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Underrepresented controls of aridity in climate sensitivity of carbon cycle models

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28 **Terrestrial ecosystems respond to changes in environmental conditions, mainly via key**
29 **climatic controls of precipitation and temperature on vegetation activities and**
30 **decomposition processes ¹. Yet, the relationship between climate and the overall**
31 **spatiotemporal dynamics and uncertainties of the global carbon cycle, i.e., gross**
32 **primary productivity (*GPP*), effective ecosystem carbon turnover times (τ), and**
33 **consequently the total ecosystem carbon stock (C_{total}), are unclear ²⁻⁵. Using a global**
34 **observation-based synthesis, we first show that the apparent partial spatial climate**
35 **sensitivities of *GPP* and τ are associated with relative availability of precipitation and**
36 **temperature, and are therefore modulated by aridity. The apparent sensitivity of *GPP***
37 **to temperature increases from arid to humid climatic regions. In contrast, its sensitivity**
38 **to precipitation is invariant throughout different climatic regions. Simultaneously, the**
39 **τ -precipitation response is strongly non-linear resulting in ~ 2 times longer τ in arid**
40 **regions compared to humid regions for a given temperature. Compared with these**
41 **observed patterns, the offline carbon cycle simulations of seven European Earth System**
42 **Models (ESMs), that participated in CMIP6, perform relatively better for climate**
43 **sensitivities of *GPP* than those of τ . This leads to a large spread and bias in C_{total} in both**
44 **warm and cold semi-arid and arid regions where only a few models capture the**
45 **observed τ -precipitation relationship. The emergence of the hydrological controls,**
46 **modulated by aridity, on global carbon cycle implies that the changes in precipitation**
47 **may moderate the temperature-driven climate feedback of the global carbon cycle**
48 **under climate change.**

49 Introduction

50 The exchange of carbon between the biosphere and atmosphere represents a key mechanism
51 controlling the effect of global changes on the carbon cycle ⁶, as well as on the water and
52 energy cycles ⁷. The land ecosystems, at the centre of biosphere-atmosphere interaction, store
53 carbon by integrating the differences in carbon captured through gross primary productivity
54 (*GPP*), and carbon released through decomposition processes. Due to the complex
55 dependencies of the photosynthesis and decomposition on climate, biomes, and carbon use
56 efficiency of vegetations ⁸, the resulting carbon stocks vary significantly across space and
57 time. The differences in modelling these complex climate-biosphere dependencies, therefore,
58 lead to large differences in Earth system model (ESM) predictions of carbon stocks ^{9,10} that
59 are prevalent under the current climate and exacerbate under future climate change scenarios.

60 The ecosystem turnover and associated carbon losses and stocks, thus, represent major
61 sources of uncertainties regarding carbon cycle – climate feedbacks ^{11,12} and the projections
62 of future carbon budgets ^{5,13,14}, and modelling and constraining them with observations still
63 pose a significant challenge to ESMs ²⁻⁴.

64 Various studies have, therefore, investigated the relationship between land carbon stocks and
65 their climate drivers. For example, the uncertainties in soil organic carbon and their responses
66 to climate change have been extensively studied ¹⁵, but mostly focused on temperature, as the
67 first principles dictate the key role of temperature in determining the current and future
68 carbon cycle dynamics ¹⁶. The studies focusing only on energy-limited humid and cold
69 regions, understandably, have shown strong associations of spatial variations of carbon stocks
70 and temperature ¹⁷. When other climatic regions globally are considered, though, temperature
71 alone only explains ~10% of the total spatial variation of the observation-based soil organic
72 carbon ¹⁰ suggesting a larger influence of additional environmental factors. In particular,
73 precipitation, which is the primary source of moisture for all land processes, is potentially a
74 strong driver of spatial variation of turnover times, the τ ¹⁸, as demonstrated by the
75 significance of moisture effects on decomposition ¹⁹ and the observation-based linkages
76 between water and carbon cycles ²⁰. The moisture availability is especially critical in arid to
77 semi-arid regions, which cover ~39% of the global vegetated land, and substantially influence
78 the interannual variabilities of global biosphere-atmosphere carbon exchange ²¹⁻²³, but the
79 effects on modelled τ has been largely ignored ²⁴.

80 In an ecosystem under a steady state, the temporal variations in total ecosystem carbon
81 storage (hereafter C_{total}) become negligible as the net input (GPP) and output (total ecosystem
82 respiration) carbon fluxes balance each other. The spatial variations of C_{total} across
83 ecosystems are, then, essentially defined by the differences in GPP and the carbon loss
84 determined by decomposition rates and τ . The climate, though, has differential influences on
85 and association with GPP and τ , which result in a unique spatial heterogeneity in C_{total}
86 compared to those of either GPP or τ . It is, therefore, critical that the sensitivities of GPP , τ ,
87 and C_{total} to climatic variations are simultaneously evaluated, especially in ESMs where the
88 uncertainties in C_{total} may be related to not only GPP ² but to both τ and GPP ⁹.

89 Here, based on observation-based estimates of the carbon cycle, we first evaluate the
90 apparent spatial sensitivities of climatological mean GPP and τ to two primary climatic
91 drivers: mean annual air temperature (MAT) and mean annual precipitation (MAP). To infer
92 effective or apparent climatological τ of an ecosystem, we assume that the ecosystem carbon

93 reaches a steady-state over multiple decades, and calculate τ as the ratio of long-term
94 averages of total ecosystem carbon stock and GPP ^{17,18,25,26}. The apparent spatial sensitivities
95 of the climatological carbon cycle are assessed in a climate phase-space of temperature and
96 precipitation for different climatic regions (arid to humid) that are delineated using an aridity
97 index, defined as the ratio of mean annual precipitation and potential evapotranspiration (see
98 Methods and **Figure A1**). While aridity itself is not directly mechanistically connected to
99 physiological and decomposition processes within an ecosystem, it is a rather clear indicator
100 of relative availability of limiting moisture and energy resources that define the soil moisture
101 regime (**Figure A2**), and consequently, the vegetation responses and patterns²⁷⁻²⁹. The
102 climate sensitivities of τ and GPP are represented using non-linear relationships with
103 temperature and precipitation (see Methods). The relationships are then used as the basis for
104 evaluation of the offline carbon cycle model simulations of seven European ESMs from
105 CRESCENDO project (see Methods), which participated in the Sixth Phase of Coupled
106 Model Intercomparison Project (CMIP6).

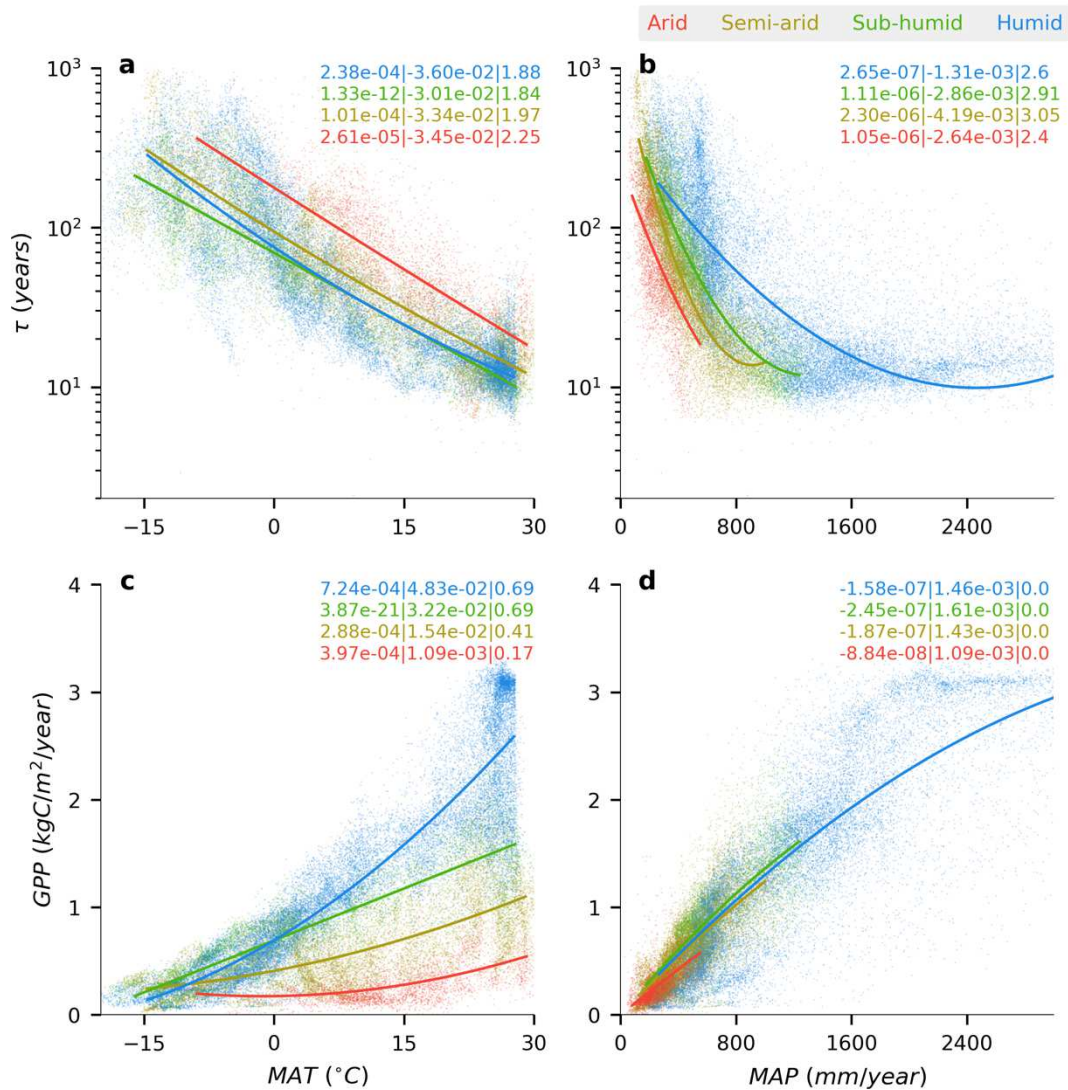
107 Observation-based climate sensitivities

108 Both τ and GPP exhibit unique sensitivities to the spatial variabilities of precipitation and
109 temperature in all climatic regions despite large heterogeneity within a climatic region
110 (**Figure 1, Table A4**). First, τ varies strongly across both temperature and precipitation
111 gradients in all climatic regions. The sensitivity of τ to temperature is well-documented for
112 humid regions¹⁷. Interestingly, there is a significant offset in τ as the climate gets drier with
113 the longest τ in arid regions ($\tau=178$ years at 0°C) compared to humid regions (76 years). In
114 fact, for any given temperature, τ is longer in the arid regions compared to humid regions,
115 suggesting an influence of, or covariation with, precipitation across climatic regions. The
116 sensitivities to temperature, i.e., the slope of the fitted lines in **Figure 1a**, are all within $\sim 17\%$
117 across different climatic regions (**Table A3**). It should be noted that a significant number of
118 grid cells, with a mean temperature less than 0°C , have longer τ than under warmer
119 temperatures within the same climatic region. Yet, the non-linear increase in temperature
120 sensitivity with decreasing temperature is not as strong as reported previously for τ of soil
121 organic carbon¹⁷ and the linear coefficients dominate the non-linear coefficients in different
122 climatic regions (inset of **Figure 1**, and **Table A3**). While several factors may lead to such
123 differences (e.g., differences in observed data, methodology, etc.), one key reason may also
124 be the selection of climatic regions. For instance, in regions with temperature $>10^\circ\text{C}$,

125 ignoring arid to semi-arid regions with a systematically longer τ than humid region would
126 skew the overall distribution of τ , which would then lead to a hyper-logarithmically nonlinear
127 τ - temperature relationship.

128 The apparent sensitivity of τ to precipitation is large when the precipitation is lower than
129 ~ 1000 mm/year across all climatic regions (**Figure 1b**). Only within 0-1000 mm/year range
130 of precipitation, τ varies by more than an order of magnitude. Contrasting to temperature, the
131 τ -precipitation relationship saturates at higher precipitation (>1000 mm/year) in all regions
132 except arid regions where precipitation never crosses the threshold. The overall apparent
133 sensitivity of τ to precipitation is, therefore, hyper-logarithmically nonlinear, as indicated by a
134 clear positive curvature. While the functional relationship of precipitation is almost the same
135 for all but energy-limited humid regions, the sensitivity of τ to precipitation is smaller for
136 humid regions compared to arid regions, indicating a saturation of the precipitation effect on
137 τ . The difference of τ across different climatic regions is the smallest in the lowest
138 precipitation ranges. Similar to the τ -temperature relationship, though, there is still a large
139 variability of τ for given precipitation within all climatic regions (as indicated by low r^2 and
140 higher r_{mad} of fitted relationships in **Figure 1** and **Table A4**).

141 *GPP* also has a clear relationship with temperature, the strength of which is dependent on the
142 climatic region (**Figure 1c**). The temperature sensitivity is the largest in humid and the
143 smallest in arid climatic region. In the humid region, *GPP* sensitivity to temperature increases
144 with temperature. The *GPP* increases steadily for increasing precipitation with very small
145 differences across different climatic regions (**Figure 1d**). The increase in *GPP* with
146 precipitation is quasi-linear in all climates, as *GPP* saturates at the highest precipitation
147 values, especially in the humid regions. This, again, suggests that precipitation plays an
148 important role in determining *GPP* when the vegetation activities are likely to be limited by
149 moisture. While a strong relationship of *GPP* with precipitation has been shown previously
150^{30–32}, the minimal difference of *GPP* across different climatic regions for given precipitation
151 shows that the spatial variation of *GPP* is mainly related to precipitation alone.



152

153 **Figure 1. Relationship between observation-based ecosystem turnover time of carbon (τ ,**
 154 **years) and gross primary productivity (GPP, $\text{kgC}/\text{m}^2/\text{year}$) with climate.** In the top row,
 155 the relationship of τ with a) mean annual temperature (MAT, $^{\circ}\text{C}$) and b) precipitation (MAP,
 156 mm/year) are plotted. The bottom row shows the same for GPP (c and d). The different
 157 colours indicate different climatic regions defined by the aridity index, and individual grid-
 158 cells are plotted as dots. The lines show a non-linear least square fit (see Methods) for the
 159 variation of τ and GPP with MAT and MAP within each climatic region. The inset text shows
 160 the parameters of the fit (non-linear coefficient | linear coefficient | constant) while the fitting
 161 performances are provided in **Table A4**. Note the logarithmic vertical axis for τ in **a** and **b**.

