

Regional synchrony amplifies the fire signal in global CO₂ growth rate

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1 Regional synchrony amplifies the fire signal in global CO₂ 2 growth rate

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8 Abstract

9 Interannual atmospheric CO₂ growth variability reflects changes in land and ocean carbon exchange, but
10 the role of fluxes from regional disturbances such as fire remains unclear. Here we show that regional
11 annual fire-carbon anomalies shifted from partial cancellation in 2001–2010 to reinforcement in 2015–
12 2024. Global fire-emission variance increased about seven-fold despite nearly unchanged mean emissions,
13 with cross-region covariance accounting for 84% of the increase and seasonally separated boreal and
14 tropical anomalies accounting for 44% of the covariance increase. At the same time, global fire anomalies
15 became strongly correlated with whole-atmosphere CO₂-growth anomalies (R^2 from 0.06 to 0.83).
16 Subtracting fire emissions reduces the year-to-year variance of the atmospheric CO₂ growth rate by 57%
17 in the recent decade, compared with 6% in the earlier one. More generally, our analysis shows that a
18 global Earth-system quantity can become far more variable mainly because its regional contributors shift
19 from cancelling to reinforcing one another, without growing larger individually.

20

21 The land sink has absorbed about a quarter of anthropogenic CO₂ emissions over recent decades¹, and its
22 year-to-year fluctuations dominate the interannual variability of the atmospheric CO₂ growth rate. This
23 variability is usually attributed to photosynthesis and respiration responding to temperature, water
24 availability and large-scale climate modes^{2–6}. Fire is a third process by which ecosystems release carbon to
25 the atmosphere. It responds to the same climate controls, since the hot and dry conditions that promote
26 fire also suppress photosynthesis and enhance respiration^{7,8}, but combustion releases carbon within
27 weeks and in discrete, regionally concentrated episodes. Such episodes, from the 1997–1998 tropical fires
28 to the recent extreme fire years in Australia, Siberia, Canada and Amazonia, have produced substantial
29 atmospheric anomalies^{9–15}, yet attribution of growth-rate variability has focused mainly on
30 photosynthesis and respiration. Global burned area has declined over the satellite era as agricultural
31 expansion reduced savanna and grassland burning^{16,17}, while rising extratropical forest-fire emissions
32 have kept total emissions roughly stable and shifted them towards forests^{18,19}.

33 Regional fire seasons occur at different times of year, so a year's global fire anomaly depends on whether
34 seasonally separated regional anomalies reinforce or cancel one another. A large anomaly in one region
35 can be partly cancelled by below-average burning elsewhere, whereas moderate same-sign anomalies
36 across several regions can add up to a pronounced global disturbance. We refer to the positive covariation
37 of annual regional anomalies, in which high- and low-fire years in different regions tend to coincide, as
38 regional fire synchronization (Fig. 1). Because the variance of a global sum depends on the covariance
39 among regions as well as on the variance of each region, global fire variability can rise either because
40 individual regions become more variable or because regions covary more strongly. Ocean–atmosphere
41 modes are known to synchronize fire across large regions^{20,21}, and days of extreme fire weather
42 increasingly coincide across broad geographic domains²². Synchronous fire weather does not, however,
43 imply synchronized carbon emissions, which also depend on fuel, vegetation state, ignition and
44 management. Whether realized fire-carbon anomalies have become more synchronized across regions,
45 and whether such a change is detectable in the global atmospheric CO₂ record, remain open.

Here we analyse fire-carbon emissions from the Global Fire Emissions Database²³ (GFED) across its 14 basis regions over 2001–2024, the period with direct satellite burned-area observations, and compare the first and last decades of this record, 2001–2010 and 2015–2024. We find that seasonally separated regional anomalies, including those of boreal and tropical fires, shifted from cancelling to reinforcing one another between the two decades. This shift amplified global fire variability despite nearly unchanged mean emissions and coincided with a pronounced strengthening of the association between global fire emissions and the whole-atmosphere CO₂ growth rate.

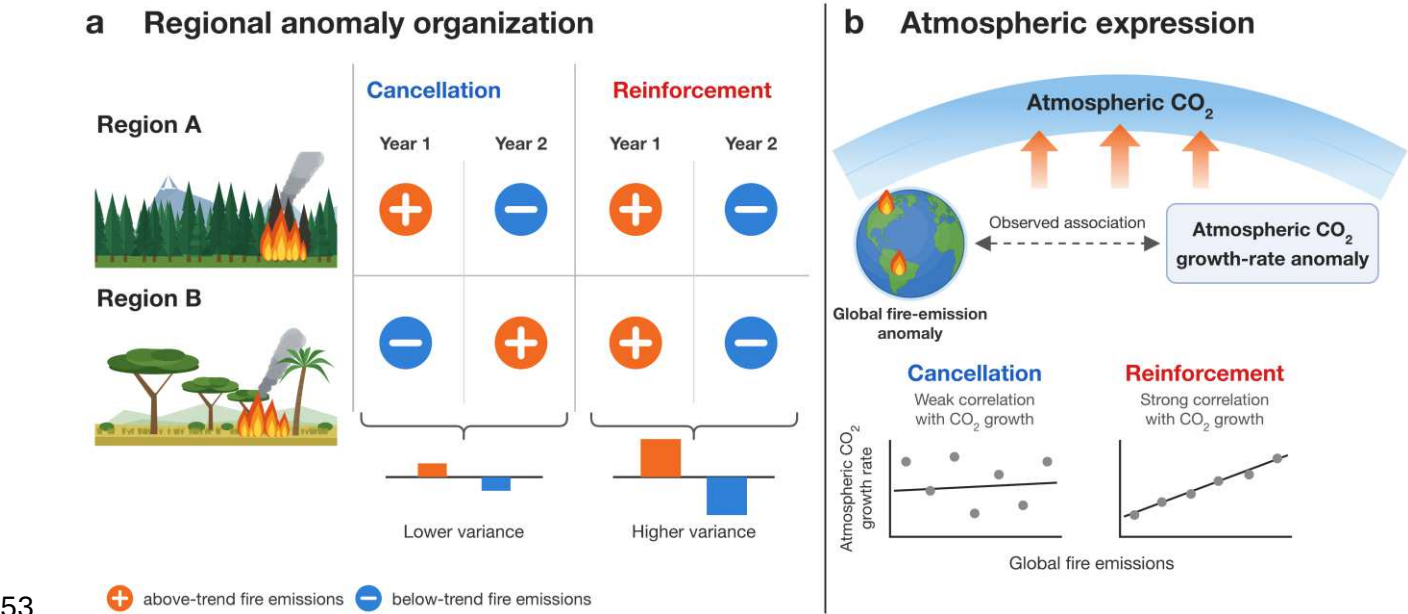


Figure 1 | Regional fire anomalies and their global atmospheric CO₂ expression. Conceptual illustration; neither panel is drawn from data. **a**, Annual fire-carbon anomalies (+, above trend; –, below trend) for two regions with different fire seasons in two example years, under cancellation and under reinforcement: opposite signs partly cancel in the global sum, whereas same signs reinforce, so the global anomaly varies more from year to year (bars). **b**, The global fire-emission anomaly is compared with the whole-atmosphere CO₂ growth-rate anomaly; the sketches show the weak correlation expected under cancellation and the strong correlation expected under reinforcement.

