Impact of the 2015/2016 El Niño on the terrestrial carbon cycle constrained by bottom-up and top-down approaches

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Evaluating the response of the land carbon sink to the anomalies in temperature and drought imposed by El Niño events provides insights into the

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1. Introduction

The global terrestrial CO₂ sink has increased steadily in the past decades but presents high year-to-year variations that, in turn, dominate inter-annual variability (IAV) in the atmospheric CO₂ growth rate [1]. As the atmospheric CO₂ growth rate is highly correlated with tropical temperature [2], IAV in the land sink has been mainly attributed to tropical forests [2], but semi-arid ecosystems appear to be increasingly important [3–5].

The El Niño/Southern Oscillation (ENSO) is an atmosphere–ocean variability pattern that drives temperature and rainfall variations in the tropics, with teleconnections that extend worldwide [6]. El Niño events strongly reduce the global land sink by up to 2PgC [7], leading to high atmospheric CO₂ growth rates [1]. El Niño events promote drought conditions in the Amazon forest, leading to increased tree mortality and reduced carbon storage [8,9] and widespread fires, particularly in southeast Asia [10]. ENSO impacts extend beyond the tropics, controlling IAV in sub-tropical ecosystem productivity [11], especially water-limited ecosystems in the Southern Hemisphere [3,4,12]. Most Coupled Model Intercomparison Project Phase 5 (CMIP5) models projected a two-fold increase in the frequency of extreme El Niño events in the future decades [13], associated with intensification of ENSO-related anomalies in the carbon cycle [14]. However, nonlinear ENSO dynamics found in observations and one model might imply suppressed extreme El Niño events under warming [15].

Additionally, ENSO affects key regions and processes that are sources of uncertainty in future carbon cycle projections [3,16]. It is still unclear if temperature [2] or water-availability [3,9,11] drive ecosystems’ response to ENSO, and how gross primary productivity (GPP) and terrestrial ecosystem respiration (TER) contribute to IAV. Analysis of model ensembles suggests that because water availability enhances both GPP and TER, its effects are cancelled out, and only the temperature signal emerges [2,5]. Jung et al. [5] also showed that water availability is the primary driver of carbon fluxes at the local scale, but anomalies tend to compensate spatially, so temperature emerges as a stronger driver with increasing spatial aggregation.

More generally, IAV in the carbon cycle is still not well understood, and neither data-driven models [17] nor Earth-System Models [18] capture its amplitude. In the 2017 Global Carbon Budget [1], land–atmosphere CO₂ fluxes from land-surface models (LSMs, bottom-up) forced with observed climate and land-use change (LUC) show good agreement with estimates from atmospheric transport model inversions (top-down) for global totals but differ at regional or zonal scale [1]. The 2015/2016 El Niño is especially interesting, as 2015 registered record atmospheric CO₂ growth rate in spite of widespread record-breaking greening and stabilization of fossil-fuel emissions [1,19]. The 2015/2016 El Niño therefore provides a good case study to understand the response of ecosystems to warm and dry extremes potentially concurrent with global vegetation greening.

The strong El Niño event started around May 2015 and persisted until mid-2016, being the strongest event since the 1950s [20]. Record-breaking temperatures and drought were registered in the Amazon from October 2015 onwards. The drought extent in the Amazon was comparable to 1997/1998 but the extreme temperatures led to an exacerbation of dryness, with extreme drought conditions affecting double the extent of 1997/1998 [20].

According to LeQuéré et al. [1], the atmospheric CO₂ growth rate in 2015 and 2016 was 1.6 and 1.5 PgC yr⁻¹ higher than during the 2011–2016 period, respectively, yet CO₂ emissions from fossil fuel and LUC combined were only 0.2–0.4 PgC yr⁻¹ above the previous 5-year mean. Ocean uptake was estimated to be slightly larger (0.2 PgC yr⁻¹) in 2015/2016 than the 2010–2014 average. Table 1 shows the residual sink needed to close the global carbon budget: the terrestrial CO₂ uptake had to be reduced by 1.4 PgC yr⁻¹ in 2015 and by 1.5 PgC yr⁻¹ in 2016. In the same period, but using the year of 2011 as a reference, Liu et al. [21] reported much higher losses of CO₂ over the pan-tropical regions in 2015 alone (2.5 PgC). Contrary to the 1997/1998 event, the anomaly in the land sink during 2015/2016 does not appear to be associated with major fire emissions. Although the development of El Niño coincided with enhanced fire activity in Southeast Asia, fire emissions in the region were reported to be only half of the emissions during the previous El Niño in 1997/1998, following rainfall return in November 2015 [22]. GFED4s [23] reports fire emissions 0.3 PgC yr⁻¹ higher than the previous 5 years in 2015, but lower by 0.1 PgC yr⁻¹ in 2016 (table 1).

