Dear reviewer,

We appreciate your insightful comments and suggestions. Below, we provide detailed responses to each point raised. In this document, the reviewer's comments and suggestions are highlighted in red, our responses are in blue, and references to the original manuscript content are in black.

We understand your concerns regarding the limited validation in the manuscript, particularly the inclusion of only one case study. While additional cases would indeed strengthen the validation for operational use, the primary aim of this paper is to introduce and demonstrate the mitigation approach we have developed. This work serves as an introduction to new physics-based mitigation methods for OCO retrievals, distinct from existing statistical bias correction methods.

We appreciate your suggestion to focus more on the results. However, as this paper introduces new methods, we believe it is essential to provide a detailed description of the methodology and setup, in addition to demonstrating the methods. To address your comment, we will add a 'manuscript guide' at the end of the introduction in the revised version of the manuscript, which clearly separates the sections of the manuscript that are intended to introduce the methodology vs. the sections that present preliminary results. Again, the emphasis of this manuscript is to bring a bias-correction to real-world data, and that requires the introduction of a rather extensive radiative transfer tool.

In response to the feedback, we included two additional cases applying the same bypass parameters and a comparison with the baseline method in this response document on page 2. Due to manuscript length considerations, we will add the first case as an example in the appendix. We remain committed to enhancing this methodology and will continue to expand validation in future work.

General comments:

Overall, the subject of the study is very compelling and a significant contribution to the community. Especially considering future upcoming green house gas missions.

Thank you for your positive feedback on our research. We appreciate your recognition of its relevance for future missions. We have carefully considered your comments and provided detailed responses to address your concerns.

Major Comments

However, the study misses depth in how far the 3D cloud bias correction has been investigated.

We acknowledge the extensive efforts made by the community to address 3D cloud bias, such as recent advancements using machine learning approaches (e.g., applying the machine learning bias correction from Mauceri et al. (2023) on V11 data product). However, the methods adopted by the OCO team so are not fully physics-based, which means that they do not operate at the radiance level (where cloud-induced 3D-RT effects introduce perturbations), instead focusing on the product level in a statistical manner. Here, we operate at the radiance *and* footprint level for real-world satellite spectroscopy data – to our knowledge the first time that this has been done. The most closely related publications to our study are the ones by Emde et al. (2022) and Merrelli et al. (2015) since they studied the impact of cloud-induced spectroscopic perturbations on the products. However, neither of these studies worked with real-world data, focusing on synthetic data instead. The value of our study lies in presenting a mitigation strategy that directly addresses the 3D cloud bias from a physical (radiance) perspective, focusing on the mechanisms behind these biases rather than relying solely on empirical corrections (as done in previous, statistical studies). In this sense, we would actually say that our manuscript *adds* depth over previous studies. We might have missed what the reviewer is referring to specifically, perhaps details of the current retrieval algorithm. However, since it is stated in the manuscript, we probably do not need to point out here that the physics of the current operational algorithm does not account for horizontal photon transport and therefore by definition misses an important piece of reality, which we bring back with our work.

**Major concern is that the developed approach has been applied only to a single, hand-picked scene. This is simply not enough to make any guesses towards the performance of the approach when applied operationally.**

We understand where this concern is coming from, and are glad that the reviewer is pointing out this perception. Indeed, this paper starts out with a specific scene, and we acknowledge that more cases are needed to fully evaluate the method's performance for operational use. However, the primary goal of this study is to describe the methodology, and in that regard, the scene we used is simply used for illustration. We did not specifically hand-pick a scene because 'it worked." In reality, we have tried this method on several scenes, and the selected case simply provided a clear illustration to demonstrate the mechanics of the approach. However, this does not mean that the other cases did *not* work. To show this, we include two other cases in this response. Because of considerations regarding manuscript length, we will add only the first additional case as an example in the appendix. In future work, we plan to apply the method to a larger set of scenes to assess its robustness and operational applicability, but that future work is distinct from our intention here, which lays the ground work and describes the methodology. On this note: Future version of the algorithm will come with improvements, part of which were motivated by the reviewer comments to the release version of our code, documented with this publication.

To address your comment on validation, we have included two additional cases from the same month and general geographic area as the case in Fig. 2. These cases apply the bypass mitigation method based on parameters outlined in Table R1 (Table 2 in the manuscript) and are compared to the baseline method as validation examples (shown below). 1D-RT and 3D-RT simulations were conducted for these two cases to derive the correct slope and intercept parameters. Thus, we can evaluate the bypass mitigation based on Table R1, with the comparisons illustrated in Figs. R3 and R6.

The results from case 1 indicate that the bypass method yields a mitigation trend similar to that of the baseline method, although with lower magnitudes. The difference between Fig. R2a and b is potentially due to differences in surface altitude and albedo, solar geometry, AOD, and other environmental factors. This case demonstrates promising results, yet adjustments to the bypass parameters with more scene variables are necessary for effective operational use.

In contrast, case 2 shows less favorable performance of the bypass method compared to the baseline method. In case 2, the baseline method reveals a weaker correlation between $\Delta X_{CO2}$ and effective cloud distance, likely due to confounding factors, such as surface albedo effects. This indicates that the bypass method may be less effective in mixed or complex cloud-surface conditions. Given the length constraints of the current manuscript, we have decided to add only case 1 as an example in the appendix.

Table R1. The same table as Table 2 in the manuscript. Amplitude and e-folding distances for ***s*** and ***i*** fittings of the simulation with a homogeneous aerosol layer in the $O_2$-A, $WCO_2$, and $SCO_2$ bands for 1.0 km geometric cloud thickness of low clouds.

| | Slope | | | Intercept | | |
|---|---|---|---|---|---|---|
| | $s_{O_2-A}$ | $s_{WCO_2}$ | $s_{SCO_2}$ | $i_{O_2-A}$ | $i_{WCO_2}$ | $i_{SCO_2}$ |
| $a_s$ or $a_i$ | 0.457 ± 0.094 | 0.123 ± 0.037 | 0.250 ± 0.041 | 0.755 ± 0.327 | 0.648 ± 0.227 | 0.847 ± 0.406 |
| $d_s$ or $d_i$ (km) | 3.82 ± 0.44 | 5.04 ± 0.89 | 4.58 ± 0.78 | 2.69 ± 0.32 | 2.91 ± 0.31 | 2.35 ± 0.33 |

Additional case 1:

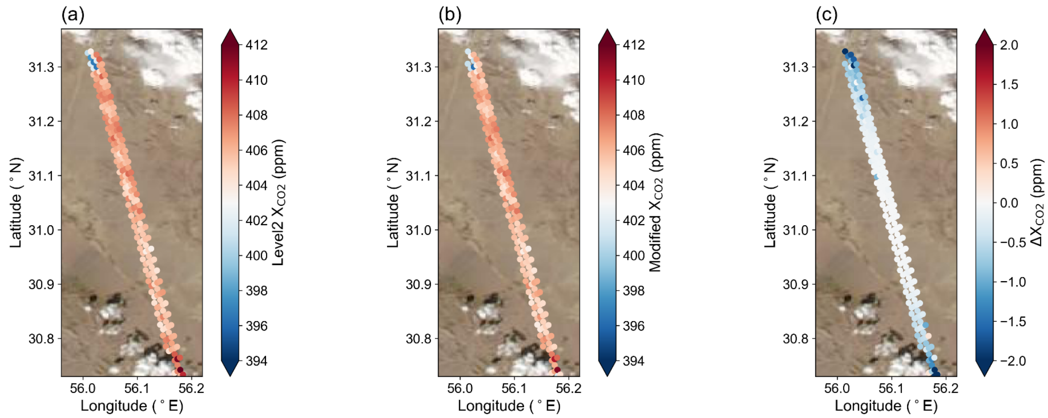



Figure R1. Satellite true-color imagery of MODIS Aqua from NASA Worldview on 5 October 2019 with (a) $X_{CO2}$ in OCO-2 level 2 data, (b) mitigated $X_{CO2}$ retrieved from the adjusted spectra and (c) difference between the mitigated and original $X_{CO2}$ values.

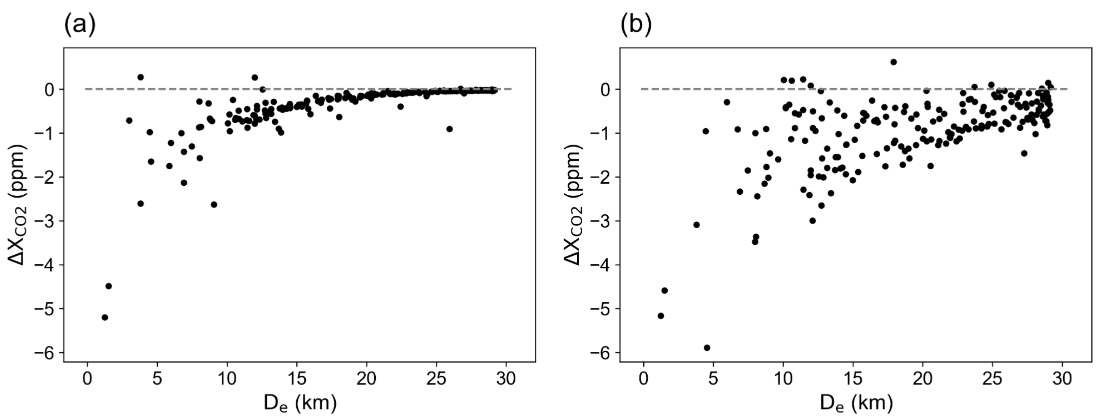



Figure R2. (a) Relationship of $\Delta X_{CO2}$ with $D_e$ based on parameterized slopes and intercepts from the bypass method in Table 2. (b) Corresponding relationship using slopes and intercepts derived from the baseline approach for Fig. R3.