Results

Regional fire anomalies shift from cancellation to reinforcement

Over the satellite burned-area record (2001–2024), global fire emissions became far more variable between its first and last decades without becoming substantially larger (Fig. 2). Their variance increased

about seven-fold (Fig. 2c), and the detrended standard deviation over trailing ten-year windows rose from 0.14 to 0.36 PgC yr⁻¹, 2.6 times its 2001–2010 value, whereas mean emissions were nearly unchanged (Fig. 2b). For the detrended annual anomalies F_r of the 14 GFED regions, indexed by r and s , the variance of the global total $F_g = \sum_r F_r$ within each ten-year window is

$$\text{Var}(F_g) = \sum_r \text{Var}(F_r) + \sum_{r \neq s} \text{Cov}(F_r, F_s),$$

where the first term grows only if individual regions become more variable, and the second is negative when regional anomalies tend to cancel, zero when they are uncorrelated and positive when they tend to reinforce. Of the 0.111 PgC² yr⁻² increase in $\text{Var}(F_g)$, 0.018 PgC² yr⁻² arose from increased variance within individual regions and 0.093 PgC² yr⁻² from covariance among regions; that covariance term reversed sign from -0.034 to +0.058 PgC² yr⁻² and accounted for 84% of the increase in global variance. Most of the increase therefore came from regional anomalies reinforcing rather than cancelling one another in the global total. A covariance swap, that is, keeping the 2001–2010 regional variances and imposing only the 2015–2024 covariance term, would still raise global variance nearly six-fold (Methods).

The shift is visible in the regional anomalies themselves (Fig. 2a). In 2001–2010, positive and negative regional anomalies frequently cancelled one another in the global sum, and fewer than half of all region pairs were positively correlated. In 2015–2024, same-sign anomalies more often coincided and reinforced, and two-thirds of region pairs were positively correlated. Two years illustrate this: in 2022, 13 of the 14 regions burned below their trends, and in 2024, 10 of the 14 burned above them (trends fitted within each window; Methods). Because regions moved together in both high- and low-fire years, the recent decade produced larger global anomalies in both directions than the first (Supplementary Note 3).

A major component of this shift was reinforcement between boreal and tropical fire regions (Fig. 2d). Summed over each group, boreal and tropical detrended annual anomalies went from partial cancellation in 2001–2010 ($r = -0.23$) to reinforcement in 2015–2024 ($r = +0.48$), so their covariance turned from

88 negative to positive and alone accounted for 44% of the increase in cross-region covariance. The term
89 stayed positive when 2023 was removed and when preliminary 2025 data were added (Supplementary
90 Note 3; Supplementary Table 1).

91 Most of the reinforcement links fires that burn in different seasons. Boreal Asia burns mainly from April to
92 July and Southeast Asia from January to April (Supplementary Table 2), so their fire seasons barely
93 overlap. Yet their annual anomalies went from partly cancelling in 2001–2010 ($r = -0.34$) to reinforcing in
94 2015–2024 ($r = +0.75$). Across all region pairs, emissions in different seasons supplied about 70% of the
95 recent cross-region covariance (Supplementary Note 1). Regional fire synchronization therefore reflects
96 seasonally separated emissions being anomalously high or low in the same year, rather than globally
97 simultaneous burning (Supplementary Fig. 1).

98 The synchronization is not specific to one dataset or choice of years. It appears in burned area itself
99 (Supplementary Fig. 2), and the Global Fire Assimilation System (GFAS), an emissions product built from
100 the heat given off by active fires rather than from burned area, shows the same change in cross-region
101 covariance (Supplementary Fig. 3). Fire emissions inferred from satellite observations of atmospheric
102 carbon monoxide (CO) reproduce the regional anomalies and their synchronization over 2019–2024
103 (Supplementary Note 2; Supplementary Fig. 4b). The recent reinforcement also held for other window
104 lengths and when individual years were left out. The rise in coherence (the mean correlation across all
105 region pairs) is less robust: it depended on which periods were compared and is absent in GFAS, where
106 the reinforcement is concentrated in the regions with the largest year-to-year swings (Supplementary
107 Notes 1 and 3).

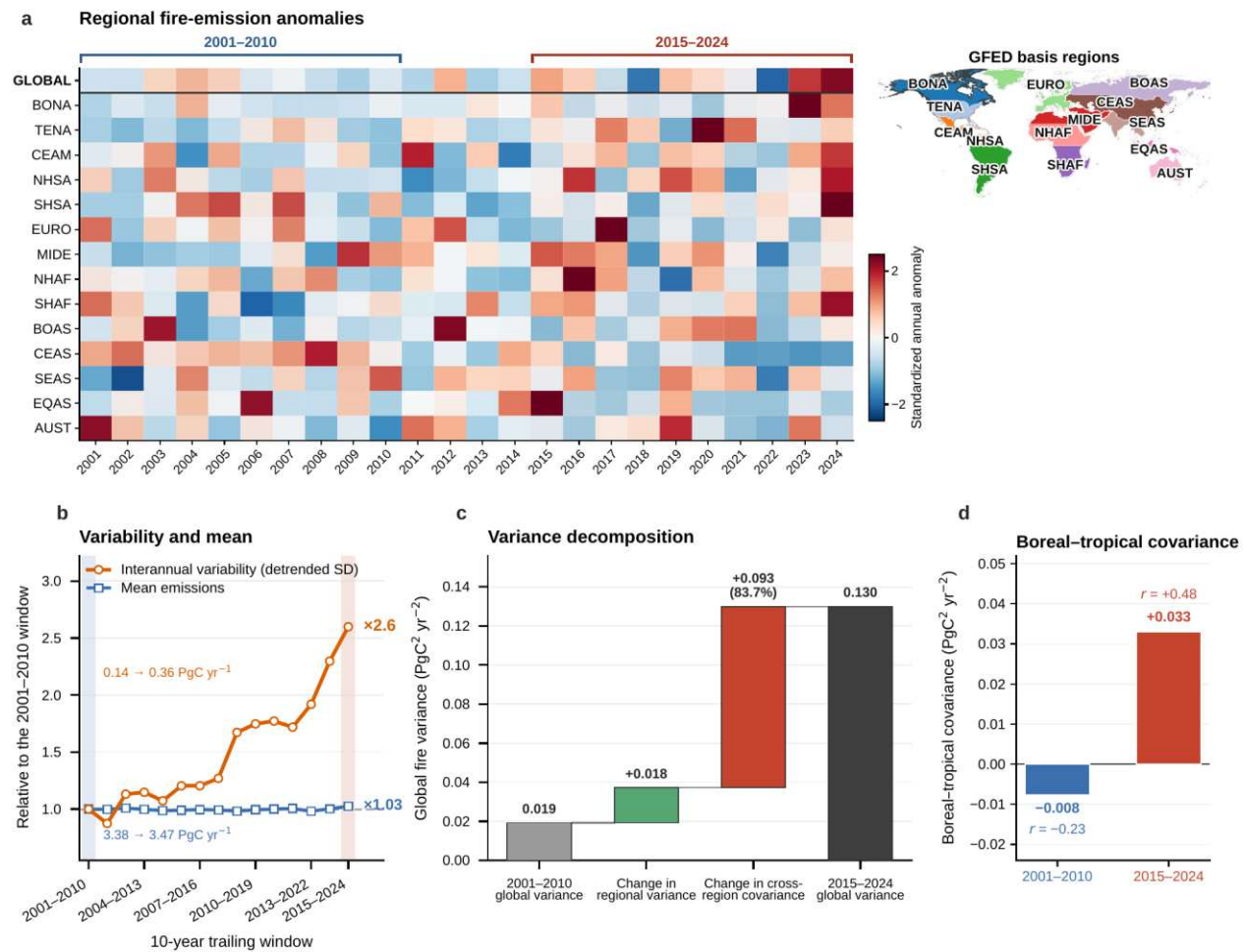


Figure 2 | Regional fire anomalies and global fire-carbon variance in the satellite era (2001–2024). **a**, Annual fire emissions for the 14 GFED basis regions and their global sum, 2001–2024, each standardized by its 2001–2024 mean and standard deviation without detrending; the inset identifies the GFED basis regions (abbreviations in Supplementary Table 2). Positive and negative values denote emissions above and below the 2001–2024 mean; emissions for 2023–2024 come from the near-real-time GFED extension. **b**, Ten-year trailing interannual variability (detrended standard deviation) and mean global fire emissions, each normalized to its 2001–2010 value; labels give the ratio between the two windows and, beneath it, the 2001–2010 and 2015–2024 values. Blue and red shading marks the two comparison windows. **c**, Global fire-emission variance in 2001–2010 and its increase to 2015–2024, split into the part from larger variance within individual regions and the part from covariance between regions, and the resulting 2015–2024 variance. **d**, Boreal–tropical covariance term in the two comparison windows, computed from the aggregate detrended annual anomalies of the two boreal regions, Boreal North America and Boreal Asia, and the seven tropical regions, Central America, Northern and Southern Hemisphere South America, Northern and Southern Hemisphere Africa, Southeast Asia and Equatorial Asia; labels give the corresponding correlations.

