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Increased Amazon carbon emissions mainly from decline in law enforcement

Luciana V. Gatti[1,2*], Camilla L. Cunha[1], Luciano Marani[1], Henrique L. G. Cassol[1], Cassiano Gustavo Messias [1], Egidio Arai[1], Luciana Soler[1], Claudio Almeida[1], Alberto Setzer[1], Luiz E. O. C. Aragão[1], Luana S. Basso[1], Lucas Gatti Domingues[2,3], A. Scott Denning[4], John B. Miller[5], Manuel Gloor[6], Caio S. C. Correia[1,2], Graciela Tejada[1], Raiane A. L. Neves[1], Raoni Rajao[7], Felipe Nunes[7], Britaldo S.S. Filho[7], Jair Schmitt[7], Carlos Nobre[8], Sergio M. Corrêa[9], Alber H. Sanches[1], Liana Anderson[10], Celso Von Randow[1], Stephane P. Crispim[1], Francine M. da Silva[1], Guilherme B.M. Machado[1]

[1]General Coordination of Earth Science (CGCT), National Institute for Space Research (INPE), São José dos Campos, Brazil.

[2]Nuclear and Energy Research Institute (IPEN), São Paulo, Brazil.

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

[4]Colorado State University; CO, USA

[5]Global Monitoring Laboratory, National Oceanic and Atmospheric Administration (NOAA), Boulder, CO, USA

[6]University of Leeds, School of Geography, Leeds, UK;

[7]Universidade Federal de Minas Gerais, Belo Horizonte, Brazil

[8]USP – University of São Paulo, IEA, São Paulo, Brazil;

[9]Rio de Janeiro State University (UERJ), Rio de Janeiro, Brazil;

[10]CEMADEN, São Jose dos Campos, Brazil;

*luciana.gatti@inpe.br or lvgatti@gmail.com

Summary

The Amazon Forest carbon sink is declining mainly as a result of land use and climate change[1–4]. Here we investigate how changes in law enforcement of environmental protection policies may have affected the Amazonian carbon balance between 2010-2018 compared to 2019 and 2020, based on atmospheric CO_2 vertical profiles[5,6], deforestation[7] and fire data[8], and infraction notices related to illegal deforestation[9]. We estimate that Amazonia carbon emissions increased from 0.24±0.08 PgC y^{-1} 2010-18 mean to 0.44±0.10 in 2019 and 0.52±0.10 PgC y^{-1} in 2020 (± uncertainty). The observed increase in deforestation were 82% and 77% (94% accuracy) and burned area of 14% and 42% in 2019 and 2020 compared to the 2010-2018 mean, respectively. We find that the number of notifications of infractions against flora decreased by 30% and 54% and fines paid by 74% and 89% in 2019 and 2020, respectively. Carbon losses during 2019-20 were comparable to the record warm El Nino (2015-16) without an extreme drought event. Statistical tests show that the observed differences between 2010-18 mean and 2019-20 are unlikely to have arisen by chance. The changes in Amazonia's carbon budget during 2019-20 were mainly due to western Amazonia becoming a carbon source. Our results suggest that a decline in law enforcement led to increases in deforestation, biomass burning and forest degradation which increased carbon emissions and enhanced drying and warming of the Amazon forests.

Introduction

Amazonia hosts the largest tropical forest on the planet and has proven to be an important carbon sink in the recent past[1–3]. This carbon sink is declining, mainly due to increased tree mortality[1] as a result of deforestation and climate change[4]. The Amazon Forest represents around 50% of the global tropical rainforest and contains about 90 Pg C in above and below ground vegetation biomass[10,11], which can be quickly released and thus result in substantial positive feedback on global climate[12]. Furthermore, deforestation and forest degradation reduce the forest´s capability to act as a carbon sink[1–3,13].

In the Amazon the relationships between ecosystem carbon and water cycles and climate are complex. Several studies have estimated that evapotranspiration is responsible for up to 50% of water recirculation in Amazonian precipitation. Hydrologically, Amazonia is one of the three main air upwelling regions in the tropics and rainfall in the whole basin averages about 2,200 mm per year[14]. Large-scale human disturbance alters these ecosystem-climate interactions. In the last 40 to 50 years, human impact has increasingly affected Amazonia, resulting in a forest loss of around 18%, of which 14% has been converted mainly to agricultural land (89% pastures and 10% crops)[3].

It has been widely reported that illegal deforestation rose 80% since 2019[7], compared to the 2010-18 period as a result of changes in law enforcement policy. We analysed how these changes affect the Amazonian carbon balance and how they are linked to deforestation and fire feedbacks. Forest removal reduces evapotranspiration and rainfall while increasing temperature[15–18]. Additionally, regional deforestation followed by fires and selective logging causes degradation of adjacent forests, increasing vulnerability to fires[13]. Regional and global warming are synergistic and mutually reinforcing.

We compared the mean Amazonian carbon balance over 9 years (2010-18)[4] with the subsequent two years (2019 and 2020). In this recent period, there has been an intense reduction in public policies to control deforestation[19]. We used deforestation data analysis map to georeferenced carbon sources (limited to the Brazilian Amazon – PRODES), as well as fire spots incidence (Pan-Amazônia) and burned area, in addition to other parameters (see methods) to understand the main factors responsible for converting the Amazonia into a carbon source.

Atmospheric carbon vertical profiles

We performed 742 vertical profiles (VPs) from 2010 to 2020, using small aircraft over four Amazon sites, representing large upwind regions (Extended Data Fig. 1), where the VPs reflect the result of all carbon sources and sinks between the Brazilian Atlantic coast and the VP sites[4]. As in past studies, the VP sites were SAN (northeast region: 2.86° S 54.95° W), ALF (southeast region: 8.80° S 56.75° W), RBA (southwest region: 9.38° S 67.62° W), and in the northwest region TAB (northwest region: 5.96° S 70.06° W); from 2013 in TEF (3.39° S 65.6° W)[4]. The sampling frequency was approximately 2 times per month in each location, from 4.4 km height (a.s.l.) to close to the surface, and usually carried out between 12:00 and 13:00 local time. The CO_2 and CO samples were analysed at INPE's LaGEE (Greenhouse Gas Laboratory), in São Jose dos Campos.

