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Long-term thermal sensitivity of Earth's tropical forests

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1 **Abstract**

2 The sensitivity of tropical forest carbon to climate is a key uncertainty in predicting global climate
3 change. While short-term drying and warming are known to impact forests it is unknown if such effects
4 translate into long-term responses. Here we analyse 590 permanent plots measured across the tropics to
5 derive the equilibrium climate controls on forest carbon. Maximum temperature is the most important
6 predictor of aboveground biomass ($-9.1 \text{ Mg C ha}^{-1} \text{ }^\circ\text{C}^{-1}$), primarily by reducing woody productivity, and
7 with a greater rate of decline in the hottest forests. Our results nevertheless reveal greater thermal
8 resilience than observations of short-term variation imply. Realising the long-term climate adaptation
9 potential of tropical forests will require both protecting them and stabilising the Earth's climate.

10

11

12 **One sentence summary.** Biome-wide variation in tropical forest carbon stocks and dynamics shows
13 long-term thermal resilience.

14 Main text

15 The response of tropical terrestrial carbon to environmental change is a critical component of global
16 climate models (1). Land-atmosphere feedbacks depend on the balance of positive biomass growth
17 stimulation by CO₂ fertilisation (i.e. β) and negative responses to warmer temperatures and any
18 change in precipitation (i.e. γ). Yet the climate response is so poorly constrained that it remains one of
19 the largest uncertainties in Earth system models (2, 3), with the temperature sensitivity of tropical land
20 carbon stocks alone differing by $> 100 \text{ Pg C } ^\circ\text{C}^{-1}$ among models (2). Such uncertainty impedes our
21 understanding of the global carbon cycle, limiting our ability to simulate the future of the Earth
22 system under different long-term climate mitigation strategies. A critical long-term control on tropical
23 land-atmosphere feedbacks is the sensitivity to climate (γ) of tropical forests, where c. 40 % of the
24 world's vegetation carbon resides (4).

25 The sensitivity of tropical biomass carbon stocks, their rate of production and their persistence to
26 environmental change can all be estimated by relating their short-term and inter-annual responses to
27 variation in climate (5-7). These sensitivities are then used to constrain longer-term projections of
28 climate responses (2). Such approaches typically find that higher minimum temperatures are strongly
29 associated with slower tree growth and reduced forest carbon stocks, likely due to increased
30 respiration at higher temperatures (7-9). Tropical forest carbon is also sensitive to precipitation (10),
31 with, for example, elevated tree mortality occurring during drought events (11).

32 Yet, the sensitivity of ecosystems to inter-annual fluctuations may be an unreliable guide to their
33 longer-term responses to climate change. Such responses will also be influenced by physiological
34 acclimation (12), changes in demographic rates (13), and shifts in species composition (14). For
35 example, both respiration and photosynthesis can acclimate under sustained temperature increases
36 (15-17), and tropical trees exhibit physiological plasticity (18) and shifts in species composition (14)
37 under sustained drought. These processes could mean that tropical forests are less sensitive to climate
38 than estimates derived from inter-annual variability imply. An alternative, complimentary approach to
39 assessing sensitivity to climate is to measure and analyse spatial variation in tropical ecosystems
40 across climate gradients as a space-for-time substitution. Such biome-wide spatial variation in forest

41 carbon stocks, fluxes and persistence offers a unique and largely unexplored window into the potential
42 equilibrium sensitivity of tropical forest vegetation to warming, as it captures real-world vegetation
43 responses that allow for physiological and ecological adaptation (12).

44 To assess the long-term climate controls on tropical forest growth and carbon stocks, here we have
45 assembled, measured, and analysed a pan-tropical network of 590 permanent, long-term inventory
46 plots (Fig. 1, see Figs. S1-2 for ability to capture biome climate space). Our analysis combines
47 standardised measurements from across South American, African, Asian and Australian tropical
48 lowland forests (273, 239, 61 and 17 plots respectively). For every plot we calculated aboveground
49 carbon stocks (19). Then, to better assess the dynamic controls on aboveground carbon stocks, we
50 also computed the rate of carbon gained by the system (aboveground woody carbon production,
51 calculated as tree growth plus newly recruited trees, in $\text{Mg C ha}^{-1} \text{ yr}^{-1}$), and its longevity in living
52 biomass (carbon residence time, calculated as the ratio of stocks to gains, in years).

53 We find considerable variation in biomass carbon among continents, with lower stocks per unit area
54 in South America compared with the Paleotropics even after accounting for environmental variables
55 (Fig. 1). Continents with high carbon stocks had either large carbon gains (Asia), or long carbon
56 residence times (Africa, Fig. 1). Because of these differences among continents, which are potentially
57 due to differences in evolutionary history (20), we analyse the environmental drivers of spatial
58 variation in carbon stocks while accounting for biogeographical differences. We fitted linear models
59 with explanatory variables representing hypothesised mechanistic controls of climate on tropical
60 forest carbon (Table S1). We also included soil covariates, continent intercepts and eigenvectors
61 describing spatial relationships amongst plots to account for other sources of variation (21).

62 Forest carbon stocks were most strongly related to maximum temperature (-5.9% per 1°C increase in
63 maximum temperature, 95 % CI = -8.6 to -3.1% , Fig. 2, equivalent to $9.1 \text{ Mg C ha}^{-1} \text{ }^\circ\text{C}^{-1}$ for a stand
64 with the mean carbon stocks in our dataset, $154.6 \text{ Mg C ha}^{-1}$), followed by rainfall ($+2.4\%$ per 100
65 mm increase in precipitation in the driest quarter, 95 % CI = $0.6 - 4.3\%$, Fig. 2), with no statistically
66 significant relationship with minimum temperature, wind speed or cloud cover (Fig 2). The effects of
67 maximum temperature and precipitation are also evident in an analysis considering a wider suite of

68 climate variables than those tied to hypothesised mechanisms (Fig. S3), and in an additional
69 independent pantropical dataset of 223 single-census plots (for which carbon gains and residence time
70 cannot be assessed, Fig. S4).

71 The negative effect of maximum temperature on aboveground carbon stocks mainly reflects reduced
72 carbon gains in hotter forests (-4.0 % per 1°C, 95% CI = -6.2 to -1.8 %, Fig. 2) while the positive
73 effect of precipitation emerges through longer carbon residence times in wetter forests (3.3 % per 100
74 mm, 95 % CI = 0.9 – 5.7 %, Fig. 2). Carbon residence time also increased with the proportion of clay
75 in the soil (Fig. 2). The additive effects of precipitation and temperature on carbon stocks were
76 modified by an interaction between them (Δ AIC = 15.4 comparing full linear model with or without
77 interaction), with temperature effects more negative when precipitation is low (Fig. S6). The
78 interaction was through shortening carbon residence time (Δ AIC = 11.9) rather than reducing carbon
79 gains (model without interaction better, Δ AIC = 1.4).

80 An alternative analysis using decision tree algorithms (22) also showed maximum temperature and
81 precipitation to be important (Fig. S7). This decision tree approach, which can capture complex non-
82 linear relationships (22), indicated potential non-linearity in the relationships between carbon stocks
83 and both temperature and precipitation, with the positive effect of increasing dry season precipitation
84 on residence times strengthening when precipitation was low, and the negative effect of maximum
85 temperature intensifying at high temperatures (Fig. S7).

86 We further investigated non-linearity in the temperature relationship using breakpoint regression
87 (supported over linear regression based on lower AIC, Δ AIC = 15.0), which revealed that above 32.2
88 °C (95 % CI = 31.7 – 32.6 °C) the relationship between carbon stocks and maximum temperature
89 became more negative (cooler than breakpoint: -3.8 % °C⁻¹, warmer than breakpoint: -14.7 % °C⁻¹,
90 Fig. 3). By partitioning carbon stocks into their production and persistence we find that this non-
91 linearity reflects changes to carbon residence time (Δ AIC = 10.6) rather than gains (Δ AIC = 1.7).
92 Overall, our results thus indicate two separate climate controls on carbon stocks: a negative linear
93 effect of maximum temperature through reduced carbon gains, and a non-linear negative effect of

94 maximum temperature, ameliorated by high dry-season precipitation, through reduced carbon
95 residence time.

96 The effect of temperature on carbon residence time only emerges when dry season precipitation is
97 low, so is consistent with theoretical expectations that negative effects of temperature on tree
98 longevity are exacerbated by moisture limitation rather than being independent of it (i.e. due to
99 increased respiration costs alone) (23). This could occur through high vapour pressure deficits in hot
100 and dry forests increasing mortality risk by causing hydraulic stress (23, 24), or carbon starvation due
101 to limited photosynthesis as a result of stomatal closure (23). Notably, the temperature-precipitation
102 interaction we find for aboveground stocks is in the opposite direction to temperature-precipitation
103 interactions reported for soil carbon. In soils, moisture limitation suppresses the temperature response
104 of heterotrophic respiration (25), while in trees moisture limitation enhances the mortality risks of
105 high temperatures.

106 The temperature effects on biomass carbon stocks and gains are primarily due to maximum rather
107 than minimum temperature. This is consistent with high daytime temperatures reducing CO₂
108 assimilation rates, for example due to increased photorespiration or longer duration of stomatal
109 closure (26, 27), whereas if negative temperature effects were to have increased respiration rates there
110 should be a stronger relationship with minimum (i.e. night-time) temperature. Critically, minimum
111 temperature is unrelated to aboveground carbon stocks both pan-tropically and in the one continent,
112 South America, where maximum and minimum temperature are largely decoupled ($r = 0.33$; Fig. S8).
113 While carbon gains are negatively related to minimum temperature (Fig S9) this bivariate relationship
114 is weaker than with maximum temperature, and disappears once the effects of other variables are
115 accounted for (Fig. 2). Finally, in Asia, the tropical region which experiences the warmest minimum
116 temperatures of all, both carbon stocks and carbon gains are highest (Fig. 1, Fig. S11).

117 Overall our results suggest that tropical forests have considerable potential to acclimate and adapt to
118 the effects of night-time minimum temperatures, but are clearly sensitive to the effects of daytime
119 maximum temperature. This is consistent with ecophysiological observations suggesting that the
120 acclimation potential of respiration (15) is greater than that of photosynthesis (17). The temperature

121 sensitivity revealed by our analysis is also considerably weaker than the short-term sensitivities
122 associated with inter-annual climate variation (8). For example, by relating short-term annual climate
123 anomalies to responses in plots, the effect of a 1°C increase in temperature on carbon gains has been
124 estimated as more than three-fold our long-term, pantropical result (28). This stronger long-term
125 thermal resilience is likely due to a combination of individual acclimation and plasticity (15-17),
126 differences in species' climate responses (29) leading to shifts in community composition due to
127 changing demographic rates (12) and the immigration of species with higher performance at high
128 temperatures (12).

129 Our pantropical analysis of the sensitivity to climate of aboveground carbon stocks, gains and
130 persistence shows that warming reduces carbon stocks and gains from woody productivity in tropical
131 forests. Using a reference carbon stock map (30) and applying our estimated temperature sensitivity
132 (including non-linearity) while holding other variables constant leads to a biome-wide reduction of
133 14.1 Pg C in live biomass (including scaling to estimate carbon in roots) for a 1°C increase in
134 maximum temperature (95 % CI = 6.9 – 20.7 Pg). In comparison, coupled climate-carbon cycle
135 models (2) give a median tropical land temperature sensitivity of 53 Pg C °C⁻¹ (95 % CI = 19.7 – 86.3
136 Pg), although these also incorporate the response of heterotrophic respiration and fire. In the future,
137 reporting Earth System Model outputs for live biomass carbon separate from other changes would
138 assist in comparing model outcomes with direct observations.

139 Our results suggest that global surface temperature increases of 2°C above pre-industrial levels will
140 cause a potential biome-wide loss of 35.3 Pg C (95 % CI = 20.9 – 49.0 Pg) based on responses to
141 warming from the 1970-2000 baseline (31). The greatest reductions in carbon stocks are projected in
142 South America, where baseline temperatures and future warming are both highest (Fig. 4, Fig. S12).
143 This warming would push 71 % of the biome beyond the thermal threshold – maximum temperature
144 of 32.2°C – where larger reductions in biomass are expected. Of course, growth stimulation by carbon
145 dioxide (32) will partially or wholly offset the effect of this temperature increase, depending on both
146 the level of atmospheric carbon dioxide that limits warming to 2°C above pre-industrial levels and the
147 fertilization effect of this carbon dioxide on tropical trees. Using a variety of published estimates of

148 the carbon dioxide fertilization effect (Table S3), partial or full amelioration is expected in the
149 Paleotropics, although reductions in forest carbon stocks are predicted in South America in all
150 scenarios (Fig. S15).

151 The long-term climate sensitivities derived from our pan-tropical field measurements incorporate
152 ecophysiological and ecological adaptation, and so provide a model-independent estimate of the long-
153 term quasi-equilibrium response of tropical vegetation to climate, which can inform long-term model
154 predictions (33). We note that the thermal adaptation measured here may not be fully realised because
155 (i) the speed of temperature rises may exceed species' adaptive capabilities, (ii) habitat fragmentation
156 may limit species' ability to track changes in the environment, and (iii) other human impacts such as
157 logging and fire can increase the vulnerability of forest carbon stocks to high temperatures.

158 Predictions based on short-term inter-annual sensitivity and our long-term pan-tropical sensitivity
159 likely represent the upper and lower bounds of transient responses to rising temperatures over the
160 coming decades. While many tropical forests are under severe threat of conversion, our results show
161 that, in the long-run, tropical forests that remain intact can continue to store high levels of carbon
162 under high temperatures. Achieving the biome-wide climate resilience potential we document
163 depends on limiting heating and on large-scale conservation and restoration to protect biodiversity and
164 allow species to move.

165

166

167 **References and Notes**

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402 the collection of field data, M.J.P.S. analysed the data, M.J.P.S., S.L.L. and O.L.P. wrote the
403 manuscript with contributions from other authors. All co-authors commented on or approved the
404 manuscript. **Competing interests:** The authors declare no competing financial interests. **Data and**
405 **materials availability:** Plot-level input data and R scripts will be deposited as a data package on
406 ForestPlots.net (doi-xxx).

