

1 **FORCAsT-gs: Importance of stomatal conductance parameterisation to estimated**  
2 **ozone deposition velocity**

3

4 **Frederick Otu-Larbi<sup>1†</sup>, Adriano Conte<sup>2</sup>, Silvano Fares<sup>2,3</sup>, Oliver Wild<sup>1</sup>, Kirsti Ashworth<sup>1†</sup>**

5 <sup>†</sup>Joint first authors

6 <sup>1</sup>Lancaster Environment Centre, Lancaster University, Lancaster, LA1 4YQ, UK

7 <sup>2</sup>Council for Agricultural Research and Economics (CREA) - Research Centre for Forestry and Wood,  
8 Viale Santa Margherita 80, 52100 Arezzo, Italy

9 <sup>3</sup>National Research Council of Italy - Institute of BioEconomy. Via dei Taurini 19, 00185 Rome, Italy.

10 *Correspondence to:* Kirsti Ashworth ([k.s.ashworth1@lancaster.ac.uk](mailto:k.s.ashworth1@lancaster.ac.uk))

11

12 **Key Points:**

- 13 • Medlyn coupled stomatal conductance-photosynthesis model best reproduces observed plant  
14 productivity (GPP) across various ecosystems
- 15 • Modelled GPP and stomatal conductance across forest ecosystems differ by up to a factor of 2  
16 between different model configurations
- 17 • Ozone deposition rates could vary by ~13% depending on stomatal conductance model used  
18 with implications for estimated tropospheric ozone

19

20

21

22

23

24

25

26 **Abstract**

27

28       The role of stomata in regulating photosynthesis and transpiration, and hence governing global  
29   biogeochemical cycles and climate, is well-known. Less well-understood, however, is the importance  
30   of stomatal control to the exchange of other trace gases between terrestrial vegetation and the  
31   atmosphere. Yet these gases determine atmospheric composition, and hence air quality and climate,  
32   on scales ranging from local to global, and seconds to decades. Vegetation is a major sink for ground-  
33   level ozone via the process of dry deposition and the primary source of many biogenic volatile organic  
34   compounds (BVOCs). The rate of dry deposition is largely controlled by the rate of diffusion of a gas  
35   through the stomata, and this also governs the emission rate of some key BVOCs. It is critical therefore  
36   that canopy-atmosphere exchange models capture the physiological processes controlling stomatal  
37   conductance and the transfer of trace gases other than carbon dioxide and water vapour. We  
38   incorporate three of the most widely used coupled stomatal conductance-photosynthesis models into  
39   the one-dimensional multi-layer FORest Canopy-Atmosphere Transfer (FORCAsT1.0) model to  
40   assess the importance of choice of parameterisation on simulated ozone deposition rates. Modelled  
41   GPP and stomatal conductance across a broad range of ecosystems differ by up to a factor of two  
42   between the best and worst performing model configurations. This leads to divergences in seasonal  
43   and diel profiles of ozone deposition velocity of up to 30% and deposition rate of up to 13%,  
44   demonstrating that the choice of stomatal conductance parameterisation is critical in accurate  
45   quantification of ozone deposition.

46

47

48

49

50

51

52 **Plain language summary**

53

54 Plants open and close their stomata to regulate the uptake of carbon dioxide (photosynthesis)  
55 and the release of water vapour into the atmosphere. Trace gases like ozone can also enter the stomata  
56 causing damage to leaves, reducing plant growth and productivity in the process. Stomatal  
57 conductance, the measure of stomatal opening, is therefore important for assessing the concentration  
58 of ozone in the atmosphere and the impacts of pollutants on plants. It is critical that canopy-atmosphere  
59 exchange models capture the processes controlling stomatal conductance and the transfer of trace gases  
60 other than carbon dioxide and water vapour. We incorporate three widely used coupled stomatal  
61 conductance-photosynthesis models into a 1-Dimensional multi-layer model to assess how the choice  
62 of model parameters affect the rate at which ozone is deposited onto plant surfaces. We first validate  
63 the model using observations from various forests sites and then compare ozone deposition rates  
64 between the best and worst performing model at each site. We find that ozone deposition rates can  
65 vary by up 13% in response to changes in model parameters, demonstrating that the choice of stomatal  
66 conductance parameterisation is crucial in understanding ozone deposition, a major process through  
67 which ozone is removed from the troposphere.

68 1      **Introduction**

69            Photosynthesis and transpiration of the world's forests drive the carbon, hydrological and  
70 nutrient cycles, governing climate, ecosystem health and productivity, and biodiversity. Forests also  
71 serve as a sink for trace gases which are deposited onto plant surfaces and taken up through the stomata.  
72 Dry deposition of ozone is of particular importance as it represents a major sink of this tropospheric  
73 pollutant. It is also of particular concern because ozone can damage photosynthetic apparatus limiting  
74 growth and productivity. The rates of photosynthesis and uptake of ozone are both dependent on the  
75 degree of stomatal opening, referred to as stomatal conductance. Plants open and close the stomata to  
76 maintain a balance between photosynthesis (CO<sub>2</sub> uptake) and leaf transpiration (water loss), thereby  
77 regulating the exchange of CO<sub>2</sub> and water vapour between vegetation and the atmosphere  
78 (Hetherington & Woodward, 2003).

79            Gases and particles deposited on leaf surfaces may be taken up through the stomata or cuticle  
80 into the leaf tissue. Stomatal uptake is the dominant of these routes for most reactive trace gases like  
81 ozone (Royal Society, 2008). The rate of stomatal diffusion and uptake is dependent on both the  
82 diffusivity of the gas and the size of the stomata: the wider the stomatal aperture the lower the  
83 resistance to diffusion through the stomata. As gases diffuse through the stomata, their concentrations  
84 are reduced at the leaf surface, increasing the concentration gradient between the leaf and the  
85 atmosphere above it. This concentration gradient also drives deposition – the greater the gradient the  
86 higher the deposition velocity. Total deposition rates are therefore dependent both directly and  
87 indirectly on stomatal conductance.

88            Ozone taken up through stomata is detrimental to plant growth and health leading to a decrease  
89 in productivity, causing billions of dollars in crop losses annually (Ainsworth et al., 2012, Avner et  
90 al., 2011). Ozone damage has been shown to reduce gross primary productivity (GPP) by up to 10%  
91 in different forest ecosystems under current climatic conditions, although this impact is projected to

92 decline in future as increased CO<sub>2</sub> and drought severity reduce stomatal conductance and hence  
93 stomatal ozone uptake (Oliver et al., 2018; Otu-Larbi et al., 2020b).

94 Stomatal conductance is a key factor controlling ozone deposition velocity and deposition  
95 rates, and therefore the extent and severity of damage. It is critical that models that couple the land  
96 surface and the atmosphere are able to accurately reproduce stomatal conductance in order to account  
97 fully for the processes driving photosynthesis and trace gas deposition rates. Many empirical and  
98 semi-empirical approaches have been developed to simulate stomatal conductance. One of the earliest  
99 and most widely used is a multiplicative model (Jarvis, 1976) which reduces stomatal conductance  
100 from its potential maximum according to observed responses to changing environmental conditions.  
101 Each environmental influence is assumed independent of the others (Damour et al., 2010) and the  
102 approach does not consider physiological interactions or feedbacks that could alter stomatal movement  
103 (Yu et al., 2004). Subsequent research demonstrated that stomatal aperture was also directly regulated  
104 by current photosynthesis rate (Wong et al., 1979) leading to the development of semi-empirical  
105 coupled models that assume a linear relationship between photosynthesis (*An*) and *gs*, and iterate to  
106 simultaneously solve for both (e.g. Ball et al., 1987). More recently, optimisation theory has been  
107 applied to these coupled photosynthesis-stomatal conductance models to replicate the ‘regulatory’ role  
108 of stomata, i.e. that plants control stomatal aperture to maximize carbon gain while minimizing water  
109 loss (Medlyn et al., 2011; Cowan and Farquhar, 1977).

110 These model formulations adopt different approaches to account for the impacts on stomatal  
111 conductance of environmental factors such as drought, and physiological factors such as phenology.  
112 Each requires specific parameters which can be difficult to obtain for particular species and climates  
113 leading to the use of generic values for similar plant functional types. As estimates of stomatal  
114 conductance are sensitive to both model formulation and parameter value there are large uncertainties  
115 associated with modelled stomatal conductance and photosynthesis rates. Interestingly though, some  
116 studies report little difference between conductance estimated based on optimisation theory and semi-

117 empirical methods, suggesting that for some species and ecosystems the choice of model formulation  
118 is not a major factor in determining model performance (Franks et al., 2017; Franks et al., 2018).

119 The multi-layer canopy-atmosphere model FORCAsT1.0 (FORest Canopy-Atmosphere  
120 Transfer) was initially developed as an atmospheric chemistry tool for upscaling leaf-level biogenic  
121 emissions to the canopy scale and interpreting measurement data from intensive field campaigns at  
122 forest sites (CACHE; Forkel et al., 2006). It has since been modified to better capture observed  
123 dynamics and turbulent transport (CACHE; Bryan et al., 2012) and to reflect our improved  
124 understanding of the atmospheric chemistry of biogenic volatiles, particularly in low-NO<sub>x</sub>  
125 environments (FORCAsT1.0; Ashworth et al., 2015). Parameterisations of the response of isoprene  
126 emissions to water stress and re-wetting have also been incorporated into the model and demonstrated  
127 to improve model reproduction of changes in isoprene concentrations at a temperate deciduous  
128 woodland during an extended heatwave-drought (Otu-Larbi et al., 2020a).

129 The model has demonstrated considerable skill in reproducing observed concentrations and  
130 fluxes of short-lived biogenic reactive trace gases and their products over short time periods at a  
131 number of Northern Hemisphere forest sites (Forkel et al., 2006; Bryan et al., 2012; 2015; Ashworth  
132 et al., 2015). However, production outweighs loss processes for some gaseous species, suggesting that  
133 either deposition rates or vertical transport out of the canopy are too slow, or foliage emissions  
134 overestimated. These processes are dependent on the rate of gas exchange through the stomata, and  
135 hence the skill of the model in capturing stomatal conductance over time periods from minutes, to  
136 hours, to seasons.

137 Explicit inclusion of physiological processes in FORCAsT1.0 has the additional benefit of  
138 enabling model performance to be evaluated against canopy-scale photosynthesis and transpiration  
139 (represented by canopy-top fluxes of CO<sub>2</sub> and water vapour) which are routinely measured and readily  
140 available over long time periods across a wide range of ecosystems. This allows a more thorough  
141 exploration and constraint of the physical and dynamical processes occurring within the canopy than

142 is possible from concentration and flux measurements of short-lived reactive species made during short  
143 intensive field campaigns. Constraining these processes would allow us to focus more closely on the  
144 mechanisms of the production and loss of short-lived atmospherically relevant biogenic trace gases.

145 We incorporate three parameterisations of stomatal conductance and photosynthesis into  
146 FORCAsT1.0 to assess:

147 1) the ability of different coupled stomatal conductance-photosynthesis models to reproduce  
148 observed CO<sub>2</sub> fluxes across a range of different forest ecosystems and climate regions  
149 2) the divergence of simulated ozone deposition velocities and deposition rates due to  
150 differences in stomatal conductance modelling approach and parameterisation

151 We use observation data from five forest sites within the FLUXNET2015 dataset (Pastorello  
152 et al., 2020), the most comprehensive high-quality data available from worldwide flux networks, to  
153 evaluate the performance of each of the three stomatal conductance-photosynthesis models. The sites  
154 cover three different forest ecosystems classified by the International Geosphere-  
155 Biosphere Programme (IGBP) as Evergreen Broadleaf Forests (EBF), Evergreen Needleleaf Forests  
156 (ENF) and Deciduous Broadleaf Forests (DBF), and three climate regions: boreal, temperate and  
157 tropical, with two of the temperate sites further sub-classified as Mediterranean. Our ultimate goal is  
158 to understand and quantify the uncertainties in modelled gross primary productivity and ozone  
159 deposition rates due to the choice of stomatal conductance model and model parameters.

160

161

162 2 Methods

163 2.1 FORCAsT-gs

164 The 1-D (vertical column) model, FORest Canopy-Atmosphere Transfer (FORCAsT1.0), was  
165 developed to simulate exchanges of reactive biogenic volatiles between a forest site and the  
166 atmospheric boundary layer. Previous versions (CACHE: Forkel et al., 2006; Bryan et al, 2012; 2015;  
167 and FORCAsT1.0: Ashworth et al., 2015; Otu-Larbi et al., 2020a) have focused on the atmospheric  
168 processes governing the concentration and distribution of these volatiles and their oxidation products  
169 within and above the canopy. FORCAsT uses 40 vertical levels as a default, 20 of which are in the  
170 vegetation canopy space, with the remainder of the levels representing the planetary boundary layer  
171 above. The thickness of the layers increases with height, permitting greater resolution in the canopy  
172 space, which is further sub-divided into a trunk space (10 levels) and crown space (10 levels). More  
173 details about how vegetation is treated in the model can be found in Ashworth et al. (2015).

174 Heat and mass fluxes are calculated at each model level by solving the continuity equations,  
175 shown here for (gas-phase) mass:

$$176 \frac{\partial c}{\partial t} = \frac{\partial}{\partial z} \left( K \frac{\partial c}{\partial z} \right) + S_c, \quad (1)$$

177 where  $c$  is the concentration or mixing ratio of a chemical species or water vapour,  $z$  is the height of  
178 the layer,  $K$  is the turbulent exchange coefficient and  $S_c$  represents all sources and sinks of the species  
179 (i.e. emissions, deposition, chemical production and loss, and advection). All are explicitly  
180 parameterised within the model and have been fully described by Bryan et al. (2012) and Ashworth et  
181 al. (2015). We briefly re-cap those that remain unchanged from FORCAsT1.0 (Ashworth et al., 2015)  
182 before fully describing the coupled stomatal conductance-photosynthesis models we have now  
183 incorporated into FORCAsT-gs.

184 Leaf-level volatile emissions are calculated for each foliated canopy layer in FORCAsT-gs  
185 following the light- and temperature-dependent emission algorithms developed by Guenther et al.  
186 (1995):

187  $F = LAI \cdot \varepsilon \cdot \gamma_{TS} \cdot \gamma_{LS}$ , (2)

188 where LAI is the leaf area index in each leaf-angle class and layer,  $\varepsilon$  is the emission factor or  
189 base emission rate (i.e. at standard conditions of 30 °C and 1000  $\mu\text{mol m}^{-2} \text{s}^{-1}$  photosynthetically active  
190 radiation, PAR) and  $\gamma_{TS}$  and  $\gamma_{LS}$  are activity factors that scale the base emission rate according to actual  
191 temperature and PAR. For temperature-dependent-only emissions from specialised storage pools,  $\gamma_{TS}$   
192 and  $\gamma_{LS}$  in Eqn. 2 is replaced by  $\gamma_{TP}$  based on Steinbrecher et al. (1999). Further details of the activity  
193 factors and parameters are presented in Ashworth et al. (2015). The chemistry in FORCAsT-gs is  
194 unchanged from that described by Ashworth et al. (2015). Users can use either the Regional  
195 Atmospheric Chemistry Mechanism (RACM; Stockwell et al., 1997; Geiger et al., 2003) or the Caltech  
196 Atmospheric Chemistry Mechanism (CACM; Griffin et al., 2003, 2005; Chen et al., 2006). The former  
197 includes 84 species and 249 reactions, and the latter 300 species and 630 gas-phase reactions with  
198 partitioning to aerosol via the Model to Predict the Multiphase Partitioning of Organics (MPMPO;  
199 Chen et al., 2006; Ashworth et al., 2015).

200 Vertical mixing in and above the canopy are based on Baldocchi (1988) and Gao et al. (1993)  
201 respectively, following first-order K-theory (Blackadar, 1963). Eddy diffusivity is constrained by  
202 friction velocity measurements made close to but just above the top of the canopy as K-theory breaks  
203 down in the highly turbulent canopy sub-layer (Bryan et al., 2012).