To construct annual mean vertical profile enhancements (ΔVP) for each site (Extended Data Fig. 2), we subtracted the background concentration (bkg) for each flask (height), from each VP, and then calculated the monthly mean enhancement per height and per year. This study extends results and analysis of ΔVP for the years 2019 and 2020. We present the weighted mean all-Amazonia vertical profile (Figure 1) based on regions of influence for each site per year, which represents an advance over the previous study[4] (see methods). The ΔVP are a large scale indicator of ecosystem functioning and strongly related to the carbon budget. In Figure 1 we present the Amazonian annual mean ΔVP from 2010 to 2020, comparing the years 2019 and 2020 to the previous 2010-18 mean. We observed net positive CO_2 contribution to the atmosphere for the ΔVP mean 2010-18 of 0.24 ppm. This indicates that Amazonia is a carbon source to the atmosphere, including all natural and anthropogenic processes of CO_2 emissions and absorptions. This result is a direct indication of the regional source in the global carbon budget, though there are well known discrepancies from many studies using different methodologies (bottom-up, top-down techniques, and a wide variety of global, regional and inversion models)[1–4,13,20–24].

Comparing the Amazonian mean ΔVP in 2019 and 2020 with the mean for 2010-18, we observed an increase of 50% and 142%, respectively. This strong and rapid increase in concentration gradient represents a similarly strong increase in total carbon emissions and coincides with strong increases in deforestation. According to PRODES[7], deforestation in the studied area[4] (black line indicating the area delimitation in Figure 2, but limited to the Brazilian Amazon) increased by 82% and 77% (94% accuracy) for the years 2019 and 2020 compared with the mean for 2010-18 (Figure 2, Extended data Fig. 3a). For the same period and comparison, considering the whole Amazonia, burned area retrieved by MODIS (collection 6, see methods) increased 14% in 2019 and 42% in 2020 (Extended data Table 1). Fire spots from INPE[8] were used to map fire distribution in Amazonia and were underestimated compared with burned area (see methods). Fire spots increased 3% in 2019 and 22% in 2020 relative to the previous period (Extended Data Fig. 3c & 4a). There was a 693% increase in wood exports[25] and a 58% increase corn and 68% soybean plantation area[26] in 2019-2020, compared with 2010-18 (the soy moratorium is still in force). The cattle population increased by 13% in the Amazonia[27] and decreased by 4% in the Brazilian territory excluding the Amazonia (Extended Data Fig. 5a,b), indicating the deforestation drivers. See methods for the methodology details and uncertainty.

After the revision of the Forest Code in 2012[28], which granted a large amnesty to past deforesters, deforestation in Brazilian Amazonia has risen gradually culminating in 2021 with the highest annual rate since 2006[7]. This upsurge in deforestation rates along with higher carbon emissions coincides with a decline of federal environmental agencies in charge of law enforcement in the region, especially after 2018, when field notifications and judgments resulting in fines paid reached the lowest number on record over the last decade (Figure 3). From 2010 to 2018, an annual mean of 4734 infraction notices were filed in the Amazonia for violations against flora (mostly illegal deforestation). In 2019 notices fell to 3331 and in 2020 to 2193 representing a reduction of 30% and 54%, respectively. In addition, the annual mean of judgments and the respective number of fines paid up to the subsequent year dropped by 74% and 89%, respectively.

Environmental law enforcement

Brazil's past success in curbing illegal deforestation in the Amazon has been credited to a combination of public and private policies[29]. Chief among them were the expansion of protected areas[30], the implementation of the DETER[7] system providing near-real time monitoring of deforestation and strengthening of law enforcement under the Action Plan for the Prevention and Control of Deforestation in the Legal Amazonia (PPCDAm)[31]. A decline of 84% in deforestation rates took place from 2004 to 2012 (Extended Data Fig. 3a). However, the more stringent law enforcement produced a backlash. In 2012, rural lobbies pressed and succeeded to relax the Forest Code in the national congress, which granted amnesty for 58% of all illegal deforestation prior to 2008 and suspended the collection of environmental fines, in addition to providing 20 years for landowners to comply with Forest Code rules[28]. Illegal loggers, miners and land grabbers intensified their actions, encouraged by the action limitation of IBAMA employees to seize and/or destroy the equipment of the offenders[32]. The resulting sense of impunity, in addition to attempts to roll back conservation gains, has increasingly influenced the rise of deforestation since 2012 and its acceleration from 2018 onwards[19]. In 2019, the annual deforestation rate reached 10,129 km^2, the highest since 2008 (Extended Data Fig. 3a,b) raising international concerns. The increase in deforestation was stimulated by the public stance of the Brazilian government against forest law enforcement and the environmental agencies themselves, which the ex-president Bolsonaro called as “industry of fines”[32].

The past decline in deforestation rates in the Amazonia was the consequence of a wide variety of actions and policies, such as fines, embargoes, arrests and destruction of equipment, but also initiatives as soybean moratorium, during the first phases of the PPCDAm[33–35]. From 2004 to

2008, the average annual number of infraction notices for crimes against the flora, mostly deforestation but also other forms of native vegetation suppression, increased by 36%, whereas the average annual deforestation rate fell by 18% in relation to that of the previous period (2000-2003). In the following years, satellite-based refinements to detect offenders and characterize environmental damages – both crucial to effective environmental inspection and accountability – were implemented through geotechnologies developed by the National Institute of Space Research (INPE). From 2004 to 2011, over 52 thousand fines were issued alongside sanctions directed to decapitalize offenders such as embargoes and seizures in the Legal Amazonia.

After the revision of the Forest Code in 2012, driven by economic factors such as commodity prices and exchange rates that affected the profitability of agricultural exports, there was a slow return to increased deforestation[33]. From 2012 to 2018, 32.3 thousand fines were applied, however, the total deforestation during this period was 44,057 km^2 (Figure 3). In phase IV of PPCDAm, which should take place between 2016-2020, the strategy to avoid deforestation should be through "market instruments", including programs such as payment for ecosystem services (PES)[36]. As a result, deforestation rates in 2019-20 increased by 80% compared to the 2010-18 period, accelerating the slow growth trend started in the previous decade. During this period there was a 50% reduction in fines and the dismantling of environmental policies[37] (Extended Data Fig. 3a,b). The decrease in fines took place in the ten municipalities with the highest deforestation rates between 2019 and 2020, as a consequence of the removal of the federal environmental inspection strategy focused on priority municipalities, which was successful in previous years (Supplementary Fig. 1).

