectively. The senescence dates did not change with the uncertainty in the scaling equation (mean slope and 95% CI: 0.53 ± 0.03 , Fig. 4a). The in-situ observer's record on the leaf senescence dates was DOY 285, 287, and 317, for 2009, 2010, and 2011, respectively. The mean bias and RMSE of the leaf senescence dates were 2 and 4.8 days, respectively. Complete leaf-off dates were clearly identified visually (Fig. 4b). They were DOY 355, 340, and 333 for the years 2009, 2010, and 2011, respectively. Senescence started earlier, and complete senescence was delayed in 2009 compared to the other years analyzed.

3.6. MODIS LAI

MODIS LAI includes both tree and grass LAI, thus great care is needed for a direct comparison between the MODIS LAI product and camera-derived tree LAI. During the summer when grasses were dead at the study site, MODIS LAI was 0.8–1 (Fig. 6a), which was comparable with camera-derived LAI (Fig. 5a). MODIS LAI did not capture the sudden decrease of LAI caused by wind-storm events. To evaluate the MODIS LAI product indirectly for the other seasons, we inferred grass LAI by subtracting tree LAI derived from upward-pointing cameras (Fig. 5a) from the MODIS LAI (Fig. 6a). The seasonal patterns of grass LAI data were reasonable and included the start of grass development in November, the peak grass LAI in May and the dead grass (LAI of zero) in summer (Ryu et al., 2008) (Fig. 6b). In particular, the grass leaf-out dates visually identified (Fig. 6b) were DOY 283, 293 and 271 for 2009, 2010 and 2011, respectively. These were comparable with in-situ observations for grass leaf-out dates: DOY 283, 294 and 276 for 2009, 2010, and 2011, respectively (mean bias: –2 days, RMSE: 3 days). Overall, the MODIS LAI product provided a realistic time series that integrated tree and grass phenology, but was limited in capturing sudden and small canopy changes.

4. Discussion

4.1. How to convert PAI from upward-pointing cameras to LAI?

Our method to convert PAI to LAI described in Section 2.4 enabled us to quantify ecosystem LAI with accuracy comparable to the independent estimates of LAI ($y=x$, $r^2=0.94$, RMSE=0.05, Fig. 5b). Although our method is not a process-oriented approach, we believe it offers semi-empirical, but realistic, estimates of continuous measurements of LAI in this ecosystem.

Optical sensors 'see' both leaves and woody materials; thus, LAI derived from optical sensors is usually called PAI. Converting PAI to LAI is essential to model canopy carbon and water fluxes and evaluate remote sensing derived LAI products. It is possible to see substantial woody elements by looking up at the canopy from the ground; however, the woody elements are mostly not seen from the sky, as the woody elements are covered by leaves. For example, it was reported that most branch area was covered by leaves at zenith direction in boreal forests (Kucharik et al., 1998). Our study confirmed this observation, showing that the peak PAI derived from one upward pointing camera was almost identical to the peak LAI derived from the litterfall collections around one of the three digital cameras (Fig. 2), and the peak ecosystem PAI derived from upward pointing cameras (~0.85, Fig. 4) was similar to the peak ecosystem LAI estimated from litterfall collections (0.82, Fig. 5b). Thus, PAI approximated LAI under full-leaf conditions.

During canopy development and senescence periods when substantial amounts of woody elements are not covered by leaves, it is uncertain how much wood contributed to the estimation of LAI. We linearly interpolated LAI values for this period (Fig. 5a). Clearly identifying the start date of senescence was difficult, in particular when leaves fell gradually during the summer (see Fig. 3c). We empirically determined the start date of senescence (Fig. 2). Further theoretical and experimental work is needed on quantifying the change of LAI with changing contributions by woody elements to light interception, especially during the transitional periods in spring and autumn.

