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1 **Understanding the land carbon cycle with space data: current status and prospects**

2

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25 **Abstract**

26 Our understanding of the terrestrial carbon cycle has been greatly enhanced since satellite
27 observations of the land surface started. The advantage of remote-sensing is that it provides
28 wall-to-wall observations including in regions where in situ monitoring is challenging. This
29 paper reviews how satellite observations of the biosphere have helped improve our
30 understanding of the terrestrial carbon cycle. First, it details how remotely-sensed
31 information of the land surface has provided new means to monitor vegetation dynamics,
32 estimate carbon fluxes and stocks. Second, we present examples of studies which have used
33 satellite products to evaluate and improve simulations from global vegetation models. Third,
34 we focus on model-data integration approaches ranging from bottom-up extrapolation of
35 single variables to carbon cycle data assimilation system able to ingest multiple types of
36 observations. Finally, we present an overview of upcoming satellite missions which are likely
37 to further improve our understanding of the terrestrial carbon cycle and its response to
38 climate change and extremes.

39

40

41 **1. Introduction**

42 Terrestrial ecosystems help offset climate change by absorbing 25–30% of anthropogenic
43 emissions of carbon dioxide (CO₂) each year (Canadell et al., 2007; Le Quéré et al., 2018).
44 The global land carbon sink is calculated as the residual between reported fossil-fuel
45 emissions, measurements of the atmospheric CO₂ growth and constrained estimates of ocean
46 carbon uptake (see e.g. Le Quéré et al. 2018 for more details). The spatiotemporal
47 distribution of the land carbon sink is estimated using an ensemble of process-based
48 terrestrial ecosystem models (TEMs; Sitch et al. 2015). However, these largely unconstrained
49 models exhibit significant differences in the location, magnitude and sign of the land carbon
50 balance. This lack of agreement leads to large uncertainties in Earth system models’
51 projections of the response of terrestrial ecosystems to future climate change (Friedlingstein
52 et al. 2006, Arora et al. 2013). This is further complicated by the interplay of vegetation CO₂
53 uptake and emissions from land use and land cover change (Arneeth et al. 2017) such as
54 deforestation (van der Werf et al. 2009).

55 A key issue for TEMs has been the challenge of integrating global observations to calibrate
56 process parameters. Model spread seems to emerge from the lack of understanding of
57 processes that control carbon allocation, turnover and mortality (Friend et al. 2014). Although
58 networks of eddy-covariance towers (e.g. FLUXNET, Baldocchi et al. 2001) provide useful
59 information to improve models (Williams et al. 2009, Kuppel et al. 2014), their distribution is
60 highly skewed toward temperate regions of the northern hemisphere which challenges their
61 applicability to other ecosystems. However, in recent years the multiplication of continuous
62 Earth Observation (EO) has allowed the production of observational datasets relevant to the
63 biosphere. While satellites do not measure carbon stocks and fluxes directly, they provide
64 covariates for the extrapolation of in situ data to global gridded products related to ecosystem
65 carbon fluxes (e.g. Jung et al. 2009) and biomass stocks (e.g. Saatchi et al. 2011; Baccini et

66 al. 2012; Avitabile et al. 2016) through machine-learning. Integrating EO to constrain
67 process-based models has led to breakthrough in our understanding of the terrestrial carbon
68 cycle, allowing a robust attribution of the increasing atmospheric CO₂ amplitude to the
69 response of high latitude productivity (Forkel et al. 2016).
70 In this paper we review studies in which satellite-driven datasets have been used to improve
71 our understanding of the terrestrial carbon cycle. We first focus on studies in which EO
72 products have been used to monitor vegetation dynamics, carbon fluxes and stocks. Then, we
73 illustrate how EO products can be used to evaluate TEMs, understand their biases and
74 improve projections of the carbon cycle. Third, we present model-data integration approaches
75 in which EO products are used to constrain TEMs using automated model-data fusion
76 approaches. Finally, we review the foreseeable improvements future satellite missions are
77 likely to generate.

78

79 **2. Earth Observation to monitor vegetation dynamics, carbon fluxes and stocks**

80 Satellite observations of the land surface allow a continuous monitoring of vegetation
81 dynamics through the calculation of spectral indices (Myneni et al. 1995). One of the most
82 common metrics is the Normalized Difference Vegetation Index (NDVI). It is calculated such
83 as $NDVI = (NIR+RED)/(NIR-RED)$ where RED and NIR are the spectral reflectance in the
84 visible red and near-infrared region of the photosynthetically active radiation spectrum,
85 respectively. Because chlorophyll strongly absorbs visible light during photosynthesis, active
86 canopies have higher NDVI values.

87 NDVI has been used in numerous studies to characterize the response of plant phenology and
88 productivity to climate trends and interannual variability. Bimonthly NDVI from the
89 Advanced Very High Resolution Radiometer (AVHRR) spans the period since July 1981
90 until present. This long-term dataset has allowed describing a lengthening of the growing

91 season in temperate regions of the Northern Hemisphere due to an earlier disappearance of
92 snow in warming conditions (Myneni et al. 1997). Using the third generation of the AVHRR-
93 based Global Inventory Modelling and Mapping System (GIMMS) NDVI dataset (Pinzon
94 and Tucker, 2014), Buitenwerf et al. (2015) detected significant changes in phenological
95 cycles for more than half of the land surface between 1981 and 2012. This long-term dataset
96 has also been used to identify dominant climate modes driving the inter-annual variability in
97 the start of growing season across North America (Dannenberg et al. 2018).

98 Higher resolution NDVI data from the Moderate resolution Imaging Spectroradiometer
99 (MODIS) sensor (Huete et al. 2002) have been provided by the National Aeronautics and
100 Space Administration (NASA) since the year 2000. These data have been used to attribute the
101 anomalous greening of the Northern Hemisphere land surface in 2015 to a strong state of the
102 Pacific Decadal Oscillation (Bastos et al. 2017). The MODIS archive also includes an
103 Enhanced Vegetation Index (EVI) which performs well better in high biomass regions (Huete
104 et al. 2002). It has been used to describe leaf growth across the Amazon basin during the dry
105 season, which promotes primary productivity in sunnier conditions (Huete et al. 2006). EVI
106 has also been used to describe the phenological response of Australian ecosystems to climate
107 IAV (Broich et al. 2014), in particular the continental greening that followed the extremely
108 wet 2010/11 La Niña episode (Fasullo et al. 2013).

