1 The seasonal cycle of satellite chlorophyll fluorescence
2 observations and its relationship to vegetation
3 phenology and ecosystem-atmosphere carbon exchange

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17 **Abstract**

Mapping of terrestrial chlorophyll fluorescence from space has shown potential for providing global measurements related to gross primary productivity (GPP). In particular, space-based fluorescence may provide information on the length of the carbon uptake period. Here, for the first time we test the ability of satellite fluorescence retrievals to track seasonal cycle of photosynthesis as estimated from a diverse set of tower gas exchange measurements from around the world. The satellite fluorescence retrievals are obtained using new observations near the 740 nm emission feature from the Global Ozone Monitoring Experiment 2 (GOME-2) instrument offering the highest temporal and spatial resolution of available global measurements. Because

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GOME-2 has a large ground footprint ($\sim 40 \times 80 \text{ km}^2$) as compared with that of the flux towers and the GOME-2 data require averaging to reduce random errors, we additionally compare with seasonal cycles of upscaled GPP estimated from a machine learning approach averaged over the same temporal and spatial domain as the satellite data surrounding the tower locations. We also examine the seasonality of absorbed photosynthetically-active radiation (APAR) estimated from satellite measurements. Finally, to assess whether global vegetation models may benefit from the satellite fluorescence retrievals through validation or additional constraints, we examine seasonal cycles of GPP as produced from an ensemble of vegetation models. Several of the data-driven models rely on satellite reflectance-based vegetation parameters to derive estimates of APAR that are used to compute GPP. For forested (especially deciduous broadleaf and mixed forests) and cropland sites, the GOME-2 fluorescence data track the spring onset and autumn shutoff of photosynthesis as delineated by the upscaled GPP estimates. In contrast, the reflectance-based indicators and many of the models, particularly those driven by data, tend to overestimate the length of the photosynthetically-active period for these biomes. Satellite fluorescence measurements therefore show potential for improving the seasonal dependence of photosynthesis simulated by global models at similar spatial scales.

Keywords: Fluorescence, Vegetation, fluorescence, chlorophyll, GOME-2,
 Gross Primary Productivity, Light-use efficiency, flux tower, growing
 season, carbon uptake period, phenology

21 1. Introduction

22 Vegetation phenology, the study of the timing and length of the ter-
23 restrial growing season and its connection to climate, has shown important
24 relationships with climate change, surface meteorology, and the carbon cycle;
25 it influences both spatial and temporal variability in ecosystem productivity
26 (*e.g.*, *Gu et al.*, 2003; *White and Nemani*, 2003; *Churkina et al.*, 2005; *Piao*
27 *et al.*, 2008; *Gu et al.*, 2009; *Richardson et al.*, 2009, 2010, 2012, and refer-
28 ences therein). For example, the timing of leaf out, particularly for deciduous
29 forests, is an important indicator of responses to climate change. It has ma-
30 jor implications for the seasonal variation of numerous interactions between
31 the biosphere and atmosphere including the partitioning of available energy
32 into sensible and latent heat exchange as well as impacts to surface radia-
33 tion budgets and dynamics (*e.g.*, *Randerson*, 1999; *Baldocchi et al.*, 2004;
34 *Churkina et al.*, 2005, and references therein). The duration of the carbon
35 uptake period (CUP), controlled by leaf out and senescence, can explain 80%
36 of the spatial variance in annual net carbon exchange of ecosystems (NEE),
37 defined as the amount of carbon entering and leaving an ecosystem (*Baldoc-*
38 *chi et al.*, 2001). *Bauerle et al.* (2012) have shown that while temperature is
39 an important driver of seasonal changes in photosynthetic physiology, pho-
40 toperiod also regulates leaf activity, particularly following summer solstice.
41 They further show that proper accounting for this effect can significantly im-
42 prove predictions of seasonal variations in atmospheric CO₂ within a global
43 carbon-cycle model.

44 Several studies in North American forests (*Richardson et al.*, 2009, 2010;
45 *Dragoni et al.*, 2010) show that earlier spring onset consistently results in

46 higher gross ecosystem photosynthesis (GEP), as well as smaller increases
47 in ecosystem respiration, leading to increased net ecosystem productivity
48 (NEP) for both spring and annual flux integrals. *Piao et al.* (2008) find that
49 autumnal warming produces increases in both photosynthesis and respira-
50 tion, with greater increases in respiration. *Dragoni et al.* (2010) further show
51 that in a North American deciduous forested site, the sensitivity of the car-
52 bon cycle to climate variability depends on the timing of the climate change
53 with respect to phenological stages as well as to its sign and magnitude.

54 Terrestrial biosphere models have a large spread in the magnitude of
55 predicted gross primary productivity (GPP) and show substantial differences
56 in the temporal and biome-related (spatial) variability of GPP (*Huntzinger*
57 *et al.*, 2012). They show generally poor performance as compared with flux
58 tower GPP estimates (*Schaefer et al.*, 2012) and consistently predict that
59 the growing season begins too early and ends late for deciduous forests; this
60 results in an over-prediction of gross ecosystem photosynthesis during spring
61 and autumn (*Richardson et al.*, 2012). There is need for additional data to
62 validate and improve these models.

63 The CUP and other phenological indicators have been estimated using
64 satellite vegetation indices such as the Normalized Differential Vegetation
65 Index (NDVI) and the Enhanced Vegetation Index (EVI) (*e.g.*, *Zhou et al.*,
66 2001; *Zhang et al.*, 2003; *Churkina et al.*, 2005; *Ma et al.*, 2013). These
67 indices have also been used within parameterized models to estimate gross
68 primary productivity (GPP), defined as the total amount of carbon dioxide
69 taken up from the atmosphere via photosynthesis (*e.g.*, *Xiao et al.*, 2008;
70 *Running et al.*, 2004; *Wang et al.*, 2010). Many of these estimates are based

71 on the light-use efficiency (LUE) model (*Monteith*, 1972) given by

$$\text{GPP}(t) = \text{LUE}(t) \times \text{fPAR}_{\text{chl}}(t) \times \text{PAR}_{\text{chl}}(t) = \text{LUE}(t) \times \text{APAR}_{\text{chl}}(t), \quad (1)$$

72 where fPAR_{chl} is the fractional absorbed (by chlorophyll) photosynthetically-
73 active radiation (PAR_{chl}), LUE is defined as the amount of carbon a spe-
74 cific vegetation type can fix biochemically per unit of absorbed solar energy,
75 APAR_{chl} is the absorbed PAR (for convenience the subscript ‘chl’ is hence-
76 forth dropped), and t is time. For example, satellite reflectance-based fPAR
77 estimates are given in the MOD15A2 product from the MODerate-resolution
78 Imaging Spectroradiometer (MODIS), and LUE can be parameterized as a
79 function of meteorological parameters for a given biome. However, the use of
80 reflectance-based indicators such as fPAR can be problematic in areas where
81 vegetation indices do not drop when vegetation stays green while photosyn-
82 thesis declines, (*e.g.*, in evergreen needleleaf forests), in regions affected by
83 seasonal snow cover under the canopy, and possibly in areas with high het-
84 erogeneity within a satellite pixel (*e.g.*, *Churkina et al.*, 2005; *Xiao et al.*,
85 2004). In these cases, LUE models must rely more heavily on their LUE
86 parameterizations.

87 Fluorescence measurements, particularly global observations from space,
88 offer an alternative means of remotely sensing the functional status of veg-
89 etation. Fluorescence is generated during the photosynthetic process. The
90 excitation for chlorophyll fluorescence in nature is provided by sunlight. The
91 broad-band emission has two chlorophyll-related peaks at red and far-red
92 wavelengths near 685 and 740 nm, respectively (*e.g.*, *Corp et al.*, 2003; *Camp-*
93 *bell et al.*, 2008).

94 At the canopy level, steady-state fluorescence from chlorophyll in veg-

etation at emission wavelength $\lambda_{\text{em}} = 740 \text{ nm}$, henceforth denoted F_{740} , in general can be expressed as an integral of contributions over all excitation wavelengths from ultraviolet to near-infrared wavelengths, i.e.,

$$F_{740}(t) = e(\lambda_{\text{em}} = 740 \text{ nm}, t) \int_{\lambda_{\text{ex}}} \Theta_F(\lambda_{\text{ex}}, \lambda_{\text{em}}, t) \text{fPAR}_F(\lambda_{\text{ex}}, t) I(\lambda_{\text{ex}}, t) d\lambda_{\text{ex}}, \quad (2)$$

where λ_{ex} is the excitation wavelength, I is incident radiation at the surface, e is the fractional amount of fluorescence that escapes the canopy, and Θ_F is the fluorescence efficiency. Here it is recognized (by use of the subscript F) that fPAR for chlorophyll fluorescence (fPAR_F) may differ slightly from fPAR for photosynthesis (fPAR_{chl}). fPAR_F and e are determined by canopy structure and vegetation biochemistry, captured in spectral optical properties.

A more simplified formulation has also been used to express steady state fluorescence (e.g., *Louis et al.*, 2005; *Berry et al.*, 2013), i.e.,

$$F_{740}(t) \simeq e(t)\Theta_F(t) \times \text{fPAR}_F(t) \times \text{PAR}_F(t) = e(t)\Theta_F(t) \times \text{APAR}_F(t). \quad (3)$$

Again, we recognize that PAR_F may differ somewhat from PAR_{chl} (typically assumed to be 400-700 nm) as the action spectrum for fluorescence may weight ultraviolet wavelengths more heavily (*Chappelle and Williams*, 1987; *Rosema et al.*, 1991; *Middleton et al.*, 2008). Equation 3 is similar in form to Eq. 1. Conversely, Eq. 1 could also be written in a somewhat more complex form similar to Eq. 2 as an integral over photosynthetically-active wavelengths. Equation 3 may be used to approximate Eq. 2 provided that the spectral structure of Θ_F , fPAR_F , and I remains relatively constant with time.

If Eq. 3 is taken as is and $\text{APAR}_F(t) \simeq \text{APAR}_{\text{chl}}(t)$, then the ratio of

116 GPP(t) to $F_{740}(t)$ is proportional to the ratio of LUE(t) to $e(t)\Theta_F(t)$. There
 117 is theoretical evidence to support that under strong illumination, the ratio
 118 of LUE to Θ_F remains relatively constant, at least for fluorescence from
 119 photosystem II (*Berry et al.*, 2013). Experimental studies have also shown
 120 that in high light conditions (*i.e.*, in the early afternoon and late morning
 121 when many satellite measurements are made), chlorophyll fluorescence is
 122 positively correlated with APAR, LUE, and GPP (*e.g.*, *Flexas et al.*, 2002;
 123 *Louis et al.*, 2005; *Meroni et al.*, 2008; *van der Tol et al.*, 2009; *Zarco-Tejada*
 124 *et al.*, 2009; *Amoros-Lopez et al.*, 2008; *Guanter et al.*, 2014). Therefore, we
 125 may expect similar seasonal variability in GPP and F_{740} for a given vegetation
 126 type as long as e remains relatively constant.

127 The main objective of this study is to test the ability of F_{740} to accu-
 128 rately track the seasonal cycle of GPP across different vegetation types. A
 129 new F_{740} data set derived from observations from the GOME-2 satellite in-
 130 strument provides the temporal and spatial resolution needed for a first direct
 131 comparison with global flux tower gas exchange measurements in terms of
 132 the seasonality of photosynthesis. Towards our goal, we compare the sea-
 133 sonal cycle of GOME-2 F_{740} , averaged over multiple years, with that of GPP
 134 from a diverse set of flux towers from around the world at middle latitudes
 135 where there is a distinct cycle in photosynthesis. Because the spatial scale of
 136 the tower measurements is much smaller than the large footprint GOME-2
 137 satellite measurements (additionally averaged over time and space to reduce
 138 random errors), we also compare with upscaled GPP estimated with the
 139 Max Planck Institute for Biogeochemistry (MPI-BGC) machine learning al-
 140 gorithm; these upscaled GPP estimates are averaged at the same spatial

141 resolution and over the same time period as the GOME-2 F_{740} retrievals.
 142 This allows us to assess potential representativeness errors in the comparison
 143 between GOME-2 F_{740} and GPP from flux towers. We perform additional
 144 comparisons to determine whether the seasonal cycle of fluorescence more
 145 closely tracks photosynthesis as compared with absorbed photosynthetically-
 146 active radiation (APAR), derived from satellite reflectances. Finally, in or-
 147 der to assess whether fluorescence data may provide additional validation of
 148 and/or constraints for global vegetation models, we compare seasonal cycles
 149 of GOME-2 F_{740} and GPP generated from an ensemble of state-of-the-art
 150 physically-based and data driven models; the mostly global models are typ-
 151 ically run at similar spatial resolutions as compared with the GOME-2 F_{740}
 152 data set.

153 2. Data

154 2.1. GOME-2 fluorescence at 740 nm (F_{740})

155 2.1.1. Background on remote sensing of terrestrial chlorophyll fluorescence

156 Fluorescence from chlorophyll in terrestrial vegetation has been measured
 157 with ground-, aircraft, and satellite-based instrumentation at wavelengths in
 158 and surrounding the O₂ A- and B-bands (*e.g.*, Moya *et al.*, 2004; Amoros-
 159 Lopez *et al.*, 2008; Meroni *et al.*, 2009; Rascher *et al.*, 2009; Middleton *et*
 160 *al.*, 2010; Guanter *et al.*, 2007, 2013, and references therein). The filling-in
 161 of solar Fraunhofer lines by terrestrial fluorescence at wavelengths on both
 162 shoulders of the O₂-A absorption band (755 and 770 nm) has been observed
 163 using the Japanese Greenhouse gases Observing SATellite (GOSAT) (Joiner
 164 *et al.*, 2011, 2012; Frankenberg *et al.*, 2011a; Guanter *et al.*, 2012). Joiner *et*

165 *al.* (2012) found a small filling-in of the broad solar Fraunhofer ionized cal-
 166 cium (Ca II) line at 866 nm consistent with fluorescence using the SCanning
 167 Imaging Absorption spectroMeter for Atmospheric CHartographY (SCIA-
 168 MACHY) instrument flying on the European Space Agency’s (ESA’s) En-
 169 viSat.

170 *Joiner et al.* (2013) demonstrated that fluorescence can be retrieved near
 171 the 740 nm emission peak using atmospheric hyperspectral satellite-based in-
 172 strumentation. They applied their approach to data from the Global Ozone
 173 Monitoring Experiment 2 (GOME-2) flying on operational European mete-
 174 orological (MetOp) satellites. GOME-2 provides the highest fidelity satellite
 175 fluorescence data set currently available; the data, gridded to a spatial reso-
 176 lution of about 0.5° latitude by 0.5° longitude at a monthly time resolution,
 177 have estimated errors of $0.1\text{--}0.4\text{ mW/m}^2/\text{nm/sr}$.

