

1 **Large impact of coarse-resolution atmospheric transport model error on land-ocean**  
2 **and tropic-extratropic partitioning and seasonal cycle in CO<sub>2</sub> inversion**  
3

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13 **Key Points:**

- 14 ● Error from the coarse-resolution atmospheric transport model can introduce systematic  
15 biases to CO<sub>2</sub> modeling and inversed flux estimates.
- 16 ● The coarse-resolution transport error leads to stronger land and extratropical sink  
17 estimates and weaker ocean and tropical sink estimates.
- 18 ● The error also induces an underestimated seasonal amplitude and a reversed seasonal  
19 phase in the northern land and ocean, respectively.

## 20 **Abstract**

21 We show that forward simulations of global CO<sub>2</sub> using an atmospheric transport model (ATM) at  
22 0.5° × 0.625° and 4° × 5° resolutions differ significantly in vertical and meridional distribution.  
23 Comparing two observing simulation system experiments at 4° × 5° resolution that assimilate  
24 pseudo observations sampled from the two forward simulations, we isolated the impact of  
25 coarse-resolution ATM error on regional flux estimates that a significant amount of annual  
26 carbon uptake from the ocean and tropics is improperly redistributed to the land and extratropics,  
27 respectively. In addition, this error leads to an underestimated seasonal amplitude in the northern  
28 extratropical land and a reversed seasonal phase in the northern extratropical ocean. The reversed  
29 seasonal phase has also been shown in a real data assimilation experiment and state-of-the-art  
30 inversions, suggesting that ocean glint retrieval error may not be as significant as previously  
31 thought and reasonable ocean flux estimates depend strongly on the accuracy of ATM.

## 32 **Plain Language Summary**

33 Credible regional carbon budget estimates from atmospheric CO<sub>2</sub> measurements rely on the  
34 accuracy of atmospheric transport models (ATMs). However, the simulated atmospheric vertical  
35 motions in ATMs are usually simplified and spatiotemporally averaged, leading to systematic  
36 biases in simulating the long-lived atmospheric CO<sub>2</sub> and estimating surface carbon fluxes. Even  
37 though the atmospheric approach is increasingly applied to account for country-level carbon  
38 budget in global synthesis activities. Our finding suggests that current coarse-resolution ATMs  
39 lead to improper attribution of annual carbon uptake from the ocean and tropics to the land and  
40 extratropics, respectively, resulting in overestimated natural carbon uptake and reduced  
41 emissions reduction duty in most advanced countries that target carbon neutrality. Furthermore,  
42 since the seasonal variation of carbon flux in the ocean is much smaller than in the land, the  
43 results indicate that a small seasonal bias from the land can overwrite and even reverse the real  
44 flux signal in the ocean.

## 45 **1 Introduction**

46 Quantifying the country-level CO<sub>2</sub> budget using atmospheric CO<sub>2</sub> inversion technique is  
47 one of the critical approaches in the upcoming Global StockTake assessment (Chevallier, 2021;  
48 Jiang et al., 2022; Weir et al., 2022; Deng et al., 2022; Byrne et al., 2023). However, several  
49 fundamental issues in CO<sub>2</sub> inversion (e.g., transport, satellite retrieval, and a priori errors) have  
50 not been fully addressed, challenging the derivation of robust regional CO<sub>2</sub> budget estimation  
51 (Fu et al., 2021; O'Dell et al., 2018; Philip et al., 2019; Schuh et al., 2019). Inversion systems  
52 use an offline atmosphere transport model (ATM) to relate the surface land and ocean carbon  
53 fluxes with observed CO<sub>2</sub> concentration. An offline ATM is driven by the meteorology  
54 reanalysis data generated from a general circulation model (GCM), which significantly reduces  
55 the computational cost but simplifies and spatiotemporally averages some nonlinear atmospheric  
56 processes (J. Liu et al., 2011; Basu et al., 2018; Schuh et al., 2019). The averaging processes  
57 include remapping the GCM output from seconds to hours and irregular grid to latitude-  
58 longitude grid, and spatial interpolation from native to coarse horizontal resolution, which  
59 induces underestimated transient vertical motion and reduced vertical transport (Yu et al., 2018).  
60 Recent forward modeling studies find that the simulated CO<sub>2</sub> concentrations are significantly  
61 different in vertical and meridional distribution using different ATM configurations and ATMs  
62 (Schuh et al., 2019; Schuh & Jacobson, 2022). These biases can influence the estimates of

63 regional carbon budgets (Wang et al., 2020; Schuh et al., 2022) and seasonal cycles (Cui et al.,  
64 2022) estimates. A large discrepancy between the inversion estimates and process  
65 understandings is the land-ocean and tropic-extratropic partitioning of carbon fluxes. The  
66 inversions usually estimate a large carbon sink in the northern extratropics and a weak carbon  
67 sink or carbon source in the tropics recently, while process models or inventories suggest more  
68 carbon uptake in the tropics (Schimel et al., 2015; Friedlingstein et al., 2022). Evidence from the  
69 vertical CO<sub>2</sub> observation profiles indicates that inversions may overestimate the northern sink  
70 and underestimate the tropical sink (Stephens et al., 2007).

