

## Responses to Referee's Comments

We would like to thank the reviewer for carefully reading our manuscript and for the helpful suggestions. These comments have greatly assisted us in strengthening the paper. We have revised the manuscript accordingly (highlighted in red) and included our specific responses in blue below.

### Reviewer 1

The authors estimate regional carbon sinks over East Asia using a GOSAT-based atmospheric inversion system. Overall, the manuscript is generally well written, and the study is clearly structured, particularly in terms of how the authors evaluate the inversion results and interpret the resulting flux estimates.

I also appreciate that the analysis focuses on East Asia, where carbon budget estimates remain highly uncertain, and that the results are further broken down by country/region to discuss both regional carbon budgets and their responses to ENSO-related climate variability.

However, there are several aspects of the inversion configuration that are not sufficiently described or justified (e.g., boundary conditions and the treatment of the initial state). In addition, the manuscript would benefit from a more thorough discussion of previous efforts to quantify carbon budgets over East Asia. The evaluation of the inferred flux estimates relies on a limited set of comparison datasets, and more appropriate and comprehensive datasets should be considered to strengthen the credibility of the results.

I encourage the authors to carefully address the comments below, as I believe the study has strong potential to make a valuable contribution once these issues are resolved.

1. The manuscript would benefit from a more comprehensive discussion of previous efforts to quantify the carbon budget over East Asia. In particular, the current literature review appears incomplete, as a substantial number of relevant studies and synthesis activities have been conducted beyond those cited in this paper.

Especially, the RECCAP (REgional Carbon Cycle Assessment and Processes) efforts are not discussed. Given that RECCAP provides coordinated regional carbon budget estimates in East Asia, these studies should be properly acknowledged. Where possible, the authors should also compare their inferred flux estimates against RECCAP-based budgets and related regional assessments to provide an independent benchmark for evaluating the reliability of their results.

Below I provide a key RECCAP-related reference that I recommend the authors consider. I also encourage the authors to review the references cited within this paper and incorporate additional relevant studies into the manuscript as appropriate.

Wang, X., Gao, Y., Jeong, S., Ito, A., Bastos, A., Poulter, B., ... & Piao, S. (2024). The greenhouse gas budget of terrestrial ecosystems in East Asia since 2000. *Global Biogeochemical Cycles*, 38(2), e2023GB007865.

→ We added the following discussion of RECCAP and Wang et al. (2024):

Lines 42–49: REgional Carbon Cycle Assessment and Processes (RECCAP) is an international initiative aimed at quantifying regional greenhouse gas budgets, including CO<sub>2</sub> (Canadell et al., 2011). Coordinated assessments have also been conducted for East Asia. In particular, Wang et al. (2024) provided a comprehensive evaluation of greenhouse gas budgets over East Asia for the 2000s and 2010s using both top-down and bottom-up approaches. In their framework, the top-down estimates represented integrated net land–atmosphere CO<sub>2</sub> fluxes at the regional scale rather than NEE alone. Bottom-up NEE estimates were also reported, although these were based on the

TRENDY v9 dynamic global vegetation model ensemble (Sitch et al., 2015) rather than being newly derived within that study. These estimates are briefly compared with the results of this study in Section 5.

Lines 454–455: The magnitude of the terrestrial carbon sink inferred in this study ( $-0.31 \text{ PgC yr}^{-1}$ ) is broadly consistent with the terrestrial sink estimate reported by Wang et al. (2024) for East Asia during 2000–2019 ( $-0.27 \text{ PgC yr}^{-1}$ ; Figure 5).

2. The manuscript does not clearly highlight how the inversion performed in this study differs from previous inversion studies, or what merits it provides. I suggest that the authors revise the manuscript to better emphasize the unique aspects of their inversion framework. For example, since this study applies a regional inversion system, one potential advantage could be the use of higher-resolution meteorological forcing compared to global inversions.

→ We added the following paragraph to clarify the unique aspects and advantages of our regional nested inversion system:

Lines 70–81: In contrast to previous global inversion systems, the present study employs a regional nested inversion framework over East Asia, enabling higher-resolution meteorological fields and improved representation of regional transport processes. Such a configuration is particularly important in East Asia, where strong emission gradients and complex circulation patterns can amplify transport representation errors in coarse-resolution global inversions. In addition, we explicitly account for prior uncertainties in both terrestrial and oceanic fluxes using data-informed estimates from multi-model ensembles. Terrestrial uncertainties are derived from the standard deviation of the TRENDY ensemble (Sitch et al., 2015), while ocean flux uncertainties are based on the standard deviation among ocean models contributing to the Global Carbon Project (Friedlingstein et al., 2023), rather than prescribing fixed percentage values. We further incorporate both land and ocean GOSAT soundings as observational constraints through uncertainty-based weighting, thereby maximizing observational coverage while accounting for retrieval-specific errors. These methodological features provide a more regionally consistent and physically constrained estimate of East Asian NEE, strengthening the robustness of the inferred carbon fluxes. Such refinements support evidence-based policymaking and climate-mitigation strategies.

3. L42–45: The statement difficult to agree with and suggest revising it for clarity. In general, reported uncertainties for ocean XCO<sub>2</sub> retrievals are often smaller than those for land retrievals. The primary reason ocean retrievals have been excluded in many previous inversion studies is therefore not simply their random uncertainty, but rather the concern that ocean retrievals may exhibit larger systematic biases compared to land retrievals.

In this context, the authors' statement that using the retrieval uncertainties provided in the GOSAT product represents a "new strategy" is not well supported. Many existing inversion systems already use the reported retrieval uncertainties from satellite products; the key issue has been whether to assimilate ocean observations given the potential for systematic biases. Thus, this aspect should not be framed as a clear methodological novelty relative to prior work.

→ We revised the following text to clarify why both land and ocean soundings were retained in the East Asian inversion framework:

Lines 62–69: Whereas Wang et al. (2019) excluded oceanic soundings due to large uncertainties associated with glint-mode retrievals (Wunch et al., 2017), such exclusions may not be optimal for East Asia. The region lies within the mid-latitude westerly belt, where strong anthropogenic emissions are transported eastward over

adjacent oceans, making ocean soundings particularly informative for constraining continental outflow signals. Moreover, glint-mode retrievals over the ocean can exhibit precision comparable to, and under certain conditions even higher than, land retrievals owing to more homogeneous surface reflectance conditions (Worden et al., 2017). In this study, we therefore retain both land and ocean soundings and incorporate their reported retrieval uncertainties into the weighting through the observation error covariance matrix, rather than excluding ocean soundings.

4. As highlighted in Thompson et al. (2016), uncertainties in fossil fuel CO<sub>2</sub> emissions represent a major contributor to the overall uncertainty in estimating terrestrial carbon fluxes over East Asia. Given the large magnitude of anthropogenic emissions in this region, fossil fuel emission uncertainty can strongly influence inversion-based estimates of biospheric fluxes through potential attribution errors.

Even if the authors are not able to explicitly account for fossil fuel emission uncertainty within their inversion framework, this issue should be discussed in more detail, particularly in the context of East Asia.