178 2.1.2. The GOME-2 instrument

179 GOME-2 is a grating spectrometer that measures backscattered sunlight
 180 in a nadir-viewing geometry at wavelengths between 270 and 800 nm in four
 181 separate channels (*Munro et al.*, 2006). It has been launched on the MetOp
 182 A and B platforms on 19 October 2006 and 17 September 2012, respectively.
 183 Both MetOp A and B are in sun-synchronous orbits with an equator crossing
 184 time near 09:30 AM, but approximately 45 minutes (half an orbit) apart.

185 Here, we use data from MetOp A covering 2007–2011. We use radiances
 186 from channel 4 at a spectral resolution of $\sim 0.5\text{ nm}$ with a signal-to-noise ratio
 187 of ~ 1000 . The nominal ground pixel lengths at nadir are approximately 40
 188 and 80 km in the along- and across-track directions, respectively. The default
 189 swath width is 1920 km. This enables global coverage of the Earth’s surface

190 within about 1.5 days. The actual coverage for fluorescence retrievals is
191 reduced because data in heavily clouded overcast conditions are filtered out
192 as described in more detail below.

193 2.1.3. Retrieval of far-red fluorescence from GOME-2

194 We derive GOME-2 F_{740} primarily from the filling-in of solar Fraunhofer
195 lines in the vicinity of the 740 nm far-red fluorescence emission peak as in
196 *Joiner et al.* (2013). The basis for the retrieval relies on the fact that an
197 additive signal such as fluorescence produces a filling-in of a solar line when
198 an Earth backscattered spectrum is normalized with respect to the solar
199 spectrum or a reference spectrum that does not contain fluorescence. The
200 retrieval uses a principal component analysis approach with a simplified ra-
201 diative transfer model to disentangle the spectral signatures of three basic
202 components: atmospheric absorption, surface reflectance, and fluorescence
203 emission. GOME-2 F_{740} is given in radiance units ($\text{mW}/\text{m}^2/\text{nm}/\text{sr}$) and
204 varies somewhat with viewing geometry (*Joiner et al.*, 2012; *Guanter et al.*,
205 2012).

206 The retrieval algorithm performed well when tested with simulated data
207 and was applied to radiances from GOME-2 (*Joiner et al.*, 2013). Fluores-
208 cence from GOME-2 compared well in terms of spatial and temporal vari-
209 ability with that from GOSAT (*Guanter et al.*, 2012) obtained with a more
210 simple retrieval approach. The GOME-2 fluorescence data set provides sub-
211 stantially improved sampling and precision (and therefore spatial resolution)
212 as compared with GOSAT; therefore only GOME-2 data are used in this
213 study.

214 We have made some minor changes to the approach of *Joiner et al.* (2013)

215 that bring the GOME-2 results into slightly better agreement with GOSAT
 216 and reduce small biases where no fluorescence is expected. We use a spectral
 217 fitting window between 715 and 758 nm and a single set of principal compo-
 218 nents (PCs), derived from cloudy data over ocean, to estimate the spectral
 219 structure of atmospheric absorption; absorption is dominated by water va-
 220 por over this spectral range. The O₂ A-band is not included in the fitting
 221 window. The principal components are derived from radiance spectra here
 222 as opposed to the logarithm of the radiance spectra as in *Joiner et al.* (2013).
 223 We also attempted to correct for drift in the absolute instrument calibration
 224 by fitting a degradation factor to the GOME-2 solar spectra.

225 2.1.4. Processing of GOME-2 fluorescence retrievals

226 For cloud screening of GOME-2 data as in *Joiner et al.* (2013), we make
 227 use of the concept of the effective cloud fraction, f_e , described in detail
 228 by *Stammes et al.* (2008). f_e can be computed by inverting the following
 229 equation:

$$I_m = I_{\text{clr}}(1 - f_e) + I_{\text{cld}}f_e, \quad (4)$$

230 where I_m is the measured radiance, and I_{clr} and I_{cld} are considered to be
 231 clear and cloudy subpixels (i.e., the independent pixel approximation). I_{clr} is
 232 computed using a surface albedo data set as described in *Joiner et al.* (2013)
 233 and I_{cld} is modeled as a Lambertian surface with an effective reflectivity
 234 of 0.8. In this mixed Lambertian model of cloudy scenes, f_e is not a true
 235 geometrical cloud fraction, but rather represents an estimated fraction of the
 236 surface that is completely shielded by clouds (i.e., the satellite sensor sees
 237 only the clear fraction of a pixel approximated by $1 - f_e$).

238 Here, we retain only pixels with $f_e < 40\%$. The impact of this empirically
 239 chosen threshold is described in more detail in Sect. 3. Due to uncertainties
 240 in the GOME-2 absolute calibration and the surface albedo data set used in
 241 the calculation of f_e , our cloud screening procedure primarily removes heav-
 242 ily clouded (overcast) pixels; cases of thin and broken clouds are retained in
 243 the sample. Clouds do not affect the spectral signature of fluorescence as is
 244 the case for vegetation indices derived from satellite reflectances. Therefore,
 245 the main effect of clouds on fluorescence measurements is a shielding effect,
 246 i.e., a fraction of the surface is shielded by clouds/aerosol from satellite ob-
 247 servation. Radiative transfer simulations show that a substantial fraction of
 248 the fluorescence signal ($\sim 80\%$) can penetrate through clouds/aerosols of low
 249 to moderate optical thickness (up to 5) (*Frankenberg et al.*, 2012). *Joiner et*
 250 *al.* (2012) similarly estimate that with a 40% geometrical cloud cover, 80%
 251 or more of the surface will be seen for cloud optical thicknesses up to 10.

252 We generate climatological 8 day mean GOME-2 F_{740} values using GOME-
 253 2 data averaged over the time period Jan. 2007 through Dec. 2011. The 8-day
 254 intervals were chosen to match those of the MODIS fPAR (MOD15) data set
 255 as described below. For comparison with data from a given flux tower site,
 256 we average quality-controlled pixels that have centers within 1° latitude and
 257 1° longitude of the tower location; we apply quality control checks as de-
 258 scribed in *Joiner et al.* (2013). In addition, we use only GOME-2 pixels
 259 with solar zenith angles (SZA) less than 70° to avoid possible biases due to
 260 rotational-Raman scattering (*Vasilkov et al.*, 2013).

261 We estimated uncertainties in each 8-day bin as the root sum square of the
 262 standard error of the mean (of all samples in the bin) and a nominal GOME-2

263 F_{740} constant error of $0.2 \text{ mW/m}^2/\text{nm/sr}$. The standard errors alone appear
 264 to underestimate the uncertainties as the large numbers of samples used in
 265 the averaging process lead to relatively small standard errors in most bins.
 266 The constant error is introduced to account for other error sources such as
 267 cloud contamination.

268 2.2. AmeriFlux and FluxNet tower measurements

269 We use quality-controlled 1/2 hourly GPP from the FluxNet synthesis
 270 project (<http://www.fluxdata.org/>) (*Baldocchi et al.*, 2001) and additional
 271 US stations in the AmeriFlux site synthesis project (*Barr et al.*, 2013a,b).
 272 Table 1 provides tower station details including the starting and ending years
 273 of the observational record used here and the International Geosphere Bio-
 274 sphere Programme (IGBP) vegetation type at the station. Table 1 also lists
 275 the dominant vegetation type, according to an IGBP land cover map, corre-
 276 sponding to the area over which the GOME-2 F_{740} data are averaged (within
 277 1° latitude, 1° longitude of a station location), denoted IGBP_{avg} . Here, we
 278 combined open and closed shrublands into a single type (shrublands), and
 279 woody savannas and savannas into one type (savannas). Our mixed forest
 280 type contains the IGBP type ‘grass + mixed forest’ in addition to ‘mixed for-
 281 est’. We provide the approximate percentage (%) of the satellite-averaging
 282 box covered by the dominant vegetation type IGBP_{avg} in Table 1. Figure 1
 283 displays locations and vegetation types in a mapped format.

284 We compute 8-day means of GPP estimated from the tower data in a
 285 manner similar to our processing of GOME-2 data. Each 8-day value is an
 286 average over all available years for a particular tower. The 8-day intervals
 287 match those of the MOD15 data set. We do not include gap-filled data in

our data processing. We use all available GPP data regardless of the cloud conditions and average data over all hours. We checked that the derived seasonal cycle of GPP does not change substantially if we use only data near the satellite overpass time.

For inclusion of a site in our analysis, at least 40 quality-controlled GOME-2 pixels must have been collected for a given 8 day period and at least 75% of the 8-day bins within the year must be filled. Unfortunately, the tower observational time records do not generally coincide with those of GOME-2. Therefore, we must compare seasonal cycles that have been averaged over different sets of years (for each site). This may produce some differences between the tower and other satellite data sets as there can be interannual variability, particularly in the initiation of photosynthesis (e.g., *Gu et al.*, 2008). Comparisons of derived seasonal cycles of photosynthesis from flux towers and GOME-2 satellite data are considered to be climatological. By using averages over several years, we may smooth out some of the interannual variability.

Uncertainties in the GPP derived from flux tower measurements have been computed for the Ameriflux sites (*Schaefer et al.*, 2012); total uncertainties include contributions from random errors, threshold friction velocity uncertainty, and partitioning uncertainty (owing to uncertainty in the estimated ecosystem respiration). The partitioning uncertainty is based on the variance produced by different partitioning algorithms (*Desai et al.*, 2008). Random uncertainty is the largest contributor to the total uncertainties (50–90%).

Using the available Ameriflux data, we find that total uncertainties in the

313 weekly-mean GPP ($\text{GPP}_{\text{weekly}}$) varies with $\text{GPP}_{\text{weekly}}$. We fit a general expo-
 314 nential function to the Ameriflux data to approximate the weekly-averaged
 315 total GPP uncertainties ($\sigma_{\text{GPP}_{\text{tot}}}$), i.e.,

$$\sigma_{\text{GPP}_{\text{tot}}} = 0.5085 * e^{0.1088 * \text{GPP}_{\text{weekly}}} . \quad (5)$$

316 We then apply this formulation to all tower sites to approximate uncertainties
 317 in the derived 8-day GPP.

318 2.3. The MPI-BGC data-driven model of GPP

319 Estimates of GPP from the Max Planck Institute for Biogeochemistry
 320 (MPI-BGC) originate from upscaling a global dataset of eddy covariance
 321 based measurements (*Jung et al.*, 2011). A machine learning algorithm
 322 (Model Tree Ensembles, MTE) as described by *Jung et al.* (2009) was trained
 323 to predict monthly observed GPP at the tower sites based on remotely sensed
 324 fPAR, climate, and vegetation type data. The trained model was then applied
 325 using spatial grids of the explanatory variables to generate global monthly
 326 GPP estimates at a 0.5° spatial resolution (see *Jung et al.*, 2011, for details).

327 We averaged monthly MPI-BGC GPP estimates from Jan. 2007–Dec. 2011,
 328 the same time period used for GOME-2 data. We then averaged all gridboxes
 329 within 1° latitude and longitude of each flux tower location, the same spatial
 330 scale as represented by the GOME-2 data. We may then use the upscaled
 331 MPI-BGC GPP estimates to assess the effect of the different spatial scales
 332 of the flux tower and GOME-2 satellite data. We use Eq. 5 to estimate
 333 uncertainties in the upscaled GPP.

334 2.4. GPP model ensemble

335 We also examine seasonal cycles (weekly output) of GPP as produced by
336 an ensemble of 24 models that were used in the study of *Schaefer et al.* (2012).
337 MPI-BGC is not included in the ensemble. The models were driven with gap-
338 filled meteorological data from each tower site. Other input parameters and
339 biophysical characteristics were derived from local observations as discussed
340 in *Schaefer et al.* (2012).

341 The model ensemble includes 14 physically-based models that have prog-
342 nostic phenology and 10 data-driven models that use remote sensing data to
343 determine leaf area index (LAI) and/or GPP. The models were classified in
344 *Schaefer et al.* (2012) as either enzyme-kinetic (EK) (17 models) or LUE (7)
345 models. Both EK and LUE groupings include a combination of data-driven
346 and physically-based approaches to estimate LAI and/or GPP. Because some
347 of the models are targeted for a particular biome (e.g., forest or agriculture),
348 not all of the models produced a simulation for a given site. Therefore, each
349 site has a different model ensemble associated with it.

350 2.5. MODIS fPAR/APAR (MOD15)

351 We used 8-day means of the canopy fPAR derived from the Terra MODIS
352 collection 5 (MOD15A2) (*Myneni et al.*, 2002) obtained from the Oak Ridge
353 National Laboratory’s Distributed Active Archive Center (*ORNL DAAC*,
354 2010). We used quality controlled data averaged over approximately 7 km
355 $\times$ 7 km regions centered on a flux tower. The original data are produced
356 as an 8-day maximum value composite at 1 km spatial resolution. Because
357 the MODIS data set is produced as a composite using maxima rather than
358 means (as was done for the F_s and tower GPP data) and are then specified

as a single value at the midpoint of the compositing period, it should be noted that the values may be weighted towards earlier dates in spring during the onset of greening (by up to ~ 4 days or half the compositing period) and similarly towards later dates in autumn as greenness is declining.

APAR values are computed using the MOD15A2 fPAR $\times \cos(\Theta)$, where Θ is the average solar zenith angle for each time period near the MetOp-A and Terra local overpass times; $\cos(\Theta)$ is a proxy for the seasonal cycle of potential PAR. We compute a climatological seasonal cycle of APAR by averaging data for each 8-day interval over the time period Feb. 2000–Oct. 2011. The averaged data are then plotted at the midpoint of the time interval. We estimate uncertainties similar to what was done for GOME-2 F_{740} as described above; for each 8-day bin, we estimate the uncertainty as the root sum square of the standard error of the mean (for each 8-day interval) and a nominal constant error of 0.03 intended to account for additional error sources such as cloud contamination and compositing effects.

3. Results and Discussion

3.1. Seasonal variations in tower-based and upscaled GPP, MODIS-based APAR, and GOME-2 F_{740}

In this section, we assess the ability of GOME-2 F_{740} to track the seasonality of photosynthesis as delineated by tower-based and upscaled GPP estimates. Figures 2–3 show average seasonal cycles of GPP (normalized to unity at the maxima) from towers along with the upscaled GPP from MPI-BGC, GOME-2 F_{740} , and MODIS-based estimates of APAR, for sites representing a variety of biomes. Similar plots for the other sites listed in

383 Table 4 are provided in the supplemental information (SI). All GOME-2 pix-
 384 els with centers within 1° latitude and longitude of the flux tower site are
 385 averaged here, and similarly all MPI-BGC gridboxes within 1° latitude and
 386 longitude of the site are averaged. The GOME-2 F_{740} and MPI-BGC GPP
 387 data are averaged over the same years (2007–2011). Therefore, we expect
 388 better agreement of GOME-2 F_{740} with MPI-BGC GPP as compared with
 389 tower-based GPP due to the closer collocation in both time and space of
 390 GOME-2 F_{740} with MPI-BGC GPP.