71 To reduce the main transport error, running global inversions at the native resolution is a  
72 straightforward strategy. However, native resolution inversions can be very slow due to reading  
73 and writing a large amount of data and poor parallel methods in some ATMs (e.g., classic  
74 GEOS-Chem) (The International GEOS-Chem User Community, 2021). For example, forward  
75 simulation of global CO<sub>2</sub> at a native horizontal resolution of  $0.5^\circ \times 0.625^\circ$  using GEOS-Chem  
76 requires around 60 gigabytes (GB) of memory and could be paralleled using OpenMP only that a  
77 one-year simulation costs more than 1 week using 1 Central Processing Unit (CPU) with 20  
78 cores. The computation costs will increase dramatically by at least an order of magnitude when  
79 conducting ensemble or adjoint simulation, thus not possible in real inversion applications but  
80 acceptable in simple forward simulation. In this study, instead of conducting native inversion  
81 directly, we, for the first time, derived the impact of coarse resolution transport model error on  
82 large-scale flux distribution in the context of observing simulation system experiments (OSSEs)  
83 and further suggested that the estimated northern ocean fluxes in current state-of-the-art  
84 inversion systems are likely driven by the transport error instead of observation information or  
85 satellite retrieval errors. Section 2 describes the data and method; Section 3 shows the results; the  
86 conclusion and discussion are presented in the last section.

## 87 **2 Data and method**

88 We use the Carbon in Ocean-Land-Atmosphere (COLA) system (Z. Liu et al., 2022,  
89 2023) to understand the transport impact on flux estimation in the context of Observing  
90 Simulation System Experiments (OSSEs) and a real data assimilation experiment. COLA  
91 optimizes the land ( $F_{TA}$ ) and ocean ( $F_{OA}$ ) carbon fluxes using a local ensemble transform Kalman  
92 filter and a constrained ensemble Kalman filter, while terrestrial fire flux ( $F_{IR}$ ) and anthropogenic  
93 fossil fuel emissions ( $F_{FE}$ ) are not optimized. The atmosphere transport model used in COLA is  
94 GEOS-Chem of version 13.0.2, driven by the Modern-Era Retrospective analysis for Research  
95 and Applications Version 2 (MERRA-2) meteorology reanalysis (Gelaro et al., 2017; The  
96 International GEOS-Chem User Community, 2021). The native spatial resolution of MERRA-2  
97 is  $0.5^\circ \times 0.625^\circ$ .

98 In this study, two sets of OSSEs are performed from December 2014 to the end of 2015.  
99 In the first OSSE (EXP-biased), the assimilation run is conducted at  $4^\circ \times 5^\circ$  resolution while the  
100 nature run is conducted at the native  $0.5^\circ \times 0.625^\circ$  resolution. In the second OSSE (EXP-perfect),  
101 both the assimilation run and nature run are conducted at  $4^\circ \times 5^\circ$  resolution. The pseudo surface  
102 and satellite observation network are almost identical to Liu et al. (2022) but with additional  
103 ocean glint observations from the Orbiting Carbon Observatory-2 (OCO-2) (O'Dell et al., 2018;  
104 Baker et al., 2022). This kind of observation network was usually called LNLGOGIS in the  
105 OCO-2 flux model intercomparison project (OCO2MIP) (Crowell et al., 2019; Peiro et al., 2022;  
106 Byrne et al., 2023). Then the pseudo observations in each OSSE are sampled from their

107 corresponding nature runs and randomly perturbed based on the error scales described in Liu et  
108 al. (2022). The nature runs start from the same initial CO<sub>2</sub> concentration and are forced by  
109 identical surface carbon fluxes with the F<sub>FE</sub> from the Open-source Data Inventory of  
110 Anthropogenic CO<sub>2</sub> emissions (ODIAC) (Oda et al., 2018), the F<sub>IR</sub> from Global Fire  
111 Assimilation System (GFAS) (Kaiser et al., 2012), the F<sub>OA</sub> from Rödenbeck et al. (2014), and the  
112 F<sub>TA</sub> generated from the terrestrial model of Simple Biosphere Model Version 4 (SiB4) (Haynes  
113 et al., 2019). To separate the impact of model resolution while with less impact from a priori  
114 fluxes, the a priori F<sub>TA</sub> and F<sub>OA</sub> used in the assimilation runs are similar as in the nature runs but  
115 from 4 years ago.

116 In addition to the two OSSEs, a real data assimilation experiment (EXP-real) is  
117 conducted at 4° × 5° resolution that assimilates the LNLGOGIS observations. And the a priori  
118 fluxes and assimilation period are identical to the nature run of EXP-biased. An ensemble of  
119 global inversion results (Ames, Baker, CSU, CT, OU, and TM5-4DVAR) within version 10 of  
120 OCO2MIP that assimilate the LNLGOGIS observations and without very tight ocean a priori  
121 constraint is used to validate the transport bias impact further (Byrne et al., 2023). Moreover, 4 a  
122 priori of "bottom-up" ocean flux products in the OCO2MIP systems are used as references.