407

408 **Supplementary Materials:**

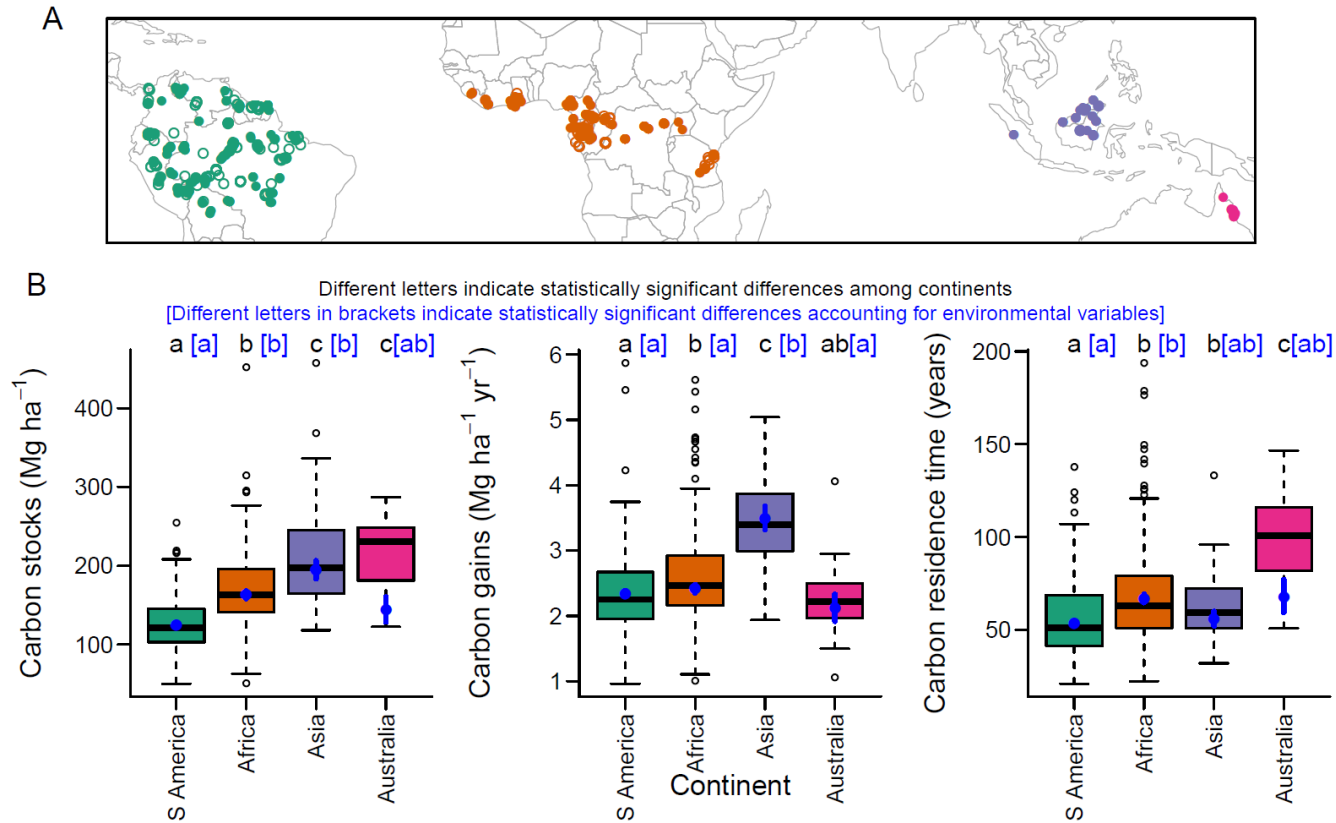
409 Materials and Methods

410 Figures S1-S15

411 Tables S1-S3

412 References (34-83)

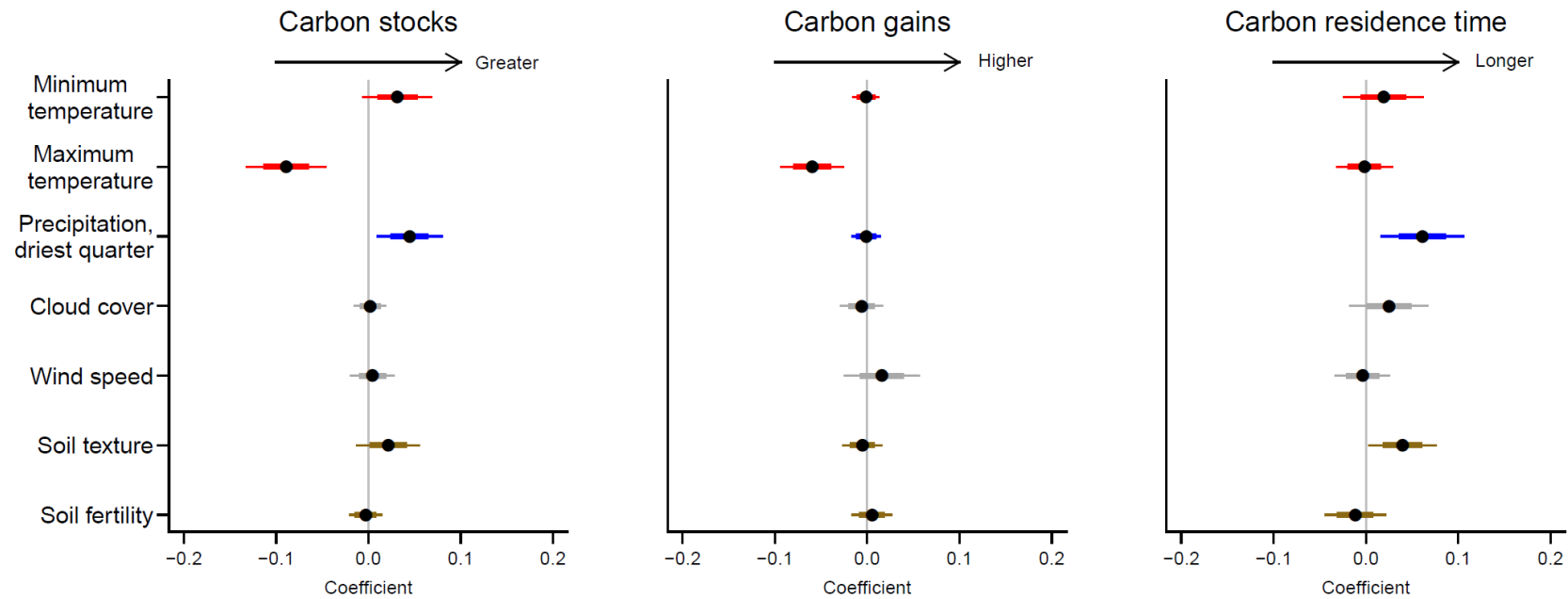
413



414

415 **Figure 1.** Spatial variation in tropical forest carbon. (A) Our plot network. Filled symbols show multi-census plots used in the main analysis, open symbols
 416 show single-census plots used as an independent dataset. (B) Variation in carbon among continents. Boxplots show raw variation while blue points show
 417 estimated mean values (\pm SE) after accounting for environmental variation. Letters denote statistically significant differences between continents ($P < 0.05$)
 418 based on raw data (black) or accounting for environmental effects (blue, square brackets).

419

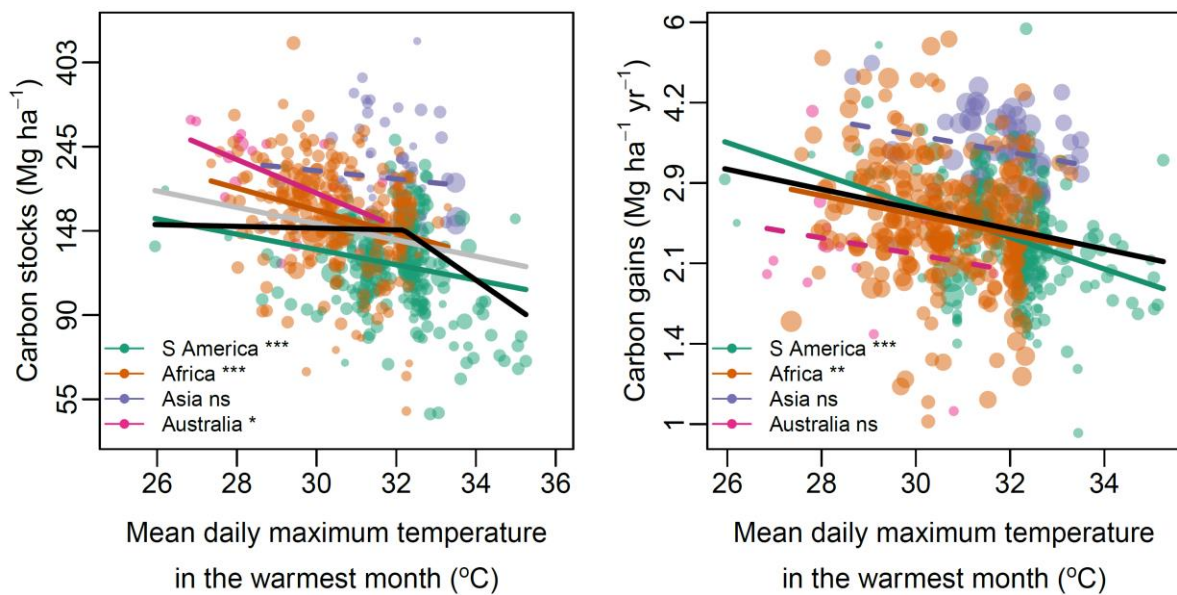


420

421 **Figure 2.** Correlates of spatial variation in tropical forest carbon. Points show coefficients from model-averaged general linear models. Variables that did not
 422 occur in well-supported models are shrinkage adjusted towards zero. Coefficients are standardised so that they represent change in the response variable for
 423 one standard deviation change in the explanatory variable. Error bars show standard errors (thick lines) and 95% confidence intervals (thin lines). Soil texture
 424 is represented by the percentage clay, and soil fertility by cation exchange capacity. The full models explained 44.1 %, 31.4 % and 30.9 % of spatial variation
 425 in carbon stocks, gains and residence time respectively. Coefficients are shown in Table S2. Results are robust to using an alternative allometry to estimate
 426 tree biomass (Fig. S5).

427

428



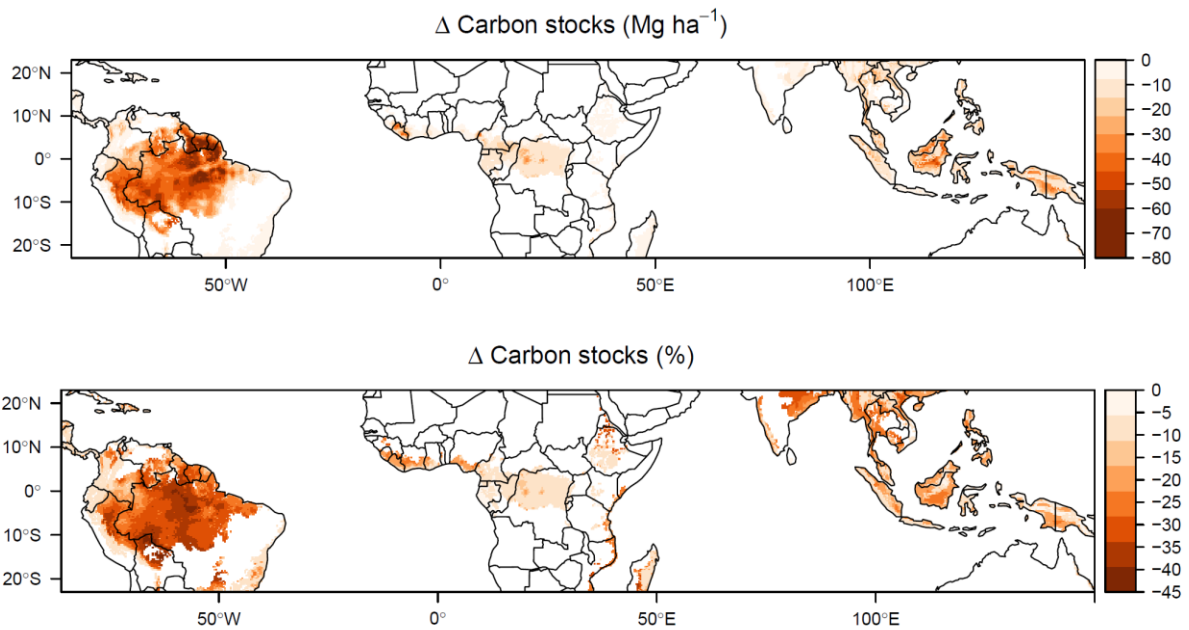
429

430

431 **Figure 3.** Temperature effects on tropical forest carbon stocks (left) and carbon gains from woody
 432 productivity (right). Black lines show the best pan-tropical relationships accounting for environmental
 433 covariates. The grey line shows the additional linear pan-tropical relationship for carbon stocks.
 434 Coloured lines show bivariate relationships within each continent. Statistically significant
 435 relationships are shown with solid lines, non-significant with dashed lines. Symbol point size is
 436 proportional to weights used in model fitting based on plot size and monitoring length, see SI
 437 Materials and Methods. Linear and break-point pan-tropical relationships are all statistically
 438 significant ($P < 0.001$), as are better sampled continents. Relationships with other variables are shown
 439 in Fig. S8-S10. *** $P < 0.001$, ** $P < 0.01$, * $P < 0.05$, ns $P \geq 0.05$.

440

441



442

443 **Figure 4.** Long-term change in carbon stocks due to global surface temperature warming of
444 approximately 2°C. Future temperatures come from an ensemble of 15 climate models for RCP4.5,
445 2040-2060, which give global mean surface temperatures ~ 1.9°C above pre-industrial. Maps show
446 the predicted absolute and relative change in tropical forest carbon stocks if global temperatures
447 equilibrated at these new levels, based on the increase in maximum temperature from 1970-2000
448 baseline climate. Note parts of the biome become warmer than currently observed in our dataset (Fig.
449 S13). See Fig. S14 for predictions using alternative carbon reference maps. Predictions are based on
450 temperature alone and do not include precipitation changes (for which future patterns of change are
451 uncertain) or potential moderation via elevated CO₂ (see Fig. S15).