The Impacts on Amazonian Carbon Fluxes

We compared the changes in Amazonia carbon flux and balance during the years 2019 and 2020 related to the mean from 2010 to 2018 as reported in the previous study[4]. We calculated total carbon flux (FC_{Total}) using a column budget technique (see methods). FC_{Total} is the sum of all natural and anthropogenic carbon sink and sources between the coast and aircraft vertical profiles sites[4]. Using identical methods, CO was used to determine the fraction of FC_{Total} arising from biomass burning (FC_{Fire}), where we used a mean ratio CO:CO_2 specific for each site (see methods). The residual between total carbon and fire flux is designated Net Biome Exchange (NBE). The FC_{NBE} includes photosynthesis, respiration, decomposition and other non-fire anthropogenic emissions. Decomposition can come from natural process but also from land use change and degradation[38] (all emissions following fire). From 2010 to 2018 the mean FC_{Total} was 0.09±0.03 gC m^{-2} d^{-1} (± all results show uncertainty calculated by Monte Carlo error propagation, see methods), equivalent to 0.25±0.08 PgC y^{-1}, considering Amazonian area of 7,256,362 km^2. In 2019 the calculated FC_{Total} indicated an enhancement of 89% in total carbon emissions (0.17±0.04 gC m^{-2} d^{-1}; 0.44±0.10 PgC y^{-1}) and in 2020 a greater increase of 122% (0.20±0,04 gC m^{-2} d^{-1}; 0.52±0.10 PgC y^{-1}) relative to the 2010-18 mean (Figure 4a,b).

The statistical tests to compare the differences between the two periods of 2010-18 (9 years) and 2019-20 (2 years) showed the difference with 95% CI (Welch *t-test* p= 0.024). Considering the uncertainties for the means, these differences are not so clear, but it is unlikely that the observed differences in the means have arisen by chance. The statistical significance of this inference is modest due to the relatively short time period for the perturbed state of the system. Furthermore, considering during the period 2010-18 there were 2 extreme drought events (2010, 2015/2016), and removing these 2 drought events, the mean became 0.11±0.09 PgC y^{-1}, and comparing with 2019-20 (0.44±0.10 PgC y^{-1}; 0.52±0.10 PgC y^{-1}) the anomaly becomes even more evident (p= 0.003). Applying the statistical tests in the western Amazonia (region 2, see Extended Data Fig. 6), the post-2018 period shows similar results as whole Amazonia (p= 0.049; p=0.007, respectively), showing that the most important changes in the Amazon occur on the western side. Statistical tests are summarized in Supplementary Tables 1 and 2.

Amazonia total carbon emissions in 2019 and 2020 were comparable to carbon losses during the extreme El Nino event of 2015/16 (Figure 4b), during which the rate of growth of atmospheric CO_2 was one of the highest ever measured[39–41]. In 2019, climatological conditions do not explain the increases in deforestation by 82%, in burned area by 14%, and in carbon emissions by 89%, since the observed precipitation and temperature were within the variability for the period 2010-18 (Extended data Fig. 7b) and during wet season, a weak El Niño (maximum +0.7 indices /warm) was observed (Extended data Fig. 7a). In 2020 during the dry season a moderate La Nina (maximum -1.3 /cold)[42] was observed and also in the anomaly precipitation by INMET (Extended Data Fig. 7a and Supplementary Fig. 2). The resultant of 122% increase in carbon emissions in 2020 is the combination of increases of 77% in deforestation and 42% in burned area, and a 12% reduction in the annual precipitation. The reduction was mainly during wet season (January, February and March loss of 26%) and the temperature in the same period increased by 0.6˚C (Extended data Table 1 and Extended data Fig. 7b). Precipitation reduction during the wet season impacts carbon emissions mainly in the dry season, when water availability for the forest is lower. Figure 2a, b and c present the strong increase in deforestation in 2019 and 2020 in some Brazilian Amazonia regions. Figure 4 (CF_{Total}) and Extended Data Fig. 8 (FC_{Fire} and NBE) show the seasonality and interannual variability in carbon emissions, where Fig. 4b shows the similar magnitude in carbon emissions for 2019 and 2020, but without the extreme drought conditions (Extended data Table 1 and Extended data Fig. 7b). Seasonal carbon fluxes integrated across Amazonia show that the increase happens mainly during the dry season in both years (Fig. 4a) from July to November.

To increase the number of samples for the statistical analysis about the differences between the period 2010-18 and 2019-20, we considered the monthly mean total carbon flux from July to November for all years, since the anomaly appears during this period (Fig. 4a, Supplementary Table 1 and 2). Considering all years (45 samples) the anomaly was significant for the whole

Amazonia and for the western region by the Welch *t-test* (p= 0.018, p= 0.022, respectively), and also by Tukey test, Wilcoxon test and Kruskal Wallis test (see Supplementary Table 2).

Fire emissions calculated by our method (FC_{Fire}) show a mean 2010-18 emission rate of 0.15±0.01 gC m^{-2} d^{-1} (0.40±0.03 PgC y^{-1}) with 8% and 4% increases during 2019 and 2020, respectively (Extended Figure 8a,c). The larger increases in total carbon emissions across Amazonia during these years come mainly from NBE, where the mean 2010-18 (FC_{NBE}) was -0.06±0.03 gC m^{-2} d^{-1} (-0.15±0.09 PgC y^{-1}), in 2019 was +0.01±0.04 gC m^{-2} d^{-1} and 2020 was +0.05±0.04 gC m^{-2} d^{-1}, representing near carbon neutrality for forest (excluding fire) for the last 2 years of this time series. As we are using a fixed CO:CO_2 ratio for each site and we know that the driest forest will be more flammable, we need to consider the possibility that a fraction of fire emissions may also have been incorporated into the NBE, as we observe its variability from month by month and year by year, depending on climate conditions[4]. Uncertainties and variability in CO:CO_2 ratios used to calculate FC_{Fire} may help explain the discrepancy between the near-absence of FC_{Fire} anomalies in the 2019-2020 period and the clear anomalies in fire hot spots and burned area. The fact that NBE represents the largest increase indicates that the forest carbon sink was lower than the emissions from natural and anthropogenic process (deforestation and degradation). Regardless of whether it is enhanced respiration, decomposition or fire associated with deforestation and degradation, our FC_{Total} results show that Amazonia is emitting more carbon, amplifying the consequence of global climate[4].

