

Accepted Article

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/GCB.15905](https://doi.org/10.1111/GCB.15905)

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3 **The CO₂ record at the Amazon Tall Tower**
4 **Observatory: a new opportunity to study**
5 **processes on seasonal and inter-annual scales**

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1 | ABSTRACT

High quality atmospheric CO₂ measurements are sparse in Amazonia, but can provide critical insights into the spatial and temporal variability of sources and sinks of CO₂. In this study we present the first six years (2014-2019) of continuous, high-precision measurements of atmospheric CO₂ at the Amazon Tall Tower Observatory (ATTO, 2.1°S, 58.9°W). After subtracting the simulated background concentrations from our observational record, we define a CO₂ regional signal ($\Delta\text{CO}_{2_{obs}}$) that has a marked seasonal cycle with an amplitude of about 4 ppm. At both seasonal and inter-annual scales we find differences in phase between $\Delta\text{CO}_{2_{obs}}$ and the local eddy covariance net ecosystem exchange (EC-NEE), which is interpreted as an indicator of a decoupling between local and non-local drivers of $\Delta\text{CO}_{2_{obs}}$. In addition, we present how the 2015/2016 El Niño-induced drought was captured by our atmospheric record as a positive 2σ anomaly in both the wet and dry season of 2016. Furthermore, we analyzed the observed seasonal cycle and inter-annual variability of $\Delta\text{CO}_{2_{obs}}$ together with net ecosystem exchange (NEE) using a suite of modeled flux products representing biospheric and aquatic CO₂ exchange. We use both non-optimized and optimized (i.e., resulting from atmospheric inverse modeling) NEE fluxes as input in an atmospheric transport model (STILT). The observed shape and amplitude of the seasonal cycle was captured neither by the simulations using the optimized fluxes nor by those using the diagnostic Vegetation and Photosynthesis Respiration Model (VPRM). We show that including the contribution of CO₂ from river evasion improves the simulated shape (not the magnitude) of the seasonal cycle when using a data-driven non-optimized NEE product (FLUXCOM). The simulated contribution from river evasion was found to be 25% of the seasonal cycle amplitude. Our study demonstrates the importance of the ATTO record to better understand the Amazon carbon cycle at various spatial and temporal scales.

2 | INTRODUCTION

Amazonia covers approximately one third of South America, and 70-80% of its area is rain forest (Goulding et al., 2003). This vast expanse of forest stores approximately 85-130 Pg of carbon in above- and below-ground biomass, making it one of the largest carbon pools on the globe (Malhi et al., 2006; Saatchi et al., 2007; Feldpausch et al., 2012; Baccini et al., 2012). Hence, Amazonia plays a fundamental role in the global carbon cycle not only by storing massive amounts of carbon, but also by acting as an immense "biogeochemical reactor" (Andreae, 2001). The exchange between the biosphere and the atmosphere occurs mainly through CO₂ exchange (Friedlingstein et al., 2020). Therefore, atmospheric mole fraction measurements of CO₂ can provide information about this exchange, as they integrate signals from the underlying ecosystem over large scales. Atmospheric CO₂ can thus be used to study the spatial and temporal variability of the dominant sources and sinks of carbon, which in the central part of Amazonia are mainly photosynthesis and respiration (Malhi et al., 2015).

The principal threats to Amazonia are forest degradation and deforestation, agricultural expansion and climate variability (Davidson et al., 2012; Mitchard, 2018). Deforestation was recently shown to cause disturbed rainfall patterns upwind and downwind of the cleared areas during the dry season in Amazonia (Khanna et al., 2017). In addition, deforestation and agricultural expansion are directly associated with biomass burning (van der Werf et al., 2010; Barlow et al., 2020), which in turn can be intensified by severe drought (Gatti et al., 2014; van der Laan-Luijckx et al., 2015; Marengo and Espinoza, 2016; Aragão et al., 2018). Extremes in the hydrological cycle include both droughts and flooding, which can be enhanced by large-scale events, such as those occurring during the extreme phases of the El Niño Southern Oscillation (ENSO) cycle (Marengo and Espinoza, 2016; van Schaik et al., 2018; Malhi et al., 2018). Variability in the hydrological cycle in the Amazon has increased over the last two decades (Gloor et al.,

2015), with more frequent extreme events. At the same time, a significant increase in the length of the dry season in southern Amazonia has been reported by Fu et al. (2013). Gloor et al. (2012) suggest that even though biospheric carbon uptake currently compensates for deforestation and fossil fuel emissions in South America, the continent could become a net source of carbon over the next decades, as projected by up-scaled plot level studies (Brienen et al., 2015; Hubau et al., 2020). Therefore, observational ground sites (such as ATTO) that can provide ground truth data for evaluating predictions are critical to improve our understanding of the carbon cycle in Amazonia.

The ecosystem net carbon exchange can be estimated using either a top-down or a bottom-up approach. Atmospheric inversions (i.e., the top-down approach) use measurements of atmospheric CO₂ mole fractions to optimize a prior estimate of net ecosystem exchange (NEE) fluxes at global (Gurney et al., 2002; Rödenbeck et al., 2003; van der Laan-Luijckx et al., 2017) and continental scales (Gerbig et al., 2003; Peters et al., 2007; Schuh et al., 2010; Shiga et al., 2018; Kountouris et al., 2018; Hu et al., 2019). This method is highly dependent on well-calibrated accurate measurements, their spatial density and representativeness (Gerbig et al., 2009). Typically, fluxes in regions with few measurements will be estimated with high uncertainties that will lead to limited understanding of spatial and temporal patterns (Gurney et al., 2002; Peylin et al., 2013; van der Laan-Luijckx et al., 2015; Thompson et al., 2016). Global inverse models have been found to be under-constrained (Gurney et al., 2002; Gaubert et al., 2019) and to a large extent hampered by model uncertainties and insufficient measurements in the Amazon region (Molina et al., 2015). Moreover, the density of remotely-sensed satellite columns over the region, characterized by deep convection, is highly reduced due to persistent cloud cover (Liu et al., 2017; Basu et al., 2018). The combination of these factors makes it difficult to constrain the seasonal and inter-annual variability of carbon exchange in Amazonia (Molina et al., 2015). The aircraft network of CO₂ profiles (Gatti et al., 2014) at several sites across Amazonia represents an important advance in the regional effort to improve the observational constraint for inverse modeling studies (van der Laan-Luijckx et al., 2015; Alden et al., 2016), yet identifying the relevant processes responsible for inter-annual and seasonal changes remains challenging.

Process-based biosphere models (representing the bottom-up approach) provide an alternative to constrain carbon exchange across a wide range of ecosystems (Sitch et al., 2015). However, the inability to reproduce the cycle of gross primary productivity (GPP), which influences the amplitude and phase of NEE at equatorial sites in Amazonia is one of the important limitations of biosphere models (Restrepo-Coupe et al., 2017). Others include e.g. CO₂ fertilization effect (Fleischer et al., 2019) and ecosystem respiration (Carvalho et al., 2014). While process-based model simulations show a decline in dry-season GPP at equatorial sites, presumably based on an incorrect assumption of water-limitation, observations typically suggest that GPP increases during the dry season (Huete et al., 2006; Myneni et al., 2007; Brando et al., 2010; Restrepo-Coupe et al., 2013; Borchert et al., 2015; Wu et al., 2016; Green et al., 2020). This discrepancy may be explained by the lack of leaf phenology in model formulations (Gonçalves et al., 2020). Chen et al. (2020) recently corroborated this by implementing this mechanism in the biosphere model ORCHIDEE, yet it is still missing in other biosphere models.

The evaluation of model-based biosphere-atmosphere flux estimates is generally performed by comparing simulated fluxes with in-situ flux measurements. Eddy-flux and plot-level studies serve such purposes and are valuable for understanding processes and underlying drivers of carbon exchange (Verbeeck et al., 2011; von Randow et al., 2013; Restrepo-Coupe et al., 2017). An alternative approach to evaluate both biosphere models and inverse modeling results is to use surface fluxes as an input in atmospheric transport models, and compare simulated and observed mole fractions at independent measurement sites. This method has the advantage of attributing the observed CO₂ regional signal to a larger spatial area, as compared to local eddy-flux spatial coverage, especially when atmospheric CO₂ is measured at a tall tower (Gloor et al., 2001). However, atmospheric transport errors can add additional biases that should be considered when interpreting patterns at different temporal scales (Gerbig et al., 2008). This leads to

106 different models presenting widely varying perspectives on the processes influencing Amazonia's carbon budget, with
107 most of them being poorly constrained by actual observations.

108 All things considered, accurate atmospheric CO₂ measurements at high temporal resolution can provide valuable
109 information about the spatial and temporal variability of sources and sinks of CO₂. In this work, we present six years
110 of observations from the Amazon Tall Tower Observatory (ATTO) in central Amazonia, and demonstrate how they
111 can be used to increase our process understanding by identifying the main sources of variability at seasonal and
112 inter-annual scales. Furthermore, we use the CO₂ measurements to evaluate state-of-the-art top-down as well as
113 bottom-up NEE products using an atmospheric transport model. A highlight of this study is that we use three different
114 estimates of NEE fluxes generated using CarbonTracker South America (an inverse modeling system) (van der Laan-
115 Luijckx et al., 2015), the Vegetation Photosynthesis and Respiration diagnostic model (VPRM) (Mahadevan et al., 2008),
116 and a statistically upscaled NEE product (Bodesheim et al., 2018) (FLUXCOM). With such a diverse dataset of NEE
117 fluxes, we cover the inherent variability of different model formulations. We also evaluate the capability of an inversion
118 system, using different data streams for optimization, to constrain the variability of atmospheric CO₂ at ATTO. Thus,
119 we provide valuable insights that will serve not only to better understand the processes that control atmospheric CO₂
120 at ATTO, but also to evaluate biosphere flux models from an atmospheric perspective.

121 3 | DATA AND METHODS

122 3.1 | Site description

123 The Amazon Tall Tower Observatory (ATTO) site (2.14°S, 58.99°W, see Figure 6) has been described extensively in
124 Andreae et al. (2015). In this paper, we present aspects considered important for our study. ATTO is located in the
125 Uatumã Sustainable Development Reserve (USDR) in central Amazonia, 150 km northeast of the closest large city,
126 Manaus. The main infrastructure and research facilities were built in the dense upland forest (terra firme, at 130 m
127 a.s.l.), where the highest vegetation is found. The canopy height at the tower location is around 37 m, however the
128 average tree height on the terra firme forest plateau is 20.7 ± 0.4 m (Andreae et al., 2015).

129 The local precipitation regime shows a distinct seasonality (see Figure S1 left panel), and agrees very well ($r=0.8$,
130 $p\text{-value}<0.01$) with the Multi-Satellite Precipitation Analysis from the Tropical Rainfall Measuring Mission (TRMM
131 3B42-daily at a resolution of 0.25 deg, obtained from: https://disc.gsfc.nasa.gov/datasets/TRMM_3B42_Daily_7/summary) (Huffman et al., 2016) sampled at the grid cell closest to ATTO (2.12°S, 58.87°W). However the local
132 measurements show a lower mean annual precipitation (MAP) than the climatological average obtained using the
133 TRMM dataset (1934.1 mm yr⁻¹ vs 2382.2 mm yr⁻¹). The monthly and annual mean biases of the TRMM estimate with
134 respect to the local measurements is +40 mm and +489 mm, respectively. The local time series is based on an 8-year
135 record (2012-2019), and thus the seasonal average is highly affected by the 2015/2016 El Niño drought. Therefore,
136 we consider the longer TRMM dataset (ATTO-TRMM 1998-2019 in Table 1) to be more reliable as a climatology. Thus,
137 we use the ATTO-TRMM (1998-2019) record as a reference; the dry season length (DSL) is 3 months with a mean dry
138 season precipitation of 63.3 mm month⁻¹. The annual minimum average precipitation (MiAP) is 45.1 mm month⁻¹.
139 A comparison of these values between the local record and the TRMM dataset is shown in Table 1. For this study
140 we have defined the climatological dry season as the months whose seasonal median is lower than 100 mm (July to
141 October). For the wet season we selected the months whose 25th percentile was clearly above 200 mm (February to
142 June), see Figure S1 right panel for details.
143

TABLE 1 Mean annual precipitation (MAP), mean dry season precipitation (DSP), mean dry season length (DSL) and annual minimum average precipitation (MiAP) at ATTO using the local precipitation measurements (2012-2019) and data from the tropical rainfall measuring mission (TRMM) from 1998-2019 (Huffman et al., 2016). For comparison we show the same values reported by Restrepo-Coupe et al. (2017) for the research station (K34) for the period 1998-2014.