Here we quantify the response of the terrestrial carbon cycle to El Niño in 2015/2016 using multiple data-based and modelled datasets. We track the evolution of anomalies in the net land–atmosphere CO₂ flux during the development and decline of the 2015/2016 El Niño estimated by two atmospheric transport model CO₂ inversions [24,25] and compare them with the net terrestrial CO₂ uptake and its component fluxes (gross primary productivity (GPP), total ecosystem respiration (TER), fire) simulated by 16 LSMs in the latest TRENDY intercomparison project (v6, table 2) [1,42]. We evaluate the consistency and robustness of carbon spatio-temporal dynamics between top-down and
The land sink is estimated here as the residual from the global carbon budget (i.e. \( E_\text{FF} + E_\text{LUC} - G_{\text{ATM}} = 0 \)). Fire emission anomalies from GFED4.1s (1997–2016) are shown for comparison with the values in the terrestrial sink.

<table>
<thead>
<tr>
<th>C budget (PgC yr(^{-1}))</th>
<th>( G_{\text{ATM}} )</th>
<th>( E_\text{FF} )</th>
<th>( E_\text{LUC} )</th>
<th>sinks (ocean + land)</th>
<th>land</th>
<th>fire emissions</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010–2014</td>
<td>4.6</td>
<td>9.6</td>
<td>1.4</td>
<td>6.3</td>
<td>2.4</td>
<td>4.0</td>
</tr>
<tr>
<td>2015</td>
<td>6.2 (+1.6)</td>
<td>9.8 (+0.2)</td>
<td>1.5 (+0.1)</td>
<td>4.1 (+1.2)</td>
<td>2.6 (+0.2)</td>
<td>2.6 (+1.4)</td>
</tr>
<tr>
<td>2016</td>
<td>6.1 (+1.5)</td>
<td>9.9 (+0.3)</td>
<td>1.3 (+0.1)</td>
<td>5.3 (+1.0)</td>
<td>2.6 (+0.2)</td>
<td>2.4 (+1.6)</td>
</tr>
</tbody>
</table>

2. Material and methods

(a) Atmospheric CO\(_2\) inversion fluxes

Here we use three observation-based datasets of net land–atmosphere surface fluxes: the Copernicus Atmosphere Monitoring Service (CAMS) atmospheric inversion (henceforth simply ‘inversion’) version 16r1 [24,43], and the Jena CarboScope inversion (update of [25,44] compare with Rödenbeck et al. [45] versions s76_v4.1 and s04_v4.1 (CarboScope76 and CarboScope04 henceforth). The inversions provide terrestrial (and oceanic) surface CO\(_2\) fluxes, CAMS weekly fluxes at 1.9° latitude \times 3.75° longitude resolution, and CarboScope daily fluxes at 4° longitude \times 5° longitude resolution. CAMS 16r1 uses 119 atmospheric stations over the different time frames for which they provide data, starting in 1979. CarboScope76 (CarboScope04) uses 10 (59) stations continuously available throughout 1976–2016 (2004–2016). All inversions are regularized by a priori information. CAMS uses climatological natural fluxes and time-varying ocean, wildfire and fossil-fuel fluxes with error correlation lengths of 4 weeks and 500 km (1000 km) over land (ocean) [46]. CarboScope uses a zero land prior, and a priori correlations of about 1600 km in longitude direction, 800 km in latitude direction and about 3 weeks. The inversions further differ in the transport model used, and other characteristics. Thus, they provide a range of uncertainty for observation-based top-down CO\(_2\) flux estimates [19]. We focus on the 38-year period from 1979 until 2016 and calculate monthly anomalies of net land–atmosphere fluxes by subtracting the mean seasonal cycle and the monthly long-term trend (using a simple linear fit). We aggregate the inversion results over large regions (global terrestrial surface and tropical band between 23°S and 23°N), as flux estimates from inversions carry smaller relative uncertainties on the larger spatial scale [47].

