Impact of leaf area index from various sources on estimating gross primary production in temperate forests using the JULES land surface model

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Impact of leaf area index from various sources on estimating gross primary production in temperate forests using the JULES land surface model

HoonTaek Lee, Juhan Park, Sungsik Cho, Minsu Lee, Hyun Seok Kim

1. Introduction

Terrestrial gross primary production (GPP) is the largest component of the global carbon cycle (Beer et al., 2010; Li et al., 2018b) and serves as an indicator of the terrestrial ecosystem’s carbon sink capacity (Battin et al., 2009). Despite its importance in the global carbon cycle, it is impossible to measure GPP directly, especially at the stand or larger scales (Beer et al., 2010; Anav et al., 2015; Ma et al., 2015). Alternatively, a land surface model (LSM) can be used as a key tool in understanding the global carbon cycle as it can simulate the interaction between biosphere and atmosphere (Slevin, 2016). However, these simulations are complicated because they occur at various spatial and temporal scales (Medvigy et al., 2009), and are affected by multiple biological and non-biological factors (Xia et al., 2015). GPP therefore remains highly variable and uncertain in the carbon cycle (Anav et al., 2011; Murray-Tortarolo et al., 2013; Cao et al., 2015). LAI is a major component that affects GPP simulations in a LSM (Chen et al., 2002; Richardson et al., 2012). For example, one method of GPP calculation multiplies species’ light use efficiency (LUE) with the photosynthetically active radiation absorbed by the vegetation canopy (APAR) (Li et al., 2018b). Because APAR can be formulated as a function of LAI (e.g., Turner et al., 2006), GPP can be directly formulated using LUE and LAI. Thus, an LAI higher or lower than the actual value can cause over- or under-estimates, respectively, of GPP by an LSM.
(e.g., Chen et al., 2015; Slevin et al., 2017), and GPP simulation of an LSM can be improved by using the correct maximum annual LAI, as derived from remote sensing (Slevin et al., 2015).

LAI can be measured directly or indirectly. Direct LAI measurements through leaf collection, whether by destructive harvesting or non-destructive litter trap, are time-consuming and laborious (Dufrêne and Bréda, 1995; Johnckheere et al., 2004). In addition, it is not possible to cover the entire seasonality of LAI because direct measurement cannot cover leaf-out and leaf-expansion phases (e.g., Chason et al., 1991; Bréda, 2003; Kwon et al., 2016). Indirect methods such as canopy photography and comparisons of light above and below the canopy are frequently used to retrieve LAI data (van Gardingen et al., 1999; Johnckheere et al., 2004). However, both direct and indirect methods are suitable only for local-scale studies and are difficult to apply to larger spatial scales (Johnckheere et al., 2004; Sprintsin et al., 2009).

Many studies therefore extracted their LAI values from phenology models (e.g. Arora and Boer, 2006; Murray-Tortarolo et al., 2013; Cao et al., 2015) or satellite-based data (e.g. Lawrence and Slingo, 2004; Beer et al., 2016; Slevin et al., 2015) because these sources are easily accessible and can produce results in usable time steps over the desired space.

However, an LAI from phenology models is often incorrect in terms of magnitude and seasonality (e.g. Lim et al., 2010; Anav et al., 2013; Murray-Tortarolo et al., 2013; Cao et al., 2015). For example, Richardson et al. (2012) reported that among 14 terrestrial biosphere models, no single model adequately characterized LAI dynamics at five deciduous forest sites for seven years. Errors in leaf phenology models are caused mainly by imperfect understanding of phenological processes (Arora and Boer, 2005; Richardson et al., 2012). There are many accounted drivers of leaf phenology, such as precipitation (Shen et al., 2015), irradiance (Saleska et al., 2007), temperature, carbon allocation (Richardson et al., 2012), day length, and soil moisture content (Arora and Boer, 2005). Because these drivers and their mechanisms vary by species and biome, current phenology models show considerable discrepancies from real values (Richardson et al., 2012; Tang et al., 2016).

In the case of satellites, each has unique spatial (from a few meters to a few kilometers) and temporal (< 1 day to 16 days) resolutions. This variety in resolution affects LAI accuracy (Colombo et al., 2003) and eventually ecosystem productivity measurements. This effect is more significant in temperate forests, where vegetative cover is heterogeneous and both evergreen needleleaf species and deciduous broadleaf species can be contained within one pixel (e.g. Kwon et al., 2016; Moon et al., 2016; Park et al., 2018b), just as the heterogeneous composition of temperate forest affects simulated GPP by an LSM (Park et al., 2018a). In spite of a variety of studies comparing satellite-based LAs with different spatial resolution, (e.g., Soudani et al., 2006; Tong and He, 2013; Chen et al., 2017; Li et al., 2018a), there are still no studies on the effect of differences in LAI from the spatial resolution of satellites on GPP simulation by LSM. Liu et al. (2018) concluded that differences in retrieving algorithms of satellite-based LAI affect the differences in simulated GPP by LSM. Spatial resolution of satellites may also cause discrepancies in GPP simulations, and if it is confirmed that low-resolution data are a reasonable choice with a small loss of accuracy, the opportunities to save computing costs will grow (Slevin et al., 2017). A comparison of the effects of LAI at various spatial resolutions on LSM operation and development would therefore be useful.

In this study, we simulated GPP in temperate needleleaf and broadleaf forests using the Joint UK Land Environment Simulator (JULES) with various LAs, including in situ observations, values from two satellites with different temporal and spatial resolutions, and simulations from a leaf phenology model. We investigated how seasonal and interannual variations in stand-level GPP differed between according to the various LAs. Additionally, we explained some of the limitations of the JULES leaf phenology model, and suggested simple modifications to improve it. We expect this study will help readers understand the effect of LAs on GPP simulation by an LSM, select which type of LAI to use, and improve leaf phenology models. Specifically, we hope to explain the following research questions: How different is GPP simulation at the stand level using satellite-based and phenology-model LAs from that using in situ–measured LAI? Does spatial resolution affect GPP simulations of LSM at the stand level? Does inter-annual and seasonal variation of GPP estimation at the stand level by LSM vary depending on the type of LAI?