109 NDVI and EVI are useful proxies for vegetation activity but they are not biophysical
110 variables directly relatable to TEMs. However, two key state variables for these models can
111 also be derived from EO: the Fraction of Absorbed Photosynthetically Active Radiation
112 (FAPAR) and Leaf Area Index (LAI), the one-sided area of leaves per units of ground.
113 FAPAR and LAI are related to NDVI (Zhu et al. 2013) but can also be retrieved using
114 physically-based (Knyazhikin et al. 1998) or machine-learning (Baret et al. 2013) methods.

115 FAPAR is a key driver for light use efficiency models of primary productivity (e.g. Potter et
116 al. 1993; Field et al. 1995; Prince and Goward 1995; Knorr 2000). Global MODIS-based
117 FAPAR (Myneni et al. 2002) is used to produce high resolution (~ 1km) estimates of gross
118 and net primary productivity across the global land surface (Running et al. 2004). This
119 dataset has provided insights in a possible reduction of global net primary productivity
120 because of a drying in the Southern Hemisphere (Zhao and Running 2010). It helped
121 characterized the influence of the El Niño – Southern Oscillation on regional and global NPP
122 (Bastos et al. 2013) and the impact of recent European heatwaves on productivity (Bastos et
123 al. 2014).

124 LAI represents the physiologically active part of the vegetation which interacts with the
125 atmosphere and is a key state variable for land surface and ecosystem models (Kala et al.
126 2014). Figure 1 presents mean annual LAI for the year 2015 derived from the European
127 Space Agency (ESA)'s Proba-V satellite (Baret et al. 2013) as part of the European Union's
128 Copernicus programme and from NASA's MODIS sensor. There is a good agreement in the
129 spatial distribution of LAI between these datasets but the MODIS products reports higher
130 LAI values for tropical which may lead to non-negligible differences in the calculation of
131 energy, water and carbon fluxes (Kala et al. 2014). MODIS LAI data has been helpful to
132 understand the seasonality of the Amazon (Myneni et al. 2007). Zhu et al. (2013) used the
133 relationship between AVHRR NDVI and MODIS FAPAR and LAI products to create the
134 GIMMS FAPAR3g and LAI3g dataset extending back to the 1980s. This long-term dataset
135 exhibits a greening trend, i.e. an increase in LAI during the growing season (Zhu et al. 2016).
136 A recent advance in remote sensing has been the production of Solar-Induced Fluorescence
137 (SIF) retrievals (Frankenberg et al. 2011). SIF is directly related to plant photosynthetic
138 activity; therefore, SIF data provide a more direct measure of gross C uptake than
139 reflectance-based indicators like NDVI or FAPAR (Porcar-Castell et al. 2014). There has

140 been an increase in the availability of global SIF products derived from space-borne
141 instruments like GOSAT (Frankenberg et al. 2011; Guanter et al. 2012), GOME-2 (Joiner et
142 al. 2013; Köhler et al., 2015), SCIAMACHY (Joiner et al. 2016) and OCO-2 (Sun et al.,
143 2018). More details about SIF is provided in section 3.2.3 of the review by Scholze et al.
144 (2017).

145 Additionally to plant productivity, satellite datasets have been used for over three decades to
146 monitor fire, a fundamental component of the terrestrial carbon cycle which accounts for a
147 large degree of the inter-annual variability of the terrestrial land sink (van der Werf et al.,
148 2010; Le Quéré et al., 2018). Observations of decadal trends in burned area (Flannigan et al.,
149 1986; Giglio et al., 2013; Andela et al., 2017) have been used to establish the role of fires as a
150 key component of the long-term C balance evolution (Le Quéré et al., 2018; Arora & Melton,
151 2018, amongst others). A range of satellite-based observations of fire have also radically
152 advanced insight into continental-scale fire characteristics and processes, including
153 understory fires (Morton et al., 2013); fire radiative power (Freeborn et al., 2014), and
154 interactions between fire and species distribution (Rogers et al., 2015). Archibald et al.
155 (2013) identified 5 dominant types of fire regimes using remotely-sensed observation of fire
156 frequency, radiative power and size. Active fire detection also offers a crucial constraint on
157 land C fire losses, with current observing system such as VIIRS offering new possibilities to
158 detect boreal fires (Waigl et al. 2017).

159 Beyond monitoring vegetation dynamics and inferring land-atmosphere fluxes, satellite
160 observations have allowed the creation of high resolution maps of above-ground biomass
161 (AGB) covering large regions such as the pantropics (e.g. Saatchi et al., 2011; Baccini et al.
162 2012). Pantropical maps were created using allometric equations (e.g. Chave et al. 2014)
163 relating tree height measured by NASA's Geoscience Laser Altimeter System sensor onboard
164 the Ice, Cloud, and land Elevation Satellite (Zwally et al. 2002) to AGB. These wall-to-wall

165 maps allow a first-order approximation of remotely-sensed deforestation (e.g. Hansen et al.
166 2013) on AGB stocks in the tropics (Harris et al., 2012; Baccini et al., 2012). Recently, maps
167 by Saatchi et al. (2011) and Baccini et al. (2012) have been fused with additional in situ
168 measurements to create a third map, currently considered as the state-of-the-art (Avitabile et
169 al. 2016).

170 Thurner et al. (2014) created a map for the northern boreal and temperate forests paper using
171 retrievals of Growing Stock Volume from Envisat Advanced Synthetic Aperture Radar
172 (Santoro et al. 2011, 2015), databased information about wood density (Chave et al. 2009)
173 and allometric equations. Thurner et al. (2016) used this map in combination with MODIS
174 NPP to evaluate gradients in turnover dynamics across these regions.

175 While these previous studies relied on a single AGB map to produce estimates of gross
176 emissions from deforestation, more recent studies have produced annually-resolved AGB
177 maps which allow tracking the counteracting impact of regrowth and derive net changes of
178 biomass globally. For example, Liu et al. (2015) used the correlation between Vegetation
179 Optical Depth and AGB from Saatchi et al. (2011) to produce annual biomass maps for
180 1993–2012 at a 0.25° spatial resolution. They concluded to a loss of global AGB driven by a
181 loss of tropical forests partially compensated by gains over boreal, temperate and savannah
182 regions. More recently, Brandt et al. (2018) used a similar approach to describe a net carbon
183 loss across sub-Saharan Africa for the period 2010–2016. Baccini et al. (2017) also
184 concluded that the tropics are a net source of atmospheric CO₂ based on annual maps they
185 constructed from 2003–2014.