(b) Land-surface models

LSMs simulate the key energy, hydrological and carbon cycle processes in ecosystems, allowing insights on the mechanisms controlling anomalies in land–atmosphere CO\(_2\) fluxes and their drivers. The TRENDY intercomparison project coordinated historical LSM simulations and compiled outputs of CO\(_2\) fluxes among other variables [42]. We use 16 LSMs from the latest TRENDYv6 simulations [1] (table 2), which provide monthly CO\(_2\) fluxes during 1860–2016. In TRENDYv6 S3 simulations, models are forced by historical data of (i) atmospheric CO\(_2\) concentrations, (ii) climate observations from CRU-NCEP v8 [48,49] and (iii) human-induced land-cover changes and management from the HYDE [50,51] and the Land-Use Harmonization LUH2 v2 h [52] datasets (extended to 2016 as described in [1]). We analyse monthly values of net biome productivity (NBP), GPP, total ecosystem respiration (TER) and fire emissions simulated by the models (only 7 models) and annual leaf-area index (LAI, 12 models). NBP corresponds to the simulated net atmosphere–land flux (positive sign for a CO\(_2\) sink) and is comparable to top-down estimates of net land–atmosphere CO\(_2\) fluxes, although the latter include lateral C fluxes (the land–ocean transport of C in freshwater and coastal areas and C fluxes due to trade/import export) [1,53] not simulated by the models. However, we focus on flux anomalies that should not be substantially affected by lateral fluxes because they are assumed to vary little between years. To produce a spatially consistent ensemble, model outputs were remapped to a common regular 1° \times 1° grid. The model data were selected for the 38-year long period 1979–2016, common to inversions.

(c) Satellite-based data

We compare anomalies from inversions and LSMs with two remote-sensing datasets that provide proxies for ecosystem activity and a satellite-based GPP product.
LAI is defined as the one-sided green leaf area per unit ground area in broadleaf canopies and as one-half of the green needle surface area in needleleaf canopies, which depicts the greenness of vegetation. We used Collection 6 Terra and Aqua MODIS LAI products (MOD15A2H and MYD15A2H) [54,55]. The original datasets were available as 8-day composites in 500 m sinusoidal projection. We checked the quality flags (clouds, aerosols, etc.) to get high-quality LAI as described by Samanta et al. [56]. The original data were re-projected onto a 1/12° grid by averaging the high-quality LAI. After that, the two LAI datasets were combined to bi-monthly time-steps by taking the mean of LAI values in each 8-day composite, weighted by the number of days that each 8-day composite locates in the specific half-month window. Finally, the annual average LAI and its anomaly relative to the record period (2000–2016) were calculated for each pixel. Anomalies in LAI reflect changes in the canopy leaf density and can therefore track plant stress response to drought.

Cheng et al. [57] used ground-based and remotely sensed land and atmospheric observations, combined with water use efficiency (WUE) model and evapotranspiration data from global land evaporation Amsterdam model (GLEAM), to calculate global annual GPP between 2000 and 2016 at 0.5 × 0.5° resolution. The WUE model was developed by upsampling leaf WUE directly and considers the controls of vapour pressure deficit and physiological functioning on WUE. The model has been derived independently from GPP and evapotranspiration data, and therefore, can be used to evaluate simulated GPP.

Vegetation optical depth (VOD) is an estimate of the vegetation extinction effects on microwave radiation and increases with increasing vegetation density, being therefore a good proxy of biomass [38]. Brandt et al. [59] have shown that the new L-band soil moisture and ocean salinity (SMOS) VOD (L-VOD) retrieved from the SMOS-IC algorithm (Version V105 [60]) relates almost linearly to biomass and is thus relevant to monitor carbon stocks at continental scales. In this algorithm, no auxiliary data (either from atmospheric models or remote sensing optical observations) are used, except for surface temperature data from European Centre for Medium-Range Weather Forecasts (see [58,60] for more details). As L-VOD shows a strong relationship with aboveground biomass stocks, the time-derivative of L-VOD can be directly related to variations in biomass, and thus comparable with the aboveground component of NBP.