452

453

454 **Supporting information for Long-term thermal Sensitivity of the Earth's Tropical**
 455 **Forests**

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503

504

505 **This file includes:**
506 Materials and Methods
507 Figures S1 – S15
508 Tables S1 – S3
509

510 **Materials and Methods**

511 Forest census data

512 Our plots come from the RAINFOR, AfriTRON, and T-FORCES networks. Forest inventory plots
513 were located in lowland (<1200 m), old-growth, closed-canopy forests that were not known to have
514 been subject to anthropogenic disturbance through fire or selective logging. Plots characterised
515 floristically as dry forest were not included, as were plots that received less than 1200 mm
516 precipitation each year. We also did not include plots in white sand, swamp and seasonally flooded
517 forests, as we expect these to experience marked edaphic constraints (extreme nutrient limitation for
518 white sand forests (34), stress caused by hypoxic conditions for swamp and seasonally flooded forests
519 (35)). All plots were ≥ 0.2 ha (median size = 1 ha) and were monitored for at least two years (median
520 monitoring period = 9.7 years). All censuses were prior to the 2015-16 very strong El Niño event, as
521 we expected that event to suppress carbon gains relative to the long-term mean.

522 Forest inventory plots were sampled using standardised protocols (36), where all live stems with
523 diameter ≥ 100 mm were measured at 1.3 m or 50 cm above buttresses and deformities. Trees were
524 tagged so that the same tree could be identified in subsequent censuses. In some cases the point of
525 diameter measurement (POM) had to be moved due to upward growth of buttresses and deformities.
526 For these trees we use the D_{mean} approach from Talbot et al. (37).

527 In a few cases (6 plots) the minimum diameter measured changed over time, or palms and
528 *Phenakospermum* were excluded in some censuses. For these, we estimated aboveground biomass
529 (AGB, subsequently converted to carbon stocks) and aboveground woody production (AGWP,
530 subsequently converted to carbon gains) using a minimum diameter or taxonomic protocol that could
531 be consistently applied across censuses, and scaled these values by the aboveground biomass ratio
532 between that protocol and all stems ≥ 100 mm protocol for censuses when all stems were measured.
533 Some plots had nested designs where the plot was split into subplots with different minimum diameter
534 protocols (69 plots). For these, we only analysed the area conforming to our minimum diameter
535 protocol. For analysis, we grouped small (≤ 0.5 ha) plots within 1 km of each other, and also grouped

536 contiguous larger plots (18 plots), as these will experience equivalent climate and larger plots are less
537 sensitive to stochastic tree fall events (38).

538 Data were curated in ForestPlots.net (39, 40), or were subject to equivalent offline handling, and
539 experienced the same quality control procedures. Details of quality control procedures are described
540 in Brien et al. (41). Our final dataset consists of 590 sampling units (hereafter plots) covering 637.2
541 ha, with 2.2 million measurements of 670,499 unique stems. For validating models of carbon stocks
542 an additional dataset of 223 single-census plots using the same measurement protocols was assembled
543 from the same networks (see section “Validation with independent single-census plot dataset” below).

544

545 Estimating above-ground biomass

546 Diameter measurements were converted to estimates of aboveground biomass (AGB). For dicot trees
547 we used the allometric equation

$$548 \text{ AGB} = 0.673 \times (\rho D^2 H)^{0.976}, \quad [1]$$

549 from Chave et al. (42), where ρ is wood density (from (43, 44)) and H is tree height estimated using
550 allometric equations described below. For monocots and tree ferns, we used a palm-specific
551 allometric equation

$$552 \ln(\text{AGB}) = -3.3488 + 2.7483 \ln(D), \quad [2]$$

553 from Goodman et al. (45), where D is the measured diameter.

554 The heights of a subset of trees in our dataset were measured in the field, either with a laser
555 rangefinder, hypsometer, or clinometer, or directly by climbing the tree. We filtered this dataset to
556 stems with measured diameters, height ≤ 90 m, diameters ≥ 90 mm DBH, as height-diameter
557 allometries of saplings differ from those of more mature trees, and to stems that were not broken,
558 leaning or fallen. This gave a total of 78,899 height measurements. We used this dataset to fit local
559 height-diameter allometric models, as these refine AGB estimates by capturing spatial variation in
560 height-diameter allometries missed by large-scale allometric models (46). Height data were not

561 available from every plot, so to ensure consistent treatment of plots height-diameter models were
562 constructed for each biogeographic region. We fitted three parameter asymptotic models (47) of the
563 form

$$564 \quad H = a(1 - \exp(-bD^c)), \quad [3]$$

565 where a , b and c are estimated parameters ('Weibull' models, 48). We fitted these models either
566 treating each observation equally or with case weights proportional to each trees' basal area. These
567 weights give more importance to large trees during model fitting. We selected the best fitting of these
568 models, determining this as the model that minimised prediction error of stand biomass when
569 calculated with estimated heights or observed heights (46). Weibull models were implemented using
570 the nls function in R with default settings. Starting values of $a = 25$, $b = 0.05$ and $c = 0.7$ were chosen
571 following trial and error as they led to regular model convergence. Where models did not converge
572 this was usually because the height-diameter relationship did not reach an asymptote, so in these cases
573 we used the log-log model $\ln(H) = a + b(\ln(D))$ to estimate height, where b gives the scaling exponent
574 of a power law relationship between height and diameter. We checked if models gave unrealistic
575 predictions by applying models to predict the height of all trees in the biogeographic region, and
576 excluded models that predicted any tree height 10 % higher than the tallest tree we recorded in that
577 continent.

578

579 Estimating above-ground woody production

580 We estimated AGWP following Talbot et al. (37). AGWP is comprised of four components, (1) the
581 sum of growth of surviving trees, (2) the sum of AGB of new recruits, (3) the sum of unobserved
582 growth of trees that died during a census interval and (4) the sum of growth of unobserved recruits
583 that entered then died during a census interval. Accounting for the latter two components is necessary
584 to avoid census-interval length effects, as more AGWP in these components will be missed due to the
585 greater mortality of trees that accumulates over longer census intervals.

586 Components 3 and 4 can be estimated using two quantities that can be calculated from observed stem-
 587 dynamics in each plot; per-area annual recruitment (R_a) and per-capita annual mortality (m_a). Per-
 588 capita mortality is calculated from the ratio of surviving stems to initial stems, using equation 5 in
 589 Kohyama et al. (49). Per-area annual recruitment is calculated using estimated mortality rates and the
 590 observed change in the number of stems over a census interval, using equation 11 of Kohyama et al.
 591 (49).

592 To estimate the unobserved growth of stems that died during a census interval, we first use plot-level
 593 per-capita mortality rates (m_a) to estimate how many trees are expected to have died in each year of
 594 the census interval, and from that calculate the mean number of years that trees that died during the
 595 census interval would have lived before death. The diameter of tree at death (D_{death}) can then be
 596 estimated as

$$597 \quad D_{\text{death}} = D_{\text{start}} \times G \times Y_{\text{mean}} \quad [4]$$

598 where D_{start} is the diameter at the start of the census interval, G is the plot-level median growth rate of
 599 the size class the tree was in at the start of the census interval (size classes are defined as $D < 200$ mm,
 600 $400 \text{ mm} > D \geq 200$ mm, and $D \geq 400$ mm) and Y_{mean} is the mean number of years trees survived in
 601 the census interval before dying. The diameter at death is then converted to AGB at death using
 602 allometric equations (equation 1, except for ferns and monocots where equation 2 is used), and the
 603 unobserved growth is calculated as the difference between AGB at death and AGB at the start of the
 604 census.

605 To estimate the growth of recruits that were not observed because they died during the census
 606 interval, we first need to estimate the number of unobserved recruits. This can be estimated from per-
 607 area annual recruitment (R_a) and per-capita annual mortality (m_a): R_a gives the number of stems per ha
 608 that recruit in a given year, and the probability of each recruit surviving until the next census (P_{surv}) is
 609 $P_{\text{surv}} = (1 - m_a)^T$, where T is the number of years remaining in the census interval. The number of
 610 recruits in a given year that survive to the next census is $R_a - P_{\text{surv}}R_a$. Summing this for each year in a
 611 census interval gives the total number of unobserved recruits in that census interval. We then need to

612 estimate how long each recruit was alive for. From m_a we can calculate the number of recruits in a
613 given year that died in each subsequent year, and from this calculate the mean life-span of recruits in a
614 given year that died before the next census. The average life-span of unobserved recruits ($Y_{mean-rec}$) is
615 the weighted mean of each cohort's lifespan, weighted by the number of unobserved recruits in each
616 year. Diameter at death is given in mm by

$$617 \quad D_{death} = 100 + (G \times Y_{mean-rec}) \quad [5]$$

618 where G is the plot-level median growth rate of the smallest size class (i.e. $D < 200$ mm).

619 Aboveground biomass of recruits at the time of death is estimated using equation 1. These corrections
620 for unobserved growth have a marginal impact on AGWP calculations, collectively accounting on
621 average for just 2.3 % of estimated plot-level AGWP.

622 AGB was calculated for each census, and AGWP was calculated for each census interval, and the
623 time-weighted mean of each was taken to give one value per plot. We used a time-weighted mean to
624 give greater importance to AGB estimates separated by longer census-intervals, as these will be more
625 independent. Estimates of AGB and AGWP were converted to carbon stocks and carbon gains by
626 multiplying by 0.456 (50). Carbon residence time was then estimated as carbon stocks /carbon gains,
627 and represents the length of time carbon resides in living biomass before being passed to the litter and
628 necromass pools (51). Calculations to estimate AGB and AGWP were performed using the R package
629 BiomasaFP (52).

630

631 Obtaining environmental data

632 Most climate data were obtained from climate data from Worldclim2 (31) as it provides the highest
633 resolution (~ 1 km) pantropical climate data, although we note that some regions, such as central
634 Africa, have limited station data. We extracted monthly data for the following variables: mean daily
635 minimum temperature, mean daily maximum temperature, precipitation, solar radiation and wind
636 speed, In addition to calculating the standard series of 19 bioclimatic variables, using the dismo R
637 package (53), we calculated 1) mean daily maximum temperature, $BIO1 + BIO2/2$, 2) mean daily

638 minimum temperature, BIO1 – BIO2/2, 3) maximum cumulative water deficit as the minimum across
639 the year of monthly cumulative water deficit W ,

$$640 \quad W_i = W_{i-1} - \min(0, P_i - 100), \quad [6]$$

641 where P is monthly precipitation in mm, and 100 represents measured evapotranspiration. This
642 calculation was run for a year from the wettest month in the year, starting at a water deficit of zero, 4)
643 the number of months where monthly cumulative water deficit was negative, 5) the number of months
644 where monthly precipitation was below 100 mm (i.e. less than evapotranspiration), 6) mean annual
645 solar radiation, 7) mean annual wind speed, and 8) vapour pressure deficit ($VPD = SVP - \text{vapour}$
646 pressure , where saturated vapour pressure, $SVP, = 0.611 \times e^{(17.502 \text{ temperature}) / (\text{temperature} + 240.97)}$). We also
647 obtained data on cloud frequency at ~1 km resolution from Wilson & Jetz (54), who processed twice-
648 daily MODIS satellite images. Temperature values were adjusted for differences in altitude between
649 the plot and the 1 km grid cell used for Worldclim interpolation, as these can differ in topographically
650 diverse regions, using lapse rates, so that $T_{plot} = T_{worldclim} + 0.005 \times (A_{worldclim} - A_{plot})$, where T is
651 temperature ($^{\circ}\text{C}$) and A is altitude (m). Temperature values were also corrected for systematic
652 warming trends. To do this, the mean annual temperature in each grid-cell in each year was extracted
653 from the CRU TS 3.24 dataset (55), and robust linear regression used to estimate grid-cell specific
654 warming rates. These were used to adjust Worldclim2 temperature values for the difference between
655 the midpoint of plot monitoring and the midpoint of the Worldclim2 climatology.

656 Data on soil texture and chemistry was obtained at 1 km resolution from the SoilGrids dataset (56),
657 with this resolution selected to match the resolution of the climate data. From this we extracted CEC,
658 representing soil fertility, and percentage clay, representing soil texture. For each soil variable we
659 calculated the depth-weighted average for 0 – 30 cm.

660 Statistical analysis

661 We used linear models to relate carbon, carbon gains and carbon residence time to environmental
662 explanatory variables. The role of different explanatory variables was assessed using multi-model
663 inference.

664 Response variables were positively skewed and had positive mean-variance relationships, so were
665 log-transformed to meet the assumption of normality and reduce heterogeneity in variances. The log-
666 normal nature of forest carbon stocks and dynamics means that there is greater potential for variation
667 when forests are large, which could be due to the non-linear scaling of tree biomass and tree basal
668 area.

669 We selected explanatory variables to represent hypothesised ways in which climate could affect
670 carbon stocks (Table S1). We assessed collinearity within this set of explanatory variables using
671 variance inflation factors (VIF) and pairwise correlations. Because of collinearity, we had to exclude
672 VPD, total precipitation, use only one of MCWD and precipitation in the driest quarter, and could
673 include both minimum and maximum temperature but not mean annual temperature. We used
674 precipitation in the driest quarter rather than MCWD as the latter is zero truncated and so is less
675 amenable to regression analysis. After removing these variables all pairwise correlations (including
676 with soil explanatory variables) were weak enough not to cause problems through collinearity ($r < 0.6$
677 and $VIF < 3$).

678 To account for variation other than in climate we also included soil variables relating to texture (%
679 clay) and fertility (CEC), and included continent specific intercepts to account for biogeographic
680 variation in carbon. To account for unmeasured environmental gradients (e.g. soil variation not
681 captured by the SoilGrids variables), we used Moran's eigenvector maps as explanatory variables,
682 selecting eigenvectors that corresponded to positive spatial autocorrelation in the distance matrix (57).
683 These variables act as a proxy for unmeasured spatial gradients by capturing positive spatial
684 associations between plots.

