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Abstract

The terrestrial carbon cycle contains pools with turnover times from months to centuries. An extreme carbon-loss year depletes fast pools such as leaves, fine roots and litter, with turnover times of months to a few years. We hypothesize that after a loss year these pools must refill and enhance land uptake in the following months. We test whether this recovery, or overshoot sink, can be detected in annual and monthly atmospheric CO₂ growth rates (CGR), in time-varying net CO₂ flux maps from atmospheric inversions, and in the pools and fluxes of dynamic global vegetation models. Across 10 high-CGR events since 1959, the following-year anomaly averaged -0.22 ± 0.08 ppm yr⁻¹, compared with -0.17 ± 0.04 ppm yr⁻¹ across all below-threshold years, a difference that was not statistically significant ($p = 0.28$). Monthly inversion fluxes and satellite growth rates likewise showed no clear excess uptake after carbon-loss episodes. Vegetation models simulated enhanced uptake after observed high-CGR events, driven largely by increased photosynthesis, but no clear additional uptake after model-defined carbon-loss events; litter refill exceeded random-year levels, with an approximate flux scale of about one-fifth of that uptake. Thus, atmospheric CO₂ reversals cannot distinguish climate-driven uptake after a loss event followed by favourable climate from the legacy replenishment of previously depleted carbon pools.

Introduction

Over 2015–2024, the land biosphere absorbed 21% of anthropogenic emissions, but this carbon sink is highly sensitive to annual climate variability and extremes (Friedlingstein et al., 2026; Ballantyne et al., 2012; Wang et al., 2013; Reichstein et al., 2013). El Niño years bring warmer and drier conditions across the tropics, with regional differences among continents (Liu et al., 2017). These conditions weaken land carbon uptake and produce spikes in the global atmospheric CO₂ growth rate (CGR) (Keeling et al., 1995; Zeng et al., 2005; Jones and Cox, 2005; Humphrey et al., 2018). Conversely, wetter and cooler La Niña conditions tend to be associated with lower CGR (Liu et al., 2024).

We ask whether an abnormally large carbon loss in one year is followed by additional uptake in the next. Carbon moves through interconnected terrestrial pools with turnover times ranging from months to centuries (Carvalhais et al., 2014). Following standard carbon-pool theory (Oeschger et al., 1975; Luo et al., 2017), a simple one-pool representation of the land carbon balance is

$$\frac{dC}{dt} = I - kC. \quad \dots\dots\dots (1)$$

where C is the carbon stock, t is time, I is the carbon input from the atmosphere, and k is the turnover rate. The loss rate kC is proportional to the amount stored. If inputs and losses balance before a disturbance, the disturbance can deplete the pool by abruptly reducing inputs or increasing losses. Once inputs and turnover return to their previous values, the smaller stock loses less carbon than it receives. The difference between inputs and losses forms a recovery sink that diminishes exponentially as the pool refills. Fast pools such as leaves or litter could respond within the following year. This simple balance illustrates how replenishment could increase uptake above what the same recovery-year climate would produce without the preceding carbon loss. We call this additional uptake an overshoot sink. If large

enough, it would lower the following year's global CO₂ growth rate after a high-CGR disturbance such as an El Niño year.

Recovery after disturbances is observed locally; for example, gross primary production recovers from drought on timescales that vary among ecosystems and climate conditions (Schwalm et al., 2017). However, photosynthesis can recover without restoring the carbon stocks lost during the disturbance. At the global scale, recovery-year climate also makes it difficult to identify uptake caused by the preceding carbon loss. A La Niña following an El Niño, for example, can increase land uptake independently of any depletion of carbon pools. Thus, a decline in CGR after a high-CGR year does not by itself establish an overshoot sink.

We analyse the global CGR record since 1959 to test whether growth rates following high-CGR events are unusually low compared with years below the selection threshold. Atmospheric inversions provide monthly, spatially explicit estimates of land uptake, allowing us to examine shorter periods of enhanced uptake that annual averages could conceal. Conceptual carbon-pool models show how following-year uptake depends on which pools lose carbon. Dynamic global vegetation models (DGVMs) allow us to examine whether enhanced uptake is accompanied by replenishment of those pools, although their responses to climate variability are imperfect (Piao et al., 2013).

Results

Annual CO₂ growth rates

Figure 1a shows the annual CO₂ growth rate from the combined Scripps Institution of Oceanography and National Oceanic and Atmospheric Administration (NOAA) global marine boundary layer record for 1959–2025 (Masarie and Tans, 1995; Lan et al., 2026; Conway et al., 1994). We linearly detrended the CGR record and selected years with anomalies above its 80th percentile ($q_{80} = +0.34 \text{ ppm yr}^{-1}$), yielding 14 high-CGR years (Fig. 1b). Merging consecutive high-CGR years into single events gave 10 events (Table S1). We define the recovery year as the year after the final high-CGR year of each event.

Because an event ends when CGR falls below q_{80} , we compare recovery years with all below-threshold years to test whether their anomalies are unusually negative. The mean anomaly of the ten recovery years was $-0.22 \pm 0.08 \text{ ppm yr}^{-1}$, compared with $-0.17 \pm 0.04 \text{ ppm yr}^{-1}$ across all 53 below-threshold years, including the recovery years themselves. Uncertainties are standard errors across the years. The recovery mean lies well inside the central 95% range of means of ten below-threshold years drawn at random (-0.35 to 0.00 ppm yr^{-1} ; grey band in Fig. 1b), and the difference was not statistically significant (one-sided $p = 0.28$; Fig. S1c), indicating that there is no evidence of a global overshoot sink in the annual CGR record. The year-to-year analysis also shows why a large decline in CGR alone does not demonstrate a recovery sink (Supplementary Text S1; Fig. S1a, b). Alternative annual estimates of whole-atmosphere growth give the same result: the growth rate implied by the Global Carbon Budget 2025 (GCB2025) inversion ensemble, and growth rates from the Greenhouse Gases Observing Satellite (GOSAT) and the Orbiting Carbon Observatory-2 (OCO-2) (Pandey et al., 2024) extended back to 2000 with the inversion record, show no recovery excess, although the inversion median ends before the 2025 recovery (Supplementary Text S2; Fig. S2; Table S2).