391 The tower data indicate a relatively short growing season for the agricul-
 392 tural Nebraska site US-Ne1 (Fig. 2a), composed of continuous maize crops.
 393 This short duration of photosynthesis is similarly shown by both GOME-
 394 2 F_{740} and the upscaled MPI-BGC GPP estimates. The upscaled GPP and
 395 GOME-2 F_{740} display a slightly wider mean growing season as compared with
 396 the tower-based GPP. This may be expected as GOME-2 F_{740} and the up-
 397 scaled GPP estimates are analyzed at similar and larger spatial scales as com-
 398 pared with the tower measurements. The larger footprints of GOME-2 F_{740}
 399 and MPI-BGC GPP likely contain contributions from different crops such as
 400 soybeans that have somewhat lengthier growing seasons and vegetation types
 401 other than croplands; this may explain the more gradual increases(decreases)
 402 in spring(autumn). It should be noted that monthly mean MPI-BGC GPP
 403 estimates are in excellent agreement with 8-day mean GOME-2 F_{740} ; this
 404 indicates that monthly-mean values are adequate for the present analysis.

405 A significantly earlier springtime rise and later autumn decline is seen
 406 in MODIS-based APAR as compared with GOME-2 F_{740} and the GPP es-
 407 timates for the US-Ne1 agricultural site and similarly for the agricultural

408 US-IB1 site (see SI). The later decline in autumn may be expected as APAR
409 does not contain information about LUE and therefore may remain high in
410 the presence of green vegetation that is not engaging in photosynthesis. How-
411 ever, the almost symmetrical early rise in spring is more difficult to explain
412 as green vegetation in spring should be photosynthetically-active.

413 One explanation is that the reflectances used to generate MODIS (MOD15)
414 fPAR are sensitive to pigments in vegetation and soil other than chlorophyll.
415 It has been shown that the MOD15 estimate of fPAR applies to the whole
416 vegetation canopy, both photosynthetic and nonphotosynthetic components,
417 and does not provide consistent relationships to photosynthetic processes at
418 the ecosystem scale (*Turner et al.*, 2003a,b, 2006; *Zhang et al.*, 2009). Al-
419 ternative methods have emerged to improve estimates of fPAR related to
420 only the photosynthetic component (see *Zhang et al.*, 2013, and references
421 therein). One such approach involves the retrieval of a new fPAR parameter
422 related only to the chlorophyll-containing foliage (called fPAR_{chl}) (*Zhang et*
423 *al.*, 2005, 2006, 2009, 2012). This parameter shows a seasonal cycle more
424 consistent with tower-based GPP for several tower sites used in our study in-
425 cluding the agricultural sites US-Ne2 and US-Ne3, and a deciduous broadleaf
426 forest site (US-Bar) (*Cheng et al.*, 2014).

427 The MODIS-based APAR also shows a slightly earlier spring onset of
428 activity for the northern deciduous broadleaf forest (DBF) and mixed-forest
429 (MF) sites (US-UMB and US-Ha1) in Fig. 2b and c, respectively, and is
430 lagged in the autumn decline with respect to the tower GPP at these sites.
431 We note that MODIS fPAR typically stays above 0.2 throughout the year
432 for these sites. For some sites such as US-Ha1, fPAR remains very high

433 (~ 0.5) throughout the winter, possibly owing to contributions from evergreen
 434 needleleaf vegetation or other pigments in the woody parts of the vegetation.
 435 While multiplication of fPAR by the PAR-proxy brings MODIS-based APAR
 436 to near zero in winter, GOME-2 F_{740} minimum winter values are at or closer
 437 to zero. MODIS-based APAR shows a much closer relationship with tower-
 438 based GPP at the more southern US-Dk3 site (Fig. 2d) where GPP does not
 439 drop to zero in winter.

440 GOME-2 F_{740} tracks the sharp springtime rise and autumn drop in GPP,
 441 as shown in the upscaled MPI-BGC GPP product, at sites composed pri-
 442 marily of DBF and MF in the northeast, midwest, and southern US shown
 443 in (US-Ha1, US-UMB, and US-Dk3 sites in Fig. 2b-d, respectively). Similar
 444 results are obtained at other US DBF and MF sites in the northeast and mid-
 445 west US (see SI) such as US-Syv, US-PFa, US-WCr, and US-MMS (stations
 446 in Wisconsin and Indiana) and New England sites (US-Bar and US-Ho1,2).
 447 The GOME-2 F_{740} and MPI-BGC GPP seasonal variations also closely follow
 448 those from the tower-based GPP estimates at these relatively homogeneous
 449 sites.

450 For most forested sites, GOME-2 F_{740} appears to begin to decline slightly
 451 earlier than both GPP estimates. This decline, starting near summer solstice,
 452 is consistent with seasonal changes in leaf photosynthetic capacity (V_{cmax})
 453 across a variety of tree species reported by *Bauerle et al.* (2012). It should
 454 be noted that the uncertainties in the tower GPP, particularly due to parti-
 455 tioning, are relatively large at this time of year. Another explanation is that
 456 the seasonal variations in fluorescence efficiency differ slightly from those of
 457 light use efficiency.

458 The Oklahoma US-Shd site shown in Fig. 2e is relatively heterogeneous
 459 in terms of vegetation type in the surrounding satellite averaging area and is
 460 composed primarily of grasslands. The upscaled GPP from MPI-BGC shows
 461 a somewhat more broad and smooth seasonal cycle as compared with the
 462 tower-estimated GPP. GOME-2 F_{740} agrees to within estimated uncertainties
 463 with the MPI-BGC GPP at this site, while the MODIS APAR shows a more
 464 lengthy duration of activity.

465 GOME-2 F_{740} and MPI-BGC upscaled GPP compare reasonably well
 466 with each other as well as with tower GPP at the evergreen needleleaf forest
 467 (ENF) US-NR1 site (Figs. 2f). MODIS-based APAR does not show a drop
 468 to near zero in winter. This is likely a result of the evergreen vegetation or
 469 other non-photosynthetic components that are absorbing PAR in winter but
 470 not engaging in photosynthesis. The GOME-2 F_{740} errors are proportionally
 471 higher for this site as compared with the others owing to the overall lower
 472 observed values. Therefore, the empirically-derived constant component of
 473 the error ($0.2 \text{ mW/m}^2/\text{nm/sr}$) produces an effectively lower signal-to-noise
 474 ratio for sites with lower fluorescence signals. Other examples are shown in
 475 the supplemental material for shrublands and savannas that also display low
 476 fluorescence values.

477 The seasonality of GPP and GOME-2 F_{740} at the savannas tower sites
 478 in Africa and Australia (see Fig. 3a and c) shows similar patterns. In both
 479 cases MODIS-based APAR does not display as much variability as GOME-
 480 2 F_{740} or the GPP estimates. In contrast, the evergreen broadleaf forest
 481 site in Australia (Fig. 3b) shows different seasonality of both upscaled MPI-
 482 BGC GPP and GOME-2 F_{740} as compared with MODIS-based APAR and

483 tower GPP. This is likely due to spatial heterogeneity around the site that is
484 surrounded by pastures that display a peak in GPP around day 280 similar
485 to that shown in MPI-BGC GPP and GOME-2 F_{740} (J. Beringer, private
486 communication, 2014).

487 GOME-2 F_{740} tracks the seasonality of GPP reasonably well for the Eu-
488 ropean sites dominated by croplands and mixed-forest within the satellite
489 averaging area (Fig. 3d-f). It should be noted that these sites are also rel-
490 atively heterogeneous as indicated by differences shown in sites contained
491 within approximately the same satellite averaging area (see SI). In these
492 cases, GOME-2 F_{740} is in good agreement with the upscaled MPI-BGC GPP
493 estimates. However, as shown for the mixed-forest dominated US sites and
494 discussed above, a somewhat earlier decline at the start of senescence is shown
495 for GOME-2 F_{740} as compared with the GPP estimates for the DE-Tha site
496 (Fig. 3f).

497 In order to show that the displayed seasonal variability of GPP is not
498 driven primarily by the seasonality of PAR, we alternatively repeated this
499 comparison by normalizing GPP estimates and GOME-2 F_{740} with respect
500 to incoming potential PAR (results not shown). This analysis showed that
501 the seasonality of GPP (and GOME-2 F_{740}) is dictated largely by that of
502 LUE and fPAR. Results in *Cheng et al.* (2014) support this conclusion.

503 The general conclusions discussed above were not substantially impacted
504 by varying the value of the f_e threshold for the GOME-2 F_{740} data. We also
505 checked whether the conclusions hold if tower data are filtered for clouds
506 using the reported incident short-wave radiation. While cloud filtering quan-
507 titatively affects monthly-mean GPP and to some extent GOME-2 F_{740} val-

ues (changes absolute values), it does not substantially alter the qualitative
spatio-temporal variations of normalized GPP.

3.2. Comparisons with multi-model mean weekly GPP

In this section, we examine whether GOME-2 F_{740} offers a means to constrain or validate global vegetation models in terms of the simulated seasonality of photosynthesis. Figure 4 shows the multi-model weekly mean GPP from data driven (DD) and prognostic (Prog) models along with the tower-based GPP and GOME-2 F_{740} for the same sites as in Fig. 2. The multi-model means, particularly for the DD models, show a somewhat lengthier duration of photosynthesis for northern and midwestern DBF and MF sites such as US-Ha1 and US-UMB, the agricultural US-Ne1 site, and the grasslands US-Shd site as compared with tower-based GPP. Like the MODIS APAR estimates, the models, especially DD models, show better agreement of the estimated GPP seasonal cycle with the tower data for the southern MF-dominated US-Dk3 site. The models also generally fall within the range of observational uncertainties for the ENF-dominated US-NR1 site.

Some of the DD models contained in the multi-model means calculate GPP using the LUE model as in Eq. 1. Errors in these types of models can result from errors in fPAR and/or LUE. In areas containing dormant green vegetation, such as MF and ENF in winter, APAR may remain high owing to the greenness of the vegetation (including non-chlorophyll containing pigments) when solar radiation is being absorbed but not used for photosynthesis. In this situation, models that utilize reflectance-based parameters like fPAR must then depend upon their LUE parameterization to control GPP.

In regions with cold winters, low winter temperatures are generally suf-

533 ficient to reduce LUE and subsequently GPP; when LUE can be estimated
534 reliably as near or equal to zero (e.g., temperatures near or below freezing),
535 it can be assumed that GPP is likewise near or equal to zero. Under these
536 conditions, the GPP estimate is not influenced by any errors in fPAR/APAR.

537 However, in areas where temperatures are near or above freezing out-
538 side of the main part of growing season and fPAR remains high, it is more
539 challenging to estimate the spring initiation and autumn decline of photo-
540 synthesis through the LUE parameterization. As a result, an incorrect GPP
541 may be generated outside the main growing season when fPAR is at a mod-
542 erate value. This has been reported previously for the MODIS GPP product
543 (MOD17) (e.g., *Turner et al.*, 2003a, 2006; *Heinsch et al.*, 2006, and ref-
544 erences therein); MOD17 is one of the models contained in our data-driven
545 ensemble and one that specifically uses the MOD15 fPAR product. Improved
546 seasonal cycles of GPP have been obtained in an LUE model by using fPAR_{chl}
547 as compared with MODIS fPAR ($\text{fPAR}_{\text{canopy}}$) (*Cheng et al.*, 2014).

548 Our results suggest that GOME-2 F_{740} may provide an additional con-
549 straint for estimating the seasonal rise and fall of GPP, particularly for the
550 deciduous and mixed forest sites. Given the results shown in the previous
551 subsection, it is suggested that F_{740} can offers estimates of the seasonality of
552 photosynthesis in areas not well covered by flux tower measurements that can
553 be used for model validation. In addition, GOME-2 F_{740} provides a global
554 data set at a spatial resolution similar to that of global models.

555 3.3. *Timing indicators associated with different stages of photosynthetic ac-* 556 *tivity*

557 There is no standard way to compute phenological indicators, such as
558 onset of greenness or photosynthetic activity in spring, using satellite data
559 (see e.g., *Gu et al.*, 2003; *Fisher et al.*, 2006, and references therein). It has
560 been shown for deciduous vegetation and many crops that the spring pattern
561 of leaf emergence, followed by rapid growth, and then a stable period of
562 maximum leaf area can be represented using a logistical model (e.g., *Zhang*
563 *et al.*, 2003, and references therein). A reverse pattern can be modeled for
564 the transition from senescence to dormancy.

565 We identify various timing indicators following the approach of *Zhang et*
566 *al.* (2003) as illustrated in Figure 5 for the US-Bar site. We have augmented
567 the approach by computing uncertainties for the indicators as described be-
568 low. The first step is to fit either the greenup or senescence portions of the
569 seasonal cycle of the various parameters (GPP, MODIS APAR, or GOME-2
570 F_{740}) to a function of the form

$$y(t) = \frac{c}{1 + e^{a+bt}} + d. \quad (6)$$

571 Then, using the fitted parameters in Eq. 6, the rate of change in the curvature
572 can be computed analytically. Transition dates are defined for the times when
573 the rate of change in the curvature reaches local minima or maxima.

574 In the greenup(or declining) portion of the seasonal cycle, the photosyn-
575 thetic(or senescence) onset is defined as the first peak/valley in the curvature-
576 change rate. The next large peak is known as the inflection or stability point
577 where GPP or satellite parameters are changing at a large rate. The last

578 peak occurs at the onset of maximum photosynthetic activity in the greenup
 579 portion or at the onset of dormancy in the declining phase.

580 Here, we focus exclusively on forested and cropland sites in North America
 581 for which this fitting approach works well. We inspected the results for each
 582 site and discarded a few sites (e.g., US-Bkg, US-MOz, US-SP1-3) where the
 583 fitting procedure was not well behaved (e.g., owing to a too narrowly peaked
 584 maximum, multiple peaks, or incomplete dormancy).

585 To compute the uncertainties in the timing indicators, we use a Monte
 586 Carlo approach centered about the initial fit with 1000 perturbations. To
 587 illustrate the range of uncertainties for the rate of change in curvature shown
 588 in Fig. 5, we use standard linear error analysis to propagate observation
 589 errors through the fitting procedure. Specifically, we compute the Jacobian
 590 of Eq. 6, K , and assume that the observation error covariance matrix, S_y is
 591 a diagonal matrix (i.e., errors are assumed to be unbiased and uncorrelated
 592 with respect to each other). The estimated error covariance for the fitted
 593 parameters in Eq. 6, S_f , is given by

$$S_f = (K^t (S_y)^{-1} K)^{-1}. \quad (7)$$

594 S_f is then further propagated linearly using Eq. 7 with the analytically com-
 595 puted Jacobian of the rate of change of curvature function (see *Zhang et al.*,
 596 2003, for formulation of the rate of change of curvature). This provides a
 597 full error covariance for the rate of change of curvature. We show the error
 598 standard deviations for reference in Fig. 5 (note that errors are correlated
 599 with respect to each other). The errors from the Monte Carlo simulation for
 600 the timing parameters are also shown in Fig. 5.