Atmospheric CO₂ expression of regional fire reinforcement

As regional reinforcement made global fire emissions about seven times more variable, those emissions also came to covary closely with the atmospheric CO₂ growth rate (Fig. 3). We take the growth rate from

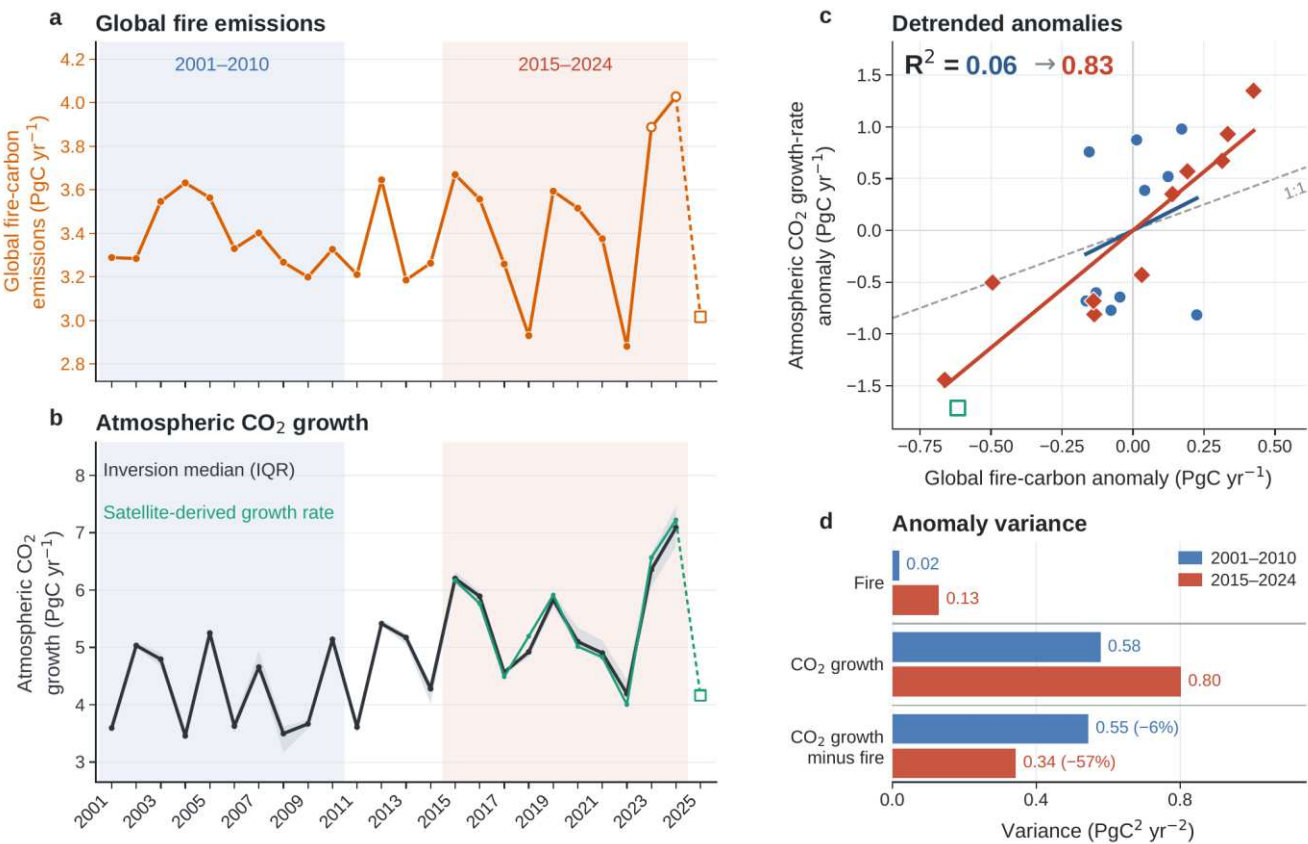
127 the median of six Global Carbon Budget atmospheric inversions, whose posterior fluxes track the CO₂
128 burden of the whole atmosphere^{1,24,25} (Methods), rather than from the National Oceanic and Atmospheric
129 Administration (NOAA) marine-boundary-layer record, which reflects surface air at remote marine sites.
130 The NOAA record nonetheless shows a strengthening of the fire–CO₂ association, although a weaker one
131 (Supplementary Note 2; Supplementary Fig. 4a).

132 The detrended fire and growth-rate anomalies were weakly correlated in 2001–2010 ($R^2 = 0.06$) but
133 strongly correlated in 2015–2024 ($R^2 = 0.83$; Fig. 3c). The stronger association did not arise from a more
134 variable atmosphere: the spread of the growth-rate anomalies changed little between the windows,
135 whereas that of the fire anomalies grew 2.6-fold. In 2015–2024 the two records moved together in both
136 sign and size: years with larger fire anomalies had proportionally larger growth-rate anomalies (Fig. 3c).
137 In 2001–2010 even the sign could disagree: 2004, the year of highest fire emissions, had the lowest CO₂
138 growth of the window. In 2015–2024 the growth-rate anomalies were larger than the fire anomalies
139 themselves (Fig. 3c, dashed line), which means that fires occurred within a broader land-carbon response
140 in which photosynthesis and respiration covaried with combustion, as expected when the same hot, dry
141 conditions act on all three (Supplementary Note 2B).

142 Subtracting the direct fire-carbon anomaly from the growth rate reduces its variance by 57% in 2015–
143 2024, compared with 6% in 2001–2010 (Fig. 3d); this reduction exceeds fire’s own share of the growth-
144 rate variance because fire also covaried with the rest of the growth rate (Supplementary Note 2B). Direct
145 combustion was a substantial part of the growth-rate anomalies: in 2015–2024 the standard deviation of
146 the fire anomaly was 40% of that of the growth-rate anomaly (Supplementary Table 3B). For the record
147 year 2024, the subtraction lowers the CO₂ growth anomaly, taken relative to a single 2001–2024 trend,
148 from the largest in the record to the fourth largest (Supplementary Note 2B), consistent with CO-based
149 analyses of the 2024 Amazon fires^{15,26}.

150 Preliminary 2025 fire and CO₂ growth-rate data, which entered no fire–CO₂ fit, showed the same
151 association: both fire emissions and CO₂ growth fell below their trends, and the pair lies close to the

2015–2024 regression line (open squares in Fig. 3; Methods). Further sensitivity tests found a strengthening in each of the six inversions; the recent association also held for the satellite-derived growth rate, available from 2015, and when any single 2015–2024 year was omitted (Supplementary Notes 2 and 3).