The impacts in the four studied sub-regions on the carbon fluxes were related to the increase in deforestation. At SAN, in the northeast, the region 36% deforested until 2018, showed increases in deforestation of 67% and 45% in 2019 and 2020, respectively, relative to the 2010-2018 period, where we observed reduction of 42% in precipitation during the wet season peak of January, February and March (JFM) of 2019 and an annual increase of 78% in FC_{Total} emissions. In 2020, there was less impact in precipitation resulting in similar carbon emissions to the 2010-

18 mean. In the southeast region (ALF) historically 29% deforested, increases in deforestation of 80% and 87% were observed in 2019 and 2020, respectively. Burned area decreased 34% in 2019 and FC_{Total} was similar to the mean of 2010-18, but increased 53% in 2020. The southwest region (RBA), historically 17% deforested, was nearly carbon neutral during the period 2010-18, and continued to be in 2019, but in 2020 total carbon emissions (FC_{Total}) were positive. Deforestation increased 81% in 2019 and 76% in 2020 relative to 2010-18, and burned area decreased in 2019. Precipitation was 41% less during the wet season of JFM and temperature warmed by 0.8˚C. These represent increases in climate stress to the forest. The least human-impacted northwest region (TAB_TEF), currently 15% deforested, exhibited a near neutral carbon budget for the period 2010-18, but in 2019 became a carbon source with FC_{Total} increasing more than tenfold and fivefold in 2020. The main reason was that NBE became a carbon source. In 2019 and 2020, deforestation increased by 95% and 73% relative to the previous period with reductions of 23% in precipitation during JFM in 2019 and 42% during 2020, and temperature also increased by 0.5˚C for the same period. The detailed analyses for each of the four sites related to the fluxes (Total, NBE and Fire), climatological conditions and changes in the 2019 and 2020 compared with 2010-18 period are presented in Supplementary Information 1 and Extended Data Table 1. A summary figure is presented in Extended Data Fig. 9. Seasonal variability of studied parameters and carbon fluxes and ΔVP for the 4 sites are presented in Supplementary Fig. 3 and Extended Data Fig. 2, respectively.

Deforestation and global warming have been accompanied by reduced precipitation and warmer temperatures that have made the dry season drier, hotter, and longer[4]. This shift promotes stress conditions in the forest[18]. These conditions imply a strong stress for the trees, providing an imbalance between photosynthesis and respiration, increasing the flammability of the trees, which produces an intensification of degradation in these regions, as fire penetrates into remaining forests areas. This process appears to have intensified since 2018, when deforestation increased by 80% and, as a consequence of the reduction of public policies, we observed a 50% reduction in fines. We estimate that carbon emissions doubled in the years 2019 and 2020, compared to the previous study (2010-18)[4], as a consequence of these changes, but in 2020 also due to a climatic stress condition during the wet season peak (26% lower precipitation and 0.6 °C higher temperature) which could also represent an additional cause of carbon emission.

To evaluate changes in Amazonia carbon emissions over the 11-year time series (Figure 4), we split them into two five-year groups: 2010-14 and 2016-20. Comparing the two periods for the entire Amazonia, we observe a 50% increase in total carbon emissions (FC_{Total} 0.21±0.09 PgC y^{-1} and 0.31±0.08 PgC y^{-1}, for 2010-14 and 2016-20, respectively), and a 31% reduction in carbon sink (FC_{NBE} -0.15±0.10 PgC y^{-1} and -0.10±0.09 PgC y^{-1}, respectively) and an increase of 16% in fire emissions (FC_{Fire}. 0.36±0.04 PgC y^{-1} and 0.42±0.04 PgC y^{-1}, respectively). This increase in the last 5 years demonstrates the importance of public policies to prevent deforestation, degradation and fire. Zero deforestation in the Amazonia and forest restoration will be very important to reduce this climate stress on the forest, which is amplified by global climate change, resulting in a decrease in carbon sink ability, as well as impact on the water cycle.

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Figure 1 | Amazonia Annual Mean Vertical Profiles. Amazonia annual means vertical profile for each year (2010-2020), constructed from vertical profile monthly mean (each height was subtracted by the background) producing (ΔVP). 2015 and 2016 are not plotted because of missing data at some sites. The mean for each height using the 4 sites is reproduced by the same methodology used for the Amazonia mean flux, separating Amazonia in 3 regions (see methods and Extended data Fig. 6a). The thick black line represents the 2010-2018 Amazonia mean vertical profiles, the thick red line the 2019 mean and blue thick line the 2020 mean. ΔVP annual mean for each site and each year are show in Extended Data Fig 2.

Figure 2 | Amazon deforestation map. Deforestation area (km^2) maps limited to the Brazilian Amazonia in grid cells of 0.25°x0.25°, from PRODES[7]. Mean deforestation area per grid cell between 2010-18 (left); Absolute deforested area in 2019 (centre); Absolute deforested area in 2020 (right). Deforestation maps are given in grid cells were the increment (left) or the absolute deforested area (centre, right), are composed by polygons higher than 0.0625 km^2, and are shown in deforested km^2 per grid cell.

Figure 3 | Environmental law enforcement and accountability for crimes against the Amazon Forest. a) number of infractions against flora issued by IBAMA and deforestation alerts by INPE in support of IBAMA´s environmental field operations (Deter-Modis and Deter-B). b) number of administrative judgments of infraction notices against flora and the number of fines paid by the following year from the judgment (see methods). Monetary values were adjusted for inflation and converted to USD using a rate of R$ 5 (Brazilian Reais) per U.S.$ 1.

Figure 4 | Amazonia carbon flux 2010-20. a) Seasonal Amazonia total carbon flux (FC_{Total}). Black line for 2010-18 mean, where grey bands denote the standard deviation of the monthly mean. Red line shows the seasonal FC_{Total} for 2019 and blue line for 2020. b) Annual mean Amazonia total carbon flux blue bar and the ONI classification in the background showing El Niño and La Niña[42] (see Extended Data Fig. 7a and methods).

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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 (lvgatti@gmail.com or luciana.gatti@inpe.br).

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.

