



1 **Uncertainties in OCO-2 satellite retrievals of XCO₂ limit diagnosis of**
2 **transport model simulation uncertainty**

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13 **Abstract.** Estimating regional CO₂ sources and sinks is challenging due to limited data and uncertainties in
14 transport models. Orbiting Carbon Observatory-2 (OCO-2) overcomes measurement limits, providing CO₂
15 variations beyond in-situ networks. This study analyses altitude-wise model-observation CO₂ differences from
16 surface to upper troposphere using aircraft observations from ATom, Amazon, and CONTRAIL campaigns over
17 OCO-2 total column CO₂ (XCO₂) sampling location to characterise sources of uncertainty in MIROC4-ACTM.
18 We show model aligns better with ATom tropospheric columns (0.03 ± 0.03 ppm) than OCO-2 XCO₂ (0.2 ± 0.5
19 ppm), especially over oceans, highlighting the need for expanded profile measurements to characterise errors
20 robustly. Altitude-wise comparisons reveal this differences primarily occur in the lower troposphere (0-2 km),
21 likely due to ACTM's near-surface land CO₂ flux errors. In contrast, ACTM better matches aircraft CO₂ in the
22 middle (2-5 km) and upper (5-8 km) troposphere, likely due to accurate large-scale transport representation. Over
23 the Amazon, CO₂ differences with aircraft and OCO-2 differ, likely due to a lack of regional surface sites for
24 inversion and insufficient high-altitude profile (~4km) not representative of XCO₂. Over Asian megacity airports,
25 which are significant emission hotspots, the model shows a large negative difference with CONTRAIL than OCO-
26 2. This discrepancy likely hints that MIROC4-ACTM is unable to capture urban fossil CO₂ emission signals at
27 airports due to coarse resolution (~2.8° x 2.8°) and higher resolution of OCO-2 limits ability to fully capture actual
28 emission footprints.

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30 **Keywords:** Carbon dioxide; Aircraft; Transport Model; OCO-2

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41 **1. Introduction**

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43 Atmospheric CO₂ is the most significant anthropogenic greenhouse gas (GHG) present in the Earth's atmosphere,
44 responsible for a major global warming and climate change since the preindustrial era, circa 1750 (Canadell et al.,
45 2022). Therefore, recognizing its importance in direct impact on climate, monitoring of highly accurate surface
46 CO₂ measurements were first started from the South Pole (SPO) and Mauna Loa (MLO), Hawaii (Keeling, 1960)
47 and later expanded across the globe. These in-situ measurements are widely used for estimating surface CO₂
48 fluxes using Bayesian-based "top-down" chemistry transport models due to their long-term record and high
49 measurement accuracy (Chandra et al., 2022; Chevallier et al., 2010; Peylin et al., 2013). However, in-situ CO₂
50 measurement sites around globe is sparse, mostly situated in mid-latitude north America and Europe, with less
51 coverage over tropical land (Patra et al., 2011; Schimel et al., 2015) and open oceans, which increase difficulties
52 in inferring surface CO₂ fluxes from inverse models in data void regions (Chevallier et al., 2010, 2011).

53
54 To increase spatiotemporal monitoring of CO₂, spaced-based measurements such as SCanning Imaging
55 Absorption spectroMeter for Atmospheric CartographY (SCIAMACHY), Greenhouse Gases Observing Satellite
56 "IBUKI" (GOSAT), and the Orbiting Carbon Observatory-2 (OCO-2) were launched to provide column-
57 average dry-air mole fraction or mixing ratio of CO₂, termed XCO₂ (Bovensmann et al., 1999; Crisp, 2008; Kuze
58 et al., 2009). NASA's OCO-2 satellite launched in 2014 to achieve finer spatial resolution and better precision as
59 compared to previous satellites. This advancement has proved beneficial for understanding global and regional
60 carbon cycle science in various satellite based studies (Crisp, 2015; Das et al., 2023; Liang et al., 2017; Liu et al.,
61 2017; Chatterjee et al., 2027). OCO-2 version 10 XCO₂ measurements has shown retrieval error with mean bias
62 (RMSE) of 0.24 (0.81) ppm over land and 0.43 (0.84) ppm over ocean globally, compared against more accurate
63 WMO scale maintained XCO₂ from surface-based Total Carbon Column Observation Network (TCCON) sites
64 (Taylor et al., 2023; Wunch et al., 2017). Studies reported that assimilation of OCO-2 XCO₂ available at greater
65 spatial density (~ 100 times of GOSAT) into an inversion requires the data to be extremely precise, stable and
66 regionally unbiased to effectively estimate surface CO₂ fluxes in regional scale (Byrne et al., 2017, 2023; Crowell
67 et al., 2019; Philip et al., 2022; Rastogi et al., 2021). Also, Miller et al. (2007) reported that satellite-retrieved
68 XCO₂ needs regional precision of 1-2 ppm to reduce uncertainty in inversion-derived flux estimates from in-situ
69 networks. Because, XCO₂ retrievals having many sources of uncertainty hinder their fidelity to utilize inversion
70 approach to accurately estimate surface CO₂ flux (Chevallier et al., 2014; Villalobos et al., 2020). These retrieval
71 errors in OCO-2 include cloud effects (Massie et al., 2021;Merrelli et al., 2015), instrumental errors, retrieved
72 surface pressure, and then aerosol, the largest source of systematic error can be approximately 2 ppm over land
73 regions (Connor et al., 2016). Therefore, to enhance the accuracy of surface CO₂ flux estimations, studies are
74 focussing on improving retrieval algorithm by correcting for cloud effects and incorporating a digital elevation
75 model (DEM) to correct surface pressure (Jacobs et al., 2023; Mauceri et al., 2023). Apart from retrieval errors,
76 misrepresentation of transport and uncertainty in prior fluxes can further reduce reliability in top-down model
77 inferred surface CO₂ fluxes (Chandra et al., 2022; Fu et al., 2021; Schuh et al., 2019). To address and assess such
78 kind of errors impact on top-down CO₂ budgets, OCO-2 model intercomparison project (MIP) is formed with
79 different CO₂ inverse modelling groups assimilating OCO-2, in-situ and combination of both (
80 https://gml.noaa.gov/ccgg/OCO2_v10mip/index.php).



81 Previous studies have attempted to reconstruct observation based CO₂ profiles combining ship, aircraft and model
82 simulation to compare with GOSAT XCO₂, but are limited to characterise inversion errors (Müller et al., 2021;
83 Inoue et al., 2013; Wofsy, 2011). Frankenberg et al. (2016), showed using HIPPO aircraft CO₂ vertical profiles,
84 that the retrievals of GOSAT, TES, AIRS satellites and inversion simulation can have large difference of ~ 4 ppm
85 due to inaccurate vertical transport in higher latitude during vegetation growing or decaying periods. These studies
86 often lack in providing uncertainties linked with inversion through altitude-based CO₂ comparison from near
87 surface to different tropospheric layers between inversion-based model simulations, surface, and aircraft data.
88 This gap is particularly evident in regions with in-situ sparse data coverage, such as vast oceanic areas, as well as
89 in emission or sink hotspots over land while OCO-2 dense measurements have not helped to overcome precision
90 issues providing global coverage. However, no studies attempted to understand how OCO-2 retrieval errors or
91 accuracy hampers its full potential to uncover the uncertainties associated with inverse models. The present study
92 aims to understand sources of error associated with the MIROC4-ACTM model through altitude-based CO₂
93 comparison among MIROC4-ACTM, OCO-2 and aircraft observation across different tropospheric layers. To
94 accomplish this we leverage highly accurate and precise aircraft vertical CO₂ measurements from ATom
95 campaigns over northern America, Pacific, Atlantic, Southern Ocean regions, CONTRAIL over airports in Asia
96 and four specific sites in Amazon. Before analysing, we first validated the MIROC4-ACTM model simulated
97 tropospheric column CO₂ (XCO₂) with highly precise CO₂ vertical profiles from independent aircraft
98 measurements over open oceanic regions, Amazon and local urban hotspot over Asia.

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100 2. Data and Methodology

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102 2.1 Aircraft and surface CO₂ measurements

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104 We have used individual independent aircraft and surface in-situ CO₂ measurements around the globes from
105 NOAA's obspack_co2_1_GLOBALVIEWplus_v8.0 data product (Schuldt et al., 2022) and WDCGG (World
106 Data Centre for Greenhouse Gases) respectively. We have selected a few individual campaigns such as ATom,
107 Amazon aircraft campaigns, CONTRAIL because of their extensive latitudinal/longitudinal spatial coverage over
108 ocean and land regions, multiple vertical CO₂ profile measurements and extended period of measurements. A
109 brief description of each aircraft measurement is discussed in the next paragraphs.

110

111 ATom is an aircraft field campaign, providing airborne measurements of remote tropospheric and lower
112 stratospheric CO₂ from Northern America, Arctic, Pacific, Southern and Atlantic Oceans (Thompson et al., 2022).
113 ATom has four campaigns conducted using NASA DC-8 aircraft, taking vertical profile of CO₂ from near surface
114 (0.15 km) to 13 km altitude range over four seasons from 2016 to 2018. Four campaigns each lasted around 28
115 days, namely, ATom-1, 28 July-22 August 2016; ATom-2, 26 January-22 February 2017; ATom-3, 28
116 September-26 October 2017; ATom-4, 24 April to 21 May 2018 respectively (Wofsy et al., 2021). These vertical
117 CO₂ measurements enable the validation of XCO₂ measurements from the satellites because most of XCO₂
118 variability is constrained in the troposphere, therefore, these vertical measurements effectively serve as a reference
119 for satellite-retrieved CO₂ validation (Frankenberg et al., 2016). We have utilised these CO₂ measurements freely
120 available at <https://gml.noaa.gov/ccgg/obspack/data.php>.

