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Decrease in Amazonia carbon uptake linked to trends in deforestation and climate

Luciana V. Gatti[1,2], Luana S. Basso[1], John B. Miller[3], Manuel Gloor[4], Lucas G. Domingues[5,1,2], Henrique L.G. Cassol[6], Graciela Tejada[1], Luiz E.O.C. Aragão[6], Carlos Nobre[7], Wouter Peters[8,9], Luciano Marani[1], Egidio Arai[6], Alber H. Sanches[10], Sergio M. Corrêa[11,1], Liana Anderson[12], Celso Von Randon[10], Caio S. C. Correia[1,2], Stephane P. Crispim[1], Raiane A.L. Neves[1]

[1]National Institute for Space Research (INPE), Earth System Science Center (CCST), Greenhouse Gases Laboratory (LaGEE), Av. dos Astronautas, 1758, Jardim da Granja, Sao Jose dos Campos, Brazil, CEP: 12.227-010

[2]Nuclear and Energy Research Institute (IPEN), Av. Lineu Prestes, 2242, 05508-000, São Paulo, SP, Brazil

[3]NOAA - Global Monitoring Laboratory, Boulder, Colorado 80305, USA

[4]University of Leeds, School of Geography, Woodhouse Lane, LS9 2JT, Leeds, UK

[5]National Isotope Centre, GNS Science, Lower Hutt, New Zealand

[6]Remote Sensing Division, National Institute for Space Research (INPE), Av. dos Astronautas, 1758, 12.227-010, São José dos Campos, SP, Brazil

[7]USP – University of São Paulo, IEA, Sao Paulo, Brazil

[8]Wageningen University, Department of Meteorology & Air Quality, Wageningen

[9]University of Groningen, Centre for Isotope Research, Groningen, Netherlands

[10]INPE – CCST – Av. dos Astronautas, 1758, Sao Jose dos Campos, Brazil, CEP: 12.227-010, São José dos Campos, SP, Brazil

[11]UERJ - Rio de Janeiro State University, Resende, Brazil, sergiomc@uerj.br

[12]National Center for Monitoring and Early Warning of Natural Disasters – CEMADEN, Estrada Doutor Altino Bondesan, 500, São José dos Campos/SP, Brazil, CEP:12.247-016

Summary

Amazonia hosts Earth's largest tropical forests and has represented a globally important sink for atmospheric CO_2 over recent decades, although the sink appears to be declining due increasing in mortality[1–3]. To improve diagnosis of Amazonia's carbon cycle, starting in 2010, we initiated regular observation of lower troposphere CO_2 and CO concentrations at four aircraft vertical profiling sites spread over the Brazilian Amazonia[4]. Using an air column budgeting technique, which integrate vertical profiles CO_2 subtracting the correspondent background for each flask/height and considering the air parcels travel time from coast to site, we calculate total and biomass burning C fluxes in the regions upwind of each site, from 2010 to 2018. Over our study period, total C emissions are larger in the east than in the west, which mainly results from spatial differences in CO-derived fire emissions. For the southeast Amazonia, in particular, net C flux (total flux minus fire) represent a source to the atmosphere. Over the past 40 years, the eastern Amazonia has been subject to more deforestation, rapid warming, and moisture stress[5], than the less human impacted west, especially during the dry season, with the southeast experiencing the strongest trends. The higher eastern C fluxes could be explained by climate and disturbance trends promoting both higher fire emissions and greater stress on ecosystems, increasing mortality and reducing photosynthesis[1,6].

Introduction

Amazonia forests contain on the order of 123 ± 23 Pg C of biomass above and belowground[7], which can be released rapidly and may thus result in sizeable positive feedbacks on global climate[8]. Additionally, deforestation and forest degradation reduce Amazonia's capacity to act as carbon sink. Hydrologically, Amazonia is one of the three major air upwelling regions in the tropics, resulting in the rainforest receiving rainfall on average across the whole Amazon around 2200 mm y^{-1}. Amazonia exhibits complex relationships between ecosystem carbon and water fluxes and climate[9,10]. For example, evapotranspiration has been estimated from several studies to be responsible for 25 to 35%

of total rainfall[10–12]. Large-scale human disturbance of these ecosystems can reasonably be expected to alter these ecosystem-climate interactions. Over the last 40 to 50 years human impact has increasingly affected Amazon, resulting in forest loss of around 17%, of which 14% has been converted mostly to agriculture (89% pasture and 10% crops)[13]. Removal of forests causes increases in temperatures[9,14–16] and reduces evapotranspiration, and has been shown to reduce precipitation downwind of deforested areas[10,17,18]. Regional deforestation and selective logging furthermore lead to degradation of adjacent forests, which increases their vulnerability to fires promoting further degradation[4,9,19]. These effects are further enhanced by temperature increases caused by a decrease in forest cover[17,20] and are superimposed on the backdrop of global warming.

Atmospheric carbon vertical profiles

A large-scale integrating indicator of the state of an ecosystem is its greenhouse gases balance, mainly the carbon balance. Here, we report CO_2 fluxes between 2010 and 2018 based on almost 600 CO_2 (Extended Data Fig. 1a) and CO aircraft vertical profiles that tell us about responses of Amazonian ecosystems to direct human impact and regional climate change. Fig. 1 shows the regions of influence and the location for four vertical profiling sites. Profiles extend from near the surface to approximately 4.5 km above sea level and are collectively sensitive to surface fluxes from a large fraction of Amazonia. The air arriving at our sampling sites comes predominantly from the east with the north-south component of the flow dependent on the seasonally varying position of the ITCZ (Fig. 1, Extended Data Fig. 2a). As a result, air samples collected at the four sites are influenced by regions with differing levels of human disturbance (Fig. 1). Site-specific regions of influence were determined using air-mass back-trajectory calculations (Extended Data Fig. 2, see Methods). We use quarterly-resolved regions of influence to determine the average spatially-weighted magnitudes of potential carbon flux drivers such as historical deforestation extent, temperature, and precipitation, upwind of each site. Additionally, the regions of influence for each site are used to calculate spatially-weighted mean fluxes for all of Amazonia (see Methods).