→ We added the following discussion of the potential influence of fossil fuel emission uncertainties on inferred terrestrial carbon fluxes over East Asia:

Lines 532–536: In addition, fossil fuel emissions were prescribed and not optimized in this study. Thompson et al. (2016) estimated that uncertainty in the growth rate of these emissions accounted for about 32% of the uncertainty in the inferred East Asian land sink. Given the large magnitude of anthropogenic emissions in East Asia, differences among fossil fuel emission inventories may influence inversion-based estimates of terrestrial carbon fluxes and should therefore be considered when interpreting our results.

**5. L70–71:** Boundary conditions are a very important component of a regional inversion system. However, the manuscript currently provides very limited information on how the boundary conditions were specified. For example, did the authors use a CO<sub>2</sub> concentration field obtained from a global inversion, or did they apply some correction based on observations?

If the boundary conditions were not constrained by observations, the estimated enhancement of terrestrial carbon uptake could potentially reflect biases in the boundary conditions rather than a true observational signal within the domain. Therefore, the reliability of the inversion results may depend strongly on how the boundary conditions were prescribed, and this aspect should be described more clearly.

→ We added the following clarification on the boundary conditions:

Lines 131–134: Boundary conditions for the nested simulation were taken from global 2° × 2.5° CO<sub>2</sub> fields, which were first constrained by a global inversion using the same inversion framework and GOSAT XCO<sub>2</sub> retrieval product as in this study. Both simulations also shared the same prior flux inventories. This approach helps reduce potential biases in background concentrations entering the nested domain.

**6. Line 84:** It is unclear how the initial conditions for the inversion were obtained. The authors mention that a 5-year spin-up was performed, but it is not explained what observational datasets were assimilated during this spin-up period.

Based on my understanding, a common approach is to conduct an inversion for several months using an independent observational dataset and then use the optimized CO<sub>2</sub> concentration fields as the initial state. Alternatively, some studies prescribe published optimized CO<sub>2</sub> fields as initial conditions. Which approach was adopted in this study? The authors should clarify how the initial atmospheric state was generated.

→ We added the following clarification on how the initial atmospheric state was generated for the inversion:

Lines 141–145: The spin-up simulation was performed from 2005 to 2009 without any observational constraint. At the beginning of each annual inversion, the initial 3D CO<sub>2</sub> field was adjusted to ensure that the domain-mean model concentration matched the domain-mean GOSAT XCO<sub>2</sub>, following the method of Patra et al. (2021). Independent inversions were then performed for each year from 2010 to 2019.

7. L226–227: It would be helpful to include a figure showing the spatial distribution of GOSAT observations used in this study. Since seasonally and regionally different observational coverage is one of the main factors explaining regional differences in flux adjustments, I encourage the authors to add a discussion on the relationship between the inferred flux adjustments and the spatial/temporal coverage of the observations.

In addition, the authors state that uncertainties are large over ocean regions. However, land XCO<sub>2</sub> retrievals generally have larger reported uncertainties than ocean retrievals. The main challenge in optimizing ocean fluxes using satellite-based inversions is not necessarily the retrieval uncertainty itself, but rather the fact that ocean fluxes are about an order of magnitude smaller than land fluxes at the grid scale. As a result, the contribution of ocean fluxes to XCO<sub>2</sub> variability is relatively small over the Northern Hemisphere, making it difficult for satellite observations to effectively constrain ocean fluxes. Therefore, the interpretation in this part should be reconsidered and clarified.

→ We added Figure S2 showing the spatial distribution of the GOSAT observations used in this study, along with the following discussion of observational coverage:

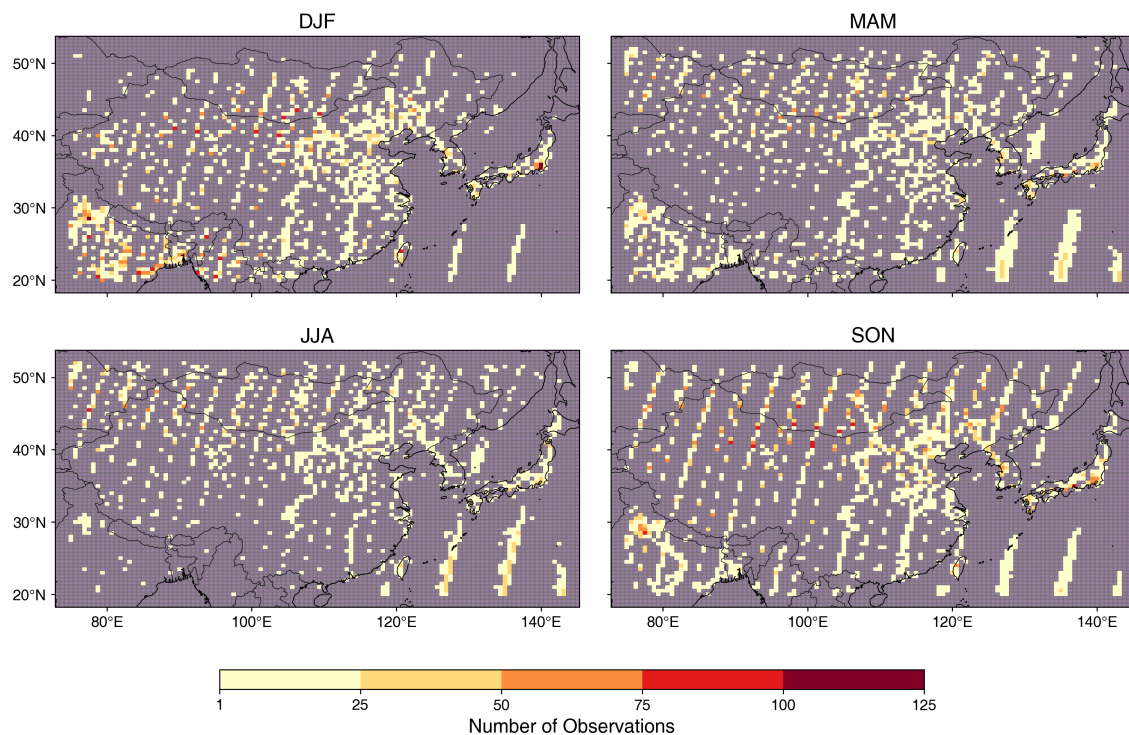


Figure S2. Seasonal spatial distribution of GOSAT XCO<sub>2</sub> observations over East Asia during 2010–2019. Panels show the number of observations for each season: DJF, MAM, JJA, and SON. Colors indicate the number of observations per grid cell.

→ We revised the following text to clarify the interpretation for ocean regions:

Lines 289–291: In addition, ocean fluxes are generally much smaller than land fluxes at the grid scale, resulting in a weaker contribution to XCO<sub>2</sub> variability and making them more difficult to constrain using satellite observations.

Lines 292–293: While seasonal differences in observational coverage are relatively small, observations are denser over land and more limited over the ocean (Figure S2).

**8. L256–278:** This section appears to describe methodological details rather than results. I suggest moving this part to the Methods section to improve the overall structure and readability of the manuscript.

→ We moved the methodological description of EVI from the Results section to the Methods section. The Methods section now describes the EVI dataset and product used in this study, while the Results section focuses on the interpretation of carbon flux variability.