2. Data and methods

2.1. Study site

This study was conducted at Mt. Taehwa, Gyeonggi Province, Korea, between 2015 and 2017. The mean (± standard deviation) annual precipitation was 953 ± 107 mm and mean annual temperature was 12.7°C (−17.8°C to 33.9°C) according to the study site weather station. There are two types of vegetative cover in our study site—evergreen coniferous forest (TCK; 37.30482 N, 127.317489 E; 178 m a.s.l.) and deciduous broadleaf forest (TBK; 37.304047 N, 127.314244 E; 234 m a.s.l.). TBK is registered in the AsiaFlux network (http://asiaflux.net/).

Approximately 50-year-old planted Korean pine (Pinus koraiensis Siebold et Zucc.) dominates the TCK upper canopy. Stand density is approximately 400 trees ha−1. Mean diameter at breast height of Korean pines is 29.1 ± 5.1 cm, and the basal area is 27.4 m2 ha−1, which occupies more than 90% of total basal area (Park et al., 2018b). Korean azalea (Rhododendron yedoense f. poukhanense (H. Lév.) M. Sugim. ex T. Yamaz.) and East Asian sumac (Toxicodendron trichocarpum (Michx.) O. Kuntze) make up the understory.

TBK is a natural forest and oak trees (Quercus ailena Blume, and Q. variabilis Blume) dominate the upper canopy. Stand density is 1080 trees ha−1. Mean diameter at breast height of oak trees is 18.6 ± 5.1 cm, and the basal area is 17.6 m2 ha−1, which is 75% of total basal area. Fragrant styrax (Styrax obasua Siebold et Zucc.), royal azalea (R. schlippenbachii Maxim), East Asian sumac (T. trichocarpum (Michx.) O. Kuntze), and Korean mountain ash (Sorbus alnifolia (Siebold et Zucc.) K. Koch) form the understory.

2.2. LAI sources

2.2.1. In situ observation

In situ LAI observations were made using an LAI-2200 plant canopy analyzer (Li-Cor, Lincoln, NE, USA). We measured the LAI (LAIobs) every three weeks for the period with leaves (April to November), and once in December and March for the period without leaves (December to March). Radiation differences between above the canopy and bottom of canopy from LAI-2200 were converted to LAI using FV2200 software, which Li-Cor provided. In the conversion, two rings from the bottom (53° and 68°) were excluded to prevent overestimation of LAI by accounting for the slope of land at our site (Dufrêne and Bréda, 1995). In addition, we subtracted the mean LAI of TBK during winter from all LAI data to prevent overestimation of LAI by accounting for the slope of land at our site (Dufrêne and Bréda, 1995). After excluding unreliable spiky data, the observation data were smoothed using the smooth.spline() function in R (R Core Team, 2018), and then linearly interpolated into half-hourly values for JULES input or into daily values for further analysis.

2.2.2. Remote sensing

We used the LAI and enhanced vegetation index (EVI) (Huete et al., 2002) products from the moderate-resolution imaging spectro-radiometer (MODIS) and the EVI calculated from the Landsat surface reflectance product (Table 1). The MODIS LAI product (MCD15A3H, LAI.MODIS.LAI) (Myneni et al., 2015), which was obtained from two satellites (Terra and Aqua), is a four-day composite with a spatial average.
resolution of 500 m. Both MODIS EVI products from Terra (MOD13Q1) (Didan, 2015a) and Aqua (MYD13Q1) (Didan, 2015b) are 16-day composites with a spatial resolution of 250 m. Downloads were performed with the MODIS subset tool from the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL DAAC) (https://modis.ornl.gov). LaSRC is an atmospherically corrected product with a spatial resolution, TCK and TBK belonged to different pixels. Unrealistically high values during the winter and leaf-expansion period were either replaced with reliable previous values or interpolated in the time series (Kang et al., 2003; Slevin et al., 2015).

Landsat 8 operational land imager (OLI) and the thermal infrared sensor (TIRS)surface reflectance (LaSRC) product (Vermote et al., 2016) was retrieved from the Earth Explorer website (http://earthexplorer.usgs.gov). Surface reflectance was converted to an EVI using the following equation:

$$EVI = \frac{2.5f(NIR - RED)}{f(NIR + 6RED - 7.5BLUE)} + 1$$

where $f$ is a scale factor of 0.0001 (U.S. Geological Survey (U.S. Geological Survey, USGS, 2017) and RED, NIR, and BLUE are spectral reflectances with ranges of 620–670, 841–876, and 459–479 nm, respectively. In Landsat, RED corresponds to band 4, NIR corresponds to band 5, and BLUE corresponds to band 2. The coefficients 6 and 7.5 are for aerosol resistance; the coefficient for canopy background adjustment is 1 (Huete et al., 2002).

The EVI from the two satellites was converted to LAI using the two-period relationship method as described by Potithep et al. (2013). We separated the whole season into two periods: leaf-out to full expansion (period 1), and full expansion to senescence (period 2). For each period, the best-fitting models were selected from four types (simple, log-transformed, second-order polynomial, and third-order polynomial) of regression with the EVI as the independent variable and the observed LAI as the dependent variable (Table 1). In general, TBK, which has larger seasonal variation, and Landsat, which has higher resolution, showed a better relationship than TCK and MODIS (Fig. 1). As the observed LAI was addressed, remote-sensing LAls were smoothed using the smooth.spline() function of R and then linearly interpolated for further simulation and analysis (Fig. 2).

### 2.2.3. Leaf phenology model of JULES and its modification

Appendix A contains descriptions of how the phenology model of JULES estimates were made for LAI and how JULES upscaled leaf-level photosynthesis to the canopy scale. More detailed information can be found in Clark et al. (2011) and Cox (2001).