Annual mean vertical profile (VP) (Extended Data Fig. 1b) enhancements or depletions (ΔVP) are a function of the cumulative effect of all C sources and sinks between the Atlantic coast and each site. We examine ΔVP as a direct data analysis approach to gain a first-order understanding of C source and sink patterns. Annual mean ΔVP is calculated by subtracting background (BKG) concentrations determined from Atlantic Ocean remote sites from CO_2 concentrations at each VP sampling height (Fig. 2) and the annual mean concentration integrated from the surface to the top of the profile (Extended Data Fig. 1c) (see Methods). Figure 2 shows the annual and nine-years mean ΔVP for each site. The eastern sites SAN (at northeast Amazon, hereafter referred to as SAN-NE) and ALF (at southeast Amazon, hereafter ALF-SE) exhibit higher CO_2 relative to background, when integrated from the surface to the top of the profile (see Methods), than the western sites RBA (southwest-central Amazon, hereafter RBA-SWC) and TAB_TEF (northwest-central Amazonia, hereafter TAB_TEF-NWC). Vertically integrated ΔVP (Extended Data Fig. 1c), which are proportional to surface flux, suggest that ALF-SE has the largest CO_2 emission to the atmosphere, followed by SAN-NE. In contrast VPs after BKG subtraction for the western sites RBA-SWC and TAB_TEF-NWC indicate near neutral or C sinks.

An alternative way of examining the VPs is to not subtract BKG, but just consider the vertical differences between the top of the profiles (> 3.8km) and that portion below the planetary boundary layer (~ >1.5km) (Extended Data Fig. 1d). As with the BKG subtraction approach, positive enhancements suggest a land source, while negative depletions suggest a sink. This vertical difference approach shows similar behavior to the BKG subtraction approach, with positive CO_2 surface emission to the atmosphere from eastern sites (SAN-NE and ALF-SE) and almost neutral or removal of CO_2 from surface for the western sites (RBA-SWC and TAB_TEF-NWC). At ALF-SE annual mean ΔVP (Fig. 2) is observed after the last strong El Nino 2015/16 higher CO_2 concentrations near surface, representing increasing in emissions. Only RBA-SWC exhibits significantly different behavior from the two approaches with near neutral C balance with BKG subtraction and apparent C uptake when examining vertical differences (Extended Data Fig. 1c&d). The annual mean RBA-SWC VP shows clearly the strongest carbon sink compared to the other regions, and when we just consider the vertical differences between >3.8km and <1.5km the uptake from surface is more evident. Long travel times of air masses from the coast to vertical profile sites allows for a more convective process promoting vertical mixing between the atmosphere's layers we measure and those above it. The result of such mixing is that some surface flux signal can be lost through the top of our measurement domain. In the case of CO, during the dry season, we observe larger enhancements in the difference >3.8km and BKG indicating loss of signal, although CO plumes, in particular are associated with pyro-convection and not the same degree of signal loss for CO_2 (Supplementary Information Fig. 1). Vertical loss of signal is one source of uncertainty in our approach that we account for (see Methods).

Regional Amazonia Carbon Fluxes

Partial columns of CO_2 are used to determine total carbon fluxes (FC_{Total}) that represents the result of all surface sources and sinks (natural and anthropogenic) between the coast and the sample site. CO is used to determine the fraction of FC_{total} derived from biomass burning emissions (FC_{Fire}). Removing FC_{Fire} from FC_{Total} we obtain Net Biome Exchange (FC_{NBE}) for the region upwind of given vertical profile (a negative NBE represents C sink). Total, fire and NBE carbon fluxes were combined into monthly, annual and long-term averages, and into east, west and basin-wide totals (Extended Data Table 2; see Methods).

For SAN-NE, the nine-year mean fluxes for FC_{Total}, FC_{Fire} and FC_{NBE} are 0.41±0.25, 0.53±0.03 and -0.11±0.26 gC m^{-2} d^{-1}, respectively (Fig. 3; Extended Data Table 2). This region presented the highest carbon fluxes among our sites. The seasonality of carbon fluxes (Extended Data Fig. 3 & 4) is the second largest for SAN-NE as is true for the seasonalities of precipitation, temperature, and Enhanced

Vegetation Index (EVI, a measure of vegetation of greenness, see Methods). ALF-SE shows the second highest FC$_{\text{Total}}$ over nine years (0.32±0.09 gC m^{-2} d^{-1}; Fig. 3) and exhibits the strongest seasonality for carbon fluxes, precipitation, temperature, and EVI. At dry season low EVI value reflects a susceptible period of drier biomass for ignition, which this region presented the highest burned area (Extended Data Table 2). Over nine-years, FC$_{\text{NBE}}$ for this region is a possible carbon source to the atmosphere (+0.11±0.13 gC m^{-2} d^{-1}) representing one third of FC$_{\text{Total}}$. Seasonally, the region is a weak sink only during part of the wet season with most positive FC$_{\text{Total}}$ in the dry season resulting from fire emissions and net respiration (Extended Data Fig. 3). Note, however, that part of the seasonality in fluxes observed for ALF-SE may result from the region of influence shifting southward to areas of greater historical disturbance in the 2nd and 3rd quarters regions of influence (see Climate Trends and Human Impact below), which corresponds to the end of wet season (April-May) and dry season (June-September) (Extended Data Fig. 2a,b). The Cerrado (savanna) biome to the south and east of the rainforest may represent about 40% in the 2nd and 3rd quarters of the region of influence (Extended data Fig 2a). Over the 9 years studied (2010 - 18), NBE for ALF-SE indicates that it is a source each year greater, presenting an increase rate (slope) per year of 0.036±0.015 gC m^{-2} d^{-1} (Pearson's correlation, $r = 0.68$, $p = 0.045$) (Extended Data Fig. 5a). Between 2010 and 2018, annual FC$_{\text{Fire}}$ averages 0.20±0.01 g C m^{-2} d^{-1}. RBA-SWC, which has experienced less disturbance than the east, averaged a weak source over nine years (FC$_{\text{Total}}$: 0.05±0.02), with FC$_{\text{NBE}}$ an annual mean sink (-0.10±0.02), compensating about two thirds of FC$_{\text{Fire}}$ (0.14±0.01 gC m^{-2} d^{-1}). The mean seasonal cycle of NBE exhibits a wet season sink from November through March (Extended Data Fig. 3). RBA FC$_{\text{Fire}}$ is high due in large part to the fact that the "Arc of Deforestation" is in the southern portion of the region upwind of the site (Extended Data Fig. 2).