Data Availability The CO_2 VP data that support the findings of this study are available from PANGAEA Data Archiving, at https://doi.org/10.1594/PANGAEA.926834 for data from 2010-18 and for data 2019 and 2020 it is available at https://doi.org/10.1594/PANGAEA.949643.

Methods

Sites, air sampling and analysis Here we are reporting the results from measurements at the four Amazonian aircraft vertical profile sites of the CARBAM project (SAN: 2.86° S 54.95° W; ALF: 8.80° S 56.75° W; RBA: 9.38° S 67.62° W; in 2010-2012 for TAB: 5.96° S 70.06° W; and since 2013 for TEF; 3.39° S 65.6° W) for 2019 and 2020, in addition to the measurements between 2010 and 2018 detailed at Gatti et al.[4]. Our samples were done typically twice per month, resulting in approximately 742 vertical profiles over these 11 years, in a descending spiral profile from 4,420 m to 300 m above sea level (a.s.l.). In 2015 the data collection flights were stopped in April at all sites, returning in November at RBA. In 2016, profiles were performed only at RBA and ALF. The VPs were usually taken between 12:00 and 13:00 local time. Air samples were analysed by a non-dispersive infrared analyser for CO_2 and by gas chromatography with

HgO reduction detection for CO. The detailed analytical and sampling methods were presented in previous studies[4,43]. We defined the Amazon study area similarly to Gatti et al.[4], according to subregions from Eva et al.[44] and biomes from Olson et al.[45], where the studied area in the Amazonia was determined considering forest ecosystems sub-regions: Amazônia stricto sensu, Guianas, Andes and Gurupi, with a total area of 7,256,362 km^2 [4].

Annual Mean Vertical Profiles The annual mean ΔVP for each site was calculated starting with individual profiles where for each altitude (sampled flask) the CO_2 concentration was subtracted from the correspondent background (bkg), then averaging first to monthly and later to annual mean by height (Extended Data Fig. 2). To calculate the annual mean Amazonia vertical profile, we apply the same method used to obtain the mean Amazonia flux. To scale for the whole Amazonia, we separated Amazonia in 3 regions (Extended Data Fig. 6a). To compose the ΔVP Region 1 (SAN + ALF) the weighted mean concentration of CO_2 minus bkg was produced for each height, proportional to the respective areas. The compose the ΔVP Region 2 (RBA + TAB: for the years 2010 to 2012; RBA + TEF: for the years 2013 to 2018), it was reproduced the same procedure used for Region 1. And for Region 3, the remain Amazonia area, not covered by the vertical profile's regions of influence, were used the same concentrations minus bkg from Region 2. To compose the ΔVP for Amazonia it was produced the weighted mean for each height ΔCO_2 concentration considering the 3 regions and producing the weighted mean.

Carbon fluxes estimation We used a column budget technique to estimate carbon total fluxes, which consists of the difference between CO_2 mole fraction measured in the vertical profile and the estimated background mole fraction (ΔCO_2) considering the travel time of air parcels along the trajectory from the coast to the site (eq. M1), following the methodology in Miller et al.[46], Gatti et al.[47], D'Amelio et al.[48], Gatti et al.[43], Basso et al.,[49,50] and Gatti et al.[4].

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

To apply in eq. M1 we converted 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 or 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[4]. To estimate the travel time t of air-masses from the coast to each sample site, we used back-trajectories for each altitude of the vertical profile, where 13-day backward trajectories are derived from the online version of the HYSPLIT model[51,52].

Our background mole fraction estimates were calculated according to the methodology described by Domingues et al.[53], using the geographical position of each air-mass back-trajectory when it intersects two virtual limits: 1) a latitude limit, from the Equator southwards at 30° W, and 2) a line from the Equator to the NOAA Global Monitoring Laboratory (NOAA/GML) observation site at Ragged Point, Barbados (RPB). Based on the atmospheric air circulation pattern over Amazonia we could relate the position where an air mass crosses the virtual line with the concentrations measured at remote sites in the Atlantic—RPB, Ascension Island, UK (ASC) and Cape Point, South Africa (CPT)—from NOAA/GML to determine the background[53].

Carbon fire fluxes were estimated based on eq. M2, where FCO is the total CO flux and is calculated identically to CO_2 fluxes according to eq. M1; and to isolate the CO from biomass burning process, we subtract the 'natural' CO flux from the total CO flux. $FCO_{natural}$, arising from direct soil CO emissions, and mainly CO from oxidation of volatile organic compounds (VOCs), such as isoprene that is emitted from the forest according to the methodology described at Gatti et al.[4]. We also used fire emission ratios calculated by site ($CO:CO_2$, in units of parts per billion-ppb CO per ppm CO_2) from measured CO concentrations from clearly identifiable plumes in the VPs during the dry season (ALF $CO:CO_2 = 53.4 \pm 9.9$ (2σ variability); SAN $CO:CO_2 = 55.5 \pm 14.7$; RBA $CO:CO_2 = 73.2 \pm 15.1$; and TAB_TEF $CO:CO_2 = 71.6 \pm 17.2$ ppbCO : ppmCO_2[4].

NBE represents the result of emissions and uptake from all processes in the influenced area for a specific VP, monthly and annual mean, excluding fire C emissions (NBE = total − fire).

$$FC_{\mathrm{Fire}} = R_{CO_2:CO}\,(F_{CO} - F_{CO}^{Natural}) \qquad \text{M2}$$

To scale for the whole Amazonia carbon fluxes was applied the same procedure as for Amazonia ΔVP and described in eq. 3 and 4.

$$FC_{region1} = \frac{(FC_{SAN} * Area_{SAN}) + (FC_{ALF} * Area_{ALF})}{Area_{SAN} + Area_{ALF}} \qquad \text{M3}$$

$$Balance_{Am.} = \left(FC_{reg.1} * Area_{reg.1}\right) + \left(FC_{reg.2} * Area_{reg.2-reg.1}\right) + \left(FC_{reg.2} * Area_{reg.3}\right) \qquad \text{M4}$$

Fluxes Uncertainty Analysis by Monte Carlo error propagation We estimated our fluxes uncertainties by error propagation using Monte Carlo randomization running 1000 iterations. The considered uncertainty for each step of flux calculation (M1) were: CO_2 measurements uncertainty by our analytical system is around 0.03 ppm. For background (BKG) uncertainties we considered that mole fraction uncertainties from ASC, CPT and RPB come from the standard deviation of the residuals to fit CO_2 smooth curve, according to Gatti et al.[4,43]. We assumed uncertainties of back-trajectory travel times are normally distributed with a standard deviation of $\sigma = 0.2$ days for SAN, $\sigma = 0.6$ days for RBA and TAB, and $\sigma = 0.4$ for ALF and TEF. In addition, to calculate the carbon fire emissions and NBE, it was considered the uncertainty from $CO:CO_2$ ratio and CO fluxes. For fluxes from fire, we used the standard deviation of emission ratios at each site and account for the CO flux uncertainties (estimated as for the CO_2 fluxes), and considered the uncertainty in natural CO emission of 25%.