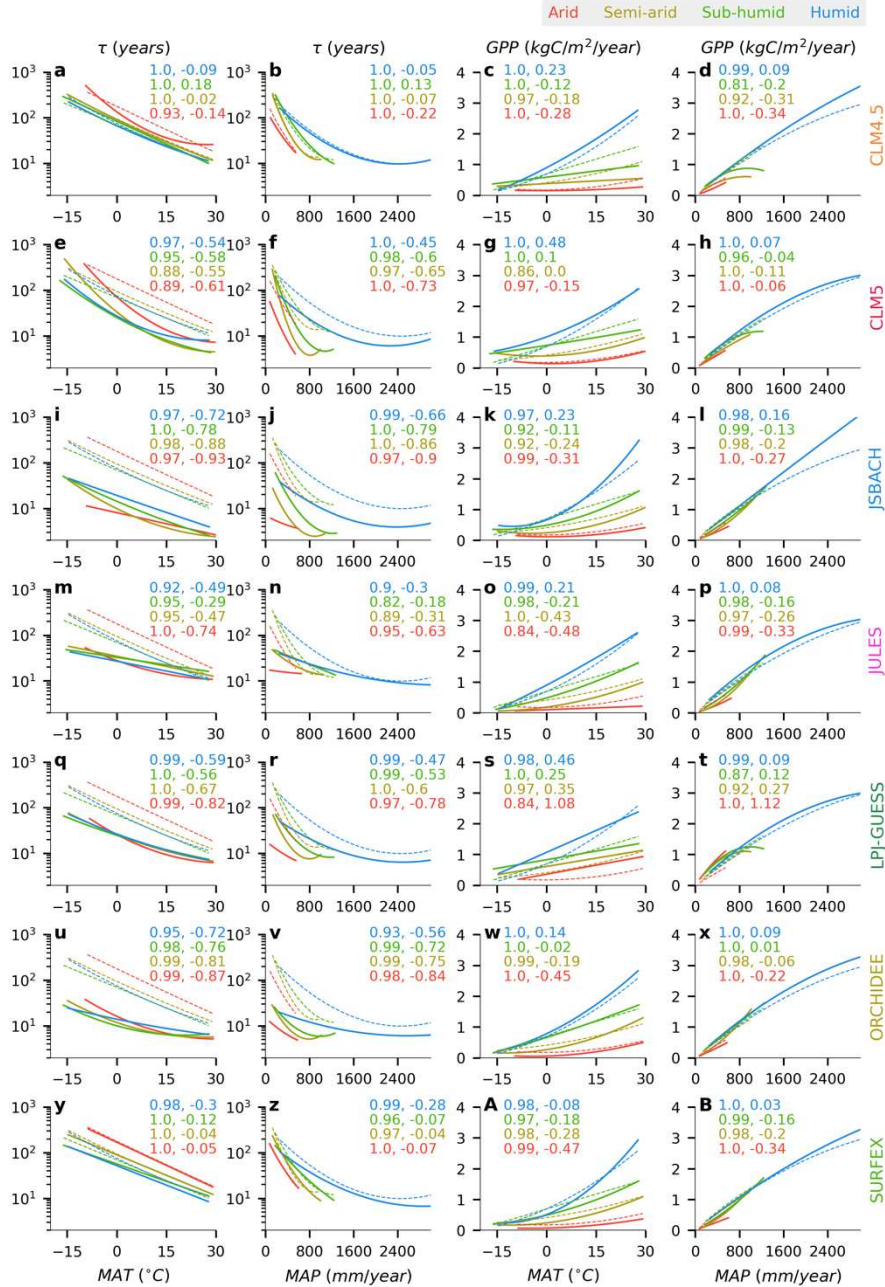
162 Climate sensitivities in Carbon Cycle models

163 In the CRESCENDDO model simulations, the apparent sensitivities of τ to climate have
 164 larger biases than those of GPP to climate, when compared against respective observation-
 165 based sensitivities (**Figure 2**). First, the comparison of the τ -temperature relationship reveals
 166 that all models, except CLM4.5 and SURFEX, have a shorter τ than observation across all
 167 climatic regions while the linear correlation between the model and observation-based

168 relationships are generally high (first column, **Figure 2**). This is accompanied by a large bias
169 in τ with most models, except CLM4.5, showing a clear underestimation. The differences
170 between models and observation and among models also remain fairly similar across all
171 climates. For example, the model with the longest τ in the arid region also has the longest τ in
172 other climatic regions. This suggests that the temperature dependence of τ in a given model
173 remains fairly consistent across different climatic regions. Of the models, only CLM5 shows
174 a stronger sensitivity of τ to temperature with a hyper-logarithmically nonlinear increase in τ
175 when the temperature decreases below 0°C (Figure 2e).

176 Similar to observation, the models also exhibit a tendency of non-linear increase in τ for
177 decreasing precipitation, with the largest sensitivity in arid regions and the smallest
178 sensitivity in humid regions (second column of **Figure 2**). Most models, though, show a
179 smaller sensitivity to precipitation than the observation with a consistent underestimation bias
180 across all climate, with the largest difference in the arid regions. In fact, only CLM4.5 and
181 SURFEX show a significant increase of τ in the lower precipitation range that is akin to the
182 observation.

183 For *GPP*, the models show increased sensitivity to temperature from arid to humid climatic
184 regions (third column of **Figure 2**) except for CLM4.5 (**Figure 2c**), which shows a smaller
185 increase in *GPP* at a higher temperature in all but the humid region, and LPJ-GUESS (**Figure**
186 **2s**) with much larger *GPP* in arid regions. In general, all models represent the sensitivity of
187 *GPP* to temperature fairly well with a relatively smaller biases than the same of τ . The
188 sensitivity of *GPP* to precipitation also shows a small spread among the models (fourth
189 column of **Figure 2**). Only in the humid regions, a large number of models, e.g., CLM4.5 and
190 JSBACH, over-predict *GPP* in the highest precipitation range, where the observation-based
191 *GPP* shows a saturating tendency.



192

193 **Figure 2. Evaluation of sensitivities of climatological carbon cycle dynamics to climate**
 194 **in CRESCENDO models.** In the first and second columns, the relationships between
 195 ecosystem turnover time of carbon (τ , years) versus mean annual temperature (MAT) and
 196 precipitation (MAP) are presented, followed by those for gross primary productivity (GPP ,
 197 $\text{kgC}/\text{m}^2/\text{year}$) in the third and fourth columns. Along the row, the comparisons for different
 198 models against the observation are presented. The different colours indicate different climatic
 199 regions defined by the aridity index. The dotted lines indicate the observation-based
 200 relationship, and the solid lines indicate relationship from the model simulations. The inset
 201 text shows coefficient of determination (r^2) and mean relative bias between the fitted
 202 relationships from the models and observation. Note the logarithmic vertical axis for τ in the
 203 first and second columns.

204 Partial correlations with climate

205 To elucidate the regional variations of τ , GPP and the resulting C_{total} , and eliminate
206 collinearity between precipitation and climate, here, we evaluate the zonal variations and
207 their partial associations with precipitation and temperature.

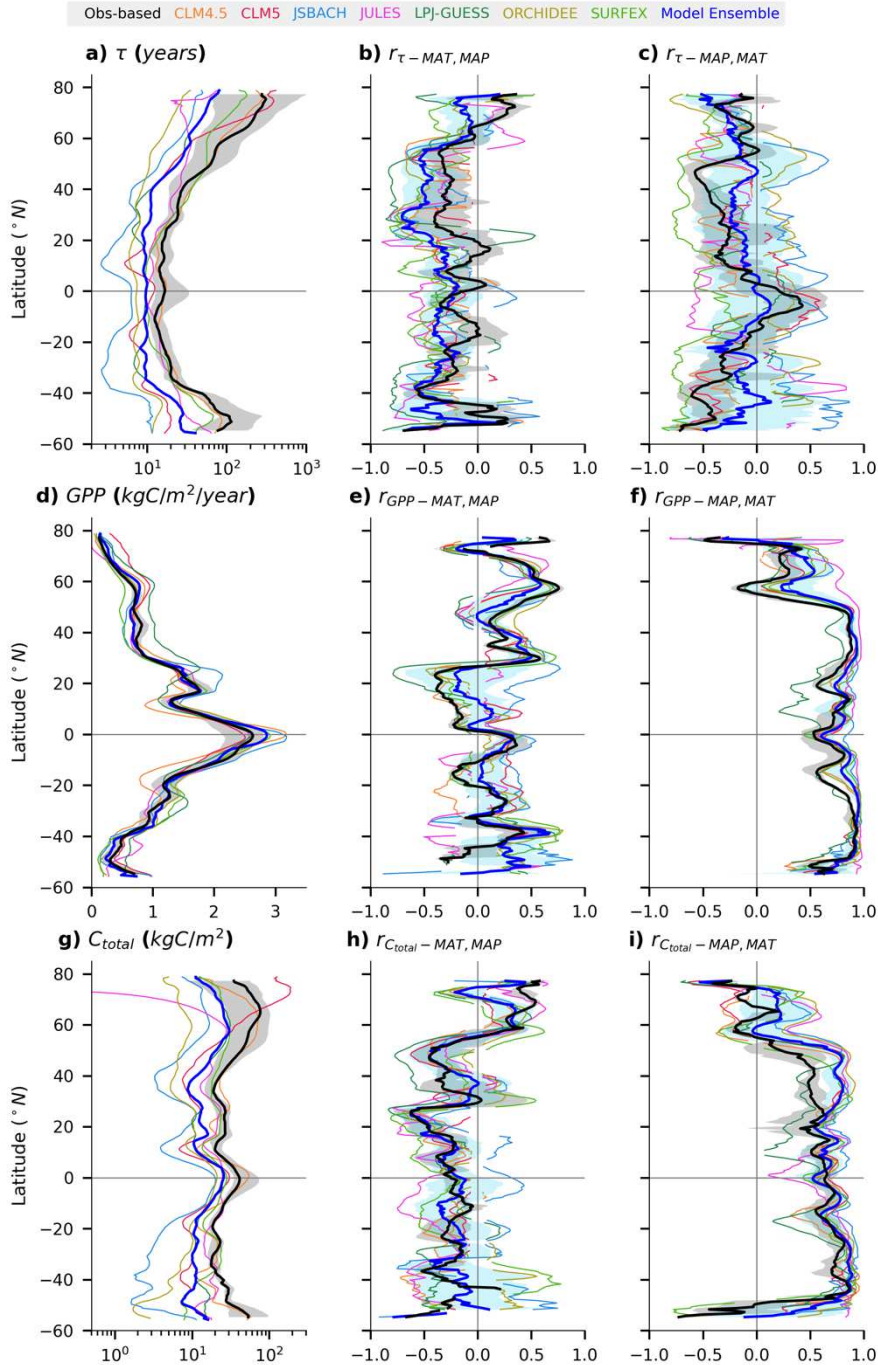
208 In general, the large-scale zonal distribution of τ follows temperature, and that of GPP
209 follows precipitation (first column of **Figure 3**, and **Figure A4**). The τ is the shortest in
210 tropical regions with the highest temperature and the longest in high latitudes with the lowest
211 temperature (**Figure 3a**). Similarly, GPP is the largest in the wettest tropical regions with the
212 highest precipitation (**Figure 3d**). The zonal distribution of C_{total} reveals a smaller variation
213 across the latitude compared to τ and GPP (**Figure 3g**). Nonetheless, the largest C_{total} occur in
214 either the humid tropics with the largest GPP or in the high latitudes with the longest τ . In
215 general, the CRESCENDO models produce zonal variations similar to observation-based
216 estimates, with the smallest bias for GPP , and a consistent underestimation bias of τ and C_{total}
217 across the latitude.

218 The observation-based τ has a stronger negative correlation with temperature in the energy-
219 limited regions such as the tropics and high latitudes of both hemispheres compared to the
220 moisture-limited regions (**Figure 3b**). In general, the latitudinal variation of τ -temperature
221 correlation is much stronger in the models than in the observation. This is especially true for
222 sub-tropical mid-latitudes (40°S to 40°N) except the humid tropical regions. In the same
223 regions, the local variation of τ has a stronger correlation with precipitation than with
224 temperature (**Figure 3c**). The τ -precipitation relationships in the models have a larger spread,
225 and most models have a weaker τ -precipitation correlation than in the observation. This is
226 especially clear in the subtropical southern hemisphere and temperate northern hemisphere.
227 This weaker τ -precipitation correlation is concurrent with a stronger τ -temperature correlation
228 in the models suggesting a dominant temperature control on carbon cycle sensitivity to
229 climate. In these regions, only SURFEX shows a strong local-scale τ -precipitation correlation
230 that is consistently stronger than the observation, but it also exhibits a stronger bias in the
231 high latitudes.

232 Further, both the observations and models show a much stronger correlation of GPP with
233 precipitation (**Figure 3f**) than with temperature (**Figure 3e**) across most of the latitudes. Only
234 in the northern high latitudes over $\sim 50^\circ\text{N}$ (with $\text{MAT} < 0^\circ\text{C}$), GPP has a stronger correlation
235 with temperature than with precipitation. In fact, in these regions, the low winter temperature

236 affects the MAT significantly, and correcting for winter reveals a clearer role of temperature
237 in the high latitudes (see **Figure A6**). The model spread is also relatively smaller for the
238 correlation of *GPP* with climate than of τ with climate. This shows that the models, in
239 general, reproduce both the global and local responses of *GPP* to temperature and
240 precipitation much better than those of τ .

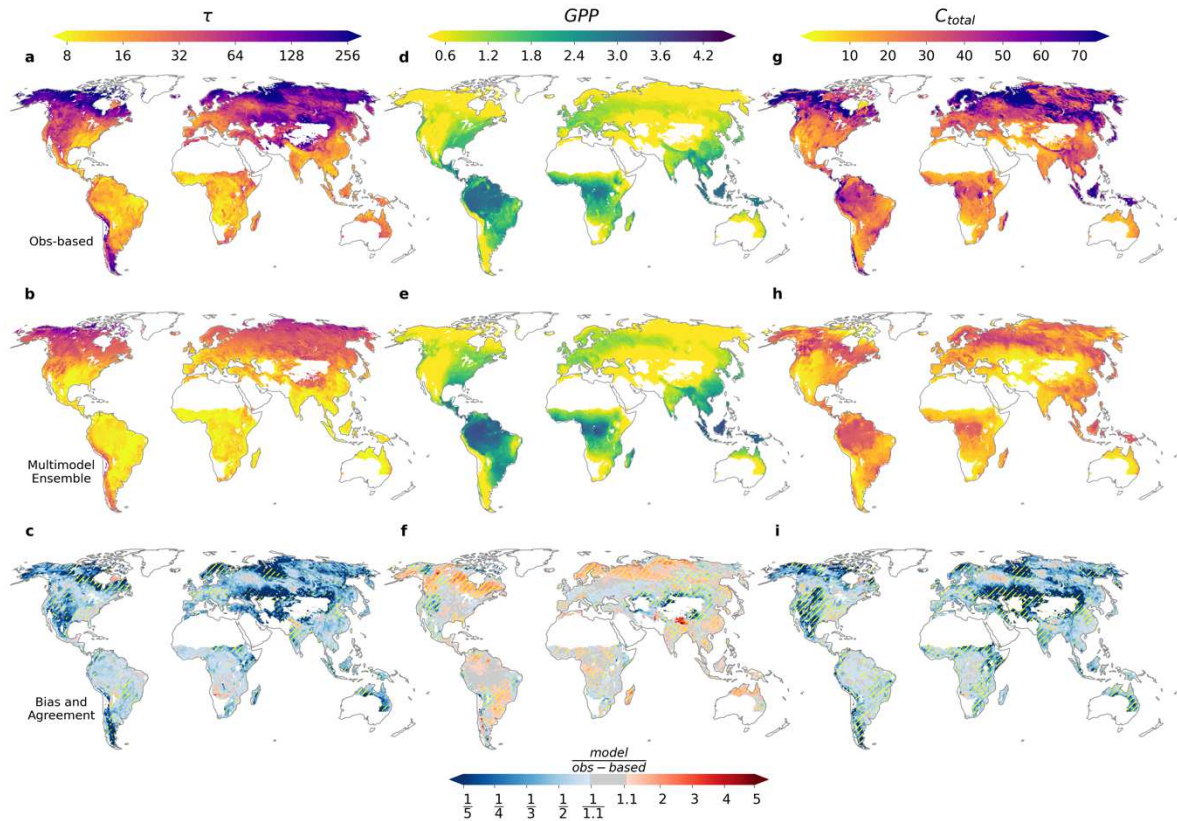
241 Further, as expected, the observation-based relationship of C_{total} and climate is a complex
242 amalgam of those of *GPP* and τ . For example, C_{total} -temperature correlation is relatively
243 small in magnitude (**Figure 3h**) due to the opposing τ -temperature (negative) and *GPP*-
244 temperature (positive) correlations. The C_{total} -precipitation correlation follows the same zonal
245 variation as that of *GPP* but with a lower magnitude (**Figure 3i**) due to predominantly
246 negative τ -precipitation correlation. The CRESCENDO models generally exhibit a stronger
247 positive correlation of C_{total} with climate than in the observation. This strong C_{total} -
248 precipitation correlation in the models is due to a strong correlation between C_{total} and *GPP*
249 (see **Figure A6**).



