A grid dataset of leaf age-dependent LAI seasonality product (Lad-LAI) over tropical and subtropical evergreen broadleaved forests

Xueqin Yang[1,2,3], Xiuzhi Chen[1,*], Jiashun Ren[1,4], Wenping Yuan[1], Liyang Liu[5], Juxiu Liu[6], Dexiang Chen[7], Yihua Xiao[7], Shengbiao Wu[8], Lei Fan[9], Xiaoai Dai[4], Yunpeng Wang[3], and Yongxian Su[2]

[1] Guangdong Province Data Center of Terrestrial and Marine Ecosystems Carbon Cycle, Guangdong Province Key Laboratory for Climate Change and Natural Disaster Studies, School of Atmospheric Sciences, Sun Yat-sen University & Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), Zhuhai 519082, China

[2] Key Lab of Guangdong for Utilization of Remote Sensing and Geographical Information System, Guangdong Open Laboratory of Geospatial Information Technology and Application, Guangzhou Institute of Geography, Guangdong Academy of Sciences, Guangzhou 510070, China

[3] Guangzhou Institute of Geochemistry, Chinese Academy of Sciences, Guangzhou, 510640, China

[4] College of Earth Sciences, Chengdu University of Technology, Chengdu 610000, China;

[5] Laboratoire des Sciences du Climat et de l'Environnement, IPSL, CEA-CNRS-UVSQ, Université Paris-Saclay, 91191 Gif sur Yvette, France

[6] Dinghushan Forest Ecosystem Research Station, South China Botanical Garden, Chinese Academy of Sciences, Guangzhou 510650, China;

[7] Pearl River Delta Forest Ecosystem Research Station, Research Institute of Tropical Forestry, Chinese Academy of Forestry, Guangzhou 510650, China;

[8] School of Biological Sciences, The University of Hong Kong, Pokfulam, Hong Kong

[9] Chongqing Jinfo Mountain Karst Ecosystem National Observation and Research Station, School of Geographical Sciences, Southwest University, Chongqing 400715, China

*Correspondence: Xiuzhi Chen (chenxzh73@mail.sysu.edu.cn)

Abstract

Quantification of large-scale leaf age-dependent leaf area index has been lacking in tropical and subtropical evergreen broadleaved forests (TEFs) despite the recognized importance of leaf age in influencing leaf photosynthetic capacity in this biome. Here, we simplified the canopy leaves of TEFs into three age cohorts (i.e., young, mature and old one with different photosynthesis capacity ($V_{c,max}$)) and proposed a novel neighbor-based approach to develop a first grid dataset of monthly leaf age-dependent LAI product (**referred to as Lad-LAI**) at 0.25-degree spatial resolution over the continental scale during 2001-2018 from satellite observations of sun-induced chlorophyll fluorescence (SIF) that was reconstructed from MODIS and TROPOMI (the TROPOspheric Monitoring Instrument). The new Lad-LAI products show good performance in capturing the seasonality of three LAI cohorts, i.e., young (LAI_{young}) (R=0.36), mature (LAI_{mature}) (R=0.77) and old (LAI_{old}) (R=0.59) leaves, at the eight sites (four in south America, three in subtropical Asia and one in Congo) and can also represent their interannual dynamics at the Barrocolorado site, with R being equal to 0.54, 0.64 and 0.49 for LAI_{young}, LAI_{mature} and LAI_{old}, respectively. Additionally, the abrupt drops in LAI_{old} are mostly consistent with the seasonal litterfall peaks at 53 *in situ* measurements across the whole tropical region (R=0.82). The LAI seasonality of young and mature leaves also agrees well with the seasonal dynamics of Enhanced Vegetation Index (EVI) (R=0.61), which is a good proxy of effective leaves. Spatially, the grid Lad-LAI captures a dry-season green-up of canopy leaves across the wet Amazonia areas where mean annual precipitation exceeds 2,000 mm yr^{-1}, consistent with previous satellite-based analyses. The spatial patterns clustered from the three LAI cohorts also coincide with those clustered from climatic variables over the whole TEF region. The seasonality of LAI_{young}, LAI_{mature} and LAI_{old} derived from the estimated GPP based on a simple linear SIF-GPP relationship show the highest correlation with the *in situ* measurements at 8 observed sites compared with those derived from Orbiting Carbon Observatory-2-based SIF (GOSIF) GPP and eddy covariance flux tower

measurements (FLUXCOM) GPP. Additionally, the Lad-LAI products developed by the neighbor-based approach using 2*2 and 4*4 neighboring pixels show stable seasonality in LAI_{young}, LAI_{mature} and LAI_{old} across the whole tropical region, respectively. We provide the average seasonality of three LAI cohorts as the main dataset, and their time-series as a supplementary dataset. These two products are available at https://doi.org/10.6084/m9.figshare.21700955.v3 (Yang et al., 2022).

1. Introduction

Tropical and subtropical evergreen broadleaved forests (TEFs) account for approximately 34% of global terrestrial primary productivity (GPP) (Beer et al., 2010) and 40-50% of the world's gross forest carbon sink (Pan et al., 2011; Saatchi et al., 2011). Despite a perennial canopy, TEFs shed and rejuvenate their leaves continuously throughout the year, leading to significant seasonality in canopy leaf demography (Wu et al., 2016; Chen et al., 2021). This phenological changes in leaf demography is the primary cause of GPP seasonality in TEFs (Saleska et al., 2003; Sayer et al., 2011; Leff et al., 2012) and thus largely regulates their seasonal carbon sinks (Beer et al., 2010; Aragao et al., 2014; Saatchi et al., 2011).

A key plant trait linking canopy phenology with GPP seasonality was shown to be leaf age (Wu et al., 2017; Xu et al., 2017). At leaf scale, the newly-flushed young leaves and maturing leaves show higher maximum carboxylation rates ($V_{c,max}$) than the old leaves being replaced (De Weirdt et al., 2012; Chen et al., 2020). Such age-dependent variations in $V_{c,max}$ is associated with changes in leaf nutritional contents (nitrogen, phosphorus and potassium etc.) and stomatal conductance over time (Menezes et al., 2021). Xu et al. (2017) and Menezes et al. (2021) monitored *in situ* leaf age and leaf demography combined with leaf-level $V_{c,max}$ in Amazonian TEFs and found that $V_{c,max}$ of newly-flushed leaves increases rapidly with leaf longevity, peaks at approximately 2-month old and then declines gradually as leaf grows older (leaf age > 2 months). At canopy scale, it was hypothesized that leaf demography and seasonal differences in leaf

85   age compositions of tree canopies control the GPP seasonality in TEFs (Wu et al., 2016;

86   Albert et al., 2018). Similar mechanism was also observed by the ground-based LiDAR

87   which showed an increasing trend in upper canopy leaf area index (LAI) during the dry

88   season, whereas a decrease in lower canopy LAI (more old leaves) (Smith et al., 2019).

89   Wu et al. (2016) classified canopy leaves of Amazonian TEFs into three leaf age cohorts

90   (young: 1-2 months, mature: 3-5 months and old: ≥ 6 months). LAI of young and mature

91   leaves increases during the dry seasons and consequently promotes dry-season canopy

92   photosynthesis. Based on above age-dependent $V_{c,max}$ at leaf scale (Xu et al., 2017) and

93   LAI seasonality of different leaf age cohorts at canopy scale (Wu et al., 2016), Chen et

94   al. (2020; 2021) developed a climate-triggered leaf litterfall and flushing model and

95   successfully represented the seasonality of canopy leaf demography and GPP at four

96   Amazonian TEF sites. Overall, leaf age-dependent LAI seasonality is one of the vital

97   biotic factors in influencing the GPP seasonality in TEFs (Wu et al., 2016; Chen et al.,

98   2020).

99   Although the leaf age-dependent LAI seasonality can be well documented at site

100   level using phenology cameras (Wu et al., 2016), it is still rarely studied and remains

101   unclear at the continental scale. The key causation is that leaf flushing and litterfall of

102   TEFs in different climatic regions experience different seasonal constraints of water

103   and light availability during recurrent dry and wet seasons (Brando et al., 2010; Chen

104   et al., 2020; Davidson et al., 2012; Xiao et al., 2005). Thus, the seasonal patterns of LAI

105   in different leaf age cohorts become very complex at the continental scale (Chen et al.,

106   2020; Xu et al., 2015). Satellite-based remote sensing (Saatchi et al., 2011, Guan et al.,

107   2015) and land surface model (LSM) technologies (De Weirdt et al., 2012; Chen et al.,

108   2020; 2021) are two commonly used approaches for detecting the spatial heterogeneity

109   of plant phenology at a large scale. However, for satellite-based studies, most optical

110   signals are saturated in TEFs due to the dense covered canopies and thus fail to capture

111   the seasonality of total LAI in TEFs, much less decompose the LAI into different leaf

112   age cohorts. These limitations prevent satellite-based studies from accurately

representing the age-dependent LAI seasonality. Moreover, most ESM models also show poor performances in simulating the LAI seasonality in different leaf age cohorts (De Weirdt et al., 2012; Chen et al., 2020). This is because that the underling mechanisms linking seasonal water and light availability with leaf flushing and litterfall seasonality are currently highly debated and remain elusive at regional scale (Leff et al., 2012; Saleska et al., 2003; Sayer et al., 2011). This vague notion imposes a challenge for accurately modeling continental-scale GPP seasonality in most LSMs (Restrepo-Coupe et al., 2017; Chen et al., 2021).

To fill the research gap, this study aims to produce a global grid dataset of leaf age-dependent LAI seasonality product (Lad-LAI) over the whole TEF biomes from 2001 to 2018. For this purpose, we first simplified that canopy GPP was composed of three parts that were produced from young, mature and old leaves, respectively. GPP was then expressed as a function of the sum of the product of each LAI cohort (i.e., young, mature and old leaves, denoted as LAI_{young}, LAI_{mature}, and LAI_{old}, respectively) and corresponding net CO_2 assimilation rate (An, denoted as An_{young}, An_{mature}, and An_{old} for young, mature and old leaves, respectively) (**Equation 1**). Then, we proposed a novel neighbor-based approach to derive the values of three LAI cohorts. It was hypothesized that forests in adjacent four cells in the grid map exhibited consistent seasonality in both GPP, and LAI cohorts (LAI_{young}, LAI_{mature}, and LAI_{old}). Based on this assumption, we applied **Equation 1** to each pixel and combined the four equations of 2*2 neighboring pixels to derive the three LAI cohorts using a linear least-squares with constrained method. An was calculated using the Farquhar-von Caemmerer-Berry (FvCB) leaf photochemistry model (Farquhar et al., 1980); and GPP was linearly derived from an arguably better proxy—TROPOMI (the TROPOspheric Monitoring Instrument) Solar-Induced Fluorescence (SIF) based on a simple SIF-GPP relationship established by Chen et al. (2022) (see **Methods** for details). This grid dataset of three LAI cohorts provides new insights into tropical and subtropical phenology with more details of sub-canopy level of leaf seasonality in different leaf age cohorts and will be

141   helpful for developing accurate tropical phenology model in ESMs.

142

2. Study area and material

2.1 Tropical and subtropical evergreen broadleaved forest biomes

145   In this study, we focused on the whole tropical and subtropical evergreen broadleaf

146   forests (TEFs). The pixels labeled TEFs according to the International Geosphere-

147   Biosphere Program (IGBP) classification were extracted as the study area based on the

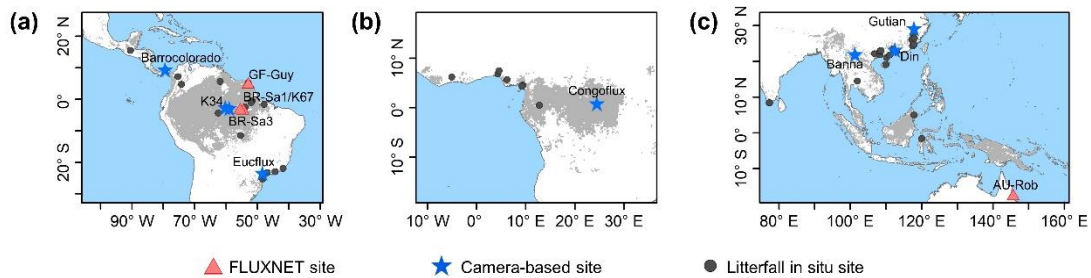
148   0.05° spatial resolution MODIS land cover map (**Fig. 1**) (MCD12C1, Sulla-Menashe et

149   al., 2018). The study area contains three regions: South America (30°S–18°N; 40°W–

150   90°W), the world's largest and most biodiverse tropical rain forest, Congo (10°S–10°N;

151   10°W−30°E), the western part of the Africa TEF region, and Tropical Asia (20°S–30°N;

152   70°E−150°E), covering the Indo-China Peninsula, the majority of the Malay

153   Archipelago and the northern Australia.

154

155   **Figure 1.** Study areas over tropical and subtropical evergreen broadleaves forests (TEF).

156   Red triangles: observed GPP seasonality at four eddy covariance (EC) tower sites. Blue

157   pentangles: observed LAI cohorts at eight camera-based observation sites. Black circles:

158   observed litterfall seasonality at 53 observation sites.

159

2.2 Input datasets for calculating GPP and An parameters

161   The TROPOspheric Monitoring Instrument (TROPOMI) Solar-Induced

162   Fluorescence (SIF) data were used to derive the continent-scale GPP (denoted as

163   RTSIF-derived GPP) according to the SIF-GPP relationship established by Chen et al.

164   (2022) which used 15.343 as a transformation coefficient to covert SIF to GPP. The air

165 temperature data from ERA5-Land (Zhao, Gao et al., 2020), vapor pressure deficits

166 (VPD) data from ERA-Interim (Yuan et al., 2019) and downward shortwave solar

167 radiation (SW) from Breathing Earth System Simulator (BESS) (Ryu et al., 2018) were

168 used to calculate K_C, K_O, Γ^*, R_{dark} and $V_{c,max}$ and thus to calculate An according to

169 equations in **Table S4** . The calculation processes were illustrated in **Fig. 2**. All datasets

170 were aggregated at the same spatial (0.125°) and temporal resolutions (month) (**Table**

171 **S3**).