3. Results
(a) Global and tropical net biome productivity anomalies

Figure 1 compares annual global and tropical NBP from inversions and LSMs after removing the mean seasonal-cycle and linear trend during 1979–2016. Anomalies are indicated in subscript and positive values indicate stronger-than-average CO2 sinks or lower-than-average CO2 sources. The shades in the background of both panels show the ENSO states (red – El Niño and blue – La Niña).
Mt. Pinatubo eruption [1,61], the latter not included in the TRENDY forcing.

Inversions and LSMs agree well in global \( NB_{\text{anom}} \) during the two El Niño events in the 1980s (anomalies of ca. –1 to –2 PgC yr\(^{-1}\)). In 1982, anomalies from inversions and LSMs are very close to the GCB2017 estimate, while in 1987 both approaches underestimate the negative anomaly (especially CarboScope04). In 1997/1998, inversions differ by up to 0.5 PgC yr\(^{-1}\) (1998), and some LSMs indicate a global sink anomaly, rather than a source anomaly. The MMEM average anomalies in 2015/2016 (–1.0 yr\(^{-1}\)) are close to the GCB2017 residual sink anomalies (–1.1 PgC yr\(^{-1}\)), while inversions point to weaker anomalies (–0.7 PgC yr\(^{-1}\) for CAMS, –0.4 PgC yr\(^{-1}\) for CarboScope04, –0.5 PgC yr\(^{-1}\) for CarboScope04). In the tropical band, LSMs agree better with inversions (CAMS and CarboScope04) for most ENSO events than at global scale, but estimate larger negative anomalies than inversions in 1983 and 2016. CarboScope04 shows too low variability and therefore we use CarboScope04 for the analysis of the 2015/2016 event.

(b) Spatial net biome productivity anomalies in 2015/2016

The two inversions differ not only in aggregated global and tropical \( NB_{\text{anom}} \) during 2015/2016 (figure 1) but also in the spatial distribution of \( NB_{\text{anom}} \) during both years (figure 2). CAMS produces a typical source anomaly in most of the tropics and Southern Hemisphere but a sink anomaly over the Amazon in both years, although the low density of the surface observations might not be sufficient to isolate the Amazon from the larger scale (figure 2a,b). In 2015, CarboScope04 reports negative \( NB_{\text{anom}} \) evenly distributed over the tropics (excluding the Sahel), intensified in 2016 in Africa and Southeast Asia (figure 2c,d). The MMEM points to negative \( NB_{\text{anom}} \) in the tropics, particularly in the Amazon and eastern Brazil, southern Africa and Australia (figure 2c,f). Generally, inversions and LSMs agree on a transition from weak to strong negative \( NB_{\text{anom}} \) in southern Africa between 2015 and 2016 (figure 2; electronic supplementary material, figures S1 and S2). In the Amazon, the evolution of \( NB_{\text{anom}} \) during 2015/2016 differs widely between LSMs, with some reporting negative anomalies (relative source) in both years (e.g. CLM4.5, VEGAS), others an anomalous source in 2015 followed by an anomalous sink in 2016 (e.g. ISAM, ORCHIDEE) or the inverse (JSBACH). Large differences in simulated NBP in 2015/2016 are also observed in central and southern Africa.

(c) Seasonal evolution of NBP anomalies in 2015/2016

Strong El Niño conditions started around May 2015, earlier than typical El Niño events, and ceased before the end of 2016. We analyse whether LSMs are able to capture the seasonal terrestrial sink response to the evolution of El Niño, compared to the two atmospheric inversions (figure 3a–c). We follow the approach by Yue et al. [19] and analyse consecutive trimesters over the 2 years. During January–March and April–June 2015 (Q1, Q2), inversions and the MMEM report close-to-average global and tropical sinks (anomalies below 0.2 PgC/season, negative for CAMS and LSMs, and positive for CarboScope04), consistent with pre-El Niño conditions. LSMs and inversions agree on the general decrease of the global and tropical C-sinks during the onset, peak and demise of El Niño from July–September 2015 (Q3) to April–June 2016 (Q6), but show differences in the exact timing and magnitude of anomalies.