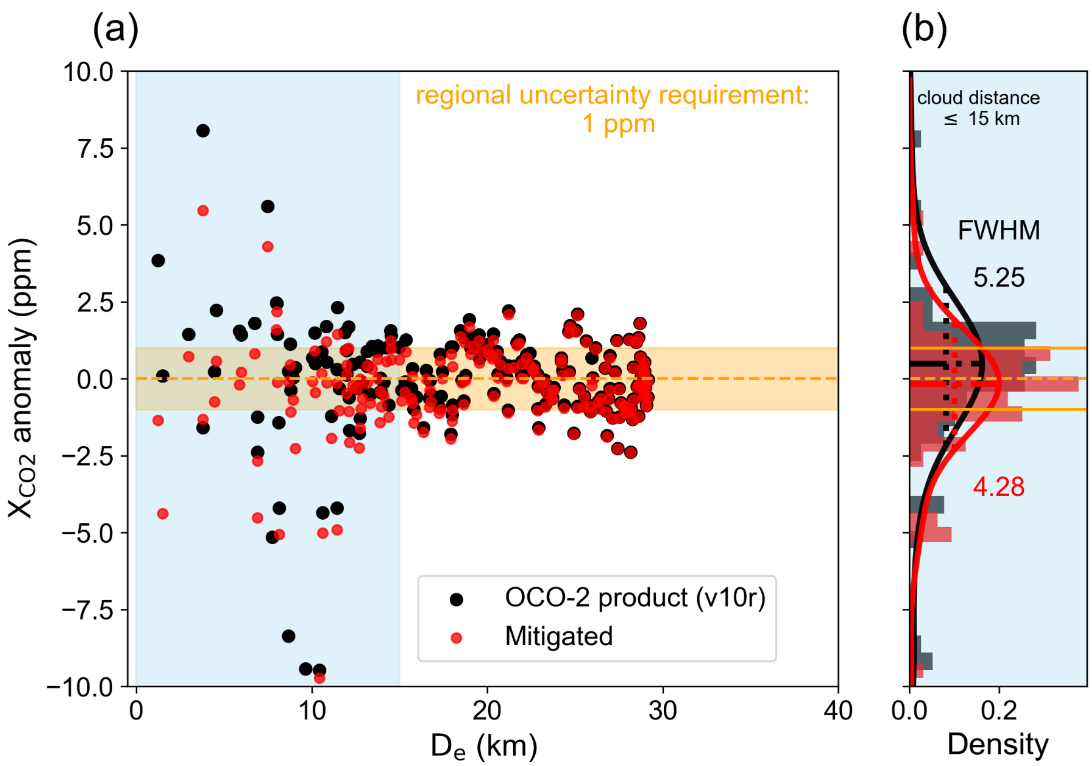



Figure R3. (a) Scatter plot comparing the $X_{CO2}$ anomaly of the OCO-2 L2 product (in black) to its value post-spectra adjustment (in red) for the case shown in the figure above, plotted against $D_e$. The $X_{CO2}$ anomaly is defined as retrieved $X_{CO2}$ – true $X_{CO2}$, with the true $X_{CO2}$ defined by the average $X_{CO2}$ of footprints with a $D_e$ greater than 15 km (405.96 ppm in this case). The orange shade indicates the 1 ppm mission requirement. (b) Histograms and probability density functions (PDFs) for the $X_{CO2}$ anomaly of the OCO-2 L2 product (in black) and post spectra adjustment (in red) within a 15 km $D_e$. This corresponds to the blue-shaded region in (a). The FWHM values of the PDFs of v10r and adjusted data points are 5.25 and 4.28, and the PDF averages are 0.93 and 0.18, respectively. The average change in $X_{CO2}$ after the spectra adjustment for De less than 15 km is -0.86 ppm.

Additional case 2:

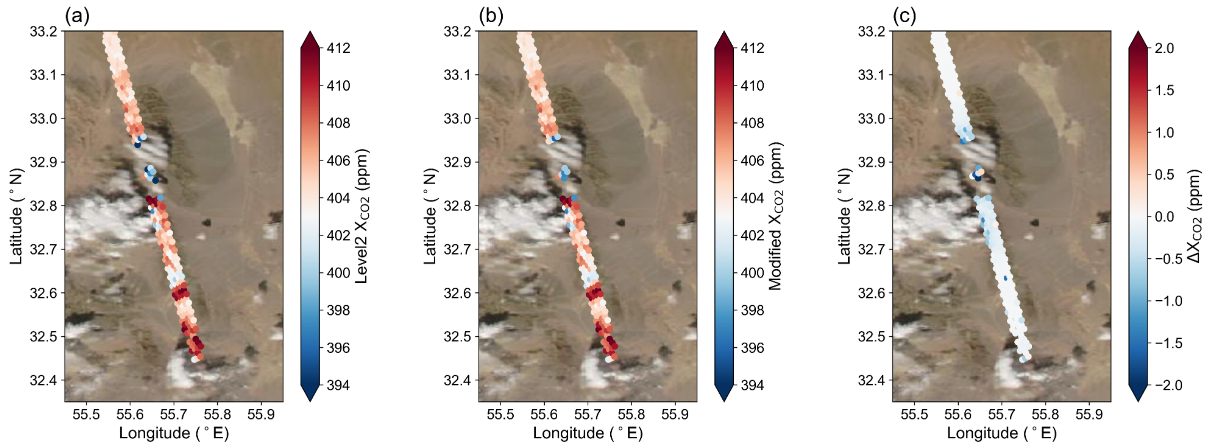



Figure R4. Satellite true-color imagery of MODIS Aqua from NASA Worldview on 18 October 2018 with (a) $X_{CO2}$ in OCO-2 level 2 data, (b) mitigated $X_{CO2}$ retrieved from the adjusted spectra and (c) difference between the mitigated and original $X_{CO2}$ values.

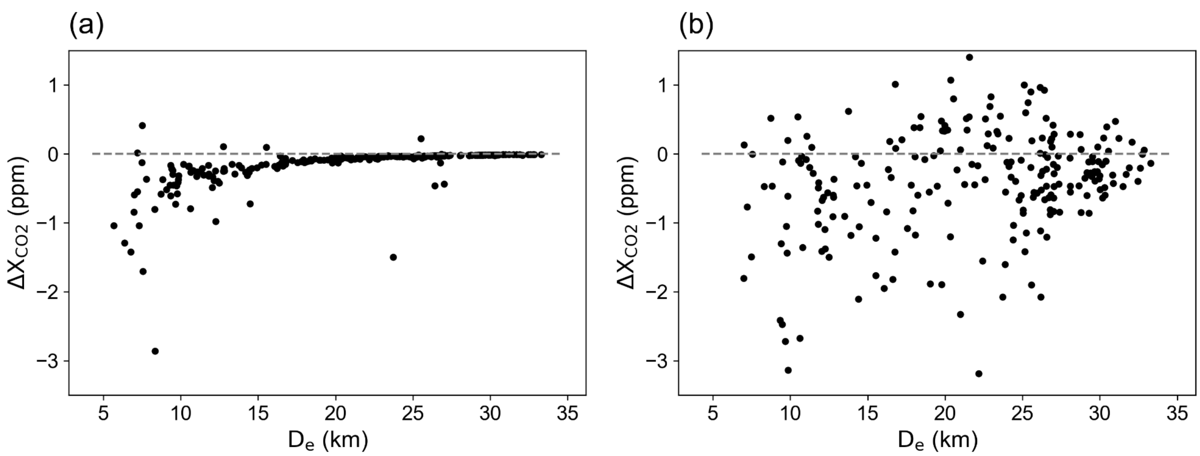



Figure R5. (a) Relationship of $\Delta X_{CO2}$ with $D_e$ based on parameterized slopes and intercepts from the bypass method in Table 2. (b) Corresponding relationship using slopes and intercepts derived from the baseline approach for Fig. R5.

