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Risky future for Mediterranean forests unless they undergo extreme carbon fertilization

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1 **Risky future for Mediterranean forests unless**
2 **they undergo extreme carbon fertilization**

3 **Running head:** Mediterranean forests, climate change and CO₂

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15
16 **Abstract**

17 Forest performance is challenged by climate change but higher atmospheric [CO₂] (c_a)

18 could help trees mitigate the negative effect of enhanced water stress. Forest projections

19 using data-assimilation with mechanistic models are a valuable tool to assess forest

20 performance. Firstly, we used dendrochronological data from 12 Mediterranean tree

21 species (6 conifers, 6 broadleaves) to calibrate a process-based vegetation model at 77

22 sites. Secondly, we conducted simulations of gross primary production (GPP) and radial

23 growth using an ensemble of climate projections for the period 2010-2100 for the high-

24 emission RCP8.5 and low-emission RCP2.6 scenarios. GPP and growth projections

25 were simulated using climatic data from the two RCPs combined with: (i) expected c_a;

26 (ii) constant $c_a = 390$ ppm, to test a purely climate-driven performance excluding
27 compensation from carbon fertilization. The model accurately mimicked the growth
28 trends since the 1950s when, despite increasing c_a , enhanced evaporative demands
29 precluded a global net positive effect on growth. Modeled annual growth and GPP
30 showed similar long-term trends. Under RCP2.6 (i.e. temperatures below $+2^\circ\text{C}$ with
31 respect to preindustrial values) the forests showed resistance to future climate (as
32 expressed by non-negative trends in growth and GPP) except for some coniferous sites.
33 Using exponentially growing c_a and climate as from RCP8.5, carbon fertilization
34 overrode the negative effect of the highly constraining climatic conditions under that
35 scenario. This effect was particularly evident above 500 ppm (which is already over
36 $+2^\circ\text{C}$), which seems unrealistic and likely reflects model miss-performance at high c_a
37 above the calibration range. Thus, forest projections under RCP8.5 preventing carbon
38 fertilization displayed very negative forest performance at the regional scale. This
39 suggests that most of western Mediterranean forests would successfully acclimate to the
40 coldest climate change scenario but be vulnerable to a climate warmer than $+2^\circ\text{C}$ unless
41 the trees developed an exaggerated fertilization response to $[\text{CO}_2]$.

42

43 **Keywords:** Dendroecology; process-based models; carbon fertilization; climate change;

44 MAIDEN; water stress; forest dynamics.

45 **Type of paper:** Original research article

46 **Introduction**

47 Future climate will trigger changes in ecosystem functioning, including
48 enhancement in forest vulnerability to water stress (Giorgi & Lionello 2008; van der
49 Molen et al. 2011; Anderegg et al. 2015). Understanding how forests will respond to
50 warmer conditions but under higher than present c_a is crucial to assess future forest
51 performance. Theoretically, plants should enhance growth and net primary productivity
52 (NPP) by optimization of different functional traits in response to elevated $[CO_2]$ (i.e. c_a
53 levels way above present values, eCO_2) if this was a limiting factor. In practice, rising c_a
54 has enhanced intrinsic water-use efficiency (iWUE) in forests but this was not generally
55 translated on a net increase of growth, meaning that other factors such as water stress
56 and/or nutrient limitation have overridden the potential positive effect of CO_2 (Peñuelas
57 et al. 2011; Keenan et al. 2013; Reichstein et al. 2013; van der Sleen et al. 2014; Kim et
58 al. 2016).

59 The net effect on tree growth of the interaction 'Climate x CO_2 ' can depend
60 nonlinearly on c_a levels (Reichstein et al. 2013). Observational data show evidence up
61 to current $c_a < 403$ ppm whereas future emission scenarios project c_a far above this level
62 (IPCC 2014). Free-Air Carbon dioxide Enrichment (FACE) experiments were designed
63 to address this issue. In these experiments $[CO_2]$ was elevated up to 600-800 ppm but
64 they were carried out under current environmental conditions mostly on temperate
65 forests (Battipaglia et al. 2013; De Kauwe et al. 2013; Baig et al. 2015; Kim et al. 2016;
66 Norby et al. 2016). Thus, the effect of eCO_2 on forest performance in relation to climate
67 and other environmental factors needs to be addressed in other biomes where more
68 constraining (warmer and drier) conditions are expected for the future (Giorgi &
69 Lionello 2008; García-Ruiz et al. 2011; IPCC 2014). The role that CO_2 could play to
70 compensate the negative impact of increasing water stress on forests has long been

71 debated. Plants can coordinate different functional traits in response to eCO₂ and
72 drought-prone species at dry sites could benefit more from eCO₂ (Medlyn & De Kauwe
73 2013; Duursma *et al.* 2016; Kelly *et al.* 2016). Leaf-level responses are easier to predict
74 than canopy or ecosystem-level responses (Fatichi *et al.* 2015). Consequently, there is
75 still uncertainty on how the forest carbon cycle will adjust in the future because multiple
76 interactive factors determine the net response of forests at different scales (Breda *et al.*
77 2006; Niinemets 2010; van der Molen *et al.* 2011; Kattge *et al.* 2011).

78 Vegetation models combine the effect of different stress factors on different
79 functional traits to achieve a proper understanding of forest functioning. These models
80 should be able to combine C-sink and C-source limitations to provide key information
81 on how forests will develop in the future (Sala *et al.* 2012; McDowell *et al.* 2013;
82 Fatichi *et al.* 2014; Anderegg *et al.* 2015; Walker *et al.* 2015). There is a constant need
83 to improve the representation of hydrological, physical and biological processes in
84 models. In addition, improvement of model performance needs to be achieved through
85 benchmarking and data-assimilation (Peng *et al.* 2011; Pappas *et al.* 2013; Medlyn *et al.*
86 2015; Prentice *et al.* 2015). Dendrochronological data have long been used to assess
87 empirical relationships between climate and growth, which can be used as an indicator
88 of tree fitness and performance (Fritts 1976). Process-based models can take into
89 account the influence of CO₂ on plant functional acclimation. Thus they can help to
90 reduce uncertainty in growth projections but need continuous feedback from multiproxy
91 data to ensure realism (Guiot *et al.* 2014; Walker *et al.* 2015). Dendrochronological
92 records can be used to improve complex process-based models and help to assess forest
93 dynamics under global change (Babst *et al.* 2014). Assessing forest dynamics is
94 particularly challenging in ecosystems like those under Mediterranean climate (Morales
95 *et al.* 2005) where two stress periods (cold in winter and drought in summer) limit plant

96 performance. Warmer winters could enlarge the growing season and promote higher
97 photosynthetic rates (just in evergreens) but also higher respiration rates, whereas
98 warmer summers would exert a negative impact (higher water stress) on forests.
99 Modeling the net effect on trees of the balance between these two periods is critical to
100 assess the future forest response to climate change.

101 We analyzed the effect that forthcoming changes in climate and c_a will yield over
102 Mediterranean forests, which are expected to face a high vulnerability to future climate
103 (Giorgi & Lionello 2008; García-Ruiz *et al.* 2011; IPCC 2014). We calibrated a stand
104 mechanistic model using a network of tree-ring growth chronologies including an
105 ensemble of species covering a wide ecological and geographic range to ensure realism
106 and biological robustness when simulating future forest performance at the regional
107 scale under different climate and c_a scenarios. C-assimilation and C-allocation were
108 explicitly controlled by climate and CO_2 at different phenological stages (Misson 2004;
109 Gea-Izquierdo *et al.* 2015). Importantly, the model includes a C storage pool to take into
110 account carry-over effects and its daily scale can fit different limiting environmental
111 conditions at different periods within and among years (Sala *et al.* 2012; Fatichi *et al.*
112 2014). Thus, the net effect in response to the winter and summer stress periods was
113 explicitly assessed. Forest projections were implemented using two contrasting
114 representative concentration pathways (RCPs, van Vuuren *et al.* 2011). Using model
115 simulations of future forest growth and GPP we addressed the following questions: (i)
116 what will be the net effect of a warmer climate for Mediterranean forests?; (ii) to what
117 extent could rising c_a help compensate the expected negative effect of climate warming
118 on forest growth and productivity? (iii) how will Mediterranean forests perform in
119 relation to the maximum temperature threshold for future climate (i.e. +2.0°C respect to
120 preindustrial levels) agreed in the COP21 (<http://www.cop21paris.org/>)?

121

122 **Material and Methods**

123 *Forest sites: growth data for model calibration*

124 To calibrate the model at the regional scale we used dendrochronological data from
125 77 forest sites including 12 Mediterranean tree species: 6 conifers and 6 broadleaves
126 (App. 1). These data were either owned by the authors or obtained from databases
127 (ITRDB, [https://www.ncdc.noaa.gov/data-access/paleoclimatology-data/datasets/tree-](https://www.ncdc.noaa.gov/data-access/paleoclimatology-data/datasets/tree-ring)
128 [ring](https://www.ncdc.noaa.gov/data-access/paleoclimatology-data/datasets/tree-ring); DendroDB, <https://dendrodb.eccorev.fr/framedb.htm>). We explored the data to
129 avoid chronologies where major site disturbances could have affected the decadal-to-
130 multidecadal growth variations. The chronologies included were older than 80 years in
131 order to avoid the effect of juvenile growth (data used for calibration started in 1950)
132 and ended later than 1995. Exceptionally, some sites ending before 1995 in Algeria
133 were included to ensure enough data from that region. The resulting calibration period
134 slightly differed across sites due to the different time-span of chronologies, but always
135 fell between 1950 and 2010 and was greater than 40 years. For the analysis, ring-width
136 growth data were transformed to basal area increments (BAI, $\text{cm}^2 \text{year}^{-1}$). One output
137 from the model is C allocated to the tree stem ($\text{g C m}^{-2} \text{year}^{-1}$). To make BAI and model
138 output comparable for model calibration both data were normalized to unitless indices
139 (Misson 2004; Gaucherel et al. 2008).

