

Asynchronous carbon sink saturation in African and Amazonian tropical forests

ForestPlots

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1 Asynchronous Carbon Sink Saturation in African and Amazonian Tropical Forests

2

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150

151

152 **Summary**

153

154 **Structurally intact tropical forests sequestered ~50% of global terrestrial carbon uptake over**
155 **the 1990s and early 2000s, removing ~15% of anthropogenic CO₂ emissions¹⁻³. Climate-driven**
156 **vegetation models typically predict that this tropical forest ‘carbon sink’ will continue for**
157 **decades^{4,5}. Here, we assess trends in the carbon sink using 244 structurally intact African**
158 **tropical forests spanning 11 countries, we compare them with 321 published plots from**
159 **Amazonia and investigate the underlying drivers of the trends. The carbon sink in live**
160 **aboveground biomass in intact African tropical forests has been stable for the three decades to**
161 **2015, at 0.66 Mg C ha⁻¹ yr⁻¹ (95% CI:0.53-0.79), in contrast to the long-term decline in**
162 **Amazonian forests⁶. Thus, the carbon sink responses of Earth’s two largest expanses of**
163 **tropical forest have diverged. The difference is largely driven by carbon losses from tree**
164 **mortality, with no detectable multi-decadal trend in Africa and a long-term increase in**
165 **Amazonia. Both continents show increasing tree growth, consistent with the expected net effect**
166 **of rising atmospheric CO₂ and air temperature⁷⁻⁹. Despite the past stability of the African**
167 **carbon sink, our data suggest a post-2010 increase in carbon losses, delayed compared to**
168 **Amazonia, indicating asynchronous carbon sink saturation on the two continents. A statistical**
169 **model including CO₂, temperature, drought and forest dynamics accounts for the observed**
170 **trends and indicates a long-term future decline in the African sink, while the Amazonian sink**
171 **continues to rapidly weaken. Overall, the uptake of carbon into Earth’s intact tropical forests**
172 **peaked in the 1990s. Given that the global terrestrial carbon sink is increasing in size,**
173 **observations indicating greater recent carbon uptake into the Northern hemisphere landmass¹⁰**
174 **reinforce our conclusion that the intact tropical forest carbon sink has already saturated. This**
175 **tropical forest sink saturation and ongoing decline has consequences for policies to stabilise**
176 **Earth’s climate.**

177 **Main text**

178

179 Tropical forests account for approximately one-third of Earth's terrestrial Gross Primary Productivity
180 and one-half of Earth's carbon stored in terrestrial vegetation¹¹. Thus, small biome-wide changes in
181 tree growth and mortality can have global impacts, either buffering or exacerbating the increase in
182 atmospheric CO₂. Models^{2,4,5,7,12}, ground-based observations¹³⁻¹⁵, airborne atmospheric CO₂
183 measurements^{3,16}, inferences from remotely sensed data¹⁷, and synthetic approaches^{3,8,18} each suggest
184 that, after accounting for land-use change, remaining structurally intact tropical forests (i.e. not
185 impacted by direct anthropogenic impacts such as logging) are increasing in carbon stocks. This
186 structurally intact tropical forest carbon sink is estimated at ~1.2 Pg C yr⁻¹ over 1990-2007 using
187 scaled inventory plot measurements¹. Yet, despite its policy relevance, changes in this key carbon
188 sink remain highly uncertain^{19,20}.

189

190 Globally the terrestrial carbon sink is increasing^{2,7,8,21}. Between 1990 and 2017 the land surface
191 sequestered ~30% of all anthropogenic carbon dioxide emissions^{1,21}. Rising CO₂ concentrations are
192 thought to have boosted photosynthesis more than rising air temperatures have enhanced respiration,
193 resulting in an increasing global terrestrial carbon sink^{2,4,7,8,21}. Yet, for Amazonia, recent results from
194 repeated censuses of intact forest inventory plots show a progressive two-decade decline in sink
195 strength primarily due to an increase of carbon losses from tree mortality⁶. It is unclear if this simply
196 reflects region-specific drought impacts^{22,23}, or potentially chronic pan-tropical impacts of either
197 heat-related tree mortality^{24,25}, or internal forest dynamics resulting from past increases in carbon
198 gains leaving the system²⁶. A more recent deceleration of the rate of increase in carbon gains from
199 tree growth is also contributing to the declining Amazon sink⁶. Again, it is not known if this is a
200 result of either pan-tropical CO₂ fertilisation saturation, or rising air temperatures, or is merely a
201 regional drought impact. To address these uncertainties, we (i) analyze an unprecedented long-term

202 inventory dataset from Africa, (ii) pool the new African and existing Amazonian records to
203 investigate the putative environmental drivers of changes in the tropical forest carbon sink, and (iii)
204 project its likely future evolution.

205

206 We collected, compiled and analysed data from structurally intact old-growth forests from the
207 African Tropical Rainforest Observation Network²⁷ (217 plots) and other sources (27 plots) spanning
208 the period 1968 to 2015 (Extended Data Figure 1; Supplementary Table 1). In each plot (mean size,
209 1.1 ha), all trees ≥ 100 mm in stem diameter were identified, mapped and measured at least twice
210 using standardised methods (135,625 trees monitored). Live biomass carbon stocks were estimated
211 for each census date, with carbon gains and losses calculated for each interval (Extended Data Figure
212 2).

213

214 **Continental Carbon Sink Trends**

215 We detect no long-term trend in the per unit area African tropical forest carbon sink over three
216 decades to 2015 (Figure 1). The aboveground live biomass sink averaged $0.66 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$ (95%
217 CI: 0.53-0.79; $n=244$) and was significantly greater than zero for every year since 1990 (Figure 1).
218 While very similar to past reports ($0.63 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$)¹³, this first estimate of the temporal trend in
219 Africa contrasts with the declining Amazonian trend⁶ (Figure 1). A linear mixed effect model shows
220 a significant difference in the slopes of the sink trends for the two continents over the common time
221 window (pooled data from both continents, common time window, 1983-2011.5; $p=0.017$). Thus, the
222 per unit area sink strength of the two largest expanses of tropical forest on Earth diverged in the
223 1990s and 2000s.

224

225 The proximal cause of the divergent sink patterns is a significant increase in carbon losses (from tree
226 mortality, i.e. the loss of carbon from the live biomass pool) in Amazonian forests, with no

227 detectable trend over three decades in African forests (Figure 1). A linear mixed effects model using
228 pooled data shows a significant difference in slopes of carbon losses between the two continents over
229 the common 1983-2011.5 time window ($p=0.027$). Long-term trends in carbon gains (from tree
230 growth and newly recruited trees) on both continents show significant increases (Figure 1), and we
231 could detect no difference in slopes between the continents ($p=0.348$; carbon gains from tree growth
232 alone also show no continental difference in long-term trends, $p=0.322$). However, an assessment of
233 how underlying environmental drivers affect carbon gains and losses is needed to understand the
234 ultimate causes of the divergent sink patterns.

235

236 **Understanding the Carbon Sink Trends**

237 We first investigate environmental drivers exhibiting long-term change that impact theory-driven
238 models of photosynthesis and respiration: atmospheric CO_2 concentration, surface air temperature,
239 and water availability. A linear mixed effects model of carbon gains, with censuses nested within
240 plots, and pooling the new African and published Amazonian data, shows a significant positive
241 relationship with CO_2 , and significant negative relationships with mean annual temperature (MAT)
242 and drought (measured as the Maximum Climatological Water Deficit, MCWD¹⁴; Figure 2;
243 Extended Data Table 1). These results are consistent with a positive CO_2 fertilisation effect, and
244 negative effects of higher temperatures and drought on tree growth, consistent with temperature-
245 dependent increases in autotrophic respiration, and temperature- and drought-dependent reductions
246 in carbon assimilation. By contrast, the equivalent model for carbon losses (i.e. tree mortality) shows
247 no significant relationships with CO_2 , MAT or MCWD (Figure 2; Extended Data Table 1).

248

249 We further investigate the responses of carbon gains and losses (for which the above analysis has no
250 explanatory power) by expanding our potential explanatory variables to additionally include the
251 change in environmental conditions (CO_2 -change, MAT-change, MCWD-change, see Extended Data

252 Figure 3 for calculation details), and two attributes of forests that may influence their response to the
253 same environmental change: plot mean wood density (which in old-growth forests correlates with
254 below-ground resource availability^{28,29}), and the plot carbon residence time (which measures how
255 long fixed carbon remains in the system, hence dictates when past increases in carbon gains leave the
256 system as elevated carbon losses³⁰).

257

258 The minimum adequate carbon gain model using our expanded explanatory variables (best ranked
259 model using multimodel inference) has a positive relationship with CO₂-change, and negative
260 relationships with MAT, MAT-change, MCWD, and wood density (Table 2; model-average results
261 are similar, see Methods and Supplementary Tables 2-4). The retention of both MAT and MAT-
262 change suggests that higher temperatures correspond to lower tree growth, and that trees only
263 partially acclimate to recently rising temperatures, which further reduces growth, consistent with
264 warming experiments³¹ and observations⁹. The inclusion of higher wood density, and it being related
265 to lower carbon gains (Extended Data Figure 4), alongside no temporal trends in wood density
266 (Extended Data Figure 5), suggests that old-growth forests with denser-wooded tree communities
267 typically have fewer available below-ground resources, or such patterns may also emerge from
268 disturbance regimes lacking large-scale exogenous events, consistent with prior studies^{26,28,32}.

269

270 The minimum adequate carbon gain model using our expanded explanatory variables also highlights
271 continental differences. Between 2000 and 2015 African forest carbon gains increased by 3.1%
272 compared with a 0.1% decline in Amazonia over the same interval (Table 2). In Africa, from 2000 to
273 2015, the increase was composed of a 3.7% increase from CO₂-change, partially offset by increasing
274 droughts depleting gains by 0.5%, and only a slight decline in gains of 0.1% resulting from
275 temperature increases (Table 2), because the rate of temperature change (MAT-change) decelerated
276 over this time window (Extended Data Figure 5). For Amazonia, the same 3.7% increase due to CO₂-

277 change was seen, while increasing droughts—and these forests’ greater sensitivity to drought—
278 reduced gains by 2.7% (five times the impact in Africa), and temperature increases at the same rate
279 as in the past (i.e. MAT-change is zero) further reduced gains by 1.1% (ten times the impact in
280 Africa), leaving a net change in gains slightly below zero (Table 2). Thus, the recent stalling of
281 carbon gain increases in Amazonia⁶ is a response to drought and temperature and not due to an
282 unexpected saturation of CO₂ fertilisation. Overall, the larger modelled increase in gains in Africa
283 relative to Amazonia appear to be driven by slower warming, fewer or less extreme droughts, lower
284 forest sensitivity to droughts, and overall lower temperatures (African forests are on average ~1.1°C
285 cooler than Amazonian forests, as they typically grow at ~200 m higher elevation). Other continental
286 differences may also be influencing the results, including higher nitrogen deposition in African
287 tropical forests due to the seasonal burning of nearby savannas³³ and biogeographic history resulting
288 in differing contemporary species pools and resulting functional attributes^{34,35}.

289

290 The minimum adequate carbon loss model using our expanded explanatory variables shows higher
291 losses with CO₂-change and MAT-change, and lower losses with MCWD and the carbon residence
292 time (CRT; Table 2). Thus, changes in carbon losses appear to be largely a function of carbon gains.
293 First, the greater losses in forests with shorter CRT conform to a ‘high-gain high-loss’ forest
294 dynamics pattern²⁶. Second, wetter plots have a longer growing season and so have higher gains and
295 correspondingly higher losses, explaining the negative relationship with MCWD. Third, as
296 increasing CO₂ levels result in additional carbon gains, after some time these additional past gains
297 leave the system resulting in greater carbon losses, explaining the positive relationship with CO₂-
298 change. Finally, in addition to these relationships with carbon gains, the inclusion of MAT-change
299 ($p < 0.001$) indicates heat- or vapour pressure deficit-induced tree mortality²⁴. Overall, our results
300 imply that chronic long-term environmental change factors, temperature and CO₂, rather than simply

301 the direct effects of drought, underlie longer-term trends in tropical forest tree mortality, although
302 other changes such as rising liana infestation rates seen in Amazonia^{36,37} cannot be excluded.

303

304 The minimum adequate carbon loss model using our expanded explanatory variables replicates the
305 continental trends (Figure 3). The overall lower loss rates in Africa reflect their longer CRT (69 yrs,
306 95% CI, 66-72), compared with Amazonian forests (56 yrs, 95% CI, 54-59) while over the 2000-
307 2015 window the much smaller increase in loss rates in Africa compared to Amazonia results from a
308 slower increase in warming and a stable CRT in Africa compared to continued warming at previous
309 rates and a shortening CRT in Amazonian forests (Extended Data Figure 5). Furthermore, given that
310 losses appear to lag behind gains they should relate to the long-term CRT of plots. This is what we
311 find: the longer the CRT the smaller the increase in carbon losses, with no increase in losses for plots
312 with $CRT \geq 77$ years (Extended Data Figure 6). Consequently, due to the typically longer residence
313 times of African forests, increasing losses in Africa ought to appear 10-15 years after the increase in
314 Amazon losses began (c.1995). Strikingly, in Africa the most intensely monitored plots suggest that
315 losses began increasing from c.2010 (Extended Data Figure 7), and plots with shorter CRT are
316 driving the increase (Extended Data Figure 8). Thus, a mortality-dominated African carbon sink
317 decline appears to have begun very recently.

318

319 **Future of the Tropical Forest Carbon Sink**

320 Our carbon gain and loss models (Table 2) can be used to make a tentative estimate of the future size
321 of the per unit area intact forest carbon sink (Figure 3). Extrapolations of the changes in the predictor
322 variables from 1983-2015 forward to 2040 (Extended Data Figure 5) show declines in the sink on
323 both continents (Figure 3). By 2030 the carbon sink in aboveground live biomass in intact African
324 tropical forest is predicted to decline by 14% from the measured 2010-15 mean, to $0.57 \text{ Mg C ha}^{-1} \text{ yr}^{-1}$
325 ¹ (2σ range, 0.16-0.96; Figure 3). The Amazon sink continues to decline, reaching zero in 2035 (2σ

326 range, 2011-2089; Figure 3). Our estimated sink strength on both continents in the 2020s and 2030s
327 is sensitive to future CO₂ emissions pathways (CO₂-change)³⁸, resulting temperature increase (MAT,
328 MAT-change) and hydrological changes (MCWD), plus changes in forest dynamics (CRT), but the
329 sink is always lower than levels seen in the 2000s (see Methods and Supplementary Table 5). Thus,
330 the carbon sink strength of the world's two most extensive tropical forests have now saturated, albeit
331 asynchronously.