172

173 **2.3 Datasets for validating leaf age-dependent LAI seasonality**

174 **Ground-based seasonal LAI cohorts and litterfall data**. Top-of-canopy

175 imageries observed by ground-based phenology cameras were used to decompose

176 canopy LAI into LAI_{young}, LAI_{mature} and LAI_{old}. In total, imageries from eight

177 observation sites across the whole TEF region were used to validate the simulating

178 results (blue pentangles in **Fig. 1**, **Table S1**). Additionally, the seasonal litterfall data

179 from 53 *in situ* sites (black circles in **Fig. 1**, **Table S6**) spanning the TEFs were collected

180 from globally published articles to compare with the phase of simulated LAI_{old}

181 seasonality (see **Methods** for details). The multiyear monthly litterfall data were

182 averaged to the monthly mean to compare with the seasonality of simulated LAI_{old}.

183 Four eddy covariance flux tower sites (red triangles in **Fig. 1**, **Table S2**) provided *in*

184 *situ* seasonal GPP data to evaluate the seasonality of RTSIF-derived GPP.

185 **Satellite-based seasonal EVI data**. To evaluate the LAI seasonality of

186 photosynthesis-effective leaves, i.e., young and mature leaves, this study used satellite-

187 based MODIS Enhanced Vegetation Index (EVI) (Huete et al., 2002; Lopes et al., 2016;

188 Wu et al., 2018) as a remotely sensed proxies alternatives of effective leaf area changes

189 and new leaf flush, i.e., $LAI_{young+mature}$ (Wu et al., 2016; Xu et al., 2015). To prove the

190 robustness of the products over a large spatial coverage, the seasonal LAI cohorts of

191 young and mature leaves were evaluated against the enhanced vegetation index (EVI)

192 product, which was considered as a proxy for leaf area changes of photosynthetic

193   effective leaves (Xu et al., 2015; Wu et al., 2016; de Moura et al., 2017).

194

3. Methods

3.1 Decomposing LAI cohorts (young, mature and old) from SIF-derived GPP

Figure 2 illustrates the overall framework used to generate leaf age-dependent LAI seasonality product (Lad-LAI). The majority of the tropical and subtropical EBFs retain leaves year-round and their total LAI shows marginally small spatial and seasonal changes (Wu et al., 2016) (**Figs. S3, S4**). Therefore, previous modelling studies have assumed a constant value for the total LAI in tropical and subtropical EBFs (Cramer et al., 2001; Arora and Boer, 2005; De Weirdt et al., 2012). Based on this, we collected observed seasonal LAI dynamics in tropical and subtropical EBFs from previously published literatures which showed a constant value of LAI around 6.0 (**Figs. S3**, **S4**, **Table S5**). Thus, in this study, we simplified to assume that the seasonal LAI was approximately equaling to 6.0 in tropical and subtropical EBFs. We grouped the canopy leaves of tropical and subtropical EBFs into three leaf age cohorts, i.e., young, mature and old leaves, respectively. Then, the total GPP was defined as the sum of those produced by the young, mature and old leaves, respectively. According to the Farquhar-von Caemmerer-Berry (FvCB) leaf photochemistry model (Farquhar et al., 1980), GPP can be expressed as function of the sum of the products of each LAI cohort (LAI_{young}, LAI_{mature}, and LAI_{old}) and corresponding net CO_2 assimilation rate (An_{young}, An_{mature}, and An_{old}) (**Equation 1**).

$$GPP = LAI_{young} \times An_{young} + LAI_{mature} \times An_{mature} + LAI_{old} \times An_{old} \quad (1)$$

where LAI_{young}, LAI_{mature} and LAI_{old} are the leaf area index of young, mature and old leaves, respectively; An_{young}, An_{mature} and An_{old} are the net rate of CO_2 assimilation dependent on three leaf age classes; GPP is canopy total gross primary production. The sum of LAI_{young}, LAI_{mature} and LAI_{old} was set as a constant in this study, equaling to 6.0.

The grid GPP data over the whole EBFs were derived from SIF (denoted as RTSIF-derived GPP) using a linear SIF-GPP regression model (see sect. 3.2) which were

221 established based on *in situ* GPP from 76 eddy covariance (EC) sites (Chen et al., 2022).

222 The An_{young}, An_{mature} and An_{old} were calculated according to the FvCB biochemical

223 model (Farquhar et al., 1980; Bernacchi et al., 2003) (see section 3.3). As there were

224 three unknow variables (i.e., LAI_{young}, LAI_{mature} and LAI_{old}) to be solved in **Equation**

225 **1**, we hypothesized that the adjacent four pixels exhibited homogenous EBFs and

226 consistent leaf demography and canopy photosynthesis. Then, we used the GPP and An

227 data from adjacent four pixels to estimate their LAI_{young}, LAI_{mature} and LAI_{old} based on

228 **Equation 1** using a linear least-squares with constrained method. The inputs grid

229 datasets (i.e., RTSIF-derived GPP and An derived from T_{air}, VPD and SW) (**Table S3,**

230 **Fig. 2**) were sampled at 0.125-degree spatial resolution; while the output maps of

231 LAI_{young}, LAI_{mature}, and LAI_{old} were at 0.25-degree spatial resolution. Therefore, the

232 output maps of LAI_{young}, LAI_{mature}, and LAI_{old} were at a 0.25-degree spatial resolution.

233 Additionally, to test the robustness of the neighbor-based decomposition approach, we

234 increased the number of adjacent pixels from 4 (2*2) to 16 (4*4) to produce another

235 version of Lad-LAI products with spatial resolution of 0.5-degree. All our analyses

236 were conducted using the Python (version 3.7, http://www.python.org) and Matlab

237 (version R2019b) software.

238

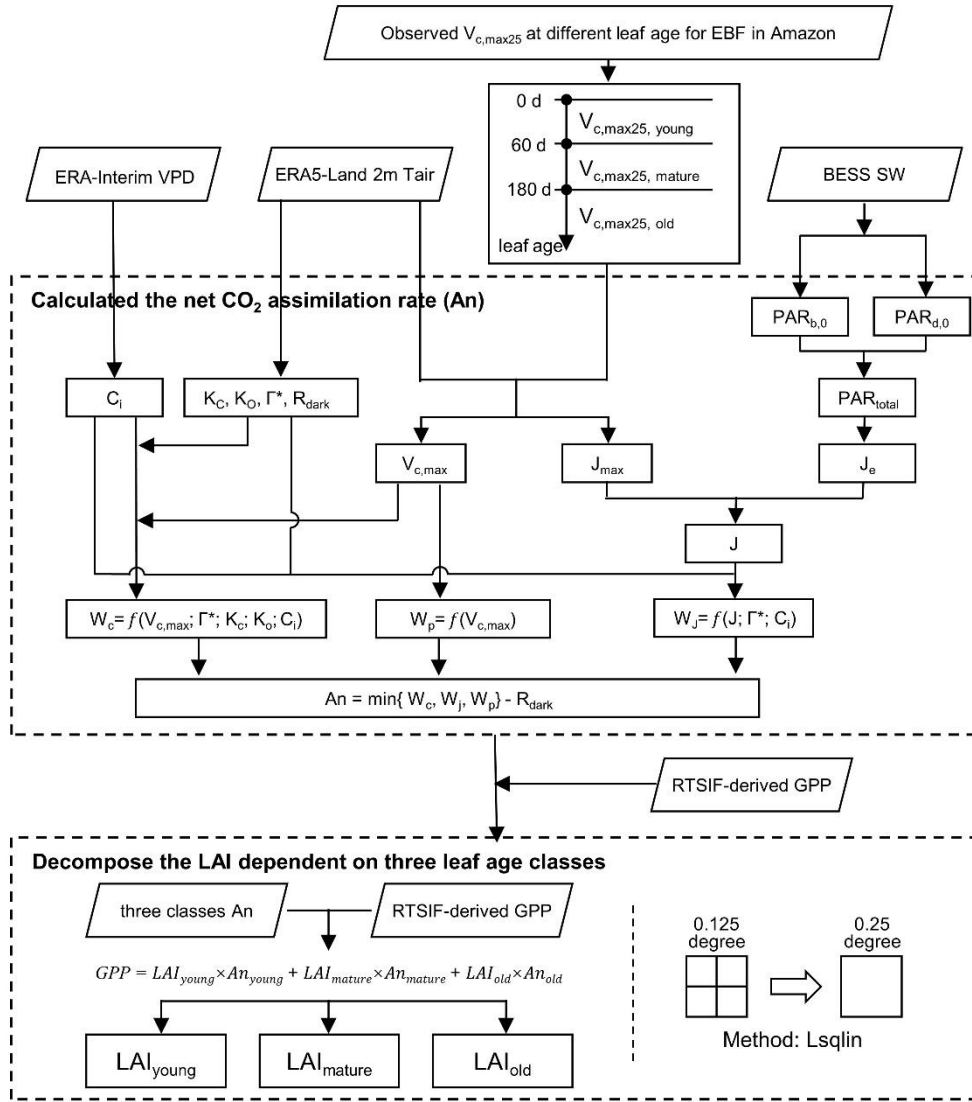



Figure 2. The workflow for mapping Lad-LAI using the Lsqlin method. Lsqlin is the abbreviation of Linear least-squares solver with bounds or linear constraints. All the abbreviations were described in supplementary **Tables S4**.

242

3.2 Calculating the GPP (RTSIF-derived GPP) from TROPOMI SIF

Satellite-retrieved solar-induced chlorophyll fluorescence (SIF) is a widely used proxy for canopy photosynthesis (Yang et al., 2015; Dechant et al., 2020). Here, we used a long-term reconstructed TROPOMI SIF dataset (RTSIF) (Chen et al., 2022) to estimate GPP seasonality. Previous analyses showed that RTSIF was strongly linearly correlated to eddy covariance (EC) GPP and used 15.343 as a transformation coefficient

249   to covert RTSIF to GPP (Fig. 8a in Chen et al., 2022). In this study, we followed

250   previously published literatures to set a constant value of LAI around 6.0 for the whole

251   tropical and subtropical EBFs (**Figs. S3**, **S4**, **Table S5**). We collected seasonal GPP data

252   observed at four EC sites from the FLUXNET 2015 Tier 1 dataset (**Table S2**; Pastorello

253   et al., 2020) and validated the Chen's simple SIF-GPP relationship (**Fig. S1**). Results

254   confirmed the robustness of Chen's simple SIF-GPP relationship in estimating the GPP

255   seasonality in tropical and subtropical EBFs (R>0.49). Despite potential overestimation

256   (**Fig. S1 b**) or underestimation (**Fig. S1 h**) of the magnitudes, RTSIF-derived GPP

257   mostly captured the seasonality of the EC GPP at all the four sites (d_{phase} < 0.26).

258

259   **3.3 Calculating the net rate of CO_2 assimilation (An)**

260   We calculated the net CO_2 assimilation (An) using the FvCB biochemical model

261   (Farquhar et al., 1980). In this model, the parameter An was calculated as the minimum

262   of Rubisco (W_c), RuBP regeneration (W_j) and TPU (W_p) to minus dark respiration (R_{dark})

263   (Bernacchi et al., 2013). The formulas for calculating An, W_c, W_j, W_p, R_{dark} and

264   corresponding intermediate variables were listed in **Tables S4**.

265   ***Calculation of W_c.*** W_c is expressed as a function of internal CO_2 concentration (c_i),

266   Michaelis-Menton constant for carboxylase (K_c), Michaelis-Menton constant for

267   oxygenase (K_o), CO_2 compensation point (Γ^*) and maximum carboxylation rate ($V_{c,max}$)

268   (**Table S4-part1**) (Lin et al., 2015; Bernacchi et al., 2013; Ryu et al., 2011; Medlyn et

269   al., 2011; June et al., 2004; Farquhar et al., 1980). The K_c, K_o, Γ^* and $V_{c,max}$ are

270   temperature-dependent variables. Thus, we used **Equation 2** to calculate their values at

271   T_k by converting from those at 25°C. Then, we used the Medlyn's stomatal conductance

272   model (Medlyn et al., 2011) to estimate internal CO_2 concentration (c_i) (**Equation 3**),

273   which is expressed as a function of vapor pressure deficit (VPD) rather than relative

274   humidity (Lin et al., 2015). The method for calculating the $V_{c,max}$ of each LAI cohort

275   was introduced in section 3.4. The formulas for calculating corresponding intermediate

276   parameters were presented in **Table S4**.

277 $$Para = Para_{25} \times exp\left(\frac{(T_k-298.15)\times \Delta H_{para}}{R \times T_k \times 298.15}\right) \qquad (2)$$

278 where *Para* denotes a correction factor arising from the temperature dependence of

279 $V_{c,max}$; $Para_{25}$ are values of the temperature-dependent parameters (K_c, K_o, Γ^* and $V_{c,max}$)

280 at the temperature 25°C; T_k denotes temperature in Kelvin; ΔH_{para} is the activation

281 energy for temperature dependence; R is the universal gas constant.

282 $$c_i = c_a \times \left(1 - \frac{1}{1.6 \times \left(1 + \frac{g_1}{\sqrt{VPD}}\right)}\right) \qquad (3)$$

283 where c_a is atmospheric CO_2 concentration, 380 ppm; VPD is calculated from air

284 temperature and dew point temperature of the global ERA-Interim reanalysis dataset

285 (Dee et al., 2011) using the method of Yuan et al. (2019). The calculation formula of

286 VPD was described in supplementary files. In this study, we used the value of 3.77 for

287 the stomatal slope (g_1) in the stomatal conductance model according to Lin et al. (2015).

288   ***Calculation of W_p.*** W_p was calculated as the function of $V_{c,max}$, which were given

289 different values for different LAI cohorts based on multiple *in situ* observations (section

290 3.4).