121



122 Additionally, aircraft vertical campaign CO₂ measurements from four sites such as TEF (3.39° S, 65.6° W), SAN
123 (2.86° S, 54.95° W), RBA (9.38° S, 67.62° W) and ALF (8.80° S, 56.75° W) in the Amazon region are also
124 considered for the present study and more details about these measurements can be found in Gatti et al. (2021a).
125 In ALF, RBA, SAN, CO₂ measurements are available from 2010 to 2018, whereas TEF has measurements from
126 2013-2018. Bi-monthly vertical CO₂ profile measurements were taken during 12:00 and 13:00 local time at all
127 these sites covering altitude from 0.3 to 4 km when the daytime boundary layer is well mixed. These measurements
128 were taken using an automatic sampler onboarded in the light aircraft, which underwent accuracy and precision
129 testing at greenhouse gas laboratory at National Institute of Space Research (LaGEE/INPE), Brazil (Gatti et al.
130 2014). We have used a set of vertical CO₂ profiles during September, 2014 till 2018, freely available at:
131 <https://doi.pangaea.de/10.1594/PANGAEA.926834> (Gatti et al., 2021b).

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133 Further, CONTRAIL aircraft program CO₂ measurements over Asian regions are also considered for the current
134 analysis (Ishijima et al., 2021; Machida et al., 2008; Matsueda et al., 2008). In this program, several regular
135 passenger aircraft operated by Japan Airlines (JAL) are installed with instruments like CME (Continuous CO₂
136 Measuring Equipment) to provide extensive spatial CO₂ data coverage in the upper troposphere and lower
137 stratosphere (UT/LS) region. We have only considered measurements during OCO-2 measurements period at four
138 representative zones in Asia, specifically around airports, to retrieve vertical CO₂ profiles during ascent or descent
139 of the aircraft, following Niwa et al., 2011. The measurements dataset is freely accessible at
140 <https://www.cger.nies.go.jp/contrail/>.

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142 2.2 OCO-2

143

144 OCO-2 is a sun-synchronous satellite, retrieves XCO₂ to understand the carbon source-sink activity throughout
145 the globe (Eldering et al., 2017). The satellite uses three high-resolution grating spectrometers to retrieve the
146 reflected sunlight spectral signature of weak CO₂ (1.61 μm), strong CO₂ (2.06 μm) and O₂A (0.76 μm) which are
147 later analysed through Atmospheric Carbon Observations from Space (ACOS) algorithm to estimate global
148 spatiotemporal XCO₂ distribution (Crisp, 2015; Crisp et al., 2017; Eldering et al., 2017). It has a spatial resolution
149 of 1.29 km × 2.25 km (nadir mode), and a temporal periodicity of sixteen days. We have utilised OCO-2 version
150 10 which is an update from previous version v8/v9 in terms of important changes in spectroscopy, aerosol, CO₂
151 prior source, and solar continuum model which reduced RMSE validated against XCO₂ measured at TCCON sites
152 for land and ocean-glint measurement (Taylor et al., 2023). In this study, we have used level-2 OCO-2 version
153 10r data product (available at:
154 https://disc.gsfc.nasa.gov/datasets/OCO2_L2_Standard_10r/summary?keywords=OCO-2) and have considered
155 only bias-corrected quality checked soundings (XCO₂_quality_flag = 0 or good data) for analysis.

156

157 2.3 Transport model

158

159 The Model for Interdisciplinary Research on Climate, version 4, based Atmospheric Chemistry Transport Model
160 (MIROC4-CTM) chemistry transport model is used, which is run at T42 spectral spatial resolution (~2.8° ×
161 2.8° latitude-longitude grid) with 67 vertical hybrid-pressure levels from the surface to 90 km to simulate the CO₂



162 concentration and fluxes (Patra et al., 2018). For realistic representation of the transport in the model, model
163 meteorology, horizontal winds (zonal and meridional) and temperature is nudged to Japanese 55-year Reanalysis
164 or JRA-55 data (Kobayashi et al., 2015). The MIROC4-ACTM model conducted two distinct simulations: one
165 utilizing bottom-up model a prior or “FG” fluxes and the other employing a posteriori or “InvFG” fluxes derived
166 from top-down inversion using 50 inversion sites (Figure S1). To derive total concentration in the simulation
167 different bottom-up tracers are utilised, gridded GridFED fossil fuel; $CO_{2,ff}$ (Jones et al., 2021), annually balanced
168 CASA biospheric flux; $CO_{2,ind}$ (Randerson et al., 1997) and ocean exchange i.e., sea-air CO_2 flux; $CO_{2,ocn}$
169 (Takahashi et al., 2009). Then, prior CO_2 simulation case of MIROC4-ACTM is prepared by adding the prior
170 tracers as follows: $CO_{2,ff}$ (GridFED) + $CO_{2,ind}$ (CASA-3hr) + $CO_{2,ocn}$ (Taka-Ocn). A detailed discussion on this
171 is given in Chandra et al. 2022. Further, to minimise the edge effect on the simulated dataset, we discarded the
172 first two years and last one year of our simulation period (2012-2022), only analysed CO_2 of both simulation and
173 observation during 2014-2021. Model performance evaluated by comparing with each vertical profile of
174 independent observations of ATom CO_2 not used in the inversion as well as at two surface sites, MLO (19.53 °N,
175 155.57 °W) and SYO (69.01 °S, 35.59 °W) representative of northern and southern hemisphere CO_2 variability
176 (Fig. S2, 3). To do that firstly, model simulated CO_2 is resampled to the nearest grid of the aircraft and surface
177 sampling locations, considering linear interpolations at spatial grid and time. We have not considered any other
178 co-location criteria unless it is mentioned, e.g., geometric and dynamic for comparison; therefore, estimated
179 CO_2 difference is essentially uncertainty either in observation or inversion (Kulawik et al., 2016, 2019). The
180 result shows good performance with lesser bias with InvFG over prior at different latitudes, showing an overall
181 good match of InvFG CO_2 and ATom at different latitudes (Fig. S2, 3). Similarly at surface sites, InvFG showed
182 better performance over prior with correlation of 0.99 with observation ($p < 0.05$) (Fig. S4). Then, to compare
183 OCO-2 XCO_2 and ACTM- XCO_2 , we formulated XCO_2^{ACTM} following the Patra et al., 2017. Here, ACTM
184 simulated CO_2 profile or CO_2^{ACTM} resampled at each OCO-2 retrieval location (latitude, longitude) with further
185 use of corresponding OCO-2 priori and column average kernel sensitivity (A_i) represents instrumental sensitivity
186 for 20 vertical levels from top of atmosphere (TOA) to surface to produce XCO_2^{ACTM} using the following equation.

$$187 \\ 188 \quad XCO_2^{ACTM} = \sum_i (CO_2^{priori} \cdot dP_i) + \sum_i A_i \cdot dP_i (\sum_i CO_2^{ACTM}_i - \sum_i CO_2^{priori}) \quad (1)$$

189 CO_2^{priori} = OCO-2 priori; A_i = OCO-2 column averaging kernel; dP_i = thickness of each pressure layer.

190

191 We have also resampled XCO_2^{ACTM} at 21 TCCON sites around the globe to validate model performance with
192 more accurate XCO_2 measurements at surface-based TCCON sites (Wunch et al., 2011). To perform that we first
193 filtered data points considering only good quality retrieval, then curve fitted the remaining retrieval to remove
194 outliers and finally considered retrievals with solar zenith angle $< 60^\circ$ following methodology mentioned in
195 Appendix C of Crowell et al. 2019. Figure S5 shows a good agreement between ACTM and TCCON XCO_2 for
196 majority of TCCON sites considering the fact that TCCON has its own bias due to topography, surface brightness
197 and aerosols as well as latitudinal varying bias (Wunch et al., 2017).

198

199 2.4 Data analysis

200



201 To conduct the spatial discrepancy analysis of XCO₂ difference between ACTM and OCO-2, bias corrected and
202 quality checked good soundings from OCO-2 XCO₂ retrieval or XCO₂^{OCO-2} and ACTM simulated XCO₂ or
203 XCO₂^{ACTM} is re-gridded into 0.5° × 0.5° latitude-longitude grid boxes. Further, to assess this XCO₂^{ACTM} -
204 XCO₂^{OCO-2} difference, we used aircraft vertical CO₂ measurement available at different vertical tropospheric
205 layers, essentially to conduct an altitude-wise comparison of CO₂ among ACTM, OCO-2 and aircraft. Therefore,
206 we have employed a methodology outlined using a schematic in Figure 1, specifically designed to provide CO₂
207 profile from aircraft, OCO-2 and ACTM.