685 Plots differed in their area and the length of time they were monitored for. This is likely to affect the
686 variance of carbon stocks, carbon gains and carbon residence time, as smaller plots or plots only
687 monitored for short periods are more likely to be sensitive to the mortality of a few large trees. To
688 account for this, we used case weights relating to plot area and monitoring period. Following Lewis et
689 al. (58), we selected weights by relating residuals from our linear models to plot area and to plot
690 monitoring period, and subsequently assessing which root transformation of plot area/ monitoring

691 period removed the pattern in the residuals when used as a weight. Selected weights were: carbon
692 stocks, Area^{1/3}; carbon gains, Monitoring length^{1/7}; carbon residence time, Area^{1/9} + Monitoring
693 length^{1/12} -1.

694 We fitted all subsets of the general linear model with explanatory variables described above, forcing
695 spatial eigenvectors into all models. We then averaged the subset of models where $\Delta AIC < 4$, using
696 full averaging so variables that do not appear in the model get the value of zero for their coefficients.
697 This means that model averaged coefficients of terms with limited support exhibit shrinkage towards
698 zero. Multi-model inference was performed using the MuMIn R package (59).

699 We assessed whether the two climate variables found to have important additive effects on carbon
700 stocks in this analysis (mean daily maximum temperature in the warmest month and precipitation in
701 the driest quarter) interacted with each other by adding an interaction term between these variables to
702 the full generalised linear model of carbon stocks as a function of other climate and soil variables,
703 continent and spatial eigenvectors. We compared these two models using AIC. We repeated this with
704 carbon gains and carbon residence time as response variables.

705 To assess whether the temperature carbon relationship was non-linear we used breakpoint regression
706 implemented in the segmented R package (60). This estimates a breakpoint in the explanatory variable
707 at which the slope of the relationship with the response variable changes. We estimated the breakpoint
708 for the mean daily maximum temperature in the warmest month variable in the full model with a
709 temperature-precipitation interaction described above. We assessed the support for the breakpoint by
710 comparing the AIC of the model with a breakpoint with the AIC of a model with a linear relationship.
711 We repeated this with carbon gains and carbon residence time as response variables.

712 We also analysed spatial variation in carbon stocks as a function of the above climate and soil
713 variables and spatial eigenvectors using Random Forest decision tree algorithms (22) implemented
714 using the randomForest R package (61). We assessed variable importance by calculating the average
715 increase in node purity across all decision trees (measured by residual sum of squares) when using the
716 variable to split the data. We assessed modelled relationships between response and explanatory

717 variables using partial plots, which show predicted change in the response variable, averaged across
718 trees, when changing the explanatory variable and holding all other variables constant.

719 To compliment this analysis based on relationships expected *a priori*, we also performed an
720 exploratory analysis to assess whether other climate variables excluded from the full general linear
721 models had an effect on carbon. To do this, we fitted linear models to assess the bivariate relationship
722 of carbon with each climate variable, with continent also included as an explanatory variable to
723 account for biogeographic variation in forest characteristics.

724

725 Validation with independent single-census plot dataset

726 We assessed whether the relationships with environmental variables identified in the analyses of
727 multi-census plot data described above held when applied to an additional dataset of 223 single-
728 census plots. As the single-census data were not used in any of the analyses above they did not
729 influence modelling decisions, so provide an independent test of the relationships identified with the
730 multi-census plot analysis.

731 Single-census plots were extracted from the ForestPlots.net database (39, 40) using the same plot-
732 selection criteria as for the multi-census plots, except that censuses during or following the 2015-16
733 strong El Niño were included in the single-census plot dataset as we expected that carbon stocks,
734 unlike gains, would still remain close to their long-term mean.

735 We fitted a general linear model with the five climate explanatory variables, soil fertility and texture,
736 continent and spatial eigenvector, and model averaging of all subsets of this model as described for
737 the multi-census plots. We performed this analysis using just the single-census plots and a combined
738 dataset of single and multi-census plots.

739

740 Scaling results to the biome

741 We applied the relationship between carbon stocks and mean daily maximum temperature in the
742 warmest month identified by the breakpoint regression to estimate the total change in carbon stock
743 due to temperature effects alone for different scenarios of temperature increase. We delimited the
744 biome extent using the WWF tropical and subtropical moist broadleaved forest biome (62), restricted
745 to tropical latitudes, and further refined it by excluding grid-cells with $< 50 \text{ Mg C ha}^{-1}$ using data from
746 (30), as these are unlikely to be forest. Calculations were conducted at 10-minute resolution. For each
747 grid-cell we predicted the percentage change in carbon for a given temperature increase from our
748 statistical model, holding all other variables constant. We then used a reference carbon stock map (30)
749 to convert percentage change to change in carbon stocks per hectare (in Mg ha^{-1}). To calculate change
750 in carbon stocks for the whole grid-cell, we multiplied change per hectare by the area of the grid-cell
751 in hectares, and then adjusted this by the proportion of the grid-cell that was forested by multiplying
752 by 2014 forest cover (63). Total change for the biome (in Pg) was calculated by summing these grid-
753 cell level values. Uncertainty due to our statistical model was assessed by generating multiple
754 predictions by resampling model parameters (breakpoint threshold, slope below breakpoint, slope
755 above breakpoint), and extracting quantiles from the resultant distribution of predicted change values.
756 Aboveground biomass carbon values were scaled to include root biomass based on a root to shoot
757 ratio of 0.19 in tropical evergreen forests (64).

758 The Avitabile et al (30) aboveground biomass map was chosen to provide reference carbon stocks.
759 While other maps have previously been produced by Saatchi et al. (65) and Baccini et al. (66) we
760 selected the Avitabile map because it synthesises the earlier maps (see Mitchard et al. (67) for
761 discussion of substantial differences between these maps) and is anchored by more field data.
762 Importantly, the Avitabile map reproduces spatial patterns in aboveground biomass that have been
763 described from field data but are absent in the Saatchi or Baccini maps, including the much higher
764 biomass density of north-east Amazonian forests due to tall trees and very high wood density (68).
765 Nevertheless, we also investigated the consequences of using the Saatchi or Baccini maps for our
766 estimates of biomewide thermal sensitivity and spatial patterns of change in carbon stocks (Fig S15).

767 We investigated three temperature change scenarios. Firstly, we applied a 1°C increase to all
768 locations. Secondly, we assessed the consequence of a 1.5°C increase in global temperature from pre-
769 industrial levels for the equilibrium temperature response of tropical forest carbon. Finally, we
770 assessed the consequence of a 2°C increase in global temperature from pre-industrial levels. For the
771 latter two we obtained data from CMIP5 climate models, using downscaled future climate projections
772 based on the Worldclim climatology (69). As downscaling was performed using Worldclim version
773 1.4 (70) and our statistical models use Worldclim version 2, we calculated the warming anomaly in
774 each grid-cell from the current Worldclim version 1.4 conditions, and applied this to the Worldclim 2
775 data to obtain future temperature. RCP scenarios and time-points were chosen to give global
776 temperature increases that best match 1.5°C and 2°C above pre-industrial. For 1.5°C we used RCP 2.6
777 averaged for 2040-2060 (median temperature increase across models = 1.5°C, (71)). For 2°C, we used
778 RCP 2.6 averaged for 2040-2060 (median temperature increase models = 1.9°C (71)). Note that
779 predicted increases in maximum temperatures were often considerably greater than the global
780 increase, especially in South America. For both scenarios we used the median predicted temperature
781 change for each grid-cell from an ensemble of 15 models (BCC-CSM1-1, CCSM4, CNRM-CM5,
782 GFDL-CM3, GFDL-ESM2G, GISS-E2-R, HadGEM2-AO, HadGEM-ES, IPSL-CM5A-LR, MIROC-
783 ESM-CHEM, MIROC-ESM, MIROC5, MPI-ESM-LR, MRI-CGCM3, NorESM1-M).

784 We assessed the potential for long-term carbon dioxide growth stimulation to offset these long-term
785 temperature effects. We used CO₂ concentrations from the RCP scenarios and time-points described
786 above, which approximate the long-term concentrations if the climate stabilised at the new
787 temperatures (72). Thus the 1.5°C and 2°C scenarios were associated with CO₂ concentrations of 443
788 ppm and 487 ppm respectively (73). We cannot assess the effect of CO₂ on biomass from our spatial
789 dataset, so instead used independent estimates of CO₂ effects from other sources. Firstly, we obtained
790 CO₂ only effects on net primary production (NPP) extracted from an ensemble of CMIP5 earth system
791 models by (74). This gives the proportional change in NPP for evergreen forests (note that this also
792 includes boreal forests) over 1980-2010, standardised to a 100 ppm increase in CO₂ concentration. To
793 propagate this through to changes in AGB under future CO₂ conditions we first estimated the

794 logarithmic dependency of NPP on CO₂ (75) by substituting values of NPP and CO₂ at time zero and t
 795 (from (74)) into the equation,

$$796 \quad NPP_t = NPP_0 \left[1 + \beta \ln \left(\frac{[CO_2]_t}{[CO_2]_0} \right) \right] \quad [7]$$

797 This equation can be used to compute NPP annually given an initial NPP estimate and a time series of
 798 atmospheric CO₂ concentrations (from a combination of the observed record from pre-industrial and
 799 the RCP 4.5 scenario, modified so that it stabilises at 487 or 443 ppm depending on warming
 800 scenario). Initial pre-industrial NPP was back-calculated from present-day values using Equation 7,
 801 with 13.3 Mg C ha⁻¹ yr⁻¹ (mean of nine Amazon plots where NPP has been measured, from (76)) used
 802 for present-day NPP. To propagate NPP into change in woody biomass (following (51)) we used the
 803 equation

$$804 \quad \frac{dM_{wood}}{dt} = \alpha_{wood} N_P - \frac{M_{wood}}{\tau_{wood}} \quad [8]$$

805 where M_{wood} is woody biomass, N_p is NPP, α_{wood} is the allocation of NPP to wood (taken as 0.33, the
 806 mean value across nine plots from (76)) and τ_{wood} is the residence time of woody biomass, taken as
 807 59.1 years (the median value across plots used in this study). This model (equations 7 and 8) was run
 808 from pre-industrial to 2500, enabling us to see the equilibrium effect of increased CO₂ concentrations
 809 on biomass, assuming temporally invariant allocation and residence time. We calculated the
 810 proportional change in biomass from 2000 to 2500, and applied this to the reference carbon stock map
 811 to obtain predicted equilibrium change in aboveground biomass due to CO₂ effects.

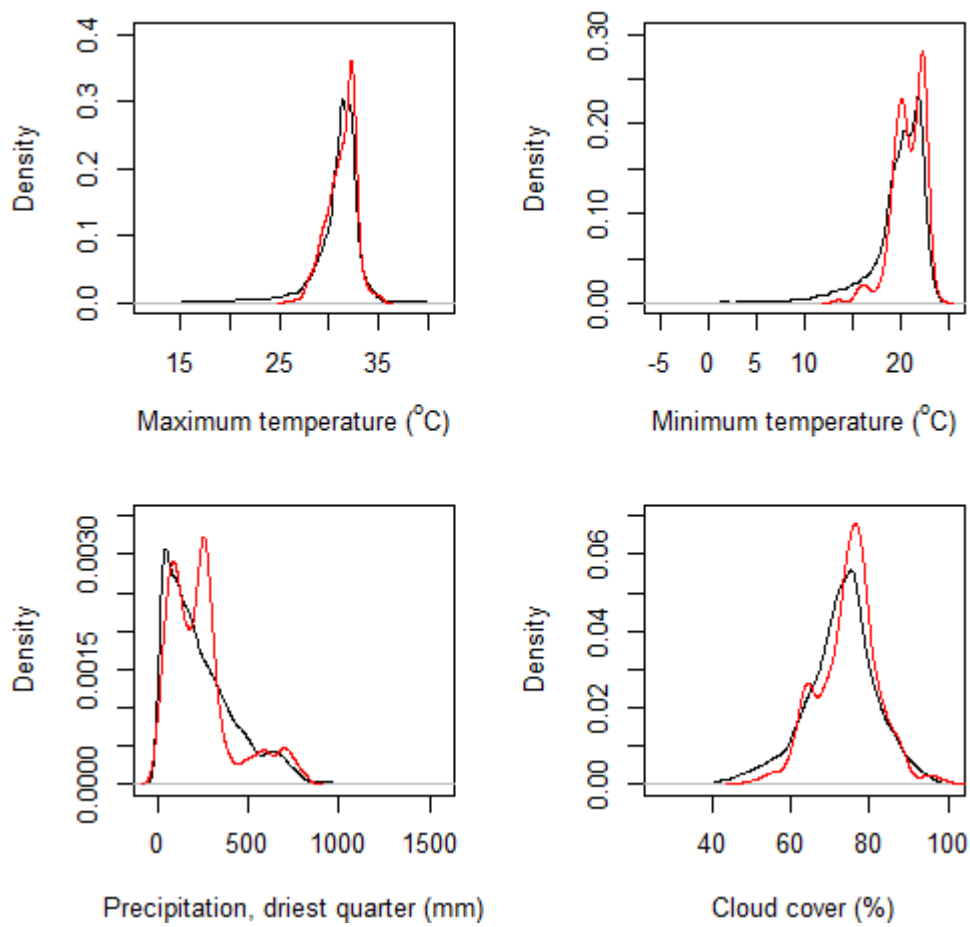
812 The effects of CO₂ in earth system models have been reported to be larger than those deduced from
 813 satellite data or CO₂ enrichment experiments (74), so we also ran the above model using changes in
 814 NPP reported from a synthesis of free-air CO₂ enrichment experiments conducted in forests (74).
 815 Finally, we looked at the impact of using CO₂ effects derived from a recent large meta-analysis of
 816 CO₂ enrichment experiments (77), which reported a 12.5 % increase in biomass of tropical trees for a
 817 250 ppm increase in CO₂ concentration. As this relationship was reported to be linear (77) we used
 818 linear interpolation to estimate the change in biomass under CO₂ concentrations associated with each

819 warming scenario (i.e. 443 and 487 ppm). To estimate long-term changes in biomass accounting for
820 both temperature and carbon dioxide, we first applied the CO₂ relationship to estimate the change in
821 biomass due to carbon dioxide growth stimulation, and then assessed the effects of warmer
822 temperatures from this revised baseline. Our approach allows a simple assessment of CO₂ effects
823 exploring a range of different effect strengths. Real-world responses will likely be more complex,
824 with, for example, nutrient limitation potentially affecting the extent to which growth is stimulated by
825 CO₂ (77).