332

333 **Scaling Results to the Pan-tropics**

334 Scaling our estimated mean sink strength by forest area for each continent signifies that Earth
335 recently passed the point of peak carbon sequestration into intact tropical forests (Table 1). The
336 continental sink in Amazonia peaked in the 1990s, followed by a decline, driven by sink strength
337 peaking in the 1990s and a continued decline in forest area (Table 1). In Africa the per unit area sink
338 strength peaked later in the 2000-2010 period, but the continental African sink peaked in the 1990s,
339 due to the decline in forest area in the 2000s outpacing the small per unit area increase in sink
340 strength. Including the modest uptake in the much smaller area of intact Asian tropical forest
341 indicates that total pan-tropical carbon uptake peaked in the 1990s (Table 1). From peak pan-tropical
342 intact forest uptake of 1.26 Pg C yr⁻¹ in the 1990s, we project a continued decline reaching just 0.29
343 Pg C yr⁻¹ in the 2030s (multi-decade decline of ~0.24 Pg C yr⁻¹ decade⁻¹), driven by (i) reduced mean
344 pan-tropical sink strength decline of 0.1 Mg C ha⁻¹ yr⁻¹ decade⁻¹ and (ii) ongoing forest area losses of
345 ~13.5 million ha yr⁻¹ (see Extended Data Table 2 for forest area details). Critically, climate-driven
346 vegetation model simulations have not predicted that peak net carbon uptake into intact tropical
347 forests has already been passed^{2,4,5}.

348

349 **Discussion**

350 Our method of scaling to arrive at a pan-tropical sink estimate – in common with other studies using
351 similar datasets^{1,6,13} – is limited. Yet, pervasive net carbon uptake is expected given that we find a
352 strong and ongoing CO₂ fertilisation effect. Using our CO₂ response in Table 2, we find an increase
353 in aboveground carbon stocks of 10.8 ± 3.7 Mg C ha⁻¹ 100 ppm⁻¹ CO₂, or $6.5 \pm 2.2\%$ (\pm SE; using an
354 area-weighted pan-tropical mean aboveground C stock of 165 Mg C ha⁻¹), comparable to the
355 $5.0 \pm 1.2\%$ increase in tropical forest C stocks 100 ppm⁻¹ CO₂ derived from a recent synthesis of CO₂
356 fertilisation experiments, despite a lack of data from mature tropical forests³⁹. Our result is within the
357 range of climate-driven vegetation models^{2,7}, although it is greater than a number of recently-
358 published models that include potential nutrient constraints, reported as 5.9 ± 4.7 Mg C ha⁻¹ 100 ppm⁻¹
359 CO₂ (Ref.⁴⁰). We find that the CO₂ fertilisation uptake is currently only partially offset by the
360 negative impacts of similarly widespread rising air temperatures (-2.0 ± 0.4 Mg C ha⁻¹ °C⁻¹, from
361 Table 2), consistent with models⁷, limited experiments³¹ and independent observations⁹, plus
362 negative responses to drought^{41,42}. Long-term and extensive increases in satellite-derived greenness
363 in tropical regions not experiencing major changes in land-use management^{17,43}, particularly in
364 central Africa in the past decade⁴⁴, indicate increases in tropical forest net primary productivity,
365 providing further evidence that the sink is a widespread phenomenon⁴⁴.

366

367 Nonetheless, our analyses show that this pervasive tropical forest sink in live biomass is in long-term
368 decline, first saturating in Amazonia, and more recently followed by African forests, explaining the
369 prior Africa-Amazon carbon sink divergence as part of a longer-term pattern of asynchronous
370 saturation and decline. From an atmospheric perspective the full impacts of the contribution to the
371 saturation of the sink from slowing carbon gains are experienced immediately, but the contribution
372 from rising carbon losses is delayed because dead trees do not decompose instantaneously.
373 Decomposition of this dead tree mass is ~50% in 4 yrs, and ~85% in 10 yrs, thus rising carbon losses

374 result in delayed carbon additions to the atmosphere⁴⁵. Hence, from an atmospheric perspective the
375 intact tropical forest biomass carbon sink likely peaked a few years later than our plot data indicate
376 and the full impacts are not yet realised. The pan-tropical carbon sink in live biomass reduced by
377 0.27 Pg C yr⁻¹ between the 1990s and 2000s (Table 1), but accounting for dead wood
378 decomposition⁴⁵ shows a smaller 0.17 Pg C yr⁻¹ reduction from an atmospheric perspective (see
379 Methods).

380

381 Given that the global terrestrial carbon sink is increasing, a weakening intact tropical forest sink
382 implies that the extra-tropical carbon sink has increased over the past two decades. Independent
383 observations of inter-hemispheric atmospheric CO₂ concentration indicates that carbon uptake into
384 the Northern hemisphere landmass has increased at a greater rate than the global terrestrial carbon
385 sink since the 1990s, with a further disproportionate increase in the 2000s¹⁰. The inter-hemispheric
386 analysis suggests a weakening of the tropical forest sink by ~0.2 Pg C yr⁻¹ between the 1990s and
387 2000s¹⁰, which is similar to the 0.17 Pg C yr⁻¹ weakening over the same time period that we find.
388 This reinforces our conclusion that the intact tropical forest carbon sink has already saturated.

389

390 In summary, our results indicate that while intact tropical forests remain major stores of carbon and
391 are key centres of biodiversity¹¹, their ability to sequester additional carbon is waning. In the 1990s
392 intact forests removed 17% of anthropogenic CO₂ emissions. This has declined to 6% in the 2010s,
393 because the pan-tropical weighted average per unit area sink strength declined by 33%, forest area
394 decreased by 19%, and CO₂ emissions increased by 46%. Although tropical forests are more
395 immediately threatened by deforestation⁴⁶ and degradation⁴⁷, and the future carbon balance will also
396 depend on secondary forest dynamics⁴⁸ and forest restoration plans⁴⁹, our analyses show that they are
397 also impacted by atmospheric chemistry and climatic changes. Given that the intact tropical forest
398 carbon sink is set to end sooner than even the most pessimistic climate-driven vegetation models

399 predict^{4,5}, our analyses suggest that climate change impacts in the tropics may become more severe
400 than predicted. Furthermore, the carbon balance of intact tropical forests will only stabilise once CO₂
401 concentrations and the climate stabilises.

402

403 Continued on-the-ground monitoring of the world's remaining intact tropical forests will be required
404 to test our prediction that the intact tropical forest carbon sink will continue to decline. Such direct
405 ground-based measurements also provide a constraint on estimating the size and location of the
406 terrestrial carbon sink. In addition, our conclusion that tree mortality and internal forest dynamics are
407 important controls on the future of the tropical forest carbon sink, may assist in improving the
408 vegetation components of future Earth System Models⁵⁰ and contribute to reducing terrestrial carbon
409 cycle feedback uncertainty^{19,20}. Our findings also have policy implications. At the country-level:
410 given intact tropical forests are a carbon sink, but the size is changing, national greenhouse gas
411 reporting will require careful forest monitoring. At the international-level: given tropical forests are
412 likely to sequester less carbon in the future than Earth System Models predict, an earlier date to reach
413 net zero anthropogenic greenhouse gas emissions will be required to meet any given commitment to
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415

416 **References**

417

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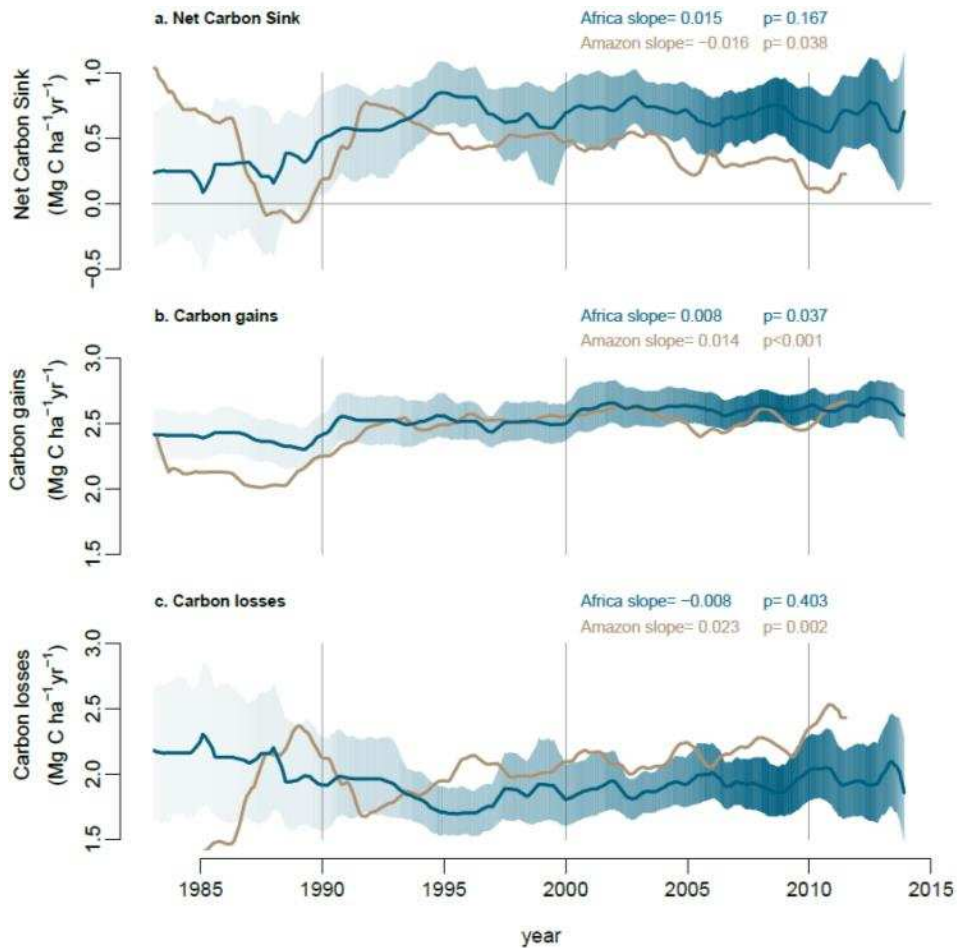
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657 S.L.L. conceived and managed the AfriTRON forest plot recensus programme, O.L.P., T.C.H.S.,
658 L.J.T.W. and Y.M. contributed to its development. W.H., S.L.L., O.L.P., B.S. & M.J.P.S. developed
659 the study. W.H., S.L.L., O.L.P., K.A.-B., H.B., A.C.-S., C.E.N.E., S.F., D.S., B.S., T.C.H.S., S.C.T.,
660 K.A.A., S.A.-B., C.A.A., T.R.B., L.F.B., F.Ba., S.K.B., F.Be., R.B., Y.E.B., P.Boe., P.Bou., T.B.,
661 E.C., G.B.C., C.J.C., M.C., J.A.C., D.C., A.K.D., G.C.D., T.d.H., M.D.K., J.-L.D., T.R.F., A.F.,
662 E.G.F., M.G., C.G., S.G.-F., J.S.H., A.C.H., D.J.H., T.B.H., M.B.N.H., A.H., S.A.I., K.J.J., T.J.,
663 E.K.Y., E.K., D.K., M.E.L., J.A.L., J.L., J.C.L., J.-R.M., Y.M., A.R.M., J.M., E.H.M., F.M.M.,
664 V.P.M., V.M., E.T.A.M., S.M., J.M.M., P.K.T.M., N.N.B., L.O., F.E., K.P., A.D.P., J.R.P., L.Q.,
665 J.R., F.R., M.D.S., H.T., J.Tal., J.Tap., D.M.T., D.W.T., B.T., J.T.M., D.T., P.M.U., G.V.D.H., H.V.,
666 J.V., L.J.T.W., S.W., H.W., J.T.W. and L.Z. contributed data (larger field contributions by S.L.L.,
667 W.H., A.C.-S., B.S., H.T., A.K.D., C.E.N.E., J.M.M., K.A.-B. and S.F.). O.L.P., T.R.B., S.L.L. and
668 G.L.-G. conceived and managed forestplots.net; O.L.P., T.R.B., S.L.L., E.G., G.L.-G., G.C.P., A.L.,
669 R.J.W.B., T.R.F. and M.J.P.S. developed it. W.H., M.J.P.S., S.L.L., O.L.P., R.J.W.B., A.L., G.L.-G.,
670 A.E.-M., A.K., E.G., T.R.B., A.C.B. and G.C.P. contributed analysis tools. W.H. and S.L.L. analysed
671 the data (with important contributions from M.J.P.S.). S.L.L. and W.H. wrote the paper. All co-

672 authors read and approved the manuscript (with important insights provided by O.L.P., S.F.,
673 R.J.W.B., E.G., H.B., D.S., M.J.P.S., S.G.-F., P.B., H.V. and S.C.T).

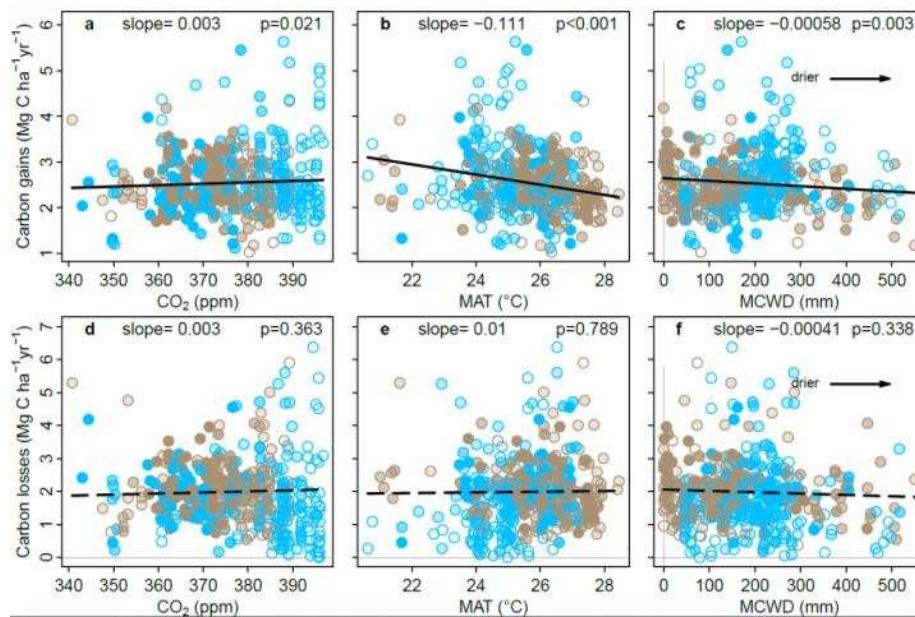
674

675 **Main Figures**



676

677 **Figure 1. Long-term carbon dynamics of structurally intact tropical forests in Africa (blue)**
678 **and Amazonia (brown).** Trends in net aboveground live biomass carbon sink (a), carbon gains to
679 the system from wood production (b), and carbon losses from the system from tree mortality (c),
680 measured in 244 African inventory plots (blue lines) and contrasting published⁶ Amazonian
681 inventory data (brown lines; 321 plots). Shading corresponds to the 95% CI, with less transparent
682 shading indicating a greater number of plots monitored in that year (most transparent: minimum 25
683 plots monitored). The CI for the Amazonian dataset is omitted for clarity, but can be seen in Figure
684 3. Slopes and p-values are from linear mixed effects models (see Methods).