204 Here, we describe how FORCAsT1.0 estimates deposition velocity and subsequently  
205 investigate how the choice of model formulation and parameters affect these estimates. The rate of dry  
206 deposition to the soil and foliage is calculated for all gas-phase compounds for each model layer in the  
207 canopy following the parameterisations of Wesely (1989) and Gao et al. (1993), and is described in

208 full in Bryan et al. (2012). Deposition is assumed to occur at a rate dependent on a species-specific  
 209 Henry's law coefficient, diffusivity relative to water vapour and a nominal reactivity factor accounting  
 210 for enhanced uptake of some species due to reactions occurring within plant cells following uptake.  
 211 Of importance here is the method of calculating the deposition velocity within the foliar layers, based  
 212 on four resistances: the quasi-laminar boundary layer at the leaf surface ( $R_b$ ), stomatal ( $R_s$ ), mesophyll  
 213 ( $R_m$ ), and cuticular ( $R_c$ ) resistances, such that for each trace gas ( $i$ ), the deposition velocity ( $v_d$ ) at each  
 214 level is:

$$215 \quad v_{d,i}(z) = \frac{1}{R_{b,i}(z)+R_s(z)\frac{D_{H_2O}}{D_i}+R_{m,i}(z)} + \frac{2}{R_{b,i}(z)+R_{c,i}(z)} \quad (3)$$

216 where  $z$  is the height of the midpoint of the model level, and  $D_{H_2O}/D_i$  (=1.6 for ozone) is the ratio of  
 217 the molecular diffusivities of water to the trace gas of interest (Gao et al., 1993). Resistances depend  
 218 on factors such as LAI, leaf length and the reactivity factor of the trace gas and are calculated on-line  
 219 in the model. Stomatal resistance,  $R_s$ , is deduced as the inverse of stomatal conductance (Ashworth et  
 220 al., 2015).

221 The ozone deposition rate,  $D_r$ , is then calculated as:

$$222 \quad D_r = v_d \times [O_3] \quad (4)$$

223 where  $[O_3]$  is the average concentration of ozone at leaf-level in each canopy layer.

224 In FORCAsT1.0, stomatal conductance is calculated using the Jarvis multiplicative model.  
 225 Here we extend the Jarvis approach to include photosynthesis and incorporate two coupled stomatal  
 226 conductance-photosynthesis models into FORCAsT-gs, allowing the user to select between three  
 227 different approaches to calculating photosynthesis and stomatal conductance (see Section 2.2). In all  
 228 other respects, dry deposition remains unchanged (Bryan et al., 2012; Ashworth et al., 2015).

229 2.2 Physiology: coupled stomatal conductance-photosynthesis models

230 There are currently three distinct approaches to modelling stomatal conductance and net  
231 photosynthesis: empirical multiplicative models that estimate stomatal conductance and thence  
232 photosynthesis rate (e.g. Jarvis, 1976); coupled stomatal conductance-photosynthesis models that  
233 simultaneously solve for both (e.g. Ball et al., 1987); and optimisation models that simultaneously  
234 maximise carbon assimilation while minimising water loss (e.g. Medlyn et al., 2011). We describe  
235 below the key aspects of the three that we incorporated into FORCAsT-gs. A more detailed description  
236 of the mathematical formulations for each model is presented in the supplementary information.

237 The Jarvis model (Jarvis, 1976) assumes stomatal aperture is downregulated from a theoretical  
238 maximum by the effects of environmental conditions such as temperature, PAR, and leaf age. The  
239 scale of each down-regulation is based on experimental observations and  $g_s$  is then calculated as:

240 
$$g_s = g_{max} \times f_{phen} \times f_{light} \times \max\{f_{min}, (f_{temp} \times f_{VPD} \times f_{SWC})\} \quad (5)$$

241 where  $g_s$  ( $\text{mol m}^{-2} \text{s}^{-1}$ ) is stomatal conductance at each model level and  $g_{max}$  ( $\text{mol m}^{-2} \text{s}^{-1}$ ) is the plant  
242 species-specific maximum value of canopy stomatal conductance for water vapour. The scaling  
243 functions,  $f_{phen}$ ,  $f_{light}$ ,  $f_{temp}$ ,  $f_{VPD}$ , and  $f_{SWC}$  have values between 0 and 1 and account for the reduction in  
244 stomatal conductance due to leaf age (phenology), photosynthetic photon flux density (PPFD,  $\mu\text{mol}$   
245  $\text{m}^{-2} \text{s}^{-1}$ ; defined as the intensity of PAR reaching each square meter of the canopy per second),  
246 temperature ( $T$ ,  $^{\circ}\text{C}$ ), vapour pressure deficit (VPD, kPa), and volumetric soil water content (SWC,  $\text{m}^3$   
247  $\text{m}^{-3}$ ), respectively.  $f_{min}$  is the minimum stomatal conductance during daylight. Details of the  
248 calculations of each of the functions are given in S1.1.

249 Net photosynthesis rate,  $A_n$ , is then assumed to be directly proportional to the conductance,  $g_s$ ,  
250 such that:

251 
$$A_n = g_s \times C_i \quad (6)$$

252 where  $C_i$  is the ratio of ambient to internal concentrations of CO<sub>2</sub> and is normally taken as 0.7.  
253 Parameter values for each site were determined from field measurements, lab-based experiments or  
254 taken from literature for the nearest equivalent and are shown in Table S2.

255 The Ball-Berry coupled stomatal conductance-photosynthesis model assumes that stomatal  
256 conductance is regulated directly by the instantaneous rate of photosynthesis to balance CO<sub>2</sub>  
257 concentrations inside the leaf with ambient levels. Photosynthesis rate ( $A$ ; μmol m<sup>-2</sup> s<sup>-1</sup>) at each level  
258 in the canopy is calculated following the formulations of Farquhar et al. (1980), Harley et al. (1992)  
259 and Baldocchi (1994):

260 
$$A = V_c - 0.5V_o - R_d \quad (7)$$

261 where  $V_c$  is the carboxylation rate,  $V_o$  the oxygenation rate,  $R_d$  the dark respiration rate and

262 
$$V_c - 0.5V_o = \min[A_c, A_j] \times (1 - \Gamma/C_i) \quad (8)$$

263 i.e. assuming that the photosynthesis rate is limited by either Ribulose bisphosphate saturation during  
264 carboxylation ( $A_c$ ) or by the rate of electron transport for Ribulose bisphosphate regeneration during  
265 oxygenation ( $A_j$ ).  $\Gamma$  is the CO<sub>2</sub> compensation point (the CO<sub>2</sub> concentration at which net CO<sub>2</sub> fixation  
266 is zero at a given O<sub>2</sub> level and temperature (Moss et al., 1969)) in the absence of dark respiration, and  
267  $C_i$  is the intercellular CO<sub>2</sub> concentration (Farquhar and von Caemmerer, 1982).

268 The internal CO<sub>2</sub> concentration of the leaf,  $C_i$  is:

269 
$$C_i = C_s - \frac{A}{g_s} \quad (9)$$

270 where  $g_s$  is stomatal conductance and  $C_s$  is the CO<sub>2</sub> concentration at the leaf surface. Here,  $g_s$  was  
271 calculated following Ball et al. (1987) as:

272 
$$g_s = g_o + m \frac{A^{*RH}}{C_s} \quad (10)$$

273 where  $g_o$  is the residual stomatal conductance as  $A$  tends to zero,  $m$  is a species-specific coefficient  
274 expressing the sensitivity of  $g_s$  to changes in  $A$ , and  $RH$  is the relative humidity at the leaf surface.

275 Medlyn et al. (2011) also assume that photosynthesis rate at each level in the canopy is the  
276 minimum of carboxylation and electron transport rate. The version incorporated into FORCAsT-gs is  
277 based on the parameterisations of Farquhar et al. (1980) for photosynthesis rate ( $A$ ;  $\mu\text{mol m}^{-2} \text{s}^{-1}$ ) in  
278 C3 plants such that:

$$279 \quad A = \min(A_j, A_c) - R_d \quad (11)$$

280 where  $R_d$  ( $\text{mol m}^{-2} \text{s}^{-1}$ ) is the leaf dark respiration.

281 Stomatal conductance ( $g_s$ ) is then modelled following optimisation theory (Medlyn et al., 2011)  
282 in which stomatal aperture is regulated to maximise carbon gain while simultaneously minimising  
283 water loss:

$$284 \quad g_s \approx g_o + \left(1 + \frac{g_1}{\sqrt{D}}\right) \frac{A}{C_s} \quad (12)$$

285 where  $g_o$  ( $\text{mol m}^{-2} \text{s}^{-1}$ ) is the residual stomatal conductance as  $A$  approaches zero and  $g_1$  is the slope of  
286 the sensitivity of  $g_s$  to changes in  $A$ .  $D$  (kPa) is the vapour pressure deficit and  $C_s$  ( $\mu\text{mol mol}^{-1}$ ) the  $\text{CO}_2$   
287 concentration at the leaf surface as before. The values of  $g_o$  and  $g_1$  are determined at the species or  
288 plant functional type (PFT) level from experimental data, and in this study were obtained from Lin et  
289 al. (2015) and De Kauwe et al. (2015). Values for each site are listed in Table S2.

290 The Jarvis model includes soil moisture stress as one of the factors limiting stomatal  
291 conductance. The relationship between SWC and  $g_s$  is modelled following Büker et al. (2015):

292

293    
$$f_{swc} = \begin{cases} 1 & \text{for } PAW_t \leq PAW \leq 1 \\ (1 - f_{min}) \frac{PAW}{PAW_t} + f_{min} & \text{for } 0 < PAW < PAW_t \end{cases} \quad (13)$$

294

295 where PAW is plant available water and is given by:

296    
$$PAW = \frac{\theta - \theta_w}{\theta_f - \theta_w} \quad (14)$$

297 where  $\theta$  is the volumetric soil water content (SWC,  $m^3 m^{-3}$ ),  $\theta_f$  and  $\theta_w$  are the SWC at field capacity  
298 and wilting point respectively, and  $PAW_t$  is a site-specific threshold of the fraction of water in the soil  
299 that is available to the plant estimated from site soil characteristics.

300        For both the Ball-Berry and Medlyn models, we assumed the effect of water stress on  
301 photosynthesis to be the result of biochemical limitations as demonstrated in previous studies (e.g see  
302 Egea et al., 2011). A soil moisture stress function ( $\beta$ ) was therefore applied to the maximum rate of  
303 RuBP carboxylation ( $V_{max}$ ) and the maximum rate of electron transport ( $J_{max}$ ) to reflect the impact of  
304 soil moisture deficit on plant gas exchange.  $\beta$  ranges between 1 (in the absence of water stress) to 0 (at  
305 wilting point) and is calculated based on soil water content following Porporato et al. (2001); Keenan  
306 et al. (2009); Keenan et al. (2010):

307        
$$\beta = \begin{cases} 1 & \text{for } \theta \geq \theta_c \\ \left[ \frac{(\theta - \theta_w)}{(\theta_c - \theta_w)} \right]^q & \text{for } \theta_w < \theta < \theta_c \\ 0 & \text{for } \theta < \theta_w \end{cases} \quad (15)$$

308 where  $\theta$  ( $m^3 m^{-3}$ ) is the volumetric soil moisture,  $\theta_w$  is the wilting point ( $m^3 m^{-3}$ ), and  $\theta_c$  is a critical  
309 soil moisture content above which water stress is found not to affect plant-atmosphere CO<sub>2</sub> and water  
310 vapour exchange (Egea et al., 2011). Porporato et al. (2001) reported a non-linear relationship between  
311 soil moisture deficit and limitation of plant physiological processes such as stomatal conductance and  
312 photosynthesis, encapsulated here by  $q$ , a site-specific empirical factor. The nature of the impact of  
313 drought stress on different plant species and at different sites (drought tolerance) can be varied by the

314 choice of value of  $q$  in model soil-moisture parameterisations. A more detailed derivation of  $q$  can be  
315 found in Porporato et al. (2001) and Keenan et al. (2010). In this study,  $q$  was based on observations  
316 at each site.

317 Photosynthesis and stomatal conductance are then estimated using the water-stressed values  
318  $V_{cmax^*}$  and  $J_{max^*}$ :

319 
$$V_{cmax^*} = V_{cmax} \times \beta \quad (16a)$$

320 
$$J_{max^*} = J_{max} \times \beta \quad (16b)$$

321 The Medlyn model further assumes direct limitation to stomatal conductance due to water stress  
322 following De Kauwe et al. (2015), such that stomatal conductance becomes:

323 
$$g_s \approx g_o + \left(1 + \frac{g_1 \beta}{\sqrt{D}}\right) \frac{A}{c_s} \quad (17)$$

324 These soil moisture stress functions are applied in all of the simulations conducted here.

### 325 2.3 FLUXNET sites and data

326 Five sites representative of the major forest biomes (tropical, temperate and boreal) have been  
327 used in this study. An overview of each site is given below with further information provided in Table  
328 S1 and Figure S1. The sites are all included in the FLUXNET2015 dataset which categorises each  
329 location by IGBP ecosystem type (Loveland et al., 2000).

330 We obtained hourly and half-hourly observations of PAR, air temperature, CO<sub>2</sub> concentration,  
331 volumetric soil water content, wind speed and direction, relative humidity and atmospheric pressure  
332 (Pa) from the FLUXNET2015 dataset. These data were used as driving data for FORCAsT  
333 simulations. The measured CO<sub>2</sub> from net ecosystem exchange (NEE) is partitioned into GPP and  
334 ecosystem respiration (Reco) using model parameterizations based on nighttime or daytime fluxes  
335 (Lasslop et al., 2010; Richstein et al., 2005). We use GPP estimated from nighttime fluxes

336 (GPP\_NT\_VUT\_REF) for model evaluation as this is a standard benchmarking protocol in the land  
337 surface modelling community (see e.g Harper et al., 2021; Otu-Larbi et al., 2020b). In this study, GPP  
338 is assumed to be zero in the absence of light. The methodology for estimating GPP and gap-filling of  
339 meteorological variables via Marginal Distribution Sampling (MDS) are fully described in Pastorello  
340 et al. (2020).

341 Ozone concentration data were obtained for IT-Cp2, FI-Hyy, and US-Blo but are not readily  
342 available for US-Ha1 or BR-Sa1 for the periods considered in this study (Table S1). For these sites we  
343 used reanalysis data from the Copernicus Atmospheric Monitoring Service (CAMS;  
344 <https://atmosphere.copernicus.eu>) which have been shown to reproduce observed tropospheric ozone  
345 to within 10% (see e.g. Inness et al., 2013; Wagner et al., 2021).

### 346 2.3.1 Santarém-Km67-Primary Forest (BR-Sa1)

347 BR-Sa1 is in Amazonian Brazil and consists of primary forest comprising a wide range of tree  
348 species of varied ages, epiphytes, and high numbers of decaying logs. A flux tower, which was  
349 established in 2000 for the Large-scale Biosphere-Atmosphere (LBA) experiment (Rice et al., 2004)  
350 is sited on a large level plateau with forest cover stretching 5-40 km in all directions (Goulden et al.,  
351 2004). There is closed-canopy forest to an average height of 40 m within the footprint of the flux tower,  
352 with numerous emergent trees up to 55m in height (Rice et al., 2004).

353 Figure 1 shows volumetric soil moisture and meteorological data from BR-Sa1 (yellow line)  
354 for an average annual profile. The site is categorised as Tropical Evergreen Forest and has a hot humid  
355 tropical environment with average rainfall of 1920 mm y<sup>-1</sup> and annual average temperature of ~25°C,  
356 with little diurnal or seasonal variability (Rice et al., 2004).