JULES phenology LAI ($LAI_{\text{pheno}}$) was obtained with default parameter values, with leaf-off temperature ($T_{\text{off}}$) in Eq. (A.2) set to $-40{}^\circ C$ and 5°C for TCK and TBK, respectively (Clark et al., 2011). This original LAIpheno was used for simulations and is reported throughout the results section. This phenology model was modified for each site based on observed values. For TCK, $T_{\text{off}}$ was increased to 5°C and the minimum value of the scale factor $p$ (Eq. (A.1)) was increased from 0.01 to 0.6875. For TBK, $T_{\text{off}}$ was also 5°C, and a new parameter representing the threshold temperature above which leaf onset starts ($T_{\text{out}}$) was set to 14.25°C. Adjustment of the threshold temperature was applied to other temperature-based phenology models (MacBean et al., 2015; Zhang et al., 2019). The latter modification in TBK (adding $T_{\text{out}}$) changed Eq. (A.2) to:

$$y_{\text{out}} = \begin{cases} y_0 + d_1(T_{\text{off}} - T_i), & T_i \leq T_{\text{off}} \\ y_0 + d_1(T_i - T_{\text{out}}), & T_i \leq T_{\text{out}} \end{cases}$$

where $T_{\text{out}}$ is the dormancy-to-non-dormancy transition period (from January to June), and $T_{\text{off}}$ is the non-dormancy-to-dormancy period (from July to December). The transition month (July) was selected because the summer solstice, which is an important physiological trigger of leaf phenology in temperate forests (Asaadi et al., 2018; Luo et al., 2018; Zhang et al., 2019), occurs around the third week of June, and the maximum annual LAI of temperate broadleaf forests such as TBK in East Asia (e.g. Potithep et al., 2013), Eastern USA (e.g. Asaadi et al., 2018), and Europe (e.g. Wang et al., 2005) is reached around that time. This modification enabled JULES to consider leaf-out and -fall temperatures separately.

### 2.3. Model setup and input data

JULES, a combined model of MetOffice Surface Exchange Scheme (MOSES, Cox et al., 1999) and Top-down Representation of Interactive Foliage and Flora Including Dynamics (TRIFFID, Cox et al., 2001), is a land surface model of the Met Office Unified Model that simulates land surface schemes (Clark et al., 2011). JULES represents surfaces with nine types of tile: five plant functional types (broadleaf trees, needleleaf trees, C3 grass, C4 grass, and shrubs) and four non-vegetated tiles (urban, inland water, bare soil, and ice). JULES uses LAI input from a predefined constant value, forced LAI, or calculated from the TRIFFID leaf phenology model.

JULES v4.7 was used in this study. All required meteorological forcing data (downward short-wave radiation, downward long-wave radiation, precipitation, wind speed, air temperature, air pressure, and specific humidity) were measured or calculated from measurements at the sites (e.g., vapor pressure to specific humidity). Diverse LALs were used as mentioned in Section 2.2 (Table 2). Soil evaporation and infiltration in JULES were modified as in Van den Hoof et al. (2013) (details are in Section 3.1.3). JULES parameter setup information is described in Table 3. The maximum rate of carboxylation ($V_{\text{max}}$) at 25°C was controlled using $\text{neff}_i$, which produces 4 $V_{\text{max}}$ at 25°C by multiplying by the top leaf nitrogen concentration (Clark et al., 2011), drawing on the $V_{\text{max}}$ value of 77.7 µmol m$^{-2}$ s$^{-1}$ for TCK (Han et al.,...
2004) and 74.4 μmol m$^{-2}$ s$^{-1}$ for TBK (Watanabe et al., 2014). The canopy structure factor was set to 0.5, based on stand density (Pinty et al., 2006). The simulation period (year/month/day) was from 2015/01/01 to 2017/12/31 for TCK and from 2015/03/01 to 2017/12/31 for TBK according to the duration of available meteorological data at each site. Spin-up was performed to stabilize initial soil moisture and temperature in JULES (Li et al., 2011) with a sufficient number of maximum cycle (101) and threshold (0.00001%).

### 2.4. Intra- and inter-annual variation in GPP

To calculate intra- and inter-annual variation compared with observed data, six transition dates were set as in Richardson et al. (2012) for all LAIs and GPPs with some modification based on field observation. Prior to the transition dates setup, daily GPP values were smoothed using the `smooth.spline()` function of R with a spar of 0.9 to prevent unrealistic transition dates due to fluctuating weather data. The six transition dates consisted of the three first spring dates on which GPP rose to 20%, 50%, and 80% of the amplitude (maximum GPP – minimum GPP), and the three last autumn dates on which GPP dropped below 20%, 50%, and 70% of the amplitude. We used a 20% threshold of first spring dates as the start of season (SOS) and a 20% threshold of last autumn dates as the end of season (EOS). We then calculated the anomalies (difference in number of days) of the SOS and EOS compared with those of LAI$_{obs}$ and GPP$_{obs}$ over the three years.

Annual GPP was compared with that of GPP$_{obs}$ for each year. In addition, all GPPs were divided into four seasons consisting of 1) spring (March–May), 2) summer (June–August), 3) autumn (September–November), and 4) winter (December–February). The seasonal GPP of each year and the average over the three years were calculated and compared to determine the contribution of each season to the difference in GPP among LAI sources.

### 2.5. Model evaluation and statistical analysis

We used root mean squared error (RMSE, Eq. (2)) and bias (Eq. (3)) to evaluate simulation results. RMSE was used as a metric for seasonal patterns, and the bias indicated degree of under- or overestimation. Each was calculated for the period during which observed LAI was greater than zero.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n} (x_t - \bar{x}_t)^2}{n}}$$

$$\text{Bias} = \frac{\sum_{t=1}^{n} x_t}{n} - \frac{\sum_{t=1}^{n} \bar{x}_t}{n}$$

where $x_t$ is an LAI other than LAI$_{obs}$ or GPP$_{JULES}$, $x_{t-1}$ is LAI$_{obs}$ or GPP$_{obs}$, and $n$ is number of data.

For the smoothed and interpolated daily LAI of each configuration, one-way repeated-measures analysis of variance was used to identify differences in mean LAI among the configurations. Through this analysis, we tried to determine whether any configuration pairs had different averages for LAI values of each day within a configuration as repeated measurements. Tukey’s honestly significant difference (Tukey’s HSD) was used as a post hoc test if the differences were significant. A Student’s t-test was used to check whether 1) average SOS

![Fig. 1. Relationship between estimated LAI from satellite-derived EVI and observed LAI for each site (TCK and TBK) and satellite (MODIS and Landsat). Solid lines are fitted from simple linear regression analysis; dashed lines are 1:1 lines. $R^2$ is the coefficient of determination, and asterisks (***) denote statistical significance ($p < 0.001$) of F-tests.](image)

![Fig. 2. LAI time series for three years (from January 2015 to December 2017 for TCK, and from March 2015 to December 2017 for TBK) of each LAI type in (a) TCK and (b) TBK. Description of abbreviations is in the legend in Table 2, or in the text.](image)

### Table 2

Configuration name of simulations and source of their LAI.

