# 1 A Roadmap for Improving the Representation of Photosynthesis in Earth System Models

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3 Alistair Rogers<sup>1</sup>, Belinda E. Medlyn<sup>2</sup>, Jeffrey S. Dukes<sup>3</sup>, Gordon Bonan<sup>4</sup>, Susanne von

4 Caemmerer<sup>5</sup>, Michael C. Dietze<sup>6</sup>, Jens Kattge<sup>7,8</sup>, Andrew D.B. Leakey<sup>9</sup>, Lina M Mercado<sup>10,11</sup>, Ülo

5 Niinemets<sup>12</sup> I. Colin Prentice<sup>13,14,15</sup>, Shawn P. Serbin<sup>1</sup>, Stephen Sitch<sup>10</sup>, Danielle A. Way<sup>16</sup>, Sönke

- 6 Zaehle<sup>17</sup>
- 7 <sup>1</sup>Environmental and Climate Sciences Department, Brookhaven National Laboratory, Upton, NY
- 8 11973-5000, USA
- 9 <sup>2</sup>Hawkesbury Institute for the Environment, University of Western Sydney, Locked Bag 1797,
- 10 Penrith NSW 2751, Australia
- <sup>3</sup>Department of Forestry and Natural Resources and Department of Biological Sciences, Purdue
- 12 University, West Lafayette, IN 47907-2061, USA
- 13 <sup>4</sup>National Center for Atmospheric Research, Boulder, CO 80307-3000, USA
- <sup>5</sup>Research School of Biology, College of Medicine, Biology and the Environment, Linnaeus

15 Building (Bldg 134) Linnaeus Way, The Australian National University, Canberra ACT 0200

- 16 Australia
- <sup>6</sup>Department of Earth and Environment, Boston University, Boston, MA 02215, USA
- <sup>7</sup>Max Planck Institute for Biogeochemistry, 07701, Jena, Germany.
- 19 <sup>8</sup>German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Deutscher Platz
- 20 5e, 04103 Leipzig, Germany
- <sup>9</sup>Department of Plant Biology and Institute for Genomic Biology, University of Illinois at Urbana-
- 22 Champaign, IL 61801, USA
- <sup>10</sup>Geography Department, College of life and Environmental Sciences, University of Exeter,
- 24 Exeter, EX4 4SB, UK
- 25 <sup>11</sup>Centre for Ecology and Hydrology, Wallingford, OX10 8BB, UK
- 26 <sup>12</sup>Department of Plant Physiology, Estonian University of Life Sciences, Kreutzwaldi 1, 51014
- 27 Tartu, Estonia
- 28 <sup>13</sup>AXA Chair of Biosphere and Climate Impacts, Grand Challenges in Ecosystems and the
- 29 Environment and Grantham Institute for Climate Change, Department of Life Sciences, Imperial
- 30 College London, Silwood Park Campus, Buckhurst Road, Ascot SL5 7PY, UK
- <sup>14</sup>Department of Biological Sciences, Macquarie University, North Ryde, NSW 2109, Australia
- 32 <sup>15</sup>State Key Laboratory of Soil Erosion and Dryland Farming on the Loess Plateau, College of
- 33 Forestry, Northwest Agriculture & Forestry University, Yangling 712100, China
- <sup>16</sup>Department of Biology, University of Western Ontario, London, ON, Canada, N6A 5B7 and
- 35 Nicholas School of the Environment, Duke University, Durham, NC, USA 27708
- 36 <sup>17</sup>Biogeochemical Integration Department, Max Planck Institute for Biogeochemistry, Hans-
- 37 Knöll-Str. 10, 07745 Jena, Germany

# 38 Corresponding Author

- 39 Alistair Rogers
- 40 Environmental and Climate Sciences Department
- 41 Brookhaven National Laboratory
- 42 Upton, NY 11973-5000
- 43 USA
- 44 arogers@bnl.gov
- 45 +1 631 344 2948
- 46

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- 48 Summary
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Accurate representation of photosynthesis in terrestrial biosphere models (TBMs) is
 essential for robust projections of global change. However, current representations
 vary markedly between TBMs, contributing uncertainty to projections of global carbon
 fluxes.

- Here we compared the representation of photosynthesis in seven TBMs by examining
   leaf and canopy level responses of *A* to key environmental variables: light, temperature,
   carbon dioxide concentration, vapor pressure deficit and soil water content.
- We identified research areas where limited process knowledge prevents inclusion of
   physiological phenomena in current TBMs and research areas where data are urgently
   needed for model parameterization or evaluation.
- We provide a roadmap for new science needed to improve the representation of
- 61 photosynthesis in the next generation of terrestrial biosphere and Earth System Models.
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63 Key Words: carbon dioxide, light, stomatal conductance, soil water content, temperature,

64 terrestrial biosphere models, vapor pressure deficit.

## 65 Introduction

Fossil energy use is the dominant driver of the increase in atmospheric  $CO_2$  concentration ( $C_a$ ) and the principal cause of global climate change (IPCC, 2013). Many of the observed and projected impacts of rising  $C_a$  portend increasing environmental and economic risk, yet the uncertainty surrounding the projection of our future climate by Earth System Models (ESMs) is unacceptably high (Friedlingstein *et al.*, 2006, Friedlingstein *et al.*, 2014).

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Although CO<sub>2</sub> emissions associated with anthropogenic activity are notable (11 Pg C year<sup>-1</sup>), 72 73 they represent less than 10% of the gross carbon fluxes between the land surface and the 74 atmosphere (Beer et al., 2010, Boden et al., 2013, Le Quéré et al., 2015). Terrestrial 75 photosynthetic  $CO_2$  assimilation (A) is the largest of these  $CO_2$  fluxes (~120 Pg C year<sup>-1</sup>), 76 subsidizing our use of fossil fuels through the net assimilation of about one-third of the CO2 77 emissions associated with anthropogenic activities (Le Quéré et al., 2015). However, there is 78 critical uncertainty about how the terrestrial carbon sink will be affected by changes in A with rising C<sub>a</sub>, temperature and drought (Friedlingstein *et al.*, 2014, Gregory *et al.*, 2009, IPCC 2013). 79 80 Therefore, reducing the uncertainty associated with model representation of A is an essential 81 part of improving confidence in projections of global change (Ciais et al., 2013).

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In this study we have focused on photosynthesis, but recognize that improving the understanding and projection of the terrestrial biosphere's response to global change also depends on realistically representing many additional processes that are down stream of carbon assimilation (e.g. carbon allocation, plant and soil respiration, and nutrient cycling). Of particularly relevance to photosynthesis is the allocation of extra carbon to leaf area in trees grown at elevated  $C_a$  (Ainsworth & Long, 2005). Model representation and integration of these processes, and how the balance between them shifts in their individual and combined responses to environmental drivers, will also be critical in order to capture whole system responses, but such a comprehensive discussion is beyond the scope of this study.

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93 We examined model representations of A in seven Terrestrial Biosphere Models (TBMs). These 94 models include four that represent the land component of ESMs which were part of the recent 95 Coupled Model Intercomparison Project (CMIP5) - the main resource for the IPCC Fifth 96 Assessment Report (Friedlingstein et al., 2014, IPCC, 2013). Our approach focuses on how 97 physiological responses are represented by TBMs. We compared modeled responses of A to 98 key environmental variables in order to identify areas of model divergence that reflect gaps in 99 current understanding of the physiological and environmental controls of A. In the second half 100 of the paper, we turn to issues of scale - vertical, horizontal and temporal - and consider how 101 representation and parameterization of leaf-level processes is scaled to the canopy within 102 current model frameworks.

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We had three goals: (1) understand how models differ in their representation of *A*; (2) identify gaps in current understanding of *A* that contribute to uncertainty in model output; (3) identify areas where current process knowledge and emerging data sets can be used to improve model skill. This study provides recommendations for immediate improvements that can be made to

108 current model representation of *A* and also highlights the scientific activity needed to further109 advance representation of *A* in the next generation of TBMs.

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## 111 Representation of Leaf Photosynthesis in Terrestrial Biosphere Models

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#### 113 Current model structure and parameterization

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115 The Farquhar, von Caemmerer and Berry (FvCB) model of A (Farquhar et al., 1980, von 116 Caemmerer, 2000, von Caemmerer & Farquhar, 1981) provides a robust mechanistic 117 representation of A in C<sub>3</sub> species, and is the foundation for model estimation of gross primary 118 production (GPP) in many TBMs (Cramer et al., 2001, Rogers, 2014), including the seven models 119 considered here (BETHY, CLM, ED2, G'DAY, JSBACH, JULES and O-CN; Table 1). The formulations 120 of the FvCB model used in these TBMs include elements of; Collatz et al. (1991), in CLM, ED2 121 and JULES; Foley et al (1996), in ED2; and Kull & Kruijt (1998), in O-CN (Table 1). The FvCB 122 model represents photosynthetic CO<sub>2</sub> assimilation as the most limiting of two biochemical 123 processes: Rubisco carboxylation, and ribulose-1,5-bisphosphate (RuBP) regeneration driven by 124 electron transport. These processes limit A in most environments; however, Sharkey (1985) 125 subsequently described how limitations on triose phosphate utilization (TPU limitation) could 126 also limit A under some conditions. Only two models in this study included TPU limitation (CLM 127 and JULES, Table 1).

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Similar biochemical models have been developed for the  $C_4$  photosynthetic pathway (von Caemmerer et al. 2000). For reasons of space, we limit our discussion to model treatment of  $C_3$ photosynthesis. However we note that a similar exercise focused on  $C_4$  photosynthesis would be valuable.

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134 Models typically represent stomatal conductance  $(q_s)$  using a coupled relationship with A that 135 varies with atmospheric, or leaf-surface,  $CO_2$  concentration, and some measure of atmospheric 136 humidity. This model approach was originally formulated by Ball et al. (1987), who used a direct 137 dependence on relative humidity (RH) in their equation for  $q_s$ . Ball et al.'s equation is still 138 widely used in many TBMs, including CLM. Leuning (1995) suggested an alternative equation 139 that depends on vapor pressure deficit (VPD) rather than RH. ED2 uses the Leuning (1995) 140 equation, while JULES uses a very similar equation developed by Jacobs (1994). The approaches 141 to represent  $g_s$  implemented by the models considered here are quite diverse (Table 1) which 142 has a wide-ranging impact on the model outputs we considered.