156

Figure 3 | Fire emissions and the atmospheric CO₂ growth rate. **a**, Annual GFED fire-carbon emissions. Open circles mark the near-real-time GFED5NRT values for 2023–2024, and the open square marks the full-year 2025 total. **b**, CO₂ growth rate from the median of six Global Carbon Budget atmospheric inversions for 2001–2024 (black, with the interquartile range in grey) and from satellites for 2015–2024 (teal). The satellite-derived growth rate (GRESO, Growth Rate Estimation from Satellite Observations) is the mean of the Orbiting Carbon Observatory-2 (OCO-2) and Greenhouse gases Observing SATellite (GOSAT) estimates (Methods), and the open square is its 2025 value. Shading in **a** and **b** marks the 2001–2010 (blue) and 2015–2024 (red) windows. **c**, Within-window detrended anomalies of fire emissions and of the inversion-median growth rate for 2001–2010 (blue circles) and 2015–2024 (red diamonds), with least-squares fits and their R². The dashed one-to-one line marks where the growth-rate anomaly equals the fire anomaly. The open square is the 2025 pair of GFED5NRT fire and GRESO growth rate, each relative to its own 2015–2024 trend. **d**, Variance of the within-window detrended fire, growth-rate and growth-minus-fire anomalies in each ten-year window. Percentages beside the growth-minus-fire bars give the reduction in variance relative to the growth rate in the same window (Supplementary Note 2B). Open squares in **a–c** mark preliminary 2025 values, which are excluded from the fits in **c**.

172 Climate context for regional fire synchronization

173 Fire synchronization increased alongside a rise in the coherence of regional temperature (Fig. 4a). To
174 compare fire with climate, we use coherence rather than the covariance term. In their own units, the
175 cross-region covariances of temperature and vapour pressure deficit (VPD) would weight each region by
176 how variable its climate is rather than by how variable its fire emissions are. Coherence is proportional to
177 the covariance term recalculated after each regional series is divided by its own standard deviation
178 (Methods), so it has no units, weights all region pairs equally and applies in the same way to fire and to
179 each climate variable. Between 2001–2010 and 2015–2024, temperature coherence rose from about 0.13
180 to 0.36 and fire coherence from -0.03 to $+0.15$, whereas VPD coherence changed little; of these changes,
181 only the fire change is statistically significant for these two windows (Supplementary Note 4). Because the
182 regions burn in different seasons, calendar-year climate need not be what fires respond to, so we also
183 averaged climate over each region's four-month fire season, and over that season together with the eight
184 months before it (Methods; Supplementary Note 4). Temperature coherence changed little within the fire
185 season but rose over the longer window almost as much as at the annual scale, whereas VPD coherence
186 stayed low under either choice (Fig. 4b). Temperature coherence thus rose as fire coherence did, although
187 less certainly and with little rise within the fire season itself. We therefore treat the rise in temperature
188 coherence as context for the fire synchronization rather than as its cause. Our analysis does not isolate a
189 single shared climate mechanism.

190 The two decades also sit differently within the record of the El Niño–Southern Oscillation (ENSO) since
191 1950 (Fig. 4c). By two sea-surface-temperature indices, the Oceanic Niño Index and detrended Niño-3.4,
192 2001–2010 was a comparatively quiet decade and 2015–2024 among the most variable. The Multivariate
193 ENSO Index v2 also rises between the two decades, but its recent decade sits near the middle of its shorter
194 record, which begins in 1979.

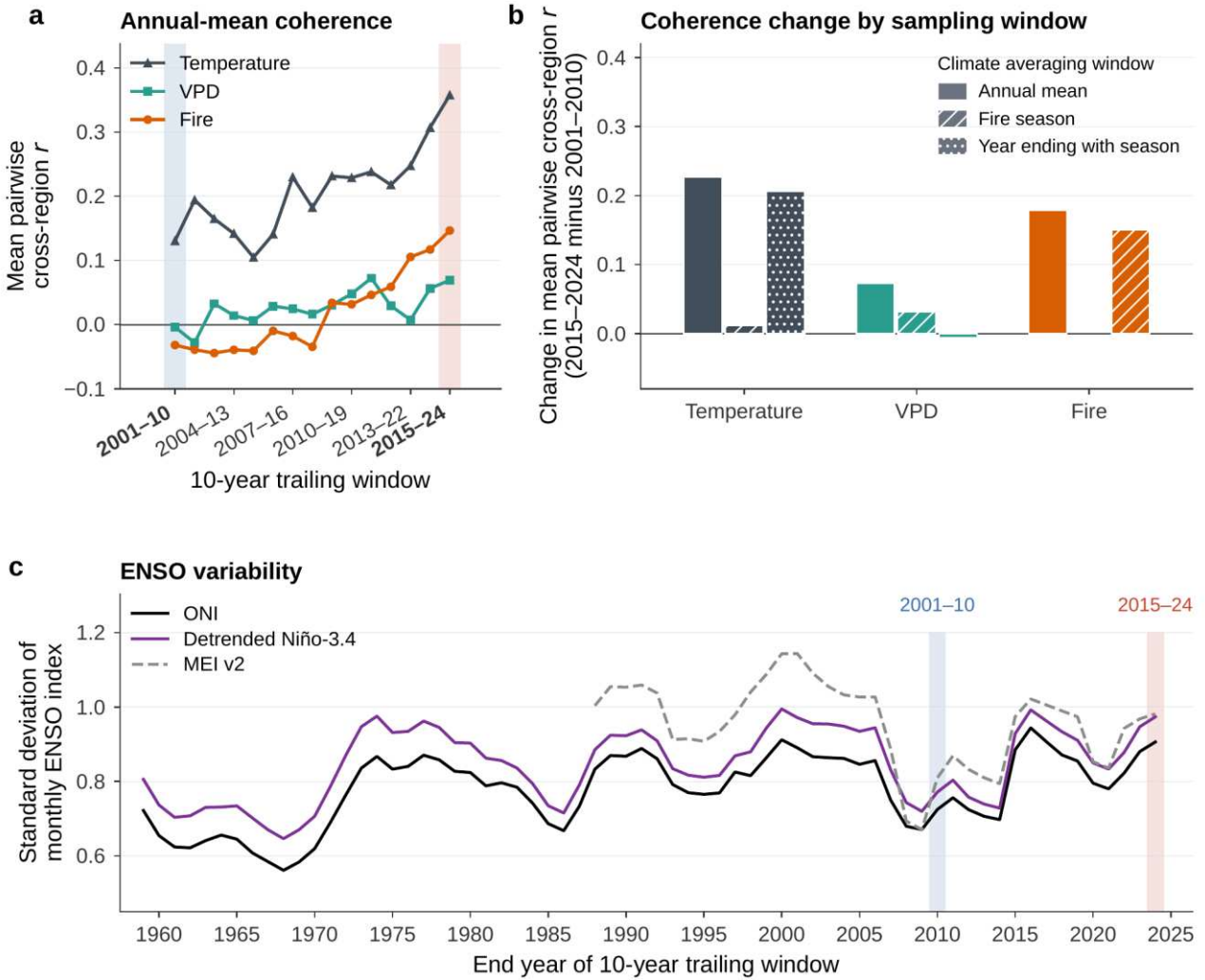


Figure 4 | Climate context for regional fire synchronization. **a**, Coherence, defined here as the mean pairwise cross-region correlation of within-window detrended annual series across the 14 GFED regions, in ten-year trailing windows for fire emissions, temperature and VPD; shading marks the windows ending in 2010 (blue) and 2024 (red). **b**, Change in coherence between 2001–2010 and 2015–2024 for temperature, VPD and fire. Bars give the change with climate averaged over the calendar year (solid), the fixed fire season (diagonal hatching) or the fire season and the eight months before it (dotted); fire is shown for annual and fire-season averaging, and the horizontal line marks no change. **c**, Ten-year trailing standard deviation of monthly ENSO indices for windows ending 1959–2024. The Oceanic Niño Index (ONI; black) and detrended Niño-3.4 (purple) are sea-surface-temperature indices in °C, whereas the Multivariate ENSO Index v2 (MEI v2; grey dashed; windows ending from 1988) is dimensionless, so amplitudes are comparable only between the first two; shading as in **a**.