<table>
<thead>
<tr>
<th>Configuration Name</th>
<th>LAI Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs</td>
<td>Measured by LAI-2200</td>
</tr>
<tr>
<td>Pheno</td>
<td>JULES phenology model</td>
</tr>
<tr>
<td>MODIS_LAI</td>
<td>MODIS LAI product</td>
</tr>
<tr>
<td>MODIS_EVI</td>
<td>MODIS EVI product</td>
</tr>
<tr>
<td>Landsat</td>
<td>Landsat EVI product</td>
</tr>
</tbody>
</table>

![Table 2](image)
September of 2015 and 2017 was 3.97 m² m⁻² respectively. All pairs of configurations were almost unbiased compared with LAIobs (Table 4). The differences between LAI MODIS_EVI and LAI Landsat were 4.47 m² m⁻² respectively. RMSE for the entire period of LAI Landsat (0.30 m² m⁻²) was larger than that of LAI Landsat and LAI MODIS_EVI. Maximums of LAI MODIS_EVI, LAI Landsat, and LAI MODIS_LAI were significantly different. LAI pheno had a minimum of 0.05 m² m⁻², and its maximum LAI was about 5.00 m² m⁻². RMSE for the entire period of LAI pheno (1.06 m² m⁻²) was larger than that of LAI MODIS_LAI. Among the different configurations except for LAI obs and LAI Landsat had a statistically different mean according to Tukey’s HSD. The JULES leaf phenology model (LAI pheno) provided a constant LAI of 4.00 m² m⁻² in TCK, LAI pheno ranged from 2.53 m² m⁻² in April 2016 to 4.46 m² m⁻² in July 2016 (Fig. 2a, Table 4). The maximum LAI Landsat in September of 2015 and 2017 was 3.97 m² m⁻² and 4.10 m² m⁻² respectively. All pairs of configurations except for LAI obs and LAI Landsat had a statistically different mean according to Tukey’s HSD. The JULES leaf phenology model (LAI pheno) provided a constant LAI of 4.00 m² m⁻². LAI pheno showed a larger RMSE and bias (0.73 m² m⁻² and 0.49 m² m⁻², respectively) than those of LAI Landsat and LAI MODIS_LAI. Differences between LAI pheno and LAI obs ranged from −0.46 m² m⁻² to 1.46 m² m⁻², and this maximum difference from LAI obs was larger than that of LAI Landsat and LAI MODIS_LAI. Maximums of LAI MODIS_EVI and LAI Landsat were 4.47 m² m⁻² and 4.12 m² m⁻², respectively. RMSE for the entire period of LAI Landsat (0.30 m² m⁻²) was slightly smaller than that of LAI MODIS_LAI (0.37 m² m⁻²); however, both were almost unbiased compared with LAI obs (Table 4).

### Table 3

<table>
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<tr>
<th>Parameter</th>
<th>Description</th>
<th>TCK</th>
<th>TBK</th>
<th>Reference</th>
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<td>Soil ancillary</td>
<td>b</td>
<td>4.74</td>
<td>NIMS (2016)</td>
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<tr>
<td>sathb</td>
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</table>

3. Results

#### 3.1. LAI

In TCK, LAI obs ranged from 2.53 m² m⁻² in April 2016 to 4.46 m² m⁻² in July 2016 (Fig. 2a, Table 4). The maximum LAI Landsat in September of 2015 and 2017 was 3.97 m² m⁻² and 4.10 m² m⁻² respectively. All pairs of configurations except for LAI obs and LAI Landsat had a statistically different mean according to Tukey’s HSD. The JULES leaf phenology model (LAI pheno) provided a constant LAI of 4.00 m² m⁻². LAI pheno showed a larger RMSE and bias (0.73 m² m⁻² and 0.49 m² m⁻², respectively) than those of LAI Landsat and LAI MODIS_LAI. Differences between LAI pheno and LAI obs ranged from −0.46 m² m⁻² to 1.46 m² m⁻², and this maximum difference from LAI obs was larger than that of LAI Landsat and LAI MODIS_LAI. Maximums of LAI MODIS_EVI and LAI Landsat were 4.47 m² m⁻² and 4.12 m² m⁻², respectively. RMSE for the entire period of LAI Landsat (0.30 m² m⁻²) was slightly smaller than that of LAI MODIS_LAI (0.37 m² m⁻²); however, both were almost unbiased compared with LAI obs (Table 4).

### Table 4

<table>
<thead>
<tr>
<th>Site</th>
<th>Configuration</th>
<th>Min LAI (m² m⁻²)</th>
<th>Mean LAI (m² m⁻²)</th>
<th>Max LAI (m² m⁻²)</th>
<th>RMSE (m² m⁻²)</th>
<th>Bias (m² m⁻²)</th>
<th>RMSE growing (m² m⁻²)</th>
<th>Bias growing (m² m⁻²)</th>
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<td>3.51*</td>
<td>4.46</td>
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<td>MODIS, EVI</td>
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<td>0.09</td>
</tr>
<tr>
<td></td>
<td>Landsat</td>
<td>0.01</td>
<td>3.49*</td>
<td>4.91</td>
<td>0.58</td>
<td>0.11</td>
<td>0.63</td>
<td>0.04</td>
</tr>
</tbody>
</table>

and EOS in term of LAI and GPP over the three years and 2) average seasonal GPP over the three years were different between observation and other configurations. All statistical analyses were performed in R with a significance level (α) of 0.05.