Line 106–117: To aid the interpretation of variability in inferred terrestrial carbon flux, we used the Enhanced Vegetation Index (EVI) as an ancillary satellite-based indicator of vegetation activity. EVI is derived from MODIS surface reflectance and was designed to improve sensitivity in high-biomass regions while reducing canopy-

background and atmospheric effects (Huete et al., 2002; Didan and Barreto-Muñoz, 2019). In the MODIS algorithm, EVI is defined as

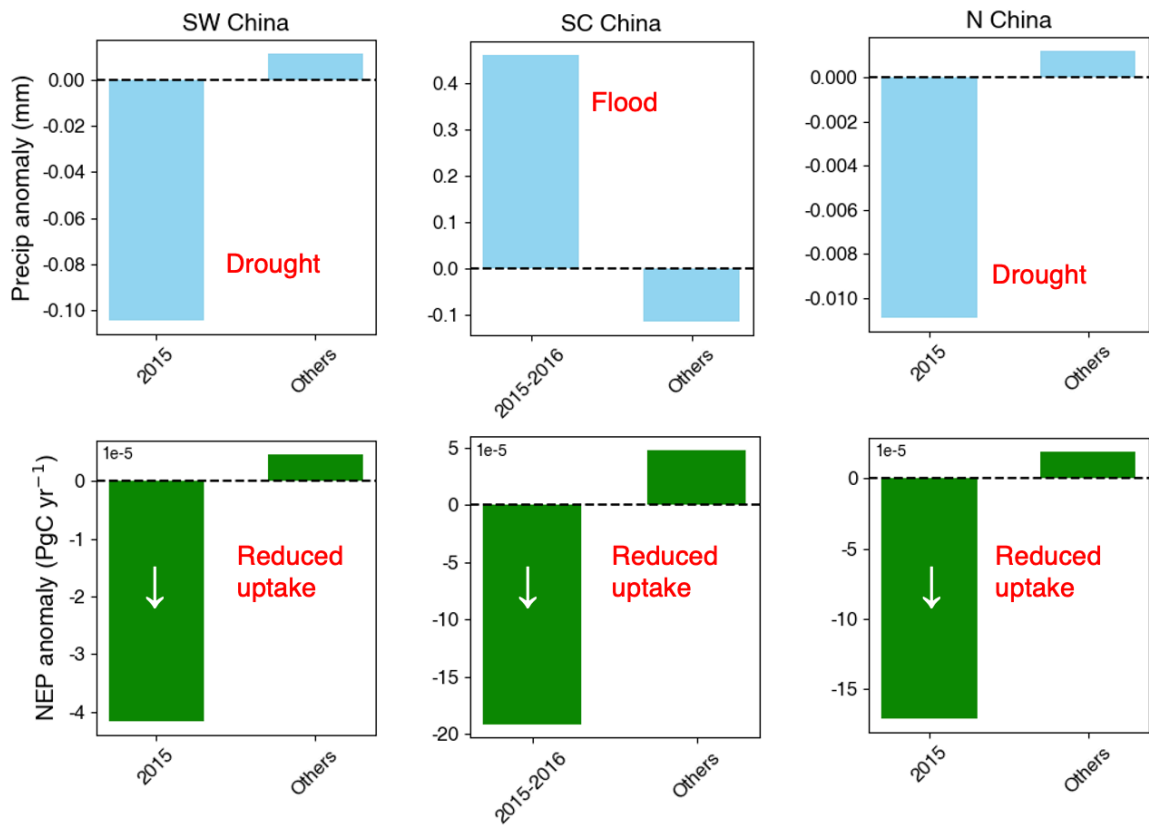
$$EVI = G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \rho_{red} - C_2 \rho_{blue} + L} \quad (1)$$

, where  $\rho_{NIR}$ ,  $\rho_{red}$ , and  $\rho_{blue}$  denote the near-infrared, red, and blue surface reflectances, respectively;  $L$  is the canopy background adjustment term;  $C_1$  and  $C_2$  are aerosol-resistance coefficients; and  $G$  is a gain factor. For the standard MODIS EVI product,  $L = 1$ ,  $C_1 = 6$ ,  $C_2 = 7.5$ , and  $G = 2.5$  (Didan and Barreto-Muñoz, 2019). In this study, we used monthly EVI data from MOD13C2, the MODIS Collection 6.1 monthly climate modeling grid product, which provides global vegetation index fields at  $0.05^\circ$  spatial resolution (Didan, 2021).

**9. L279–316:** This section represents one of the key strengths of the manuscript compared to previous inversion studies. I appreciate that the authors attempt to interpret the inferred carbon flux variability in relation to ENSO.

However, the current discussion mainly provides an indirect interpretation and suggests possible mechanisms without clearly demonstrating them. To strengthen this part, I encourage the authors to include a more direct analysis, for example by examining precipitation and/or soil moisture anomalies and quantitatively evaluating their correlations with the inferred carbon flux anomalies. Such an analysis would provide stronger support for the proposed ENSO-related interpretation.

→ We added a quantitative analysis of the relationship between inferred posterior  $\text{CO}_2$  flux anomalies and precipitation anomalies across East Asia as Figures S3 and S4. Short excerpts from the corresponding regional discussion are also provided below each panel.



... Southwest China underwent persistent drought due to weakened southward moisture transport (Ma et al., 2018). This region suffered from **prolonged drought conditions from summer 2015 through spring 2016**

South Central China similarly exhibited enhanced precipitation and **frequent flooding during 2015–2016** (Ma et al., 2018),

... precipitation deficits prevailed **during the 2015 El Niño peak**, especially in North China, where severe summer droughts were reported (Zhai et al., 2016)

Figure S3. Regional anomalies in precipitation (sky blue) and terrestrial carbon uptake expressed as NEP (= -NEE; green) over Southwest China, South Central China, and North China. The text below each panel is excerpted from the corresponding discussion in the main text.