291   ***Calculation of W_j.*** W_j was calculated from $V_{c,max}$, c_i and the rate of electrons

292 through the thylakoid membrane (J) (Bernacchi et al., 2013). The parameter J was

293 calculated from maximum electron transport rate (J_{max}) and the rate of whole electron

294 transport provided by light (J_e) (Bernacchi et al., 2013). J_{max} was expressed as a

295 temperature dependence function of maximum electron transport rate ($J_{max,25}$) at 25°C

296 and temperature (T_{air}) and J_e was expressed as a function of total PAR absorbed by

297 canopy (PAR_{total}) that was the sum of active radiation in beam ($PAR_{b,0}$) and diffuse

298 ($PAR_{d,0}$) light firstly (Weiss et al., 1985), which were calculated from downward short-

299 wave radiation (SW) (Ryu et al., 2018). The formula for PAR_{total} was given in **Equation**

300 **4** and formulas for other intermediate parameters (i.e., $PAR_{b,0}$, $PAR_{d,0}$, ρ_{cb}, ρ_{cd}, $k^{'}_b$, $k^{'}_d$,

301 and *CI*) were listed in **Table S4**.

302 $$PAR_{total} = (1-\rho_{cb}) \times PAR_{b,0} \times \left(1 - exp(-k'_b \times CI \times LAI_{total})\right) + (1-\rho_{cd}) \times$$

303 $$PAR_{d,0} \times \left(1 - exp(-k'_d \times CI \times LAI_{total})\right) \qquad (4)$$

where PAR_{total} is total PAR absorbed by canopy; $PAR_{b,0}$ is the active radiation; $PAR_{d,0}$ is diffuse radiation; LAI_{total} is a total LAI. Here, we used a constant value of 6.0 according to De Weirdt et al. (2012).

3.4 Classifying three LAI cohorts with different $V_{c,max}$

In this study, we collected *in situ* samples of $V_{c,max25}$ data against different leaf age across tropical and subtropical EBFs from previous publications. Mature leaves (leaf age: 70-160 days) show highest $V_{c,max25}$ than those of new flushed leaves (leaf age: <60 days) and old leaves(leaf age: >200 days) as Menezes et al. (2021). Therefore, in this study, we classified the canopy leaves into three cohorts: young (leaf age: <2 months), mature (leaf age: 3-5 months) and old cohorts (leaf age: >6 months) as Wu et al. (2016). The $V_{c,max25}$ for young, mature and old cohorts were set as 60, 40 and 20 μmol m^{-2} s^{-1}, respectively, according to previous ground-based observations by Chen et al. (2020).

3.5 Decomposing camera-based LAI into three leaf age cohorts

We classified the canopy leaves into young, mature and old age cohorts based on the green-color band from the top-of-canopy imageries observed by RGB camera. It is because that the brightness of different leaf age leaves differs greatly in the values of green-color band. Raster density slicing is a useful classification method for detecting the attributes of various ground objects (Kartikeyan et al., 1998). Therefore, we set three brightness thresholds to divide young (blue), mature (green), old (yellow) leaves and background (gray) for the same canopy extent in each month (**Fig. S2**). This analysis was conducted in ENVI5.3 software.

3.6 Evaluating the $LAI_{young+mature}$ seasonality and its spatial patterns using satellite-based EVI products

To compare the seasonality of $LAI_{young+mature}$ with those of EVI, we calculate mean squared deviation (MSD) and their three components—d_{bias}, which denotes the

332   differences about absolute value, d_{var}, which denotes the differences of seasonal

333   fluctuations, and d_{phase}, which denotes the differences of peak phase to evaluate this

334   consistence, comprehensively (see section 3.8). Additionally, we compared the spatial

335   patterns of the wet- minus dry-season differences (Δ) between observed and simulated

336   variables, following the work of Guan et al. (2015). To determine the wet and dry

337   seasons in each grid cell, we defined a month as dry one when its monthly average

338   precipitation was smaller than the potential evapotranspiration (PET) computed using

339   the method of Maes et al. (2019); other months were classified as wet ones. The wet-

340   minus dry-season $LAI_{young+mature}$ (denoted as $\Delta LAI_{young+mature}$) was calculated for each

341   grid cell as the wet-season average $LAI_{young+mature}$ value minus the dry-season average

342   value of $LAI_{young+mature}$.

343

344   **3.7 Evaluating the LAI_{old} seasonality using ground-based litterfall data**

345   Litterfall is closely related to the seasonal dynamics of old leaves, i.e., LAI_{old} (Chen

346   et al., 2020; Yang et al., 2021). Previous analyses indicated that, in general, a sharping

347   decrease in LAI_{old} corresponded to a peak in litterfall (Pastorello et al., 2020; Midoko

348   Iponga et al., 2019; Ndakara, 2011; Barlow et al., 2007; Dantas and Phillipson, 1989).

349   Based on this causal relationship between litterfall and LAI_{old}, we compared the time

350   of seasonal litterfall peak with the time of abrupt drops in LAI_{old}, to indirectly evaluate

351   the simulated LAI_{old} seasonality. To accurately detect the onset date of old leaves

352   shedding and the day of litterfall peak, we used a least-square regression analysis

353   method developed by Piao et al. (2006) to smoothen LAI_{old} and litterfall seasonal curves.

354   The sixth-degree polynomial function (n=6) was applicable to the regression (**Equation**

355   **5**).

356    $LAI_{old} = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4 + a_5 x^5 + a_6 x^6$ (5)

357   where x is the day of a year.

358   The slope of seasonal LAI ($LAI_{old,\ ratio}$) was calculated in **Equation 6**. The date of

359   abrupt drops in LAI_{old} was defined as the time with most negative values of $LAI_{old,\ ratio}$.

360     $LAI_{old,ratio(t)} = \left(LAI_{old(t+1)} - LAI_{old(t)}\right)/\left(LAI_{old(t)}\right)$ (6)

361   where $LAI_{old,\ ratio}$ is the slope of seasonal LAI_{old} curve. $LAI_{old(t+1)}$ and $LAI_{old(t)}$ are the

362   corresponding monthly LAI at time t+1 and t, respectively.

363

364   **3.8 Evaluation Metrics**

365   Two metrics were chosen to evaluate the seasonality of Lad-LAI against the that of

366   other proxies: the Kobayashi decomposition of the Mean Square Difference between

367   model and observation (Kobayashi and Salam, 2000) and the Pearson correlation

368   coefficient (Pearson, 1896) for gridded fields.

369   ***Mean squared deviation (MSD).*** The mean squared deviation (MSD) was given

370   by Kobayashi and Salam (2000):

371     $MSD = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2$ (7)

372     $SB = (\bar{x} - \bar{y})^2$ (8)

373     $SD_s = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}$ (9)

374     $SD_m = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2}$ (10)

375     $SDSD = (SD_s - SD_m)^2$ (11)

376     $LCS = 2SD_sSD_m(1 - r)$ (12)

377   where mean squared deviation is the square of RMSD; i.e., MSD = RMSD^2; and x_i is

378   the simulated data at time t, and y_i is the observed one at time t (month). The lower the

379   value of MSD, the closer the simulation is to the measurement. MSD can be

380   decomposed into the sum of three components: the squared bias (d_{bias}), d_{bias}=SB; the

381   squared difference between standard deviations (variance-related difference, d_{var}),

382   d_{var}=$SDSD$; and the lack of correlation weighted by the standard deviations (phase-

383   related difference, d_{phase}), d_{phase}=LCS; r indicates the correlation coefficient between x

384   and y.

385   ***Pearson correlation coefficient (R)***. The Pearson correlation coefficient is a

386   measure of linear correlation between two variables (Merkl and Waack, 2009). The

387   correlation coefficient between X and Y was as:

388    $$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X\sigma_Y} = \frac{E\big((X-\mu_X)(Y-\mu_Y)\big)}{\sigma_X\sigma_Y} \qquad (13)$$

389

390   **3.9 The quality control (QC) for the Lad-LAI product**

391   To warn potential uncertainties, we provided information of data quality control

392   (QC) along with the Lad-LAI product (**Fig. S5**). In the QC system (**Table S7**), data

393   quality was divided into four levels: level 1 represents the highest quality; level 2 and

394   level 3 represent good and acceptable quality, respectively; and level 4 warns to be used

395   cautiously. This QC product was generated according to residual sum of squares (RSS)

396   (Melgosa et al., 2008) obtained from the constrained least-squares method that was used

397   to estimate derive monthly Lad-LAI data.

398

399   **4. Results**

400   **4.1 Comparison of LAI cohort seasonality with sparse site observations**

401   The simulated leaf age-dependent LAI seasonality product was validated against

402   the camera-based measurements of LAI_{young}, LAI_{mature}, and LAI_{old} at four sites in south

403   America, one site in Congo and three sites in China. Overall, the LAI seasonality of

404   mature and old classes from the new Lad-LAI products agrees well at these sites with

405   very fine-scale collections of monthly LAI of mature (R=0.77, MSD=0.69) and old

406   leaves (R=0.59, MSD=0.62). However, the seasonality of simulated LAI from young

407   leaves performs a little poor (R=0.36, MSD=0.45). It is also interesting to note that the

408   canopy leaf phenology of TEFs at these sites differ greatly. In south America, at K67,

409   K34 and Eucflux sites, both *in situ* and simulated LAI_{young} and LAI_{mature} decrease at

410   early dry season around February and convert to increase at early wet season around

411   June (**Fig. 3 a, b, d, e, j, k**). At the Barrocolorado site, LAI_{young} increases from the late

412   dry to early wet season around Mar in response to the increasing incoming shortwave

413   radiation and in contrast, LAI_{mature} starts to increase at wet season around June (**Fig. 3**

414   **g, h**). However, in subtropical Asia, LAI_{young} and LAI_{mature} increase during the wet

428

Figure 4. Seasonality of simulated LAI_{young}, LAI_{mature}, and LAI_{old} in comparison with observed data at one site in Congo. (a) Simulated LAIs; (b) observed LAIs; and (c) scatterplots between simulated and observed LAIs. Limegreen dots are LAI_{young}; green dots are LAI_{mature}; orange dots are LAI_{old}.

433

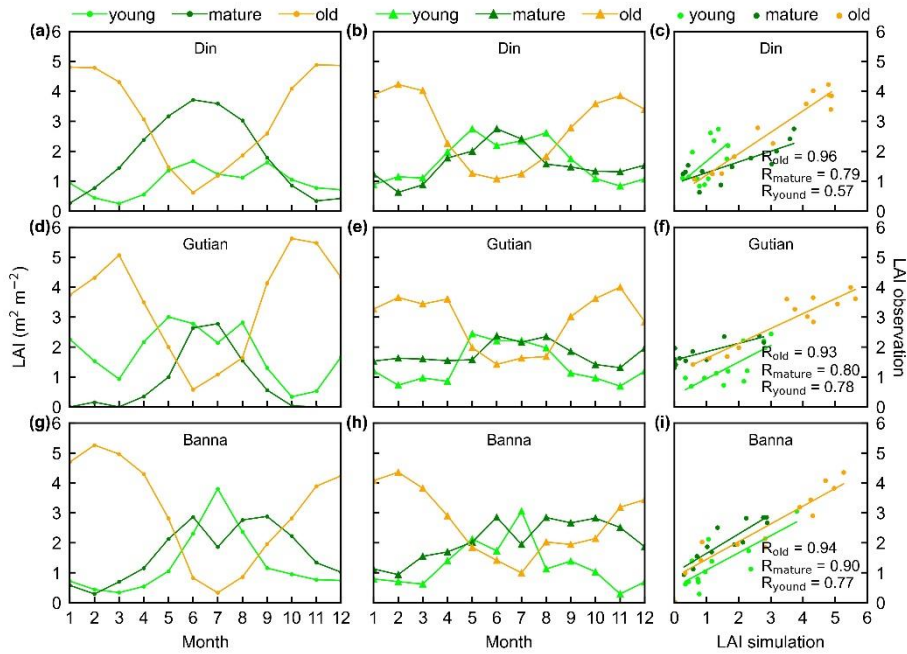
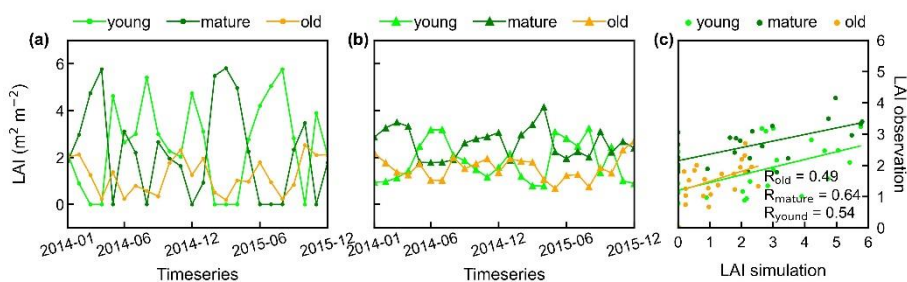



Figure 5. Seasonality of simulated LAI_{young}, LAI_{mature}, and LAI_{old} in comparison with observed data at 3 sites in tropical Asia. (Panels a, d and g) simulated LAIs; (panels b, e and h) observed LAIs; (panels c, f and i) scatterplots between simulated and observed LAIs. Limegreen dots are LAI_{young}; green dots are LAI_{mature}; orange dots are LAI_{old}.