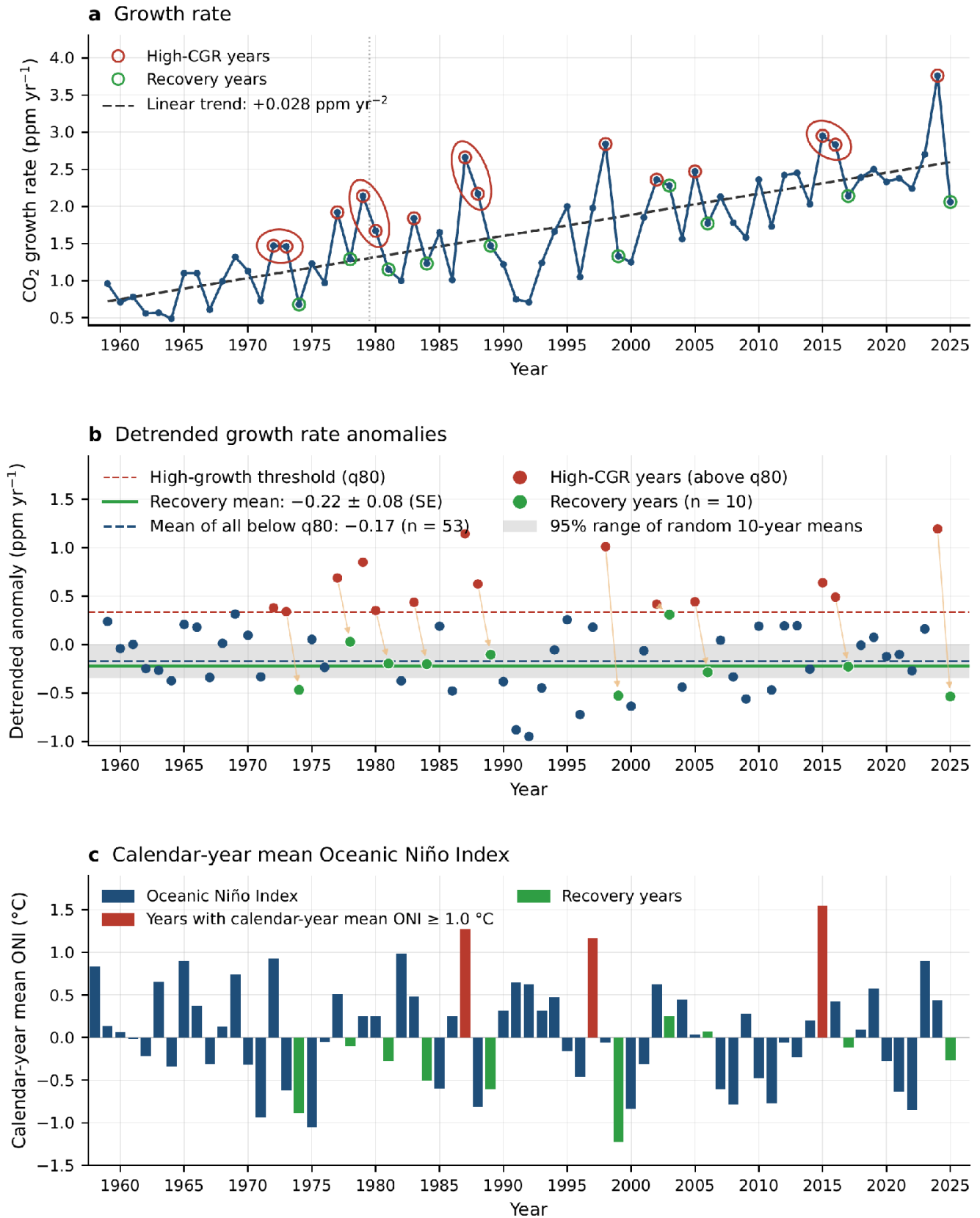


Figure 1 | Marine boundary layer CO₂ growth rate, 1959–2025. a, Annual growth rate and fitted linear trend (+0.028 ppm yr⁻²; black dashed line); red circles mark high-CGR years, green circles their recovery years, and ellipses join consecutive high-CGR years. b, Detrended growth-rate anomalies. Red dots exceed q80 (+0.34 ppm yr⁻¹; red dashed line); green dots mark ten recovery years, and blue dots mark other years. Light orange arrows connect the final high-CGR year of each event to its recovery year. The green line shows the recovery mean (-0.22 ± 0.08 ppm yr⁻¹; ± 1 standard error). The blue dashed line shows the mean of all 53 below-q80 years, including recovery years (-0.17 ± 0.04 ppm yr⁻¹), and the grey

band the central 95% range of means of ten years drawn at random from those years (-0.35 to 0.00 ppm yr^{-1}). c, Calendar-year mean of the Oceanic Niño Index (ONI), the Niño 3.4 sea surface temperature anomaly from version 5 of the Extended Reconstructed Sea Surface Temperature analysis (ERSSTv5; Huang et al., 2017), as distributed by NOAA Climate Prediction Center (2026). Red bars mark years with calendar-year mean ONI ≥ 1.0 °C (1987, 1997 and 2015); green bars mark the ten recovery years.

If larger carbon losses during strong El Niño events leave larger deficits in fast carbon pools, their subsequent replenishment should produce a stronger recovery sink. We therefore selected only strong El Niño years by a calendar-year mean Oceanic Niño Index (ONI) of at least 1.0 °C, a criterion independent of the CGR record, which identifies 1987, 1997 and 2015 (Fig. 1c). Each of these strong El Niño years lies within or immediately precedes a high-CGR event (1987–1988, 1998 and 2015–2016), so their recovery years are 1989, 1999 and 2017. Their recovery-year mean is -0.29 ± 0.13 ppm yr^{-1} , an excess of -0.12 ppm yr^{-1} over the same below-threshold years and roughly twice the excess obtained from all ten q80 high-CGR events (Fig. S1c). However, with only three events, a mean this negative would still occur about one time in four by chance alone ($p = 0.25$). The strongest El Niño events thus show the sign expected of an overshoot sink, but three events are too few to tell that signal apart from chance. All three recovery years also had negative calendar-year mean ONI (-0.6 , -1.2 and -0.1 °C). These cooler conditions could themselves strengthen land uptake, independently of any refilling of fast carbon pools. Across all ten events the recovery anomaly tracks recovery-year ONI more closely than the size of the preceding loss, and the second-largest event has one of the weakest recoveries (Supplementary Text S1; Table S1).

If carbon loss leaves depleted pools whose legacy affects uptake in the following year, the preceding CGR anomaly might help predict recovery-year growth beyond what climate alone explains. We tested this possibility in five recovery years using the Mauna Loa record. Adding the preceding anomaly to climate and emissions information did not improve predictions (Supplementary Text S3; Fig. S3).