140

141 *Climate and c_a : historical data and future scenarios*

142 Daily precipitation and temperature data used for model calibration for 1950-2010
143 were either obtained from <http://www.meteo.unican.es/datasets/spain02> (Herrera *et al.*,
144 2012) for Spain (20 km grid) or from <http://hydrology.princeton.edu/data.php> (Sheffield
145 *et al.* 2006) for the rest (1° grid). Data were downscaled to match mean climatic local

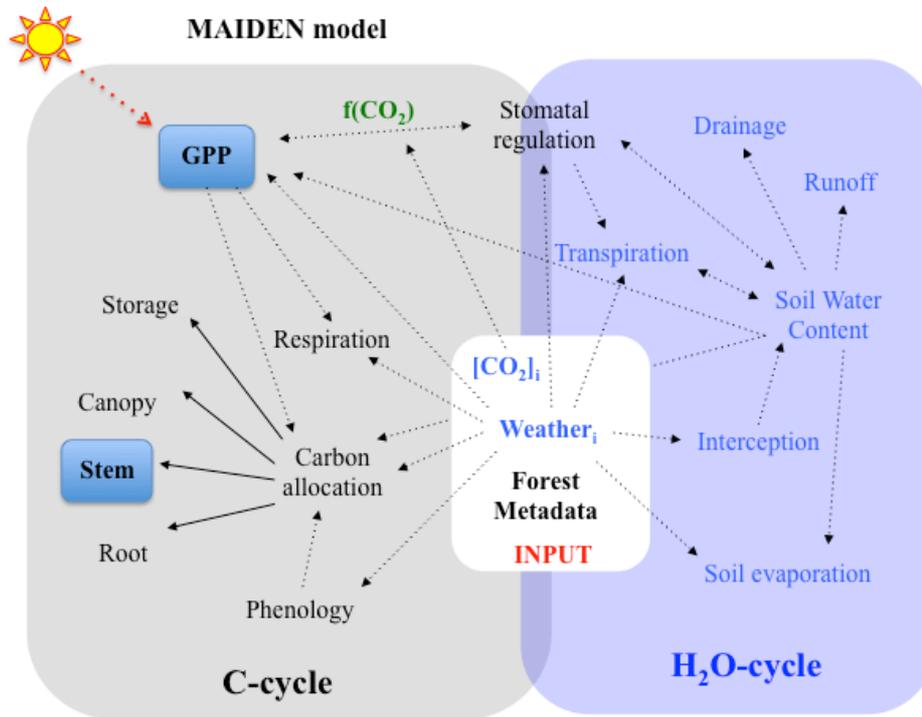
146 values where these were available. For the future forest projections we used two
147 greenhouse gas (GHG) radiative forcing scenarios developed for the Fifth Report of the
148 IPCC (IPCC 2014), called RCPs (Van Vuuren *et al.* 2011). RCP8.5 (GHGRF<8.5
149 W/m²) is the “business as usual” scenario. RCP2.6 is the most optimistic and stringent
150 among RCPs, corresponding to strong mitigation policies with a GHG radiative forcing
151 constrained to remain <2.6 W/m². RCP2.6 is the only RCP limiting global warming to
152 +2°C relative to the pre-industrial level. We used a multimodel ensemble of 19
153 simulations for RCP2.6 and 18 simulations for RCP8.5 performed by 13 climatic
154 institutes (see App. 2). The global climate models have a coarse resolution, from one to
155 more than five degrees depending on the model. There is often some mismatch between
156 the stand level and input climatic data (Körner 2003; Potter *et al.* 2013; Pappas *et al.*
157 2015). This was minimized as possible by downscaling climate scenarios to match the
158 shared period of the historical data. Under RCP8.5 the projected climate for our study
159 sites describes a relative increase in mean annual temperature (MAT) of +5.0°C and a
160 decrease of over 40% in mean annual precipitation (MAP) by 2100 respect to current
161 values. Under RCP2.6 the projected climate forecasts a mean increase in MAT of
162 +1.0°C by 2068, stabilizing thereafter, with no decrease in MAP respect to current
163 conditions (App. 3).

164

165 *The process-based model MAIDEN*

166 The vegetation model MAIDEN (Fig. 1) was originally developed to be used with
167 dendrochronological data by being calibrated to both time series of radial growth and
168 estimates of transpiration from sap-flow experiments (Misson 2004). Recently, the
169 model has been further developed to be used with evergreen Mediterranean taxa with a
170 multiproxy approach using gross primary productivity (GPP) estimates from Eddy

171 covariance stations and plot growth data (Gea-Izquierdo *et al.* 2015). Inputs are daily
 172 climatic data (precipitation, maximum and minimum temperatures) and c_a . In addition



173 Fig. 1. Outline of MAIDEN. Only GPP (gross primary production) and biomass
 174 allocated to the stem (used to calibrate the model sitewise) estimates (blue boxes) are
 175 reported along the manuscript. Daily output of each variable is generated based on the
 176 input data of day i . 'Weather' corresponds to daily integrals of precipitation as well as
 177 maximum and minimum daily temperatures. GPP and 'Stomatal conductance' are
 178 functions of CO₂, whereas variability within the other processes is mostly driven by
 179 meteorological inputs directly or indirectly (e.g. SWC). For more details on the
 180 functions and processes outlined see Misson (2004) and Gea-Izquierdo *et al.* (2015).
 181

182
 183 the model requires as input different site related physiographic characteristics and
 184 species functional traits (see Gea-Izquierdo *et al.* 2015 for details). The processes within
 185 the model are mainly functions of climate, CO₂ and soil water availability (hence water

186 stress). The model acts at the stand level calculating carbon and water fluxes (Fig. 1)
187 using a coupled photosynthesis-stomatal conductance model. It uses the standard
188 biochemical model of Farquhar *et al.* (1980) in which photosynthesis is driven by the
189 most limiting between Rubisco-limited activity and electron-transport. Stomatal
190 conductance is also estimated using a widely used equation as a function of vapor
191 pressure deficit (VPD, Leuning 1995). After GPP and autotrophic respiration have been
192 estimated carbon is allocated to different tree components. Photosynthesis and
193 allocation are driven by decoupled non-linear (daily) functions of climate. Thus growth
194 is not only a direct function of C availability and the model is designed to address in
195 time not only C-source but also C-sink limitations, which is an important step required
196 to achieve more robust and realistic vegetation models (Muller *et al.* 2011; Sala *et al.*
197 2012; Fatichi *et al.* 2014). The model is particularly sensitive to water stress by
198 implicitly modeling as functions of climate and water stress some functional and
199 demographic traits such as leaf area, carbon allocation, leaf- and canopy-level
200 photosynthesis and transpiration (Muller *et al.* 2011; Gea-Izquierdo *et al.* 2015;
201 Duursma *et al.* 2016; Kelly *et al.* 2016). [CO₂] only affects photosynthesis and stomatal
202 conductance, i.e. leaf area or respiration are direct functions of climate but not CO₂. A
203 brief outline of the model is shown in Fig. 1.

204

205 *Model calibration and ecological coherence of the parametric space*

206 Calibration of complex multiparametric models is necessary to improve model
207 performance and because of the presence of collinearities between parameters and
208 absence of an exact solution (Prentice *et al.* 2015). To ensure good model performance,
209 it is important to assess the functional coherence of parameters to be calibrated. In
210 addition to calibration, it is desirable to run independent validations particularly when

211 models are fitted for prediction purposes. Nevertheless, we could not run an
212 independent crossvalidation for two reasons: (1) we calibrated against annual growth
213 (i.e. we had a number of observations between 40 and 60) estimates by integrating
214 annually the daily estimates from the model, therefore our data was too short to be split
215 in two, (2) a jackknife was intractable both computationally and also because
216 continuous (daily) time data series are needed to run the model, i.e. in case individual
217 years were left out the model could not calculate the carbon and water dynamics needed
218 to compute the complete time series at each site.

219 We implemented a species-specific approach rather than using plant functional
220 types (PFTs) as it is often applied in ecosystem models (Kattge *et al.* 2011; Atkin *et al.*
221 2015; Pappas *et al.* 2016). We applied the model at the regional scale and to different
222 species to analyze forest performance under future climate and c_a . Data-assimilation
223 was used to apply the model to different ecological conditions and species (Peng *et al.*
224 2011; Medlyn *et al.* 2015). Overall, the growth data did not show a positive trend
225 whereas c_a increased steadily in the calibration period (1951-2010). Therefore, by
226 calibrating the model site-wise using non-detrended (but normalized) growth data and
227 observed c_a levels we assured that the model excluded an artificial carbon fertilization
228 effect on past growth. Additionally, to avoid overestimation of photosynthesis and get
229 unbiased simulations (Schaefer *et al.* 2012), we ensured that maximum GPP daily
230 integrals yielded within ranges given in Baldocchi *et al.* (2010): 4-6 g C m⁻² day⁻¹ for
231 evergreens and of 10-14 g C m⁻² day⁻¹ for deciduous species. Similarly, we constrained
232 annual GPP and NPP estimates to be within those measured for similar ecosystems (see
233 Table 3 in Falge *et al.* 2002 and Table 3 in Luysaert *et al.* 2007). Species Specific leaf
234 area (SLA) was obtained from Mediavilla *et al.* (2008) and Kattge *et al.* (2011).