To calculate the uncertainty for each vertical profile flux, from 1000 iterations using Monte Carlo randomization error propagation. To produce the monthly mean flux, taking into account the variability between the fluxes within the same month, we applied the pooled standard deviation to each month throughout the year to account the uncertainty of each monthly mean within the annual mean flux. For the whole period of 9 and 2 years we used quadratic mean as eq. M5[54], where n is the number of years.

$$\bar{x}_q = \sqrt{\frac{\sum x_i^2}{n}} \qquad \text{M5}$$

Additional source of uncertainty is the sampling height limitation to 4.4 km. Along the way of air masses trajectory that can vary from 2 to 9 days mean time until to the sampling sites, convective process can represent loss of carbon sources and sink surface contributions. Comparing the background concentration and the top of vertical profiles is one way to verify the possible loss of information. Supplementary Fig. 4 shows the seasonal dispersion along the time series for the differences between the top of VP (>3.8 to 4.4 km) and the background. According to the method we use, the flux is obtained by the difference between of the measured CO_2 concentration in the VP and the background concentration and considering the travel time in the integration. Observing the Supplementary Fig. 4 it is clear that during the dry season is the period in which the loss of information is larger to positive (VP > bkg), because during burning season (peak of dry season) the top of VP starts with higher CO_2 and CO concentration due to convective processes promoted by biomass burning.

Another possible source of uncertainty is related to moisture in the samples. NOAA/GML have found that CO_2 concentration is artificially reduced when air samples with high water vapor (> 1.7%) are pressurized in PFP flasks to 2.7 bar, as a result of condensation[55]. A preliminary study using vertical profiles near Manaus (Amazonas state) compared PFP samples measured for CO_2 at LAGEE to onboard measurements from a trace gas flight analyser (Picarro model G2401-m) and found depletions in PFP CO_2 nearly similar to those from the Baier et al study. This influence is likely greater near the surface, as humidity increases at lower altitudes. Thus, the true CO_2 below the boundary layer (~1.2km from surface) may be higher than measured, which means that current fluxes may be underestimated. However, this effect will be present in both periods (2010-18 and 2019-2020), not affecting their comparison.

Statistical Analysis in Total Carbon Fluxes We applied parametric (Welch *t-test* and Tukey test) and non-parametric (Wilcoxon test and Kruskal-Wallis test) tests to compare and determine whether the annual and monthly total fluxes for 2019-2020 are significantly different from the 2010-2018 total fluxes period in the Amazonia. We also applied the statistical tests separating Amazonia in Region 1 and Region 2 (Extended Data Figure 6), since we observed new regions with intense deforestation in Region 2. First, we verified the normal distribution and the number of samples to decide the recommended test to be used in the statistical analysis, them before the test of comparison (parametric or non-parametric) we verified the distribution of the variable (Supplementary Table 1). Before to be applied the test of comparison (parametric or non-parametric) it was necessary to verify the distribution of the variable, for this we applied the Shapiro-Wilk (shapiro.test), Anderson-Darling (ad.test) and Kolmogorov-Smirnov (ks.test) tests. Monthly and annual fluxes for all years from 2010 to 2020 were evaluated, considering and removing the drought years (2010, 2015 and 2016). It was also considered only the monthly fluxes from July to November of the time series, with and without the drought years. The normal distribution of the total flux was confirmed in all cases in which the null hypothesis was accepted, that is, when p-value > 0.05. For all cases whose normal distribution was confirmed, the variance test was performed to ensure that the variance was equal for all samples (p-value > 0.05, Supplementary Table 2). Satisfied these two conditions, the parametric tests were performed. All test results were obtained with 95% of confidence, as shown in Supplementary Table 1 and 2.

Missing data imputation The *missForest* algorithm was applied to fill in the missing data for total and Fire C monthly fluxes at ALF, SAN, RBA and TAB_TEF sites, which occurred due to sampling and laboratory logistics issues. This non-parametric missing value imputation algorithm is based on the random forest methodology[56,57] and was implemented in R language[58] using the *missForest* package[59]. The known monthly data were used to adjust the *missForest* parameters (number of iterations, number of trees, number of variables randomly sampled in each division and others) for each site. Monthly variables (temperature, precipitation, burned area, EVI, GRACE and VPD) were used in the imputation method for total C flux (FC_{Total}) and fire C flux (FC_{Fire})[4]. These calculations were performed 1000 times, and the results are incorporated in the mean values for the missing months (Supplementary Fig. 5). The normalized RMSE was less than 0.0045 for all sites and fluxes. The RMSE values were 0.0041, 0.0060, 0.0027 and 0.0021 gC m^{-2} d^{-1} for total fluxes and 0.0008, 0.0019, 0.0004 and 0.0001 gC m^{-2} d^{-1} for fire fluxes in ALF, SAN, RBA and TAB_TEF, respectively. NBE missing data was obtained subtracting the Fire C fluxes from the Total C Fluxes. These RMSE values were used in the uncertainty calculation for the months with missing fluxes.

Regions of influence We define regions of influence as those areas covered by the density of back-trajectories integrated over all vertical profiles and altitudes (up to 3500 m) for each site integrated on an annual (Extended data Fig. 1) and a quarterly basis (Supplementary Fig. 6)[4,60]. Here we used the same regions of influence from Gatti et al.[4], for the period between 2010-18, and were calculated new areas for 2019 and 2020, which were estimated using Hysplit trajectory model[52,61] to calculated individual back-trajectories for each sample for each vertical profile and all flights between 2010 and 2018 at a resolution of 1 hour using 1˚x1˚ Global Data Assimilation System (GDAS) meteorological data. For each site, all the back-trajectories in a quarter (January-March, April-June, July-September, October-December) 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 in each grid cell up to an altitude of 3,500 m a.s.l.. In the annual regions of influence were excluded the grid cells with the lowest 2.5% trajectory density distribution. The mean annual regions of influence 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 and then averaging all nine years[60].