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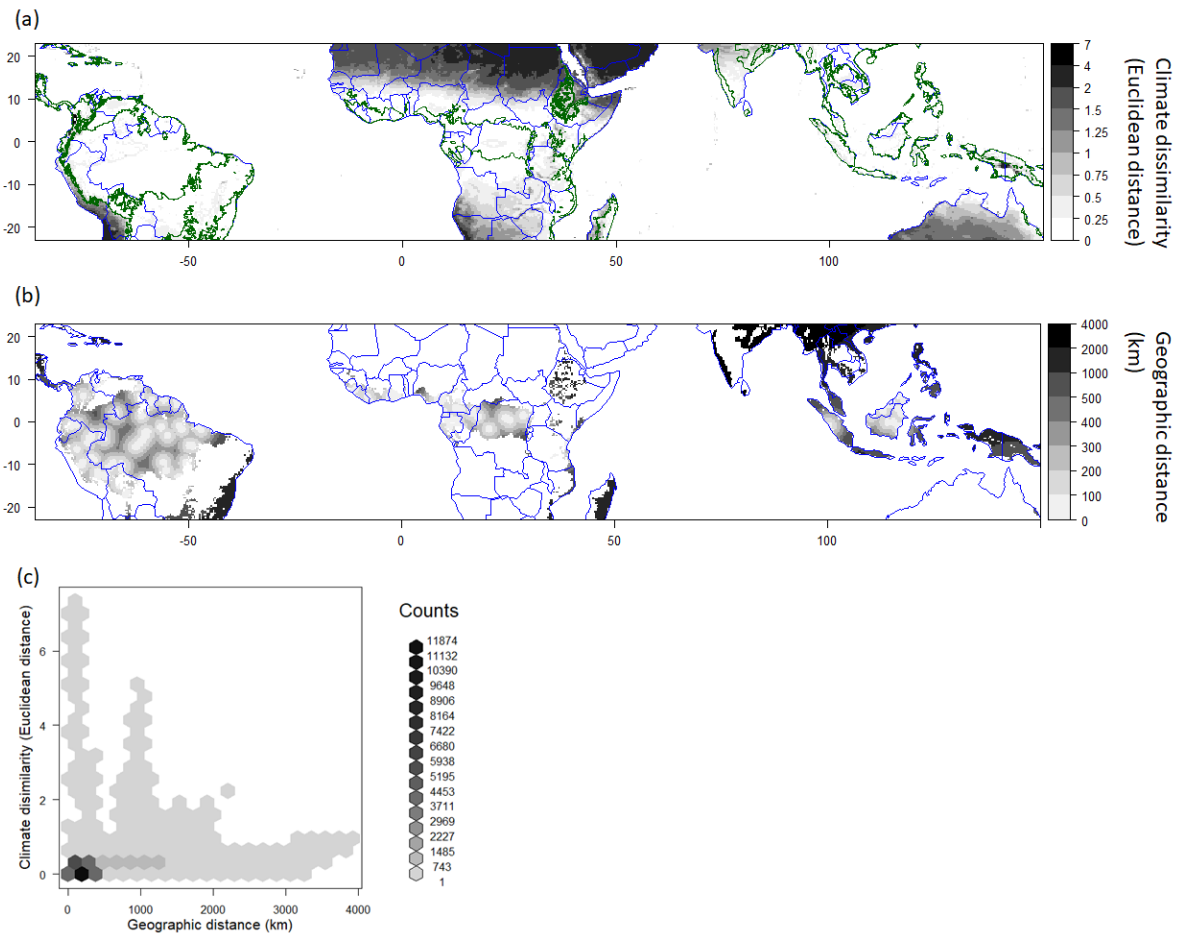


829

830 **Figure S1.** Climate space represented by our plot network. Red lines show the probability density
831 function of each variable in our multi-census plot network. Black lines show the probability density
832 across 10 minute grid-cells in the biome, restricted to areas with forest cover in GLC 2000 (78).

833

834



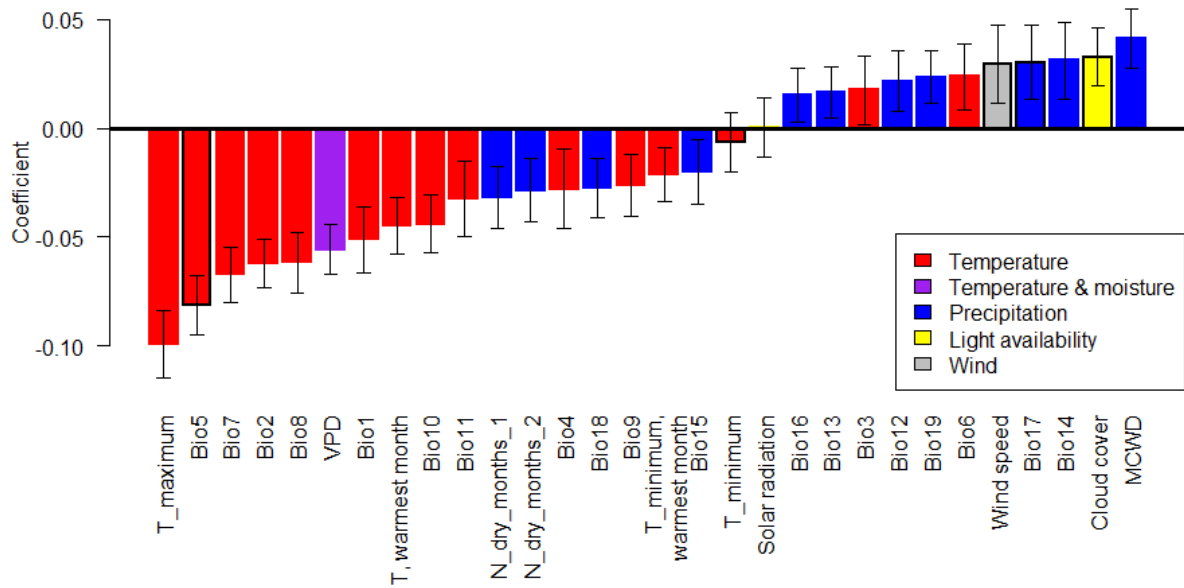
835

836 **Figure S2.** Ability of our plot network to represent the climate conditions found in the moist tropical
 837 forest biome. (a) Minimum climate dissimilarity (measured as Euclidean distance on climate variables
 838 scaled by their standard deviation) between 10 minute grid cells and the multi-census plot network.
 839 Climate variables used are the same as in Fig. 2. Green lines indicate the extent of the biome. (b)
 840 Geographic distance (km) between grid cells and the multi-census plot network. (c) Relationship
 841 between climatic and geographic distance of 10 minute grid cells across the tropical forest biome to
 842 our plot network. The lack of relationship between climate dissimilarity and geographical distance,
 843 alongside the mostly low climatic dissimilarities, shows that our sampling is sufficient to capture the
 844 environmental space of the biome and that we can reasonably extrapolate to geographically distant
 845 areas from our plots, which are in any case largely deforested already and hence contribute very little
 846 to our projected biome-wide carbon response to climate change. (These tropical moist forest areas that
 847 are poorly sampled and largely lost include the Atlantic Forests in Brazil, Andean Forests in western

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848 South America, eastern Caribbean, Madagascar, and much of tropical South Asia, south China,
849 continental Southeast Asia, Philippines, Sumatra and Java).

850



851

852 **Figure S3.** Relationships between individual climate variables and tropical forest aboveground carbon

853 stocks. Standardised coefficients are from models with the climate variable and continent as

854 explanatory variables and show change in $\ln(\text{carbon})$ for a standard deviation change in the

855 explanatory variable. Error bars show standard errors. Variables used in the main analysis have black

856 outlines. Full variable names are: T_maximum – mean daily maximum temperature, Bio5 – mean

857 daily maximum temperature in the warmest month, Bio7 – annual temperature range, Bio2 – mean

858 diurnal temperature range, Bio8 – mean temperature in the wettest quarter, VPD – vapour pressure

859 deficit, Bio1 – mean annual temperature, Bio10 – mean temperature in the warmest quarter, Bio11 –

860 mean temperature in the coldest quarter, N_dry_months_1 – number of months with negative

861 cumulative water deficit, N_dry_months_2 – number of months where precipitation is less than

862 evapotranspiration, Bio4 – temperature seasonality, Bio18 – precipitation in the warmest quarter, Bio9

863 – mean temperature in the driest quarter, T_minimum warmest month – mean daily minimum

864 temperature in the warmest month, Bio15 – precipitation seasonality, T_minimum – mean daily

865 minimum temperature, Bio16 – precipitation in the wettest quarter, Bio13 – precipitation in the

866 wettest month, Bio3 – isothermality, Bio12 – annual precipitation, Bio19 – precipitation in the coldest

867 quarter, Bio6 – mean daily minimum temperature in the coldest month, Wind speed – mean daily

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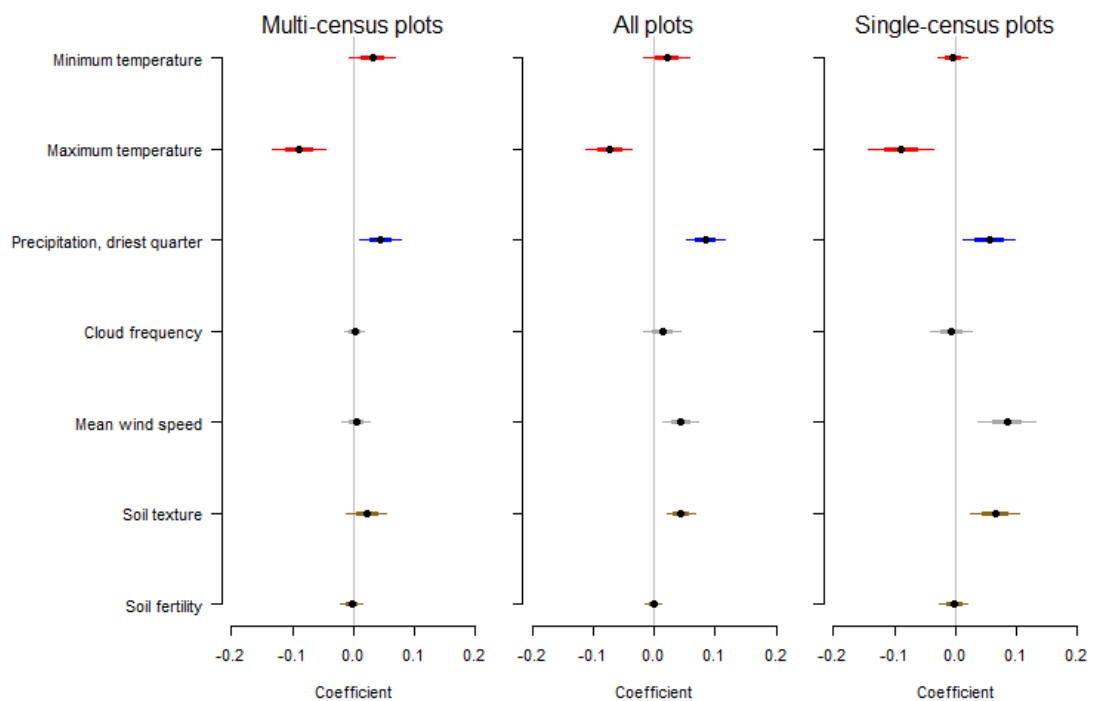
868 wind speed, Bio17 – precipitation in the driest quarter, Bio14 – precipitation in the driest month,
869 Cloud cover – proportion of MODIS passes with cloud present, MCWD – maximum cumulative
870 water deficit (note this is negative when water deficit is high, so a positive relationship with MCWD
871 indicates higher carbon when water deficits are less).

872

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876

877 **Figure S4.** Validation of tropical forest carbon stock sensitivity model against an independent dataset

878 of 223 single-census plots from our networks measured with the same protocols. Model-averaged

879 shrinkage adjusted coefficients from multiple regression models of biomass carbon stocks as a

880 function of climate, soil, biogeography and spatial eigenvectors. Models were either fitted to the

881 multi-census plot dataset (as in Fig. 2), to the single-census plot dataset, or to the combined dataset.

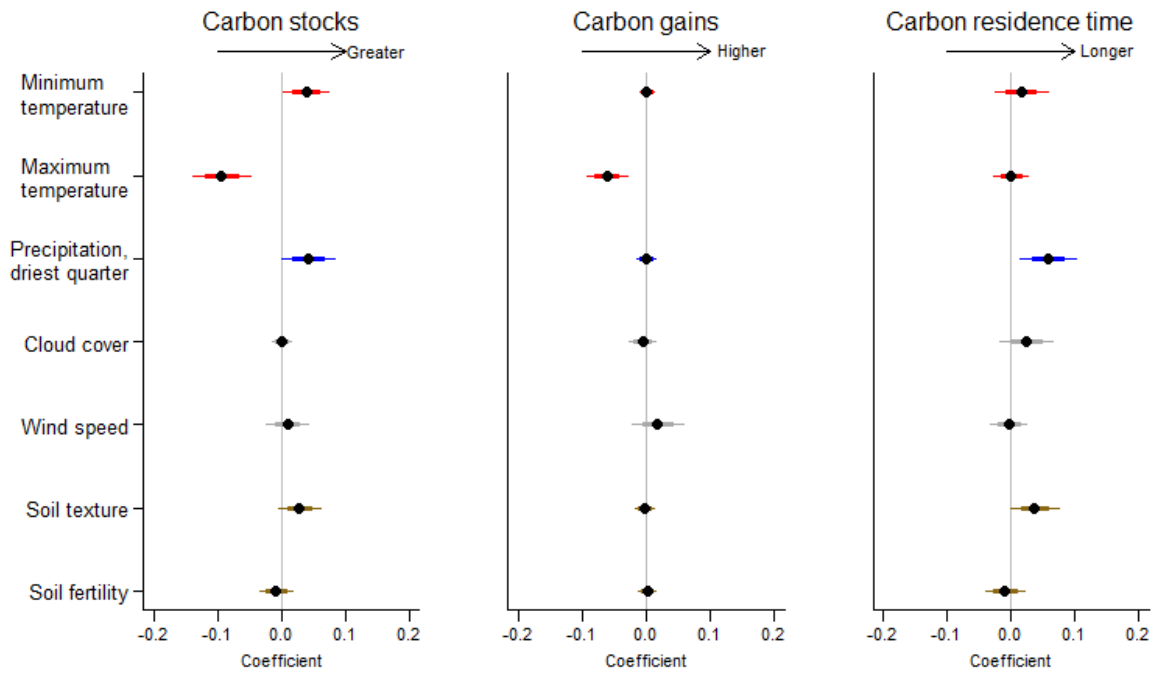
882 This analysis shows that the relationships identified to be most important in the main multi-census

883 plot analysis (i.e. the negative relationship between carbon stocks and maximum temperature and

884 positive relationship with precipitation in the driest quarter) are also found in an independent dataset,

885 which was not used for preliminary analysis so did not influence the choice of explanatory variables.