4.2. Could upward-pointing cameras detect important changes in the canopy structures?

The daily ecosystem LAI derived from cameras enabled us to identify key phenological events, such as leaf-out dates (RMSE: 5.4 days) and leaf senescence dates (RMSE: 4.8 days) (Fig. 4). The complete

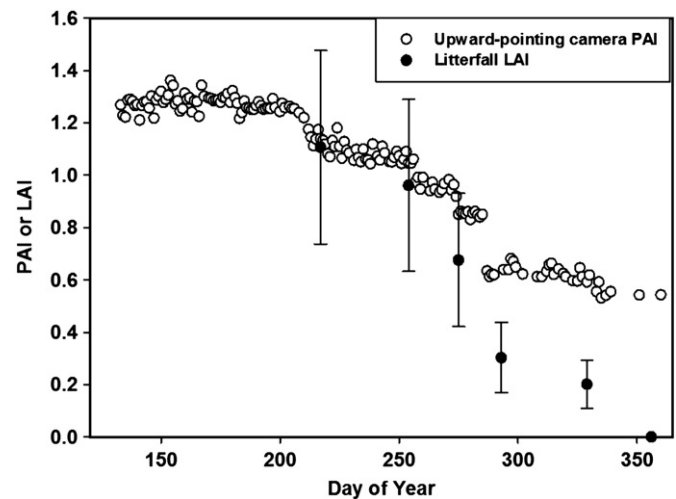


Fig. 2. Comparison between plant area index (PAI) derived from one upward-pointing digital camera and leaf area index (LAI) derived from periodic litterfall collections in 2009. Error-bar indicates 95% confidence interval. Six litterfall traps were located within 20 m from one of the three upward-pointing digital cameras.