208

209 It shows typical CO₂ concentration vertical profiles and relative altitude range captured in OCO-2, aircraft
210 measurements, and corresponding MIROC4-ACTM simulations. OCO-2 measures XCO₂ concentration from
211 space, representing CO₂ profile from top of the atmosphere to surface so as the ACTM simulation at those pressure
212 levels is represented by a blue colour double-headed arrow. On the other hand, aircraft tropospheric columns of
213 CO₂ typically capture concentration variability up to an altitude of 15 km and ACTM resampled concentration
214 values at those measurement locations represented by orange colour double headed arrows. Since the main
215 purpose is to compare the aircraft tropospheric column CO₂ against OCO-2 XCO₂ and ACTM simulations, we
216 subdivided the tropospheric CO₂ column into three different vertical tropospheric layers, namely, the lower
217 troposphere: lowest level to 2 km, middle troposphere: 2–5 km, and upper troposphere: 5–8 km to understand the
218 model performance in each of the vertical layers. In addition, a total tropospheric vertical CO₂ column of aircraft
219 or aircraft XCO₂ is calculated only when the vertical measurements reach at least 8 km altitude; otherwise, any
220 profile not reaching 8 km is discarded from the analysis unless otherwise mentioned specifically. For each vertical
221 tropospheric layer, pressure-weighted partial column CO₂ is calculated to consider air mass variation between
222 pressure levels for each considered tropospheric layer. Moreover, to become more robust on the analysis, each
223 vertical depth layer is subdivided into 200 bins unless otherwise mentioned and 80% of vertical bins having
224 measurements for the specific tropospheric layer only considered for analysis. For instance, middle troposphere
225 (upper troposphere), i.e., 2–5 (5–8) km is divided into 15 vertical bins each of 200 meters, then in a specific
226 latitude or longitude while calculating a partial column of CO₂, we only considered profiles that encompass a
227 minimum 12 vertical bins in them.

228

229 3. Results

230

231 3.1. MIROC4-ACTM intercomparison with OCO-2 and surface measurements

232

233 Figure 2a shows a monthly mean spatial XCO₂ difference (XCO₂^{ACTM} - XCO₂^{OCO-2}) during January, 2015 –
234 December, 2021. It reveals a heterogeneous signature of spatial XCO₂ difference or mismatch across the globe
235 with maximum negative XCO₂ difference of approximately 2 ppm over Amazon, Africa, south-east Asia, China,
236 primarily in the global tropical land regions. This is likely due to the lack of long-term surface CO₂ measurements
237 (Figure S1) available for inversion particularly over the global tropics to constrain the prior CO₂ flux (also
238 discussed in Chandra et al., 2022). Further, humid tropics is also the region of lesser valid OCO-2 retrievals due
239 to the persistent shallow cumulus cloud blocking the infrared signals, makes it challenging to validate the transport
240 model and studies has shown sparse sampling over land increases chances of the error almost two times
241 (Frankenberg et al., 2024; Kulawik et al., 2019). On the other hand, high-latitude land regions, North America



242 and Russia, exhibit a positive XCO₂ difference of nearly 2 ppm, however, XCO₂ differences over ocean regions
243 are generally within ± 1 ppm, possibly because of lesser variability in ocean CO₂ flux compared to land CO₂ flux
244 and oceanic regions are minimally affected by land air mass. Further, we observed a negative XCO₂ difference
245 especially over northern extra-tropics between 30° N to 60° N of nearly -0.6 ppm in agreement with Byrne et al.
246 2023 likely attributed to OCO-2 ocean glint (OG) retrieval biases that adds up a layer of complexity of diagnosing
247 the transport model against OCO-2 retrievals over this vast ocean. Further, studies showed that sampling
248 variance between land and ocean could also lead significant uncertainty (Basu et al., 2018). Additionally, we
249 observed a bias in the Southern Hemisphere, the underlying causes of which are still unknown and need further
250 research (Byrne et al., 2023). Overall, our results show some regions under/over-estimated by ACTM, however,
251 it is challenging to comprehend quantitatively and qualitatively about sources of error across diverse regions
252 (source-sink dynamics and transport mechanism) as it could result either due to inaccuracies in the inversion (prior
253 fluxes, transport) or errors in satellite retrievals (Chandra et al., 2022; Chevallier et al., 2014). Furthermore, to
254 check the time variation of these XCO₂ differences, we analysed the time versus latitude distribution of XCO₂
255 difference taking the average across global longitude from 180° W to 180° E (Fig. 2b). We observed that XCO₂
256 difference has a seasonal and spatially varying repeating signature, with maximum (minimum) difference during
257 February-March-April (September-October-November) consistent across study period. A prominent positive
258 (negative) systematic XCO₂ difference is observed over the southern hemisphere tropic to mid-latitude from 10°
259 S–40° S and northern latitude around 30° N (northern tropic to mid latitude) this is in agreement with Kulawik et
260 al. (2019). However, after separating time vs latitude distribution of XCO₂ difference into land and ocean, we
261 observed that this systematic XCO₂ difference mainly originates from the southern ocean part, which matches
262 well with overall (land and ocean) time vs latitude XCO₂ difference distribution (Fig. S6). However, it is
263 challenging to explain the difference since ocean glint has biases (Byrne et al., 2023) and a study by Kulawik
264 et al. (2019) also reported a systematic error of 0.6 ± 0.1 ppm could arise over the ocean and land in OCO-2
265 satellite XCO₂ retrievals.

266

267 To further examine whether this difference comes from inversion or XCO₂ retrieval because both have
268 uncertainties. We similarly analysed time versus latitude distribution of surface CO₂ concentration difference with
269 respect to ACTM simulation or CO₂^{ACTM} - CO₂^{In-situ} considering accurate surface CO₂ concentration data from 53
270 measuring sites around the globe. Most of these sites are situated in the northern hemisphere having at least 90%
271 data during study period (all sites geographical location can be visualised in Figure S7 in supporting information).
272 MIROC4-ACTM simulated CO₂ near the surface is resampled to the nearest grid of surface sites (latitude,
273 longitude, altitude) and measurement time from hourly interval model output. For each of the 53 sites, CO₂
274 concentration difference between ACTM and surface CO₂ concentration is calculated first, and then we linearly
275 interpolate it spatially as presented in Figure 2(c). Results show no such annually and spatially systematic
276 signature of CO₂ difference near the surface between equator to 45° S considering six stations (SEY: 4.7° S, ASC:
277 8° S, SMO: 14.2° S, NMB: 23.6° S, CPT: 34.4° S, CGO: 40.7° S) situated at different latitudes within this latitude
278 band (Fig. S7). Considering the fact that inferred CO₂ difference may arise due to much lower data density for the
279 in situ measurements within mentioned latitude bands, the analysis with the available sites suggests that systematic
280 signatures of difference exist when we compared with OCO-2 XCO₂ (Fig. 2b). It hints at uncertainties in OCO-2
281 retrieval or systematic vertical transport error in the model (Schuh et al., 2019), given the relatively lower



282 uncertainty in in-situ CO₂ measurements compared to OCO-2 XCO₂. This vast part of the region remained
283 challenging for a model to understand its error characteristics due to OCO-2 retrieval error. Further, we also
284 compared the latitudinal average time series of CO₂ (XCO₂) difference of ACTM with surface (OCO-2) in Fig.
285 2(d). It shows an overall agreement of CO₂ difference with a correlation coefficient of 0.68 at 99% significance
286 level with total time series variability (1- σ STDEV) of 0.28 and 0.19 ppm in CO₂ difference in surface as compared
287 to OCO-2. Overall, this CO₂ space-time variability analysis clearly demonstrates that systematic signature in
288 XCO₂ difference, primarily concentrated in southern mid and northern high latitudes, previous studies also
289 indicated towards potential uncertainties may arise in retrieval over the ocean and or misrepresentation of vertical
290 transport in inversion (Byrne et al., 2023; Frankenberg et al., 2016; Schuh et al., 2019). Since systematic errors in
291 transport could result in inaccurate CO₂ flux estimates and, consequently, posterior simulated concentration (Deng
292 et al., 2015; Stephens et al., 2007). In an inversion estimation, transport, surface CO₂ flux and CO₂ spatial gradient
293 are closely interconnected so any misrepresentation in vertical or horizontal mixing consequently affects the
294 estimated flux. This highlights the complexity of interpreting CO₂ differences across diverse regions,
295 measurement platforms and error quantification of the optimised flux of inversions from surface and satellite
296 measurements. Therefore, to better understand the consistency of CO₂ differences across different global regions
297 and identify regions of major uncertainty which will enable us to address them effectively, we analysed CO₂
298 variation in different vertical tropospheric layers using vertical CO₂ profile datasets from aircraft measurements,
299 discussed in section 3.2.

300

301 3.2 CO₂ difference in tropospheric layers

302 3.2.1 Over Globe

303

304 Figure 3 represents mean CO₂ difference or CO₂^{ACTM}-CO₂^{aircraft} across different latitudes using individual aircraft
305 observations for different tropospheric layers LT (light red), MT (orange), UT (dodger blue) and tropospheric
306 Total Column (teal), color coded to represent different altitude ranges. Aircraft measurements are generally
307 available in two modes: continuous measurements from the same site over a long period, and campaign
308 measurements that cover extensive vertical and horizontal distances with high data density over a limited period.
309 Therefore, we have subdivided aircraft measurements into two subcategories for our analysis: specific site
310 aircrafts having latitude coverage maximum 5°(Fig. 3a) and campaign aircrafts having latitude coverage
311 maximum 30° (Fig. 3b). Only those aircrafts having measurements during OCO-2 period are selected, each
312 aircraft sampling location, number of data points at different latitude bins of 30° and altitude bins of 1000 meters
313 is provided in the supplementary material (Fig. S8 and S9 gif for each aircraft category). Then, we calculated
314 model-observation CO₂ difference for each aircraft measurement category. Therefore, estimated CO₂ difference
315 serves as a model and observation mismatch for specific latitude (entire latitude range) for specific sites
316 (campaign) aircraft with latitude information mentioned inside parenthesis of first x-axis tick marks in Fig. 3a
317 (3b). Here, the second x-axis shows the number of data points in the corresponding aircraft campaign. Here, the
318 number of data points or samples is critical when comparing CO₂ differences among aircraft. A higher number of
319 samples provides better confidence to the calculated CO₂ difference while aircraft with fewer samples are
320 considered less weightage.