Additionally, only one ground site (Barrocolorado site in Panama) had time-series camera-based phenological imageries, which was then used to evaluate capacity of Lad-LAI in representing the interannual dynamics of three LAI cohorts, with R values being equal to 0.54, 0.64, 0.49 for LAI_{young}, LAI_{mature}, LAI_{old}, respectively (**Fig. 6**). However,

450

451 **Figure 6.** Timeseries of simulated LAI_{young}, LAI_{mature}, and LAI_{old} in comparison with

452 observed data at Barrocolorado site in Panama. (a) Simulations LAIs; (b) observation

453 LAIs; and (c) scatterplots between simulated and observed LAIs.

454

455 **4.2 Comparison of patterns of grid LAI cohort seasonality with previous climatic**

456 **and phenological patterns**

457   The *in situ* measurements of LAI_{young}, LAI_{mature}, and LAI_{old} suggested diverse

458 patterns of Lad-LAI seasonality over the TEFs. Nevertheless, the sparse coverage of

459 these sites raised challenging for a comprehensive and direct evaluation of leaf age-

460 dependent LAI seasonality product. To continue the grid Lad-LAI seasonality product

461 at the regional scale, we further conducted spatial clustering analyses of LAI_{young},

462 LAI_{mature}, and LAI_{old} using the *K*-means analysis method.

463   Surprisingly, the spatial patterns of Lad-LAI product clustered from satellite-based

464 vegetative signals (**Fig. 7 g-i**) coincide well with those clustered from in-dependent

465 climatic variables (rainfall and radiation etc.) (**Fig. 7 a-c**). These patterns are also

466 similar as those of the climate-phenology rhythms mapped by Yang et al. (2021), which

467 suggest different correlations of litterfall seasonality with canopy phenology between

different climate-phenology rhythms (**Fig. 7 d-f**). In central (sub-region S2) and south (sub-region S3) Amazon (**Fig. 7 g**), the seasonality of LAI_{young}, LAI_{mature}, and LAI_{old} (**Fig. 8 b, c**) are similar as those of BR-Sa1 and BR-Sa3 sites. And in subtropical Asia (sub-region S6) (**Fig. 7 i**), the seasonality of three LAI cohorts (**Fig. 8 f**) are similar as those of Din, Gutian and Banna sites. Notably, the sub-region S8, located geographically between sub-regions S6 and S7, shows a LAI_{young} peak at July and a bimodal phenology in LAI_{mature} (**Fig. 8 h**). The remaining 4 sub-regions (sub-regions S1, S4, S5, S7) are all located nearby the equator. The magnitudes of seasonal changes in LAI cohorts are smaller than those in sub-regions S2, S3, S6 and S8 away from the Equator. It is worth noting that for these sub-regions around the Equator there is a bimodal seasonality pattern for LAI_{mature}, with the first peak around March and the second peak around August (**Fig. 8 a, d, e, g**). This is consistent with the findings of Li et al. (2021) which found that tropical and subtropical TEFs changed from a unimodal phenology at higher-latitudes to a bimodal phenology at lower-latitudes.

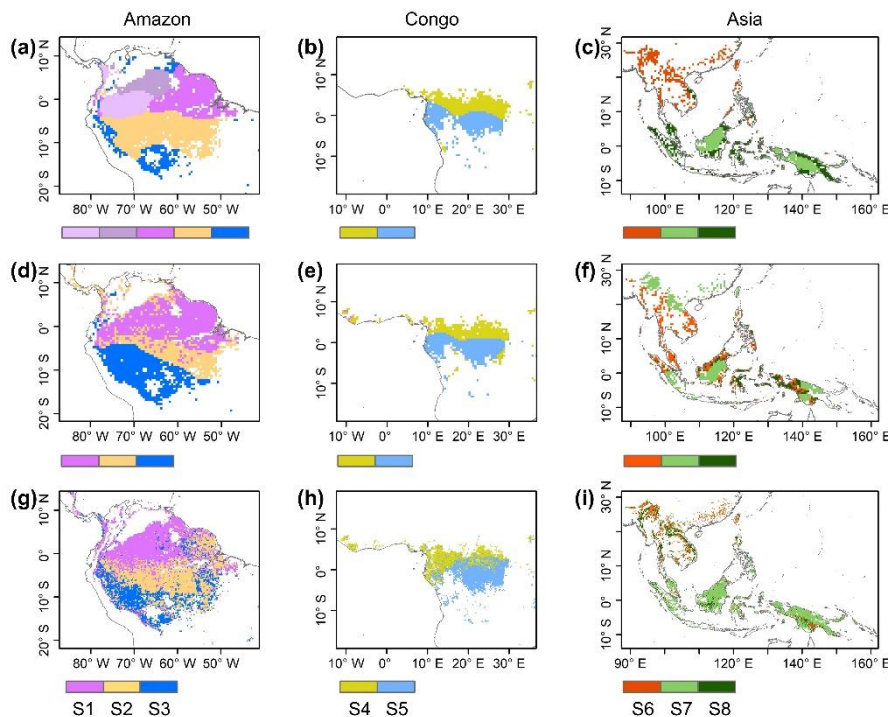
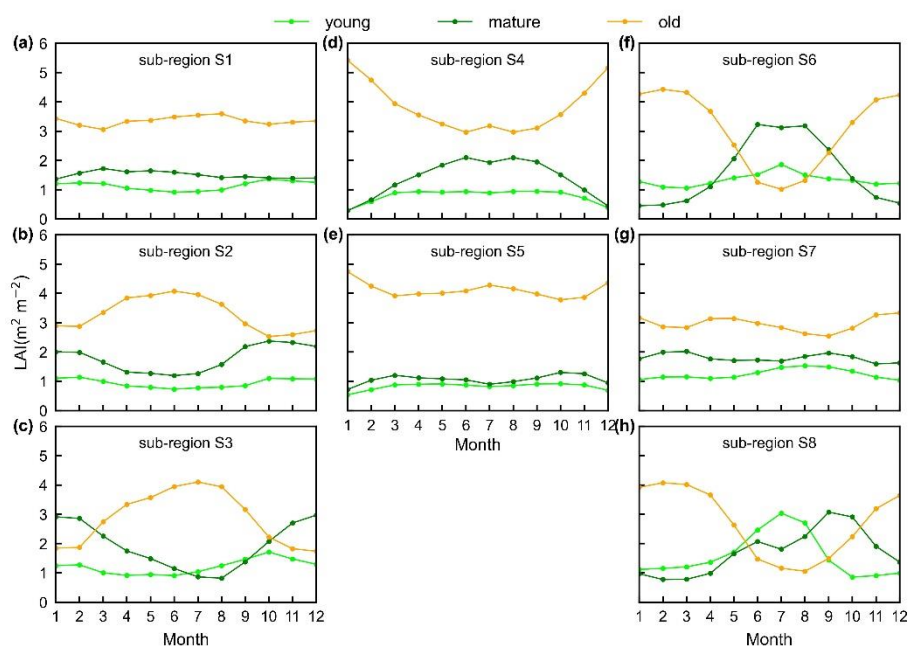



Figure 7. Comparison of sub-regions of Lad-LAI products (plots g-i) with those of climatic factors classified by the K-means clustering analysis (plots a-c) (Chen et al., 2021) and those of the three climate-phenology regimes (plots d-f) developed by Yang

486   et al. (2021).

487

488   **Figure 8.** Seasonality of simulated LAI_{young}, LAI_{mature}, and LAI_{old} in 8 sub-regions

489   classified by the K-means clustering analysis.

490

491   **4.3 Sub-regional evaluations of grid $LAI_{young+mature}$ seasonality using satellite-based**

492   **EVI products**

493   The grid dataset of $LAI_{young+mature}$ seasonality was indirectly evaluated using the

494   satellite-based EVI products (Wang et al., 2017; de Moura et al., 2017; Xiao et al., 2005;

495   Wu et al., 2018), as previous studies indicated that EVI can be considered as a proxy

496   for leaf area change of those leaves with high photosynthesis efficiency (Huete et al.,

497   2006; Lopes et al., 2016; Wu et al., 2018). It is because that EVI are very sensitive to

498   changes in near-infrared (NIR) reflectance (Galvão et al., 2011) while young and

499   mature leaves also reflect more NIR signals than the older leaves they replace (Toomey

500   et al., 2009). The linear correlation and MSD decompositions (see **methods**) between

501   simulated and satellite-based EVI were displayed in **Fig. 9**. Overall, the seasonal

502    $LAI_{young+mature}$ is well correlated with satellite-based EVI (R > 0.40) in 78.26% of the

503   TEFs and the average correlation coefficient is equaling to 0.61(**Fig. 9 a-c**). The MSD

504   is smaller than 0.1 in 89.69% of the whole tropical and subtropical TEFs (**Fig. 9 d-f**).

Statistics in the 8 clustered sub-regions show that the seasonal $LAI_{young+mature}$ of Lad-LAI data mostly correlate better with seasonal EVI in high-latitude areas (sub-region S2: R=0.65, sub-region S3: R=0.71, sub-region S6: R=0.67) than those in low latitudes (sub-region S1: R=0.46, sub-region S5: R=0.61, sub-region S7: R=0.44, sub-region S8: R=0.64) except for sub-region S4 (R=0.72) (**Figs. 10, S7**). The MSD components also confirm the better performance of $LAI_{young+mature}$ seasonality in high-latitude areas (sub-region S2: d_{bias}=0.009, d_{var}=0.001, d_{phase}=0.030; sub-region S3: d_{bias}=0.009, d_{var}=0.002, d_{phase}=0.030; sub-region S6: d_{bias}=0.016, d_{var}=0.005, d_{phase}=0.040) than in low-latitude areas near the Equator (sub-region S1: d_{bias}=0.012, d_{var}=0.001, d_{phase}=0.041; sub-region S4: d_{bias}=0.020, d_{var}=0.001, d_{phase}=0.031; sub-region S5: d_{bias}=0.017, d_{var}=0.001, d_{phase}=0.032; sub-region S7: d_{bias}=0.018, d_{var}=0.002, d_{phase}=0.043; sub-region S8: d_{bias}=0.012, d_{var}=0.005, d_{phase}=0.035) (**Figs. 11, S7**). This happens because that the accuracy of Lad-LAI in representing the seasonality of LAI cohorts depends highly on that of input SIF data, which is low sensitive to canopy phenology and shows marginally small seasonal changes nearby the Equator, for example in tropical Asia (Guan et al., 2015; 2016).

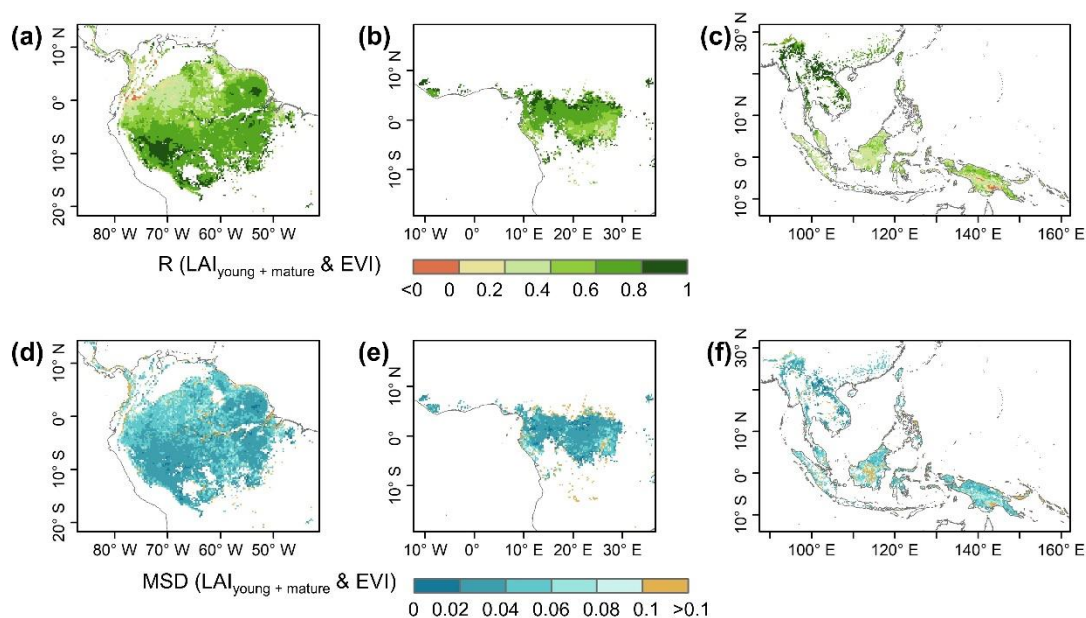
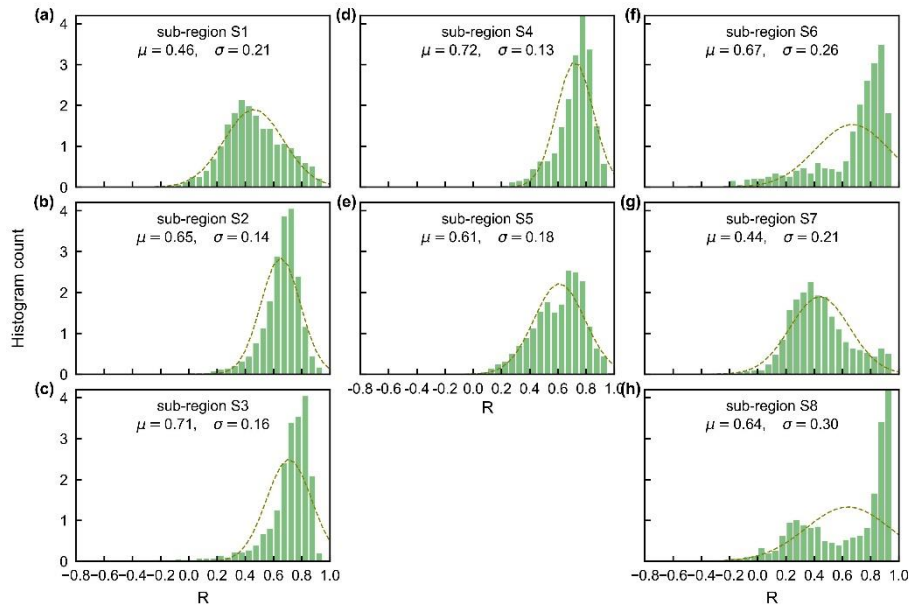



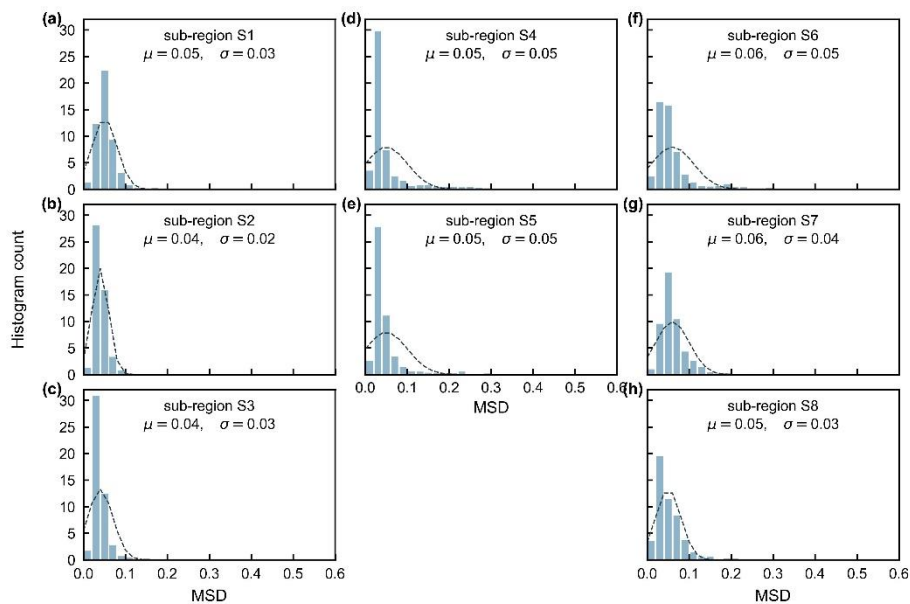
Figure 9. Pearson correlation coefficient (R) and mean squared deviation (MSD) between seasonality of simulated $LAI_{young+mature}$ and MODIS Enhanced Vegetation

524   Index (EVI).

525

526

527   **Figure 10.** Statistics of the Pearson correlation coefficient (R) between seasonality of

528   simulated LAI$_{young+mature}$ and MODIS Enhanced Vegetation Index (EVI) in the 8

529   clustered sub-regions.