Site	Lat (°)	Lon(°)	MAP (mm yr ⁻¹)	DSP (mm month ⁻¹)	DSL (months)	MiAP (mm month ⁻¹)
ATTO-Local (2012-2019)	-2.14	-58.99	1934.1	53.2	3.8	25.3
ATTO-TRMM (2012-2019)	-2.12	-58.87	2422.6	63.3	2.8	42.2
ATTO-TRMM (1998-2019)	-2.12	-58.87	2382.2	63.3	3	45.1
K34-TRMM (1998-2014)	-2.61	-60.21	2672.6	99.7	1-2	99.7

144 3.2 | Atmospheric mole fraction measurements

145 The continuous measurement system was installed in March 2012 at the 81 m walk-up tower at ATTO and has been
 146 described in Andreae et al. (2015) and Botía et al. (2020). Here we highlight the features relevant for this study. The
 147 atmospheric mixing ratio data presented here were collected with two cavity ring-down-based analyzers (Picarro Inc.,
 148 USA), a G1301 and a G1302 measuring CH₄/CO₂ and CO₂/CO, respectively. Both analyzers provide CO₂ data at
 149 a 15-minute resolution calibrated on the World Meteorological Organization (WMO) CO₂ X2007 scale. These data
 150 were subsequently averaged to half-hourly data. The overall accuracy of both analyzers, including the uncertainties
 151 of the water vapor correction, are estimated to be 0.09 ppm CO₂ (1 ppm = 1 μmol mol⁻¹ of dry air). The analyzers
 152 measure the air from five lines connected to inlets located at 79, 53, 38, 24 and 4 m above ground. Downstream
 153 of each sampling line, a stainless steel sphere (8 liters volume) acts as a buffer volume. By mixing the sampled air,
 154 these buffers integrate the atmospheric signal, allowing a continuous, near-concurrent measurement from all heights
 155 (Winderlich et al., 2010). The time series presented here is based on only daytime dry air mole fractions (i.e., 13:00 to
 156 17:00 local time (LT)), representative of well-mixed convective conditions. In order to maximize the data coverage, we
 157 use observations from both instruments whenever they are available, with the mean calculated for the periods when
 158 both were operational simultaneously. The mean bias between the datasets at half-hourly resolution was estimated to
 159 be 0.02 ppm CO₂. The data presented here are available upon request at <https://attodata.org> (last access: 25 January
 160 2021).

161 3.3 | Phenology measurements and leaf area index age classes

162 Upper canopy leaf phenology is monitored with a RGB Stardot Netcam model XL 3MP (2048×2536 pixels) mounted
 163 on the top of the 81 m tower. For an in-depth description of the camera set-up, radiometric calibration and detection
 164 of phenostages, we refer the reader to Lopes et al. (2016). We used only pictures obtained in the morning (i.e., no
 165 backlit crowns), under cloudy sky or under the shadow of a cloud, providing a spatially even and temporally consistent
 166 illumination of the irregular canopy surface. For each crown (n=194), we were able to detect abrupt increase in
 167 greenness (i.e., leaf flush) or abrupt green-down (i.e., leaf abscission). By counting the number of individual trees per
 168 month for each category (flush or abscission), we built a monthly time series for the period between July 2013 and
 169 November 2018. From the trees that the camera sees, 69% (n=134) have clear flushing and abscission patterns, and
 170 from these the time series was built.

171 Using the number of days after each individual flushing event, we determined leaf age classes and attributed a
 172 fraction of the upper canopy crowns to an age class at monthly intervals. As in Wu et al. (2016), we defined the

173 following leaf age classes: i) young leaves (0-2 months), ii) mature leaves (2-6 months), and iii) old leaves (>6 months).
174 Next, we partitioned the age classes into classes of leaf area index (LAI) (i.e., young, mature, and old LAI) by nor-
175 malizing each leaf age class with the total LAI measured at ATTO. We used a constant LAI of $5.32 \text{ m}^2 \text{ m}^{-2}$ for all
176 months, as the variability of this number throughout the year was not statistically significant (unpublished results).
177 For the normalization we took into account the total number of trees in the camera frame ($n=194$), assuming that
178 the 30% that does not have clear flushing patterns are part of the old age class. For more details on the methods
179 and assumptions for the separation of LAI into leaf age classes, see Wu et al. (2016). LAI was measured using two
180 LAI-2200 PCA sensors (LI-COR Inc., Lincoln, NE, USA) recording simultaneous readings above and within the canopy.
181 The sensor above the canopy (the reference) was installed on the 80 m tower (approximately 50 meters above top
182 canopy). All measurements were performed under diffuse light conditions. The within-canopy measurements were
183 carried out using 40 cm supports (sampling points) on the ground. The spatial sampling design was a square grid
184 with 42 sampling points (21x2 and 80m between points). We carried out monthly campaigns from March 2016 to
185 March 2019. The flushing and abscission data (<http://doi.org/10.17871/atto.223.7.840>) together with the raw LAI
186 age classes (<http://doi.org/10.17871/atto.230.4.842>) are available upon request request at <https://attodata.org>.

187 3.4 | Eddy covariance measurements

188 In this study, we use eddy covariance (EC) measurements from 2014 to 2019. They were done using a 3-D sonic
189 anemometer (CSAT3, Campbell Scientific Inc., Logan, USA) and an open-path infrared gas analyser (LI7500, Li-COR
190 Inc., Lincoln, USA), both installed at the top of the 81 m tower, approximately 40 m above the local canopy top.
191 Half-hourly EC-sensible heat (EC-H), EC-latent heat (EC-LE), and EC-CO₂ fluxes were calculated by using EddyPro
192 software (Li-COR Inc., Lincoln, USA). Raw time series data were de-spiked and screened according to Vickers and
193 Mahrt (1997), and data quality control on half-hourly EC-H/LE/CO₂ fluxes was carried out following the method of
194 Mauder and Foken (2004). EC flux data meeting the highest quality criteria (flags 0 and 1) for H, LE and CO₂ and from
195 the EC-favourable wind direction ($[-90^\circ : +90^\circ]$ sector) were selected for further analysis. The raw eddy-flux data are
196 available upon request at <https://attodata.org> (last access: 25 January 2021).

197 Net ecosystem exchange (EC-NEE) was calculated as the sum of the half-hourly EC-CO₂ flux and storage CO₂
198 flux. The storage flux was obtained using the 5-inlet CO₂ mole fraction profile measurements at the 81 m tower
199 (cf. section 3.2) following the calculation procedure of Winderlich et al. (2014). When the profiles were missing
200 measurements from one or two heights, the storage flux was obtained from 3 or 4 inlets that included both the 4 m
201 and 79 m heights, this occurred only 2.42% of the time over the six years. In cases where only half-hourly EC-CO₂ flux
202 data were available, missing CO₂ storage fluxes were gap-filled with mean diurnal variations over ± 14 -day periods
203 as performed by the REddyProc package (Wutzler et al., 2018). In addition, negative EC-NEE data during nighttime
204 periods (defined as 18:00 to 6:00 with global radiation (R_g) $< 20 \text{ W m}^{-2}$) were removed. In cases where nighttime R_g
205 data were not available, we discarded negative EC-NEE data between 19:00 and 5:00.

206 A distribution of friction velocity (u^*) thresholds (5th, 50th and 95th percentiles) in each year was estimated
207 according to Papale et al. (2006) using REddyProc. For this study, we used the yearly median (50th percentile) u^*
208 values as representative for our site (see Table S1). Our u^* values are lower than those from previous studies due to
209 the higher measurement height (81 m), we refer the reader to Table S2 for a comparison of u^* values in other sites
210 in Amazonia. After the u^* filtering, 20.4 % of EC-NEE data remained. The effect of having more or less data due to
211 a larger or lower u^* threshold does not affect the seasonal cycle of neither EC-NEE, GPP nor R_{eco} , this is shown in
212 Figure S2. The gap-filling of the EC-NEE data was performed using REddyProc and then negative gap-filled nighttime
213 EC-NEE data were screened out. The missing nighttime EC-NEE data were gap-filled by a linear interpolation for less

214 than two missing hours or a mean NEE value over one nighttime period. Nighttime EC-NEE was assigned as nighttime
215 ecosystem respiration (R_{eco}), and daytime R_{eco} was derived from averaging R_{eco} over two adjacent nighttime periods,
216 similar to Restrepo-Coupe et al. (2013). Then, gross primary productivity (GPP) was obtained by subtracting EC-
217 NEE from R_{eco} . We adopted the above NEE partitioning method because nighttime R_{eco} did not correlate well with
218 nighttime air temperature, which is needed for commonly used methods (e.g., the nighttime method (Reichstein et al.,
219 2005), the daytime method (Lasslop et al., 2010) and modified daytime methods (Keenan et al., 2019)). In this study,
220 we interpret EC-GPP (hereafter GPP) as gross ecosystem productivity (GEP).

221 3.5 | STILT simulations

222 3.5.1 | STILT model description

223 The Stochastic Time Inverted Lagrangian Transport (STILT) model (Lin et al., 2003) is useful for diagnosing the impact
224 of surface emissions at a specific measurement location or receptor by resolving transport in the near-field (i.e., the
225 surface with which the planetary boundary layer air has had contact with). STILT simulates the transport in the near-
226 field by following the time evolution of an ensemble of particles (to be interpreted as an air parcel) and by interpolating
227 meteorological fields to the sub-grid location of each particle. Turbulent motions in the planetary boundary layer
228 (PBL) are modelled as a Markov chain process using turbulent velocity statistics (Lin et al., 2003). Moist convection
229 in STILT uses vertical profiles of convective mass fluxes within updrafts and downdrafts, as well as entrainment and
230 detrainment fluxes into and out of the up- and downdrafts (for details, see Nehr Korn et al., 2010). Vertical profiles of
231 in-cloud mass fluxes are derived from the driving meteorological fields using the Tiedtke scheme (Tiedtke, 1989).

232 The time-inverted feature of the model refers to the capability of resolving the near-field transport of the particle
233 ensemble prior to its arrival at the receptor location. In this study, the model was run at hourly resolution for the six-
234 year period from 2014 to 2019. Every hour a 100-particle ensemble was released at the receptor height of 80 m above
235 ground, and the back trajectories were calculated for the preceding 10 days to ensure most backward trajectories have
236 left the continent, such that the footprints represent the full influence of surface fluxes on measurements at ATTO. The
237 difference between the modelled receptor height and the air inlet is only 1 meter, which we assume can be neglected.
238 The model was driven by 3-hourly meteorological fields from ECMWF short-term forecasts (following the contem-
239 porary IFS cycle development; for more info see <https://www.ecmwf.int/en/publications/ifs-documentation>).
240 The original meteorological fields were preprocessed and interpolated to a spatial resolution of 0.25° by 0.25° , cov-
241 ering South America between 20°S – 15°N latitude and 85°W – 35°W longitude bands. The original vertical structure
242 was maintained, however only the 89 lowest of the 137 total levels were used, limiting the top model level to an
243 altitude of about 21 km.

244 3.5.2 | Seasonally-averaged footprint calculation

245 To better interpret our measurements and attribute signals to particular regions, spatially explicit surface influence
246 maps or footprints were calculated using the STILT model. From the back trajectory particle ensembles we derived
247 hourly-gridded footprints. The footprints are derived at higher spatial resolution ($1/12^\circ$ by $1/8^\circ$) than the driving
248 meteorological data, and they can be defined as the flux sensitivity of mole fractions measured at the receptor loca-
249 tion, with units of ppm per $\mu\text{mol m}^{-2} \text{ s}^{-1}$. To obtain the seasonally-averaged footprints, we first filtered for daytime
250 (i.e., 13:00–17:00 LT at the receptor) values to ensure well-mixed convective conditions at the measurement location.
251 These individual hourly footprints were aggregated to a climatological monthly mean. From these monthly means we

252 averaged over: November, December, January (NDJ), February, March, April (FMA), May, June, July (MJJ) and August,
253 September and October (ASO). The averaging periods were chosen in this way to allow a good distinction between wet
254 and dry seasons (FMA and ASO), as well as the transition periods in between (NDJ and MJJ). The monthly climatology
255 of concentration footprints generated for this study is available at <http://doi.org/10.17871/atto.208.8.811>.

256 The regional extent of the seasonally-averaged footprints is shown in Figure 6 to provide an idea of the dominant
257 vegetation types within the areas of influence. The 50th percentile footprint during NDJ and FMA covers an area of
258 mainly intact forest, whereas in MJJ and ASO the footprints cover areas characterized by a larger presence of disturbed
259 forest, located on the southern bank of the Amazon River. The area of the 50th percentile footprint increases from
260 208,058 km² in NDJ to 236,969 km² in FMA and decreases from 244,482 km² in MJJ to 207,812 km² in ASO. Note
261 that the Cerrado and Caatinga biomes (semiarid ecosystems), are within the 75th percentile footprint in MJJ and ASO,
262 although their relative influence on the signals measured at ATTO is estimated to be low.

263 3.5.3 | STILT tracer simulations

264 Lateral Boundary Conditions (LBC)

265 As we are dealing with an atmospheric transport model within a limited domain, we have to consider the influence of
266 the air masses entering it at its borders (LBC, Lateral Boundary Conditions) to compare the simulated mole fractions
267 to in situ observations. This additional signal, hereafter also referred to as "background", is added in STILT to the CO₂
268 mole fractions related to fluxes from within the domain. In the case of ATTO, it is almost exclusively advected from the
269 northeastern or eastern border of our domain (see Figure 6). The LBC include the global information that influences
270 our domain of interest, such as the increasing trend due to fossil fuel burning and variations on seasonal and synoptic
271 scales. In this study, we have used the Jena CarboScope (s04ocv4.3) as our LBC. We refer the reader to Rödenbeck
272 et al. (2003) and to <http://www.bgc-jena.mpg.de/CarboScope/> to get more details on the data assimilated in this
273 system.