685

686 **Figure 2. Potential environmental drivers of carbon gains and losses in structurally intact old-**

687 **growth African and Amazonian tropical forests.** Aboveground carbon gains, from woody

688 production (**a-c**), and aboveground carbon losses, from tree mortality (**d-f**), presented as time-

689 weighted mean values for each plot, i.e. each census within a plot is weighted by its length, against

690 the corresponding values of atmospheric carbon dioxide concentration (CO₂), mean annual air

691 temperature (MAT) and drought (as Maximum Climatological Water Deficit, MCWD), for African

692 (blue) and Amazonian (brown) inventory plots. Each data point therefore represents an inventory

693 plot, for visual clarity, and the level of transparency represents the total monitoring length, with

694 empty circles corresponding to plots monitored for ≤ 5 years and solid circles for plots monitored for

695 >20 years. Solid lines show significant trends, dashed lines non-significant trends calculated using

696 linear mixed effect models with census intervals (n=1566) nested within plots (n=565), using an

697 empirically derived weighting based on interval length and plot area, on the untransformed pooled

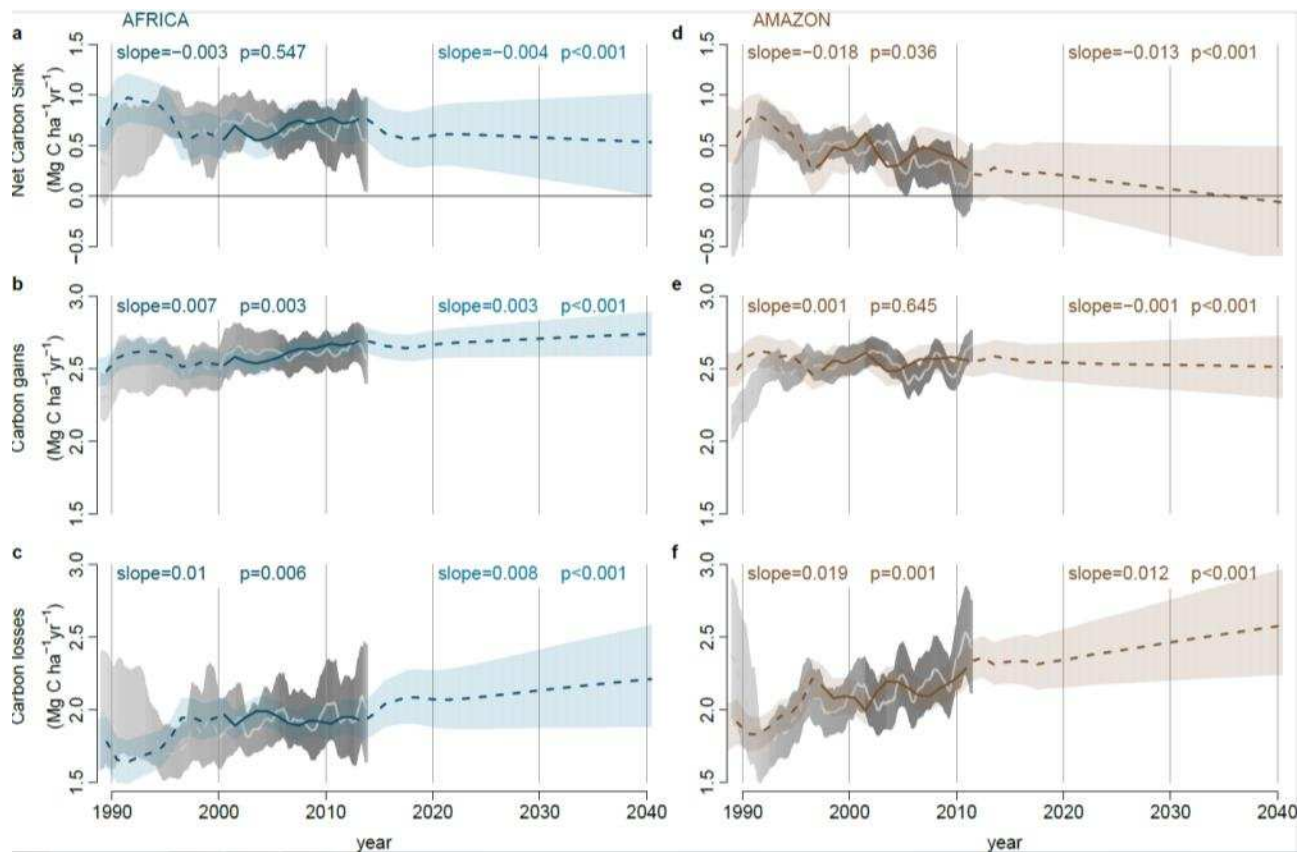
698 Africa and Amazon dataset (see Methods). Slopes and p-values are from the same linear mixed

699 effects models. Carbon loss data and models are presented untransformed for comparison with

700 carbon gains, but transformation is needed to fit normality assumptions; linear mixed effects models

701 on transformed carbon loss data does not change the significance of the results, nor does including

702 all three parameters and transformed data in a model (see Extended Data Table 1).



703

704

Figure 3. Modelled past and future carbon dynamics of structurally intact tropical forests in

705

Africa and Amazonia. Predictions of net aboveground live biomass carbon sink (a,d), carbon gains

706

(b,e), and carbon losses (c,f), for African (left panels) and Amazonian (right panels) plot inventory

707

networks, based on CO₂-change, Mean Annual Temperature, Mean Annual Temperature-change,

708

drought (as Maximum Climatological Water Deficit), plot wood density, and plot carbon residence

709

time, using observations in Africa until 2014 and Amazonia until 2011.5, and extrapolations of prior

710

trends to 2040. Model predictions are in blue (Africa) and brown (Amazon), with solid lines

711

spanning the window when $\geq 75\%$ of plots were monitored to show model consistency with the

712

observed trends, and shading showing upper and lower confidence intervals accounting for

713

uncertainties in the model (both fixed and random effects) and uncertainties in the predictor

714

variables. Light grey lines and grey shading are the mean and 95% CI of the observations from the

715

African and Amazonian plot networks.

716 **Main Tables**

717

718 **Table 1. Carbon sink in intact forests in Africa, Amazonia and the pan-tropics: 1980-2015 and**719 **predictions to 2040.** Mean values in bold, future predictions in italics, uncertainty in parentheses,720 95% bootstrapped confidence intervals for 1980-2015, and 2 σ for the predictions (2010-2040).

Period	No. plots		Per unit area aboveground live biomass C sink				Total C sink *		
			(Mg C ha ⁻¹ yr ⁻¹)				(Pg C yr ⁻¹)		
			Af. Am.	Africa	Amazon	Pan-tropics†	Africa	Amazon	Pan-tropics†
1980-1990	45	73	0.33 (0.06-0.63)	0.35 (0.06-0.59)	0.35 (0.07-0.62)	0.28 (0.05-0.53)	0.49 (0.08-0.82)	0.87 (0.16-1.52)	
1990-2000	96	172	0.67 (0.43-0.89)	0.53 (0.42-0.65)	0.57 (0.39-0.74)	0.50 (0.32-0.66)	0.68 (0.54-0.83)	1.26 (0.88-1.63)	
2000-2010	194	291	0.70 (0.55-0.84)	0.38 (0.26-0.48)	0.50 (0.35-0.64)	0.46 (0.37-0.56)	0.45 (0.31-0.57)	0.99 (0.70-1.25)	
2010-2015	184	172	0.66 (0.40-0.91)	0.24 (0.00-0.47)	0.40 (0.15-0.65)	0.40 (0.24-0.56)	0.27 (0.00-0.52)	0.73 (0.25-1.18)	
2010-2020 ‡	-	-	0.63 (0.36-0.89)	0.23 (-0.05-0.50)	0.38 (0.11-0.65)	0.37 (0.21-0.53)	0.25 (-0.05-0.54)	0.68 (0.17-1.16)	
2020-2030 ‡	-	-	0.59 (0.24-0.93)	0.12 (-0.29-0.51)	0.30 (-0.08-0.67)	0.31 (0.13-0.49)	0.12 (-0.29-0.52)	0.47 (-0.15-1.07)	
2030-2040 ‡	-	-	0.55 (0.08-0.99)	0.00 (-0.54-0.49)	0.21 (-0.29-0.67)	0.26 (0.04-0.47)	0.00 (-0.50-0.46)	0.29 (-0.46-0.97)	

721 * Total Continental C sink is the per unit area aboveground C sink multiplied by intact forest area for
722 1990-2010 (from ref.¹, see Extended Data Table 2) and continent specific extrapolations to 2040.
723 Total Continental C sink includes continent-specific estimates of trees <100 mm DBH, lianas and
724 roots (see Methods).

725 † Pan-tropical aboveground live biomass C sink is the area-weighted mean of African, Amazonian
726 and Southeast Asian sink values. Southeast Asian values were from published per unit area carbon
727 sink data¹⁵ (n=49 plots) for 1990-2015, with 1980-1990 assumed to be the same as 1990-2000 due
728 very low sample sizes. Pan-tropical total C sink is the sum of African, Amazonian and Southeast
729 Asian total continental carbon sink values. The continental sink in Southeast Asia is a modest and
730 declining contribution to the pan-tropical sink, due to the very small area of intact forest remaining,
731 at 0.11, 0.08, 0.07 and 0.06 Pg C yr⁻¹ in the 1980s, 1990s, 2000s and 2010s, hence uncertainty in the
732 Southeast Asian sink cannot reverse the pan-tropical declining sink trend.

733 ‡ Per unit area total C sink for 2010-2020, 2020-2030 and 2030-2040 was predicted using parameters
734 from Table 2, except for the 2010-2020 sink in Africa which is the mean of the measured sink from
735 2010-2015 and the modelled sink from 2015-2020. For the Asian sink we assumed the parameters as
736 for Africa, as Asian forest median CRT is 61 years, close to African median, 63 years.

737

738 **Table 2. Minimum adequate models to predict carbon gains and losses in African and**
 739 **Amazonian tropical forests. These are the best ranked gains and loss models.** Where continental
 740 values differ, those for Africa are reported first, followed by Amazonian values.

Carbon gains, Mg C ha ⁻¹ yr ⁻¹					
Predictor variable	Parameter value	Standard Error	t-value	p-value	2000-2015 change in gains (%) *
(Intercept)	5.255 5.395	0.603 0.614	8.7 8.8	<0.001	-
CO ₂ -change (ppm yr ⁻¹) †	0.238	0.096	2.5	0.013	3.69% 3.71%
MAT (°C)	-0.083	0.025	-3.3	0.001	-0.67% -1.07%
MAT-change (°C yr ⁻¹) ‡	-1.243	0.233	-5.3	<0.001	0.58% 0.00% §
MCWD (mm x1000)	-0.405 -1.391	0.381 0.24	-1.1 -5.8	0.289 <0.001	-0.52% -2.73%
WD (g cm ⁻³)	-1.295	0.530	-2.4	0.015	0.05% 0.00%
Carbon losses, Mg C ha ⁻¹ yr ⁻¹					
Predictor variable	Parameter value	Standard Error	t-value	p-value	2000-2015 change in losses (%) *
(Intercept)	1.216	0.086	14.1	<0.001	-
CO ₂ -change (ppm yr ⁻¹) †	0.130	0.059	2.2	0.026	11.38% 14.81%
MAT-change (°C yr ⁻¹)	0.766	0.162	4.7	<0.001	-1.56% 0.00%
MCWD (mm x10000) ‡	-0.232	0.107	-2.2	0.030	-1.21% -2.42%
CRT (yr)	-0.003	0.001	-6.1	<0.001	-0.57% 1.39%

741 * The 2000-2015 change in gains/losses for each predictor variable was estimated allowing only the
 742 focal predictor to vary; this change was then expressed as a percentage of the annual gains/losses in
 743 the year 2000 allowing all predictors to vary.

744 † Change over the past 56 years.

745 ‡ Change over the past 5 years.

746 § A positive value for Africa indicates that MAT increased more slowly over 2000-2015 compared
 747 to the mean increase over 1983-2015, therefore contributing to an increase in gains; a zero value for
 748 Amazonia indicates that the rate of MAT increase was the same over 2000-2015 as the mean
 749 increase over 1983-2015.

750 || Carbon loss values were normalized via power-law transformation, $\lambda = 0.361$.