Reduced carbon release can also lower CGR without an overshoot sink. We therefore compared annual NOAA growth rates with emissions from the Global Fire Emissions Database, version 5.1 (GFED5.1; van der Werf et al., 2025a, 2025b), to assess the contribution of reduced burning. Because fire emissions are included in net land carbon exchange, a drop in burning after an extreme fire year can appear as a stronger land sink without depleted pools refilling. Declining fire emissions account for 16 to 32% of the CGR decline in three transitions with reliable estimates, and for 28% of the 2024–2025 decline when the near-real-time GFED extension is used, providing a partial explanation that does not require a recovery sink (Supplementary Text S4; Fig. S4).

Monthly CO₂ growth rates and land uptake

Looking only at annual atmospheric CO₂ growth rates can conceal a short-lived increase in land uptake. We therefore repeated the event analysis at monthly resolution, asking whether the land sink becomes unusually strong in the months after a loss episode. Atmospheric inversions combine CO₂ measurements with atmospheric transport models to estimate monthly maps of land–atmosphere fluxes; by design they reproduce the observed growth rate. We used the GCB2025 inversion ensemble (Friedlingstein et al., 2026; Luijkx et al., 2025) and, as an independent atmospheric record, growth rates estimated directly from satellite CO₂ retrievals (Pandey et al., 2024).

Figure 2 shows three monthly records treated in the same way as the annual growth rate: the land carbon flux from the median of the six surface-only GCB2025 inversions, which assimilate surface station data, for 2000–2024 (Fig. 2b), the land flux from the median of the eight inversions that assimilate GOSAT or OCO-2 satellite retrievals for 2010–2024 (Fig. 2c), and the atmospheric growth rate estimated from OCO-2 retrievals alone by the GRESO method (growth rate estimated from satellite observations) for 2015–2025, extended back to 2010 with the GOSAT record (Fig. 2d). Each record was deseasonalized, detrended and smoothed with a centred three-month mean. We report land fluxes as positive for release, opposite to the net biome production (NBP) convention used below for the vegetation models: a positive land-flux anomaly means greater release to the atmosphere and a negative anomaly means stronger net

uptake, matching the direction of the atmospheric growth-rate anomaly. We selected months with anomalies above each record's own 80th percentile ($q_{80} = 0.99, 1.10$ and 1.18 PgC yr^{-1}), giving 60, 36 and 38 high months. High months form one event until three consecutive months fall below q_{80} , so that a brief dip within a loss episode does not split it. This gives 16, 7 and 5 events; the three records agree on the 2012–2013, 2015–2016, 2019 and 2023–2024 episodes (Fig. 2a shows the accompanying El Niño–Southern Oscillation, or ENSO, conditions). We define the recovery window as the twelve months after the final high month of each event, the counterpart of the recovery year in the annual analysis. These fixed windows can include high months from a later event; the comparison windows can also contain high months.

Because a twelve-month window can itself contain high months, we compare the recovery windows with random twelve-month windows that start in below-threshold months, rather than with individual months. The mean flux anomaly over the recovery windows was $-0.16 \pm 0.17 \text{ PgC yr}^{-1}$ for the surface-only inversions (14 events with a complete window), -0.54 ± 0.24 for the satellite-assimilating inversions (5 events) and -0.27 ± 0.36 for the GRESO growth rate (5 events), against random-window means of -0.14 , -0.25 and -0.18 , giving differences of -0.02 , -0.29 and $-0.09 \text{ PgC yr}^{-1}$. All three are negative, that is weaker release than the fitted trend, and so in the direction of additional uptake. Uncertainties are standard errors across events. None of the differences was statistically significant (one-sided $p = 0.47$, 0.21 and 0.42 ; Fig. 2b–d). The surface-only inversion record gives an uptake excess of 0.02 PgC yr^{-1} , compared with about 0.3 PgC yr^{-1} needed for a difference at the one-sided 5% level. The corresponding comparison threshold is about 0.5 PgC yr^{-1} for each satellite record. These thresholds describe the random reference; they are not upper bounds on the actual recovery sink (Methods). The monthly records therefore show no evidence of an overshoot sink in the year after a loss episode. A separate examination of regional inversion fluxes found no clear additional uptake during months 3–12 after large global loss onsets in twelve continental regions (Supplementary Text S5; Fig. S5; Table S5).

The recovery-window length affects the comparison. An event ends when the anomaly drops below q_{80} , but the anomaly can remain positive and continue falling for several months. Windows of three to six months therefore still contain the tail of the event and show release of 0.3 – 0.8 PgC yr^{-1} above random windows in all three records (Table S3). These differences decrease by nine months. Longer windows of 18–24 months give release of 0.1 – 0.4 PgC yr^{-1} below random windows in all three records ($p = 0.08$ – 0.36 ; Table S3). La Niña conditions occupy 28–44% of these longer inversion windows and 14–20% of the satellite growth-rate windows, compared with a common reference of 30% over 2000–2025 (Fig. 2a; Table S3). The records cover different periods, and this comparison does not separate the contributions of climate and pool replenishment to the later uptake.

The GRESO record extends one year beyond the inversions and covers the twelve months after the 2023–2024 episode, the longest in the record at seventeen months and the largest in cumulative anomaly (2.9 PgC , against 2.1 PgC for 2015–2016). Over that window, December 2024 to November 2025, the growth rate averaged 1.2 PgC yr^{-1} below trend, the lowest of its five recovery windows and the sixth lowest of all 179 twelve-month stretches in the record ($p = 0.04$). It is consistent with the annual 2025 anomaly of $-0.54 \text{ ppm yr}^{-1}$, the sixth most negative in the NOAA record. Whether it reflects pool recovery, the weak La Niña of late 2024 or reduced emissions awaits the 2025 inversion fluxes; the other four recovery windows in the record do not show it.