Air samples from TAB_TEF-NWC are sensitive to the northwest and central Amazonia, one of the regions least impacted by human activities. Vertical profiles of CO$_2$ and CO were measured at TAB from 2010 to 2012, and at TEF from 2013 to 2018, but their regions of influence and flux seasonal cycles are very similar, so we have analysed them as a single time series (Supplementary Information 2 and Extended Data Fig. 4). Combining TAB and TEF, the nine-year mean FC_{Total} is near neutral (0.03±0.08), with FC_{NBE} (-0.06±0.08) nearly compensating for fire emissions (0.08±0.01 gC m^{-2} d^{-1}) (Extended Data Table 2). Seasonality in both FC_{Total} and FC_{NBE} is absent for TAB_TEF, with both FC_{Total} and FC_{NBE} near neutral all year. This lack of seasonality may result from the near absence of dry months (less than 100 mm of precipitation) in the upwind region, which is also expressed as low seasonal fire fluxes and burned area; EVI seasonality is also the smallest of all sites. Lack of EVI seasonality is related to a relatively high constant fraction of photosynthetically active radiation (fPAR) absorbed by plants, and thus a lower fraction of dry biomass throughout the year, reducing fire risk (Extended Data Fig. 3 & 4).

CO_2 gradients from the annual mean vertical profiles and the estimated carbon fluxes for these sites indicated a link between areas more impacted by land use and cover change and higher carbon emissions to the atmosphere.

Considering the upwind areas of each site, we combine fluxes from all sites to calculate a total Amazonia carbon balance for our nine-year study period (see Methods) of 0.29±0.40 PgC y^{-1} (FC_{Total} 0.11±0.15 gC m^{-2} d^{-1}), where fire emissions represent 0.41±0.05 PgC y^{-1} (FC_{Fire} 0.15±0.02 gC m^{-2} d^{-1}) with NBE removing only 31% of fire emissions from the atmosphere, -0.12±0.40 PgC y^{-1} (FC_{NBE} -0.05±0.15 gC m^{-2} d^{-1}). The east (region 1 at Extended Data Fig 6) represents 24% of the whole Amazonia, 27% deforested, is responsible for 72% of total Amazon carbon emission, where 62% is from fires. Forest fires contribute with cumulative gross emissions of carbon of. ~126.1 Mg CO_2 ha^{-1} for 30 y after a fire event and a mean annual flux value of 4.2 Mg CO_2 ha^{-1} y^{-1} (0.48 PgC y^{-1} using the same area from our study). Cumulative CO_2 uptake only offsets 35% of these[21]. Another recent study pointed out fire emissions from Amazonia ~0.21±0.23 PgC y^{-1} [9]. Recently, Van der Werf et al.[22] estimated for the period between 1997-2009 that globally, fires were responsible for an annual mean carbon emission of 2.0 Pg C yr^{-1}, where about 8% appears to have been associated with forest fires, based on estimates from the Global Fire Emission Dataset (GFED) product for South America. The RAINFOR project showed for mature forest a decline in sink ability due increase in mortality[1–3]. Considering a mean value for these three studies, the 90's ~-0.56, 00's ~-0.38 and 10's -0.20 Pg C y^{-1}. The NBE from this study represents (decade 10's) the uptake from forest, but also all non-fire emissions (more comparisons can be found at Supplementary Information Table 2).

Climate trends and human impact

The regions of influence for the four sites differ substantially with regard to human impact, in particular deforestation. Using site-specific regions of influence averaged over our nine-year study period (Extended Data Figure 2c), we determine cumulative historical deforestation fractions of the areas upwind of SAN-NE, ALF-SE, RBA-SWC and TAB_TEF-NWC to be 31%, 26%, 13% and 7%, respectively (see Methods). SAN-NE and ALF-SE vertical profiles sample air affected by yet higher levels of deforestation during the 2nd and 3rd quarters of the year (Extended Data Fig. 2a,b). For SAN-NE, deforestation increases to 39 and 42%; for ALF-SE increases are 32 and 39%, respectively.

Regions of influence of eastern and western Amazonia sites also differ with regard to long-term climate trends. We found similar annual mean warming trends for the whole Amazonia (1.02±0.12˚C) as for the global average (0.98˚C)[23] between 1979 and 2018 (see Methods). However, warming trends differ between months, and the largest increases were observed for three dry season months of August, September and October (ASO; 1.37±0.15˚C). Annual mean precipitation has not significantly changed, but similar to temperature trends, ASO precipitation has decreased by 17%, enhancing the dry-season/wet-season contrast (Extended Data Fig. 7 and Table 1).

Between 1979 and 2018 there are also considerable regional contrasts in temperature and precipitation trends, mainly in the dry season. Those for the eastern regions SAN-NE and ALF-SE, which have the largest fractions of historically deforested land, stand out, highly impacted mainly by livestock and, to a lesser extent, by crops[13]. For the SAN-NE, deforested 37%, it was the unique region where the annual mean precipitation has decreased 9% in the past 40 years (208±167mm), where the largest reduction was during ASO (34%) (Fig. 4 & 5 and Extended Data Table 1). Although annual mean precipitation upwind of ALF-SE has not changed significantly, ASO precipitation decreased by 24%, as noted previously for a similar region of Amazonia[17,20,24]. Although the fractional and absolute reduction rate in ASO precipitation for SAN-NE and ALF-SE is similar to the western sites (Extended Data Table 1), the impact of this drying on the ecosystems is probably greater, because dry season moisture in the east is lower than the west during the last 4 decades (Fig. 4 and Extended Data Figure 8). Temperature trends for the eastern regions are also larger than for Amazonia as a whole: 1.38±0.15˚C at SAN-NE and 1.46±0.11˚C at ALF-SE annually, with changes of 1.86±0.16˚C and 2.54±0.29˚C, respectively, during ASO (Extended Data Fig. 8 & Table 1). Moreover, these trends appear to be accelerating over the last 40, 30, and 20 years (Extended Data Table 1). For ALF-SE, temperature has also increased by 3.07±0.29˚C for the two hottest months August and September (AS) (Extended Data Fig. 8). These temperature and precipitation changes are also associated with a large positive trend in Vapor Pressure Deficit in the southeast Amazonia[5], which suggests increasing plant stress. For ALF-SW, two phenomena are acting to increase the temperature: global climate change[5,18,25–27] and large-scale deforestation and forest degradation amplifying these trends in this region.