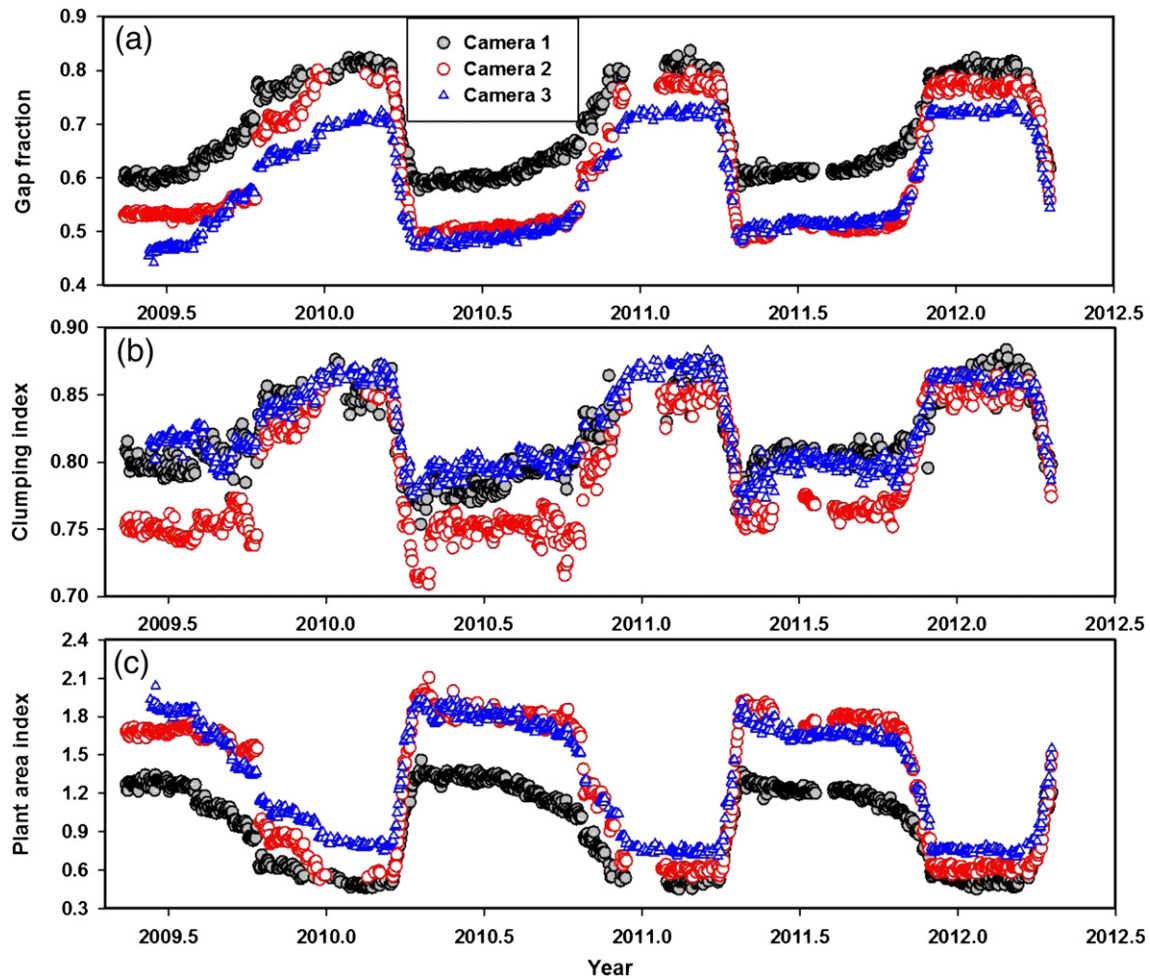


Fig. 3. Time series of daily gap fraction (a), clumping index (b) and plant area index (c) using three upward-pointing digital cameras in an oak-grass savanna.

leaf-off dates were clearly identifiable from the camera-derived LAI (Figs. 3 and 4), but there were no in-situ observer's records to confirm them.

The cameras captured the interannual variability of canopy development. The leaf-out date in 2010 was 15 days earlier than in 2011, while the monthly mean air temperature in March in 2010 was about 2 °C warmer than in March of 2011. The leaf senescence date in 2009 (DOY 280) was earlier than in 2011 (DOY 314). Such differences were reflected in the precipitation during the spring months (from March to June): 174 mm in 2009 and 307 mm in 2011. Clearly, warmer springs would advance the timing of the leaf-out (Penuelas & Filella, 2001), while a spring drought would advance leaf senescence at the end of summer (Angert et al., 2005).

The cameras also identified sudden decreases of LAI caused by windstorms. Many disturbances, such as windstorms, are sudden and of short duration. Thus, it is important to monitor ecosystem structure at a high temporal resolution. On DOY 286 in 2009, the study site experienced a storm with 40 mm rainfall and 10 m s⁻¹ wind speed. The cameras captured this event, which reduced PAI by 30% (see arrows in Fig. 4). Most phenology models predict leaf-senescence timings based on physiological factors inferred from temperature or a water stress index (Botta et al., 2000; Hanninen & Kramer, 2007; Jolly et al., 2005). Such models are tested against in-situ observations or satellite images, which are prone to miss short-term small physical disturbance events that cause abrupt decreases of LAI. For example, the MODIS LAI product did not capture the sharp reduction of LAI caused by windstorms (Fig. 6a) although it captured the large scale disturbances (e.g. fire and hurricane) that

substantially reduced LAI (Peckham et al., 2008; Vargas et al., 2010). The daily observation of LAI with upward-pointing cameras could be useful to determine the short- and long-term factors of leaf senescence, which would be helpful to improve phenology models at a local scale.

4.3. How can upward-pointing digital cameras be used to evaluate and augment MODIS LAI product?

MODIS LAI product showed good agreement with tree LAI derived from upward-pointing cameras (LAI ~ 0.9) when the grass was dead (Fig. 6a). We calculated grass LAI by differencing MODIS LAI and tree LAI derived from upward pointing cameras, determining that the time series of grass LAI showed realistic seasonal patterns and identified the leaf-out dates of grass (RMSE: 3 days) (Fig. 6b).