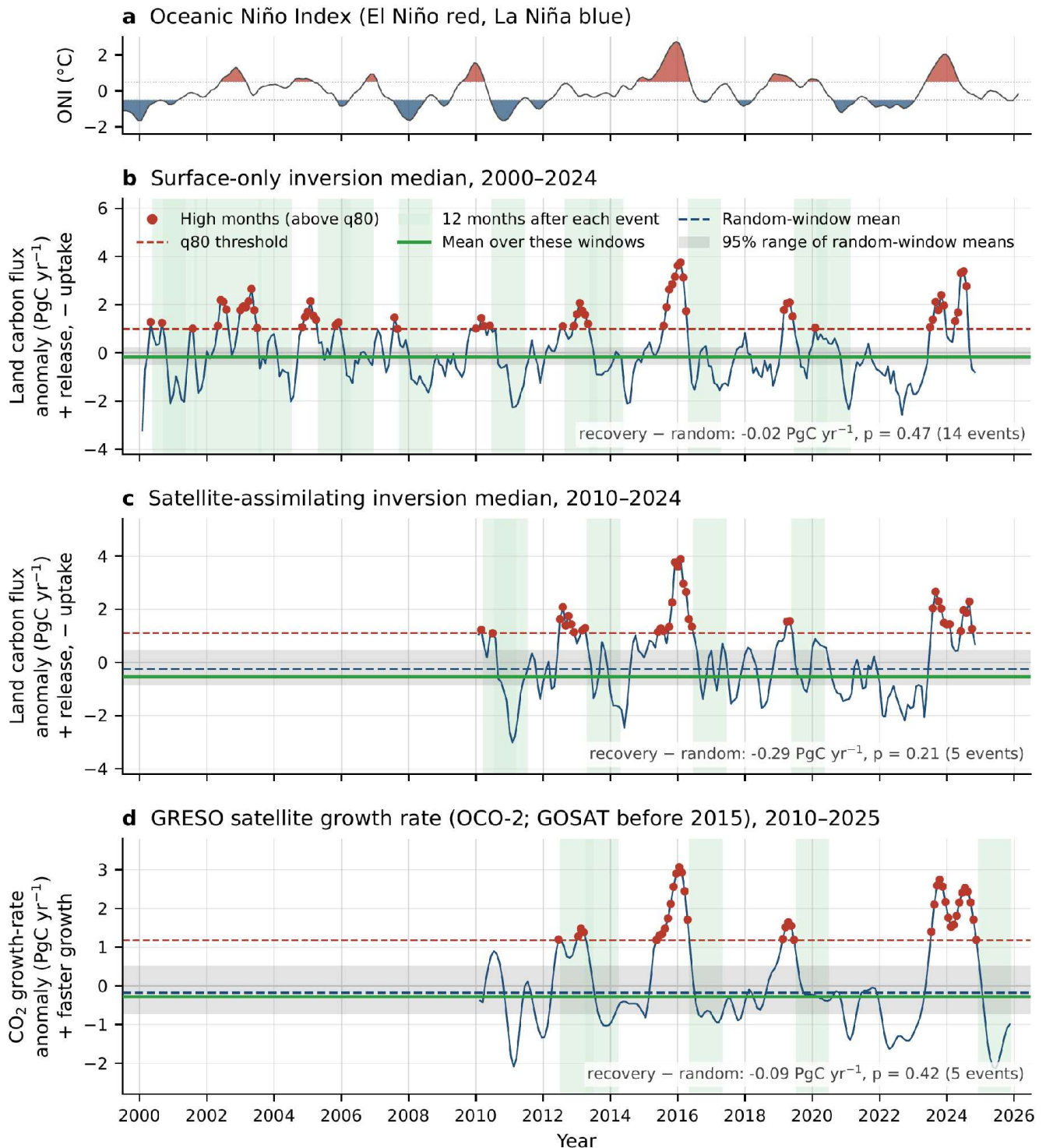


Figure 2 | Monthly event analysis on three records. a, Seasonal Oceanic Niño Index (ERSSTv5); red fill marks El Niño conditions ($\geq +0.5 \text{ }^{\circ}\text{C}$) and blue fill La Niña conditions ($\leq -0.5 \text{ }^{\circ}\text{C}$). b, Land carbon flux anomaly from the median of six surface-only GCB2025 inversions, 2000–2024. c, Land carbon flux anomaly from the median of the eight inversions that assimilate GOSAT or OCO-2 retrievals, 2010–2024. d, Atmospheric CO_2 growth-rate anomaly from the GRESO satellite method (OCO-2 from 2015; GOSAT for 2010–2014), converted to PgC yr^{-1} . Series are deseasonalized, detrended and smoothed with a centred three-month mean. In b and c land flux is positive for release, so positive anomalies mean greater release from land to the atmosphere and negative anomalies stronger net uptake; the axis labels give the two directions, and d points the same way. Note that this is the opposite convention to the net biome production used for the vegetation models, which is positive for uptake. Red dots mark months above each record's 80th percentile (red dashed line); an event lasts until three consecutive months fall below the threshold. Light green bands mark the fixed twelve months after the last high month of each event. A later event can begin within a band, so some red high-month dots lie inside these windows. The green line

is the mean anomaly over these windows; the blue dashed line is the mean of random twelve-month windows starting in below-threshold months, and the grey band their central 95% range. Text gives the difference between the two means and its one-sided p value.

Carbon-pool controls on following-year uptake

The observational analyses do not identify a clear global recovery sink. To understand when such a sink would be expected, we extended the input–loss balance in Equation 1 to two connected carbon pools, biomass and litter, with illustrative turnover times set to 33 and 2 years. In this two-pool model, carbon leaving biomass through turnover enters litter, whose decomposition releases carbon to the atmosphere with a delay. We imposed a 2 PgC disturbance over one year, then returned the disturbance terms to zero, holding the turnover rates constant (Fig. 3). This isolates the uptake caused by episodic depletion of carbon pools from the effects of changing recovery-year climate. Model equations and parameters are described in Methods and Supplementary Text S6.