The two western sites, RBA-SWC and TAB_TEF-NWC, also exhibit their strongest trends during the dry season. There has been no significant annual mean change in precipitation for RBA-SWC, but ASO precipitation has dropped by 20% (Fig. 4). Its annual mean temperature increases similarly to global rates, although it is also largest during ASO (1.72±0.15˚C). The relatively pristine region upwind of TAB_TEF-NWC (7% historical deforestation), also shows a decreasing trend in ASO precipitation of 20%, but no significant annual mean trend (Fig. 4). A possible reason for this 20% decrease in precipitation in both western regions, less deforested, is the cascade effect[10]. That is, deforestation in the eastern Amazonia may be reducing evapotranspiration, which in turn may be reducing the recycling of water vapor that is transported to the western Amazonia. Annual mean temperature trends of TAB and TEF have been similar to global trends, and although ASO temperature trends are larger than for the annual mean, they are smaller than for the other regions (Extended Data Table 1). The analysis of 40 years of temperature and precipitation data over Amazonia shows the relationship between deforestation extent and decreases in precipitation and increases in temperature, mainly during the dry season, with different trends observed for the eastern, western and whole Amazonia.

East versus West Amazonia contrasts

Dividing Amazonia into regions (Extended Data Fig. 6a) influencing eastern (SAN and ALF: region 1) and western (RBA and TAB_TEF: region 2) sites reveals notable differences. The east side (region 1) represents approximately 1.6 x 10^6 km^2, with cumulative historical deforestation of approximately 27%. The west (region 2), on the other hand, has a much larger region of influence (approximately 4.1 x 10^6 km^2) and a much smaller fraction of deforested land (11%). The historical deforestation and climate changes in the east could be reflected in eastern average annual mean FC_{Total} of 0.35±0.11, FC_{Fire} of 0.31±0.01 and FC_{NBE} of +0.04±0.11 gC m^{-2} d^{-1} (see Methods). The eastern averages are strongly influenced by the southeast Amazonia, represented by observations from ALF-SE, which is characterized by a positive NBE (carbon emission), very strong changes in dry season with increase of temperature, decrease of precipitation and large historical deforestation (Extended Data Table 1 & 2).

At ALF-SE, for the 2010 - 2018 period of our CO_2 and CO observations, we can directly observe the relationship between moisture and temperature and FC_{NBE} and FC_{Fire}. The positive trend in NBE at ALF-SE correlates with the annual mean temperature and GRACE (equivalent water thickness) satellite soil water storage anomalies (see methods) (multivariate linear correlation, r = 0.88, p = 0.011), suggesting that temperature and water availability in the soil have a significant impact on the vegetation carbon balance at least in the southeast (Extended Data Fig. 3, 4 & 5b). Interannual variations of FC_{Fire} at ALF-SE are strongly correlated with ASO (peak of dry season) temperature and precipitation (r = 0.81 and r = -0.73, respectively), showing that temperature and moisture impact both components of FC_{Total}. This region also exhibits almost twice the burned area of any other region (Extended Data Fig. 3 & 4), and interannual burned area is highly correlated with FC_{Fire} (r = 0.97). Historically, the eastern Amazonia has experienced strong increase in dry season temperature, reduced precipitation and increased duration[5,17,20,25,28–31], which together are creating an increasingly severe environment for vegetation, not only during extreme drought years, but every year, especially for the southeast[32].

In contrast, the regions influencing the western sites have experienced relatively lower levels of human disturbance and dry season climate trends. For the regions upwind of TAB_TEF-NWC and RBA-SWC, we observed a near neutral FC_{Total} of 0.04±0.07 gC m^{-2} d^{-1}, minimal fire emissions (0.11±0.01) and a carbon sink (FC_{NBE}) of -0.08±0.07 gC m^{-2} d^{-1} (Extended Data Table 2). In a scenario where the whole Amazonia had the same NBE as western sites, the whole area would act as a sink of 0.20 PgC y^{-1}.

The east-west difference in total flux can be explained mainly on the basis of CO-based fire emissions and burned area (Fig. 5 and Extended Data Table 2). However, the dry season climate trends and the stronger historical deforestation and degradation in the east could make the area more susceptible to fire[9]. Historical land use change and climate trends could also explain higher (positive) NBE, especially in the southeast. Recent study pointed out that after 30 years burned area still is a CO_2 source to the atmosphere, which 73% resulted from subsequent tree mortality and decomposition[21]. This decomposition emission could not be compensated by CO_2 uptake by photosynthesis. For undisturbed forests, increasing temperatures and moisture stress may increases in tree mortality[1–3,6], as well as, negatively impact photosynthetic C uptake by trees via a decline in photosynthetic capacity[31]. Moreover, higher air temperatures generally lead to higher rates of soil carbon decomposition in both intact forests and disturbed land. Historical trends of regional climate and land disturbance in Amazonia may be connected; our results suggest that such interactions may have long-term impacts on the C balance of Amazonia.

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Fig. 1 | Regions of influence. Average Regions of Influence (2010-2018), delimited by light blue line based on the density of HYSPLIT back trajectories (see Methods and Extended Data Fig. 2c for detailed regions of influence) inside Amazon Mask, (purple line, $7.25\text{x}10^6$ km^2) for each vertical profile site: TAB_TEF (northwest; TAB, 2010-2012 and TEF 2013-2018), SAN (northeast), ALF (southeast) and RBA (southwest). The aircraft vertical profiles sites (Flight sites) are shown as black circles. Deforestation data is from PRODES only for the Brazilian Amazon up to 2018 (see Methods).

Fig. 2 | Annual Mean Vertical Profiles. From vertical profile monthly mean (for each height was subtracted the background) was produced the Annual Mean Vertical Profile for each year (2010-2018), where the concentrations were corrected by the correspondent air density for each level. The black line represents the 9 years mean vertical profiles for each site. The mean for annual vertical profiles for each site in ppm and the site mean are presented at Extended Data Fig 1c.

