

Neutral tropical African CO₂ exchange estimated from aircraft and satellite observations

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Plain Language Summary

Satellite CO₂ observations over land imply a major revision to our understanding of the global carbon cycle linked to large emissions from northern tropical Africa during the dry season, from October to May. We use aircraft observations made over the Atlantic Ocean in four seasons to evaluate flux models driven by a range of ground and satellite observations. Our results show that models using satellite observations over land overestimate annual emissions from northern tropical Africa by approximately 1 PgC yr⁻¹, concentrated in the dry season. At other times of year, satellite CO₂ observations provide improved estimates of northern tropical Africa exchange, with a stronger CO₂ uptake during the wet season.

Key Points:

- Emergent constraints derived from aircraft CO₂ measurements and inversions estimate a near neutral northern tropical African CO₂ budget.

- 54 • Inversions using satellite observations overestimate annual emissions from northern
55 tropical Africa by approximately 1 PgC yr⁻¹.
- 56 • Satellite CO₂ observations imply a strong sink during the wet season over northern
57 tropical Africa.

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Abstract

Tropical lands play an important role in the global carbon cycle yet their contribution remains uncertain owing to sparse observations. Satellite observations of atmospheric carbon dioxide (CO₂) have greatly increased spatial coverage over tropical regions, providing the potential for improved estimates of terrestrial fluxes. Despite this advancement, the spread among satellite-based and in-situ atmospheric CO₂ flux inversions over northern tropical Africa (NTA), spanning 0-24°N, remains large. Satellite-based estimates of an annual source of 0.8-1.45 PgC yr⁻¹ challenge our understanding of tropical and global carbon cycling. Here, we compare posterior mole fractions from the suite of inversions participating in the Orbiting Carbon Observatory 2 (OCO-2) Version 10 Model Intercomparison Project (v10 MIP) with independent in-situ airborne observations made over the tropical Atlantic Ocean by the NASA Atmospheric Tomography (ATom) mission during four seasons. We develop emergent constraints on tropical African CO₂ fluxes using flux-concentration relationships defined by the model suite. We find an annual flux of 0.14 ± 0.39 PgC yr⁻¹ (mean and standard deviation) for NTA, 2016-2018. The satellite-based flux bias suggests a potential positive concentration bias in OCO-2 B10 and earlier version retrievals over land in NTA during the dry season. Nevertheless, the OCO-2 observations provide improved flux estimates relative to the in situ observing network at other times of year, indicating stronger uptake in NTA during the wet season than the in-situ inversion estimates.

1 Introduction

Tropical terrestrial ecosystems are an important component of the global carbon cycle as both a strong source of atmospheric CO₂ from land-use emissions (e.g., Hong et al., 2021) and a strong sink in intact forests, most likely owing to the CO₂ fertilization effect on photosynthesis (Lewis et al., 2009; Schimel et al., 2015). African ecosystems are large contributors to the uncertain positive climate-carbon cycle feedback of reduced photosynthesis and increased soil and plant respiration associated with hotter, drier conditions (Friedlingstein et al., 2006, 2010; Cox et al., 2013; Wang et al., 2014; Arora et al., 2020). Atmospheric inverse models constrained with in-situ observations estimate that the sum of land carbon fluxes from the tropics and southern extratropics has been near-neutral since the 2000s (Gaubert et al., 2019). The Global Carbon Budget 2021 (Friedlingstein et al., 2022) also estimates a near-balanced budget (excluding fossil fuel) in the tropics during the past decade that is derived from both process models and a set of atmospheric inversions.

CO₂ biomass burning emissions from sub-Saharan Africa show a marked seasonal cycle with large sources during the dry season, from October to May in the northern hemisphere (e.g., Roberts et al., 2009). Satellite observations from the NASA Orbiting Carbon Observatory-2 (OCO-2) indicate a strong and rapid increase in column CO₂ that coincides with the biomass burning season of northern hemispheric sub-Saharan Africa (Eldering et al., 2017; Crisp et al., 2022). Inversions of OCO-2 land nadir and land glint data (version B7.1) suggested that northern tropical Africa (NTA, 0-24 °N, Fig. 1) net biosphere exchange was a carbon source of approximately 1.5 PgC yr⁻¹ to the atmosphere in 2015 and 2016 (Palmer et al., 2019; Crowell et al., 2019). OCO-2 land nadir and land glint inversions from version 9 of the OCO-2 Model Inter-comparison Project (v9 MIP, using version B9.1 OCO-2 data) also estimate a large source of carbon (1.26 ± 0.58 PgC yr⁻¹) over NTA, for the 4-year period of 2015-2019 (Peiro et al., 2022). This contrasts with the far less constrained in-situ set of v9 MIP inversion results for NTA, which provide a mean value of 0.23 ± 0.4 PgC yr⁻¹. Interannual variability in these in-situ inversions ranges between an NTA sink of 0.2 PgC yr⁻¹ in 2018 and a source of 0.6 PgC yr⁻¹ in 2016, during the 2015-2016 El Niño (Peiro et al., 2022).

In addition to the large uncertainties in the net budget, the component processes responsible for the large source indicated by OCO-2 observations have yet to be corroborated. Conceptually, net carbon exchange results from the the balance of varying gross fluxes,

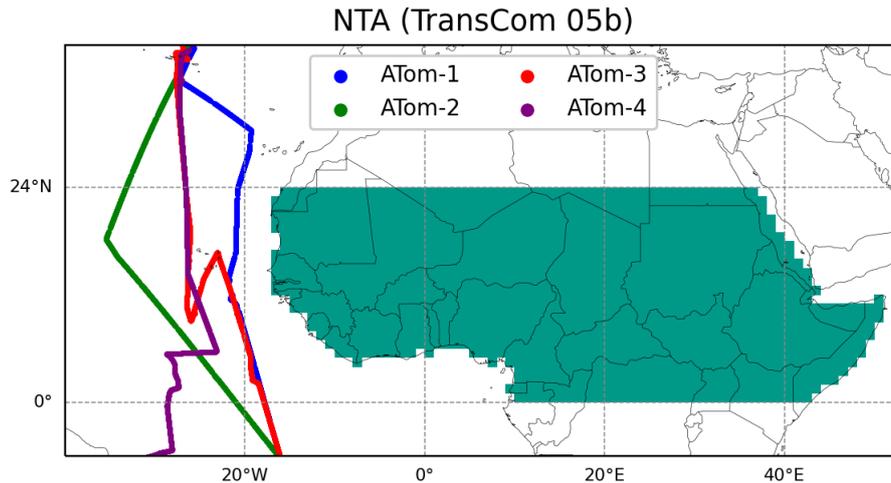


Figure 1. The TransCom 05b or northern tropical Africa (NTA) region. The NTA region encompasses various ecoregions including tropical forests, sub-humid savanna, semi-arid savanna, desert to semidesert, and shrubland areas. The four ATom flight tracks are also displayed.

109 including photosynthetic responses to drought, changes to plant and soil respiration, and
 110 direct effects of land use. Specific proposed mechanisms include soil emissions due to sus-
 111 tained land degradation (Palmer et al., 2019) and increased ecosystem respiration due to
 112 high surface temperature anomalies during the 2015-2016 El Niño (J. Liu et al., 2017). An-
 113 other possibility is biases in the satellite measurements. Generating accurate OCO-2 CO₂
 114 retrievals remains a challenge despite continuous improvements in the bias correction proce-
 115 dure (O'Dell et al., 2018). CO₂ retrieval biases can result from spectroscopic errors (Connor
 116 et al., 2008), aerosols and clouds over northern Africa (O'Dell et al., 2018; Nelson & O'Dell,
 117 2019) and from surface pressure errors that are maximal over the tropics (Kiel et al., 2019).
 118 The empirically derived bias correction to OCO-2 data has an isolated maximum over NTA
 119 that is approximately +0.6 ppm higher than the global average. This is illustrated in Fig-
 120 ure S1 and in Figure 4 of Taylor et al. (2023). Fires play an important role in the African
 121 carbon cycle, but are thought to be compensated by CO₂ uptake during the growing season
 122 (Valentini et al., 2014). The sub-Saharan region is dominated by shifting agriculture that
 123 is characterized by small and human-induced fires (Curtis et al., 2018). Emission estimates
 124 for this type of fire are uncertain and likely to be underestimated because global-scale fire
 125 emission models are typically based on satellite-derived burned area from relatively coarse-
 126 resolution sensors that are unable to detect most small fires (Randerson et al., 2012; Ichoku
 127 et al., 2016; Roteta et al., 2019; T. Liu et al., 2020). For 2016, a recent study (Ramo
 128 et al., 2021) used Sentinel-2 enhanced spatial resolution images to estimate burned area, and
 129 calculated for the African continent an increase of 31 % in fire carbon emissions compared
 130 to the Global Fire Emissions Database with small fires GFED4s (van der Werf et al., 2017).
 131 Estimates of annual-mean CO₂ emissions (Fig. S3) from fires range from 0.29 to 0.55 PgC/yr
 132 for 2016. Despite large uncertainties, an increase in 30 to 50 % in fire emissions does not
 133 suffice to explain the discrepancies in inversion results (Crowell et al., 2019; Palmer et al.,
 134 2019).