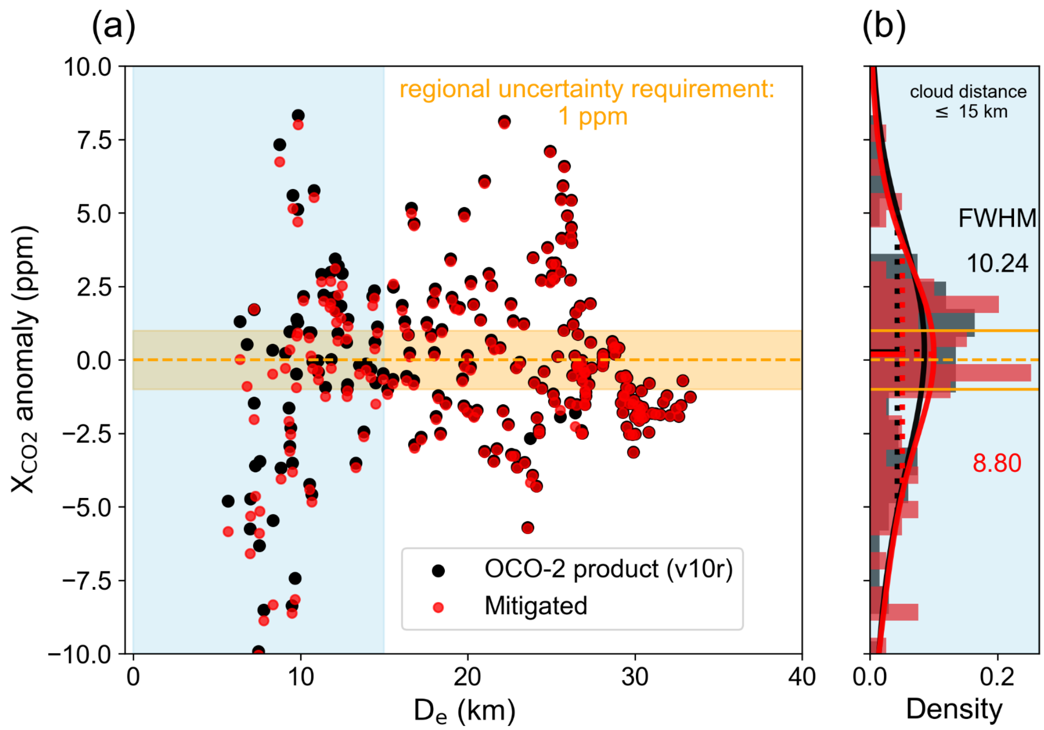



Figure R6. (a) Scatter plot comparing the $X_{CO2}$ anomaly of the OCO-2 L2 product (in black) to its value post-spectra adjustment (in red) for the case shown in the figure above, plotted against $D_e$. The $X_{CO2}$ anomaly is defined as retrieved $X_{CO2}$ – true $X_{CO2}$, with the true $X_{CO2}$ defined by the average $X_{CO2}$ of footprints with a $D_e$ greater than 15 km (405.69 ppm in this case). The orange shade indicates the 1 ppm mission requirement. (b) Histograms and probability density functions (PDFs) for the $X_{CO2}$ anomaly of the OCO-2 L2 product (in black) and post spectra adjustment (in red) within a 15 km $D_e$. This corresponds to the blue-shaded region in (a). The FWHM values of the PDFs of v10r and adjusted data points are 10.24 and 8.80, and the PDF averages are 0.27 and 0.20, respectively. The average change in $X_{CO2}$ after the spectra adjustment for De less than 15 km is -0.45 ppm.

The study states that it developed a software tool for the automated calculation of spectral radiances from OCO-2. However, **the automation is not exploited to analyze a representative sample size of OCO-2 observations.**

We agree that analyzing the entire dataset, or even 1% of OCO-2 observations, using full 3D-RT simulations is impractical due to the high computational cost. This constraint motivated the development of the bypass method, which aims to significantly reduce the need for extensive 3D-RT calculations. However, before the bypass method can be applied operationally, we still need to use the tool to analyze several dozen to hundreds of cases under diverse conditions to build a more generalized parameterization. While the automation feature helps streamline radiance calculations, further validation with additional cases is a key focus for future work. We are currently in the method development stage, with larger-scale case analyses planned as the next step.

**Furthermore, for this single selected scene the strongest biases seem to be collocated with cloud shadows while the authors argue that those shadows are outside the scope of this study.** For this research to be useful to the community it needs to show that it can be generalized (e.g. various SZA, ocean (where 3D cloud effects are strongest), land surface types, different cloud types, different viewing modes (nadir and glint)).

As mentioned in lines 381-384, we refer to Massie et al. (2023), who found that relatively few cloud shadow retrievals exist in the OCO-2 Lite files due to the pre-retrieval cloud screening algorithms. In addition, B11 retrieval has improved in filtering out footprints under shadow (at least for the cases we analyzed). We don't think that the remaining few cloud-shadow footprints passing the pre-screening have the same importance as the clear-sky footprints affected by clouds in the vicinity.

We agree that demonstrating the method's applicability to a broader range of conditions, such as different solar zenith angles, surface types, cloud types, and viewing geometries (nadir and glint), is crucial for generalization. To address part of your concern, we will add a section before Section 5.5 (3D effect mitigation) discussing the impact of surface albedo (related to surface types) and solar zenith angle (SZA).

Fig. R7 and R8 present the exponential decay fitting of the slope and intercept of the O2-A band under SZA and surface albedo. The x-axes are the effective horizontal cloud distance ($D_e$), which is defined as the average distance of the pixel to the surrounding cloudy pixels, weighted by the inverse square distance to the cloudy pixel (Eq. R1, Eq. 5 in the manuscript):

$$D_e = \frac{\sum_{i \in \{\text{surrounding clouds}\}} w_i D_i}{\sum_{i \in \{\text{surrounding clouds}\}} w_i} \quad \text{(R1)}$$

The exponential decay relationships in Fig R7-8 are fitted between slope (***s***) and intercept (***i***) parameters and $D_e$ using Eq. R2-3 (Eq. 6-7 in the manuscript). The amplitude ($a_s$, $a_i$) and e-folding distance ($d_s$, $d_i$) are the fitting parameters (separate sets for ***s*** and ***i***). The result of amplitude and e-folding distance are presented in Table R1.

$$\boldsymbol{s} = a_s \times \exp(-\frac{D_e}{d_s}) \quad \text{(R2)}$$

$$\boldsymbol{i} = a_i \times \exp(-\frac{D_e}{d_i}) \quad \text{(R3)}$$

We have tested these approaches for ocean glint cases and plan to have the next paper discussing specific ocean cases since their biases behave differently than land nadir cases. However, EaR$^3$T-OCO is already capable of simulating glint cases. The impact of cloud types and properties will be studied in the future.

- Additional text to be added in Section 5.5:

"Solar geometry and surface albedo are significant factors influencing the 3D cloud effect. Figures R9 and R10 (will be added in the appendix) illustrate how these variables impact the 3D cloud effect in the $O_2$-A band under different conditions. By combining results across various solar zenith angles and surface albedo values, we developed a two-variable linear parameterization using $a_s$ and $d_s$ (slope parameters) and $a_i$ and $d_i$ (intercept parameters). As summarized in Table R1, we observe that the amplitude of the slope and intercept is inversely proportional to surface albedo and directly proportional to the cosine of the solar zenith angle (denoted as μ). Additionally, the e-folding distances of the slope are negatively proportional to both surface albedo and μ, while those of the intercept are positively proportional to surface albedo and negatively proportional to μ. In general, higher surface albedo reduces the 3D cloud effect, as additional photons reaching the sensor represent a smaller fraction of the total signal. Conversely, lower solar zenith angles result in a smaller amplitude but longer e-folding distance, causing the 3D effect to extend further from the clouds."

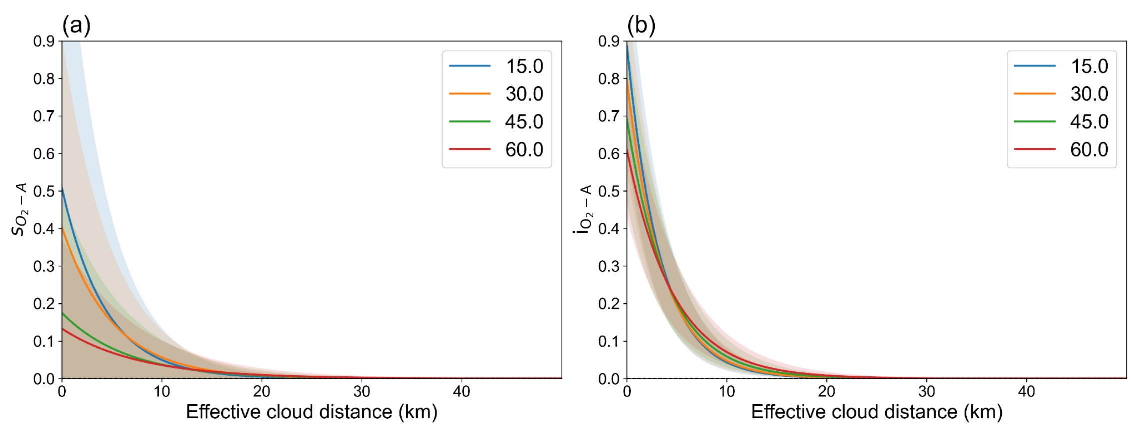



Figure R7. Parameterization of (a) slope and (b) intercept for $O_2$-A band with effective cloud distance, varied by solar zenith angle, while holding surface albedo and aerosol optical depth (AOD) constant.