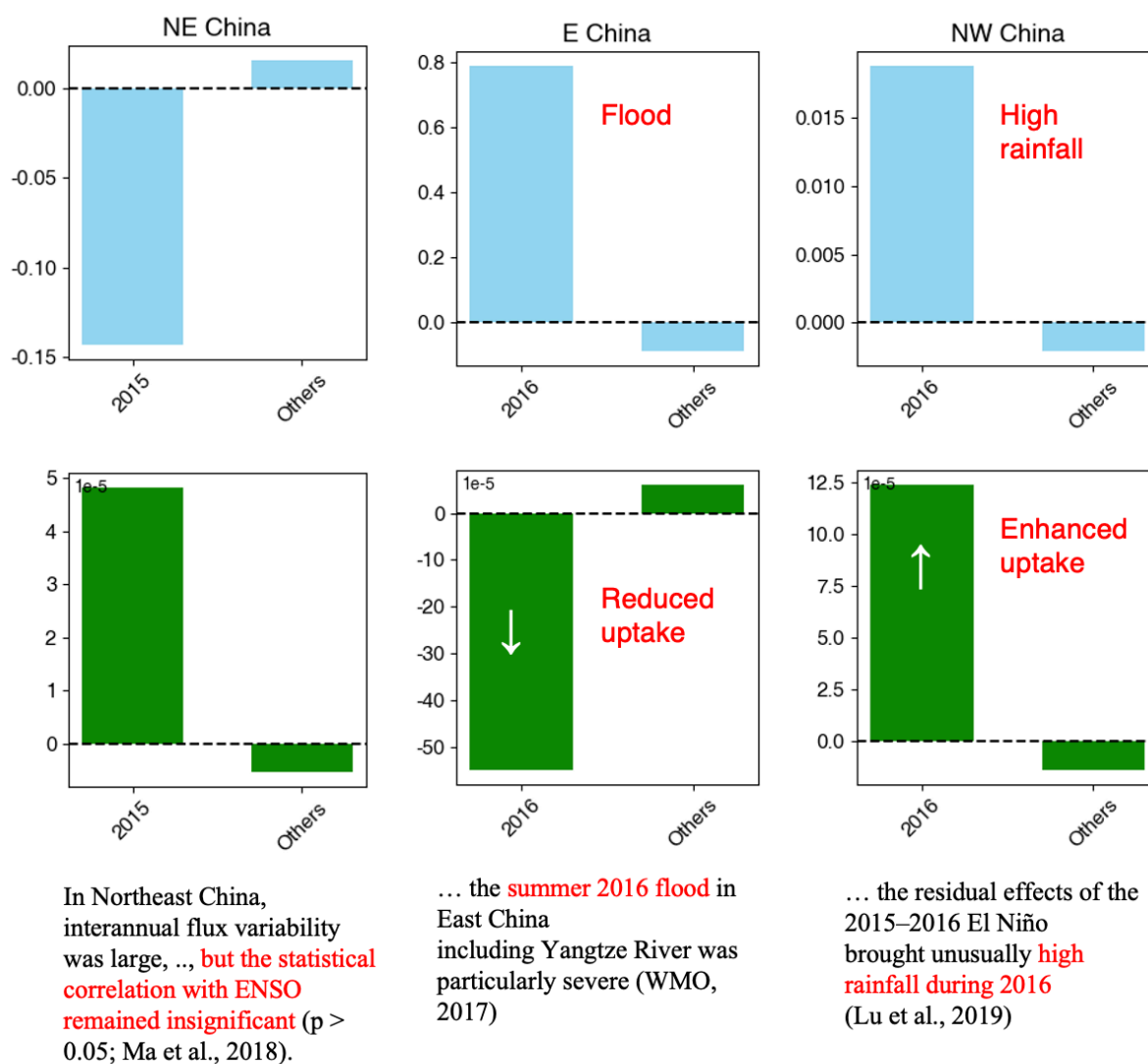


Figure S4. Same as Figure S3, but for Northeast China, East China, and Northwest China.

**10. Section 5:** The datasets used for comparison in this section do not appear to be fully appropriate or sufficient to robustly evaluate the inversion results. For example, FLUXCOM provides NEE estimates, and it is not a top-down product but rather closer to a bottom-up estimate.

In addition, TRENDY NEE was used as the prior in this study, and it is therefore unclear why the TRENDY values shown in Figure 5 differ from the prior fluxes presented in this manuscript. This discrepancy should be clarified.

Furthermore, CMS-Flux provides estimates of NBE (NEE + fire) as well as ocean fluxes, which could provide a more consistent benchmark.

The Global Carbon Project (GCP) also provides multiple  $pCO_2$ -based ocean flux estimates beyond those from GOBMs.

In addition, the OCO-2 v10 MIP provides satellite-based NBE estimates for the 2015–2020 period, which would be highly relevant for comparison.

Finally, RECCAP-2 provides country-level carbon budget estimates for East Asia based on both top-down and bottom-up approaches, and incorporating these results would substantially strengthen the evaluation.

Overall, I recommend that this section be substantially revised based on more widely used inversion products and published carbon budget estimates, in order to provide a more rigorous and credible comparison framework.

→ We thank the reviewer for the helpful suggestions regarding the comparison datasets used in Section 5. Following these comments, we substantially revised this section by incorporating additional widely used products and clarifying the role of each dataset used for comparison.

First, regarding FLUXCOM, given that the title of Section 5 is "5. Comparison of our top-down estimates with other products," FLUXCOM was intentionally included as a bottom-up estimate. We believe that comparing our inversion results with both top-down and bottom-up products provides useful context for evaluating the magnitude and variability of the inferred fluxes.

Second, the reviewer noted that TRENDY NEE was used as the prior, and therefore questioned why the TRENDY values shown in Figure 5 differ from the prior fluxes used in this study. We clarify that the prior flux used in our inversion is DLEM, not TRENDY NEE (see Section 2, Data and Methods).

Third, following the reviewer's suggestion, we tested the use of CMS-Flux products. However, CMS-Flux provides NBE (NEE + fire) rather than NEE. To enable comparison, we attempted to remove the fire contribution using GFED4. In practice, however, the resulting values were extremely small and differed substantially from both our estimates and other products. Because of this large discrepancy, we decided not to include these results in the main text or supplement, but we provide the comparison here for reference (Figure R1).

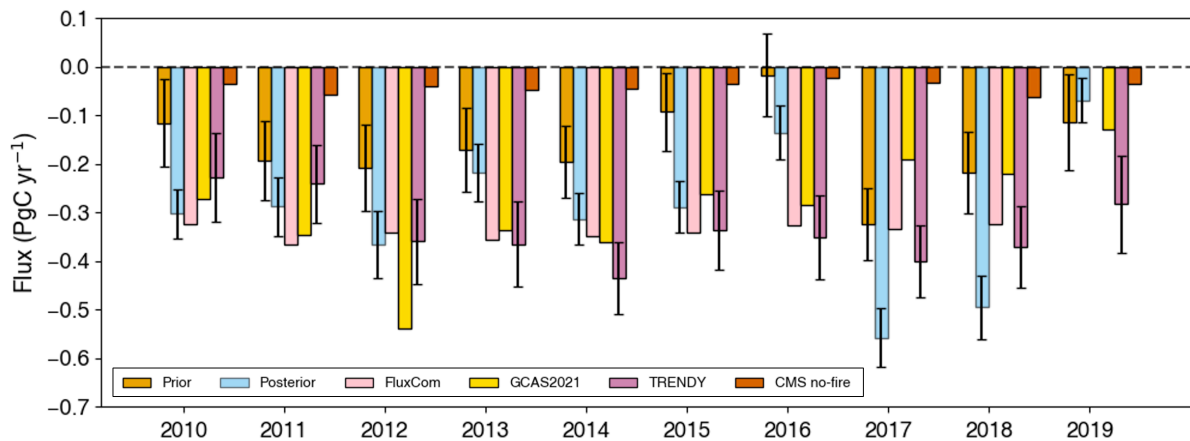


Figure R1. Comparison of annual terrestrial CO<sub>2</sub> flux estimates over East Asia from different products for 2010–2019. The posterior flux from this study is compared with prior fluxes and estimates from FLUXCOM, GCAS2021, TRENDY, and CMS-Flux (without fire emissions).

Fourth, following the reviewer's suggestion, we expanded the ocean comparison using Global Carbon Budget (GCB) products. Specifically, we included both the process-based and observation-based ensembles provided in GCB (Figure 5). As CMEMS is already included within the observation-based ensemble, we removed the separate CMEMS dataset to avoid redundancy.

Fifth, we added the OCO-2 v10 MIP product for comparison, as suggested by the reviewer. Because this dataset provides NBE, we converted it to NEE by removing the fire component using GFED4 before performing the comparison. The manuscript has been revised accordingly.