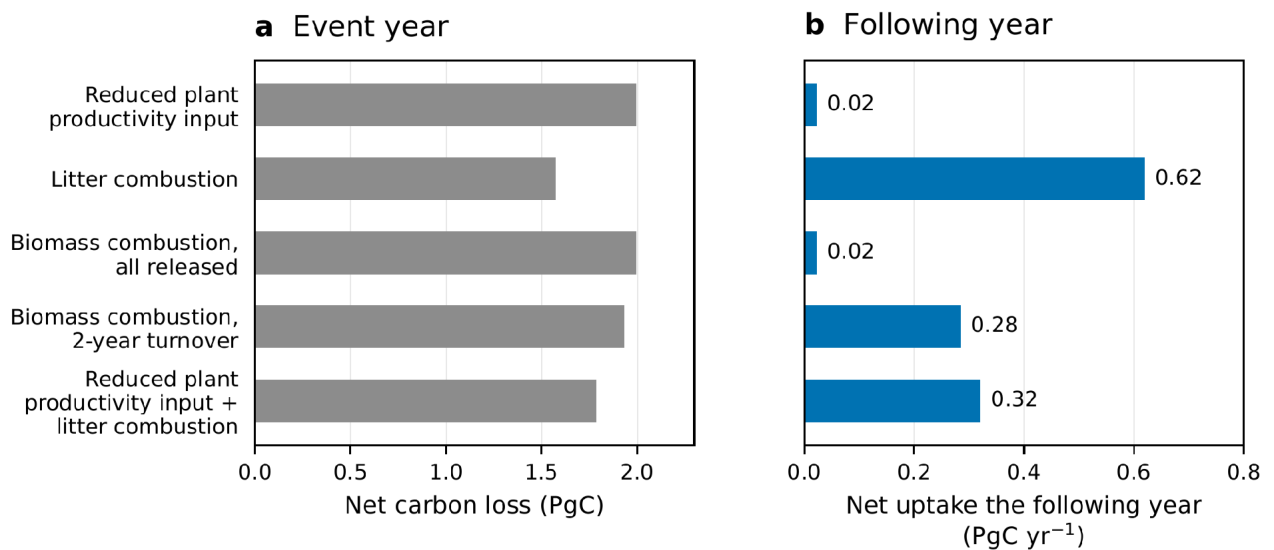


Figure 3 | Carbon loss and following-year uptake in a two-pool model. The model represents biomass and litter, with turnover times of about 33 and 2 years respectively. a, Net carbon loss during a one-year disturbance under different scenarios, the carbon deficit left at the end of that event year. b, Additional uptake in the following year, after the disturbance terms return to zero. Reduced plant productivity input means a decrease in carbon entering biomass from the atmosphere, corresponding to a reduction in I in Equation 1. Litter and biomass combustion represent fire losses from the fast litter pool and the living-biomass pool. Reduced plant productivity input and biomass combustion with all the burned carbon released give identical trajectories in this model, so their bars coincide (Methods); the fourth experiment repeats biomass combustion with a 2-year biomass turnover time, as in grass and shrub systems. Each disturbance has a prescribed magnitude of 2 PgC; actual losses differ because the pools adjust during the event. The combined disturbance comprises equal contributions from reduced plant productivity input and litter combustion. Both panels show changes in total stored carbon over one year, quoted as an amount in a and as a mean annual rate in b for comparison with the flux anomalies elsewhere in the paper. Model equations and parameters are given in Methods; settings and outcomes are in Supplementary Text S6 and Table S4.

Following-year uptake depended strongly on which pool lost carbon. A prescribed 2 PgC loss from litter combustion, which left an actual deficit of 1.6 PgC, produced an additional sink of 0.62 PgC yr⁻¹ in the following year, compared with about 0.02 PgC yr⁻¹ after reduced carbon input, or after biomass combustion when all the burned carbon is released (Fig. 3b). After litter is depleted, less carbon is

released through decomposition, while carbon continues to enter from biomass. Inputs therefore temporarily exceed losses, creating a recovery sink. In woody vegetation, biomass turns over slowly, so its depletion produces little additional uptake within the following year. Setting biomass turnover to 2 years, as in grass and shrub systems, raises the sink to 0.28 PgC yr^{-1} , still below the litter case because biomass depletion first reduces litter supply, delaying the reduction in decomposition (Fig. 3b). Combining reduced input and litter combustion gave an intermediate response. Although the disturbances had the same prescribed magnitude, their actual carbon losses differed as the pools adjusted during the event (Fig. 3a). A recovery sink is therefore physically possible, but a large carbon loss need not produce a large sink in the following year. The litter-combustion experiment represents an idealized biomass-burning event that depletes rapidly turning over litter while leaving living biomass intact. Its following-year sink of 0.62 PgC yr^{-1} follows from that prescribed litter loss and the 2-year litter turnover time, with continued carbon inputs at their undisturbed rate (Table S4). This illustrates recovery after fire loss from a fast pool, rather than estimating uptake after the observed high-CGR events, which can involve different combinations of reduced input and losses from fast or slow pools.

Vegetation-model fluxes and pools after high-CGR years

Our observational analyses do not establish additional recovery uptake and cannot identify which pools lost carbon. We therefore examined vegetation-model carbon stocks alongside their fluxes to assess whether enhanced uptake was associated with replenishment of depleted pools. Conceptual models such as the two-pool model tested above describe how recovery depends on the affected pools in an idealized way, but do not represent spatial differences in climate and ecosystems. We therefore analysed the TRENDY v14 S3 ensemble of DGVMs (Sitch et al., 2024; Friedlingstein et al., 2026), using NBP, the net land carbon balance, with positive values denoting net uptake. We screened the 22 analysed models for record length, plausible global mean and variability, and for the expected negative correlation between detrended NBP and observed CGR; 21 passed. CARDAMOM was excluded because its record spans only 22 years. Repeating the analysis with all 22 gives a similar result (Methods; Supplementary Text S7).

We applied the ten observed events of Figure 1 to the models, keeping their dates from the NOAA growth-rate record: year t is the last high-CGR year of an event and year $t+1$ its recovery year. TRENDY ends in 2024, so nine of the ten recovery years fall within the model period; the recovery of the 2024 event is 2025. Across those nine years the DGVMs simulated a mean global NBP anomaly of $+0.68 \text{ PgC yr}^{-1}$ (Fig. 4a, blue point at $t+1$). In comparison, their mean anomaly in the 52 years that are not high-CGR years, which include the recovery years themselves, was $+0.21 \text{ PgC yr}^{-1}$ (blue dotted line), giving additional recovery-year uptake of $+0.47 \pm 0.08 \text{ PgC yr}^{-1}$. This difference was positive in 20 of 21 models; the uncertainty is the standard error across model means. For the same nine recovery years, the excess inferred from atmospheric CGR above its own below-threshold mean corresponds to approximately $+0.03 \text{ PgC yr}^{-1}$ of uptake. This atmospheric estimate reflects the full carbon budget, whereas the model result is net land uptake (Supplementary Text S7; Table S6).

The models' largest carbon losses need not coincide with observed high-CGR years. We therefore also examined recovery after model-defined carbon-loss events, that is, years with strongly negative NBP anomalies, grouping consecutive years of unusually weak NBP and taking the following year as the recovery year. Each model supplies its own events, a median of ten recovery years per model. Uptake in these recovery years exceeded the mean for ordinary non-loss years by only $+0.022 \pm 0.035 \text{ PgC yr}^{-1}$ ($p = 0.55$; Supplementary Text S7; Table S6). Thus, the enhanced uptake after observed events was not reproduced as a clear additional sink after model-defined events.