601 The computed timing indicators and associated uncertainties are shown

in Figures 6–7 for tower and upscaled GPP, GOME-2 F_{740} , MODIS APAR, and the multi-model mean (results from both DD and Prog models are averaged together here). Note that the indicators for the multi-model means are available only for Ameriflux sites. Bias and χ^2 statistics with respect to the tower GPP (considered as the standard) are computed and averaged for each vegetation type and summarized in Table 2. Again, note that the multi-model mean uses only the available Ameriflux sites to compute these statistics.

Figure 6 shows the duration of photosynthesis (similar to the carbon uptake period), from the onset of photosynthesis (the left edge of the various colored bars with corresponding uncertainties) to the onset of dormancy on the right edge of the bars. For MF and DBF sites in the northeast and northern midwest US, the photosynthesis onset according to the tower-based data occurs between about days 70 and 130. For these sites, both the MPI-BGC GPP and GOME-2 F_{740} track the tower onset reasonably well, while MODIS-based APAR shows a substantially earlier rise ranging from $\sim$ day 60–90. The multi-model mean shows a similar early onset of photosynthesis for many of these sites. Photosynthetic onset from MODIS APAR compares better with the tower data for the ENF-dominated sites.

For the midwest cropland sites, the onset of photosynthesis occurs much later, generally around day 150 according to the tower estimates. The larger scale GOME-2 F_{740} and MPI-BGC GPP detects photosynthetic onset somewhat earlier, around days 110–135, likely due to a mixture of other vegetation types within their averaging area. Despite the fact that the MODIS data are averaged over a much smaller area near the tower site, the MODIS APAR

627 results again show a substantially earlier photosynthesis onset between days
 628 50–80 for all agricultural sites except US-Bo1 where the onset was near day
 629 115. The multi-model mean onset of photosynthesis is generally comparable
 630 to the MPI-BGC GPP results for the US-NE1–3 cropland sites.

631 Similarly, for the onset of dormancy in Fig. 6 (the end of the colored bars),
 632 MODIS APAR is somewhat late with respect to the tower data for croplands.
 633 The MPI-BGC GPP and GOME-2 F_{740} dormancy onset estimates are closer
 634 to the tower data and also closer to each other for croplands. For most of the
 635 MF and DBF sites, GOME-2 F_{740} provides dormancy onset estimates that
 636 are generally within uncertainty ranges of both MPI-BGC and tower-based
 637 GPP. The MODIS APAR and multi-model mean dormancy onset results are
 638 somewhat late with respect to the tower data for several sites but still fall
 639 within the uncertainty ranges for other sites. The dormancy onset results
 640 for the ENF sites from all estimates agree relatively well with each other to
 641 within the uncertainties.

642 Figure 7 shows the duration of maximum photosynthesis from the onset
 643 of maximum photosynthesis and senescence onset; uncertainties tend to be
 644 larger for these estimates. The onset of maximum photosynthesis derived
 645 from the various datasets is in general agreement to within the relatively
 646 large uncertainties.

647 In contrast with the onset of dormancy, GOME-2 F_{740} shows consistently
 648 early onset of senescence for MF and DBF sites, although the error bars
 649 are quite large for some sites. This was similarly shown in Sect. 3.1 in the
 650 seasonal plots for representative sites. Again, this could be an indication
 651 that Θ_F starts to decline slightly earlier than LUE, although errors bars for

652 GOME-2 F_{740} and MPI-BGC generally overlap. Additional ground-based
653 fluorescence and other measurements would be helpful to sort out this issue.

654 Table 2 highlights the cases of statistically significant differences in the
655 timing indicators with respect to the tower GPP (considered to be the stan-
656 dard) and reinforces conclusions drawn from the barplots. For example,
657 MODIS-based APAR and the multi-model mean show an early onset of pho-
658 tosynthesis for croplands, DBF, and MF in general as compared with the
659 tower estimates. This early onset is also reflected in the multi-model mean
660 for the same IGBP types. The early rise in MODIS APAR continues to
661 the spring inflection point for these biomes which is not the case for the
662 multi-model mean.

663 GOME-2 F_{740} and MPI-BGC GPP show an early onset of photosynthesis
664 for croplands; this could be related to their larger spatial footprints. GOME-
665 2 F_{740} has a significant early bias in the onset of senescence for croplands,
666 DBF, and MF sites even with the relatively large error bars. MODIS APAR
667 also shows later dates for dormancy onset and the autumn inflection point for
668 some vegetation types. GOME-2 F_{740} shows a late bias in dormancy onset
669 in croplands that again could be related to the spatial footprint. MPI-BGC
670 GPP similarly shows a late bias, but it is not statistically significant given the
671 estimated errors. Both MPI-BGC GPP and GOME-2 F_{740} show early biases
672 in the autumn inflection point for DBF and MF sites, though the biases are
673 significant only for GOME-2 F_{740} .

674 Tables 3-5 summarize the results of the timing indicators for representa-
675 tive cropland and forested sites. The results are divided by majority biome
676 type within the satellite averaging area and are ordered by latitude. These

677 tables highlight that there is significantly more variability in the timing indi-
678 cators for the ENF and MF sites that cover a larger range of latitudes. For
679 example, the southern-most MF site (US-WBW) has a significantly longer
680 duration of photosynthesis than most of the more northern sites as deter-
681 mined from tower and upscaled GPP as well as GOME-2 F_{740} . Some of
682 the MF sites at similar latitudes also show significant differences; the north-
683 ern midwestern sites, US-UMB and US-WCr (as well as other sites located
684 nearby and not shown in the table), have significantly shorter durations of
685 photosynthesis as compared with the US-Ho1 site located in the northeast US
686 at a similar latitude, and US-UMB has a longer duration of photosynthesis as
687 compared with US-WCr. Again, this is shown by tower and upscaled GPP as
688 well as GOME-2 F_{740} . While MODIS and multi-model mean data produce
689 significantly larger estimates of duration of photosynthesis, they generally
690 show the same spatial variability.

691 We attempted to compare individual yearly estimates of the timing pa-
692 rameters from GOME-2 F_{740} , MPI-BGC GPP, and available flux tower mea-
693 surements. In general, the interannual variability is smaller than the es-
694 timated uncertainties. To reduce uncertainties in the current data sets, we
695 would need to average data over larger (regional) scales. We intend to pursue
696 this in more detail in future studies.

697 4. Conclusions and ongoing work

698 Our direct comparisons of GOME-2 F_{740} with tower-based and upscaled
699 GPP indicate that GOME-2 F_{740} tracks the spring onset and autumn de-
700 cline of photosynthesis for several different biomes. Moderate to high values

701 of MODIS-derived fPAR ($>0.2-0.5$) are maintained throughout the year at
 702 many sites for which green vegetation may absorb light but not utilize the
 703 energy for photosynthesis, particularly in winter. Our study suggests that
 704 GOME-2 F_{740} may be used to better constrain this aspect of GPP simulated
 705 by data-driven models and improve parameterizations in process-based mod-
 706 els. We acknowledge the inherent difficulties in comparing the relatively small
 707 spatial scale tower-based GPP estimates with those of the larger-footprint
 708 GOME-2 data that were produced for different sets of years. The use of the
 709 MPI-BGC upscaled GPP estimates for the same time periods as the GOME-
 710 2 data has provided a means of assessing potential differences arising from
 711 the differing spatial scales and temporal periods of tower- and satellite-based
 712 data.

713 Ecosystem models and reflectance-based data products from Earth-orbiting
 714 satellites (*e.g.*, NDVI, EVI, LAI) are currently used to predict or monitor the
 715 seasonal dynamics of vegetated ecosystems that correspond with the growing
 716 season and carbon uptake period. However, as noted above, these models
 717 and satellite observations often do a poor job of describing the length of
 718 the growing season, as found in our current study and by others (*e.g.*, *Gar-*
 719 *rrity et al., 2011; Richardson et al., 2012*). Over- and under-estimation of
 720 the growing season and related carbon uptake period can lead to errors in
 721 predicting interannual variability in ecosystem-atmosphere carbon exchange
 722 and can negatively impact our ability to assess long term trends in ecosystem
 723 response to climate change (*Garrrity et al., 2011*). Reflectance-based satel-
 724 lite products are typically linked to seasonal morphological development of
 725 plant canopies (*e.g.*, LAI). Time lags between morphological and physiolog-

ical development can lead to significant error in estimating seasonal carbon flux (*Morecroft et al.*, 2003; *Richardson et al.*, 2009, 2010). In contrast, our results show very good agreement between GPP and fluorescence for several important vegetation types (croplands and several forest types); this suggests that GOME-2 F_{740} may better capture seasonal dynamics of canopy physiology relevant to carbon flux in some ecosystems as compared with existing models and satellite data products.

Following the recent launch of a second GOME-2 instrument on the MetOp-B platform, the MetOp-A GOME-2 is now operating in a smaller pixel mode (since day 196 of 2013); ground pixels are now 40×40 km² with a 960 km wide swath. The MetOp-B operates in the standard wider swath mode as described above. This enables smaller pixel fluorescence observations of similar quality although with less frequent overpasses. Use of the two GOME-2 instruments should lead to improved fluorescence data sets for further studies in the future. In addition, the upcoming launches of the Orbiting Carbon Observatory-2 (OCO-2) (*Frankenberg et al.*, 2011b, 2014) and the Sentinel-5 precursor TROPOMI (*Veefkind et al.*, 2012) will enable additional measurements near the O₂-A band at higher spatial resolution. The FLuorescence EXplorer (FLEX) (*Rascher*, 2007), an ESA Explorer 8 Mission selected for Phase A/B1 in early 2011, is designed specifically to make chlorophyll fluorescence measurements (*Guanter et al.*, 2010) and would provide additional spectral information across the visible-NIR spectrum.

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 806 US-Syv, US-WCr), Beverly Law (US-Me2–US-Me5), Danilo Dragoni (US-
 807 MMS), Lianhong Gu (US-MOz), Shashi Verma, Andrew Suyker, Joseph
 808 Berry, Todd Schimelfenig (US-Ne1–US-Ne3, US-Shd), Russell K. Monson
 809 (US-NR1), Dennis Baldocchi (US-Ton, US-Var), Jiquan Chen (US-Oho),
 810 Walter Oechel (US-SO2), Timothy Martin (US-SP1–US-SP3), Peter Curtis,
 811 Gil Bohrer (US-UMB), Andrew Richardson (US-Bar), and Tilden Meyers
 812 (US-Aud, US-Bkg, US-Bo1, US-FPe, US-Goo, US-WBW), Niall P. Hanan,
 813 Robert J. Scholes (ZA-Kru).

814 References

- 815 Amoros-Lopez, J., Gomez-Chova, L., Vila-Frances, J., Alonso, L., Calpe, J.,
 816 Moreno, J. & del Valle-Tascon, S. (2008). Evaluation of remote sensing
 817 of vegetation fluorescence by the analysis of diurnal cycles. *International*
 818 *Journal of Remote Sensing*, 29, 5423–5436.
- 819 Baldocchi, D. D., Falge, E., Gu, L. H., Olson, R., Hollinger, D., Running, S.,
 820 et al. (2001). FLUXNET: A new tool to study the temporal and spatial

821 variability of ecosystem-scale carbon dioxide, water vapor, and energy flux
822 densities. *Bulleting of the American Meteorological Society*, 82, 2415–2434.

823 Baldocchi, D. D., Black, T. A., Curtis, P. A., Falge, E., Fuentes, J. D.,
824 Granier, A., et al. (2004). Predicting the onset of net carbon uptake by
825 deciduous forests with soil temperature and climate data: a synthesis of
826 FLUXNET data. *International Journal of Biometeorology*, 49, 377–387.

827 Barr, A. G., Richardson, A. D., Hollinger, D. Y., Papale, D., Arain, M. A.,
828 Black, T. A., et al. (2013). Use of change-point detection for friction-
829 threshold evaluation in eddy-covariance studies. *Agricultural and Forest*
830 *Meteorology*, 171–172, 31–45.

831 Barr, A. G., Ricciuto, D. M., Schaefer, K., Richardson, A. D. Agarwal, D.,
832 Thornton, P. E., et al. (2013). NACP Site: Tower Meteorology, Flux Ob-
833 servations with Uncertainty, and Ancillary Data, Data set, Oak Ridge
834 National Laboratory Distributed Active Archive Center, Oak Ridge, Ten-
835 nessee, USA <http://dxdoiorg/103334/ORNLDAAAC/1178>.

836 Bauerle, W. L., Oren, R., Way, D. A., Qian, S. S., Stoy, P. C., Thornton,
837 P. E., Bowden, J. D., Hoffman, F. M., & Reynolds, R. F. (2012). Photope-
838 riodic regulation of the seasonal pattern of photosynthetic capacity and
839 the implications for carbon cycling. *Proceedings of the National Academy*
840 *of Sciences*, doi:10.1073/pnas.1119131109.

841 Beringer, J., Livesley, S. J., Randle, J. & Hutley, L. B. (2013). Carbon dioxide
842 fluxes dominate the greenhouse gas exchanges of a seasonal wetland in the

- 843 wet-dry tropics of northern Australia. *Agricultural and Forest Meteorology*,
844 *182–183*, 239–247.
- 845 Beringer, J., Hacker, J., Hutley, L. B., Leuning, R., Arndt, S. K., Amiri, R.,
846 et al. (2011). SPECIAL Savanna patterns of energy and carbon integrated
847 across the landscape. *Bulletin of the American Meteorological Society*, *92*,
848 1467–1485.
- 849 Berry, J., Frankenberg, C., Wennberg, P., Baker, I., Bowman, K.,
850 Castro-Contreas, S., et al. (2013). New methods for measurements
851 of photosynthesis from space. Presented at the 2013 NASA terres-
852 trial ecology science team meeting, La Jolla, CA, April 30-May 2, 2013,
853 <http://www.kiss.caltech.edu/workshops/photosynthesis2012/NewMethod2.pdf>.
- 854 Billesbach, D. P., Fischer, M. L., Torn, M. S., & Berry, J. A. (2004). A
855 Portable Eddy Covariance System for the Measurement of Ecosystem-
856 Atmosphere Exchange of CO₂, Water Vapor, and Energy. *J. Atmospheric*
857 *and Oceanic Technology*, *21*, 639–650.
- 858 Bonan, G. B., Lawrence P. J., Oleson K. W., Levis S., Jung M., Reich-
859 stein M., et al. (2011). Improving canopy processes in the Community
860 Land Model version 4 (CLM4) using global flux fields empirically in-
861 ferred from FLUXNET data. *Journal of Geophysical Research*, G02014,
862 doi:10.1029/2010JG001593.
- 863 Bracho, R. G., Starr, G., Gholz, H. L., Martin, T. A., Cropper, W. P. Jr., &
864 Loescher, H. W. (2012). Controls on carbon dynamics by ecosystem struc-

ture and climate for southeastern U.S. slash pine plantations. *Ecological Monographs*, 82, 101–128.