Finally, regarding RECCAP-2, the East Asia assessment presented in Wang et al. (2024) optimized net land-atmosphere CO<sub>2</sub> flux rather than separating NEE and ocean fluxes. In addition, the bottom-up estimates in that study are derived from the TRENDY v9 ensemble (Table R1). Because these estimates are not provided as annual values comparable to those shown in Figure 5, a direct year-by-year comparison is limited. We therefore refer to this study in the discussion and also include it in Figure 5 as an orange dashed line for reference. A brief comparison has been added in the manuscript.

Overall, Section 5 has been substantially revised following the reviewer’s suggestion. We added the GCB ocean ensemble and the OCO-2 v10 MIP product, and removed the redundant CMEMS dataset. The revised comparison now includes up to four independent NEE products and five ocean flux products. We note that differences among products are expected, as substantial spread also exists among the external datasets themselves. The purpose of Section 5 is therefore not to demonstrate exact agreement, but to show that the magnitude and variability of our inferred fluxes are broadly comparable with those reported by other studies.

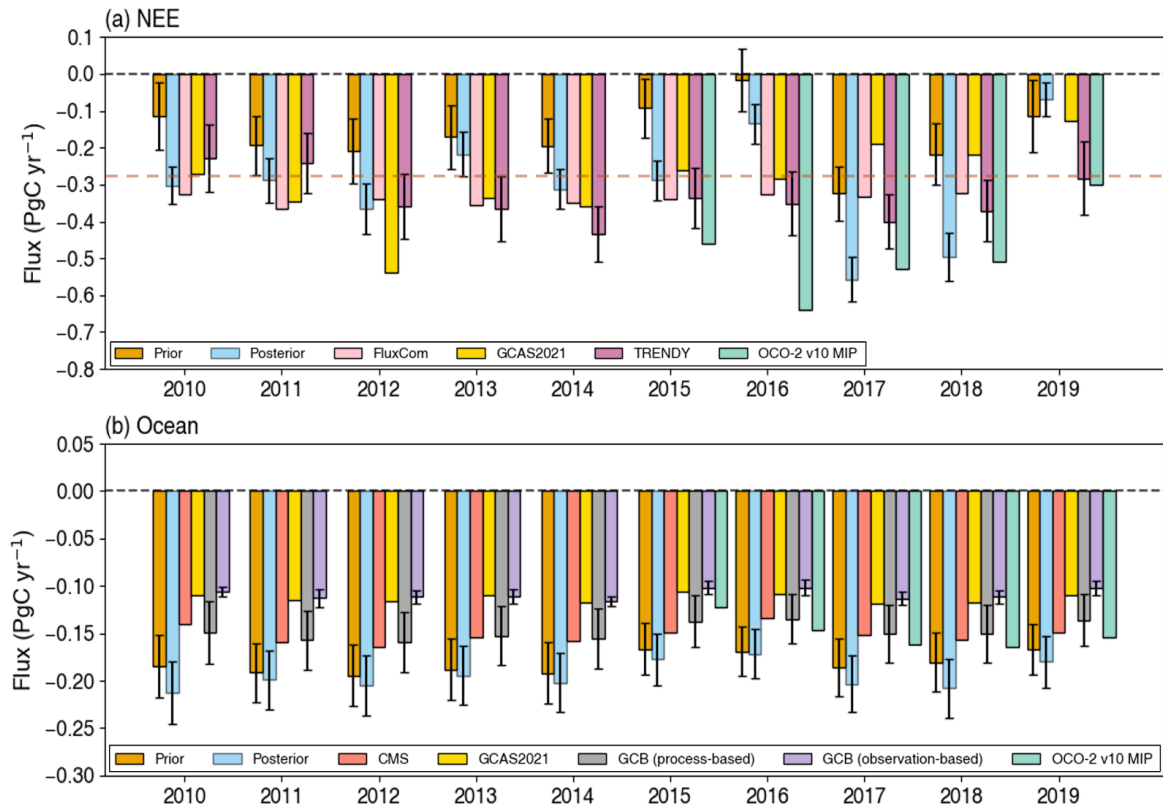


Figure 5. Comparison of prior and posterior flux estimates with other flux products from 2010 to 2019. (a) NEE and (b) Ocean carbon flux over East Asia. Bars indicate annual mean fluxes from each dataset. Error bars represent the uncertainty ranges for the prior and posterior estimates, while those for TRENDY and GCB Ocean denote the inter-model standard deviations. The orange dashed line is the NEE of East Asia for 2000-2020 calculated by RECCAP-2 (Wang et al., 2024)

Table R1. The GHG Budget from Wang et al. (2024)

Sectors		CO <sub>2</sub> (Tg CO <sub>2</sub> yr <sup>-1</sup> )		CH <sub>4</sub> (Tg CH <sub>4</sub> yr <sup>-1</sup> )		N <sub>2</sub> O (Tg N <sub>2</sub> O yr <sup>-1</sup> )		
		Mean	Uncertainty <sup>a</sup>	Mean	Uncertainty	Mean	Uncertainty	
1. Human activities	1.A Fossil Fuel	9493.35	221.83	23.40	1.90	0.58	0.05	
	1.B Waste and Landfill			11.38	3.20	0.32	0.48	
	<b>Subtotal</b>	<b>9493.35</b>	<b>221.83</b>	<b>34.79</b>	<b>3.72</b>	<b>0.90</b>	<b>0.49</b>	
2. Carbon stock change	2.A Forests	-788.55	142.22	-	-	-	-	
	2.B Shrublands	-126.25	42.21	-	-	-	-	
	2.C Grasslands	-36.37	45.24	-	-	-	-	
	2.D Croplands	-66.27	15.44	-	-	-	-	
	2.E Wetlands	-44.66	0.40 <sup>b</sup>	-	-	-	-	
	2.F Urban Construction	1.62	0.83	-	-	-	-	
	2.G Burial	-37.79	24.24	-	-	-	-	
	2.H Wood Products	-103.07	10.46	-	-	-	-	
		<b>Subtotal</b>	<b>-1201.33</b>	<b>158.09</b>	-	-	-	-
		NEE	-978.94	316.76	-	-	-	-
	Land Cover and Land Use Change	-290.17	281.72	-	-	-	-	
	<b>Subtotal</b>	<b>-1269.10</b>	<b>423.92</b>	-	-	-	-	
3. Lateral adjustments	3.A Net Trade	-171.11	70.75	-	-	-	-	
	3.B Lateral Transport to Ocean	-152.48	11.68	-	-	-	-	
	3.C Fossil Fuel RCC	322.67	18.33	-	-	-	-	
	3.D Biogenic RCC	135.67	66.00	-	-	-	-	
4. Agriculture	4.A Enteric Fermentation	-	-	9.60	1.34	-	-	
	4.B Manure Management	-	-	1.91	0.92	0.30	0.11	
	4.C Agricultural Soil	-	-	9.26	2.82	0.80	0.26	
	4.D Aquaculture	54.93	21.00	2.27	0.94	0.07	0.05	
	<b>Subtotal</b>	-	-	<b>23.04</b>	<b>3.37</b>	<b>1.17</b>	<b>0.29</b>	
5. Other sectors	5.A Wetlands	-	-	3.46	0.50	-	-	
	5.B Natural Soil	-	-	-2.62	0.26	0.78	0.09	
	5.C Fires	84.36	12.56	0.28	0.03	0.01	0.00	
	5.D Inland Waters	348.40	146.66	4.09	1.77	0.04	0.03	
	5.E Termites	-	-	0.32	-	-	-	
	<b>Subtotal</b>	-	-	<b>5.53</b>	<b>1.86</b>	<b>0.83</b>	<b>0.09</b>	
	5.H Geological Seepage <sup>c</sup>	-	-	2.17	0.43	-	-	
	TD Inversion	-1516.55	419.46	30.30	5.17	1.34	0.83	
<b>Balance</b>	<b>BU Land Budget</b>	<b>-1353.81</b>	<b>158.52</b>	<b>28.57</b>	<b>3.85</b>	<b>2.00</b>	<b>0.31</b>	
	<b>TD Land Budget</b>	<b>-1229.33</b>	<b>430.86</b>	<b>30.30</b>	<b>5.17</b>	<b>1.34</b>	<b>0.83</b>	