Globally, CarboScope04 reports \( NB_{\text{anom}} \) of –0.2 to –0.6 PgC/season from Q3 until Q6, and CAMS reports large negative \( NB_{\text{anom}} \) of –0.9 and –0.8 PgC/season in Q4 and Q5. Both inversions agree on the strong contribution of the tropics to the global NBP anomalies, 67% and 105% for CAMS (the value over 100% indicating a compensating effect from the extra-tropics) and 42–89% for CarboScope04. During the El Niño event (i.e. from Q3 to Q5, figure 3), CAMS and CarboScope04 report global integrated \( NB_{\text{anom}} \) of –1.6 PgC and –1.2 PgC (93% and 58% in the tropics, respectively), while MMEM estimates global \( NB_{\text{anom}} \) of –1.8 PgC (of which 83% in the tropics). Global C-sink anomalies during Q4–Q5 from LSMs are within the range of the two inversions with –0.7 PgC/season, but with a substantially more negative anomaly in Q3 (–0.4 PgC/season). These differences are mainly due to the larger negative
anomalies at the onset of El Niño (in Q3) by LSMs compared to inversions.

Focusing on the tropics, LSMs show an earlier decrease in NBP\textsubscript{anom} than inversions, with negative NBP\textsubscript{anom} already in Q3. After Q3, LSMs and inversions show a remarkable agreement, with a peak negative NBP\textsubscript{anom} occurring in January–March 2016 (Q5) then recovering and returning to neutral conditions by Q6 and Q7.

In terms of magnitude, MMEM anomalies (\(-0.7\) PgC/season and \(-0.8\) PgC/season in Q4 and Q5, respectively) are between the two inversions, which report a decrease of NBP by \(0.4–0.95\) PgC/season in Q4 and by \(0.6–0.8\) PgC/season in Q5.

The overestimation of global NBP\textsubscript{anom} in Q3 is mainly explained by the tropics, potentially due to too high fire emissions simulated by LSMs during the onset of the El Niño event. Fire emission anomalies from those models simulating fire (reported by only 7 out of 16 LSMs) (electronic supplementary material, figure S3) are indeed, on average, \(0.2\) PgC yr\(^{-1}\) and \(0.3\) PgC yr\(^{-1}\) higher than the annual anomalies of GFED4.1s in 2015 and 2016, respectively. This overestimation probably occurs in Q3 and Q4, when models report very high fire emissions, and consequently, stronger negative NBP\textsubscript{anom} (\(-0.7\) PgC/season for models with fire, compared to \(-0.4\) PgC/season for other models in Q3). In Q4, anomalies in the tropics from LSMs are closer to the lower value of CAMS.

**Figure 3.** Evolution of carbon cycle anomalies during the 2015/2016 El Niño event. (a–c) Seasonal NBP\textsubscript{anom} between January 2015 and December 2016 estimated by CAMS (dark blue) and CarboScope04 (magenta) and LSMs (boxplots indicate the model distribution) for the globe (a) and the tropics (b) and integrated values during El Niño, i.e. the sum of anomalies during Q3–Q5, indicated by the light red-shades ((c), bars for inversions and boxplots LSMs). (d–f): seasonal GPP\textsubscript{anom} (green) and TER\textsubscript{anom} (red) for the globe (d) and tropics (e) from LSMs during 2015–2016 and integrated during El Niño (f). The boxplots show the inter-quartile range (IQR) and median of anomalies estimated by LSMs, the whiskers the interval corresponding to 1.5 IQR and + markers indicate outliers.

**(d) Driving processes**

For further insight into the processes driving the land sink response to El Niño, we analyse the seasonal evolution of GPP\textsubscript{anom} and TER\textsubscript{anom} simulated by the LSMs (figure 3d–f) during 2015/2016. Electronic supplementary material, figure S4 additionally shows spatial GPP\textsubscript{anom} estimated by the MMEM from Q1 to Q8. LSMs indicate a strong negative global and tropical GPP\textsubscript{anom} during the peak of El Niño (Q3 and Q5), mostly over the Amazon and eastern Brazil, as well as extra-tropical southern Africa and Australian regions (electronic supplementary material, figure S4). LSMs simulate weak negative GPP\textsubscript{anom}
in India and Southeast Asia. The sharp recovery in Q6 and Q7 is seen in global GPP, but not yet in the tropics, as GPP in northern South-America, southern Africa, northern Australia and Southeast Asia remains below average. The MMEM indicates positive global TERanom (causing a greater source or lower sink) during both years and in particular near the end of the El Niño event (Q6 and Q7). However, in the tropics, TER decreases in phase with GPP (but with smaller magnitude) during the entire El Niño event, dropping in Q4 and Q5 and recovering in Q6 and Q7. During the peak of El Niño, MMEM shows strong negative or close to neutral TERanom over most of the tropics (electronic supplementary material, figure S5), except for central Africa (where above-average GPP is simulated). The spatio-temporal evolution of simulated TERanom appears, thus, to be mainly dominated by changes in GPP.