In the models, stronger uptake after observed high-CGR events occurred mainly in the tropics, while the northern extratropics showed slightly weaker uptake than usual (Fig. 4a). The largest change after a high-CGR event came from increased photosynthesis, measured as gross primary production (GPP). The GPP change was about eight times the change in carbon released through decomposition and nine times the change in fire emissions (Supplementary Text S7). We also asked whether recovery-year uptake differed among models according to how rapidly carbon cycles through their ecosystems, estimating an

overall turnover time as total ecosystem carbon divided by annual GPP. Across the 16 models with the required data, there was no clear relationship between this turnover estimate and recovery-year NBP anomalies ($r = +0.22$, $p = 0.42$; Fig. 4b). Because this whole-ecosystem estimate combines fast and slow pools, we next examined whether individual pools were replenished after the events.

We tested whether pools that lost more carbon during a loss event gained more carbon in the following year, and whether this relationship was stronger after observed high-CGR events than in other years. Figure 4c shows the additional refill per unit of preceding carbon loss, rather than a carbon flux in PgC yr^{-1} . Litter gave a positive slope difference of $+0.32$ (one-sided $p = 0.002$), outside the central 95% random-year range (-0.23 to $+0.23$; Fig. 4c). Soil gave $+0.10$ ($p = 0.20$), inside its random range; vegetation and leaves gave negative estimates within their ranges. Using the size of the modelled litter-stock anomalies to express the litter result as a carbon flux gave approximately 0.10 PgC yr^{-1} , about one-fifth of the additional net uptake of 0.47 PgC yr^{-1} . This conversion is approximate and does not isolate the contribution of litter replenishment to net uptake (Methods; Supplementary Text S7). The DGVMs therefore show enhanced uptake and more litter refill after observed events than after random years, but this comparison does not separate uptake caused by prior depletion from uptake driven by recovery-year climate.

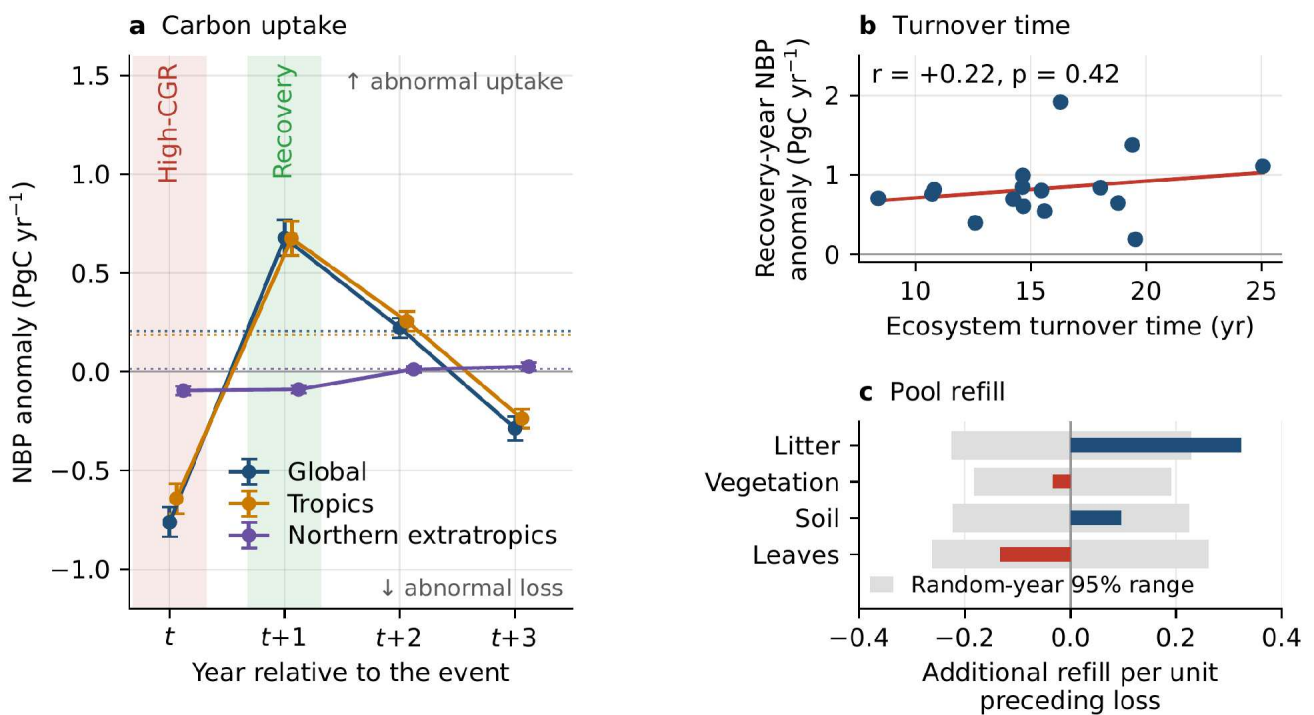


Figure 4 | Carbon uptake and pool replenishment predicted by the TRENDY DGVMs after observed high-CGR events. Events are the ten merged high-CGR events of Figure 1, dated from the NOAA growth-rate record; nine have recovery years inside the TRENDY period. a, Mean net biome production (NBP) anomalies across 21 models for the nine events with full t to $t+3$ coverage; positive values indicate abnormal uptake and negative values abnormal loss relative to the fitted trend. Red shading marks year t , the last high-CGR year with carbon loss, and green shading marks the recovery year $t+1$; error bars show sample standard errors across models (sample standard deviation divided by the square root of 21). Dotted lines mark non-high-CGR means. b, Recovery-year NBP anomalies versus ecosystem turnover time (total carbon stocks divided by annual GPP) for 16 models; the red line is fitted to unrounded values. c, Coloured bars show additional pool refill per unit of preceding carbon loss, relative to non-event years. Grey bands show the central 95% range from 2,000 random assignments of event years within each model; litter exceeds its range, whereas soil, vegetation and leaves lie within theirs. Regional boundaries, pool-specific model counts and methods are given in Supplementary Text S7.

Summary and discussion

Across the annual and monthly analyses, recovery periods showed no clear average excess uptake relative to the comparison periods. This finding does not contradict the recovery mechanism described by Equation 1. For a pool initially in balance, depletion produces a sink once carbon inputs and the turnover rate return to their previous values. Whether this produces a detectable global sink in the following year depends on which pools were depleted, their turnover times and how carbon inputs recover. These conditions are not established by a high atmospheric CO₂ growth rate alone. TRENDY models show more litter refill after observed events than after random years, alongside enhanced net uptake. The causal separation of replenishment from recovery-year climate remains open, as does the contribution of individual pools to the net sink.