186 EO is useful to identify land cover change (e.g. Hansen et al. 2013) and, by extension, intact
187 forest landscapes (Potapov et al., 2008). Potential AGB maps, representative of the
188 hypothetical undisturbed landscape, can be reconstructed using the relationship between
189 AGB (Saatchi et al. 2011; Baccini et al. 2012; Liu et al. 2015) and climate (New et al. 2002)

190 in these intact regions. This approach attributes ~1.5% of the recent increase in atmospheric
191 CO₂ to the Amazonian deforestation (Exbrayat and Williams 2015) while climate change has
192 reduced the capacity of these forests to recover (Exbrayat et al. 2017).

193 International policy efforts such as the Paris agreement on climate change and the Bonn
194 challenge for forest restoration have raised the interest of countries to produce country-scale
195 maps for monitoring and reporting. For example Rodríguez-Veida et al. (2016) used local
196 information from the Mexican forestry. Similarly, Xu et al. (2017) produced a biomass map
197 for the Democratic Republic of Congo using additional data which were not available to
198 pantropical maps. Both studies presented measurable increase in mapping quality and
199 uncertainty quantification.

200

201 **3. Evaluating terrestrial ecosystem models**

202 Land surface models are key components of Earth system models that simulate energy and
203 mass transfers between the land and the atmosphere, hence, these are key components in the
204 prediction of climate variations from short to long time scales (Pitman 2003). EO of the
205 biosphere provides unprecedented means to evaluate vegetation dynamics, carbon fluxes and
206 biomass stocks simulated by land surface models in a temporally and spatially-explicit
207 manner. The evaluation strategies have been largely focusing on aspects related to: the timing
208 of seasonal vegetation development, and long term trends in vegetation greenness; the
209 seasonal and spatial variations in photosynthesis patterns; the spatial variations in plant
210 carbon stocks; and EO-derived estimates of carbon turnover times on land.

211 The representation of phenology in land surface models is a major source of uncertainty for
212 the calculation of energy, water and carbon fluxes (Kala et al. 2014). Many studies have
213 focused on in-situ evaluation of modelled LAI (e.g. Richardson et al. 2012; Migliavacca et al.
214 2012) but long-term EO-derived products have also been used. Zhu et al. (2013) described a

215 systematic overestimation of LAI by 18 Earth system models compared to the GIMMS
216 LAI3g dataset. This was accompanied by a shift toward earlier peak in LAI in boreal regions.
217 Similarly, Anav et al. (2013) evaluated models participating in the fifth phase of the Coupled
218 Model Intercomparison Project (CMIP5; Taylor et al. 2012) which underpinned the fifth
219 Assessment Report of the Intergovernmental Panel on Climate Change. They described a
220 tendency for CMIP5 models to overestimate LAI, although most models captured LAI trends.
221 The poor performance of models to represent phenology has led several intercomparison
222 projects to impose EO-derived LAI dataset to all participating models (Huntzinger et al.
223 2013; Haarsma et al. 2016).

224 EO-derived products have also been used to assess vegetation productivity simulated by
225 ecosystem models. Kolby-Smith et al. (2015) created a long-term NPP dataset based on
226 MODIS NPP algorithm (Running et al. 2004; Zhao and Running 2010) driven by long-term
227 GIMMS FAPAR3g (Zhu et al. 2013). They compared this new dataset with five CMIP5
228 models which exhibited a much stronger trend of increasing NPP than the EO-based product.
229 They concluded that models' sensitivity to increasing atmospheric CO₂ was too high,
230 probably owing to the lack of representation of nutrient limitation on productivity. Ito et al.
231 (2017) showed that spatial and seasonal variations of GPP simulated by eight ecosystem
232 models were in agreement with the MODIS GPP product. However, they also showed that
233 models failed to simulate GPP anomalies in response to extreme events such as the 1997–
234 1998 El Niño or the eruption of Mount Pinatubo in 1991. Slevin et al. (2017) identified an
235 underestimation of GPP in the tropics when comparing the Joint UK Land Environment
236 Simulator (JULES; Clark et al. 2011) with EO-derived GPP products.

237 EO-derived products of GPP and NPP now allow skill-based ensemble averaging studies to
238 be applied to ecosystem models. These post-processing procedures have been used in
239 atmospheric sciences for many decades (e.g. Krishnamurti et al. 1999) and can be applied to

240 ecosystem models in a spatially-explicit way. Schwalm et al. (2015) applied the Reliability
241 Ensemble Averaging method (Giorgi and Mearns 2012) constrained by FLUXNET MTE-
242 GPP and biomass estimates to ten ecosystem models participating to the MsTMIP
243 (Huntzinger et al. 2013). Exbrayat et al. (2018) used a similar method to constrain projections
244 of 21st century change in NPP predicted by 30 simulations from the ISIMIP ensemble (Friend
245 et al. 2014; Warszawski et al. 2014). They showed that the uncertainty in global change in
246 NPP could be reduced by two-third using a skill-based ensemble averaging whilst gaining
247 confidence on the sign of the change for more than 80% of the global land surface.

248 A recent emphasis has been put on the need to move beyond the separate evaluation of pools
249 and fluxes by terrestrial land models. For many years, global models have been initialized
250 using a spin-up procedure from which biomass stocks would emerge as a result of input
251 fluxes and turnover times at steady-state (Exbrayat et al. 2014). However, models perform
252 poorly to simulate vegetation carbon stocks in agreement with observation-based products.
253 For example, Figure 2 presents a comparison of the recent pantropical biomass map from
254 Avitabile et al. (2016) with models from the ISIMIP ensemble (Friend et al. 2014;
255 Warszawski et al. 2014). There is a large uncertainty represented by the inter-model spread
256 while they tend to overestimate biomass stocks in regions of the Americas and Africa located
257 north of 10°N and south 15°S. Friend et al. (2014) clearly demonstrated that the highest
258 disagreement between models resides in the internally modelled residence times of carbon
259 which can be inferred from the ratio between observable fluxes and stocks (Friend et al.
260 2014; Sierra et al. 2017). Under the same future changes in environmental and climate
261 conditions models alternatively predict longer or shorter turnover times of carbon in
262 vegetation. This mismatch reflects a disagreement in the sign of the terrestrial carbon cycle
263 feedback on future changes in climate and atmospheric CO₂. Current EO-based estimates
264 suggest a pervasive control of hydrology on whole ecosystem apparent turnover times of