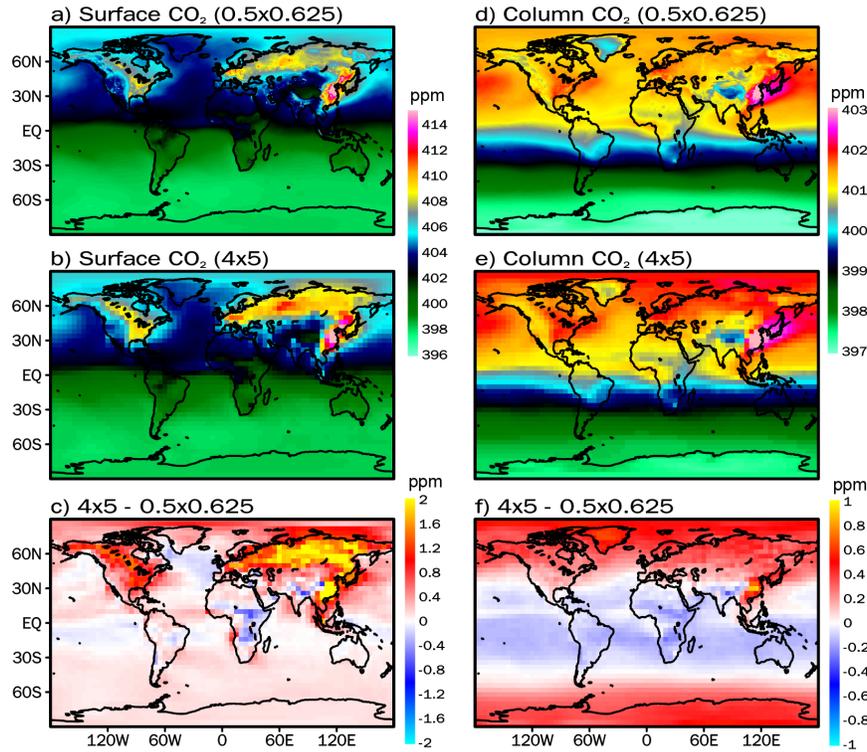
## 123 **3 Results**

### 124 **3.1 Land-ocean and tropic-extratropic partitioning**

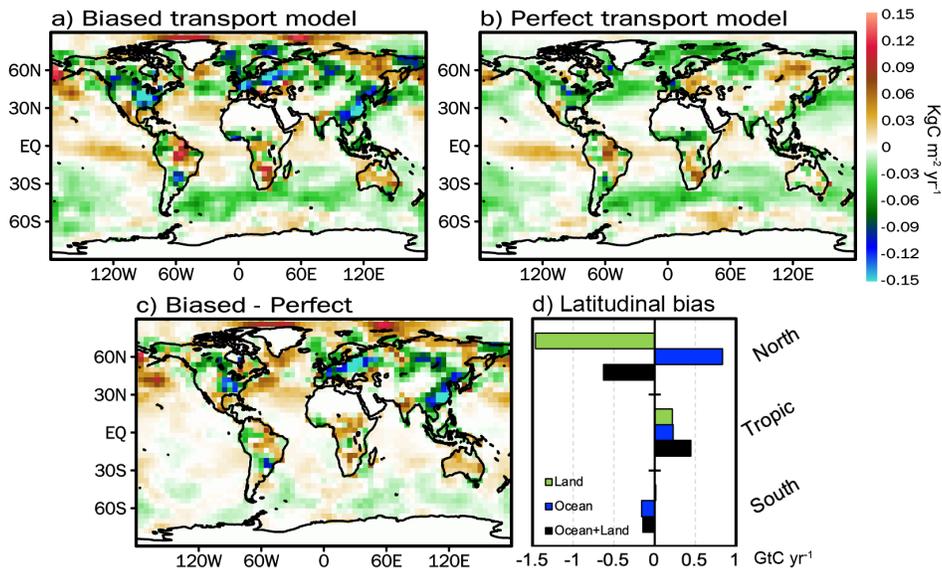
125 First, we analyze the surface CO<sub>2</sub> and column CO<sub>2</sub> (XCO<sub>2</sub>) concentration in the nature  
126 runs of EXP-bias (Figure 1a, d) and EXP-perfect (Figure 1b, e). Even though the two nature runs  
127 are driven by the same surface fluxes (Figure S1), the biased ATM at 4° × 5° resolution tends to  
128 trap the CO<sub>2</sub> fluxes within the near-surface in the Northern Hemisphere than the ATM at native  
129 0.5° × 0.625° resolution on an annual average basis, especially in Eurasia that the biases can  
130 reach to over 2 ppm. The XCO<sub>2</sub> bias has clear latitudinal distribution with positive bias in the  
131 Northern (30°N~ 90°N) and Southern (-90°S~ -30°S) middle and high latitudes and negative  
132 bias near the tropics (-30°S~ 30°N). Moreover, the annual bias is averaged from the seasonal  
133 varying biases. In Eurasia, the positive surface bias of over 5 ppm from January to March is  
134 reversed to the negative surface bias of over -3 ppm from July to September (Figure S2, S3). The  
135 seasonal variation of XCO<sub>2</sub> bias is relatively smaller than the surface CO<sub>2</sub>. The persistent dipole  
136 tropic versus extratropic bias pattern moves southward from winter to summer.

137 The systematic error of simulated CO<sub>2</sub> concentration caused by the coarse-resolution  
138 ATM is expected to cause significant bias in flux estimates. The first assimilation run of EXP-  
139 biased assimilates the "perfect" observations but uses the "biased" ATM, which is similar to the  
140 real-world scenario. Instead, the second assimilation run of EXP-perfect has no transport model  
141 error issue that assimilates the "perfect" observations and uses the "perfect" ATM. The  
142 difference in estimated fluxes between the two assimilation runs is expected to be the impact of  
143 transport error on flux estimation. Annually, the absolute value of regional land fluxes in EXP-  
144 biased is significantly larger than EXP-perfect (Figure 2a, b). In the northern mid-latitudes land  
145 area, the carbon sink is largely overestimated in EXP-biased, especially in eastern China, eastern  
146 North America, and Europe. About half of this sink is compensated by the surrounding  
147 weakened ocean sink and carbon release in the high latitude of East Siberia (Figure 2d). Moving  
148 southward, EXP-biased shows less carbon sink in the tropical ocean, South America, Australia,  
149 and Africa and more carbon sink in the Southern Ocean. Generally, relative to EXP-perfect, the

150 transport error tends to enhance the land carbon sink by 1.23 GtC yr<sup>-1</sup> and weaken the ocean  
 151 carbon sink by 0.9 GtC yr<sup>-1</sup>. Moreover, more carbon sink of 0.77 GtC yr<sup>-1</sup> is attributed to the  
 152 extratropics (-90 °S~ -23 °S and 23 °N~ 90 °N), and 0.44 GtC yr<sup>-1</sup> more carbon is released from  
 153 the tropics (-23 °S~ 23 °N), resulting in a global net flux bias of -0.33 GtC yr<sup>-1</sup>. Due to the high  
 154 computation and memory cost, we only conduct tests for 1 year. Further research on how ATM  
 155 bias affects interannual flux estimation is worth investigating in the future.