235 Here, within the processes in Fig. 1 we show those functions with parameters
 236 involved in the calibration phase. For more details, we refer to the original model in
 237 Misson (2004) and the updated modified last version in Gea-Izquierdo *et al.* (2015).

$$238 \quad (i) \quad \theta_g(i) = \frac{1}{1 + \exp(\text{soil}_b \cdot (\text{SWC}(i) - \text{soil}_{ip}))} \quad [\text{E1}]$$

$$239 \quad (ii) \quad a_{31}(i) = (1 - \exp(p_{3moist} \cdot \text{SWC}(i)) \cdot \left(\exp\left(-0.5 \cdot \left(\frac{T_{max}(i) - p_{3temp}}{p_{3sd}}\right)^2\right)\right) \quad [\text{E2}]$$

$$240 \quad (iii) \quad a_{32}(i) = (1 - \exp(st_{3moist} \cdot \text{SWC}(i)) \cdot \left(\exp\left(-0.5 \cdot \left(\frac{T_{max}(i) - st_{3temp}}{st_{3sd_temp}}\right)^2\right)\right) \quad [\text{E3}]$$

$$241 \quad (iv) \quad a_4(i) = (1 - \exp(st_{4temp} \cdot T_{max}(i)) \cdot \left(\exp\left(-0.5 \cdot \left(\frac{\text{SWC}(i)}{st_{4sd_moist}}\right)^2\right)\right) \quad [\text{E4}]$$

242 θ_g is a soil water stress function affecting stomatal conductance. a_{31} , a_{32} and a_4 are
 243 allocation functions for two different phenological periods (3 and 4). a_{31} is related to the
 244 leaves and a_{32} to the stem, whereas a_4 determines C allocation between the stem and
 245 storage. SWC is soil water content and T_{max} is daily maximum temperature. We
 246 calibrated soil_{ip} from [E1]; p_{3moist} and p_{3temp} from [E2]; st_{3moist} and st_{3temp} from
 247 [E3]; and st_{4sd_moist} and st_{4temp} from [E4]. The rest of parameters were set following
 248 Gea-Izquierdo *et al.* (2015). All parameters except soil_{ip} (which is related to the
 249 stomatal response) help to define carbon allocation in relation to soil water content and
 250 air temperature during the active period.

251 We calibrated these model parameters taking into account variability in functional
 252 traits and the response to climate of plant processes related to site and species. To
 253 address the local phenotypic response of species (Montwé *et al.* 2016), some of those
 254 parameters (≤ 7) described in the previous paragraph were calibrated site-wise using
 255 maximum likelihood principles and a global optimization algorithm (Gaucherel *et al.*
 256 2008; Gea-Izquierdo *et al.* 2015). A maximum of 7 allocation parameters from [E1] to
 257 [E4] were optimized depending on species by comparing normalized annual integrals of

258 modeled C allocation to the stem and normalized annual growth series. We calculated
259 different statistics to check the goodness of fit: the coefficient of determination (R^2), the
260 linear correlation (ρ), and the correlation (r_{low}) between filtered (using splines with a
261 50% frequency cutoff of 30 years) observed and modelled growth. r_{low} was calculated to
262 analyse the model capability to mimic the interannual and decadal growth trends. To
263 discuss the validity of our modelling exercise and since we could not run an
264 independent verification to the calibration conducted, coherence of the intersite
265 multiparametric space was analysed by exploring the ecological significance of
266 parameters compared to different site characteristics including latitude, longitude,
267 altitude, precipitation, temperature, and Penman-Monteith potential evapotranspiration
268 (PET), which was calculated for each site following Allen *et al.* (1998). The
269 relationship between the 7 model parameters fitted at each of the 77 sites and the mean
270 site ecological covariates was explored through pointwise correlations: (i) using site
271 individual indices; (ii) using the principal components (PCs) of the 7 x 77 matrix
272 (Legendre & Legendre 1998).

273

274 *Forest performance under climate change and different c_a scenarios*

275 Once the model had been calibrated we implemented forest projections at the 77
276 sites using simulated climatic data generated under RCP2.6 and RCP8.5. To discuss the
277 effect of c_a on the net response of forests to climate change we compared two type of
278 forest simulations driven by the multimodel climatic scenarios:

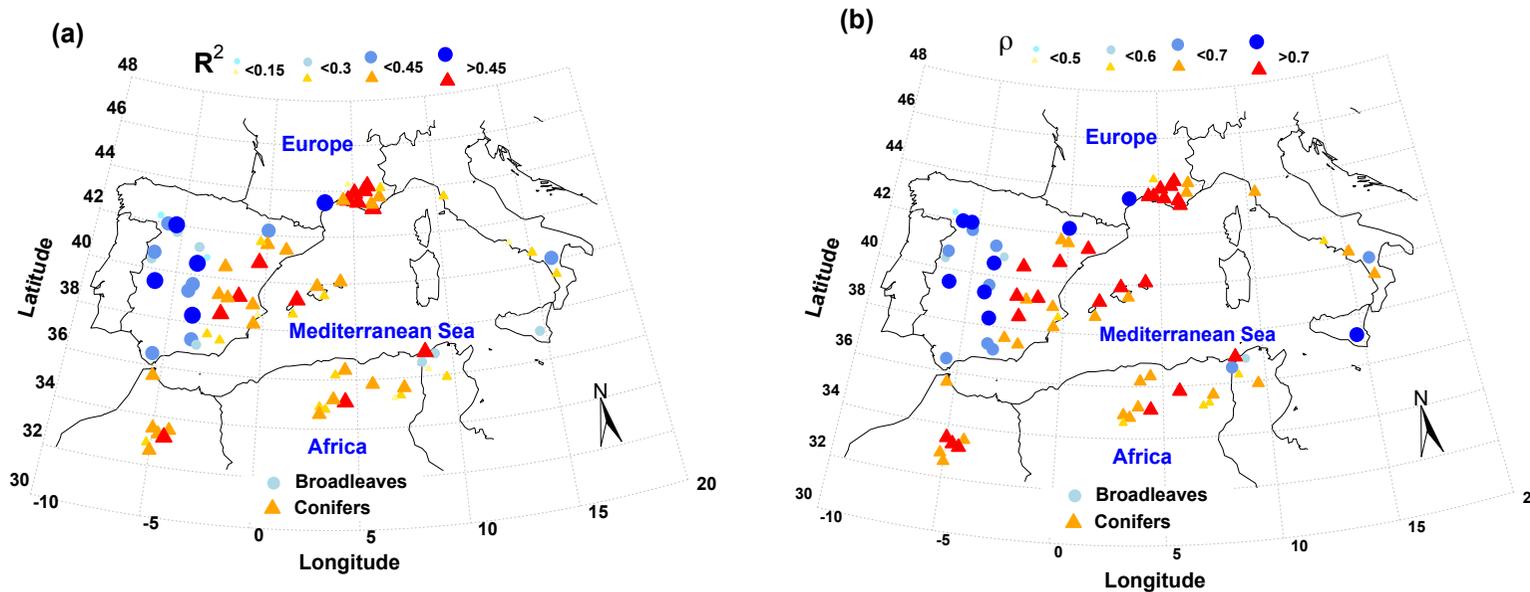
- 279 (i) ‘fertilization’ scenario: with c_a levels expected for RCP2.6 and RCP8.5.
- 280 (ii) ‘non-fertilization’ scenario: using climate from RCP2.6 and RCP8.5 but constant c_a
281 = 390 ppm after 2010.

282 We report GPP in addition to growth projections. Future growth trends were assessed

Group	n	R^2		r		r_{low}	
		Mean (sd)	Max (Min)	Mean (sd)	Max (Min)	Mean (sd)	Max (Min)
Broadleaves	22	0.343 (0.168)	0.643 (0.0)	0.675 (0.084)	0.821 (0.483)	0.728 (0.185)	0.929 (0.114)
Conifers	55	0.356 (0.141)	0.710 (0.073)	0.676 (0.070)	0.855 (0.537)	0.786 (0.156)	0.968 (0.249)
Total	77	0.353 (0.148)	0.710 (0.0)	0.675 (0.074)	0.855 (0.483)	0.769 (0.165)	0.968 (0.114)

283 Table 1. Mean values of goodness of fit statistics. n= number of forest sites; R^2 =coefficient of determination; r=coefficient of correlation;

284 r_{low} =coefficient of correlation of filtered data (see material and methods for details).



285

286 Fig. 2. Map showing the coefficient of determination (R^2) and correlation (ρ) between dendrochronological data and modeled stem growth data

287 using MAIDEN at the 77 forest sites. R^2 is shown in (a) whereas ρ in (b). For R^2 we split in four classes: $0 \leq R^2 < 0.15$; $0.15 \leq R^2 < 0.3$;

288 $0.3 \leq R^2 < 0.45$; $0.45 \leq R^2$. For ρ in: $0.45 \leq \rho < 0.5$; $0.5 \leq \rho < 0.6$; $0.6 \leq \rho < 0.7$; $0.7 \leq \rho$. Triangles depict conifers, whereas circles broadleaves.

289 through the slope of simple regressions between simulated growth (or GPP) for a given
290 scenario and site against year for the periods 2010-2100, 2010-2050 and 2051-2100.

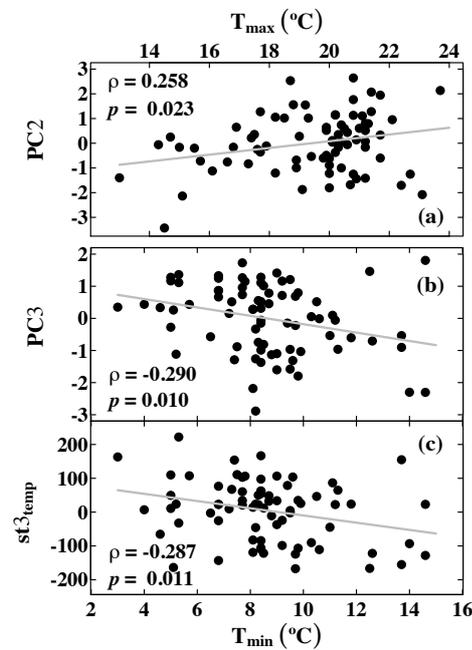
291

292 **Results**

293 *Model calibration across western Mediterranean forests*

294 The model fit against the calibration data is shown in Fig. 2 and Table 1 and the
295 parameters fitted in App. 4. Importantly, data used to calibrate the model did not show
296 an overall significant increase in growth, hence did not suggest evidence of a global net
297 carbon fertilization effect during the last decades (Table 2). The observed growth trends
298 were highly correlated with the model output (ρ and particularly r_{low} in Table 1).
299 Correlation between model output (carbon allocated to the stem) and growth data was in
300 average 0.67 whereas mean R^2 was 0.36 (Table 1). The multiparametric space of the 77
301 fitted models was explored through PCA. The eigenvalues corresponding to the three
302 first principal components (PCs) were over the mean, hence significant according to the
303 Kaiser-Guttman criterion (Legendre & Legendre 1998). These three PCs including the 7
304 parameters fitted in the calibration phase explained 60.9 % of the variability (PC1 24.7
305 %, PC2 19.7 % and PC3 16.6%). PC1 was mostly related to parameters linked to
306 humidity: a positive relation with moisture parameters such as $soil_{ip}$ and st_{4sd_moist} , and
307 a negative one with st_{3moist} (not shown). PC2 was mostly related to parameters linked
308 to temperatures: positively with st_{4temp} and negatively with p_{3temp} and st_{3temp} . PC3
309 was positively correlated with the humidity parameter p_{3moist} (not shown). The 77
310 parameters and the PCs (2 and 3) showed some significant relationships with the site
311 ecological characteristics (Fig.3). Most of the site-based relationships between the fitted
312 parameters and the ecological characteristics of the 77 sites were linked to site
313 temperatures (Fig. 3), whereas almost no significant relationships were found with the

314 other tested covariates (e.g. site precipitation or PET). These relationships suggest the
 315 existence of some ecological coherence within the parametric space fitted for the 77
 316 forest sites, which would support the robustness of the model parameterization used.