Note. Bold values represent the subtotal of each sector or the total budget of each GHG. <sup>a</sup>The reported uncertainty represents the standard deviation. <sup>b</sup>The uncertainty for 2.E is estimated as 21% of the mean value (NCCC, 2018). <sup>c</sup>Geological seepage is not contained within the boundaries of our terrestrial ecosystem framework.

Lines 434–441: We further include the OCO-2 v10 Model Intercomparison Project (MIP), specifically the LNLGOGIS inversion configuration, which assimilates OCO-2 XCO<sub>2</sub> retrievals from land nadir, land glint, and ocean glint observations together with in situ measurements (Crowell et al., 2019). The OCO-2 MIP ensemble provides an independent set of atmospheric inversion estimates using multiple transport models and prior flux assumptions, thereby serving as an additional benchmark for evaluating both terrestrial and ocean carbon flux estimates. It should be noted that the OCO-2 v10 MIP provides net biosphere exchange (NBE) rather than net ecosystem exchange (NEE). To ensure consistency with our flux definition, we therefore subtracted fire emissions from the NBE estimates using the GFED4 fire inventory, which is also used in our inversion framework.

Lines 454–455: The magnitude of the terrestrial carbon sink inferred in this study ( $-0.31 \text{ PgC yr}^{-1}$ ) is broadly consistent with the terrestrial sink estimate reported by Wang et al. (2024) for East Asia during 2000–2019 ( $-0.27 \text{ PgC yr}^{-1}$ ; Figure 5).

**11. Lines 402–403:** It would be helpful if the authors could provide a brief explanation of how the atmospheric carbon stock was calculated. Adding a short description of the calculation method would improve clarity and make this part easier to follow.

→ We added the following description of the method used to calculate atmospheric carbon stock in Appendix A to improve clarity.

Lines 551–587:

### Appendix A : Calculation of the East Asia carbon budget

The carbon budget over East Asia was estimated based on the conservation of carbon mass within the regional atmospheric column. The carbon balance over the domain can be expressed as

$$\frac{dC_{\text{atm}}}{dt} = F_{\text{net}} - F_{\text{export}},$$

where  $C_{\text{atm}}$  is the atmospheric carbon mass within the East Asia domain,  $F_{\text{net}}$  is the net surface carbon flux, and  $F_{\text{export}}$  represents the net lateral carbon transport out of the domain.

The net surface carbon flux was calculated as the sum of fossil fuel emissions (FF), biomass burning emissions (BB), terrestrial net ecosystem exchange (NEE), and ocean–atmosphere carbon flux:

$$F_{\text{net}} = F_{\text{FF}} + F_{\text{BB}} + F_{\text{NEE}} + F_{\text{ocean}},$$

where positive values denote carbon release to the atmosphere and negative values represent carbon uptake by land or ocean. Using the mean fluxes during 2010–2019, fossil fuel emissions and biomass burning contributed  $+3.86$  and  $+0.11 \text{ PgC yr}^{-1}$ , respectively, while terrestrial and ocean uptake were  $-0.31$  and  $-0.21 \text{ PgC yr}^{-1}$ . The resulting net surface flux over East Asia is therefore

$$F_{\text{net}} = +3.45 \text{ PgC yr}^{-1},$$

Atmospheric carbon storage within the East Asia domain was estimated by vertically integrating posterior  $\text{CO}_2$  concentrations over the atmospheric column and converting the result to units of PgC. The atmospheric carbon mass can be written as

$$C_{\text{atm}} = \int_V X_{\text{CO}_2} \rho_{\text{air}} dV,$$

where  $X_{CO_2}$  is the CO<sub>2</sub> dry mole fraction,  $\rho_{air}$  is the air density, and  $V$  represents the atmospheric volume over the East Asia domain. This integration yields annual atmospheric carbon stock values  $C_{atm}(t)$  for each year during 2010–2019. The mean atmospheric carbon stock during the study period was estimated to be 38.97 PgC.

The temporal change in atmospheric carbon storage was derived from the difference between the 2019 and 2010 carbon stocks:

$$\frac{dC_{atm}}{dt} = \frac{C_{atm,2019} - C_{atm,2010}}{\Delta t},$$

which corresponds to an average storage increase of approximately

$$\frac{dC_{atm}}{dt} = 0.24 \text{ PgC yr}^{-1}.$$

Finally, the net carbon export from the East Asia domain was diagnosed as the residual of the mass balance equation:

$$F_{export} = F_{net} - \frac{dC_{atm}}{dt}.$$

Substituting the estimated values yields

$$F_{export} = 3.45 - 0.24 = +3.21 \text{ PgC yr}^{-1}.$$

This result indicates that most of the carbon emitted within East Asia is transported out of the region by atmospheric circulation rather than accumulating locally within the atmospheric column.

Minor comments

L26: vegetation -> terrestrial ecosystems

→ Revised as suggested.

L101: vegetation -> terrestrial ecosystems

The author's inversion system does not directly provide information on vegetation carbon uptake alone, but rather constrains net carbon fluxes of the terrestrial systems.

→ Revised as suggested.

Table 4 caption: vegetation CO2 uptake -> terrestrial ecosystems CO2 uptake

→ Revised as suggested.

Table 4 : When calculating the correlations between anomalies of vegetation indices and NEE, did the authors also use NEE anomalies with the seasonal cycle removed?

→ In this study, the correlations between EVI and NEE were calculated based on annual mean values rather than monthly anomalies with the seasonal cycle removed. The objective of this analysis was to assess interannual variability rather than intra-seasonal variations. Because annual means were used, the influence of the seasonal cycle is inherently minimized through the averaging process, and therefore no additional seasonal cycle removal was performed. As a result, the correlations are not affected by artificial phase locking associated with monthly seasonal variability.

## Reviewer 2

The manuscript explores the East Asian flux estimation using an inverse modeling framework based on GEOS-Chem and GOSAT-ACOS product. The objectives are scientifically sound, and the manuscript is generally well-written in terms of motivation, objectives, language, numerical experiments, and explanations. However, still there remains considerable scope for major improvement before the manuscript can be considered for publication.

I therefore strongly recommend major revision of the manuscript in its current form. The detailed comments below, if carefully addressed, could substantially improve the quality and clarity of the work.