This global result remains compatible with smaller or regional recovery sinks. Uptake in recovering ecosystems can coincide with continued losses elsewhere. Drought can suppress subsequent tree growth (Anderegg et al., 2015), and the effects of tropical disturbances can persist into later years (Yang et al., 2018; Wigneron et al., 2020; Bloom et al., 2020). Recovery-year climate conditions also affect land uptake. The unusually low satellite-derived CO₂ growth after the 2023–2024 episode illustrates that individual events can differ from the average, although these data do not establish whether the low growth rate in 2025 reflects pool replenishment, climate or reduced emissions.

Distinguishing these explanations requires measurements of changes in vegetation, litter and soil carbon alongside land–atmosphere exchange. These measurements would show which pools lost carbon and whether they subsequently refilled. Vegetation-model experiments could compare ecosystems with and without a preceding disturbance under identical recovery-year climate. This comparison, unavailable in the archived TRENDY output analysed here, would isolate the influence of the preceding disturbance. Tracking carbon inputs and losses in each pool would help identify the contribution of replenishment.

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Generative AI was used in parts of the research workflow. ARTOS (Agentic Research and Targeted-audit Orchestration System; <https://github.com/sudshu/ARTOS>) is an agentic framework that uses multiple large language models, including Claude Fable and OpenAI GPT-5.6 Sol. The authors formulated the hypotheses in plain language; ARTOS devised specific tests of them and implemented those tests, covering analysis design, code generation, execution of selected analyses and adversarial checking of results. The authors reviewed and verified the tests, analysis outputs and interpretations; all scientific decisions and responsibility for the results and conclusions reported here remained with the authors.

Author contributions

P.C. conceived the study and the original hypothesis. S.P. curated the data, designed and performed the analyses using the ARTOS agentic AI framework, and produced the figures. P.C. and S.P. discussed the results and wrote the manuscript.

Data availability

All datasets analysed in this study are publicly available except where stated. The NOAA global marine boundary layer CO₂ growth-rate record is available at doi:10.15138/9N0H-ZH07 (Lan et al., 2026). The Global Carbon Budget 2025 gridded inversion flux fields are available at doi:10.18160/VZ3B-GHYQ (Luijkx et al., 2025) and the accompanying budget tables at doi:10.18160/GCP-2025 (Global Carbon Project, 2026). Fire emissions are from the Global Fire Emissions Database version 5.1 (doi:10.5281/zenodo.16794692; van der Werf et al., 2025b) and its near-real-time extension GFED5NRT (doi:10.5281/zenodo.18702700; Chen et al., 2026b). The Oceanic Niño Index based on ERSSTv5 is distributed by the NOAA Climate Prediction Center at https://www.cpc.ncep.noaa.gov/products/analysis_monitoring/enso/oni/v5/, and the Niño3 index by the NOAA Physical Sciences Laboratory at https://psl.noaa.gov/data/timeseries/month/Nino3_CPC/. TRENDY v14 S3 per-model simulation output (Sitch et al., 2024) was downloaded from the public Global Carbon Budget 2025 land-output archive at <https://s3.eu-west-1.wasabisys.com/gcb-2025-upload/land/output/>, indexed by the file list at <https://github.com/mdosullivan/GCB>. The GRESO satellite growth-rate record was derived from GOSAT and OCO-2 retrievals using the method of Pandey et al. (2024) and is available from the authors on request.

Competing interests

The authors declare no competing interests.

Methods

Atmospheric records, ENSO and units

We used NOAA's global marine boundary layer CO₂ growth-rate (CGR) record for 1959–2025, version 2026-08 (Lan et al., 2026; Conway et al., 1994). The file was created on 5 August 2026; its latest-year value, 2.06 ppm yr⁻¹ for 2025, is official but revisable. Annual growth is the difference between successive seasonally corrected December–January CO₂ means. Before 1980, the record combines Mauna Loa and South Pole observations (Masarie and Tans, 1995).

We also used growth rates from the median of six Global Carbon Budget 2025 (GCB2025) surface-only inversions, which assimilate data from atmospheric stations located mainly in the surface boundary layer. Because inversions assimilate station or satellite mixing ratios, they predict a CGR close to the observed one by design. We additionally used CGR from the GRESO (growth rate estimated from satellite observations) method, derived directly from GOSAT and OCO-2 observations (Pandey et al., 2024). GRESO estimates CGR from changes in CO₂ throughout the atmosphere, allowing us to test whether the recovery result depends on how well marine boundary layer measurements represent the whole atmosphere (Pandey et al., 2025). Monthly land fluxes use separate medians of surface-only and satellite-assimilating inversions. Record construction is described in Supplementary Text S2.

We described El Niño–Southern Oscillation (ENSO) using the Oceanic Niño Index (ONI), the three-month running mean sea surface temperature anomaly in the Niño 3.4 region (5°N–5°S, 170–120°W) from ERSSTv5, taken relative to centred 30-year base periods (Huang et al., 2017; NOAA Climate Prediction Center, 2026). Positive ONI values indicate warmer conditions and negative values cooler conditions. We retained the ERSSTv5 ONI snapshot dated 3 April 2026, ending in the January–March (JFM) 2026 season (SHA-256: f56425232f9e1d821c8c3aa43fe7ba6ce7f609328b6351aa0b61e8a8aeb49138). The file has no embedded release stamp; the Climate Prediction Center (CPC) updates the centred 30-year base periods every five years.

One ppm corresponds to 2.124 PgC (Friedlingstein et al., 2026). Net biome production (NBP) in the DGVMs is positive for uptake and includes fire, land-use and other carbon exports. Figure 2 reports land flux as positive for release, opposite to the NBP convention of Figure 4, so positive anomalies indicate greater release from land to the atmosphere, matching the direction of atmospheric growth; its axis labels state both directions. Figure 4 keeps the NBP convention, positive for uptake, and its axis is labelled accordingly.

Annual events and comparisons

We calculated annual CGR anomalies by subtracting the fitted straight-line trend (+0.028 ppm yr⁻²). We calculated the 80th percentile, q80, by linear interpolation between ordered anomalies and retained the unrounded threshold for selection. Fourteen years exceeded q80 (+0.34 ppm yr⁻¹). Merging consecutive high years gave ten events. Recovery is the year after the final high year. Because recovery years fall below q80, we compared them with all 53 below-threshold years, including recovery years.

We generated 200,000 reference means by randomly selecting ten different years from those 53 years. The one-sided p value is the fraction of reference means as low as or lower than the observed recovery mean. Reported uncertainties are standard errors across years. The grey band in Figure 1b contains the central 95% of random reference means; it differs from uncertainty on the observed mean.