274 The validity of the LBC is a fundamental aspect in our tracer simulations. To assess this validity and potential
275 biases, we evaluated the 3D fields of CO₂ used as LBC at three background stations located at the east and northeast
276 of our regional domain: Ragged Point Barbados (RPB, 13.16°N, 59.43°W), Ascension Island (ASC, 7.94°S, 14.35°W)
277 and Cape Verde (CVR, 15.12°N, 23.60°W). We sampled the original global fields at the location of each station and
278 calculated the difference between the simulated and observed mole fractions (see Figure S3). Since the data from the
279 above stations were assimilated in the Jena CarboScope inversion system, they have small Mean Bias Errors (MBE)
280 (-0.09 ± 0.26 ppm at RPB, -0.036 ± 0.28 ppm at ASC and -0.176 ± 0.8 ppm at CVR). Even though these small MBE
281 indicate a strong constraint on the LBC, we have bias corrected the LBC used to calculate the observed regional signal.
282 The magnitude of the bias-correction will be shown in the Results section. We define an observed regional signal
283 ($\Delta\text{CO}_{2_{obs}}$, which is bias-corrected) and a simulated regional signal ($\Delta\text{CO}_{2_{sim}}$). The first is calculated by subtracting the
284 LBC from the measured CO₂ mole fractions, and the second by leaving the LBC tracer out of equations 1 and 2.

285 Input fluxes

286 To obtain simulated mole fractions at the tower location, we coupled the footprints with the surface fluxes at hourly
287 resolution. By adding all the tracer components and the LBC, we can obtain multiple realizations of simulated CO₂
288 mole fractions at the ATTO site that can be compared to observations, and assess how the underlying fluxes affect
289 the simulated signal. To account for all the sources and sinks of CO₂ and their uncertainties in Amazonia, we use
290 a wide range of available data sets, including both optimized (i.e., resulting from atmospheric inverse modeling) and
291 non-optimized NEE flux fields (see Table 2).

292 Equations 1 and 2 show the main tracer components that were added to obtain the integrated CO₂ mole fractions
 293 at ATTO. The subscripts represent the flux categories associated with different processes and the * indicates we use
 294 multiple NEE sources for each equation as we explain below. The complete overview of input flux fields used for each
 295 tracer is given in Table 2.

$$CO_{2TopDown} [ppm] = \sum CO_{2k}, \quad k = LBC, NEE_{TopDown}^*, ocean, fires, fossilfuel \quad (1)$$

$$CO_{2BotUp} [ppm] = \sum CO_{2k}, \quad k = LBC, NEE_{BotUp}^*, ocean, fires, rivers, fossilfuel \quad (2)$$

296 As vegetation dominates the CO₂ exchange within our domain, we used five Net Ecosystem Exchange (NEE) data
 297 sets, three of which are optimized using an atmospheric inversion system. The atmospheric inversion system (Peters
 298 et al., 2005) utilizes available in situ and remote sensing measurements for the assimilation process; it should be noted,
 299 however, that observations from ATTO were not assimilated in any of the products discussed here. In equations 1
 300 and 2, NEE is replaced according to the list in Table 2 and thus we obtain five STILT-model results for simulated CO₂
 301 mole fractions at ATTO.

302 The optimized NEE flux fields (i.e. Top-down) were produced using different settings but the same CarbonTracker
 303 Data Assimilation System (CTDAS, van der Laan-Luijkx et al. (2017)). All inversions use the transport model TM5
 304 (Krol et al., 2005), where the default run (CTE2020) uses a global transport resolution of 3°x 2° with 1°x 1° zoom
 305 regions over Europe and North America, and two South-America-specific setups of the system (CT-SAM, van der
 306 Laan-Luijkx et al. (2015); Koren (2020): CT-SAM-OCO2 and CT-SAM-Flask) use a global resolution of 6°x 4° with a
 307 nested zoom over South America of 3°x 2° and 1°x 1°. The three inversions also use different sets of atmospheric
 308 CO₂ data for the assimilation: surface flask measurements from ObsPack GLOBALVIEWplus 5.0 (available here: <https://doi.org/10.25925/20190812>) (CTE2020), the same GLOBALVIEWplus 5.0 but with additional aircraft profiles (Gatti
 309 et al., 2014) from different locations in Amazonia (CT-SAM-Flask), or OCO2 satellite column retrievals (CT-SAM-
 310 OCO2). For the CT-SAM-OCO2 the NASA retrieval v9r was used (https://docserver.gesdisc.eosdis.nasa.gov/public/project/OC0/OC02_DUG.v9.pdf). The column observations were aggregated to 10-second super observa-
 311 tions (following the method described in (Crowell et al., 2019)) and retrievals above water were excluded. CT-SAM
 312 optimizes NEE on a gridded state vector of 1°x 1° over South America, whereas CTE2020 optimizes NEE in the re-
 313 gion using larger "ecoregions" following the plant-functional types in the prior biosphere model (SiBCASA, (Schaefer
 314 et al., 2008)). Note that the driving meteorology in CTE2020 uses ERA5 (C3S, 2017) instead of ERA-interim, as in
 315 CT-SAM-Flask and CT-SAM-OCO2.
 317

318 The non-optimized NEE fluxes (VPRM and FLUXCOM, i.e. bottom-up) use different approaches. The Vegetation
 319 Photosynthesis and Respiration model (VPRM) estimates NEE using a simple diagnostic light-use-efficiency model
 320 driven by the Enhanced Vegetation Index (EVI) and Land Surface Water Index (LSWI), derived from surface reflectance
 321 measured by the Moderate Resolution Imaging Spectroradiometer (MODIS), together with 2-m air temperature and
 322 shortwave radiation at the surface provided from the meteorological model (Mahadevan et al., 2008), in this case
 323 STILT. Two parameters per vegetation type (Jung et al., 2006) are optimized based on eddy covariance measurements
 324 from 9 sites between 2001 and 2010, obtained from the LBA-ECO repository (https://daac.ornl.gov/daacdata/1ba/carbon_dynamics/CD32_Brazil_Flux_Network/data/, last access: 19 October 2020). The FLUXCOM product
 325 is derived from up-scaling site-level data (FLUXNET, <http://fluxnet.fluxdata.org/> (last access: 29 September
 326 2020)) to global scales by using a set of predictors which are fed to a random forest regression (Bodesheim et al.,
 327 2018). The reader is referred to Bodesheim et al. (2018) and Jung et al. (2020) for more information on the predictors
 328

TABLE 2 Input fluxes and lateral boundary condition data sets used in STILT. Column "Input type" indicates whether the fluxes are based on atmospheric inversions (prefix "Opt").

Tracer	Product Name	Input type	Time coverage	Notes	Reference
LBC	Jena CarboScope (s04ocv4.3)	mole fractions	2014-2019	LBC - lateral boundary condition	Rödenbeck et al. (2003)
Ocean	CTE2020	Opt flux	2014-2019	Top-down (TD) and Opt. atm. inversion	van der Laan-Luijkx et al. (2017)
NEE	CTE2020	Opt flux	2014-2019	TD and Opt.	van der Laan-Luijkx et al. (2017)
NEE	FLUXCOM	Flux	2014-2019	Bottom-up (BU)	Bodesheim et al. (2018)
NEE	VPRM	Flux, online	2014-2019	BU	Mahadevan et al. (2008)
NEE	CT-SAM-OCO2	Opt flux	2015-2017	TD, not used for other years (Opt)	Koren (2020)
NEE	CT-SAM-Flask	Opt flux	2014-2017	TD, 2018 and 2019, 2008-2017 average (Opt)	Koren (2020)
Rivers	ORCHILEAK	Flux	2014-2019	1980-2010 - Climatology	Hastie et al. (2019)
Biomass burning	GFAS	Emissions	2014-2019		Kaiser et al. (2012)
Fossil Fuels	EDGAR 4.3.2	Emissions	Annual mean	All sectors, aggregated	Janssens-Maenhout et al. (2017)

329 and the up-scaling methods.

330 We use river CO₂ fluxes from the updated version (Hastie et al., 2019) of the ORCHILEAK model (Lauerwald et al.,
 331 2017), which uses a high spatial resolution (100 m) wetland distribution map (Hess et al., 2015). We only add the river
 332 flux component to the bottom-up simulations, as for the top-down simulations the river signal should be captured by
 333 the assimilated observations (Kondo et al., 2020). In order to avoid double counting of fluxes from floodplains, which
 334 could be captured by VPRM and FLUXCOM during a low water stage, we only used the river CO₂ evasion component
 335 from the ORCHILEAK model. The tracers that are not varied in equations 1 and 2 (i.e., ocean, fires, fossil fuel) are
 336 always added to the simulated mole fraction of each STILT-model realization.

337 We also simulated the anthropogenic signal component using the annual mean emissions from EDGAR v4.3.2
 338 (Janssens-Maenhout et al., 2017) reported for 2012; original gridded emissions (0.1°x 0.1°spatial resolution) from all
 339 fossil fuel sectors were aggregated into an emission field of a single tracer. Since anthropogenic emissions are of minor
 340 importance in our domain we assumed constant annual emissions in our simulations. For the contribution of biomass
 341 burning or fires we use daily emissions from the Global Fire Assimilation System (GFAS) at 0.1°x 0.1°spatial resolution
 342 (Kaiser et al., 2012). Last but not least, we use optimized oceanic CO₂ fluxes from CTE2020. It is worth mentioning
 343 that in CTE2020, different from previous releases, the ocean prior flux is taken from the Jena CarboScope system.

344 3.5.4 | Input flux adjustments for STILT simulations

345 The input fluxes have been converted for use in STILT into units of $\mu\text{mol m}^{-2} \text{s}^{-1}$. Furthermore, we have adjusted
 346 the weekly mean posterior NEE fluxes of CTE2020, CT-SAM-OCO2 and CT-SAM-Flask to represent the original
 347 diurnal variability of its prior biosphere model (SIBCASA) before using them as input in STILT. Equation 3 describes
 348 this adjustment, which projects the original 3-hourly deviations from the monthly average diurnal cycle back onto
 349 the weekly mean posterior flux. For CTE2020, equation 3 was used for each week (k) that fluxes are available, in
 350 which the deviation of the 3-hourly ($j=1..8$) flux from the corresponding monthly (i) mean is added to the weekly
 351 posterior. For the CT-SAM-OCO2 and CT-SAM-Flask the prior and diurnal mean NEE in equation 3 (1^{st} and 2^{nd} term
 352 on the right-hand side) were replaced by its climatology for each month ($i=1-12$), as their multi-annual record was
 353 smaller and included an ENSO extreme event. This adjustment was performed in order to convert monthly optimized
 354 NEE fluxes (CTE2020, CT-SAM-OCO2 and CT-SAM-Flask) to hourly resolution and thus couple them with the hourly
 355 footprints. This is important because the diurnal variability in atmospheric transport has to be considered for more
 356 accurate simulations. We consider that the adjustment is precise enough because the simulated diurnal cycle of CO₂

at the tower resembles that of the other simulations which are originally provided as hourly fluxes. This is shown in Figure S4.

$$NEE_{post3h_{k,j}} = (NEE_{prior3h_{k,j}} - DiurnalMeanNEE_{prior3h_{i,j}}) + NEE_{postWeekly_k} \quad (3)$$

4 | RESULTS

4.1 | ATTO atmospheric CO₂ time series

The observed CO₂ trend (Figure 6a) at ATTO for the 6-year record is 2.38 ppm year⁻¹ (2.18-2.60 95% CI), which is very similar to the mean global CO₂ growth rate of 2.49 ± 0.08 ppm year⁻¹ reported by Dlugokencky and Tans (2020) for the same time period. From the monthly record, we can highlight the wet seasons of 2016 and 2019 as two distinctive events of important inter-annual variability in which the footprint of the tower was likely a source of CO₂ to the atmosphere. In the transition from wet to dry seasons, our measurements reach a peak that is followed by a consistent decline throughout the dry season. On average, this decline has an onset in July and August. We also note that the monthly variability is lower in the dry season than in the wet season, strengthening the consistency of the dry season decline.

The simulated background mole fractions (LBC-CScope) have a marked seasonality, reaching the highest values during the wet season, indicating that the air masses coming into our domain are enriched with CO₂. This is in accordance with Figure 6, in which we showed that the surface influence during the wet season is oriented to the northeast, bringing air from the northern hemisphere. When subtracting the simulated background mole fractions from our measurements, we can diagnose specifically the regional signal of CO₂, defined as ΔCO_{2,obs} in Section 3.5.3. The seasonal cycle of ΔCO_{2,obs} (Figure 6b) has an amplitude of 4.14 ppm (default) and 4.11 ppm (bias-corrected) and two distinct periods in which the signal at ATTO is below the LBC tracer (< 0 ppm). It is worth mentioning that ΔCO_{2,obs} contains information about the real fluxes in our domain, but it also has an atmospheric transport component, making it difficult to interpret it solely as a source (> 0 ppm) or an uptake (< 0 ppm) of CO₂.

As ΔCO_{2,obs} is the object of study in this paper, we have assessed its uncertainty by obtaining a range between an independent LBC estimate and a bias corrected version of the LBC-CScope. The first, was calculated by taking the measurements at the background stations ASC and RPB and interpolating a new LBC based on the latitude of the STILT-particles once they exit our domain. To account for the minor biases of the LBC-CScope at the background stations, we have bias corrected the LBC-CScope, the magnitude of this correction is shown in Figure 6a by the dashed blue line. The min-max range of these two ΔCO_{2,obs} estimates is lower than the inter-annual monthly standard deviation of the ΔCO_{2,obs}, which strengthens the robustness of this quantity. For the rest of this study we will use the bias-corrected ΔCO_{2,obs}.