135 The atmospheric transport pathways exporting emissions from the African continent
 136 have been thoroughly studied by monitoring plumes over the Atlantic ocean using satellite
 137 remote sensing observations to track desert dust, smoke aerosols, and trace gases such as
 138 carbon monoxide (CO) (e.g., Prospero, 1999; Edwards et al., 2006; Adams et al., 2012;
 139 Barkley et al., 2019). Given the sparsity of other CO₂ observations downwind of tropical

140 Africa, the NASA airborne Atmospheric Tomography Mission (ATom) provides a unique
 141 opportunity to assess the ability of CO₂ inverse models to reproduce the atmospheric signa-
 142 tures of tropical African carbon fluxes over the Atlantic basin. The ATom campaign utilized
 143 the fully instrumented NASA DC-8 research aircraft to survey the chemical environment
 144 of the remote atmosphere around the world (Thompson et al., 2022). The ATom payload
 145 included three in situ CO₂ instruments and two whole air samplers with CO₂ measurements.
 146 ATom sampled vertical profiles along meridional transects of the Pacific and Atlantic Ocean
 147 basins (Fig. 1) during four month-long campaigns between August 2016 and May 2018.

148 In this study we use 54 OCO-2 v10 MIP inversions (Byrne et al., 2023) in the form of
 149 fourteen inverse models running five experiments assimilating different sets of observations.
 150 We apply an emergent-constraint approach (e.g., M. S. Williamson et al., 2021; Cox, 2019)
 151 in which we develop relationships between posterior CO₂ concentrations over the Atlantic
 152 and net biosphere fluxes from NTA (Fig. 1), and then use these to derive new flux estimates
 153 by comparison to the aircraft observations. The NTA region (TransCom 05b) is a subregion
 154 of the TransCom 05 region defined in the original TransCom experiment (Gurney et al.,
 155 2002; Gurney & Denning, 2008), spanning 0-24°N. The NTA region includes the Sahara
 156 desert and the CO₂ fluxes are primarily confined south of ~18°N, across various ecoregions
 157 including tropical forests, sub-humid savanna, and semi-arid savanna.

158 2 Materials and Methods

159 2.1 OCO-2 v10 Model Intercomparison Project

160 The OCO-2 v10 Model Intercomparison Project (v10 MIP) consists of a large ensemble
 161 of atmospheric inversions from 14 modeling groups using primarily five combinations of
 162 in situ and OCO-2 satellite observations (Byrne et al., 2023). The models have different
 163 unoptimized prior flux distributions, model transport, and data assimilation techniques.
 164 Byrne et al. (2023) presented a description of the participating inverse models and of the
 165 assimilated datasets used in the OCO-2 v10 MIP. One notable difference to the preceding
 166 v9 MIP (Peiro et al., 2022) is that the OCO-2 v10 MIP uses OCO-2 observations over
 167 a longer time period and from a new XCO₂ retrieval, i.e. the B10 version (Taylor et
 168 al., 2023) of the Atmospheric Carbon Observations from Space (ACOS) column-averaged
 169 dry air mole fraction of atmospheric CO₂ (XCO₂) retrieval (Byrne et al., 2023; O'Dell
 170 et al., 2018; Kiel et al., 2019). The post-retrieval data processing also includes a quality
 171 filtering and a bias correction procedure (Kiel et al., 2019). The atmospheric inversions were
 172 conducted following a formal protocol with regard to the set of assimilated observations
 173 and their treatment. Five experiments were defined to investigate the impact of OCO-2
 174 assimilation across viewing modes and to compare to the assimilation of baseline in-situ
 175 network observations. The experiments consist of: 1) in situ (IS), 2) OCO-2 land nadir and
 176 land glint (LNLG), 3) OCO-2 ocean glint (OG), 4) joint LNLG with IS (LNLGIS) and 5)
 177 a combination of all in situ and satellite data (LNLGOGIS). There were 12 participating
 178 inversion systems that provided outputs at the ATom locations, but not for all experiments
 179 for all of the simulations. We included the LoFI simulation in only the IS group. We include
 180 all of the available submissions when calculating an experiment average, which are 10 for
 181 LNLG, 11 for IS when including LoFI, and 11 for OG, LNLGIS, and LNLGOGIS.

182 2.2 Observations

183 We first merge the 10-second ATom dataset (Wofsy et al., 2021) and the ObsPack
 184 (Masarie et al., 2014) formatted posterior concentration files provided by the OCO-2 v10
 185 MIP. Only airborne measurements along the northbound Atlantic transects were considered
 186 by selecting measurements made at longitudes between 70°W and 15°E. We excluded the
 187 last 15 min of the ATom-4 flight arriving in Recife, Brazil and the first 60 seconds of the
 188 flight departing to avoid local pollution influences. All of the data were then bin averaged
 189 on a 5° latitude by 50 hPa pressure grid. We define the metric ΔCO_2 (Eq. 1) by subtract-

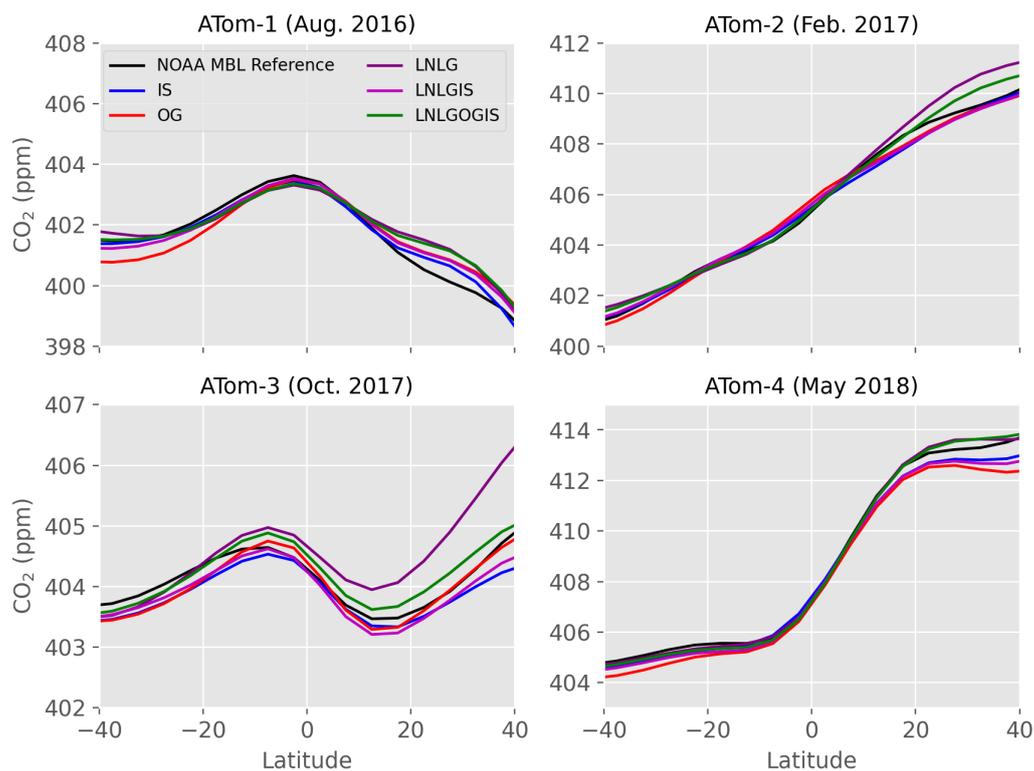


Figure 2. NOAA marine boundary layer reference CO₂ concentrations used to define ΔCO_2 for each ATom campaign. We also show the experiment average posterior marine boundary layer references estimated by the inversions. We use model-specific reference curves in the model posterior ΔCO_2 calculation.

Table 1. Optimized box boundaries (latitude in °N and pressure in hPa), flight dates intersecting boxes, correlation coefficients between the NTA fluxes and posterior ΔCO_2 in the corresponding box estimated by the v10 MIP ensemble, observed ΔCO_2 plus uncertainty, and estimated NTA flux plus uncertainty.