The spatio-temporal evolution of simulated GPPanom mentioned above followed the progressive drying as El Niño developed (evaluated using a multi-scalar drought index at 6-month time-scale; electronic supplementary material, figure S6). The peak of El Niño in Q4 and Q5 corresponded to increasing intensity and spatial extent of drought conditions, affecting almost all tropical regions in South America, Asia and Australia and persisting until Q6 or even Q7 (South America and Australia). Even though in South America the peak of drought coincided with widespread negative GPPanom, the largest decreases in productivity are observed in typically dry regions, while humid areas (central Amazon) show smaller anomalies in productivity and recover faster (with positive anomalies in Q7). In Africa, the dipole of wet conditions in central tropics versus strong dryness in the south largely matches that of GPPanom.

(e) Comparison with satellite-based data

We evaluate whether simulated anomalies in vegetation status and productivity are consistent with LAI from MODIS and GPP derived from satellite data using a water-use efficiency model (GPP-WUE), shown in figure 4. We further evaluate changes in vegetation-optical depth as a proxy for changes in aboveground biomass. LSMs estimate widespread negative LAI anomalies in most of the tropics in both years, consistent with MODIS LAI. LSMs simulate positive LAIanom for the humid forests in Africa, where MODIS LAIanom shows more heterogeneity. Both MODIS and simulated LAI report an amplification of negative anomalies in 2016, also extending to parts of the Amazon.

The regions with strongest LAI decrease roughly coincide with those regions where below-average anomalies are found in both WUE-derived and simulated GPP: dry forests in tropical South America, the southern section of Africa and the Sahel, continental Southeast Asia and northern Australia. The agreement between WUE-GPPanom and MMEM GPPanom is better in 2015 than in 2016, though. In humid forests in Africa, WUE-GPP shows generalized negative anomalies in 2016, while LSMs simulate positive GPPanom.

The L-VOD index used here is more sensitive to the whole vegetation layer than other indices, which are more sensitive to the upper part of the canopy [59]. Even though L-VOD decrease (biomass reduction) is registered in the dry forests and savannahs of South America as in LAI and GPP, positive
L-VOD changes (i.e. biomass accumulation) are observed in regions with negative LAI and WUE-GPP$_{anom}$, e.g. India and Southeast Asia in 2016. This might indicate areas where vegetation is more resilient to the drought and appears to be more consistent with LSM and inversion estimates (figure 2). In the Amazon, on the other hand, L-VOD indicates a mixed pattern of negative and positive changes during 2015 and positive during 2016, while LSMS present predominantly negative GPP$_{anom}$ and NBP$_{anom}$ (figures 2 and 4).

4. Discussion

Our results show that the LSMS in TRENDYv6 can reproduce IAV patterns of the global terrestrial C-sink very close to the anomaly in the residual sink from GCR2017 and within the spread of atmospheric transport model inversions. The two inversions differ by up to 0.5 PgC yr$^{-1}$ in particular years, especially in the tropics during El Niño events (e.g. 1997 and 2015). NBP from LSMS captures the general response of the carbon cycle to El Niño globally and over the tropics, but the agreement with inversions depends on the particular event considered. In 2015/2016, LSMS and inversions consistently estimate a decrease in terrestrial C uptake (2.0 PgC for MMEM, 1.5 PgC in 2015/2016 for CAMS and 1.0 PgC for CarboScope04), but smaller than the Global Carbon Budget (3PgC in the 2 years, table 1).

At the seasonal scale, the LSMS simulate peak decrease in NBP in the late 2015 and early 2016 (Q3 to Q5), consistent with anomalies reported by inversions (figure 3). These results are also in line with observations of total column CO$_2$ from OCO-2 [63] that show an increase in tropical CO$_2$ concentrations from August 2015 onwards, in response to increased fire emissions and reduced terrestrial CO$_2$ uptake.

