Authors' Response

Paper Number: egusphere-2023-1347
Paper Title: Direct Estimation of Global Anthropogenic CO2 Emissions Using Satellite Data

The authors thank the reviewers for their valuable comments which help to improve the quality of this manuscript. We have carefully considered all the points raised and have made the necessary revisions to address them. Please find below our point-by-point response and corresponding changes made in the revised paper.

Sincerely,
On behalf of all authors,
Jia He

RC1

General comments

This manuscript attempts to estimate anthropogenic CO2 emissions using satellite observations of column-averaged CO2 amount (XCO2) data and the geographically and temporally weighted regression (GTWR) model. This study's topic is significant and timely, given the increasing interest in emission mitigation monitoring from various sectors. This study trains the regression model using the ΔXCO2 data derived from GOSAT and other ancillary variables (i.e., Wind speed, Air temperature, Total column water vapor, Fire emissions) as regressors and ODIAC's CO2 emission estimates as a response variable. However, this study does not describe any physical basis that explains the relationship between the response variable (y) and regressors (x), making it difficult to justify scientifically. The authors evaluate the regression model by comparing the model estimates against the ODIAC CO2 emissions data. Therefore, even with the reasonable agreement between the regression model estimates and the ODIAC emission estimates, there is no supporting evidence that the emission estimate presented in this study is close to "true" emissions nor any practical advantages for policy-relevant applications. The manuscript's presentation quality is well constructed, allowing readers to follow the model development and evaluation process easily. Providing a more "Physical" basis for the regression model and demonstrating the advantage of the satellite-based regression model approach over other methods (i.e., "bottom-up" emission inventories or "top-down" satellite inversion studies) will improve the overall quality of the manuscript. The following are specific comments to the authors.

Reply: We would like to thank the reviewer for this comment. Conventional emission estimations are based on statistical data reported by economic sector or by fuel type. In the top-down approach, atmospheric CO_2 concentrations, global circulation models, and tracer transport models are adopted to estimate the emissions and uptake of CO_2 by various sources and sinks (Nassar, R., et al., 2011; Basu, S., et al., 2016; Lauvaux, T., et al., 2016). We acknowledge that physical models can improve the understanding of global carbon cycle, enhance the accuracy of emission estimates, and contribute to climate change mitigation strategies. However, these models rely on empirical observations and are often specific to a particular system. As the distribution, trends, and patterns of anthropogenic CO_2 emissions vary across different regions and over time due to local conditions, using physical models can be time-consuming and may not fully capture all aspects of the real-world system. In this study, we adopted the GTWR model to infer the spatiotemporal relationship between atmospheric measurements of CO_2 concentrations and CO_2 emissions.

The GTWR model is a statistical model that aims to capture the spatial and temporal relationships within the data to mathematically represent the real-world system. However, unlike traditional regression models that assume constant relationships, the GTWR model estimates localized parameter that can capture local variations, providing a more detailed understanding of spatiotemporal relationships. The physical basis of the GTWR model lies in the assumption that the relationships between the dependent and independent variables vary due to different local conditions, processes, and factors that influence the variables. It uses a distance-based kernel function (Gaussian) to weight observations based on both their spatial and temporal proximity to the location and period being modeled. It assigns higher weights to observations that are closer in space and time to the target location and time point. Therefore, the GTWR model can provide more accurate and detailed insights into the emission estimation.

In this study, we adopt the ODIAC product as the reference data for model training and testing, as it is the only global, spatially explicit EI data product that meets the requirements of Ciais et al. (2015) and has been intensively used for global and regional atmospheric inversion (e.g. Thompson et al. 2016). We acknowledge that there are potential emission modeling errors and uncertainties associated with ODIAC grided product. This study assumes that those errors and uncertainties are minor when compared with other grided emission inventories. It is judicious to use this dataset for training and testing the model. However, it is challenging to evaluate the 'accuracy' of the model at grid level objectively due to the lack of physical measurements (e.g., Andres et al. 2016; Oda et al. 2017). Therefore, we didn't make assumptions about the accuracy. Nevertheless, we believe that it is important to compare the differences among emission estimations, and as such, an intercomparison was conducted among EDGAR, ODIAC, and satellite-based estimations.