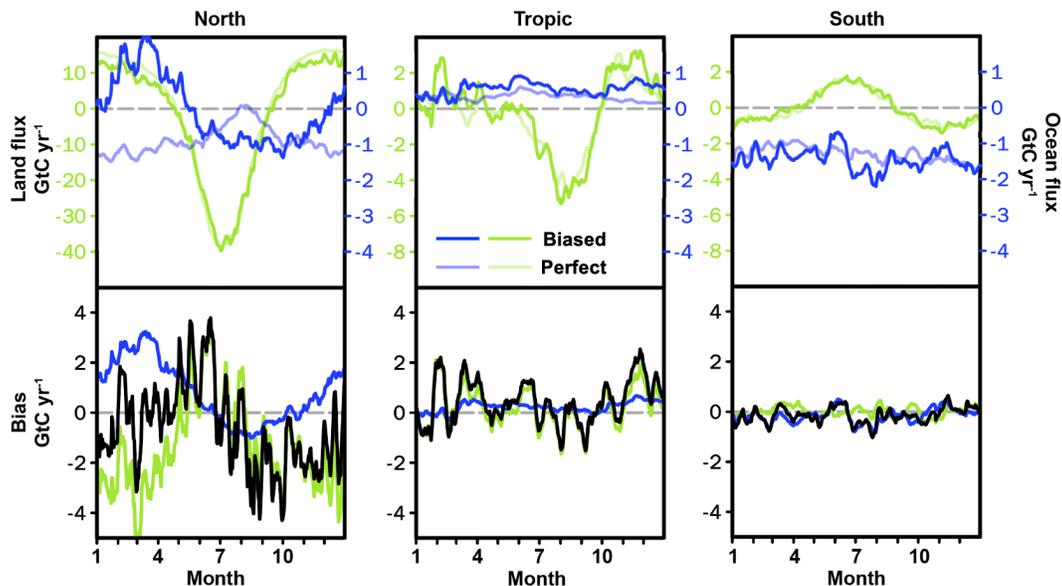
156 **Figure 1. The annual mean surface CO<sub>2</sub> and column CO<sub>2</sub> pattern of nature runs at**  
 157 **horizontal resolutions of 0.5°x0.625° (a, d) and 4°x5° (b, e). (c, f) The difference between**  
 158 **the two nature runs.**  
 159



161 **Figure 2. The spatial pattern of optimized annual mean land and ocean fluxes of**  
 162 **assimilation runs of EXP-biased (a) and EXP-perfect (b). (c) The difference between the**  
 163 **two assimilation runs. (d) The difference in land and ocean fluxes between the two**  
 164 **assimilation runs in latitude bands of northern extratropics (23 °N ~ 90 °N), tropics (-23 °S**  
 165 **~ 23 °N), and southern extratropics (-90 °S ~ -23 °S).**

### 166 3.2 Seasonal cycle

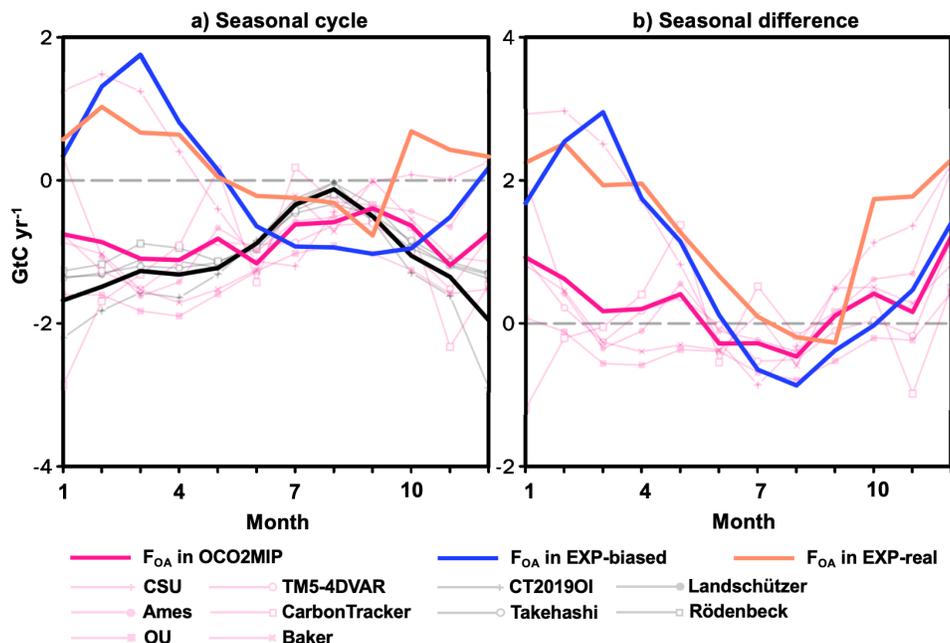
167 At the seasonal scale, the seasonal amplitude of the northern extratropical land flux is  
 168 significantly underestimated in EXP-biased, mainly due to less carbon release during the non-  
 169 growing seasons (Figure 3). In the northern extratropical ocean, the seasonal phase is reversed  
 170 and the seasonal strength is enhanced, which partly compensates for the weakened seasonal  
 171 amplitude in the northern extratropical land. The seasonal biases are smaller in the tropics and  
 172 southern extratropics. From January to May, a large amount of carbon is released from the  
 173 northern ocean. And the relative impact of transport error on the ocean flux is significantly larger  
 174 than the land flux, implying that the ocean flux estimation in the context of the transport error  
 175 may not be better than those a priori estimations. To overcome this limitation, inverse modelers  
 176 usually apply tight a priori constraints on ocean flux in the real-world scenario (Peylin et al.,  
 177 2013).