The good agreement of tree canopy LAI between MODIS and the cameras confirmed previous results that evaluated the MODIS LAI product for savanna ecosystems in Australia (Sea et al., 2011) and Africa (Privette et al., 2002; Scholes et al., 2004). The previous studies conducted intensive field measurements during dry seasons when the grass was dead for one year; thus, their evaluations were limited to very short periods of time.

Our study comprises 3-year observational data of tree canopy LAI at the ecosystem scale. We hoped to test seasonal to interannual variation of the MODIS LAI product for tree canopy, in particular for spring and autumn, when tree LAI showed large interannual variation such as with the advanced senescence in 2009 (Figs. 4, 5). However, both trees and grass were co-dominant in the spring and autumn;

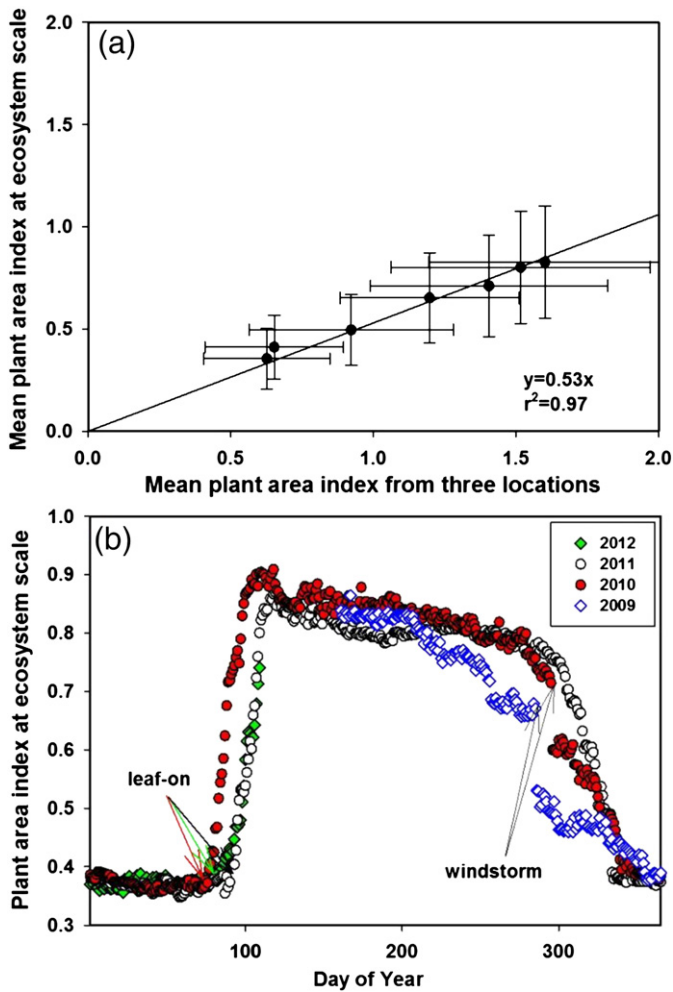


Fig. 4. (a) Comparison of mean plant area index (PAI) derived from upward-pointing cameras between three locations ($n=3$) where photos were automatically taken and ecosystem scale ($n=33$) where spatially extensive measurements were made for seven dates. Error bars indicate 95% confidence interval. The linear regression was forced to pass the origin. (b) PAI at ecosystem scale by applying the linear regression of panel (a).

therefore, we were unable to evaluate tree LAI of the MODIS LAI product for this time period. Instead, we evaluated the MODIS LAI product indirectly after inferring grass LAI by subtracting camera-derived tree LAI from the MODIS LAI (Fig. 6b). The inferred grass LAI data represented the seasonal variations of grass development well. We do not have grass LAI data at the ecosystem scale; however, at the study site the peak grass LAI was reported as ~ 1.5 (Xu et al., 2004), which is similar to the peak grass LAI inferred from MODIS and upward-pointing cameras (Fig. 6b). In the fall of 2011, we observed that grass germinated on DOY 276 after the first rain. However, further rainfall did not follow and the young grass community experienced drought, which caused a decrease in grass LAI. After sufficient rainfall, the grass community started to grow again. This pattern of grass LAI was captured in the inferred grass LAI time series (Fig. 6b).