250

251 **Figure 3. Zonal distribution of ecosystem turnover time of carbon (τ , years), gross**
 252 **primary productivity (GPP , $\text{kgC}/\text{m}^2/\text{year}$), and total ecosystem carbon stock (C_{total} ,**
 253 **kgC/m^2) and their relationships with climate.** The zonal means are plotted in the left
 254 column, and the correlations with temperature and precipitation are plotted in the centre and
 255 right column, respectively. The correlation with precipitation is controlled for temperature
 256 and vice-versa. The Pearson's correlation coefficient for each latitude is calculated for a
 257 moving window of 10 grid cells along the latitude (5°). Only the coefficients that are
 258 statistically significant at 5% significance level are shown. The individual models are plotted
 259 in coloured thin lines, and the multimodel ensemble in thick blue lines. In the correlation
 260 plots, the thick dashed blue lines show the normalized mean correlation of all models with
 261 shades indicating variation within one standard deviation. The observation is plotted as a
 262 thick black line with shade indicating the range within the 5th and 95th percentiles.

264 Model biases and agreement



265

266 **Figure 4. Global distributions of ecosystem turnover time of carbon (τ , years), gross**
 267 **primary productivity (GPP , $\text{kgC}/\text{m}^2/\text{year}$), and total ecosystem carbon stock (C_{total} ,**
 268 **kgC/m^2) and their biases. The multimodel ensemble, observation-based estimate, and the**
 269 **bias and agreement are presented in the first, second, and third row, respectively. Multimodel**
 270 **ensemble is calculated as the median of the seven CRESCENDO models. The bias is**
 271 **calculated as the ratio between multimodel ensemble and the corresponding observation. In**
 272 **the global maps of bias (third row), stippling indicates the regions where only two or fewer**
 273 **models fall within the range of observational uncertainties (5th and 95th percentiles).**

274 Spatially, the CRESCENDO multi-model ensembles exhibit similar global distributions
 275 compared to the corresponding observation-based estimates of τ (**Figure 4a, b**), GPP (**Figure**
 276 **4d, e**), and C_{total} (**Figure 4g, h**). Globally, the observation-based τ is the shortest in tropical
 277 regions with high GPP as well as a relatively high C_{total} , and the longest in high latitude
 278 regions with a relatively lower GPP but high C_{total} . The longer τ is also prevalent in cold and
 279 dry arid regions, such as the surroundings of the Gobi Deserts, where both GPP and C_{total} are
 280 lower than other regions. The observation-based C_{total} shows a pattern of large carbon
 281 storages in either a region with high GPP or a longer τ . Additionally, larger C_{total} are also
 282 evident in the Arctic North America and Boreal Eurasia characterized by occurrences of peat.

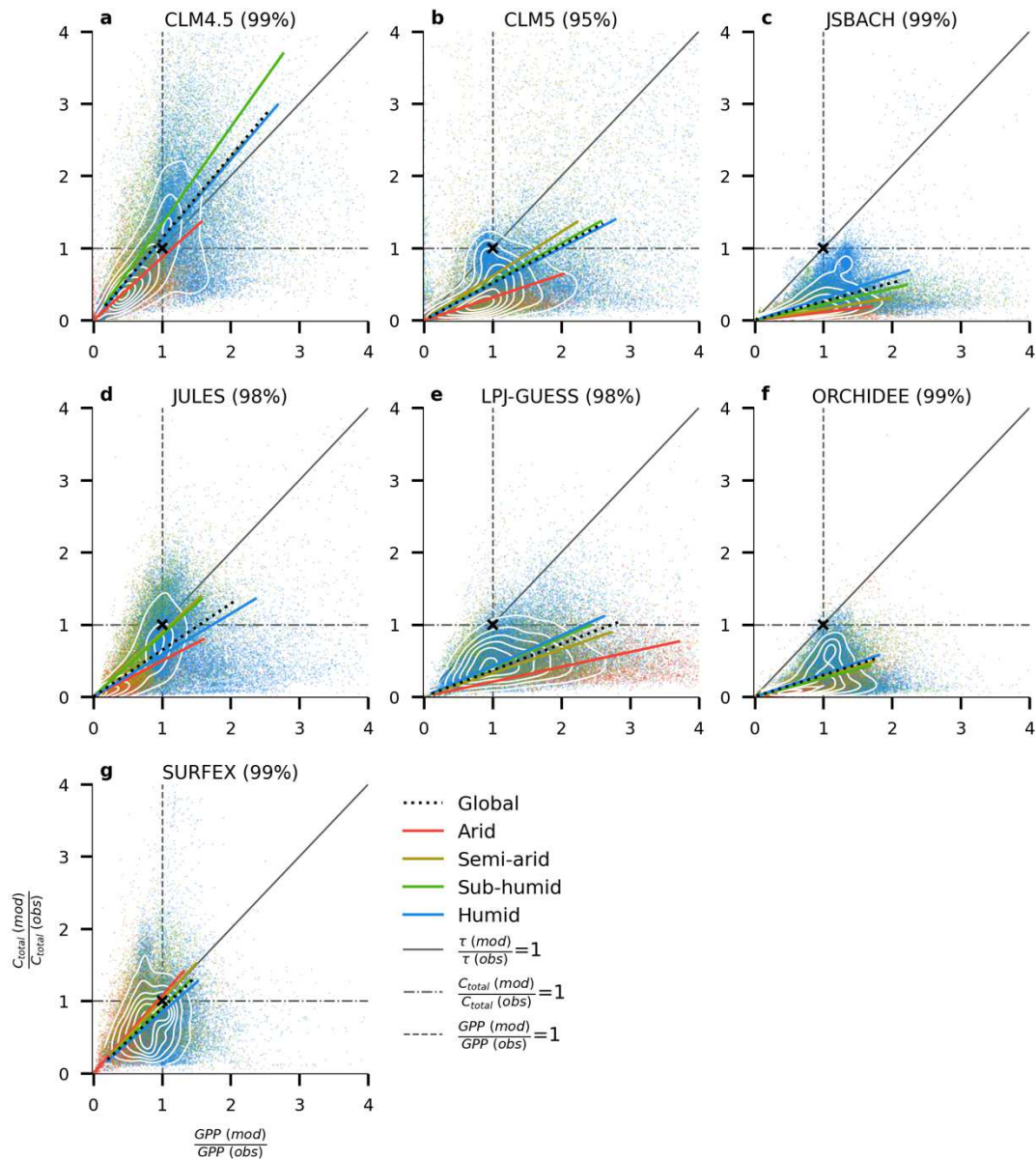
283 On a broad scale, the CRESCENDO multimodel ensemble τ also exhibits a similar spatial
284 gradient with shorter τ in the tropics and longer τ in the northern high latitudes. Such spatial
285 gradients are reproduced by individual models as well (**Figure A8**). Despite the similarity in
286 spatial variability, the multimodel ensemble τ still has a substantial underestimation bias in
287 the semiarid regions (sub-Saharan Sahel, central Asia, northern Australia, and western United
288 States), where the multimodel ensemble is ~ 5 times shorter than the observation (**Figure 4c**).
289 The models tend to agree with each other more in the northern high latitudes and the humid
290 tropics than they do in the arid and semi-arid regions with large biases, as also shown
291 previously for CMIP5 models (Carvalhais et al., 2014). Moreover, fewer than two models are
292 within the observational uncertainty (hereafter referred to as low agreement) in $\sim 22\%$ of the
293 total grid cells. In the semi-arid region, the underestimation of τ (the overestimation of
294 turnover rate) is prevalent in all but three models (CLM4.5, JULES and SURFEX in **Figure**
295 **A7**).

296 Both the spatial variability and magnitude of GPP in CRESCENDO models compare better
297 with the corresponding observation than in the case of τ (see **Figure A9** as well). In the
298 tropical humid and semi-arid regions, the GPP bias is small in relative terms (**Figure 4f**). In
299 semi-arid regions of south America and Australia, the relative bias in GPP is high due to
300 relatively lower GPP values in the observation. But the largest overestimation bias can be
301 seen in the northern high latitudes which have low GPP . The models also agree less in the
302 regions with the largest bias with almost $\sim 35\%$ of global grid cells having a low model
303 agreement. Note that such low agreement is also due to small uncertainty range in the
304 ensemble of GPP observations (bar charts in **Figure A7b**). When the global and regional
305 GPP are compared, almost all models are within the observational uncertainty globally due to
306 better performance in the humid and sub-humid climate compared to other regions (**Figure**
307 **A7b**).

308 Lastly, the spatial variability of C_{total} in most CRESCENDO models is similar to that from
309 observation-based estimate (**Figure A10**), even though the distinctly large storage in
310 peatlands is not reproduced by most models. The bias in C_{total} bears a striking similarity to the
311 spatial pattern of bias of τ . There are, however, also regions where the opposing biases in τ
312 and GPP lead to unbiased C_{total} . For example, in the Iberian Peninsula and Hudson Bay, the
313 overestimation of GPP is compensated by an underestimation of τ (overestimation of
314 turnover rate) resulting in a relatively unbiased C_{total} . Due to such compounding effects, there
315 is even more widespread occurrence of low model agreement for C_{total} ($\sim 40\%$ of global grid

316 cells), and biases, mostly similar with those of τ , are widespread across different climatic
317 regions (**Figure A7c**).

318 To attribute the bias in C_{total} , we compare the biases in GPP , C_{total} , and τ in each
319 CRESCENDO model (**Figure 5**). Note that an ideal model would have low biases in all GPP ,
320 τ and C_{total} . The contrast between the biases in GPP and C_{total} reveals a dominant control of τ
321 on the C_{total} bias. The JSBACH, LPJ-GUESS, and ORCHIDEE models show consistently
322 lower C_{total} than observation-based estimate, that is likely associated with an underestimation
323 of τ , as the biases in GPP are relatively lower than those in C_{total} (larger density of points
324 along the axis of no bias in GPP). Other models perform better for both GPP and τ in all but
325 arid climatic region. Only CLM4.5 and SURFEX show a good agreement of τ in arid region
326 (red lines close to 1:1 line). CLM4.5, though, also has a slight overestimation bias in C_{total} in
327 all other climatic regions arising from overestimation of τ . In fact, in CLM5, the biases in τ
328 are reduced across all climatic regions. Only JULES and SURFEX produce a larger density
329 of grid cells where biases are low for GPP , τ , and C_{total} . In JULES, τ and C_{total} are
330 underestimated mainly in the arid and humid region. Globally, only CLM4.5 has larger range
331 of spatial variability than in the observation (the slope of the fitted global line greater than 1).



332

333 **Figure 5. Relationship of biases in gross primary productivity (GPP) and total**
 334 **ecosystem carbon stock (C_{total}) in CRESCENDO model simulations.** The different colours
 335 indicate different climate defined by the aridity classes, and individual grid-cells are plotted
 336 as dots. The percentage values in the parenthesis of the title shows the fraction of the global
 337 grid cells that are within the range of bias between 0.1 and 4. The dashed vertical line shows
 338 the axis of no bias in GPP (ratio of GPP from model to that from observation = 1), the same
 339 for C_{total} is shown by a horizontal dashed line. The grey solid line indicates the axis along
 340 which there is no bias in τ . An ideal point of no biases in GPP , C_{total} , and τ is indicated by a
 341 cross 'x'. The coloured lines indicate the main axis of variations of biases in GPP and C_{total}
 342 (linearly fitted lines that passes through origin). The white contour lines indicate the density
 343 of grid cells, with higher density of lines showing larger occurrence of grid cells.

344 Conclusions and discussion

345 Adding to a well-established association of carbon cycle with temperature, we show that
346 precipitation also plays a key role in defining primary climate controls on spatial variabilities
347 of *GPP* and carbon turnover times. The moisture control results in an emergent association of
348 turnover time with aridity (**Figure 1**) that encompasses a wide range of precipitation and
349 temperature regimes. Aridity regulates the moisture availability and, thus, modulates the
350 apparent climate sensitivities of climatological carbon cycle dynamics. Despite uncertainties
351 in the observation-based data, the presented observation-based climate sensitivities of carbon
352 cycle are robust across full factorial of the latest estimates of *GPP*, soil and vegetation carbon
353 stocks (**Figure A11**). We note that the apparent sensitivities presented here only reveals the
354 primary controls, which is also indicated by a large spread within a climatic region (**Figure**
355 **1**). The additional heterogeneities may be associated with differences in soil and land
356 properties, along with differences in secondary moisture effects such as photodegradation and
357 pulsing of microbial activity from rainfall, drought-related mortality³³, disturbances and fire
358 regimes^{34,35}, etc.

359 We found that the offline simulations of the latest generation of Earth System Models from
360 CRESCENDO project reproduce well the association of *GPP* with climate, but fall short for
361 turnover times, especially in semiarid and arid regions leading to large uncertainties in
362 simulated carbon stocks. The models with relatively lower biases in turnover time and carbon
363 stock in arid and semiarid regions produce a better zonal variation of τ -precipitation
364 relationship, while the poorer model performance is characterized by biases in τ -temperature
365 relationship. This implies an insufficient model representation of moisture control on
366 climatological carbon cycle dynamics even though all models include the moisture effects on
367 both *GPP* and decomposition rates (**Table A2**).