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The TBMs in this study represent vegetation using broad plant functional types (PFTs). The FvCB model is parameterized with a number of important constants that are typically the same for all PFTs. PFTs are distinguished with respect to photosynthesis through differences in the estimates of the maximum carboxylation rate of Rubisco ( $V_{c,max}$ ), the maximum rate of electron transport ( $J_{max}$ ) and the slope of the stomatal conductance response. Several groups are now working towards next-generation vegetation models in which PFTs are replaced by "trait-based approaches" (Wullschleger *et al.* 2014). This catchall phrase includes leveraging traitenvironment linkages (Ali et al. 2015, Reich 2014, van Bodegom et al. 2014), optimality approaches (Xu et al. 2012, Meir et al. 2015), trait filtering (Fisher et al. 2012) and adaptive global vegetation models (Scheiter et al. 2013). However, our review is relevant to these approaches as well, as they still employ similar representations of photosynthesis. The key difference lies in parameterization, which we discuss when considering scaling to landscapes.

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## 157 Mesophyll conductance

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159 In C<sub>3</sub> species, mesophyll conductance  $(q_m)$  describes the conductance to CO<sub>2</sub> diffusion from the 160 intercellular airspace within a leaf to the sites of carboxylation within chloroplasts (Flexas et al., 161 2012, von Caemmerer & Evans, 1991). It is one of the four main physiological processes limiting 162  $CO_2$  uptake and fixation, the others being  $q_s$  and the biochemical activity of Rubisco and RuBP 163 regeneration. To our knowledge, there are no land models that currently contribute to the IPCC 164 assessments that consider  $g_m$ . This absence reflects the challenge of adding further complexity 165 to the models, but also the uncertainty and technical difficulty of the measurements required 166 to estimate  $g_m$ .

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Response curves of *A* to intercellular  $[CO_2]$  (*C<sub>i</sub>*) are routinely used to infer the maximum biochemical activity of Rubisco and RuBP regeneration, i.e.  $V_{c,max}$  and  $J_{max}$ . When the FvCB model was conceived, the assumption was made that the difference between *C<sub>i</sub>* and the  $[CO_2]$ within the chloroplast (*C<sub>c</sub>*) was sufficiently small that it could be ignored. Subsequently, improved measurement techniques for *g<sub>m</sub>* have shown that it can impose a significant 173 limitation on A which varies with temperature, and there are significant species differences in 174 these responses (von Caemmerer & Evans, 2015). If  $g_m$  is not taken into account in the analysis of A-C<sub>i</sub> curves, the true  $V_{c,max}$  will be underestimated (Niinemets et al., 2009, Sun et al., 2014, 175 176 von Caemmerer, 2000). Furthermore, temperature responses of  $V_{c,max}$  and  $J_{max}$  derived from 177 gas exchange measurements will not necessarily reflect the temperature dependence of the 178 underlying biochemistry alone, but will also reflect the temperature response of  $q_m$  (Medlyn et 179 al., 2002a). The use of apparent parameters is problematic if modelers wish to incorporate new 180 data on the underlying biochemistry of photosynthesis. For example, a recent biochemical 181 survey of the catalytic diversity in Rubisco revealed significant and marked variation in key 182 parameters across 75 species (Orr et al. 2016). These data cannot be used directly in models 183 without including  $q_m$  in model structures, highlighting the need for improved understanding 184 and model representation of  $g_m$ .

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Several TBMs currently use linear relationships between apparent  $V_{c,max}$  (obtained from  $A-C_i$ curves) and leaf nitrogen to derive  $V_{c,max}$  prognostically. If  $g_m$  were to be incorporated into future TBMs, new algorithms linking  $V_{c,max}$  to leaf N content would be required as the  $V_{c,max}$ used in the relationship would need to be derived as a function of  $C_c$  not  $C_i$ . Currently a reliance on apparent  $V_{cmax}$  - leaf N relationships means that models underestimate the amount of N partitioned to Rubisco, or put another way, overestimate the nitrogen use efficiency of  $CO_2$  carboxylation by Rubisco.

194 It is clear that an improved understanding of  $g_m$  remains a critical research area. Despite recent 195 important progress that may simplify prediction of  $g_m$  (Tholen et al. 2012), we feel that 196 immediate inclusion of  $g_m$  in TBMs is premature. "Apparent" parameters derived from  $A-C_i$ 197 response curves, which implicitly account for  $g_m$ , have been used successfully to model A in 198 many ecosystems at the leaf and canopy level (e.g. Bernacchi et al. 2003; Medlyn et al. 2005; 199 Thum et al. 2007). Until understanding and measurement of  $q_m$  matures, its inclusion in TBMs 200 will likely drive additional uncertainty. Furthermore, the modeling community currently has 201 access to a substantial dataset (albeit heavily biased to the mid-latitudes) of "apparent" 202 parameters but almost no data for  $V_{c,max}$  and  $J_{max}$  derived from A-C<sub>c</sub> curves. Including  $g_m$  now 203 would dramatically shrink the amount of data available for model parameterization. However, 204 it is important to note that inclusion of  $g_m$  in models is essential if carbon isotope 205 discrimination is to be inferred (Ethier & Livingston, 2004; Suits et al. 2005).

206 Recommendation: (1) Greater process knowledge of  $g_m$  will be required before it can be 207 included in TBMs. Specific needs include improved understanding of variation in  $g_m$  across PFTs 208 and how it is affected by environmental drivers such as light and temperature.

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### 210 Short-term leaf level responses to environmental variables in current model structures

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Our goal was to understand and compare the physiological responses inside these seven TBMs (Table 1). We focused on one particular PFT - a broad leaved deciduous tree - and defined several environmental and physiological variables which provided standard conditions for model intercomparison: instantaneous quantum flux density (Q) = 1500 µmol mol<sup>-1</sup>, upper canopy sunlit leaf temperature = 25°C,  $C_a$  = 380 µmol mol<sup>-1</sup>,  $[O_2]$  = 210 mmol mol<sup>-1</sup>, *VPD* = 1 kPa, soil moisture content at field capacity and  $V_{c,max}$  = 60 µmol m<sup>-2</sup> s<sup>-1</sup>. In the following sections we present and discuss leaf level responses to light, temperature,  $C_a$ , *VPD* and soil water content.

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## 221 Short-term response to light

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223 The initial slope of the photosynthetic light response curve is determined by the maximum 224 quantum yield of CO<sub>2</sub> assimilation. For clarity, here we distinguish between the intrinsic 225 quantum yield ( $\phi_{int}$ ), which is the initial slope of the relationship between A and absorbed Q 226 under non-photorespiratory conditions and the *realized* quantum yield ( $\Phi_{real}$ ), which we define as the photosynthetic rate per unit incident light at  $Q = 100 \mu \text{mol m}^{-2} \text{ s}^{-1}$  in our standard 227 228 conditions (Table 2 and the initial slope of the A-Q response in Fig. 1a). The  $\phi_{int}$  is generally an 229 input parameter to the models (Table 2) whereas the realized quantum yield is calculated by the models using the FvCB equations, and depends not only on the  $\Phi_{int}$  but also on the 230 231 assumed values for the Rubisco kinetic constant  $\Gamma^*$  (the CO<sub>2</sub> compensation point in the absence 232 of mitochondrial respiration), the low light  $C_i$ , the leaf absorptance (a), and the convexity of the 233 light response curve ( $\Theta$ ). Model variation in the choice of kinetic constants, low light  $C_i$ , a and  $\Theta$ 234 are summarized in Table 2. The CLM model assumes that  $\Phi_{int}$  is equal to the theoretical 235 maximum of (1-f)/8, where f=0.15 and is used to correct for the spectral quality of light (von Caemmerer, 2000). As a result, CLM has the highest  $\Phi_{real}$  (0.053 mol mol<sup>-1</sup>, Table 2, Fig. 1a). 236 237 The other models are parameterized with quantum yield inputs that result in a calculated  $\phi_{int}$ 

that is below the theoretical maximum and the resulting values for  $\Phi_{real}$  are lower than those for CLM (Table 2). Despite a parameterization that is broadly consistent with other models, the initial slope of the *A*-*Q* response of O-CN is strikingly low and results from a limitation of *A* by light harvesting at low *Q* (Kull & Kruijt, 1998; Table 1).

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Experimental studies focused on understanding natural variation in quantum yield have shown 243 244 that there is little variation in  $\Phi_{int}$  under unstressed conditions across a wide range of species, with an average value of 0.092 mol mol<sup>-1</sup> (Long et al. 1993; Singsaas, Ort & DeLucia, 2001), 245 246 comparable with the range of  $\Phi_{int}$  used in the models considered here (0.07 – 0.106, Table 2). 247 However,  $\Phi_{int}$  can be substantially lower in the field, particularly in stressed conditions (Medlyn 248 et al 2007; Niinemets et al. 2004, 2014; Singsaas, Ort & DeLucia, 2001). As discussed above, the 249  $\Phi_{real}$  in models depends on several assumptions, not just the  $\Phi_{int}$ , highlighting the need to 250 better parameterize and test modelled light responses with data from field conditions. For 251 example, most existing measurements have been made within a narrow temperature range (20 252 - 30°C) and the scarcity of data collected at low temperature has been highlighted as an 253 important driver of model uncertainty at high latitudes (Dietze *et al.*, 2014).

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Leaf level light-saturated  $CO_2$  uptake ( $A_{sat}$ ) varies considerably between models (Fig 1a). The variation in modelled  $A_{sat}$  is driven by differences in prescribed Rubisco kinetic constants and their temperature dependencies (see below and Table 2), as well as the  $C_i$ , which is dependent on the choice of stomatal model. The inflection point of the light response curve marks the transition between light limitation and light saturation of A. There is a wide range in the Q at which *A* becomes light saturated and therefore the greatest model divergence in *A* occurs when some models have light saturated *A* and others do not (i.e.  $Q = 400-800 \ \mu\text{mol m}^{-2} \text{ s}^{-1}$ , Fig. 1). In addition to differences in the model representation of light limited and light saturated *A*, variation in the transition phase is attributable to model structure (Table 1), and when present, parameterization of the convexity term ( $\Theta$ , Table 2), which determines the relative influence of  $\Phi_{real}$  or  $A_{sat}$  on *A* at a given *Q*.

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Moving from the leaf to the canopy level, responses to irradiance (Fig 1, b-d) are not only dependent on the factors discussed above but also on the method used to scale physiology from the leaf to the canopy level, the representation of the light environment within the canopy, and the partitioning of foliage between sunlit and shaded leaves (Gu *et al.* 2002, Mercado *et al.* 2009). As a result, canopy scaling exacerbates existing differences between the TBMs and introduces new structural variation that further diversifies model output (Fig. 1 b-d). Canopy scaling is discussed in detail below.

274 Recommendation: (2) Modeled responses of photosynthesis to light need to be parameterized
275 and evaluated against data from field conditions, particularly at low temperature.