The grass layer in the savanna ecosystem is temporally and spatially highly variable owing to scarce water resources and infrequent rain (Rodríguez-Iturbe et al., 1999). For the deciduous oak savanna, the overstorey canopy is also variable compared to the evergreen canopies of other savanna systems world-wide. Such variability in both the over- and understory canopies poses an enormous challenge for remote-sensing technologies, to both quantify the gas-exchanging surface of different vegetation layers and also detect important phenological events in each layer (Archibald & Scholes, 2007; Higgins et al., 2011). We found that the integration of the MODIS LAI product

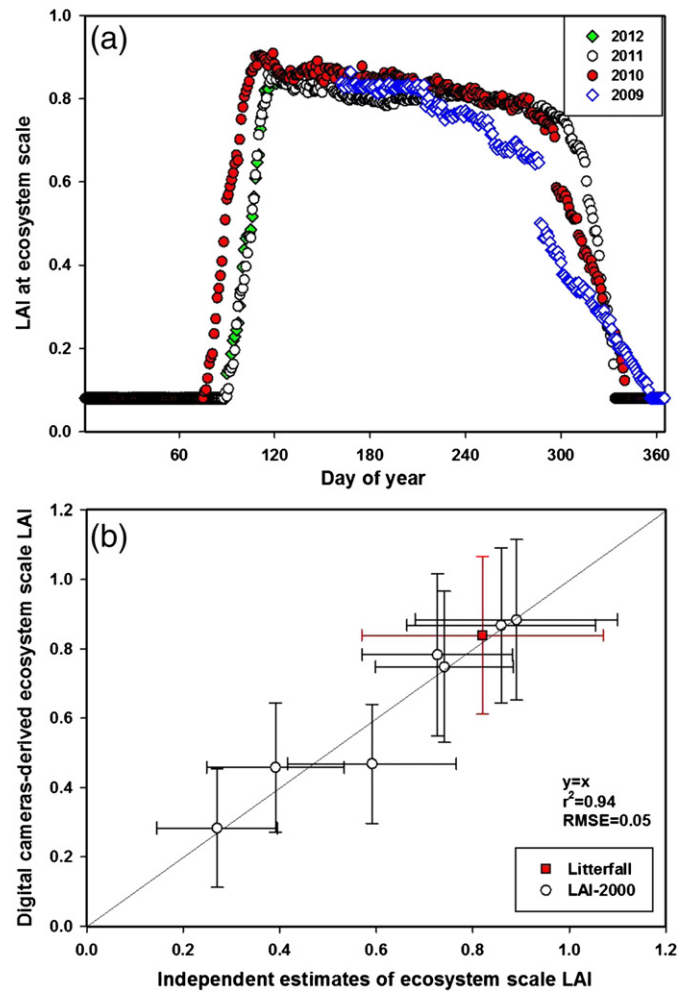


Fig. 5. (a) Time series of leaf area index (LAI) at ecosystem scale. (b) Comparison of LAI between upward-pointing camera and independent methods that include litterfall traps and LAI-2000 instrument. Error bars indicate 95% confidence intervals. RMSE is root mean squared error. The linear regression was forced to pass the origin.

with automated, high temporal resolution monitoring of the tree canopy allowed us to estimate LAI of both layers and identify important phenological events at high temporal resolution.

4.4. Strengths, improvements and future directions for upward-pointing digital cameras

Upward-pointing cameras are useful in evaluating canopy structural variables derived from remote sensing. For example, upward-pointing cameras can validate LiDAR-derived gap fraction data, which has a very narrow field of view along the nadir direction (Chen et al., 2008; Lefsky et al., 2002). It is possible to match fields of view between LiDAR and photos taken using cameras by extracting a portion of a photo (Kobayashi et al., 2012). Also, upward-pointing cameras can be used to evaluate satellite-based LAI products (Fuentes et al., 2008). Ecosystem scale observations of Ω with cameras could be used to evaluate satellite-derived Ω products (He et al., 2012).