4.1.1 | Drivers of seasonal variability

ΔCO_{2,obs} is affected by local (eddy covariance scale) and non-local scales (concentration footprint scale). At the local scale, we confront the ΔCO_{2,obs-bio} with the EC-NEE in Figure 6a. The ΔCO_{2,obs-bio} was calculated using the bias-corrected ΔCO_{2,obs} and subtracting the simulated contribution of rivers, fires, fossil fuel and ocean. The phase of the seasonality of ΔCO_{2,obs-bio} differs from that of EC-NEE, mainly in January, February and March and in October, November and December. From April to July EC-NEE exhibits an increasing source that can influence the increasing

392 pattern in $\Delta\text{CO}_{2_{\text{obs-bio}}}$. The dry season decline in $\Delta\text{CO}_{2_{\text{obs-bio}}}$ can be partly attributed to a decrease in EC-NEE which
 393 is triggered mainly by a reduction in R_{eco} from May to August and a gradual increase in GPP after August (Figure 6b).
 394 The effect of atmospheric transport is also important here. For example, the height of the PBL is a variable that affects
 395 the measured CO_2 mole fractions at the tower. The PBL height tends to be deeper during the dry season (1300-1500
 396 m) than in the wet season (1100-1200 m), which means that the volume in which CO_2 mole fractions are diluted
 397 is larger, causing more negative $\Delta\text{CO}_{2_{\text{obs-bio}}}$. This example illustrates how the seasonal effects of the footprint and
 398 the PBL height can influence $\Delta\text{CO}_{2_{\text{obs-bio}}}$. The observed phase differences indicate that $\Delta\text{CO}_{2_{\text{obs-bio}}}$ can decouple
 399 from the local EC-NEE in some months of the year, suggesting that the seasonality in $\Delta\text{CO}_{2_{\text{obs-bio}}}$ is controlled by
 400 overlapping effects of local and non-local drivers.

401 One of the most important non-local drivers of $\Delta\text{CO}_{2_{\text{obs-bio}}}$ is the heterogeneity of NEE across the seasonally-
 402 changing footprint area. The amplitude of the seasonal cycle of EC-NEE in Amazonia varies along the precipitation
 403 gradient (Saleska et al., 2009). Locations with a higher mean annual precipitation (MAP) ($>2500 \text{ mm yr}^{-1}$), like K34
 404 (2.61°S , 60.21°W) have a smaller seasonal cycle amplitude, whereas drier sites ($2000\text{-}2200 \text{ mm yr}^{-1}$) further east in
 405 the Tapajós National Forest (K67 and K83) display a more pronounced seasonal cycle (Saleska et al., 2009). EC-NEE
 406 at ATTO (2.14°S , 58.99°W) shows interesting patterns as it falls between the range mentioned above, with a MAP of
 407 2382 mm yr^{-1} and a seasonal EC-NEE range of approximately $60 \text{ g C m}^{-2} \text{ month}^{-1}$ ($600 \text{ kg C ha}^{-1} \text{ month}^{-1}$). Thus,
 408 we observed a seasonal variability with a midyear source peak, different from the sustained net uptake throughout
 409 the year reported for K34 by Restrepo-Coupe et al. (2017). ATTO is located about 140 km northeast of K34: the sites
 410 are relatively close, yet exhibit different MAP and seasonal EC-NEE patterns. ATTO EC-NEE is more similar to that
 411 measured at the Tapajós National forest in having a dry season decline, reaching neutrality in September and October
 412 (Saleska et al., 2003; Goulden et al., 2004; Baker et al., 2008; Hayek et al., 2018), but it differs in that the wet season
 413 shows on average a weak source, which after March increases towards a seasonal peak in May. Interestingly, the
 414 ATTO EC-NEE seasonality has a similar phase to the Caxiuana (CAX) site (Restrepo-Coupe et al., 2017). Following the
 415 classification in Saleska et al. (2009), the EC-NEE amplitude at ATTO falls close to the sites where R_{eco} is the most
 416 important factor.

417 From the $\Delta\text{CO}_{2_{\text{obs-bio}}}$ perspective, R_{eco} can be important from March to July, when EC-NEE and $\Delta\text{CO}_{2_{\text{obs-bio}}}$ are
 418 in phase. Further inspection of the local processes at ATTO indicates that R_{eco} correlates significantly with EC-NEE
 419 ($r=0.55$, $p\text{-value} < 0.01$). Furthermore, river CO_2 evasion (Figure 6d) could also contribute to $\Delta\text{CO}_{2_{\text{obs-bio}}}$, mainly from
 420 April to July, with a peak contribution of 1.7 ppm in May and June. Simulated aquatic CO_2 signals are in phase with
 421 water levels as shown by the Equivalent Water Height anomalies. We consider this timing realistic, as CO_2 evasion
 422 from rivers and floodplains is enhanced at high water stages (Richey et al., 2002; Amaral et al., 2020), due to larger
 423 inundation areas and an increased water depth that leads to more respiration in the water column (Devol et al., 1995;
 424 Forsberg et al., 2017). Considering that the tower's STILT footprint during MJJ covers the main branch of the Amazon
 425 River (see Figure 6), we believe aquatic signals play an important role when interpreting the seasonal cycle of CO_2
 426 measurements at ATTO.

427 GPP was found to be negatively correlated with EC-NEE but not significantly ($r=-0.14$, $p\text{-value}=0.21$). There-
 428 fore, the offset of photosynthesis by R_{eco} suggests that the first is less important for $\Delta\text{CO}_{2_{\text{obs-bio}}}$ at the local scale.
 429 Nevertheless, the local processes controlling GPP during the dry and wet seasons are worth highlighting here. The
 430 gradual rise in GPP during the dry season is driven by increasing light availability and a younger age distribution of
 431 leaves in the canopy (Figure 6c). Note that PAR increases simultaneously with a decline in the old class of leaf area
 432 index (LAI) and the increment of the mature and young LAI classes. Such leaf demography dynamics are similar to
 433 what Wu et al. (2016) showed for other sites in Amazonia, and consistent with the dry season green-up reported
 434 by several in-situ (Restrepo-Coupe et al., 2013; Lopes et al., 2016) and regional (Huete et al., 2006; Doughty et al.,

2019) studies. Moreover, Wu et al. (2016) demonstrated that mature leaves are the most light-use efficient with the highest photosynthetic capacity ($\text{mol CO}_2 \text{ mol}^{-1} \text{ photon}^{-1}$) of all leaf age classes. Thus, the seasonal shift in LAI age classes produces a younger age composition of the canopy relative to the wet season, which on average has a higher photosynthetic capacity per leaf area (Wu et al., 2016; Albert et al., 2018). In addition, reduced GEP (interpreted here as GPP) for June and July was reported by Restrepo-Coupe et al. (2013) and Wu et al. (2016) for equatorial sites (e.g. Tapajós National Forest (K67), Cuieras Reserve (K34), and Caxiuana National Forest (CAX)).

4.1.2 | Drivers of inter-annual variability

Although our CO_2 time series is rather short for inferring inter-annual patterns, we present the response of $\Delta\text{CO}_{2_{obs}}$ and $\Delta\text{CO}_{2_{obs-bio}}$ to the 2015/2016 El Niño-induced drought (Figure 6a). Interestingly, the standardized anomalies of $\Delta\text{CO}_{2_{obs}}$ and $\Delta\text{CO}_{2_{obs-bio}}$ follow the same pattern, suggesting that the inter-annual variability is controlled by the vegetation signal and that contributions of rivers, fires, fossil fuels and ocean are negligible at this scale. For this reason, in the rest of this Section we refer to $\Delta\text{CO}_{2_{obs}}$ only, but the findings apply equally to $\Delta\text{CO}_{2_{obs-bio}}$.

The $>+1\sigma$ anomaly of $\Delta\text{CO}_{2_{obs}}$ in MJJ coincides with the onset of the El Niño, which started in June of 2015, with values above 1 according to the Multivariate El Niño Index (MEI) (Figure 6b). In the dry season of the same year (ASO), we observe a -1σ anomaly, illustrating a variable response of $\Delta\text{CO}_{2_{obs}}$ to El Niño in 2015. In contrast, in 2016 our observations reveal two $>+1.5\sigma$ anomalies, centered in the wet and dry seasons. Note that El Niño lasted until May in 2016, but the effects in $\Delta\text{CO}_{2_{obs}}$ seemed to persist well into the dry season of 2016.

It is interesting to note that the local EC-NEE (Figure 6a) anomaly is not always in phase with that of $\Delta\text{CO}_{2_{obs}}$. In 2015 the EC-NEE anomaly was in opposite sign to that of $\Delta\text{CO}_{2_{obs}}$ during MJJ and ASO, while in 2016 they followed similar patterns. Such differences in phase between EC-NEE and $\Delta\text{CO}_{2_{obs}}$ anomalies suggest that in 2015 the effects of El Niño at the EC-NEE scale were apparent only after ASO, whereas in the $\Delta\text{CO}_{2_{obs}}$ record it was already evident in MJJ. Therefore, the 2015 anomalies appear to be driven by a non-local (i.e. larger than the EC-NEE footprint) response to the El Niño. In contrast, the contribution to the positive anomalies in 2016 appears to be both at the local and non-local scales.

The variable response of the $\Delta\text{CO}_{2_{obs}}$ anomalies in 2015 are marked by an erratic behavior, showing opposing signs in MJJ (+) and ASO (-). The MJJ event is driven by an above average value in July, whereas that in ASO is pulled down by a negative value in September and October (not shown). Our eddy covariance data suggest that the $\Delta\text{CO}_{2_{obs}}$ positive anomaly in July can not be attributed to a local source of carbon, as the EC-NEE (see Figure S5) for 2015 was within the seasonal variability of the 2014-2019 record. The negative anomaly in ASO, can not be explain by local factors either. A reduction in the observed CO_2 mole fractions due to a deeper boundary layer height, a 15% percent increase with respect to 2014 as shown by Carneiro and Fisch (2020), is likely but non-local factors are yet to be studied. Interestingly, the GPP reductions in 2015 reported in Koren et al. (2018) and van Schaik et al. (2018) for the region that overlaps with our MJJ footprint (i.e. Region B in that study) have an onset in October, failing to explain our July observation and indicating that the effect of the extreme heat and drought had a late onset at ATTO.

The positive anomaly in $\Delta\text{CO}_{2_{obs}}$ during the dry season of 2016 has local and non-local contributions. Locally, a source of carbon in our EC-NEE record, driven by a higher than normal R_{eco} (Figure S5), can explain the $\Delta\text{CO}_{2_{obs}}$ 2016-ASO anomaly. Non-local drivers of this anomaly are attributed to a drought legacy effect (Kannenberg et al., 2020) that has been already characterized by Koren (2020) using atmospheric inverse modeling and remote sensing. Koren (2020) reported basin-wide positive anomalies in top-down-NEE and reductions in remote sensing proxies for GPP in the dry season of 2016. Persistent soil moisture depletion following the 2015/16 El Niño was put forward as a potential mechanism driving this legacy drought. A contributing factor to this 2016-dry-season anomaly, based on

476 the results by Wu et al. (2016) and Gonçalves et al. (2020), is that drought in 2015 caused some trees (approximately
477 15%) to undergo an anomalous leaf flush in March of 2016 (see Figure S6). This precocious flush altered the normal
478 leaf age distribution over the following months, such that the abundance of photosynthetically efficient mature-stage
479 leaves (2-6 months of age) was spread out over a longer period.

480 The meteorological effects of El Niño at local scale were measured later in 2015. Positive anomalies in air tem-
481 perature within and above the canopy together with soil temperature (Figure 6c) reached values close to $+2\sigma$ from
482 November of 2015 to February of 2016. The negative soil moisture anomalies in the last four months of 2015 were
483 driven by the negative precipitation anomalies during the same time (Figure 6d,e). The soil moisture anomalies at 40
484 cm and 100 cm bounced back to values higher than -1σ in March 2016. However, even when precipitation returned
485 to close-to-climatology values in February and March 2016, soil moisture at 10 cm depth did not fully recover until late
486 2016. This pattern shows a fast recovery in deep soil moisture compared to a persistent ($<-1\sigma$) soil moisture anomaly
487 at 10 cm depth. The re-wetting of deeper layers, together with a still high soil temperature anomaly at 20 and 40 cm
488 depth, could have reactivated heterotrophic respiration leading to above-average soil respiration rates during the wet
489 season of 2016 (see Figure S5).

490 The $\Delta\text{CO}_{2_{obs}}$ anomalies in the transition months of NDJ in 2018 and 2019 occurred in the absence of a large scale
491 climate-driven phenomenon. Based on the EC-NEE response, it seems that both $\Delta\text{CO}_{2_{obs}}$ anomalies are due to non-
492 local signals. During the 2018-NDJ event, all meteorological variables (air temperature, soil moisture and temperature,
493 and precipitation) were within the 1σ range. To interpret the signals in 2019, it is worth mentioning two aspects. First,
494 the 2019-NDJ average contains values only for November and December, as January data were not yet available
495 at the time of writing. Second, the year 2019 was characterized by widespread fires driven by deforestation which
496 began early in the year (Barlow et al., 2020). Thus, we suggest that the 2019-NDJ positive anomaly could have a
497 contribution from fires, but the magnitude could be reduced when the January average is included.