321 Mean (variability) of CO₂ difference for LT, MT, UT and tropospheric column for specific sites aircraft are -0.45
322 (± 0.49), -0.32 (± 0.48), -0.34 (± 0.5), and -0.2 (± 0.41) respectively (Fig. 3a). It shows the highest mismatch in
323 terms of mean exist in LT as compared to other tropospheric layers MT, UT and total tropospheric column, likely
324 due to uncertainty in prior CO₂ flux or transport in LT. Studies have shown that in the LT, concentration changes
325 are mainly regulated by surface CO₂ fluxes and diurnal-synoptic mixing patterns (Law et al., 2008; Patra et al.,
326 2008). However, CO₂ change in UT is mainly dominated by changes in large scale dynamical transport, where
327 surface emission has subdued influence. Hence, studies have found that coarse spatial resolution transport models
328 adequately simulated CO₂ in the MT to UT regions (Baier et al., 2020; Niwa et al., 2011). Additionally, it is also
329 noted that there is a systematic underestimation by the model in terms of magnitude in all tropospheric layers.
330 Result shows minimum or maximum (near zero) model-observation CO₂ difference (ppm) observed for “esp” or
331 “rta” (cma) aircraft at 49.48° N or 21.19° S (38.83° N) in the LT for specific sites aircraft. In the tropospheric
332 column, maximum (minimum) CO₂ difference is observed in “cma” (“car”) aircraft at 38.83° N (40.66° N)
333 respectively. Further, it has been observed that the tropospheric column CO₂ difference matches pattern of CO₂
334 difference at LT at most aircraft sites; LT apparently contributes more to the total tropospheric column than MT
335 and UT. Further, it could be seen that the overall mean model-observation CO₂ difference is highest in the northern
336 mid-latitudes compared to the tropical latitudes of the northern and southern hemispheres.

337

338 Further, we have calculated $XCO_2^{ACTM} - XCO_2^{OCO-2}$ at those specific sites aircraft location considering $5^\circ \times 5^\circ$ grid
339 box surrounding it to check the difference similarity between XCO₂ and tropospheric column CO₂ selecting only
340 specific times from OCO-2 of aircraft measurement. Results show XCO₂ difference mean (variability) of -
341 0.37 (± 0.38), highlighting that the model is underestimating and also has minimum variability as compared to any
342 individual layers. On the other hand, CO₂ difference with campaign aircraft showed similar results; overall highest
343 mean and variability exists in LT observed. Further, the overall mean (variability) of the tropospheric column is -
344 0.39 (± 0.1) controlled largely by CO₂ difference in LT. Here, we also check XCO₂ difference at those campaign
345 aircraft considering their covered tracks and then taking the average of all XCO₂ differences to calculate a mean
346 XCO₂ difference. Results show lesser variability in XCO₂ as compared to other layers and also negative mean
347 XCO₂ represents overall underestimation by the model. It has been observed in both aircraft categories that the
348 model has underestimated overall CO₂ concentration in all tropospheric layers and total columns, also the
349 maximum mean and variability of CO₂ difference are in LT. These differences are attributed possibly due to
350 underestimation by prior flux in the inversion or misrepresentation of transport in the model. To further investigate
351 CO₂ differences altitude-wise, we considered individual vertical CO₂ profiles from different campaigns for
352 different regions North America, Pacific, Southern Ocean, Atlantic, Amazon and Asia discussed in detail in
353 subsequent sections.

354

355 3.2.2 North America, Pacific, Southern and Atlantic ocean

356

357 Figure 4(a) illustrates integrated tracks traversed by the aircraft during ATom campaign (ATom-1, ATom-2,
358 ATom-3, ATom-4) across oceanic and land parts, subdivided into four segmented track categories corresponding
359 to specific geographical regions delineated with different colours. Represented segments are North America and
360 neighbours; east to west aircraft campaigning (magenta), Pacific; north to south aircraft campaigning (yellow),
361 Southern Ocean; west to east aircraft campaigning (red), and Atlantic; south to north aircraft campaigning (green).



362 Figure 4(b) shows the mean XCO₂ difference taken considering a collocation criteria of 5° × 5° latitude-longitude
363 grid box around sampling location and XCO₂ retrievals during corresponding ATom campaign period. We
364 observed a maximum XCO₂ difference of nearly 2 ppm over 120° W and 90° W in North America and
365 neighbouring land regions whereas oceanic regions, particularly Pacific and Atlantic are mostly confined within
366 ±1 ppm at any specific latitude. We also checked the latitudinal bias MIROC4-ACTM against TCCON XCO₂
367 across the latitude during the ATom campaign period shown in Figure S11. This comparison also showed higher
368 bias over this latitude location against TCCON sites at Park Falls, JPL, Lamont and East Trout Lake. Therefore,
369 model bias is consistent both against OCO-2 and TCCON. Then, to understand the altitude-wise variation of
370 CO₂^{ACTM} - CO₂^{aircraft} difference at different tropospheric depths (LT, MT, UT, tropospheric column), we used
371 ATom vertical CO₂ dataset. We also compared these CO₂ differences with OCO-2 across segmented ATom tracks
372 (Fig. 4c-f). Result shows largest CO₂ difference in terms of mean ± STDEV (calculated taking 1-σ standard
373 deviation) of CO₂ differences across longitude range is -0.41 ± 0.94 ppm exist in LT as compared to the other
374 tropospheric layers likely due to uncertainty and large variability in prior land CO₂ flux near surface (Fig. 4c).
375 When we compare CO₂ differences from other layers of different track segments, North America and neighbour's
376 CO₂ difference at LT appears to be the highest, mainly occurring during the ATom-1 period (Figure S10).
377 Moreover, OCO-2 XCO₂ difference also showed large variability with longitudinal mean CO₂ difference of -0.34
378 ± 1.07 ppm compared to aircraft tropospheric column CO₂ of -0.01 ± 0.48 ppm. This essentially reflects the
379 model's overall good performance against ATom as compared to OCO-2 XCO₂. Similarly, ACTM and ATom
380 CO₂ discrepancy was also evident in vertical cross-section, highest approximately ~ 2 ppm appeared at high
381 latitude land regions during vegetation growing (respiration) period of northern hemisphere July-August, 2016 in
382 ATom-1 (April-May, 2018 in ATom-4) (Figure S10). This large difference occurs across the vertical altitude
383 range prominent above 8000 meters likely arises due to the coarse resolution of the ACTM model unable to
384 represent the vertical transport. Needs further research on improving convective transport parameterization in
385 forward model to improve vertical mixing (Patra et al., 2018). These results are also in line with the study
386 Frankenberg et al., 2016. We have also validated model simulation with TCCON measurements during the ATom
387 period, results also shown differences up to 1 ppm at the sites over northern America (Figure S11).

388
389 Other three segments of CO₂^{ACTM} - CO₂^{aircraft} difference are primarily focused over oceanic regions (Southern,
390 Pacific, Atlantic) where magnitude of ocean CO₂ flux variability is less as compared to land regions as much as
391 10 times less. Land and ocean CO₂ flux variability over the longitude and latitude band around ATom tracks for
392 different campaigns is shown in Figure S12. Figure 4d shows that over the Southern Ocean, the model-observation
393 CO₂ difference is lowest within ±0.2 ppm for each vertical tropospheric layer and 0.06 ppm for the aircraft
394 tropospheric column, with minimal variability compared to other layers. When compared with other ATom
395 segments, the Southern Ocean shows the lowest CO₂ difference in both mean and variability. This is because the
396 aircraft sampling is at the background troposphere and is farthest from land having little influence from land CO₂
397 air mass. This reflects that the optimized MIROC4-ACTM model, considering 50 ground-based sites, simulates
398 fairly well the aircraft background concentrations, however, it is unable to match a similar level of reproducibility
399 for OCO-2 XCO₂. Further, the latitudinal CO₂ difference variability against the aircraft tropospheric column
400 (lowest 8 km) is 0.15, compared to 0.77 with OCO-2 XCO₂. In most latitudes, OCO-2 XCO₂ differences are larger
401 than aircraft CO₂, indicating likely retrieval errors in OCO-2 given the lower uncertainty in aircraft CO₂