276

277 Don't mix & match

278 One issue that emerged here, but is relevant throughout this paper, is the need to avoid 279 piecemeal approaches to model parameterization. For example, we need to carefully and 280 consistently use kinetic constants and temperature response functions because the models are 281 highly sensitive to them. Any constants and functions used when deriving photosynthetic

parameters from data have to be the same ones used in the model. For example, if a value of 282 283  $V_{c,max}$  at 25°C is used in a model, that model must use the same Michaelis-Menten constants ( $K_c$ and  $K_o$ ) and  $\Gamma^*$  (e.g. see Table 2), and the associated temperature dependencies, that were 284 285 used to estimate  $V_{c,max}$  from the original A-C<sub>i</sub> response curve as well as the same temperature 286 response function (e.g. see Table 1) used to scale  $V_{c,max}$  from the measurement temperature to 287 25°C. This problem, that derived parameters depend on the equations used to derive them, 288 introduces error when trying use the parameters to perform meta-analyses or calibrate models 289 (Medlyn *et al.* 2002, Dietze 2014). As we make progress to provide models with richer data sets 290 for use in model parameterization and evaluation, we need to archive our raw gas exchange 291 data so that, for example, new kinetic constants and temperature response functions can be 292 applied to old data, maintaining its value as understanding advances. The estimation of 293 quantum yield provides another example where the assembly of parameters (e.g.  $\Phi_{int}$ , a,  $\Gamma^*$ ,  $\Theta$ ) 294 and approaches (e.g. estimation of low light  $C_i$ ) is not coordinated and where archived data 295 would be useful.

Recommendations: (3) Models need to make careful and consistent use of kinetic constants and
temperature response functions. (4) Physiologists should archive their raw data to enable
coordinated parameterization and the preservation of their data for future analysis.

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#### 300 Short-term response to temperature

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The temperature response of *A* is complex and dependent on additional variables such as *Q* and  $C_i$  (Fig 2). The  $C_i$  in turn depends on  $g_s$  and hence *VPD*, such that the temperature and *VPD*  304 response of  $g_s$  also impacts the shape of the temperature response of A (Medlyn *et al.*, 2002a; 305 Lin et al., 2012). The model by Farquhar et al. (1980) suggests that A is Rubisco-limited at low 306 temperature - but note that TPU limitation can limit A in some species at low temperature 307 (Sage & Sharkey, 1987). The decline in A at high temperature (Fig. 2) can be brought about by 308 the temperature dependence of  $J_{max}$  and the strong increase in photorespiration and 309 mitochondrial respiration with increasing temperature (Farguhar et al., 1980; von Caemmerer, 310 2000). High temperature limitations on Rubisco activase could also cause decline in A but this 311 mechanism is currently absent from all these models (Salvucci & Crafts-Brandner 2004a; 312 Salvucci & Crafts-Brandner 2004b, Sage & Kubien 2007). The steep decline of A at temperatures 313 above 30°C in the Farguhar et al. (1980) model is largely driven by the temperature 314 dependence of  $J_{\text{max}}$ . This effect needs to be treated with some caution as it may be due to 315 irreversible inhibition in the in vitro system, from which the function was derived. June et al. 316 (2004) provided a simpler empirical equation for fitting the temperature dependence of  $J_{max}$ . 317 The temperature dependence of A is also driven by the choice of kinetic parameters and their 318 temperature dependencies as discussed above. Some TBMs use spinach (Jordan and Ogren 319 1984) or tobacco (Bernacchi et al. 2001) temperature response functions for V<sub>c.max</sub> for all 320 species. However, as there are important differences in the response of  $V_{c,max}$  to temperature 321 among warm and cool climate plant species (Kattge & Knorr 2007; Galmes et al. 2015), 322 continued acquisition of temperature response functions from different biomes is critically 323 important. The temperature optimum of A  $(T_{opt})$  depends on environmental conditions such as 324 Q and  $C_a$ , with  $T_{opt}$  being more pronounced at high Q and  $C_a$  (e.g. compare Figs 2a & c with 2b 325 & dd). Here, two models stand out for their temperature responses; unlike the majority of

326 models that show an optimum ~24.5°C, ED2 has an emergent temperature optimum at 16°C, despite a  $V_{c,max}$  optimum at 39°C, and JSBACH shows no high temperature limitation on A 327 (Table 1, Fig 2). It is usual for  $T_{opt}$  to shift to a slightly higher temperature as  $C_a$  rises (Long, 328 329 1991) because at high  $C_a$  the rate of photorespiration is reduced, thereby extending the 330 temperature range where positive CO<sub>2</sub> assimilation occurs. The CO<sub>2</sub> effect on T<sub>opt</sub> is evident in 331 Fig. 2 in a number of the models at both the leaf and canopy level. Here, elevating  $C_a$  from 380 to 550  $\mu$ mol mol<sup>-1</sup> shifts the  $T_{opt}$  up by ~2°C (Fig 2 b,d). Two models do not show this shift in 332 333  $T_{opt}$ : JSBACH has no  $T_{opt}$ , and the  $T_{opt}$  for ED2 remains at 16°C despite the increase in  $C_a$  from 334 380 to 550  $\mu$ mol mol<sup>-1</sup>.

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Current empirical models predict the response of  $g_s$  to temperature based on a relationship 336 337 between  $g_s$  and A that is modified by VPD. This approach is successful in many cases (e.g. 338 Duursma et al. 2014) although the mechanisms underlying the response remain poorly 339 understood (Mott, 2009; Busch, 2013). In addition, there is evidence that the correlation 340 between  $g_s$  and A breaks down at high temperatures (> 35°C) in some species, with stomata 341 remaining open while A goes to zero (e.g. Lu et al. 2000; Scafaro et al. 2012; Slot et al. 2016; 342 Teskey et al. 2015; von Caemmerer and Evans 2015). Presumably this response allows the plant 343 to maintain leaf temperatures at non-damaging levels via transpirational cooling. It is not 344 known how widespread this response is (Teskey et al. 2015) nor to what extent it occurs in the 345 field. Slot et al. (2016), for example, find this response in glasshouse-based measurements but 346 not in field trees.

Recommendations: (5) Physiologists need to continue measuring temperature response functions for  $V_{c,max}$  and  $J_{max}$ . (6) More field-based research into the independent temperature response of  $g_s$  is required to better understand the mechanism underlying the response of A to high temperatures.

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#### 352 Short-term response to CO<sub>2</sub>

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At low  $C_a$ , when A is limited by the amount of active Rubisco available for carboxylation ( $V_{c,max}$ ), 354 355 A increases with rising  $C_a$  for two reasons: (1) the affinity of Rubisco for  $CO_2$  is low, and 356 therefore increasing the substrate concentration increases carboxylation rates; (2)  $CO_2$ 357 competitively inhibits the oxygenation reaction, reducing CO<sub>2</sub> losses associated with 358 photorespiration (Fig. 3). At higher  $C_a$  - i.e. above the inflection point of the A- $C_a$  curve (most 359 notable in the leaf level responses shown in Figs 3a & b) - A becomes limited by the supply of 360 ATP and NADPH to regenerate the CO<sub>2</sub> acceptor RuBP. At this point A will still rise with 361 increasing  $C_a$ , but the CO<sub>2</sub> responsiveness (the increase in A for a given increase in  $C_a$ ) is 362 reduced as further increases in A are attributable solely to the inhibition of the oxygenation 363 reaction, which increases the availability of ATP and NADPH for RuBP regeneration (Long 1991, 364 Long et al. 2004).

365

The shape of the *A*-  $C_a$  response curve is a critical model feature that determines the ability of the terrestrial carbon sink to respond to rising  $C_a$  and it is affected by model structure and parameterization (Fig. 3, Tables 1 & 2). Variation in the initial slope of the *A*- $C_a$  response is

369 attributable to  $C_i$  and the choice of kinetic constants. For this example of a broad leafed 370 deciduous tree PFT in our standard conditions, all models show that light-saturated A appears to be Rubisco limited (RuBP saturated) below a  $C_a$  of 500 µmol mol<sup>-1</sup> (Fig. 3). As a result the CO<sub>2</sub> 371 responsiveness of A below a  $C_a$  of 500 µmol mol<sup>-1</sup> is similar for all models. However, as  $C_a$  rises 372 above 500 µmol mol<sup>-1</sup> differences in model structure and parameterization lead to substantial 373 374 variation in CO<sub>2</sub> responsiveness. Three models (CLM, ED2 and JULES) stand out for smooth 375 response curves that lack a clear inflection point (most noticeable in Fig 3a). All three models 376 adopt the co-limitation approach described by Collatz et al. (1991) which smooths transitions 377 between Rubisco limited and RuBP limited A (Collatz et al. 1991; Foley et al. 1996; Clark et al. 378 2011; Oleson *et al.* 2013, Table 1). This approach contributes to the greater CO<sub>2</sub> responsiveness at higher  $C_a$  observed in CLM and JULES (Fig 3a). In addition, the four models 379 380 that lack this smoothing function (BETHY, G'DAY, JSBACH and O-CN) have a marked inflection point between Rubisco limited and RuBP limited A, but the  $C_a$  at which this inflection occurs 381 spans a large range (~300  $\mu$ mol mol<sup>-1</sup>, Fig. 3) contributing to the variation in CO<sub>2</sub> responsiveness 382 above 500  $\mu$ mol mol<sup>-1</sup>. The variation in  $C_a$  at which the inflection point occurs has several 383 causes, but the main drivers of this variation are the choice of kinetic constants (~60 µmol mol<sup>-</sup> 384 <sup>1</sup>, Table 2), the JV<sub>ratio</sub>, which for a fixed  $V_{c,max}$  sets the inflection point  $C_i$  (~125 µmol mol<sup>-1</sup>, Table 385 2) and the stomatal model, which determines the  $C_a$  at which the inflection point  $C_i$  is reached 386 (~175  $\mu$ mol mol<sup>-1</sup>, Table 1). 387

388

As  $V_{c,max}$  is reduced (Fig. 3b, 3d), the responses of A to changes in  $C_a$  are qualitatively similar but model divergence is constrained. Model variation in canopy level responses to rising  $C_a$  (Fig

391 3c & d) is also attributable to different approaches to canopy scaling as discussed below. The 392 differences seen here in CO<sub>2</sub> responsiveness are substantial - highlighting the impact of 393 different model representations of the FvCB equations, stomatal model choices and the need to 394 better understand controls on the inflection point of the A- $C_a$  response. The  $C_a$  at which the 395 inflection point occurs drives uncertainty in the  $CO_2$  stimulation of A at the  $C_a$  that will be 396 experienced in the second half of the century, and it is at this higher  $C_a$  where model 397 uncertainty is greatest. This effect probably contributes to the model differences in GPP 398 reported in the recent FACE model-intercomparison project (Zaehle *et al.* 2014).

Recommendation: (7) We need improved understanding and model evaluation of the controls
on the inflection point of CO<sub>2</sub> response curves.