LSMS point to the generalized decrease in tropical GPP at the end of 2015 and persisting until mid-2016 contributing the most to tropical NBP$_{anom}$. The spatial patterns of LAI$_{anom}$ and GPP$_{anom}$ in 2015/2016 estimated by the MMEM are in good agreement with MODIS LAI and WUE-GPP$_{anom}$, adding confidence to the simulated results, but are partly in contradiction to a recent study by Liu et al. [21]. Liu et al. contrast 2015 with 2011 (a La-Niña year associated with record breaking land-sink [11]), while we report anomalies relative to results from any single model [65]. In the climate community, the diversity amongst models is considered a healthy added value of using MMEM is recognized Earth system modelling, and several examples exist of applications in which combined information from several models is superior to results from any single model [65]. In the climate community, the diversity amongst models is considered a healthy aspect and provides a basis for estimating uncertainty [66].
5. Conclusion

We show that the LSM ensemble reproduces the spatial and temporal impacts of the 2015/2016 El Niño on the terrestrial C-sink within the inversions’ range. We find that the decrease in the global terrestrial sink during El Niño in 2015/2016 can be mainly explained by decreased tropical GPP, in response to the ENSO-related drought in transitional to semi-arid regions, with a secondary role of the increase in fires and ecosystem respiration. It is still unclear whether TER plays an important role in controlling $NBP_{\text{mean}}$ during El Niño events. Our results agree with recent work highlighting the control of NBP by water availability [3,5]. However, this agreement might be ENSO event-dependent, as we found larger disagreement between inversions and LSMs in 1997/1998 than in 2015/2016. Understanding how terrestrial biogeochemical processes contribute to the emergent response of ecosystems to warming and drying during El Niño events is crucial to comprehend the vulnerability of land ecosystems to future changes in climate in the tropics and other sensitive regions.

**Data accessibility.** CO$_2$ fluxes from the CAMS atmospheric inversion are freely available at http://atmosphere.copernicus.eu/. CarboScopes datasets are available at http://www.bgc-jena.mpg.de/CarboScopes/. The monthly time series of global and tropical CO$_2$ fluxes are provided for each inversion in electronic supplementary material. Outputs from land surface models from the TRENDYv6 project used in this study are provided in electronic supplementary material. These are the time series of global/tropical average monthly NBP, GPP, TER and fire emissions from each individual model, as well as the annual and seasonal gridded anomalies of the MMEM NBP, GPP, TER and LAI. Annual and seasonal anomaly NBP maps from inversions, and annual NBP maps from individual models are also provided. The full TRENDYv6 dataset including other outputs is available, subject to the individual modelling groups’ agreement, via a request to S. Sitch (s.a.sitch@exeter.ac.uk). The results from the Global Carbon Budget 2017 are available for download at http://www.globalcarbonproject.org/carbonbudget/17/data.htm. Annual anomalies of WUE-GPP are provided in electronic supplementary material. The GFED4s fire emission database is publicly available at http://www.globalfiredata.org/data.html. MODIS data are freely available at https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table. The L-VOD data can be accessed at Centre Aval de Traitement des Données SMOS (CATDS): ftp://ext-catds-cesm.catsd.cesm2010eftp.ifremer.fr/Land_products/L3_SOMOS_IC_Soil_Moisture/Seasonal_Averages/. The Standardized Precipitation-Evapotranspiration Index is freely available at http://spei.csic.es/.

**Authors’ contributions.** A.B. and P.F. designed the study, conducted the analysis and wrote the manuscript. S.S and P.F coordinated the TRENDY simulations and maintained the TRENDYv6 data. F.C and C.R. developed the atmospheric inversion datasets. C.C and R.M. are responsible for the development and pre-processing of the LAI3 g dataset. A.M. and J.-P.W. pre-processed and provided the L-VOD data. L.C. developed and pre-processed the WUE-GPP dataset. V.K.A., P.R.B., C.D., V.H., A.K.J., F.J., E.K., S.L., D.L., J.R.M., J.E.M.S.N., B.P., R.S., H.T., N.V., N.Vu., A.P.W., J.Y., S.Z., N.Z. and D.Z. performed the TRENDYv6 simulations. All authors contributed to the writing of the manuscript.

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**References**