498 4.2 | STILT tagged tracer simulations

499 4.2.1 | Simulated CO_2 and spatial distribution at seasonal scale

500 At the ATTO site, a clear seasonal variation of the footprint throughout the year (Figure 6a) can be observed, consis-
501 tent with the large scale atmospheric circulation of the intertropical convergence zone (ITCZ) previously described
502 in Andreae et al. (2012) and Pöhlker et al. (2019). The seasonal atmospheric circulation affects the mole fractions
503 measured at ATTO by varying the areas of near- and far-field influence of the surface fluxes and also the origin of the
504 background air masses. In general, during the wet season ATTO is located to the north of the ITCZ and is under the
505 influence of the air coming from the Northern Hemisphere (NH), whereas during the dry season, the station is located
506 south of the ITCZ, and thus the long range transport is from the Southern Hemisphere (SH) (Andreae et al., 2015). It
507 is worth highlighting that during MJJ and ASO the main branch of the Amazon River is well covered by the 50th and
508 75th footprint percentiles.

509 The different NEE fluxes used as inputs in STILT show large spatial variability amongst them (Figure 6b-d). While
510 CTE2020 and CT-SAM-Flask follow a similar spatial pattern, CT-SAM-OCO2 tends to predict a larger source of carbon
511 to the atmosphere in MJJ. When comparing the bottom-up fluxes (Figure 6e-f) to those resulting from atmospheric
512 inversions, it is clear that the former shows a stronger sink, which is particularly visible in the FLUXCOM data. The main
513 differences between FLUXCOM and VPRM are the source regions in NDJ and ASO, more pronounced in FLUXCOM
514 than in VPRM. Despite the aforementioned differences, in the core of the dry season (ASO) all products are consistent
515 (with varying extent and magnitude) in the source regions in northeastern Brazil, in the states of Ceará, Pernambuco,

516 Bahía, Piauí and Tocantins (see Figure S7 for the names and locations of the northeastern states of Brazil).

517 We find that none of the simulations accurately capture the amplitude of $\Delta\text{CO}_{2_{obs}}$. Only in the case of FLUXCOM,
518 does the shape of the seasonal cycle show a decline in the dry season and a wet-to-dry season increase similar to
519 the pattern observed at ATTO. The latter increase is also better predicted if the original product is augmented with
520 additional fluvial fluxes (compare both panels in Figure 6). However, FLUXCOM-driven mole fractions predicted by
521 our model are constantly lower than our measurements by 5 ppm, indicating a strong and persistent uptake of CO_2
522 (negative NEE) as shown in Figure 6. Such a strong sink was expected, as this product was previously found to have
523 a too strong tropical carbon sink, due to a mixture of systematic biases in the eddy-covariance data used in upscaling,
524 and the lack of site history effects on NEE (Jung et al., 2020). Simulations of $\Delta\text{CO}_{2_{sim}}$ based on VPRM, CTE2020,
525 CT-SAM-Flask and CT-SAM-OCO2 fluxes show a very different seasonal cycle than $\Delta\text{CO}_{2_{obs}}$, showing an earlier and
526 more rapid drop to a minimum in July. In terms of the amplitude of the seasonal cycle, VPRM predicts the largest with
527 5.94 ppm, followed by CTE2020 with 5.88 ppm, CT-SAM-OCO2 with 5.07 ppm, CT-SAM-Flask with 4.94 ppm and
528 finally FLUXCOM with 3.21 ppm. The last two are the closest to the observed $\Delta\text{CO}_{2_{obs}}$ of 4.14 ppm.

529 The accuracy of the VPRM simulations was worse than expected considering that the model parameters were cal-
530 ibrated using eddy covariance measurements at several sites within Amazonia (Mahadevan et al., 2008). We find that
531 the dry season increase in VPRM- $\Delta\text{CO}_{2_{sim}}$ could be triggered by increasing simulated R_{eco} associated with increasing
532 temperature. VPRM represents R_{eco} as a linear function of temperature and does not include the effects of moisture
533 (Mahadevan et al., 2008). Furthermore, the decrease in VPRM- $\Delta\text{CO}_{2_{sim}}$ from May to July, which anticipates that of
534 $\Delta\text{CO}_{2_{obs}}$ by a month, could also be associated with the lack of moisture effects in R_{eco} . Note that the eddy covariance
535 R_{eco} is higher than GPP from May to June in Figure 6b, suggesting an overall source of carbon to the atmosphere.

536 4.2.2 | Simulated inter-annual variability and tracer contribution

537 In general, the observed inter-annual variability is not well captured by our STILT simulations (Figure 6a). In particular
538 for the 2015 and 2016 anomalies associated with El Niño, the simulations show either an anticipation of the anomaly
539 (i.e. 2015-NDJ) or output a signal with an opposite sign (i.e. 2016-ASO). Despite the spread between models in 2014-
540 MJJ, 2015-MJJ and 2018-FMA, it is worth highlighting the general agreement between them, not only in 2015-NDJ
541 and 2016-ASO but also in 2017-ASO, 2018-ASO, 2019-ASO and 2019-NDJ. The latter indicates that the disagree-
542 ment between simulations is largest in the first part of the year, in which the influence of river CO_2 is predicted to be
543 highest.

544 The influence of rivers, fires, fossil fuel emissions and ocean fluxes on the simulated CO_2 signal is very small
545 compared to that of NEE (Figure 6b-e). Note that the simulated NEE contribution in general tends to show a sink of
546 CO_2 , mainly in the transition from wet to dry season, in contrast to $\Delta\text{CO}_{2_{obs}}$ and $\Delta\text{CO}_{2_{bio}}$. For the $\Delta\text{CO}_{2_{bio}}$ the signal
547 from rivers, fires, fossil fuels and ocean was subtracted, which did not change the seasonal pattern when compared
548 to $\Delta\text{CO}_{2_{obs}}$. Rivers contribute with 1 to 2 ppm depending on the month of the year. Note that the spatial resolution
549 of the gridded flux for rivers is coarse ($1^\circ \times 1^\circ$) and we have used a monthly climatology from Hastie et al. (2019) in
550 STILT, thus the variable magnitude from year to year in the river tracer is mainly due to atmospheric transport. Fires
551 and anthropogenic emissions (fossil fuels in equations 1, 2) add up to a contribution ranging from 0.2 to 0.4 ppm,
552 concentrated in the dry season. The ocean is the least significant tracer component, contributing less than 0.1 ppm to
553 the regional signal, reaching the highest values during NDJ. These simulations highlight the relevance of CO_2 evasion
554 at the ATTO site.

555 When evaluating the model performance at a monthly scale, the CT-SAM-OCO2 simulation was the best, with an
556 RMSE of 4.15 ppm. Note that the CT-SAM-OCO2 simulations were performed only for three years (i.e. 2015-2017).

557 The VPRM and the CT-SAM-Flask followed with RMSE values of 4.21 ppm and 4.63 ppm respectively. CTE2020 and
558 FLUXCOM had higher RMSE values with 4.96 ppm and 5.6 ppm. These RMSE scores are indicative of regional fluxes
559 not covered by our footprints or the LBC, or from differences in vertical transport between the STILT model used for
560 the footprints relative to the TM5 model (used in CarbonTracker).

561 5 | DISCUSSION

562 5.1 | Decomposing the $\Delta\text{CO}_{2_{obs}}$ signal

563 We showed that $\Delta\text{CO}_{2_{obs}}$ is controlled by local and non-local factors. The phase match/mismatch at seasonal and
564 inter-annual scales between EC-NEE and $\Delta\text{CO}_{2_{obs}}$ was described as an indicator of the different spatial extents driv-
565 ing $\Delta\text{CO}_{2_{obs}}$. Amongst the local factors analyzed was EC-NEE, which was partitioned into GPP and R_{eco} to better
566 understand the underlying processes contributing to the local net flux. GPP and R_{eco} presented a considerable sea-
567 sonal variation, mainly characterized by a R_{eco} -dominated wet season and a late dry season increase in both GPP and
568 R_{eco} . Seasonally, we found that EC-NEE was mainly controlled by R_{eco} . However, it is worth mentioning that when
569 leaving 2015 and 2016 out of our analysis, we see a clear sink in the EC-NEE during the dry season. In contrast, focus-
570 ing only on 2015 and 2016 we observe a suppression of GPP during the dry season and EC-NEE shows a sustained
571 source as R_{eco} is always larger than GPP. Therefore, seasonally we observed a larger role of R_{eco} and a clear effect of
572 the 2015/2016 El Niño in GPP, R_{eco} , EC-NEE and $\Delta\text{CO}_{2_{obs}}$ (see Figure 6).

573 At a more regional scale, the effects of the 2015/2016 El Niño-induced drought in Amazonia have been stud-
574 ied from multiple perspectives. The immediate effects of the drought (namely occurring in 2015 and 2016) caused
575 reductions in GPP (Liu et al., 2017; van Schaik et al., 2018) (in line with our local measurements) and sun-induced flu-
576 orescence (SiF) (Koren et al., 2018; Castro et al., 2020). The study of Castro et al. (2020), which described the effect
577 of the 2015/2016-El Niño event on SiF across the Amazon basin, sheds light on the variable response of vegetation
578 to drought. At the regional scale, they found a widespread reduction in SiF, yet at the eco-region scale where ATTO is
579 located, SiF reductions were comparatively less. However, Doughty et al. (2021) found positive anomalies in SiF and
580 GPP at the Amazon basin scale and at the grid cell in which ATTO is located. Therefore, the debate about the sign
581 of the anomaly in 2015 remains open. The effects of the 2015/2016 El Niño drought caused long-term impacts on
582 vegetation, Wigneron et al. (2020) found that the above-ground carbon stocks did not recover until 2017. Further-
583 more, top-down studies of previous droughts (Gatti et al., 2014; van der Laan-Luijkx et al., 2015) have shown that
584 the Amazon carbon budget can turn from almost neutral in a wet year (i.e., 2011), into a source during drought (i.e.,
585 2010). A reduction in biospheric uptake and an increase in CO_2 fire emissions were suggested as the main causes for
586 the regional response in 2010, which was well captured by widespread aircraft measurements of CO_2 concentrations
587 over the basin. Given these previous findings, local/non-local GPP reductions, long-term vegetation effects and fire
588 emissions are factors that can in principle influence $\Delta\text{CO}_{2_{obs}}$, in addition to the role of R_{eco} and river signals, which
589 were presented in our results. However, for the present study we found that even during the 2015/2016-El Niño the
590 fire contribution to the local measurements was very small (see Figure 6), yet we do not rule out that this can be more
591 important in the future, with a possible expansion of the agricultural frontier within the $\Delta\text{CO}_{2_{obs}}$ footprint.

592 The differential response of vegetation within the seasonally-changing footprint is an important non-local driver
593 of $\Delta\text{CO}_{2_{obs}}$ that is worth discussing further. We have already mentioned the findings of Castro et al. (2020) in which
594 they showed substantial variability of SiF at the eco-region scale. However, within the ATTO eco-region the SiF
595 reductions were not as large as those regionally, which is in contrast to the effect of the 2015/2016-El Niño on GPP
596 at ATTO, which showed a notable reduction in 2015 (see Figure S5). This apparent discrepancy remains to be studied

597 further, however some plausible hypotheses are a non-linear behavior between SiF and GPP caused by extreme heat
598 and drought (Martini, D. 2021 personal communication) in 2015 or that the GPP reduction observed at ATTO was a
599 local phenomenon within the eco-region used in Castro et al. (2020). Nevertheless, Doughty et al. (2021) showed a
600 linear relationship of GPP and SiF at different spatial scales, so the discrepancy of our eddy tower GPP with both SiF
601 studies remains to be studied further.

602 Now, shifting to a more seasonal perspective, sites at the Tapajós National Forest (K67 and K83) and Caxiuanã
603 (CAX) show a dry-season increase in GPP, which is driven by leaf age and not by seasonal LAI (Wu et al., 2016). It
604 is interesting that at ATTO we observe this dry-season GPP increase on the mean seasonality, yet the amplitude
605 of EC-NEE is different at all sites, being larger at the Tapajós sites followed by ATTO, CAX and K34 (Saleska et al.,
606 2009). At the sites with larger EC-NEE amplitude, the role of R_{eco} modulating the EC-NEE is more important, which
607 in turn is determined by the annual average rainfall as shown by Saleska et al. (2009). A further example of regional
608 heterogeneity is given by the study of Restrepo-Coupe et al. (2013), in which they showed that sites where the dry
609 season is very long or the soil is shallow, GPP does not increase during the dry season. This is the case for Rondônia,
610 which has a long dry season similar to the Tapajós sites but with a shallow rocky soil, while Tapajós has deep soil which
611 buffers the water available to plants (Nepstad et al., 2007).