317 Fig. 3. Ecological coherence of model parameters at the 77 forest sites (only those
 318 relationships that were significant are shown): (a) PC2 and site T_{max} ; (b) PC3 and site
 319 T_{min} ; (c) $st3_{temp}$ and site T_{min} .

321

322 *Growth-GPP projections under changing climate and c_a*

323 The model allocates carbon to different plant compartments driven by different non-
 324 linear functions of environmental variability, hence it allows some decoupling between
 325 GPP, NPP and secondary growth. In this sense, 59% and 80% of the simulations
 326 presented correlations between GPP and growth higher than 0.5 for RCP2.6 and
 327 RCP8.5, respectively (App. 5). Thus the majority of sites showed a good agreement
 328 between interannual GPP and growth (i.e. generally the modeled interannual variability
 329 of growth was driven by that of GPP). Furthermore, the growth trends (long-term,
 330 multiannual) were of similar sign (positive, negative or neutral) as those of GPP (Table

Group	Observed past Growth	Growth projections 2010-2099							
		Allowing fertilization (i.e. predicted c_a)				No fertilization (i.e. $c_a = 390$ ppm)			
		GPP		Growth		GPP		Growth	
		2010-2050	2051-2099	2010-2050	2051-2099	2010-2050	2051-2099	2010-2050	2051-2099
Broadleaves	0.79 (0.96)	0.60 c (2.03)	-0.62 c (0.38)	0.35 b (0.71)	-0.24 d (0.16)	-2.2 a (2.75)	0.26 a (0.47)	-0.65 b (0.89)	0.08 a (0.18)
Conifers	0.17 (0.71)	0.78 c (1.98)	-0.98 d (1.42)	0.14 c (0.31)	-0.08 c (0.13)	-3.64 b (3.92)	-0.02 b (0.82)	-0.34 a (0.38)	0.02 b (0.11)
Total	0.35 (0.83)	0.73 (1.98)	-0.88 (1.22)	0.20 (0.47)	-0.13 (0.16)	-3.21 (3.67)	0.06 (0.74)	-0.43 (0.58)	0.04 (0.13)
Broadleaves	0.79 (0.96)	2.11 b (2.20)	3.21 b (2.79)	0.93 a (0.96)	1.37 a (1.13)	-4.32 c (3.14)	-5.48 c (2.42)	-1.30 c (1.11)	-1.05 d (0.73)
Conifers	0.17 (0.71)	3.38 a (1.74)	3.75 a (2.51)	0.37 b (0.45)	0.78 b (0.62)	-5.68 d (3.77)	-6.4 d (3.21)	-0.61 b (0.46)	-0.57 c (0.53)
Total	0.35 (0.83)	3.02 (1.96)	3.60 (2.58)	0.53 (0.68)	0.95 (0.83)	-5.29 (3.63)	-6.11 (3.02)	-0.81 (0.77)	-0.71 (0.63)

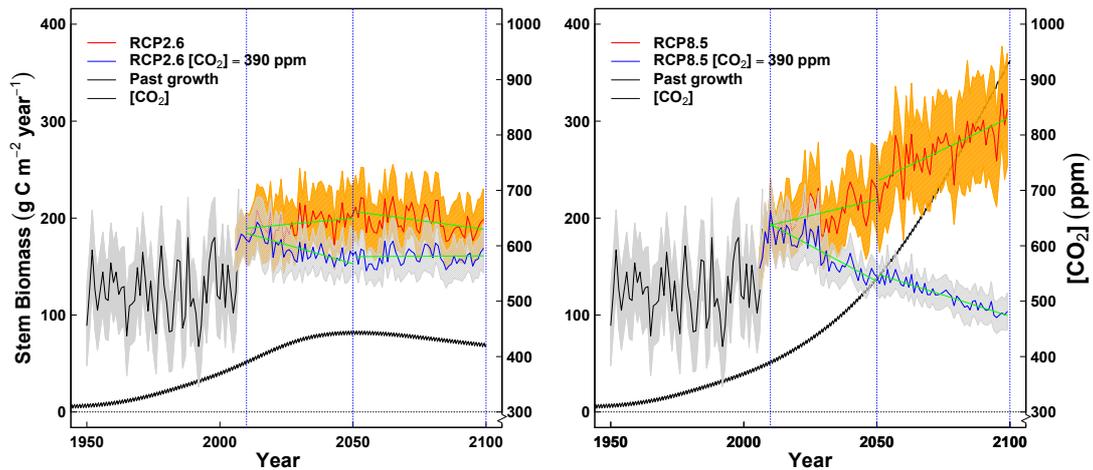
331

332 Table 2. Growth trends as estimated by the slopes of linear regressions between growth (slopes in $\text{cm}^2 \cdot \text{year}^{-2}$) or GPP (slopes in $\text{g C m}^{-2} \text{ year}^{-2}$)

333 and year. Mean slopes are shown for observed past growth and for projected growth and GPP for the periods 2010-2050 and 2051-2099.

334 Standard deviations are between parentheses. One-way ANOVA differences between broadleaves and conifers (RCP2.6 and RCP85, i.e. 4 levels)

335 within columns are depicted with different letters.



336
 337 Fig. 4. Example of growth projections at one *Quercus pyrenaica* site (QUPY3 in
 338 App.1). Trends (i.e. linear regressions between mean growth and year) for 2010-2050,
 339 and 2051-2099 are shown with green lines for the ‘fertilization’ (red line) and ‘non-
 340 fertilization’ (blue line) scenarios. These trends correspond to the slopes reported in
 341 Table 2, Fig. 5 and Fig. 6. Shaded areas behind annual mean growth values (\hat{y} ; thick
 342 black line is mean past growth) correspond to the confidence intervals for the mean
 343 calculated as $\hat{y} \pm 1.96 \cdot sd_{\hat{y}}/\sqrt{n}$ ($sd_{\hat{y}}$ is the combined standard deviation of the model
 344 estimates and the variability among climatic scenarios; n is sample size). c_a values
 345 ($[CO_2]$) corresponding to the two scenarios considered (i.e. RCP2.6, RCP8.5) are shown
 346 as thin black lines.

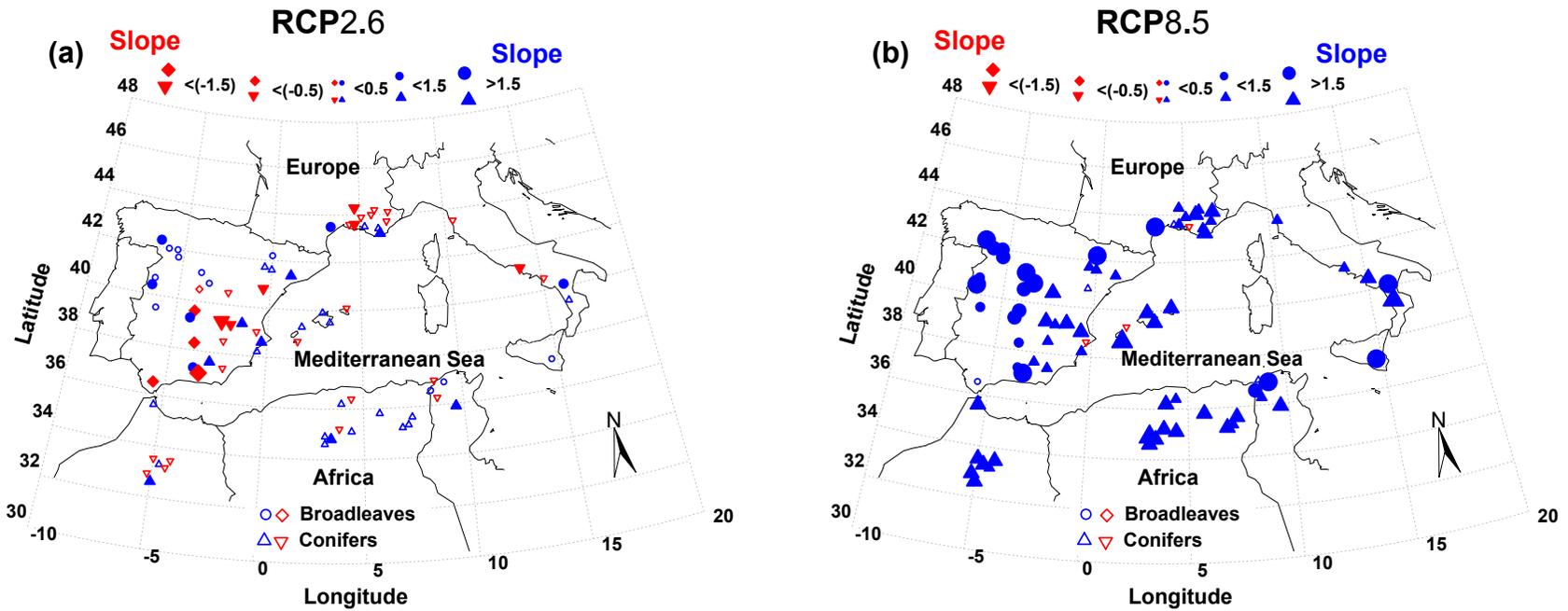
347

348 2). GPP projections exhibited steeper trends (both positive and negative) for
 349 Mediterranean conifers (all evergreen species), whereas the growth trends were steeper
 350 for broadleaves (mostly deciduous) than for conifers (Table 2). An example of a model
 351 simulation and how the reported trends (i.e. slopes) were calculated is depicted in Fig.
 352 4. Model simulations yielded the greatest GPP and growth in more mesic sites, as
 353 expected (App. 6).