368 The identification of exact mechanisms of moisture control on carbon cycle, especially
369 without an observation-based soil moisture that extends beyond top few centimetres of soil, is
370 still challenging. For example, we cannot clarify if the modelled soil moisture is itself biased
371 or if the response of carbon cycle to soil moisture is misrepresented. Nevertheless, an
372 evaluation of evapotranspiration shows a very consistent performance across models in all
373 climatic regions (**Figure A12**), which should lead to a consistent soil moisture across models.
374 Yet, the spatial covariation of carbon fluxes-moisture-temperature reveals diverse moisture-
375 temperature relationships across different models (**Figure A13**). The temperature responses
376 of *GPP* and respiration are highly consistent, but the moisture responses differ significantly

377 across different models. The model performing better in arid and semi-arid regions (e.g.,
378 SURFEX) has contrasting responses than the models with poorer performance providing
379 secondary evidence of the potential weakness in the model representation of moisture
380 controls. Factorial experiments of each model are necessary to identify the reasons behind,
381 and to bridge the differences between, the apparent moisture controls presented in this study.
382 Lastly, the weaker performance of precipitation-turnover relationships leads to large
383 uncertainties of carbon stocks especially in arid and semi-arid climatic regions, as the biases
384 in C_{total} are largely associated with biases in turnover time rather than those in GPP .
385 Additionally, we found that biases of GPP and turnover time manifest to a larger bias in
386 C_{total} . This has serious implications in the predictions of changes in carbon stock under
387 climate change, as the changes in precipitation, temperature, and thus aridity³⁶ will have a
388 non-negligible influence. The reduction of uncertainties in modelled carbon stock under
389 global changes is, therefore, not a carbon-cycle only challenge and it must be addressed with
390 a broader scope of improving the hydrological influences on the terrestrial carbon cycle.

391

392 Methods

393 **Ecosystem carbon turnover time:**

394 A turnover rate of a storage is broadly defined as the rate of fractional loss of storage per unit
395 time. For an ecosystem under natural condition, the turnover time, an inverse of turnover rate,
396 is, therefore, the time duration carbon stays in the ecosystem between carbon assimilation
397 through photosynthesis and loss to atmosphere through respiration and decomposition
398 processes. Under steady state assumption, the output carbon fluxes equilibrate with the input
399 primary productivity, and temporal changes in carbon storage become small. Thus, the
400 steady-state turnover time of an ecosystem can be effectively calculated as the ratio of carbon
401 storage and the input flux to the ecosystem as,

$$402 \quad \tau = \frac{C_{Total}}{GPP} \quad (1),$$

403 where, τ is the ecosystem turnover time (years), C_{total} is the long-term average total ecosystem
404 carbon storage per unit area (kgC/m^2) and GPP is the annual mean gross primary productivity
405 ($\text{kgC}/\text{m}^2/\text{year}$). As stated and used in previous studies ^{17,18,25,26}, the τ in Eqn (1) is under the
406 assumption of a steady state ecosystem and represents the apparent or effective turnover time
407 of the whole ecosystem carbon storage. It emerges as the diagnostic property of an
408 ecosystem, rather than the intrinsic property of decomposition processes that explicitly
409 controls C_{total} .

410 **Observation-based datasets:**

411 Due to potential uncertainties in the global observation-based estimates, we used an ensemble
412 of six GPP datasets, four soil carbon (C_{soil}) and four vegetation carbon (C_{veg}) stock datasets.
413 The data ensembles, spanning a wide range of sources and methods, represent the current
414 state-of-the-art of global observation-based estimates of the carbon cycle components and,
415 likely, cover the full range of observational uncertainties. As we use only a single ensemble
416 estimate from each product, we assume that the differences and uncertainties are larger across
417 the datasets than within a single dataset.

418 The GPP ensemble includes Model Tree Ensembles (MTE) (Jung et al., 2011) and its recent
419 successors from FLUXCOM based on remote sensing and that with additional meteorological
420 forcing ³⁸, solar-induced fluorescence (SIF) based GOSIF GPP ³⁹, light use efficiency based
421 GPP from vegetation photosynthesis model (VPM) ⁴⁰, and lastly, an independent machine
422 learning prediction from FluxSat ⁴¹ that uses corrected satellite-based reflectance. All GPP
423 products are either upscaled from or extensively evaluated against eddy covariance

424 observations of carbon fluxes from FLUXNET (www.fluxdata.org) sites (Baldocchi et al.,
425 2001). For example, the MTE, FLUXCOM, and FluxSat products use different combinations
426 and corrections of training data and drivers from satellite remote sensing and meteorological
427 dataset to upscale site-level observation to the global scale using different machine learning
428 algorithms. VPM, a light use efficiency model, is similar to MODIS *GPP* but with an
429 additional validation for FLUXNET sites, and GOSIF *GPP* uses a set of *GPP*-SIF
430 relationships to produce an ensemble of high resolution global *GPP* fields that are
431 independent of reflectance-based remote sensing products. While the spatial variability of the
432 mean *GPP* is one of the most robust features when comparing different observation-based
433 *GPP* products, it is desirable to use an ensemble as no single data is superior to all others
434 universally ⁴³.

435 For C_{soil} , we use the full depth soil organic carbon estimates including a data that combines
436 inventories from Harmonized World Soil Database ⁴⁴ with the Northern Circumpolar Soil
437 Carbon Database ⁴⁵ extrapolated to full depth ¹⁸; from SoilGrids that uses machine learning
438 method to upscale soil profile measurements with land and climate characteristics as
439 predictors⁴⁶; and from Sanderman et al. that corrects for land use and forest cover ⁴⁷. Due to
440 differences in number and locations of observed soil profiles used, predictors, and prediction
441 methods, the soil carbon estimates are uncertain, especially in high latitude regions, with a
442 large C_{soil} but a relatively fewer measurement profile. Nonetheless, the global distributions of
443 C_{soil} in these products are robust ⁴⁸, and their differences reflect potential uncertainties across
444 all observation-based global estimates. We note that the SoilGrids data has been recently
445 updated, but the new version of the data, the LANDGIS, has not been used in this analysis
446 owing to lack of extensive validation and potential over-estimation issue in the northern high
447 latitudes ^{48,49}. It should here be noted that using the LANDGIS instead of SoilGrids does not
448 significantly affect the main findings of this study (see **Figure 1** and **Figure A3**).

449 The C_{veg} ensemble includes four different RADAR and LIDAR satellite-based estimates of
450 aboveground biomass with a corresponding estimate for belowground biomass ⁴⁸. As
451 different data are based on different satellites and algorithms, and have been validated with
452 observations whenever and wherever available, they are indicative of global vegetation
453 biomass and associated uncertainties in observation-based estimates.

454 An ensemble of observation-based τ was then obtained using Eqn (1) for a full factorial
455 combination of all C_{soil} , C_{veg} , and *GPP* products resulting in 96 different τ maps.

456 In this study, for GPP , C_{total} and τ , the ensemble median across data products was used as the
457 representative observation-based estimate, and the 5th and 95th percentiles were used as
458 uncertainty range.

459 Lastly, for an additional evaluation of CRESCENDO models, the ensemble estimates of
460 evapotranspiration from FLUXCOM remote sensing products ⁵⁰ was used.

461 **Climatic regions based on aridity index:**

462 The aridity index, calculated as the ratio of mean precipitation and potential
463 evapotranspiration (PET), is used to delineate different climatic regions based on relative
464 availability of moisture and energy. For consistency, the CRU-NCEP precipitation, used to
465 force the CRESCENDO model simulations, is also used for calculating the aridity index. The
466 PET data is based on an estimate from the latest climate datasets at a high resolution ⁵¹.
467 Different climatic regions were then delineated based on the aridity index ranges suggested
468 by UNEP ⁵² as: arid (<0.2), semi-arid, sub-humid, and humid (see **Figure A1**). The average
469 annual precipitation (temperature) varies from 245 mm/year (7.6°C) in arid regions to 880.3
470 mm/year (0.9°C) in humid regions. These regions constitute 8.2%, 24.3%, 15.1%, and 52.4%
471 of the total area considered in this study. In relative terms, the arid and semiarid regions
472 contribute ~18% of the global GPP and hold ~24% of the global carbon stock (**Table A1**).
473 Combined, these regions have a τ of ~43 years, which is ~34% longer than the global τ of ~32
474 years.

475 **Climate sensitivities:**

476 The overarching aim of this study is to investigate the climate sensitivities of climatological
477 mean carbon cycle dynamics across all major climatic regions globally and assess the
478 apparent sensitivities of spatial covariations of carbon cycle with climate. Under humid
479 climate, spatial sensitivity of τ is itself dependent on temperature ¹⁷. But, to what extent the
480 same applies to other climatic regions and carbon cycle variables is unclear. This is especially
481 critical with regard to precipitation that represents the potential moisture supply for an
482 ecosystem that determines both the carbon assimilation and decomposition processes.
483 Further, we hypothesize that the relative availability of moisture (supplied by precipitation)
484 and energy (determined by temperature) plays a central role in defining the carbon cycle
485 dynamics across spatiotemporal scales. We, therefore, investigate the relationships between
486 the carbon turnover time and GPP with precipitation and temperature across different

487 climatic regions characterized by an aridity index. We assume that the relationship between
488 τ/GPP and climate are non-linear and assume it to be of a second-degree polynomial form as,

$$489 \quad y = ax^2 + bx + c \quad (2),$$

490 where, y is the response/dependent variable, x is the independent variable, and a , b and c are
491 the parameters of the quadratic equation. The terms a and b are the coefficients of the non-
492 linear and linear terms, respectively, and c is the constant term that defines the
493 offset/intercept when the independent variable is zero. As τ is expected to have a non-linear
494 exponential relationship with temperature, we log-normalize it and use $\log(\tau)$ as the
495 dependent variable.

496 The parameters of Eqn (2) for each climatic region are estimated using a robust non-linear
497 least square regression with Huber loss function⁵³ that is less sensitive to outliers in the data.

498 **CRESCENDO model simulations:**

499 We use the observation-based climate sensitivities to evaluate the process representations in
500 land surface schemes of (used in) the ESMs from seven different European research
501 institutes. The stand-alone offline land simulations were carried out as a part of the
502 CRESCENDO project (<https://ukesm.ac.uk/crescendo/>) to understand and evaluate the carbon
503 and nitrogen cycle processes in the current state-of-the-art ESMs. The same land surface
504 schemes were used in the ESM simulations for the sixth phase of coupled model
505 intercomparison project (CMIP6). Following the TRENDY protocol⁵⁴, the models were
506 forced by CRUNCEP v7⁵⁵ forcing dataset
507 ([https://vesg.ipsl.upmc.fr/thredds/catalog/work/p529viov/cruncep/V8_1901_2016/catalog.ht](https://vesg.ipsl.upmc.fr/thredds/catalog/work/p529viov/cruncep/V8_1901_2016/catalog.html)
508 [ml](https://vesg.ipsl.upmc.fr/thredds/catalog/work/p529viov/cruncep/V8_1901_2016/catalog.html)), observed atmospheric CO₂ concentration, nitrogen deposition, and annual land-use
509 changes. The offline simulations forced with an observation-based dataset are suitable for
510 evaluating the response of the land carbon cycle processes to the climate forcing, as they are
511 less prone to biases and uncertainties arising from differences in carbon-climate feedbacks in
512 the coupled simulations of ESM.

513 The data of CRESCENDO model simulations were last accessed in January, 2019. While the
514 simulations are available for longer time period, the simulation results from 2001 to 2010
515 inclusive, consistent with the time period across different observation-based estimates of
516 carbon cycle variables, were used for evaluations in this study. The C_{total} was calculated as a
517 sum of all the carbon pools respiring to the atmosphere. Similar to the observation, τ was
518 calculated as the ratio of C_{total} and GPP .

519 All models were forced in an offline mode with the same meteorological drivers, but at a
520 different resolution with a different experimental and process setup (see **Table A2** for an
521 overview). Regarding carbon cycle spinup, all models except JULES were initialized with
522 zero carbo stock, and forced by the repeated meteorological data of the first few years for a
523 total of 500-10000 years. It should be noted that, in essence, irrespective of the initial
524 condition, the JULES model produces a consistent model state at the end of spinup period ⁵⁶,
525 and, in general, by definition, the spin-up and initial condition are not systematically related
526 to the biases in the model states. There are further differences in soil physics and model
527 structure therein. For example, CLM5, JULES, and SURFEX have a finer discretization of
528 soil layers and/or represent soil physics with freeze-thaw dynamics.

529 CLM4.5, the terrestrial component of the CMCC coupled model version 2 ⁵⁷ within CMIP6,
530 was used in its Biogeochemical (BGC) configuration ^{58,59} for the CRESCENDO simulations.
531 CLM4.5 describes photosynthetic, hydrologic, and decomposition processes. Photosynthesis
532 is based on Ball-Berry model, and hydrology includes soil moisture and groundwater
533 processes. The decomposition rates are dependent on soil temperature, soil moisture, oxygen
534 and depth.

535 CLM5, the terrestrial component of NorESM, builds on CLM4.5, with major updates on soil
536 hydrology and carbon coupling ⁶⁰. Soil hydrology is based on variable soil thickness with
537 high resolution layers and spatially varying root profile. Photosynthesis is based on the
538 Medlyn-model and includes nitrogen limitation using optimality principles. The
539 representation of the decomposition process is updated with a new metric for the apparent
540 soil carbon turnover ¹⁷ in which the temperature affects the moisture limitation of
541 decomposition through freezing of liquid water.

542 JSBACH version 3.2 ⁶¹ is the terrestrial component of MPI-ESM1.2. As compared to its
543 predecessor, it includes novel components of soil carbon, nitrogen limitation, a five-layer
544 hydrology scheme, the wildfire model SPITFIRE, as well as improved land use
545 representations ⁶². The soil carbon decomposition processes are based on the YASSO model
546 ⁶³ and include five different soil carbon pools according to the chemical quality of the organic
547 matter, each for woody and non-woody litter. The vertical distribution of soil carbon is not
548 resolved and permafrost is not considered in the applied version. Decomposition rates depend
549 on air temperature and precipitation, due to the foundation of YASSO on observed litter
550 decomposition rates.

551 JULES ⁵⁶, the land component of UKESM1, includes the improvements in parameterization
552 of the vegetation dynamics, canopy structural properties, and the parameters affecting the
553 photosynthesis and respiration fluxes ⁶⁴. The nutrient availability limits the photosynthesis
554 indirectly by controlling the biomass and leaf area index. The litter and exudate fluxes
555 convert to the soil organic carbon through controls of nitrogen availability, and the soil
556 decomposition process are controlled further by temperature and moisture.

557 LPJ-GUESS ⁶⁵ is the dynamic vegetation model of EC-Earth used in CMIP6. LPJ-GUESS
558 employs a two-layer leaky bucket soil hydrology scheme with percolation between layers and
559 deep drainage. Photosynthesis is controlled by nitrogen limitation following whole plant
560 optimal nitrogen content. The soil organic matter dynamics are based on the CENTURY soil
561 model in which the decay rates depend on the moisture content of the top soil layer, soil
562 temperature, texture, lignin fractions, tillage and nitrogen limitation.

563 ORCHIDEE, the land surface scheme of the IPSL-CM5 ESM, consists of a multi-layer soil
564 that accounts for transport of water by diffusion and deep drainage, and of heat with
565 improved thermodynamics and conduction process ⁶⁶. The resulting soil moisture and
566 temperature are used for analytically solving soil organic matter dynamic that guarantees
567 steady-state conditions. Photosynthesis is based on the Farquhar-model and is limited by the
568 leaf nitrogen. The soil heterotrophic respiration is independent of the nitrogen content of soil
569 organic matter.