265 carbon, which are not captured by current Earth system models (Carvalhais et al. 2014). In
266 particular, the spatial patterns of vegetation C turnover times in forests suggest strong
267 climatic controls in mortality patterns associated to drought and heat, but also extreme winter
268 cold temperatures which could expand plant mortality, or reduce it, via reductions in
269 herbivore activity (Thurner et al. 2016). An across model comparison also revealed that most
270 state of the art global vegetation models do not reflect the direct effects of climate induced
271 mortality (Thurner et al. 2017), emphasizing the present challenge of understanding mortality
272 induced by climate extreme (Hartmann et al. 2015). Furthermore, recent results have also
273 emphasize the role of land use, in addition to land cover, as a substantial factor for an overall
274 reduction in carbon residence times in terrestrial vegetation (Erb et al. 2016).
275 In general, all of these works have been emphasizing the mismatch between model and
276 observation-derived ecosystem dynamics, and hypothesizing on the missing, or
277 misrepresented, underlying mechanisms that drive carbon dynamics. Downstream, a full
278 body of research has also been focusing on formally integrating these observations into
279 model-data-assimilation frameworks to maximize information transfer from observation to
280 models.

281

282 **4. Model-data integration**

283 While EO can be used to benchmark models, they do not measure all aspects of the terrestrial
284 carbon cycle. Therefore, models are needed to fill gaps but benchmarking studies reviewed in
285 section 3 have generally pointed to poor performances and systematic biases in forward
286 models. Model-data integration aims to synergize data and models through an interactive
287 process. There exists multiple forms of model-data integration in which EO has been used to
288 provide global covariates for the extrapolation of in situ data (e.g. Jung et al. 2011), retrieve
289 state variables such as LAI from reflectance through a complex radiative transfer scheme

290 (Lewis et al. 2012), constrain productivity and phenology model parameters in terrestrial
291 Carbon Cycle Data Assimilation Systems (CCDAS; e.g. Knorr et al. 2010) or even provide
292 initial conditions to detailed forest models (e.g. Rödiger et al. 2017, 2018).

293 The global coverage of EO has allowed the development of a range of “bottom-up”
294 approaches to upscale data-driven in situ models to spatially explicit gridded estimates. One
295 major development in this area has relied on training machine-learning algorithm to
296 reproduce local ecosystem fluxes as a function of climate and vegetation properties available
297 from EO (e.g. NDVI, FAPAR). The first example of this approach was reported by Papale
298 and Valentini (2003) who used an Artificial Neural Network trained at 16 European sites to
299 generate continental maps of forest productivity using information about land cover, seasonal
300 temperatures and maximum NDVI from AVHRR. Jung et al. (2009) developed the Model
301 Tree Ensemble (MTE) algorithm to create gridded products of GPP and latent heat fluxes.
302 They first demonstrated the potential for their approach in a synthetic example using LPJmL
303 simulations as training data. Using this method driven by fluxes measured at several
304 FLUXNET sites has allowed the first data-driven description of the distribution of global GPP
305 between biomes and an attribution of dominant regional climate drivers for the period 1998-
306 2005 (Beer et al. 2010). Building on this approach, monthly gridded estimates of GPP
307 extending back to 1982 have been created using GIMMS FAPAR data (Jung et al. 2011).
308 They identified semiarid and sub-humid as experiencing a high inter-annual variability in
309 productivity due to rainfall variations. These data, used in combination with process-based
310 models, further helped identify the response of savannah ecosystems to ENSO as the
311 dominant driver of the variability in the land carbon sink (Poulter et al. 2014). Multiple
312 machine-learning approaches, relying on various algorithms, have been compared by
313 Tramontana et al. (2016). The evaluation of different approaches was performed as part of
314 the FLUXCOM initiative (<http://www.fluxcom.org>). The conclusion of this comparison was

315 that machine-learning approaches were skilled at reproducing heat and productivity fluxes
316 but may be biased to predict net ecosystem carbon fluxes due to the lack of feedback
317 representation and knowledge of historical disturbance regimes. Nevertheless, bottom-up and
318 top-down approaches estimates of GPP are in good agreement. Figure 3 presents mean
319 annual GPP estimated by FLUXCOM during 2000-2013 and compares it to the MODIS GPP
320 product. Both approaches are partly driven by the same estimates of MODIS FAPAR which
321 yields a high spatial correlation ($r = 0.80$; $p \ll 0.001$). FLUXCOM indicates a mean annual
322 GPP of $124.7 \text{ Pg C y}^{-1}$ while MODIS estimates a $136.4 \text{ Pg C y}^{-1}$, a 9% relative difference.
323 Beyond empirical approaches, the increasing availability of EO has played a key role in the
324 development of more “top-down” terrestrial Carbon Cycle Data Assimilation Systems
325 (CCDAS). Unlike “bottom-up” approaches which consist in extrapolating in situ models,
326 “top-down” CCDAS are centred around using EO, including non-carbon variables (Scholze
327 et al. 2017), to constrain process-based models in a spatially explicit way. One of the first
328 CCDAS was based on the Bethy ecosystem model (Knorr 2000). It has been incrementally
329 improved with additional processes such as dynamic phenology (Knorr et al. 2010). An
330 interesting aspect of CCDAS studies has been to focus on the development and comparison
331 of inversion strategies (e.g. Ziehn et al. 2012) to reduce the computational cost of the
332 assimilation. We refer the reader to a detailed review of the evolution of CCDAS by
333 Kaminski et al. (2013) for more information about this particular framework. One strategy
334 introduced by Peylin et al. (2016) has also been to use a stepwise approach to first constrain
335 parameters related to phenology in the ORCHIDEE model before assimilating fluxes in a
336 subsequent step.