Fig. 3 | Annual carbon fluxes. Annual carbon fluxes for the regions upwind of SAN, ALF, RBA and TAB_TEF (TAB 2010-2012 and TEF 2013-2018). Blue bars are total C Flux, red bars are fire C Flux and green bars NBE (total less fire flux). Error bars are uncertainties of annual means (see Methods).

Fig. 4 | 40-years precipitation and temperatures trends. Precipitation trends using GPCP V2.3 (upper panels) and temperature trends using ERA-Interim, from 1979 to 2018 (lower panels), for 4 sites. Annual (black), ASO (red; August, September and October) and JFM (blue; January, February and March) totals (for precipitation) and means (for temperature) between 1979 and 2018 (see Methods). TAB_TEF ASO and JFM is shown only for TEF, since there is no dry season at TAB; annual values are shown for the combination of both sites

Fig. 5 | Spatial results overview. Summary of deforestation per site (orange arrows), reduction in precipitation during the months August, September and October (ASO) (light blue arrows), increase in temperature in ASO (white arrows) and carbon fluxes (Total: dark blue bars, NBE: green bars, fire: red bars).

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Author Information Reprints and permissions information is available at npg.nature.com/reprints and permissions. The authors declare no competing financial interests. Correspondence and requests for materials should be addressed to LVG (luciana.gatti@inpe.br or lvgatti@gmail.com).

Additional Information Extended Data and Supplementary Information is available for this paper. Correspondence and requests for materials should be addressed to luciana.gatti@inpe.br.

Methods

Sites, Air sampling and analysis The Amazon study area was defined according to Eva et al.[33] subregions and Olson et al.[34] biomes. For the Amazon mask we considered the subregions of Amazon *sensu stricto*, Andes, Guiana and Gurupi given a total study area of 7,256,362 km^2; we excluded the Planalto sub-region as it is outside the Tropical and subtropical moist broadleaf forest biome (Supplementary Information Fig. 3).

The four aircraft vertical profiles sites from the CARBAM project at Amazon were started in 2010: SAN (2.86S 54.95W); ALF (8.80S 56.75W); RBA (9.38S 67.62W); TAB (5.96S 70.06W) from 2010-2012, and TEF (3.39S 65.6W), starting in 2013. The sampling period was typically twice per month. Over nine years, 590 vertical profiles were performed (Extended Data Fig. 1a,b) in a descending spiral profile from 4420 m to 300 m a.s.l. A mean of 75 vertical profiles was performed per year from 2010 to 2018 at the 4 sites, except for 2015 and 2016. In 2015 the flight collection was stopped in April at all sites, returning only in November at RBA. In 2016 only RBA and ALF were measured. The vertical profiles were usually taken between 12:00 and 13:00 local time. Air is sampled by semi-automatic filling of 0.7 L boro-silicate flasks inside purpose-built suitcases[35]; there are two versions, one with 17 flasks at SAN, and another with 12 flasks at TAB_TEF, ALF and RBA. This suitcase is connected to a compressor package, containing batteries, which is connected to an air inlet on the outside of the aircraft at wing or window, depending on the aircraft model (Supplementary Information Fig. 4a,b). Air samples were analyzed with a non-dispersive infrared (NDIR) analyzer for CO_2 and by gas chromatography HgO reduction detection (GC-RGD) for CO. Detailed methods have been presented earlier[3]. To ensure accuracy and precision, we analyzed CO_2 mole fraction from "target tanks" (calibrated CO_2 in air in high pressure cylinders treated as unknowns) and demonstrated long-term repeatability of 0.02 ppm and a difference between measured and calibrated values of 0.03 ppm[36].

Annual Mean Vertical Profiles We calculated annual mean partial column averages from our vertical profiles as a simple way to assess the robustness of our annual fluxes. For each site annual mean profiles were calculated starting with individual profiles and then averaging to monthly and annual values (Extended Data Fig. 1b). We also constructed the annual mean vertical profiles subtracting the background values at each altitude of each vertical profiles (ΔVP) to produce the annual mean enhancement or depletion at each altitude (Fig. 2). The air density-weighted column mean was then calculated and compared to the annual mean flux calculated from the same profiles (Extended Data Fig. 1c). For all sites, we observed a high positive correlation between the column means and fluxes suggesting that at least at the annual mean level our fluxes, which incorporate more detail, such as travel time, are consistent with a simpler interpretation of the data.

Carbon Flux estimation Fluxes for each vertical profile were calculated using a column budget technique, that consist in the difference between trace gas concentration at the sites and corresponding background values for each flask (ΔX) and the travel time of air parcels along the trajectory from the coast to the site t (eq. M1). Detailed information can be found at Gatti et al.[4], and was also used by Miller et al.[37], Gatti et al.[38], Basso et al. [39] and D'Amelio et al.[40].

$$F_X = \int_{z=0(agl)}^{4.4\,km(asl)} \frac{\Delta X}{t(z)} dz \qquad \text{(M1)}$$

To apply eq. M1 we convert mole fractions {μmol CO_2 (mol dry air)$^{-1}$, i.e. ppm} to concentrations (mol CO_2 m^{-3}) using the density of air, where temperature (T) and pressure (P) were measured during the vertical profiles and for situations where weren't, it were calculated T, P using the equation derived for temperature and pressure based in all measured T and P relating to height for each site. The used equations are presented M2 to M9, where x: height (m), T (˚C), P (mbar).

SAN_Temperature $y = 1.9586x^2 - 249.49x + 5815$ $r^2 = 0.97$ (M2)
SAN_Pressure $y = 0.0024x^2 - 12.46x + 11069$ $r^2 = 0.87$ (M3)
ALF_Temperature $y = 0.4202x^2 - 170.62x + 5201$ $r^2 = 089$ (M4)
ALF_Pressure $y = 0.0059x^2 - 20.21x + 14402$ $r^2 = 0.87$ (M5)
RBA_Temperature $y = 0.1985x^2 - 167.77x + 4953$ $r^2 = 097$ (M6)
RBA_Pressure $y = 0.0079x^2 - 21.10x + 13872$ $r^2 = 0.89$ (M7)
TAB_Temperature $y = 2.415x^2 - 253.98x + 5542$ $r^2 = 0.95$ (M8)
TAB_Pressure $y = 0.0051x^2 - 18.87x + 13828$ $r^2 = 0.87$ (M9)

For assigning background concentrations, we use the geographical position of each air-mass back-trajectory when it intersects two virtual limits. The first one is a latitude limit, from the Equator southwards at 30° W, and the second segment is a line from the Equator to the NOAA/GML observation site at Ragged Point, Barbados (RPB). The atmospheric air circulation over Amazonia is characterized by trade-wind easterlies coming from the tropical Atlantic Ocean[37] and moving towards the Andes (west). This behaviour allows us to relate the position that airmass crosses the virtual line with the concentrations measured at the remote sites in the Atlantic: RPB, ASC and CPT from the NOAA Global Monitoring Laboratory (NOAA/GML) to determine background. This method is published in Domingues et al.[41] (supplementary Information Fig. 5).