ATom	date	lat min/max	pressure max/min	r	Obs \pm Unc. (ppm)	ATom-EC \pm Unc. (PgC yr^{-1})
ATom-1	17 Aug. 2016	10/25	850/650	0.74	-0.65 ± 0.25	-2.81 ± 0.6
ATom-2	15 Feb. 2017	-5/10	950/500	0.77	1.9 ± 0.24	3.15 ± 0.6
ATom-3	17-20 Oct. 2017	-5/10	600/400	0.77	-1.11 ± 0.26	-2.22 ± 0.48
ATom-4	14 May 2018	-5/10	650/450	0.65	-0.71 ± 0.1	-0.26 ± 0.37

190 ing from the ATom observations and inversion posterior CO_2 the NOAA Greenhouse Gas
 191 Marine Boundary Layer (MBL) Reference surface (Dlugokencky et al., 2019) as defined by
 192 observations for ATom and as defined by the respective posterior CO_2 simulated at surface
 193 stations for the inversions.

$$\Delta\text{CO}_2 = \text{CO}_2^{\text{ATom}} - \text{CO}_2^{\text{MBL}} \quad (1)$$

194 The NOAA MBL reference product is derived from atmospheric CO_2 mole fraction mea-
 195 surements from the NOAA ESRL Carbon Cycle Cooperative Global Air Sampling Network
 196 (Dlugokencky et al., 2019). In order to generate a consistent MBL reference for both the
 197 model and observations, we ran the Python version of the curve fitting and smoothing al-
 198 gorithm developed by Thoning et al. (1989) over the period 2015–2020 using the subset
 199 of stations available during this time. We linearly interpolate the MBL reference values
 200 to our 5° latitude bins. We use the weekly values that are closest in time to the ATom
 201 measurements, 16 August 2016 (ATom-1), 15 February 2017 (ATom-2), 16 October 2017
 202 (ATom-3), and 17 May 2018 (ATom-4). Figure 2 shows the selected MBL reference values
 203 used to define ΔCO_2 for the observations and as averaged for each experiment. The ex-
 204 periment mean posterior MBL gradients diverge up to 1 ppm from the observations. Thus,
 205 subtracting reference values specific to each model and experiment is an important step to
 206 isolate NTA signals from those originating elsewhere.

207 2.3 Averaging box selection

208 We identified optimal pressure and latitude bounded boxes by maximizing the across-
 209 inversion correlation coefficient between ΔCO_2 averaged over a given ATom box and fluxes
 210 for the same month from the NTA TransCom region. This results in a correlation calculation
 211 across 54 data pairs. Note that the ATom Atlantic flights all generally occurred in the middle
 212 of the month (Table 1) leading to our use of monthly mean fluxes. Also, back trajectories
 213 indicate that NTA had a strong influence on the measurements over the preceding several
 214 weeks (Fig. 3). We imposed that the boxes have a minimum width of 15° in latitude and a
 215 minimum height of 200 hPa, to avoid spurious correlations. We then calculated correlation
 216 coefficients for all different possible configurations spanning 40°S to 40°N in latitude and
 217 from the surface to 200 hPa. While significant relationships (with p -value lower than 0.05)
 218 are found for many different boundary options (Fig. S4), we select the box that provides
 219 the greatest correlation coefficient (Table 1). Given transport differences across models,
 220 we interpret these regions as having the greatest agreement across models as to where
 221 NTA fluxes influence the observed concentrations. Table 1 includes the boundaries of the
 222 optimized boxes and the Pearson correlation coefficient between the posterior ΔCO_2 box
 223 average and the respective TransCom subregion monthly net land fluxes.

224 2.4 Observation uncertainty

225 We use CO_2 measurements made by three in-situ analyzers: the NOAA Picarro instru-
 226 ment, the Harvard quantum cascade laser spectrometer (QCLS, Santoni et al., 2014), and

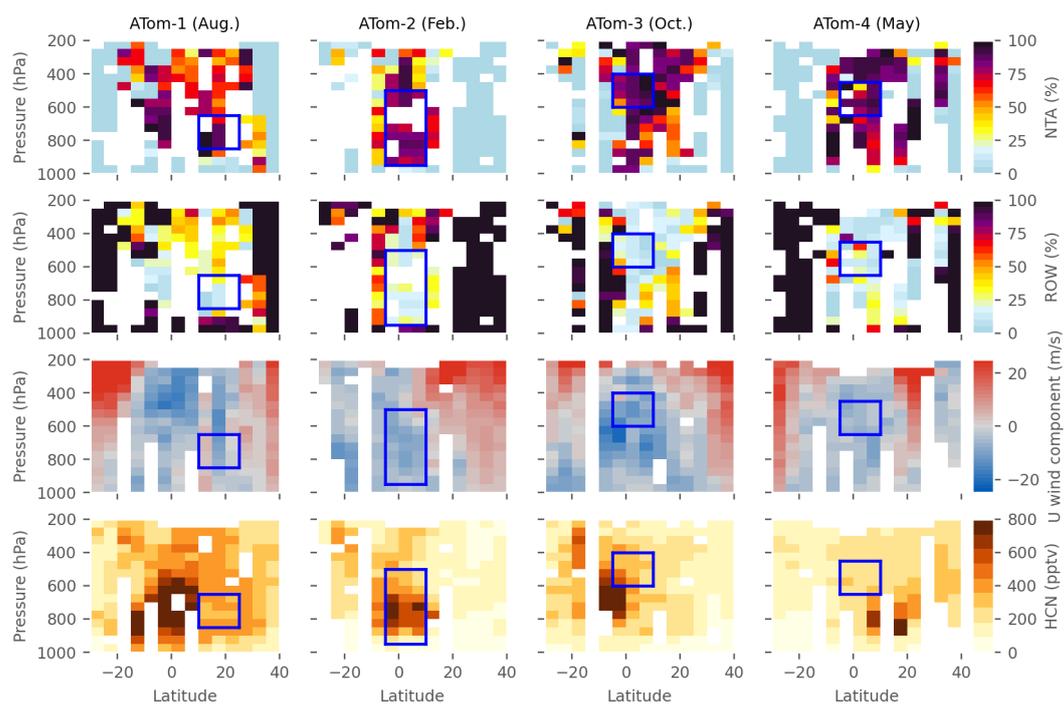


Figure 3. Relative contributions from the the NTA region (first row) and the rest of world (second row) to the Atlantic ATom observations, based on 14-day back-trajectories. Distribution of the U zonal wind speed (third row) and HCN (fourth row) over the Atlantic for all four ATom campaigns. In these plots solid blue lines show the optimized boxes. Bins containing no flight data are white.

227 the National Center for Atmospheric Research (NCAR) airborne oxygen instrument (AO2,
 228 Stephens et al., 2021). We also use CO₂ measured in flasks collected by the NCAR/Scripps
 229 Medusa whole-air sampler (Stephens et al., 2021) and NOAA Programmable Flask Packages
 230 (PFP) (Sweeney et al., 2015). The ΔCO_2 values used in the emergent constraint have been
 231 calculated using the NOAA Picarro data as it is most closely tied to the WMO CO₂ scale,
 232 has the greatest data coverage, and is the record the models used for reporting matched
 233 posterior concentrations. To assess uncertainty in these observations, we compare ΔCO_2 es-
 234 timates among all five in-situ measurement or sampling systems. More specifically, to allow
 235 for different periods of missing data for each instrument owing to in-flight calibrations and
 236 the reduced coverage of the flask systems, we first calculate sensor-sensor differences using
 237 the NOAA Picarro data as the common reference and then calculate box averages of these
 238 differences. We then use the standard deviation of these four differences, also including zero
 239 for the NOAA Picarro minus itself, as the observational uncertainty on box-averaged ΔCO_2
 240 for each campaign (Table 1).

241 2.5 Emergent constraints

242 We use weighted orthogonal distance regression (Boggs & Rogers, 1990), a method
 243 which accounts for errors in both the explanatory and response variables, to construct
 244 emergent constraints between ΔCO_2 (here the explanatory variable) and NTA flux (here
 245 the response variable). Weighted ODR requires knowledge of the variances of the errors
 246 associated with each variable. As scaling factor for the flux errors we use the empirical
 247 standard deviation of the flux estimates, while for the ΔCO_2 errors we use the empirical
 248 standard deviation of the ΔCO_2 values. The linear fit and its associated coefficient un-
 249 certainty depend only on the ratio of these scaling factors, so we are implicitly assuming
 250 that the signal to noise ratio (defined as the variance of the data divided by the variance
 251 of the associated errors) of the fluxes is the same as that of ΔCO_2 . In the absence of more
 252 information about the sources of variation in the errors, this is a reasonable assumption.