354 According to our projections forest growth would not be much altered when
355 assuming the low emission RCP2.6 scenario with predicted c_a (Fig. 5). Under the c_a
356 pathway from RCP2.6, which reaches the c_a maximum (446 ppm) in 2051, the model
357 simulates a slight increase in growth up to 2050 followed by a slight decrease (Table 2).
358 The resulting overall trend up to 2100 depends on site conditions: most forests exhibited
359 non-significant or reduced trends under RCP2.6 for both c_a scenarios (Fig. 5, 6).
360 However, for the ‘non-fertilization’ scenario, model simulations suggested significant
361 negative growth trends for some coniferous sites e.g. in Southern France and Eastern
362 Spain (Fig. 6). Therefore the results of the model mostly suggested that forests would
363 acclimate at the regional scale to the climate proposed by RCP2.6. Yet, negative local
364 impacts for some coniferous species would pop up when constraining the carbon
365 fertilization effect.

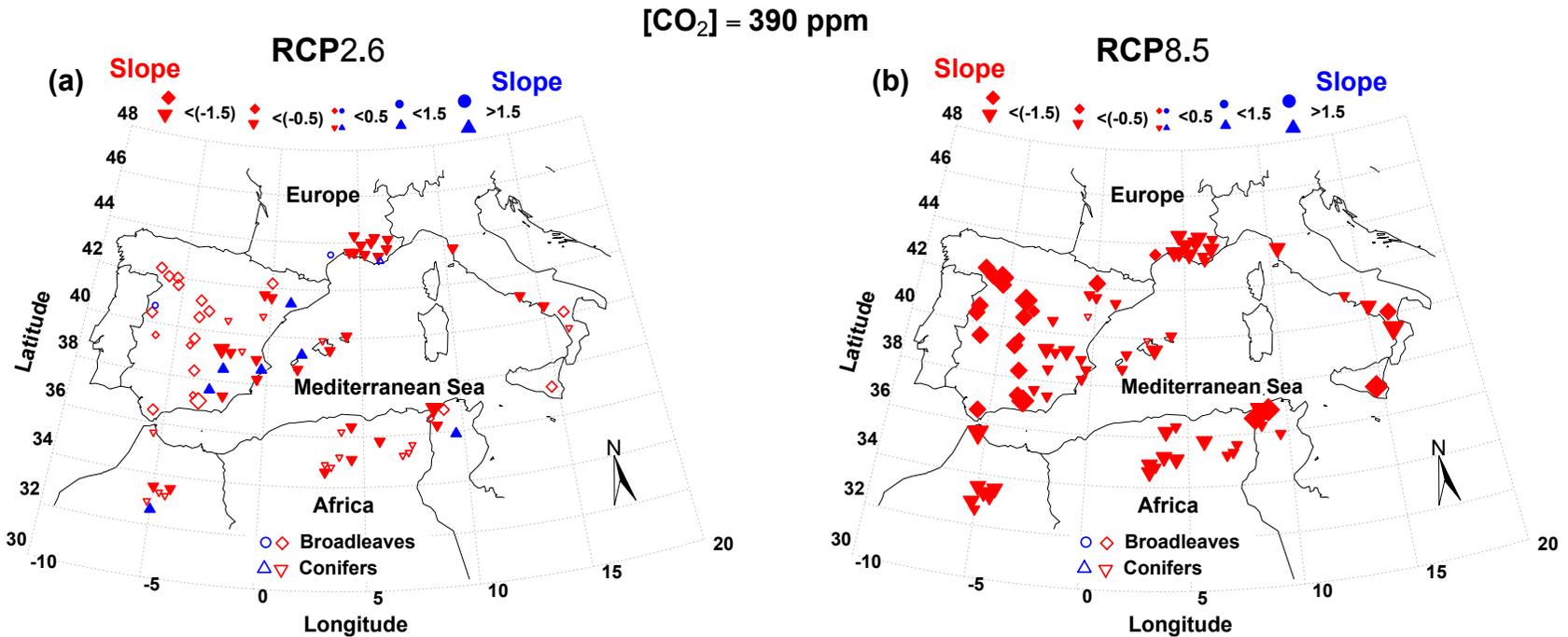
366 Climate simulations under RCP8.5 forecast a much warmer scenario with less
367 precipitation than RCP2.6 (App. 3). In response, forest growth projections under this
368 scenario showed a different picture to that described for RCP2.6. For the ‘non-
369 fertilization’ scenario (i.e. constant 390 ppm) future forest growth trends would be
370 negative across all the western Mediterranean. Both conifers and broadleaves would
371 suffer huge decreases in GPP and growth concurrent with the increase in PET expected
372 under RCP8.5. These negative trends were much steeper than those for RCP2.6 (Table
373 2) and in some cases converged towards zero. In contrast, under the coherent c_a pathway
374 (exponential increase in c_a to 935 ppm in 2100) for RCP8.5, the model suggested that
375 plants would not only compensate the more stressing climate but also that growth and
376 GPP would be enhanced across the study region regardless of species (Fig. 6; Table 2).

377 In average RCP8.5 predicts for the studied area in average a +2°C warmer climate
378 (with c_a = 504 ppm) and a slight MAP reduction by 2050 (App. 3) compared to present



379

380 Fig. 5. Future growth simulations trends using climatic scenarios RCP2.6 (a) and RCP8.5 (b), with predicted (increasing) c_a between 2010 and
 381 2099. Trends are estimated as the slopes of the linear regressions between stem biomass growth and year (see Fig. 4). Symbols are scaled as a
 382 function of the slope value. Red symbols correspond to negative trends whereas blue symbols to positive trends. Solid symbols correspond to
 383 significant trends ($\alpha=0.05$) whereas empty symbols to non-significant trends.



384
 385 Fig. 6. Future growth simulations trends between 2010 and 2099 using climatic scenarios RCP2.6 (a) and RCP8.5 (b), with constant $c_a = 390$
 386 ppm. Trends are estimated as the slopes of linear regressions between stem biomass growth and year (see Fig. 4). Symbols are scaled as a
 387 function of the slope value. Red symbols correspond to negative trends whereas blue symbols to positive trends. Solid symbols correspond to
 388 significant trends ($\alpha=0.05$) whereas empty symbols to non-significant trends.

389 values (i.e. +2.8°C compared to preindustrial levels). This is over the reduction goal in
390 greenhouse emissions for COP21 (<http://www.cop21paris.org/>) established below +2°C,
391 which otherwise would be achieved in RCP2.6. Simulations under RCP8.5 suggested a
392 negative impact in growth and GPP of climate unless this was compensated by an
393 exaggerated fertilization effect of eCO₂. The higher the temperature, the more evident
394 and widespread this negative impact would become (Fig. 5, 6; Table 2). In contrast,
395 when allowing fertilization, the greatest positive growth trends (i.e. a greater net
396 fertilization effect) would arise after 2050 with c_a levels >500 ppm (Table 2). Growth
397 trends after 2050 were steeper than those before 2050 for the ‘fertilization’ scenario
398 (mean difference 0.42, p<0.001) but not for the ‘non-fertilization’ scenario (mean
399 difference 0.09, p=0.403). This highlights the larger influence in simulated growth and
400 GPP of eCO₂ (positive) compared to that of expected high temperatures (negative).

401

402 **Discussion**

403 *Forest future in a warmer western Mediterranean region: what is the role of c_a?*

404 Trees can enhance productivity and modify some anatomical and physiological
405 traits (e.g. iWUE) in response to eCO₂ but it is not known how they will perform under
406 future climate and c_a (Medlyn & De Kauwe 2013; Duursma *et al.* 2016; Kelly *et al.*
407 2016). A positive net effect of eCO₂ on trees can be hampered by the limiting effect of
408 other environmental constraints such as nitrogen (N) availability and water stress (De
409 Kauwe *et al.* 2013; Reichstein *et al.* 2013; Fernández-Martínez *et al.* 2014; Walker *et al.*
410 *et al.* 2015; Kim *et al.* 2016). A positive feedback of eCO₂, e.g. in leaf area (if a steady-
411 state has not been achieved yet; Körner 2006) and NPP, has been reported under current
412 climate conditions in temperate forests where non-climatic factors such as N availability
413 were limiting (Medlyn *et al.* 2015; Walker *et al.* 2015; Kim *et al.* 2016). In contrast,

414 Duursma *et al.* (2016) did not observe any change in leaf area in response to eCO₂ when
415 leaf area was limited by water availability (i.e. like in our model). Therefore, depending
416 on the most limiting factor, different ecosystems seem to express different responses to
417 eCO₂ under current climatic conditions.