357 The clay soil has little organic content and retains water well. Soil moisture is not routinely  
358 measured at BR-Sa1 and we use data from a nearby site (BR-Sa3 at the 83 km marker) located in the  
359 same area of forest. A selective logging experiment commenced at BR-Sa3 shortly after the main LBA

360 campaign and has continued to this day. Less than 5% of aboveground biomass is removed each time,  
361 leaving only small gaps between areas of closed-canopy forest (Goulden et al., 2004). Soil moisture at  
362 5 cm depth at BR-Sa3 responds quickly to precipitation, ranging between ~0.30-0.47 m<sup>3</sup> m<sup>-3</sup>. At a  
363 depth of 250 cm, there is little variation with soil moisture relatively constant at ~0.46 m<sup>3</sup> m<sup>-3</sup> during  
364 the wet season, declining gradually to ~0.42 m<sup>3</sup> m<sup>-3</sup> by the end of the dry season (Rice et al., 2004).

### 365 2.3.2 Hyytiälä (FI-Hyy)

366 FI-Hyy is located in the sub-boreal climate zone at the SMEAR II (Station for Measuring  
367 Ecosystem-Atmosphere Relation) boreal forest research station at Hyytiälä, ~220km NW of Helsinki  
368 (Hari and Kulmala, 2005; Rinne et al., 2007). The 73-m flux tower is situated on relatively level  
369 ground, surrounded by predominantly uniform age (~60-year-old) Scots pine (*Pinus sylvestris*) with  
370 an average canopy height of 14 m (Hari and Kulmala, 2005; Suni et al., 2003).

371 Figure 1 shows volumetric soil moisture and meteorological data from FI-Hyy (blue line) for  
372 an average year. The site is categorised as Boreal Evergreen Forest with climatological (1959-2014)  
373 average annual temperature of 3.5°C and precipitation of 693 mm y<sup>-1</sup> falling predominantly as snow  
374 during the winter months (Suni et al, 2003; SMEARII, 2021). Average monthly temperatures range  
375 between -7.7 °C in February, and 16 °C in July (SMEARII, 2021). Prevailing winds are SSW and are  
376 generally moderate, with average annual windspeed of ~2.8 m s<sup>-1</sup> and maximum of 14 m s<sup>-1</sup>  
377 (SMEARII, 2021). The soil comprises sandy and coarse silty glacial till (Suni et al., 2003). Soil  
378 moisture peaks at >0.45 m<sup>3</sup> m<sup>-3</sup> after snow melt and drops to ~0.30 m<sup>3</sup> m<sup>-3</sup> or lower during occasional  
379 summer droughts.

### 380 2.3.3 Castelporziano (IT-Cp2)

381 IT-Cp2 is located at Grotta di Piastra within the Presidential Estate at Castelporziano, on the  
382 Thyrrenian coast ~25 km SW of Rome. The 6000 ha Estate has been used for environmental research  
383 since 1951 with a flux tower first installed in 1996. The current tower is ~20 m tall and surrounded

384 almost exclusively by even-aged Holm oak (*Quercus ilex*) of average ~14 m height (Fares et al., 2019).  
385 This is a typical macchia species, well-adapted to an environment characterised by hot dry summers  
386 and nutrient-poor sandy soils (Fares et al., 2009).

387       Figure 1 shows volumetric soil moisture and meteorological data from IT-Cp2 (red line) for an  
388 average year. The site is categorised as Temperate Evergreen Forest and has a Mediterranean  
389 environment with an average rainfall of 745 mm  $y^{-1}$  of which <100 mm  $y^{-1}$  falls in the summer months  
390 (May-early September). Between 1996-2011, mean monthly temperatures ranged between 8.4-24.7°C,  
391 with a maximum temperature of 30.3 °C and minimum of 5.0 °C recorded in August and February  
392 respectively (Fusaro et al., 2015).

393       The soil is sandy and freely draining. Soil moisture is thus highly variable and tightly coupled  
394 to precipitation events. Soil moisture averaged over a depth of 10-50 cm ranges from ~5% at the end  
395 of the summer drought period to ~32% during the winter (Fares et al., 2019).

### 396 2.3.4 Blodgett Forest (US-Blo)

397       US-Blo is located in a uniform-age Ponderosa pine plantation in the Sierra Nevada mountain  
398 range on the western coast of the continental USA. The plantation was established in 1990 and a 15-  
399 m flux tower, which has been the site of long-term monitoring and numerous intensive field campaigns,  
400 erected in 1997 (Goldstein, 2000). The average height of the canopy is ~9 m (Park et al., 2014).

401       Figure 1 shows volumetric soil moisture and meteorological data from US-Blo (black line) for  
402 an average year. The site is categorised as Temperate Evergreen Forest with a Mediterranean climate.  
403 Annual average precipitation is ~1630 mm  $y^{-1}$  with little rain during the summer months (May-early  
404 September). Average daily temperatures range between 17-24 °C in the summer, and 0-9 °C in the  
405 winter (Goldstein, 2000).

406        The soil is predominantly free draining loam, and soil moisture tracks precipitation (Goldstein,  
407        2000). Average soil moisture at a depth of 10-20 cm ranges from  $\sim 0.10 \text{ m}^3 \text{ m}^{-3}$  during summer droughts  
408        to just below  $0.35 \text{ m}^3 \text{ m}^{-3}$  in the winter.

409        **2.3.5 Harvard Forest (US-Ha1)**

410        US-Ha1 is located within a  $\sim 1600$  ha area of old-growth (75+ years) mixed forest in NE USA  
411        that has been the site of long-term ecological and environmental monitoring since 1907. A 30-m flux  
412        tower was erected in 1990 and has been used for continuous measurements and summer field  
413        campaigns since (Goldstein et al., 1998; McKinney et al., 2011). The average height of the canopy is  
414         $\sim 24$  m (Clifton et al., 2019)

415        Figure 1 shows volumetric soil moisture and meteorological data from US-Ha1 (grey line) for  
416        an average year. The site is categorised as Temperate Deciduous Forest with the footprint of the tower  
417        dominated by red oak (*Quercus rubra*) and red maple (*Acer rubrum*), although there are a number of  
418        red and white pines (*Pinus resinosa* and *P. strobus*) to the NW of the tower (Clifton et al., 2019).  
419        Annual average precipitation is  $\sim 1000 \text{ mm y}^{-1}$  and is relatively evenly distributed through the year.  
420        Average daily temperatures range between  $\sim 20^\circ\text{C}$  in the summer and  $\sim 1^\circ\text{C}$  in the winter. The soil  
421        around the flux tower is a sandy loam (Allen, 1995). Soil moisture typically ranges from  $\sim 0.25\text{-}0.55$   
422         $\text{m}^3 \text{ g}^{-3}$ , but can drop below  $0.20 \text{ m}^3 \text{ m}^{-3}$  during (infrequent) drought years (Clifton et al., 2019).

423

424        **2.4 Simulations**

425        LAI can be estimated by FORCAsT-gs but here we use in-situ or remote sensing observations.  
426        Forests are classified as evergreen if at least 80% of the trees maintain their leaves throughout the year  
427        (Sasaki et al., 2016). Thus, we use fixed LAI values obtained from site measurements for BR-Sa1,  
428        IT-Cp2, FI-Hyy and US-Blo. For the temperate deciduous forest (US-Ha1) we use in-situ observations.

429 Stomatal conductance, photosynthesis rate (instantaneous fluxes of CO<sub>2</sub>) and deposition  
430 velocity are calculated for each leaf angle class (9 sunlit and 1 shaded) for each foliage-containing  
431 level within the canopy in FORCAsT-gs using each of the three physiological approaches outlined in  
432 Section 2.2. These are then weighted by leaf angle fraction and leaf area distribution at each level and  
433 summed over all model layers to obtain canopy-scale conductance, photosynthesis rates (canopy-top  
434 fluxes of CO<sub>2</sub>) and deposition velocity.

435 During preliminary model configuration at each site, site-specific phenological and canopy  
436 structure were set to best fit modelled to observed GPP. However, the physiological parameters used  
437 in each of the three coupled stomatal conductance-photosynthesis algorithms were set to average  
438 values reported from previous studies in-situ at similar ecosystems or in controlled environments.  
439 These semi-optimised configurations provided our baseline simulations at each site (hereafter referred  
440 to as BASE).

441 To determine the sensitivity of the model to perturbations in the physiological parameters,  
442 which are mostly derived from controlled environment experiments, and to provide uncertainty bounds  
443 for our estimates of GPP and ozone deposition rates, we conducted a series of sensitivity tests. Only  
444 parameters with a direct relationship to stomatal conductance were used in these sensitivity tests to  
445 ensure consistency in approach.

446 In the Jarvis multiplicative model, average values of  $g_{max}$  for specific plant functional types are  
447 typically used, but Hoshika et al. (2018) found variations of up to 70 % between the upper and lower  
448 bounds of  $g_{max}$  and the mean for different PFTs. Here, we use the mean values for different forest  
449 ecosystems for baseline simulations (JV) and the upper and lower bounds as JV+ and JV- respectively  
450 (Table S3).

451 For the Ball-Berry coupled stomatal conductance-photosynthesis model, the coefficient  $m$   
452 (Eqn. 10) describing the relationship between stomatal conductance and photosynthesis typically

453 ranges between 9 and 12. We use these as our lower (BB-) and upper (BB+) bounds, with the baseline  
454 (BB) set to a value of 10. See Table S3 for further details of parameter settings.

455 The equivalent coefficient,  $g_I$  (Eqn. 12), is tested in the Medlyn optimisation model. We take  
456 the upper (MD+) and lower (MD-) bounds of  $g_I$  as reported by De Kauwe et al. (2015) and Lin et al  
457 (2015) for different forest ecosystems with error margins of 2-10%. Our baseline simulations (MD)  
458 use the average value for each site. Further details of parameter settings are given in Table S3.

459 At the end of the simulation period, average annual and diel profiles of total canopy  
460 photosynthesis were calculated and compared with observed GPP. To assess the relative performance  
461 of each model at each of the five sites, we define a single summary statistic that encompasses the three  
462 key model performance indicators for temporal trends (correlation), absolute values (cRMSE) and  
463 variability (normSD) in a single value. As all three elements are important in evaluating overall model  
464 skill, we use a simple combination assigning the same weight to each. This summary statistic is  
465 calculated as:

$$466 \quad \text{Summary} = cRMSE \times (1.0 - r^2) \times |normSD - 1.0| \quad (18)$$

467 where  $r^2$  is the coefficient of determination, normSD is the normalised standard deviation and cRMSE  
468 is the centred root mean square error. The closer this value is to zero, the closer the model fits the  
469 observations.

470

471

472 3      **Results**

473 3.1    **BASE**

474        We first evaluate the skill of each of the three stomatal conductance-photosynthesis models to  
475 reproduce the average diel and annual profiles of GPP at each site for the time periods shown in Table  
476 S1. The BASE simulations presented here use the parameter values given in Table S2.

477        As shown by the orange lines on Figure 2, the multiplicative stomatal conductance model (JV)  
478 reproduces the seasonal variation in GPP at all sites except for BR-Sa1, although it substantially  
479 overestimates seasonal GPP at the three broadleaf forests (BR-Sa1, IT-Cp2 and US-Ha1) and  
480 underestimates at the Boreal needleleaf forest (FI-Hyy). At BR-Sa1, JV overestimates GPP by a factor  
481 of 1.5-2. At IT-Cp2 and US-Ha1, however, while JV overestimates GPP by 50-100% in spring and  
482 summer it performs well in the rest of the year. For FI-Hyy, JV consistently underestimates  
483 productivity from summer through to early autumn, by a factor of 2. However, the model reproduces  
484 GPP at US-Blo, which is also a needleleaf forest, to within 20% of the observations at all times of the  
485 year. This suggests that the phenology of Boreal ecosystems is not well-captured.

486        The diel profiles of modelled GPP using JV follow a similar inter-site pattern to that of the  
487 seasonal profile with overestimation of diurnal GPP at BR-SA1, IT-Cp2 and US-Ha1 by 5-200%, and  
488 underestimation of ~75% at FI-Hyy. The coupled stomatal conductance-photosynthesis model (BB)  
489 reproduces the observed seasonality and magnitude of GPP within 10-50% at all but the tropical BR-  
490 Sa1 ecosystem as shown by the brown lines on the first column of Figure 2. BB underestimates summer  
491 GPP at FI-Hyy by 30% but overestimates GPP at IT-Cp2 by a similar margin in the summer when  
492 seasonal drought occurs. It closely matches observed GPP throughout the season at US-Blo and US-  
493 Ha1 with <10% variation between model estimates and observations. Although BB overestimates GPP  
494 by as much as 50% at BR-Sa1 throughout the year, it outperforms both JV and MD at this site.

495        The diurnal profile of GPP estimated by BB confirms its superior performance at the tropical  
496 site BR-Sa1, with modelled GPP closely matching the observations during the day. The diurnal profile

497 at the other sites shows that BB underestimates GPP by ~5% in the early hours of the day at FI-Hyy  
498 and IT-Cp2 but tends to overestimate GPP by ~20% in the later afternoon. Output from the Medlyn  
499 model (MD) is shown in blue in Figure 2. While MD follows the seasonal fluctuation of GPP at BR-  
500 Sa1, estimated fluxes are a factor of ~1.5 higher than observations throughout the year. This  
501 overestimation of GPP at the tropical site is also apparent in the profile over the course of an average  
502 day. By contrast, at the two Mediterranean sites, MD reproduces both the observed seasonal and  
503 diurnal profile of GPP and is within 20% of the observed values at any time during the year or day.  
504 MD also shows excellent agreement with both the magnitude and timing of observed GPP throughout  
505 the year at FI-Hyy but overestimates the average diurnal profile of GPP by ~20%. MD performs best  
506 at the temperate deciduous forest site, US-Ha1, where there is <5% between model estimates and  
507 observations across both the year and day.

508 The superior performance of MD across sites is confirmed by the Taylor diagrams in Figure 3 and the  
509 summary statistics in Table S4. MD exhibits high correlation (0.56-0.98), and low deviation (1.01-  
510 1.92) and error (0.90-3.03). Summary statistics ranging between 0.0003 and 1.25 confirm it as the best  
511 performing model overall. As shown by the summary statistic in Table S4, which ranges between 0.01  
512 and 0.99, BB outperforms JV at all sites. As summarised by the Taylor diagram in Figure 3, BB's  
513 performance is better than that of JV, with cRMSE of 1.07 - 2.47,  $r^2$  of 0.85-0.97 (excluding BR-Sa1)  
514 and normSD of 0.80-1.82. The summary statistics for JV range from 0.02 at US-Blo where JV  
515 performs well at reproducing observed GPP to 28.86 at BR-Sa1 where it overestimates both seasonal  
516 and diurnal profile of GPP. Seasonal cRMSE ranging between 1.24-10.64, normSD between 0.40-  
517 3.72 and  $r^2$  as low as 0.01 at BR-Sa1, further confirms the relatively poor performance of JV. These  
518 results show that MD provides the best estimates of GPP at four of the five forest sites used in this  
519 study (FI-Hyy, IT-Cp2, US-Blo and US-Ha1) while BB was the overall best performer at BR-Sa1. JV  
520 was the least skilful of the three models, substantially overestimating GPP at BR-Sa1, IT-Cp2, US-

521 Ha1 and underestimating at FI-Hyy. All three models were most successful in reproducing observed  
522 GPP at the temperate deciduous forest, US-Ha1, and poorest at the tropical forest, BR-Sa1.

523 **3.2 Sensitivity of stomatal conductance to model parameters**

524 The BASE simulations used mid-range values for species-specific parameters  $g_{max}$  (JV; Eqn. 5),  $m$   
525 (BB; Eqn. 10), and  $g_l$  (MD; Eqn. 12). As described in Section 2.4, we carried out sensitivity tests using  
526 lower and upper bound estimates for these parameters. Here we analyse the effect that these parameter  
527 changes have on estimated photosynthesis rates for each of the three models, identifying similarities  
528 and differences in responses between sites and providing an estimate of uncertainty bounds for GPP  
529 and stomatal conductance in each case.

530

531 **3.2.1 JV**

532 The plant species-specific theoretical maximum value of canopy stomatal conductance for  
533 water vapour ( $g_{max}$ ; Eqn 5) is central to the performance of the JV model in reproducing observed plant  
534 gas exchange. Changes in  $g_{max}$  lead to proportional changes in both stomatal conductance (Figure S4)  
535 and GPP (Figure 4) at all sites. In general, decreasing  $g_{max}$  to its lower limit causes up to a factor of 2  
536 reduction in GPP depending on the site, while an increase to the upper bound increases GPP by similar  
537 magnitudes.