178 **Figure 3. The upper figures are the seasonal cycle of land (green) and ocean (blue) fluxes**  
 179 **of EXP-biased (darker color) and EXP-perfect (lighter color) at daily timestep in latitude**  
 180 **bands of northern extratropics (23 °N ~ 90 °N), tropics (-23 °S ~ 23 °N), and southern**  
 181 **extratropics (-90 °S ~ -23 °S). The bottom figures are the land, ocean, and net (black) fluxes**  
 182 **difference between EXP-biased and EXP-perfect.**

184 Global inversion systems were usually run at a coarse horizontal resolution of 2° to 5°,  
 185 which is around an order of magnitude coarser than the native resolution of state-of-the-art  
 186 meteorology reanalysis. Thus, the transport error is expected to significantly affect the flux  
 187 estimation in the global inversions. As indicated in the OSSEs, the northern ocean is one of the  
 188 regions that can be strongly affected by the transport bias. We further investigate it using real  
 189 data assimilation results. A priori of process understanding and oceanic pCO<sub>2</sub> observations in the

190 northern ocean provide a tight constraint on seasonal phase and amplitude of flux (Figure 4a).  
 191 However, the a posteriori estimates from the 6 OCO2MIP inversion systems in the northern  
 192 ocean diverge greatly during the non-growing seasons of the land biosphere, and the sink during  
 193 these seasons is significantly reduced (Figure 4b). It is worth noting that the seasonal phase of  
 194 the a posteriori in the CSU system and EXP-real is almost reversed from the a priori estimates.  
 195 These seasonal increments from the a priori to the a posteriori are remarkably consistent in phase  
 196 and magnitude with the ATM-induced flux bias in EXP-biased, indicating that the ATM bias  
 197 highly influences current inversion estimates of ocean carbon fluxes. The temporal correlation  
 198 between the flux bias in EXP-biased and the flux increment in EXP-real and CSU is 0.82 and  
 199 0.87, respectively. The increments in some inversion systems may not be as significant as in  
 200 EXP-real and CSU, which may be because of the different degrees of constraints from the a  
 201 priori.



202

203 **Figure 4. (a) The seasonal cycle in the northern extratropical ocean. The blue line is the a**  
 204 **posteriori flux in EXP-biased. The orange line is the a posteriori flux in EXP-real. The**  
 205 **dark pink line is the a posteriori flux of the ensemble mean of OCO2MIP systems. The thin**  
 206 **pink lines with different markers are the individual a posteriori fluxes within the**  
 207 **OCO2MIP systems. The black line is the ensemble mean of the a priori fluxes used in the**  
 208 **different OCO2MIP systems. The thin gray lines are the individual a priori fluxes used in**  
 209 **the OCO2MIP systems. (b) The difference compared with the ensemble mean of the a**  
 210 **priori fluxes.**

#### 211 4 Discussion and conclusion

212 Robust regional carbon fluxes estimate is urgently needed within the framework of the United  
 213 Nations Framework Convention on Climate Change and is possible as more ground greenhouse  
 214 gas stations and satellites are available in the future (Kuhlmann et al., 2020). However, in the  
 215 context of OSSEs, this study suggests that the coarse ATM attributes significantly more carbon  
 216 uptake in the land and extratropics than in the ocean and tropics. And the seasonal amplitude in  
 217 the northern land area is underestimated, which is consistent with a recent finding using aircraft

218 observations (Cui et al., 2022). These robust pieces of evidence indicate that previous inversion  
219 studies may largely overestimate the carbon sinks in northern extratropical countries.

220 Focusing on the northern extratropical ocean, we find that the seasonal phase of the a posteriori  
221 fluxes totally reverses from the a priori fluxes, compensating for the reduced seasonal amplitude  
222 in the northern land area. The reversed phase is also shown in a real data assimilation experiment  
223 and some state-of-the-art inversion systems within the OCO2MIP, which is impossible from a  
224 process understanding perspective. Satellite observations over the ocean have long been argued  
225 to be biased due to retrieval algorithm bias, and inversion modelers usually discard these  
226 observations and set tight a priori ocean flux constraints (Peylin et al., 2013; Crowell et al., 2019;  
227 Palmer et al., 2019; Peiro et al., 2022). Our finding indicates that the current satellite retrieval  
228 algorithm may not be as biased as previously argued, and increasing the resolution of ATM or  
229 improving the parameterization schemes of ATM should be placed at a high priority in order to  
230 derive a robust country-level carbon budget and reasonable ocean carbon cycle estimates. Recent  
231 efforts of speeding up ATMs using Graphics Processing Units (GPU) (Chevallier et al., 2023)  
232 and Message Passing Interface (MPI) (Martin et al., 2022) Parallelization are ongoing that native  
233 resolution inversion is computationally possible in the coming years.