Campbell, P. K. E., Middleton, E. M., Corp, L. A., & Kim, M. S. (2008). Contribution of chlorophyll fluorescence to the apparent vegetation reflectance. *Science of the Total Environment*, 404, 433–439.

Cernusak, L. U. C. A. S. A., Hutley L. B., Beringer J., Holtum J. A. M., & Turner B. L. (2011). Photosynthetic physiology of eucalypts along a sub-continental rainfall gradient in northern Australia. *Agricultural and Forest Meteorology*, doi:10.1016/j.agrformet.2011.01.006.

Chappelle, E. W. & Williams, D. L. (1987). Laser-induced uorescence (LIF) from plant foliage. *IEEE Transactions on Geoscience and Remote Sensing*, GE-25, 726–736.

Cheng, Y. B., Zhang, Z., Lyapustin, A. I., Wang, Y., & Middleton, E. M. (2014). Impacts of light use efficiency and fPAR parameterization on carbon modeling, *Agricultural and Forest Meteorology*, 189–190, 187–197.

Churkina, G., Schimel, D., Braswell, B. H., & Xiao, X. (2005). Spatial analysis of growing season length control over net ecosystem exchange. *Global Change Biology*, 11, 1777–1787, doi: 10.1111/j.1365-2486.2005.001012.x.

Cook, B. D. Davis, K. J., Wang, W., Desai, A. R., Berger, B. W., Teclaw, R. M., Martin, J. G., Bolstad, P. V., Bakwin, P. S., Yi, C., & Heilman, W. (2004). Carbon exchange and venting anomalies in an upland deciduous forest in northern Wisconsin, USA, *Agricultural and Forest Meteorology*. 126, 271–295, doi:10.1016/j.agrformet.2004.06.008.

- 888 Corp, L. A., McMurtrey, J. E., Middleton, E. M., Mulchi, C. L., Chappelle,
889 E. W., & Daughtry, C. S. T. (2003). Fluorescence Sensing Systems: In
890 vivo detection of biophysical variations in field corn due to nitrogen supply.
891 *Remote Sensing of the Environment*, 86, 470–4793.
- 892 Damm, A. Elbers, J., Erler, A., Giolis, B., Hamdi, K., Hutjes, R.W.A., et al.
893 (2010). Remote sensing of sun-induced fluorescence to improve modeling of
894 diurnal courses of gross primary production (GPP). *Global Change Biology*,
895 16, 171–186, doi:10.1111/j.1365-2486.200901908.x.
- 896 Davis, K. J., Bakwin, P. S., Berger, B. W., Yi, C., Zhao, C., Teclaw, R. M.,
897 & Isebrands, J. G. (2003). The annual cycle of CO₂ and H₂O exchange
898 over a northern mixed forest as observed from a very tall tower. *Global*
899 *Change Biology*, 9, 1278–1293.
- 900 Desai, A. R., Bolstad, P. V., Cook, B. D., Davis, K. J., & Carey, E. V.
901 (2005). Comparing net ecosystem exchange of carbon dioxide between an
902 old-growth and mature forest in the upper Midwest, USA. *Agricultural and*
903 *Forest Meteorology*, 128, 33–55.
- 904 Desai, A. R., Richardson, A. D., Moffat, A. M., Kattge, J., Hollinger, D. Y.,
905 Barr, A., Falge, E., Noormets, A., Papale, D., Reichstein, M., & Stauch,
906 V. J. (2008). Cross-site evaluation of eddy covariance GPP and RE decom-
907 position techniques. *Agricultural and Forest Meteorology*, 148, 821–838.
- 908 Dragoni, D., Schmid, H. P., Grimmond, C. S. B., & Loescher, H. W.
909 (2007). Uncertainty of annual net ecosystem productivity estimated us-

ing eddy covariance flux measurements. *Journal of Geophysical Research*,
112, D17102, doi:10.1029/2006JD008149.

Dragonì, D., Schmid, H. P., Wayson, C. A., Potter, H., Grimmond, C. S.
B., & Randolph, J. C. (2010). Evidence of increased net ecosystem pro-
ductivity associated with a longer vegetated season in a deciduous for-
est in south-central Indiana, USA. *Global Change Biology*, 17, D17102,
doi:10.1111/j.1365-2486.2010.02281.x, 886–897.

Elbers, J. A., Jacobs, C. M.J., Kruijt, B., Jans, W. W.P., & Moors, Eddy J.
(2011). Assessing the uncertainty of estimated annual totals of net ecosys-
tem productivity: A practical approach applied to a mid latitude temper-
ate pine forest, *Agricultural and Forest Meteorology*, 151, 1823–1830, ISSN
0168-1923, doi:10.1016/j.agrformet.2011.07.020.

Fisher, J. I., Mustard, J. F., & Vadeboncoeur, M. A. (2006). Green leaf
phenology at Landsat resolution: Scaling from the field to the satellite.
Remote Sensing of Environment, 100, 265–279.

Flexas, J., Escalona, J. M., Evain, S., Gulías, S., J., Moya, I., Osmond, C. B.,
& Medrano, H. (2002). Steady-state chlorophyll fluorescence (Fs) measure-
ments as a tool to follow variations of net CO₂ assimilation and stomatal
conductance during water-stress in C₃ plants. *Physiologia Plantarum*, 114,
231–240.

Frankenberg, C., Fisher, J. B., Worden, J., Badgley, G., Saatchi, S. S., Lee,
J. E., Toon, G.-C., Butz, A., Jung, M., Kuze, A., & Yokota, T. (2011a).
New global observations of the terrestrial carbon cycle from GOSAT: Pat-

933 terns of plant fluorescence with gross primary productivity. *Geophysical*
934 *Research Letters*, 38, L17706, doi:10.1029/2011GL048738.

935 Frankenberg, C., Butz, A., & Toon, G. C. (2011b). Disentangling chloro-
936 phyll fluorescence from atmospheric scattering effects in O2A-band spec-
937 tra of reflected sun-light. *Geophysical Research Letters*, 38, L03801,
938 doi:10.1029/2010GL045896.

939 Frankenberg, C., O'Dell, C., Guanter, L., & McDuffie, J. (2012). Remote
940 sensing of near-infrared chlorophyll fluorescence from space in scattering
941 atmospheres: implications for its retrieval and interferences with atmo-
942 spheric CO₂ retrievals. *Atmospheric Measurement Techniques*, 5, 2081–
943 2094,

944 Frankenberg, C., O'Dell, C., Berry, J., Guanter, L., Joiner, J., Köhler, P.,
945 Pollack, R., & Taylor, T. E. (2014). Prospects for chlorophyll fluorescence
946 remote sensing from the Orbiting Carbon Observatory-2. *Remote Sensing*
947 *of Environment*, 147, 1–12.

948 Garbulsky, M. F., Penuelas, J., Papale, D., Filella, I. (2008). Remote estima-
949 tion of carbon dioxide uptake by a Mediterranean forest, *Global Change*
950 *Biology*, 14, 2860–2867.

951 Garrity, S. R., Bohrer, G., Maurer, K. D., Mueller, K. L., Vogel, C. S.,
952 & Curtis, P. S. (2011). A comparison of multiple phenology data sources
953 for estimating seasonal transitions in deciduous forest carbon exchange.
954 *Agricultural and Forest Meteorology*, 151, 1741–1752.

- 955 Giasson, M.-A., Coursolle, C., & Margolis, H. A. (2006). Ecosystem-
956 level carbon fluxes from a boreal cutover in eastern Canada before
957 and after scarification. *Agricultural and Forest Meteorology*, *140*, 23–40,
958 doi:10.1016/j.agrformet.2006.08.001.
- 959 Gilmanov, T. G., Verma, S. B., Sims, P. L., Meyers, T. P., Bradford, J. A.,
960 Burba, G. G., & Suyker, A. E. (2003). Gross primary production and light
961 response parameters of four Southern Plains ecosystems estimated using
962 long-term CO₂-flux tower measurements. *Global Biogeochemical Cycles*,
963 *17*, 1071, doi:10.1029/2002GB002023.
- 964 Gilmanov, T. G., Tieszen, L. L., Wylie, B. K., Flanagan, L. B., Frank, A. B.,
965 Haferkamp, M. R., Meyers, T. P. & Morgan, J. A. (2005). Integration of
966 CO₂ flux and remotely-sensed data for primary production and ecosystem
967 respiration analyses in the Northern Great Plains: potential for quantita-
968 tive spatial extrapolation. *Global Ecology and Biogeography*, *14*, 271–292,
969 doi:http://dx.doi.org/10.1111/j.1466-822X.2005.00151.x.
- 970 Gilmanov T. G., Aires, L., Barcza, Z., Baron, V. S., Belelli, L., Beringer,
971 J., et al. (2010). Productivity, respiration, and light-response parameters
972 of world grassland and agroecosystems derived from flux-tower measure-
973 ments. *Rangeland Ecology Management*, *63*, 16–39.
- 974 Goldstein, A. H., Hultman, N. E., Fracheboud, J. M., Bauer, M. R., Panek,
975 J. A., Xu, M., Qi, Y., Guenther, A. B., & Baugh, W. (2000). Effects of
976 climate variability on the carbon dioxide, water, and sensible heat fluxes
977 above a ponderosa pine plantation in the Sierra Nevada (CA). *Agricultural
978 and Forest Meteorology*, *101* 113–129.

- 979 Gough, C. M., Hardiman, B., Vogel, C. S., Nave, L., & Curtis, P. S. (2010).
 980 Wood net primary production resilience in an unmanaged forest transi-
 981 tioning from early to middle succession, *Forest Ecology and Management*,
 982 *260*, 36–41.
- 983 Goulden, M. L., McMillan, A. M. S., Winston, G. C., Rocha, A. V., Manies,
 984 K. L., Harden, J. W., & Bond-Lamberty, B. P. (2010). Patterns of NPP,
 985 GPP, respiration, and NEP during boreal forest succession. *Global Change*
 986 *Biology*, *17*, 855–871.
- 987 Goulden, M. L., Munger, J. W., Fan, S. M., Daube, B. C., & Wofsy, S.
 988 C. (1996). Measurements of carbon sequestration by long-term eddy co-
 989 variance: Methods and a critical evaluation of accuracy. *Global Change*
 990 *Biology*, *2*, 169–182.
- 991 Grünwald, T. & Bernhofer, C. (2007). A decade of carbon, water and energy
 992 flux measurements of an old spruce forest at the Anchor Station Tharandt.
 993 *Tellus*, *59B*, 387–396.
- 994 Gu, L., Post, W.M., Baldocchi, D. D., Black, T. A., Verma, S. B., Vesala,
 995 T., & Wofsy, S. C. (2003). Phenology of vegetation photosynthesis. In:
 996 Schwartz, M.D. (Ed.) *Phenology: An Integrated Environmental Science*.
 997 Kluwer, Dordrecht, 467–485.
- 998 Gu, L., Meyers, T., Pallardy, S. G., Hanson, P. J., Yang, B., Heuer, M.,
 999 Hosman, K. P., Riggs, J.S., Sluss, D., & Wullschleger, S. D. (2006). Direct
 1000 and indirect effects of atmospheric conditions and soil moisture on surface

energy partitioning revealed by a prolonged drought at a temperate forest
 site. *Journal of Geophysical Research*, *D16102*, doi:10.1029/2006JD007161.

Gu, L., Hanson, P. J., Mac Post, W., Kaiser, D. P., Yang, B., Nemani, R.,
 Pallardy, S. G., & Meyers, T. (2008). The 2007 eastern US spring freezes:
 Increased cold damage in a warming world? *Bioscience*, *58*, 253–262.

Gu, L., Post, W. M., Baldocchi, D. D., Black, T. A., Suyker, A. E., Verma, S.
 B., Vesala, T., & Wofsy, S. C. (2009). Characterizing the seasonal dynamics
 of plant community photosynthesis across a range of vegetation types. In:
 Phenology of ecosystem processes. Springer, Dordrecht/New York.

Gu, L., Massman, W. J., Leuning, R., Pallardy, S. G., Meyers, T., Hanson,
 P. J., Riggs, J. S., Hosman, K. P., & Yang, B. (2012). The fundamen-
 tal equation of eddy covariance and its application in flux measurements.
Agricultural and Forest Meteorology, *152*, 135-148.

Guanter, L., Alonso, L., Gómez-Chova, L., Amorós-López, Vila-Francés,
 J., & Moreno, J. (2007). Estimation of solar-induced vegetation flu-
 orescence from space measurements. *Geophysical Research Letters*, *34*,
 doi:10.1029/2007GL029289.

Guanter, L., Alonso, L., Gómez-Chova, L., Meroni, M., Preusker, R., Fis-
 cher, J., & Moreno, J. (2010). Developments for vegetation fluorescence
 retrieval from spaceborne high-resolution spectrometry in the O₂-A and
 O₂-B absorption bands. *Journal of Geophysical Research*, *115*, D19303,
 doi:10.1029/2009JD013716.

- 1023 Guanter, L., Frankenberg, C., Dudhia, A., Lewis, P. E., Gómez-Dans, J.,
1024 Kuze, A., Suto, H. & Grainger, R. G. (2012). Retrieval and global assess-
1025 ment of terrestrial chlorophyll fluorescence from GOSAT space measure-
1026 ments. *Remote Sensing of Environment*, 121, 236–251.
- 1027 Guanter, L., Rossini, M., Colombo, R., Meroni, M., Frankenberg, C., Lee,
1028 J.-E., and Joiner, J. (2013). Using field spectroscopy to assess the poten-
1029 tial of statistical approaches for the retrieval of sun-induced chlorophyll
1030 fluorescence from space. *Remote Sensing of Environment*, 133, 52–61.
- 1031 Guanter, L., Zhang, Y., Yung, M., Joiner, J., Voigt, M., Berry, J. A.,
1032 et al. (2014). Global and time-resolved monitoring of crop photo-
1033 synthesis with chlorophyll fluorescence. *Proc. Natl. Acad. Sci.*, doi:
1034 10.1073/pnas.1320008111.
- 1035 Heinsch, F. Zhao, M., Running, S., Kimball, J., Nemani, R., Davis, K.,
1036 et al. (2006). Evaluation of remote sensing based terrestrial productivity
1037 from MODIS using regional tower eddy flux network observations. *IEEE*
1038 *Transactions on Geoscience and Remote Sensing*, 44, 1908–1925.
- 1039 Hendriks, D.M.D., J. van Huissteden, A.J. Dolman, & van der Molen, M.K.
1040 (2007). The full greenhouse gas balance of an abandoned peat meadow.
1041 *Biogeosciences*, 4, 411–424.
- 1042 Hendriks, D.M.D., Dolman, A.J., Van der Molen, M.K., & Van Huisste-
1043 den, J. (2008). A compact and stable eddy covariance set-up for methane
1044 measurements using off-axis integrated cavity output spectroscopy. *Atmo-*
1045 *spheric Chemistry and Physics*, 8, 431–443.