To estimate travel times (*t*, equation M1) we calculate back trajectories for each air sampling level for each flight. 13 days backwards trajectories are derived from the online version of the HYSPLIT model[42]. Then, with a resolution of 1 hour, the time when the back trajectory crosses the coast is calculated. Mean travel times (2010-2018) from the coast to SAN 2.4 ± 1.5 days, ALF 5.0 ± 2.0 days, RBA 6.6 ± 2.1 days, TAB (2010-2012) 5.9 ±1.9 days and TEF 4.9 ± 2.0 days. For each height interval, we calculate the associated flux and then sum them to obtain the flux estimate for the specific measured vertical profile. For calculating annual means, we first calculate monthly mean fluxes (typically with two fluxes per site per month) and then average them.

Fire Flux estimation To estimate fluxes due to biomass burning, we used measured CO concentrations as a biomass burning tracer. We estimate CO:CO_2 fire emission ratios from clearly identifiable plumes in the vertical profiles during the dry season, typically from August to December[4]. Average CO:CO_2 ratios were calculated by site: ALF CO:CO_2= 53.4 ± 9.9, based on 16 vertical profiles; SAN CO:CO_2= 55.5 ± 14.7, based on 19 vertical profiles; RBA CO:CO_2= 73.2 ± 15.1, based on 12 vertical profiles; and TAB_TEF CO:CO_2= 71.6 ± 17.2, based on 5 vertical profiles, where the units are [ppb CO (ppm CO_2)$^{-1}$]. The two eastern sites showed lower ratios and western sites higher ratios. The eastern sites are sensitive to more deforested and degraded land, and also receive influence from Cerrado and Caatinga. The western sites are sensitive to more preserved areas and have a higher representativity of Amazonia[43]. TAB_TEF represents a pristine area with many fewer biomass burning events.

Equation M10 was used to estimate CO_2 emission from biomass burning. F_{CO} is calculated identically to CO_2 fluxes according to eq. M1. To isolate the biomass burning flux from total CO flux we subtract the "natural" CO flux, $F_{CO}^{Natural}$, arising from direct soil CO emissions and mainly CO from oxidation of VOCs like isoprene that are emitted from the forest. Basin wide average $F_{CO}^{Natural}$ between the surface and 600 mbar (the approximate maximum altitude of the vertical profiles) was calculated for

2010 and 2011 starting with output from the Belgian Institute for Space Aeronomy (BIRA) IMAGESv2 chemical transport model (CTM). The VOC production in the model was tuned to HCHO (formaldehyde) observations from the GOME-2 and OMI satellites[44], resulting in improved estimates of atmospheric CO production from VOCs. These modeled fluxes were then adjusted on a site by site basis with a constant offset each year to match the mean late wet season, early dry season observed total CO flux, which in past studies[4,36] we have taken to be equal to the year-round biogenic CO flux (late wet season, early dry season is March – June, except for SAN, in which March is excluded, because high CO fluxes are sometimes observed). 2010 fluxes were applied to all the dry years (2010, 2015, 2016) and 2011 fluxes were applied to all wet years (2011-2014, 2017-2018). Observed, natural (modeled), and natural (adjusted), CO fluxes for 2010-2018 are shown in Supplementary Information Fig. 6. This biomass burning CO flux ($F_{CO} - F_{CO}^{Natural}$¬) was then converted to biomass burning CO_2 flux (FC_{Fire}) using the observed CO_2:CO emission ratios discussed above, on a site by site basis. NBE represents the result of emissions and uptake from all process from the influenced area for a specific vertical profile, monthly and annual mean, excepted Fire C emissions (NBE = total – fire).

$$FC_{Fire} = R_{CO_2:CO}\,(F_{CO} - F_{CO}^{Natural}) \qquad \text{(M10)}$$

Regions of Influence *Regions of Influence* are, by definition, those areas covered by the set of back-trajectories by each vertical profile and altitude integrated on an annual and a quarterly basis per site. *Annual Regions of Influence* are the average areas throughout the series upwind of the vertical profile per site (Fig 1 and Extended Data Fig 2c). We developed a method[43] that used individual back-trajectories for each sample in each vertical profile, calculated by the Hysplit trajectory model[42,45], at a resolution of 1 hour using 1˚x1˚ GDAS meteorology. For each site, all the back-trajectories in a quarter (JFM, AMJ, JAS, OND) or annually were binned, and the number of instances (at hourly resolution) that the back trajectories passed over a 1˚x1˚ grid cell was counted to determine the trajectory density, d_i, in each grid cell. The density of trajectories from a single location and height passed over a grid cell (1°x1°) from 300 to 3,500 m above sea level. We consider the cutoff 3,500 m due to three observations: first, plume rise associated with biomass burning rarely exceed 3,500 m asl; second, mole fractions of CO_2 and other gases observed above 3,500 m asl are very similar to gas mole fractions from measurements in the Tropical Atlantic marine boundary layer, which indicates minimal Amazonian surface influence; and third, changing the upper altitude limit from 3,500 to 1,300 m (typical Planetary Boundary Layer) has a minimal impact on our results. A back-trajectory may intersect a grid cell once or multiple times. The annual region of influence is defined by those grid cells with trajectories passing through them falling within the Amazon mask and further excluding grid cells associated with the lowest 2.5% of distribution of d_i (blue lines in Extended Data Fig. 2b.) Note that back-trajectories for "missing" vertical profiles (i.e. gaps in the data record) are calculated so that there are always trajectories for two vertical profiles per month, six per quarter, and 24 per year. The mean annual regions of influence (Fig. 1, limited to just the Amazon mask, and Extended Data Fig. 2c) were determined by averaging the nine annual regions of influence for each site, by the sum of the number of points (frequency) within each grid cell integrating all vertical profiles in the year (24 vertical profiles per site), and then averaging all nine years[43].