538 At the tropical and temperate forests (BR-Sa1, IT-Cp2, US-Blo and US-Ha1) where JV over-  
539 estimates GPP, using instead the lower limit of  $g_{max}$  (JV-) provides the best model-observation fit in  
540 both seasonal and diel cycles at BR-Sa1, but substantially underestimates GPP at IT-Cp2, US-Blo and  
541 US-Ha1.

542 By contrast, at FI-Hyy, where JV underestimates GPP, the use of the upper bound of  $g_{max}$  (JV+)  
543 reduced, but does not completely overcome, model underestimation through the seasons or over the  
544 course of an average day. JV+ modelled GPP was around half to two-thirds of observed fluxes, a  
545 substantial improvement on the factor of 2 underestimations in JV.

546 As shown by the Taylor plots presented in Figure 3, and Table S4, both normalised SD and  
547 centred RMSE are substantially increased in JV-. While this is a major improvement in overall model  
548 performance at BR-Sa1 (with cRMSE reduced from 10.6 in JV to 2.36 in JV-), JV- substantially  
549 worsens model fit at all the other sites. JV+ exacerbates the tendency to overestimate across all sites,  
550 with summary statistics increasing to 0.22-87.40. The correlation coefficient between modelled and  
551 measured GPP is unchanged as it essentially summarises the temporal fit.

552

553

### 554 3.2.2 BB

555 For the BB parameterisation, stomatal conductance and net photosynthesis rate are explicitly  
556 linked and solved simultaneously. Variations in species-specific response parameters therefore directly  
557 affect both  $g_s$  and GPP. Similarly to JV, the upper bound increases and lower bound reduces flux  
558 estimates compared to the baseline.

559 In BB, increasing  $m$ , i.e. the change in photosynthesis rate for a given change in stomatal  
560 conductance, results in proportionally larger increases in GPP than the decreases resulting from  
561 reducing  $m$ . GPP is slightly over-estimated by BB at all sites (except during the summer months at FI-  
562 Hyy where modelled fluxes are lower than observed). BB- therefore provides a better fit to observed  
563 GPP across all sites except FI-Hyy where BB+ performs better. It should be noted however, that  
564 changes in GPP (0.5-1.0%) are considerably smaller than those observed for JV between the upper  
565 and lower bound simulations.

566 This is further corroborated by the Taylor diagrams (Figure 3) summarising the average, upper  
567 and lower bound simulations. Across all sites, there is little change in correlation between estimated  
568 and observed GPP, reflecting the minor changes in temporal profile. NormSD also remains virtually  
569 unchanged between simulations for GPP fluxes (~1.0 at US-Blo and US-Ha1, ~0.8 at FI-Hyy and ~2.0  
570 at IT-Cp2). cRMSE is consistently low for all simulations at the extra-tropical sites (~1.0-1.2 for GPP

571 at US-Blo and FI-Hyy, and 1.4-1.8 at IT-Cp2 and US-Ha1), indicating the relatively good match to  
572 absolute values. By contrast, cRMSE remains high (>2.5) at the tropical rainforest site, BR-Sa1, where  
573 a high normSD and low correlation coefficient also confirm the poor performance of the model at  
574 capturing both the magnitude and temporal variations in GPP at this ecosystem. The BASE simulation  
575 of BB provides the closest fit to observed GPP at BR-Sa1.

576

### 577 3.2.3 MD

578 Similarly to BB, changes in  $g_l$  in MD result in very small changes in estimated GPP. At the  
579 two Mediterranean sites (IT-Cp2 and US-Blo) where GPP is overestimated in the baseline (MD)  
580 simulations, MD- provides a closer fit to observations (Figure 3) although the change is only ~1%.  
581 Changes in  $g_l$  have a negligible effect on GPP at BR-Sa1, FI-Hyy or US-Ha1 (Figure 3), where  
582 droughts are rare and there is less need for plants to conserve water, i.e. where there is less conflict  
583 between maximising photosynthesis and minimising transpiration.

584 As shown in the Taylor diagrams (Figure 3), increasing the value of  $g_l$  from the average to the  
585 upper bound improves the correlation between estimated and observed GPP at US-Blo, while  
586 decreasing the value improves the fit slightly at IT-Cp2. As suggested by the temporal profiles, there  
587 is no noticeable change in correlation at BR-Sa1, FI-Hyy or US-Ha1. The normSD for GPP are very  
588 close to 1.0 (i.e. a perfect fit to observations) and centred RMSE <0.5 at FI-Hyy, US-Ha1 and US-Blo  
589 but near 2.0 and 1.0 respectively at IT-Cp2, again likely a result of the severity of droughts at  
590 Castelporziano, where water conservation is a key driver of stomatal conductance. All three statistics  
591 remain poor at BR-Sa1, where  $r^2$  remains virtually unchanged at ~0.6, normSD at 2.0, and cRMSE at  
592 ~1.8 for all values of  $g_l$ . Considering the relatively small changes observed in GPP in response to  
593 changes in  $g_l$ , we conclude that the mean values of  $g_l$  are sufficient for estimating stomatal  
594 conductance and GPP using the Medlyn model at these sites.

595

596 **3.2.4 Summary of sensitivity tests**

597 As shown in Figures 3 and 4, and Table S4, GPP estimates in JV were more sensitive to  
598 variations in  $g_{max}$  than BB and MD estimates were to  $m$  and  $g_l$ , respectively. However, modelled GPP  
599 does not vary by the same magnitude as the variation in model parameters. For instance, modelled  
600 GPP values in JV- and JV differ from BASE (JV) estimates by as much as 100% in response to up to  
601 60% variation in  $g_{max}$  causing substantial differences in model output statistics (Figure 3 and Table S4).  
602 GPP estimates using upper and lower bounds of  $m$  (BB) and  $g_l$  (MD) only differ by 1-5% in response  
603 to a 10-20% change in the model parameterisation. It must be noted that these sensitivity tests only  
604 focus on stomatal conductance parameters in all three models. Tests conducted on photosynthetic  
605 parameters such as  $V_{cmax}$  and  $J_{max}$  have shown a greater difference in estimated GPP compared to what  
606 we find here (e.g see Fares et al., 2019) but do not have an equivalent in JV.

607

608 **3.3 Stomatal conductance**

609 As the three physiology models in FORCAsT-gs explicitly couple photosynthesis and stomatal  
610 conductance, we now assume that the parameterisation that best represents GPP (as a proxy for  
611 photosynthesis) at each of the sites also best captures fluctuations in stomatal aperture. Figure 5  
612 presents the performance of the models at each site relative to the stomatal conductance or ozone  
613 deposition rate simulated by the best-performing model.

614 The first and second columns of Figure 5 show the average seasonal and diurnal profiles of  
615 stomatal conductance at each site with that estimated by the best performing model shown as a black  
616 line (i.e. assumed as “truth”). The grey shading indicates the full range of stomatal conductance  
617 estimated by the various model configurations.

618 At the tropical site, BR-Sa1, the BB model, which best captures GPP, is taken to represent  
619 observed stomatal conductance. Stomatal conductance estimated with the model that has the lowest  
620 GPP estimates (JV-) is ~75% lower while the configuration with the greatest overestimation of GPP

621 (JV+) is ~ 25% higher. The difference between the models remains almost constant throughout the  
622 year at this tropical site. The divergences in stomatal conductance at FI-Hyy, IT-Cp2, US-Blo and US-  
623 Ha1 are seasonal. For these sites, MD- is used to represent observed  $g_s$  due to its lower summary  
624 statistics shown in Table S4. The difference between the models that over or underestimate GPP is  
625 <30% in the winter and spring and increases rapidly to >100% at IT-Cp2 and US-Blo in the summer,  
626 and >200% at FI-Hyy and US-Ha1.

627 The diel profile of stomatal conductance between the best and worst performing models is  
628 similar to the seasonal profile observed at each site. As shown by the second columns of Figure 5, BR-  
629 Sa1, IT-Cp2 and US-Blo show the widest variation in modelled stomatal conductance between the  
630 different model configurations during peak periods of the day. There is about 10% overestimation of  
631 peak daytime stomatal conductance values at FI-Hyy and US-Ha1 between the best and overestimating  
632 model configurations. On the contrary, the models that underestimate GPP at these sites (JV-) also  
633 underestimate stomatal conductance by and >50%.

634

### 635 3.4 Ozone deposition

636 The differences in simulated stomatal conductance between configurations of FORCAsT-gs  
637 affect estimated ozone deposition velocity and hence the rate at which ozone is lost to this key sink.  
638 Figure S6 shows the seasonal and diel profiles of variations in ozone deposition velocity between the  
639 models. The tropical site, BR-Sa1, and the temperate broadleaf forest, US-Ha1, have the highest  
640 estimated ozone deposition velocities as expected from their higher  $g_s$  compared to the other sites. This  
641 higher  $g_s$  and hence ozone deposition velocities are likely due to the fact that plants in these forests  
642 also have bigger leaf sizes and higher leaf area index – highlighting the role of forest structure and  
643 characteristics in plant physiological processes (Meyers & Baldocchi, 1988; Padro, 1996).

644 The deposition velocity is however dependent on several resistances as shown in Eqn. 3,  
645 including the stomatal resistance (the inverse of  $g_s$ ). As a result, the models that overestimate GPP and

646  $g_s$  do not necessarily overestimate seasonal deposition velocity when compared to the best performing  
647 model across all sites. However, the model configurations that underestimate GPP and  $g_s$  also  
648 underestimate seasonal ozone deposition velocity, although to a lesser extent. For example, JV-  
649 underestimates GPP and  $g_s$  by a factor of two during the peak growing season but only underestimates  
650 deposition velocity by ~15%, with an average value of  $0.36 \text{ cm s}^{-1}$  compared with  $0.42 \text{ cm s}^{-1}$  estimated  
651 with the best performing model (MD). Similarly, at the tropical site, the average deposition velocity  
652 in the optimal model configuration (BB) is  $0.88 \text{ cm s}^{-1}$ . These deposition velocity estimates are similar  
653 to those found in other studies for similar ecosystems and PFTs (e.g. Hardacre et al., 2015; Silva and  
654 Heald, 2018). This value is 13% higher than the average deposition velocity in JV- which  
655 underestimates GPP and 6% lower than that of JV+ which overestimates GPP.

656 The variation between modelled deposition velocities at FI-Hyy, IT-Cp2 and US-Blo between  
657 the model configurations is similar to those described for BR-Sa1 and US-Ha1 although the absolute  
658 values are smaller. The only exception here is at IT-Cp2 where JV+ overestimates deposition velocity  
659 in the summer just as it did for GPP and  $g_s$ . The model divergence in diel profile of ozone deposition  
660 velocity exhibits similar variability to that of the seasonal profile.

661 The seasonal changes in deposition velocity are also very different to that of  $g_s$  at their  
662 respective sites. Ozone deposition velocities at BR-Sa1, IT-Cp2 and US-Ha1, show the greatest  
663 variations, ranging between <5% and ~30% for model configurations that over or underestimate GPP  
664 respectively, relative to the model configuration that produces the best summary statistics for each site,  
665 as defined by Equation 18 and summarised in Table S4. The two needleleaf forests, FI-Hyy and US-  
666 Blo show the least variation in seasonal deposition velocities of <10%.

667 As shown in Eqn. 4, ozone deposition rates depend on ozone concentration as well as  
668 deposition velocity. Hence, while the differences estimated in deposition velocity would be expected  
669 to produce changes in ozone deposition rates at the study sites, they will not be directly proportional.

670       Figure S7 shows average ozone concentrations for each study site for the relevant simulation  
671      periods. As ozone is produced through photochemical processes concentrations at all sites peak during  
672      the spring and summer and decline steadily in the autumn and winter.

673       Figures 5, S8, and S9 show that the seasonal variation in ozone deposition rate closely follows  
674      the seasonal variation in ozone concentration at all sites. On the contrary, the diel profile of ozone  
675      deposition differs from that of the concentration. While ozone concentrations at all sites peak in the  
676      late afternoon or early evening, deposition rates are highest just after midday when  $g_s$  and deposition  
677      velocity are at a maximum. This clearly indicates that deposition velocity, and hence stomatal  
678      conductance, is the key determinant of deposition rates on shorter timescales, while atmospheric ozone  
679      concentrations drive longer temporal trends. The greatest variations in seasonal and diurnal deposition  
680      rates between different model configurations, indicated by the grey shaded areas on Figure 5, are  
681      observed at FI-Hyy and US-Ha1, as for the deposition velocities.

682       The diel profile of ozone deposition rates, and their variations due to changes in stomatal  
683      conductance parameterisations, are similar to those of the deposition velocities (Figure S6). Variations  
684      in deposition rates estimated by JV+ which overestimates GPP and stomatal conductance, and the best-  
685      fit models averaged 0.10% - 10% across sites. Figures S8 and S9 show that ozone deposition rates  
686      estimated with JV are more sensitive to changes in model parameters with variations of up to 20%  
687      observed between different JV configurations. MD and BB ozone deposition rates are less sensitive  
688      to model parameters with variations of less than 5% observed between BASE simulations and those  
689      using and upper and lower limits of  $g_1$  and  $m$  (Figure S8).

690       The seasonal variations observed in deposition rates are much lower than the variations in  
691      either stomatal conductance or deposition velocity across all sites. There is only ~1% variation between  
692      seasonal ozone deposition rates in model configurations which overestimate GPP and the best  
693      performing model across sites, apart from IT-Cp2 where deposition rate varies by ~5% in the summer.  
694      Seasonal deposition rates estimated by model configurations with the lowest GPP are 7-13% lower

695 than those estimated with the best performing model configurations (Figure 5). By contrast, modelled  
696 stomatal conductance and deposition velocities vary by up to 100% and up to 30% respectively for  
697 these same model configurations (Figure 5), confirming the modulating effect of ozone concentrations.

698 The role of ozone concentrations in determining ozone deposition rates is exemplified at BR-  
699 Sa1. Average  $g_s$  and deposition velocity are a factor of two higher at this site than US-Ha1 which has  
700 the next highest values. However, the average ozone deposition rates at BR-Sa1 are approximately the  
701 same as those at US-Ha1 ( $0.18 \text{ ppb cms}^{-1}$ ). This is due to lower average ozone concentrations at BR-  
702 Sa1 (20 ppb) compared to US-Ha1 (43 ppb).

703

704 4      **Discussion and Conclusion**

705            We have found that ozone deposition rates estimated using stomatal conductance simulated by  
706   two of the most widely-used stomatal conductance-photosynthesis models can vary by as much as  
707   10% depending on ecosystem, season and time of day. As dry deposition is the primary sink for  
708   tropospheric ozone, this has potentially significant implications for estimated ozone budgets across  
709   space and time. Stomatal conductance and GPP estimated using the Jarvis multiplicative model appear  
710   particularly sensitive to the choice of model parameters whereas estimates made using Ball-Berry and  
711   Medlyn coupled stomatal conductance-photosynthesis models exhibit less variability.

712            By introducing the Jarvis, Ball-Berry and Medlyn parameterisations of stomatal conductance  
713   and photosynthesis into FORCAsT1.0, a 1-D column model of trace gas exchange between a forest  
714   canopy and the atmosphere (Ashworth et al. 2015; Otu-Larbi et al., 2020a, 2020b), we were able to  
715   evaluate the performance of the three physiological models via comparison of simulated  
716   photosynthesis with long-term measurements of gross primary productivity (GPP) taken from the  
717   FLUXNET2015 dataset (Pastorello et al., 2020). We find that all three models reproduce the seasonal  
718   and diel variations in GPP well at a range of forest types, Boreal evergreen (FI-Hyy), Temperate  
719   deciduous (US-Ha1), and Mediterranean evergreen (IT-Cp2 and US-Blo), but struggle to capture  
720   seasonality at a Tropical broadleaf evergreen site (BR-Sa1).