253 Recent comparisons of different statistical methods for estimating emergent constraints
 254 found broadly consistent results (Renoult et al., 2020; Simpson et al., 2021). The emergent
 255 constraints developed here are based on an ensemble with overall good structural diversity,
 256 thanks to the assimilation of various kinds of observations and using a range of transport
 257 models. Also, there are no attempts to quantify a range of projected responses from our
 258 ensemble, which can be a problem when assessing Earth system response to a forcing or the
 259 strength of a feedback (Sanderson et al., 2021). However, it remains important to accurately
 260 quantify uncertainties (e.g., K. W. Bowman et al., 2018; D. B. Williamson & Sansom, 2019).

261 We account for uncertainties in both ATom observations and the MIP results through
 262 the following. First, we draw a sample of the regression line using the error covariance
 263 matrix of the estimated regression parameters, as well as a sample from the ATom ΔCO_2
 264 observation error distribution (as derived in the previous section). Second, we find the
 265 corresponding flux estimate using this sampled regression line and the sampled ATom ΔCO_2
 266 measurement. Third, a sample from the flux error distribution assumed by the ODR method
 267 is added onto this flux estimate; this is assumed to be a normal distribution with mean zero
 268 and variance equal to the empirical variance of the residuals from the ODR fit. We repeat
 269 this process 5000 times and then take the empirical standard deviation of the flux samples as
 270 the 1σ uncertainty of the ATom-EC flux. This method accounts for uncertainty associated
 271 with the emergent constraint fit and the ATom CO₂ measurement uncertainty, but not for
 272 the uncertainty arising from the choice of the altitude-latitude box; we discuss this form of
 273 uncertainty in Section 3.3.2 and in the supplementary material. The resulting four monthly
 274 ATom-EC values with their uncertainties are reported in Table 1.

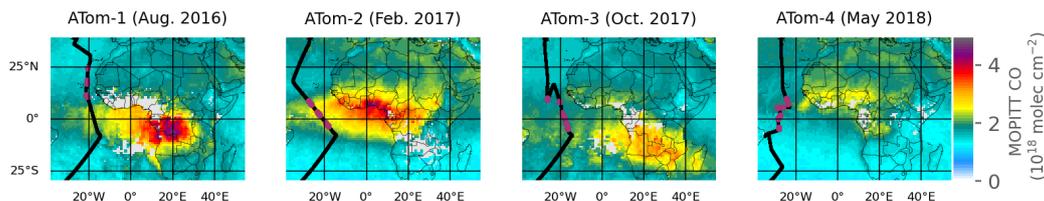


Figure 4. Terra/MOPITT V9J level 3 monthly average total column of carbon monoxide for months corresponding to the ATom campaigns, and ATom flight tracks. The ATom observations in purple correspond to the optimize boxes.

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2.6 Source Contributions and Ancillary Measurements

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For qualitative assessment of sampled air origins, backward particle trajectories were computed using the Traj3D model (K. P. Bowman, 1993; K. P. Bowman & Carrie, 2002). Model trajectories were initialized at receptors spaced 1 min apart along the ATom flight tracks, and followed backwards for 30 d (Ray, 2022; Gonzalez et al., 2021). From these trajectories, we calculated for each receptor point the surface influence functions over land only. These footprints (Fig. S5) are in units of concentration mole fraction per emission flux or $\text{ppm}/(\mu\text{mol m}^{-2} \text{s}^{-1})$. We define the relative contribution of the NTA TransCom subregion and the rest of the world (ROW) to the ATom tropical Atlantic measurements. The footprints, either for NTA or ROW, are summed and divided by the global total footprints. We show the contributions for 14-day back trajectories for each 5° latitude by 50 hPa pressure grid bin (Fig. 3). The regions of strong NTA influence are large for all ATom missions. While these back trajectories were not used in the determination of the boxes, there is a good correspondence with a majority of the air in our optimized boxes strongly influenced by fluxes from the NTA TransCom subregion (Figs. 3, S4).

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Fig. 3 shows two additional ATom measurements, the eastward (U) wind speed component and hydrogen cyanide (HCN) concentration measured by the Chemical Ionization Mass Spectrometer (CIT-CIMS) instrument. HCN is an excellent biomass burning tracer (Li et al., 2003; Crouse et al., 2009).

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Fig. 3 also shows the optimized boxes. We also show on Fig. 4 maps of the the monthly mean CO total column from the V9J MOPITT product (Deeter et al., 2022). The biomass burning plumes characterized by enhanced CO column and in-situ HCN can clearly be identified. These features correspond to plumes from NTA on ATom-2 and ATom-4, and from southern tropical Africa on ATom-1 and ATom-3.

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3 Results

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3.1 NASA ATom Concentrations

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The four ATom campaigns observed both elevated and depleted CO_2 over the tropical Atlantic relative to the NOAA Marine Boundary Layer (MBL, Fig. 2) Reference (Dlugokencky et al., 2019). We define a metric quantifying these anomalies, ΔCO_2 , by subtracting the NOAA MBL Reference at corresponding latitudes and times from the ATom CO_2 observations (Fig. 5). We qualitatively attribute these CO_2 variations to biomass burning or net ecosystem exchange in tropical Africa guided by observed winds, modeled

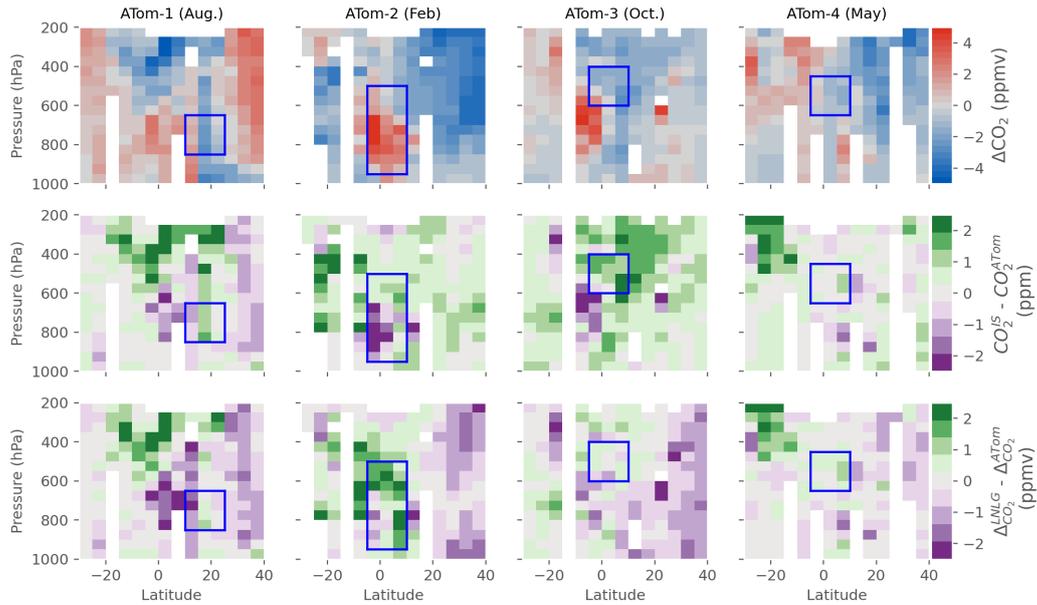


Figure 5. Latitude and altitude distribution of ΔCO_2 observations made over the Atlantic basin for the four ATom deployments. ΔCO_2 is defined by subtracting the observed or modeled NOAA MBL Reference (Dlugokencky et al., 2019) at corresponding latitudes and times from the ATom CO_2 observations or inverse models, respectively. The second and third rows show the IS and LNLG experiment mean bias, respectively. The optimized NTA-influenced boxes are delineating by solid blue lines. Bins containing no flight data are white.

307 back-trajectories, satellite CO observations, and coincident in situ measurements of biomass
308 burning tracers (Fig. 3, 4).

309 The ATom-1 deployment occurred in August 2016. Typically at this time of year,
310 the western African monsoon brings rain over western Africa, inducing a convection-driven
311 upward and westward atmospheric pattern, which is strongest near the Inter-Tropical Con-
312 vergence Zone (ITCZ) (Rodríguez et al., 2015). As a result of the NTA growing season
313 CO_2 uptake, ATom-1 observed negative ΔCO_2 throughout the troposphere north of 15°N
314 and more broadly in the upper troposphere (Fig. 5). The mean values from the IS exper-
315 iment tends to overestimate ΔCO_2 in these negative CO_2 anomaly regions, suggesting an
316 underestimated uptake.