337 We focus the following paragraphs on example of new knowledge derived from CCDAS
338 applications, and point the readers to the recent review of Scholze et al. (2017) for more
339 technical information about the type of assimilation techniques and EO used. The advantage

340 of EO is that model-data integration is performed globally and CCDAS framework such as
341 CARDAMOM (Bloom et al. 2016) and CASA-GFED (van der Werf et al. 2010) provide
342 compelling methodologies for reconciling land-surface and atmospheric constraints on the
343 terrestrial C balance, through which major uncertainties in process representation such as
344 phenology (e.g. Stöckli et al. 2011, Forkel et al. 2014), allocation (Bloom et al. 2016),
345 combustion and emission dynamics (Bloom et al., 2015; Worden et al., 2017) can be
346 explicitly constrained.

347 Phenology is a poorly represented process and assimilating reflectance-based EO of NDVI,
348 FAPAR and LAI has allowed in development and validation of new global models. For
349 example, Knorr et al. (2010) assimilated daily FAPAR at seven sites in a generic
350 phenological model. Quaife et al. (2008) demonstrated that assimilating reflectance from the
351 MODIS sensor in the Data-Assimilation Linked Ecosystem Carbon model (DALEC;
352 Williams et al. 2005) led to an improvement of simulated carbon fluxes at a coniferous forest
353 site in Oregon, US. Stöckli et al. (2011) assimilated 10 years of MODIS LAI and FAPAR
354 data in a phenological model based on the Growing Season Index concept (GSI; Jolly et al.
355 2005). They identified used the constrained model to produce a 50-year re-analysis of LAI
356 and FAPAR. Forkel et al. (2014) implemented a modified version of the GSI model in the
357 LPJmL dynamic global vegetation model. They retrieved dominant controls of phenology by
358 assimilating 30 years of GIMMS FAPAR, highlighting the codominant role of moisture stress
359 on the variability in phenology (Forkel et al. 2015) which contrasts with classical
360 temperature-based parameterizations. The importance of moisture availability was also found
361 by MacBean et al. (2015) based on the biases in the temperature-driven phenology of the
362 ORCHIDEE model. While these previous studies have relied on plant functional types,
363 Caldararu et al. (2014) successfully fitted a phenological model to pixel-wise MODIS LAI

364 data. Their approach based on carbon optimality concluded that leaf age was also a limiting
365 factor for phenology in evergreen tropical regions.

366 EO of fire has also been used to constrain emission estimates. Top-down estimates of surface
367 CO emissions amount to a robust constraint on continental-scale fire C emissions:
368 measurements of atmospheric CO – including those from ESA’s IASI instrument, NASA’s
369 MOPITT, TES and AIRS instruments – have been used to constrain atmospheric chemistry
370 and transport models in data assimilation frameworks (Jiang et al., 2015; Gonzi et al., 2011;
371 Krol et al., 2013; Kopacz et al., 2010, amongst many others). Subsequently, estimates of fire
372 CO:CO₂ ratio (Andreae & Merlet, 2001; Akagi et al., 2011) have been used to quantify
373 continental-scale fire C fluxes (Gatti et al., 2014; Bowman et al., 2017). However, CO:CO₂
374 have been identified as a potential source of error in extreme fire events (Krol et al., 2013;
375 Bloom et al., 2015), where CO:CO₂ values and their uncertainty characteristics are poorly
376 known. Overall, estimates of fire emissions derived from an array of bottom-up and top-down
377 constraints are invaluable for obtaining a spatially-explicit estimates of fire C fluxes
378 (Bowman et al., 2017; Liu et al., 2017). Ultimately, satellite-based estimation of fire C
379 emissions, characteristics, and trends are key to advance process-level understanding of fires
380 as a dynamic component of the Earth System.

381 Although a number of satellite-derived products (NDVI, LAI, FAPAR, biomass and XCO₂)
382 have been used to constrain both modelled leaf phenology, biomass, and net CO₂ fluxes
383 (Kaminski et al., 2013; Forkel et al., 2015; MacBean et al., 2015; Peylin et al., 2016; Bloom
384 et al., 2016), these data only provide indirect information on gross C uptake. For some
385 vegetation types, even ground-based net CO₂ fluxes derived from eddy covariance towers
386 only provide limited capacity in constraining the gross C fluxes (Kuppel et al., 2014).

387 Consequently, SIF products have been used in a variety of ways to assess and improve land
388 surface model (LSM) simulations: i) to benchmark GPP and SIF temporal dynamics

389 simulated for a range of sites (Lee et al., 2015; Thum et al., 2017); ii) to optimize global-scale
390 GPP estimates from a LSM inter-comparison *a posteriori* (Parazoo et al., 2014); and to
391 optimize parameters of both fluorescence and photosynthesis models at local to global scales
392 (Zhang et al., 2014; MacBean et al., 2018; Norton et al., 2018; Norton et al., in review). The
393 latter studies have demonstrated considerable potential for SIF to constrain both in situ and
394 global scale GPP simulations. MacBean et al. (2018) and Norton et al. (in review) show
395 strong reductions in both the spatio-temporal misfit (increased correlation and decreased bias)
396 across vegetation types between modelled and observed GPP and SIF, and in the simulated
397 global-scale GPP uncertainty. The reduction in GPP uncertainty is a result of constraining
398 both fluorescence, photosynthesis, and phenology-related parameters. In many of the
399 abovementioned modelling studies, an explicit formulation of the relationship between
400 photosynthesis and fluorescence has been developed – largely based on the SCOPE (Soil
401 Canopy Observation Photochemistry and Energy Fluxes) model (van der Tol et al., 2009) –
402 and implemented within each respective LSM (Lee et al., 2014; Thum et al., 2017; Norton et
403 al., 2018; Norton et al., in review). However, SIF has been shown to be linearly correlated
404 with GPP at a range of spatial and temporal scales (Frankenberg et al., 2011; Guanter et al.,
405 2012; Joiner et al., 2014; Yang et al., 2015; Zhang et al., 2016; Wood et al., 2017; Yang et
406 al., 2017). This assumed linear relationship also allows a relatively simple and
407 straightforward means by which modelled GPP and SIF can be compared with, and
408 constrained by, remote sensing SIF estimates at large spatial scales (MacBean et al., 2018).
409 Continental-scale temporal variability of the terrestrial land sink can be robustly observed
410 through atmospheric CO₂ measurements from satellites - most notably from SCIAMACHY
411 instrument onboard ENVISAT, JAXA's GOSAT and the NASA OCO-2 missions (Buchwitz
412 & Burrows, 2004; Yokota et al., 2009; Eldering et al., 2017). Terrestrial CO₂ fluxes can be
413 quantitatively retrieved through assimilation of these observations into inverse modeling