418 As reflected by our model during the observational period (see Gea-Izquierdo *et al.*
419 2015 for iWUE), the effect of recent rising c_a has generally produced an enhancement in
420 iWUE but not in growth rates (e.g. Peñuelas *et al.* 2011; Keenan *et al.* 2013; Saurer *et*
421 *al.* 2014; van der Sleen *et al.* 2014). Furthermore, studies reporting past growth
422 enhancement within the last 150 years (e.g. at species-specific high-elevation sites) did
423 not consider c_a as the main factor triggering that growth increase (Salzer *et al.* 2009;
424 Gea-Izquierdo & Cañellas 2014). According to our results, most Mediterranean forests
425 would mitigate the optimistic RCP2.6 scenario either with or without C-fertilization.
426 Hence, forests would mostly endure the +2°C warming limit set within the Paris'
427 Agreement (<http://www.cop21paris.org/>). In contrast, projections under high-emission
428 RCP8.5 would forecast big changes in forest performance. Simulations reflected a very
429 negative impact of climatic conditions under RCP8.5 and a non-fertilization scenario,
430 whereas they suggested a dominant positive effect of eCO₂ at the regional scale
431 (particularly for c_a > 500 ppm) when allowing fertilization even under the very limiting
432 climatic conditions of RCP8.5. The observed positive trends following a Temperature x
433 eCO₂ interaction were not unexpected, because the Farquhar model ensures large direct
434 responses to eCO₂ since Rubisco-limited photosynthesis responds fast to enhanced c_a
435 (Reichstein *et al.* 2013; Friend *et al.* 2014; Baig *et al.* 2015; Walker *et al.* 2015; Norby
436 *et al.* 2016). Yet, this fertilization effect both for GPP and growth under RCP8.5 looks
437 unrealistic (Körner 2006; Friend *et al.* 2014; Baig *et al.* 2015; Kelly *et al.* 2016).

438 The future long-term response of forests is uncertain but we expected no positive
439 net effect of eCO₂ on plant growth under very strong water-limitations (van der Molen
440 *et al.* 2011; Girardin *et al.* 2012; Baig *et al.* 2015). Nevertheless, this was only reflected
441 for RCP8.5 by the non-fertilization scenario. Photosynthesis is a saturating function of
442 intercellular CO₂ (Kelly *et al.* 2016) and according to Körner (2006) saturation is
443 expected at levels similar to those of RCP8.5 in 2100 (circa 1000 ppm). Likely, the
444 model does not downregulate assimilation enough under high c_a or underestimates the
445 limiting effect of other interacting factors (e.g. light, nutrients, water stress, hydraulics)
446 on e.g. maximum carboxylation. This was addressed empirically by setting a limit at
447 390 ppm but a more detailed understanding of the physiological processes in relation to
448 eCO₂ would definitely help to improve model forecasts. A global negative response of
449 Mediterranean forests to intense warming unless there is an exaggerated C-fertilization
450 effect is, thus, evident in our results. Importantly, this implies negative consequences
451 for forest performance and means that a positive effect of milder winters (e.g. earlier
452 growing season or enhanced winter assimilation in evergreens) would not counteract the
453 negative effect of longer stressing summers. There is an ample debate on the actual
454 factors causing tree death, but it seems that a combination of interrelated C-related
455 traits, hydraulically-related features and climate-related impacts of biotic agents should
456 govern the forest decline and mortality processes (Sala *et al.* 2012; McDowell *et al.*
457 2013; Aguiar *et al.* 2015; Anderegg *et al.* 2015). Regardless of the final causal factor/s,
458 steep negative growth trends like those under RCP8.5 and no-fertilization strongly
459 suggest changes in stand dynamics and composition and ultimately enhanced mortality
460 at some sites (Bigler *et al.* 2006; van der Molen *et al.* 2011; Gea-Izquierdo *et al.* 2014).
461
462 *Forest growth projections under climate change and eCO₂: utilities and uncertainties*

463 Models need continuous refinement to achieve robustness, reliability and realism
464 (Prentice et al. 2015). Forecasts of tree growth are a valuable tool to understand forest
465 performance under climate change but there are many sources of uncertainty within
466 model performance and data-assimilation that need discussion (Friend et al. 2014).
467 Caveats in models include: (i) current knowledge of the physiological processes; (ii)
468 model implementation and parameterization (including scale-dependent constraints);
469 (iii) uncertainty of model outputs outside the calibration range (Pappas *et al.* 2013;
470 Prentice *et al.* 2015). Additionally, changes in plasticity of functional traits and plant
471 acclimation processes can bias model projections (Muller et al. 2011). We assumed
472 uniformitarianism (i.e. temporal invariance of the modeled relationships) in model
473 projections but it could be that threshold related responses arise after the calibration
474 boundaries are surpassed. In this sense (iii) is minimized by explicitly modeling
475 processes but not eliminated as a result of (i) and (ii). Despite inherent limitations in
476 models and observational data (Babst *et al.* 2014), by using data-assimilation we
477 maximized the likelihood of getting unbiased past long-term trends to increase
478 reliability of growth projections (Peng *et al.* 2011; Medlyn *et al.* 2015). Forest
479 productivity was analyzed assuming present steady-state stand conditions (e.g.
480 composition, leaf area, root mass) constrained by water stress (Körner 2006). This could
481 bias the analysis of forest dynamics (Körner 2003; Friend et al. 2014; Pappas *et al.*
482 2015), particularly for mixed stands (Pappas et al. 2013). However, our aim was to
483 analyze performance of the present stands under future environmental conditions, with
484 emphasis on species long-term trends. Changes in inter-species dynamics are away from
485 the scope of our analysis and need to be studied complementary.

486 The model does not include nutrient dynamics but focuses on the water and carbon
487 cycles and the effect of water stress at different functional levels. This is because

488 nutrient availability is generally considered secondary in Mediterranean ecosystems
489 compared to water stress, which in addition is expected to increase in the future (Giorgi
490 & Lionello 2008; García-Ruiz *et al.* 2011; IPCC 2014). Thus, the limiting effect of
491 factors such as availability of N, P, or hydraulic constraints could invalidate a C
492 fertilization effect on net growth under eCO₂ (Körner 2006; Norby *et al.* 2010; Fatichi
493 *et al.* 2014; Fernández *et al.* 2014; Friend *et al.* 2014; Baig *et al.* 2015). Our model is
494 simpler than ecosystem models including nutrient and stand dynamics (e.g. Reichstein
495 *et al.* 2013; Walker *et al.* 2015). However, our scale is finer (stand, species-specific
496 compared to PFTs) and, most important, it is driven by actual growth data to ensure
497 unbiased estimation of short- and long-term trends. Other factors such as differences in
498 carry-over effects between conifers and broadleaves, changes in species composition
499 and demography, competition and tree-related traits such as ontogeny and size, partly
500 modulate the forest response to climate (van der Molen *et al.* 2011). However, long-
501 term stand productivity seems to change slightly under moderate disturbances such as
502 those produced by silvicultural treatments or insect infestation (Vesala *et al.* 2005;
503 Amiro *et al.* 2010). Therefore, we believe that climate effects are dominant and the
504 reported long-term trends are robust in relation to variability within these other factors,
505 which would affect mostly in the short-term. The model fit reported was in the range of
506 that in similar studies (Misson 2004; Li *et al.* 2014; Gea-Izquierdo *et al.* 2015; Girardin
507 *et al.* 2016). Different goodness-of-fit at different sites could result on differences in
508 model performance. However, in App. 7A we show how variability in R² did not
509 influence the estimated trends (future projections). Particularly, when the trees exhibited
510 long-term trends in the past (observational period), these showed a very high agreement
511 with the modeled growth trends (App. 7B; Table 1). As mentioned, the robustness of
512 our approach relies on the spatial (regional) scale where the model was applied, which

513 expands model implementation at a broader scale than that where it was previously
514 applied (Misson *et al.* 2004; Gaucherel *et al.* 2008; Gea-Izquierdo *et al.* 2015).

515 Model simulations can be improved by better addressing the influence of CO₂ on
516 variability of different plant traits (Kattge *et al.* 2011; Atkin *et al.* 2015; Pappas *et al.*
517 2016). Leaf photosynthesis is negatively affected by drought through several
518 mechanisms including changes in stomatal and mesophyll conductance or reductions in
519 biochemical efficiency (Flexas *et al.* 2005). Both photosynthesis and stomatal
520 conductance were modeled as direct functions of CO₂. However, warming and
521 increasing water stress in relation to eCO₂ could differently affect autotrophic
522 respiration and photosynthetic capacity, or enhance photorespiration more than
523 photosynthesis (Baig *et al.* 2015; Girardin *et al.* 2016; Rowland *et al.* 2015; Varone &
524 Gratani 2015). Our model takes into account the short-term acclimation of leaf
525 photosynthesis and stomatal conductance to CO₂, while respiration is set as a function
526 of temperature and GPP (Gea-Izquierdo *et al.* 2015). Different sources of interspecific
527 variability under eCO₂ in autotrophic respiration not explained by models (Atkin *et al.*
528 2015) or other factors such as species-specific variability in $J_{\max}/V_{c\max}$ could partly
529 impair our results. Trees modify other traits such as leaf area and sapwood area to
530 withstand xericity (Breda *et al.* 2006; Martin-StPaul *et al.* 2013; Duursma *et al.* 2016;
531 Kelly *et al.* 2016). In our model, intra-annual, inter-annual and long-term structural
532 acclimation of leaf area and allocation rules rely on climate and SWC but not on CO₂.
533 Thus, addressing the influence of CO₂ on leaf area dynamics by setting SLA and
534 allocation rules also as functions of CO₂ could also help to better assess whether the
535 reported fertilization effect is unrealistic (Duursma *et al.* 2016; Medlyn *et al.* 2015).

536 In summary, modeled forest growth reflected the observed absence of an overall net
537 positive effect of enhanced c_a under increased temperatures (i.e. PET) in the recent past.