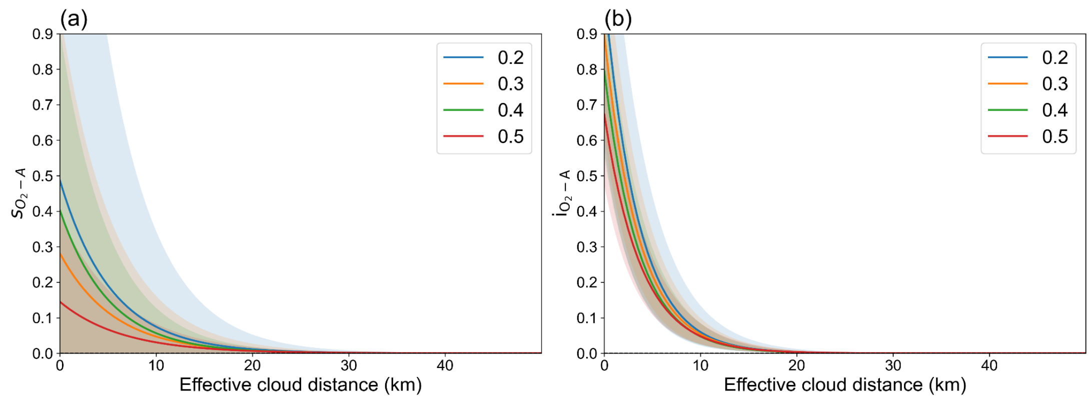



Figure R8. Parameterization of (a) slope and (b) intercept for O2-A band with effective cloud distance, varied by surface albedo, while holding solar zenith angle and AOD constant.

Table R1. The parameterization of as and ds of slope and ai and di of intercept for the three OCO-2 bands. Errors represent fitting uncertainty only and may be underestimated.

| | slope | intercept |
|---|---|---|
| $O_2$-A | $a_s = -0.34 \times alb_{O2\text{-}A} + 0.57 \times \mu - 0.03$<br>$d_s = -3.2 \times alb_{O2\text{-}A} - 9.9 \times \mu + 14.9$ | $a_i = -0.60 \times alb_{O2\text{-}A} + 0.36 \times \mu + 0.72$<br>$d_i = 0.42 \times alb_{O2\text{-}A} - 2.1 \times \mu + 5.2$ |
| $WCO_2$ | $a_s = -0.15 \times alb_{WCO2} + 0.11 \times \mu - 0.05$<br>$d_s = -30.7 \times alb_{WCO2} - 7.0 \times \mu + 27.5$ | $a_i = -2.07 \times alb_{WCO2} + 1.65 \times \mu + 1.17$<br>$d_i = 0.63 \times alb_{WCO2} - 1.6 \times \mu + 3.7$ |
| $SCO_2$ | $a_s = -0.18 \times alb_{SCO2} + 0.29 \times \mu - 0.03$<br>$d_s = -22.6 \times alb_{SCO2} - 21.2 \times \mu + 34.9$ | $a_i = -2.77 \times alb_{SCO2} + 2.22 \times \mu + 1.14$<br>$d_i = 0.51 \times alb_{SCO2} - 1.73 \times \mu + 3.35$ |

The study currently reads more like a description of the work that was performed rather than being focused on the outcome of the work. The outcome is what your reader is interested in. I would suggest picking either the 3D cloud correction based on the 3RT simulations or the ‘bypass’ method as the outcome of this work and explore the chosen method further (explore more scenes to better estimate performance once applied operationally).

We appreciate this input. However, this manuscript is intended to introduce a new method, and therefore intentionally reads like a description of the algorithm. Of course, we also present results, but we cannot talk about results without fully introducing the method first. Also, the two methods (baseline: full 3D-RT; bypass: parameterization based on 3D-RT) are strongly related, and it is difficult to elaborate on the bypass method without describing the baseline method. Since this is the first paper discussing the new method, we think it is important to describe the approaches and their settings in detail as well. To address this, we will edit the introduction to state the purpose of this study more clearly – see below.

- Original text (lines 94-110) for Introduction in Section 1:
  "In this paper, we introduce the direct application of the scene-dependent slope and intercept parameters to the correction of 3D-RT biases, using a modified version of the Education and Research 3D Radiative Transfer Toolbox (EaR$^3$T; Chen et al., 2023), tailored specifically for OCO (EaR$^3$T-OCO). This tool simulates the radiance for OCO-2 footprints, using, among other data (Section 3), imagery from the MODIS on the Aqua satellite, which is approximately 6 minutes behind OCO-2 within the NASA A-Train (afternoon) satellite constellation. From these, the slope and intercept parameters for the OCO-2 footprints of a given scene are derived, then used to undo the 3D-RT perturbation in the observed radiance spectra, and subsequently in the $X_{CO2}$ retrieval. The spectral dimensionality (3x1024 for the three OCO-2 channels), and thus computational effort, are thereby greatly reduced because our methodology (Section 4) only requires a few selected wavelengths. From our results for a few scenes in different regions of the world, we develop a parameterization of slope and intercept as a function of effective cloud distance and other scene variables (Section 5). We then show that the correction of 3D-RT biases in the spectroscopy and $X_{CO2}$ retrievals works both on the footprint-by-footprint basis, and by way of the new parameterization. This parameterization not only enhances our physics-based understanding of the $X_{CO2}$ retrieval biases introduced by clouds, but also offers a computationally efficient pathway for applying these insights globally across extensive datasets. Conclusions are drawn in Section 6, and future work is discussed in Section 7. The appendix explains the functionality of EaR$^3$T-OCO."
- Revised text for Introduction in Section 1, with the main changes underlined:
  "<u>This study introduces new physics-based mitigation approaches for addressing 3D cloud biases in OCO-2 data and demonstrates their effectiveness using real OCO-2 observations. We apply scene-dependent slope and intercept parameters directly to correct 3D-RT biases at the radiance level,</u> using a modified version of the Education and Research 3D Radiative Transfer Toolbox (EaR$^3$T; Chen et al., 2023), tailored specifically for OCO (EaR$^3$T-OCO). This tool simulates the radiance for OCO-2 footprints, using, among other data (Section 3), to derive slope and intercept parameters. The spectral dimensionality (3x1024 for the three OCO-2 channels), and thus computational effort, are thereby greatly reduced because our methodology (Section 4) only requires a few selected wavelengths. The slope and intercept parameters are then used to undo the 3D perturbation in the observed radiance spectra and subsequently in the $X_{CO2}$ retrieval (Section 5). We further develop a parameterization of slope and intercept as a function of effective cloud distance and other scene variables to bypass the 3D-RT calculation. We then show that the correction of 3D-RT biases in the spectroscopy and $X_{CO2}$ retrievals works both on the footprint-by-footprint basis, and by way of the new

bypass method. This parameterization, or bypass method, not only enhances our physics-based understanding of the $X_{CO2}$ retrieval biases introduced by clouds, but also offers a computationally efficient pathway for applying these insights globally across extensive datasets. Conclusions are drawn in Section 6, and future work is discussed in Section 7. The appendix explains the functionality of $EaR^3T$-OCO."

Minor Comments

The paper often refers to qualitative statements that should be quantified or omitted. I pointed out individual instances below.

The abstract should be shortened and more to the point. What are the key takeaways from this study. Not necessary to expose all the 'sausage making' in the abstract.

Thank you for the suggestion. We will shorten the abstract as suggested:

- Revised abstract:

"Accurate and continuous measurements of atmospheric carbon dioxide ($CO_2$) are essential for climate change research and monitoring of emission reduction efforts. NASA's Orbiting Carbon Observatory (OCO-2/3) satellites have been deployed to measure the column-averaged $CO_2$ dry air mixing ratio ($X_{CO2}$) with a designed uncertainty of less than one ppm for regional average. Although cloudy measurements are screened out, nearby clouds can still cause retrieval biases due to limitations in the forward one-dimensional (1D) radiative transfer (RT) model used in the OCO retrieval algorithm, which does not account for the scattering from clouds near the satellites' footprints. These biases, known as three-dimensional (3D) effects, can be quantified using 3D-RT models, but they are computationally expensive, especially for hyperspectral applications like OCO-2/3. This paper employs a linear approximation for each OCO-2 spectral band to represent the 3D-RT perturbations on OCO-2 spectra and reduce computational demands. We apply these metrics calculated by 3D-RT to spectrally adjust the real measured OCO-2 radiance prior to the operational retrieval to undo cloud vicinity effects without modifying the standard OCO-2 retrieval code. Additionally, a parameterization method is developed to bypass the need for 3D-RT simulations by incorporating effective cloud distance and other scene variables. The spectral adjustment mitigates $X_{CO2}$ retrieval biases in proximity to clouds over land for two cases shown in the study – the first physics-based radiance level correction of 3D-RT effects on OCO-2/3 retrievals. While the proposed method is computationally efficient for operational use, further validation is required for diverse surface and atmospheric conditions."

I would suggest to merge section 1 and 2.

Thank you for the suggestion. We agree that section 2 could be seen as an extension of the introduction. However, section 1 is already quite extensive, and combining these sections may make the introduction overly long. By keeping sections 1 and 2 separate, we aim to maintain reader focus on the linearization of the 3D effect, which is better emphasized as a distinct section.

Specific comments by Line:

L20: quantify 'high precision' or omit

Thank you for pointing out the issue. We update the text as below:

- Original text (Lines 18-20):
  "NASA's Orbiting Carbon Observatory (OCO-2/3) satellites have been deployed to measure the column-averaged $CO_2$ dry air mixing ratio ($X_{CO2}$) with very high precision."
- Revised text, with the main changes underlined:
  "NASA's Orbiting Carbon Observatory (OCO-2/3) satellites have been deployed to measure the column-averaged $CO_2$ dry air mixing ratio ($X_{CO2}$) <u>with a designed uncertainty of less than one ppm for regional average</u>."

L20 – L23: Sentence starting with 'Although …' is hard to digest and should be simplified, maybe broken up.