721            As shown in Figures 2 and 4, the Medlyn stomatal optimisation model provides the best overall  
722   performance at four of the five FLUXNET sites used in this study (FI-Hyy, IT-Cp2, US-Blo and US-  
723   Ha1), with estimates of GPP within 20%, but is out-performed by the Ball-Berry coupled stomatal  
724   conductance-photosynthesis model at BR-Sa1. The superior performance of MD compared to BB at  
725   could be expected as MD was specifically developed as an improvement on BB to optimise carbon  
726   gain while limiting water loss (Medlyn et al., 2011). Except for US-Blo, where JV reproduces the  
727   observed annual and diel profiles of GPP to within 20%, the Jarvis multiplicative model either  
728   substantially overestimates or underestimates GPP by as much as a factor of two. The relatively poor

729 performance of JV in reproducing observed GPP is perhaps not surprising since photosynthesis  
730 estimates are based on a simple assumption of a linear relationship between stomatal conductance and  
731 carbon assimilation (Eqn.6).

732 The superior performance of the Medlyn optimisation model in the two Mediterranean climates  
733 could also be due to the fact that vegetation response to soil moisture stress is better accounted for  
734 through a combination of stomatal and biochemical limitations (e.g. see De Kauwe et al., 2015; Lin et  
735 al., 2015; Otu-Larbi et al., 2020). BB, by comparison, assumes that drought stress directly  
736 downregulates photosynthesis rates or is the result of biochemical limitation only (e.g see Best et al.,  
737 2011; Clark et al., 2011; Fares et al., 2019). This finding is supported by previous work which shows  
738 that the choice of drought stress parameterisation is an important factor that determines model  
739 performance in a water stressed environment (Egea et al., 2011; Keenan et al., 2010).

740 The poor performance of the models at the tropical evergreen site (BR-Sa1) is likely due to the  
741 assumption of a uniform forest structure for this evergreen forest site throughout the year.  
742 Subsequently,  $f_{phen}$  in JV (Eqn. 5) is set to a value of 1 and constant LAI is used in estimating  
743 photosynthetic capacity in BB and MD models. A modelling study by Flack-Prain et al. (2019)  
744 indicates that changes in LAI could account for up to 33% of observed variations in Amazonian forest  
745 GPP. This suggests the need for an improved understanding of changes in forest structure and  
746 phenology in tropical ecosystems to obtain more accurate model estimation of GPP at this and other  
747 tropical sites (Rödig et al., 2018). In addition, photosynthetic rates and stomatal conductance are  
748 controlled by solar radiation and temperature and limited by stress factors like drought and air  
749 pollutants including ozone (Nemani et al., 2003). For BR-Sa1, both temperature and PAR (Figure 1a  
750 and b; orange lines) remain fairly constant throughout the year which would lead to higher modelled  
751 photosynthetic capacity in BB and MD since modelled  $V_{cmax}$  and  $J_{max}$  are reliant on temperature.  
752 Seasonal variations in  $V_{cmax}$  and  $J_{max}$  are reported to be a major source of uncertainty in GPP estimates  
753 in Amazonian forests (Flack-Prain et al., 2019). It is worth noting that US-Blo and IT-Cp2 which are

754 also evergreen forest, are treated similarly, but as shown in Figures 2 and 4, the models perform better  
755 at these sites, perhaps due to a compensating error in modelling drought stress.

756 Results from sensitivity tests conducted on key stomatal conductance parameters in JV, BB  
757 and MD models reveal that modelled GPP and stomatal conductance values are highly sensitive to the  
758 choice of conductance parameters. Variations of ~5-75% from base model estimates are observed in  
759 modelled GPP and stomatal conductance in response to ~10-60% variation in model parameters. Such  
760 wide differences could reduce the reliability of estimated reductions in crop or plant productivity due  
761 to air pollutants such as ozone.

762 The findings from this study make it imperative that more measurements of these key  
763 conductance parameters are made to improve understanding and model representation of dry  
764 deposition. The Jarvis model shows greater sensitivity to choice of parameter values than either Ball-  
765 Berry or Medlyn. It must be noted that the Jarvis parameter  $g_{max}$  is typically measured in sunlit leaves  
766 at the top of the canopy. Leaves below the canopy often differ in their shape and leaf angle from those  
767 at the top of the canopy (Niinemets, 2010). The JV model as implemented in FORCAsT and elsewhere  
768 assumes the same  $g_{max}$  for all angle classes and model levels. More work is needed to improve the  
769 parameterisation of variations in  $g_{max}$  for different levels in the canopy and leaf angle classes.

770 We conclude that the Medlyn coupled stomatal conductance-photosynthesis model would be  
771 the best default selection. However, our model simulations also point to the need for improved stomatal  
772 conductance-photosynthesis model parameterisations for tropical ecosystems where seasonality is  
773 driven by contrasts in precipitation rather than temperature and solar radiation.

774 We tested the response of ozone deposition rate in different ecosystems to changes in stomatal  
775 conductance parameterisation while keeping model calculation of other resistances unchanged. The  
776 choice of stomatal conductance model parameters is found to be a very important factor in determining  
777 ozone deposition rates across all sites. Seasonal and daily deposition rates to the forest canopy change  
778 by as much as 13% with implications for air quality modelling and assessment of ozone damage to

779 crops and plants. Most models used in assessing air quality at global, regional, and local levels consider  
780 dry deposition using variants of the same Wesely deposition scheme used in FORCAsT-gs (Hardacre  
781 et al., 2015). Many international assessments of ozone damage to crops and forests are based on dose-  
782 response parameters developed using the JV model (e.g. see Emberson et al., 2000, Hayes et al., 2007;  
783 Mills et al., 2011; Buker et al., 2015). Like air quality models, dose-response relationships rely on  
784 ozone deposition rates and their accuracy and reliability could be severely diminished if the appropriate  
785 model parameterisations are not used. Large uncertainty in modelled deposition rates due to the choice  
786 of model parameters, as found in this study, could therefore affect modelled surface ozone  
787 concentrations with negative implications for air quality monitoring as well as assessments of plant  
788 productivity losses from ozone damage. This is especially true for models that rely on the Jarvis  
789 multiplicative model to estimate stomatal conductance. Our results highlight the need to carefully  
790 consider the choice of model parameters as this will ultimately determine model performance.

791 Similar to other studies, we find higher stomatal conductance and ozone deposition velocities  
792 at tropical and broadleaf forest site compared to needleleaf and coniferous forests (e.g. see Emberson  
793 et al., 2001; Fowler et al., 2001; 2011; Kumar et al., 2011; Silva & Heald, 2018). The larger LAI at  
794 the broadleaf forests (BR-Sa1 and US-Ha1) leads to greater canopy conductance, lower stomatal  
795 resistance, and subsequently higher deposition velocity as these are important for estimating total  
796 canopy and leaf boundary resistance (Meyers & Baldocchi, 1988; Padro, 1996). Ozone deposition  
797 velocities at BR-Sa1 are up to a factor of three higher than those at IT-Cp2, US-Blo and FI-Hyy.  
798 However, the difference in ozone deposition rates are much lower (<30%) due to lower ozone  
799 concentrations at this remote forest site.

800 Our findings of the sensitivity of stomatal conductance estimates to parameter and algorithm  
801 choice could also have important implications in modelling biogenic volatile organic compound  
802 (BVOC) emissions. Current BVOC emission models rely on leaf temperature and solar radiation to  
803 drive emission rates and are known to reproduce observations for a range of forest ecosystems and

804 climates within a factor of two (e.g. see Guenther et al., 1993; 1995; 2006). However, such models  
805 have been shown to struggle to reproduce diurnal emission patterns of short-chained carboxylic acids  
806 and aldehydes, leading to suggestions that the failure to include stomatal conductance in such models  
807 could be a limiting factor in model performance (Kesselmeier et al., 1997; Martin et al., 1999; Staudt  
808 et al., 2000; Niinemets and Reichstein, 2003). Including stomatal control of emission rates in land-  
809 atmosphere models would need to account for the sensitivity of simulated stomatal conductance to the  
810 choice of physiological model.

811

812

813 **Code availability**

814 FORCAsT-gs is available for download on request to the corresponding author.

815 **Data availability**

816 FLUXNET2015 data for BR-Sa1, FI-Hyy, IT-Cp2, US-Blo, and US-Ha1 are available from  
817 <https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/>. A user account is required. The doi of each  
818 dataset is provided in Table S1.

819

820 **Author contribution**

821 All co-authors were involved in conceptualization of the research and writing of the manuscript. F.  
822 Otu-Larbi and K. Ashworth performed model simulations and analysed results.

823

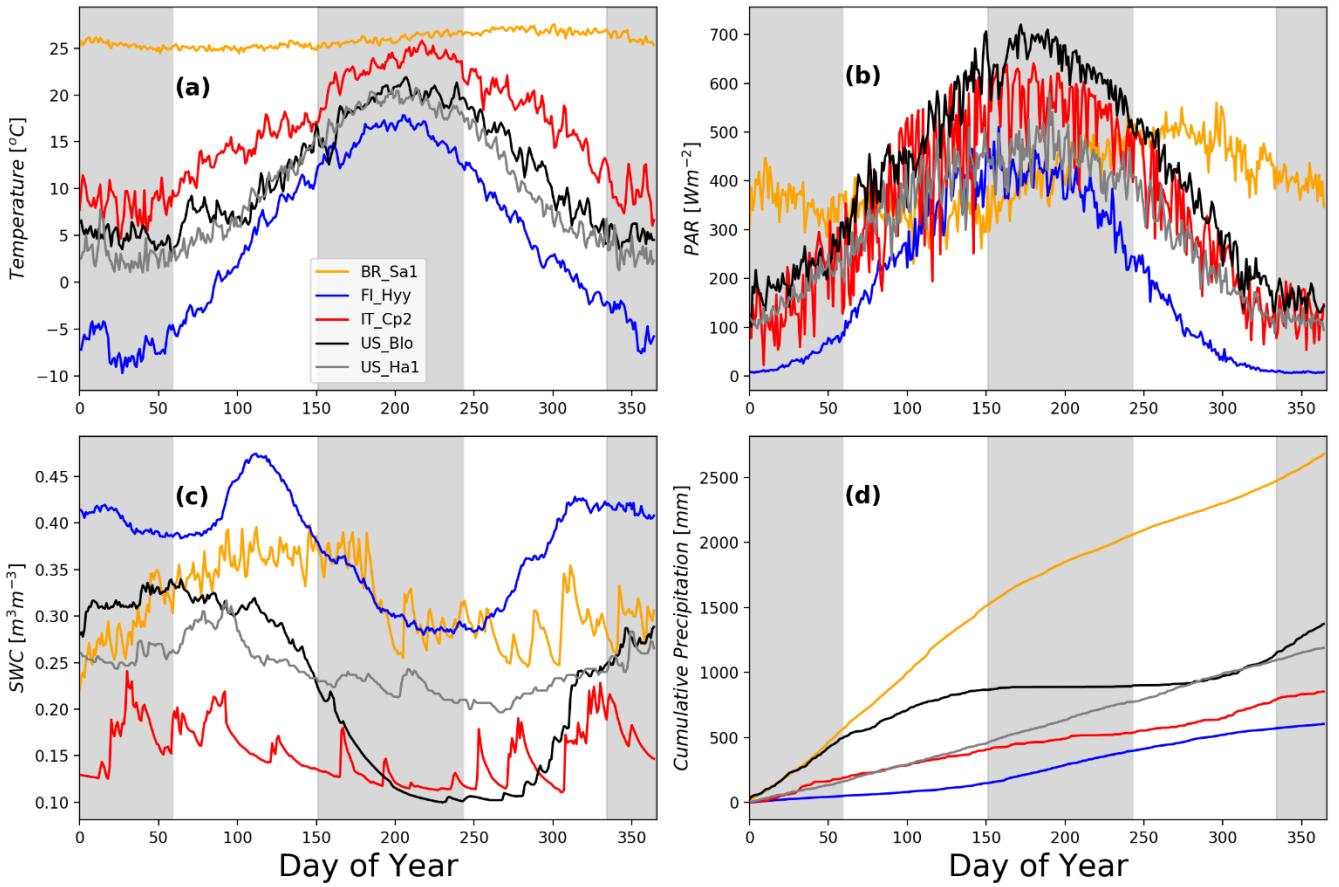
824 **Competing interests**

825 The authors declare no competing interests.

826 **Acknowledgements**

827 F. Otu-Larbi is grateful to the Faculty of Science and Technology (FST) and Lancaster  
828 Environment Centre (LEC) at Lancaster University for funding his PhD Studentship. K. Ashworth is  
829 a Royal Society Dorothy Hodgkin Fellow and thanks the Royal Society of London for their support  
830 and funding (DH150070). The authors are grateful to the FLUXNET network, and specifically the  
831 lead investigators at each of the study sites, for the ready availability of all data collected at these sites.

832



833

834 Figure 1: Site conditions and meteorology showing (a) soil moisture (volumetric soil water content,  
 835 SWC;  $\text{m}^3 \text{m}^{-3}$ ); (b) cumulative precipitation (mm); (c) 2-m air temperature ( $^{\circ}\text{C}$ ) and (d)  
 836 photosynthetically active radiation (PAR) at the top of the canopy ( $\text{W m}^{-2}$ ) for an average year at BR-  
 837 Sa1 (yellow), FI-Hyy (blue), IT-Cp2 (red), US-Blo (black) and US-Ha1 (grey)