317 ATom-2 occurred in February 2017 during the NTA dry season and sampled biomass
318 burning plumes from the region (Figs. 3, 5). During ATom-2, large positive ΔCO_2 values
319 were found centered around the equator, between 950 hPa and 500 hPa. The LNLG ex-
320 periment mean strongly overestimates ΔCO_2 within and adjacent to this observed positive
321 anomaly, whereas the IS experiment mean slightly underestimates concentrations in the
322 plume.

323 ATom-3 occurred in October 2017 during the NTA wet-to-dry transition season. The
324 negative ΔCO_2 values during ATom-3, located north of the Equator, between 600 and 400
325 hPa in the mid-troposphere, appear to originate from eastern NTA (Fig. S5). South of
326 the Equator between 600 and 800 hPa ATom-3 intercepted a biomass burning plume that
327 originated from southern tropical Africa (Fig. 3). The IS mean experiment strongly under-
328 estimates ΔCO_2 in this biomass burning plume, but overestimates ΔCO_2 in the negative

329 anomaly regions. The LNLG experiment mean performs better for both positive and nega-
 330 tive anomalies during ATom-3.

331 ATom-4 measurements were made in May 2018 during the dry-to-wet transition season
 332 for NTA. Negative ΔCO_2 values can be found over the optimized box between -5°N and
 333 10°N and 450-650 hPa. It is located just above a region of positive ΔCO_2 values that
 334 correlate with elevated HCN in the ATom data (Fig. 3). This enhancement in ΔCO_2 is
 335 slightly underestimated by both the IS and LNLG inversion means.

336 3.2 Emergent Constraints

337 Emergent constraints are powerful tools to reduce model spread and narrow uncertainty
 338 (e.g., K. W. Bowman et al., 2018; Eyring et al., 2019; M. S. Williamson et al., 2021; Simpson
 339 et al., 2021). They offer a promising way to further improve the quantification of carbon
 340 fluxes and the overall scientific understanding of the carbon cycle (e.g., Stephens et al., 2007;
 341 Cox, 2019; Keenan et al., 2021; Long et al., 2021; Barkhordarian et al., 2021). Overall, our
 342 approach here is to take advantage of the large model spread to derive robust relationships
 343 between the airborne observations and land fluxes. We utilize CO_2 gradients (ΔCO_2) ob-
 344 served during ATom as a measurable variable (predictor) to obtain a constrained estimate
 345 of net land fluxes from NTA. For each ATom deployment, we use the v10 MIP ensemble to
 346 determine an altitude-latitude box boundary within the airborne transects that best cor-
 347 relates with NTA fluxes (Fig. 5). We also tried defining boxes centered on the observed
 348 biomass burning plumes and on the basis of back-trajectories (Fig. 3). The former only cap-
 349 tured strong positive emissions while ignoring uptake signals, and the latter showed worse
 350 correlations most likely owing to differences in transport between the back-trajectory model
 351 and the inversions. Thus we chose to optimize the boxes based on empirical correlations,
 352 which to some extent can allow for differences among the transport models by expanding
 353 the boxes. We calculated the Pearson correlation coefficient between model ΔCO_2 and
 354 NTA fluxes. The optimized Pearson correlation coefficients range from $r=0.65$ for ATom-4
 355 to $r=0.77$ for ATom-2. We consider the true relationship to be unknown and we expect
 356 scatter of the v10 MIP points about the true relationship because of transport differences
 357 and other sources of errors between inversions. We also do not expect the correlations to
 358 reach one because of variations in contributions to CO_2 within the boxes from regions other
 359 than NTA.

360 Fig. 6 shows the relationships between the NTA land fluxes (excluding fossil fuel
 361 emissions) and ΔCO_2 averaged over the respective ATom box (Table 1, Fig. 5). We use
 362 these emergent relationships to estimate NTA fluxes for all four ATom periods. The fit
 363 slopes in Fig. 6 represent the sensitivity of concentrations to fluxes, as defined by this v10
 364 MIP collection of models. We plot the dependent concentration variable on the x-axis to
 365 be consistent with the emergent constraint predictor convention. We estimate fluxes in the
 366 months corresponding to each campaign as the intersection of the observation and fit lines
 367 shown in Fig. 6. We estimate the observation error by comparing the five different CO_2
 368 observing systems aboard the DC-8, three in situ and two flask samplers. We estimate 1σ
 369 flux uncertainty by propagating the observation error onto the fit prediction interval (see
 370 Section 2).

371 ATom-2 was characterized by a strong source as measured by a ΔCO_2 of around 2
 372 ppm (Table 1). Yet, the LNLG and LNLGIS experiments show a strong overestimation of
 373 this signal, with almost all inversions simulating a ΔCO_2 higher than observations. The IS
 374 models exhibit the largest spread of all experiments, but generally show a positive bias during
 375 ATom-1 and ATom-3 during the wet season and wet-to-dry season transition and a negative
 376 bias during ATom-4 during the dry season. During ATom-3, the IS group overestimates
 377 ΔCO_2 with biases up to 2 ppm. Even though ATom-3 occurred at the end of the wet
 378 season, some inversions indicate a land source of CO_2 for NTA at this time. There was
 379 no clear ranking for inversion performance between experiments as their skills were not

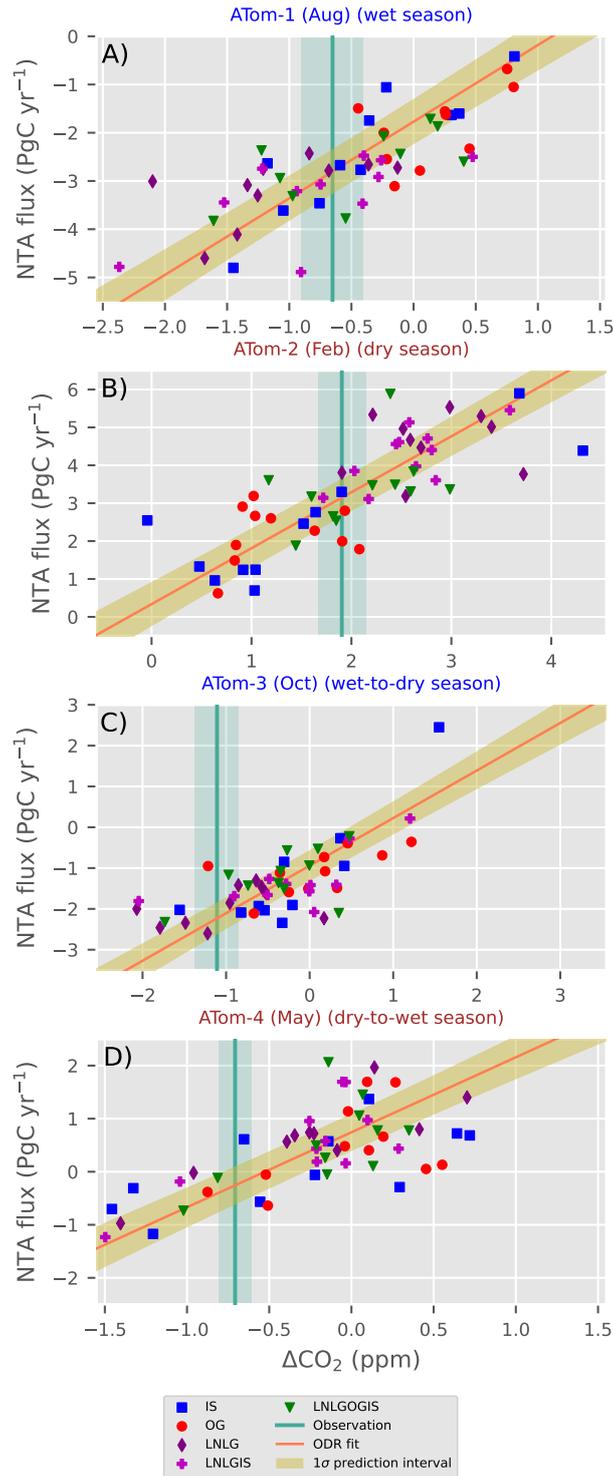


Figure 6. Emergent constraints on northern tropical African CO₂ fluxes during ATom. The relationships represent the sensitivity of airborne posterior ΔCO₂ to NTA land fluxes (excluding fossil fuel emissions). Each point shows results for a single model within one of four experiments (colors). Fluxes are averaged over the month of each campaign and the NTA TransCom subregion. The ODR fits are plotted as an orange line with a brown shading indicating 1σ prediction intervals. The vertical line in each panel represents the observed ΔCO₂, averaged over the optimized boxes shown in Fig. 5. Shading around the observation lines represents 1σ observation uncertainty (2). Note the different axis ranges between panels. The same figure with simulations colored by inverse models can be found in the supplement (Fig. S6).