530

531   **Figure 11.** Statistics of the mean squared deviation (MSD) between seasonality of

532   simulated LAI$_{young+mature}$ and MODIS Enhanced Vegetation Index (EVI) in the 8

533   clustered sub-regions.

534

535   Additionally, previous studies indicated large-scale dry-season green-up area over

536 tropical and subtropical region (i.e., Guan et al., 2015, Tang et al., 2017, Myneni et al.,

537 2007) where the average annual precipitation exceeds 2,000 mm yr^{-1}. Here, we

538 calculated the differences (Δ) between wet- and dry-season $LAI_{young+mature}$ (i.e.,

539 LAI_{young}+ LAI_{mature}), to test whether the Lad-LAI can capture this green-up spatial

540 pattern. Spatial patterns of $\Delta LAI_{young+mature}$ (**Fig. 12**) are similar to those developed by

541 (Guan et al., 2015), with higher $LAI_{young+mature}$ during the dry season (blue area) in large

542 areas north of the Equator. This indicates an emergence of new leaf flush and increase

543 of mature leaves, resulting the canopy "green-up" phenomenon observed by previous

544 satellite-based signals. It is interesting to note that the total areas (blue regions in **Fig.**

545 **12**) of this dry-season green up shown by $LAI_{young+mature}$ is smaller than those shown by

546 SIF signals that almost everywhere north of the Equator. That is because that new and

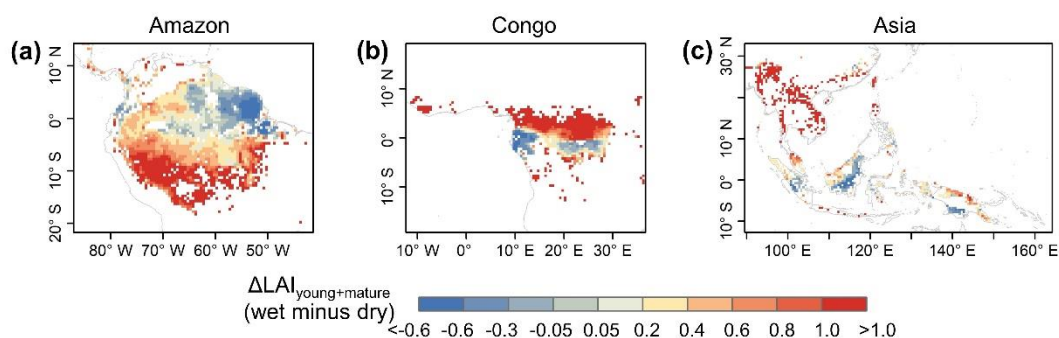
547 mature leaves often have quite a higher photosynthetic capacity than old leaves. A slight

548 or moderate "green-up" in new and mature leaves (i.e., increase in $LAI_{young+mature}$)

549 would boost strong increase in photosynthesis, inducing significant "green-up" shown

550 by photosynthesis-related signals, e.g., SIF data. Therefore, photosynthesis proxies

551 likely overestimate the areas with "green-up" of new leaves during the dry seasons in

552 the real world.

553

554 **Figure 12**. Spatial pattern of dry-season green-up using wet-season $LAI_{young+mature}$

555 minus dry-season $LAI_{young+mature}$.

556

557 **4.4 Sub-regional evaluations of grid LAI_{old} seasonality using site-based litterfall**

558 **observations**

559   The seasonal patterns of LAI_{old} were evaluated indirectly using ground-based

560 seasonal litterfall observations from 53 sites over the tropical and subtropical EBFs

561 (black circles in **Fig. 1**, **Figs. S8-S10**), Here, we selected 9 specific sites (**Fig. 13**) with

562 different patterns of litterfall seasonality and LAI_{old} seasonality, to illustrate the

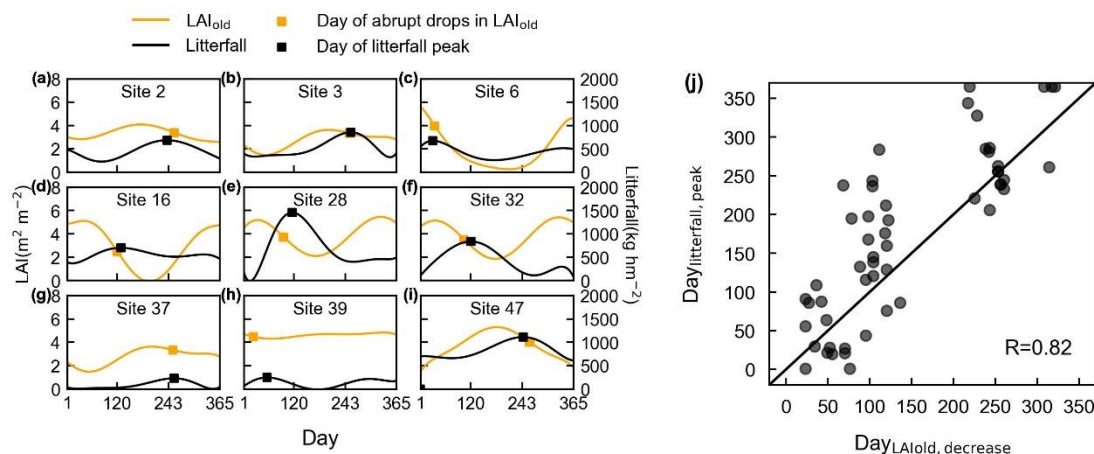
563 analyses results. **Fig. 13 a-i** illustrate the days when there is an abrupt decrease in

564 monthly LAI_{old}, which are closely to monthly litterfall peak. The days when LAI_{old}

565 decreases sharpest (Day_{LAIold}) agree well with the days when their monthly litterfall

566 peaks ($Day_{litterfall}$) (**Fig. 13 j**), mostly distributed near the diagonal lines (R=0.82). This

567 validation from seasonal litterfall data indirectly demonstrate the robustness of the

568 LAI_{old} seasonality of the Lad-LAI product.

569

570 **Figure 13.** Evaluation of simulated LAI_{old} using ground-observed litterfall seasonality.

571 (a-i) Days of an abrupt decrease in LAI_{old} in comparison with days of corresponding

572 litterfall peak at 9 specific sites for examples. The orange curves represent simulated

573 LAI_{old}. Dots on the orange curves represent the point with an abrupt decrease in LAI_{old}.

574 The black curves represent observed seasonal litterfall mass. The dots on the black

575 curves represent the point with litterfall peak. (j) Comparisons of the days when LAI_{old}

576 has an abrupt decrease (Day_{LAIold}) against the days when monthly litterfall peaks

577 ($Day_{litterfall}$).

578

579 **4.5 Testing potential uncertainties of the Lad-LAI products**

580   To prove the robustness of the neighbor-based decomposition approach, we

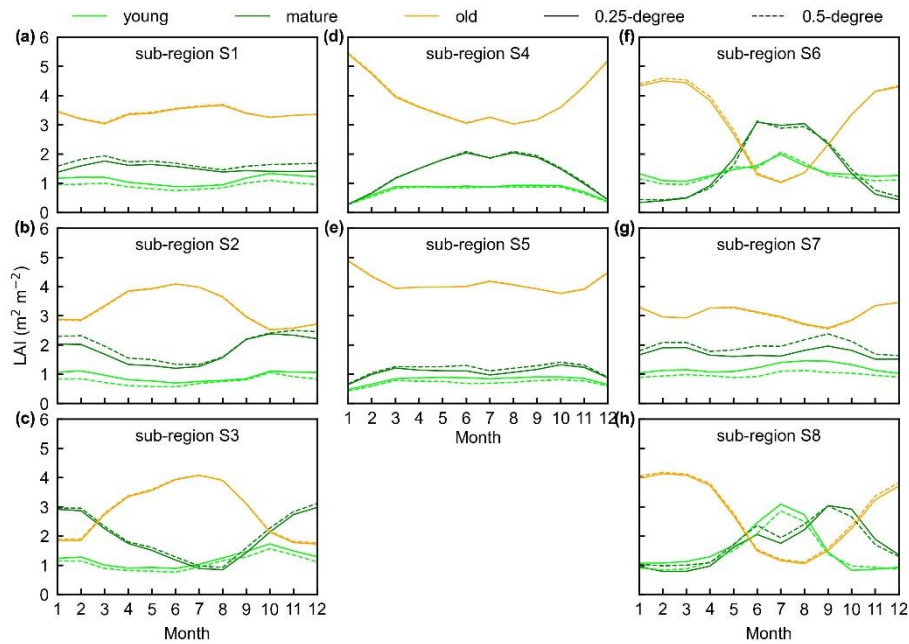
581 compared the Lad-LAI products generated based on 2*2 neighboring pixels with those

582 4*4 based on neighboring pixels. Results show that the seasonality of LAI$_{young}$,

583 LAI$_{mature}$ and LAI$_{old}$ in the 0.5-degree Lad-LAI products based on 4*4 neighboring

584 pixels are highly consistent with those of the 0.25-degree one based on 2*2 neighboring

585 pixels across the whole tropical region (**Fig. 14**), with the correlation coefficients (R)

586 being equaling to 0.63, 0.68 and 0.95, respectively (**Fig. S11**).

587

588 **Figure 14.** The seasonality of LAI$_{young}$, LAI$_{mature}$, LAI$_{old}$ between 0.25-degree and 0.5-

589 degree Lad-LAI datasets in the 8 clustered regions. Limegreen color represents LAI$_{young}$;

590 green color represents LAI$_{mature}$; and orange color represents LAI$_{old}$. Solid lines

591 represent 0.25-degree dataset and the dashed lines represent 0.5-degree dataset.

592

593 To test the uncertainties caused by the GPP estimation, we added two more GPP

594 products, i.e., GOSIF-derived GPP (Li and Xiao, 2019) and FLUXCOM GPP (Jung et

595 al., 2019), to produce another two versions of Lad-LAI products. The GPP seasonality

596 coincide well between these three data sources across all the 8 sub-regions (**Fig. S12**).

597 By comparing with the ground-based LAI cohorts at eight observation sites, results

598 show that the Lad-LAI generated from RTSIF-derived GPP show highest correlation

599 and minimal deviation with the *in situ* measurements, with R equaling to 0.36, 0.77 and

600 0.59 and MSD equaling to 0.45, 0.69 and 0.62 for LAI$_{young}$, LAI$_{mature}$, and LAI$_{old}$,

601 respectively (**Figs. 15-16**, **S13-S15**). Additionally, we also compared the seasonal

602 variability of LAI$_{young}$, LAI$_{mature}$, and LAI$_{old}$ between three Lad-LAI versions in 8 sub-

603 regions classified by the K-means clustering analysis (**Fig. 17**). In general, three

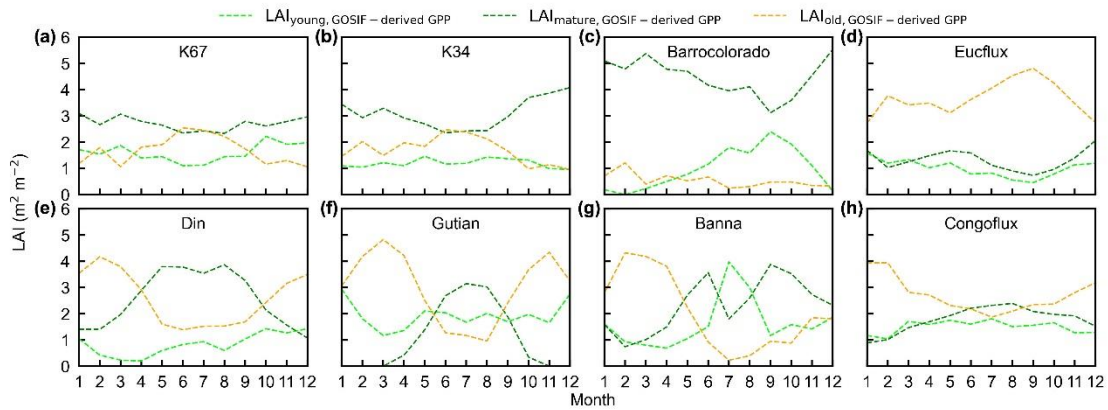
604 versions of Lad-LAI products all performed well in 8 sub-regions with the consistent

605 seasonal variability (**Fig. 17**). On regional average, sub-regions S4, S5, S6, S7 and S8

606 show high consistent seasonality of LAI$_{young}$, LAI$_{mature}$, and LAI$_{old}$ between these three

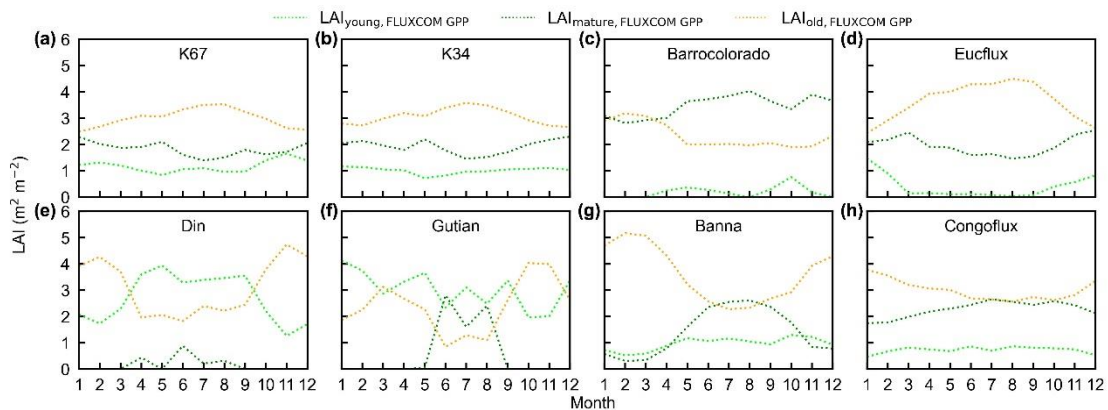
607 products; whereas the Lad-LAI generated from GOSIF-derived GPP performs a little

608 poor in capturing the seasonality of LAI cohorts in Amazon (sub-regions S1, S2 and

609 S3).

610

611 **Figure 15.** Seasonality of simulated LAI$_{young}$, LAI$_{mature}$, and LAI$_{old}$ from GOSIF-

612 derived GPP in comparison with observed data at 8 sites. (a) K67; (b) K34; (c)

613 Barrocolorado; (d) Eucflux; (e) Din; (f) Gutian; (g) Banna; (h) Congoflux.

614

615 **Figure 16.** Seasonality of simulated LAI$_{young}$, LAI$_{mature}$, and LAI$_{old}$ from FLUXCOM

616 GPP in comparison with observed data at 8 sites. (a) K67; (b) K34; (c) Barrocolorado;

617 (d) Eucflux; (e) Din; (f) Gutian; (g) Banna; (h) Congoflux.