Thank you for your comment. We will revise the sentence to improve readability, as shown below:

- Original text (Lines 20-23):
  "Although cloudy measurements are screened out, nearby clouds can still cause retrieval biases because the forward one-dimensional (1D) radiative transfer (RT) model used in the OCO retrieval algorithm does not account for the scattering induced by clouds in the vicinity of the OCO-2/3 footprints."
- Revised text:
  "While most cloudy footprints are screened out, clear-sky observations can still be biased by nearby clouds. This bias arises because the forward one-dimensional (1D) radiative transfer (RT) model used in the OCO retrieval algorithm does not account for scattering from clouds near the OCO-2/3 footprints."

L27: remove 'with two metrics (called slope and intercept)'

Thank you for the suggestion. We will edit the abstract as suggested (as shown previously).

L28: remove 'and accelerate the radiative transfer by a factor of 100'

Thank you for the suggestion. We will edit the abstract as suggested (as shown previously).

L31 – L35: Sentence starting in 'EaRT-OCO .. ' -> move out of abstract.

Thank you for the suggestion. We edited the abstract as suggested (as shown previously).

L36: remove '– the first physics-based correction of 3D-RT effects on OCO-2/3 retrievals'

We would like to clarify that the current 3D bias mitigation methods proposed by Massie et al. (2022) and Mauceri et al. (2023) for OCO are primarily statistical-based. In contrast, the methods we proposed in this study are based on a physical understanding of the mechanism difference between 1D and 3D radiative transfer.

L37-L43: shorten, simplify discussion of 'bypass' method.

Thank you for your comment. We revised the sentence as shown below:

- Original text (Lines 37-43):
  "Although the accelerated 3D-RT radiance adjustment step is faster than full 3D-RT calculations for all OCO spectral bands, it still requires at least as much computational effort as the $X_{CO2}$ retrieval itself. To bypass 3D-RT altogether, the slope and intercept metrics are parameterized as a function of the weighted cloud distance of a footprint and several other scene parameters, all of which can be derived directly from Aqua-MODIS imagery. While this method is fastest and thus feasible for operational use, it requires careful validation for various surface and atmospheric conditions."
- Revised text:

  "The accelerated radiance adjustment step is faster than full 3D-RT calculations but still requires similar computational effort as the $X_{CO2}$ retrieval. To avoid 3D-RT completely, the bypass method parameterizes the slope and intercept as a function of the weighted cloud distance. Although this approach is the fastest and suitable for operational use, it requires thorough validation under various surface and atmospheric conditions."

L62: quantify 'accuracy' requirement from the two cited studies.

Thank you for the comments. We add a description of their emphasis on accuracy.

- Line 61-63: Deng et al. (2016) and Crowell et al. (2018) also emphasize the significance of the level of $X_{CO2}$ accuracy for reliable $CO_2$ flux determination."
- Revised text, with the main changes underlined:

  "Deng et al. (2016) and Crowell et al. (2018) highlight the importance of achieving high $X_{CO2}$ measurement accuracy for reliable $CO_2$ flux estimation. <u>Deng et al. (2016) show</u>

that the assimilation of GOSAT $X_{CO2}$ data with a precision of approximately 0.5–1.0 ppm can significantly improve regional CO2 flux estimates over both land and ocean. Similarly, Crowell et al. (2018) emphasize that an $X_{CO2}$ precision of 0.5–1.0 ppm is essential for detecting regional flux perturbations, especially in cloud-prone and high-latitude regions where $CO_2$ fluxes are difficult to constrain accurately using ground-based sensors alone."

L76: remove sentence 'The cloud-related …'

Thank you for the suggestion. We remove Line 76: "The cloud-related bias is also evident when examining individual footprints." as suggested.

L90-91: Restate comment that no 'practical strategies' have been developed to correct 3D cloud effects based on the physical understanding. The study by Mauceri et al (2023) uses physics derived variables to correct for 3D cloud biases.

We appreciate your comments on the practical strategy. You are correct that the machine learning-based method developed by Mauceri et al. (2023) is indeed a practical approach to the real data. We understand that Mauceri et al. (2023) and Massie et al. (2022) use several physics-*derived* variables, such as H3D, HC, and CSNoiseRatio. However, these variables capture the 3D cloud effect only at a single band or average of continuum wavelengths. More importantly, these metrics are not used to correct the 3D cloud effect at the *radiance level*, but operate primarily on the L2 products. While cloud distance, similar to our study, can indicate potential 3D cloud biases, these variables alone cannot fully capture the reflectance-dependent 3D cloud effect across the entire spectrum. Although Mauceri et al. (2023) apply machine learning-based corrections, it is still a *statistical* mitigation approach in nature and does not go into the fundamental physics (i.e., the radiance level). We want to emphasize that our approach is based on a footprint-by-footprint *deterministic* rather than a multi-footprint *statistical* approach, albeit with some simplifications that are noted in the original manuscript (with more detail in the revised manuscript, responding to a different reviewer). It is a radiance-only approach and different from the existing statistics method. To make this more clear, we will make edits as shown below:

- Original text (Lines 89-92):
  "Although the physical mechanism of the $X_{CO2}$ 3D cloud retrieval bias is now largely understood, practical strategies for applying these insights to a bias correction have not been developed thus far. Mauceri et al. (2023) employed machine learning techniques to correct for 3D cloud biases using observations from the Total Carbon Column Observing Network (TCCON)."

- Revised text, with the main changes underlined:

  "Although the reflectance-dependent physical mechanisms of the $X_{CO2}$ 3D cloud retrieval bias are now largely understood, strategies for applying these insights to bias correction have thus far been done empirically or statistically. For example, Massie et al. (2022) proposed an empirical lookup table to correct 3D cloud biases based on a 3D metric, and Mauceri et al. (2023) used machine learning techniques combined with TCCON observations. While both approaches are operationally applicable, they rely on statistical corrections rather than true physical radiance difference of the 3D cloud effect across the entire spectrum."

L93: Please also include/cite work by Massie et al where they worked on correcting 3D cloud biases with linear fits to physics derived variables.

Thank you for the suggestion. As described above, we have included Massie et al. (2022) and discussed the physics-derived variables they used, such as H3D, HC, and CSNoiseRatio.

L106: 'on the a footprint-by-footprint '

Thank you for pointing out the typo. We change this to "on a footprint-by-footprint"

L126: specify that range 'dynamic range of interest for reflectance'

Figure 1 shows the spread of perturbations at low reflectance, which are primarily due to photon noise in the Monte Carlo RT simulations. To avoid large simulation uncertainties in this low-reflectance region, we set a transmittance threshold for each band. This threshold is defined as the minimum of (1) 40% of the maximum transmittance at each band or (2) the minimum transmittance value of each band. This ensures that the analysis focuses on the dynamic range of interest for reflectance where the simulation results are more reliable.

L142-145: Hard to follow 'Increased photon …' . Please rewrite, expand.

Thank you for pointing out the problem. We edit the sentences as below:

- Original text (Lines 142-145):
  "Increased photon path lengths from multiple scattering in 3D-RT produce non-zero perturbations (percentage differences in 1D and 3D radiances) expressed in Eq. (1). Since wavelengths with higher absorption are attenuated more than those with lower absorption, the Eq. (1) perturbations are a function of reflectance (line absorption depth), referred to later as spectral distortion."
- Revised text:
  "Multiple scattering in 3D-RT increases the photon path lengths, leading to non-zero perturbations, as expressed by Eq. (1) (percentage differences between 1D and 3D radiances). This effect is more pronounced at wavelengths with higher absorption, which are attenuated more strongly compared to wavelengths with lower absorption for

the same photon path. As a result, the perturbations vary depending on the reflectance and absorption depth, a phenomenon referred to as spectral distortion in our study."

L154: Why not use B11?

The B11 version was not publicly available when this study began, and we have encountered issues with retrieval code compilation for B11. Once these issues are resolved, we plan to update our analysis using B11 in future work. We plan to keep updating our algorithm, and switching to B11 will be one of these updates, to be documented in the next publication related to EaR$^3$T-OCO.

L244: 'To mitigate excessive computational demands, we opt to use solely the wavelengths of the first footprint.' -> how does this impact the results?

The primary difference among the eight footprints in the same swath is the instrument line shape (ILS), which can slightly influence the gas absorption optical depth. Although we have not yet run simulations with varying ILS, we expect the overall trends for the slope and intercept to remain similar. This is because the perturbations are calculated using the *differences* between footprint-level 1D-RT and 3D-RT simulations, where any variations due to ILS are irrelevant. Then, the spectral radiance perturbations are applied to other footprints, with slightly different ILS and dispersion. Since the un-perturbation based on the calculated perturbations operates in radiance (reflectance) space rather than wavelength space, small changes in spectral attributes of other footprints are not expected to have any significant impact on the algorithm. However, further analysis would be needed to confirm this. Relative to other factors such as cloud geometry, sun-sensor geometry, etc., this effect is most likely negligible. Again, this will be studied more thoroughly in forthcoming publications.

L262: how did the various reflectance thresholds influence the results.

The reflectance thresholds significantly impact cloud detection and subsequent radiance simulations. If the reflectance threshold is set too high, thin clouds may go undetected, resulting in an underestimation of cloud impact. Conversely, if the threshold is set too low, some bright surface pixels could be misclassified as clouds, leading to overestimating cloud effects. Both scenarios deviate from real conditions, making it difficult to accurately represent the 3D cloud effect and potentially bias the simulation results.

L263: why did you need to develop a new cloud detection approach?