401

#### 402 Short-term response to VPD

403 Increasing VPD causes stomatal closure, which decreases  $C_i$ . The magnitude of the decrease in 404 A resulting from lower  $C_i$  is determined by the shape of the A- $C_i$  response as described above 405 and shown in Fig. 3. Figure 4 shows the response of A to VPD; model divergence increases with 406 rising VPD, largely due to differences in the parameterization of VPD sensitivity among models. 407 The strong sensitivity of the CLM model seen in Figure 4 is due to the use of RH in the model 408 formulation, and the fact that RH must drop dramatically to obtain increasing VPD with 409 constant temperature, as shown in this plot. There are some models, of which JSBACH in this 410 study is an example, that do not incorporate a stomatal response to RH or VPD (Table 1, Figure 411 4). Such formulations were necessary when driving data sets for atmospheric humidity were 412 not available. Given advances in the understanding of stomatal responses and the availability

413 of appropriate driver datasets, stomatal response to RH or VPD should be adopted. However, 414 we believe that formulations involving VPD, such as those adopted by ED2, G'DAY and JULES (Table 1) are theoretically preferable because, unlike RH, VPD is directly proportional to water 415 416 loss, more closely reflects stomatal mechanics (e.g. Aphalo & Jarvis 1991; de Beeck, 2010), and 417 is strongly linked to productivity (Lobell et al. 2014; Ort & Long, 2014). In addition, formulations 418 involving VPD, rather than RH, will likely be better able to project the response of vegetation to 419 future climate scenarios, because RH is predicted to change little in the future whereas VPD will 420 increase with warming (Sato *et al.* 2015).

421

422 Similar coupled  $q_s$ -A models can also be developed from optimization principles. Cowan & 423 Farguhar (1977) proposed that stomatal behavior is optimal when A less the cost of 424 transpiration is maximized, and a number of authors have shown that this theory leads to a 425 relationship between q<sub>s</sub> and A that is similar in behavior to empirical formulations (e.g. Hari et 426 al. 1986; Katul et al. 2010; Medlyn et al. 2011). Optimization approaches have the advantage of 427 being based in theory, yielding meaningful parameter values, and providing  $g_s$  responses to 428 future environmental conditions where we lack robust measurements, and we encourage their 429 use. However, we also caution that optimization can lead to physiologically incorrect behavior 430 in some circumstances – such as incorrect CO<sub>2</sub> responses, and instability near the transition 431 between Rubisco-limited and RuBP regeneration-limited A – implying that simple, empirically 432 verified equations based on optimization may be more reliable than direct application of 433 numerical optimizations that are also dependent on the careful application of model 434 constraints within TBMs and the optimization approach used.

435

436 Large-scale parameterization of stomatal models has been data-limited, with models typically 437 using one nominal set of parameter values for all  $C_3$  vegetation. A major advance in this area 438 was made by Lin et al. (2015), who collated a substantial new stomatal conductance database 439 and demonstrated a predicted response of the stomatal slope parameter  $(g_1)$  to temperature 440 and consistent differences in  $g_1$  among broadly defined PFTs. This dataset provides a valuable 441 foundation for stomatal model parameterization. However, the coverage of this database is still 442 limited. There is still relatively little information about how  $q_1$  varies among species or 443 genotype, and almost no information on acclimation or plasticity in these parameters in 444 response to abiotic or biotic factors (Way et al. 2011). Models are also sensitive to the 445 minimum stomatal conductance parameter,  $q_0$ , particularly under low light and high VPD 446 conditions (Bauerle et al. 2014), but this parameter is poorly quantified.

447 Recommendation: (8) Models should adopt approaches that include formulations where  $g_s$ 448 responds to VPD. (9) We need more information about how  $g_1$  and  $g_0$  (or their equivalents) vary 449 among PFTs and in response to environmental drivers.

450

- 451 Short-term response to Soil Moisture Content
- 452

Soil moisture availability is a key constraint on *A*. As soil moisture availability decreases, stomates close, decreasing  $C_i$ , and eventually preventing *A* and transpiration (Fig. 5). Drought can also reduce the biochemical capacity for *A*, expressed as lower  $V_{c,max}$  and  $J_{max}$  in models, but the relative balance of these stomatal and biochemical limitations is subject to significant debate (Chaves *et al* 2009). Current approaches to modelling the effects of soil moisture on *A*can be classified into several types: empirical reduction factors; hydraulic limitations;
physiological approaches; and a simple supply constraint approach (BETHY). The latter assumes
that plant transpiration cannot exceed the potential supply of soil water and that plants can
photosynthesize provided there is a sufficient water supply (Table 1).

462

463 The empirical reduction factor approach involves multiplying parameters by a soil water stress 464 factor (typically denoted  $\beta$ , ranging from 0 to 1) when soil moisture falls below a given model 465 model-dependent threshold. Three of the models in our sample used this approach (CLM, 466 G'DAY and O-CN, Table 1 & Fig. 5). However, there is disagreement among models as to whether the  $\beta$  factor should be applied to the stomatal slope parameter, apparent V<sub>c.max</sub>, or 467 468 both (De Kauwe *et al.* 2013). Here, all three models applied the  $\beta$  factor to stomatal model 469 parameters, either the slope (G'DAY and O-CN) or the intercept (CLM), and also to the 470 photosynthetic parameters  $V_{c,max}$  (CLM) or  $V_{c,max}$  and  $J_{max}$  (G'DAY and O-CN, Table 1). Increasing 471 evidence suggests that both stomatal slope and  $V_{c,max}$  are affected by low soil moisture, with 472 the reduction in apparent  $V_{c,max}$  possibly in part due to lower  $g_m$  (Keenan et al. 2010; Egea et al. 473 2011; Zhou *et al.* 2013). Several TBMs do include both limitations, but the β factor is tied to the 474 soil water content and therefore models cannot capture the impact of potentially different 475 trajectories of drying and rewetting episodes (Williams et al. 2009).

476

477 The hydraulic approach offers a number of theoretical advantages over the  $\beta$ -factor approach. 478 Stomatal conductance is modelled as a function of leaf water potential ( $\psi_{leaf}$ ), which is

479 calculated from soil moisture potential  $\psi_{soil}$  and plant and soil hydraulic conductances. There 480 may be a threshold minimum  $\psi_{leaf}$  (Williams *et al.* 1996) or a sigmoidal functional dependence (Tuzet et al. 2003). Implementations also differ on whether responses to VPD are captured by 481 482 the responses to  $\psi_{leaf}$  (Williams *et al.* 1996, Tuzet *et al.* 2003) or whether an additional VPD 483 response is also needed (Bonan et al. 2014). The hydraulic approach is appealing to plant 484 physiologists because it reflects some of the key mechanisms thought to influence plant 485 response to drought (Leuning et al. 2004). Because soil hydraulic conductance is assumed to 486 vary with  $\psi_{soil}$  this approach also incorporates a dynamic weighting of soil layers whereby lower 487 soil layers become more important as drought progresses (De Kauwe et al. 2015). Furthermore, 488 there is evidence that the photosynthetic response to soil moisture can depend on plant leaf 489 area (e.g. Kelly et al. 2015), an effect that is captured by the hydraulic approach but not the  $\beta$ -490 factor approach. The chief disadvantage of the hydraulic approach is that it requires additional 491 parameters to represent plant hydraulic conductance and stomatal dependence on leaf water 492 potential. These parameters are not well quantified and can lead to additional uncertainty.

493

The physiological approaches are based on an understanding of stomatal function and suggest that both metabolic and hydraulic stomatal regulation involves the hormone abscisic acid (*ABA*), known to promote tolerance against abiotic stress (Jones *et al.*, 2015). Wilkinson and Davies (2002) proposed a coordinated model of plant responses to stress whereby water stress sensed by the root system stimulates *ABA* biosynthesis. This signal is then communicated to the guard cells which subsequently induce stomatal closure and reduce water loss. Both roots and leaves synthesize ABA and increasing concentrations of xylem ABA correlate with stomatal
closure (Sauter *et al.*, 2001; Wilkinson and Davies, 2002, Christmann *et al.* 2007).

502

503 There are few mathematical descriptions of stomatal control including xylem ABA signaling 504 (Tardieu and Davies, 1993; Dewar, 2002; Huntingford et al., 2015). Tardieu and Davies (1993), 505 combined hydraulic and chemical signaling control of stomatal functioning. The approach of 506 Dewar (2002) is an extension of this approach that also considers xylem embolism and the 507 possible role of combined leaf hydraulic and chemical signaling in addition - or as a possible 508 alternative - to existing root signals. Huntingford et al. (2015) revisited the work by Dewar 509 (2002) and provided a  $g_s$  formulation which depends on only four variables: soil water content, 510  $C_a$ , evapotranspiration and net A. This is an exciting approach, however there is an acute need 511 for more empirical data to be able to parameterize and evaluate approaches of estimating  $q_s$ 512 that include ABA.

513

514 The TBMs presented here showed dramatic divergence in the response of A to drought (Fig. 5), 515 with the canopy level responses mostly mirroring the responses seen at the leaf level. Whilst 516 much of this divergence could be explained by the different approaches taken by each model 517 (Table 1), the method used to estimate soil water availability also varies between models. Some 518 models estimate soil water availability using soil moisture content (e.g. O-CN) and others using 519  $\psi_{soil}$  (e.g. CLM). Since soil water retention curves are highly nonlinear and dependent on soil 520 type, this can be a major source of model divergence (Medlyn et al. 2016). From a physiological 521 perspective,  $\psi_{soil}$  is thought to be more relevant to plant function than soil moisture content.

522 However, the use of  $\psi_{soil}$  can result in unrealistically steep responses to the onset of drought 523 unless it is dynamically averaged over the soil profile (De Kauwe *et al.*, 2016).

524

525 Uncertainties in root and stomatal responses are major drivers of TBM uncertainty in predicted 526 NPP across a wide latitudinal gradient (Dietze et al. 2014; De Kauwe et al. 2013). Improved 527 model representation of drought responses will require evaluation of underlying mechanisms 528 as well as comparison of high level model outputs to ecosystem fluxes during drought periods. 529 Evaluation of the response of key variables associated with alternative stomatal models against 530 field data is needed. This is challenging as evaluation of alternative mechanisms (e.g. the 531 hydraulic and physiological approaches) requires field level manipulation or exploitation of 532 natural gradients and weather events coupled with substantial campaigns that include parallel 533 measurement of many leaf parameters (e.g.  $\psi_{leaf}$ , in situ gas exchange and  $V_{c,max}$ ) in 534 coordination with plant hydraulic parameters (e.g. soil moisture content,  $\psi_{soil}$ , sap flux, 535 hydraulic conductivity and cavitation vulnerability).