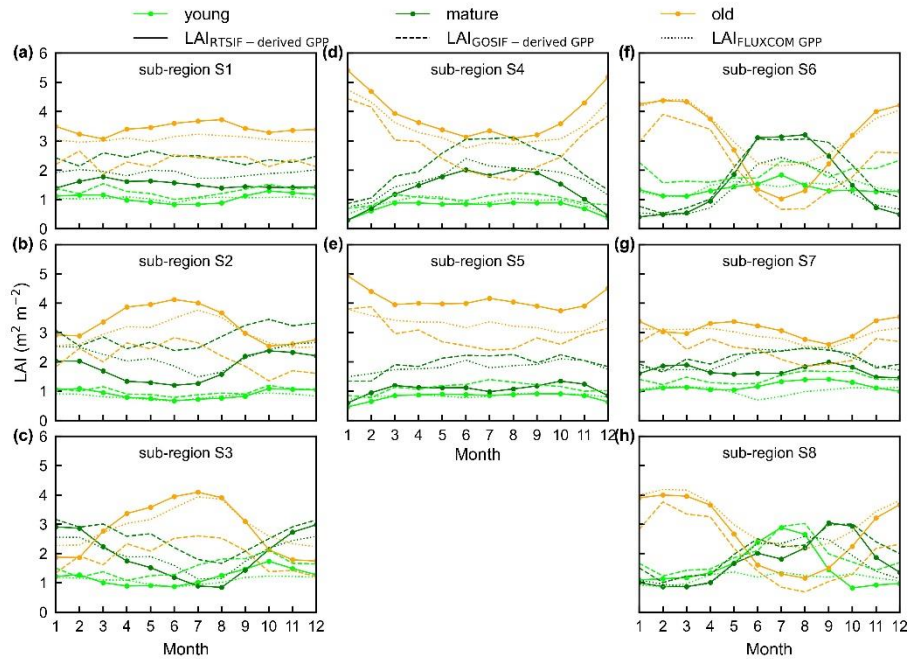



Figure 17. Seasonality of simulated LAI_{young}, LAI_{mature}, and LAI_{old} from three version products in 8 sub-regions classified by the K-means clustering analysis. Solid lines represent LAI generated from RTSIF-derived GPP; dashed lines represent LAI generated from GOSIF-derived GPP; and dotted lines represent LAI generated from FLUXCOM GPP. Limegreen represents LAI_{young}; green represents LAI_{mature}; and orange represents LAI_{old}.

5 Discussion

Leaf age-dependent LAI performs well in describing the seasonal replacements of canopy leaves in TEFs (Wu et al., 2016; Chen et al., 2020), showing to be a critical plant trait for representing the tropical and subtropical phenology (Doughty and Goulden, 2008; Saleska et al., 2007). However, to our knowledge, there are currently no continental-scale information of such leaf age-dependent LAI data over the whole TEFs, as it can neither be mapped from sparse site observations (Wu et al., 2016), nor be modeled from ESMs which are triggered by unclear climatic drivers (Chen et al., 2020). These hinder global researches on accurately simulations of large-scale photosynthesis (GPP) seasonality using remote sensing approaches and ESMs (Chen et al., 2020).

637  The Lad-LAI product developed in this study is a new continental-scale grid dataset

638 of monthly LAI in different leaf age cohorts. Although lacking of enough *in situ*

639 observations for adequate validations, the seasonality of three LAI cohorts performs

640 well at the eight sites (four in south America, three in subtropical Asia and one in Congo)

641 with very fine-scale collections of monthly LAI_{young}, LAI_{mature}, and LAI_{old}. To test the

642 robustness of the grid Lad-LAI products over the whole TEFs, the seasonality of

643 LAI_{mature} seasonality are also validated pixel by pixel using satellite-based EVI products

644 and the phase of LAI_{old} seasonality are compared with the those of seasonal litterfall

645 data from 53 site measurements, respectively. Moreover, the $LAI_{young+mature}$ from the

646 new Lad-LAI products can also directly represent the large-scale dry-season green-up

647 of canopy leaves north of the Equator. Overall, direct and indirect evaluations both

648 demonstrated the robustness of the developed Lad-LAI products.

649  It should be noted that, over the regions with large magnitude of annual

650 precipitation nearby the Equator, there is no obvious dry seasons and thus tree canopy

651 phenology changes smaller than higher-latitude ones throughout the year (Yang et al.,

652 2021). The LAI of young, mature and old leaf cohorts all show a bimodal phenology

653 with marginally small seasonal changes nearby the Equator, which is captured by the

654 developed Lad-LAI product. Secondly, we used a constant coefficient to transfer from

655 SIF data to GPP and also assume a constant value for the total LAI over the whole TEFs,

656 which might bring unexpected uncertainties. This can be seen from the MSD

657 evaluations, where the bias-related term dominates the total MSD, especially in regions

658 nearby the Equator. However, this bring less impacts on the seasonality of Lad-LAI, as

659 the phase-related term of MSD is much smaller.

660  Additionally, the maximum carboxylation rate ($V_{c,max}$) of leaves changes

661 significantly with leaf age (Xu et al., 2017). Currently, most Earth system models

662 (ESMs) define $V_{c,max}$ as a function of leaf age whereas their relationship is still less well

663 understood in TEFs due to sparse in-situ measurements (Chen et al., 2020). This

664 consequentially leads to the poor representation of LAI and GPP seasonality in ESMs

(De Weirdt et al., 2012). To overcome this challenge, here we simplified the tree canopy into three big leaves (i.e., young, mature and old) in TEFs, similar as the two-big leaves model developed for temperate and boreal forests (Best et al., 2011; Clark et al., 2011; Harper et al., 2016), which simplified tree canopy into sun and shade leaves. However, some uncertain remains on the assumption, as it neglects the spatial and temporal variations of $V_{c,max}$, which also changes with seasonal climate anomaly and also differs between nearby pixels in high heterogeneous forest ecosystems. This assumption may bring uncertainties for simulating seasonal An and therefore influence the seasonality of Lad-LAI.

In summary, we developed a new method to produce the first global grid dataset of leaf age-dependent LAI product across the whole EBFs over the continental scale. Although some uncertainties might remain, the Lad-LAI products could provide seasonal age-dependent LAI data at the pixel-level to develop a common phenology model for the whole tropical and subtropical EBFs in ESMs that are currently run at a coarser resolution. Besides, with the development of remote sensing technology, finer temporal and spatial resolutions of SIF products will enable finer temporal and spatial resolutions maps of Lad-LAI products in the future.

6. Data availability

The 0.25-degree leaf age-dependent LAI seasonality (Lad-LAI) data from 2001-2018 are presented in this paper as the main one, and their time-series are as a supplementary dataset. The two datasets are available at https://doi.org/10.6084/m9.figshare.21700955.v3 (Yang et al., 2022). Besides, we also provided another two versions of Lad-LAI generated from GOSIF-derived GPP and FLUXCOM GPP, respectively. These datasets are compressed in GeoTiff, with a spatial reference of WGS84. Each file in those dataset is named like "LAI_{leaf age}_{spatial resolution}_{month/year-month}.tif".

7. Conclusion

This study for the first-time mapped continental-scale grid dataset of monthly LAI in three leaf age cohorts from 2001-2018 RTSIF data. The LAI seasonality of young, mature and old leaves was evaluated using *in situ* measurements of seasonal LAI data, satellite based EVI and *in situ* measurements of seasonal litterfall data. The evaluations from these datasets demonstrate the robustness of the seasonality of three leaf age cohorts. The new Lad-LAI products indicate diverse patterns over the whole tropical and subtropical regions. In central and south Amazon, LAI_{young} and LAI_{mature} decrease at early dry season around February and convert to increase at early wet season around June. On the contrary, in subtropical Asia, LAI_{young} and LAI_{mature} increase during the wet season and peak with largest rainfall at June or July. In regions nearby the Equator, the LAI cohorts show a bimodal phenology but with marginally small changes in magnitudes. The proposed method will enable to produce finer temporal and spatial resolutions maps of Lad-LAI products by using precise temporal and spatial resolutions data as the inputs. The Lad-LAI products will be help for diagnosing the adaption of tropical and subtropical forest to climate change; and will also help improve the development of phenology models in ESMs.

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Reference:

733 Albert, L. P., Wu, J., Prohaska, N., de Camargo, P. B., Huxman, T. E., Tribuzy, E. S.,
734   Ivanov, V. Y., Oliveira, R. S., Garcia, S., Smith, M. N., Oliveira Junior, R. C.,
735   Restrepo-Coupe, N., da Silva, R., Stark, S. C., Martins, G. A., Penha, D. V., and
736   Saleska, S. R.: Age-dependent leaf physiology and consequences for crown-scale
737   carbon uptake during the dry season in an Amazon evergreen forest, New Phytol,
738   219, 870-884, 10.1111/nph.15056, 2018.

739 Aragao, L. E., Poulter, B., Barlow, J. B., Anderson, L. O., Malhi, Y., Saatchi, S., Phillips,
740   O. L., and Gloor, E.: Environmental change and the carbon balance of Amazonian
741   forests, Biol Rev Camb Philos Soc, 89, 913-931, 10.1111/brv.12088, 2014.

742 Arora, V. K. and Boer, G. J.: Fire as an interactive component of dynamic vegetation
743   models, Journal of Geophysical Research: Biogeosciences, 110, n/a-n/a,
744   10.1029/2005jg000042, 2005.

745 Barlow, J., Gardner, T. A., Ferreira, L. V., and Peres, C. A.: Litter fall and decomposition
746   in primary, secondary and plantation forests in the Brazilian Amazon, Forest
747   Ecology and Management, 247, 91-97, 10.1016/j.foreco.2007.04.017, 2007.

748 Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rodenbeck,
749   C., Arain, M. A., Baldocchi, D., Bonan, G. B., Bondeau, A., Cescatti, A., Lasslop,
750   G., Lindroth, A., Lomas, M., Luyssaert, S., Margolis, H., Oleson, K. W., Roupsard,
751   O., Veenendaal, E., Viovy, N., Williams, C., Woodward, F. I., and Papale, D.:
752   Terrestrial gross carbon dioxide uptake: global distribution and covariation with
753   climate, Science, 329, 834-838, 10.1126/science.1184984, 2010.

754 Bernacchi, C. J., Pimentel, C., and Long, S. P.: In vivo temperature response functions
755   of parameters required to model RuBP-limited photosynthesis, Plant, Cell &
756   Environment, 26, 1419-1430, 10.1046/j.0016-8025.2003.01050.x, 2003.

Bernacchi, C. J., Bagley, J. E., Serbin, S. P., Ruiz-Vera, U. M., Rosenthal, D. M., and Vanloocke, A.: Modelling C(3) photosynthesis from the chloroplast to the ecosystem, Plant Cell Environ, 36, 1641-1657, 10.1111/pce.12118, 2013.

Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R. L. H., Ménard, C. B., Edwards, J. M., Hendry, M. A., Porson, A., Gedney, N., Mercado, L. M., Sitch, S., Blyth, E., Boucher, O., Cox, P. M., Grimmond, C. S. B., and Harding, R. J.: The Joint UK Land Environment Simulator (JULES), model description–Part 1: Energy and water fluxes. Geoscientific Model Development, 4, 677–699, 2011.

Brando, P. M., Goetz, S. J., Baccini, A., Nepstad, D. C., Beck, P. S., and Christman, M. C.: Seasonal and interannual variability of climate and vegetation indices across the Amazon. Proceedings of the National Academy of Sciences, 200908741. 2010.

Chen, X., Huang, Y., Nie, C., Zhang, S., Wang, G., Chen, S., and Chen, Z.: A long-term reconstructed TROPOMI solar-induced fluorescence dataset using machine learning algorithms, Sci Data, 9, 427, 10.1038/s41597-022-01520-1, 2022.

Chen, X., Maignan, F., Viovy, N., Bastos, A., Goll, D., Wu, J., Liu, L., Yue, C., Peng, S., Yuan, W., Conceição, A. C., O'Sullivan, M., and Ciais, P.: Novel Representation of Leaf Phenology Improves Simulation of Amazonian Evergreen Forest Photosynthesis in a Land Surface Model, Journal of Advances in Modeling Earth Systems, 12, 10.1029/2018ms001565, 2020.