414 frameworks (Houweling et al., 2015; Deng et al., 2016), although we note that absolute CO₂
415 flux estimates are susceptible to a number of model and observation biases (Feng et al., 2016;
416 Miller et al., 2017; Worden et al., 2017b, Basu et al., 2018). Notable insights into terrestrial C
417 cycle processes from satellite-constrained estimates of land C fluxes include multi-year
418 constraints on the Australian C balance (Detmers et al., 2015) regional constraints on the
419 seasonal and inter-annual Amazon C fluxes (Parazoo et al., 2013; Bowman et al., 2017) and
420 Indonesia fire C emissions during the 2015 ENSO (Heymann et al., 2017). Pan-tropical
421 continental-scale estimates of inter-annual CO₂ flux variations by Liu et al., (2017)
422 demonstrated the synergistic capacity of GOSAT and OCO-2 CO₂ measurements – along
423 with ancillary constraints from solar-induced fluorescence – to disentangle the processes
424 regulating the temporal variability of the terrestrial C sink.

425 While previous studies have focused on fluxes, reconciling stocks is key as these are
426 responsible for uncertainty in residence times (Carvalhais et al., Friend et al. 2014). Bloom et
427 al. (2016) have used pantropical biomass estimates from Saatchi et al. (2011) to constrain
428 global retrievals of carbon allocation and residence times in the CARDAMOM framework.
429 Figure 4 shows an updated version of these data based on the assimilation of biomass
430 estimates from Avitabile et al. (2016) and MODIS LAI for the period 2000-2015. These
431 simulations, limited to the area covered by Avitabile et al. (2016), provide EO constrained
432 estimated of NPP (43.3 Pg C y⁻¹), Rh (40.2 Pg C y⁻¹), fire emissions (1.2 Pg C y⁻¹) and Net
433 Biome Exchange (-1.7 Pg C y⁻¹, corresponding to a sink).

434 Furthermore, an accurate representation of stocks in ecosystem models is required to robustly
435 estimate emissions related to land use change. Li et al. (2017) used estimates of current
436 biomass compiled by Carvalhais et al. (2014) to constrain centennial emissions from land use
437 change in an ensemble of nine models. While global numbers of cumulative emissions from
438 land use change were similar between the unconstrained and constrained models, regional

439 differences appeared. For example, the data-constrained estimates yielded larger emissions
440 from land use change in the tropics, and smaller in temperate regions, compared to the
441 unconstrained estimates. In a more recent study Lienert and Joos (2018) also used biomass
442 data from Carvalhais et al. (2014) to constrain emissions from land use change using
443 alternative representation of emissions due to net and/or gross land use transitions.

444 Studies presented in previous paragraphs have focused on using EO data to constrain fluxes
445 and state variables in conceptual models. However, remotely-sensed information of
446 vegetation structure can be connected to highly detailed forest models to provide mechanistic
447 estimates of forest biomass and productivity (Shugart et al. 2015, Knapp et al. 2018a, Knapp
448 et al. 2018b). Forest structure is indeed an important element to describe the state of forests.

449 Precise estimates of forest structure need to consider small-scale variations resulting from
450 local disturbances, on the one hand, and require large-scale information on the state of the
451 forest that can be detected by remote sensing, on the other hand (Rödig et al. 2017). Local
452 forest models can simulate and analyse different kinds of local disturbances and thus small-
453 scale changes in forest structures more accurately than global ecosystem models. Remote
454 sensing has the potential to provide global high-resolution measurements of the structure of a
455 forest (e.g. forest height by Lidar or interferometric Radar measurements).

456 As an example, Rödig et al. (2017) used remote sensing data with a resolution of 1km² (i.e.
457 canopy height map derived from ICESat) to establish large-scale applications of a local forest
458 gap model (i.e. FORMIND, Fischer et al. 2016). Forest gap models (Shugart et al. 2018)
459 simulate forest succession at the individual tree level. The advantage of using a local forest
460 model at the large scale is that it brings along information on many different forest attributes
461 (e.g. productivity, carbon sequestration, water fluxes) in a very fine resolution. In
462 combination with remote sensing, this enables the derivation of high-resolution maps of
463 carbon stocks and fluxes – which was conducted for the whole Amazon (Rödig et al. 2017,

464 Rödiger et al. 2018). By this approach, it was possible to simulate each tree in the Amazon.
465 Finally growth of more than 410 billion trees was analysed. According to this study, forests
466 in the Amazon store high amounts of aboveground biomass (76 Gt of carbon) and are an
467 important sink of 0.56 Gt C a⁻¹ under current conditions (Rödiger et al. 2018).

468

469 **5. Outlook**

470 EO has made an essential contribution to our understanding of the terrestrial carbon cycle
471 since the 1980s. It ranges from the continuous monitoring of vegetation activity through
472 NDVI, FAPAR and LAI to providing wall-to-wall constraints for model-based estimates of
473 land-atmosphere carbon fluxes. Nowadays, multiple dedicated missions and services, such as
474 the Sentinel satellites of the European Union's Copernicus programme, provide almost real-
475 time observations with a high level of quality. For example, the ESA TROPOMI instrument
476 of Sentinel-5P provides CO measurements with an unprecedented spatiotemporal coverage
477 (Bordsorff et al., 2018). In the next few years, multiple sensors will be launched to
478 complement the existing constellation of Sentinels and provide coincident observations of
479 several aspects of the biosphere (Stavros et al. 2017).

480 NASA's Global Ecosystem Dynamics Investigation (GEDI) mission, a LIDAR system on-
481 board the International Space Station (ISS), will provide a global coverage of canopy height
482 and foliage vertical profiles. It will provide updated and more detailed structural information
483 for integration with forest models (e.g. Rödiger et al. 2017, 2018). ESA's 7th Earth Explorer
484 BIOMASS (Le Toan et al. 2011) will provide repeated measurements of tropical biomass
485 with a P-band synthetic aperture radar. In contrast with currently available biomass maps,
486 temporally-resolved information losses from deforestation and gain from regrowth will be
487 especially useful to reduce the uncertainty and correct bias in CCDAS framework (Smallman
488 et al. 2017).