570 SURFEX/ISBA-CTRIP, the land surface scheme of the CNRM-ESM2-1 in CMIP6 ^{67,68}
571 solves the energy and water balance of one vegetation canopy, 12 snow layers, and up to 14
572 soil layers in deep soils and permafrost. Soil texture, albedo and carbon content determine the
573 thermal and hydraulic properties of the soil. The litter and soil organic matter processes are
574 based on the soil carbon part of the CENTURY model, and the soil heterotrophic respiration
575 is limited under high soil moisture. The nitrogen limitation leaf growth is empirically based
576 on a meta-analysis of CO₂ enrichment experiments that limit leaf nitrogen content and
577 specific leaf area.

578

579 **Zonal variations and correlation:**

580 The zonal variations and correlations are computed using a moving window of 10 grid cells
581 along the latitude (5° coverage). The zonal means of the *GPP* and *C_{total}* are weighted by the
582 area of the grid cell which vary along the latitude, and the zonal mean of τ was estimated as

583 the ratio of zonal C_{total} and GPP , and not as a zonal mean of τ in different grid cells. The
584 observational uncertainty band for the zonal means are calculated as 5th and 95th percentiles
585 of the zonal value using different data products.

586 The correlations between τ or GPP or C_{total} and temperature or precipitation were calculated
587 as the partial Pearson's correlation coefficient controlling for the other. To accommodate for
588 the influence of the extreme cold winter temperature on the mean annual temperature in high
589 latitude regions, the monthly temperature below -5°C were considered physiologically (for
590 photosynthesis) and metabolically (for respiration) irrelevant, and these values were set to -
591 5°C while calculating the mean annual temperature. Note that the processing is only relevant
592 for high latitude regions where the duration of and temperature in winter vary significantly
593 within a moving window (see **Figure 3** and **Figure A1**).

594 Within a moving window, one percent grid cells were discarded to minimize the effects of
595 outliers on the correlation coefficient. Unless otherwise mentioned in the captions, the
596 uncertainty band around the observation are the ranges within 5th and 95th percentile of the
597 values calculated from different data products. The partial correlation coefficients were tested
598 for statistical significance at 5% level of significance, and all insignificant correlations are
599 masked out when plotting.

600

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608 Change) project of the Max Planck Society.

609 Author Contributions

610 SK and NC conceptually designed the study. SK carried out the analysis and prepared the
611 manuscript. CJ, VB, CD, YF, VG, EJ, HL, SM, JN, DP, PP, DW, AW contributed to and or
612 provided CRESCENDO model simulations. All authors had intellectual and/or direct input to
613 the discussion of the results and completion of the manuscript.

614 Data and Code Availability

615 All the datasets used in this study are available in the public domain, and can be obtained by
616 following the original publications that are cited in respective sections. The python code used
617 to analyse the data and plot the results are available publicly at [https://github.com/koir-](https://github.com/koir-su/c_cycle_eval)
618 [su/c_cycle_eval](https://github.com/koir-su/c_cycle_eval).

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621 Extended Tables

622

623 **Table A1.** Summary of the median and the range of observation-based gross primary
 624 productivity (GPP in pgC/year), total carbon storage (C_{total} in pgC) and turnover time (τ in
 625 years) globally, and in different climatic regions. The median is calculated from the ensemble
 626 members of the observation-based data. The range indicates the values within 5th and 95th
 627 percentile of the ensemble members.

	Global	Arid	Semi-arid	Sub-humid	Humid
GPP	109.5 (98.3-119.6)	2.7 (2.3-3.1)	16.8 (14.8-19.3)	12.8 (11.1-13.6)	77.6 (69.0-85.3)
C_{total}	3482.9 (2245.0-4804.8)	149.2 (105.3-162.4)	680.3 (424.7-811.5)	493.9 (289.3-698.0)	2150.4 (1418.0-3151.5)
τ	31.9 (18.9-47.4)	52.9 (35.1-73.2)	39.7 (22.9-54.1)	38.8 (21.4-62.1)	27.7 (16.8-44.3)

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Table A2. An overview of the CRESCENDO models, the major processes therein, and the simulation setup. Human activities include human need-driven processes that affects the vegetation carbon stock such as crop harvest (H), pasture (P), wood harvest (W), deforestation (D), land use changes (LUC), and nitrogen deposition (NDep). All models include carbon losses from heterotrophic respiration (RH), and some models include the carbon losses from soil due to leaching of dissolved organic carbon (DOC).

SN	Model Name (LSM/ESM)	Institution	Spinup (years)	Initial carbon stock	Forcing for spinup (repeat years)	Native spatial resolution (° latitude x ° longitude)	Dynamic vegetation process	Human activities	Soil physics (number of layers, total depth)	Soil carbon sink terms
1	CLM4.5/CMCC-ESM	Euro Mediterranean Centre on Climate Change (CMCC) Foundation	1020 accelerated + 300 non-accelerated	0	30 years	1.25°x0.9375°	no	LUC, W, D	15 layers, 35.1776 m	RH
2	CLM5/No rESM	NORCE Norwegian Research Centre, Bergen, Norway	1526	0	30 years	0.5°x0.5°	no	LUC, W, D	20 layers, 8.5 m	RH; carbon cost for nutrient processes
3	JSBACH/MPI-ESM	Max Planck Institute for Meteorology	> 10000	C stock from TRENDY v6 simulation	20 years	~1.875°x1.875° (T63)	not activated	LUC, NDep, W, H	Soil physics: 5 layers, 9.834 m; soil carbon: 1 layer	RH
4	JULES/UKESM	Met Office Hadley Centre, UK NERC	10000	C stock from independent simulation	20 years	~1.25°x1.875° (N96)	yes	LUC, NDep, H	4 layers, 3 m	RH
5	LPJ-GUESS/EC-Earth	Department of Physical Geography and Ecosystem Science, Lund University	Soil: 40500; Vegetation: 500	0	30 years, no IAV of temperature	0.5°x0.5°	yes	LUC, NDep, H, P	Soil moisture: 2 layers, 1.5 m; soil carbon: 1 layer	RH; DOC
6	ORCHIDEE/IPSL-CM5	Institut Pierre Simon Laplace (IPSL), France	340 for litter input; cSoil: until steady state	0	30 years	0.5°x0.5°	no	LUC, W, H, D	Soil moisture: 11 layers, 2 m; soil carbon: 1 layer	RH
7	SURFEX/CNRM-CM5	CNRM, Meteo-France/CNRS/Université Fédérale de Toulouse	Soil: 8875; Vegetation: 470	0	20 years	1°x1°	no	LUC	Soil temperature: 14 layers, 12 m; soil moisture: 14 layers, till rooting depth (1m for grasses, 8m for tropical forests)	RH; DOC

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Table A3. Summary of the parameters of the non-linear least square fitting of the relationships between τ and *GPP* and climate: a: coefficient for the quadratic term, b: coefficient for the linear term, and c: constant.

		Arid			Semi-arid			Sub-humid			Humid		
		a	b	c	a	b	c	a	b	c	a	b	c
τ-MAT	Obs-based	2.61E-05	-3.45E-02	2.25	1.01E-04	-3.34E-02	1.97	1.33E-12	-3.01E-02	1.84	2.38E-04	-3.60E-02	1.88
	CLM4.5	9.51E-04	-5.23E-02	2.13	1.36E-04	-3.48E-02	1.96	7.23E-16	-3.33E-02	1.92	1.92E-04	-3.32E-02	1.82
	CLM5	1.01E-03	-6.36E-02	1.86	9.70E-04	-5.82E-02	1.53	4.41E-04	-3.96E-02	1.40	7.31E-04	-3.93E-02	1.44
	JSBACH	1.04E-20	-1.62E-02	0.91	5.00E-04	-3.55E-02	1.00	1.56E-04	-3.11E-02	1.16	2.06E-05	-2.53E-02	1.29
	JULES	3.94E-04	-2.56E-02	1.45	9.43E-20	-1.50E-02	1.54	1.52E-18	-1.11E-02	1.51	7.76E-16	-1.44E-02	1.43
	LPJ-GUESS	5.86E-04	-3.81E-02	1.41	2.84E-04	-2.81E-02	1.41	1.70E-04	-2.36E-02	1.39	2.16E-04	-2.67E-02	1.42
	ORCHIDEE	5.55E-04	-3.32E-02	1.21	4.82E-04	-2.49E-02	1.07	4.93E-04	-2.01E-02	1.00	1.05E-04	-1.50E-02	1.15
	SURFEX	3.31E-14	-3.37E-02	2.23	1.48E-17	-2.98E-02	1.95	5.78E-20	-2.54E-02	1.75	2.85E-17	-2.84E-02	1.72
τ-MAP	Obs-based	1.05E-06	-2.64E-03	2.40	2.30E-06	-4.19E-03	3.05	1.11E-06	-2.86E-03	2.91	2.65E-07	-1.31E-03	2.60
	CLM4.5	9.25E-07	-2.26E-03	2.19	2.03E-06	-3.90E-03	2.96	8.09E-07	-2.57E-03	2.93	2.63E-07	-1.27E-03	2.52
	CLM5	1.54E-06	-3.44E-03	2.01	3.97E-06	-6.45E-03	3.20	2.00E-06	-4.32E-03	3.00	2.74E-07	-1.24E-03	2.18
	JSBACH	2.86E-07	-6.45E-04	0.84	1.79E-06	-3.21E-03	1.83	1.22E-06	-2.99E-03	2.28	2.20E-07	-1.05E-03	1.84
	JULES	7.30E-08	-1.87E-04	1.25	4.86E-07	-1.16E-03	1.81	1.80E-31	-4.95E-04	1.76	7.74E-08	-5.02E-04	1.72
	LPJ-GUESS	4.23E-07	-1.02E-03	1.28	2.19E-06	-3.50E-03	2.28	9.63E-07	-2.25E-03	2.23	1.79E-07	-8.92E-04	1.92
	ORCHIDEE	5.30E-07	-1.15E-03	1.18	1.65E-06	-2.61E-03	1.74	9.30E-07	-1.84E-03	1.68	9.53E-08	-4.91E-04	1.41
	SURFEX	9.71E-07	-2.51E-03	2.38	9.44E-07	-2.69E-03	2.69	2.63E-07	-1.50E-03	2.41	1.76E-07	-1.01E-03	2.27
GPP-MAT	Obs-based	3.97E-04	1.09E-03	0.17	2.88E-04	1.54E-02	0.41	3.87E-21	3.22E-02	0.69	7.24E-04	4.83E-02	0.69
	CLM4.5	1.35E-04	2.77E-04	0.15	3.68E-15	5.76E-03	0.38	3.85E-34	1.35E-02	0.59	4.17E-04	5.60E-02	0.90
	CLM5	5.20E-04	-2.19E-03	0.14	5.74E-04	3.08E-03	0.38	4.42E-05	1.66E-02	0.73	6.07E-04	3.89E-02	1.00
	JSBACH	3.57E-04	-6.90E-04	0.11	7.05E-04	6.56E-03	0.24	7.18E-04	1.97E-02	0.49	1.89E-03	3.95E-02	0.66
	JULES	4.85E-15	4.02E-03	0.10	4.40E-04	1.50E-02	0.18	4.03E-04	3.02E-02	0.48	2.07E-04	5.62E-02	0.90
	LPJ-GUESS	2.12E-18	1.97E-02	0.36	1.06E-15	1.80E-02	0.61	6.14E-22	1.87E-02	0.83	4.63E-15	4.74E-02	1.07
	ORCHIDEE	4.04E-04	3.40E-03	0.05	6.45E-04	1.67E-02	0.26	1.54E-04	3.36E-02	0.66	8.37E-04	5.06E-02	0.78
	SURFEX	2.61E-04	2.62E-03	0.07	5.66E-04	1.27E-02	0.24	5.08E-04	2.57E-02	0.49	1.64E-03	4.20E-02	0.51
GPP-MAP	Obs-based	-8.84E-08	1.09E-03	0.00	-1.87E-07	1.43E-03	0.00	-2.45E-07	1.61E-03	0.00	-1.58E-07	1.46E-03	0.00
	CLM4.5	3.30E-07	5.79E-04	0.00	-7.28E-07	1.33E-03	0.00	-9.64E-07	1.84E-03	0.00	-1.01E-07	1.48E-03	0.00
	CLM5	8.81E-08	9.87E-04	0.00	-2.28E-07	1.31E-03	0.00	-8.16E-07	1.96E-03	0.00	-2.27E-07	1.68E-03	0.00
	JSBACH	2.44E-07	6.05E-04	0.00	6.06E-07	6.19E-04	0.00	3.00E-07	9.70E-04	0.00	-1.31E-08	1.40E-03	0.00
	JULES	3.77E-07	4.79E-04	0.00	9.44E-07	3.75E-04	0.00	5.15E-07	8.24E-04	0.00	-2.40E-07	1.73E-03	0.00
	LPJ-GUESS	-9.69E-07	2.55E-03	0.00	-1.33E-06	2.42E-03	0.00	-1.23E-06	2.47E-03	0.00	-2.34E-07	1.70E-03	0.00
	ORCHIDEE	1.74E-07	7.45E-04	0.00	7.27E-07	8.20E-04	0.00	-4.85E-08	1.48E-03	0.00	-1.77E-07	1.62E-03	0.00
	SURFEX	3.38E-08	6.52E-04	0.00	7.23E-07	6.34E-04	0.00	3.42E-07	9.49E-04	0.00	-1.09E-07	1.42E-03	0.00

637 **Table A4.** Performance metrics for least square regression of the relationship between τ , GPP , and climate: r^2 : coefficient of determination. r_{mad} :
638 relative median absolute deviation calculated as the median of absolute deviation normalized by the interquartile range of the observation.