751

752 **Online Methods**

753

754 **Plot Selection**

755 Closed canopy (i.e. not woody savanna) old-growth mixed-age forest inventory plots were selected
756 using commonly used criteria^{6,13,27}: free of fire and industrial logging; all trees with diameter at
757 reference height ≥ 100 mm measured at least twice; ≥ 0.2 ha area; < 1500 m.a.s.l. altitude; MAT
758 $\geq 20.0^\circ\text{C}^{51}$; annual precipitation ≥ 1000 mm⁵¹; located ≥ 50 m from anthropogenic forest edges. Of the
759 244 plots included in the study, 217 contribute to the African Tropical Rainforest Observatory
760 Network (AfriTRON; www.afritron.org), with data curated at www.ForestPlots.net^{52,53}. These
761 include plots from Sierra Leone, Liberia, Ghana, Nigeria, Cameroon, Gabon, Republic of Congo,
762 Democratic Republic of Congo (DRC), Uganda and Tanzania^{52,53} (Extended Data Figure 1). Fifteen
763 plots are part of the TEAM network, from Cameroon, Republic of Congo, Tanzania, and Uganda⁵⁴⁻
764 ⁵⁷. Nine plots contribute to the ForestGEO network, from Cameroon and DRC⁵⁸ (9 plots from DRC,
765 codes SNG, contribute to both AfriTRON and ForestGEO networks, included above in the
766 AfriTRON total). Finally, three plots from Central African Republic are part of the CIRAD
767 network^{59,60}. The large majority of plots are sited in terra firme forests and have mixed species
768 composition, although four are in seasonally flooded forest and 14 plots are in *Gilbertiodendron*
769 *dewevrei* monodominant forest, a locally common forest type in Africa (Supplementary Table 1).
770 The 244 plots have a mean size of 1.1 ha (median, 1 ha), with a total plot area of 277.9 ha. The
771 dataset comprises 391,968 diameter measurements on 135,625 stems, of which 89.9% were
772 identified to species, 97.5% to genus and 97.8% to family. Mean total monitoring period is 11.8
773 years, mean census length 5.7 years, with a total of 3,214 ha years of monitoring. The 321 Amazon
774 plots are published and were selected using the same criteria⁶, except in the African selection criteria
775 we specified a minimum anthropogenic edge distance and added a minimum temperature threshold.

776

777 **Plot Inventory and Tree Biomass Carbon Estimation**

778 Tree-level aboveground biomass carbon is estimated using an allometric equation with parameters
779 for tree diameter, tree height and wood mass density⁶¹. The calculation of each is discussed in turn.
780 All calculations were performed using the R statistical platform, version 3.2.1 (ref.⁶²) using the
781 BiomasaFP R package, version 0.2.1 (ref.⁶³).

782

783 Tree Diameter: In all plots, all woody stems with ≥ 100 mm diameter at 1.3 m from the base of the
784 stem ('diameter at breast height', DBH), or 0.5 m above deformities or buttresses, were measured,
785 mapped and identified using standard forest inventory methods^{64,65}. The height of the point of
786 measurement (POM) was marked on the trees and recorded, so that the same POM is used at the
787 subsequent forest census. For stems developing deformities or buttresses over time that could
788 potentially disturb the initial POM, the POM was raised approximately 500 mm above the deformity.
789 Estimates of the diameter growth of trees with changed POM used the ratio of new and old POMs, to
790 create a single trajectory of growth from the series of diameters at two POM heights^{6,13,65}. We used
791 standardised protocols to assess typographical errors and potentially erroneous diameter values (e.g.
792 trees shrinking by >5 mm), missing values, failures to find the original POM, and other issues.
793 Where necessary we estimated the likely value via interpolation or extrapolation from other
794 measurements of that tree, or when this was not possible we used the median growth rate of trees in
795 the same plot, census and size-class, defined as DBH = 100-199 mm, or 200-399 mm, or >400 mm⁶⁵.
796 We interpolated measurements for 1.3% of diameters, extrapolated 0.9%, and used median growth
797 rates for 1.5%.

798

799 Tree height: Height of individuals from ground to the top leaf, hereafter H_i , was measured in 204
800 plots, using a laser hypsometer (Nikon forestry Pro) from directly below the crown (most plots), a
801 laser or ultrasonic distance device with an electronic tilt sensor, a manual clinometer, or by direct

802 measurement, i.e. tree climbing. Only trees where the top was visible were selected⁶⁶. In most plots,
803 tree selection was similar: the 10 largest trees were measured, together with 10 randomly selected
804 trees per diameter from five classes: 100-199 mm, 200-299 mm, 300-399 mm, 400-499 mm, and
805 500+ mm trees, following standard protocols⁶⁶. We measured actual height of 24,270 individual trees
806 from 204 plots. We used these data and the local.heights function in R package BiomasaFP⁶³ to fit 3-
807 parameter Weibull relationships: $H_t = a \times (1 - e^{(-b \times (DBH/10)^c)})$ (equation 1). We chose the Weibull
808 model as it is known to be robust when a large number of measurements are available^{66,67}. We
809 parameterised separate H_t -DBH relationship for four different combinations of edaphic forest type
810 and biogeographical region: (i) terra firme forest in West Africa, (ii) terra firme forest in Lower
811 Guinea and Western Congo Basin, (iii) terra firme forest in Eastern Congo Basin and East Africa,
812 (iv) seasonally flooded forest from Lower Guinea and Western Congo Basin (there were no
813 seasonally flooded forest plots in the other biogeographical regions). The parameters are: (i) terra
814 firme forest in West Africa, $a=56.0$; $b=0.0401$; $c=0.744$; (ii) terra firme forest in Lower Guinea and
815 Western Congo Basin, $a=47.6$; $b=0.0536$; $c=0.755$; (iii) terra firme forest in Eastern Congo Basin
816 and East Africa, $a=50.8$; $b=0.0499$; $c=0.706$; and finally (iv) seasonally flooded forest from Lower
817 Guinea and Western Congo Basin, $a=38.2$; $b=0.0605$; $c=0.760$. For each of these combinations of
818 forest type and bioregion, the local.heights function combines all height measurements from all plots
819 belonging to that forest type/bioregion and fits the Weibull model parameters using non-linear least
820 squares (nls function in R with default settings), with starting values of $a = 25$, $b = 0.05$ and $c = 0.7$
821 chosen as they led to regular model convergence. We fitted these models either treating each
822 observation equally or with case weights proportional to each trees' basal area. These weights give
823 more importance to large trees during model fitting. We selected the best fitting of these models,
824 determining this as the model that minimised prediction error of stand biomass when calculated with
825 estimated heights or observed heights. The parameters were used to estimate H_t from DBH for all
826 tree DBH measurements for input into the allometric equation. Mean measured individual total tree

827 height is 20.5 m; the height range is 1.5 to 72.5 m. The root mean squared error (RMSE) between the
828 full dataset of measured heights and the predicted heights, is 5.7 m, which is 8.0% of the total range.
829 Furthermore, RMSE is 5.3 m in terra firme forest in West Africa (7.5% of the range; n=9771 trees);
830 RMSE is 6.4 m in terra firme forest in Lower Guinea and Western Congo Basin (8.7% of the range;
831 n=10,838 trees); RMSE is 4.8 m in terra firme forest in Eastern Congo Basin and East Africa (8.8%
832 of the range; n=3269 trees); and RMSE is 4.1 m in seasonally flooded forest from Lower Guinea and
833 Western Congo Basin (12.5% of the range; n=392 trees).

834

835 Wood Density: Dry wood density (ρ) measurements were compiled for 730 African species from
836 published sources and stored in www.ForestPlots.net; most were sourced from the Global Wood
837 Density Database on the Dryad digital repository (www.datadryad.org)^{68,69}. Each individual in the
838 tree inventory database was matched to a species-specific mean wood density value. Species in both
839 the tree inventory and wood density databases were standardized for orthography and synonymy
840 using the African Plants Database (www.ville-ge.ch/cjb/bd/africa/) to maximize matches¹³. For
841 incompletely identified individuals or for individuals belonging to species not in the ρ database, we
842 used the mean ρ value for the next higher known taxonomic category (genus or family, as
843 appropriate). For unidentified individuals, we used the mean wood density value of all individual
844 trees in the plot^{13,52}.

845

846 Allometric equation: For each tree we used a published allometric equation⁶¹ to estimate
847 aboveground biomass. We then converted this to carbon, assuming that aboveground carbon (AGC)
848 is 45.6% of aboveground biomass⁷⁰. Thus: $AGC=0.456 \times (0.0673 \times (\rho \times (DBH/10)^2 \times H_t)^{0.976}) / 1000$
849 (equation 2), with DBH in mm, dry wood density, ρ , in $g\ cm^{-3}$, and total tree height, H_t , in m (ref.⁶¹).

850

851 Aboveground Carbon (AGC, in Mg C ha⁻¹) in living biomass for each plot at each census date was
852 estimated as the sum of the AGC of each living stem, divided by plot area (in hectares).

853

854 **Carbon Gain and Carbon Loss estimation**

855 Net Carbon Sink (in Mg C ha⁻¹ yr⁻¹) is estimated as carbon gains minus carbon losses. Calculation
856 details are explained below.

857

858 Carbon Gains (in Mg C ha⁻¹ yr⁻¹) are the sum of the aboveground live biomass carbon additions from
859 the growth of surviving stems and the addition of newly recruited stems, divided by the census
860 length (in years) and plot area (in hectares). For each stem that survived a census interval, carbon
861 additions from its growth (Mg C ha⁻¹ yr⁻¹) were calculated as the difference between its AGC at the
862 end census of the interval and its AGC at the beginning census of the interval. For each stem that
863 recruited during the census interval (i.e. reaching DBH \geq 100 mm), carbon additions were calculated
864 in the same way, assuming DBH=0 mm at the start of the interval⁶⁵. Carbon Losses (in Mg C ha⁻¹ yr⁻¹)
865 are estimated as the sum of aboveground biomass carbon from all stems that died during a census
866 interval, divided by the census length (in years) and plot area (in hectares). Both carbon gains and
867 carbon losses are calculated using standard methods⁶, including a census interval bias correction,
868 using the SummaryAGWP function of R-package BiomasaFP^{63,64,68}.

869

870 As carbon gains are affected by a census interval bias, with the underestimate increasing with census
871 length, we corrected this bias by accounting for (i) the carbon additions from trees that grew before
872 they died within an interval (unobserved growth) and (ii) the carbon additions from trees that
873 recruited and then died within the same interval (unobserved recruitment)^{65,71}.

874

875 Component (i), the unobserved growth of a stem that died during a census interval, is estimated as
876 the difference between AGC at death and AGC at the start of the census. These are calculated using
877 equation 2, from respectively DBH_{death} and DBH_{start} . The latter is part of the data, the first can be
878 estimated as: $DBH_{\text{death}} = DBH_{\text{start}} \times G \times Y_{\text{mean}}$, where G is the plot-level median diameter growth rate
879 (mm yr^{-1}) of the size class the tree was in at the start of the census interval (size classes are defined
880 as $D < 200 \text{ mm}$, $200 \text{ mm} < D \leq 400 \text{ mm}$ and $D > 400 \text{ mm}$) and Y_{mean} is the mean number of years
881 trees survived in the census interval before dying. Y_{mean} is calculated from the number of trees that
882 are expected to have died in each year of the census interval, which is derived from the plot-level
883 per-capita mortality rate (m_a ; % dead trees yr^{-1}) calculated following equation 5 in ref.⁷¹.

884

885 Component (ii), growth of recruits that were not observed because they died during the census
886 interval, is estimated by calculating the number of unobserved recruits and diameter at death for each
887 unobserved recruit. The number of unobserved recruits ($\text{stems ha}^{-1} \text{yr}^{-1}$) is estimated as: $N_{\text{u,r}} = R_a -$
888 $P_{\text{surv}} \times R_a$, where R_a ($\text{recruited stems ha}^{-1} \text{yr}^{-1}$) is the per area annual recruitment calculated following
889 equation 11 in ref.⁷¹ and P_{surv} is the probability of each recruit surviving until the next census: $P_{\text{surv}} =$
890 $(1 - m_a)^T$, where T is the number of years remaining in the census interval. Summing $N_{\text{u,r}}$ for each year
891 in a census interval gives the total number of unobserved recruits in that census interval. We then
892 estimate diameter at death for each unobserved recruit, which is given in mm by $DBH_{\text{death,u,r}} = 100 +$
893 $(G_s \times Y_{\text{mean-rec}})$, where G_s is the plot-level median diameter growth rate (mm yr^{-1}) of the smallest size
894 class (i.e. $D < 200 \text{ mm}$) and $Y_{\text{mean-rec}}$ is the mean life-span of unobserved recruits calculated as the
895 mean life-span of recruits in a given year, weighted by $N_{\text{u,r}}$. The mean life-span of recruits in a given
896 year is calculated from the number of recruits that died in that year, which is derived from the plot-
897 level per-capita mortality rate (m_a ; % dead trees yr^{-1}). Growth of each unobserved recruit (mm yr^{-1}) is
898 then calculated as $DBH_{\text{death,u,r}}$ divided by $Y_{\text{mean-rec}}$.

899

900 The census interval bias correction (components i and ii together) typically add <3% to plot-level
901 carbon gains. Carbon Losses are affected by the same census interval bias, hence we corrected this
902 bias by accounting for (i) the additional carbon losses from the trees that were recruited and then
903 died within the same interval, and (ii) the additional carbon losses resulting from the growth of the
904 trees that died in the interval^{6,15,63}. These two components are calculated in the same way as for
905 Carbon gains and typically add <3% to plot-level carbon losses.

906

907 Carbon gains include both gains from the growth of surviving stems and new recruits. Separating
908 carbon gains from tree growth of surviving stems and newly recruited stems, shows that carbon gains
909 from recruitment are small overall, and are significantly lower in Africa than in the Amazon, likely
910 due to the lower stem turnover rates and longer carbon residence time (Africa: 0.17 Mg C ha⁻¹ yr⁻¹;
911 CI: 0.16-0.18 versus Amazon: 0.27 Mg C ha⁻¹ yr⁻¹; CI: 0.25-0.28, p<0.001; two-way Wilcoxon test),
912 but this is compensated by carbon gains from survivors being significantly larger in Africa (2.33 Mg
913 C ha⁻¹ yr⁻¹; CI: 2.27-2.39) than in the Amazon (2.13 Mg C ha⁻¹ yr⁻¹; CI: 2.09-2.17, p=0.014).
914 Therefore, gains overall (sum of gains from surviving stems and newly recruited stems) are
915 indistinguishable between the continents (Africa: 2.57 Mg C ha⁻¹ yr⁻¹; CI: 2.51-2.67 vs Amazon: 2.46
916 Mg C ha⁻¹ yr⁻¹; CI: 2.41-2.50, p=0.460; two-way Wilcoxon test).

917

918 **Long-term Gain, Loss and Net Carbon Sink Trend Estimation, 1983-2014**

919 The estimated mean and uncertainty in carbon gains, carbon losses and the net carbon sink of the
920 African plots from 1983-2014 (Figure 1, Extended Data Figure 7 and Extended Data Figure 8) were
921 calculated following ref.⁶ to allow direct comparison with published Amazonian results. First, each
922 census interval value was interpolated for each 0.1-yr period within the census interval. Then, for
923 each 0.1-yr period between 1983 and 2014, we calculated a weighted mean of all plots monitored at

924 that time, using the square root of plot area as a weighting factor⁶. Confidence intervals for each 0.1-
925 yr period were bootstrapped.