Between LAI MODIS, EVI and LAI Landsat varied from −0.98 m² m⁻² to 0.68 m² m⁻², and, for LAI Landsat, from −0.82 m² m⁻² to 0.74 m² m⁻². In TBK, LAI Landsat ranged from 0.00 m² m⁻² in the period without leaves to 4.96 m² m⁻² in July 2016 (Fig. 2b, Table 4). The maximum LAI obs in 2015 and 2017 was 4.35 m² m⁻² in September and 4.96 m² m⁻² in July, respectively. All pairs of configurations except for LAI MODIS, EVI-LAI MODIS, LAI MODIS, EVI-LAI Landsat, and LAI MODIS, LAI MODIS, LAI Landsat were significantly different. LAI pheno had a minimum of 0.05 m² m⁻², and its maximum LAI was about 5.00 m² m⁻². RMSE for the entire period of LAI pheno (1.06 m² m⁻²) was larger than that of satellite-based LAI. Also, LAI pheno had the highest absolute value of bias for the entire period (0.6 m² m⁻²). Differences from LAI Landsat ranged from −2.59 m² m⁻² to 3.47 m² m⁻² for LAI pheno. Even though the pixels of the MODIS LAI product included both TCK and TBK sites, LAI MODIS, LAI showed a pattern of deciduous forest. LAI MODIS, LAI MODIS, EVI, and LAI Landsat had maximums of 6.49 m² m⁻², 5.02 m² m⁻², and 4.91 m² m⁻², respectively. Kwon et al. (2016) measured LAI in TBK by the litter trap method, resulting in a maximum annual LAI (5.2 m² m⁻²) similar to our measurement; this supports that our measured maximum value would be more reasonable than that of LAI MODIS, LAI. Among the three remote-sensing-based LAI, LAI Landsat had the smallest RMSE and absolute bias for the entire period (0.63 m² m⁻² and 0.04 m² m⁻², respectively), and LAI MODIS, LAI had the highest values (1.26 m² m⁻² and 0.10 m² m⁻², respectively). Differences from LAI obs varied from...
3.2. Average GPP

In TCK, yearly mean (± standard deviation) GPP for the entire period with observed LAI (GPP_LAI) was 1751.0 ± 80.3 g C m⁻² yr⁻¹. Compared with GPP_LAI, differences ranged from 0.0% (GPP_Landsat) to 4.5% (GPP_pheno) (Fig. 3a, Table 5). RMSE ranged from 0.29 g C m⁻² day⁻¹ to 0.45 g C m⁻² day⁻¹, and bias ranged from 0.00 g C m⁻² day⁻¹ to 0.21 g C m⁻² day⁻¹. GPP_pheno showed larger differences from GPP_LAI than did GPP using satellite-based LAI by RMSE and bias. GPP_MODIS_EVI was almost the same with GPP_Landsat, and these two results showed only a slight difference from GPP_LAI. In Fig. 3a, among the three configurations for the whole period, GPP_Landsat is closest to GPP_LAI, and GPP_MODIS_EVI is in almost the same position as GPP_Landsat. GPP_pheno placed farther from GPP_LAI than did GPP_MODIS_EVI and GPP_Landsat.

In TBK, GPP_LAI was 1548.2 ± 36.2 g C m⁻² yr⁻¹. Compared with GPP_LAI, differences ranged from 0.8% (GPP_MODIS_LAI) to 4.6% (GPP_Landsat) (Fig. 3b, Table 5). RMSE ranged from 0.76 g C m⁻² day⁻¹ to 1.05 g C m⁻² day⁻¹, and bias ranged from 0.03 g C m⁻² day⁻¹ to 0.20 g C m⁻² day⁻¹. GPP_pheno showed a relatively small difference from GPP_LAI (2.1%) compared with the large RMSE and bias of LAI. Unexpectedly, GPP_MODIS_LAI had the smallest difference and bias (0.8% and 0.03, respectively) among different configurations despite the large difference in maximum LAI (31%, Table 4). GPP_MODIS_EVI and GPP_Landsat were similar to each other, with 3.7% and 4.6% differences, respectively (Table 5). However, in terms of RMSE, GPP_Landsat and GPP_MODIS_EVI provided smaller errors than those of GPP_MODIS_LAI. In Fig. 3b, GPP_Landsat located the closest position to GPP_LAI followed by GPP_MODIS_EVI, GPP_pheno, and GPP_MODIS_LAI.

3.3. Inter- and intra-annual variation in GPP

Fig. 5 shows inter-annual variation in GPP of each configuration compared with GPP_LAI. In TCK, it ranged from −3.5% to 6.0%. GPP_pheno, which was simulated using constant LAI (LAI_pheno), was larger than GPP_LAI in every year, but the degree of overestimation was smallest in 2017. GPP_MODIS_EVI and GPP_Landsat had relatively small differences compared with GPP_LAI for all three years (from −3.8% to 2.8%). As with GPP_pheno, both had over-estimates in 2015 and 2016 and under-estimates in 2017. The differences in GPP were larger in TBK than in TCK. Inter-annual variations compared with GPP_LAI ranged from −6.5% to 10.9% for TBK. All configurations underestimated in 2017 and overestimated in 2015 and 2016, as GPP_MODIS_EVI and GPP_Landsat did in TCK. The degree of absolute difference was the largest in 2016.

Fig. 6 shows average and each year’s differences in the SOS and EOS for each configuration in terms of LAIobs and GPPobs, respectively. In TCK, none of the SOS and EOS in terms of LAI and GPP from model and satellites did not differ significantly from those of LAIobs and GPPobs. However, there were significant yearly variations. For example, the SOS dates of LAI_MODIS_EVI and LAILandsat were 13 and 25 days earlier in 2016, respectively, while they were 30 and 17 days later in 2017, respectively. The EOS dates of LAI_MODIS_EVI and LAILandsat were 5 and 13 days earlier in 2016, respectively, while both were 10 days later in 2015. The SOS and EOS based on GPP showed much smaller differences than those of LAI. The maximum difference was 9 days from EOS of GPP_pheno in 2016.

Unlike TCK, however, there were significant differences in LAI_MODIS_LAI and GPP_MODIS_LAI in TBK (Fig. 6b, d). MODIS_LAI had an earlier EOS in terms of LAI (∼39 ± 3 days, p = 0.002) and GPP (−19 ± 8 days, p = 0.049). Among the three years, the SOS was earlier in 2016 and later in 2017 in all configurations. As with TCK, the SOS in 2017 was later than the observed one. However, unlike the SOS, the yearly pattern of differences in the EOS was not the same for each configuration. The differences in the SOS of LAILandsat were 25 days earlier in 2016 and 13 days later in 2017, respectively. The differences in the EOS of LAILMODIS_EVI were 3 days earlier and 18 days later in 2016 and 2017, respectively. For GPP, the yearly patterns in SOS and EOS were similar to that of LAI. The maximum difference was 27 days from EOS of GPP_MODIS_LAI in 2015.