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238 inventory joint assessment of carbon emissions in typical industrial parks under dual-carbon  
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## 241 **Conflict of Interest**

242 The authors declare no competing interests.

## 243 **Data Availability Statement**

244 The OSSE results can be accessed at <https://doi.org/10.5281/zenodo.7826041>. The OCO2MIP  
245 inversion results can be accessed from: [https://gml.noaa.gov/ccgg/OCO2\\_v10mip/download.php](https://gml.noaa.gov/ccgg/OCO2_v10mip/download.php).  
246 The codes related to the COLA can be accessed at <https://doi.org/10.5281/zenodo.7592827> and  
247 <https://doi.org/10.5281/zenodo.5746140>.

## 248 **References**

- 249 Baker, D. F., Bell, E., Davis, K. J., Campbell, J. F., Lin, B., & Dobler, J. (2022). A new  
250 exponentially decaying error correlation model for assimilating OCO-2 column-average CO<sub>2</sub>  
251 data using a length scale computed from airborne lidar measurements. *Geoscientific Model*  
252 *Development*, 15(2), 649–668. <https://doi.org/10.5194/gmd-15-649-2022>  
253 Basu, S., Baker, D. F., Chevallier, F., Patra, P. K., Liu, J., & Miller, J. B. (2018). The impact of  
254 transport model differences on CO<sub>2</sub> surface flux estimates from OCO-2 retrievals of column

- 255 average CO<sub>2</sub>. *Atmospheric Chemistry and Physics*, 18(10), 7189–7215.  
256 <https://doi.org/10.5194/acp-18-7189-2018>
- 257 Byrne, B., Baker, D. F., Basu, S., Bertolacci, M., Bowman, K. W., Carroll, D., Chatterjee, A.,  
258 Chevallier, F., Ciais, P., Cressie, N., Crisp, D., Crowell, S., Deng, F., Deng, Z., Deutscher, N.  
259 M., Dubey, M. K., Feng, S., García, O. E., Griffith, D. W. T., ... Zeng, N. (2023). National  
260 CO<sub>2</sub> budgets (2015–2020) inferred from atmospheric CO<sub>2</sub> observations in support of the  
261 global stocktake. *Earth System Science Data*, 15(2), 963–1004. <https://doi.org/10.5194/essd-15-963-2023>
- 262  
263 Chevallier, F. (2021). Fluxes of Carbon Dioxide From Managed Ecosystems Estimated by  
264 National Inventories Compared to Atmospheric Inverse Modeling. *Geophysical Research  
265 Letters*, 48(15). <https://doi.org/10.1029/2021GL093565>
- 266 Chevallier, F., Lloret, Z., Cozic, A., Takache, S., & Remaud, M. (2023). Toward High-  
267 Resolution Global Atmospheric Inverse Modeling Using Graphics Accelerators. *Geophysical  
268 Research Letters*, 50(5), e2022GL102135. <https://doi.org/10.1029/2022GL102135>
- 269 Crowell, S., Baker, D., Schuh, A., Basu, S., Jacobson, A. R., Chevallier, F., Liu, J., Deng, F.,  
270 Feng, L., McKain, K., Chatterjee, A., Miller, J. B., Stephens, B. B., Eldering, A., Crisp, D.,  
271 Schimel, D., Nassar, R., O'Dell, C. W., Oda, T., ... Jones, D. B. A. (2019). The 2015–2016  
272 carbon cycle as seen from OCO-2 and the global in situ network. *Atmospheric Chemistry and  
273 Physics*, 19(15), 9797–9831. <https://doi.org/10.5194/acp-19-9797-2019>
- 274 Cui, Y. Y., Zhang, L., Jacobson, A. R., Johnson, M. S., Philip, S., Baker, D., Chevallier, F.,  
275 Schuh, A. E., Liu, J., Crowell, S., Peiro, H. E., Deng, F., Basu, S., & Davis, K. J. (2022).  
276 Evaluating Global Atmospheric Inversions of Terrestrial Net Ecosystem Exchange CO<sub>2</sub> Over  
277 North America on Seasonal and Sub-Continental Scales. *Geophysical Research Letters*,  
278 49(18). <https://doi.org/10.1029/2022GL100147>
- 279 Deng, Z., Ciais, P., Tzompa-Sosa, Z. A., Saunio, M., Qiu, C., Tan, C., Sun, T., Ke, P., Cui, Y.,  
280 Tanaka, K., Lin, X., Thompson, R. L., Tian, H., Yao, Y., Huang, Y., Lauerwald, R., Jain, A.  
281 K., Xu, X., Bastos, A., ... Chevallier, F. (2022). Comparing national greenhouse gas budgets  
282 reported in UNFCCC inventories against atmospheric inversions. *Earth System Science Data*,  
283 14(4), 1639–1675. <https://doi.org/10.5194/essd-14-1639-2022>
- 284 Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Bakker, D. C. E., Hauck, J., Le  
285 Quéré, C., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Canadell, J. G., Ciais, P., Jackson,  
286 R. B., Alin, S. R., Anthoni, P., Bates, N. R., Becker, M., Bellouin, N., ... Zeng, J. (2022).  
287 Global Carbon Budget 2021. *Earth System Science Data*, 14(4), 1917–2005.  
288 <https://doi.org/10.5194/essd-14-1917-2022>
- 289 Fu, Y., Liao, H., Tian, X., Gao, H., Jia, B., & Han, R. (2021). Impact of Prior Terrestrial Carbon  
290 Fluxes on Simulations of Atmospheric CO<sub>2</sub> Concentrations. *Journal of Geophysical  
291 Research: Atmospheres*, 126(18). <https://doi.org/10.1029/2021JD034794>
- 292 Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A.,  
293 Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C.,  
294 Akella, S., Buchard, V., Conaty, A., da Silva, A. M., Gu, W., ... Zhao, B. (2017). The  
295 Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2).  
296 *Journal of Climate*, 30(14), 5419–5454. <https://doi.org/10.1175/JCLI-D-16-0758.1>
- 297 Haynes, K. D., Baker, I. T., Denning, A. S., Stöckli, R., Schaefer, K., Lokupitiya, E. Y., &  
298 Haynes, J. M. (2019). Representing Grasslands Using Dynamic Prognostic Phenology Based  
299 on Biological Growth Stages: 1. Implementation in the Simple Biosphere Model (SiB4).