- 1046 Huntzinger, D. N., Post, W. M., Wei, Y., Michalak, A. M., West, T. O.,
1047 Jacobson, A. R., et al. (2012). North American Carbon Program (NACP)
1048 regional interim synthesis: Terrestrial biospheric model intercomparison.
1049 *Ecological Modelling*, 232, 144–157.
- 1050 Jenkins, J. P., Richardson, A. D., Braswell, B. H., Ollinger, S. V., Hollinger,
1051 D. Y., & Smith, M.-L. (2007). Refining light-use efficiency calculations
1052 for a deciduous forest canopy using simultaneous tower-based carbon flux
1053 and radiometric measurements. *Agricultural and Forest Meteorology*, 143,
1054 64–79.
- 1055 Joiner, J., Yoshida, Y., Vasilkov, A. P., Yoshida, Y., Corp, L. A., &
1056 Middleton, E. M. (2011). First observations of global and seasonal ter-
1057 restrial chlorophyll fluorescence from space. *Biogeosciences*, 8, 637–651,
1058 doi:10.5194/bg-8-637-2011.
- 1059 Joiner, J., Yoshida, Y., Vasilkov, A. P., Yoshida, Y., Middleton, E. M., Camp-
1060 bell, P. K. E., Kuze, A., & Corp, L. A. (2012). Filling-in of broad far-red
1061 solar lines by terrestrial fluorescence and atmospheric Raman scattering as
1062 detected by GOME-2 satellite measurements. *Atmospheric Measurement*
1063 *Techniques* 4, 6185–6228, doi:10.5194/amtd-4-6185-2011.
- 1064 Joiner, J., Guanter, L., Lindstrot, R., Voigt, M., Vasilkov, A. P., Middle-
1065 ton, E. M., Huemmrich, K. F., Yoshida, Y., & Frankenberg, C. (2013).
1066 Global monitoring of terrestrial chlorophyll fluorescence from moderate
1067 spectral resolution near-Infrared satellite measurements: Methodology,
1068 simulations, and application to GOME-2. *Atmospheric Measurement Tech-*
1069 *niques*, 6, 2803–2823, doi:10.5194/amt-6-2803-2013.

- 1070 Jung, M., Reichstein, M., & Bondeau, A. (2009). Towards global empirical
1071 cal upscaling of FLUXNET eddy covariance observations: validation of a
1072 model tree ensemble approach using a biosphere model. *Biogeosciences*, 6,
1073 2001-2013.
- 1074 Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D.,
1075 Arain, M. A., et al. (2011). Global patterns of land-atmosphere fluxes of
1076 carbon dioxide, latent heat, and sensible heat derived from eddy covari-
1077 ance, satellite, and meteorological observations. *Journal of Geophysical*
1078 *Research*, 116, doi:10.1029/2010JG001566.
- 1079 Kilinc, M., Beringer, J., Hutley, L. B., Tapper, N. J. & McGuire, D. A.
1080 (2013). Carbon and water exchange of the worlds tallest angiosperm forest,
1081 *Agricultural and Forest Meteorology*, 182-183, 215-224.
- 1082 Kross, A. (2011). Characterization of the variability and controls of the car-
1083 bon dioxide exchange in northern peatlands. PhD thesis, McGill University.
- 1084 Lafleur, P. M., Roulet, N. T., & Admiral, S. W. (2001). Annual cycle of
1085 CO₂ exchange at a bog peatland. *Journal of Geophysical Research*, 106,
1086 3071-3081.
- 1087 Loescher, H. W., Law, B. E., Mahrt, L., Hollinger, D. Y., Campbell, J.,
1088 & Wofsy, S. C. (2006). Uncertainties in, and interpretation of, carbon
1089 flux estimates using the eddy covariance technique. *Journal of Geophysical*
1090 *Research*, 111, D21S90.
- 1091 Louis, J., Ounis, A., Ducruet, J.-M., Evain, S., Laurila, T., Thum, T., Au-
1092 rela, M., Wingsle, G., et al. (2005). Remote sensing of sunlight-induced

1093 chlorophyll fluorescence and reflectance of Scots pine in the boreal forest
1094 during spring recovery. *Remote Sensing of the Environment*, 96, 37–48.

1095 Luo, Y., Medlyn, B., Hui, D., Ellsworth, D., Reynolds, J., & Katul, G.
1096 (2001). Gross primary productivity in Duke Forest: Modeling synthesis of
1097 CO₂ experiment and eddy-flux data. *Ecological Applications*, 11, 239–252.

1098 Ma, X., , Huete, A., Yu, Q., Restrepo, C. N., Davies, K., Broich, M., Ratana,
1099 P., Beringer, J., Hutley, L. B., Cleverly, J., Boulain, N. & Eamus, D.
1100 (2013). Spatial patterns and temporal dynamics in savanna vegetation phe-
1101 nology across the North Australian Tropical Transect, *Remote Sensing of*
1102 *Environment*, 139, 97–115.

1103 Meroni, M., Picchi, V., Rossini, M., Cogliati, S., Panigada, C., Nali, C.,
1104 Lorenzini, G., & Colombo, R. (2008). Leaf level early assessment of ozone
1105 injuries by passive fluorescence and photochemical reflectance index. *In-*
1106 *ternational Journal of Remote Sensing*, 29, 5409–5422.

1107 Meroni, M., Rossini, M., Guanter, L., Alonso, L., Rascher, U., Colombo, R.,
1108 & Moreno, J. (2009). Remote sensing of solar-induced chlorophyll fluores-
1109 cence: Review of methods and applications. *Remote Sensing of Environ-*
1110 *ment*, 113, 2037–2051.

1111 Middleton, E. M., Cheng, Y.-B., Corp, L. A., Huemmrich, K. F., Kustas, W.
1112 & Campbell, P. K. E. (2010). Diurnal and directional responses of chloro-
1113 phyll fluorescence and the PRI in a cornfield. 4nd International Workshop
1114 on Remote Sensing of Vegetation Fluorescence, Valencia, Spain, November
1115 15-17, 2010, 6pp.

- 1116 Middleton, E. M., Corp, L. A., & Campbell, P. K. E. (2008). Comparison
1117 of measurements and FluorMOD simulations for solar induced chlorophyll
1118 fluorescence and reflectance of a corn crop under nitrogen treatments. *In-*
1119 *ternational Journal of Remote Sensing*, 29, 5193–5213.
- 1120 Migliavacca, M., Reichstein, M., Richardson, A. D., Colombo, R., Sut-
1121 ton, M. A., Lasslop, G., et al. (2010). Semiempirical modeling of abi-
1122 otic and biotic factors controlling ecosystem respiration across eddy co-
1123 variance sites. *Global Change Biology*. 17, 390–409, doi: 10.1111/j.1365-
1124 2486.2010.02243.x.
- 1125 Misson L., Baldocchi, D., Black, T., Blanken, P., Brunet, Y., Curielyuste,
1126 J., Dorsey, J., Falk, M., Granier, A., & Irvine, M. (2007). Partitioning
1127 forest carbon fluxes with overstory and understory eddy-covariance mea-
1128 surements: A synthesis based on FLUXNET data. *Agricultural and Forest*
1129 *Meteorology*, 144, 14–31.
- 1130 Monson, R. K., Turnipseed, A. A., Sparks, J. P., Harley, P. C., Scott-Denton,
1131 L. E., Sparks, K., & Huxman, T. E. (2002). Carbon sequestration in a
1132 high-elevation, subalpine forest. *Global Change Biology*, 8, 459–478.
- 1133 Monteith, J. L. (1972). Solar radiation and productivity in tropical ecosys-
1134 tems. *Journal of Applied Ecology*, 9, 747–766.
- 1135 Morecroft, M. D., Stokes, V. J., & Morison, J. I. L. (2003). Seasonal changes
1136 in the photosynthetic capacity of canopy oak (*Quercus robur*) leaves: the
1137 impact of slow development on annual carbon uptake. *International Jour-*
1138 *nal of Biometeorology*, 47, 221–226.

1139 Moya I., Camenen, L., Evain, S., Goulas, Y., Cerovic, Z. G., Latouche, G.,
1140 Flexas, J., & Ouinis, A. (2004). A new instrument for passive remote sens-
1141 ing: 1. Measurements of sunlight-induced chlorophyll fluorescence. *Remote*
1142 *Sensing of the Environment*, 91, 186–197.

1143 Munro, R., Eisinger, M., Anderson, C., Callies, J., Corpaccioli, E., Lang, R.,
1144 Lefebvre, A., Livschitz, Y., & Perez Albinana, A. (2006). GOME-2 on
1145 MetOp, from In-Orbit Verification to Routine Operations. In: Proceedings
1146 of EUMETSAT Meteorological Satellite Conference, Helsinki, Finland, 12–
1147 16 June 2006.

1148 Myneni, R. B., Hoffman, W., Knyazikhin, Y., Privette, J. L., Glassy, J.,
1149 Tian, Y., et al. (2002). Global products of vegetation leaf area and frac-
1150 tion absorbed PAR from year one of MODIS data. *Remote Sensing of*
1151 *Environment*, 83, 214–231.

1152 Oak Ridge National Laboratory Distributed Active Archive Center (ORNL
1153 DAAC) (2010). MODIS subsetted land products, Collection 5. Available
1154 on-line [<http://daac.ornl.gov/MODIS/modis.html>] from ORNL DAAC,
1155 Oak Ridge, Tennessee, U.S.A. Accessed Nov. 11, 2011.

1156 Piao, S., Ciais P., Friedlingstein, P., Peylin, P., Reichstein, M., Luyssaert, S.,
1157 et al. (2008). Net carbon dioxide losses of northern ecosystems in response
1158 to autumn warming. *Nature*, 451, 49–53.

1159 Piao, S., Cui, M., Chen, A., Wang, X., Ciais P., Liu, J., & Tang, Y. (2011).
1160 Altitude and temperature dependence of change in the spring vegetation

- 1161 green-up date from 1982 to 2006 in the Qinghai-Xizang Plateau. *Agricul-*
1162 *tural and Forest Meteorology*, 151, 1599–1608.
- 1163 Powell, T.L., Gholz, H.L., Clark, K.L., Starr, G., Cropper, W.P. Jr., &
1164 Martin, T.A. (2008). Carbon exchange of a mature naturally-regenerated
1165 pine forest in north Florida. *Global Change Biology*, 14, 2523–2538.
- 1166 Randerson, J. T., Field, C. B., Fung, I. Y. & Tans, P. P. (1999). Increases
1167 in early season ecosystem uptake explain recent changes in the seasonal
1168 cycle of atmospheric CO₂ at high northern latitudes. *Geophysical Research*
1169 *Letters*, 26, 2765–2768, doi:10.1029/1999GL900500.
- 1170 Rascher, U. (2007). FLEX – Fluorescence Explorer: A remote sensing ap-
1171 proach to quantify spatio-temporal variations of photosynthetic efficiency
1172 from space. *Photosynthesis Research*, 91, 293–294.
- 1173 Rascher, U. Agati, G., Alonso, L., Cecchi, G., Champagne, S., Colombo,
1174 R., et al. (2009). CEFLES2: the remote sensing component to quantify
1175 photosynthetic efficiency from the leaf to the region by measuring sun-
1176 induced fluorescence in the oxygen absorption bands. *Biogeosciences*, 6,
1177 1181–1198.
- 1178 Richardson, A. D., Hollinger, D. Y., Dail, D. B., Lee, J. T., Munger, J. W.,
1179 & OKeefe, J. (2009). Influence of spring phenology on seasonal and annual
1180 carbon balance in two contrasting New England forests. *Tree Physiology*,
1181 29, 321–331, doi:10.1093/treephys/tpn040.
- 1182 Richardson, A. D., Black, T. A., Ciais, P., Delbart, N., Friedl, M. A., Gobron,
1183 N., et al. (2010). Influence of spring and autumn phenological transitions

1184 on forest ecosystem productivity. *Philosophical Transactions of the Royal*
1185 *Society, Series B*, 365, 3227–3246, doi: 10.1098/rstb.2010.0102.

1186 Richardson, A. D. Anderson, R. S., Arain, M. A., Barr, A. G.,Bohrer, G.,
1187 Chen, G. et al. (2012). Terrestrial biosphere models need better represen-
1188 tation of vegetation phenology: Results from the North American Car-
1189 bon Program Site Synthesis. *Global Change Biology*, 18, 566–584, doi:
1190 10.1111/j.1365-2486.2011.02562.x.

1191 Rosema, A., Verhoef, W., Schoote, J., & Snel, J. F. H. (1991). Simulating flu-
1192 orescence light-canopy interaction in support of laser-induced fluorescence
1193 measurements. *Remote Sensing of Environment*, 37, 117–130.

1194 Rotenberg, E. & Yakir, D. (2010). Contribution of semi-arid forests to the
1195 climate system. *Science*, 327, 451–454, doi:10.1126/science.1179998.

1196 Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M. &
1197 Hashimoto, H.. (2004). A continuous satellite-derived measure of global
1198 terrestrial primary production. *BioScience*, 54, 547–560.

1199 Schaefer, K., Schwalm, C. R., Williams, C., Altaf Arain, M., Barr, A., Chen,
1200 J. M., et al. (2012). A model-data comparison of gross primary produc-
1201 tivity: Results from the North American Carbon Program site synthesis.
1202 *Journal of Geophysical Research*, 117, G03010, doi:10.1029/2012JG001960.

1203 Schmid, H. P., Grimmond, C. S. B., Cropley, F., Offerle, B., & Su, H.B.
1204 (2000). Measurements of CO₂ and energy fluxes over a mixed hardwood
1205 forest in the mid-western United States. *Agricultural and Forest Meteorol-*
1206 *ogy*, 103, 357–374.