886



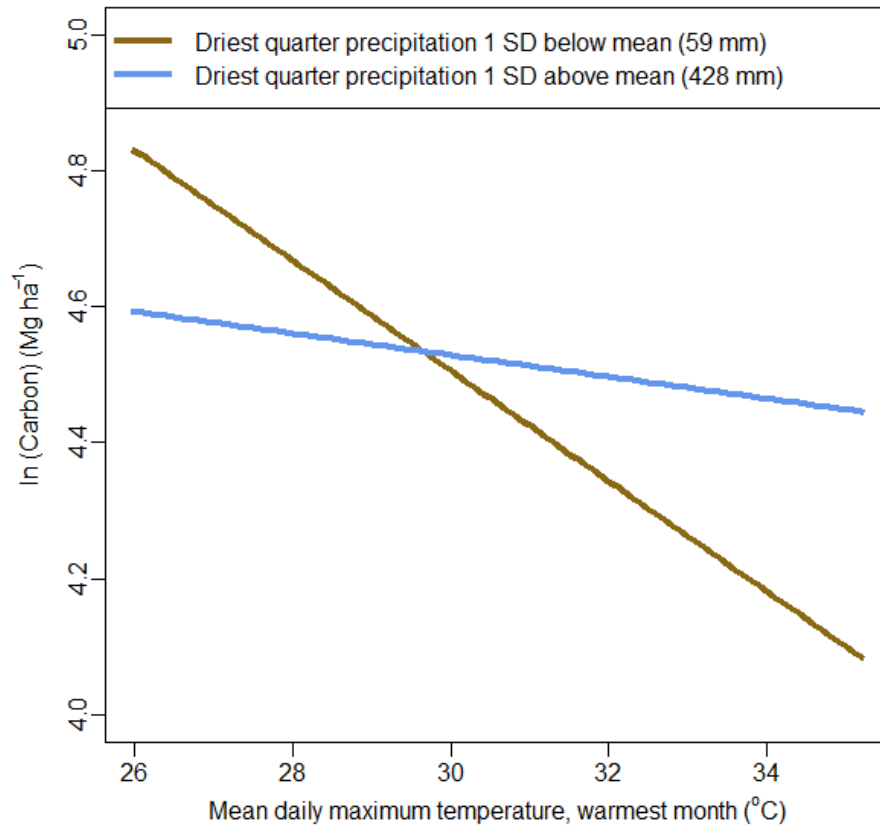
887

888 **Figure S5.** As Figure 2, but with aboveground biomass estimated using the Chave et al. 2005 (79)
889 moist forest allometric equation, which does not include a height term and is instead based on a third-
890 order polynomial relationship between diameter and aboveground biomass. This indicates that our
891 results are robust to using an alternative allometry to estimate aboveground biomass.

892

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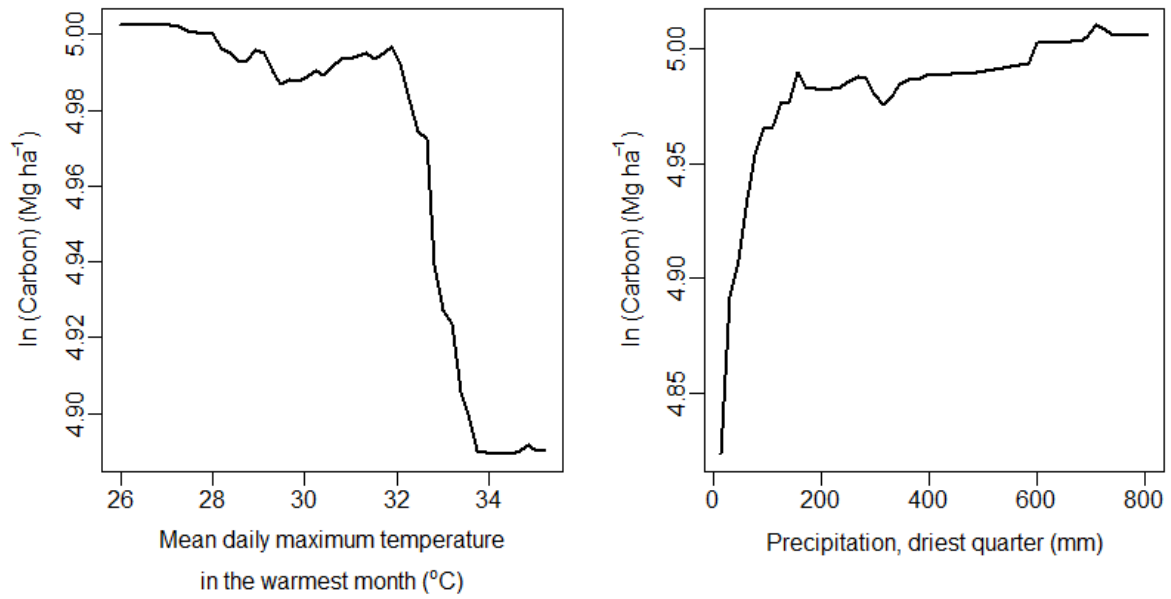


895

896 **Figure S6.** Interaction between mean daily maximum temperature in the warmest month and
897 precipitation in the driest quarter in determining aboveground tropical forest carbon stocks. Modelled
898 relationships with temperature are shown holding precipitation either one standard deviation above or
899 below the mean. Note that the temperature-carbon relationship is steeper when precipitation is low.

900

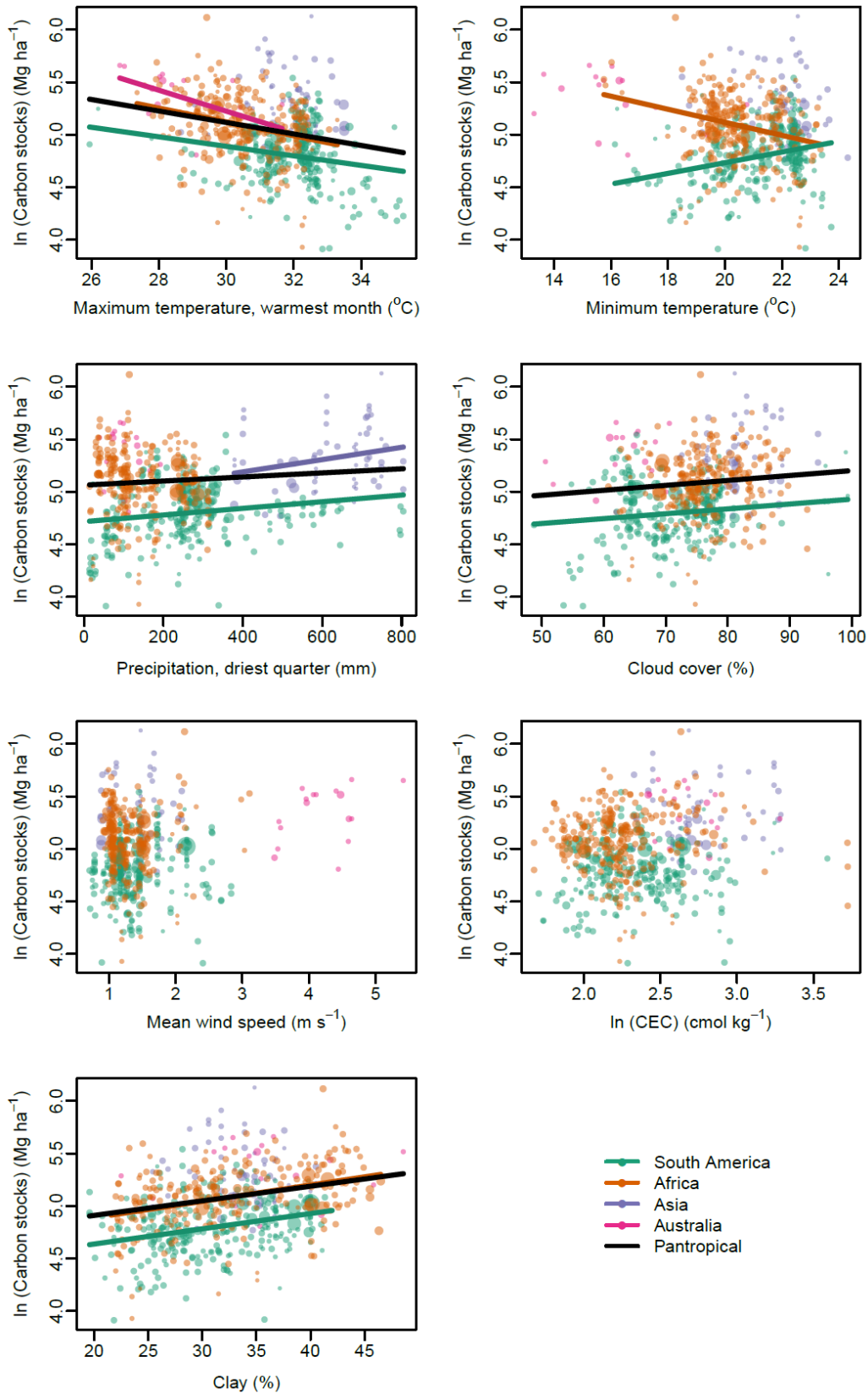
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902

903 **Figure S7.** Partial relationships between tropical forest carbon stocks and the two climate variables
904 identified to be most important by the random forest decision tree algorithm. Partial plots show
905 predicted values of carbon stocks averaged across an ensemble of decision tree models when
906 changing the explanatory variable of interest and holding other variables constant. The importance of
907 variables in random forest analysis is assessed by calculating the average increase in node purity
908 across all decision trees (measured by residual sum of squares) when using the variable to split the
909 data. Higher values indicate greater importance. Maximum temperature increased node purity by 4.8
910 and precipitation by 4.7. For all other climate variables increases in node purity were < 3.5.

911



912

913 **Figure S8.** Relationships between aboveground tropical forest carbon stocks and environmental

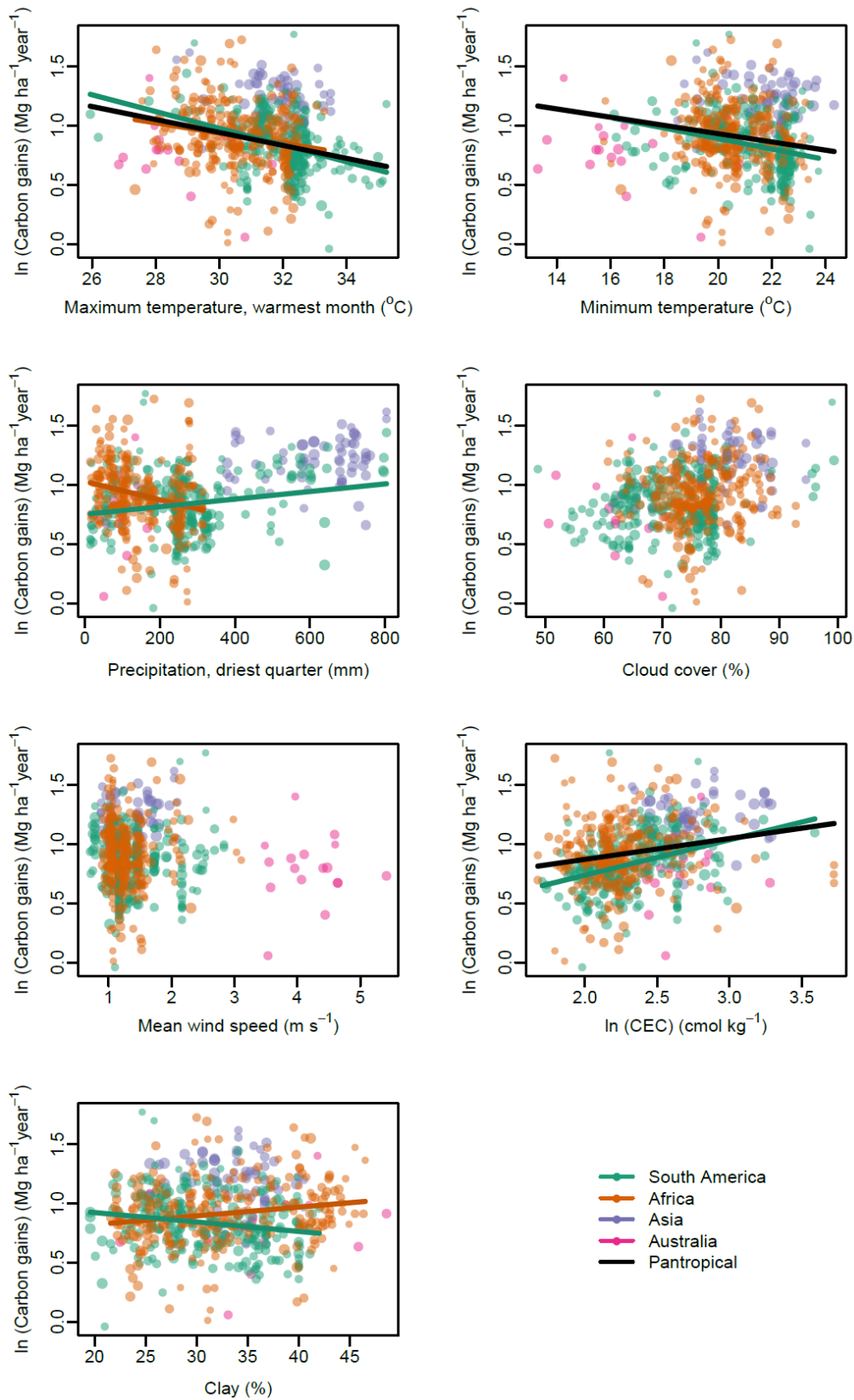
914 predictors. Symbols and colours as in Fig. 3. Coloured lines show bivariate relationships in each

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915 continent, and black lines show pan-tropical relationships also accounting for the effect of continent.