612 The seasonal patterns of R_{eco} can be grouped into water-limited and oxygen-limited sites (Saleska et al., 2009).
613 Water-limited sites, like the one in the Tapajós National forest (Saleska et al., 2003; Hutyrá et al., 2007), exhibit dry
614 season declines of R_{eco} as a result of an inhibited heterotrophic respiration due to a long dry season length that leads
615 to the desiccation of decomposition sources near the surface (Saleska et al., 2003). The soil component of R_{eco} at
616 oxygen-limited sites is inhibited with increasing soil moisture content, which is the case for K34 (Chambers et al.,
617 2004). Our results suggest that the R_{eco} at ATTO follows an oxygen-limited regime with a MAP of 2383 mm yr⁻¹
618 despite having a relatively long dry season length (3 months, see Table 1). Note that when including 2015 and 2016
619 in our analysis, R_{eco} does not show an increase in October, being suppressed during the dry season (see Figure 6).
620 Therefore, the response of R_{eco} to disturbance at ATTO is in contrast to what was reported by Davidson et al. (2004)
621 after a rainfall exclusion experiment for another site located on clay-dominated soil, where no significant effect was
622 found.

623 One of the novelties of our study is the use of results from the recently-developed model (ORCHILEAK) for
624 aquatic CO₂ evasion in Amazonia (Hastie et al., 2019) as an input in our atmospheric transport simulations. We have
625 shown that the seasonal peak of $\Delta\text{CO}_{2_{obs}}$ in June and July is influenced by a net carbon source driven by R_{eco} and the
626 CO₂ evaded from rivers. The aquatic signal peaks in May and June (Figure 6), just when the $\Delta\text{CO}_{2_{obs}}$ footprint covers
627 the main branch of the Amazon River, including its delta (see MJJ in Figure 6 and 6). Therefore, we suggest that the
628 $\Delta\text{CO}_{2_{obs}}$ maximum in June has a larger contribution of CO₂ from rivers, while in July R_{eco} could be more relevant in
629 the $\Delta\text{CO}_{2_{obs}}$. We furthermore highlight that by adding aquatic CO₂ signals to FLUXCOM- $\Delta\text{CO}_{2_{sim}}$: The shape of the
630 seasonal cycle is closer to that of $\Delta\text{CO}_{2_{obs}}$, indicating that aquatic CO₂ evasion is important to correctly represent the
631 seasonal cycle of CO₂ mole fractions at ATTO.

632 A full error propagation from the river flux fields to our simulated tracer is out of the scope of this study. How-
633 ever, we provide an estimate for the relative error of about 35% for the river flux fields, which scales linearly to our
634 simulated river signals. This estimate was based on Hastie et al., (2019), specifically the annual CO₂ evasion of 746
635 (526-998) Tg C per year. It is important to note that this relative error has to be interpreted with caution, as our atmo-
636 spheric transport model (STILT) has a higher spatial resolution and the footprints do not cover the entire basin as the
637 ORCHILEAK model does. This model represents an important advance in coupling the terrestrial carbon cycle with the
638 lateral forest-river continuum, though the additional sources of uncertainty can be highlighted here. In ORCHILEAK
639 the carbon sources of the CO₂ degassed from aquatic surfaces are attributed to: (1) dissolved organic carbon (DOC)

640 and dissolved CO₂ transported laterally from the upland soil and (2) decomposition of submerged organic carbon
641 and litter and respiration of submerged roots in wetlands and rivers (see Lauerwald et al. (2017) and Lauerwald et al.
642 (2020)). Lateral transport from upland soil (1) is important for small streams (Johnson et al., 2006, 2007), which are
643 lacking in ORCHILEAK. In addition, the lack of aquatic plants in ORCHILEAK introduces uncertainty in (2). Including
644 small streams and aquatic plants in ORCHILEAK would enable the model to better simulate CO₂ evasion from aquatic
645 habitats.

646 5.2 | Fluxes are the major source of error in STILT simulations

647 Our study is the first to use the CO₂ ATTO record to independently evaluate optimized and non-optimized gridded
648 NEE fluxes when transported in the atmosphere. From this evaluation we highlight two main important findings. The
649 first is that none of the simulations, including the ones using optimized fluxes, accurately reproduce the seasonal cycle
650 of the observed signal ($\Delta\text{CO}_{2_{obs}}$), which represents the regional flux and atmospheric transport influence. $\Delta\text{CO}_{2_{obs}}$
651 is almost always lower than the background inflow, indicating a sustained regional sink of CO₂. The second, is the
652 importance of river CO₂ signals at ATTO when interpreting the CO₂ measurements and simulated biospheric signals.
653 We showed that the phase of the seasonal cycle is better captured by FLUXCOM only when adding river signals
654 (Figure 6), and that the amplitude of the seasonal cycle is overestimated by 0.8 ppm to 1.8 ppm (CT-SAM-Flask and
655 VPRM).

656 We attribute the incapability of our system to accurately simulate $\Delta\text{CO}_{2_{obs}}$ mainly to errors in the input fluxes,
657 which fail to capture the seasonal variability of NEE in the footprint area. Dynamic vegetation models are known to
658 have difficulties simulating the seasonality of carbon fluxes in the equatorial (5°S to 5°N) band of Amazonia (Verbeeck
659 et al., 2011; Restrepo-Coupe et al., 2017), but here we show that even when NEE of a process-based model (such
660 as SiBCASA) is optimized with different data streams (using surface CO₂ observations CTE2020, additional aircraft
661 profiles within the Amazonia CT-SAM-Flask and, satellite columns CT-SAM-OCO2), it does not capture the seasonality
662 of $\Delta\text{CO}_{2_{obs}}$ sampled at ATTO. This finding is similar to that of Molina et al. (2015), in showing the difficulties of
663 reproducing the seasonal cycle of NEE after an atmospheric inversion, but we further show the remaining challenges
664 of a denser observational network, which could either be aircraft profiles (e.g., CT-SAM-Flask) within Amazonia or
665 satellite columns (e.g., CT-SAM-OCO2). A still limited observational coverage, even with the aircraft network and the
666 OCO2 columns, is perhaps one of the main remaining challenges.

667 The mismatch between the optimized fluxes and $\Delta\text{CO}_{2_{obs}}$ at inter-annual scale could be related to an incorrect
668 seasonality in the prior NEE flux (i.e. NEE before optimization), but also to the frequency and spatial distribution of
669 observations used in the assimilation. For CTE2020, CT-SAM-Flask and CT-SAM-OCO2 the same prior model is used
670 (i.e. SiBCASA), but different data streams are assimilated. Tests indicate that the use of the same NEE prior leads to
671 a similar shape of the seasonal cycle in the posterior NEE (not shown) and thus the $\Delta\text{CO}_{2_{sim}}$ in this study, regardless
672 of the data assimilated for the optimization. Furthermore, the effects of temperature, soil moisture and precipitation
673 anomalies in the underlying prior biosphere models (in particular for VPRM and SiBCASA) could produce inaccurate
674 vegetation NEE responses in terms of timing and/or sign. This could result in NEE fluxes with either an early too
675 strong source (i.e. 2015-NDJ) or the opposite in sign in the same month possibly due to an enhanced uptake (i.e.,
676 2016-ASO).

677 This study is the first time that the FLUXCOM NEE product has been evaluated using atmospheric transport to
678 obtain CO₂ mole fractions at a particular site in the tropics. Interestingly, we found similar inter-annual patterns in
679 $\Delta\text{CO}_{2_{sim}}$ to those using the optimized fluxes, but not with the observations. Jung et al. (2020) found a consistency in
680 NEE anomalies between FLUXCOM and atmospheric inversions at global scales, and here we show that this finding

681 holds at regional scales when using FLUXCOM in simulations of atmospheric CO₂. According to Jung et al. (2020),
682 the reasons for the global consistency between FLUXCOM and atmospheric inversions are: 1. a spatial compensation
683 of processes that are not well represented by the underlying model formulations and 2. the tendency of such models
684 to be more sensitive to temperature signals, which are more important at larger spatial scales, as discussed in detail
685 by Jung et al. (2017). Here we suggest that the spatial scale of our analysis can still suffer from the weaknesses
686 listed above. In particular, note that the temperature sensitivity can be spotted by comparing Figures 6a and 6a; the
687 bottom-up and top-down simulations converge in a 2σ anomaly in 2015-NDJ, coinciding with temperature anomalies
688 of similar magnitude.

689 Inter-annual drought-induced impacts on vegetation in Amazonia can include: shifting carbon allocation from
690 the canopy to fine roots following drought (Doughty et al., 2014), reduced growth due to water stress and warm
691 temperatures (Clark et al., 2010), prioritizing growth at the expense of maintenance and defence (Doughty et al., 2015),
692 and increased tree mortality (da Costa et al., 2010; Wang et al., 2012) together with reduced vegetation productivity
693 (Feldpausch et al., 2016). In addition to the mechanisms listed above, the implementation of the different seasonal
694 phenological stages (as shown in Figure 6 but also by Restrepo-Coupe et al. (2013), Lopes et al. (2016) and Wu et al.
695 (2016)) needs to be improved in dynamic vegetation models as well as in process-based biosphere models, to produce
696 more accurate NEE and thus $\Delta\text{CO}_{2_{sim}}$ estimates. Improving the sensitivity of tropical vegetation in dynamic vegetation
697 models to water availability could also reduce the disagreement between top-down and bottom-up estimates for the
698 global carbon budget (Bastos et al., 2020).

699 Atmospheric transport uncertainties are also a source of errors in our simulations, mainly associated with the
700 model's capability to resolve moist (deep) convection (Betts et al., 2009), vertical mixing within the boundary layer
701 (Gerbig et al., 2008) and advection (i.e., wind speed and wind direction) correctly. The seasonality of convection
702 in STILT shows more activity during the wet season (FMA) over the footprint area, consistent with the timing of
703 convective events reported by Horel et al. (1989). Therefore, the probability of a particle being captured by an updraft
704 or downdraft is higher during the wet season. We are aware that errors in representing deep convection could lead
705 to a potential bias in the turnover time of the air between the mid and upper troposphere and the boundary layer.
706 We acknowledge this limitation, but if present, such a bias is more likely to occur in the wet season. STILT is as good
707 as the driving meteorological fields and their ability to capture convective events. Convection is a sub-grid process
708 that can impact the ability of Eulerian models to reproduce tracer transport at the mesoscale in Amazonia (Beck et al.,
709 2013) and it can also be triggered by small scale processes (Burleyson et al., 2016), which present difficulties for their
710 representation in atmospheric transport models. Thus, using higher spatial resolution driving fields, such as ERA5 (C3S,
711 2017), is expected to improve the model's representation of convection, as shown specifically for Lagrangian models
712 by Hoffmann et al. (2019). To reduce vertical mixing errors, we filter both the STILT simulations and the observations,
713 so as to obtain only afternoon values (13:00-17:00 LT) (see in Figure S4 the convergence of simulated and observed
714 CO₂ in the afternoon).

715 Moreover, to evaluate advection errors at the receptor height (80 m), we compared local wind speed and direction
716 measured at ATTO with the simulated quantities. We found a small bias in wind speed (-0.08 m s^{-1}) and a moderate
717 bias in wind direction (-39°). However, when evaluating directly the errors of the driving meteorological winds using
718 three afternoon (14:00 LT) radiosondes at ATTO, we found that they decrease with height (Figure S9). This indicates
719 that as the particle trajectories reach higher elevations, the error tends to decrease; the particle height after 2 days
720 of back trajectory was on average 1400 m. A study using a Lagrangian model to evaluate the role of the Amazon
721 Basin moisture in the hydrological cycle (Drumond et al., 2014) supports the orientation of the footprints shown here.
722 Drumond et al. (2014) show that moisture sources in Amazonia during the austral summer are coming from the tropical
723 North Atlantic Ocean, which is in line with our footprints for NDJ and FMA. Overall, given these findings, we conclude

724 that the errors in fluxes are much larger than those in transport.

725 6 | CONCLUSIONS AND OUTLOOK

726 In this study we presented and analysed the first six years of the CO₂ record from the Amazon Tall Tower Observa-
727 tory. Using a Lagrangian atmospheric transport model we evaluated how well we could reproduce the observed CO₂
728 concentrations at ATTO. By combining atmospheric transport from STILT with a set of different NEE flux products,
729 we found that the inversion results were not able to constrain the seasonal variability of $\Delta\text{CO}_{2_{obs}}$ in the footprint of
730 the tower and very likely at the regional scale. It seems that the optimized products cannot adjust the prior seasonal
731 cycle of NEE regardless of the data stream assimilated. Furthermore, we have presented evidence of the importance
732 of river CO₂ evasion for getting the shape (but not the magnitude) of the seasonal cycle when using the FLUXCOM
733 product, mainly capturing the increase in $\Delta\text{CO}_{2_{obs}}$ from May to July. We have further shown that the main controls
734 of $\Delta\text{CO}_{2_{obs}}$ at seasonal and inter-annual scales result from the combined effect of local and non-local drivers, which
735 can be inferred by the phase difference in EC-NEE and $\Delta\text{CO}_{2_{obs}}$.