639

		MAT								MAP							
		Arid		Semi-arid		Sub-humid		Humid		Arid		Semi-arid		Sub-humid		Humid	
		r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}	r^2	r_{mad}
τ	Obs-based	0.06	0.25	0.45	0.14	0.44	0.14	0.37	0.13	0.00	0.27	0.58	0.14	0.57	0.14	0.00	0.18
	CLM4.5	0.00	0.32	0.00	0.11	0.31	0.10	0.00	0.11	0.00	0.48	0.00	0.16	0.32	0.10	0.00	0.18
	CLM5	0.00	0.36	0.00	0.18	0.00	0.25	0.00	0.24	0.00	0.37	0.00	0.30	0.01	0.26	0.00	0.35
	JSBACH	0.23	0.42	0.40	0.22	0.34	0.14	0.65	0.16	0.01	0.44	0.40	0.29	0.48	0.15	0.62	0.20
	JULES	0.00	0.39	0.00	0.31	0.01	0.30	0.20	0.17	0.00	0.49	0.00	0.38	0.01	0.32	0.22	0.17
	LPJ-GUESS	0.17	0.31	0.10	0.19	0.23	0.14	0.11	0.14	0.00	0.47	0.11	0.22	0.25	0.14	0.00	0.19
	ORCHIDEE	0.51	0.40	0.66	0.22	0.67	0.22	0.66	0.19	0.01	0.45	0.00	0.25	0.04	0.26	0.47	0.24
	SURFEX	0.14	0.22	0.49	0.14	0.68	0.16	0.86	0.07	0.00	0.29	0.60	0.16	0.74	0.14	0.00	0.12
GPP	Obs-based	0.22	0.41	0.51	0.32	0.77	0.20	0.84	0.13	0.52	0.32	0.60	0.24	0.73	0.20	0.80	0.18
	CLM4.5	0.03	0.47	0.11	0.54	0.23	0.51	0.54	0.30	0.69	0.32	0.23	0.47	0.29	0.48	0.69	0.31
	CLM5	0.19	0.37	0.36	0.37	0.33	0.42	0.63	0.26	0.74	0.31	0.44	0.31	0.33	0.43	0.70	0.25
	JSBACH	0.14	0.49	0.43	0.45	0.63	0.27	0.74	0.16	0.70	0.39	0.59	0.36	0.68	0.28	0.83	0.15
	JULES	0.02	0.71	0.49	0.26	0.77	0.23	0.84	0.18	0.69	0.52	0.82	0.16	0.89	0.18	0.90	0.14
	LPJ-GUESS	0.39	0.37	0.38	0.40	0.29	0.40	0.46	0.36	0.33	0.35	0.43	0.36	0.36	0.37	0.49	0.36
	ORCHIDEE	0.23	0.37	0.59	0.25	0.73	0.21	0.82	0.12	0.60	0.43	0.71	0.20	0.71	0.22	0.79	0.17
	SURFEX	0.19	0.34	0.61	0.24	0.79	0.19	0.85	0.10	0.57	0.33	0.78	0.17	0.80	0.13	0.78	0.17

640

Extended Figures

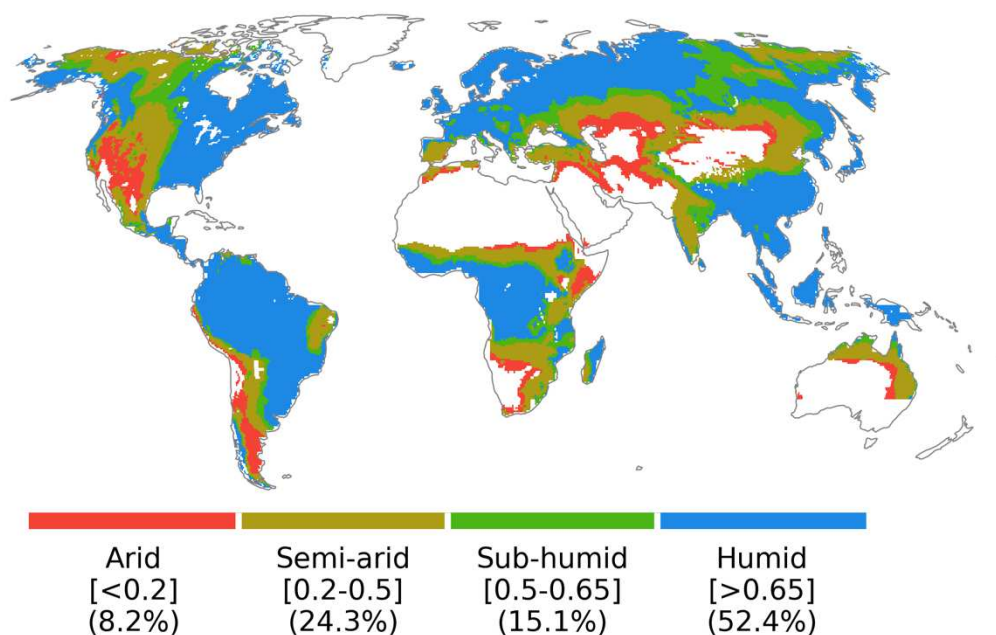


Figure A1. Global distribution of climatic regions. The climatic regions are defined using the ranges of aridity index, which is calculated as the ratio of mean annual precipitation and potential evapotranspiration. The ranges of aridity (in square brackets) that define different climate regions are taken from UNEP (United Nations Environment, 1992). From the original UNEP classification, the hyper-arid climate was merged into arid climate because it only comprised 0.1% of grid cells after excluding the desert regions. The percentage values (in parenthesis) indicate the fraction of the valid grid cells with the climate.

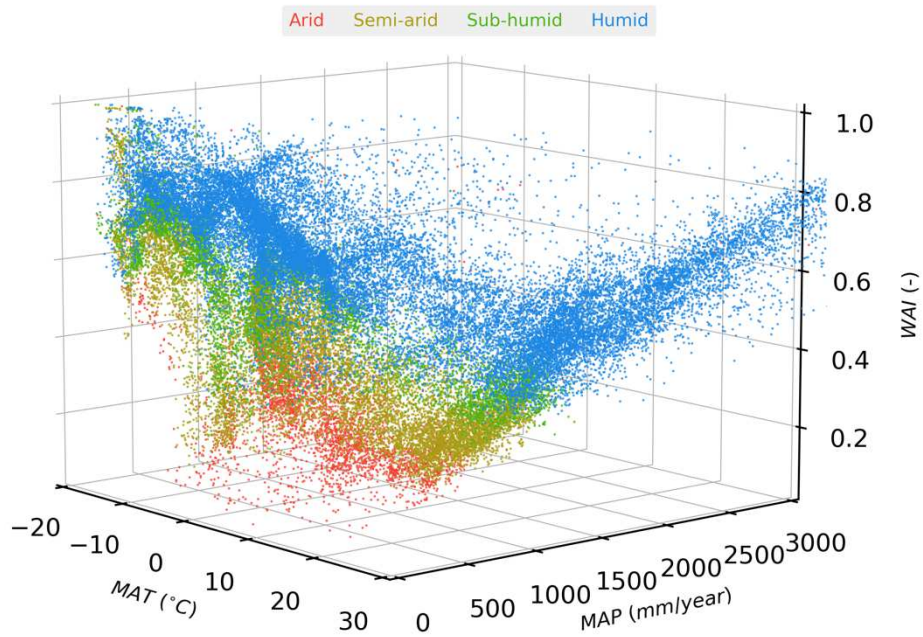


Figure A2. Covariation of climate and moisture. Mean annual precipitation (MAP, mm/year), mean annual temperature (MAT, °C) and water availability index (WAI, -)⁵⁰ are plotted in X, Y and Z axes respectively. The different colours indicate different climatic regions defined by aridity index, and individual grid-cells are plotted as dots. The WAI is a proxy for soil moisture content based on the water balance concept, and it varies between 0 (dry) and 1 (wet).

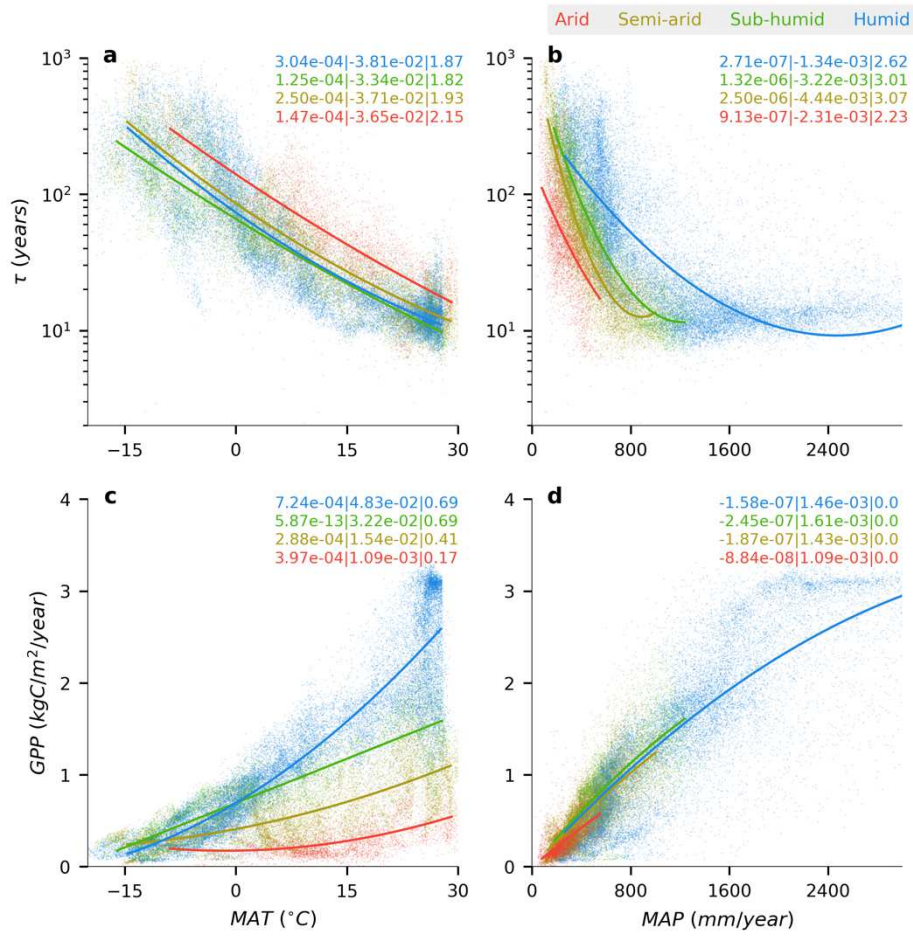


Figure A3. Same as **Figure 1**, but using the LANDGIS⁶⁹ instead of SoilGrids⁴⁷ dataset in the observation-based ensemble of soil organic carbon estimates.

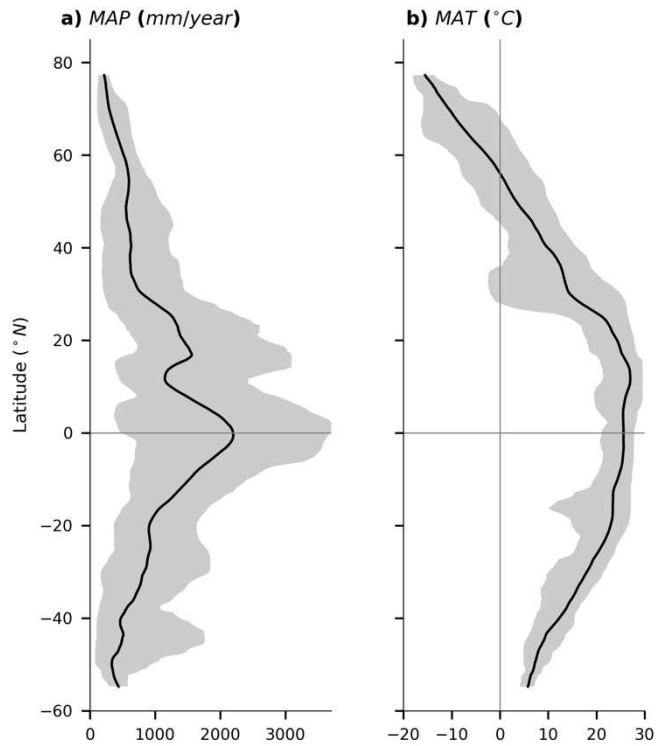


Figure A4. Zonal distributions of mean annual precipitation (mm/year) and mean air temperature (°C). The values for each latitude are calculated as mean within a moving window of 10 grid cells along the latitude (5°). The shaded region indicates the 5th and 95th percentiles within the latitudinal moving window.

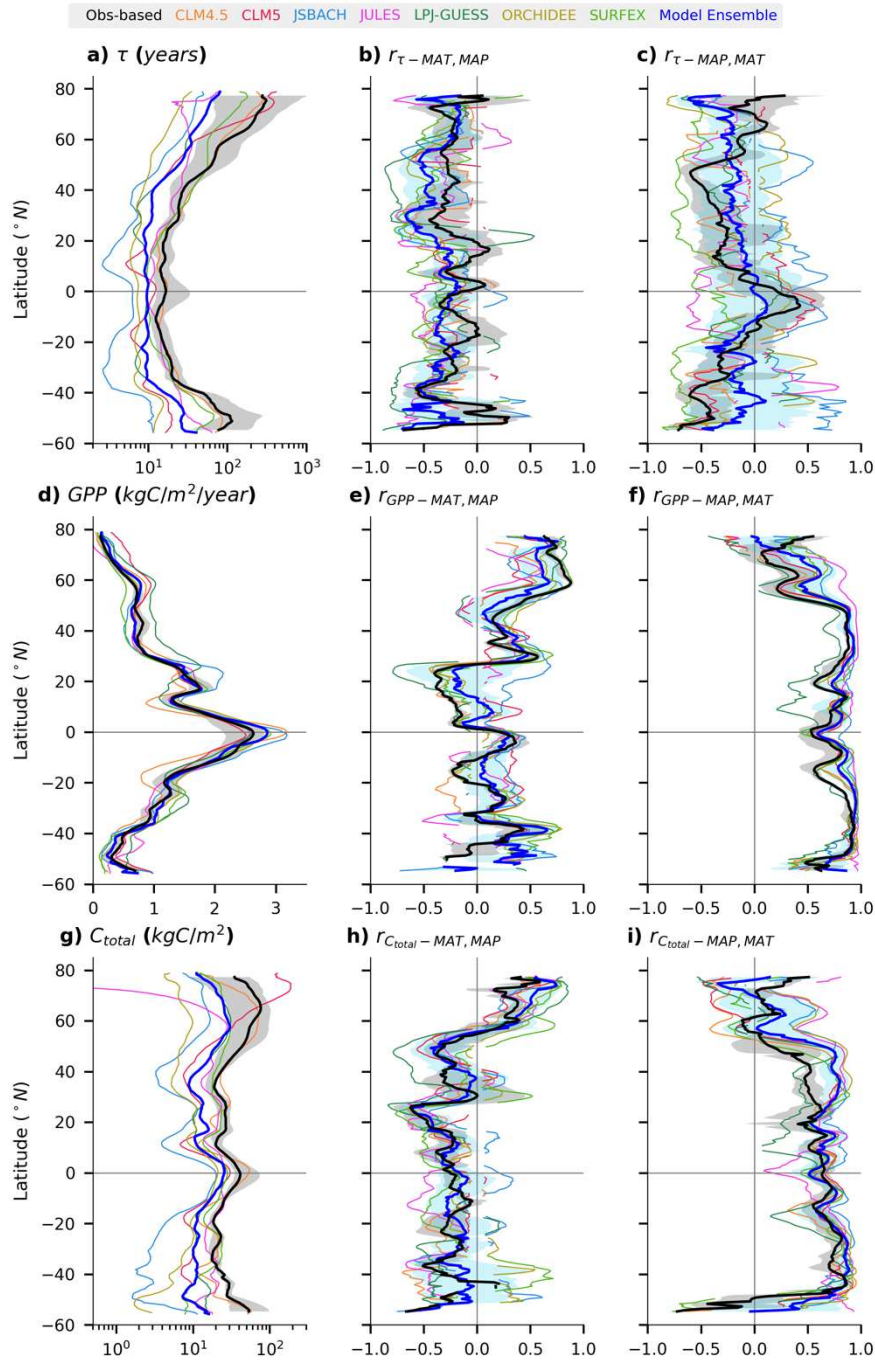


Figure A5. Same as **Figure 3** but using the average temperature that is corrected for low winter temperature below freezing point. For the correction, the temperature of months below 0°C are set at 0°C before calculating the mean annual temperature, which results in an estimate that only includes physiologically relevant months while considering the duration of the period with below freezing temperature.