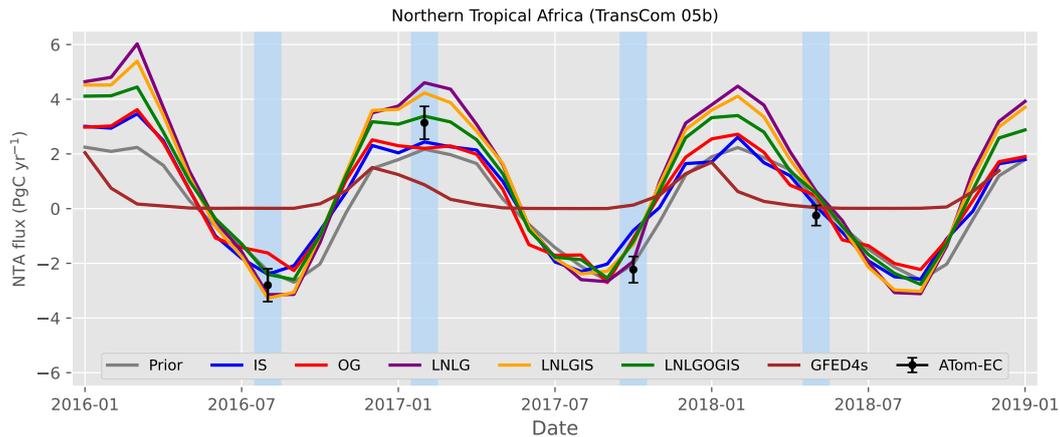


Figure 7. Monthly mean northern tropical Africa net land CO₂ fluxes for the different OCO-2 MIP experiments compared to the observational estimates. Lines represent means across all models within each experiment. The ATom emergent constraint (ATom-EC) is plotted in black with each 1 σ prediction interval as an errorbar. We also show the mean prior fluxes used in the inversions and biomass burning fluxes from GFED4s (v4.1) (van der Werf et al., 2017), used as prior fire fluxes by 3 out of 12 inversion models.

380 consistent across the four campaigns (Fig. 6). Although we present experiment means in
 381 Fig. 7 for visual clarity, Fig. 6 suggests that experiment means do not necessarily reflect
 382 best estimates. It is also not clear that any particular models perform better or worse than
 383 others across all four campaigns. Thus, we do not evaluate individual models, but do provide
 384 a version of Fig. 6 colored by model in the supplement (Fig. S6).

385 3.3 Northern Tropical African Land Fluxes

386 3.3.1 Monthly Time Series

387 Figure 7 shows the monthly average land fluxes averaged for each experiment, from
 388 2016 to 2018, along with our ATom emergent constraint (hereafter ATom-EC) estimates
 389 for the four ATom missions. The ATom-1 emergent constraint suggests a strong wet-season
 390 land sink that is more closely reproduced with the inversions that assimilate OCO-2 LNLG
 391 data. During ATom-2, which occurred during the dry season, all the experiments indicate
 392 a larger source than was predicted by the prior fluxes. The spread between experiments is
 393 also maximal for ATom-2, with the LNLG and LNLGIS mean overestimating the ATom-EC
 394 and IS and OG slightly underestimating. The LNLGOGIS mean is closest to our ATom-2
 395 estimate as it combines the LNLG overestimation and the IS/OG underestimation, as shown
 396 on Fig. 6b. The IS flux mean underestimates the magnitude of the seasonal cycle as it is
 397 positively biased during ATom 1 and 3 and negatively biased during ATom 2 and 4. During
 398 the shoulder seasons, the spread among the four experiment means is smaller and the OCO-
 399 2 LNLG based inversion mean is in agreement with the ATom-EC for ATom-3 in showing
 400 a much lower flux. Our results indicate that the assimilation of OCO-2 data improves the
 401 inversions for ATom-1 and ATom-3.

402 These campaign differences are related to seasonal patterns evident in the multi-year
 403 monthly-mean fluxes. On average, the inversions that assimilate OCO-2 land data (LNLG,
 404 LNLGIS, LNLGOGIS) have a stronger source during the dry season (Figure S7). The LNLG
 405 and LNLGIS fluxes are higher than the other experiments from January to May. However,
 406 the LNLG and LNLGIS inversion fluxes are more negative than the IS fluxes in the wet

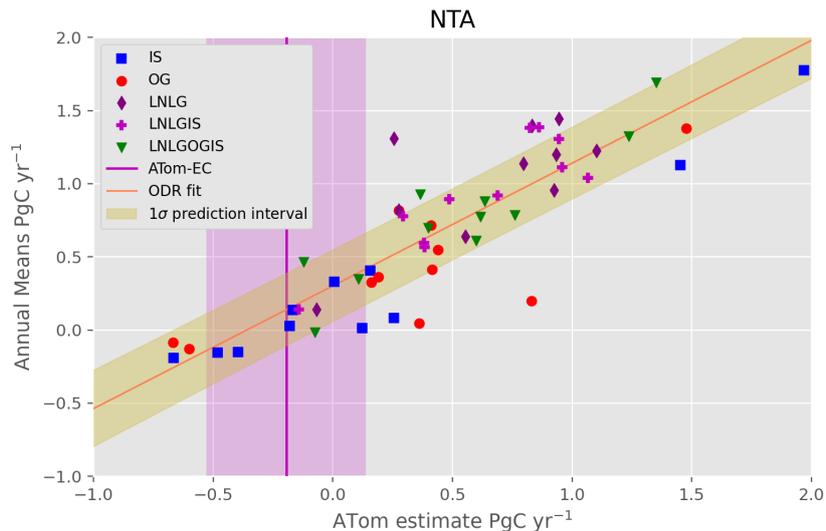


Figure 8. NTA three-year mean emergent constraint: True modeled three-year means (2016-2018) versus estimates based on model flux estimates corresponding to the four ATom campaigns. The fit represents the correction of the ATom-based estimates to the true three-year means (2016-2018) for temporal sampling biases. The ODR fit is plotted as an orange line with shading indicating the 1σ prediction interval. The vertical line represents the ATom-derived preliminary three-year mean flux estimate. Shading around the observation line represents the 1σ ATom-EC mean flux uncertainty.

407 season, from August to October. As a result, all the experiments using OCO-2 land data
 408 have a stronger seasonal cycle than the IS experiment. This is in line with a recent study
 409 that found a stronger seasonal amplitude when comparing the OCO-2 LNLG inversions with
 410 the IS inversion over South Asia (Philip et al., 2022). The OG experiment fluxes are close
 411 to those of the IS experiment, but in 2018 higher than IS during the dry season. With no
 412 data constraints over NTA, the IS and OG inversions remain close to the prior estimates.
 413 It is important to note that for OG the land flux is estimated by data over the ocean only
 414 and also that potential biases in OG observations may impact the posterior fluxes (Crowell
 415 et al., 2019; Peiro et al., 2022).

416 *3.3.2 2016-2018 Mean Flux Estimates*

417 We derive an initial multi-year annual mean NTA flux estimate by scaling the inversion
 418 average climatological seasonal flux cycle to optimally fit the four ATom-EC flux estimates
 419 (2016-2018). We fit the 4 ATom estimates to the average seasonal cycle derived from all
 420 the inversions. We input the 1σ uncertainty described above to account for uncertainties in
 421 each ATom. To account for the assumption of a specified seasonal cycle shape, we repeat
 422 the fit using all the individual modelled seasonal cycles and add the standard deviation in
 423 quadrature to the fit error.