736 This is not the first study to highlight the underlying processes that should be better represented in biosphere
737 models, but it is the first evaluation of bottom-up and top-down NEE fluxes using an independent station with a
738 long-term and continuous record in Amazonia. We therefore highlight the potential of the ATTO station, and the
739 upcoming 325 m continuous record, as an independent validation site for atmospheric transport of CO₂ and for
740 regional inversion estimates, which we are currently working on. Equally important are the seasonal patterns of carbon
741 exchange, ecosystem respiration and leaf phenology that we have presented here, which add to the current body of
742 literature (Saleska et al., 2003; von Randow et al., 2004; Hutyra et al., 2007; Baker et al., 2008; Restrepo-Coupe et al.,
743 2013; Wu et al., 2016; Lopes et al., 2016) and provide in-situ information for constraining the heterogeneity of these
744 processes in Amazonia. These findings are of utmost importance for regional carbon budget assessments, like the
745 RECCAP2 initiative (<https://climate.esa.int/en/projects/reccap-2/>). By guiding the choice of prior fluxes to
746 estimates with better NEE seasonality, improved posterior flux distributions and thus, regional carbon budgets, can
747 be attained.

748 acknowledgements

749 This work and the ATTO project was funded by the German Federal Ministry of Education and Research (BMBF,
750 contracts 01LB1001A and 01LK1602A) and supported by the International Max Planck Research School for Global
751 Biogeochemical Cycles (IMPRS-gBGC). The ATTO project is furthermore funded by the Brazilian Ministério da Ciência,
752 Tecnologia e Inovação (MCTI/FINEP contract 01.11.01248.00) and the Max Planck Society. We acknowledge the
753 Instituto Nacional de Pesquisas da Amazonia as well as the Amazon State University (UEA), FAPEAM, LBA/INPA and
754 SDS/CEUC/RDS-Uatumã for continuous support and logistical management. Many thanks to the people coordinating
755 the scientific support at ATTO, in particular Susan Trumbore, Carlos Alberto Quesada, Bruno Takeshi, and Reiner Ditz.
756 We want to thank all the personnel at the research site involved in technical and logistical support, especially Andrew
757 Crozier, Stefan Wolff, Sam Jones, Leonardo Ramos de Oliveira, Nagib Alberto de Castro Souza, Roberta Pereira de
758 Souza, Amauri Rodrigues Pereira, Hermes Braga Xavier, Wallace Rabelo Costa, Antonio Huxley Melo Nascimento, Uwe
759 Schultz, Thomas Seifert, Steffen Schmidt and Thomas Disper. We express our gratitude to the data providers, Jessica
760 Baker (Figure 1, underlying vegetation) and Rosa Santos (Radiosondes for evaluation), Sophia Walter and Martin Jung
761 (FLUXCOM), Christian Roedenbeck (Jena Carboscope) and Ronny Lauerwald (river fluxes - ORCHILEAK). Many thanks

762 to John Melack for his fruitful comments about CO₂ river evasion measurements and regional estimates. Finally, we
763 would like to acknowledge the two anonymous reviewers, whose comments improved the paper significantly. W.P.
764 and G.K. were funded by an ERC-Consolidator grant (649087) as part of the ASICA (Airborne Stable Isotopes of
765 Carbon from the Amazon) project.

766 **conflict of interest**

767 The authors declare no conflicts of interest.

Accepted Article

Figure captions

Figure 1. The 50th and 75th percentiles for the seasonally averaged footprint for NDJ and FMA (left panel) and MJJ and ASO (right panel) overlap with the distribution of intact forest (dark green), non-intact forest (pale green), moderately deforested (pink) and severely deforested (magenta). Cerrado and Caatinga biomes are labeled but not coloured. The ATTO site is indicated with a red triangle. The distribution of vegetation state is taken from Baker and Spracklen (2019).

Figure 2. Monthly time series of the ATTO CO₂ measurements together with the simulated background concentrations without bias correction (continuous blue line) and with bias correction (dashed blue line) (a). The observed mole fractions at ATTO (measurement height 79 m) are shown in a thicker black line in (a) and the error bar represents $\pm 1 \sigma$. The thin black line represents the linear trend fitted using the Theil-Sen slope. In (b) the seasonal cycle of the regional signal ($\Delta\text{CO}_{2_{obs}}$) is shown. The grey shading represents the min-max range given by the spread of the independent $\Delta\text{CO}_{2_{obs}}$, calculated using the interpolation between ASC and RPB, and the bias corrected $\Delta\text{CO}_{2_{obs}}$. To aggregate to monthly averages we selected only daytime values (i.e. 13:00-17:00 LT) to ensure well-mixed conditions in the PBL. The dry and wet seasons in (b) are the climatological seasons calculated with the TRMM dataset described in Section 3.1.

Figure 3. Mean seasonal cycle of the observed CO₂ regional signal $\Delta\text{CO}_{2_{obs}}$ and $\Delta\text{CO}_{2_{obs-bio}}$, together with monthly box-and-whisker plots of the eddy-covariance-derived NEE (EC-NEE) flux are shown in (a). Note that the EC-NEE includes the storage flux and the means are shown as triangles connected by a dotted line. Averaged seasonal cycles of Gross Primary Productivity (GPP) and ecosystem respiration (R_{eco}) (b) and, of Photosynthetic Active Radiation (PAR) together with the age classes of Leaf Area Index (LAI) (c). In (d) the monthly mean precipitation from the TRMM dataset (1998-2019), the STILT-simulated averaged seasonal signal of CO₂ [ppm] evasion from rivers (see Table 2 to see input fluxes used in STILT) and the Equivalent Water Height anomalies from the Gravity Recovery and Climate Experiment (GRACE) are shown (all available at: <https://grace.jpl.nasa.gov/data-analysis-tool/>. Last access: February 02, 2021). The area over which the GRACE data were integrated is marked with a purple square in the small inset on the lower right of (d). The markers in (a) and (b) are shifted to improve visibility and all the error bars represent the monthly standard deviation. The shaded areas in the background highlight the wet (Feb-Jun) and dry (Jul-Nov) seasons. The dry and wet seasons are the climatological seasons calculated with the TRMM dataset described in Section 3.1.

Figure 4. Standardized anomalies of $\Delta\text{CO}_{2_{obs-bio}}$, $\Delta\text{CO}_{2_{obs}}$ and EC-NEE (a) averaged over three-month periods, calculated against the 2014-2019 period, centered on the wet (FMA) and dry (ASO) seasons, with transition periods in between (MJJ and NDJ). The error bars denote the standard deviation for each season, calculated before aggregating to the seasonal mean. Thus, it shows the internal variation of each season for each year. In (b) the bi-monthly Multivariate El Niño index shows the strength of the El Niño event as measured by five different variables and aggregated in one index (data obtained from: <https://psl.noaa.gov/enso/mei/>; accessed on June 10, 2020), with values higher than 0.5 corresponding to a strong El Niño event. In the last panels, we show monthly standardized anomalies of air temperature at 81, 26 and 4 m and soil temperature at 20 and 40 cm (c), soil moisture at 10, 40 and 100 cm in (d) and precipitation (e). Soil moisture, air and soil temperature were measured at the ATTO site. Precipitation is taken from the TRMM dataset (1998-2019).

Figure 5. Seasonally-averaged concentration footprint (row a) for the inlet level of 80 m. These footprints were calculated with the output of hourly simulations of the STILT model covering the 2014-2019 time period. The first column in row (a) shows the regional context of the footprints and highlights the area shown in the rest of the panels. The ATTO site is indicated with a red marker. In the rest of the panels the location of the research site is indicated by the intersection of the parallel and meridian lines. NEE fluxes are shown in rows b to f.

811 Figure 6. Mean seasonal cycle of the regional signal for each of the simulated ($\Delta\text{CO}_{2_{sim}}$) and observed ($\Delta\text{CO}_{2_{obs}}$)
812 mole fractions of CO_2 . On the left panel the simulations using bottom-up NEE fluxes (i.e. VPRM and FLUXCOM)
813 include the river signals. On the right panel river signals are not included in the bottom-up NEE fluxes, shown with
814 a dashed line. The error bar in the observations represents $\pm 1 \sigma$. For the simulated and observed mole fractions
815 we selected only daytime values (i.e. 13:00-17:00 LT) to ensure well-mixed conditions in the PBL. The dry and wet
816 seasons in are the climatological seasons calculated with the TRMM dataset described in Section 3.1.

817 Figure 7. Standardized anomalies of $\Delta\text{CO}_{2_{obs}}$ and the simulated tracers in STILT (a) averaged over three-month
818 periods, calculated against the 2014-2019 period and centered on the wet (FMA) and dry (ASO) seasons, with tran-
819 sition periods in between (MJJ and NDJ). The error bars denote the standard deviation for each season, calculated
820 before aggregating to the seasonal mean. Thus, it shows the internal variation of each season for each year. Note
821 that CT-SAM-OCO2 is not shown here since we did not have enough simulated years to calculate an anomaly. The
822 climatological standard deviation used for the standardization is shown in Figure ?? . The monthly contribution of
823 simulated NEE, $\Delta\text{CO}_{2_{obs}}$ and $\Delta\text{CO}_{2_{bio}}$ is shown in (b). $\Delta\text{CO}_{2_{bio}} = \Delta\text{CO}_{2_{obs}} - (\text{river}, ff, fires, ocean)$. In (c), (d) and (e),
824 the contribution of rivers, oceans and fires and fossil fuels are shown. Note the different scales on the y-axis.

825 Figure 8. Regional CO_2 signal ($\Delta\text{CO}_{2_{obs}}$) and EC-NEE averaged over non-ENSO years (2014, 2017-2019) (a) and
826 ENSO years 2015-2016 (b). In (c) and (d) the same time periods are shown but for GPP and R_{eco} .