The cloud products provided by MODIS have a spatial resolution of 1 km, which is too coarse for our simulation needs. To address this, we developed a new cloud detection approach to optimize detection specifically for the study case, ensuring higher accuracy in identifying clouds. While the method used by Chen et al. (2023) is more generalized and suitable for a wide range of scenarios, it may miss some thin clouds. Our customized approach helps to better capture these thin cloud features, which is crucial for accurately modeling the 3D cloud effects in the selected scene.

L298: ‘uncertainties’ : keep in mind that the uncertainties in s, I, depend on many more factors than captured by the uncertainty in the line fit. Thus, you would underestimate the true uncertainties with that approach.

Thank you for the comment. Indeed, in Tables 1 and 2, we currently only quantify the uncertainties associated with the linear fit. We acknowledge that the true uncertainties are influenced by additional factors, such as variations in geometry, cloud properties, and aerosol characteristics. These contributions will be considered in future studies as we expand our analysis to include a wider range of conditions.

We will add a description in the table caption in response to your comment.

- Original text (line 433; lines 473-474; 503-504):
  “Table 1. Amplitude and e-folding distances for ***s*** and ***i*** fittings in the $O_2$-A, $WCO_2$, and $SCO_2$ bands.”
  “Table 2. Amplitude and e-folding distances for ***s*** and ***i*** fittings of the” simulation with a homogeneous aerosol layer in the $O_2$-A, $WCO_2$, and $SCO_2$ bands.”
  “Table 3. Amplitude and e-folding distances for ***s*** and ***i***, determined using different average grid points in simulations with a homogeneous aerosol layer for the $O_2$-A, $WCO_2$, and $SCO_2$ bands.”
- Revised text, with the main changes underlined:
  “Table 1. Amplitude and e-folding distances for ***s*** and ***i*** fittings in the $O_2$-A, $WCO_2$, and $SCO_2$ bands. <u>Errors represent fitting uncertainty only and may be underestimated.</u>”
  “Table 2. Amplitude and e-folding distances for ***s*** and ***i*** fittings of the” simulation with a homogeneous aerosol layer in the $O_2$-A, $WCO_2$, and $SCO_2$ bands. <u>Errors represent fitting uncertainty only and may be underestimated.</u>”
  “Table 3. Amplitude and e-folding distances for ***s*** and ***i***, determined using different average grid points in simulations with a homogeneous aerosol layer for the $O_2$-A, $WCO_2$, and $SCO_2$ bands. <u>Errors represent fitting uncertainty only and may be underestimated.”</u>

L307: what are those ‘various processes’?

The retrieval accounts for various processes, including water vapor absorption, surface albedo variations, cloud and aerosol scattering in the 1D-RT model, radiance polarization effects, and the impact of the instrument line shape, among others.

L310: The code on Gituhub is not the code used for the operational retrieval.

Thank you for pointing out the issue. While the code on GitHub is not the same as the operational retrieval code, we have tested it using B10r (i.e., B10.0.04_sdos_testing_1) and obtained the same $X_{CO2}$ values as those in the L2 $X_{CO2}$ data. This confirms that the GitHub code is functionally equivalent to our analysis. A future version of our method could therefore easily be integrated into the data stream that uses the actual operational code (after further testing of our code with more data and updating it as needed, of course).

L320: explain terms in equation

We edit the sentence and add the description as below:

- Original text (Lines 142-145):
  "Upon deriving the 3D parameters in Section 4.3, we can convert the OCO-2 spectra using Eq. (4) with the observed radiance spectra and corresponding reflectance, slope, and intercept. Assuming the absence of 3D effects in the adjusted 1D radiance, we can employ the B10.04 retrieval algorithm with un-perturbed spectra to obtain mitigated $X_{CO2}$."
- Revised text, with the main changes underlined:
  "Upon deriving the 3D parameters in Section 4.3, we can convert the OCO-2 spectra using Eq. (4) with <u>the observed radiance spectra ($I^{IPA}_{\lambda}$) and corresponding reflectance ($R^{obs}_{\lambda}$), slope ($s_{xy}$), and intercept ($i_{xy}$).</u> Assuming the absence of 3D effects in the adjusted 1D radiance, we can employ the B10.04 retrieval algorithm with un-perturbed spectra to obtain mitigated $X_{CO2}$."

$$I_{\lambda}^{IPA\,(adjusted)}(x, y) = \frac{I_{\lambda}^{IPA\,(obs)}(x, y)}{\left(\frac{i_{xy}+s_{xy}\times R_{\lambda}^{obs}}{100\%} + 1\right)}$$

L325: 'parameters that accurately represent'

We interpret this as a suggestion to clarify how the slope and intercept parameters are defined to represent the 3D cloud effect in OCO-2 observations accurately. The original sentence aims to convey that realistic radiance simulations near the satellite's footprint are essential for deriving these parameters precisely. Although achieving perfect accuracy in the simulations is challenging, we strive to approximate real conditions as closely as possible using MODIS observations. If further clarification was intended, we would appreciate any additional guidance.

- Original text (Lines 325-326):
  "In order to derive the slope (s) and intercept (i) parameters that accurately represent the 3D cloud effect in the OCO-2 observations, it is crucial to perform realistic radiance simulations near the satellite's footprint."

L330: Quantify 'shows a good agreement'

We will add an $R^2$ and slope for the scatter plot in the sentence.

- Original text (Line 330):
  "The heat map in Fig. 3c shows a good agreement between the simulation and observation."
- Revised text:
  "The heat map in Fig. 3c shows a good agreement between the simulation and observation with $R^2$=0.69 and a slope of 0.71."

L330: remove sentence 'As a result, …'

Thank you for the suggestion. We will remove Lines 330-331: "As a result, we are confident that the simulation at other wavelengths is able to approach the actual condition." as suggested.

L332: COT repeated twice

Thank you for pointing out the typo. One COT should be "CTH" instead.

Figure 3: How much was the COT and CER tuned to agree? Could we get the right answer for the wrong reason?

We currently apply 1D-RT reflectance-to-COT mapping and fixed CER values for low and high clouds, which can lead to biases and often overestimate COT for low radiance and underestimate it for high radiance. Accordingly, the 3D-RT cloudy pixel radiance will also differ from the observation, as shown in Fig. R9. However, since our primary focus is on the bright areas, we prioritize capturing the radiance differences over these regions rather than achieving perfect agreement for all cloudy pixels. We aim to capture the general trend in the bright areas, where minor uncertainties in cloud and aerosol setups are acceptable compared to the larger differences observed between 1D-RT and 3D-RT simulations.

However, it is important to understand how COT and CER change for the same cloud field can alter the 3D cloud effect magnitude. This is crucial to evaluate the result uncertainty. We will investigate the influence of the cloud properties in the future as well as more parameters. We appreciate your question on this topic.

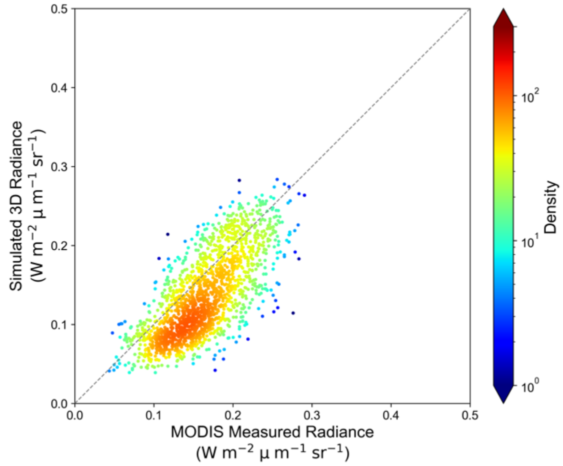
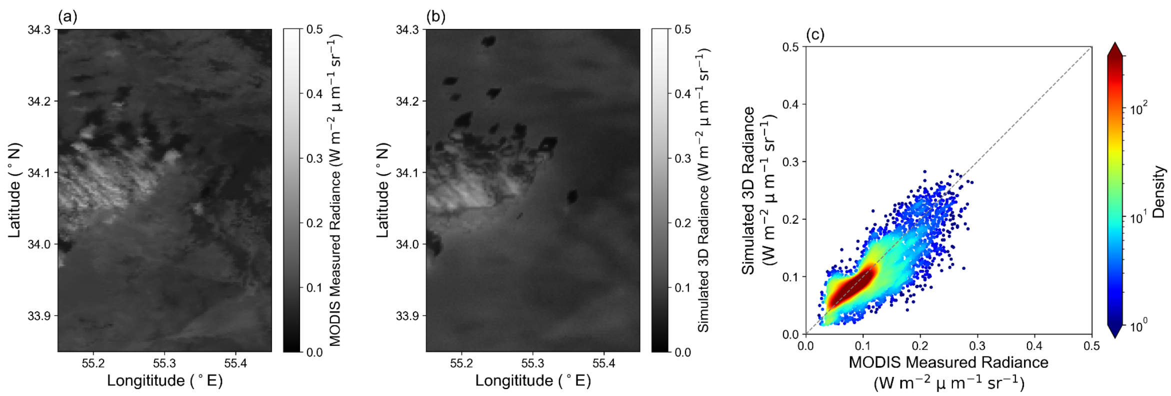



Figure R9. A scatter comparison between Fig. 3a and 3b (Fig. R10 below) for pixels with COT greater than 0.