Fig. 7 shows average and each year’s difference in GPP for each season compared with GPP_LAI in TCK, GPP_pheno, which had a constant LAI, showed a larger GPP in spring (18.9 ± 12.3 g C m⁻² month⁻¹, p = 0.002) and winter (6.9 ± 3.4 g C m⁻² month⁻¹, p = 0.0003), which occupied 13.0% and 4.7% of mean monthly GPP_LAI, respectively. The pattern of yearly variation was not the same for each configuration.
and season, but both had the highest inter-annual variation in spring. Among the three years the differences in spring GPP were largest in 2016 and were less overestimated or underestimated in 2017. The maximum difference of spring GPP was 29.4 g C m⁻² month⁻¹ from GPP_phenology in 2016.

Like TCK, TBK also had the largest yearly variation in GPP in spring. All configurations had insignificantly large mean GPP differences in spring. There were only nonsignificant and trivial differences in summer. In autumn, GPP_MODIS_LAI was smaller than GPP_obs (p < 0.01); the others also had negative GPP differences but none were significant. In winter, all configurations had positive differences. GPP_MODIS_LAI showed a significant difference (p < 0.001) in winter, and it occupied 6.2% of mean monthly GPP_obs.

3.4. Modification of the phenology model

The JULES phenology model showed limitations in estimating LAI at stand level for both sites. In TCK, it displayed a constant LAI of 4.00 m² m⁻² throughout the entire period (Fig. 2a). This constant LAI was the outcome of a low default value of threshold temperature (−40 °C) in JULES for needleleaf forest (Clark et al., 2011) — far less than the minimum temperature at the study site (−17.6 °C). This problem of stationary LAI could be resolved by increasing the threshold temperature (Fig. 8a mod1). However, this modification caused a drop in LAI to near 0 m² m⁻², similar to LAI_phenology of TBK. The JULES phenology model could not produce a realistic LAI for evergreen needleleaf forests, which have seasonal variability in LAI, with the minimum value (2.75 m² m⁻² in TCK) greater than 50% of the maximum LAI. Additional modification of LAI scaling factor ρ to 0.6875 (explained in Section 2.3) improved the seasonal fluctuation of LAI in TCK (Fig. 8a mod2). The absolute bias became closer to 0 (from 0.49 m² m⁻² to −0.19 m² m⁻²), and RMSE dropped from 0.73 m² m⁻² to 0.49 m² m⁻².

In TBK, JULES was inflexible in simultaneously adjusting the SOS and EOS. That is, in the model, if the SOS begins late, EOS ends early, and EOS is later when SOS is earlier. It was not possible to let both SOS and EOS be earlier or later at the same time. The JULES phenology model determines leaf-out and leaf-fall using a threshold temperature (Clark et al., 2011). With a default value of the threshold temperature, there were many discrepancies in the timing of leaf-out and leaf-fall from the observed dates (Fig. 2b). After applying a modified threshold temperature and a new parameter for leaf-out temperature, JULES LAI estimates in TBK improved to provide more realistic EOS and SOS dates (Fig. 8b) compared with the previous dates (Fig. 2b). For the entire season, the absolute bias decreased from 0.49 m² m⁻² to −0.13 m² m⁻² with a slight increase in RMSE (from 0.95 m² m⁻² to 1.00 m² m⁻²). For the growing season, as for the entire season, the absolute bias decreased from 0.60 m² m⁻² to −0.25 m² m⁻², with a small trade-off in RMSE (from 1.06 m² m⁻² to 1.15 m² m⁻²).

4. Discussion

4.1. LAI source and JULES GPP inter- and intra-annual variation

Before addressing model outputs, we investigated how reliably the JULES with LAI_observations simulated GPP of the two sites compared with flux tower measurements by eddy covariance (GPP_EC in preparation). Although JULES underestimated annual GPP by 3% in TCK and 9.6% in TBK, it represented the general tendency of GPP_EC at the daily scale (Fig. 9). This supports the idea that JULES outputs with different LAIs are suitable for driving further discussion on yearly and seasonal variation in GPP estimates.

GPP was generally overestimated in 2015 and 2016 and underestimated in 2017 in both TCK and TBK (Fig. 5). The over- and under-estimates resulted from differences in seasonal GPP, especially in spring. Differences in spring GPP among different configurations showed the highest variation among the four seasons (Fig. 7). The high variation in spring GPP resulted from differences in the timing of leaf-out. For example, most configurations at both sites showed smaller spring GPP in 2017 (Fig. 7) because of late SOS (Fig. 6), in agreement with previous studies (e.g. Barr et al., 2002; Jolly et al., 2004; Richardson et al., 2010) that reported that the timing of spring onset directly affected spring productivity. GPP anomalies in autumn and winter as well as spring also caused interannual variation in GPP. LAI_MODIS_LAI consistently contained leaves during winter (Fig. 2b),
Fig. 6. (a) Average (± standard deviation) difference in number of days for start of season (SOS) and end of season (EOS) between (a), (b) observed LAI and other LAIs (except LAI from JULES phenology model in TCK) and (c), (d) simulated GPP using observed LAI and using other LAIs. Asterisks denote statistical significance of one-sample t-test investigating whether or not the average difference in number of days is 0 (*, $p < 0.05$; **, $p < 0.01$).

Fig. 7. Comparison of seasonal GPP among simulations with different LAI sources. Bars indicate average (± standard deviation) difference in GPP for each season between simulated GPP using observed LAI and other LAIs. A year was divided into four intervals: 1) spring (March to May), 2) summer (June to August), 3) autumn (September to November), and 4) winter (December to February). Asterisks denote statistical significance of one-sample t-testing of whether the average difference in GPP is 0 or not (*, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$).
which caused an average of 13.7 g C m$^{-2}$ month$^{-1}$ higher GPP$_{MODIS,LAi}$ in winter. Although GPP$_{MODIS,LAi}$ had significant differences from GPP$_{obs}$ in autumn and winter and an insignificant difference in spring, it had only a 0.8% difference from GPP$_{obs}$ in annual GPP (Table 5). The GPP discrepancies in autumn and winter compensated for each other, which resulted in a slight difference in annual GPP (Fig. 7b). Small annual GPP differences like these should be interpreted with caution because they can easily be construed as good agreement within the simulations, despite seasonal anomalies within them (Richardson et al., 2012).