Precipitation, temperature, GRACE, EVI, burned area and VPD data We used the quarterly regions of influence maps as spatial weighting functions for all studied parameters to determine how each parameter influenced the carbon flux, following Gatti et al.[4]

We used the databased GPCP (http://eagle1.umd.edu/GPCP_ICDR/GPCP_Monthly.html), version 1.3 for precipitation analysis (described by Huffman et al.[62]), which contains daily data since 1996 with a resolution of 1° × 1° latitude–longitude.

For temperature we used 2-m temperatures from ERA-5 that are monthly means of daily means since 1959 and were used with a resolution of 0.25° × 0.25° latitude–longitude, obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF; https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=overview)[63].

We used the gridded monthly global water storage/height anomalies (equivalent water thickness) relative to a time-mean, derived from GRACE (Gravity Recovery and Climate Experiment) and GRACE-FO and processed at JPL (Jet Propulsion Laboratory) using the Mascon approach (Version2/RL06), with 0.5° × 0.5° resolution[64,65].

The VPD product is a measure of the indirect vapour pressure deficit in kPa (resolution of 2.5 arc-minute) of monthly means of temperature and humidity, provided by Climatic Research Unit (CRU) CRU Ts4.0[66]. The dataset was resampled to a 1°x1° spatial resolution using the monthly mean.

Evaluation of burned area was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) Collection 6 MCD64A1 burned area product[67]. The related uncertainty estimated as 4-5.5%[68]. Collection 6 provides monthly tiles of burned area with 500 m spatial resolution over the globe. The algorithm uses several parameters for detecting burned area from the Terra and Aqua satellite products, including daily active fire (MOD14A1 and Aqua MYD14A1), daily surface reflectance (MOD09GHK and MYD09GHK), and annual land cover (MCD12Q1)[69–71]. The burned area product was resampled to 1x1° spatial resolution.

The Enhanced Vegetation Index (EVI) is a vegetation index that aims to highlight the fraction of photosynthetically active radiation (fPAR) from terrestrial vegetation targets. In general, high positive values show a higher proportion of fPAR, and therefore, greater biomass. The EVI product used was the MANVI: MODIS multiangle implementation of atmospheric correction (MAIAC) nadir-solar adjusted vegetation indices for South America, generated by in spatial resolution of 1 km and temporal resolution of 16 days[72].

Validation of temperature data The ERA5 was validated using thirty-five automatic meteorological field stations for temperature data from the INMET (National Institute of Meteorology, Brazil), covering the period between 1979 and 2018, respectively. In our study, the least-squares regression analysis was carried out by using the ERA5 data as the dependent variable and the automatic meteorological field stations as the independent variable. The ERA5 dataset explained 49 to 98% of the temperature variability captured by the automatic meteorological field stations. The RMSE varied ±0.4˚C to ±1.84 ˚C (see Supplementary Fig. 7).

Deforestation The procedures to retrieve deforestation as a geographic data built by PRODES/INPE[7,73,74] based on historical series of LandSat images provides deforestation annual increments in the Brazilian Amazon. Detailed information of PRODES methodology is available and can be accessed[74]. The where the accuracy is 93.5%[75]. We adopted the data period between 2010 and 2020. Using QGIS software it was generated a grid cell of 0.25° x 0.25° for the entire

Brazilian Amazon which was filled with absolute values of deforested area of deforestation calculated for each cell and in each year of the series. The mean area of deforestation was calculated for the period within 2010-2018 inside each grid's cell. Absolute annual deforestation for 2019 and 2020 were also calculated with the same methodology. Both, the mean or the absolute values of deforestation were calculated in each study site of the measured VPs considering the sum of all cell values completely enclosed in each site.

Fire spots Fire spots in Pan-Amazonia between 2010 and 2020 and burned area in Brazil´s Amazon were retrieved from INPES´s "Queimadas" wildfire monitoring program[8]. The number of fire spots detected per year in the grid cells and the overall means were calculated for each study site using QGIS software. "Fire spots" refer to fire pixels detected in the daily afternoon images of the MODIS sensor on board the AQUA NASA satellite since 2002 using the "Collection 6" algorithm that provides world-wide coverage of active vegetation fires[76–78]. Fire spots represent an under sampling of the actual fire extent in the vegetation since the monitoring miss most understory low-temperature fires as well as those occurring under cloudy skies and between consecutive satellite overpasses. However, relying on a stable sensor and proven algorithms, the data is an excellent indicator of temporal and spatial tendencies of fire occurrences[76]. Counts of fire pixel are indicators that allow the comparison of occurrences for periods and areas of interest; since they are detected by satellites and thus limited by cloud cover, image acquisition time and dense tree canopy, they are not an absolute measure of the total fire impact. The INPE fire products use the same NASA active fire detection algorithms and source data[79], adding a filter to remove fixed heat sources such as specific industries. Validation studies indicate less than 1 % of false detections in Amazonia[8] and 3% in Indonesia[80]. The procedures retrieved fire spots from Queimadas Project (INPE) between 2010 and 2020. The absolute number of fire spots registered per year between 2010 and 2020 was calculated in each study site, using QGIS software. Also calculated were the mean values of fire spots in the period between 2010 and 2018 in each study site.

Environmental law enforcement and accountability for illegal deforestation We set up and systematized a comprehensive database for the Amazon encompassing all available records of infractions notices and administrative judgments between 2010 and 2020. IBAMA field inspection and judgments data between 2010 and 2020 were obtained from the Brazilian Open Data Portal[9]. We removed duplicate records by applying a composite primary key encompassing the columns *"seq_auto_infracao", "num_auto", "ser_auto", "cpf_cnpj", "valor_auto", "quant_area" and "num_processo"* and filtered data for the states of the Legal Amazon: Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, Tocantins, and Mato Grosso and Maranhão. We used only infraction notices and fines related to crimes against the flora (basically illegal deforestation but also other forms of native vegetation suppression and associated crimes). The infraction notice informs citizens, companies, or institutions about committed acts violating administrative rules or the law, which are subject to penalties such as fines, seizures, and embargoes after due administrative judgments. The periods described in the text are related to the PPCDAm Phases I to IV[31,81]. The Brazilian government program for payment for ecosystem services (PES), not implemented can be found at MMA homepage[81].