Discussion

We find that the variance of global fire emissions increased about seven-fold, and we attribute most of this increase to the rise in cross-region covariance rather than to greater variability within individual regions:

210 regional anomalies shifted from partial cancellation to reinforcement. This weakening of spatial
211 cancellation, known to damp land-carbon variability in the global total²⁷, would on its own have made
212 global fire emissions nearly six times more variable. The shift was especially evident between boreal and
213 tropical regions despite their different fire seasons, and operated in both directions: most regions burned
214 above trend in 2024, whereas almost every region burned below trend in 2022, towards the end of the
215 2020–2023 La Niña²⁸. That deficit, the largest global anomaly of either decade, came from widespread
216 shortfalls rather than from one or two regions: the largest single regional deficit supplied only about a
217 fifth of it (Supplementary Note 3). Global fire emissions also came to covary much more closely with
218 atmospheric CO₂ growth. Our results complement evidence of increasingly synchronous extreme fire
219 weather²² with a related synchronization in realized carbon emissions and its global atmospheric
220 expression.

221 The atmospheric response exceeded direct combustion, consistent with fire occurring within a wider
222 land-carbon response to the same climate anomalies. Studies of the 2015–2016 El Niño found different
223 tropical continents contributing through fire, reduced uptake and increased respiration^{29–31}, and an
224 analysis based on satellite-constrained inversions attributed the record 2024 growth rate mainly to
225 increased ecosystem respiration in grass and shrub lands under hot, wet conditions³². Fire is thus both a
226 substantial carbon flux and an observable indicator of wider land-carbon disturbance. Its net carbon
227 consequence also extends beyond the fire year, through post-fire decomposition, suppressed uptake and
228 regrowth that differ between boreal and tropical fire types^{33–35}.

229 Shared climate conditions offer a plausible pathway linking fire anomalies across regions and seasons (Fig.
230 4). One hypothesis is that elevated temperatures before and during the fire season increase evaporative
231 demand (the atmosphere’s drying power, measured here by VPD), which dries fuels and increases the
232 likelihood of fire occurrence and of rapid fire spread; the same evaporative demand couples fuel dryness
233 to vegetation carbon exchange^{8,36,37}. In the tropics, large-scale east–west redistribution of rainfall can also
234 alter live and dead fuel moisture and surface litter, and with them fuel continuity and fire intensity³⁸.

235 Because temperature coherence rose over the twelve months ending with the fire season, with little rise
236 within the season itself, and VPD coherence changed little (Fig. 4b), a synchronizing effect of this pathway
237 could act through fuel conditions accumulated over that longer window rather than through evaporative
238 demand that itself became more coherent across regions. A climate field with low coherence can still
239 influence fire within each region.

240 ENSO is one candidate organizer of such climate conditions. It drives a cascade of drought and fire, from
241 the El Niño year into the next, across tropical continents that burn in different seasons²¹. A decade of large
242 ENSO swings is a plausible backdrop for regional fire synchronization, although how far ENSO variability
243 translates into synchronized fire-carbon anomalies depends on regional teleconnections, vegetation, fuel
244 and management. Concurrent regional droughts are mostly driven by ENSO and are projected to become
245 more likely with increased ENSO variability and warming³⁹, and extreme tropical drought has been linked
246 to multidecadal changes in CO₂ growth-rate variability⁴⁰; synchronized fire is one pathway by which such
247 concurrent drought can be expressed in the atmosphere. The next step is to identify how antecedent
248 climate, vegetation, fuel, ignition and management combined to make regional fire anomalies reinforce
249 one another in the recent decade.

250 Two limitations qualify these results. First, the record establishes a recent reinforcing state, but neither
251 how it arose nor whether it persists: it shows no steady trend towards the reinforcement and no single
252 year at which it began (Supplementary Note 3), and a single preliminary year, 2025, cannot establish
253 persistence. Second, the independent atmospheric check on regional fire emissions, from CO-constrained
254 inversions, covers only 2019–2024 and retains some dependence on the fire inventories those inversions
255 start from and on the CO-to-CO₂ conversion, so it tests the recent synchronized state but not the change
256 between decades (Supplementary Note 2).

257 The land sink of the global carbon budget is estimated with dynamic global vegetation models of varying
258 fire representation¹. The budget's year-to-year imbalance (total emissions minus the atmospheric growth
259 rate and the ocean and land sinks) reflects, in part, variability in land and ocean fluxes that these estimates

260 leave unresolved^{1,24}. Emergent constraints on the tropical carbon–climate feedback in Earth-system
261 projections use the sensitivity of interannual CO₂ growth to temperature², so their reliability also depends
262 on how models represent fire’s contribution to that growth. Models used for both purposes should
263 therefore reproduce how regional fire anomalies combine into global fluctuations and how climate modes
264 such as ENSO synchronize burning across continents, as well as mean emissions, burned area and each
265 region’s response to climate^{41–43}.

266 The regional fire synchronization presented here, and its association with CO₂ growth, need not be
267 permanent to be consequential: periods in which regional fire anomalies reinforce rather than cancel can
268 alter global carbon-cycle variability. In years when many regions burn above their trends at once, as in
269 2024, fire-management demands could also peak in geographically distant regions together, limiting the
270 scope for sharing response capacity. More broadly, we suggest that interpreting any change in the
271 variability of a global Earth-system quantity requires asking how its regional components covary, not only
272 how variable each has become.

273

274 Methods

275 Data

276 Fire-carbon emissions are from the Global Fire Emissions Database version 5.1 (GFED5.1), which provides
277 monthly gridded emissions and the 14 basis regions used throughout²³; the near-real-time extension
278 GFED5NRT^{44,45} supplies 2023–2025. GFED5 estimates fire-carbon emissions as the product of satellite
279 burned area and modelled fuel consumption; we use the total carbon emitted (GFED variable C) rather
280 than a CO₂ estimate obtained with species emission factors, because most non-CO₂ fire carbon is CO,
281 which is oxidized to CO₂ within months. Annual regional emissions are sums over the grid cells of each
282 basis region, in PgC yr⁻¹.

283 The 2025 value is the full-calendar-year GFED5NRT total and is shown as preliminary. It is excluded from
284 the main comparison and from every fire–CO₂ fit; its only fitted use is the explicitly labelled annual fire-
285 only sensitivity in Supplementary Note 3 and Supplementary Table 1. We also test synchronization using
286 GFED burned area¹⁷ (Supplementary Note 1 and Supplementary Table 4) and fire-radiative-power-based
287 emissions from the Global Fire Assimilation System⁴⁶ (GFAS; Supplementary Note 1 and Supplementary
288 Figs 3 and 5).

289 Atmospheric fire constraints come from regional inversions¹⁵ of TROPospheric Monitoring Instrument
290 (TROPOMI) CO observations over 2019–2024 (Supplementary Table 3), run separately with the Quick
291 Fire Emissions Dataset (QFED) and GFAS fire priors, whose year-to-year variation comes from satellite
292 fire radiative power rather than from GFED burned area. Posterior biomass-burning CO emissions are
293 converted to CO₂ emissions as described by Yun et al.¹⁵. Agreement between the two runs indicates how
294 far the recent regional structure depends on the choice of prior.