The upward-pointing camera is an inexpensive, easy, fast, and accurate method to monitor ecosystem LAI under forest canopies. The technique is easy to replicate and could be applied along regional vegetation gradients for scaling information on LAI and phenology. Unlike digital hemispherical photography or LAI-2000, which requires observation under overcast skies, upward-pointing cameras can be used during daytime if sunlit leaves, which cause high scattered

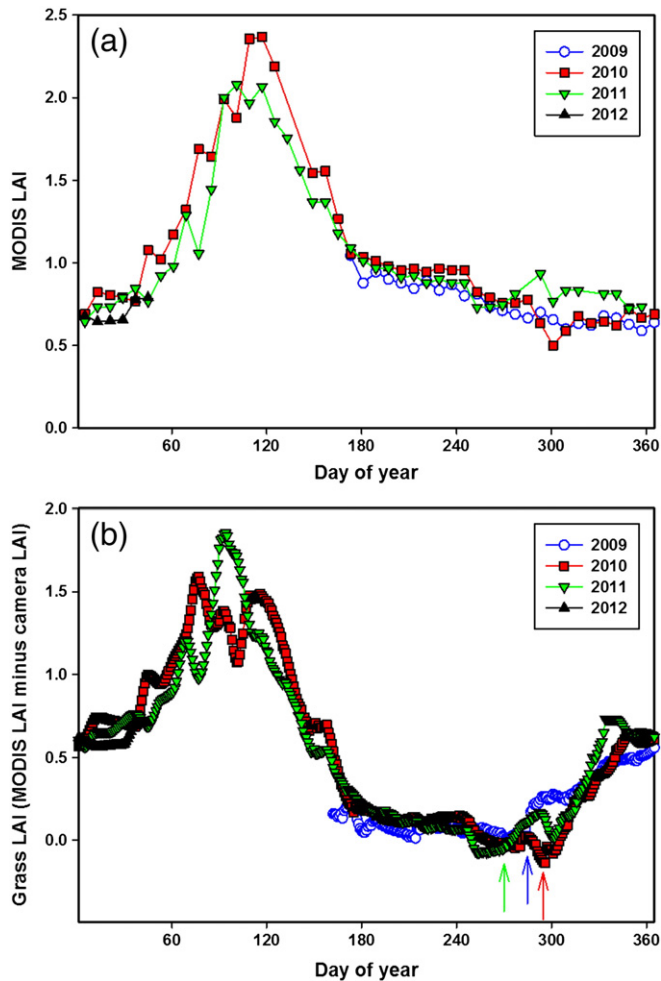


Fig. 6. (a) Time series of leaf area index (LAI) derived from MODIS (MOD15A2, 8-day product). (b) Time series of grass LAI by differencing MODIS LAI and camera-derived canopy LAI (i.e. panel (a) minus Fig. 5(a)). The 8-daily MODIS LAI product was interpolated into daily intervals using cubic interpolation method. The arrows indicate grass leaf-out dates identified visually.

radiation (Kobayashi et al., in review) and can disappear in the photos, are not included in the field of view. Due to the narrow field of view used (in this study 30°) and the possibility to extract a narrower area in the photo (Kobayashi et al., 2012), it is often possible to avoid sunlit leaves in the image.

Owing to the narrow field of view, a few upward-pointing cameras at fixed locations are unlikely to represent an entire ecosystem. Calibrating LAI derived from a few cameras with a spatially extensive observation of LAI is essential. In this study, the integration of continuous observations of LAI using three cameras with periodic, but spatially extensive, observations of LAI allowed us to monitor ecosystem LAI within a reasonable margin of error (Fig. 5). The peak LAI in each camera (1.2–2.1, Fig. 3) was higher than the peak LAI at the ecosystem scale (0.9, Fig. 5) because the three fixed upward-pointing cameras were located beneath tree canopies. Thus calibration of LAI estimated from a few cameras should be made to measure ecosystem scale LAI accurately.