402 measurements. This XCO₂ difference with OCO-2 over the southern ocean is mainly during the ATom-2 period
403 (Fig. S14); however large XCO₂ difference pixels near 50° W and 70° W are during ATom-3 (September-October
404 2017; Fig. S15). Previous studies reported that OCO-2 ocean glint retrieval over southern ocean has more residual
405 biases while comparing against individual measurements (TCCON, In-situ, OCO-2 land) in top-down inversion
406 (Byrne et al. 2023; O'Dell et al., 2018). In addition, this is also location of the southern hemisphere zone of
407 stratosphere-troposphere exchange (STE) vary greatly spatiotemporally due to significant vertical mixing which
408 strongly changes with season, less constrained by model transport, which may also result in an error in estimated
409 posterior concentration. Next, we analysed CO₂ differences over the southbound Pacific segments of the ATom
410 campaign (Fig. 4e), it shows latitudinal CO₂ difference mean (variability) is highest of about -0.16 (± 0.53) ppm
411 in LT, compared to MT and UT. On the other hand, aircraft tropospheric columns showed a mean (variability)
412 difference of approximately -0.04 (± 0.38) ppm whereas OCO-2 XCO₂ with a value of 0.27 (± 0.42) ppm. This
413 shows although the mean is significantly different however the variability in both CO₂ differences is close to each
414 other, this is reflected in overall matching of both aircraft columns and OCO-2 XCO₂ (Fig. 4e). Lastly, we
415 analysed CO₂ difference over the Atlantic i.e., longest northbound part of ATom campaign shown in Figure 4(f).
416 Aircraft tropospheric column CO₂ difference of aircraft shows value of 0.03 ppm as compared to XCO₂ difference
417 with OCO-2 showing value of 0.26 ppm. Although, it has been observed that the latitudinal CO₂ difference in the
418 aircraft tropospheric column closely matches pattern in OCO-2 XCO₂. Another important point is that overall
419 CO₂ differences variability in the Atlantic is observed higher as compared to the Pacific segment especially over
420 tropics within 30° S–30° N, more in-situ aircraft measurements are required to better understand the underlying
421 error. Individual ATom campaigns results are presented in supplementary Figure S13-16.

422

423 3.2.3 Amazon

424

425 The climate-sensitive global tropic is a crucial part of the global carbon cycle due to the threats posed by climate
426 change, especially the Amazon region, which holds the largest above-ground biomass (AGB) pool of
427 approximately 123 ± PgC (Malhi et al., 2006; Santoro et al., 2010). Inversion based estimate showed Amazon
428 was a carbon source of 0.3 ± 0.2 PgC/yr in agreement with bottom-up calculation (Alden et al., 2016; Beienet
429 et al., 2015; Gatti et al., 2014, 2021a,c) during 2010-2019, though significant uncertainty remain. This is also the
430 region under-sampled by OCO-2 retrievals due to clouds and high spatial resolution satellite monitoring is needed
431 in the future (Frankenberg et al., 2024). Prevalent uncertainty in flux estimation in modelling approach and low
432 sampling of satellites highlight the need for more research in understanding error better way and improving both
433 inversion and retrievals methods over Amazon. In section 3.1, we observed large model-observation XCO₂
434 differences exist over South America, especially over Amazon. To investigate it further, we have utilised the
435 vertical profile (VP) of CO₂ measurements from vertical aircraft campaigns across Brazilian Amazon sites, SAN,
436 ALF, RBA, and TEF presented in Figure 5(a). The aircraft measurement has an accuracy of ~0.03 ppm (Gatti et
437 al., 2023) and a detailed description of measurements can be found in Gatti et al., 2021a. Studies have shown that
438 although these VPs are taken up to an altitude range of 4 km, they provide important insights into CO₂ variability
439 near the surface (Gatti et al., 2023; Tejada et al., 2023). An important point to note here, since Amazon aircraft
440 campaigns measure VPs of CO₂ approximately at an altitude up to 4 km, therefore, we considered the tropospheric
441 column as 0 to 4 km and only those VPs having measurements at least 4 km are chosen for calculation. We kept



442 the same criteria for the data availability of 80% vertical bin filter for 500-meter bin resolution as mentioned
443 previously in the methodology section.

444

445 Before analysing the ACTM bias against the Amazon aircraft CO₂, we validated ACTM simulated CO₂ with the
446 aircraft CO₂ at these sites which are not used in the inversion, showing a good correlation (*r*) of ~0.8 at 95%
447 significance level shown in Figure S17. We also checked that model able to capture TCCON XCO₂ at Manaus,
448 Brazil with time series XCO₂ difference mean of 0.05 ppm, but the model shows higher differences (-1 ppm) with
449 OCO-2 XCO₂ in Figure 2. It hints, OCO-2 retrieval likely have error could arise from Amazon dense vegetation
450 cover, cloud cover-aerosols and high humid conditions which can block sunlight spectra, reduce the signal
451 strength, limit valid sampling and increase retrieval error (Frankenberg et al., 2024; Taylor et al., 2016; Yu et al,
452 2019). These retrieval challenges precludes robust understanding of inversion error across the broader Amazonian
453 region. To further check this error altitude wise, a monthly mean time series of ACTM-aircraft CO₂ difference
454 considering all vertical profiles within a month is calculated for three vertical tropospheric layers, LT (lowest–2
455 km), MT (2–4 km) and tropospheric column (lowest-4 km) during OCO-2 measurement periods is presented in
456 Figure 5c-f. Figure 5c represents CO₂ difference at SAN aircraft campaign sites having data gaps from mid-2015
457 to early-2017 because of no measurements conducted during this period. Maximum model-observation
458 differences in terms of mean(variability) of 0.93(± 3.36) ppm observed in LT as compared to MT and tropospheric
459 column. This mismatch is comparable with previous study by Basso et al. 2023. Further, OCO-2 XCO₂ difference
460 showed overall negative mean of -0.83 ppm with variability of ± 1.04 ppm as compared to aircraft VPs profile
461 with aircraft tropospheric column shown better constrained having value of 0.76 ppm. Further, we analysed VPs
462 at the ALF site presented in Figure 5(d) shows overall that aircraft model-observation CO₂ difference matches
463 well with XCO₂. CO₂ differences at LT, MT, tropospheric column, XCO₂ shows mean (STDEV) are -0.9 (± 4.24),
464 0.08 (± 2.03), -0.13 (± 2.48), -0.65 (± 1.03) respectively. Basso et al. 2023 has shown that some of this difference
465 between inversion and aircraft CO₂ could be significantly improved (57% below 1.5 km and 49% above 3.5 km)
466 when using regional aircraft CO₂ data in the inversions. . In RBA, CO₂ difference at LT, MT, tropospheric
467 column, XCO₂ shows mean (STDEV) are -0.61 (± 4.33), -0.03 (± 2.52), 0.27 (± 2.95), -0.69 (± 1.04) respectively
468 shown in Figure 5e. Therefore, it shows CO₂ difference with the aircraft tropospheric column (OCO-2 XCO₂) has
469 opposite signature; it represents ACTM over (under) estimates considering the whole time window. In TEF, CO₂
470 difference at LT, MT, tropospheric column, XCO₂ shows mean (STDEV) are -0.4 (± 4.29), 0.64 (± 3.02), 0.19 (±
471 2.89), -1.37 (± 0.99) respectively presented in Figure 5f. Except for SAN, at all other sites, we observed that the
472 ACTM matches in total column better with aircraft than OCO-2, and but this profile is still insufficient to match
473 with XCO₂ needs further high profile measurement over this location. It is worth noting that the large discrepancy
474 or bias in LT in RBA, TEF (SAN, ALF) during January-March (August-December) in west-central (south-east)
475 Amazon regions may potentially arise due to fire CO₂ emission is reported in Basso et al. 2023. Since our inverse
476 simulations using CASA biospheric flux lack observation-based biomass burning data, this could also affect the
477 overall simulated concentration as well. We also checked monthly land CO₂ flux anomaly, calculated by taking
478 area mean around campaign sites within 5° × 5° degree and then removing seasonal cycle from actual time series.
479 We noticed no such anomalous flux change during the anomalous CO₂ difference period, likely due to the coarse
480 resolution of the MIROC4-ACTM and also because no regional CO₂ data from Amazon is used in our inversion
481 which could potentially capture Amazon land CO₂ flux changes better way (Fig. 5b; Fig. S1). Basso et al. 2023



482 highlighted the importance of assimilating Amazon aircraft measurements in deriving regional land CO₂ flux. In
483 all Amazon aircraft sites, an increase in land CO₂ flux during 2015-16 was observed due to strong ENSO events
484 occurred during this period also reported in Das et al. (2022).