Quarterly Region of Influence are maps of "weighted trajectory density", w_i, which are simply maps of trajectory density, d_i, divided by the sum of all densities over South American land, where k is the number of all land grid cells (Extended Data Fig 2a,b, limited to the Amazonia mask). There are seasonal differences in circulation patterns, where the first and fourth quarters receive contributions from Northern Hemisphere, when the ICTZ (Intertropical Convergence Zone) lies below equator, and in the second and third quarters when air masses always have origins south of the Equator, producing important differences in the regions of influence throughout the year[43].

$$\mathrm{w_i} = \frac{d_i}{\sum_{\mathrm{i=1}}^{\mathrm{k}} d_i} \tag{M11}$$

Weighted Mean We used maps of $\mathrm{w_i}$ as spatial weighting functions for all studied parameters (temperature, precipitation, EVI, burned area and GRACE) to determine how each parameter influenced the carbon flux.

Temperature We used 2 meter temperature from ERA Interim, monthly means of daily means, obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF), available at (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim>, accessed on: January 25, 2019)[46]. Monthly data are available since 1979 and were used with a resolution of 1˚x1˚ latitude-longitude. For the 40-year study we used maps of quarterly mean weights, $\mathrm{w_i}$, averaged from 2010-2018, to determine the mean temperature upwind of each site (Fig. 4 and Extended Data Fig. 7 & 8 & Table 1). For comparison with the vertical profiles from January 2010 to December 2018 (Extended Data Fig. 3 & 4), we used trajectory-based weights corresponding to the specific quarter (2010 JFM, 2010, AMJ etc.).

Precipitation We used the data-based Global Precipitation Climatology Project (GPCP) (<http://eagle1.umd.edu/GPCP_ICDR/GPCP_Monthly.html>, accessed on: 25 January 2019). We used version 2.3 (described by Adler *et al.*)[47] and version 1.3 (described by Huffman *et al.*)[48]. Version 2.3 represents monthly mean global precipitation with resolution of 2.5° x 2.5° lat-long, since 1979 and was used for the 40-year analysis (Fig. 4, Extended Data Fig. 7 & 8 & Table 1). Version 1.3 is daily data with resolution of 1° x 1° lat-long, since 1996 and was used for comparison with calculated carbon fluxes (Extended Data Fig. 3 & 4).

Temperature and Precipitation data Validation The GPCP and ERA Interim dataset were validated using thirty-five automatic meteorological field stations for rainfall and temperature data from the INMET (National Institute of Meteorology, Brazil), covering the period between 1996 to 2018, and 1979 to 2018, respectively. Precipitation from GPCP was also validated by Santos et al.[49]. In our study, the least-squares regression analysis was carried out by using the GPCP and ERA Interim data as the dependent variable and the automatic meteorological field stations as the independent variable. The GPCP and ERA Interim dataset explained 62% to 94% and 16 to 93% of the rainfall and temperature variability captured by the automatic meteorological field stations, respectively (Supplementary Information Fig. 7). The RMSE for the entire region was estimated to be ±68.22 mm and ±1.19 ºC, but it is not homogeneous in the study area, varying from ±49.5mm to ±99.5mm and ±0.82 ºC to ±2.99 ºC for the rainfall and temperature, respectively.

GRACE For equivalent water thickness we used the JPL (Jet Propulsion Laboratory) monthly land mass grids which contain land water mass anomaly given as equivalent water thickness derived from GRACE (Gravity Recovery & Climate Experiment) time-variable gravity observations at 1.0° x 1.0° resolution[50]. For more details see Landerer and Swenson[51].

Burned Area The evaluation of the burned area (BA) was carried out with the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 MCD64A1 burned area product[52]. Collection 6 provides monthly tiles of burned area with 500 m spatial resolution over the globe with an overall accuracy of 97%[52]. The algorithm uses several parameters for detecting BA from the Terra and Aqua satellite products, such as a daily active fire (MOD14A1 and Aqua MYD14A1), daily surface reflectance (MOD09GHK and MYD09GHK), and annual land cover (MCD12Q1)[53–55]. The updated algorithm has the advantages of better detection of small fires (26% increase) and also reducing the temporal reporting accuracy from 68% in 2 days after the active fire[52]. The BA product was resampled to 1x1° spatial resolution using the fraction of area burned in that grid cell and summed for each quarter in the IDL/ENVI®.

EVI The Enhanced Vegetation Index (EVI) is a vegetation index that aims to highlight the fraction of absorbed photosynthetically active radiation (fPAR) from terrestrial vegetation targets, similar to NDVI - Normalized Difference Vegetation Index. In general, high positive values show a higher proportion of fPAR, and therefore, greater vegetation greenness (vegetation vigor). EVI can also reveal the seasonality of different vegetation types, where tree-individuals partly lose leaves during the dry season, become drier, thus reducing the index value. Unlike NDVI, EVI includes a blue band that minimizes the influence of aerosols and other adjustments to improve signal/noise ratio. Moreover, in high leaf area index environments such as the Amazon, NDVI can saturate, whereas EVI will not. EVI is computed as Eq M11[56]:

$$EVI = G\ x\ \frac{(NIR-Red)}{(NIR+C1*Red-C2*Blue+L)} \tag{M11}$$

where Near-infrared (NIR) (0.841-0.876 µm), Red (0.62-0.67 µm), and Blue (0.459-0.479 µm) are the atmospherically-corrected surface reflectance bands from MODIS; L is the correction of radiative transfer gain between NIR and Red in the canopy L = 1; C1 and C2 are the aerosol correction terms for NIR and Red, respectively C1 = 6, C2 = 7.5; G is the gain factor G = 2.5. The EVI product used was the MANVI: MODIS multiangle implementation of atmospheric correction (MAIAC) nadir-solar adjusted vegetation indices for South America, generated by spatial resolution of 1 km and temporal resolution of 16 days[57].