- 1207 Scholes, R.J., Gureja, N., Gianneccinni, M., Dovie, D., Wilson, B., David-
1208 son, N., et al. (2001). The environment and vegetation of the flux mea-
1209 surement site near Skukuza, Kruger National Park. *Koedoe*, 44, 73–83.
- 1210 Sims, D. A., Rahman, A. F., Cordova, V. D., Baldocchi, D. D., Flanagan,
1211 L. B., Goldstein, A. H., Hollinger, D. Y., Misson, L., Monson, R. K.,
1212 & Schmid, H. P. (2005). Midday values of gross CO₂ flux and light use
1213 efficiency during satellite overpasses can be used to directly estimate eight-
1214 day mean flux. *Agricultural and Forest Meteorology*, 131, 1–12.
- 1215 Stammes, P., Sneep, M., de Haan, J., Veefkind, J. P., Wang, P., & Lev-
1216 elt, P. F. (2008). Effective cloud fractions from the Ozone Monitoring In-
1217 strument: Theoretical framework and validation. *Journal of Geophysical*
1218 *Research*, 113, D16S38, doi:10.1029/2007JD008820.
- 1219 Stoy, P. C, Katul, G. G., Siqueira, M. B. S., Juang, J. Y., Novick, K. A.,
1220 McCarthy, H. R., Oishi, A. C., & Oren, R. (2008). Role of vegetation in
1221 determining carbon sequestration along ecological succession in the south-
1222 eastern United States. *Global Change Biololgy*, 14, 1409–1427.
- 1223 Stylinski, C. D., Gamon, J. A., & Oechel, W. C. (2002). Seasonal patterns of
1224 reflectance indices, carotenoid pigments and photosynthesis of evergreen
1225 chaparral species. *Oecologia*, 131, 366–374.
- 1226 Sulman, B. N., Desai, A. R., Cook, B. D., Saliendra, N., & Mackay, D. S.
1227 (2009). Contrasting carbon dioxide fluxes between a drying shrub wetland
1228 in Northern Wisconsin, USA, and nearby forests. *Biogeosciences*, 6, 1115–
1229 1126.

- 1230 Sun, G., Alstad, K., Chen, J., Chen, S., Ford, C. R., Lin, G., Liu, C., Lu,
1231 N., McNulty, S. C., & Miao, H. (2010). A general predictive model for
1232 estimating monthly ecosystem evapotranspiration. *Ecohydrology*, 4, 245–
1233 255.
- 1234 Suyker, A. E., Verma, S. B., Burba, G. G., & Arkebauer, T. J. (2005).
1235 Gross primary production and ecosystem respiration of irrigated maize
1236 and irrigated soybean during a growing season. *Agricultural and Forest*
1237 *Meteorology*, 131, 180–190.
- 1238 Thornton, P. E., Law, B. E., Gholz, H. L., Clark, K. L., Falge, E., Ellsworth,
1239 D. S. et al. (2002). Modeling and measuring the effects of disturbance
1240 history and climate on carbon and water budgets in evergreen needleleaf
1241 forests. *Agricultural and Forest Meteorology*, 113, 185–222.
- 1242 van der Tol, C., Verhoef, W., & Rosema, A. (2009). A model for chloro-
1243 phyll fluorescence and photosynthesis at leaf scale. *Agricultural and Forest*
1244 *Meteorology*, 149, 96–105.
- 1245 Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Zhao, M., Running,
1246 S. W., Wofsy, S. C., Urbansky, S., Dunn, A. L., & Munger, J. W. (2003a).
1247 Scaling Gross Primary Production (GPP) over boreal and deciduous forest
1248 landscapes in support of MODIS GPP product validation. *Remote Sensing*
1249 *of Environment*, 88, 256–270.
- 1250 Turner, D. P., Urbansky, S., Bremer, D., Wofsy, S. C., Meyers, T., Gower,
1251 S. T., & Gregory, M. (2003b). A cross-biome comparison of daily light use
1252 efficiency for gross primary production. *Global Change Biology*, 9, 383–395.

1253 Turner, D. P., Riffs, W. D., Cohen, W. B., Gower, S. T., Running, S. W.,
1254 Zhao, M., et al. (2006). Evaluation of MODIS NPP and GPP products
1255 across multiple biomes. *Remote Sensing of Environment*, 102, 282–292.

1256 Urbanski, S., Barford, C., Wofsy, S., Kucharik, C., Pyle, E., Budney,
1257 J., et al. (2007). Factors controlling CO₂ exchange on timescales from
1258 hourly to decadal at Harvard Forest. *Journal of Geophysical Research*,
1259 112, #G02020.

1260 Vasilkov, A., Joiner, J., and Spurr, R. (2013). Note on rotational-Raman
1261 scattering in the O₂ A- and B-bands. *Atmos. Meas. Tech.*, 6, 981–990,
1262 doi:10.5194/amt-6-981-2013.

1263 Veefkind, J. P., Aben, I., McMullan, K., Forster, H., de Vries, J., Otter, G.,
1264 Claas, J., et al. (2012). TROPOMI on the ESA Sentinel-5 Precursor:
1265 a GMES mission for global observations of the atmospheric composition
1266 for climate, air quality and ozone layer applications. *Remote Sensing of*
1267 *Environment*, 120, 70–83.

1268 Veenendaal, E. M., Kolle, O. L. A. F., & Lloyd, J. (2004). Seasonal variation
1269 in] energy fluxes and carbon dioxide exchange for a broad-leaved semi-arid
1270 savanna (Mopane woodland) in Southern Africa. *Global Change Biology*,
1271 10, 318–328.

1272 Verma, S. B., Dobermann, A., Cassman, K. G., Walters, D. T., Knops,
1273 J. M., Arkebauer, T. J., et al. (2005). Annual carbon dioxide exchange in
1274 irrigated and rainfed maize-based agroecosystems. *Agricultural and Forest*
1275 *Meteorology*, 131, 77–96.

- 1276 Wang, Z., Xiao, X., & Yan, X. (2010). Modeling gross primary production of
1277 maize cropland and degraded grassland in northeastern China. *Agricultural*
1278 *and Forest Meteorology*, 150, 1160–1167.
- 1279 White, M. A., & Nemani, R. R. (2003). Canopy duration has little influence
1280 on annual carbon storage in the deciduous broad leaf forest. *Global Change*
1281 *Biology*, 9, 967–972.
- 1282 White, M. A., de Beurs, K. M., Didan, K., Inouye, D. W., Richardson,
1283 A. D., Jensen, O. P., et al. (2009). Intercomparison, interpretation, and
1284 assessment of spring phenology in North America estimated from remote
1285 sensing for 1982–2006. *Global Change Biology*, 15, 2335–2359.
- 1286 Xiao X., Hollinger, D. Y., Aber, J. D., Goltz, M., Davidson, E. A., Zhang,
1287 Q., & Moore, B. III (2004). Satellite-based modeling of gross primary pro-
1288 duction in an evergreen needleleaf forest. *Remote Sensing of Environment*,
1289 89, 519–534.
- 1290 Xiao, J. F., Zhuang, Q. L., Baldocchi, D. D., Law, B. E., Richardson, A. D.,
1291 Chen, J. Q., et al. (2008). Estimation of net ecosystem carbon exchange
1292 for the conterminous United States by combining MODIS and AmeriFlux
1293 data. *Agricultural and Forest Meteorology*, 148, 1827–1847.
- 1294 Yuan, W., Liu, S., Zhou, G., Zhou, G., Tieszen, L. L., Baldocchi, D., et al.
1295 (2007). Deriving a light use efficiency model from eddy covariance flux data
1296 for predicting daily gross primary production across biomes. *Agricultural*
1297 *and Forest Meteorology*, 143, 189–207.

- 1298 Zarco-Tejada, P. J., Berni, J. A. J., Suarez, L., Sepulcre-Cantó, G., Morales,
1299 F., & Miller, J. R. (2009). Imaging chlorophyll fluorescence with an air-
1300 borne narrow-band multispectral camera for vegetation stress detection.
1301 *Remote Sensing of Environment*, 113, 1262–1275.
- 1302 Zhang, Q., Middleton, E. M., Cheng, Y.-B. & Landis, D. R. (2013). Vari-
1303 ations of foliage chlorophyll fAPAR and foliage non-chlorophyll fAPAR
1304 (fAPAR_{chl}, fAPAR_{non-chl}) at the Harvard Forest. *IEEE Journal of Selected*
1305 *Topics in Applied Earth Observations and Remote Sensing*, 6, 2254–2264.
- 1306 Zhang, Q., Middleton, E. M., Gao, B. C., & Cheng, Y.-B. (2012). Using
1307 EO-1 Hyperion to simulate HypsIRI products for a coniferous forest: The
1308 fraction of PAR absorbed by chlorophyll (fAPAR_{chl}) and Leaf Water Con-
1309 tent (LWC). *IEEE Transactions on Geoscience and Remote Sensing*, 50,
1310 1844–1852.
- 1311 Zhang, Q., Middleton, E. M., Margolis, H. A., Drolet, G. G., Barr, A. A.,
1312 & Black, T. A. (2009). Can a satellite-derived estimate of the fraction of
1313 PAR absorbed by chlorophyll (fAPAR_{chl}) improve predictions of light-use
1314 efficiency and ecosystem photosynthesis for a boreal aspen forest? *Remote*
1315 *Sensing of Environment*, 113, doi:10.1016/j.rse.2009.01.002, 880–888.
- 1316 Zhang, Q., Xiao, X., Braswell, B., Linder, E., Ollinger, S., Smith, M.-L.,
1317 Jenkins, J. P., Baret, F., Richardson, A. D., Moore, B., & Minocha, R.
1318 (2006). Characterization of seasonal variation of forest canopy in a temper-
1319 ate deciduous broadleaf forest, using daily MODIS data. *Remote Sensing*
1320 *of Environment*, 105, 189–203.

- 1321 Zhang, Q., Xiao, X., Braswell, B., Linder, E., Baret, F., & Moore, B. (2005).
1322 Estimating light absorption by chlorophyll, leaf and canopy in a deciduous
1323 broadleaf forest using MODIS data and a radiative transfer model. *Remote*
1324 *Sensing of Environment*, 99, 357-371.
- 1325 Zhang, X., Friedl, M. A., Schaaf, C. B., Strahler, A. H., Hodges, J. C. F.,
1326 Gao, F., Reed, B. C., & Huete, A. (2003). Monitoring vegetation phenology
1327 using MODIS. *Remote Sensing of Environment*, 84, 471–475.
- 1328 Zhou, L., Tucker, C. J., Kaufmann, R. K., Slayback, D., Shabanov, N. V., &
1329 Myneni, R. B. (2001). Variations in northern vegetation activity inferred
1330 from satellite data of vegetation index during 1981 to 1999. *Journal of*
1331 *Geophysical Research*, 106, 20,06920,083, doi:10.1029/2000JD000115.

Figure 1: Locations of flux towers and their designations used in this study; Purple, blue, and red indicate that the primary vegetation type (IGBP) covers approximately 75-100%, 50-75%, and 0-50%, respectively, of the surrounding satellite averaging area; Symbols show dominant vegetation type for the satellite averaging area; +: Mixed Forest (including 'grass + MF'); *: Croplands; x: Grasslands; ◇: Deciduous Broadleaf Forest; △: Evergreen Needleleaf Forest; square: Savannas (including woody); ○: Shrublands (open and closed); ●: Evergreen Broadleaf Forest.

Figure 2: Seasonal cycle (means) of tower-based and upscaled GPP from MPI-BGC, GOME-2 F_{740} , and MODIS-based APAR for a variety of vegetation types. Curves are normalized with respect to unity at the maximum annual value. Contours indicate estimated uncertainties as discussed in the text. Site names, US state, and majority vegetation type within the satellite averaging area are indicated.

Figure 3: Similar to Figure 2 but showing sites from Australia, Africa, and Europe for a variety of vegetation types.

Figure 4: Similar to Figure 2 showing seasonal variability in tower-based GPP, GOME-2 F_{740} , and multi-model ensemble means that use data-driven (DD) and prognostic (Prog) approaches to estimate LAI/GPP.

Figure 5: Example of how timing indicators are computed at US-Bar tower; Black solid line with gray shading: Normalized curves corresponding to left axes with associated uncertainties; Blue solid with vertical bar shading: computed rate of change in the curvature from the fitting logistical function with computed error standard deviations along with timing indicators (symbols) and corresponding uncertainties (1σ , horizontal line) from the Monte Carlo simulation corresponding to right-side axes.

Figure 6: Summary of the duration of photosynthesis from the photosynthetic onset (left end of horizontal bars with uncertainties indicated) to the dormancy onset (right end of horizontal bars) (see text for details) for various forest and cropland sites and data sets. The site name and majority IGBP vegetation type are indicated on the left. Timing indicators derived from the multi-model mean data are only available for Ameriflux sites.

Figure 7: Similar to Fig. 6 but showing the duration of maximum photosynthesis from onset of maximum photosynthesis (left end of horizontal bars) to the senescence onset (right end of horizontal bars).

Table 1: Network sites used in analysis (see text for more details)