485

486 3.2.4 Asia

487 In Asia there are very few aircraft campaigns for CO₂ measurements compared to Northern America and Europe
488 (Crevoisiera et al., 2010; Xueref-Remy et al., 2011). Although, efforts have been made to measure CO₂ vertical
489 profile over monsoon-dominated Indian subcontinents for a shorter time period (Vogel et al., 2023). Therefore,
490 available long-term CO₂ measurements like CONTRAIL is very important to provide unprecedented insights into
491 long-term CO₂ variability in UT/LS and model evaluations over these regions (Bisht et al., 2021; Das et al., 2022;
492 Niwa et al., 2011). Therefore, we have utilised these measurements to compare and understand model-
493 observations CO₂ difference for OCO-2 and CONTRAIL aircraft in different regions across Asia. Figure 6a
494 depicts the spatial distribution of the CONTRAIL campaign CO₂ sampling location from January 2015-December,
495 2021, covering altitudes ranging up to ~12 to 14 km with topographic altitudes information (topography elevation
496 data is downloaded from <https://www.ncei.noaa.gov/products/etopo-global-relief-model>). Here, we have selected
497 four separate regions around airport locations delineated through deep green colors having CO₂ vertical profiles
498 resulting from aircraft ascent or descent near airports. The four regions are namely Far East Asia, Southeast
499 China, northern Southeast Asia and Equatorial Southeast Asia, based on the locations of airports. In Far East Asia,
500 two airports are considered: Tokyo International Airport, Japan (site code: HND) (35.6° N, 139.8° E) and Narita
501 International Airport (site code: NRT) (35.8° N, 140.4° E) are considered together, named TYO (35.7° N, 140.8°
502 E); in Southeast China, Hong Kong International Airport (site code: HKG) (22.2° N, 113.6° E); in northern
503 Southeast Asia, Suvarnabhumi International Airport, Thailand (site code: BKK) (13.7° N, 100.7° E); and in
504 southern Southeast Asia, Singapore Changi International Airport, Singapore (site code: SIN) (1.4° N, 104.0° E),
505 all airports are marked with a small square box in Figure 6a ,b. During the aforementioned period, no vertical
506 sampling was performed over the Indian subcontinent and other two airports highlighted on map Incheon
507 International Airport (site code: ICN) and Shanghai Pudong International Airport (site code: PVG), were not
508 considered due to less number of sampling dataset. Figure 6b presents mean model-OCO-2 XCO₂ differences over
509 sampling locations of CONTRAIL, showing mainly negative CO₂ difference ranging -0.5 to -1 ppm over boxed
510 airports location highlighting likely reason is underestimation overall fossil emission of urban CO₂ signature in
511 the model. There is very limited TCCON sites over city scale that validates OCO-2 XCO₂, however, Rißmann et
512 al. (2022) using Munich Urban Carbon Column network (MUCCnet) XCO₂ across three sites over Germany
513 found out OCO-2 has a RMSE of 0.6 ppm in urban site. Since OCO-2 has retrieval error over city scale it makes
514 it challenging to discuss the sources of error could come from the model.

515 To understand this we analysed more robust CONTRAIL aircraft CO₂ (~0.2 ppm for each CONTRAIL data point),
516 figure 6c-f represents a time series of model-observation CO₂ differences over each airport for different vertical
517 depths of troposphere and XCO₂. Here, we have considered all CO₂ vertical profiles, selecting aircraft ascent and
518 descent flight modes over airports within a month and done a monthly average for 200-meter vertical bins to
519 calculate partial column CO₂ for aircraft and similarly for model simulations resampled at aircraft measurement
520 location considering methodology described in section 2.4. For OCO-2, we computed the mean over designated



521 airports to calculate model-observation difference for XCO₂ for the specific months. Results show in far east Asia,
522 TYO location CO₂ difference in LT, MT, UT, tropospheric column, XCO₂ shows mean of -2.0, -0.88, -0.73, -
523 1.02, and -0.3 respectively. In HKG airport, the number of samples in LT was very less therefore ignored in the
524 analysis however CO₂ difference in MT, UT, tropospheric column, XCO₂ shows values of -1.2, -0.99, -1.13 and
525 -0.02 respectively. For northern Southeast Asia, BKK airport CO₂ difference at LT, MT, UT, tropospheric
526 column, XCO₂ shows mean (STDEV) of -2.71 (± 1.67), -0.83 (± 0.74), -0.6 (± 0.59), -1.06 (± 0.71), and -0.1 (±
527 0.71) respectively. Further, in equatorial Southeast Asia, SIN airport difference at LT, MT, UT, tropospheric
528 column, XCO₂ shows mean (STDEV) of -1.89 (± 1.26), -1.03 (± 0.54), -0.81 (± 0.59), -1.05 (± 0.56), and -0.25
529 (± 0.42) respectively.

530 Result indicates that in northern Southeast Asia and southern Southeast Asia, mean and variability of model-
531 observation CO₂ difference is higher in LT as compared to UT, MT and weighs more. In all regions, model-
532 observation difference for OCO-2 showed better constrained compared to aircraft measurements and readily
533 observable that it closely matches the tropospheric column pattern. A notable fact in all regions is that the total
534 time series mean of model-observation difference is negative for both aircraft (-1.02 to -1.13 ppm) and OCO-2 (-
535 0.02 to -0.3 ppm), which would imply an underestimation of model simulated CO₂. While the OCO-2 XCO₂ vs
536 MIROC4-ACTM differences are not statistically significant but the large and systematic CONTRAIL CO₂ vs
537 MIROC4-ACTM differences may suggest that actual emission footprints captured by satellite observations are
538 greater than the measurement resolution (~1.29 × 2.25 km² for OCO-2). It suggests OCO-2 capturing emissions
539 from broader urban areas than its nominal resolution, possibly either due to the well-mixed nature of CO₂ and
540 OCO-2 measuring total column or the spatial extent of urban footprint. Further, the large variability and significant
541 differences between the aircraft CO₂ column and XCO₂ are evident in all regions. This is likely attributable to the
542 selection of a specific box area, which surrounds airport locations situated in urban areas, one of the significant
543 sources for fossil CO₂ emission. This inference is discussed in earlier studies (Patra et al., 2011; Umezawa et al.
544 2020), wherein they reported an urban emission footprint in CONTRAIL aircraft measurements conducted over
545 airport megacities. The inversion process, utilized in this context, exclusively optimizes total CO₂ fluxes, for
546 biosphere and ocean regions considering background sites, whereas this CONTRAIL measurement over airports
547 having signature of urban interiors. Consequently, noteworthy disparities may emerge due to uncertainties
548 associated with fossil fuel CO₂ emissions and also coarse horizontal resolution of MIROC4-ACTM (T42, ~2.8°
549 × 2.8°) unable to reproduce the sub-grid-scale variations. This limitation does not influence optimized flux for the
550 large area studies but affect our ability to simulate posterior concentrations, leading to underprediction of
551 concentration near the surface over the emissions or sinks hotspots, e.g., anthropogenic emissions at the megacity
552 areas or plumes of intense biomass burning. Note that the location of ascent and descent of the aircraft may change
553 by seasons following the meteorological conditions, and thus the location of measurements less strictly follows
554 year around. Previous studies underscore the critical role of fossil fuels in shaping simulated CO₂ dynamics,
555 emphasizing their potential to introduce systematic errors in optimized surface fluxes (Suntharalingam et al.,
556 2005; Wang et al., 2020).

557 3.3 Discussion and conclusions



558 The availability of the OCO-2, aircraft, and in-situ CO₂ observations, along with MIROC4-ACTM simulation at
559 their corresponding measurement location and time, allows us with an opportunity to understand fine-scale CO₂
560 difference between the ACTM and OCO-2 more robustly. Because, this enables diagnosing CO₂ difference from
561 near surface to different tropospheric layers, utilising surface, and aircraft observation to highlight persistent
562 limitations in addressing inversion uncertainties.

563 • We demonstrated that MIROC4-ACTM, using only 50 surface-based CO₂ sites globally, accurately
564 simulates tropospheric column and OCO-2 XCO₂, showing strong agreement with aircraft and TCCON
565 data (correlation = 0.9, $p < 0.0001$) at most sampling sites.

566 • Our analysis highlighted that the regional hemispheric MIROC4-ACTM CO₂ difference with OCO-2
567 and in-situ measurements has heterogeneous signatures of CO₂ differences, particularly over land.
568 However, Kulawik et al. 2019, noting that OCO-2 retrievals over lands have more random errors
569 especially over Amazon which is less sampled by OCO-2 makes retrieval less reliable for comparison
570 (Frankenberg et al., 2024). Additionally, comparison against in-situ indicates that OCO-2 likely has a
571 systematic retrieval error over the southern hemisphere oceanic region. Both random error over land, less
572 sampling of OCO-2 over global tropics and systematic error over ocean makes it difficult to detect and
573 understand the uncertainties in inverse models in a global perspective. We need more vertical aircraft
574 profile measurements to more robustly understand this error especially over the global tropics.

575 • Altitude wise comparison of CO₂ difference from categorical specific and campaign aircraft
576 measurements around the globe consistently highlight the model's highest mismatch in LT as compared
577 to MT, UT, and tropospheric columns. Additionally, LT contributes more to the mean and variability
578 to the total tropospheric column than the MT, UT. This maximum uncertainty in the LT likely arises
579 from the uncertainties in prior fluxes near the surface. In contrast, the MT and UT, where large-scale
580 dynamical mixing predominates, show better model performance, likely due to realistic transport of the
581 forward model. Further, aircraft tropospheric CO₂ columns are better reproduced by MIROC4-ACTM
582 compared to individual tropospheric layers and OCO-2 XCO₂. Further, studies have shown OCO-2
583 XCO₂ is more prone to erroneous retrieval due to near surface aerosol and cloud contamination in LT
584 which makes it challenging for total column comparison with model (Connor et al., 2016; Massie et al.,
585 2021).

586 • Results from ATom show large CO₂ difference variability over North America regions as compared to
587 other integrated tracks over ocean, likely because of the influence of land air mass having large variability
588 in land CO₂ flux. Similarly, large CO₂ differences in aircraft sites over Amazon may likely arise due to
589 uncertainty in prior flux and coarse resolution of the model unable to represent small scale variation
590 requires more regional measurements in inversion, however, comparison against OCO-2 highlights
591 robust requirement of good amount of valid retrievals to diagnose the inversion from large region
592 perspective as well as insufficient high-altitude profile measurements (~4 km) demands more high profile
593 measurements. Aircraft measurements over the remote background troposphere in the Pacific, Southern
594 Ocean, and Atlantic showed the best match within 0.03 ppm when compared to OCO-2 with 0.2 ppm,



595 especially over the Southern Ocean. However, the model comparison with CONTRAIL has shown
596 consistent more (less) underestimation against aircraft (OCO-2) CO₂ measurements for all airports in
597 Asia. This discrepancy is likely due to the coarse resolution of the inversions unable to capture the
598 signature of urban fossil CO₂ emissions and also for OCO-2 unable to capture the whole urban footprint.
599

600 **Code availability**

601 Data and figure processing codes prepared for this study will be made available upon reasonable request from the
602 corresponding author. Inversion code used here is available on <https://github.com/prabirp/co2l2r84>.