Deforestation Deforestation was calculated inside the Amazon mask for the whole Amazon and for each region of influence using the annual mean region of influence (Fig. 1) and quarterly mean region of influence (Extended Data Fig. 2) from 2010 to 2018. The deforestation data was from the Deforestation Monitoring Program known as PRODES produced by INPE[58] (2015) that measures the annual and official deforestation (larger than 6.25 ha) rate in the Brazilian Legal Amazon since 1988[59]. We normalized the trajectories density of the different influence areas, and also calculated the weighted deforestation (see weighted mean section).

Missing Data Imputation Total, fire, and NBE fluxes were missing for months in red in Supplementary Information Fig 8 at ALF, SAN, RBA, TAB_TEF due to sampling and laboratory logistical issues. To fill these gaps, we applied "Miss Forest", a nonparametric missing value imputation using Random Forest methodology[60]. It is used to impute continuous and/or categorical data, mainly when involved phenomena show complex interactions and nonlinear relations[61]. After each iteration of the method, the difference between the previous and the new imputed data matrix is assessed for all variables. To adjust the set parameters, such as number of iterations, number of trees, number of variables randomly sampled at each split and others, all monthly known data of each site were used. We did the imputation of total C Flux (FC_{Total}) and fire C Flux (FC_{Fire}) one at a time[62] and to train the method we used 85% of the following monthly variables with the remaining 15% withheld for cross-validation: temperature, precipitation, EVI, burned area and GRACE. FC_{Fire}, $FC_{Total,}$ and cross-validation calculations were computed 1000 times and the results are the mean values, presented in Fig. 3 and Extended Data Fig. 3 & 4 for missing months. Cross-validation was conducted with 15% of random known data for each site for both fire and total fluxes at each site. The NRMSE (Normalized root mean squared error) was below 0.0043 for all sites and fluxes. The root mean squared errors (RMSE) for the cross-validation statistics were 0.0064, 0.0253, 0.0047, and 0.0054 gC m^{-2} d^{-1} for total fluxes and 0.0013, 0.0029, 0.0011, and 0.0003 gC m^{-2} d^{-1} for fire fluxes at ALF, SAN, RBA, and TAB_TEF, respectively. These values were used in our uncertainty calculations for months with missing fluxes. We used the MissForest implementation from the R Language[63].

Uncertainty analysis - Monte Carlo error propagation For Monte Carlo error propagation we take into account the uncertainty in the background concentration and the uncertainty in air parcel travel time. For separation of total fluxes in fire and land vegetation fluxes unrelated to fire, we account for the uncertainty in emission ratios, CO total fluxes and natural CO flux. The uncertainty due to CO_2 measurement uncertainty (< 0.1 ppm) is negligibly small. In the calculation of the background values, we account for the difference between the top of profile mean concentration above 3.8 km and the background mean concentration for the same levels (Supplementary Information Fig. 1), using the root-mean-square error (RMSE). Using this difference, we addressed to the background uncertainties the possible losses of surface flux through the top of our measurement domain (4.4 km of altitude) due vertical mixing. We estimate back-trajectory uncertainties based on the comparison between HYSPLIT and two additional models, FLEXPART Lagrangian particle dispersion model[64] and back-trajectories derived from the meso-scale model BRAMS[65], for all profiles of 2010 (Supplementary Information Table 1a). We consider the largest difference in mean profile travel time from HYSPLIT and the other two models using the RMSE values. For fluxes from fire we use the standard deviation of emissions ratios of each site and account the CO flux uncertainties (estimated as for CO_2 fluxes) and consider uncertainty in natural CO flux. All parameters used in the Monte Carlo error propagation are listed at Supplementary Information Table 1b. The theoretical uncertainty for the nine-year mean fluxes is [sigma = sqrt(sum(sigma_i^2))/9], but this assumes that annual fluxes are uncorrelated. To be conservative, allowing for significant year to year correlation, we calculate the nine-year uncertainties as [sigma = sum(sigma_i)/9].

Scaling to the Amazon mask Since the aircraft sites influenced areas flux are very different comparing east and west sites, we decided to separate Region of Influence (SAN + ALF) region 1 in the Extended Data Fig 6a, since it was observed interannual variability, the area was calculated by year. Region 2 is RBA influenced area integrated with TAB (2010 to 2012) and TEF (2013 to 2018), with the subtraction of region 1. And region 3 is the remaining region not covered by regions 1 and 2. The Carbon flux for region 1 was calculated using the weighted mean flux SAN and ALF for total, Fire and NBE C flux. For region 2 also was calculated weighted mean flux of RBA and TAB (2010-2012) and RBA and TEF (2013+2018). Extended Data Fig. 6b show the results for the 9 years for the 3 regions. The Balance is related to the Amazonia mask (7,256,362 km^2).

DATA AVAILABILITY STATEMENT Data is available at PANGAEA Data Archiving & Publication PDI-25578 (Data submission 2020-09-18T17:00:40Z (Luciana V. Gatti, Instituto Nacional de Pesquisas Espaciais) (This data will receive a DOI)

Extended Data Figure 1 | Vertical profiles, time series and annual mean CO_2 concentrations. a) Time series of mean vertical Profiles (VP) CO_2 mole fractions of the flasks below 1.5 km height (red circles) and above 3.8 km height (blue circles) for SAN, ALF, RBA and TAB_TEF sites (590 VP) and background sites RPB (Ragged Point Barbados), ASC (Ascension Island, UK) and CPT (Cape Point, South Africa). b) Annual mean vertical profiles for 4 sites (annual mean per height, see Methods), c) Annual mean ΔVP is calculated by subtracting background (BKG) concentrations determined from Atlantic Ocean remote sites from CO_2 concentrations at each height and nine-years mean, d) Annual mean differences from below 1.5 km height and the top of vertical profile (higher than 3.8 km height) (see Methods)

Extended Data Figure 2 | Regions of Influence. a) Mean quarterly region of influence for ALF, SAN, RBA, TEF and TAB sites, averaged between 2010 and 2018, calculated by density of back trajectories (see Methods), b) Deforestation inside quarterly regions of influence and the Amazon mask (purple line) using data from PRODES (see Methods), c) Annual mean regions of influence (trajectory densities) averaged between 2010 and 2018.