Strong El Niño years had a calendar-year mean ONI ≥1.0 °C. The 0.75 °C threshold sensitivity is shown in Supplementary Text S1 and Fig. S1c.

Monthly growth rates and land fluxes

Atmospheric inversions estimate land–atmosphere exchange from CO₂ observations and atmospheric transport. We used GCB2025 medians from six surface-only inversions (2000–2024) and eight inversions

using satellite observations, sometimes alongside surface observations (2010–2024) (Friedlingstein et al., 2026; Luijkx et al., 2025). Each monthly median required at least three surface-only or two satellite-assimilating members. Satellite CGR came from the GRESO method (Pandey et al., 2024), using OCO-2 for 2015–2025 and GOSAT for 2010–2014.

We removed a fitted curved trend and seasonal cycle from inversion fluxes, and a straight-line trend from satellite CGR. Each value was then averaged with the preceding and following months. Supplementary Text S5 gives the fitted functions and record preparation.

High months exceeded each record's q80. High months belonged to one event until three consecutive months fell below q80. Recovery covered the fixed twelve months after the last high month; events without complete recovery coverage were excluded. Later high months were retained in both recovery and comparison windows. We compared the recovery mean with 10,000 random sets containing the same number of twelve-month windows, starting in below-threshold months. The p value was calculated as for annual events. Uncertainties are standard errors across events; Figure 2 shading contains the central 95% of random reference means. For a one-sided 5% comparison, we used the gap between the random-reference mean and its 5th percentile. Supplementary Text S5 explains this threshold and tests other window lengths (Table S3); Table S5 gives regional boundaries.

Conceptual carbon-pool experiments

We applied Equation 1 to two connected pools, biomass and litter. Writing b and l for the departures of the biomass and litter stocks from their undisturbed values (PgC),

$$\frac{db}{dt} = i - k_B b - E_B \quad \dots\dots\dots (2)$$

$$\frac{dl}{dt} = k_B b - k_L l - E_L \quad \dots\dots\dots (3)$$

where i is the change in carbon input from Equation 1, with reduced plant productivity input corresponding to negative i , and E_B and E_L are additional direct releases from biomass and litter to the atmosphere. These three flux terms have units of PgC yr⁻¹. The turnover rates are $k_B = 0.03$ yr⁻¹ for biomass and $k_L = 0.5$ yr⁻¹ for litter; the turnover times quoted in the main text are their reciprocals, $\tau = 1/k$, giving $\tau_B \approx 33$ years and $\tau_L = 2$ years. Biomass turnover supplies litter, so that transfer cancels when the two budgets are added, and the net sink anomaly, positive for uptake, is

$$S = \frac{d(b+l)}{dt} = i - k_L l - E_B - E_L \quad \dots\dots\dots (4)$$

Both stock anomalies start at zero, and absolute reference stocks do not enter the equations. Each experiment imposed a 2 PgC disturbance over one year, after which the disturbance terms returned to zero; the turnover rates were held constant within each experiment. Because i and E_B enter Equations 2 and 4 with equal magnitude and opposite sign, so that a reduced input of i is indistinguishable from a direct release $E_B = -i$, reduced plant productivity input and biomass combustion give identical trajectories in this model; they differ only in the gross flux causing the loss. One further experiment repeats biomass combustion with $k_B = 0.5$ yr⁻¹, a 2-year biomass turnover time representative of grass and shrub systems. Actual losses differed because pools adjusted during the disturbance. The turnover times are illustrative values chosen to separate a slow from a fast pool rather than estimates fitted to observations. Following-year uptake equals the increase in total stored carbon. Numerical settings and the disturbance implementation are in Supplementary Text S6 and Table S4.

Vegetation models and pool replenishment

We used TRENDY v14 S3 fluxes and stocks for 1959–2024 (Sitch et al., 2024; Friedlingstein et al., 2026). Models required at least 30 years of global NBP, a mean within ± 20 PgC yr⁻¹, annual variability (standard deviation) below 6 PgC yr⁻¹, and a negative correlation of any magnitude between detrended NBP and observed CGR. Twenty-one of the 22 analysed models qualified; CARDAMOM was excluded because it

covers only 2003–2024, a 22-year record. Supplementary Text S7 lists exclusions and the all-model comparison (Table S6).

NBP anomalies subtract a fitted quadratic curve, allowing the long-term trend to bend. For observed events, we compared recovery uptake with each model's mean in non-high-CGR years. Model-defined carbon-loss events comprise consecutive years with NBP anomalies strictly below the linearly interpolated 20th percentile ($< q_{20}$); their following years were compared with years outside that group. Standard errors and two-sided t-tests describe differences across models, which are not independent observations.

We removed a quadratic trend from each pool's stock record, then measured the fall in its anomaly during the event and the rise in the following year. We fitted two straight lines relating refill to preceding loss, one for event years and one for other years. The difference between slopes gives additional refill per unit of loss. We repeated this comparison after randomly assigning event years within each model 2,000 times, preserving each model's event count. Figure 4c shows the central 95% of these random estimates. The approximate litter-flux conversion and calendar adjustments are described in Supplementary Text S7; the CLM alignment test improves agreement but does not independently establish the stock sampling convention.

For sixteen models with the required data, whole-ecosystem turnover time divides mean vegetation, litter and soil stocks by mean annual gross primary production (GPP) over 1995–2024. This long-term turnover diagnostic uses annual-mean stocks. Leaves are already included in vegetation. This comparison and the photosynthesis, respiration and fire analyses use straight-line detrending.

Climate predictions and fire emissions

We fitted relationships between Mauna Loa growth rates, Niño3 and fossil emissions over 1960–2009, then predicted five later recovery years with and without the preceding growth-rate anomaly. Fitted relationships and the event threshold were kept unchanged. Supplementary Text S3 gives the annual growth definition, climate timing and comparison with the earlier average recovery anomaly. This test cannot separate pool replenishment from climate effects that occur together.

Fire calculations compared NOAA CGR with GFED5.1 emissions for 1997–2022 (van der Werf et al., 2025a, 2025b) and with the near-real-time extension GFED5NRT for 2023–2025 (Chen et al., 2026a, 2026b). We use total fire carbon in preference to CO₂-only estimates because the non-CO₂ fire carbon is oxidized to CO₂ within months; the GFED5NRT emission variable is taken as total fire carbon in grams per the product description (Chen et al., 2026a, 2026b). We divided the decline in fire emissions by the decline in atmospheric accumulation in matching carbon units. Very small CGR changes give unstable percentages and were excluded from interpretation (Supplementary Text S4).

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