Major comments:

1. In the abstract, author mentioned that most of the subregions of East Asia as net carbon sinks over the past decade—indicating East Asia as a net sink. However, shortly thereafter, they mentioned that natural sinks offset only ~13.6% of fossil fuel emission, leaving a substantial source. These two statements appear contradictory and may confuse readers. I request to revise the abstract carefully.

→ We clarified the net carbon balance of East Asia when fossil fuel and biomass burning emissions are included:

Line 17–18: When fossil fuel and biomass burning are included, East Asia released a net flux of +3.4 5 PgC yr<sup>-1</sup> to the atmosphere during 2010–2019. Natural sinks offset only ~13.6% of fossil fuel emissions, leaving a substantial residual source.

2. The introduction would benefit from rearrangement. The flux estimation terminology, such as “inverse modeling” is referred before being formally introduced (which occurred in second paragraph).

→ We revised the Introduction to introduce the concept of inverse modeling earlier in the text:

Line 38–39: In contrast, top-down methods infer surface fluxes by applying inverse techniques to atmospheric CO<sub>2</sub> concentration data, a process commonly referred to as atmospheric inverse modeling.

3. The calculation of apriori flux error is unclear. For error in terrestrial fluxes, author appear to use monthly NEE fluxes from eight land models and calculate ensemble standard deviation at each grid point and time step, which would result the 3D error field (*time x latitude x longitude*). How the table 1 values are calculated? Do these values represent ensemble standard deviation of regional annual total flux? In addition, final row of table 1 appears to be the average across years. Since standard deviation is a measure of dispersion, averaging standard deviation directly is not statistically well defined. I recommend to combine them as variance across, compute average and then convert to standard deviation again.

→ We clarified how the values in Table 1 were calculated and how the final row should be interpreted.

Lines 209–213: For each region and each year, annual total fluxes were first calculated separately for each model by spatially integrating the model fluxes over the region, and  $\sigma_a$  was defined as the ensemble

standard deviation of these regional annual total fluxes. The resulting annual  $\sigma_a$  values for each region are summarized in Table 1. Note that this mean was computed by averaging the  $\sigma_a$  values directly, not by averaging the variances and then taking the square root.

4. Public TCCON data do not provide vertical weighting function, which is needed to calculate the XCO<sub>2</sub>. Please clarify how XCO<sub>2</sub> was calculated for the TCCON evaluation?

→ Thank you for the comment. If the “vertical weighting function” refers to the averaging kernel (AK), we used the AK provided in the TCCON dataset. The AK was limited in earlier releases (e.g., GGG2014) but is fully available in the GGG2020 product (<https://tccon-wiki.caltech.edu/Main/GGG2020DataChanges>). If the reviewer refers to the pressure weighting function used to calculate XCO<sub>2</sub>, it follows the formulation described in Connor et al. (2008).

5. The manuscript doesn't describe how posterior flux uncertainties is calculated. This information is essential to assess the robustness of the inversion flux. I strongly suggest adding a clear description about the posterior error estimation method. Additionally, a spatial map of uncertainty reduction would be highly informative and could be included in supplementary material.

→ We added the following description of the posterior error estimation method and included a spatial map of uncertainty reduction in the Supplement (Figure S1):

Lines 197–200: Analogous to the construction of  $S_a$ , the diagonal elements of the posterior error covariance matrix  $\hat{S}$  correspond to the squared posterior uncertainties ( $\hat{\sigma}$ ). The decrease from prior to posterior uncertainty reflects the degree to which the observations constrain the flux estimates. Accordingly, the uncertainty reduction indicates how much the prior uncertainty is reduced after applying the GOSAT observational constraints.

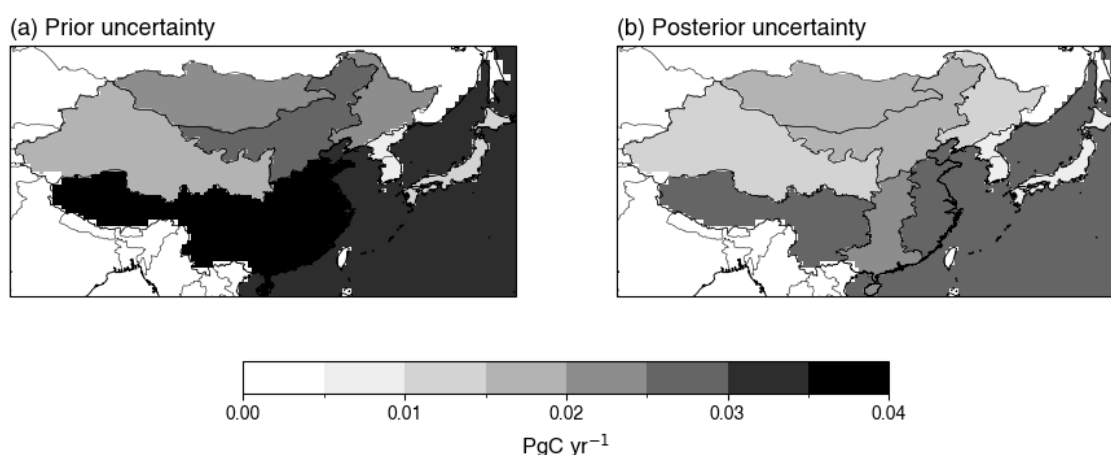
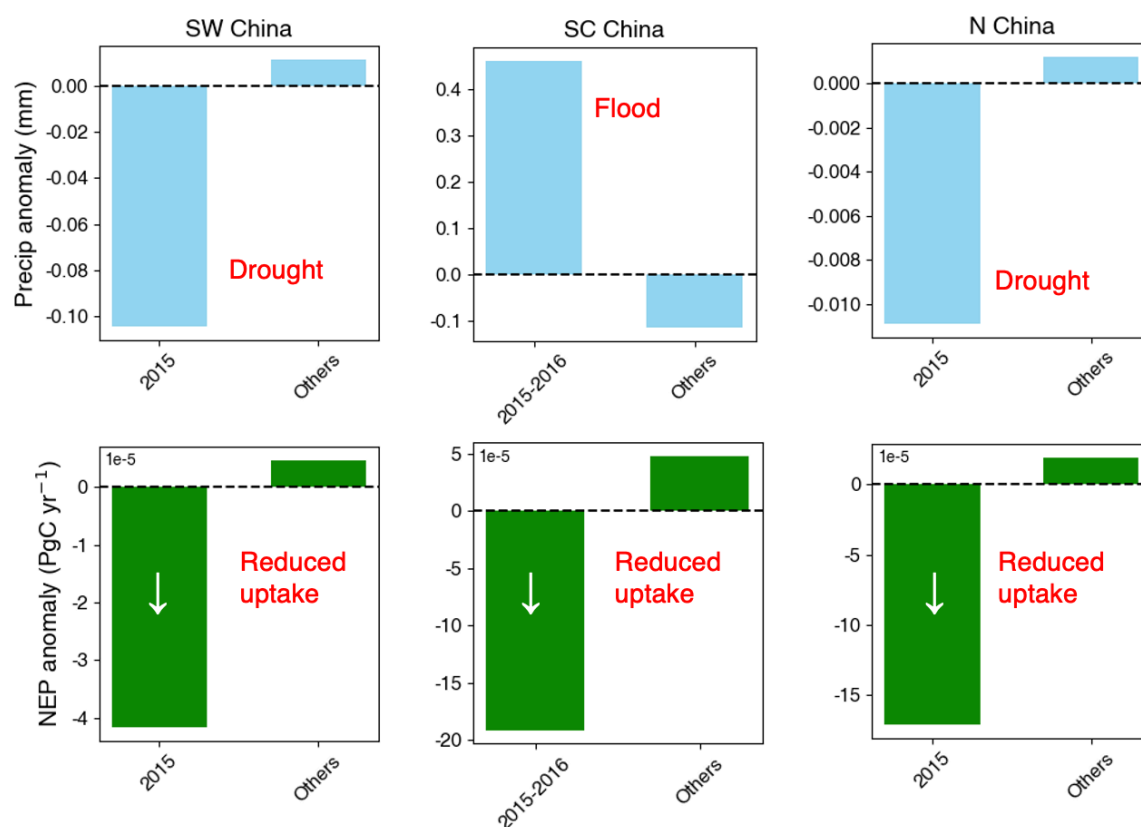