- 300 *Journal of Advances in Modeling Earth Systems*, 11(12), 4423–4439.  
301 <https://doi.org/10.1029/2018MS001540>
- 302 Jiang, F., He, W., Ju, W., Wang, H., Wu, M., Wang, J., Feng, S., Zhang, L., & Chen, J. M.  
303 (2022). The status of carbon neutrality of the world's top 5 CO<sub>2</sub> emitters as seen by carbon  
304 satellites. *Fundamental Research*, 2(3), 357–366. <https://doi.org/10.1016/j.fmre.2022.02.001>
- 305 Kaiser, J. W., Heil, A., Andreae, M. O., Benedetti, A., Chubarova, N., Jones, L., Morcrette, J.-J.,  
306 Razinger, M., Schultz, M. G., Suttie, M., & van der Werf, G. R. (2012). Biomass burning  
307 emissions estimated with a global fire assimilation system based on observed fire radiative  
308 power. *Biogeosciences*, 9(1), 527–554. <https://doi.org/10.5194/bg-9-527-2012>
- 309 Kuhlmann, G., Brunner, D., Broquet, G., & Meijer, Y. (2020). Quantifying CO<sub>2</sub> emissions of a  
310 city with the Copernicus Anthropogenic CO<sub>2</sub> Monitoring satellite mission. *Atmospheric  
311 Measurement Techniques*, 13(12), 6733–6754. <https://doi.org/10.5194/amt-13-6733-2020>
- 312 Liu, J., Fung, I., Kalnay, E., & Kang, J.-S. (2011). CO<sub>2</sub> transport uncertainties from the  
313 uncertainties in meteorological fields. *Geophysical Research Letters*, 38, L12808.  
314 <https://doi.org/10.1029/2011GL047213>
- 315 Liu, Z., Zeng, N., Liu, Y., Kalnay, E., Asrar, G., Cai, Q., & Han, P. (2023). *Assimilating the  
316 dynamic spatial gradient of a bottom-up carbon flux estimation as a unique observation in  
317 COLA (v2.0)*. <https://doi.org/10.5194/gmd-2023-15>
- 318 Liu, Z., Zeng, N., Liu, Y., Kalnay, E., Asrar, G., Wu, B., Cai, Q., Liu, D., & Han, P. (2022).  
319 Improving the joint estimation of CO<sub>2</sub> and surface carbon fluxes using a constrained ensemble  
320 Kalman filter in COLA (v1.0). *Geosci. Model Dev.*, 15, 5511–5528.  
321 <https://doi.org/10.5194/gmd-15-5511-2022>
- 322 Martin, R. V., Eastham, S. D., Bindle, L., Lundgren, E. W., Clune, T. L., Keller, C. A., Downs,  
323 W., Zhang, D., Lucchesi, R. A., Sulprizio, M. P., Yantosca, R. M., Li, Y., Estrada, L., Putman,  
324 W. M., Auer, B. M., Trayanov, A. L., Pawson, S., & Jacob, D. J. (2022). Improved advection,  
325 resolution, performance, and community access in the new generation (version 13) of the  
326 high-performance GEOS-Chem global atmospheric chemistry model (GCHP). *Geoscientific  
327 Model Development*, 15(23), 8731–8748. <https://doi.org/10.5194/gmd-15-8731-2022>
- 328 Oda, T., Maksyutov, S., & Andres, R. J. (2018). The Open-source Data Inventory for  
329 Anthropogenic CO<sub>2</sub>, version 2016 (ODIAC2016): A global monthly fossil fuel CO<sub>2</sub> gridded  
330 emissions data product for tracer transport simulations and surface flux inversions. *Earth  
331 System Science Data*, 10(1), 87–107. <https://doi.org/10.5194/essd-10-87-2018>
- 332 O'Dell, C. W., Eldering, A., Wennberg, P. O., Crisp, D., Gunson, M. R., Fisher, B.,  
333 Frankenberg, C., Kiel, M., Lindqvist, H., Mandrake, L., Merrelli, A., Natraj, V., Nelson, R. R.,  
334 Osterman, G. B., Payne, V. H., Taylor, T. E., Wunch, D., Drouin, B. J., Oyafuso, F., ...  
335 Velasco, V. A. (2018). Improved retrievals of carbon dioxide from Orbiting Carbon  
336 Observatory-2 with the version 8 ACOS algorithm. *Atmospheric Measurement Techniques*,  
337 11(12), 6539–6576. <https://doi.org/10.5194/amt-11-6539-2018>
- 338 Palmer, P. I., Feng, L., Baker, D., Chevallier, F., Bösch, H., & Somkuti, P. (2019). Net carbon  
339 emissions from African biosphere dominate pan-tropical atmospheric CO<sub>2</sub> signal. *Nature  
340 Communications*, 10(1), 3344. <https://doi.org/10.1038/s41467-019-11097-w>
- 341 Peiro, H., Crowell, S., Schuh, A., Baker, D. F., O'Dell, C., Jacobson, A. R., Chevallier, F., Liu,  
342 J., Eldering, A., Crisp, D., Deng, F., Weir, B., Basu, S., Johnson, M. S., Philip, S., & Baker, I.  
343 (2022). Four years of global carbon cycle observed from the Orbiting Carbon Observatory 2  
344 (OCO-2) version 9 and in situ data and comparison to OCO-2 version 7. *Atmospheric  
345 Chemistry and Physics*, 22(2), 1097–1130. <https://doi.org/10.5194/acp-22-1097-2022>