838

839

840

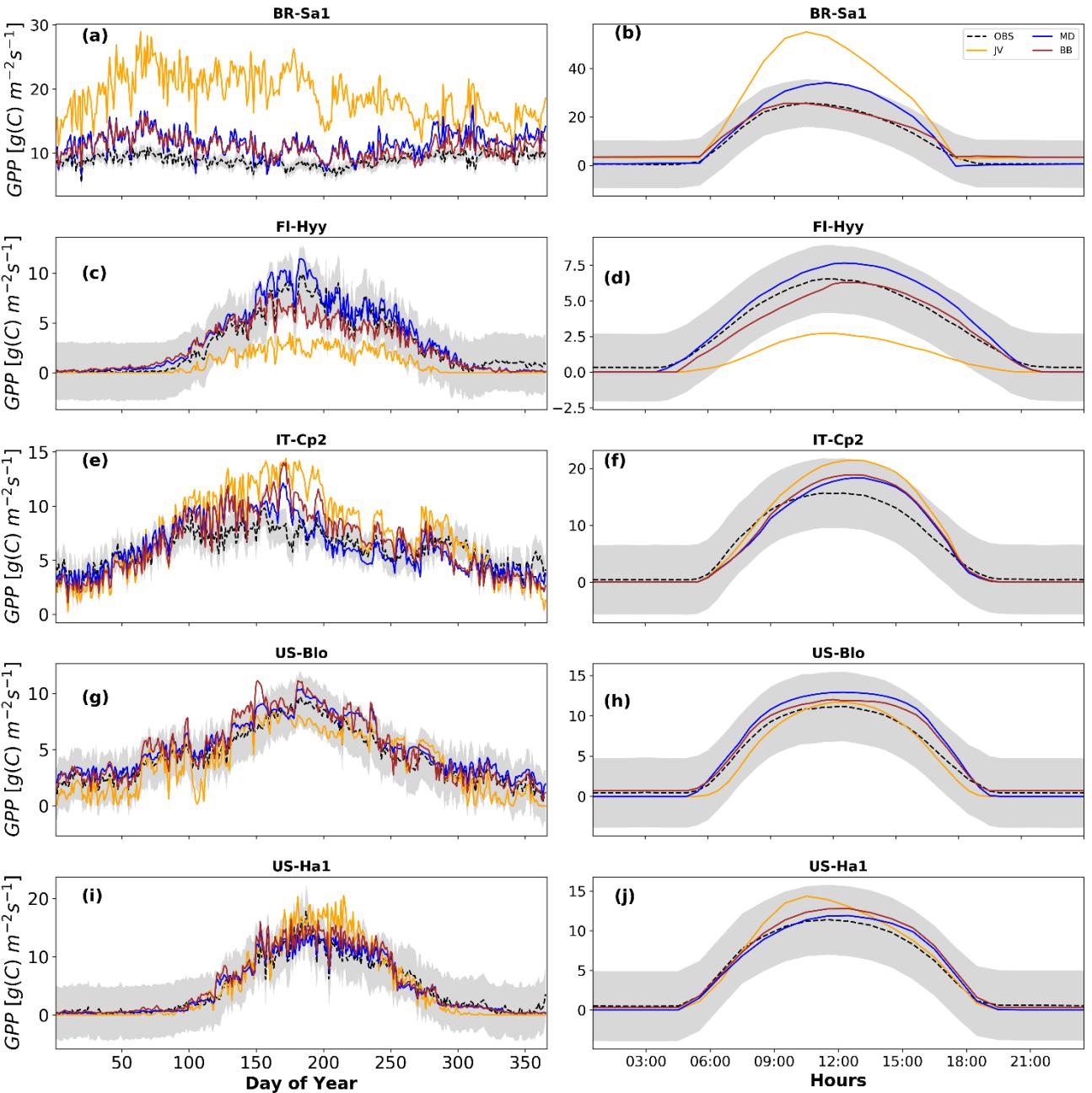
841

842

843

844

845



846

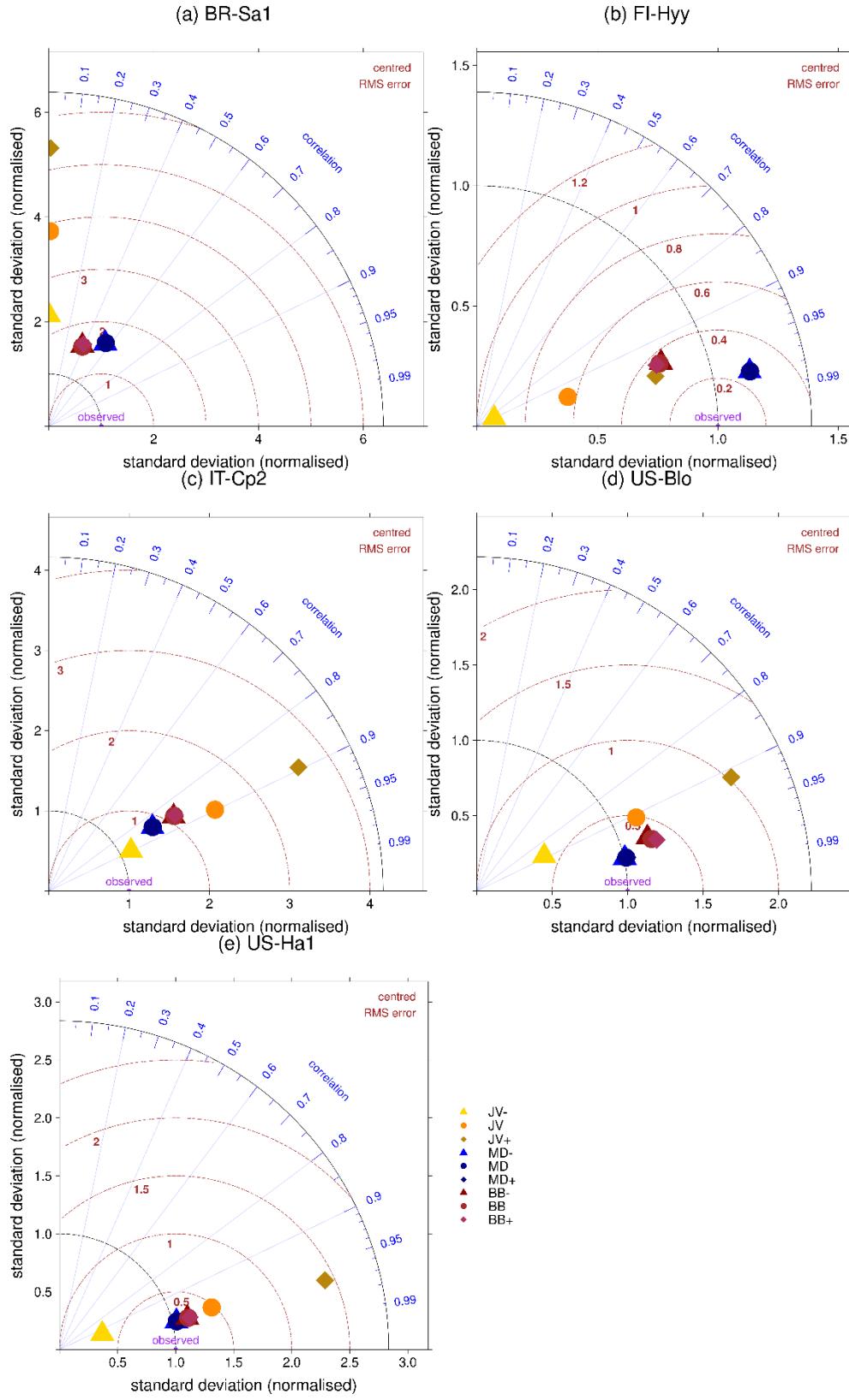
847

848 Figure 2: Net photosynthesis for an average year at each of the five FLUXNET sites, from top to  
 849 bottom row: BR-Sa1, FI-Hyy, IT-Cp2, US-Blo, US-Ha1. The left column shows average annual and  
 850 the right average diel profiles of Gross Primary Productivity (GPP, a measure of photosynthesis rate)  
 851 estimated from the Jarvis multiplicative (gold), Ball-Berry coupled (red) and Medlyn stomatal  
 852 optimisation coupled (blue) stomatal conductance-photosynthesis models. The black dashed lines  
 853 show observed GPP, with grey shaded areas indicating  $\pm$  one standard deviation from the daily average  
 854 GPP.

855

856

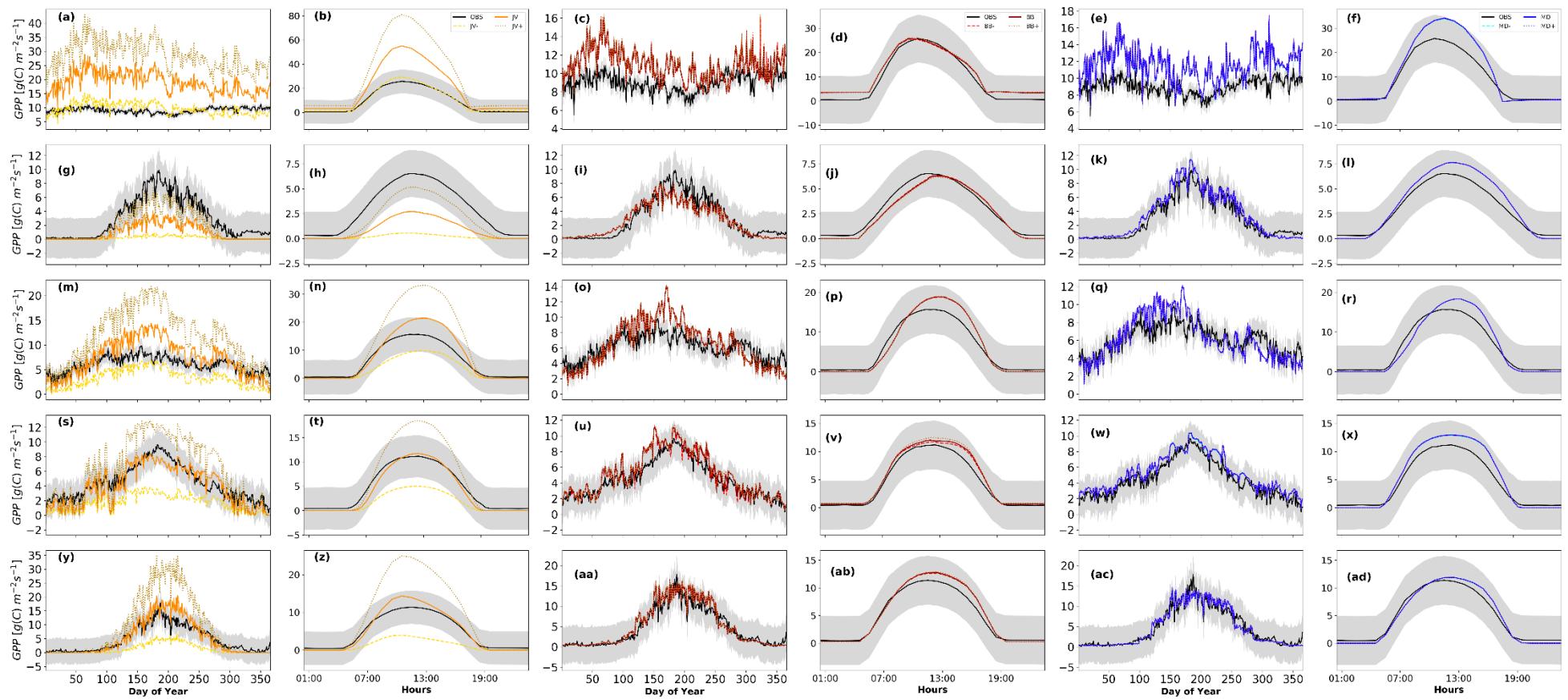
857



858  
859  
860  
861  
862  
863  
864  
865

ss

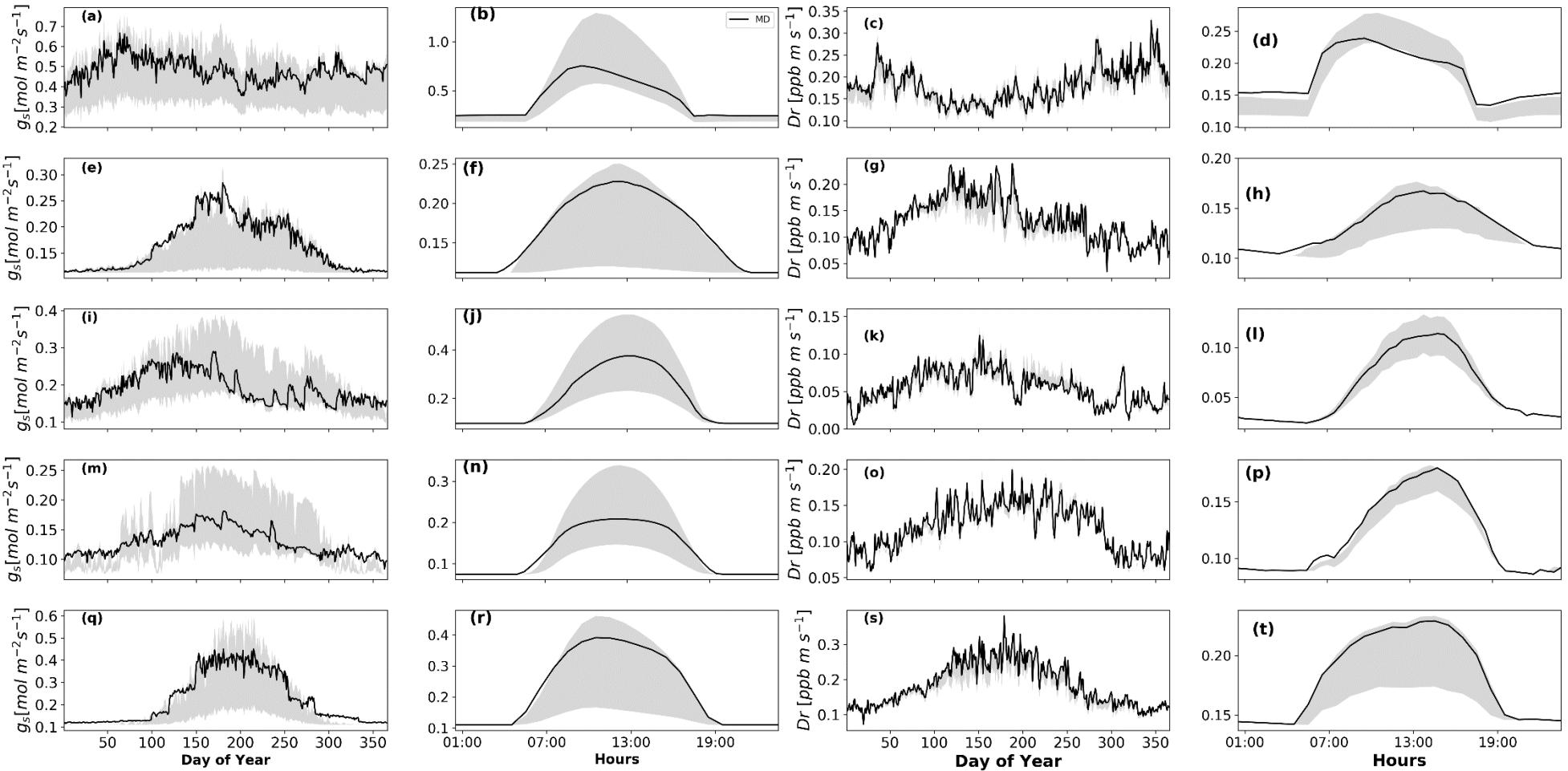
Figure 3: Taylor Diagram summarising model output statistics from FORCAsT sensitivity tests. Observed GPP has SD=1.0, RMSE=0.0 and r=1.0 (purple circle). Black and brown dashed curves and blue lines show normalised standard deviation (SD), centred root mean squared error (RMSE) and correlation coefficients (r) respectively against observations for each model on each diagram. The summary statistics for each JV simulation are shown by gold symbols, BB by red, MD simulation by blue. BASE simulations are denoted by circles, lower bounds (TEST-) by triangles, and upper bounds (TEST+) by diamonds. Note that JV, MD and BB in these plots are the BASE simulations described in sections 2.5.1 and 3.1, and Figure 2.



866

867

868 Figure 4: Modelled and observed GPP for an average year at, from top to bottom: BR-Sa1, FI-Hyy, IT-Cp2, US-Blo, US-Ha1. Columns 1 and 2 (gold)  
 869 are Jarvis (), columns 3 and 4 (red) Ball-Berry, and columns 5 and 6 (blue) Medlyn . Solid lines denote the unperturbed (BASE) simulation as shown in  
 870 Figure 2 for each model, with dashed paler line for TEST- and dashed darker line for TEST+ simulations respectively. The black lines show observed  
 871 GPP at each site with grey shaded areas indicating  $\pm$  one standard deviation from daily and hourly average GPP.



872

873 Figure 5: Stomatal conductance (columns 1 and 2) and ozone deposition rates (columns 3 and 4) for an average year and day at each of the five FLUXNET  
 874 sites, from top to bottom: BR-Sa1, FI-Hyy, IT-Cp2, US-Blo, and US-Ha1. Solid lines black lines denote the output from the model that best reproduced  
 875 GPP at each site as shown in Figure 3 and 4. The shaded regions indicate the spread in stomatal conductance and deposition rates across all the model  
 876 sensitivity tests.