538 According to model projections, western Mediterranean forests would mostly mitigate
539 the negative effect of a climate remaining below the maximum warming levels (+2°C)
540 agreed in COP21 (i.e. scenario RCP2.6) but the situation would be very different above
541 those levels (as represented by RCP8.5). Our results suggest that fertilization could
542 override the negative effect of stressing climatic conditions under high-emission
543 RCP8.5 but this fertilization effect of eCO₂ looks unrealistic according to the literature,
544 being most likely a result of miss-performance of models way above the calibration c_a
545 levels. Consequently, simulations precluding fertilization under high-emission scenarios
546 show very negative forest performance at the regional scale in the future for both
547 conifers and broadleaves. Our results suggest that western Mediterranean forests would
548 not resist the stressing conditions of a much warmer climate unless species exhibited an
549 exaggerated C fertilization effect. It is necessary to include c_a variability in forest
550 models but it is not enough. We still need a better understanding of the physiological
551 processes governing the capacity of acclimation of different plant traits (e.g. V_{cmax}) to
552 the interaction between water stress, eCO₂ and nutrient availability. In this sense, our
553 simulations precluding a fertilization effect seems more realistic than those allowing
554 fertilization under c_a levels way above those used to calibrate models. Our study
555 provides a comprehensive data-driven analysis of the likely performance of western
556 Mediterranean forests under predicted climate change and c_a. Yet model performance
557 still needs to be refined under high c_a as expected in the future.

558

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564 have been extracted from the CMIP5 site ([https://esgf-index1.ceda.ac.uk/projects/esgf-
ceda/](https://esgf-index1.ceda.ac.uk/projects/esgf-
565 ceda/)) and processed with the help of Romain Suarez.

566

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774 App. 1. List of chronologies used and their source. Lat=latitude; Long=longitude; Altit=altitude; MAP = mean annual precipitation; MAT= mean
 775 annual temperature (°C); PET_{pm}=Penman-Monteith annual evapotranspiration; P=annual precipitation.

#	Site	Species	Country	Lat (°)	Long (°)	Altit (m)	MAP (mm)	MAT (°C)	PET _{pm} (mm)	P-PET (mm)	P/PET	Source
1	QUPY2			42.2	-6.7	1300	985	9.65	962.4	22.6	1.02	
2	QUPY3			41.9	-6.2	760	453.9	12.3	1108.9	-655.0	0.41	
3	QUPY4			40.3	-6.8	900	1135.7	14.1	1213.3	-77.6	0.94	
4	QUPY5			40.7	-3.7	1300	580	10.1	1017.0	-437.0	0.57	
6	QUPY7	<i>Quercus pyrenaica</i> Willd.	Spain	39.5	-4.3	900	496.5	14.3	1228.9	-732.4	0.40	Gea-Izquierdo <i>et al.</i> (2014)
6	QUPY8			38.2	-4.1	890	474	15.0	1356.4	-882.4	0.35	
7	QUPY9			37.2	-4.0	1486	509.8	11.3	1164.8	-655.0	0.44	
8	QUPY10			37.0	-3.7	1550	619.3	9.8	984.5	-365.2	0.63	
9	QUPY11			40.8	-4.2	1056	599.9	10.1	1001.8	-401.9	0.6	
10	QUIL1			41.6	-5.6	740	433.8	12.5	1139.7	-705.9	0.38	
11	QUIL2			40.6	-6.7	700	562.6	12.9	1220.6	-658.0	0.46	
12	QUIL3	<i>Quercus ilex</i> L.	Spain	40.4	-4.2	600	516.6	13.3	1169.5	-652.9	0.44	Gea-Izquierdo <i>et al.</i> (2011)
13	QUIL4			39.4	-6.4	390	544.1	16.1	1269.4	-725.3	0.43	
14	QUIL5			43.2	3.0	270	1009.1	12.8	1001.5	7.6	1.01	
15	QUFG1			41.9	-5.7	680	453.9	12.3	1107.8	-653.9	0.41	Gea-Izquierdo (Unpublished data)
16	QUFG2	<i>Quercus faginea</i> Lam.	Spain	39.2	-4.5	900	496.5	14.3	1231.7	-735.2	0.40	
17	QUFG3			41.5	-0.3	550	326.1	15.3	1272.3	-946.2	0.26	https://www.ncdc.noaa.gov/paleo/study/10475
18	QUPU1	<i>Quercus pubescens</i> Willd.	Italy	37.1	14.4	430	537.1	15.8	964.2	-427.1	0.56	Garfi (2000)
19	QUCE1	<i>Quercus cerris</i> L.	Italy	40.4	15.8	590	767.3	11.2	878.5	-111.2	0.87	Battipaglia (unpublished data)
20	QUCA1			36.4	-5.9	330	988.4	16.1	1195.4	-207.0	0.83	
21	QUCA5	<i>Quercus canariensis</i> Willd.	Spain	36.8	8.8	758	649.3	16.5	1319	-669.7	0.49	Gea-Izquierdo <i>et al.</i> (2010)

22	QUCA6			36.5	8.1	760	625.2	15.9	1338.8	-713.6	0.47		
23	PINI2	<i>Pinus nigra</i> J.F. Arnold	Algeria	36.3	4.1	1560	580	14.8	1201.0	-621.0	0.48	Touchan <i>et al.</i> (2011)	
24	PINI5	<i>Pinus heldreichii</i> H.Christ	Italy	39.3	15.9	1430	806.1	12.4	901.1	-95.0	0.89	https://dendrodb.eccorev.fr/framedb.htm	
25	PIPI2	<i>Pinus pinaster</i> Ait.	Morocco	35.5	-5.7	900	611.3	16.4	1156.4	-545.1	0.53	Touchan <i>et al.</i> (2011)	
26	PIPNI			40.4	-2.6	1055	443.3	11.4	1217.1	-773.8	0.36	https://www.ncdc.noaa.gov/paleo/study/2863	
27	PIPNI2		Spain	39.1	-1.7	705	379.8	14.0	1269.4	-889.6	0.30	https://www.ncdc.noaa.gov/paleo/study/2866	
28	PIPNI3	<i>Pinus pinea</i> L.		39.2	-2.3	720	264.3	14.1	1330.4	-1066.1	0.20	https://www.ncdc.noaa.gov/paleo/study/2867	
29	PIPNI4		39.2	-2.8	700	343.3	14.5	1347.4	-1004.1	0.25	https://www.ncdc.noaa.gov/paleo/study/2865		
30	PIPNI8		Italy	43.4	10.2	10	962.1	15.3	1019.4	-57.3	0.94	https://www.ncdc.noaa.gov/paleo/study/16755	
31	PIPNI9	41.0		13.6	9	571.8	17.7	974.1	-402.3	0.59	Battipaglia <i>et al.</i> (2016)		
32	PIHA1		France	43.1	5.9	420	645.9	14.7	1201.2	-555.3	0.54	Gea-Izquierdo <i>et al.</i> (2015)	
33	PIHA2			36.9	8.3	23	630.3	18.7	1283.0	-652.7	0.49	Gea-Izquierdo (unpublished data)	
34	PIHA3		Tunisia	36.2	8.4	950	619.8	15.1	1297.7	-677.9	0.48		
35	PIHA4			35.8	9.3	800	542.3	14.7	1322.1	-779.8	0.41	Touchan <i>et al.</i> (2011)	
36	PIHA5			34.8	2.8	1380	349.6	14.5	1315.3	-965.7	0.27		
37	PIHA8			35.2	6.9	1300	380.8	14.6	1330.3	-949.5	0.29		
38	PIHA9			35.7	5.5	1200	431.2	15.6	1292.6	-861.4	0.33		
39	PIHA10			35.3	7.1	1650	380.8	14.6	1333.9	-953.1	0.29		
40	PIHA11	<i>Pinus halepensis</i> Mill.	Algeria	35.0	4.1	1100	390.2	15.6	1304.3	-914.1	0.30	Safar (1994), Safar <i>et al.</i> (1992)	
41	PIHA12			35.1	3.5	1060	417.2	15.4	1304.8	-887.6	0.32		
42	PIHA13			34.7	3.1	1410	350.8	14.3	1305.5	-954.7	0.27		
43	PIHA14				34.7	2.8	1350	350.8	14.3	1306.5	-955.7	0.27	
44	PIHA15				35.1	6.6	1450	380.8	14.6	1333.1	-952.3	0.29	
45	PIHA16				44.1	5.6	600	845.3	11.4	916.2	-70.9	0.92	
46	PIHA17			France	43.5	4.4	190	743.9	14.0	1029.2	-285.3	0.72	Nicault (1999)
47	PIHA18		43.8		4.8	330	788.9	13.2	1004.1	-215.2	0.79		
48	PIHA19		43.4		6.3	300	742.4	13.2	973.0	-230.6	0.76		

49	PIHA20		43.2	5.8	200	713.2	14.6	1015.3	-302.1	0.70		
50	PIHA21		43.7	5.4	170	816.3	11.8	944.8	-128.5	0.86		
51	PIHA22		44.0	6.4	600	1073.5	9.4	816.0	257.5	1.32		
52	PIHA23		43.4	5.0	150	749.1	13.6	986.4	-237.3	0.76		
53	PIHA28		44.2	4.4	350	888	12.2	966.6	-78.6	0.92		
54	PIHA31		43.8	4.1	300	743.6	14.2	1023.0	-279.4	0.73		
55	PIHA32		38.6	-2.6	1000	350.6	14.7	1203.4	-852.8	0.29		
56	PIHA34		37.3	-2.5	1280	287.6	14.7	1311.1	-1023.5	0.22		
57	PIHA35		38.9	-0.9	800	333.7	13.8	1270.0	-936.3	0.26		
58	PIHA36		40.8	-0.7	850	453.3	13.7	1152.7	-699.4	0.39		
59	PIHA37		38.1	-0.8	10	276.2	18.0	998.5	-722.3	0.28		
60	PIHA38		38.5	-0.6	900	380.1	14.2	1194.3	-814.2	0.32		
61	PIHA39		37.5	-3.2	1150	380.6	12.8	1362.8	-982.2	0.28		
62	PIHA40	Spain	41.6	-0.3	500	335.9	14.4	1203.3	-867.4	0.28	Ribas (2006)	
63	PIHA41		41.3	0.8	750	304	14.2	1197.8	-893.8	0.25		
64	PIHA42		41.8	-0.7	350	310.2	14.2	1194.5	-884.3	0.26		
65	PIHA43		38.7	1.3	80	362.4	18.2	1177.3	-814.9	0.31		
66	PIHA44		40.0	3.9	0	486.9	16.7	1071.7	-584.8	0.45		
67	PIHA45		39.4	3.0	250	430.5	17.9	1080.0	-649.5	0.4		
68	PIHA46		39.8	2.6	700	548.7	14.3	1228.7	-680	0.45		
69	PIHA47		39.1	1.5	175	327.6	17.1	1303.5	-975.9	0.25		
70	PIHA48	Italy	40.3	14.8	8	711.5	15.1	1000.7	-289.2	0.71	Battipaglia <i>et al.</i> (2014)	
71	CEAT1		32.2	-5.5	1920	483	9.9	1255.1	-772.1	0.38	Touchan <i>et al.</i> (2011)	
72	CEAT2		33.1	-4.5	2180	526.5	15.2	1266.8	-740.3	0.42		
73	CEAT3	<i>Cedrus atlantica</i> (Endl.) Manetti ex Carrière	Morocco	32.3	-5.3	2100	463.7	12.2	1339.1	-875.4	0.35	Esper <i>et al.</i> (2007)
74	CEAT4		33.2	-5.3	1830	539.4	10.5	1213.3	-673.9	0.44		
75	CEAT5		32.6	-5.0	2200	492.2	13.5	1360.5	-868.3	0.36		