926

927 Trends in carbon gains, losses and the net carbon sink over time were assessed using linear mixed
928 effects models (lmer function in R, lme4 package⁷²), providing the linear slopes reported in Figure 1.

929 These models regress the mid-point of each census interval against the value of the response variable

930 for that census interval. Plot identity was included as a random effect, i.e. assuming that the intercept

931 can vary randomly among plots. We did not include slope as a random effect, consistent with

932 previously published Amazon analyses⁶, because models did not converge due to some plots having

933 too few census intervals. Observations were weighted by plot size and census interval length.

934 Weightings were derived empirically, by assuming a priori that there is no significant relation

935 between the net carbon sink and census interval length or plot size, following ref.¹³. The following

936 weighting removes all pattern in the residuals: $\text{Weight} = \sqrt[3]{\text{length}_{\text{int}}} + \sqrt[4]{\text{plotsize}} - 1$ (equation 3),

937 where $\text{length}_{\text{int}}$ is the length of the census interval, in years. Significance was assessed by regressing

938 the residuals of the net carbon sink model against the weights (p=0.702).

939

940 Differences in long-term slopes between the two continents for carbon gains, carbon losses and net

941 carbon sink, reported in the main text, were also assessed using linear mixed effects models, as

942 described above, but performed on the combined African and Amazonian datasets and limited to

943 their common time window, 1983 to 2011.5. For these three tests on the pooled data we included an

944 additional interaction term between census interval date and continent, where a significant

945 interaction would indicate that the slopes differ between continents. The statistical significance of

946 continental differences in slope were assessed using the F-statistic (Anova function in R, car

947 package⁷³). Shortening the common time window to the 20 years when the continents are best-

948 sampled, 1991.5 to 2011.5, gave very similar results, including a divergent continental sink (p=0.04).

949

950 **Continental and Pan-Tropical Carbon Sink Estimates**

951 The per unit area total net carbon sink (in $\text{Mg C ha}^{-1} \text{ yr}^{-1}$) for each time period in Table 1 (each
952 decade between 1980 and 2010; and 2010-2015) is the sum of three components. The first
953 component is the per unit area aboveground carbon sink from living trees and lianas with $\text{DBH} \geq 100$
954 mm. For Africa we use the per unit area net carbon sink values presented in this paper. For
955 Amazonia, we use data in ref.⁶. For Southeast Asia, we use inventory data collected using similar
956 standardised methods from 49 plots in ref.¹⁵. For each time window, we use all plots for which
957 census dates overlap the period, weighted by the square root of plot area, as for the solid lines in
958 Figure 1. The second component is the per unit area aboveground carbon sink from living trees and
959 lianas with $\text{DBH} < 100$ mm. This is calculated as 5.19%, 9.40% and 5.46% of the first component (i.e.
960 aboveground carbon of large living trees) in Africa, Amazonia and Southeast Asia respectively^{13,74}.
961 The third component is the per unit area belowground carbon sink in live biomass, i.e. roots. This is
962 calculated as 25%, 37% and 17% of the aboveground carbon of living trees with $\text{DBH} \geq 100$ mm in
963 Africa¹³, Amazonia⁶ and Southeast Asia⁷⁵ respectively.

964

965 For each time period in Table 1 we calculated the continental-scale total carbon sink (Pg C yr^{-1}) by
966 multiplying the per unit area total net carbon sink described above by the area of intact forest on each
967 continent at that time interval (in ha) reported in Extended Data Table 2. Decades are calculated from
968 1990.01 to 1999.99. For comparability with previous continental-sink results, we used continental
969 values of intact forest area for 1990, 2000 and 2010 as published in ref.¹, i.e. total forest area minus
970 forest regrowth. We used the 1990-2010 data to fit an exponential model for each continent and used
971 this model to estimate intact forest area for 1980 and 2015.

972

973 Finally, in the main text we calculated the proportion of anthropogenic CO_2 emissions removed by Earth's
974 intact tropical forests, as the total pan-tropical carbon sink from Table 1 divided by the total anthropogenic

975 CO₂ emissions. Total anthropogenic CO₂ emissions are calculated as the sum of emissions from fossil fuel and
976 land-use change and are estimated at 7.6 Pg C yr⁻¹ in the 1990s, 9.0 Pg C yr⁻¹ in the 2000s, and 11.1 Pg C yr⁻¹
977 in the 2010s (ref.²¹, assuming 1.7% growth in fossil fuel emissions in 2018 and 2019, and mean 2010-2017
978 land-use change emissions for 2018 and 2019).

979

980 **Carbon Sink from an Atmospheric Perspective**

981 To estimate the evolution of the carbon sink from an atmospheric perspective, we assumed that the
982 contribution to the atmosphere from carbon gains are experienced immediately, while the
983 contribution to the atmosphere from carbon losses must take into account the delay in decomposition
984 of dead trees. We did this by calculating total forest carbon loss (Mg C ha⁻¹ yr⁻¹) for each year
985 between 1950-2015, using the mean 1983-2015 records from Figure 1 and assuming constant losses
986 prior to 1983 (1.9 and 1.5 Mg C ha⁻¹ yr⁻¹ for Africa and Amazonia respectively). Then, for each focal
987 year between 1950-2015, we calculated how much carbon was released to the atmosphere in the
988 subsequent years as: $y_t = x_0 \times e^{-0.17 \times (t-1)} - x_0 \times e^{-0.17 \times t}$, where x_0 is the total forest carbon loss of the
989 focal year; y_t is the carbon released to the atmosphere at t years from the focal year; and -0.17 yr⁻¹ is
990 a constant decomposition rate calculated for tropical forests in the Amazon⁴⁵. For example, carbon
991 loss was 1.95 Mg C ha⁻¹ in 1990 in African forests (Figure 1), from which 0.31 Mg C ha⁻¹ was
992 released to the atmosphere in 1991; 0.26 Mg C ha⁻¹ in 1992; 0.22 Mg C ha⁻¹ in 1993; 0.07 Mg C ha⁻¹
993 in 2000 and 0.01 Mg C ha⁻¹ in 2010. Hence, of the full 1.95 Mg C ha⁻¹ dead tree biomass from 1990,
994 ~50% was released to the atmosphere after 4 yrs, ~85% after 10 yrs, and ~97% after 20 years.
995 Finally, for each year between 1983 and 2015, the total contribution to the atmosphere from carbon
996 losses was calculated as the sum of all carbon contributions released at that year, from all total yearly
997 forest carbon loss pools of the previous years. We then calculated decadal-scale mean contributions
998 to the atmosphere from carbon losses, reported in the main text.

999

1000 **Predictor Variable Estimates, 1983-2014**

1001 For each census interval of each plot, we examined potential predictor variables that may explain the
1002 long-term trends in carbon gains and carbon losses, reported in Extended Data Table 1 and main text
1003 Table 2. First, the environmental conditions during the census interval; second the rate of change of
1004 these parameters; and third forest attributes that may affect how different forests respond to the same
1005 environmental change. The predictor variable estimates for each census need to avoid bias due to
1006 seasonal variation, for example the intra-annual variability in atmospheric CO₂ concentration. We
1007 therefore applied the following procedure to avoid seasonal variability impacts on long-term trends:
1008 (i) the length of each focal census interval was rounded to the nearest complete year (e.g. a 1.1 year
1009 interval became a 1 year interval); (ii) we computed dates that minimised the difference between
1010 actual fieldwork dates and complete-year census dates, while ensuring that subsequent census
1011 intervals of a plot do not overlap. The resulting sequence of non-overlapping census intervals was
1012 used to calculate interval-specific means for each environmental predictor variable to remove
1013 seasonal effects. The mean difference between the actual fieldwork dates and the complete-year
1014 census dates is 0.01 decimal years.

1015

1016 The first group of potential predictor variables, estimated for each census interval of each plot, are
1017 theory-driven choices: atmospheric CO₂ concentration (CO₂), mean annual temperature (MAT), and
1018 drought intensity, which we quantified as maximum climatological water deficit (MCWD)^{14,20,76,77}.

1019

1020 Atmospheric CO₂ concentration (CO₂, in ppm) is estimated as the mean of the monthly mean values
1021 from the Mauna Loa record⁷⁸ over the census interval. While atmospheric CO₂ concentration is
1022 highly correlated with time ($R^2=0.98$), carbon gains are slightly better correlated with CO₂
1023 ($R_{adj}^2=0.0027$) than with time ($R_{adj}^2=0.0025$).

1024

1025 Mean Annual Temperature (MAT, in °C) was derived from the temporally resolved (1901-2015)
1026 dataset of monthly mean temperature from the Climatic Research Unit (CRU TS version 4.03; ~3025
1027 km² resolution; released 15 May 2019; <https://crudata.uea.ac.uk/cru/data/hrg/>)⁷⁹. We downscaled the
1028 data to ~1 km² resolution using the WorldClim dataset^{51,80}, by subtracting the difference in mean
1029 monthly temperature, and applying this monthly correction to all months⁸¹. We then calculated MAT
1030 for each census interval of each plot using the downscaled monthly CRU record.

1031

1032 Maximum Climatological Water Deficit (MCWD, in mm) was derived from the ~3025 km²
1033 resolution Global Precipitation Climatology Centre dataset (GPCC version 6.0) that includes many
1034 more rain gauges than CRU in tropical Africa^{82,83}. As GPCC ends in 2013 we combined it with
1035 satellite-based Tropical Rainfall Measurement Mission data (TRMM 3B43 V7 product, ~757 km²
1036 resolution)⁸⁴. The fit for the overlapping time period (1998-2013) was used to correct the systematic
1037 difference between GPCC and TRMM: $GPCC' = a + b * GPCC$, with GPCC' the adjusted GPCC
1038 record and a and b different parameters for each month of the year and for each continent.
1039 Precipitation was then downscaled to ~1 km² resolution using the WorldClim dataset^{51,80}, by dividing
1040 by the ratio in mean monthly rainfall, and applying this monthly correction to all months⁸¹. For each
1041 census interval we extracted monthly precipitation values and estimated evapotranspiration (ET) to
1042 calculate monthly Climatological Water Deficit (CWD), a commonly used metric of dry season
1043 intensity for tropical forests^{14,76,77}. Monthly CWD values were calculated for each subsequent series
1044 of 12 months (complete years)⁷⁷. Monthly CWD estimation begins with the wettest month of the first
1045 year in the interval, and is calculated as 100 mm per month evapotranspiration (ET) minus monthly
1046 precipitation (P). Then, CWD values for the subsequent 11 months were calculated recursively as:
1047 $CWD_i = ET - P_i + CWD_{i-1}$, where negative CWD_i values were set to zero⁷⁷ (no drought conditions).
1048 This procedure was repeated for each subsequent complete 12 months. We then calculated the annual
1049 MCWD as the largest monthly CWD value for every complete year within the census interval, with

1050 the MCWD of a census interval being the mean of the annual MCWD values within the census
1051 interval. Larger MCWD indicates more severe water deficits.

1052

1053 We assume ET is 100 mm month⁻¹ on both continents, based on measurements from Amazonia^{76,77},
1054 more limited measurements from West Africa summarized in ref.⁸⁵, predictive skill⁸⁶, and use in past
1055 studies on both continents^{14,87}. MCWD therefore represents a precipitation-driven dry season deficit,
1056 as ET remains constant. An alternative assessment, using a data-driven ET product^{88,89}, gave a mean
1057 ET of 95 and 98 mm month⁻¹ for the African and Amazonian plot networks respectively. Using these
1058 values did not affect the results.

1059

1060 To calculate the environmental change of potential predictor variables, CO₂-change (in ppm yr⁻¹),
1061 MAT-change (in °C yr⁻¹) and MCWD-change (in mm yr⁻¹), we selected an optimum period over
1062 which to calculate the change, derived empirically by assessing the correlation of carbon gains (all
1063 plots, all censuses) with the change in each environmental variable, using linear mixed effects
1064 models (lmer function in R, lme4 package⁷²). The annualised change in the environmental variable
1065 was calculated as the change between the focal interval and a prior interval (termed the baseline
1066 period) with a lengthening time window ranging from 1 year through to 80 years prior to the focal
1067 interval (i.e. 80 linear mixed effects models per variable). We calculated AIC for each model and
1068 selected the interval length with the lowest AIC. Thus, MAT-change (in °C yr⁻¹) = (MAT_i-
1069 MAT_b)/(date_i-date_b), where MAT_i is the MAT over the focal census interval calculated using the
1070 procedure described above, MAT_b is the MAT over a baseline period prior to the focal interval, date_i
1071 is the mid-date of the focal census interval and date_b is the mid-date of the baseline period. The lmer
1072 results show that the baseline period for MAT-change is 5 years and for CO₂-change it is 56 years,
1073 while MCWD showed no clear trend, so MCWD-change was not included in the models (see
1074 Extended Data Figure 3). All three results conform to a priori theoretical expectations. For CO₂ a

1075 maximum response to an integrated 56 years of change is expected because forest stands will
1076 respond most strongly to CO₂ when most individuals have grown under the new rapidly changing
1077 condition, which should be at its maximum at a time approximately equivalent to the carbon
1078 residence time of a forest stand^{30,90} (mean of 62 years in this dataset). For MAT, 5 years is consistent
1079 with experiments showing temperature acclimation of leaf- and plant-level photosynthetic and
1080 respiration processes over half-decadal timescales^{31,91}. MCWD has no overall trend suggesting that
1081 once a drought ends, its impact on tree growth fades rapidly, as seen in other studies^{14,92}. Also in the
1082 moist tropics wet-season rainfall is expected to re-charge soil water, hence lagged impacts of
1083 droughts are not expected.

1084

1085 We calculated estimates of two forest attributes that may alter responses to environmental change as
1086 potential predictor variables: Wood Density (WD) and Carbon Residence Time (CRT). In intact old-
1087 growth forests, mean WD (in g cm⁻³) is inversely related to resource availability^{28,93,94}, as is seen in
1088 our dataset (carbon gains and plot-level mean WD are negatively correlated, Extended Data Figure
1089 4). WD is calculated for each census interval in the dataset, as the mean WD of all trees alive at the
1090 end of the census interval, to be consistent with the previous Amazon analysis⁶. Carbon residence
1091 time (CRT, in yrs) is a measure of the time that fixed carbon stays in the system. CRT is a potential
1092 correlate of the impact of past carbon gains on later carbon losses³⁰. To avoid circularity in the
1093 models, the equation used to calculate CRT differed depending on the response variable. If the
1094 response variable is carbon loss, the CRT equation is based on gains: $CRT = AGC / \text{gains}$, with AGC
1095 for each interval based on AGC at the end of the interval, and the gains for each interval calculated
1096 as the mean of the gains in the interval and the previous intervals (i.e. long-term gains). If the
1097 response variable is carbon gains, the CRT equation is based on losses: $CRT = AGC / \text{losses}$. The
1098 equation employed for use in the carbon loss model (based on gains) is the standard formula used to
1099 calculate CRT and is retained in the minimum adequate model (see below and Table 2). The non-

1100 standard CRT equation (based on losses) used in the carbon gain model is not retained in the
1101 minimum adequate model (see below).