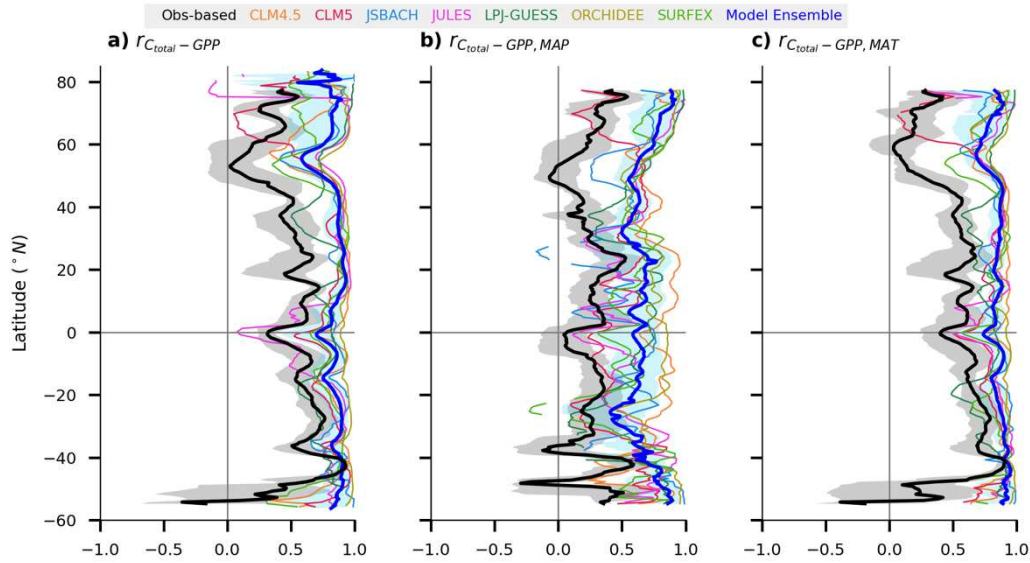


Figure A6. Zonal correlation between total ecosystem carbon stock (C_{total} , kgC/m^2) and gross primary productivity (GPP , $\text{kgC}/\text{m}^2/\text{year}$). In a) correlation between C_{total} and GPP , b) controlled for precipitation, and c) controlled for temperature are presented. The Pearson's correlation coefficient for each latitude is calculated for a moving window of 10 grid cells along the latitude (5°). The thick dashed blue lines show the normalized mean correlation of all models with shades indicating variation within 1 standard deviation. The observation is plotted as a thick black line with shade indicating the range within the 5th and 95th percentiles.

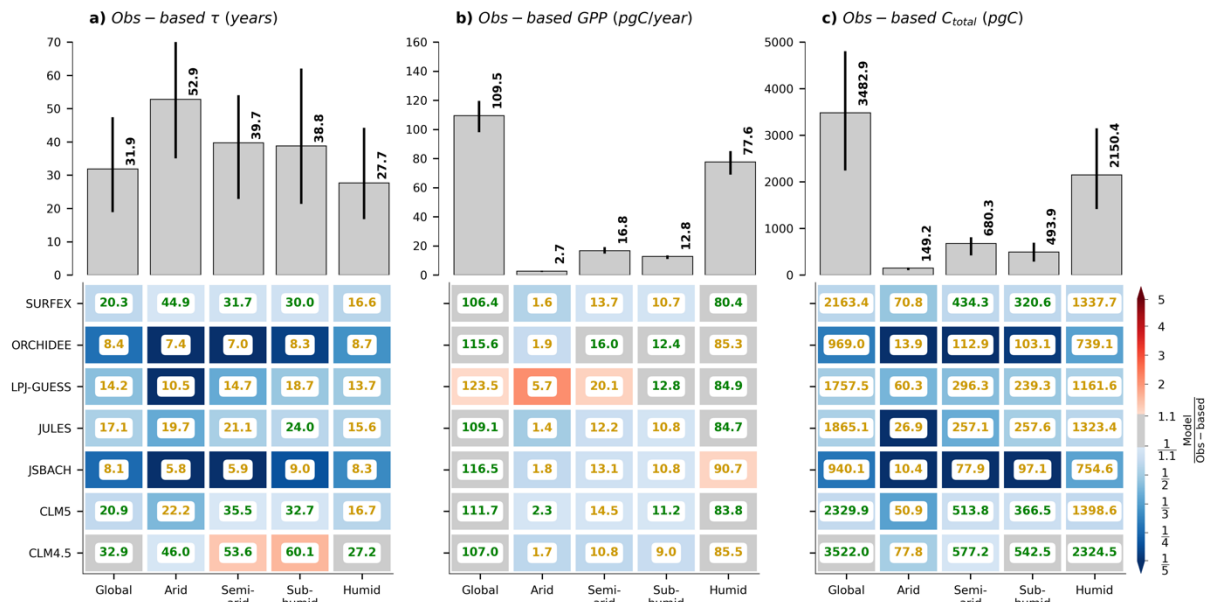


Figure A7. Evaluation of a) ecosystem turnover time (τ , years), b) gross primary productivity (GPP , pgC/year), and c) total carbon storage (C_{total} , pgC) over different climatic regions. In the bar charts, the observation and their uncertainties (5th and 95th percentiles) are plotted. In the colourmap matrix, horizontal axis shows different climatic regions and the global values, and the vertical axis shows different models or model ensembles. The colour indicates the bias, calculated as the ratio of modelled and observed values. The inset text shows τ or GPP or C_{total} for a given model and climate. The colour of

the text indicates whether the modelled values are within the range of observational uncertainty with green for those within and orange for those outside.

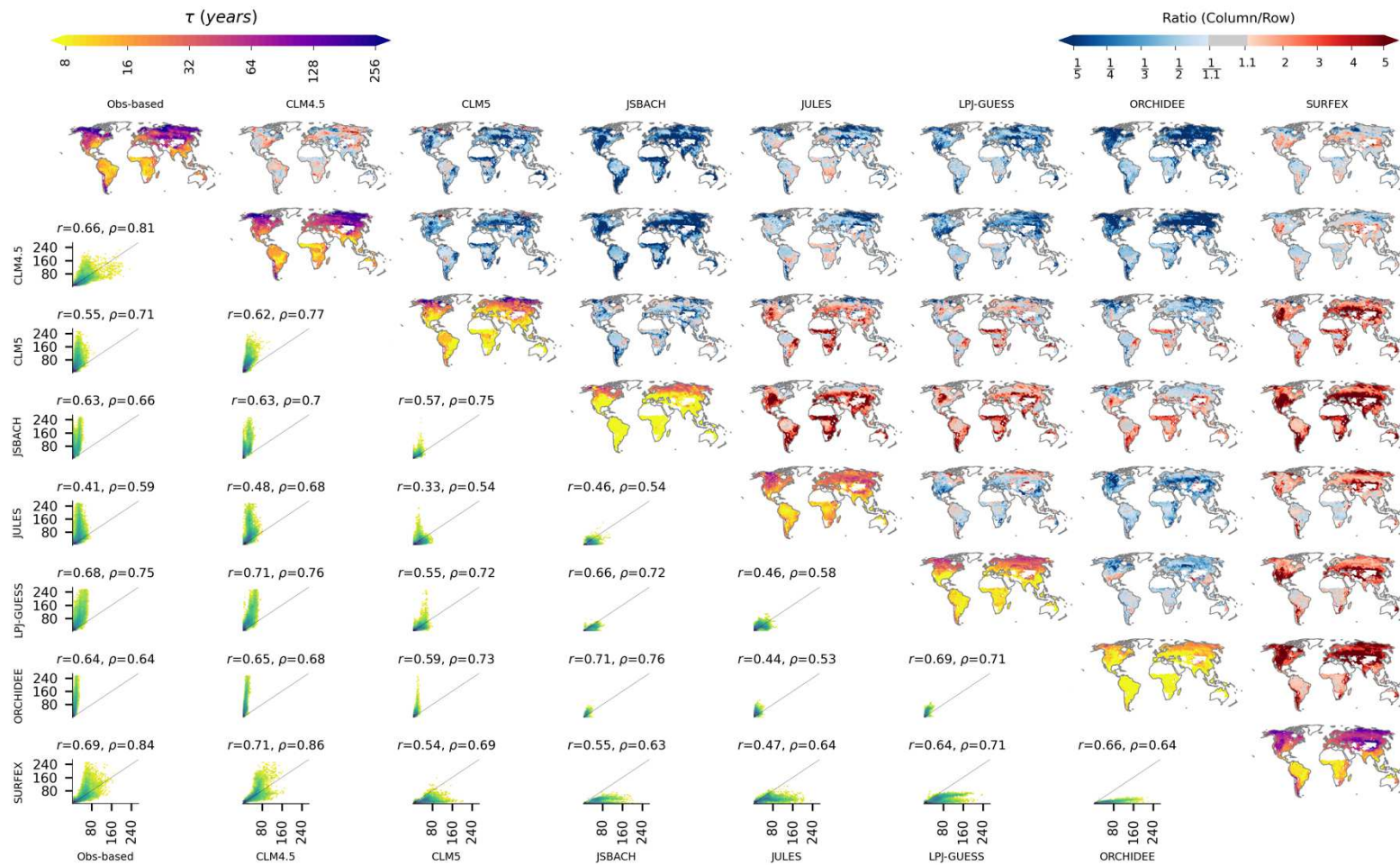


Figure A8. Comparison of the global distribution of ecosystem turnover times of carbon (τ , years) from observation-based estimate and CRESCENDO model simulations. Along the diagonal, the maps of τ from observation and model simulations are plotted. Above the diagonal, the biases (ratio of observation/model in column to observation/model along row) are plotted. Below the diagonal, density scatter plots are plotted with darker colour indicating larger density of points. The thin black line shows the 1:1 line, r and ρ indicate the spatial Pearson's and Spearman's correlation coefficient, respectively.

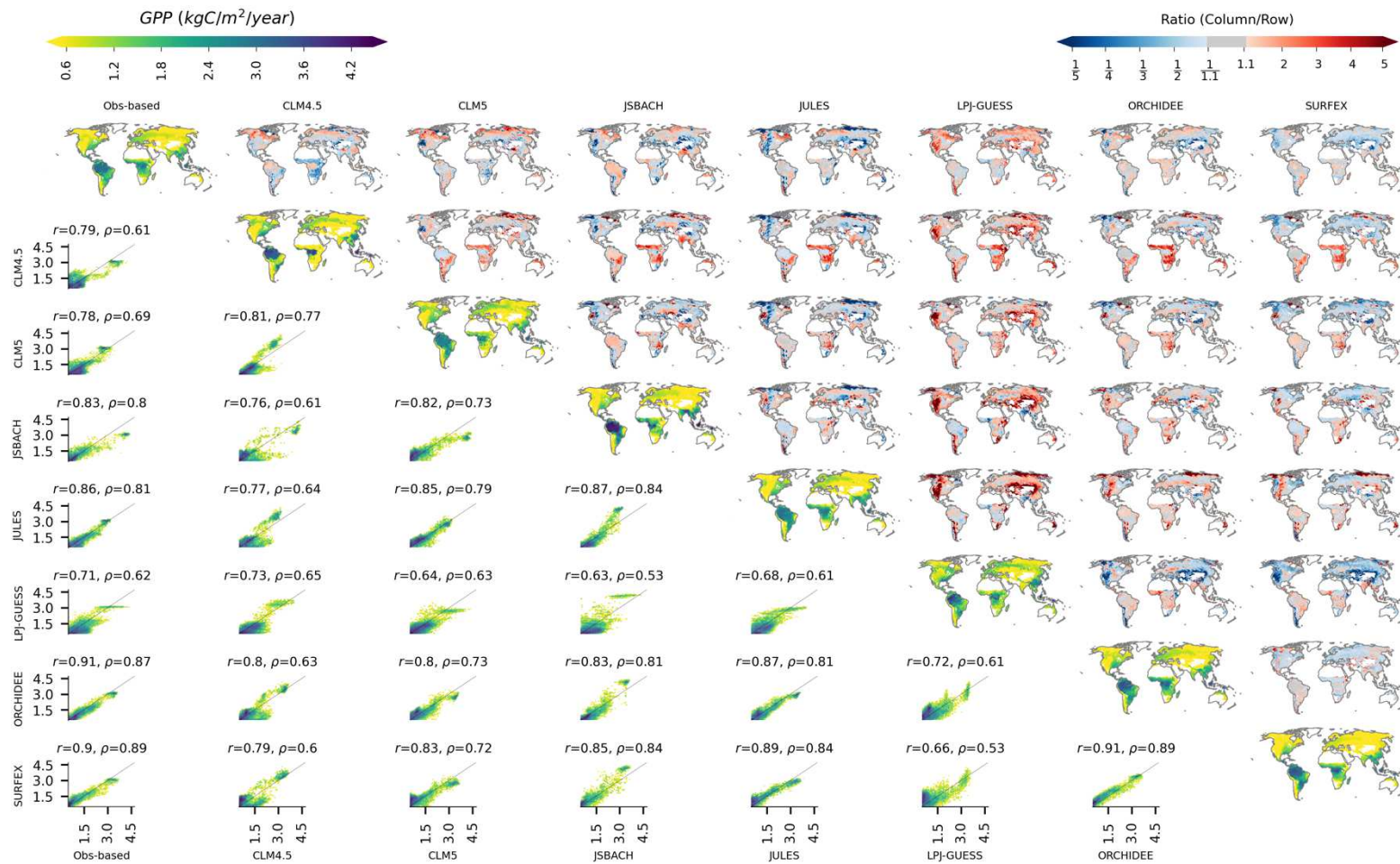


Figure A9. Comparison of the global distribution of gross primary productivity (GPP, kgC/m²/year) from observation-based estimate and CRESCENDO model simulations. Along the diagonal, the maps of GPP from observation and model simulations are plotted. Above the diagonal, the biases (ratio of observation/model along column to observation/model along row) are plotted. Below the diagonal, density scatter plots are plotted with darker colour indicating larger density of points. The thin black line shows the 1:1 line, r and ρ indicate the spatial Pearson's and Spearman's correlation coefficient, respectively.