295 The CO₂ growth rate used here is the yearwise median of six Global Carbon Budget 2025 atmospheric
296 inversions that assimilate in situ observations and cover the full record with fixed membership¹; the
297 individual members are named in Supplementary Note 2. Inversions constrain the growth of the whole-
298 atmosphere CO₂ burden, whereas the growth rate of the National Oceanic and Atmospheric

Administration (NOAA) is derived from marine-boundary-layer sites, whose growth can differ from that of the whole atmosphere in individual years^{25,47}; each inversion member and the NOAA growth rate are analysed as sensitivities (Supplementary Note 2 and Supplementary Fig. 4a), because growth rates derived from different inversion systems can differ⁴⁸. GRESO (Growth Rate Estimation from Satellite Observations), the satellite-derived growth rate in Fig. 3b, follows Pandey et al.⁴⁷ and is available for 2015–2025. It is the mean of the calendar-year growth rates from column retrievals of the Orbiting Carbon Observatory-2 (OCO-2 v11.3r), described by Jacobs et al.⁴⁹, and of the Greenhouse gases Observing SATellite processed with the Atmospheric CO₂ Observations from Space algorithm (GOSAT ACOS v11), described by O'Dell et al.⁵⁰. Growth rates in ppm yr⁻¹ are converted into PgC yr⁻¹ with the factor of 2.124 PgC ppm⁻¹ used by Ballantyne et al.⁵¹.

Monthly air temperature and relative humidity are from the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis⁵² (Reanalysis 1). Vapour pressure deficit (VPD) is computed at each grid cell from monthly-mean temperature and relative humidity with the saturation vapour pressure formulation of Bolton⁵³, then averaged over each basis region with area weighting. These temperature and VPD fields provide the annual-mean series of Fig. 4a and the fire-season and twelve-month series of Fig. 4b. The El Niño–Southern Oscillation (ENSO) is described by the Oceanic Niño Index and the detrended Niño-3.4 index from the NOAA Climate Prediction Center and by the Multivariate ENSO Index^{54,55} (version 2, MEI v2).

Windows, anomalies and statistical conventions

The primary comparison uses two ten-year windows, 2001–2010 and 2015–2024, each with $n = 10$ annual values; the recent window ends with 2023 and 2024, the two near-real-time GFED years, and results excluding them are given in Supplementary Notes 1 and 3. Our analysis starts in 2001, the first complete year of burned-area observations from the Moderate Resolution Imaging Spectroradiometer (MODIS); earlier GFED years are reconstructed from active-fire detections of earlier sensors and are used only in the sensitivity tests of Supplementary Note 3 and in the 1999–2011 climatology that fixes each

324 region's fire season (Supplementary Note 4). Regional and global fire emissions, CO₂ growth and regional
 325 climate are all detrended by ordinary least squares within each window separately; anomalies are the
 326 residuals from that window's linear fit. Within-window detrending removes each decade's trend, so that
 327 the variances, covariances and correlations compared between windows describe year-to-year variability
 328 only. The exceptions are the 2024 ranking in Supplementary Note 2B and the standardized series of
 329 Supplementary Fig. 5, which use a single trend over each record's years within 2001–2024. Trailing ten-
 330 year statistics (Figs. 2b and 4a; Supplementary Fig. 2a) apply the same detrending to each ten-year
 331 window ending in the plotted year. Fig. 2a is a display only: each regional and global series is standardized
 332 by its 2001–2024 mean and standard deviation without detrending, so its colours show departures from
 333 the 2001–2024 mean rather than the within-window anomalies used in all statistics.

334 Sample sizes are the ten annual values of each window; monthly or seasonal values are never counted as
 335 independent observations. Standard deviations and variances are sample estimates, computed with the n
 336 $- 1$ denominator. Coherence, as used here, is the mean pairwise cross-region correlation: the mean of the
 337 91 correlation coefficients between distinct region pairs; the fraction of positively correlated pairs counts
 338 the same 91 pairs. Cross-region covariance and coherence answer different questions. The covariance
 339 term is weighted by regional anomaly amplitude and therefore governs the variance of the global total,
 340 whereas coherence is unweighted and measures how broadly the regions covary; the two can move
 341 differently when the change is concentrated in a few high-variance regions. The two measures are linked:
 342 for series divided by their own within-window standard deviation, the cross-region covariance term
 343 equals 182 times the coherence, because each of the 91 region pairs enters it twice; coherence is therefore
 344 the mean cross-region covariance of standardized anomalies. We use coherence to compare fire with
 345 climate because, in their own units, the covariances of temperature and VPD would weight each region by
 346 the variability of its climate rather than of its fire emissions. Changes in variance between windows are
 347 compared with two-sided F ratios with 8 and 8 degrees of freedom, because a trend is fitted in each ten-
 348 year window (Supplementary Note 2). Where intervals are reported (Supplementary Note 2), they are 95%
 349 percentile intervals from a circular moving-block bootstrap of the years within each window, with block

length three years, 4,000 replicates, the same sampled years applied to every series entering a statistic, and seed 20260806. Sensitivities to window choice, endpoint exclusion and single-year removal are reported in Supplementary Note 3. Values are rounded to the precision of the comparison they take part in.

Window-comparison sensitivity

To account for selecting among the five window comparisons in Supplementary Note 3, we compared the largest later-minus-earlier change in coherence with its distribution across 4,000 circular moving-block resamples of the pooled, undetrended 1997–2024 regional record (three-year blocks; seed 20260806). Each resample used the same year indices for all regions and assigned the sampled rows to the original sequence of year positions. A separate linear trend was then fitted within each candidate window before recalculating the maximum across recent-window starts of 2011–2015; each pair of ten-year windows is separated by four omitted years. The one-sided P value is $(1 + \text{number of resampled maxima at least as large as the observed maximum}) / (4,000 + 1)$. This scan tests the strongest positive contrast under the pooled-block resampling model and does not estimate a transition year.

Covariance accounting

The change in global variance between the windows is partitioned into the change in the summed regional variances and the change in the cross-region covariance term of the identity given in the Results; the covariance share (84%) is the latter divided by the total change. In a covariance swap, the 2001–2010 summed regional variance ($0.054 \text{ PgC}^2 \text{ yr}^{-2}$) is combined with the 2015–2024 cross-region covariance term ($+0.058 \text{ PgC}^2 \text{ yr}^{-2}$), giving a global variance of $0.11 \text{ PgC}^2 \text{ yr}^{-2}$, 5.8 times the 2001–2010 value of $0.019 \text{ PgC}^2 \text{ yr}^{-2}$, against the observed 6.8-fold. For the boreal–tropical component (Fig. 2d), the two boreal regions (Boreal North America and Boreal Asia) and the seven tropical regions (Central America, Northern and Southern Hemisphere South America, Northern and Southern Hemisphere Africa, Southeast Asia and Equatorial Asia) are summed into two aggregate series and detrended within each window. Their correlation is reported directly; the boreal–tropical covariance term is twice their covariance,

375 because both off-diagonal blocks enter the global variance, and its change divided by the change in total
376 cross-region covariance gives the 44% share.

377 Fire-CO₂ association

378 For each window, the growth-rate anomaly is regressed on the fire anomaly by ordinary least squares; Fig.
379 3c shows the fits and their R^2 , and Supplementary Table 3A gives the 2015–2024 slopes. The variances in
380 Fig. 3d are those of the detrended fire anomaly, the detrended growth anomaly and their difference,
381 growth minus fire; because detrending is linear, the difference of the two detrended series equals the
382 detrended difference. The corresponding standard-deviation reductions, their relationship to the variance
383 fractions, and the early-to-recent variability comparisons and uncertainties are given in Supplementary
384 Note 2 and Supplementary Table 3. The preliminary 2025 pair, the full-year GFED5NRT fire total and the
385 GRESO growth rate, is placed relative to the 2015–2024 trend of each product and enters no fit. The
386 regression describes the association between two detrended records; it does not partition the growth rate
387 into sources.