1102 1103 **Statistical modelling of the Carbon Gain, Loss and Sink Trends**

1104 We first constructed two models including those environmental drivers exhibiting long-term change
1105 that impact theory-driven models of photosynthesis and respiration as predictor variables: CO₂,
1106 MAT, and MCWD. One model had carbon gains as the response variable, the other had carbon
1107 losses as the response variable (both in Mg C ha⁻¹ yr⁻¹). Models were fitted using the lme function in
1108 R, with maximum likelihood (NLME package⁹⁵). All census intervals within all plots were used,
1109 weighted by plot size and census length (using equation 3 above). Plot identity was included as a
1110 random effect, i.e. assuming that the intercept can vary randomly among plots. All predictor
1111 variables in the models were scaled without centering (scale function in R, RASTER package⁶²).
1112 Carbon gain values were normally distributed but carbon loss values required a power-law
1113 transformation ($\lambda=0.361$) to meet normality criteria. Multi-parameter models are: carbon gains =
1114 $\text{intcp} + a \times \text{CO}_2 + b \times \text{MAT} + c \times \text{MCWD}$ (model 1); carbon losses = $\text{intcp} + a \times \text{CO}_2 + b \times \text{MAT} +$
1115 $c \times \text{MCWD}$ (model 2); where intcp is the estimated model intercept, and a, b, and c are model
1116 parameters giving the slope of relationships with environmental predictor variables. For multi-
1117 parameter model outputs see Extended Data Table 1, for single-parameter relationships, Figure 2.

1118
1119 The second pair of models include the same environmental predictors (CO₂, MAT, MCWD), plus
1120 their rate of change (CO₂-change, MAT-change, but not MCWD-change as explained above), and
1121 forest attributes that may alter how forests respond (WD, CRT), as described above. We also
1122 evaluated the possible inclusion of a differential continent effect of each variable in the full model.
1123 We first constructed models with only a single predictor variable, and allowed different slopes in
1124 each continent. Next, if removal of the continent-specific slope (using stepAIC function in R, MASS

1125 package⁹⁶) decreased model Akaike Information Criterion (AIC) then the continent-specific slope
1126 was not included in the full model for that variable. Only MCWD showed a significant differential
1127 continent-specific slope. This implies that forests on both continents have common responses to CO₂,
1128 CO₂-change, MAT, MAT-change, WD and CRT, but respond differently to differences in MCWD.
1129 This is likely because wet-adapted species are much rarer in Africa than in Amazonia as a result of
1130 large differences in past climate variation³⁴. Lastly, we allowed different intercepts for the two
1131 continents to potentially account for differing biogeographical or other continent-specific factors. For
1132 the carbon loss model, we applied the same continent-specific effects for slope as for the carbon gain
1133 model. Carbon loss values were transformed using a power-law transformation ($\lambda = 0.361$) to meet
1134 normality criteria.

1135

1136 For both carbon gains and losses we parameterized a global model including the significant
1137 continent-specific effect of MCWD, selecting the most parsimonious simplified model using all-
1138 subsets regression^{97,98}. To do so, we first generated a set of models with all possible combinations
1139 (subsets) of fixed effect terms in the global model using the dredge function of the MuMIn package
1140 in R⁹⁹. We then chose the best-ranked simplified model based on the AICc criterion, hereafter called
1141 “minimum adequate carbon gain/loss model”, reported in Table 2. The minimum adequate models
1142 are: carbon gains = $\text{intcp} \times \text{continent} + a \times \text{CO}_2\text{-change} + b \times \text{MAT} + c \times \text{MAT-change} +$
1143 $d \times \text{MCWD} \times \text{continent} + e \times \text{WD}$ (model 3); carbon losses = $\text{intcp} + a \times \text{CO}_2\text{-change} + b \times \text{MAT-change}$
1144 $+ c \times \text{MCWD} + d \times \text{CRT}$ (model 4). WD was retained in the carbon gain model, likely because growth
1145 is primarily impacted by resource availability, while CRT was retained in the carbon loss model,
1146 likely because losses are primarily impacted by how long fixed carbon is retained in the system.

1147

1148 Table 2 presents model coefficients of the best-ranked gain model and best-ranked loss model
1149 selected using all-subsets regression. These best-ranked gain and loss models have weights of 0.310

1150 and 0.132 respectively, which is almost double the weight of the second ranked models (0.152 and
1151 0.075 respectively). In Supplementary Table 2 we also used the model.avg function of the MuMIn
1152 package to calculate a weighted mean of the coefficients of the best-ranked models together
1153 representing a cumulative weight-sum of 0.95 (i.e. a 95% confidence subset). Supplementary Table 2
1154 (model-averaged) and main text Table 2 (best-ranked) model parameters are very similar.
1155 Supplementary Tables 3 and 4 report the complete sets of carbon gains and loss models that
1156 contribute to the model average results.

1157

1158 The model-average results show the same continental differences in sensitivity to environmental
1159 variables as the best-ranked models. From 2000 to 2015, carbon gains increased due to CO₂-change
1160 (+3.7% in both the averaged and the best-ranked models, both continents), while temperature rises
1161 led to a decline in gains, which especially had an effect in the Amazon (-1.14% and -1.07% due to
1162 MAT and MAT-change together in the averaged and best-ranked model respectively). Finally, both
1163 models result in similar predictions of the net carbon sink over the 1983-2040 period: the future net
1164 sink trend in Africa is -0.004 and -0.003 in the best-ranked and averaged models respectively; in
1165 Amazonia the future net sink trend is -0.013 and -0.011 in the best-ranked and averaged models
1166 respectively. The Amazon sink reaches zero in 2041 using model-averaged parameters compared to
1167 2035 using the best-ranked models.

1168

1169 **Estimating Future Predictor Variables to 2040**

1170 To calculate future modelled trends in carbon gains and losses (Figure 3), we first estimated annual
1171 records of the predictor variables (CO₂-change, MAT, MAT-change, MCWD, WD and CRT) to
1172 2040 (Extended Data Figure 5).

1173

1174 To do so we first calculated annual records for the period of the observed trends for each plot
1175 location (i.e. from 1983-2014 in Africa and 1983-2011.5 in Amazonia). For CO₂-change, MAT,
1176 MAT-change and MCWD we extracted monthly records as described in section Predictor Variable
1177 Estimates (above). For WD and CRT we interpolated to a 0.1-yr period within each census interval
1178 (as in Figure 1). Then, we calculated the mean annual value of each predictor variable from the 244
1179 plot locations in Africa, and separately the mean annual value of each predictor variable from the
1180 321 plot locations in Amazonia (i.e. solid lines in ED Figure 5). For each predictor variable, we
1181 calculated annual records of upper and lower confidence intervals by respectively adding and
1182 subtracting 2σ to the mean of each annual value (shaded area in ED Figure 5).

1183

1184 Secondly, for each predictor variable we parameterised a linear model for each continent using the
1185 annual records for the period of the observed trends. Then for each predictor variable, the continent-
1186 specific linear regression models were used to estimate predictor variables for each plot location
1187 from 2014 to 2040 in Africa and from 2011.5 to 2040 in the Amazon (dotted lines in Extended Data
1188 Figure 5). For each predictor variable, we calculated annual records of upper and lower confidence
1189 intervals by respectively adding and subtracting 2σ to the slope of each linear model (shaded area
1190 around dotted lines in ED Figure 5).

1191

1192 **Estimating Future Carbon Gain, Loss and Net Carbon Sink**

1193 We used the minimum adequate models (Table 2) to predict annual records of carbon gain, carbon
1194 loss and the carbon sink for the plot networks in Africa and Amazonia over the period 1983 through
1195 to 2040 (Figure 3). We extracted fitted carbon gain and loss values using the mean annual records for
1196 each predictor variable (predictSE.lme function, AICcmodavg package¹⁰⁰). Upper and lower
1197 confidence intervals were calculated accounting for uncertainties in the model (both fixed and
1198 random effects) and predictor variables using the 2σ upper and lower confidence interval for each

1199 predictor variable (using predictSE.lme). Finally the net carbon sink was calculated by subtracting
1200 the losses from the gains. To obtain sink values in the future in Table 1, annual per unit area sink
1201 predictions, from Figure 3, were averaged over each decade and multiplied by the future forest area,
1202 as described above.

1203

1204 To test the sensitivity of the future predictions in Figure 3, we reran the analysis by modifying future
1205 trajectories of predictor variables one at a time, while keeping all others the same, to assess the mean
1206 C sink over 2010-15 and 2030 (averaging at 2030 is not necessary as trends in MAT-change and
1207 MCWD, which largely drive modelled inter-annual variability, are estimated as smooth trends in the
1208 future). For each predictor variable, we explored potential impacts of the likely bounds of possibility,
1209 (i) by taking the steepest slope of either continent from the extrapolated trends, doubling this slope
1210 and applying it on both continents; and (ii) by taking the steepest slope of either continent from the
1211 extrapolated trends, taking the opposite of this slope and applying it on both continents. These
1212 bounds represent deviations of >2 sigma from observed trends. Change in MAT also alters MAT-
1213 change, so we present the sensitivity of both parameters together.

1214

1215 Additionally, for CO₂-change and MAT, we also calculated future slopes under three future
1216 Representative Concentration Pathway (RCP) scenarios³⁸ with different radiative forcing in 2100:
1217 RCP2.6, 4.5, and 8.5. Future RCP CO₂-change slopes (ppm yr⁻¹) were calculated using RCP CO₂
1218 concentration data for the years between 2015 and 2030 inclusive. Future RCP MAT and MAT-
1219 change slopes were obtained from plot-specific MAT values extracted from downscaled 30 seconds
1220 resolution data for current⁸⁰ and future⁵¹ climate from WorldClim, and averaged over 19 CMIP5
1221 models. We subtracted the mean 2040-2060 climate MAT (i.e. 2050) from the mean 1970-2000
1222 climate MAT (i.e. 1985), divided by 65 years to give the annual rate of change. We then calculated a
1223 mean slope over all plots per continent. Finally, to avoid mismatches between RCP-derived values of

1224 CO₂ and MAT and the observed records we removed any difference in intercept between the RCP
1225 trends and observed trends, so the RCP trends were a continuation of the end-point of the observed
1226 trajectory in 2015. We did not estimate the sensitivity of MCWD under the RCP scenarios, because
1227 the CMIP5 model means do not show drought trends for our forest plot networks, unlike rain gauge
1228 data for the recent past, and thus would show little or no sensitivity to MCWD. For each modified
1229 slope, Supplementary Table 5 reports the absolute decline in the sink in each continent in 2030
1230 compared to the 2010-15 mean sink. This shows that the future sink strength is sensitive to future
1231 environmental conditions, but within both RCP scenarios and our bounds of possibility we show a
1232 decline in the sink strength in both continents over the 2020s.

1233

1234 **Data and Code Availability**

1235 Source data and R-code to generate figures and tables are available from:
1236 http://dx.doi.org/10.5521/Forestplots.net/2019_1

1237

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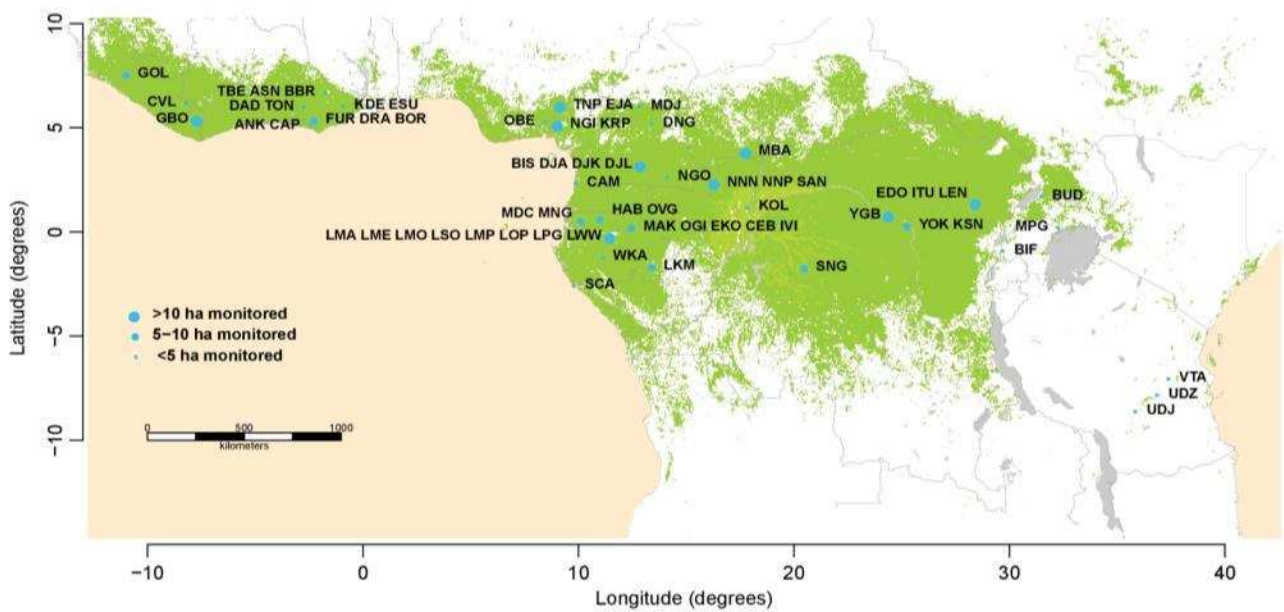
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1374 authors declare no competing financial interests. Supplementary Information is available online for
1375 this paper.