916 Lines are only plotted where statistically significant.

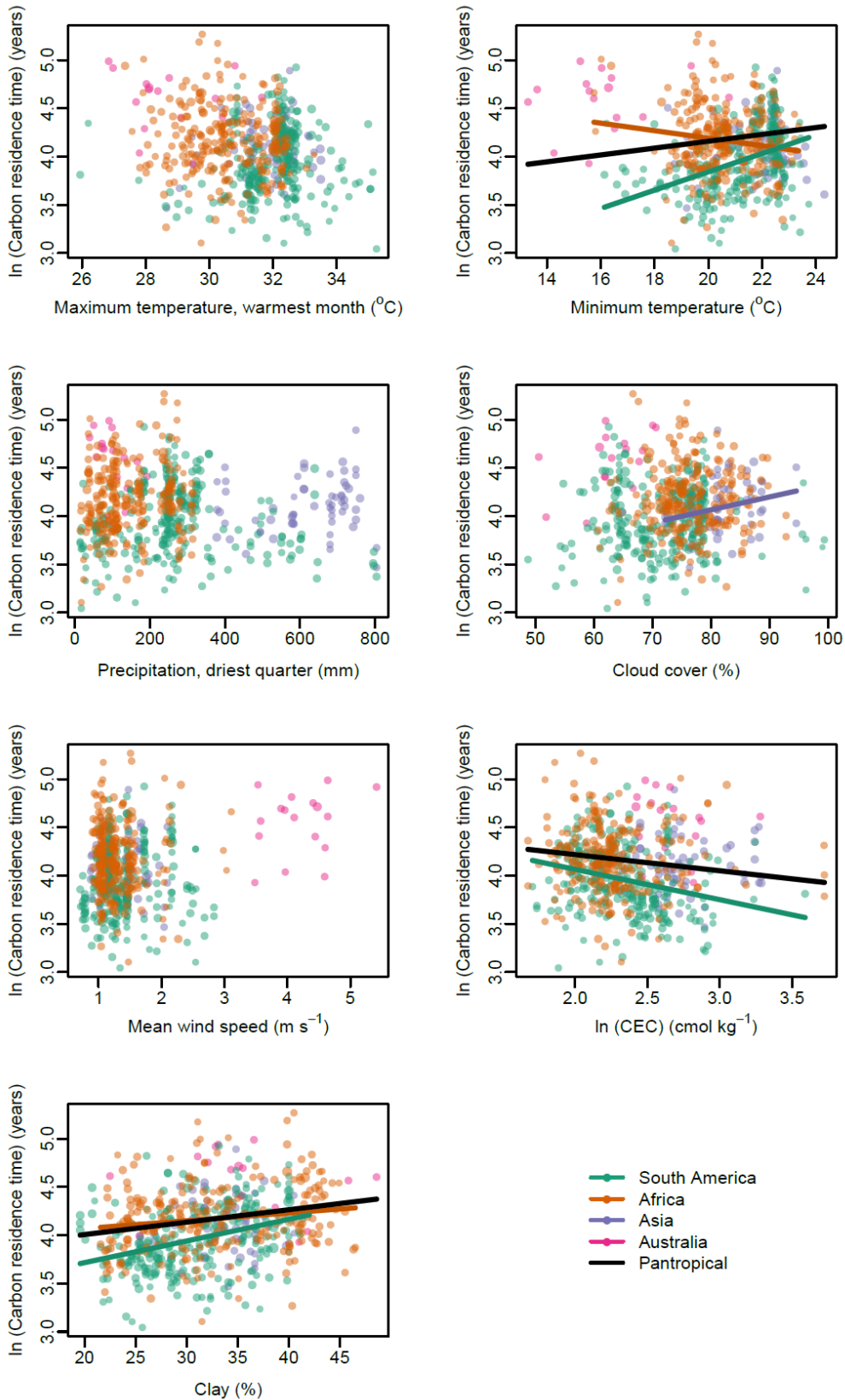
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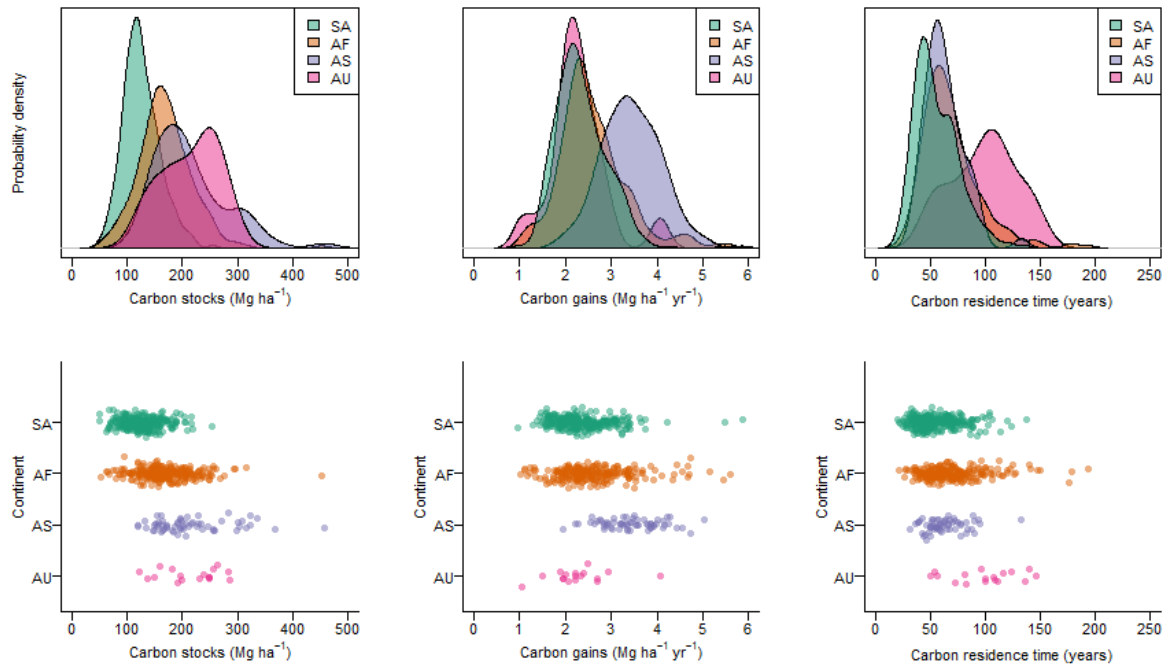
920 **Figure S9.** As Fig. S8, but showing relationships with carbon gains.



921

922 **Figure S10.** As Fig. S8, but showing relationships with carbon residence time.

923



924

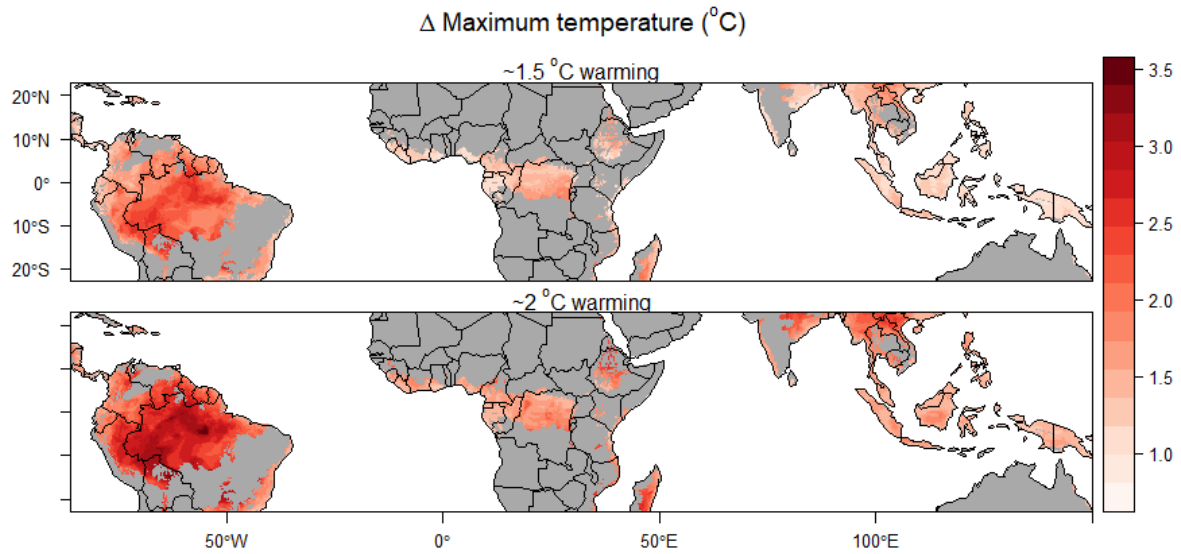
925 **Figure S11.** Variation in tropical forest aboveground carbon stocks, gains and residence time within

926 and amongst continents. Data are presented as empirical probability density functions (top row) and

927 dot-plots showing raw data points for all our multi-census plots (bottom row). SA = South America,

928 AF = Africa, AS = Asia, AU = Australia.

929



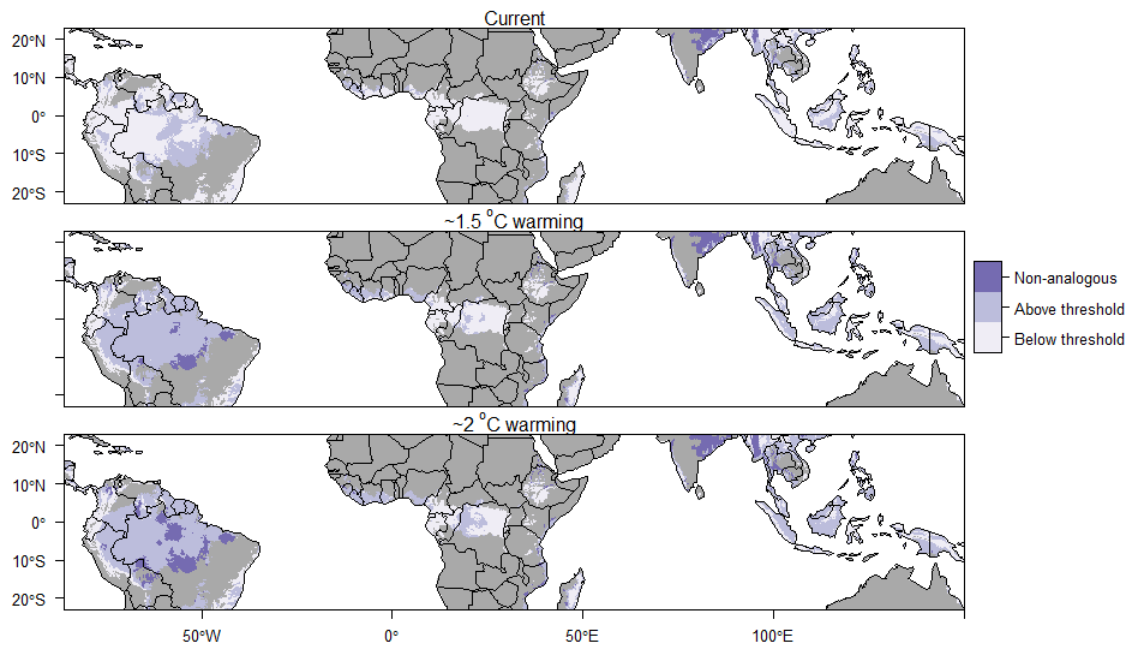
930

931 **Figure S12.** Biome-wide change in mean daily maximum temperature in the warmest month from
932 present conditions (based on the Worldclim climatology, 1970-2000), given global increases in
933 temperature of approximately 1.5 $^{\circ}\text{C}$ and 2 $^{\circ}\text{C}$ above pre-industrial levels. These levels of global
934 temperature increase are obtained from, respectively, RCP 2.6, 2040-2060 and RCP 4.5, 2040-2060.
935 Global temperature increases of 1.5 and 2 $^{\circ}\text{C}$ above pre-industrial levels (so ~0.8 $^{\circ}\text{C}$ and ~1.3 $^{\circ}\text{C}$
936 above our current baseline climate) would lead to mean increases in maximum temperature in the
937 warmest month across the tropical forest biome of 1.9 $^{\circ}\text{C}$ and 2.4 $^{\circ}\text{C}$ the current baseline climate
938 respectively.

939

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942

943 **Figure S13** Areas of the biome above or below the 32.2°C threshold, above which carbon stocks
 944 decline more rapidly with temperature, under current conditions and two warming scenarios (see Fig.
 945 4). Areas warmer than any currently observed in our dataset (35.2°C) are also shown (non-analogous
 946 conditions). Note that even the 1.5°C warming scenario pushes most South American forests above
 947 the 32.2°C threshold.