536 Recommendations: (10) Models should respond to soil water availability through  $\psi_{soil}$ , but

537 variation in  $\psi_{soil}$  with soil depth needs to be incorporated (11) We need rich data sets of

538 coordinated physiological and environmental measurements to enable evaluation of alternative

539 modeling approaches for the representation of the response of A to drought.

540

## 541 Scaling physiology

Above, we focused primarily on leaf level responses to environmental and climate change drivers, but a major challenge for model representation is how to scale process knowledge of physiology and leaf level parameterization through time (seasonal change), vertically through the canopy, spatially across the landscape, and also to represent photosynthetic acclimation to rising temperature and  $C_a$ . These issues are discussed below.

548

#### 549 Effects of day length and season

550

Photosynthesis responds to short-term environmental changes, but it also shows broad, regular seasonal changes, especially in higher latitudes. In these regions, *A* halts in the autumn as leaves senesce in deciduous species and decreases as  $V_{c,max}$  is down-regulated during the cold winter months in evergreens. Much of this temporal scaling of *A* is captured in TBMs through phenology models and the direct temperature effects on  $V_{c,max}$ .

556

557 While temperature may be a major factor in driving seasonal patterns of A, other environmental cues may be as, or even more, important. Photoperiod is known to have strong 558 effects on leaf phenology, which has indirect effects on A, but has not generally been 559 560 considered to affect A directly (Way & Montgomery, 2015). However, Bauerle et al. (2012) 561 found that photoperiod was a stronger predictor of seasonal changes in both  $V_{c,max}$  and  $J_{max}$ 562 than air temperature. In that data set,  $V_{c,max}$  peaked immediately after the summer solstice, 563 and declined steadily into the autumn, although air temperatures did not peak until a month or 564 more after the solstice. When this effect was accounted for with a photoperiod correction of

 $V_{c,max}$  in CLM, the model's ability to capture seasonal patterns of atmospheric  $C_a$  was improved 565 566 (Bonan et al. 2011; Bauerle et al. 2012). Other papers have noted that incorporating a photoperiod scalar with direct effects on  $V_{c,max}$  improves estimates of seasonal carbon fluxes in 567 568 eddy flux studies, supporting a role for photoperiod in modulating  $V_{c,max}$  (Medvigy et al. 2013; 569 Stoy et al. 2014). In controlled environments, photoperiod is tightly correlated with total leaf 570 protein content, suggesting a tradeoff between the value of protein and the cost of its 571 maintenance and provides a possible mechanistic explanation for the impact of photoperiod on 572  $V_{c,max}$  (Hannemann *et al.* 2009). However, not all PFTs show the same response to changes in 573 day length and it is possible that photoperiod corrections may be capturing leaf age effects 574 (Medlyn et al. 2002b; Medlyn et al. 2007; Busch et al. 2007; Lin et al. 2013; Stinziano et al. 575 2015). In the tropics, day-length is essentially constant and therefore photoperiod scalars will 576 fail to capture the well documented photosynthetic seasonality associated with tropical 577 evergreen forests (Doughty & Goulden, 2008). In dry season Amazonian evergreen forests recent work has shown that a higher canopy level photosynthetic capacity associated with new 578 579 leaf flushing explains seasonal dynamics of photosynthetic rate (Wu et al. 2016a).

580 Recommendations: (12) We need to elucidate the mechanism underlying the use of photoperiod 581 scalars to modify photosynthetic parameterization. (13) In order to capture photosynthetic 582 seasonality in tropical evergreen forests, we need to develop new approaches that are capable 583 of coupling prognostic leaf phenology to photosynthetic capacity.

584

585 Acclimation to temperature

586

587 The short-term photosynthetic responses to temperature covered above are themselves 588 sensitive to the temperatures experienced over longer time scales (days to weeks). This longer-589 term adjustment, known as temperature acclimation, has been widely reported and recently 590 reviewed (Smith and Dukes 2013, Way & Yamori 2014). The phenomenon is commonly 591 observed as a shift in the optimum temperature for A ( $T_{opt}$ ), which can maximize the A at the 592 growth temperature (Berry & Björkman, 1980; Yamori et al., 2014; Kattge & Knorr, 2007). The 593 mechanistic process of acclimation and its timescale have not been well described, either 594 within or across species. At the slowest and broadest scales, the process of acclimation is 595 constrained by leaf structure and rates of leaf development and turnover. Leaves that develop 596 under one set of conditions are constrained by their existing anatomy from adjusting fully to a 597 new set of conditions (Campbell et al. 2007). Within a leaf, acclimation rates are driven by the 598 rates at which biochemical and physiological processes can adjust.

599

At the leaf scale, acclimation results from temperature-driven changes in enzyme abundances 600 601 and isoforms, and of membrane composition (Yamori et al. 2014). At low growth 602 temperatures, the abundance of Rubisco and other photosynthetic enzymes increases, and 603 some plants produce enzymes with different isoforms, which have different kinetic constants. 604 Under high growth temperatures, plants are thought to increase the stability of the thylakoid 605 membrane, and their capacity for increased electron transport. Also, some plants can produce 606 a more heat-stable form of Rubisco (Crafts-Brandner et al. 1997), and increase expression of 607 heat-shock proteins. Growth temperature also affects the temperature response of respiration, with consequences for net A (e.g., Atkin & Tjoelker 2003, Way & Yamori 2014); although the 608

acclimation of respiration may affect plant growth more strongly than that of *A* for some
species (Way & Oren 2010), this topic lies beyond the scope of this paper and has recently been
considered elsewhere (Atkin *et al.* 2015).

612

613 While long-term acclimation of A to temperature has been observed in many species and 614 studies, fewer studies have quantified acclimation at the process level i.e. V<sub>c.max</sub> and J<sub>max</sub>. From 615 observed responses, one may expect seasonal variation in the temperature dependence of  $J_{max}$ 616 and changes in the *JV<sub>ratio</sub>*. Some confirmation of this was provided by Kattge & Knorr (2007) who reanalysed data from 36 (primarily temperate) plants and showed that the optimum 617 temperature of  $V_{c,max}$  and  $J_{max}$  increased by 0.44°C and 0.33°C per 1°C increase of growth 618 619 temperature, and that the  $JV_{ratio}$  at 25°C significantly decreased with increasing growth 620 temperature. However, temperature acclimation may result from different processes in different species:  $V_{c,max}$  and  $J_{max}$  measured at 25°C were, on average, unaffected by growth 621 622 temperature across tree species (Way & Oren, 2010) and showed a wide variation in responses 623 across a broad range of plant growth forms (Way & Yamori 2014).

624

The representation of  $V_{c,max}$  and  $J_{max}$  acclimation based on Kattge & Knorr (2007) has been included in some models (e.g., Raddatz *et al.* 2007, Ziehn *et al.* 2011, Arneth *et al.* 2012, Lombardozzi *et al.* 2015), and recent work suggests that incorporation of both photosynthetic and respiratory acclimation can alter projections of land carbon storage by 10-40 Pg by the end of the century (Lombardozzi *et al.* 2015, Smith *et al.* 2016). However, there is clear indication that species differ in the degree to which they acclimate to temperature (e.g., Yamori *et al.*  631 2014), and no formulations have yet been developed that capture this variation across a broad632 range of PFTs.

633

634 Researchers have recorded acclimation of different species occurring over periods lasting from 635 two days to nearly two weeks (e.g., Björkman & Badger 1979, Gunderson et al. 2010, Slatyer & 636 Ferrar 1977). Very limited evidence suggests that the exact timescale of acclimation may not be 637 critical for modeled estimates of GPP as long as it is in a range of approximately 3-45 days 638 (Dietze 2014) but the issue needs to be evaluated more thoroughly before that assumption is 639 widely adopted. A specific timescale does need to be specified in models to calculate growth 640 temperature, and is straightforward to identify experimentally. Kattge & Knorr (2007) assumed 641 an acclimation period of 30 days, using an average of day and night temperatures, but it is clear 642 that the bulk of biochemical and physiological adjustments happen over a shorter time period. 643 Recommendations: (14) Physiologists need to measure thermal acclimation of the 644 photosynthetic traits (e.g.  $V_{c,max}$  and  $J_{max}$ ) that drive model outputs rather than thermal 645 acclimation of A. (15) We need a better understanding and model representation of thermal 646 acclimation across biomes, specifically the capacity and degree to which species can acclimate, 647 the time scales over which acclimation occurs, and the degree to which temperature acclimation 648 is affected by other environmental variables. 649 650 Acclimation to rising [CO<sub>2</sub>]

651

652 Photosynthetic acclimation to elevated  $C_a$  is the reduced stimulation of A that often occurs 653 following long-term growth at elevated  $C_a$  (Ainsworth & Rogers, 2007). It is the result of a 654 reduction in V<sub>c.max</sub> relative to J<sub>max</sub> (Ainsworth & Long, 2005, Ainsworth & Rogers, 2007, Leakey et al., 2009, Long et al., 2004, Rogers & Humphries, 2000). Notably, the reduction in 655 656 photosynthetic capacity typically reduces the magnitude of the stimulation of A without 657 completely eliminating it (Leakey et al. 2009). The acclimation response reduces allocation of N 658 to Rubisco, thereby allowing N resources to be combined with the greater C supply from 659 stimulated A at elevated C<sub>a</sub> (Drake et al. 1997, Long et al. 2004). In fact, a meta-analysis of 660 Ainsworth & Long (2005) found that the decrease in leaf N content observed at elevated  $C_a$  was 661 largely attributable to the decrease in Rubisco. Consequently, the magnitude of any 662 photosynthetic acclimation is tightly coupled to the C and N status, and the source-sink 663 balance, of the plant (Medlyn, 1998; Ainsworth & Rogers, 2007, Ainsworth et al., 2004, Leakey 664 et al., 2009, Rogers et al., 2009, Rogers et al., 1998). For example, in severely N limited systems, acclimation is strong and can be attributed to a nonspecific reduction in leaf N content (Warren 665 666 et al., 2015), a mechanism that is currently accounted for by some TBMs in this study (Table 1). 667 Acclimation is also strong when the capacity of sinks to use photoassimilate is low, leading to 668 accumulation of leaf carbohydrates and induction of sugar signaling pathways that reduce 669 expression of Rubisco (Moore et al. 1999). There is evidence for variation in the acclimation 670 response among functional groups that differ in the processes limiting A at ambient  $C_a$ 671 (Ainsworth & Rogers, 2007). Acclimation is rarely observed in plants that have Rubisco-limited A at current  $C_a$  and elevated  $C_a$ . As  $C_i$  rises above the inflection point on an A- $C_i$  response curve, 672 673 A will become RuBP regeneration-limited, and carboxylation capacity will exceed requirements.