Figure S1. Spatial distributions of the (a) prior uncertainty and (b) posterior uncertainty of the estimated CO<sub>2</sub> fluxes over East Asia for the study period.

6. The manuscript reports enhanced uptake over major study regions except southwest China where strong uptake reduction is noticed. The underlying cause of this is not discussed. Please elaborate about the possible drivers.

→ The possible drivers of the uptake reduction over Southwest China are discussed in the manuscript (Lines 369–375). To make this point clearer, we added a reference to Figure S3 of the Supplement.



... Southwest China underwent persistent drought due to weakened southward moisture transport (Ma et al., 2018). This region suffered from **prolonged drought conditions from summer 2015 through spring 2016**

South Central China similarly exhibited enhanced precipitation and **frequent flooding during 2015–2016** (Ma et al., 2018),

... precipitation deficits prevailed **during the 2015 El Niño peak**, especially in North China, where severe summer droughts were reported (Zhai et al., 2016)

Figure S3. Regional anomalies in precipitation (sky blue) and terrestrial carbon uptake expressed as NEP (= -NEE; green) over Southwest China, South Central China, and North China. The text below each panel is excerpted from the corresponding discussion in the main text.

7. Details of the meteorological data used in this study (data source, resolution, temporal coverage etc.) should be explicitly mentioned.

→ We have added a description of the meteorological data used in this study in the revised manuscript.

Lines 124–130: For high-resolution CO<sub>2</sub> simulations over East Asia, we used the nested-grid version of GEOS-Chem driven by Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2; Gelaro et al., 2017) meteorological reanalysis data. MERRA-2 provides assimilated meteorological fields at 0.5° × 0.625° horizontal resolution, with variables available at hourly and 3-hourly temporal intervals depending on the data stream. MERRA-2 meteorological fields were used consistently for both the spin-up (2005–2009) and inversion (2010–2019) periods. The global simulation was conducted at 2° × 2.5° horizontal resolution, while the nested East Asia simulation was performed at the same 0.5° × 0.625° resolution as the MERRA-2 fields, with 47 vertical levels extending from the surface to 0.01 hPa.

#### Minor comments

1. GOSAT should be introduced before it is first referred in the manuscript.

→ We have added a brief introduction of GOSAT before its first appearance in the manuscript.

Lines 60–61: The Greenhouse Gases Observing SATellite (GOSAT), launched in 2009, provides global column-averaged CO<sub>2</sub> (XCO<sub>2</sub>) observations.

2. Sub-sectional numbering in section 2 is incorrect: it begins with 2.1 skips section 2.2 and then proceed to section 2.3 directly.

→ Thank you for pointing this out. It has been corrected.

3. Page 4, line 103: The term “model parameters” is not explained. Please elaborate a bit.

→ We have added a clarification of the term “model parameters” in the revised manuscript.

Lines 179–180: Here, model parameters refer to all model variables that are not optimized in the inversion.

4. While discussing observational error covariance, the authors didn't mention the instrumentation error. Please clarify whether and how instrumental uncertainty is accounted for.

→ We have clarified how instrumental uncertainty is accounted for in the observational error covariance in the revised manuscript.

Lines 235–239: The instrument errors are represented using the reported XCO<sub>2</sub> uncertainty provided in the GOSAT/ACOS v9 Level 2 Lite product (Taylor et al., 2022). This per-sounding uncertainty, with a typical magnitude of approximately 1 ppm, varies depending on observing conditions such as signal-to-noise ratio, solar zenith angle, and residual contamination by optically thin clouds or aerosols not fully removed during quality screening (O'Dell et al., 2012; Taylor et al., 2022).

5. Page 6, line 155: The statement “The XCO<sub>2</sub> uncertainty.....” is unclear. Please specify which term in the observational error equation corresponds to this “XCO<sub>2</sub> uncertainty”.

→ To avoid ambiguity, we removed this sentence and describe the construction of the observational error covariance only in Section 2.3.2.

6. Page 7, line 161: The manuscript inconsistently refers to “...GOSAT/ACOS Version 9.0 Level 2...” and “...kernel of GOSAT/ACOS v9r...”. Please ensure that the version naming is consistent and unambiguous throughout.

→ Thank you for pointing this out. We have made the version naming consistent throughout the manuscript and clearly defined the dataset name at its first appearance.

Lines 88–89: We use the Atmospheric CO<sub>2</sub> Observations from Space (ACOS) Version 9.0 Level 2 Lite product (Taylor et al., 2022), covering the period from January 2010 to December 2019 (hereafter GOSAT /ACOS v9).

7. Table 3 is not referenced anywhere in the text; it should either be cited appropriately or removed.

→ We have added a reference to Table 3 in the text.

Line 284: The mean UR values for each region during 2010–2019 are summarized in Table 3.

8. Page 10, Line 238: The statement “The 10-year mean ” needs clarification. Does “±” indicate interannual standard deviation? Please specify.

→ The ± values represent the interannual standard deviation for the period 2010–2019. We have clarified this in the revised manuscript (Line 289).

Line 301–304: The 10-year mean NEE increased from  $-0.17 \pm 0.08$  PgC yr<sup>-1</sup> to  $-0.31 \pm 0.06$  PgC yr<sup>-1</sup> (mean ± interannual standard deviation) (Figure 2a, b), while oceanic uptake showed a slight increase from  $-0.20 \pm 0.03$  PgC yr<sup>-1</sup> to  $-0.21 \pm 0.03$  PgC yr<sup>-1</sup>, although this change lies within the range of prior uncertainty and is therefore not statistically significant (Figure 2a, b).

9. Page 12, line 285: The statement “Notably, both prior and posterior estimates indicated decreased

carbon uptake during 2015–2016, coinciding with the Super El Niño.” is not consistently supported by the figure. For example, Korean peninsula and Japan show increased posterior uptake during both 2015, 2016 relative to other years. Although, the authors attempt to qualify this in the following sentence, the initial statement should be rephrased more carefully to avoid overgeneralization.

→ To avoid overgeneralization, we removed the original statement and replaced it with a more general description in the revised manuscript.

Lines 351–352: During 2015–2016, reduced carbon uptake was observed in several regions across East Asia, coinciding with the Super El Niño.