(edited Fig. 3) Figure R10. MODIS observation at 650 nm (a) and 3D radiance simulation at 650 nm by EaR$^3$T (b). A scatter comparison between (a) and (b) is depicted in (c).

L341: how did you arrive a 11 wavelengths? What happens if you use 10 or 12? Aka, how sensitive are you to this choice? Would be a great opportunity to plot accuracy vs number of wavelengths.

The choice of 11 wavelengths was made as a compromise between computational cost and fitting accuracy. Using more wavelengths would indeed result in a better fit for the full-spectrum simulation. However, increasing the number of wavelengths significantly raises computational time and cost. We have not yet systematically evaluated the sensitivity of accuracy to the number of wavelengths, but it would be a valuable analysis to explore in future work, potentially plotting accuracy versus the number of selected wavelengths to determine the optimal balance. In addition, we plan to use ALIS (Emde et al., 2022) or the acceleration method by Iwabuchi instead of our multi-wavelength method. Either of these might be even faster than our method, but we need to evaluate their accuracy.

Figure 5: how do the other bands look like? 5 a) looks very noisy far away from the clouds.

The observed noise far from the clouds in Figure 5a may be due to variations in surface reflectance across the region, which can affect the stability of the derived parameters. We will investigate this further to determine if additional filtering or adjustments are needed.

Here are similar figures for Fig. 5 but for $WCO_2$ and $SCO_2$ bands:

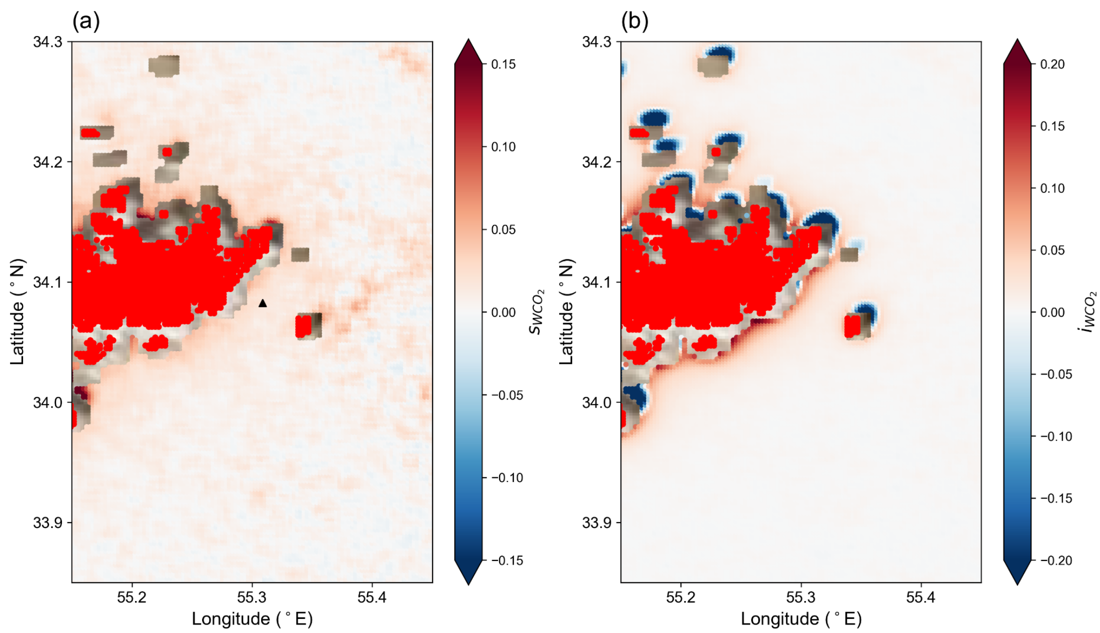


Figure R11. Distribution of (a) s and (b) i of $WCO_2$ band. Red dots denote the cloud pixels employed in the RT simulation.

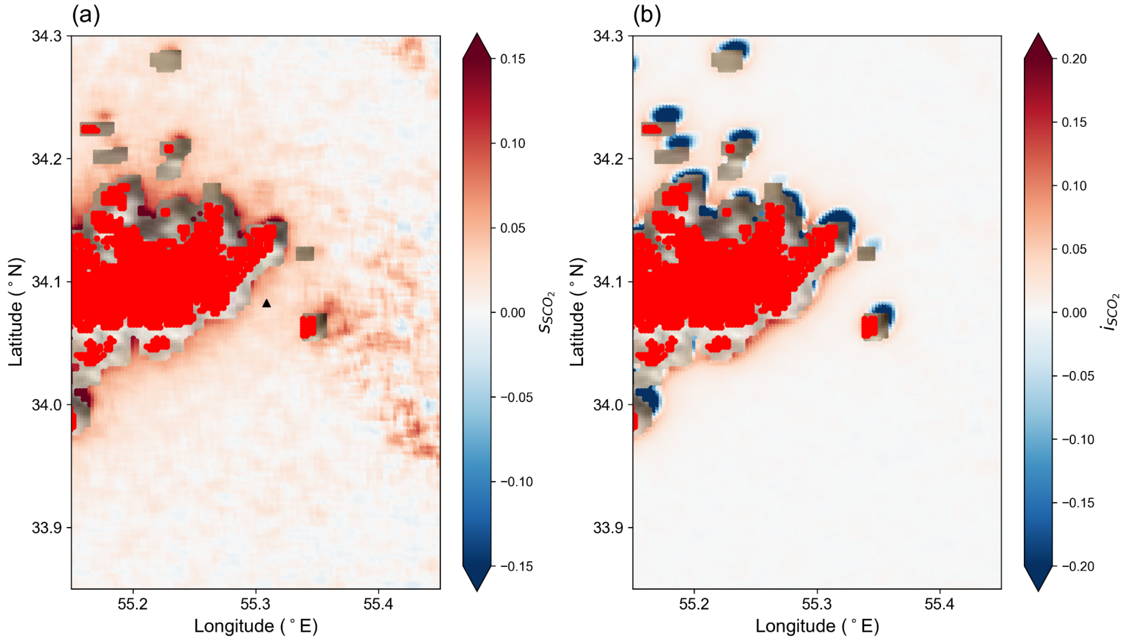



Figure R12. Distribution of (a) s and (b) i of $SCO_2$ band. Red dots denote the cloud pixels employed in the RT simulation.

L463: 'bands, potentially increasing'

We interpret this as a potential suggestion to clarify how aerosols might impact the uncertainty in deriving the 3D effect parameters. The original sentence intends to highlight that aerosols can affect both the s and i of the $O_2$-A and $SCO_2$ bands. Accurate representation of aerosol optical depth (AOD) is crucial, as inaccuracies could lead to errors in capturing the 3D effects. If further clarification was intended, we would welcome additional guidance.

- Original text (Lines 462-464):
  "We illustrate that the presence of aerosols can lead to alterations in both the s and i of the $O_2$-A and $SCO_2$ bands, potentially increasing the uncertainty associated with the derivation of 3D effect parameters."

L483: state footprint sizes of upcoming satellites, name and cite those satellites

We will add the description below:

- Original text (Lines 482-484):
  "Numerous upcoming satellites for $CO_2$ remote sensing will adopt similar retrieval algorithms but feature varying footprint sizes in accordance with their specific mission objectives."

- Revised text:
"Numerous upcoming satellites for $CO_2$ remote sensing will adopt similar retrieval algorithms but feature varying footprint sizes in accordance with their specific mission objectives. For example, the Copernicus Anthropogenic CO2 Monitoring Mission (CO2M) by the European Space Agency (ESA) plans to have a footprint size of 4 $km^2$ (2 km by 2 km; Kuhlmann et al., 2020). MicroCarb by the Centre National d'Etudes Spatiales (CNES) will have a larger footprint size of 40.5 $km^2$ (4.5 km by 9 km; Cansot et al., 2023)."

L487: why did you not investigate smaller footprints?

We did not investigate smaller footprints because the OCO-2/3 satellites currently offer the smallest footprint size available for $CO_2$ measurements among existing and upcoming satellite missions. However, newly proposed satellites for greenhouse gas remote sensing may feature smaller footprints, and we plan to consider this analysis in the future. We anticipate that 3D cloud effects could become more pronounced as footprint size decreases.

L490: 'of pronounced biases'

We remove the "pronounced" in the sentence.

- Original text (Lines 489-490):
"This decline aligns with the expectation that larger footprints would mitigate the spectral distortion effect, reducing the prevalence of pronounced biases."
- Revised text:
"This decline aligns with the expectation that larger footprints would mitigate the spectral distortion effect, reducing the magnitude of 3D cloud biases."

L490-491: not clear what changes are not significant

We edit the sentence as below:

- Original text (Lines 490-491):
"Notably, there is no statistically significant change in $a_i$ and $d_i$ of the intercept."
- Revised text, with the main changes underlined:
"There is no statistically significant change in $a_i$ and $d_i$ of the intercept <u>values across different footprint sizes.</u>"

L495: 'In conclusion, future satellite missions with any …' That is a very strong statement without any quantification. This would depend on the retrieval algorithm, chosen bands, accuracy requirements, area of interest, …

We revise the statement as below:

- Original text (Lines 495-496):
  "In conclusion, future satellite missions with any footprint size must account for 3D biases to ensure accurate remote sensing of $X_{CO2}$."
- Revised text:
  "We suggest that future satellite missions, regardless of footprint size, consider accounting for 3D biases to improve the accuracy of $X_{CO2}$ retrievals. Studies need to be conducted to ensure that given the bands, footprint size, and other attributes, the retrieval error induced by 3D clouds does not exceed the respective mission requirements – as is the case for OCO-2, as this study has shown."