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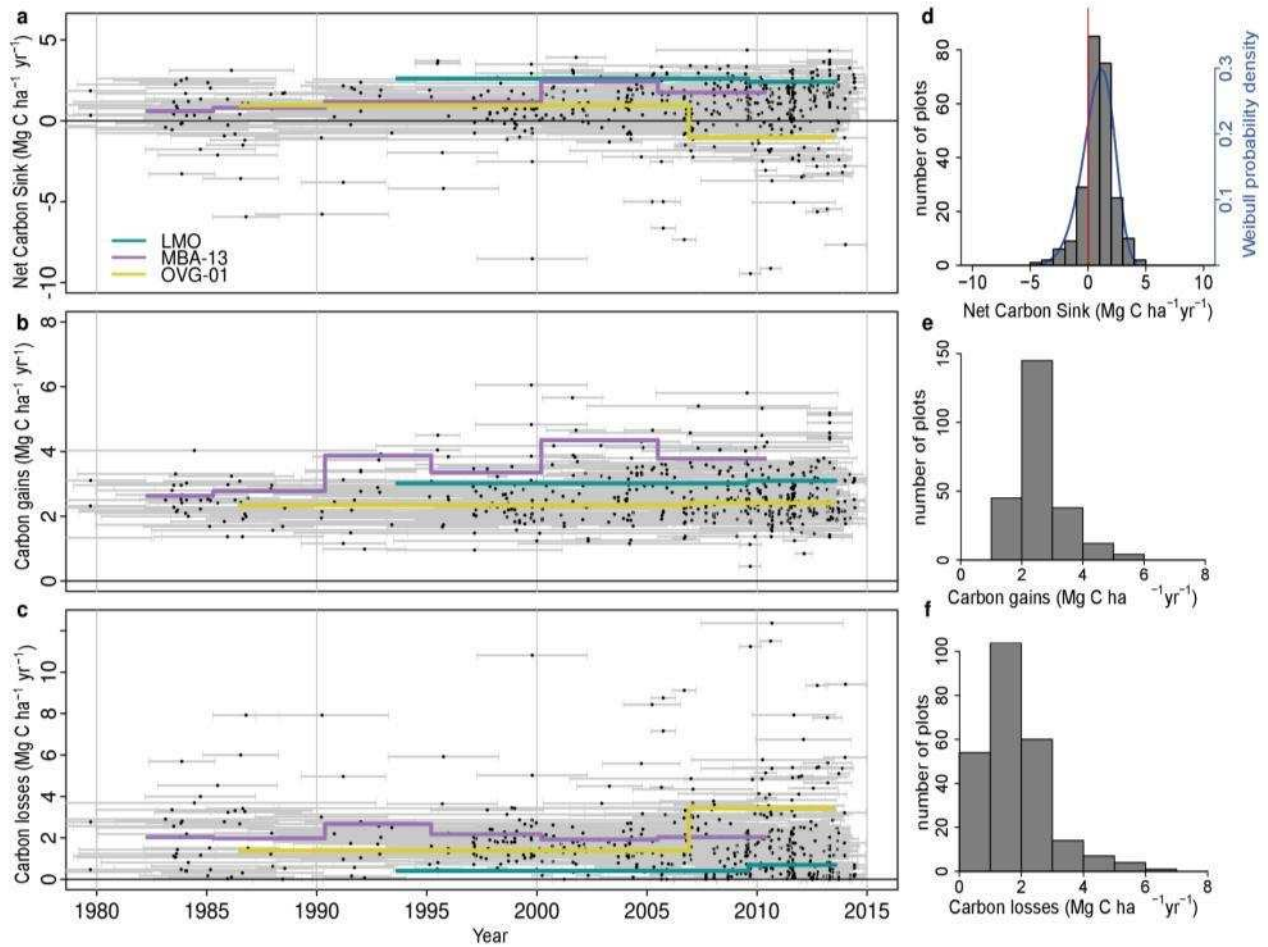
1377 **Extended Data Figures**



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1379 **Extended Data Figure 1. Map showing the locations of the 244 plots included in this study.**

1380 Dark green represents all lowland closed-canopy forests, submontane forests and forest-agriculture
1381 mosaics; light green shows swamp forests and mangroves¹⁰¹, blue circles represent plot clusters,
1382 referred to by three-letter codes (see Supplementary Table 1 for the full list of plots). Clusters <50
1383 km apart are shown as one point for display only, with the circlesize corresponding to sampling
1384 effort in terms of hectares monitored.



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Extended Data Figure 2. Long-term above-ground carbon dynamics of 244 African intact

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tropical forest inventory plots. Points in the scatterplots indicate the mid-census interval date, with

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horizontal bars connecting the start and end date for each census interval for net aboveground

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biomass carbon change (a), carbon gains (from woody production from tree growth and newly

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recruited stems) (b), and carbon losses (from tree mortality) (c). Examples of time series for three

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individual plots are shown in purple, yellow and green. Associated histograms show the distribution

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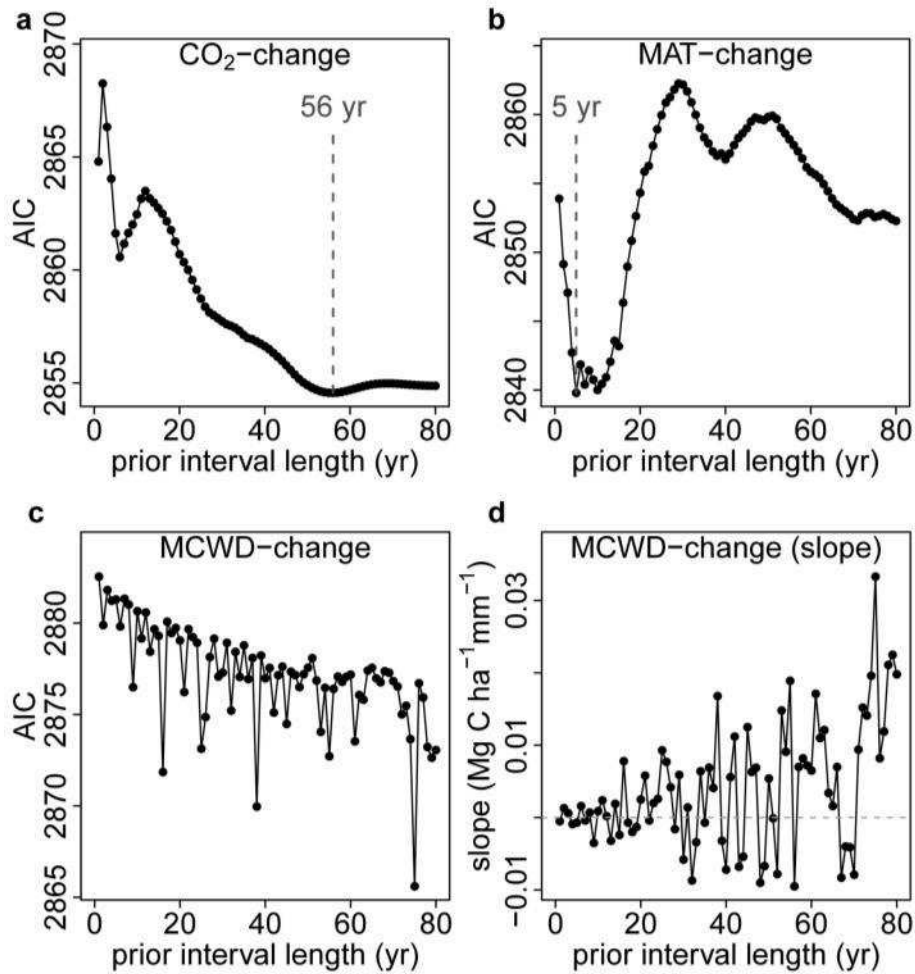
of the plot-level net aboveground biomass carbon (d) (with a three-parameter Weibull probability

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density distribution fitted in blue, showing the carbon sink is significantly larger than zero; one-tail t-

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test: $p < 0.001$), carbon gains (e), and carbon losses (f).



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Extended Data Figure 3. Akaike's Information Criterion (AIC) from correlations between the carbon gain in tropical forest inventory plots and changes in either atmospheric CO₂, temperature (as MAT) or drought (as MCWD), each calculated over ever-longer prior intervals. Panels show AIC from linear mixed effects models of carbon gains from 565 plots and corresponding, atmospheric CO₂ (CO₂-change) (a), Mean Annual Temperature (MAT-change) (b), and Maximum Climatological Water Deficit (MCWD-change) (c). For CO₂ the AIC minimum was observed when predicting the carbon gain from the change in CO₂ calculated over a 56 year long prior interval length. We use this length of time to calculate our CO₂-change parameter. Such a value is expected because forest stands will respond most strongly to CO₂ when most individuals have grown under the new rapidly changing condition, which should be at its maximum at a time approximately equivalent to the carbon residence time of a forest stand^{30,90} (mean of 62 years in this

1407 pooled African and Amazonian dataset). For MAT the AIC minimum was 5 years, which we use as
1408 the prior interval to calculate our MAT-change parameter. This length is consistent with experiments
1409 showing temperature acclimation of leaf- and plant-level photosynthetic and respiration processes
1410 over approximately half-decadal timescales^{31,91}. For MCWD the AIC minimum is not obvious, while
1411 the slope of the correlation, shown in panel (**d**), shows no overall trend and oscillates between
1412 positive or negative values, meaning there is no relationship between carbon gains and the change in
1413 MCWD over intervals longer than 1 year; thus MCWD-change is not included in our models. This
1414 result suggests that once a drought ends, its impact on tree growth fades rapidly, as seen in other
1415 studies^{14,92}. Also in the moist tropics wet-season rainfall is expected to re-charge soil water, hence
1416 lagged impacts of droughts are not expected.

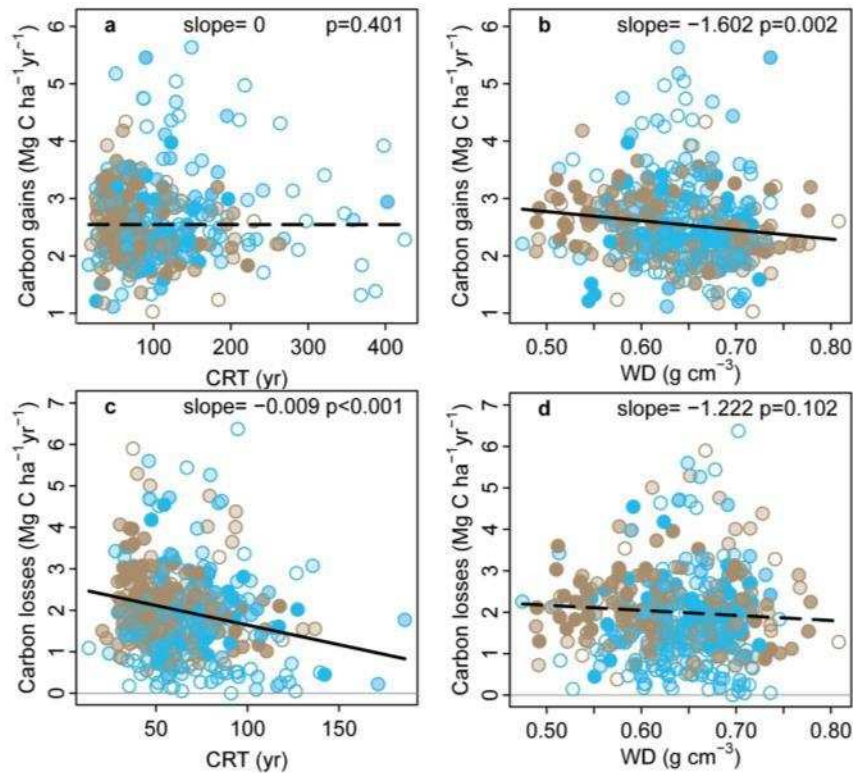
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Extended Data Figure 4. Potential forest dynamics-related drivers of carbon gains and losses in

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structurally intact African and Amazonian tropical forest inventory plots. The aboveground

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carbon gains, from woody production (**a-b**), and aboveground carbon losses, from tree mortality (**c-**

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d), are plotted against the carbon residence time (CRT), and wood density (WD), for African (blue)

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and Amazonian (brown) inventory plots. Linear mixed effect models were performed with census

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intervals (n=1566) nested within plots (n=565) to avoid pseudo-replication, using an empirically

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derived weighting based on interval length and plot area (see methods). Significant regression lines

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for the complete dataset are shown as a solid line; non-significant regressions as a dashed line. Each

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dot represents a time-weighted mean plot-level value; transparency of the inner part of the dot

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represents total monitoring length, with empty circles corresponding to plots monitored for ≤ 5 years

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and solid circles for plots monitored for >20 years. Carbon loss data are presented untransformed for

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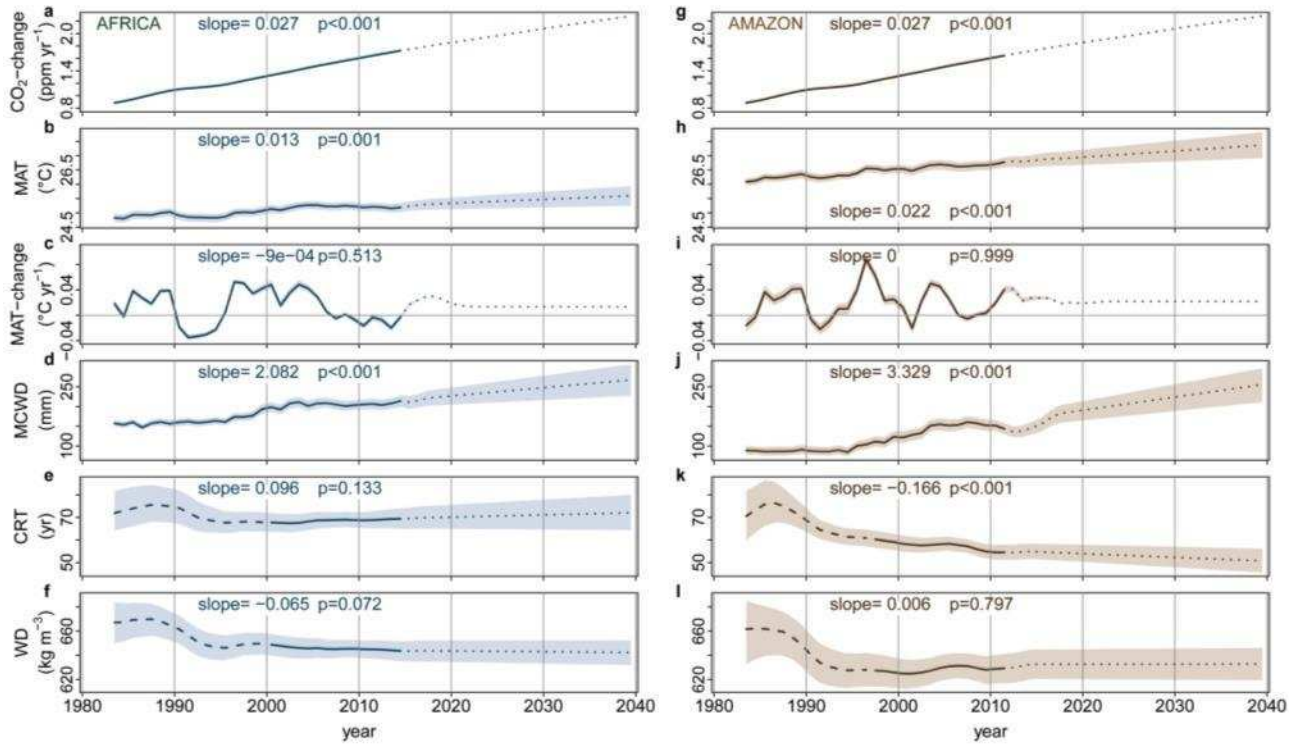
comparison with carbon gains; linear mixed effects models on transformed data to fit normality

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assumptions do not change the significance of the results. Note, CRT is calculated differently for the

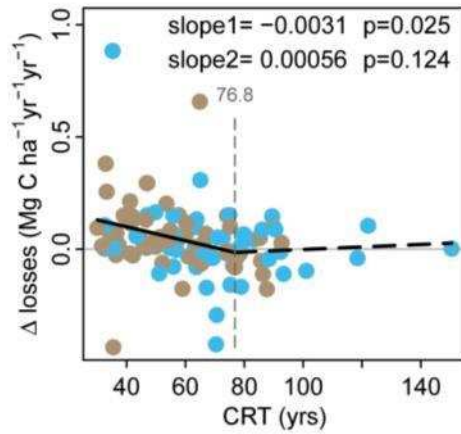
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carbon gains and losses models (see methods).