877 **References**

- 878 Ainsworth, E. A., Yendrek, C. R., Sitch, S., Collins, W. J., & Emberson, L. D. (2012).  
879 The effects of tropospheric O<sub>3</sub> on net primary productivity and implications for climate  
880 change. *Annual Review of Plant Biology*, 63, 637– 661.  
881 <https://doi.org/10.1146/annurev-arplant-042110-103829>
- 882 Allen Goldstein (1997-2007) FLUXNET2015 US-Blo Blodgett Forest,  
883 Dataset. <https://doi.org/10.18140/FLX/1440068>
- 884 Allen, A. (1995). Soil science and survey at Harvard Forest. *Soil survey horizons*, 36(4),  
885 133-142. <https://doi.org/10.2136/sh1995.4.0133>
- 886 Ashworth, K., Chung, S. H., Griffin, R. J., Chen, J., Forkel, R., Bryan, A. M., & Steiner,  
887 A. L. (2015). FORest Canopy Atmosphere Transfer (FORCAsT) 1.0: A 1-D model of  
888 biosphere–atmosphere chemical exchange. *Geoscientific Model Development*, 8(11),  
889 3765– 3784. <https://doi.org/10.5194/gmd-8-3765-2015>
- 890 Avnery, S., Mauzerall, D. L., Liu, J., & Horowitz, L. W. (2011). Global crop yield  
891 reductions due to surface ozone exposure: 1. Year 2000 crop production losses and  
892 economic damage. *Atmospheric Environment*, 45(13), 2284-  
893 2296. <https://doi.org/10.1016/j.atmosenv.2010.11.045>
- 894 Baldocchi, D. (1988). A multi-layer model for estimating sulfur dioxide deposition to a  
895 deciduous oak forest canopy. *Atmospheric Environment*  
896 22. [https://doi.org/10.1016/0004-6981\(88\)90264-8](https://doi.org/10.1016/0004-6981(88)90264-8)
- 897 Baldocchi, D. (1994). An analytical solution for coupled leaf photosynthesis and  
898 stomatal conductance models. *Tree physiology*, 14(7-8-9), 1069-  
899 1079. <https://doi.org/10.1093/treephys/14.7-8-9.1069>
- 900 Ball, J. T., Woodrow, I. E., & Berry, J. A. (1987). A model predicting stomatal  
901 conductance and its contribution to the control of photosynthesis under different  
902 environmental conditions. In *Progress in photosynthesis research* (pp. 221-224).  
903 Springer, Dordrecht.
- 904 Best, M. J., Pryor, M., Clark, D. B., Rooney, G. G., Essery, R., Ménard, C. B., ... &  
905 Harding, R. J. (2011). The Joint UK Land Environment Simulator (JULES), model  
906 description—Part 1: energy and water fluxes. *Geoscientific Model Development*, 4(3),  
907 677-699. <https://doi.org/10.5194/gmd-4-677-2011>
- 908 Blackadar, A. K. (1962). The vertical distribution of wind and turbulent exchange in a  
909 neutral atmosphere. *Journal of Geophysical Research*, 67(8), 3095-  
910 3102. <https://doi.org/10.1029/JZ067i008p03095>
- 911 Bryan, A. M., Bertman, S. B., Carroll, M. A., Dusander, S., Edwards, G. D., Forkel, R.,  
912 ... & Steiner, A. L. (2012). In-canopy gas-phase chemistry during CABINEX 2009:  
913 sensitivity of a 1-D canopy model to vertical mixing and isoprene chemistry.  
914 *Atmospheric Chemistry and Physics*, 12(18), 8829-8849. <https://doi.org/10.5194/acp-12-8829-2012>
- 915 Bryan, A. M., Cheng, S. J., Ashworth, K., Guenther, A. B., Hardiman, B. S., Bohrer,  
916 G., & Steiner, A. L. (2015). Forest-atmosphere BVOC exchange in diverse and  
917 structurally complex canopies: 1-D modeling of a mid-successional forest in northern  
918

- 919 Michigan. Atmospheric Environment, 120, 217-  
920 226.<https://doi.org/10.1016/j.atmosenv.2015.08.094>
- 921 Büker, P., Feng, Z., Uddling, J., Briolat, A., Alonso, R., Braun, S., ... & Emberson, L.  
922 D. (2015). New flux based dose-response relationships for ozone for European forest  
923 tree species. Environmental Pollution, 206, 163-174.  
924 <https://doi.org/10.1016/j.envpol.2015.06.033>
- 925 Chen, J., Mao, H., Talbot, R. W., & Griffin, R. J. (2006). Application of the CACM and  
926 MPMPO modules using the CMAQ model for the eastern United States. Journal of  
927 Geophysical Research: Atmospheres, 111(D23).  
928 <https://doi.org/10.1029/2006JD007603>
- 929 Clark, D. B., Mercado, L. M., Sitch, S., Jones, C. D., Gedney, N., Best, M. J., ... Cox,  
930 P. M. (2011). The Joint UK Land Environment Simulator (JULES), model description  
931 – Part 2: Carbon fluxes and vegetation dynamics. Geoscientific Model Development,  
932 4(3), 701– 722. <https://doi.org/10.5194/gmd-4-701-2011>
- 933 Clifton, O. E., Fiore, A. M., Munger, J. W., & Wehr, R. (2019). Spatiotemporal controls  
934 on observed daytime ozone deposition velocity over northeastern US forests during  
935 summer. Journal of Geophysical Research: Atmospheres, 124(10), 5612-5628.  
936 <https://doi.org/10.1029/2018JD029073>
- 937 Cowan, I. R., & GD, Farquhar, G.D. (1977). Stomatal function in relation to leaf  
938 metabolism and environment.
- 939 Da Rocha, H. R., Goulden, M. L., Miller, S. D., Menton, M. C., Pinto, L. D., de Freitas,  
940 H. C., & e Silva Figueira, A. M. (2004). Seasonality of water and heat fluxes over a  
941 tropical forest in eastern Amazonia. Ecological applications, 14(sp4), 22-32.  
942 <https://doi.org/10.1890/02-6001>
- 943 Damour, G., Simonneau, T., Cochard, H., & Urban, L. (2010). An overview of models  
944 of stomatal conductance at the leaf level. Plant, cell & environment, 33(9), 1419-  
945 1438.<https://doi.org/10.1111/j.1365-3040.2010.02181.x>
- 946 De Kauwe, M. G., Kala, J., Lin, Y. S., Pitman, A. J., Medlyn, B. E., Duursma, R. A., ...  
947 & Miralles, D. G. (2015). A test of an optimal stomatal conductance scheme within the  
948 CABLE land surface model. Geoscientific Model Development, 8(2), 431-  
949 452.<https://doi.org/10.5194/gmd-8-431-2015>
- 950 Egea, G., Verhoef, A., & Vidale, P. L. (2011). Towards an improved and more flexible  
951 representation of water stress in coupled photosynthesis-stomatal conductance models.  
952 Agricultural and Forest Meteorology, 151(10), 1370– 1384.  
953 <https://doi.org/10.1016/j.agrformet.2011.05.019>
- 954 Emberson, L. D., Ashmore, M. R., Simpson, D., Tuovinen, J. P., & Cambridge, H. M.  
955 (2001). Modelling and mapping ozone deposition in Europe. Water, Air, and Soil  
956 Pollution, 130(1), 577-582.<https://doi.org/10.1023/A:1013851116524>
- 957 Fares, S., Alivernini, A., Conte, A., & Maggi, F. (2019). O<sub>3</sub> and particle fluxes in a  
958 Mediterranean forest predicted by the AIRTREE model. Science of the Total  
959 Environment, 682, 494– 504. <https://doi.org/10.1016/j.scitotenv.2019.05.109>
- 960 Fares, S., Matteucci, G., Mugnozza, G. S., Morani, A., Calfapietra, C., Salvatori, E., ...  
961 & Loreto, F. (2013). Testing of models of stomatal ozone fluxes with field

- 962 measurements in a mixed Mediterranean forest. *Atmospheric environment*, 67, 242-  
963 251. <https://doi.org/10.1016/j.atmosenv.2012.11.007>
- 964 Fares, S., Mereu, S., Scarascia Mugnozza, G., Vitale, M., Manes, F., Frattoni, M., ... &  
965 Loreto, F. (2009). The ACCENT-VOCBAS field campaign on biosphere-atmosphere  
966 interactions in a Mediterranean ecosystem of Castelporziano (Rome): site  
967 characteristics, climatic and meteorological conditions, and eco-physiology of  
968 vegetation. *Biogeosciences*, 6(6), 1043-1058. <https://doi.org/10.5194/bg-6-1043-2009>
- 969 Farquhar, G. D., & Von Caemmerer, S. (1982). Modelling of photosynthetic response  
970 to environmental conditions. In *Physiological plant ecology II* (pp. 549-587). Springer,  
971 Berlin, Heidelberg.
- 972 Farquhar, G. D., von Caemmerer, S. V., & Berry, J. A. (1980). A biochemical model of  
973 photosynthetic CO<sub>2</sub> assimilation in leaves of C<sub>3</sub> species. *Planta*, 149(1), 78-90.  
974 <https://doi.org/10.1007/BF00386231>
- 975 Flack-Prain, S., Meir, P., Malhi, Y., Smallman, T. L., & Williams, M. (2019). The  
976 importance of physiological, structural and trait responses to drought stress in driving  
977 spatial and temporal variation in GPP across Amazon forests. *Biogeosciences*, 16(22),  
978 4463-4484. <https://doi.org/10.5194/bg-16-4463-2019>
- 979 Forkel, R., Klemm, O., Graus, M., Rappenglück, B., Stockwell, W. R., Grabmer, W.,  
980 ... & Steinbrecher, R. (2006). Trace gas exchange and gas phase chemistry in a Norway  
981 spruce forest: A study with a coupled 1-dimensional canopy atmospheric chemistry  
982 emission model. *Atmospheric environment*, 40, 28-42.  
983 <https://doi.org/10.1016/j.atmosenv.2005.11.070>
- 984 Fowler, D., Flechard, C., Cape, J. N., Storeton-West, R. L., & Coyle, M. (2001).  
985 Measurements of ozone deposition to vegetation quantifying the flux, the stomatal and  
986 non-stomatal components. *Water, Air, and Soil Pollution*, 130(1), 63-74.  
987 <https://doi.org/10.1023/A:1012243317471>
- 988 Fowler, D., Nemitz, E., Misztal, P., Di Marco, C., Skiba, U., Ryder, J., ... & Hewitt, C.  
989 N. (2011). Effects of land use on surface-atmosphere exchanges of trace gases and  
990 energy in Borneo: comparing fluxes over oil palm plantations and a  
991 rainforest. *Philosophical Transactions of the Royal Society B: Biological  
992 Sciences*, 366(1582), 3196-3209. <https://doi.org/10.1098/rstb.2011.0055>
- 993 Franks, P. J., Berry, J. A., Lombardozzi, D. L., & Bonan, G. B. (2017). Stomatal  
994 function across temporal and spatial scales: deep-time trends, land-atmosphere coupling  
995 and global models. *Plant Physiology*, 174(2), 583-602.  
996 <https://doi.org/10.1104/pp.17.00287>
- 997 Franks, P. J., Bonan, G. B., Berry, J. A., Lombardozzi, D. L., Holbrook, N. M., Herold,  
998 N., & Oleson, K. W. (2018). Comparing optimal and empirical stomatal conductance  
999 models for application in Earth system models. *Global change biology*, 24(12), 5708-  
1000 5723. <https://doi.org/10.1111/gcb.14445>
- 1001 Fusaro, L., Salvatori, E., Mereu, S., Silli, V., Bernardini, A., Tinelli, A., & Manes, F.  
1002 (2015). Researches in Castelporziano test site: ecophysiological studies on  
1003 Mediterranean vegetation in a changing environment. *Rendiconti Lincei*, 26(3), 473-  
1004 481. <https://doi.org/10.1007/s12210-014-0374-1>

- 1005 Gao, W., Wesely, M. L., & Doskey, P. V. (1993). Numerical modeling of the turbulent  
1006 diffusion and chemistry of NO<sub>x</sub>, O<sub>3</sub>, isoprene, and other reactive trace gases in and  
1007 above a forest canopy. *Journal of Geophysical Research: Atmospheres*, 98(D10),  
1008 18339-18353. <https://doi.org/10.1029/93JD01862>
- 1009 Gao, Y., Markkanen, T., Thum, T., Aurela, M., Lohila, A., Mammarella, I., ... Aalto,  
1010 T. (2016). Assessing various drought indicators in representing summer drought in  
1011 boreal forests in Finland. *Hydrology and Earth System Sciences*, 20, 175– 191.  
1012 <https://doi.org/10.5194/hess-20-175-2016>
- 1013 Geiger, H., Barnes, I., Bejan, I., Benter, T., & Spittler, M. (2003). The tropospheric  
1014 degradation of isoprene: an updated module for the regional atmospheric chemistry  
1015 mechanism. *Atmospheric Environment*, 37(11), 1503-  
1016 1519.[https://doi.org/10.1016/S1352-2310\(02\)01047-6](https://doi.org/10.1016/S1352-2310(02)01047-6)
- 1017 Goldstein, A. H., & Schade, G. W. (2000). Quantifying biogenic and anthropogenic  
1018 contributions to acetone mixing ratios in a rural environment. *Atmospheric  
1019 Environment*, 34(29-30), 4997-5006.[https://doi.org/10.1016/S1352-2310\(00\)00321-6](https://doi.org/10.1016/S1352-2310(00)00321-6)
- 1020 Goldstein, A. H., Goulden, M. L., Munger, J. W., Wofsy, S. C., & Geron, C. D. (1998).  
1021 Seasonal course of isoprene emissions from a midlatitude deciduous forest. *Journal of  
1022 Geophysical Research: Atmospheres*, 103(D23), 31045-  
1023 31056.<https://doi.org/10.1029/98JD02708>
- 1024 Goldstein, A. H., Hultman, N. E., Fracheboud, J. M., Bauer, M. R., Panek, J. A., Xu,  
1025 M., ... & Baugh, W. (2000). Effects of climate variability on the carbon dioxide, water,  
1026 and sensible heat fluxes above a ponderosa pine plantation in the Sierra Nevada (CA).  
1027 *Agricultural and Forest Meteorology*, 101(2-3), 113-129.  
1028 [https://doi.org/10.1016/S0168-1923\(99\)00168-9](https://doi.org/10.1016/S0168-1923(99)00168-9)
- 1029 Goulden, M. L., Miller, S. D., Da Rocha, H. R., Menton, M. C., de Freitas, H. C., e  
1030 Silva Figueira, A. M., & de Sousa, C. A. D. (2004). Diel and seasonal patterns of  
1031 tropical forest CO<sub>2</sub> exchange. *Ecological Applications*, 14(sp4), 42-54.  
1032 <https://doi.org/10.1890/02-6008>
- 1033 Griffin, R. J., Dabdub, D., & Seinfeld, J. H. (2005). Development and initial evaluation  
1034 of a dynamic species-resolved model for gas phase chemistry and size-resolved  
1035 gas/particle partitioning associated with secondary organic aerosol formation. *Journal  
1036 of Geophysical Research: Atmospheres*, 110(D5).  
1037 <https://doi.org/10.1029/2004JD005219>
- 1038 Griffin, R. J., Nguyen, K., Dabdub, D., & Seinfeld, J. H. (2003). A coupled  
1039 hydrophobic-hydrophilic model for predicting secondary organic aerosol formation.  
1040 *Journal of Atmospheric Chemistry*, 44(2), 171-190.  
1041 <https://doi.org/10.1023/A:1022436813699>
- 1042 Griffin, R. J., Nguyen, K., Dabdub, D., & Seinfeld, J. H. (2003). A coupled  
1043 hydrophobic-hydrophilic model for predicting secondary organic aerosol  
1044 formation. *Journal of Atmospheric Chemistry*, 44(2), 171-190.  
1045 <https://doi.org/10.1023/A:1022436813699>
- 1046 Guenther, A., Hewitt, C. N., Erickson, D., Fall, R., Geron, C., Graedel, T., ... Pierce, T.  
1047 (1995). A global model of natural volatile organic compound emissions. *Journal of*