L500: quantify 'to substantial 3D'

We add the description as below:

- Original text (Lines 498-500):
  "Conversely, missions designed with smaller footprint sizes than OCO-2, particularly those targeting enhanced data acquisition in cloud-prone regions such as the Amazon Basin (Frankenberg et al., 2024) will be susceptible to substantial 3D cloud biases."
- Revised text, with the main changes underlined:
  "Conversely, missions designed with smaller footprint sizes than OCO-2, particularly those targeting enhanced data acquisition in cloud-prone regions such as the Amazon Basin (Frankenberg et al., 2024), will be susceptible to 3D cloud biases, <u>which have been shown to reach -0.48 ppm for Land Nadir observations in both the northern and southern hemispheres (Massie et al., 2024)</u>."

L501: why do 3D cloud biases need to be considered in the initial planning stage? Algorithms are typically tackled much later.

While algorithm development typically occurs at later stages, the experience from OCO-2/3 has shown that 3D cloud biases can significantly impact CO2 measurements, especially when targeting regions like the cloudy Amazon. With a decade of observations highlighting this issue, it is crucial to consider 3D cloud biases during the initial planning stages of new satellite missions—particularly for those aiming for smaller footprint sizes—so that the instrument design and mission parameters can be optimized to minimize these biases from the outset. The way this is typically done at the mission development stage is in mission or science traceability matrices (STM), which are part of every proposal. Any serious mission proposal of the future needs to show that they consider the impact of ubiquitous clouds on the derivation of $X_{CO2}$ or other trace gas products from the radiances when discussing expected uncertainties. This does not require ready-made algorithms, and merely needs to consider the literature (e.g., Massie, Mauceri, Emde, our own study).

L517: How could the bypass method deal with cloud shadows?

We don't believe that this is feasible or necessary at this point. As noted in the response on page 7, only a few cloud-shadow retrievals are present in the OCO-2 Lite files due to pre-retrieval cloud screening algorithms (Massie et al., 2023). Additionally, the B11 retrieval has improved at filtering out shadowed footprints. We believe that the few remaining cloud-shadow footprints passing the pre-screening are less significant compared to the clear-sky footprints affected by nearby clouds. However, applying the same radiance adjustment for bright areas to shadowed regions could introduce additional errors. Since footprints affected by cloud shadows constitute a relatively small portion of the overall effective OCO-2 retrievals, we believe that our approach provides a reasonable average correction for the majority of clear-sky and bright-area footprints.

L524: Quality Flag =0 or 1 are not 'best quallity' data. That would only by 0

Thank you for the comment. We edit the sentence and remove the description of "best quality" as below:

- Original text (Lines 523-524):
  "Subsequently, we determine the s and i of the three bands using the coefficients in Table 2 for all footprints that are the best quality (Quality Flag = 0 or 1) data points."
- Revised text:
  "Subsequently, we determine the s and i of the three bands using the coefficients in Table 2 for all footprints that pass the pre-screening (Quality Flag = 0 or 1) data points."

L524: How are the values in Table 2 derived for the bypass method when they don't include 3D RT calculations.

We want to clarify that values in Table 2 are derived using the baseline method, which involves 3D-RT calculations for specific scenarios. The bypass method is then parameterized based on these baseline results. Our approach is to analyze various solar and viewing geometries, as well as different cloud and aerosol properties, using the baseline method. Once we establish these relationships, we can derive a generalized bypass method that can be applied under a wide range of conditions without additional 3D-RT simulations.

Figure 9: Not sure if b) is improved compared to a) outside of the cloud shadow area.

Thank you for pointing out the concern. Fig. 9c shows that footprints over both the south and north sides of clouds have a decrease in $X_{CO2}$. This means that footprints over clear-sky areas do reduce the 3D bias.

L570 – L573: You state a problem with thin or partial clouds for the bypass method. How would an operational algorithm deal with that?

Footprints containing thin or partial clouds pose additional challenges beyond 3D photon scattering, such as elevated reflectance at the continuum wavelength compared to clear-sky conditions. An operational algorithm would need to account for these effects by either incorporating additional parameters (e.g., cloud optical depth or cloud fraction) or using more complex correction models to differentiate between 3D scattering biases and direct cloud contamination. This would ensure that the bypass method remains effective in mixed or thin cloud conditions.

L585: remove 'on a cluster at the University of Colorado'

Thank you for the suggestion. We will change as suggested and leave the statement in the acknowledgments.

L592: You state that the bypass method can be supplemented by periodic full calculations. How would that work in detail? When do you run them, how do you use their results to improve the results?

The timing and frequency of performing full 3D-RT calculations would depend on how sensitive the bypass method's parameters are to changes in key state variables, such as solar and viewing geometry, cloud and aerosol properties, and surface albedo. The first step is to establish a generalized bypass method that captures the influence of these variables. If the derived parameters are found to be highly sensitive to changes in these conditions, then more frequent recalibration using full 3D-RT simulations would be necessary to maintain the accuracy of the bypass method.

In practice, this could involve periodically running full 3D-RT simulations for a subset of representative scenarios (e.g., different seasons, surface types, or cloud conditions) and updating the bypass parameterization accordingly. These recalibrated parameters would then be applied to operational retrievals, ensuring that the bypass method remains robust over time.

Figure 12. Where does the XCO2 in those scenes come from?

The result shown in Fig. 12 is derived using the bypass parameterization from Table 2. The goal of this figure is to illustrate how variations in cloud distribution can lead to different cloud-induced biases. We started with the OCO-2 radiance data presented in Figure 2 and applied radiance adjustments to introduce 3D cloud biases. This approach allows us to explore the impact of 3D cloud biases for different effective cloud distances and assess how cloud distribution influences the retrieved $X_{CO2}$ values.

L630: 'We documented the …' -> The main manuscript does not contain any documentation of the toolbox. Would remove that statement.

Thank you for the comments. We will remove Lines 630-631: “We documented the EaR$^3$T-OCO radiance simulator, an automated tool for calculating spectral radiances observed by NASA’s OCO-2 satellite.” in the conclusion.

L671: ‘more accurate level of accuracy’?

We revise the sentence to emphasize accuracy improvements near clouds:

- Original text (Line 670-672):
  “Our work can become the stepping stone toward more accurate and efficient trace gas retrievals even in complex scenes, ultimately bringing spaceborne trace gas retrievals to a more accurate level of accuracy.”
- Revised text:
  “Our work can become the stepping stone toward more accurate and efficient trace gas retrievals even in complex scenes, ultimately bringing spaceborne trace gas retrievals in the vicinity of clouds to their planned accuracy.”

L672: remove last sentence ‘It will improve …’ Your study did not show any information to draw that conclusion.

Thank you for the comment. We change the sentence as below:

- Original text (Lines 672-673):
  “It will improve current flux inversions (especially over the cloud-prone Amazon) and other applications.”
- Revised text:
  “If implemented operationally, the bypass method has the potential to improve $X_{CO2}$ accuracy in cloud-prone areas, such as the Amazon, which could, in turn, enhance the accuracy of flux inversions.“

L685: GitHub for OCO-2 toolbox leads to a 404 page not found

- Thank you for pointing this out. We will update the link from “https://github.com/ywchen-tw/OCO-2” to “https://github.com/ywchen-tw/OCO2” to resolve the issue.

Figure A3. Why is cloud effective radius only one fixed number for the whole scene?

Thank you for these questions, and we apologize for not making this clearer in the manuscript. For this study, we chose to keep the cloud effective radius (CER) constant for simplicity, which is why it appears uniform in Fig. A3c. Specifically, we assigned CER values of 10 μm for low clouds and 25 μm for high clouds. In future work, we intend to incorporate MODIS-derived CER values to better capture spatial variability.

In response to your other questions, we have clarified the description in line 265 as follows:

- Original text (Line 265):
  "Once the cloudy pixels are identified, we retrieve the cloud top height (CTH) and cloud effective radius (CER) of the nearest location from the MODIS MYD02 cloud file and assign them to each cloudy grid point."
- Revised text:
  "Once the cloudy pixels are identified, we retrieve the cloud top height (CTH) of the nearest location from the MODIS MYD02 cloud file and assign it to each cloudy grid point. The cloud effective radius (CER) is manually set to 10 μm for low clouds and 25 μm for high clouds in this study. In future versions, we plan to use the actual MODIS CER values to capture more realistic variations."

Figure A6. Would remove. There is not much information here beyond what one would expect.

Thank you for the suggestion. We will remove it as suggested.

References:


- Kuhlmann, G., Brunner, D., Broquet, G., and Meijer, Y.: Quantifying $CO_2$ emissions of a city with the Copernicus Anthropogenic $CO_2$ Monitoring satellite mission, Atmos. Meas. Tech., 13, 6733–6754, https://doi.org/10.5194/amt-13-6733-2020, 2020.
- Cansot, E., Pistre, L., Castelnau, M., Landiech, P., Georges, L., Gaeremynck, Y., and Bernard P.: MicroCarb instrument, overview and first results, Proc. SPIE 12777, International Conference on Space Optics — ICSO 2022, 1277734 (12 July 2023); https://doi.org/10.1117/12.269033.