The upward-pointing cameras enabled us to investigate seasonal variation of the Ω (Fig. 3). The Ω is important in quantifying the global carbon cycle. For example, the incorporation of Ω into a remote-sensing derived land surface model reduced global gross primary productivity (GPP) by 1.5 PgC yr^{-1} (Ryu et al., 2011) or 16 PgC yr^{-1} (Chen et al., 2012), compared to the assumption of a random canopy. The large impact of the Ω on GPP estimates underlines the necessity to further study the importance of foliage

clumping in canopy models. Thus far, most studies related to foliage clumping have focused on the peak growing season (Chen et al., 2006; Ryu et al., 2010c). In the current study we observed pronounced seasonality in the Ω that ranged 0.72–0.88 and was out-of-phase with LAI (Fig. 3). During leafless periods, the landscape looks more “homogeneous”. However, in the full-leaf period, the landscape becomes clumped, as only some portions of landscape have leaves (Ryu et al., 2010c). Detailed information on foliage clumping will be useful to improve models of canopy radiative transfer, carbon and water fluxes.

Possible seasonal variation of the extinction coefficient (k in Eq. (1)) is also challenging for continuous observations of LAI. We used the leaf inclination angle data collected in the field using a digital camera to quantify k (Ryu et al., 2010c). The technique, which measures the leaf inclination angle with a camera, was applied and tested in eight broad-leaf species (Pisek et al., 2011). However, when LAI is small, k is strongly influenced by the woody elements seen by the cameras. It is not easy to define k for the woody elements, as their sizes and angles vary substantially from thin twigs to thick stems. Furthermore, it is difficult to quantify k accurately in the transition periods between leafless and full-leaf. We assumed that the k for woody elements is the same as the k for leaves. This assumption, with GF observations, determined WAI in the leafless period to be 0.3 (Fig. 4). This value was similar to the best estimate of WAI for this site, 0.32 ± 0.08 (mean $\pm$ 95% CI) using a digital camera (Ryu et al., 2010c). The assumption of a constant k over the seasons might not work in other ecosystems. Fortunately, when LAI is small the absolute error introduced by an incorrect value of k is also small.

Finally, we envision that the small micro-cameras used in cellular phones could be replicated across the forest with a wireless network. This approach would substantially improve forest phenology studies from the individual species level to the ecosystem scale.

5. Summary and conclusions

In this study, we proposed and evaluated an approach to continuously monitor daily tree LAI at ecosystem scale. We achieved this by integrating continuous observation of LAI using three upward-pointing cameras at fixed reference locations with periodic, but spatially extensive, observations of ecosystem LAI using similar upward-pointing cameras. As the upward-pointing cameras originally quantified PAI, we converted PAI to LAI using a semi-empirical approach, which yielded a good agreement with independent estimates of LAI at the ecosystem scale (RMSE: 0.05). Our approach to monitor daily ecosystem LAI accurately identified tree leaf-out dates (RMSE: 5.4 days), tree senescence dates (RMSE: 4.8 days), disturbance events that abruptly decreased LAI $\sim 30\%$ in a day, and advanced canopy senescence in a dry year (2009). The continuous observations of ecosystem LAI were useful for evaluating the MODIS LAI product. We found that the MODIS LAI product was in good agreement with the upward-pointing cameras for tree LAI when the grass was dead. For the period when the grass was alive, we inferred grass LAI, which was the difference between MODIS LAI which includes both tree and grass and camera derived tree LAI. The grass LAI data presented realistic seasonal patterns and allowed us to identify grass leaf-out dates accurately (RMSE: 3 days). We conclude that upward-pointing cameras allow us to monitor canopy structural variables such as LAI, GF, and Ω in an inexpensive, easy and fast manner at the ecosystem scale. Further evaluation of this method should be made, in particular for dense forests.

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