Code	state/country & name	years	IGBP*	IGBP [†]	%	reference
AU-Fog	Fogg Dam, Australia	2006-2007	WET	SAV	72.2	<i>Beringer et al. (2013); Ma et al. (2013)</i>
AU-How	Howard Springs, Australia	2001-2006	WSA	SAV	61.1	<i>Beringer et al. (2011); Ma et al. (2013)</i>
AU-Tum	Tumbarumba, Australia	2001-2006	EBF	EBF	41.0	<i>Bonan et al. (2011)</i>
AU-Wac	Wallaby Creek, Australia	2005-2007	EBF	EBF	43.8	<i>Kilinc et al. (2013)</i>
BW-Ma1	Maun- Mopane Woodland, Botswana	1999-2001	WSA	SAV	91.0	<i>Veenendaal et al. (2004)</i>
CA-Mer	Quebec Eastern Peatland- Mer Bleue	1998-2005	WET	DBF	70.1	<i>Lafleur et al. (2001); Kross (2011)</i>
CA-Qcu	Quebec Boreal Cutover Site	2001-2007	ENF	ENF	72.2	<i>Giasson et al. (2006)</i>
DE-Tha	Anchor Station Tharandt, Germany	1996-2007	ENF	MF	67.4	<i>Grünwald and Bernhofer (2007)</i>
IL-Yat	Yatir, Israel	2001-2006	ENF	SH	45.1	<i>Rotenberg and Yakir (2010)</i>
IT-Amp	Amplero, Italy	2002-2006	GRA	MF	67.4	<i>Gilmanov et al. (2010)</i>
IT-Cpz	Castelporziano, Italy	1997-2007	EBF	WAT	45.1	<i>Garbulsky et al. (2008)</i>
IT-Ro1	Roccarespampani, Italy	2000-2007	DBF	MF	53.5	<i>Migliavacca et al. (2008)</i>
NL-Hor	Horstermeer, Netherlands	2004-2007	GRA	CRO	54.9	<i>Hendriks et al. (2007, 2008)</i>
NL-Loo	Loobos, Netherlands	1996-2007	ENF	CRO	48.6	<i>Elbers et al. (2011)</i>
US-ARM	OK ARM Southern Great Plains-Lamont	2000-2007	CRO	GRA	44.4	<i>Billesbach et al. (2004)</i>
US-Aud	AZ Audubon Research Ranch	2002-2006	GRA	SAV	47.2	<i>Gilmanov et al. (2010)</i>
US-Bar	NH Bartlett Experimental Fores	2004-2006	DBF	DBF	70.1	<i>Jenkins et al. (2007)</i>
US-Bkg	SD Brookings	2004-2006	GRA	CRO	79.2	<i>Gilmanov et al. (2005)</i>
US-Blo	CA Blodgett Forest	1997-2007	ENF	ENF	53.5	<i>Goldstein et al. (2000)</i>
US-Bo1	IL Bondville	1996-2007	CRO	CRO	77.1	<i>Turner et al. (2003b)</i>
US-Dk3	NC Duke Forest Loblolly Pine	1998-2005	ENF	MF	45.8	<i>Luo et al. (2001); Stoy et al. (2008)</i>
US-FPe	MT Fort Peck	2000-2006	GRA	GRA	66.7	<i>Gilmanov et al. (2003)</i>
US-Goo	MS Goodwin Creek	2002-2006	GRA	DBF	50.0	<i>Yuan et al. (2007)</i>
US-Ha1	MA Harvard Forest EMS Tower (HFR1)	1991-2006	DBF	DBF	97.2	<i>Urbanski et al. (2007); Goulden et al. (1996)</i>
US-Ho1	ME Howland Forest (main tower)	1996-2004	ENF	MF	61.8	<i>Thornton et al. (2002)</i>
US-Ho2	ME Howland Forest (west tower)	1999-2005	ENF	MF	61.8	<i>Thornton et al. (2002)</i>
US-IB1	IL Fermi Agricultural	2005-2007	CRO	CRO	50.7	<i>Xiao et al. (2008)</i>
US-IB2	IL Fermi Prairie	2004-2007	GRA	CRO	50.7	<i>Xiao et al. (2008)</i>
US-Los	WI Lost Creek	2000-2006	CSH	MF	92.4	<i>Sulman et al. (2009); Desai et al. (2008)</i>
US-MMS	IN Morgan Monroe State Forest	1999-2006	DBF	MF	37.5	<i>Schmid et al. (2000); Dragoni et al. (2007)</i>
US-MOz	MO Missouri Ozark Site	2004-2007	DBF	DBF	59.7	<i>Gu et al. (2003, 2006, 2012)</i>
US-Me2	OR Metolius Intermed. Pine	2002-2007	ENF	ENF	56.2	<i>Loescher et al. (2006)</i>
US-Me3	OR Metolius Second Young Pine	2004-2005	ENF	ENF	56.2	<i>Loescher et al. (2006)</i>
US-Me4	OR Metolius-old aged ponderosa pine	1996-2000	ENF	ENF	56.2	<i>Loescher et al. (2006)</i>
US-Me5	OR Metolius First Young Pine	1999-2002	ENF	ENF	56.2	<i>Loescher et al. (2006)</i>
US-NR1	CO Niwot Ridge	1998-2007	ENF	ENF	41.0	<i>Monson et al. (2002)</i>
US-Ne1	NE Mead - irrigated continuous maize	2001-2006	CRO	CRO	97.9	<i>Suyker et al. (2005); Verma et al. (2005)</i>
US-Ne2	NE Mead - irrigated maize-soybean rot.	2001-2006	CRO	CRO	97.9	<i>Suyker et al. (2005); Verma et al. (2005)</i>
US-Ne3	NE Mead - rainfed maize-soybean rot.	2001-2006	CRO	CRO	98.6	<i>Suyker et al. (2005); Verma et al. (2005)</i>
US-Oho	OH Oak Openings	2004-2005	DBF	CRO	69.4	<i>Sun et al. (2010)</i>
US-PFa	WI Park Falls/WLEF	1995-2005	MF	MF	96.5	<i>Davis et al. (2003); Desai et al. (2008)</i>
US-SO2	CA Shy Oaks Old	1998-2006	CSH	SH	72.9	<i>Stylinski et al. (2002)</i>
US-SP1	FL Slashpine-Austin Cary-65yr nat regen	2000-2006	ENF	MF	47.2	<i>Powell et al. (2008)</i>
US-SP2	FL Slashpine-Mize-clearcut-3yr regen	1998-2005	ENF	MF	47.2	<i>Bracho et al. (2012)</i>
US-SP3	FL Slashpine-Donaldson-mid-rot-12yr	1999-2005	ENF	MF	47.2	<i>Bracho et al. (2012)</i>
US-Shd	OK Shidler Tallgrass Prairie	1997-2000	GRA	GRA	44.4	<i>Gilmanov et al. (2003)</i>
US-Syv	MI Sylvania Wilderness Area	2001-2006	MF	MF	88.9	<i>Desai et al. (2005)</i>
US-Ton	CA Tonzi Ranch	2001-2007	WSA	SAV	55.6	<i>Sims et al. (2005)</i>
US-UMB	MI Univ. Mich. Biological Station	1999-2006	DBF	MF	84.7	<i>Gough et al. (1996)</i>
US-Var	CA Vaira Ranch- Ione	2000-2007	GRA	SAV	55.6	<i>Sims et al. (2005)</i>
US-WBW	TN Walker Branch Watershed	1995-2000	DBF	MF	49.3	<i>Misson et al. (2002)</i>
US-WCr	WI Willow Creek	1998-2006	DBF	MF	99.3	<i>Cook et al. (2004)</i>
ZA-Kru	Skukuza-Kruger Natl. Park, South Africa	2001-2003	SAV	SAV	75.7	<i>Scholes et al. (2001)</i>

*IGBP vegetation type at site - CRO: Croplands; CSH: Closed Shrublands; DBF: Deciduous Broadleaf Forest; EBF:

Evergreen Broadleaf Forest; ENF: Evergreen Needleleaf Forest; GRA: Grasslands; GMF: Grass+Mixed Forest; MF:

Mixed Forest; OSH: Open Shrublands; SAV: Savannas; SH: Shrublands; WET: Wetlands; WSA: Woody Savannas;

[†]Predominant IGBP type within satellite averaging area (see text) where WSA and SAV are combined as SAV, CSH and

OSH as SH, and MF and GMF as MF;

Table 2: Statistics for various timing indicators versus the standard (tower GPP). Significant differences in terms of the χ^2 statistic (> 2.0) are shown in bold. The units of bias are days.

	onset photosyn.		onset dormancy		inflection spring		inflection autumn		onset max. photosyn.		onset senesce.	
type	χ^2	bias	χ^2	bias	χ^2	bias	χ^2	bias	χ^2	bias	χ^2	bias
MODIS APAR vs. tower GPP												
CRO	71.9	-78.8	30.3	35.8	60.9	-38.0	16.7	18.6	2.3	2.6	0.6	0.6
DBF	21.0	-43.0	2.0	13.0	22.0	-26.3	5.1	12.7	0.7	-10.0	1.0	13.0
ENF	1.1	-17.0	1.1	18.5	1.4	-13.0	0.3	8.0	3.3	-9.0	0.4	-1.5
MF	21.2	-33.2	7.5	15.1	20.1	-17.1	11.5	12.9	0.8	-1.4	2.2	10.8
MPI BGC GPP vs. tower GPP												
CRO	3.9	-29.2	0.5	9.2	1.1	-11.0	0.1	2.6	0.3	6.6	0.1	-3.8
DBF	0.9	5.7	0.2	-6.3	0.2	-2.3	0.3	-6.7	0.4	-10.7	0.2	-6.7
ENF	0.3	-17.5	0.0	-2.0	0.7	-15.0	0.1	-3.0	0.5	-13.0	0.0	-2.5
MF	0.5	-5.9	0.7	-1.9	0.6	3.9	0.4	-5.3	0.6	13.3	0.1	-8.8
GOME-2 F ₇₄₀ vs. tower GPP												
CRO	19.6	-22.0	5.9	11.6	3.2	-8.0	0.9	1.0	1.0	5.6	2.1	-9.4
DBF	0.5	8.7	0.4	1.3	1.4	-3.7	3.7	-14.3	1.5	-16.3	3.9	-29.7
ENF	0.0	-2.0	0.1	5.5	0.1	0.5	0.3	11.0	0.3	3.5	0.1	-12.5
MF	2.6	7.9	1.6	1.7	5.3	7.7	5.7	-16.4	2.4	7.1	3.5	-34.9
Multi-model mean vs. tower GPP												
CRO	47.3	-33.5	1.5	21.7	0.6	-6.2	0.2	3.0	3.0	16.8	1.2	-15.3
DBF	11.9	-29.5	1.2	23.9	14.5	-20.5	1.0	13.9	1.1	-13.5	0.1	3.9
ENF	1.2	-14.5	0.1	-9.0	0.5	4.5	0.4	-8.0	2.2	23.5	0.2	-7.0
MF	19.9	-27.6	2.1	18.6	9.7	-13.3	1.5	7.2	0.4	0.8	0.3	-4.5

Table 3: Summary of duration of photosynthesis, growing season (length between inflection points), and duration of maximum photosynthesis as described in the text with uncertainties in parentheses for majority agricultural sites.

estimate	duration of photosyn.	duration of growing season	duration of max. photosyn.
US-Bo1 40.01°N -88.29°E			
MODIS	171 (4.0)	97 (2.1)	22 (5.7)
Tower	104 (2.5)	76 (2.3)	49 (4.3)
MPI-BGC	145 (11.4)	83 (10.9)	21 (17.5)
GOME-2	144 (3.3)	85 (1.8)	26 (4.5)
US-Ne1 41.17°N -96.48°E			
MODIS	246 (7.9)	142 (3.0)	36 (7.8)
Tower	117 (2.5)	73 (3.5)	28 (6.5)
MPI-BGC	147 (12.0)	88 (9.0)	30 (17.6)
GOME-2	143 (3.8)	82 (2.0)	22 (5.0)
Multi-model	165 (18.9)	85 (9.7)	6 (15.0)
US-Ne2 41.16°N -96.47°E			
MODIS	247 (7.9)	142 (3.0)	37 (7.9)
Tower	121 (2.5)	80 (3.0)	40 (6.0)
MPI-BGC	147 (12.0)	88 (9.0)	30 (17.6)
GOME-2	144 (3.5)	83 (2.0)	22 (5.0)
Multi-model	169 (11.6)	90 (5.8)	11 (11.8)
US-Ne3 41.18°N -96.44°E			
MODIS	222 (6.4)	122 (3.2)	21 (7.8)
Tower	110 (2.3)	75 (2.3)	39 (5.5)
MPI-BGC	147 (12.0)	88 (9.0)	30 (17.6)
GOME-2	144 (3.5)	83 (2.0)	22 (5.0)
Multi-model	181 (9.7)	82 (7.2)	6 (9.5)
US-IB1 41.86°N -88.22°E			
MODIS	256 (7.5)	160 (3.0)	64 (7.0)
Tower	117 (2.9)	76 (4.0)	34 (7.0)
MPI-BGC	175 (17.8)	101 (13.8)	27 (21.3)
GOME-2	162 (5.0)	92 (2.5)	23 (7.1)

Table 4: Similar to Table 3 but for deciduous broadleaf (DBF) and evergreen needleleaf (ENF) forest sites as indicated.

estimate	duration of photosyn.	duration of growing season	duration of max. photosyn.
US-Ha1 (DBF) 42.54°N -72.17°E			
MODIS	256 (7.1)	170 (3.0)	84 (6.7)
Tower	188 (5.9)	119 (3.8)	49 (9.6)
MPI-BGC	198 (14.4)	125 (10.3)	52 (20.0)
GOME-2	197 (9.2)	117 (3.7)	37 (9.2)
Multi-model	241 (13.2)	153 (8.2)	66 (4.9)
US-Bar (DBF) 44.06°N -71.29°E			
MODIS	245 (6.4)	166 (2.9)	87 (5.9)
Tower	176 (4.6)	129 (2.8)	80 (6.8)
MPI-BGC	183 (13.8)	120 (8.1)	56 (19.8)
GOME-2	184 (8.6)	113 (3.4)	41 (8.9)
CA-Mer (DBF) 45.41°N -75.52°E			
MODIS	249 (5.8)	158 (2.5)	67 (5.5)
Tower	218 (17.3)	129 (9.8)	40 (20.3)
MPI-BGC	165 (12.6)	119 (6.9)	73 (18.1)
GOME-2	179 (8.3)	115 (3.2)	51 (7.4)
US-NR1 (ENF) 40.03°N -105.55°E			
MODIS	255 (11.9)	149 (5.9)	43 (12.4)
Tower	209 (10.5)	148 (4.5)	85 (11.7)
MPI-BGC	218 (33.0)	141 (29.6)	66 (36.3)
GOME-2	216 (28.8)	132 (19.8)	48 (27.5)
Multi-model	215 (13.9)	136 (7.2)	55 (6.2)
CA-Qcu (ENF) 49.27°N -74.04°E			
MODIS	213 (7.3)	147 (3.5)	81 (5.6)
Tower	188 (20.8)	106 (16.3)	24 (21.6)
MPI-BGC	210 (22.3)	137 (14.9)	64 (26.0)
GOME-2	196 (26.8)	143 (23.2)	29 (27.2)

Table 5: Similar to Table 3 but for representative mixed forest sites.

estimate	duration of photosyn.	duration of growing season	duration of max. photosyn.
US-WBW 35.96°N -84.29°E			
MODIS	258 (5.6)	189 (2.3)	121 (4.8)
Tower	220 (7.5)	158 (3.2)	95 (8.5)
MPI-BGC	238 (15.5)	159 (11.3)	81 (25.5)
GOME-2	228 (9.6)	134 (3.7)	39 (10.0)
US-MMS 39.32°N -86.41°E			
MODIS	243 (4.3)	184 (1.8)	125 (4.0)
Tower	200 (5.2)	145 (3.0)	91 (7.0)
MPI-BGC	191 (15.3)	110 (12.3)	29 (19.8)
GOME-2	190 (4.8)	103 (2.5)	18 (6.8)
Multi-model	260 (16.5)	165 (10.7)	70 (7.9)
US-Ho1 45.20°N -68.74°E			
MODIS	287 (10.7)	177 (4.1)	69 (8.6)
Tower	245 (9.0)	162 (4.3)	79 (10.9)
MPI-BGC	223 (19.0)	133 (13.8)	43 (24.3)
GOME-2	192 (10.8)	111 (5.9)	31 (11.8)
Multi-model	261 (14.2)	168 (9.6)	76 (4.7)
US-UMB 45.56°N -84.71°E			
MODIS	236 (4.3)	157 (2.0)	80 (4.3)
Tower	172 (4.3)	118 (3.3)	64 (7.8)
MPI-BGC	205 (18.0)	127 (12.3)	48 (23.1)
GOME-2	201 (19.1)	112 (14.4)	19 (14.1)
Multi-model	223 (10.7)	144 (5.1)	64 (4.6)
US-WCr 45.81°N -90.08°E			
MODIS	210 (3.5)	149 (1.8)	87 (3.8)
Tower	150 (4.0)	111 (2.5)	70 (6.1)
MPI-BGC	179 (14.1)	116 (8.3)	54 (20.3)
GOME-2	176 (8.7)	105 (3.8)	33 (8.9)
Multi-model	202 (5.9)	134 (2.4)	65 (4.5)