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1438 **Extended Data Figure 5. Trends in predictor variables used to estimate long-term trends in**
 1439 **above-ground carbon gains, carbon losses and the resulting net carbon sink in African and**
 1440 **Amazonian intact tropical forest plot networks.** Mean annual CO₂-change (a), MAT (b), MAT-
 1441 change (c), MCWD (d), CRT (e), and WD (f) for African plot locations in blue, and corresponding
 1442 Amazon plots locations in brown (g-l). Solid lines for CO₂-change, MAT, MAT-change, MCWD
 1443 represent observational data, and solid lines for CRT and WD represent plot means and a time
 1444 window where >75% of the plots were monitored, long-dashed lines are plot means were <75% of
 1445 plots were monitored. Dotted lines are future values estimated from linear trends on the 1983-2014
 1446 (Africa) or 1983-2011 (Amazon) data (slope and p-value reported in each panel), see methods for
 1447 details. Upper and lower confidence intervals (shaded area) for the past (Africa: 1983-2014;
 1448 Amazonia: 1983-2011) are calculated by respectively adding and subtracting 2σ to the mean of each
 1449 annual value. Upper and lower confidence intervals for the future were estimated by adding and
 1450 subtracting 2σ from the slope of the regression model.



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1452 **Extended Data Figure 6. The change in carbon losses versus carbon residence time (CRT) of**

1453 **inventory plots in Africa and Amazonia.** For plots with two census intervals, we calculated the

1454 change in carbon losses (Δ losses, in $\text{Mg C ha}^{-1} \text{ yr}^{-1} \text{ yr}^{-1}$) as the carbon losses ($\text{Mg C ha}^{-1} \text{ yr}^{-1}$) of the

1455 second interval minus the carbon losses of the first interval, divided by the difference in mid-interval

1456 dates. For plots with more than two intervals, we calculated the change in carbon losses for each pair

1457 of subsequent intervals, then calculated the plot-level mean over all pairs, weighted by the time

1458 length between mid-interval dates. This analysis includes only plots with at least two census intervals

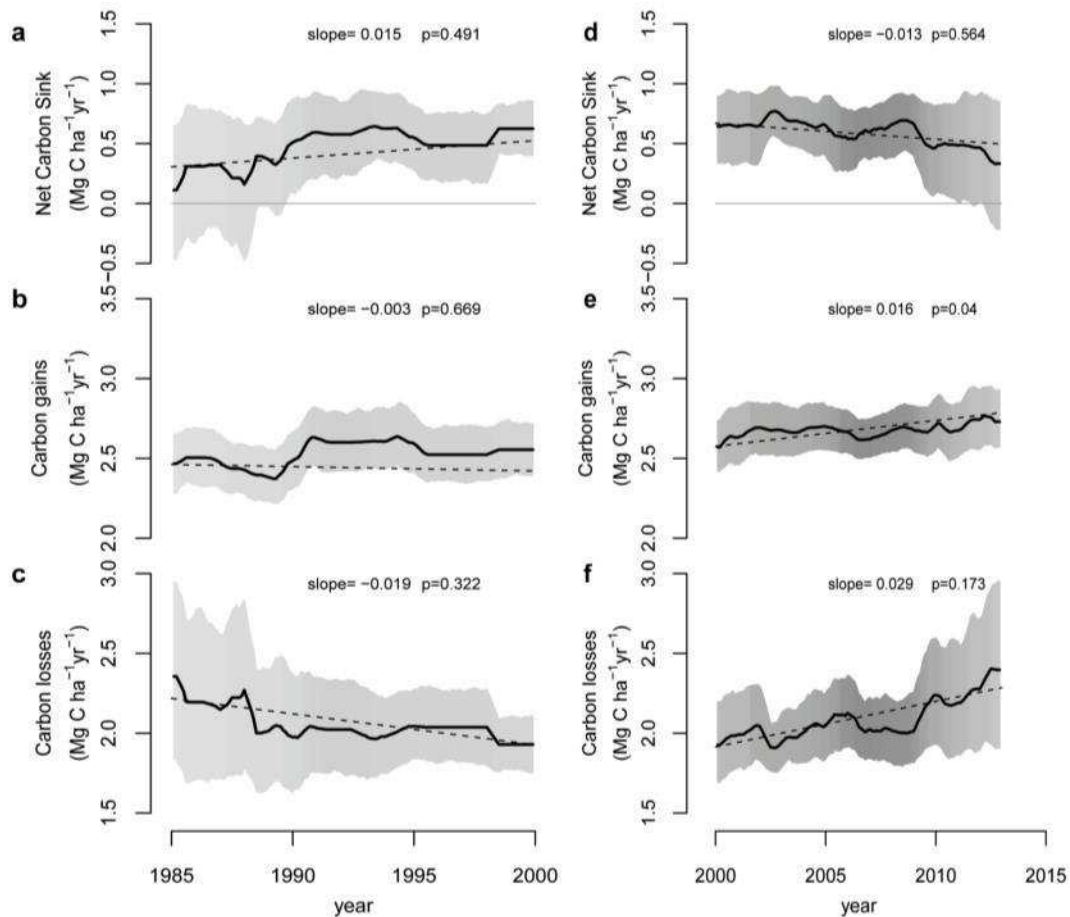
1459 and monitored for ≥ 20 years (i.e. roughly one-third of the mean CRT of the pooled African and

1460 Amazon dataset; $n = 116$). Breakpoint regression was used to assess the CRT length below which

1461 forest carbon losses begin to increase. Plots with $\text{CRT} < 77$ years show a recent long-term increase in

1462 carbon losses, longer CRT plots do not. Blue points are African plots, brown points are Amazonian

1463 plots.



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1465 **Extended Data Figure 7. Trends in African tropical forest net aboveground live biomass**

1466 **carbon, carbon gains and carbon losses, calculated for the last 15 years of the twentieth**

1467 **century (left panels a-c) and the first 15 years of the twenty-first century (right panels d-f).**

1468 Plots were selected from the full dataset if their census intervals cover at least 50% of the respective

1469 time windows, i.e. they are intensely monitored (n=56 plots for 1985-2000, and n=134 plots for

1470 2000-2015, respectively). Solid lines show mean values, shading corresponds to the 95% CI, as

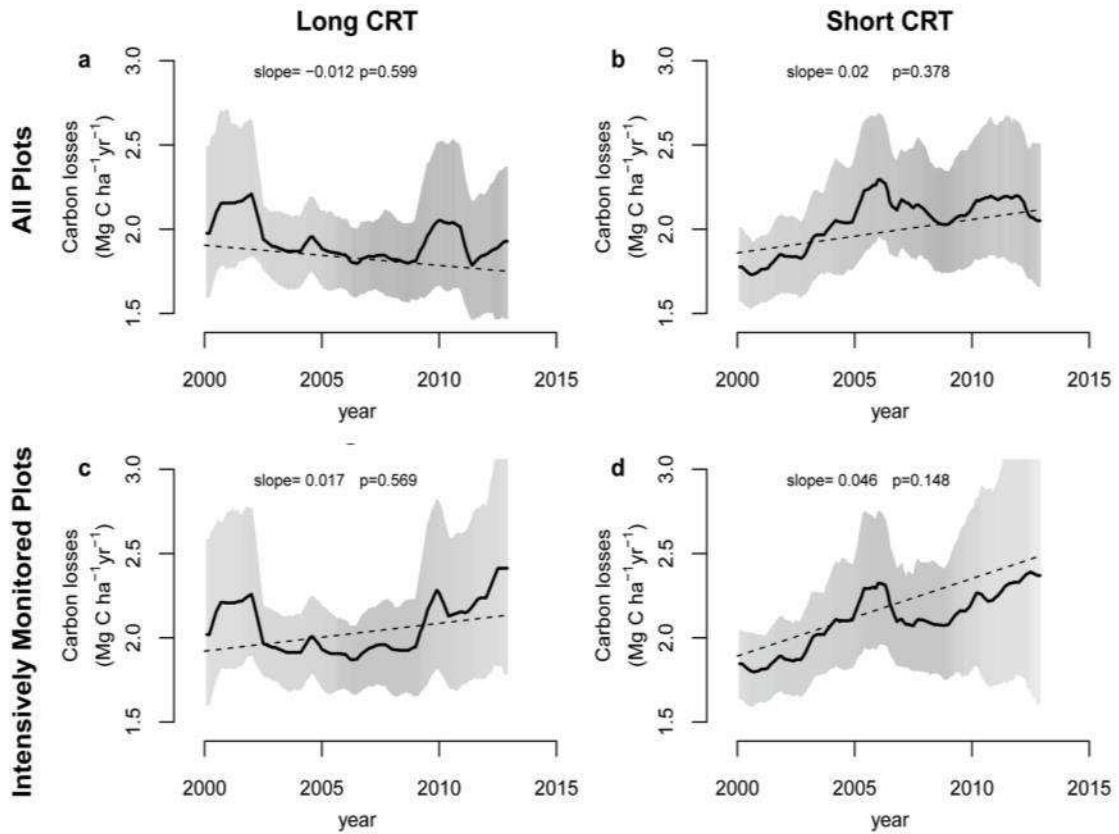
1471 calculated in Figure 1. Dashed lines, slopes and p-values are from linear mixed effects models, as in

1472 Figure 1. The data shows a difference compared to Figure 1, notably the sink decline after ~2010

1473 driven by rising carbon losses. This is because in Figure 1 we include all available plots over the

1474 1983-2015 window, which includes clusters of plots monitored only in the 2010s that had low carbon

1475 loss and high carbon sink values.



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1477 **Extended Data Figure 8. Twenty-first century trends in aboveground biomass carbon losses**
 1478 **from African tropical forest inventory plots with either long (left panels) or short (right panels)**
 1479 **carbon residence time.** Upper panels include all plots, i.e. as in Figure 1, but split into a long-CRT
 1480 group (a), and a short-CRT group (b), each containing half the 244 plots. Lower panels restrict plots
 1481 to those spanning >50% of the time window, i.e. intensely monitored plots, as in Extended Data
 1482 Figure 7, but split into a long-CRT group (c), and a short-CRT group (d), each containing half the
 1483 134 plots. Solid lines indicate mean values, shading the 95% CI, as for Figure 1. Dashed lines, slopes
 1484 and p-values are from linear mixed-effects models, as for Figure 1. Carbon losses increase at a higher
 1485 rate in the short-CRT than the long-CRT group of plots, in both datasets, although this increase is not
 1486 statistically significant.

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1490 **Extended Data Tables**

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1492 **Extended Data Table 1.** Models to predict carbon gains and losses in African and Amazonian
 1493 tropical forests, including only environmental variables, showing long-term trends that impact
 1494 theory-driven models of photosynthesis and respiration. Significant values in bold.

Carbon gains, Mg C ha ⁻¹ yr ⁻¹				
Predictor variable	Parameter value	Standard Error	t-value	p-value
(Intercept)	4.694	0.739	6.354	0.000
CO ₂ (ppm)	0.005	0.001	3.196	0.001
MAT (°C)	-0.143	0.021	-6.844	0.000
MCWD (mm x1000)	-1.232	0.210	-5.878	0.000
Carbon losses, Mg C ha ⁻¹ yr ⁻¹ *				
Predictor variable	Parameter value	Standard Error	t-value	p-value
(Intercept)	0.926	1.854	0.500	0.617
CO ₂ (ppm)	0.004	0.004	0.947	0.344
MAT (°C)	-0.011	0.044	-0.249	0.804
MCWD (mm x1000)	-0.498	0.505	-0.985	0.325

* carbon loss values were normalized via power-law transformation, $\lambda = 0.361$.

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1497 **Extended Data Table 2.** Forest area estimates used to calculate total continental forest sink.

Period	intact forest area (Mha)*			
	Africa	Amazon	Southeast Asia	Pan-tropics
1980	671.5	958.3	233.6	1863.4
1985	634.3	921.1	207.4	1762.8
1990	600.2	885.2	190.6	1676.0
1995	565.9	851.1	163.5	1580.5
2000	531.8	817.2	136.9	1485.9
2005	504.8	784.5	129.2	1418.5
2010	477.8	756.3	118.4	1352.5
2015	450.5	726.7	101.5	1278.7
2020	425.5	698.5	90.1	1214.2
2025	402.0	671.5	80.0	1153.4
2030	379.7	645.4	71.0	1096.1
2035	358.6	620.4	63.0	1042.1
2040	338.8	596.4	56.0	991.1

* Intact forest area for 1990, 2000 and 2007 is published in ref.1 (i.e. the total forest area minus forest regrowth). To estimate intact forest area for the other years in this table, we fitted exponential models for each continent using the published data.

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