489 Recent studies have demonstrated the potential for satellite CO₂ observations to constrain
490 land-atmosphere exchange (Liu et al. 2017). NASA's upcoming OCO-3 will replace OCO-2
491 on-board the ISS, while the geostationary GeoCARB will focus on the Americas. Both
492 systems, and the dedicated ESA's Fluorescence Explorer (FLEX) mission, will provide
493 measurements of SIF which has a great potential to constrain models of ecosystem
494 productivity (MacBean et al. 2018), especially following the implementation of mechanistic
495 representation of leaf physiology in CCDAS (Norton et al. 2018).

496 Finally, the carbon cycle is tightly linked to the energy and water cycles semi-arid areas in
497 particular have been pointed as key ecosystems to understand the global land carbon sink
498 (Poulter et al. 2014). Therefore, the development of new non-carbon EO and their
499 assimilation in CCDAS frameworks plays a major role in simulating the carbon cycle
500 (Scholze et al. 2017). NASA's ECOSTRESS will measure evapotranspiration (Stavros et al.
501 2017) which will be used to obtain estimates of water-use efficiency, the ratio of productivity
502 to evapotranspiration, which will be useful to drive process-based models of the biosphere.

503 Overall, the next few years will see an increase in the amount of observing systems with a
504 ever-increasing spatial resolution and higher frequency. One of the key challenges for the
505 modelling community is to build systems able to ingest all this information in an efficient
506 way to provide high confidence retrievals of the terrestrial carbon cycle.

507

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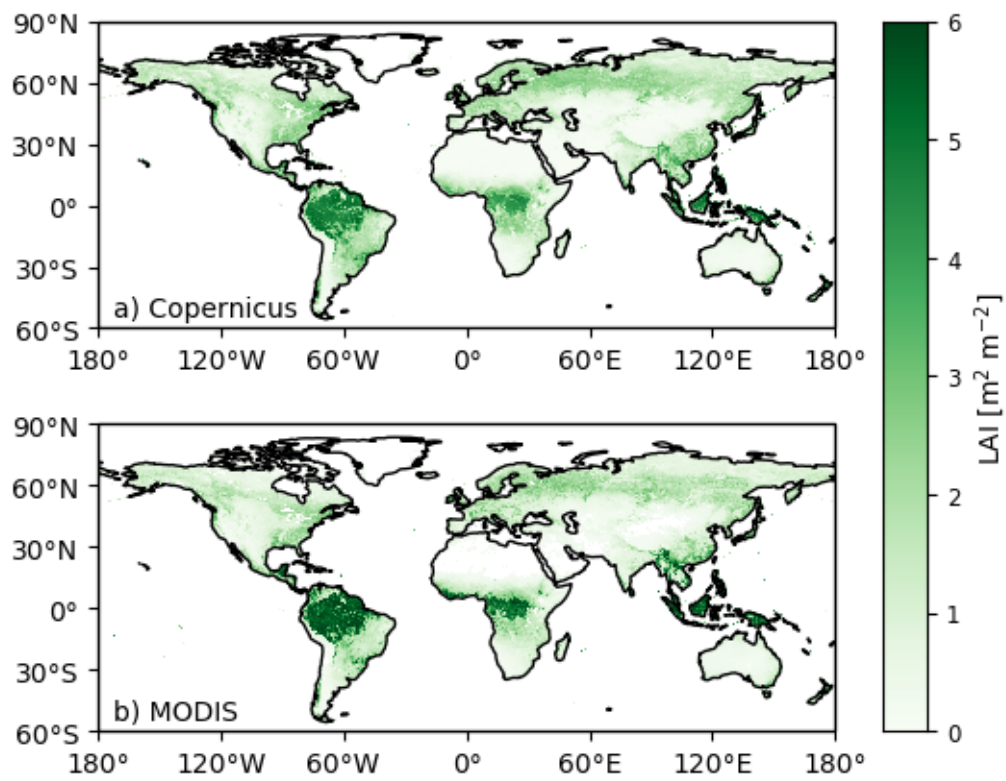
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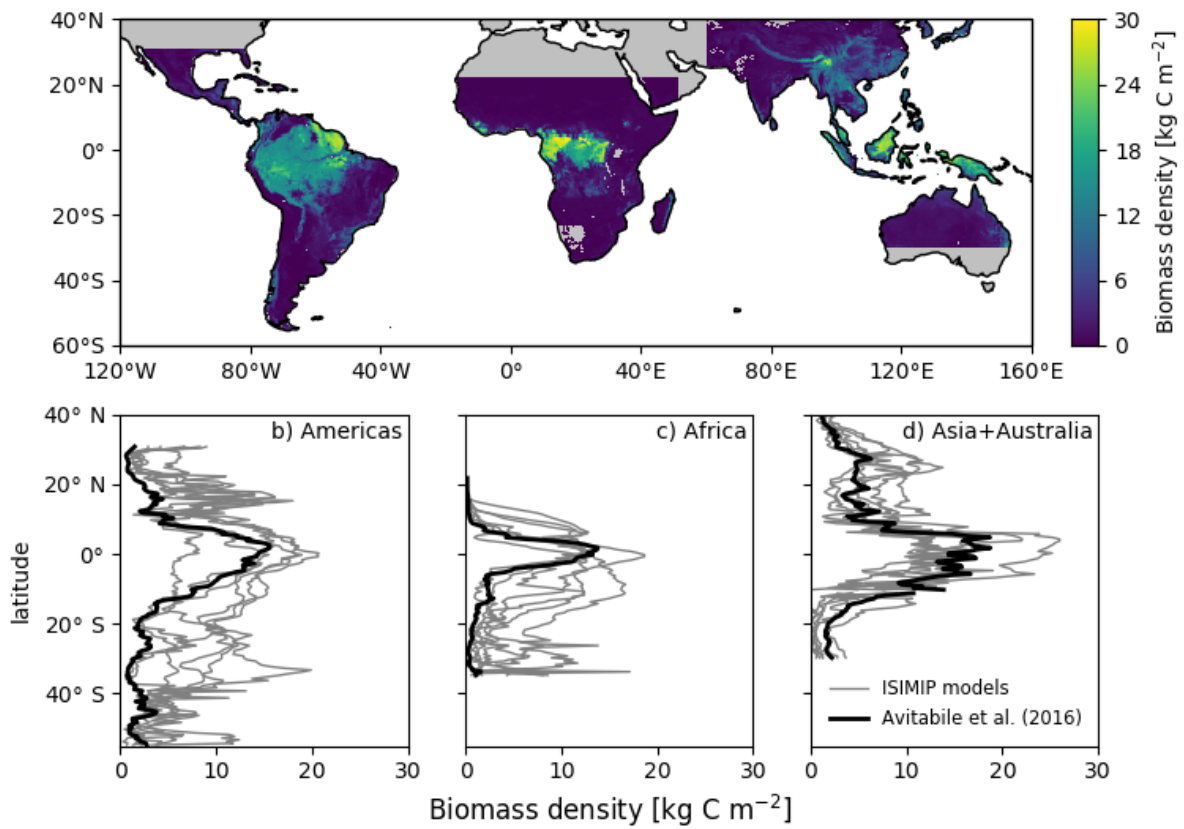
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994 Figure 1. Mean LAI in 2015 according to a) Copernicus and b) NASA's MODIS. Datasets

995 were resampled at 0.25° spatial resolution for plotting purpose.