- 346 Peylin, P., Law, R. M., Gurney, K. R., Chevallier, F., Jacobson, A. R., Maki, T., Niwa, Y., Patra,  
347 P. K., Peters, W., Rayner, P. J., Rödenbeck, C., van der Laan-Luijkx, I. T., & Zhang, X.  
348 (2013). Global atmospheric carbon budget: Results from an ensemble of atmospheric  
349 CO<sub>2</sub> inversions. *Biogeosciences*, *10*(10), 6699–6720.  
350 <https://doi.org/10.5194/bg-10-6699-2013>
- 351 Philip, S., Johnson, M. S., Potter, C., Genovesse, V., Baker, D. F., Haynes, K. D., Henze, D. K.,  
352 Liu, J., & Poulter, B. (2019). Prior biosphere model impact on global terrestrial CO<sub>2</sub> fluxes  
353 estimated from OCO-2 retrievals. *Atmospheric Chemistry and Physics*, *19*(20), 13267–13287.  
354 <https://doi.org/10.5194/acp-19-13267-2019>
- 355 Rödenbeck, C., Bakker, D. C. E., Metzl, N., Olsen, A., Sabine, C., Cassar, N., Reum, F.,  
356 Keeling, R. F., & Heimann, M. (2014). Interannual sea–air CO<sub>2</sub> flux variability from an  
357 observation-driven ocean mixed-layer scheme. *Biogeosciences*, *11*(17), 4599–4613.  
358 <https://doi.org/10.5194/bg-11-4599-2014>
- 359 Schimel, D., Stephens, B. B., & Fisher, J. B. (2015). Effect of increasing CO<sub>2</sub> on the terrestrial  
360 carbon cycle. *Proceedings of the National Academy of Sciences*, *112*(2), 436–441.  
361 <https://doi.org/10.1073/pnas.1407302112>
- 362 Schuh, A. E., Byrne, B., Jacobson, A. R., Crowell, S. M. R., Deng, F., Baker, D. F., Johnson, M.  
363 S., Philip, S., & Weir, B. (2022). On the role of atmospheric model transport uncertainty in  
364 estimating the Chinese land carbon sink. *Nature*, *603*(7901), E13–E14.  
365 <https://doi.org/10.1038/s41586-021-04258-9>
- 366 Schuh, A. E., & Jacobson, A. R. (2022). Uncertainty in Parameterized Convection Remains a  
367 Key Obstacle for Estimating Surface Fluxes of Carbon Dioxide. *Atmospheric Chemistry and*  
368 *Physics Discussion [Preprint]*. <https://doi.org/10.5194/acp-2022-616>
- 369 Schuh, A. E., Jacobson, A. R., Basu, S., Weir, B., Baker, D., Bowman, K., Chevallier, F.,  
370 Crowell, S., Davis, K. J., Deng, F., Denning, S., Feng, L., Jones, D., Liu, J., & Palmer, P. I.  
371 (2019). Quantifying the Impact of Atmospheric Transport Uncertainty on CO<sub>2</sub> Surface Flux  
372 Estimates. *Global Biogeochemical Cycles*, *33*(4), 484–500.  
373 <https://doi.org/10.1029/2018GB006086>
- 374 Stephens, B. B., Gurney, K. R., Tans, P. P., Sweeney, C., Peters, W., Bruhwiler, L., Ciais, P.,  
375 Ramonet, M., Bousquet, P., Nakazawa, T., Aoki, S., Machida, T., Inoue, G., Vinnichenko, N.,  
376 Lloyd, J., Jordan, A., Heimann, M., Shibistova, O., Langenfelds, R. L., ... Denning, A. S.  
377 (2007). Weak Northern and Strong Tropical Land Carbon Uptake from Vertical Profiles of  
378 Atmospheric CO<sub>2</sub>. *Science*, *316*(5832), 1732–1735. <https://doi.org/10.1126/science.1137004>
- 379 The International GEOS-Chem User Community. (2021). *geoschem/GCClassic: GEOS-Chem*  
380 *13.0.2* (13.0.2). Zenodo. <https://doi.org/10.5281/ZENODO.4681204>
- 381 Wang, J., Feng, L., Palmer, P. I., Liu, Y., Fang, S., Bösch, H., O'Dell, C. W., Tang, X., Yang,  
382 D., Liu, L., & Xia, C. (2020). Large Chinese land carbon sink estimated from atmospheric  
383 carbon dioxide data. *Nature*, *586*(7831), 720–723. <https://doi.org/10.1038/s41586-020-2849-9>
- 384 Weir, B., Oda, T., Ott, L. E., & Schmidt, G. A. (2022). Assessing progress toward the Paris  
385 Climate Agreement from Space. *Environmental Research Letters*.  
386 <https://doi.org/10.1088/1748-9326/ac998c>
- 387 Yu, K., Keller, C. A., Jacob, D. J., Molod, A. M., Eastham, S. D., & Long, M. S. (2018). Errors  
388 and improvements in the use of archived meteorological data for chemical transport modeling:  
389 An analysis using GEOS-Chem v11-01 driven by GEOS-5 meteorology. *Geoscientific Model*  
390 *Development*, *11*(1), 305–319. <https://doi.org/10.5194/gmd-11-305-2018>