674 In this situation, plants grown at elevated  $C_a$  typically exhibit photosynthetic acclimation and 675 reduce their investment in Rubisco (Ainsworth & Rogers, 2007).

676

677 The TBMs in this review either do not include photosynthetic acclimation to elevated  $C_a$  or link 678 it to a non-specific reduction in leaf N content that is focused on reduced N availability and 679 constrained C:N stoichiometry (Luo et al., 2004). No models currently include representation of 680 the physiological acclimation to elevated  $C_a$  described above and widely reported in Free Air 681 CO<sub>2</sub> Enrichment (FACE) studies (Long et al. 2004, Ainsworth & Rogers 2007, Leakey et al. 2009), 682 where the meta-analysis of Ainsworth & Long (2005) found that the decrease in leaf N content 683 observed at elevated  $C_a$  was largely attributable to the decrease in Rubisco. 2009). Recent 684 analysis has shown that failing to account for photosynthetic acclimation at elevated  $C_a$  leads to 685 an overestimation of yield in soybean (Twine et al., 2013) - a legume where reductions in leaf N 686 content at elevated C<sub>a</sub> are theoretically minimal (Rogers et al., 2009). Therefore, the potential for model representation of photosynthetic acclimation to elevated  $C_a$  to reduce errors of this 687 688 type when modeling other more N limited systems is likely substantial. In future TBMs we 689 believe it will be important to capture the mechanisms that control physiological acclimation to 690 rising  $C_a$  and not just acclimation resulting from reduced N availability. An approach that 691 reduces N allocation to Rubisco when  $C_a$  rises beyond the inflection point of PFT-specific CO<sub>2</sub> 692 response curves would be a good first step. However, unlike thermal acclimation, no 693 algorithms have been developed to facilitate inclusion of this concept in TBMs despite the 694 substantial research from FACE experiments. Published data from FACE experiments could 695 potentially be used for development and validation of new algorithms.

Recommendation (16) We need to develop a new model representation of the physiological
acclimation of photosynthesis to elevated C<sub>a.</sub>

698

699 Leaf to canopy scaling

700

Due to high non-linearity of photosynthetic responses to light, temperature and *VPD*, scaling *A* from leaves to canopy remains an important challenge for models (Jarvis, 1995). Central to this challenge is TBM representation of light penetration and utilization within the canopy's vertical profile and the vertical scaling of physiology within the canopy. Analogous effects arise from within-canopy variations in temperature and *VPD*, although to a lower degree (Niinemets & Anten, 2009).

707

708 Although the average light intensity typically decreases exponentially with increasing 709 cumulative leaf area index through the canopy, the extent of this decline is affected by the 710 optical properties of individual leaves (including albedo) and how these change with canopy 711 depth, season and leaf age, leaf inclination angle distribution and foliage and canopy spatial 712 clumping (Cescatti & Niinemets, 2004; Kobayashi et al., 2007; Chen et al., 2012; Disney, 2015; 713 Drewry et al. 2014; Wu et al. 2016a,b). Furthermore, due to gaps in the canopy, leaves at a 714 given value of cumulative leaf area index can be sunlit or shaded, further complicating the 715 estimation of light at the leaf surface, leaf absorption, and the subsequent numeric integration 716 of canopy-scale photosynthetic, water, and energy fluxes (de Pury & Farquhar, 1997; Wang & 717 Leuning, 1998; de Pury & Farguhar, 1999; Kobayashi et al., 2012). Here, the models differ in

how these scaling issues are addressed (Table 1) and based on how the canopy is considered,
they can be broadly divided between multi-layer models and big-leaf models.

720

721 Several TBMs have used the "big leaf" approach where a canopy approximately represents a 722 single big leaf with a single set of traits describing the photosynthetic capacity together with 723 characteristic light and temperature response functions (generally by PFT), typically scaled to 724 the canopy as a function of leaf area index (e.g., Amthor, 1994; Sands, 1996). Although 725 sometimes still used (e.g. G'DAY, Table 1), the big leaf model approach consisting of a single 726 "leaf" has been demonstrated to be prone to major integration errors due to lack of 727 consideration of sunlit and shaded leaf area classes (de Pury & Farguhar, 1997; Friend, 2001). 728 These errors were somewhat reduced by developing the "two big-leaf" model approach, which 729 consists of separate handling of a representative sunlit and a shaded big leaf (de Pury & 730 Farquhar, 1997; Chen et al., 1999; Dai et al., 2004). Indeed, separate integration of A for sunlit 731 and shaded leaf fractions provides a much more accurate integration of carbon and water 732 fluxes (de Pury & Farguhar, 1997; Dai et al., 2004), and this is the approach used in several 733 contemporary TBMs (Table 1).

734

Big leaf models differ in how whole-canopy  $V_{c,max}$  and  $J_{max}$  values are derived (or sunlit and shaded big leaf values are derived), but typically, proportionality of photosynthetic capacity and average light (deemed optimal) is assumed (Table 1, Amthor, 1994; Sands, 1995a; Sands, 1995b). Yet, such optimality is not present in nature (Niinemets, 2012). In fact, the decline of photosynthetic capacity through the canopy is much shallower than that for light (Lloyd *et al.*, 2010; Dewar *et al.* 2012; Niinemets *et al.*, 2015). Such departures from optimality have been
considered in some multi-layer models (Table 1), but nevertheless, only a few datasets have
been used to develop global parameterizations for multi-layer models (e.g., Carswell *et al.*,
2000; Lloyd *et al.*, 2010). PFT and biome-dependent within-canopy acclimation patterns have
recently been highlighted (Niinemets *et al.*, 2015) and could be used in future model
development.

746

747 Depending on the distribution of foliage inclination angles and spatial clumping, the probability for light penetration varies at a given cumulative LAI (Cescatti & Niinemets, 2004; Disney, 748 749 2015). Importantly, characteristic canopy features differ among PFTs given fundamental 750 differences in leaf habit and growth forms (Cescatti & Niinemets, 2004), as a result of land-use, 751 landscape legacies and past disturbance, but few TBMs take this into account. While the multi-752 layer models can be easily modified to incorporate different clumping and foliage inclination 753 angles, this is much less straightforward for the big leaf models. In fact, differences in canopy 754 architecture are part of the whole-canopy  $V_{c,max}$  and  $J_{max}$  values in current big leaf models, i.e. the input values get converted to canopy-scale sunlit and shaded values blurring the definition 755 756 of  $V_{c,max}$  and  $J_{max}$  and making comparison with measured leaf level values impossible. 757 Moreover, leaf optical properties and foliar traits change markedly within the vertical canopy profile (Serbin et al., 2014; Wu et al., 2016b; Yang et al., 2016), but are often assumed static, 758 759 which will generally lead to improper representation of light interception and utilization. This 760 improper representation will feed forward to the integration of leaf energy balance and carbon 761 uptake. We argue that traits like  $V_{c,max}$  and  $J_{max}$  should retain their original physiological

762 definition and that more effort is needed to improve the representation of canopy 763 architecture and subsequent scaling of foliar properties in TBMs. Modifications to the 764 underlying radiative transfer model (RTM) structure and scaling can help to improve the 765 representation of the canopy light environment and modeling of carbon, water, and energy 766 fluxes (Kobayashi et al., 2012), however increasing RTM complexity or vertical layering should 767 not come at the cost of the ability to parameterize the model. A promising means to constrain 768 these approaches is through model-data integration whereby remote sensing observations (e.g. 769 optical, LiDAR) from the leaf to landscape are used to inform the RTM structure and to 770 parameterize across spatial and temporal scales (e.g. Shiklomanov et al. 2016).

Recommendations: (17) TBMs should not use single layer big leaf models. (18) We need better
model representation of canopy architecture and vertical scaling of foliar properties, and data to
evaluate alternative radiative transfer models and scaling approaches.

774

### 775 Canopy to landscape scaling

776

There is considerable variability in plant physiological traits across space and time (Serbin *et al.*, 2015; Singh *et al.*, 2015), even within an individual species or PFT (Kattge *et al.* 2011; Serbin *et al.*, 2014). This variability is driven by differences across vegetation types, photosynthetic pathways, plant successional status, as well as a result of nutrient availability and other abiotic factors. There is a propensity for strong covariance among many key physiological traits as well as fundamental tradeoffs which determine the distribution of these properties across landscapes. Moreover, the nonlinearity in the scaling of model processes from leaf to larger

784 regions requires careful consideration of model parameterization in order to effectively capture 785 the larger-scale emergent responses (Fisher et al., 2015). Parameterization with single, fixed 786 values of photosynthetic capacity likely obscures the true response of vegetation to global 787 change across landscapes, particularly at the current climatic extents of vegetation, thus 788 inadequately capturing critical plant threshold responses to factors such as temperature and 789 precipitation. The links between leaf-level observations, environmental responses and 790 emergent landscape-scale parameterizations needed for TBMs is are not straightforward, and 791 as such global parameterizations are commonly derived through the inversion of large-scale 792 datasets (e.g. Kattge et al., 2009; Lin et al., 2015). However use of such data sets can yield 793 parameterization that is inconsistent with current model structures resulting in unrealistic 794 model outputs (e.g. Bonan et al., 2012). Furthermore, the trade-offs among variables (e.g. 795  $V_{c,max}$  v N) are themselves scale-dependent, with slopes changing depending on whether one is 796 looking at an across-PFT evolutionary constraint, a within-PFT community response, or a within-797 individual phenotypic response (Feng and Dietze 2014). Care must be taken to not use data 798 constraints at one scale (e.g. global) to drive responses at another scale (e.g. responses to 799 change over time).

800

The increasing use of trait databases (Wright *et al.*, 2004; Kattge *et al.*, 2011) in modeling activities has started to address some of these issues by leveraging more comprehensive descriptions of traits within models and across PFTs (LeBauer *et al.*, 2013; Dietze *et al.*, 2014; Fisher *et al.*, 2015). These databases should also be used to more extensively explore traitenvironment relationships. New, model-data integration frameworks (e.g. LeBauer *et al.*, 2013; 806 Dietze et al., 2014) can be used to explore the capacity to adequately parameterize existing and 807 new model representations, expand PFT descriptions, as well as identify critical model 808 uncertainties and data gaps and thus prioritize observational and model development activities 809 (Dietze *et al.*, 2014). Given the current diverse methods used to parameterize photosynthetic 810 parameters (Rogers, 2014), the available data (e.g. Kattge et al. 2011), and new opportunities 811 to markedly expand databases (e.g. Serbin et al 2012, De Kauwe et al. 2016), we recommend 812 that models should now use common parameterizations for photosynthetic parameters e.g. 813  $V_{c,max}$  and  $J_{max}$  that are constrained by the available data and consistent with known trait 814 covariance, thereby removing unnecessary uncertainty from model projections.