In summer, unlike the other three seasons, all configurations except L. L. showed no difference compared with GPP$_{obs}$. This was caused by GPP saturation with increasing LAI. In other words, GPP did not increase with LAI linearly but reached its maximum asymptotically due to a clumping effect (Chen et al., 2012) and self-shading (Street et al., 2007). JULES also showed these effects in its GPP output. For example, in TBK, GPP was saturated at an LAI of 4.5 m$^2$ m$^{-2}$ and then decreased (Fig. 10). The GPP saturation in JULES caused small differences in GPP during summer when the LAI and photosynthesis rate were the highest within a year. These resulted in relatively small differences in annual GPP among the configurations. Ecosystem productivity is largely determined by growing season length because daily productivity of many ecosystems is comparable (Kerkhoff et al., 2005). This also supports a lower contribution to interannual variation in GPP by summer GPP compared with other seasons.

4.2. Limitations of the JULES phenology model

This study modified the JULES phenology model to correct for two limitations: 1) constant LAI in TCK, and 2) inflexible adjustment of SOS and EOS due to the use of only one parameter to determine both. Temperate evergreen forests have various minimum LAs depending on the species composition of the stand. For different stands, the modification of minimum LAI used in TCK should be applied with site-specific minimum LAI.

JULES showed a constant LAI for TCK because JULES considered the LAI of boreal forest conifer species such as Abies sp. and Spruce sp., which have LAs that hardly change because of the long lifespan of the leaves (e.g., Rautiainen et al., 2012). However, conifer species have leaf lifespans ranging from less than a year to 20 years (Wright et al., 2004), and this variety determines intra-annual LAI variability. For example, some Pinus sp. in temperate forests have leaves with a lifespan of two to three years (e.g. Withington et al., 2006). Their LAI, unlike species with longer leaf lifespans, changes by 30% to 40% of the maximum value. This fluctuation becomes more than 50% for Pinus strobus (e.g. Vose and Swank, 1990), whose leaf lifespan is only one and a half years (e.g. Wright et al., 2004). Ignoring intra-annual variation in LAI could therefore generate an error in annual GPP estimates. In our cases, the amount of this error was 6.0%, according to comparisons of GPP$_{obs}$ and GPP$_{pheno}$ in TCK.

JULES was set up with leaf onset and leaf offset at the same temperature, which our study showed was not a reasonable assumption. Therefore, making the model to adjust the starting temperature of leaf onset and offset separately was an appropriate modification that gave us more flexibility to adjust SOS and EOS dates in the model. As a
matters of practice, many other phenology models parameterize the SOS and EOS independently. For instance, the Canadian Terrestrial Ecosystem Model (CTEM) uses a carbon-gain-based approach to the SOS while it uses other constraints (i.e., day length, root temperature, and air temperature) for the EOS (Arora and Boer, 2005). Other models, including the Organizing Carbon and Hydrology in Dynamic Ecosystems (ORCHIDEE) (Krinner et al., 2005) and Spatially-Explicit Individual-Based Dynamic Global Vegetation Model (SEIB-DGVM) (Sato et al., 2007) regulate the SOS by computing cumulative heat sums while the EOS is regulated by a threshold temperature. However, some models use the same threshold temperature for the SOS and EOS, including the Lund–Potsdam–Jena (LPJ) DGVM (Sitch et al., 2003) and the Geophysical Fluid Dynamics Laboratory (GFDL) Land Model 3 with Perfect Plasticity Approximation (LM3-PPA) (Weng et al., 2015). The modification used in TBK could be applied to these models to differentiate the threshold temperature values for the SOS and EOS. Values for the transition month as well as the threshold value should be adjusted to be suitable for target area.

In summary, the modifications in the current study could improve phenology modeling in JULES for other temperate forests around the world, including East Asia, Europe, and Eastern US. These modifications could also be applied to other models that have a similar parameterization structure.

Although simple solutions for the two limitations of the JULES phenology model are described above, inter-anual variation of LAI remains unresolved. The model could be further improved by a mechanism or process-based modeling of the SOS and EOS. The SOS is generally known to be driven by temperature and precipitation (Fu et al., 2014; Piao et al., 2015), while the EOS is controlled by photo-period and temperature (Delpierre et al., 2009; Lang et al., 2019). These differences should be considered in phenology modeling of JULES by parameterizing the two phenomena independently. Recently, Lang et al. (2019) proposed a phenology model for autumn that considers photoperiod and temperature concurrently. This model may be used to improve JULES autumn phenology estimates. There are many sophisticated methods of representing leaf phenology (e.g., Arora and Boer, 2006; Richardson et al., 2013; Wang et al., 2018), but no single method estimates leaf phenology accurately, demonstrating a need for additional phenology model development (Medvigy et al., 2009; Richardson et al., 2012; Fisher et al., 2018).

4.3. Effect of spatial resolution

We used data from the Landsat and MODIS to retrieve LAI. Each has different spatial resolutions (30 m for Landsat, and 250 m and 500 m for MODIS). Remote sensing with low spatial resolution cannot recognize whole types of forest cover in a spatially heterogeneous region (Colombo et al., 2003). Forest cover type is as important a component of LSMs as LAI in simulating surface fluxes (Oleson and Bonan, 2000; Hartley et al., 2017). For this reason, it should always be a concern whether the spatial resolution of a satellite is sufficient for the study site. There is also a need to understand the effect of spatial resolution on LSM performance, which has hardly been studied.

A choice of satellite-based EVI between 30 m (Landsat) and 250 m (MODIS EVI) spatial resolutions would not create any significant difference when used with assimilating observed LAI (Fig. 6, 7). Landsat and MODIS EVIs depicted both deciduous and coniferous forests in this study, and they provided only slightly different results. Specifically, their LAI (Table 4) and GPP (Table 5) did not show significant differences from each other; their inter-annual (Fig. 5) and seasonal variation (Fig. 7) in GPP were also alike. On the other hand, LAI$_{MODIS,LAI}$ showed a large discrepancy from the two previous ones. It had earlier EOS (Fig. 6d), and this led to disagreements in seasonal GPP (Fig. 7). The maximum value over the three years in TBK was 6.49 m$^2$ m$^{-2}$, which was 31% higher than that of LAI$_{obs}$.