424 The optimally scaled seasonal cycle represents a preliminary three-year annual mean
 425 flux estimate subject to potential seasonal and interannual sampling biases owing to the
 426 flights occurring at only select times of year and in select years. To correct for this, we use the
 427 inversion suite to estimate the difference between the annual mean estimated in this way from
 428 the four ATom-EC and the true three year mean from each inversion. This approach relies
 429 on the inversions, as internally consistent representations of seasonally and interannually

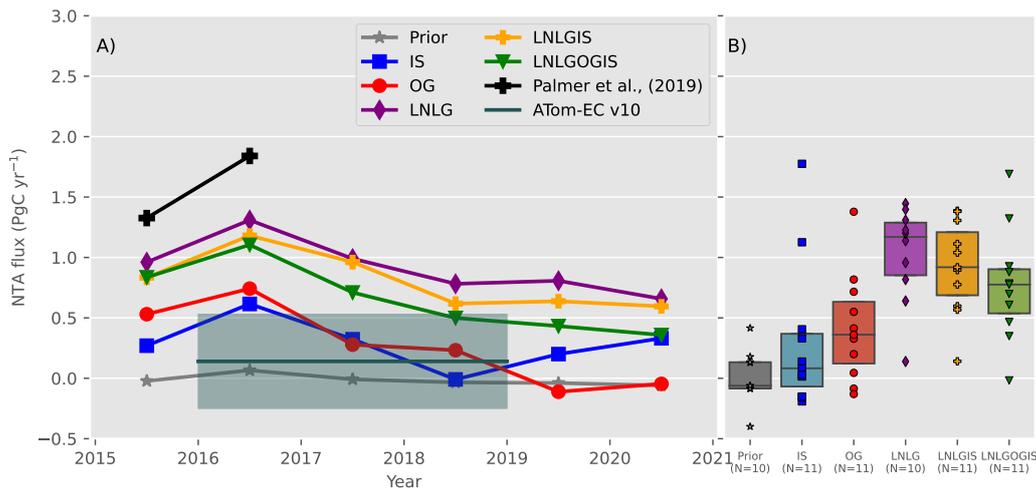


Figure 9. A) Annual mean net land CO₂ fluxes for NTA averaged for each MIP experiment and from the airborne observational constraint. The ATom emergent constraint (ATom-EC) is plotted in cyan with a shaded 1 σ error estimate. We also show the mean of five inversions for 2015 and four inversions for 2016 from Palmer et al. (2019). B) 2016-2018 means for each inverse simulation (dots), and the resulting boxplot (25th percentile, median and 75th percentile) by experiment, and also showing priors.

430 varying fluxes and concentrations, to predict our temporal sampling biases in estimating
 431 three-year mean fluxes. We first calculate three-year mean fluxes for each inversion using a
 432 linear fit of the average seasonal cycle to the four monthly fluxes corresponding to the ATom
 433 months. We then compare these to the true mean fluxes (2016-2018) from each inversion.
 434 Because the inversions suggest both an offset and slope component to this correction (Fig.
 435 8), we again use an emergent constraint approach to define the correction and its uncertainty.
 436 We calculate the relationship between the true three-year annual means and the 4-ATom
 437 estimate using the same method as for the individual campaign estimates, an ODR fit
 438 with input uncertainties scaled according to the respective standard deviations (Fig. 8).
 439 We estimate a slope of 0.84 PgC yr⁻¹ per PgC yr⁻¹ with an intercept of 0.3 PgC yr⁻¹,
 440 and a correlation coefficient of 0.87. We calculate the corrected ATom-EC 2016-2018 mean
 441 estimate and its 1 σ uncertainty by propagating the uncertainty errors using the same three
 442 step Monte-Carlo approach described in the previous section, using as inputs each ATom-EC
 443 and its 1 σ uncertainty for the observation.

444 We obtain a corrected three-year annual mean flux estimate of 0.14 PgC yr⁻¹ with a
 445 1 σ uncertainty of 0.39 PgC yr⁻¹ (Fig. 9). It is important to note that this estimate and its
 446 relatively small uncertainty come not just from the four ATom transects spread over three
 447 years but rather a combination of these transects and estimates of the underlying seasonal
 448 and interannual variations from the suite of 54 models.

449 Although for differing time periods, our estimate contrasts with the findings of Palmer et
 450 al. (Palmer et al., 2019) for 2015-16, based on the assimilation of land Atmospheric Carbon
 451 Observations from Space (ACOS) v7.1 retrievals of GOSAT (Greenhouse Gas Observing
 452 Satellite) and OCO-2, and of the v9 MIP LNLG experiment for 2015-2018 (Peiro et al.,
 453 2022) that are on average 1.6 and 1.25 PgC yr⁻¹, respectively. For the v10 MIP, the mean
 454 NTA fluxes for the same 2016-18 period are 1.03 ± 0.38 PgC yr⁻¹ for the LNLG experiment.

455 The NTA fluxes for the v10 MIP IS and OG experiments are much weaker with 2016-
 456 2018 means of 0.31 and 0.42 PgC yr⁻¹, respectively. All the v10 MIP experiments are

457 consistent in showing an enhanced 2016 source, likely due to the 2015-2016 El Niño, and a
 458 ~ 0.5 PgC yr⁻¹ reduction of the source between 2016 and 2018 (Fig. 9). The LNLGOGIS
 459 range (1.71 PgC yr⁻¹) and that of IS (1.96 PgC yr⁻¹) are larger than other experiments
 460 (Fig. 9).

461 To evaluate the impact of the choice of a single box to determine the emergent con-
 462 straints, we repeated the entire annual-mean calculation with alternate altitude-latitude
 463 boundaries for the boxes. We varied one box at a time among the 12 highest correlated
 464 boxes for each ATom and calculated all different possibilities for 10⁴ realizations. The result-
 465 ing distribution of annual mean estimates is a normal distribution with a median and mean
 466 that are both equal to the the mean estimate using only our optimal four-box ATom-EC
 467 estimate. We add the standard deviation of this distribution, 0.1 PgC yr⁻¹, in quadrature
 468 with our uncertainty as an estimate of errors in the choice of box boundaries, resulting in a
 469 final uncertainty of ± 0.39 PgC yr⁻¹.

470 4 Discussion

471 Previous studies estimated a near neutral African CO₂ budget with photosynthesis
 472 being larger than the sum of respiration, biomass burning and fossil fuel emissions combined
 473 (Ciais et al., 2009; Valentini et al., 2014). The net biospheric carbon uptake is suggested
 474 to mainly occur in intact forests (Ciais et al., 2009; Lewis et al., 2009), as estimated by
 475 vegetation models and forest inventory plots. The long-term inventory plots of the African
 476 Tropical Rainforest Observatory Network, or AfriTRON, remained a live biomass carbon
 477 sink despite extreme environmental conditions during the 2015-2016 El Niño event (Bennett
 478 et al., 2021). This implies a strong uptake in intact, old-growth, tropical forests in line
 479 with above-ground carbon storage estimates (Pan et al., 2011). However, the 2015-2016
 480 El Niño (J. Liu et al., 2017) may have had long lasting impact with a slow recovery in
 481 forest uptake. There may be other sources of CO₂ from unaccounted deforestation and
 482 degradation (Wigneron et al., 2020).

483 Global CO₂ inverse models rely on prior fluxes provided for example from model prod-
 484 ucts, such as biosphere models (Philip et al., 2019) and are subject to large-scale transport
 485 uncertainty, given their coarse horizontal and vertical resolutions (e.g., Schuh et al., 2019).
 486 Knowing the importance of transport errors through diffusive and convective vertical mix-
 487 ing in explaining the systematic differences between TM5 and GEOS-chem (Schuh et al.,
 488 2019, 2022), we repeated our emergent constraint approach using only the subset of 3 TM5
 489 (TM5-4DVAR, OU and CT) or the 5 GEOS-Chem (Ames, CMS-Flux, COLA, UT and
 490 WOMBAT) inversions (Fig. S6). A previous study on CO showed that we also expect the
 491 differences to be maximal in outflow pathways of large biomass burning sources (Ott et al.,
 492 2011). We found a three-year annual mean flux estimate of 0.27 ± 0.36 (TM5) and $0.8 \pm$
 493 0.43 (GEOS-Chem) PgC yr⁻¹. These uncertainty estimates do not reflect the bias imposed
 494 by the choice of a single transport model. This reinforces the need for emergent constraints
 495 using relationships derived by a diverse suite of models.

496 In addition, inversion algorithms are sensitive to the observations' spatial coverage and
 497 temporal frequency, and with particular relevance for satellite CO₂ observations also to mea-
 498 surement biases (e.g., Basu et al., 2018; Houweling et al., 2015). Inversion of SCIAMACHY
 499 (Kaminski et al., 2017), GOSAT and OCO-2 CO₂ retrievals over land suggest a source in the
 500 tropics, driven by NTA region emissions (Houweling et al., 2015; Palmer et al., 2019; Crowell
 501 et al., 2019; Peiro et al., 2022). Mean estimates from previous GOSAT and OCO-2 studies
 502 range between 1.25-1.6 PgC yr⁻¹. The magnitude of these unexpected sources equates to
 503 approximately half of the global net land carbon sink (Friedlingstein et al., 2022) and would
 504 require a major revision to our understanding of both the tropical and global carbon cycle.
 505 A large NTA source has not been seen in the most recent IS inverse model synthesis studies
 506 (Crowell et al., 2019; Gaubert et al., 2019; Peiro et al., 2022). Overall the larger CO₂ land
 507 source estimates are driven by satellite retrievals during the dry season (Fig. 7), when there

508 is a high aerosol loading from biomass burning and dust which may increase biases (Fig. S1)
 509 in retrievals (O'Dell et al., 2018). The lack of ground-based observations over Africa makes
 510 it challenging to verify these estimates. Thus, airborne measurements such as those from
 511 ATom are uniquely valuable in assessing the divergent inversion estimates. During ATom-2,
 512 the ATom-EC indicates a smaller source of 3.15 ± 0.6 PgC yr⁻¹ (mean $\pm 1\sigma$ uncertainty,
 513 Fig. 7) in February than the LNLG experiment with 4.6 ± 0.74 PgC yr⁻¹ (mean $\pm 1\sigma$
 514 across 10 models).