815

816 The capacity to utilize remote sensing observations to inform model parameterizations, 817 representations, and trait-environment relationships across spatial and temporal scales is 818 increasing (Dahlin et al., 2013; Serbin et al., 2015; Schimel et al., 2015; Shugart et al., 2015; 819 Singh et al., 2015). Importantly, remote sensing observations can provide a synoptic view of 820 trait variability and functional diversity across landscapes (e.g. Dahlin et al., 2013; Asner et al. 821 2015; Singh et al., 2015) and identify emergent relationships that could be included in next-822 generation trait-based models. These observations can also be used as important datasets to 823 benchmark prognostic traits at the relevant spatial scales (e.g. Fisher et al., 2015). Proposed 824 and upcoming and satellite missions, including NASA's Hyperspectral Infrared Imager (HyspIRI) 825 mission concept (Lee et al., 2015) and the European Space Agencies Environmental Mapping 826 and Analysis Program (EnMAP; Guanter et al., 2015), will provide a critical capacity to provide 827 this information for global-scale models.

Recommendations: (19) Data constraints (e.g. trait tradeoffs) must be applied at the relevant spatial and temporal scales. (20) Where possible, TBMs should use common parameterization for photosynthetic parameters. (21) TBMs should make better use of remote sensing data to inform model parameterizations and test predictions.

832

## 833 Conclusion

834

835 Realistic model representation of A, and more broadly, plant physiological processes, should be 836 an essential component of TBMs because that same plant physiology is determining the 837 response of the terrestrial biosphere to global change, including the fate of the terrestrial 838 carbon sink. However, many TBMs fail to accurately represent photosynthetic responses to key 839 environmental variables. Here, in a subset of TBMs, we have shown marked model divergence 840 in the representation of key physiological responses for a single well-defined PFT. We have 841 made 21 recommendations that highlight where steps can be taken to improve existing model 842 representation. Our recommendations include areas where immediate steps could be taken, 843 areas where model development is hindered by a lack of physiological data and several 844 important avenues of research that are critical to our understanding that are not currently 845 mature enough to include in model structures. These recommendations are summarized in Fig. 846 6.

Current model representation of *A* has a foundation in research conducted in temperate climates. However, other biomes that are climatically sensitive and globally important are understudied, and therefore process representation in these biomes is uncertain; the Arctic and

850 tropics deserve particular attention. The approach taken here, i.e. evaluating how TBMs 851 reproduce physiological responses to key environmental drivers, was found to be extremely 852 informative by all who participated. We feel the process provides a useful template for 853 meaningful collaboration between empiricists and modelers and that including the 854 physiological outputs considered here as readily available diagnostic features would be a highly 855 valuable feature to include in new TBMs. This study also highlighted the need for a multi-856 assumption model framework within which the modeling community and domain experts could 857 evaluate different model structures and parameterization approaches and quantitatively 858 evaluate their effect on model outputs. Such a framework would provide a forum where 859 modelers and, in this case, physiologists could reach agreement over the best approaches for 860 representing and parameterizing the sub-processes within complex TBMs.

861

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863

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1583 Figure Legends

1584

1585 Figure 1 The response of leaf level (a) and canopy level (b,c,d) photosynthesis (A) to 1586 instantaneous quantum flux density (Q) for three different values of leaf area index; LAI=1 (b), 1587 LAI=3 (c), and LAI=7 (d) for seven models; BETHY (red), CLM (blue), ED2 (cyan), JSBACH (pink), 1588 JULES (dark green) G'DAY (black), O-CN (green). Plots show responses in standard conditions for 1589 a single plant functional type, a generic temperate broad leaved deciduous tree. Where  $V_{c,max}$ is 60 µmol m<sup>-2</sup> s<sup>-1</sup>. VPD was fixed at 1 kPa, soil moisture content was fixed at field capacity, and 1590 atmospheric  $[O_2]$  at 210 mmol mol<sup>-1</sup>,  $C_a$  at 380 µmol mol<sup>-1</sup>. Sunlit upper canopy leaf 1591 temperature was fixed at 25°C. 1592

1593

**Figure 2** The response of leaf level (a,b) and canopy level (LAI =3; c, d) photosynthesis (*A*) to leaf temperature at two atmospheric [CO<sub>2</sub>] (380 µmol mol<sup>-1</sup> a, c and 550µmol mol<sup>-1</sup> b, d) for seven models; BETHY (red), CLM (blue), ED2 (cyan), JSBACH (pink), JULES (dark green) G'DAY (black), O-CN (green). Plots show responses in standard conditions for a single plant functional type, a temperate broad leaved deciduous tree. Where  $V_{c,max}$  is 60 µmol m<sup>-2</sup> s<sup>-1</sup>. *VPD* was fixed at 1 kPa, soil moisture content was fixed at field capacity, and atmospheric [O<sub>2</sub>] at 210 mmol mol<sup>-1</sup>, *Q* at 1500 µmol m<sup>-2</sup> s<sup>-1</sup>. Sunlit upper canopy leaf temperature was fixed at 25°C.

1601

**Figure 3** The response of leaf level (a,b) and canopy level (LAI=3; c,d) photosynthesis (*A*) to atmospheric  $[CO_2]$  ( $C_a$ ) in seven models; BETHY (red), CLM (blue), ED2 (cyan), JSBACH (pink), JULES (dark green) G'DAY (black), O-CN (green). Panels show responses in our standard 1605 conditions for a single plant functional type, a temperate broad leaved deciduous tree where 1606  $V_{c,max} = 60 \ \mu\text{mol} \ \text{m}^{-2} \ \text{s}^{-1}$  (a,c) and when  $V_{c,max} = 45 \ \mu\text{mol} \ \text{m}^{-2} \ \text{s}^{-1}$  (b, d). The *VPD* was fixed at 1 1607 kPa, soil moisture content at field capacity and *Q* at 1500  $\mu$ mol m<sup>-2</sup> s<sup>-1</sup>, atmospheric [O<sub>2</sub>] at 210 1608 mmol mol<sup>-1</sup> Sunlit upper canopy leaf temperature was fixed at 25°C.

1609

1610 **Figure 4** The response of leaf level (a) and canopy level, where LAI=3 (b) photosynthesis 1611 (*A*) to vapor pressure deficit (*VPD*) for seven models; BETHY (red), CLM (blue), ED2 (cyan), 1612 JSBACH (pink), JULES (dark green) G'DAY (black), O-CN (green). Plots show responses in 1613 standard conditions for a common plant functional type, a temperate broad leaved deciduous 1614 tree. Where  $V_{c,max} = 60 \,\mu\text{mol m}^{-2} \,\text{s}^{-1}$ . Soil moisture content was fixed at field capacity, *Q* at 1500 1615  $\mu\text{mol m}^{-2} \,\text{s}^{-1}$ ,  $C_a$  at 380  $\mu\text{mol mol}^{-1}$ , atmospheric [O<sub>2</sub>] at 210 mmol mol<sup>-1</sup> Sunlit upper canopy leaf 1616 temperature was fixed at 25°C.

1617

1618 **Figure 5** The response of leaf level (a) and canopy level, where LAI=3 (b) photosynthesis 1619 (*A*) to soil water content expressed as a fraction of field capacity for seven models; BETHY (red), 1620 CLM (blue), ED2 (cyan), JSBACH (pink), JULES (dark green) G'DAY (black), O-CN (green). Plots 1621 show responses in standard conditions for a single plant functional type, a temperate broad 1622 leaved deciduous tree. Where  $V_{c,max} = 60 \ \mu mol \ m^{-2} \ s^{-1}$ . *VPD* was fixed at 1 kPa, *Q* at 1500 \ µmol 1623 m<sup>-2</sup> s<sup>-1</sup>, *C*<sub>a</sub> at 380 \ µmol mol<sup>-1</sup>, atmospheric [O<sub>2</sub>] at 210 mmol mol<sup>-1</sup> Sunlit upper canopy leaf 1624 temperature was fixed at 25°C.

1625

**Figure 6** Summary of the main areas of scientific activity required to advance representation of photosynthesis in Earth System Models. Blue boxes show areas where fundamental research is required to advance understanding prior to incorporation into models. Yellow boxes show areas where model refinement or development is required to improve process representation. Green boxes highlight areas where data are needed to parameterize models or are required to evaluate alternative approaches. The numbers in the boxes are keyed to our recommendations in the text.

BETHY	CLM4.5	ED2	G'DAY	JSBACH	JULES	O-CN
Leaf photosynthes	sis (response to $C_a$ )					
Farquhar et al (1980), no TPU limitation	Farquhar et al (1980), includes TPU limitation and co-limitation from Collatz et al. (1991)	Collatz et al. (1991) and Foley et al. (1996); no TPU limitation	Farquhar et al (1980), no TPU limitation	Farquhar et al (1980), no TPU limitation	Collatz et al. (1991), TPU limitation included	Farquhar type (Farquhar et al 1980) following Kull and Kruijt (1998)
Stomatal conducta	ance (response to atmo	ospheric VPD, C <sub>a</sub> soil	moisture and A)			
Minimum of (1) stomatal conductance necessary to realize maximum $C_i:C_a$ and (2) soil water availability (Federer 1982).	Sensitivity to atmospheric <i>RH</i> , <i>C</i> <sub>a</sub> and <i>A</i> from Ball, Woodrow & Berry (1987) Sensitivity to soil moisture is from a beta factor applied to the intercept of the Ball, Woodrow & Berry (1987) model. The beta factor is summed over soil layers, weighted by root fraction in each layer and calculated based on soil moisture content	Sensitivity to atmospheric VPD, $C_a$ and A from Leuning et al. (1995) Water supply is proportional to soil moisture $\Box$ root biomass. If the open stomata demand exceeds supply then $g_s$ is linearly scaled between open and closed stomata.	Sensitivity to atmospheric VPD, $C_a$ and A from Medlyn et al. (2011) Sensitivity to soil moisture from beta factor applied to the slope of the stomatal response (Medlyn et al. 2011). Soil moisture content is expressed as a fraction of total plant available water and dependent on soil type	Estimates potential A for any given condition assuming a maximal $C_i:C_a$ resulting from a maximum potential $g_s$ When soil moisture content falls below 50% of plant available water maximum potential $g_s$ is reduced linearly.	Sensitivity to atmospheric VPD, $C_a$ and A from modification of Leuning et al (1995) model as proposed by Jacobs (1994)	Non-linear sensitivity to specific humidity deficit and $C_i$ . The latter is necessary because A for $g_s$ is evaluated at saturating $C_i$ . A beta factor is applied to the slope of the stomatal response when soil moisture content falls below 50% of plant available water.
	sis (response to light)				** 1 1	
Rectangular hyperbola, with realized quantum yield and $A_{sat}$ calculated from Farquhar model	Non-rectangular hyperbola, with realized quantum yield and $A_{sat}$ calculated from Farquhar model	Hyperbolic function, with realized quantum yield and $A_{sat}$ calculated from the Collatz (1991) model, no $J_{max}$ term included	Non-rectangular hyperbola, with realized quantum yield and $A_{sat}$ calculated from Farquhar model	Rectangular hyperbola, with realized quantum yield and $A_{sat}$ calculated from Farquhar model	Hyperbolic function, with realized quantum yield and $A_{sat}$ calculated from the Collatz (1991) model, no $J_{max}$ term included	Explicit separation into light saturated and limited regions: A <sub>sat</sub> is calculated from Farquhar et al (1980). Light