603 **Data availability**

604 The ObsPack data product is available at <https://gml.noaa.gov/ccg/obspace/>, CONTRAIL
605 at <https://www.cger.nies.go.jp/contrail/>, Amazon aircraft campaign at
606 <https://doi.pangaea.de/10.1594/PANGAEA.926834>, ACTM model outputs at aircraft sampling and OCO-2
607 sounding locations will be made accessible upon requests from corresponding authors.

608 **Author contributions**

609 CD, PKP and RKK developed the idea and methodology of the study. CD ran the entire analysis and prepared the
610 main manuscript and supplementary. PKP, RKK and NC helped in review and editing. KI, and TM are part of the
611 CONTRAIL CO₂ measurement group. All co-authors actively engaged in scientific discussions.

612 **Competing interests**

613

614 The authors declare that they have no conflict of interest.

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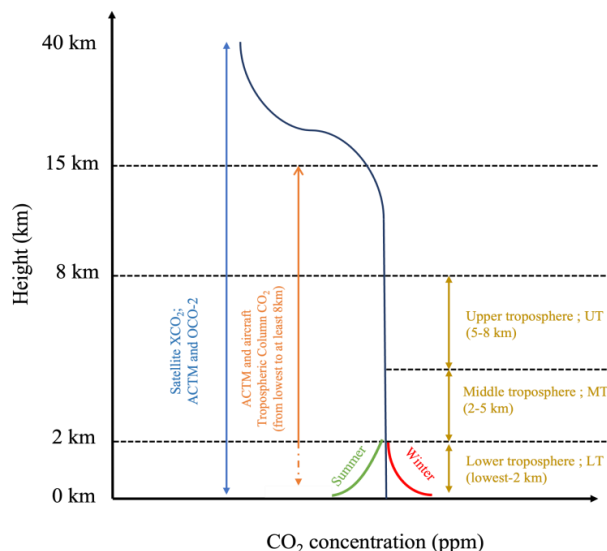
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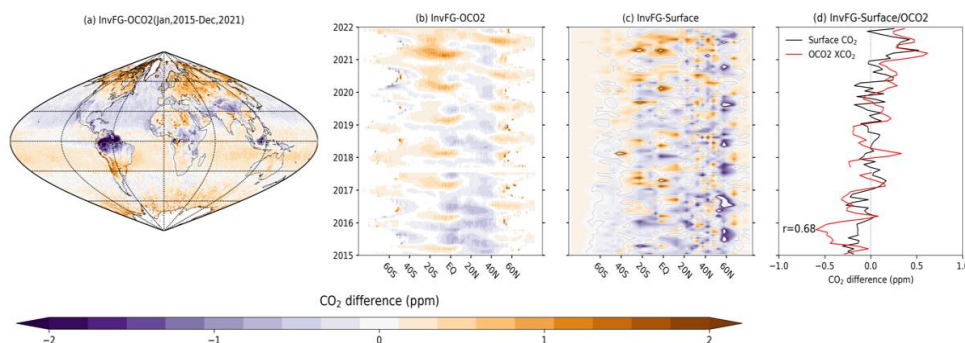
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Figures



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984 **Figure 1:** Schematic of CO₂ concentration vertical profile (dark blue line) by satellite, ACTM, and aircraft CO₂
 985 (orange, golden) Arrowheads represent different layers of the atmosphere, specifically LT (lowest–2 km), MT
 986 (2–5 km), UT (5–8 km), and the tropospheric column (lowest–8 km) corresponds to the aircraft CO₂
 987 measurement. Blue arrow represents total variation captured by satellite covers from surface to top of the
 988 atmosphere.
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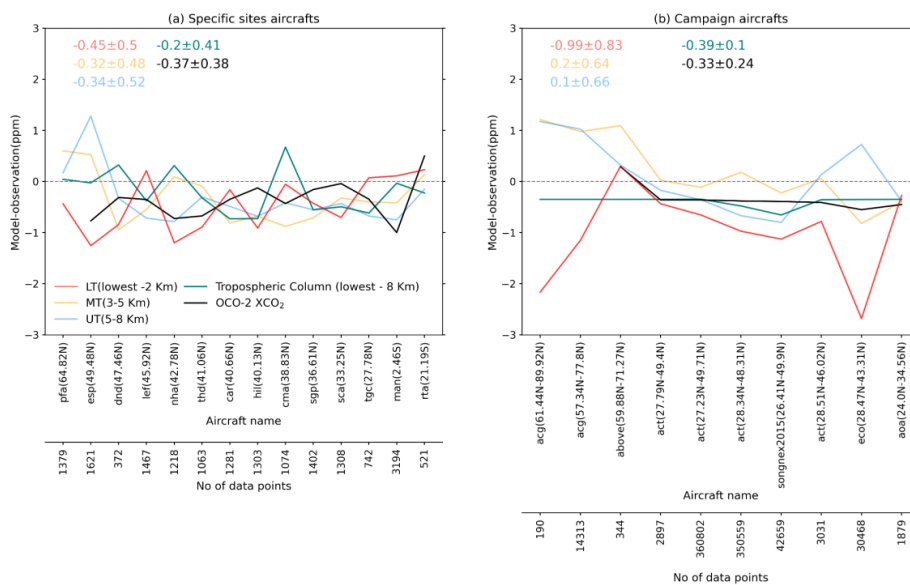
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992 **Figure 2:** CO₂ space-time variability with (a) spatial mean XCO₂ difference map between InvFG and OCO-2
 993 during January, 2015–December, 2021. (b) Time vs latitude distribution of XCO₂ difference between InvFG and
 994 OCO-2 considering mean across global longitude. (c) Time vs latitude cross-section of CO₂ concentration
 995 difference between InvFG and in-situ CO₂ measurement, considering CO₂ from 53 surface sites. (d) Latitude



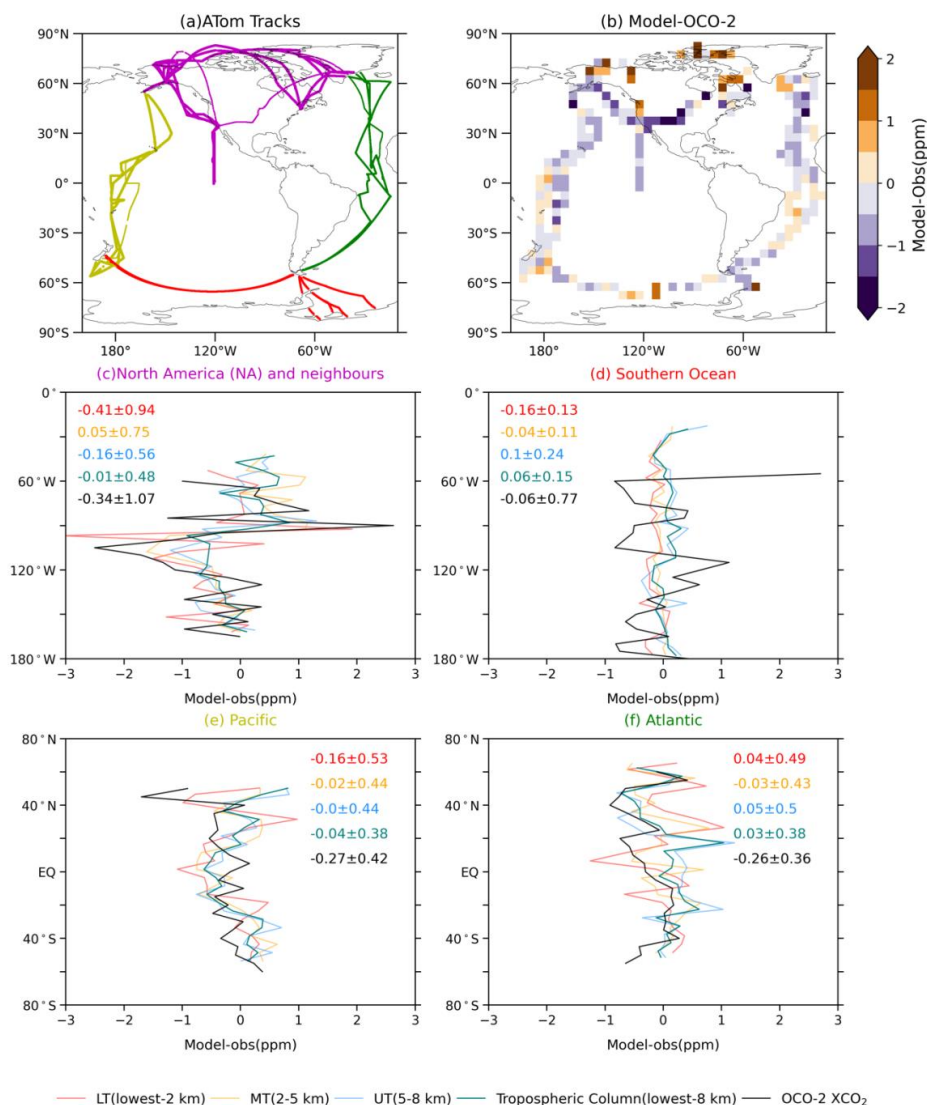
1996 averaged time series of CO₂ (XCO₂) concentration difference between InvFG and Surface (OCO-2) respectively
 1997 represented by black (red) colours. “r” value in panel-d represents correlation between time series of surface and
 1998 OCO-2 difference at 99% significance level.