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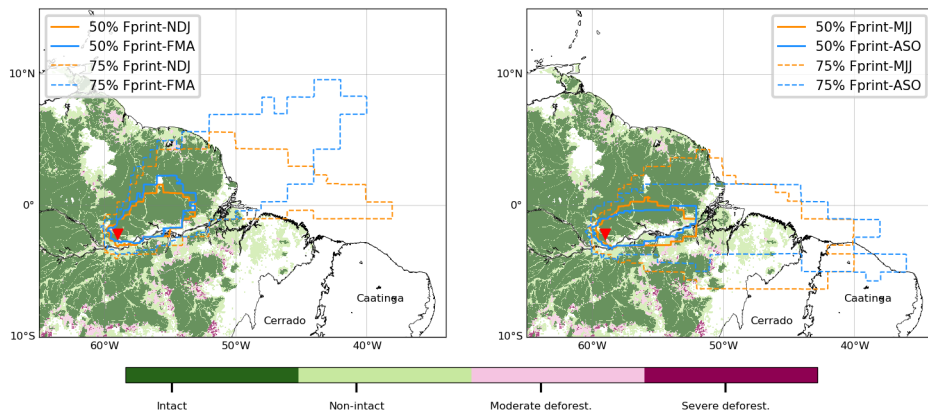
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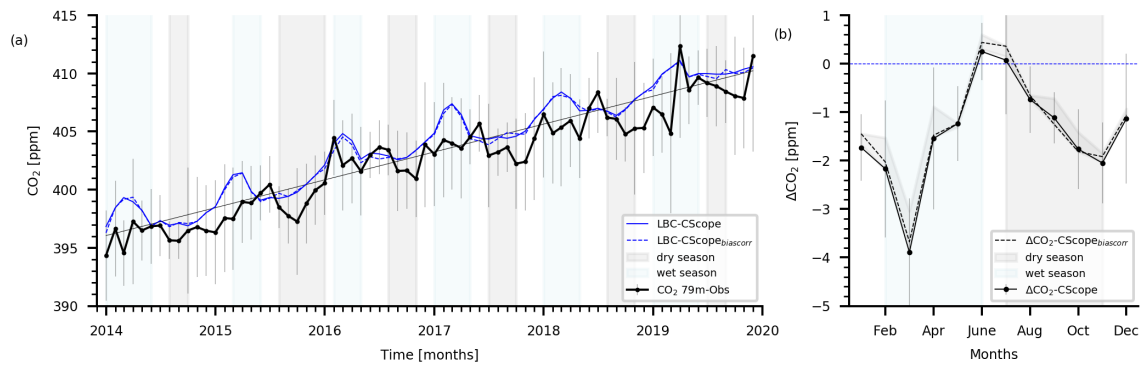
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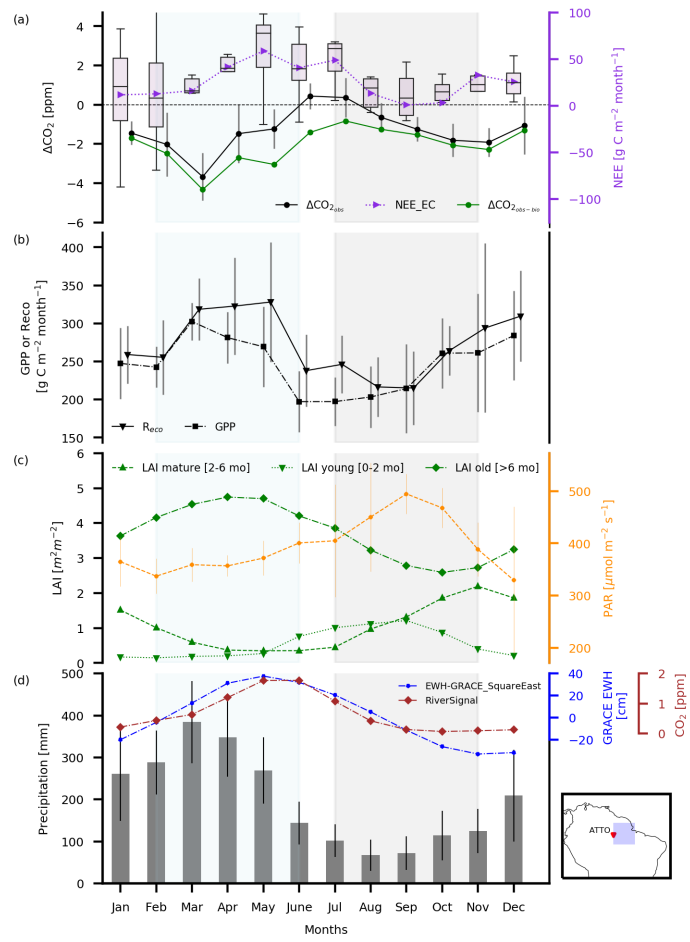
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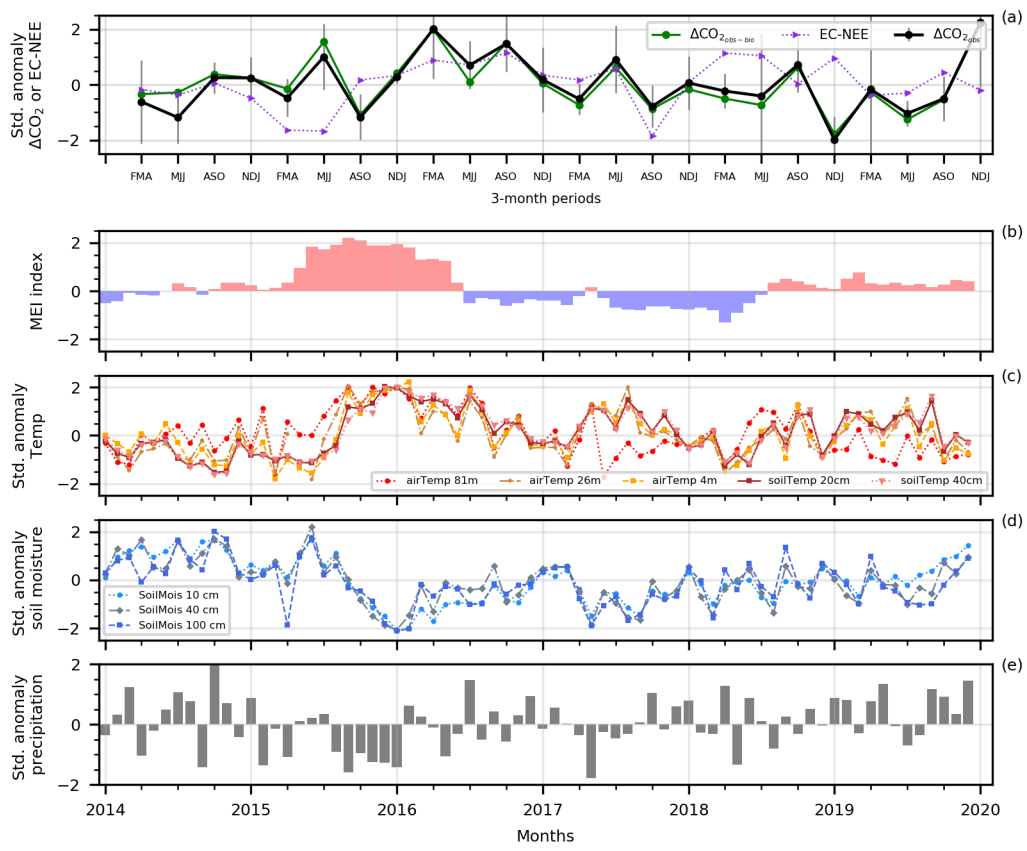
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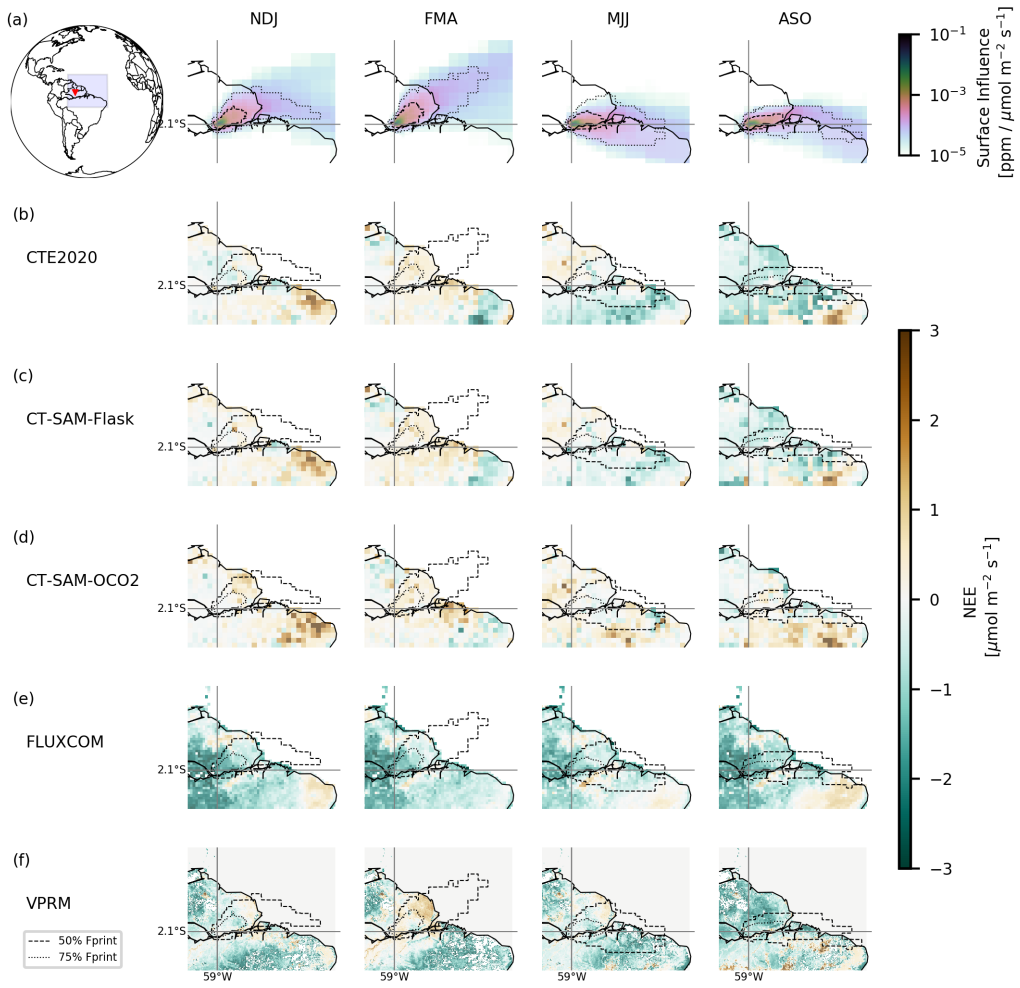
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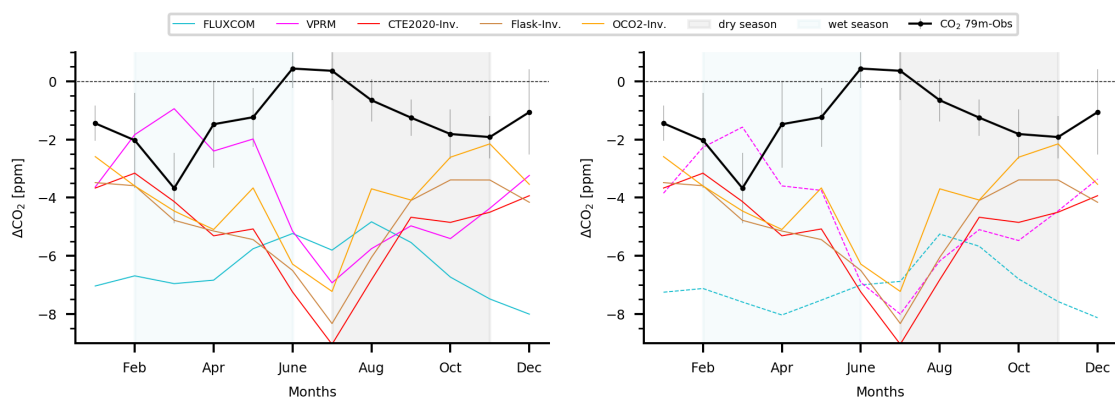
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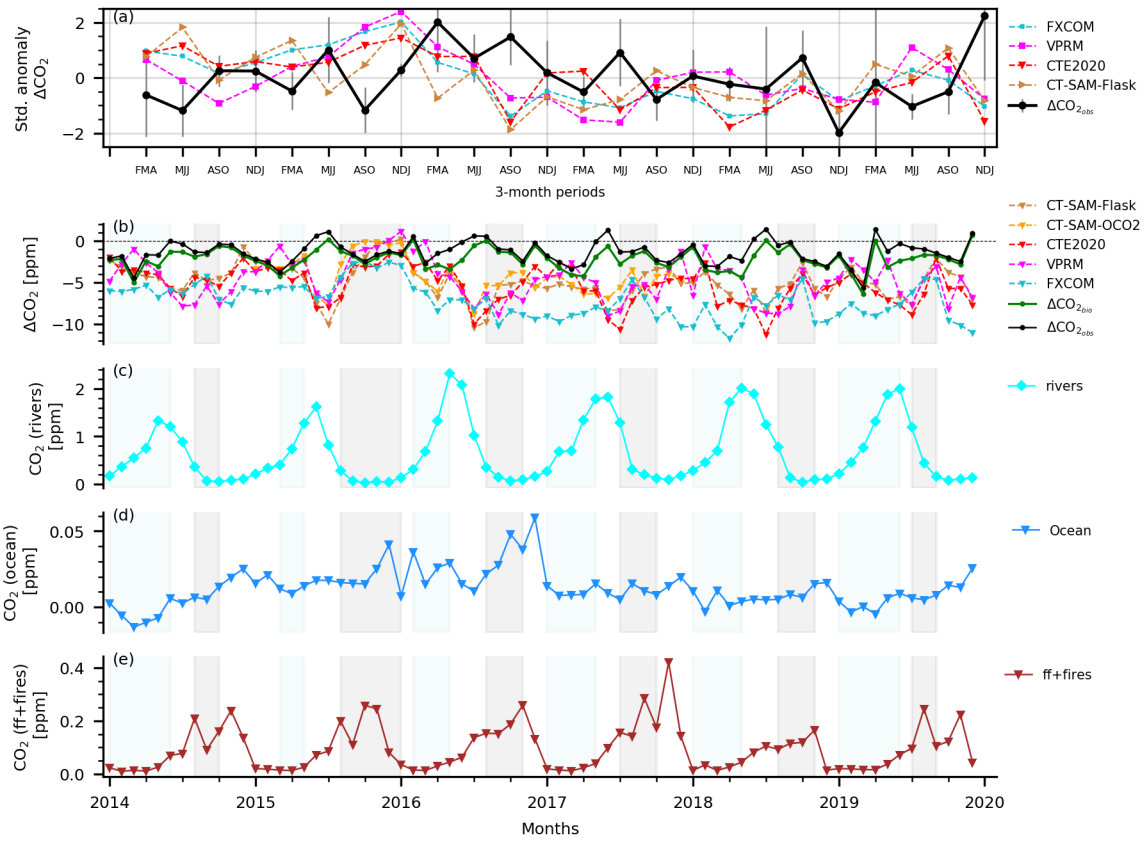
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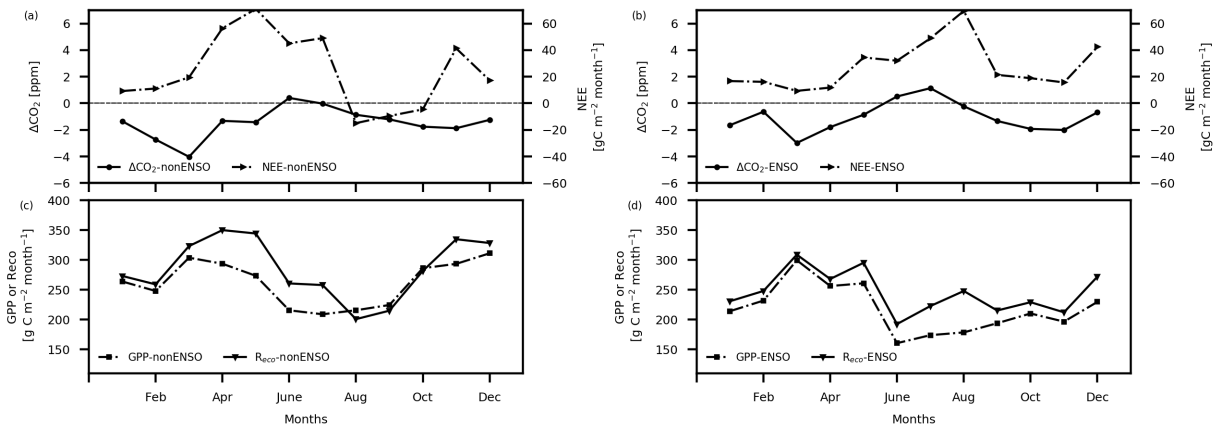
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