- 1048 Geophysical Research: Atmospheres, 100(D5), 8873– 8892.  
1049 <https://doi.org/10.1029/94JD02950>.
- 1050 Guenther, A., Karl, T., Harley, P., Wiedinmyer, C., Palmer, P. I., & Geron, C. (2006).  
1051 Estimates of global terrestrial isoprene emissions using MEGAN (Model of Emissions  
1052 of Gases and Aerosols from Nature). *Atmospheric Chemistry and Physics*, 6(11), 3181–  
1053 3210. <https://doi.org/10.5194/acp-6-3181-2006>
- 1054 Guenther, A., Zimmerman, P. R., Harley, P. C., Monson, R. K., & Fall, R. (1993).  
1055 Isoprene and monoterpene emission rate variability: Model evaluations and sensitivity  
1056 analyses. *Journal of Geophysical Research*, 98(D7), 12609.  
1057 <https://doi.org/10.1029/93JD00527>
- 1058 Hardacre, C., Wild, O., & Emberson, L. (2015). An evaluation of ozone dry deposition  
1059 in global scale chemistry climate models. *Atmospheric Chemistry and Physics*, 15(11),  
1060 6419-6436. <https://doi.org/10.5194/acp-15-6419-2015>
- 1061 Hari, P., & Kulmala, M. (2005). Station for Measuring Ecosystem Atmosphere  
1062 Relations (SMEAR II). *Boreal Environmental Research*, 10, 315– 322.
- 1063 Harley, P. C., Thomas, R. B., Reynolds, J. F., & Strain, B. R. (1992). Modelling  
1064 photosynthesis of cotton grown in elevated CO<sub>2</sub>. *Plant, Cell & Environment*, 15(3),  
1065 271-282. <https://doi.org/10.1111/j.1365-3040.1992.tb00974.x>
- 1066 Hayes, F., Mills, G., Harmens, H., & Norris, D. (2007). Evidence of widespread ozone  
1067 damage to vegetation in Europe (1990-2006). ICP Vegetation Programme Coordination  
1068 Centre, CEH Bangor, UK.
- 1069 Hetherington, A. M., & Woodward, F. I. (2003). The role of stomata in sensing and  
1070 driving environmental change. *Nature*, 424(6951), 901-  
1071 908. <https://doi.org/10.1038/nature01843>
- 1072 Hoshika, Y., Osada, Y., De Marco, A., Penuelas, J., & Paoletti, E. (2018). Global  
1073 diurnal and nocturnal parameters of stomatal conductance in woody plants and major  
1074 crops. *Global Ecology and Biogeography*, 27(2), 257-275.  
1075 <https://doi.org/10.1111/geb.12681>
- 1076 Ivan Mammarella and Timo Vesala (1996-2014) FLUXNET2015 FI-Hyy Hyttiala,  
1077 Dataset. <https://doi.org/10.18140/FLX/1440158>
- 1078 J. William Munger (1991-2012) FLUXNET2015 US-Ha1 Harvard Forest EMS Tower  
1079 (HFR1), Dataset. <https://doi.org/10.18140/FLX/1440071>
- 1080 Jarvis, P. G. (1976). The interpretation of the variations in leaf water potential and  
1081 stomatal conductance found in canopies in the field. *Philosophical Transactions of the  
1082 Royal Society of London. B, Biological Sciences*, 273(927), 593-  
1083 610. <https://doi.org/10.1098/rstb.1976.0035>
- 1084 Keenan, T., García, R., Friend, A. D., Zaehle, S., Gracia, C., & Sabate, S. (2009).  
1085 Improved understanding of drought controls on seasonal variation in Mediterranean  
1086 forest canopy CO<sub>2</sub> and water fluxes through combined in situ measurements and  
1087 ecosystem modelling. *Biogeosciences*, 6(8), 1423-1444. <https://doi.org/10.5194/bg-6-1423-2009>
- 1089 Keenan, T., Sabate, S., & Gracia, C. (2010). Soil water stress and coupled  
1090 photosynthesis-conductance models: Bridging the gap between conflicting reports on  
1091 the relative roles of stomatal, mesophyll conductance and biochemical limitations to

- 1092 photosynthesis. Agricultural and Forest Meteorology, 150(3), 443-453.  
1093 <https://doi.org/10.1016/j.agrformet.2010.01.008>
- 1094 Kesselmeier, J., Bode, K., Hofmann, U., Müller, H., Schäfer, L., Wolf, A., ... & Torres,  
1095 L. (1997). Emission of short chained organic acids, aldehydes and monoterpenes from  
1096 *Quercus ilex* L. and *Pinus pinea* L. in relation to physiological activities, carbon budget  
1097 and emission algorithms. Atmospheric Environment, 31, 119-133.  
1098 [https://doi.org/10.1016/S1352-2310\(97\)00079-4](https://doi.org/10.1016/S1352-2310(97)00079-4)
- 1099 Kolari, P., Chan, T., Porcar-Castell, A., Bäck, J., Nikinmaa, E., & Juurola, E. (2014).  
1100 Field and controlled environment measurements show strong seasonal acclimation in  
1101 photosynthesis and respiration potential in boreal Scots pine. Frontiers in plant  
1102 science, 5, 717. <https://doi.org/10.3389/fpls.2014.00717>
- 1103 Kumar, A., Chen, F., Niyogi, D., Alfieri, J. G., Ek, M., & Mitchell, K. (2011).  
1104 Evaluation of a photosynthesis-based canopy resistance formulation in the Noah land-  
1105 surface model. Boundary-layer meteorology, 138(2), 263-284.  
1106 <https://doi.org/10.1007/s10546-010-9559-z>
- 1107 Lin, Y. S., Medlyn, B. E., Duursma, R. A., Prentice, I. C., Wang, H., Baig, S., ... &  
1108 Wingate, L. (2015). Optimal stomatal behaviour around the world. Nature Climate  
1109 Change, 5(5), 459-464. <https://doi.org/10.1038/nclimate2550>
- 1110 Loveland, T. R., Reed, B. C., Brown, J. F., Ohlen, D. O., Zhu, Z., Yang, L. W. M. J., &  
1111 Merchant, J. W. (2000). Development of a global land cover characteristics database  
1112 and IGBP DISCover from 1 km AVHRR data. International Journal of Remote  
1113 Sensing, 21(6-7), 1303-1330.<https://doi.org/10.1080/014311600210191>
- 1114 Martin, R. S., Villanueva, I., Zhang, J., & Popp, C. J. (1999). Nonmethane hydrocarbon,  
1115 monocarboxylic acid, and low molecular weight aldehyde and ketone emissions from  
1116 vegetation in central New Mexico. Environmental science & technology, 33(13), 2186-  
1117 2192.<https://doi.org/10.1021/es980468q>
- 1118 McKinney, K. A., Lee, B. H., Vasta, A., Pho, T. V., & Munger, J. W. (2011). Emissions  
1119 of isoprenoids and oxygenated biogenic volatile organic compounds from a New  
1120 England mixed forest. Atmospheric Chemistry and Physics, 11(10), 4807-  
1121 4831.<https://doi.org/10.5194/acp-11-4807-2011>
- 1122 Medlyn, B. E., Duursma, R. A., Eamus, D., Ellsworth, D. S., Prentice, I. C., Barton, C.  
1123 V., ... & Wingate, L. (2011). Reconciling the optimal and empirical approaches to  
1124 modelling stomatal conductance. Global Change Biology, 17(6), 2134-2144.  
1125 <https://doi.org/10.1111/j.1365-2486.2010.02375.x>
- 1126 Meyers, T. P., & Baldocchi, D. D. (1988). A comparison of models for deriving dry  
1127 deposition fluxes of O<sub>3</sub> and SO<sub>2</sub> to a forest canopy. Tellus B, 40(4), 270-  
1128 284.DOI: 10.3402/tellusb.v40i4.15916
- 1129 Mills, G., Pleijel, H., Braun, S., Büker, P., Bermejo, V., Calvo, E., ... & Simpson, D.  
1130 (2011). New stomatal flux-based critical levels for ozone effects on  
1131 vegetation. Atmospheric Environment, 45(28), 5064-  
1132 5068.<https://doi.org/10.1016/j.atmosenv.2011.06.009>
- 1133 Moss, D. N., Krenzer, E. G., & Brun, W. A. (1969). Carbon dioxide compensation  
1134 points in related plant species. Science, 164(3876), 187-188.  
1135 [10.1126/science.164.3876.187](https://doi.org/10.1126/science.164.3876.187)

- 1136 Nemaní, R. R., Keeling, C. D., Hashimoto, H., Jolly, W. M., Piper, S. C., Tucker, C. J.,  
1137 ... & Running, S. W. (2003). Climate-driven increases in global terrestrial net primary  
1138 production from 1982 to 1999. *science*, 300(5625), 1560-1563. DOI:  
1139 10.1126/science.1082750s
- 1140 Niinemets, Ü. (2010). Mild versus severe stress and BVOCs: Thresholds, priming and  
1141 consequences. *Trends in Plant Science*, 15(3), 145– 153.  
1142 <https://doi.org/10.1016/j.tplants.2009.11.008>
- 1143 Niinemets, Ü., & Reichstein, M. (2003). Controls on the emission of plant volatiles  
1144 through stomata: Differential sensitivity of emission rates to stomatal closure  
1145 explained. *Journal of Geophysical Research: Atmospheres*, 108(D7).  
1146 DOI:10.1029/2002JD002626
- 1147 Oliver, R. J., Mercado, L. M., Sitch, S., Simpson, D., Medlyn, B. E., Lin, Y. S., &  
1148 Folberth, G. A. (2018). Large but decreasing effect of ozone on the European carbon  
1149 sink. *Biogeosciences*, 15(13), 4245-4269. <https://doi.org/10.5194/bg-15-4245-2018>
- 1150 Otu-Larbi, F., Bolas, C. G., Ferracci, V., Staniaszek, Z., Jones, R. L., Malhi, Y., ... &  
1151 Ashworth, K. (2020a). Modelling the effect of the 2018 summer heatwave and drought  
1152 on isoprene emissions in a UK woodland. *Global change biology*, 26(4), 2320-  
1153 2335.<https://doi.org/10.1111/gcb.14963>
- 1154 Otu-Larbi, F., Conte, A., Fares, S., Wild, O., & Ashworth, K. (2020b). Current and  
1155 future impacts of drought and ozone stress on Northern Hemisphere forests. *Global  
1156 Change Biology*, 26(11), 6218-6234. <https://doi.org/10.1111/gcb.15339>
- 1157 Padro, J. (1996). Summary of ozone dry deposition velocity measurements and model  
1158 estimates over vineyard, cotton, grass and deciduous forest in summer. *Atmospheric  
1159 Environment*, 30(13), 2363-2369. [https://doi.org/10.1016/1352-2310\(95\)00352-5](https://doi.org/10.1016/1352-2310(95)00352-5)
- 1160 Park, J. H., Fares, S., Weber, R., & Goldstein, A. H. (2014). Biogenic volatile organic  
1161 compound emissions during BEARPEX 2009 measured by eddy covariance and flux-  
1162 gradient similarity methods. *Atmospheric Chemistry and Physics*, 14(1), 231-244.  
1163 <https://doi.org/10.5194/acp-14-231-2014>
- 1164 Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y. W., ... &  
1165 Li, Y. (2020). The FLUXNET2015 dataset and the ONEFlux processing pipeline for  
1166 eddy covariance data. *Scientific data*, 7(1), 1-27. [https://doi.org/10.1038/s41597-020-0534-3](https://doi.org/10.1038/s41597-020-<br/>1167 0534-3)
- 1168 Porporato, A., Laio, F., Ridolfi, L., & Rodriguez-Iturbe, I. (2001). Plants in water-  
1169 controlled ecosystems: active role in hydrologic processes and response to water stress:  
1170 III. Vegetation water stress. *Advances in water resources*, 24(7), 725-744.  
1171 [https://doi.org/10.1016/S0309-1708\(01\)00006-9](https://doi.org/10.1016/S0309-1708(01)00006-9)
- 1172 Rice, A. H., Pyle, E. H., Saleska, S. R., Hutyra, L., Palace, M., Keller, M., ... & Wofsy,  
1173 S. C. (2004). Carbon balance and vegetation dynamics in an old-growth Amazonian  
1174 forest. *Ecological applications*, 14(sp4), 55-71. <https://doi.org/10.1890/02-6006>
- 1175 Rinne, J., Taipale, R., Markkanen, T., Ruuskanen, T. M., Hellén, H., Kajos, M. K., ...  
1176 & Kulmala, M. (2007). Hydrocarbon fluxes above a Scots pine forest canopy:  
1177 measurements and modeling. *Atmospheric Chemistry and Physics*, 7(12), 3361-3372.  
1178 <https://doi.org/10.5194/acp-7-3361-2007>

- 1179 Rödig, E., Cuntz, M., Rammig, A., Fischer, R., Taubert, F., & Huth, A. (2018). The  
1180 importance of forest structure for carbon fluxes of the Amazon  
1181 rainforest. *Environmental Research Letters*, 13(5), 054013.  
1182 <https://doi.org/10.1088/1748-9326/aabc61>
- 1183 Royal Society (2008). Ground-level ozone in the 21st century: future trends, impacts  
1184 and policy implications. *Science Policy Report 15/08*. The Royal Society, London.
- 1185 Scott Saleska (2002-2011) FLUXNET2015 BR-Sa1 Santarem-Km67-Primary Forest,  
1186 Dataset. <https://doi.org/10.18140/FLX/1440032>
- 1187 Silva, S. J., & Heald, C. L. (2018). Investigating dry deposition of ozone to  
1188 vegetation. *Journal of Geophysical Research: Atmospheres*, 123(1), 559-  
1189 573. <https://doi.org/10.1002/2017JD027278>
- 1190 Silvano Fares (2012-2014) FLUXNET2015 IT-Cp2 Castelporziano2,  
1191 Dataset. <https://doi.org/10.18140/FLX/1440233>
- 1192 SMEAR II (2021). <https://eu-interact.org/field-sites/hyytiala-forestry-reseach-station-smear-ii/> last accessed 19/04/2021
- 1193 Staudt, M., Bertin, N., Hansen, U., Seufert, G., Cicciolij, P., Foster, P., ... & Fugit, J. L.  
1194 (1997). Seasonal and diurnal patterns of monoterpene emissions from *Pinus pinea* (L.)  
1195 under field conditions. *Atmospheric environment*, 31, 145-156.  
1196 [https://doi.org/10.1016/S1352-2310\(97\)00081-2](https://doi.org/10.1016/S1352-2310(97)00081-2)
- 1197 Steinbrecher, R., Hauff, K., Hakola, H., & Rössler, J. (1999). A revised  
1198 parameterisation for emission modelling of isoprenoids for boreal plants. *Biogenic  
1199 VOC emissions and photochemistry in the boreal regions of Europe: Biporep*, Final  
1200 report, Contract No ENV4-CT95-0022, Air Pollution research report, (70), 29-44.
- 1201 Stockwell, W. R., Kirchner, F., Kuhn, M., & Seefeld, S. (1997). A new mechanism for  
1202 regional atmospheric chemistry modeling. *Journal of Geophysical Research: Atmospheres*,  
1203 102(D22), 25847-25879. <https://doi.org/10.1029/97JD00849>
- 1204 Suni, T., Rinne, J., Reissell, A., Altimir, N., Keronen, P., Rannik, U., ... & Vesala, T.  
1205 (2003). Long-term measurements of surface fluxes above a Scots pine forest in  
1206 Hyytiala, southern Finland, 1996-2001. *Boreal Environment Research*, 8(4), 287-302.
- 1207 Wesely, M. L. (1989). Parameterization of surface resistances to gaseous dry deposition  
1208 in regional-scale numerical models. *Atmospheric Environment*, 23 (1989), 1293-1304
- 1209 Williams, M., Rastetter, E. B., Fernandes, D. N., Goulden, M. L., Wofsy, S. C., Shaver,  
1210 G. R., ... & Nadelhoffer, K. J. (1996). Modelling the soil-plant-atmosphere continuum  
1211 in a *Quercus-Acer* stand at Harvard Forest: the regulation of stomatal conductance by  
1212 light, nitrogen and soil/plant hydraulic properties. *Plant, Cell & Environment*, 19(8),  
1213 911-927. <https://doi.org/10.1111/j.1365-3040.1996.tb00456.x>
- 1214 Wong, S. C., Cowan, I. R., & Farquhar, G. D. (1979). Stomatal conductance correlates  
1215 with photosynthetic capacity. *Nature*, 282(5737), 424-  
1216 426. <https://doi.org/10.1038/282424a0>
- 1217 Yu, Q., Zhang, Y., Liu, Y., & Shi, P. (2004). Simulation of the stomatal conductance of  
1218 winter wheat in response to light, temperature and CO<sub>2</sub> changes. *Annals of Botany*,  
1219 93(4), 435-441. <https://doi.org/10.1093/aob>
- 1220  
1221  
1222