388 Fire-season sampling and climate coherence

389 Each region's fire season is the set of four contiguous calendar months with the largest climatological
390 emissions over 1999–2011, and its season year is the calendar year of the climatological peak month
391 within that window. The seasons were fixed before any climate series was examined and are not adjusted
392 to later years; tie rules and seasons that cross the calendar year are handled as described in
393 Supplementary Note 4, and the seasons of all 14 regions are listed in Supplementary Table 2. Fire-season
394 temperature and VPD are means over those four months; twelve-month sampling averages the twelve
395 calendar months ending with the last month of the fire season, so that it contains the season and the eight
396 months before it; annual-mean sampling uses calendar-year means. Coherence is computed from within-
397 window detrended regional series for trailing ten-year windows ending 2010–2024 (Fig. 4a) and for the
398 two comparison windows under the three samplings (Fig. 4b). ENSO variability in Fig. 4c is the sample
399 standard deviation of each monthly index over each ten-year window ending 1959–2024 (MEI v2 from

1988), and the rankings of the two decades described in the Results are percentile ranks among those windows.

For uncertainty in climate coherence changes (Supplementary Note 4), early and recent years are resampled separately in circular three-year blocks, using 4,000 replicates and seed 20260806. Draws within a window are shared across regions, variables and sampling choices. Each resampled series is detrended against its sampled original years before its pairwise correlations are averaged. Intervals are the 2.5th–97.5th percentiles of the recent-minus-early difference. This within-window uncertainty calculation differs from the pooled-record window scan above.

Use of AI tools

Large language model (LLM) assistants (Codex, OpenAI; Claude, Anthropic) were used to help edit the text, to write and debug data-processing and plotting code, and to check submission files. The three illustrations in Fig. 1 (forest, savanna and globe) were drawn with Matplotlib and Cartopy, using Natural Earth coastlines; the drawing code was written with an LLM coding assistant. The authors checked all text, code, analyses and references and take full responsibility for the content of this paper.

Data availability

GFED5.1 fire emissions, burned area and the basis-region mask²³ are available at <https://doi.org/10.5281/zenodo.16794692> and <https://www.globalfiredata.org>, and GFED5NRT^{44,45} at <https://doi.org/10.5281/zenodo.18702700>. GFAS fire-radiative-power-based emissions⁴⁶ are available from the Copernicus Atmosphere Data Store at <https://doi.org/10.24381/a05253c7>. The Global Carbon Budget 2025 atmospheric inversion fluxes¹ are available from the Integrated Carbon Observation System (ICOS) Carbon Portal at <https://doi.org/10.18160/VZ3B-GHYQ>. The NOAA global CO₂ growth rate is available at https://gml.noaa.gov/ccgg/trends/gl_gr.html. OCO-2 v11.3r and GOSAT ACOS v11 Lite retrievals are available from the NASA Goddard Earth Sciences Data and Information Services Center at <https://doi.org/10.5067/C4OENLFCYVSA> and <https://doi.org/10.5067/UAY6VJYTS8OD>, respectively; the annual GRESO growth rates are available in Pandey et al.²⁵, and the series was extended to include 2025

425 using the approach described in that paper. NCEP–NCAR Reanalysis 1 fields are available at
426 <https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.html>, the Oceanic Niño Index and detrended
427 Niño-3.4 index at <https://www.cpc.ncep.noaa.gov/data/indices/>, and MEI v2 at
428 <https://psl.noaa.gov/enso/mei/>.

429 Code availability

430 The analysis and figure code that produces the numbers and figures in this study, together with the
431 derived input series, is archived on Zenodo (reserved DOI: 10.5281/zenodo.22969746). It is available to
432 editors and reviewers through a private link during peer review and will be made public with a versioned
433 release upon acceptance.

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437 Author contributions

438 S.P. designed the study, performed the analysis and wrote the manuscript. J.Y. and J.L. provided the CO
439 inversion data. J.T.R. provided the GFED data. K.W.B. and A.A.B. contributed to the framing and figure
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441 Competing interests

442 The authors declare no competing interests.

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444 References

- 445 1. Friedlingstein, P. *et al.* Global Carbon Budget 2025. *Earth System Science Data* **18**, 3211–3288
446 (2026).
- 447 2. Cox, P. M. *et al.* Sensitivity of tropical carbon to climate change constrained by carbon dioxide
448 variability. *Nature* **494**, 341–344 (2013).
- 449 3. Humphrey, V. *et al.* Sensitivity of atmospheric CO₂ growth rate to observed changes in terrestrial
450 water storage. *Nature* **560**, 628–631 (2018).
- 451 4. Humphrey, V. *et al.* Soil moisture–atmosphere feedback dominates land carbon uptake variability.
452 *Nature* **592**, 65–69 (2021).
- 453 5. Liu, L. *et al.* Increasingly negative tropical water–interannual CO₂ growth rate coupling. *Nature*
454 **618**, 755–760 (2023).
- 455 6. Li, N. *et al.* Enhanced global carbon cycle sensitivity to tropical temperature linked to internal
456 climate variability. *Science Advances* **10**, eadl6155 (2024).
- 457 7. Keppel-Aleks, G. *et al.* Separating the influence of temperature, drought, and fire on interannual
458 variability in atmospheric CO₂. *Global Biogeochemical Cycles* **28**, 1295–1310 (2014).
- 459 8. Yuan, W. *et al.* Increased atmospheric vapor pressure deficit reduces global vegetation growth.
460 *Science Advances* **5**, eaax1396 (2019).
- 461 9. Langenfelds, R. L. *et al.* Interannual growth rate variations of atmospheric CO₂ and its $\delta^{13}\text{C}$, H₂, CH₄,
462 and CO between 1992 and 1999 linked to biomass burning. *Global Biogeochemical Cycles* **16**, 1048 (2002).
- 463 10. Page, S. E. *et al.* The amount of carbon released from peat and forest fires in Indonesia during 1997.
464 *Nature* **420**, 61–65 (2002).

- 465 11. van der Werf, G. R. *et al.* Continental-scale partitioning of fire emissions during the 1997 to 2001 El
466 Niño/La Niña period. *Science* **303**, 73–76 (2004).
- 467 12. van der Velde, I. R. *et al.* Vast CO₂ release from Australian fires in 2019–2020 constrained by
468 satellite. *Nature* **597**, 366–369 (2021).
- 469 13. Zheng, B. *et al.* Record-high CO₂ emissions from boreal fires in 2021. *Science* **379**, 912–917 (2023).
- 470 14. Byrne, B. *et al.* Carbon emissions from the 2023 Canadian wildfires. *Nature* **633**, 835–839 (2024).
- 471 15. Yun, J., Pandey, S., Bowman, K., Miyazaki, K. & Liu, J. Unprecedented role of Amazon fires in the
472 record atmospheric CO₂ growth in 2024. *Preprint at ESS Open Archive* (2025)
473 doi:10.22541/essoar.175874118.83695562/v1.
- 474 16. Andela, N. *et al.* A human-driven decline in global burned area. *Science* **356**, 1356–1362 (2017).
- 475 17. Chen, Y. *et al.* Multi-decadal trends and variability in burned area from the fifth version of the
476 Global Fire Emissions Database (GFED5). *Earth System Science Data* **15**, 5227–5259 (2023).
- 477 18. Zheng, B. *et al.* Increasing forest fire emissions despite the decline in global burned area. *Science*
478 *Advances* **7**, eabh2646 (2021).
- 479 19. Jones, M. W. *et al.* Global rise in forest fire emissions linked to climate change in the extratropics.
480 *Science* **386**, eadl5889 (2024).
- 481 20. Kitzberger, T., Brown, P. M., Heyerdahl, E. K., Swetnam, T. W. & Veblen, T. T. Contingent Pacific–
482 Atlantic Ocean influence on multicentury wildfire synchrony over western North America. *Proceedings of*
483 *the National Academy of Sciences* **104**, 543–548 (2007).
- 484 21. Chen, Y. *et al.* A pan-tropical cascade of fire driven by El Niño/Southern Oscillation. *Nature Climate*
485 *Change* **7**, 906–911 (2017).