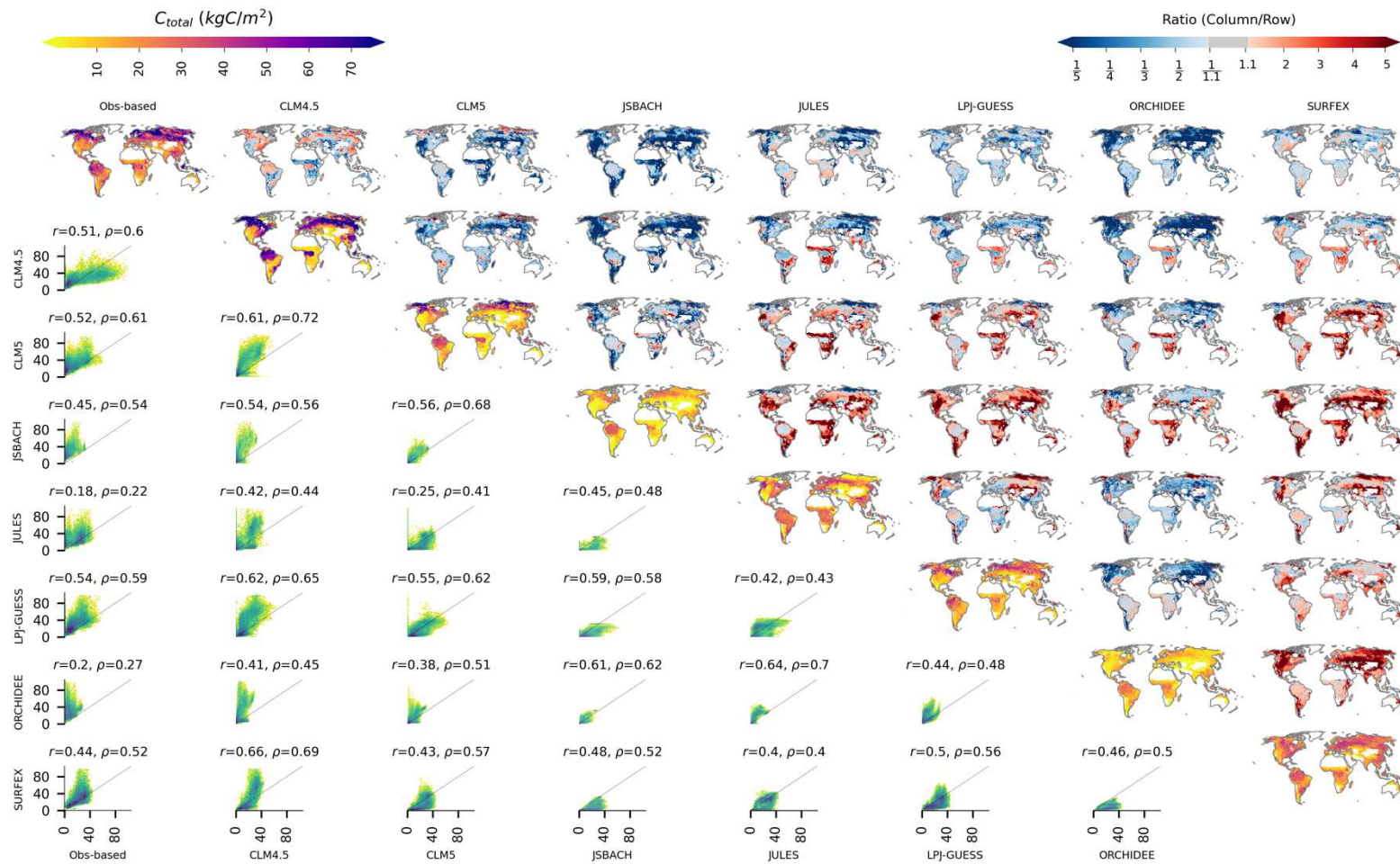


Figure A10. Comparison of the global distribution of total ecosystem carbon storage (C_{total} , kgC/m^2) from observation-based estimate and CRESCENDO model simulations. Along the diagonal, the maps of C_{total} from observation and model simulations are plotted. Above the diagonal, the biases (ratio of observation/model along column to observation/model along row) are plotted. Below the diagonal, density scatter plots are plotted with darker colour indicating larger density of points. The thin black line shows the 1:1 line, r and ρ indicate the spatial Pearson's and Spearman's correlation coefficient, respectively.

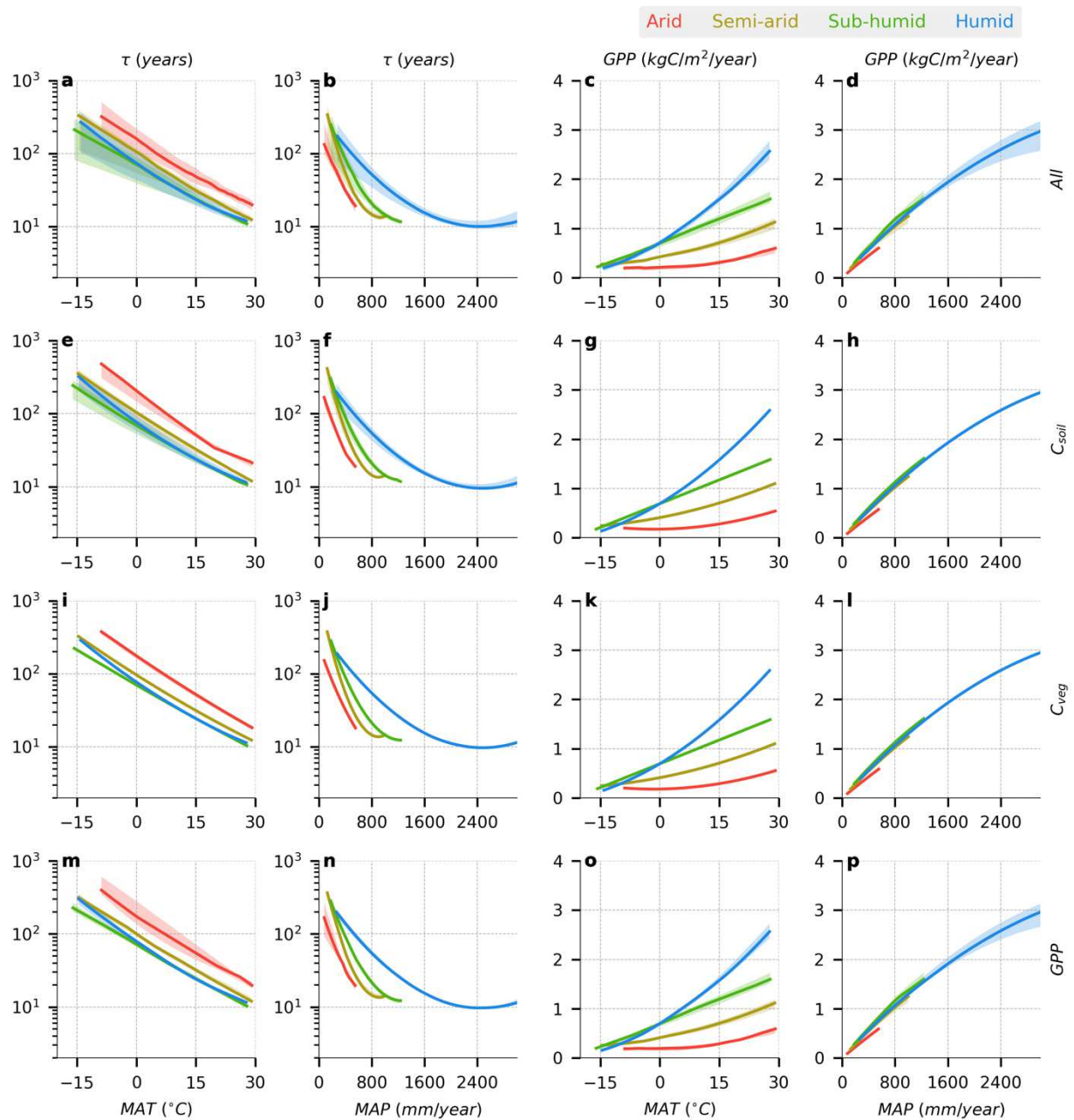


Figure A11. Same as **Figure 1** of the main text but using the state-of-the-art observation-based datasets of soil carbon (c_{Soil}) and vegetation carbon (c_{Veg}) stocks, and gross primary productivity (GPP). In total, 3 different soil carbon datasets, 4 different vegetation carbon datasets, and 6 different GPP estimations were used (see Methods). In the first row, a full factorial of all datasets generating 72 members were used. The second, third and fourth rows consider the influence of using different c_{Soils} (3), c_{Veg} (4), and GPP (6), respectively, while the other two variables are set at the ensemble medians. The thick lines and shaded regions around them indicate the median and interquartile range of all fitted relationships, respectively. Different colours indicate different climatic regions. Note the logarithmic axis for τ in the first and second columns.

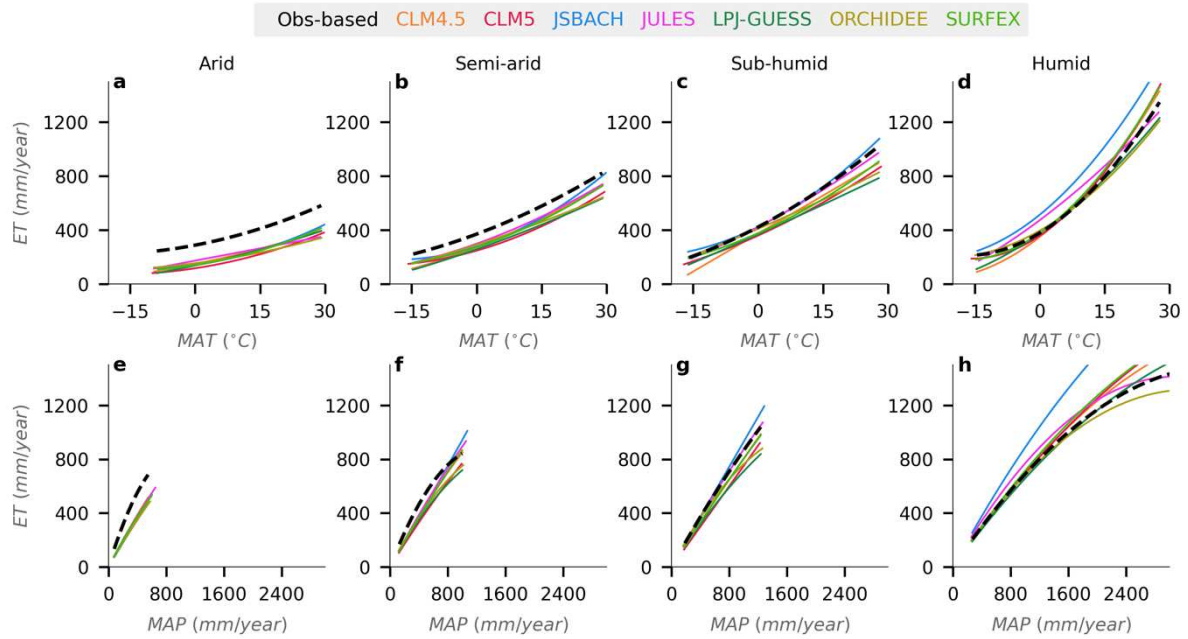


Figure A12. Evaluation of sensitivities of evapotranspiration to climate in CRESCENDO models. The relationships between total evapotranspiration (ET, in mm/day) versus mean annual temperature (MAT) and precipitation (MAP) are presented in the first and second column, respectively. Along the row, the comparisons for different models against the observation⁵⁰ are presented. The different colours indicate different climatic regions defined by the aridity index. The solid lines indicate the observation-based relationship, and the broken lines indicate relationship from the model simulations. The inset text shows the ratio between the linear coefficients and constants from the least square fits for the model and observation for each climatic region. Note that for ET-MAP relationship, the constant/intercept term is always 0.

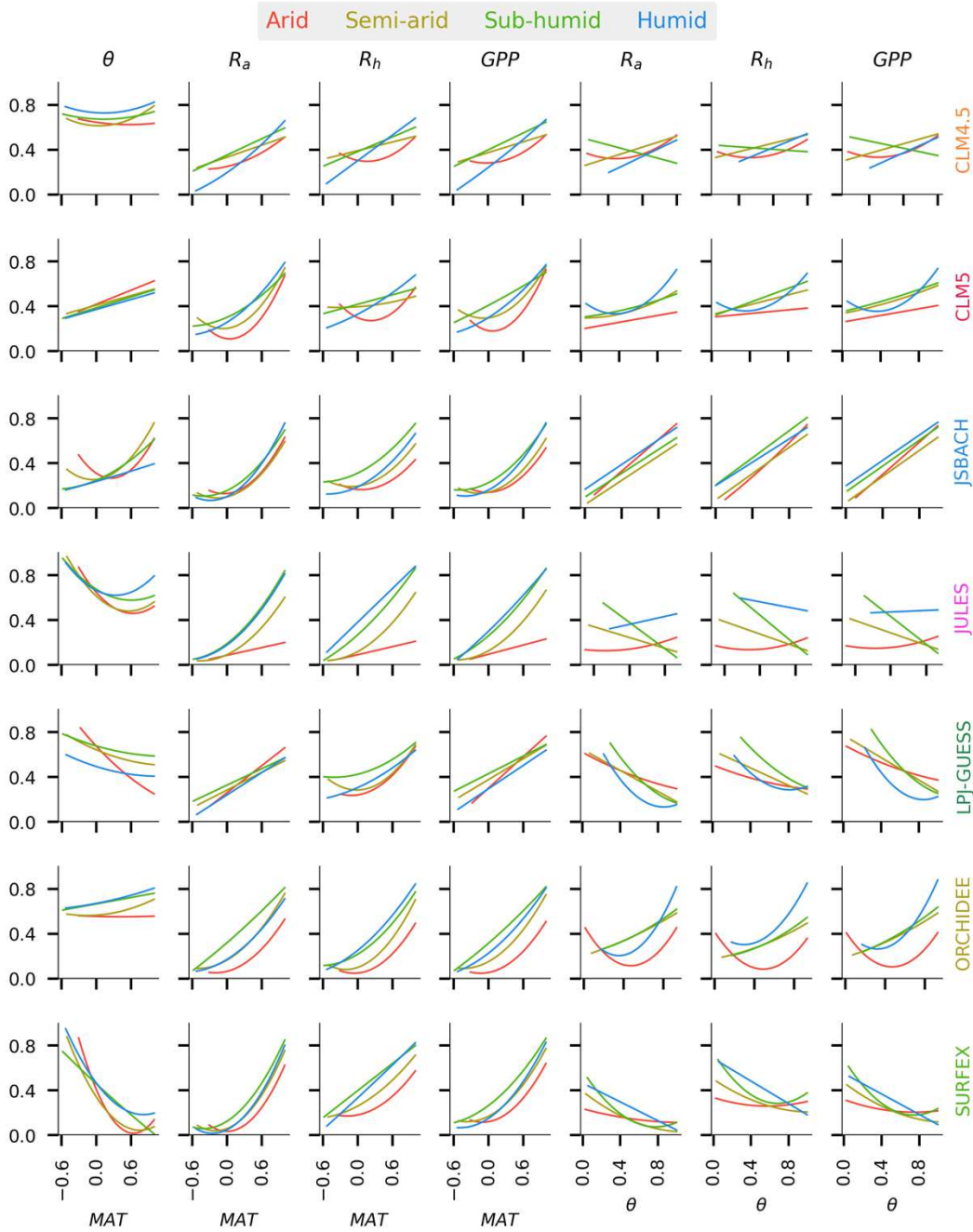


Figure A13. Spatial sensitivities of climatological total soil moisture state and carbon fluxes in CRESCENDO model simulations. In the first column, the relationship between the spatial variability of mean annual temperature (MAT) and total soil moisture (θ) is presented. In the second, third and fourth columns, the relationships of spatial variabilities of heterotrophic respiration (R_h), autotrophic respiration (R_a), and gross primary productivity (GPP) with MAT are, respectively, presented. The fifth, sixth and seventh columns repeat the same but with θ . The different colours indicate different climatic regions defined by the aridity index. The lines are the least square fits for each climatic region. Along the row, the comparisons for different models against the observation are presented. For a consistent comparison across different variables and differences in sizes of soil column in different models, all variables are scaled by the 98th percentile within each climate region so that the spatial variability is roughly normalized between 0 and 1.

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