In addition, LAI$_{MODIS,LAI}$ misrepresented the LAI of a pixel as that of deciduous forest only, although the pixel contained both deciduous and coniferous forest (Fig. 2b). To investigate how much of an error in seasonal GPP was made from the misrepresentation of forest cover type by the MODIS LAI product, we compared the GPP of the four seasons between GPP$_{MODIS,LAI}$ and GPP computed from the actual ratio (TCK:TBK = 7:3). In other words, the latter was computed by weighing GPP$_{obs}$ of TCK and TBK. As a result, the latter had larger GPP in spring (123.2 gC m$^{-2}$ yr$^{-1}$) and winter (139.7 gC m$^{-2}$ yr$^{-1}$) than GPP$_{MODIS,LAI}$, whereas it had smaller GPP in summer (−131.8 gC m$^{-2}$ yr$^{-1}$) and no difference in autumn (−1.0 gC m$^{-2}$ yr$^{-1}$). The maximum difference in winter (139.7 gC m$^{-2}$ yr$^{-1}$) was 9.0% of GPP$_{MODIS,LAI}$ which emphasized again that a large error in seasonal GPP could be caused by an error in detecting forest cover type.

As with the results above, forest cover type was more influential in GPP simulation by LSM than was the spatial scale of LAI and meteorological input (Slevin et al., 2017; Park et al., 2018a). Similarly, Slevin et al. (2017) explained that projecting real forest cover type into the model may be influential in the GPP simulation. This was shown by Park et al. (2018a), who investigated the effect of tile size of surface subgrid heterogeneity (land cover type) on an LSM. The tile size of land cover type was effective at simulating surface fluxes by the LSM, especially on GPP, because of different phenological patterns of LAI and GPP between deciduous broadleaf and needleleaf forests, which affected the GPP result when a cover type was excluded from input dataset. The error in LAI$_{MODIS,LAI}$ and GPP$_{MODIS,LAI}$ may also be the result of coarse spatial resolution, which was insufficient for forests with heterogeneous covers. Therefore, we recommend choosing an LAI with sufficiently high spatial resolution to adequately depict land cover of the study site.

5. Conclusions

This study showed that the performance of a leaf phenology model and spatial resolution of satellite-derived LAI can affect the seasonal GPP estimated by the JULES LSM. The JULES phenology model represented an LAI of needleleaf tree species in boreal forests and could not consider the difference in leaf lifespan between boreal and temperate needle forests, which caused the model to provide a constant LAI throughout the year for temperate needleleaf forest. This misrepresentation was eliminated by allowing the model to senesce only a part of leaves instead of the entire leaves at once so that the model could account for the shorter leaf lifespan of temperate conifers. In addition, the phenology model was corrected to adjust the SOS and EOS flexibly by adding a parameter for the threshold temperature of leaf offset. These two modifications enabled the model to produce more realistic LAI values and could be applied to other models with a structure similar to that of JULES. Despite the improvements in the model, further research is still needed to correct remaining problems, such as inaccurate interannual variation in LAI and an undifferentiated phenology algorithm between leaf onset and offset periods. For spatial resolution of LAI, the MODIS LAI misrepresented a pixel containing both deciduous broadleaf forest and evergreen needleleaf forest as just deciduous broadleaf forest. This misrepresentation would cause incorrect seasonal GPP, which accounts for almost 10% of annual GPP. Once LAI spatial resolution was sufficiently fine to express the forest cover types well, the GPP estimate by an LSM was substantially improved.

Data availability

The JULES (v4.7) source code is available at the JULES FCM repository with registration (https://code.metoffice.gov.uk/trac/jules). The modified leaf phenology module code, configuration files, input data sets including meteorological data, the LAIs, and the resulted GPPs can be acquired at http://hosting01.snu.ac.kr/~treephys/index.php?mid=page_AnnA77.
Declarations of interest

None.

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Appendix A. More details about JULES

A.1 Phenology module of JULES

The leaf phenology model in JULES is an independent component of TRIFFID (Cox, 2001). It calculates an LAI as the product of maximum (or balanced) LAI and $p$, which denotes the phenological state of the time step. The scale factor $p$ is updated on the user-specified time step basis (daily as the default) as:

$$
\frac{dp}{dt} = \begin{cases} 
- \gamma_p \gamma_{lm} > 2 \gamma_0 \\
\gamma_p (1 - p), \; \gamma_{lm} \leq 2 \gamma_0 
\end{cases}
$$

(A.1)

where $\gamma_p$ is leaf growth rate (20 yr$^{-1}$), $\gamma_{lm}$ is leaf mortality rate (yr$^{-1}$), and $\gamma_0$ is the minimum leaf mortality rate (0.25 yr$^{-1}$ as the default for each plant functional type). The leaf mortality rate is calculated as a function of temperature:

$$
\gamma_{lm} = \gamma_0 (1 + \frac{d_r (T_{atf} - T_{sf})}{T_{sf}}), \; T_{atf} \leq T_{sf}
$$

(A.2)

where $T_{atf}$ is surface temperature (K), $T_{sf}$ is threshold surface temperature (K) below which leaves start to drop, and the factor $d_r$ relates leaf mortality and temperature change, which is set to 9 by default. The equations mean that the leaves will fall with at a rate of 10 times the minimum mortality rate when the surface temperature drops 1°C below the threshold temperature.

A.2 Upscale process from leaf photosynthesis to GPP in the JULES

Potential leaf level photosynthesis ($A_l$) of C$_3$ plants in JULES is computed as the smoothed minimum after accounting for three limiting factors: rubisco, light, and transport of photosynthetic products. $A_l$ is then multiplied by a soil water stress factor to obtain leaf level photosynthesis ($A_l$), which is used to calculate canopy scale photosynthesis, $A_c$ (or GPP). There are five upsampling methods in JULES. In this study option 4 in Table 3 of Clark et al. (2011) was used. It uses a multi-layer approach in which a canopy is divided into $n$ layers (10 as the default) with equal LAI increments (total LAI over $n$). Inhibition of leaf respiration in light, vertical profile of radiation and leaf nitrogen (photosynthetic capacity) are taken into account. $A_c$ is computed as the sum of products of $A_l$ and LAI of each canopy layer.

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