- 486 22. Yin, C. *et al.* Increasing synchronicity of global extreme fire weather. *Science Advances* **12**,
487 eadx8813 (2026).
- 488 23. van der Werf, G. R. *et al.* Landscape fire emissions from the 5th version of the Global Fire
489 Emissions Database (GFED5). *Scientific Data* **12**, 1870 (2025).
- 490 24. Pandey, S. *et al.* Reduction in Earth's carbon budget imbalance. *Nature Communications* **16**, 6818
491 (2025).
- 492 25. Pandey, S. *et al.* Time-varying errors in the atmospheric CO₂ growth rate. *Preprint at Research*
493 *Square* (2026) doi:10.21203/rs.3.rs-9854768/v1.
- 494 26. de Laat, A. T. J. *et al.* Sentinel-5P reveals unexplained large wildfire carbon emissions in the
495 Amazon in 2024. *Geophysical Research Letters* **53**, e2025GL115123 (2026).
- 496 27. Jung, M. *et al.* Compensatory water effects link yearly global land CO₂ sink changes to temperature.
497 *Nature* **541**, 516–520 (2017).
- 498 28. Iwakiri, T. *et al.* Triple-dip La Niña in 2020–23: North Pacific atmosphere drives 2nd year La Niña.
499 *Geophysical Research Letters* **50**, e2023GL105763 (2023).
- 500 29. Huijnen, V. *et al.* Fire carbon emissions over maritime southeast Asia in 2015 largest since 1997.
501 *Scientific Reports* **6**, 26886 (2016).
- 502 30. Liu, J. *et al.* Contrasting carbon cycle responses of the tropical continents to the 2015–2016 El Niño.
503 *Science* **358**, eaam5690 (2017).
- 504 31. Patra, P. K. *et al.* The Orbiting Carbon Observatory (OCO-2) tracks 2–3 peta-gram increase in
505 carbon release to the atmosphere during the 2014–2016 El Niño. *Scientific Reports* **7**, 13567 (2017).
- 506 32. Dong, G. *et al.* Dramatic increase in ecosystem respiration causes record-breaking atmospheric
507 CO₂ growth rate in 2024. *Nature Communications* **17**, 5436 (2026).

- 508 33. Bowman, D. M. J. S. *et al.* Fire in the Earth system. *Science* **324**, 481–484 (2009).
- 509 34. Silva, C. V. J. *et al.* Drought-induced Amazonian wildfires instigate a decadal-scale disruption of
510 forest carbon dynamics. *Philosophical Transactions of the Royal Society B: Biological Sciences* **373**,
511 20180043 (2018).
- 512 35. Walker, X. J. *et al.* Increasing wildfires threaten historic carbon sink of boreal forest soils. *Nature*
513 **572**, 520–523 (2019).
- 514 36. Clarke, H. *et al.* Forest fire threatens global carbon sinks and population centres under rising
515 atmospheric water demand. *Nature Communications* **13**, 7161 (2022).
- 516 37. Xu, S. *et al.* Warming climate amplifies vapor pressure deficit limits on gross primary productivity.
517 *Nature Communications* **17**, 6149 (2026).
- 518 38. Chen, Y., Velicogna, I., Famiglietti, J. S. & Randerson, J. T. Satellite observations of terrestrial water
519 storage provide early warning information about drought and fire season severity in the Amazon. *Journal*
520 *of Geophysical Research: Biogeosciences* **118**, 495–504 (2013).
- 521 39. Singh, J. *et al.* Enhanced risk of concurrent regional droughts with increased ENSO variability and
522 warming. *Nature Climate Change* **12**, 163–170 (2022).
- 523 40. Luo, X. & Keenan, T. F. Tropical extreme droughts drive long-term increase in atmospheric CO₂
524 growth rate variability. *Nature Communications* **13**, 1193 (2022).
- 525 41. Rabin, S. S. *et al.* The Fire Modeling Intercomparison Project (FireMIP), phase 1: Experimental and
526 analytical protocols with detailed model descriptions. *Geoscientific Model Development* **10**, 1175–1197
527 (2017).
- 528 42. Li, F. *et al.* Historical (1700–2012) global multi-model estimates of the fire emissions from the Fire
529 Modeling Intercomparison Project (FireMIP). *Atmospheric Chemistry and Physics* **19**, 12545–12567 (2019).

- 530 43. Hantson, S. *et al.* Quantitative assessment of fire and vegetation properties in simulations with
531 fire-enabled vegetation models from the Fire Model Intercomparison Project. *Geoscientific Model*
532 *Development* **13**, 3299–3318 (2020).
- 533 44. Chen, Y. *et al.* Tracking recent extremes and interannual variability of global fire emissions using a
534 near-real-time extension to the Global Fire Emissions Database. *Preprint at Earth System Science Data*
535 *Discussions* (2026) doi:10.5194/essd-2026-158.
- 536 45. Chen, Y. *et al.* GFED5NRT: Global Fire Emissions Database Near-Real-Time Extension. *Zenodo*
537 (2026) doi:10.5281/zenodo.18702700.
- 538 46. Kaiser, J. W. *et al.* Biomass burning emissions estimated with a global fire assimilation system
539 based on observed fire radiative power. *Biogeosciences* **9**, 527–554 (2012).
- 540 47. Pandey, S. *et al.* Toward low-latency estimation of atmospheric CO₂ growth rates using satellite
541 observations: Evaluating sampling errors of satellite and in situ observing approaches. *AGU Advances* **5**,
542 e2023AV001145 (2024).
- 543 48. Gaubert, B. *et al.* Global atmospheric CO₂ inverse models converging on neutral tropical land
544 exchange, but disagreeing on fossil fuel and atmospheric growth rate. *Biogeosciences* **16**, 117–134 (2019).
- 545 49. Jacobs, N. *et al.* The importance of digital elevation model accuracy in XCO₂ retrievals: Improving
546 the Orbiting Carbon Observatory 2 Atmospheric Carbon Observations from Space version 11 retrieval
547 product. *Atmospheric Measurement Techniques* **17**, 1375–1401 (2024).
- 548 50. O'Dell, C. W. *et al.* The ACOS CO₂ retrieval algorithm – Part 1: Description and validation against
549 synthetic observations. *Atmospheric Measurement Techniques* **5**, 99–121 (2012).
- 550 51. Ballantyne, A. P., Alden, C. B., Miller, J. B., Tans, P. P. & White, J. W. C. Increase in observed net
551 carbon dioxide uptake by land and oceans during the past 50 years. *Nature* **488**, 70–72 (2012).

- 552 52. Kalnay, E. *et al.* The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American*
553 *Meteorological Society* **77**, 437–472 (1996).
- 554 53. Bolton, D. The computation of equivalent potential temperature. *Monthly Weather Review* **108**,
555 1046–1053 (1980).
- 556 54. Wolter, K. & Timlin, M. S. El Niño/Southern Oscillation behaviour since 1871 as diagnosed in an
557 extended multivariate ENSO index (MEI.ext). *International Journal of Climatology* **31**, 1074–1087 (2011).
- 558 55. Zhang, T. *et al.* Towards probabilistic multivariate ENSO monitoring. *Geophysical Research Letters*
559 **46**, 10532–10540 (2019).

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