Chen, X., Ciais, P., Maignan, F., Zhang, Y., Bastos, A., Liu, L., Bacour, C., Fan, L., Gentine, P., Goll, D., Green, J., Kim, H., Li, L., Liu, Y., Peng, S., Tang, H., Viovy, N., Wigneron, J. P., Wu, J., Yuan, W., and Zhang, H.: Vapor Pressure Deficit and Sunlight Explain Seasonality of Leaf Phenology and Photosynthesis Across Amazonian Evergreen Broadleaved Forest, Global Biogeochemical Cycles, 35, 10.1029/2020gb006893, 2021.

Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., Pryor, M., Rooney, G. G., Essery, R. L. H., Blyth, E., Boucher, O., Harding, R. J., Huntingford, C., and Cox, P. M.: The Joint UK Land Environment Simulator (JULES), model description–Part 2: Carbon fluxes and vegetation dynamics. Geoscientific Model Development, 4, 701–722, 2011.

Cramer, W., Bondeau, A., Woodward, F. I., Prentice, I. C., Betts, R. A., Brovkin, V., Cox, P. M., Fisher, V., Foley, J. A., Friend, A. D., Kucharik, C., Lomas, M. R., Ramankutty, N., Sitch, S., Smith, B., White, A., and Young-Molling, C.: Global response of terrestrial ecosystem structure and function to CO2 and climate change: results from six dynamic global vegetation models, Global Change Biology, 7, 357-373, 10.1046/j.1365-2486.2001.00383.x, 2001.

Dantas, M. and Phillipson, J.: Litterfall and litter nutrient content in primary and secondary Amazonian 'terra firme' rain forest, Journal of Tropical Ecology, 5, 27-

36, 10.1017/s0266467400003199, 1989.

Davidson, E. A., de Araújo, A. C., Balch, J. K., Brown, I. F., Bustamante, M. M., et al.: The Amazon basin in transition. Nature, 481(7381), 321–328. https://doi.org/10.1038/nature10717. 2012.

de Moura, Y. M., Galvão, L. S., Hilker, T., Wu, J., Saleska, S., do Amaral, C. H., Nelson, B. W., Lopes, A. P., Wiedeman, K. K., Prohaska, N., de Oliveira, R. C., Machado, C. B., and Aragão, L. E. O. C.: Spectral analysis of amazon canopy phenology during the dry season using a tower hyperspectral camera and modis observations, ISPRS Journal of Photogrammetry and Remote Sensing, 131, 52-64, 10.1016/j.isprsjprs.2017.07.006, 2017.

De Weirdt, M., Verbeeck, H., Maignan, F., Peylin, P., Poulter, B., Bonal, D., Ciais, P., and Steppe, K.: Seasonal leaf dynamics for tropical evergreen forests in a process-based global ecosystem model, Geoscientific Model Development, 5, 1091-1108, 10.5194/gmd-5-1091-2012, 2012.

Dechant, B., Ryu, Y., Badgley, G., Zeng, Y., Berry, J. A., Zhang, Y., Goulas, Y., Li, Z., Zhang, Q., Kang, M., Li, J., and Moya, I.: Canopy structure explains the relationship between photosynthesis and sun-induced chlorophyll fluorescence in crops, Remote Sensing of Environment, 241, 10.1016/j.rse.2020.111733, 2020.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N., and Vitart, F.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system, Quarterly Journal of the Royal Meteorological Society, 137, 553-597, 10.1002/qj.828, 2011.

Doughty, C. E. and Goulden, M. L.: Seasonal patterns of tropical forest leaf area index and CO_2 exchange, Journal of Geophysical Research: Biogeosciences, 113, n/a-n/a, 10.1029/2007jg000590, 2008.

Farquhar, G. D., von Caemmerer, S., and Berry, J. A.: A biochemical model of photosynthetic CO2 assimilation in leaves of C 3 species, Planta, 149, 78-90, 10.1007/BF00386231, 1980.

Galvão, L. S., dos Santos, J. R., Roberts, D. A., Breunig, F. M., Toomey, M., and de Moura, Y. M.: On intra-annual EVI variability in the dry season of tropical forest: a case study with MODIS and hyperspectral data. Remote Sens. Environ. 115, 2350–2359, 2011.

Guan, K., Berry, J. A., Zhang, Y., Joiner, J., Guanter, L., Huete, A. R., ... and Gentine, P.: Improving the monitoring of crop productivity using spaceborne solar-induced fluorescence. Global change biology, 22(2), 716-726. 2016.

Guan, K., Pan, M., Li, H., Wolf, A., Wu, J., Medvigy, D., Caylor, K. K., Sheffield, J., Wood, E. F., Malhi, Y., Liang, M., Kimball, J. S., Saleska, Scott R., Berry, J., Joiner,

837   J., and Lyapustin, A. I.: Photosynthetic seasonality of global tropical forests
838   constrained by hydroclimate, Nature Geoscience, 8, 284-289, 10.1038/ngeo2382,
839   2015.

840 Harper, A., Cox, P., Friedlingstein, P., Wiltshire, A. J., Jones, C. D., Sitch, S., . . . van
841   Bodegom, P.: Improved representation of plant functional types and physiology in
842   the Joint UK Land Environment Simulator (JULES v4.2) using plant trait
843   information. Geoscientific Model Development Discussions, 9, 2415–2440, 2016.

844 Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., and Ferreira, L. G.: Overview
845   of the radiometric and biophysical performance of the MODIS vegetation indices,
846   Remote Sensing of Environment, 83, 195-213, 10.1016/s0034-4257(02)00096-2,
847   2002.

848 Huete, A. R., Didan, K., Shimabukuro, Y. E., Ratana, P., Saleska, S. R., Hutyra, L. R.,
849   Yang, W., Nemani, R. R., and Myneni, R.: Amazon rainforests green-up with
850   sunlight in dry season, Geophysical Research Letters, 33, 10.1029/2005gl025583,
851   2006.

852 June, T., Evans, J. R., and Farquhar, G. D.: A simple new equation for the reversible
853   temperature dependence of photosynthetic electron transport: a study on soybean
854   leaf, Funct Plant Biol, 31, 275-283, 10.1071/FP03250, 2004.

855 Jung, M., Koirala, S., Weber, U., Ichii, K., Gans, F., Camps-Valls, G., Papale, D.,
856   Schwalm, C., Tramontana, G., and Reichstein, M.: The FLUXCOM ensemble of
857   global land-atmosphere energy fluxes. Sci Data 6, 74.
858   https://doi.org/10.1038/s41597-019-0076-8. 2019.

859 Kartikeyan, B., Sarkar, A., and Majumder, K. L.: A segmentation approach to
860   classification of remote sensing imagery, International Journal of Remote Sensing,
861   19, 1695-1709, 1998.

862 Kobayashi, K. and Salam, M. U.: Comparing Simulated and Measured Values Using
863   Mean Squared Deviation and its Components, Agronomy Journal, 92,
864   10.1007/s100870050043, 2000.

865 Leff, J. W., Wieder, W. R., Taylor, P. G., Townsend, A. R., Nemergut, D. R., Grandy, A.
866   S., and Cleveland, C. C.: Experimental litterfall manipulation drives large and
867   rapid changes in soil carbon cycling in a wet tropical forest. Global Change
868   Biology, 18(9), 2969–2979. https://doi.org/10.1111/j.1365-2486.2012.02749.x.
869   2012.

870 Li, Q., Chen, X., Yuan, W., Lu, H., Shen, R., Wu, S., Gong, F., Dai, Y., Liu, L., Sun, Q.,
871   Zhang, C., and Su, Y.: Remote Sensing of Seasonal Climatic Constraints on Leaf
872   Phenology Across Pantropical Evergreen Forest Biome, Earth's Future, 9,
873   10.1029/2021ef002160, 2021.

874 Li, X., and Xiao, J.: Mapping photosynthesis solely from solar-induced chlorophyll
875   fluorescence: A global, fine-resolution dataset of gross primary production derived
876   from OCO-2. Remote Sensing, 11(21), 2563; https://doi.org/10.3390/rs11212563.
877   2019.

878 Lin, Y.-S., Medlyn, B. E., Duursma, R. A., Prentice, I. C., Wang, H., Baig, S., Eamus,

D., de Dios, Victor R., Mitchell, P., Ellsworth, D. S., de Beeck, M. O., Wallin, G., Uddling, J., Tarvainen, L., Linderson, M.-L., Cernusak, L. A., Nippert, J. B., Ocheltree, T. W., Tissue, D. T., Martin-StPaul, N. K., Rogers, A., Warren, J. M., De Angelis, P., Hikosaka, K., Han, Q., Onoda, Y., Gimeno, T. E., Barton, C. V. M., Bennie, J., Bonal, D., Bosc, A., Löw, M., Macinins-Ng, C., Rey, A., Rowland, L., Setterfield, S. A., Tausz-Posch, S., Zaragoza-Castells, J., Broadmeadow, M. S. J., Drake, J. E., Freeman, M., Ghannoum, O., Hutley, Lindsay B., Kelly, J. W., Kikuzawa, K., Kolari, P., Koyama, K., Limousin, J.-M., Meir, P., Lola da Costa, A. C., Mikkelsen, T. N., Salinas, N., Sun, W., and Wingate, L.: Optimal stomatal behaviour around the world, Nature Climate Change, 5, 459-464, 10.1038/nclimate2550, 2015.

Lopes, A. P., Nelson, B. W., Wu, J., Graça, P. M. L. d. A., Tavares, J. V., Prohaska, N., Martins, G. A., and Saleska, S. R.: Leaf flush drives dry season green-up of the Central Amazon, Remote Sensing of Environment, 182, 90-98, 10.1016/j.rse.2016.05.009, 2016.

Maes, W. H., Gentine, P., Verhoest, N. E. C., and Miralles, D. G.: Potential evaporation at eddy-covariance sites across the globe, Hydrology and Earth System Sciences, 23, 925-948, 10.5194/hess-23-925-2019, 2019.

Medlyn, B. E., Duursma, R. A., Eamus, D., Ellsworth, D. S., Prentice, I. C., Barton, C. V. M., Crous, K. Y., De Angelis, P., Freeman, M., and Wingate, L.: Reconciling the optimal and empirical approaches to modelling stomatal conductance, Global Change Biology, 17, 2134-2144, 10.1111/j.1365-2486.2010.02375.x, 2011.

Melgosa, M., Huertas, R., and Berns, R. S.: Performance of recent advanced color-difference formulas using the standardized residual sum of squares index. Journal of the Optical Society of America A, 25(7), 1828-1834. https://doi.org/10.1364/JOSAA.25.001828. 2008

Menezes, J., Garcia, S., Grandis, A., Nascimento, H., Domingues, T. F., Guedes, A. V., Aleixo, I., Camargo, P., Campos, J., Damasceno, A., Dias-Silva, R., Fleischer, K., Kruijt, B., Cordeiro, A. L., Martins, N. P., Meir, P., Norby, R. J., Pereira, I., Portela, B., Rammig, A., Ribeiro, A. G., Lapola, D. M., and Quesada, C. A.: Changes in leaf functional traits with leaf age: when do leaves decrease their photosynthetic capacity in Amazonian trees? Tree Physiology, 42(5), 922-938, https://doi.org/10.1093/treephys/tpab042, 2021.

Merkl, R. and Waack, S.: Bioinformatik interaktiv, John Wiley & Sons, 2009.

Midoko Iponga, D., Mpikou, R. G. J., Loumeto, J., and Picard, N.: The effect of different anthropogenic disturbances on litterfall of a dominant pioneer rain forest tree in Gabon, African Journal of Ecology, 58, 281-290, 10.1111/aje.12696, 2019.

Myneni, R. B., Yang, W., Nemani, R. R., Huete, A. R., Dickinson, R. E., Knyazikhin, Y., Didan, K., Fu, R., Negrón Juárez, R. I., Saatchi, S. S., Hashimoto, H., Ichii, K., Shabanov, N. V., Tan, B., Ratana, P., Privette, J. L., Morisette, J. T., Vermote, E. F., Roy, D. P., Wolfe, R. E., Friedl, M. A., Running, S. W., Votava, P., El-Saleous, N., Devadiga, S., Su, Y., and Salomonson, V. V.: Large seasonal swings in leaf area of

Amazon rainforests. Proc. Natl Acad. Sci. USA, 104, 4820–4823. 2007.

Ndakara, O. E.: Litterfall and Nutrient Returns in Isolated Stands of Persea gratissima (Avocado Pear) in the Rainforest Zone of Southern Nigeria, Ethiopian Journal of Environmental Studies and Management, 4, 10.4314/ejesm.v4i3.6, 2011.

Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y. W., Poindexter, C., Chen, J., Elbashandy, A., Humphrey, M., Isaac, P., Polidori, D., Reichstein, M., Ribeca, A., van Ingen, C., Vuichard, N., Zhang, L., Amiro, B., Ammann, C., Arain, M. A., Ardo, J., Arkebauer, T., Arndt, S. K., Arriga, N., Aubinet, M., Aurela, M., Baldocchi, D., Barr, A., Beamesderfer, E., Marchesini, L. B., Bergeron, O., Beringer, J., Bernhofer, C., Berveiller, D., Billesbach, D., Black, T. A., Blanken, P. D., Bohrer, G., Boike, J., Bolstad, P. V., Bonal, D., Bonnefond, J. M., Bowling, D. R., Bracho, R., Brodeur, J., Brummer, C., Buchmann, N., Burban, B., Burns, S. P., Buysse, P., Cale, P., Cavagna, M., Cellier, P., Chen, S., Chini, I., Christensen, T. R., Cleverly, J., Collalti, A., Consalvo, C., Cook, B. D., Cook, D., Coursolle, C., Cremonese, E., Curtis, P. S., D'Andrea, E., da Rocha, H., Dai, X., Davis, K. J., Cinti, B., Grandcourt, A., Ligne, A., De Oliveira, R. C., Delpierre, N., Desai, A. R., Di Bella, C. M., Tommasi, P. D., Dolman, H., Domingo, F., Dong, G., Dore, S., Duce, P., Dufrene, E., Dunn, A., Dusek, J., Eamus, D., Eichelmann, U., ElKhidir, H. A. M., Eugster, W., Ewenz, C. M., Ewers, B., Famulari, D., Fares, S., Feigenwinter, I., Feitz, A., Fensholt, R., Filippa, G., Fischer, M., Frank, J., Galvagno, M., Gharun, M., Gianelle, D., Gielen, B., Gioli, B., Gitelson, A., Goded, I., Goeckede, M., Goldstein, A. H., Gough, C. M., Goulden, M. L., Graf, A., Griebel, A., Gruening, C., Grunwald, T., Hammerle, A., Han, S., Han, X., Hansen, B. U., Hanson, C., Hatakka, J., He, Y., Hehn, M., Heinesch, B., Hinko-Najera, N., Hortnagl, L., Hutley, L., Ibrom, A., Ikawa, H., Jackowicz-Korczynski, M., Janous, D., Jans, W., Jassal, R., Jiang, S., Kato, T., Khomik, M., Klatt, J., Knohl, A., Knox, S., Kobayashi, H., Koerber, G., Kolle, O., Kosugi, Y., Kotani, A., Kowalski, A., Kruijt, B., Kurbatova, J., Kutsch, W. L., Kwon, H., Launiainen, S., Laurila, T., Law, B., Leuning, R., Li, Y., Liddell, M., Limousin, J. M., Lion, M., Liska, A. J., Lohila, A., Lopez-Ballesteros, A., Lopez-Blanco, E., Loubet, B., Loustau, D., Lucas-Moffat, A., Luers, J., Ma, S., Macfarlane, C., Magliulo, V., Maier, R., Mammarella, I., Manca, G., Marcolla, B., Margolis, H. A., Marras, S., Massman, W., Mastepanov, M., Matamala, R., Matthes, J. H., Mazzenga, F., McCaughey, H., McHugh, I., McMillan, A. M. S., Merbold, L., Meyer, W., Meyers, T., Miller, S. D., Minerbi, S., Moderow, U., Monson, R. K., Montagnani, L., Moore, C. E., Moors, E., Moreaux, V., Moureaux, C., Munger, J. W., Nakai, T., Neirynck, J., Nesic, Z., Nicolini, G., Noormets, A., Northwood, M., Nosetto, M., Nouvellon, Y., Novick, K., Oechel, W., Olesen, J. E., Ourcival, J. M., Papuga, S. A., Parmentier, F. J., Paul-Limoges, E., Pavelka, M., Peichl, M., Pendall, E., Phillips, R. P., Pilegaard, K., Pirk, N., Posse, G., Powell, T., Prasse, H., Prober, S. M., Rambal, S., Rannik, U., Raz-Yaseef, N., Rebmann, C., Reed, D., Dios, V. R., Restrepo-Coupe, N., Reverter, B. R., Roland, M.,

Sabbatini, S., Sachs, T., Saleska, S. R., Sanchez-Canete, E. P., Sanchez-Mejia, Z. M., Schmid, H. P., Schmidt, M., Schneider, K., Schrader, F., Schroder, I., Scott, R. L., Sedlak, P., Serrano-Ortiz, P., Shao, C., Shi, P., Shironya, I., Siebicke, L., Sigut, L., Silberstein, R., Sirca, C., Spano, D., Steinbrecher, R., Stevens, R. M., Sturtevant, C., Suyker, A., Tagesson, T., Takanashi, S., Tang, Y., Tapper, N., Thom, J., Tomassucci, M., Tuovinen, J. P., Urbanski, S., Valentini, R., van der Molen, M., van Gorsel, E., van Huissteden, K., Varlagin, A., Verfaillie, J., Vesala, T., Vincke, C., Vitale, D., Vygodskaya, N., Walker, J. P., Walter-Shea, E., Wang, H., Weber, R., Westermann, S., Wille, C., Wofsy, S., Wohlfahrt, G., Wolf, S., Woodgate, W., Li, Y., Zampedri, R., Zhang, J., Zhou, G., Zona, D., Agarwal, D., Biraud, S., Torn, M., and Papale, D.: The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data, Sci Data, 7, 225, 10.1038/s41597-020-0534-3, 2020.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., et al.: A large and persistent carbon sink in the world's forests. Science, 333(6045), 988–993. https://doi.org/10.1126/science.1201609, 2011.

Pearson, K.: VII. Mathematical contributions to the theory of evolution.—III. Regression, heredity, and panmixia, Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character, 187, 253-318, 10.1098/rsta.1896.0007, 1896.

Piao, S., Fang, J., Zhou, L., Ciais, P. and Zhu, B.: Variations in satellite-derived phenology in China's temperate vegetation. Global Change Biology, 12: 672-685. https://doi.org/10.1111/j.1365-2486.2006.01123.x. 2006.

Restrepo-Coupe, N., Levine, N. M., Christoffersen, B. O., Albert, L. P., Wu, J., Costa, M. H., Galbraith, D., Imbuzeiro, H., Martins, G., da Araujo, A. C., Malhi, Y. S., Zeng, X., Moorcroft, P., and Saleska, S. R.: Do dynamic global vegetation models capture the seasonality of carbon fluxes in the Amazon basin? A data-model intercomparison, Glob Chang Biol, 23, 191-208, 10.1111/gcb.13442, 2017.

Ryu, Y., Baldocchi, D. D., Kobayashi, H., van Ingen, C., Li, J., Black, T. A., Beringer, J., van Gorsel, E., Knohl, A., Law, B. E., and Roupsard, O.: Integration of MODIS land and atmosphere products with a coupled-process model to estimate gross primary productivity and evapotranspiration from 1 km to global scales, Global Biogeochemical Cycles, 25, n/a-n/a, 10.1029/2011gb004053, 2011.

Ryu, Y., Jiang, C., Kobayashi, H., and Detto, M.: MODIS-derived global land products of shortwave radiation and diffuse and total photosynthetically active radiation at 5 km resolution from 2000, Remote Sensing of Environment, 204, 812-825, 10.1016/j.rse.2017.09.021, 2018.

Saatchi, S. S., Harris, N. L., Brown, S., Lefsky, M., Mitchard, E. T., Salas, W., Zutta, B. R., Buermann, W., Lewis, S. L., Hagen, S., Petrova, S., White, L., Silman, M., and Morel, A.: Benchmark map of forest carbon stocks in tropical regions across three continents, Proc Natl Acad Sci U S A, 108, 9899-9904, 10.1073/pnas.1019576108, 2011.

Saleska, S. R., Didan, K., Huete, A. R., and da Rocha, H. R.: Amazon forests green-up

during 2005 drought, Science, 318, 612, 10.1126/science.1146663, 2007.

Saleska, S. R., Wu, J., Guan, K., Araujo, A. C., Huete, A., Nobre, A. D., and Restrepo-Coupe, N.: Dry-season greening of Amazon forests, Nature, 531, E4-5, 10.1038/nature16457, 2016.

Saleska, S. R., Miller, S. D., Matross, D. M., Goulden, M. L., Wofsy, S. C., da Rocha, H. R., de Camargo, P. B., Crill, P., Daube, B. C., de Freitas, H. C., Hutyra, L., Keller, M., Kirchhoff, V., Menton, M., Munger, J. W., Pyle, E. H., Rice, A. H., and Silva, H.: Carbon in Amazon forests: unexpected seasonal fluxes and disturbance-induced losses, Science, 302, 1554-1557, 10.1126/science.1091165, 2003.

Sayer, E. J., Heard, M. S., Grant, H. K., Marthews, T. R., and Tanner, E. V. J.: Soil carbon release enhanced by increased tropical forest litterfall. Nature Climate Change, 1(6), 304–307. https://doi.org/10.1038/nclimate1190. 2011.

Smith, M. N., Stark, S. C., Taylor, T. C., Ferreira, M. L., de Oliveira, E., Restrepo-Coupe, N., Chen, S., Woodcock, T., dos Santos, D. B., Alves, L. F., Figueira, M., de Camargo, P. B., de Oliveira, R. C., Aragão, L. E. O. C., Falk, D. A., McMahon, S. M., Huxman, T. E. and Saleska, S. R.: Seasonal and drought-related changes in leaf area profiles depend on height and light environment in an Amazon forest. New Phytol, 222: 1284-1297. https://doi.org/10.1111/nph.15726. 2019.

Sulla-Menashe, D., Woodcock, C. E., and Friedl, M. A.: Canadian boreal forest greening and browning trends: An analysis of biogeographic patterns and the relative roles of disturbance versus climate drivers. Environmental Research Letters, 13(1), 014007, 2018.

Tang, H., and Dubayah, R.: Light-driven growth in Amazon evergreen forests explained by seasonal variations of vertical canopy structure. Proceedings of the National Academy of Sciences of the United States of America, 114(10), 2640–2644. https://doi.org/10.1073/ pnas.1616943114. 2017.

Toomey, M., Roberts, D. A. and Nelson, B.: The influence of epiphylls on remote sensing of humid forests. Remote Sens. Environ, 113, 1787–1798. 2009.

Wang, C., Li, J., Liu, Q., Zhong, B., Wu, S., and Xia, C.: Analysis of Differences in Phenology Extracted from the Enhanced Vegetation Index and the Leaf Area Index, Sensors (Basel), 17, 10.3390/s17091982, 2017.

Weiss, A. and Norman, J. M.: Partitioning solar radiation into direct and diffuse, visible and near-infrared components, Agricultural and Forest Meteorology, 34, 205-213, 10.1016/0168-1923(85)90020-6, 1985.

Wu, J., Serbin, S. P., Xu, X., Albert, L. P., Chen, M., Meng, R., Saleska, S. R., and Rogers, A.: The phenology of leaf quality and its within-canopy variation is essential for accurate modeling of photosynthesis in tropical evergreen forests, Glob Chang Biol, 23, 4814-4827, 10.1111/gcb.13725, 2017.

Wu, J., Kobayashi, H., Stark, S. C., Meng, R., Guan, K., Tran, N. N., Gao, S., Yang, W., Restrepo-Coupe, N., Miura, T., Oliviera, R. C., Rogers, A., Dye, D. G., Nelson, B. W., Serbin, S. P., Huete, A. R., and Saleska, S. R.: Biological processes dominate seasonality of remotely sensed canopy greenness in an Amazon evergreen forest,

New Phytol, 217, 1507-1520, 10.1111/nph.14939, 2018.

Wu, J., Albert, L. P., Lopes, A. P., Restrepo-Coupe, N., Hayek, M., Wiedemann, K. T., Guan, K., Stark, S. C., Christoffersen, B., Prohaska, N., Tavares, J. V., Marostica, S., Kobayashi, H., Ferreira, M. L., Campos, K. S., da Silva, R., Brando, P. M., Dye, D. G., Huxman, T. E., Huete, A. R., Nelson, B. W., and Saleska, S. R.: Leaf development and demography explain photosynthetic seasonality in Amazon evergreen forests, Science, 351, 972-976, 10.1126/science.aad5068, 2016.

Xiao, X., Zhang, Q., Saleska, S., Hutyra, L., De Camargo, P., Wofsy, S., Frolking, S., Boles, S., Keller, M., and Moore, B.: Satellite-based modeling of gross primary production in a seasonally moist tropical evergreen forest, Remote Sensing of Environment, 94, 105-122, 10.1016/j.rse.2004.08.015, 2005.

Xu, L., Saatchi, S. S., Yang, Y., Myneni, R. B., Frankenberg, C., Chowdhury, D., and Bi, J.: Satellite observation of tropical forest seasonality: spatial patterns of carbon exchange in Amazonia, Environmental Research Letters, 10, 10.1088/1748-9326/10/8/084005, 2015.

Xu, X., Medvigy, D., Joseph Wright, S., Kitajima, K., Wu, J., Albert, L. P., Martins, G. A., Saleska, S. R., and Pacala, S. W.: Variations of leaf longevity in tropical moist forests predicted by a trait-driven carbon optimality model, Ecol Lett, 20, 1097-1106, 10.1111/ele.12804, 2017.

Yang, X., Tang, J., Mustard, J. F., Lee, J.-E., Rossini, M., Joiner, J., Munger, J. W., Kornfeld, A., and Richardson, A. D.: Solar-induced chlorophyll fluorescence that correlates with canopy photosynthesis on diurnal and seasonal scales in a temperate deciduous forest, Geophysical Research Letters, 42, 2977-2987, 10.1002/2015gl063201, 2015.

Yang, X., Wu, J., Chen, X., Ciais, P., Maignan, F., Yuan, W., Piao, S., Yang, S., Gong, F., Su, Y., Dai, Y., Liu, L., Zhang, H., Bonal, D., Liu, H., Chen, G., Lu, H., Wu, S., Fan, L., Gentine, P., and Wright, S. J.: A comprehensive framework for seasonal controls of leaf abscission and productivity in evergreen broadleaved tropical and subtropical forests, Innovation (Camb), 2, 100154, 10.1016/j.xinn.2021.100154, 2021.

Yang, X., Chen, X., Ren, J., Yuan, W., Liu, L., Liu, J., Chen, D., Xiao, Y., Wu, S., Fan, L., Dai, X., Su, Y.: Leaf age-dependent LAI seasonality product (Lad-LAI) over tropical and subtropical evergreen broadleaved forests. figshare. Dataset. https://doi.org/10.6084/m9.figshare.21700955.v3. 2022.

Yuan, W., Zheng, Y., Piao, S., Ciais, P., Lombardozzi, D., Wang, Y., Ryu, Y., Chen, G., Dong, W., Hu, Z., Jain, A. K., Jiang, C., Kato, E., Li, S., Lienert, S., Liu, S., Nabel, J., Qin, Z., Quine, T., Sitch, S., Smith, W. K., Wang, F., Wu, C., Xiao, Z., and Yang, S.: Increased atmospheric vapor pressure deficit reduces global vegetation growth, Sci Adv, 5, eaax1396, 10.1126/sciadv.aax1396, 2019.

Zhao, P., Gao, L., Wei, J., Ma, M., Deng, H., Gao, J., and Chen, X.: Evaluation of ERA-Interim Air Temperature Data over the Qilian Mountains of China. Advances in Meteorology, 7353482. https://doi.org/10.1155/2020/7353482, 2020