dependence of kinetic constants follows Bernacchi et al. (2001). $V_{c,max}$ and $F_{d}$ are peaked Arrhenius functions of temperature dependent kinetic constants follows a repeaked Arrhenius of temperature response as $V_{cmax}$ . Of dependent dependent dependent dependence of kinetic constants follows a $V_{c,max}$ and $R_d$ are peaked Arrhenius function. A preature temperature response as $V_{cmax}$ . Of dependent dependence of $V_{c,max}$ and $P_d$ are modified Arrhenius functions of temperature response as $V_{cmax}$ . A deta factor is applied to $V_{c,max}$ . As beta factor is applied to $V_{c,max}$ . As beta factor is applied to $V_{c,max}$ . As beta factor is applied to $V_{c,max}$ . Soil moisture concent ti expressed response of to the temperature here as a raction of total layer, weighted by root fraction in each layer. As the tar and dependent of the temperature dependence of kinetic constants follows a $V_{cmax}$ and							limited A is assumed to be proportional to light absorption (Kull and Kruijt, 1998)
dependence of kinetic constants follows Bernacchi et al. (2001). $V_{c,max}$ and $F_{inetic}$ constants follows Bernacchi et al. (2001). $V_{c,max}$ and $F_{inetic}$ constants follows Bernacchi et al. (2001). $V_{c,max}$ and $F_{inetic}$ constants follows Bernacchi et al. (2001). $V_{c,max}$ and $F_{inetic}$ constants follows $F_{inetic}$	Leaf photosynthes	sis (response to tempe	rature)				
A beta factor is applied to $V_{c,max}$ . The beta factor, calculated based on soil moistureA beta factor is applied to $J_{max}$ and $V_{c,max}$ . Soil moisture ontent is expressed soil moisturePotential A is reduces $V_{c,max}$ and multiplied by a soil reduces $V_{c,max}$ and $J_{max}$ when plant available water soil moisture soil moistureA beta factor 	Temperature dependence of kinetic constants follows Bernacchi et al. (2001). <i>V<sub>c,max</sub></i> and <i>J<sub>max</sub></i> are peaked Arrhenius functions of temperature.	dependence of kinetic constants follows Bernacchi et al. (2001). $V_{c,max}$ and $J_{max}$ are peaked Arrhenius functions of temperature. TPU has the same temperature	al., (1991) and Foley et al., (1996). The temperature dependent kinetic constants follow a modified Arrhenius function. A phenomenological thermal downscaling of $V_{c,max}$ occurs at low and high temperatures (Medvigy et al.,	dependence of kinetic constants follows Bernacchi et al. (2001). $V_{c,max}$ , $J_{max}$ and $R_d$ are peaked Arrhenius functions (Medlyn	dependence of kinetic constants and $V_{c,max}$ follow an Arrhenius function, $\Gamma^*$ and $J_{max}$ vary linearly with	al. (1991), the temperature dependence of kinetic constants follows a Q <sub>10</sub> function. $V_{c,max}$ has a peaked temperature function calculated from $V_{c,max}$ at 25°C using vegetation- specific optimal	dependence of kinetic constants and $V_{c,max}$ follows Bernacchi et al. (2001). The temperature dependence of $J_{max}$ is derived from June et al.
applied to $V_{c,max}$ .applied to $J_{max}$ andmultiplied by a soilreduces $V_{c,max}$ andThe beta factor, $V_{c,max}$ . Soil moisturewater stress factor $J_{max}$ when plantcalculated based oncontent is expressedrelated to the meanavailable watersoil moistureas a fraction of totalsoil moisture<20% (Friend,	Leaf photosynthes		oisture content)				
		applied to $V_{c,max}$ . The beta factor, calculated based on soil moisture potential, is summed over soil layers, weighted by root fraction in each		applied to $J_{max}$ and $V_{c,max}$ . Soil moisture content is expressed as a fraction of total plant available water and dependent on soil		multiplied by a soil water stress factor related to the mean soil moisture concentration in the root zone and the critical and wilting point soil water concentrations.(Cox	reduces $V_{c,max}$ and $J_{max}$ when plant available water <20% (Friend,
	Canopy scaling	The Multi lover	Cohort based model	Dig loof model	Multiple conony	Multi lavor concre	Multiple concre

Sellers's (1987) two-stream approximation. $V_{c,max}$ and $J_{max}$ declines exponentially within the canopy following Lloyd et al. (2012).	resolves direct and diffuse radiation for sunlit and shaded leaves at each level in the canopy. Both options use Sellers's (1987) two-stream approximation for radiative transfer. Nitrogen declines exponentially with greater cumulative leaf area index.	layers equal to the number of cohorts. Cohorts differ by PFT definition. Radiation penetration is defined by LAI and the leaf and wood single scattering albedos. There is no separation of sunlit and shaded foliage in the default version	exponential light and nitrogen distributions. Daily <i>A</i> calculated using Gaussian integration (Sands 1996)	Sellers's (1987) two-stream approximation. LAI typically = 3. For LAI < 3, N (and hence $V_{c,max}$ , $J_{max}$ ) is distributed evenly in the canopy (assumed to be open). For LAI > 3, N follows the distribution of light (exponential decline).	stream approximation from Sellers (1985) solving direct and diffuse radiation for sunlit and shaded leaves at each canopy layer. Includes exponential vertical nitrogen distribution of photosynthetic capacity and leaf respiration.	diffuse and direct radiation streams following Spitters (1986). Nitrogen declines exponentially with greater cumulative leaf area index, affecting $V_{c,max}$ and $J_{max}$
Key Model Refere	ences					
Knorr &	Bonan et al (2011,	Medvigy et al		Knorr & Heimann	Best et al (2011), Clark et al (2011),	Zaehle & Friend
Heimann (2001)	2012), Oleson et al (2013)			(2001)		(2010), Friend (2010)

BETHY = Biosphere Energy Transfer Hydrology scheme, CLM4.5 = the Community Land Model version 4.5, G'DAY = Generic Decomposition And Yield model (G'DAY), JSBACH = Joint Scheme for Biosphere Atmosphere Coupling in Hamburg, JULES = Joint UK Land Environment Simulator, O-CN = An extension of the Organizing Carbon and Hydrology in Dynamic Ecosystems model that includes key N cycle processes.

Table 2 Parameters used by the models in this study (Table 1).								
	BETHY	CLM4.5	ED2	G'DAY	JSBACH	JULES	O-CN	
<i>K<sub>c</sub></i> at 25°C (μmol mol <sup>-1</sup> )	404.9	404.9	300	404.9	404.9	300	404.9	
K₀ at 25°C (mmol mol <sup>-1</sup> )	278.4	278.4	294	278.4	278.4	300	278.4	
Γ* at 25°C (μmol mol <sup>-1</sup> )	42.75	42.75	41.57	42.75	42.75	40.38	42.75	
Source of kinetic constants	Bern	Bern	Foley	Bern	Bern	Collatz	Bern	
JV <sub>ratio</sub>	1.92	1.97	N.A.	2.00	1.90	N.A.	2.08	
$J_{max}$ (µmol m <sup>-2</sup> s <sup>-1</sup> )	115(86)	115(85)	N.A.	120(90)	114(86)	N.A.	126(94)	
Absorbtance	0.88	0.85	0.73	0.85	0.88	0.85	0.80	
Convexity	N.A.	$0.98 \& 0.95^{\circ}$	N.A.	0.7	N.A.	0.83 & 0.93ª	N.A.	
$C_i$ at low light ( $\mu$ mol mol <sup>-1</sup> )	348	400	400	293	348	280	N.D.	
Model input for quantum yield	0.28 <sup>b</sup>	0.4250 <sup>b</sup>	0.08 <sup>d</sup>	0.26 <sup>c</sup>	0.28 <sup>b</sup>	0.08 <sup>d</sup>	0.08 <sup>d</sup>	
Calculated $\phi_{int}$	0.070	0.106	0.080	0.076	0.070	0.080	0.080	
$\Phi_{real}$	0.049	0.053	0.038	0.038	0.050	0.045	0.022	

The Michaelis-Menton constants of Rubisco for carbon dioxide ( $K_c$ ) and oxygen ( $K_o$ ), the CO<sub>2</sub> compensation point in the absence of non-photorespiratory michondrial respiration in the light ( $\Gamma^*$ ) and the sources of those kinetic constants (Bern = Bernacchi et al. 2001, Collatz = Collatz et al. 1991, Foley = Foley et al. 1996). Where applicable the model specific ratio of the maximum electron transport rate ( $J_{max}$ ) to maximum photosynthetic capacity ( $V_{c,max}$ ), the ( $JV_{ratio}$ ), was used to calculate  $J_{max}$  for standard conditions, low nitrogen conditions are shown in parentheses. Leaf absorbtance; the convexity term (<sup>a</sup>for the transition between Rubisco and light limited and light limited and TPU limited A respectively); the intercellular [CO<sub>2</sub>] ( $C_i$ ) at low light. Three model inputs were used to parameterize quantum yield (<sup>b</sup>quantum yield of electron transport based on absorbed light, <sup>c</sup>quantum yield of electron transport based on incident light and <sup>d</sup>quantum yield of photosynthesis based on absorbed light and measured under nonphotorespiratory conditions ( $\phi_{int}$ ). Here we also show the calculated intrinsic quantum yield for all models to enable model comparisons. The modeled realized quantum yield under our standard conditions when  $Q = 100 \ \mu mol \ mol^{-1}$ ( $\phi_{real}$ ) is the initial slope of the leaf level A-Q response shown in Fig 1a for our standard conditions where the ( $V_{c,max}$ ) was set to 60  $\ \mu mol \ m^{-2} \ s^{-1}$  (and 45  $\ \mu mol \ m^{-2} \ s^{-1}$  for low nitrogen conditions) and where temperature = 25°C, atmospheric [ $O_2$ ] = 210 mmol mol<sup>-1</sup>,  $C_a$  = 380  $\ \mu mol \ m^{-1}$ , VPD = 1 kPa and soil moisture content was at field capacity. N.A. = not applicable, N.D. = no data.