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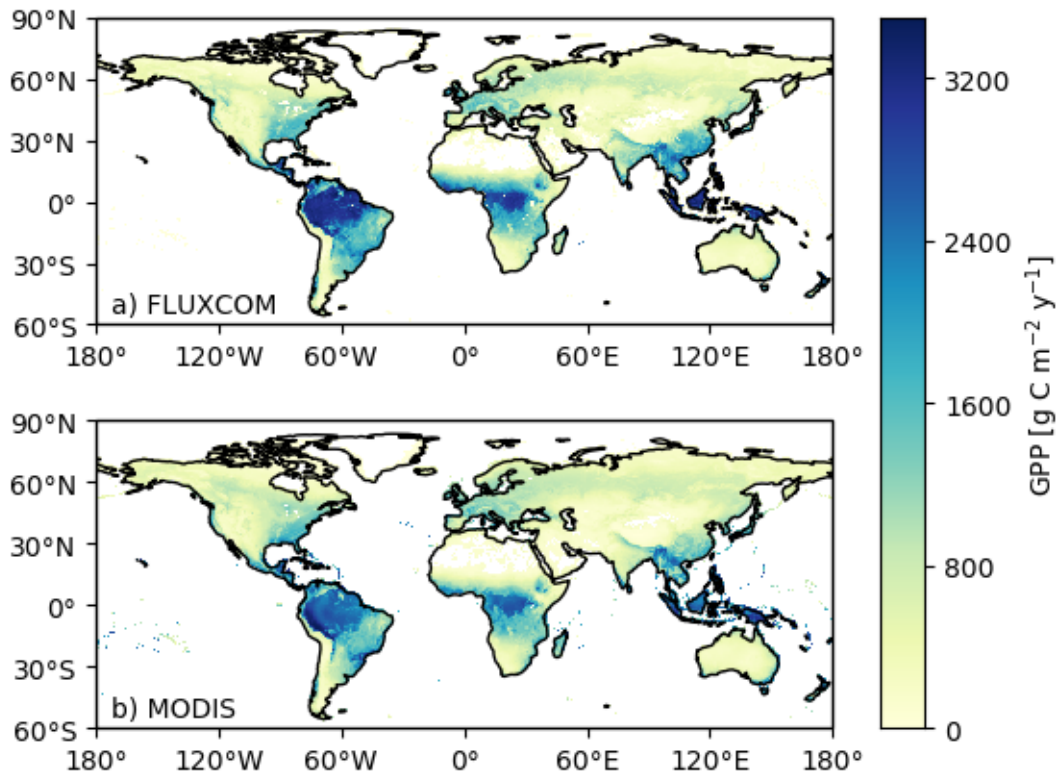
999 Figure 2. Biomass density from Avitabile (top) and comparison of zonal means simulations

1000 (bottom, as indicated) from 6 ISIMIP ecosystem models. Results indicate an

1001 overestimation of stocks by models in the Americas and Africa.

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1005 Figure 3. Mean annual GPP during 2000-2013 as reported by a) the FLUXCOM product and

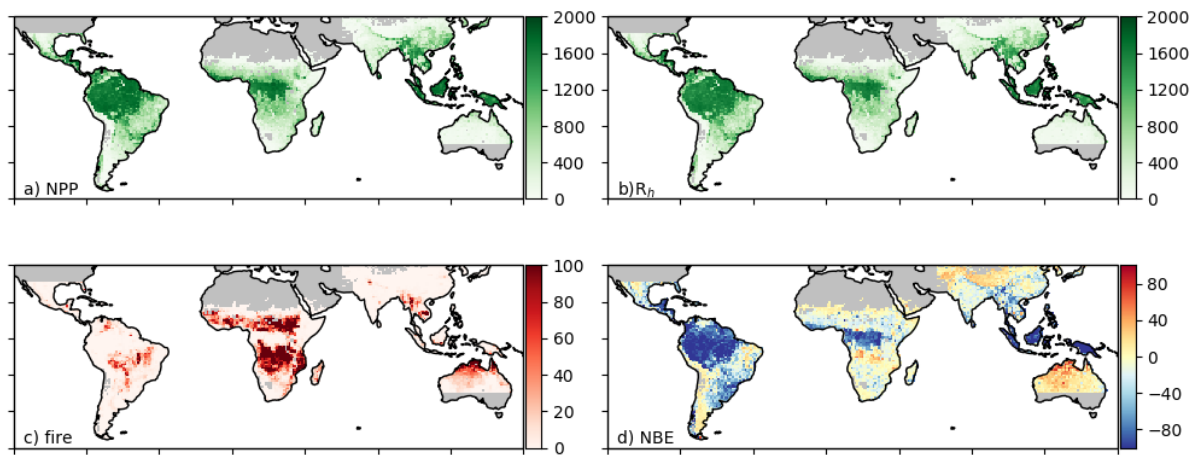
1006 b) MODIS MOD17 GPP product. FLUXCOM corresponds to eddy-covariance data

1007 upscaled at 0.5° using machine-learning. MODIS product is based on a light use

1008 efficiency model and was regrided from $30''$ ($\sim 1\text{km}$) to 0.5° .

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1011

1012 Figure 4. CARDAMOM retrievals of land-atmosphere C fluxes, averaged over 2000-2015.

1013 All fluxes are in g C m⁻². In d) NBE is calculated as $NBE = -NPP + R_h + \text{fire}$, hence <0

1014 values correspond to a sink (in blue) and >0 correspond to a source of carbon (in red).