Amazonia crops area, cattle production and wood exportation We obtained and systematized the information about Amazonia crops (soybean and corn) area production, cattle production and wood exportation for the Amazon using available official data from Brazilian government. Harvest area of soybean and corn were obtained from IBGE (2022)[26]. Wood exportation data came from Ministry of Industry, Foreign Commerce and Services (MDIC, 2022)[25]. Cattle production inside and outside Amazonia were produced by Amazon Deforestation Monitoring Project (PRODES/INPE, 2022)[27].

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Extended Data Fig. 1 | Regions of Influence. Annual mean regions of influence based on back trajectories density, calculated by Hysplit trajectory model for each flask, on each vertical profile along all studied years (2010 to 2018) for the sites SAN (2.9° S 55.0° W), RBA: 9.4° S 67.6° W; 2010-2012 for TAB: 6.0° S 70.1° W; and from 2013 for TEF; 3.4° S 65.6° W) (see Methods).

Extended Data Fig. 2 | Annual mean ΔVPs per site. Annual mean ΔVPs for each site ALF, RBA, SAN and TAB_TEF for the time series (2010–2020), constructed from the VP year mean, where the background was subtracted from each height, each flask (see methods). The black thick line represent the 2010-2018 Amazonia mean vertical profiles, the red thick line 2019 mean and blue thick line 2020 mean.

Extended Data Fig. 3 | Amazonia's Deforestation and fire spots time series. **a**) Deforestation limited to the Brazilian Amazonia classified as Legal Amazon (km^2) by PRODES / INPE[7] since 2000 to 2020; **b**) Annual infraction notices without geographic coordinates (gray bar) and with geographic coordinates (orange bar), blue line represents the embargoes and green line represents seizures, applied by IBAMA for crimes against flora at Legal Amazonia; **c**) Fire spots limited to the Brazilian Amazonia classified as Biome Amazonia by BD Queimadas/ INPE[8] since 2000 to 2020.

Extended Data Fig. 4 | Spatial fire spot distribution. Fire spots in Pan-Amazonia are given in grid cells 0.25°x0.25° and were retrieved from INPE's "Queimadas" wildfire monitoring program[8]. **a**) 2019 anomaly compared with the mean fire spot per grid between 2010-18; **b**) 2020 anomaly compared with the mean fire spot per grid between 2010-18. **c**) Fire spots detected at

Amazonas state from 2010-20. Black line mean 2010-18, grey band denotes the standard deviation of the monthly mean, red line the 2019 monthly mean, blue line the 2020 monthly mean. **d**) Fire spots detected at Roraima state from 2010-20.

Extended Data Fig. 5 | Amazonia crops area, cattle and wood exportation. Increase replacement of the forest by soybean, corn, beef, wood commerce as a consequence of deforestation. **a**) Evolution of harvested area of soybean (black line), corn (dashed line)[26], and wood exportation (blue line)[25]. **b**) Cattle production evolution inside (black line) and outside Amazonia, i.e. in others Brazilian states (blue line)[27]. (a) and (b) were built using official data from Brazilian government.

Extended Data Fig. 6 | Annual mean carbon Fluxes FC_{Total}, NBE and FC_{Fire}. a) Separation of three different areas inside the Amazon Mask (7,256,362 km^2, purple line) using mean annual influence regions of all years (2010 to 2018). Region 1: Combined ALF and SAN regions of Influence, Region 2: Combined RBA and TAB (2010-12) and TEF (2013-18) to compose regions of Influence 2 and excluding Region 1 for the quantification and composing Amazonia $\triangle$VP; Region 3: the remaining area outside regions 1 and 2 and inside the purple line. **b**) The annual mean carbon fluxes total (FC_{Total}), net biome Exchange (NBE) and fire (FC_{Fire}) were calculated according to the regional distribution shown on the map a).

Extended Data Fig. 7 | El Nino / La Nina episodes (ONI) and seasonal precipitation and temperature. a) Warm (red) and cold (blue) periods based on a threshold of +/- 0.5oC for the Oceanic Niño Index (ONI) [3 month running mean of ERSST.v5 SST anomalies in the Niño 3.4 region (5oN-5oS, 120o-170oW)], based on 30-years base periods updated every 5 years[42]. **b**) Seasonal monthly Amazon mean precipitation mean 2010-18 (solid light blue line), temperature (solid brown line). Grey bar is the standard deviation for the monthly means 2010-18 and dashed line for P and T 2019 and dotted line for P and T 2020.

Extended Data Fig. 8 | Amazonia carbon Fire and NBE flux 2010-20. a) Monthly means for Amazonia Fire carbon flux (FC_{Fire}). Black line for 2010-18 mean, where grey bands denote the standard deviation of the monthly mean. Red line 2019 and blue line 2020. **b**) Annual mean Amazonia total carbon flux (see methods).

Extended Data Fig. 9 | Amazonia results overview. Summary of Total carbon flux (white box), Fire carbon flux (red box), Net Biome Exchange (green box) and deforestation per site (orange box). The boxes are all related to the mean 2010-18 and 2019 pink arrow and 2020 blue arrow for all fluxes (gC m^{-2} d^{-1}) and deforestation (km^2).

Extended Data Table 1 | Summary results for all sites. Summary for the 4 sites and for the whole Amazonia presenting the results for total carbon flux (FC_{Total}), fire carbon flux (FC_{Fire}), net biome exchange (FC_{NBE}), deforestation (*only for Brazilian Amazon), Fire spots, Burned area, annual accumulated precipitation, wet season peak mean precipitation (months January, February and March: JFM), dry season peak mean precipitation (months August, September, October: ASO), annual temperature, wet season peak mean temperature (JFM) and dry season peak mean temperature (ASO). For each site and parameters are presented the mean for the years 2010-2018, the mean for 2019 and 2020. Considering the 11-year time series, the results of the first 5 years mean (2010-2014) and the last 5 years mean (2016-2020) to observe the trends in changes for carbon flux, on the climatological parameters, deforestation, burned area and fire spots. For the four sites the parameters are weighted mean based on region of influence, and for the whole Amazonia the parameter's mean are absolute.