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Figure 3. Mean model-observation CO₂ difference (ppm) at different vertical tropospheric depths LT (light red), MT (orange), UT (dodger blue), total column (teal) and XCO₂ for specific sites aircraft (panel-a) and campaign aircraft measurements having latitudinal coverage maximum 30° (panel-b). Aircrafts names are organized based on aircraft observations location, progressing from high latitudes in the Northern Hemisphere, through the equator, to southern latitudes. The second x-axis represents a number of data points for specific aircraft observation. The first and second number inside the panel represents mean and 1-σ standard deviation (STDEV) of model-observation difference across latitude for each tropospheric layer.

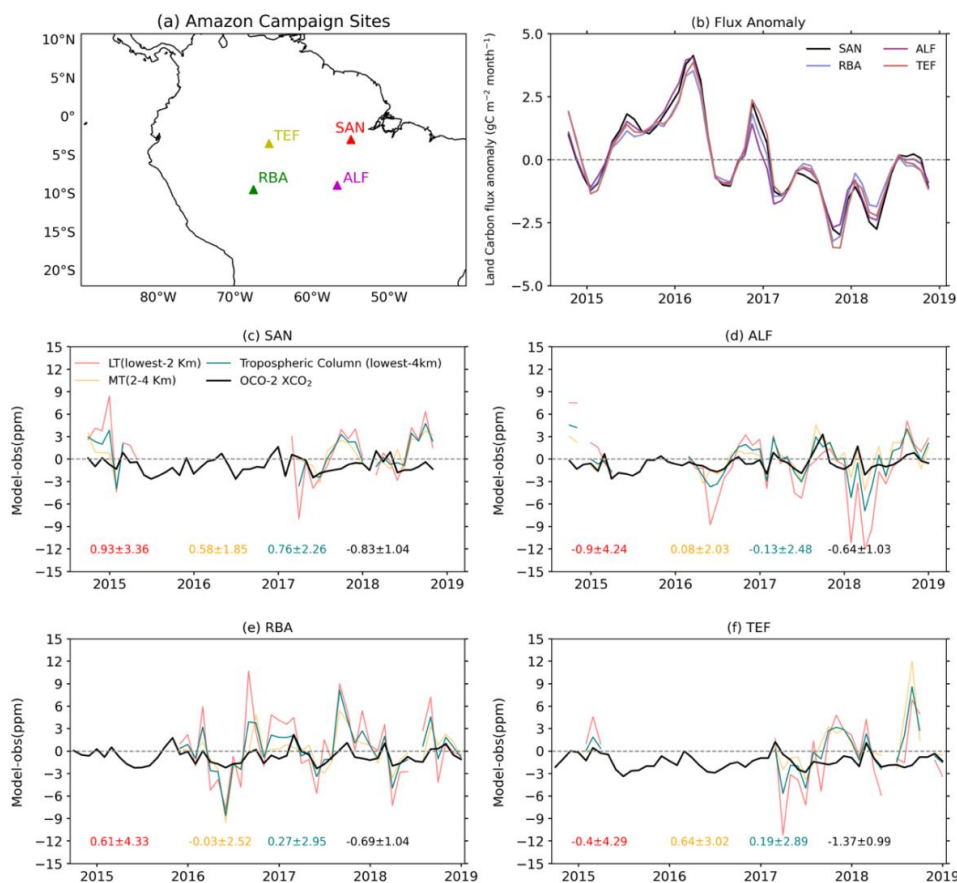


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1013 **Figure 4:** (a) Integrated tracks traversed during ATom campaigns (ATom-1, ATom-2, ATom-3 and ATom-4).
 1014 (b) Spatial model-observation XCO₂ difference against OCO-2 over ATom integrated track during campaign (c),
 1015 (d), (e), and (f) shows model-observation CO₂ difference over different tropospheric layers from vertical CO₂
 1016 profile measurements of ATom and XCO₂ from OCO-2 for North America and neighbours, Southern Ocean,
 1017 Pacific, and Atlantic segments respectively. Tropospheric layers are LT (light red), MT (orange), UT (dodger
 1018 blue) and Total Column (teal), and OCO-2 XCO₂ (black) representation for difference against OCO-2. The first
 1019 and second number on the right side of each middle and bottom panel represents the mean and 1-σ standard
 1020 deviation (STDEV) of model-observation difference across latitude or longitude, respectively.
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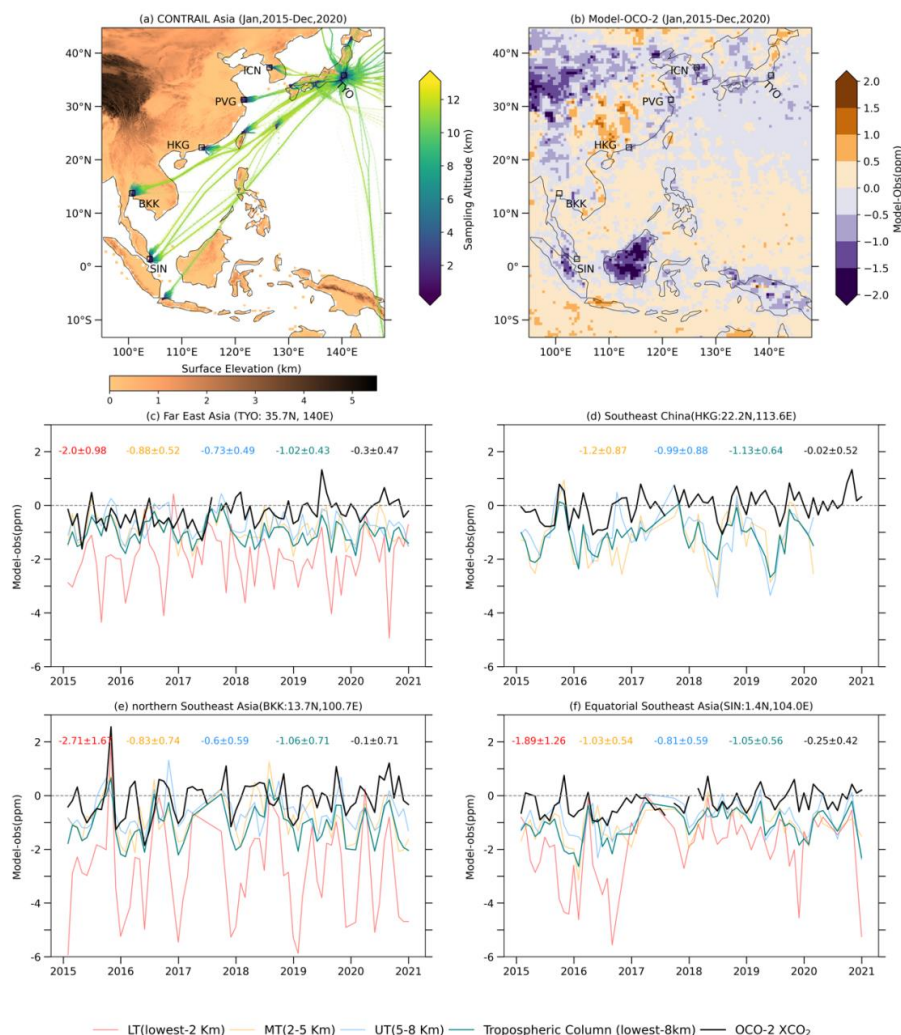


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1025 **Figure 5:** (a) Amazon aircraft vertical CO₂ profile campaign sites, SAN, ALF, RBA, and TEF. (b) Time series of
 1026 land carbon flux anomalies at the campaign sites. (c), (d), (e) and (f) represent a time series of model-observation
 1027 CO₂ differences for LT, MT, and tropospheric column, and XCO₂ during OCO-2 measurement periods for SAN,
 1028 ALF, RBA and TEF, respectively. The numbers inside the middle and bottom panels represent the mean and 1-σ
 1029 standard deviation (STDEV) of model-observation CO₂ difference over the time period.

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1032 **Figure 6:** (a) CONTRAIL aircraft sampling locations with associated colours represent sampling altitude in km
 1033 over Asia regions with surface elevation in km. There are four defined regions, each associated with specific
 1034 airports, covering various vertical zones of carbon dioxide (CO₂) profiles. Far East Asia consisting of two airports,
 1035 HND, NRT merged to prepare TYO, Southeast China with one airport HKG, northern Southeast Asia with one
 1036 airport BKK, and equatorial Southeast Asia encompassing one airport SIN. (b) mean model-OCO₂ XCO₂
 1037 differences over sampling locations during the mentioned period. (c), (d) (e), and (f) are time series of model-
 1038 observation CO₂ differences over representative airports at different vertical depths of troposphere MT, LT and
 1039 tropospheric column and XCO₂ utilising aircraft measurement and OCO-2. The numbers inside the (c), (d), (e),
 1040 and (f) panels represent the mean and 1-σ standard deviation (STDEV) of model-observation difference over the
 1041 period.