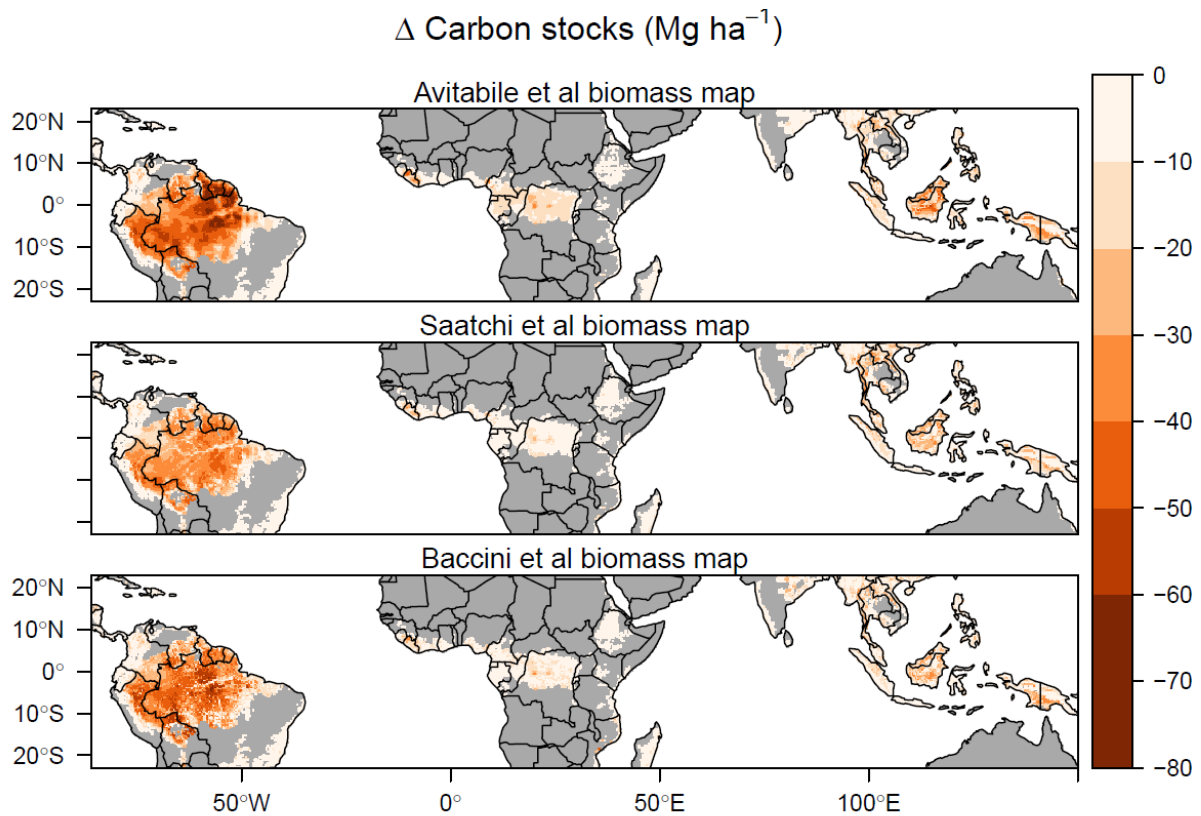
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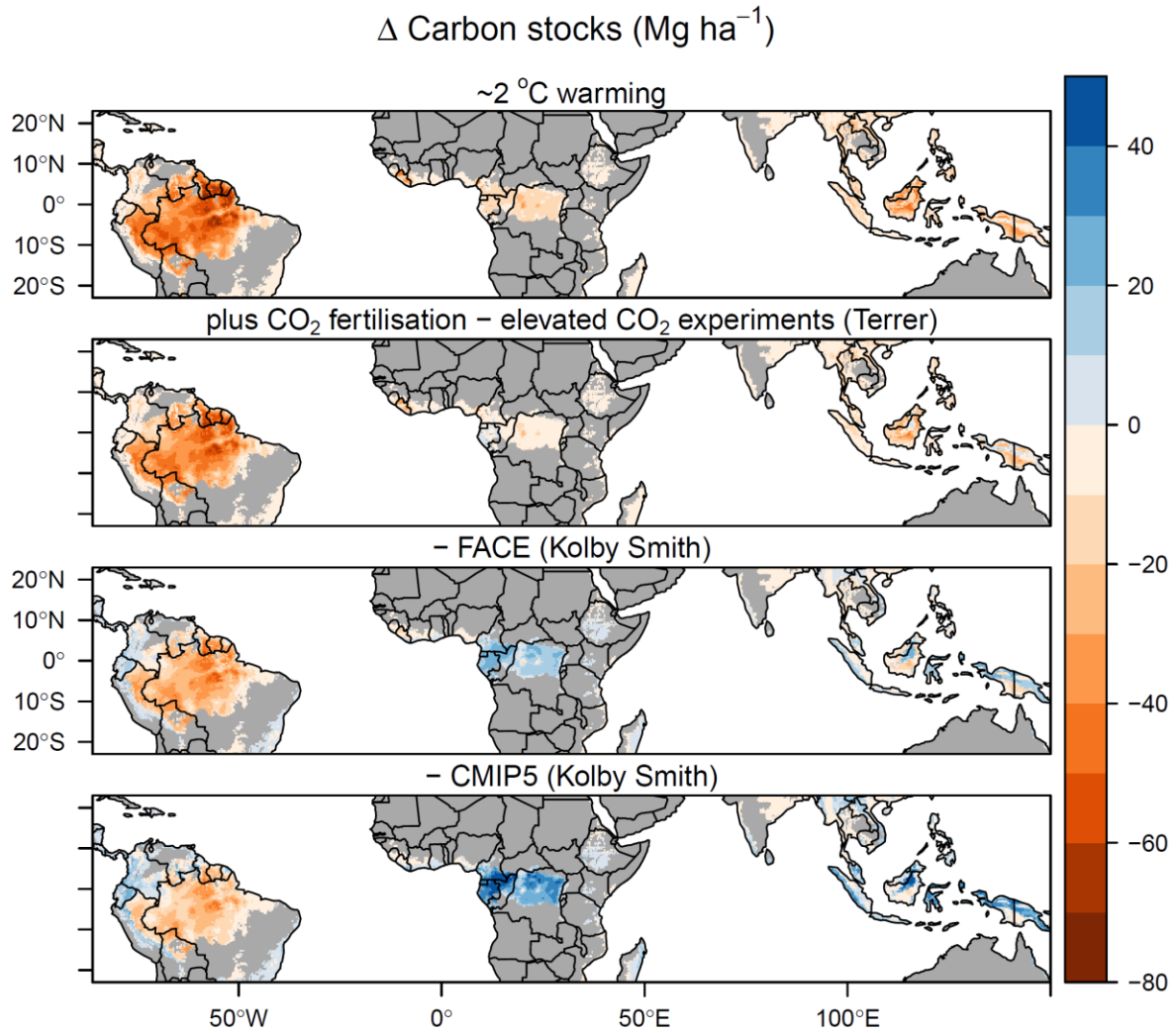
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953

954 **Figure S14.** Effect of using earlier biomass reference maps for estimates of change in long-term
955 carbon stocks for global temperature increases of $\sim 2^\circ\text{C}$. Using aboveground biomass stock maps from
956 Saatchi et al. (65) and Baccini et al. (66) predicted biome-wide reductions in biomass carbon stocks
957 are 24.0 Pg (95 % CI = 5.8 – 39.6) and 28.4 Pg (95 % CI = 16.1 – 37.5) respectively. Under the \sim
958 1.5°C warming scenario these are 18.4 Pg (5.8 – 30.5) and 21.1 Pg (10.2 – 29.4) respectively. Results
959 in the main text use the 2016 Avitabile et al. baseline map (30) – see methods for justification.

960



961

962 **Figure S15.** Predicted long-term change in aboveground carbon stocks under ~ 2°C global warming,
 963 based on either temperature effects alone or when also accounting for carbon dioxide growth
 964 stimulation. CO₂ fertilisation effects on equilibrium biomass levels were obtained from a recent
 965 synthesis of results of elevated CO₂ experiments (Terrer et al. (77)), free-air CO₂ enrichment (FACE)
 966 experiments (Kolby Smith et al. (74)) and CMIP5 earth system models (Kolby Smith et al. (74)).
 967 Depending on their strength, CO₂ effects either partially or fully ameliorate the biome-wide negative
 968 effects of increasing temperatures on biomass carbon stocks (Table S3), but these carbon stocks are
 969 predicted to decline over much of Amazonia even under the strongest CO₂ effect considered.

970

971

972 **Table S1.** Climate variables selected for analysis and mechanisms by which they can affect carbon stocks.

Climate property	Variable selected for analysis	Mechanism to affect carbon stocks
Daytime temperature	Maximum temperature in the warmest month ¹	High daytime temperatures exceed photosynthesis optima (80), increase evaporative stress, causing stomatal closure and reducing time for photosynthesis (26) and increase risk of mortality through hydraulic failure and/or carbon starvation (23).
Night-time temperature	Mean daily minimum temperature	Respiration rate increases with temperature so proportion of carbon taken through photosynthesis that is allocated to wood should decline with temperature (81). Increased respiration cost could also reduce tree longevity (23). As respiration occurs day and night, and photosynthesis only in the day, nighttime temperature should better reflect respiration effects and daytime temperature better reflect photosynthesis effects.
Moisture availability	Precipitation in the driest quarter ²	Moisture availability could limit photosynthesis and hence carbon gains, with stomata closing when moisture availability is limiting. The risk of mortality through hydraulic failure or carbon starvation is higher when moisture is limiting (23), and this could also set a limit on potential tree size and hence tree longevity.
Light availability	Cloud frequency	Increased photosynthesis and hence AGWP when light availability is greatest (i.e. cloud cover is low) (82). Alternatively, light availability could have a negative effect due to high evapotranspiration stress when cloud cover is low.
Wind speed	Mean wind speed	Carbon stocks are expected to be lower where physical damage through wind throw or breakage is higher, as carbon is removed more quickly from the system through mortality (83). But there is potential for greater carbon gains if forests are more dynamic.

973 ¹ Mean daily temperature in the warmest month (bio5) was selected instead of mean daily maximum temperature as it was more strongly decoupled from
974 other climate variables. VPD could also represent some of these effects, but was too strongly correlation with maximum temperature to include as an
975 independent variable.

976 ² Moisture availability could also be represented by MCWD (maximum cumulative water deficit) or total precipitation, but only one of the three variables
977 could be included in the model due to collinearity. MCWD was excluded as it is zero truncated, so less amenable to regression fitting.

978

979 **Table S2.** Coefficients of model-averaged general linear models of carbon stocks, gains and residence time as a function of climate, soil, continent and spatial
 980 autocorrelation. Coefficients are AIC weighted averages across models with $\Delta AIC < 4$ from the best performing model; variables are given a score of zero if
 981 they did not appear in a model. NA indicates that a term did not occur in any model in this set. MEM1-8 are spatial eigenvectors.

Variable	Carbon stocks				Carbon gains				Carbon residence time			
	Estimate	SE	Z	P	Estimate	SE	Z	P	Estimate	SE	Z	P
Intercept - Africa	4.986	0.010	476.9	<0.001	0.571	0.525	1.09	0.278	3.909	0.688	5.67	<0.001
Minimum temperature	0.031	0.019	1.67	0.096	-0.001	0.007	0.18	0.861	0.019	0.022	0.88	0.381
Maximum temperature, warmest month	-0.089	0.022	4.11	<0.001	-0.060	0.017	3.47	<0.001	-0.001	0.015	0.10	0.924
Precipitation, driest quarter	0.045	0.018	2.54	0.011	-0.001	0.008	0.14	0.887	0.061	0.023	2.70	0.007
Cloud frequency	0.002	0.008	0.24	0.814	-0.006	0.011	0.54	0.592	0.025	0.021	1.17	0.241
Wind speed	0.004	0.012	0.38	0.705	0.016	0.020	0.78	0.437	-0.004	0.015	0.24	0.807
Soil texture (% clay)	0.021	0.017	1.26	0.208	-0.005	0.011	0.49	0.628	0.040	0.018	2.17	0.030
Soil fertility (CEC)	-0.003	0.009	0.34	0.732	0.005	0.011	0.51	0.613	-0.012	0.017	0.70	0.486
MEM1	0.115	0.014	7.96	<0.001	0.319	0.559	0.57	0.569	0.375	0.734	0.51	0.610
MEM2	0.098	0.017	5.67	<0.001	0.083	0.273	0.30	0.762	0.286	0.359	0.80	0.427
MEM3	-0.025	0.014	1.84	0.065	0.014	0.041	0.34	0.735	0.007	0.054	0.12	0.904
MEM4	-0.021	0.011	1.84	0.066	-0.038	0.020	1.84	0.066	-0.002	0.027	0.07	0.945
MEM5	0.027	0.011	2.46	0.014	0.020	0.015	1.33	0.182	0.020	0.020	0.98	0.327
MEM6	0.017	0.011	1.56	0.118	0.025	0.011	2.34	0.019	-0.014	0.014	1.05	0.293
MEM7	0.010	0.011	0.93	0.353	-0.017	0.010	1.61	0.107	0.036	0.014	2.57	0.010
MEM8	-0.072	0.013	5.64	<0.001	0.057	0.012	4.91	<0.001	-0.127	0.016	7.80	0.000
Asia	NA				0.380	0.542	0.70	0.485	-0.753	0.683	1.10	0.271
Australia	NA				-0.173	0.390	0.44	0.658	0.006	0.516	0.01	0.990
South America	NA				0.643	1.164	0.55	0.582	0.542	1.530	0.35	0.724

983 **Table S3.** Predicted biome-wide changes in long-term biomass carbon stocks (scaled to include root
 984 biomass) under global temperature increases of ~ 1.5°C and ~ 2°C. Changes are based on temperature
 985 effects alone, and when also accounting for the effect of increased CO₂ concentrations on tree growth.
 986 CO₂ effects were obtained from a synthesis of results of elevated CO₂ experiments (Terrer et al. (77)),
 987 free-air CO₂ enrichment (FACE) experiments (Kolby Smith et al. (74)) and CMIP5 earth system
 988 models (Kolby Smith et al. (74)). 95% confidence intervals around changes (based on uncertainties in
 989 temperature effects alone) are shown in parentheses.

CO ₂ effect	Change in biomass carbon stocks (Pg)	
	~ 1.5°C warming (443 ppm CO ₂)	~ 2°C warming (487 ppm CO ₂)
None	-26.9 (-38.4 - -15.8)	-35.3 (-49.0 - -20.9)
Terrer et al. elevated CO ₂ experiments	-22.0 (-33.0 - -9.9)	-26.3 (-37.6 - -11.5)
Kolby Smith et al. FACE experiments	-6.2 (-16.8 - 7.7)	-9.9 (-24.3 - 3.9)
Kolby Smith et al. CMIP5 models	3.9 (-8.3 - 12.6)	2.0 (-11.9 - 19.8)

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Supporting information for Sullivan et al.

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