515 It is possible that remaining biases in version B10 OCO-2 measurements over NTA
 516 led to erroneous flux estimates in inversions using these data. NTA during the dry season
 517 exhibits very high dust and smoke aerosol loading (Fig. S1d), associated with Harmattan
 518 winds (Evan et al., 2006). The OCO-2 retrievals undergo quality filtering based on multiple
 519 parameters, including aerosol optical depth (O'Dell et al., 2018), and for NTA during dry
 520 season typically less than 10 % of retrievals pass this filter (Fig. S1b). The OCO-2 retrievals
 521 also have a multi-parameter post-retrieval empirical bias correction applied (O'Dell et al.,
 522 2018), and this bias correction is largest over NTA, with adjustments of approximately +2.7
 523 ppm, or 0.6 ppm higher than the global average correction (Fig. S1a). This large bias
 524 correction is tied primarily to two terms, one encompassing dust, water, and sea-salt aerosol
 525 loading and a second related to the difference between retrieved surface pressure and that
 526 from meteorological reanalyses, which itself may result from aerosols (Kiel et al., 2019).

527 The positive dry season OCO-2 bias correction over NTA would have to be overesti-
 528 mated if it were to explain the sign of the LNLG inversion versus ATom-EC differences we
 529 see. How large of an overestimate might be required to explain our result? Given the many
 530 interacting constraints in global CO₂ inversions, and uncertain atmospheric transport, it
 531 is difficult to quantitatively estimate the magnitude of biases necessary. For example, the
 532 LNLG mean concentration bias in the ATom-2 optimized box is 0.88 ppm. However, we
 533 expect flux signals to be more concentrated in these optimized boxes than in full column
 534 XCO₂ measurements because they only represent partial columns, but also less concen-
 535 trated because of lateral and vertical mixing between NTA and the mid-Atlantic. Previous
 536 synthetic inversion work has demonstrated a high sensitivity of continental scale inverse flux
 537 estimates to small biases in satellite XCO₂ measurements, on the order of 1 PgC yr⁻¹ per
 538 ppm (Chevallier et al., 2007). We find a correlation between the dry season XCO₂ over NTA
 539 in posterior concentration fields and NTA fluxes from the inversions with a slope of 4.16
 540 PgC yr⁻¹ per ppm or 1.39 PgC/ppm for 4 months (DJFM) (Fig. S2). This implies that
 541 the disagreement we find between the 1.03 PgC yr⁻¹ LNLG inversion experiment mean and
 542 our ATom-EC estimate of 0.14 PgC yr⁻¹ might potentially be explained by a +0.64 ppm
 543 bias concentrated in Dec-Mar or just a +0.21 ppm bias if it persists throughout the year.

544 Despite the apparent overestimated source in the LNLG experiment, our ATom-EC
 545 estimate for ATom-2 still shows a stronger NTA source than in previous and v10 MIP IS
 546 inversions. Biomass burning emissions could play a role in the enhanced source, but need
 547 improved observational constraints. Recent studies have found that the dry matter burned
 548 estimates and the number of active fire detections over Africa could be underestimated by
 549 the 500-m resolution MODerate resolution Imaging Spectroradiometer (MODIS) instrument
 550 (Ichoku et al., 2016; Roteta et al., 2019; Nguyen & Wooster, 2020). The detection and
 551 inclusion of smaller fires detected by the higher-resolution 20-m Sentinel-2 Multispectral
 552 Instrument (MSI) suggests an increase in burned area and net higher emissions as well as a
 553 longer fire season (Roteta et al., 2019; Ramo et al., 2021). Overall, other reasons related to
 554 small-scale heterogeneity can explain discrepancies in the modelling of small fire emissions
 555 (van Wees & van der Werf, 2019).

556 5 Summary

557 We evaluated inverse model calculations of northern tropical African CO₂ fluxes with
 558 aircraft measurements over the Atlantic Ocean. This collection of models shows a large

559 inter-model spread in mean land flux magnitudes and temporal variability in sub-Saharan
 560 Africa. The posterior fluxes for NTA averaged over the 2016-2018 period span from -0.2 PgC
 561 yr^{-1} to more than 1.8 PgC yr^{-1} . For posterior CO_2 concentrations averaged over optimized
 562 ATom boxes, i.e. subregions of the ATom flight transect, the range is around 3 ppm, with
 563 a standard deviation between 0.74 and 1 ppm for different campaigns. During the dry
 564 season, our ATom emergent constraint indicates that NTA land fluxes are overestimated
 565 by the LNLG experiment and underestimated by the IS and OG experiments. Inversion
 566 errors could be due to the lack of assimilated in-situ observations in the region, atmospheric
 567 transport uncertainties, in particular arising from convection, and the difficulty of achieving
 568 accurate and frequent satellite retrievals due to cloud obstruction during the wet season
 569 and aerosols during the dry season. The comparison by models, i.e., TM5 or GEOS-Chem,
 570 supports the important role of transport biases in the spread of inversions results, which
 571 underscores the importance of the Model Intercomparison Project to assess flux estimates.
 572 Based on the seasonal timing of the LNLG flux differences, we speculate that the high dust
 573 and smoke aerosol loading during the dry season may lead to an overestimated bias correction
 574 in the v10 OCO-2 data over NTA. Our results point to the need to better characterize the
 575 distribution and impact of biomass burning and dust aerosols to further refine the OCO-2
 576 retrieval or bias correction procedures.

577 Overall, we found an enhanced seasonal cycle relative to IS inversions, with a larger
 578 source during the dry season and a stronger sink during the wet season (Figure S7). Outside
 579 of the dry season, the OCO-2 based inversions agree reasonably well with the airborne
 580 estimates. The OCO-2 inversions and the ATom-1 and ATom-3 emergent constraints imply
 581 a stronger sink during the NTA wet season. Our revised budget for NTA during 2016-2018
 582 is an annual source of 0.14 ± 0.39 PgC yr^{-1} . This is much smaller than the v10 MIP LNLG
 583 mean of around 0.9 PgC yr^{-1} .

584 Past studies and this study suggest the sensitivity of continental scale fluxes to biases in
 585 XCO₂ in inversions is high, implying the magnitude of remaining biases in OCO-2 data over
 586 NTA may be relatively small and challenging to address. Furthermore, given the large spread
 587 in total emissions and seasonality of fire emission estimates, the sensitivity of posterior CO_2
 588 to the choice of prior fire flux should be assessed in future studies. Additional constraints
 589 on fire fluxes could be obtained by the assimilation of satellite observations of chemical
 590 species related to combustion such as CO (Zheng et al., 2018; Gaubert et al., 2020) and
 591 nitrogen dioxide (NO_2) and improved burned area estimates (Zheng et al., 2021). For the
 592 individual months of the ATom campaigns, we obtain an uncertainty reduction in NTA CO_2
 593 fluxes of a factor of two compared to the full v10 MIP ensemble, highlighting the potential
 594 benefit of future airborne observations over and downwind of Africa and other continents. A
 595 regular ongoing program of global-scale airborne surveys would greatly improve our ability
 596 to resolve the global carbon cycle and validate satellite emission estimates.

597 Data Availability

598 The ATom data (Wofsy et al., 2021) is available as 10-sec, NOAA PFP, and Medusa
 599 merge products [https://doi.org/10.3334/ORNLDAAC/1925\(10.3334/ORNLDAAC/1925\)](https://doi.org/10.3334/ORNLDAAC/1925(10.3334/ORNLDAAC/1925)).
 600 The OCO-2 v10 MIP model results are publicly available ([https://gm1.noaa.gov/ccgg/](https://gm1.noaa.gov/ccgg/OCO2.v10mip/)
 601 [OCO2.v10mip/](https://gm1.noaa.gov/ccgg/OCO2.v10mip/), last accessed 2 March 2023) The NOAA Greenhouse Gas Marine Boundary
 602 Layer Reference (Dlugokencky et al., 2019) is publicly available ([https://gm1.noaa.gov/](https://gm1.noaa.gov/ccgg/mb1/data.php)
 603 [ccgg/mb1/data.php](https://gm1.noaa.gov/ccgg/mb1/data.php), last accessed 27 December 2022).

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