76	CEAT6		32.6	-4.7	2200	492.2	13.5	1360.5	-868.3	0.36
77	CEAT7	Algeria	36.3	3.6	1520	576.1	14.7	1196.2	-620.1	0.50

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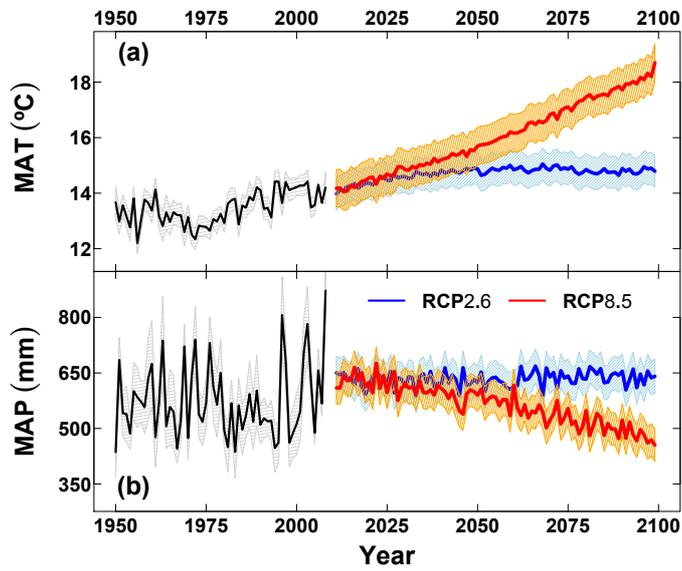
800 App. 2. Model code and Institute of CMIP5 climate simulations included in the study.

801 Crosses indicate when RCP scenarios were selected for a certain Model.

Model	Institute	RCP2.6	RCP8.5
bcc-csm1-1	Beijing Climate Center, China	X	X
bcc-csm1-1-m	Meteorological Administration	X	
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University	X	X
CanESM2	Canadian Centre for Climate modelling, Canada	X	X
CNRM-CM5	Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique, France	X	X
CSIRO-MK3-6-0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	X	X
EC-EARTH	EC-EARTH consortium	X	X
FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University	X	X
GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	X	X
GFDL-ESM2G		X	X
GFDLESM2M		X	
HadGEM2-ES	Met-Office – Hadley Center, contributed by Instituto Nacional de Pesquisas Espaciais, Spain	X	X
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	X	X
IPSL-CM5A-MR		X	X
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National MIROC-ESM-CHEM Institute for Environmental Studies	X	X
MIROC-ESM-CHEM		X	X
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for MIROC MIROC4h Environmental Studies, and Japan Agency for MIROC5 Marine-Earth Science and Technology	X	X
MPI-ESM-LR	Max-Planck Inst. Für Meteorologie, Germany	X	X
MRI-CGCM3	Meteorological Research Institute, Japan	X	X
NorESM1-M	Norwegian Climate Centre		X
# Simulations		19	18

802

803 App. 3. Mean daily annual temperature (MAT) and mean annual precipitation (MAP) of
804 the climate model simulations at each of the 77 sites for the RCP 2.6 (a) and RCP 8.5
805 (b). Shaded areas are confidence intervals at $\alpha=0.05$ for annual means.



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808 App. 4. Mean values and standard deviations of 7 fitted parameters to the 77 sites.

809

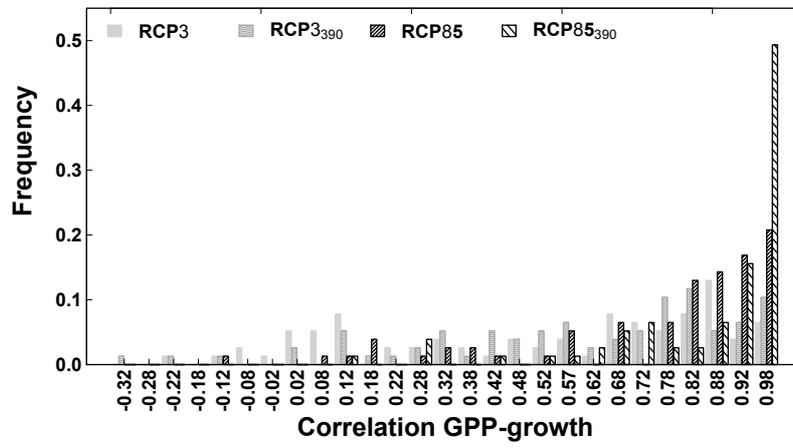
Parameter	Mean	Standard deviation	Minimum	Maximum
soil _{ip}	139.0	96.7	3.1	392.9
p _{3moist}	-0.255	0.211	-0.700	-0.001
p _{3temp}	26.7	77.8	-153.7	181.2
st _{3moist}	-0.226	0.197	-0.699	-0.006
st _{3temp}	4.8	88.2	-167.4	222.0
st _{4sd_moist}	-0.321	0.230	-0.900	-0.009
st _{4temp}	334.9	212.2	49.7	1080.2

810

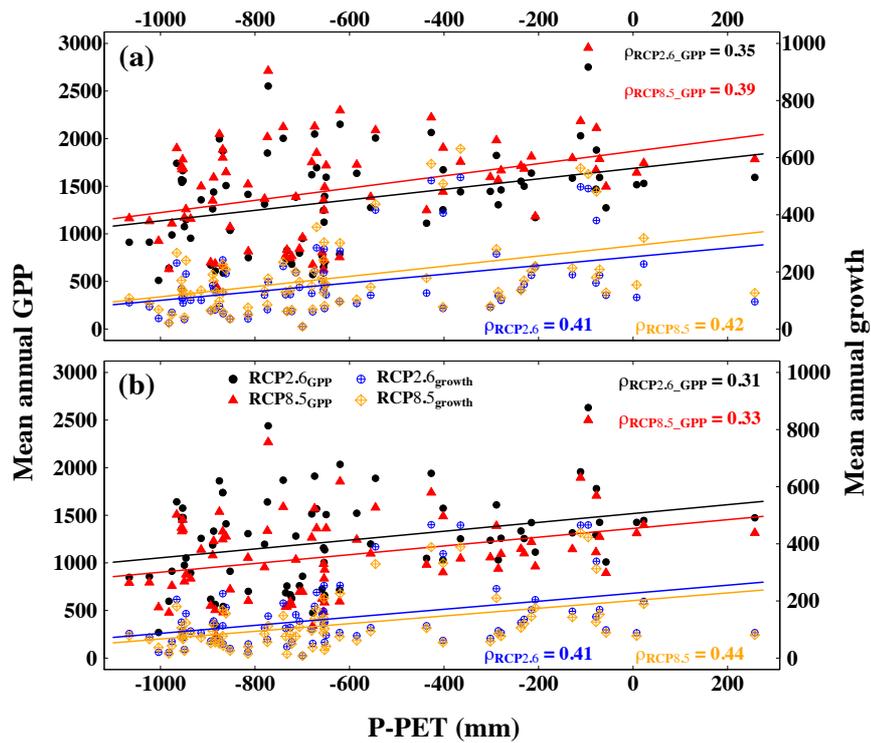
811 App. 5. Distribution of the relationship between GPP and carbon allocation to the stem
812 (i.e. radial growth) as estimated by a linear correlation.

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814



815 App.6. Mean projected GPP and growth (2010-2100) and site 'Annual precipitation
 816 minus Penman-Monteith potential evapotranspiration' (P-PET, in mm) for RCP2.6 and
 817 RCP8.5 scenarios: (a) fertilization scenario (i.e. predicted c_a); (b) non-fertilization
 818 scenario (i.e. $c_a=390$ ppm). All relationships (ρ =correlation) are significant at $p<0.01$.



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 820

821 App. 7. In this figure we show two graphs to support the robustness of our modeling
 822 approach and the future projections implemented at the regional scale. (A) The
 823 coefficient of determination (R^2) is shown as a function of the projected growth trends
 824 to demonstrate that there is no relationship between the estimated trends and the
 825 calibration R^2 . In addition, regardless of R^2 , all projections under RCP8.5 are either
 826 positive (fertilization, in blue) or negative (non-fertilization, in red), whereas variability
 827 in RCP2.6 slopes estimated is independent of the goodness of fit (as estimated by R^2 ,
 828 see (A)). In (B), to illustrate the model capacity to fit the interannual (decadal) growth
 829 trends, we show the slopes estimated on past growth observations in function of the r_{low}
 830 statistic (correlations between filtered series). r_{low} was greater than 0.7 in 73% of the
 831 models fitted (B). Most importantly, r_{low} was greater than 0.6 in all cases when there was
 832 a significant past trend (in (B) we highlight those sites where past $|\text{slope}| \geq 0.35$
 833 $\text{cm}^2 \cdot \text{year}^{-2}$), which means that the model was able to mimic the long-term growth-trends
 834 when trees exhibited some positive or negative trend in the past.