Nassar, R., et al. (2011). Inverse modeling of CO2 sources and sinks using satellite observations of CO2 from TES and surface flask measurements. Atmospheric Chemistry and Physics, 11(10), 6029-6047.
Basu, S., et al. (2016). The impact of transport model differences on CO2 surface flux estimates from OCO-2 retrievals of column-average CO2. Atmospheric Chemistry and Physics, 16(15), 9641-9658.
Lauvaux, T., et al. (2016). High-resolution atmospheric inversion of urban CO2 emissions during the dormant season of the Indianapolis Flux Experiment (INFLUX). Journal of Geophysical Research: Atmospheres, 121(10), 5213-5236.).
Andres, R. J., et al. (2016). Gridded uncertainty in fossil fuel carbon dioxide emission maps, a CDIAC example, Atmos. Chem. Phys., 16, 14979–14995.
Oda T., et al. (2017). On the Impact of Granularity of Space-based Urban CO2 Emissions in Urban Atmospheric Inversions: A Case Study for Indianapolis, IN. Elementa (Wash D C). 2017;5:28.
Ciais P., et al. (2015). Towards a European operational observing system to monitor fossil CO2 emissions, European Commission – ISBN 15 978-92-79-53482-9.
Thompson R.L., et al. (2016). Top-down assessment of the Asian carbon budget since the mid 1990s. Nat Commun 7:10724.

The following paragraphs have been added to the manuscript:

4.3 Intercomparison with EDGAR CO_2 emission

Due to the lack of physical measurements of CO_2 emissions, it is challenging to objectively evaluate the estimated emissions. To better understand the differences among various emission datasets, an intercomparison with an additional CO_2 emission dataset from the Emissions Database for Global Atmospheric Research (EDGAR version 5; Crippa et al., 2019, 2020) is conducted and discussed.

EDGAR employs a bottom-up approach to estimate emissions, utilizing multiple data sources, including national and international energy statistics, industrial production data, and activity data for various sectors, such as agriculture, waste, and land use (Crippa et al., 2019, 2020). EDGAR CO_2 emissions data is provided annually at a 0.1° x 0.1° latitude-longitude grid, providing insights into the patterns and trends of CO_2 emissions that are crucial for understanding the impact of human activities on climate change. To unify all emission datasets, the intercomparison is conducted using annual emissions at 2.5° grid resolution.

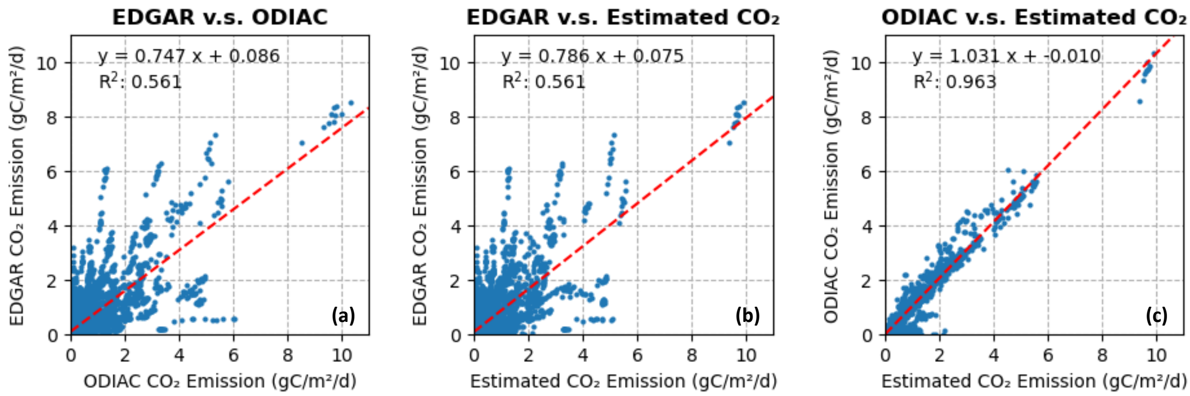


Figure 12: Scatter plot of annual CO_2 emissions during 2010 – 2019 between (a) EDGAR and ODIAC; (b) EDGAR and satellite-based estimation; (c) ODIAC and satellite-based estimation.

The scatter plots in Figure 12 compare the annual CO_2 emissions among datasets, revealing a positive correlation among them. While the satellite-based CO_2 emission estimation aligns well with the ODIAC product, showing an R^2 of 0.963, the correlation is weaker when compared with EDGAR. Additionally, the distribution map of the mean bias among annual CO_2 emissions is displayed in Figure 13. Underestimation (blue) in satellite-based estimation and ODIAC emission compared to EDGAR is observed in the central inland region of China, and northern Europe, while overestimation (red) is evident in the eastern coast of China and the southeastern United States.

It is important to note that the intercomparison does not account for the estimation accuracy. Discrepancies among different emission datasets may arise from differences in data sources, estimation methods, and the scope of emissions considered (Oda et al., 2019; Solazzo et al., 2021). Nevertheless, the observed positive correlation among EDGAR, ODIAC, and satellite-based estimation has implications for understanding global emission patterns.

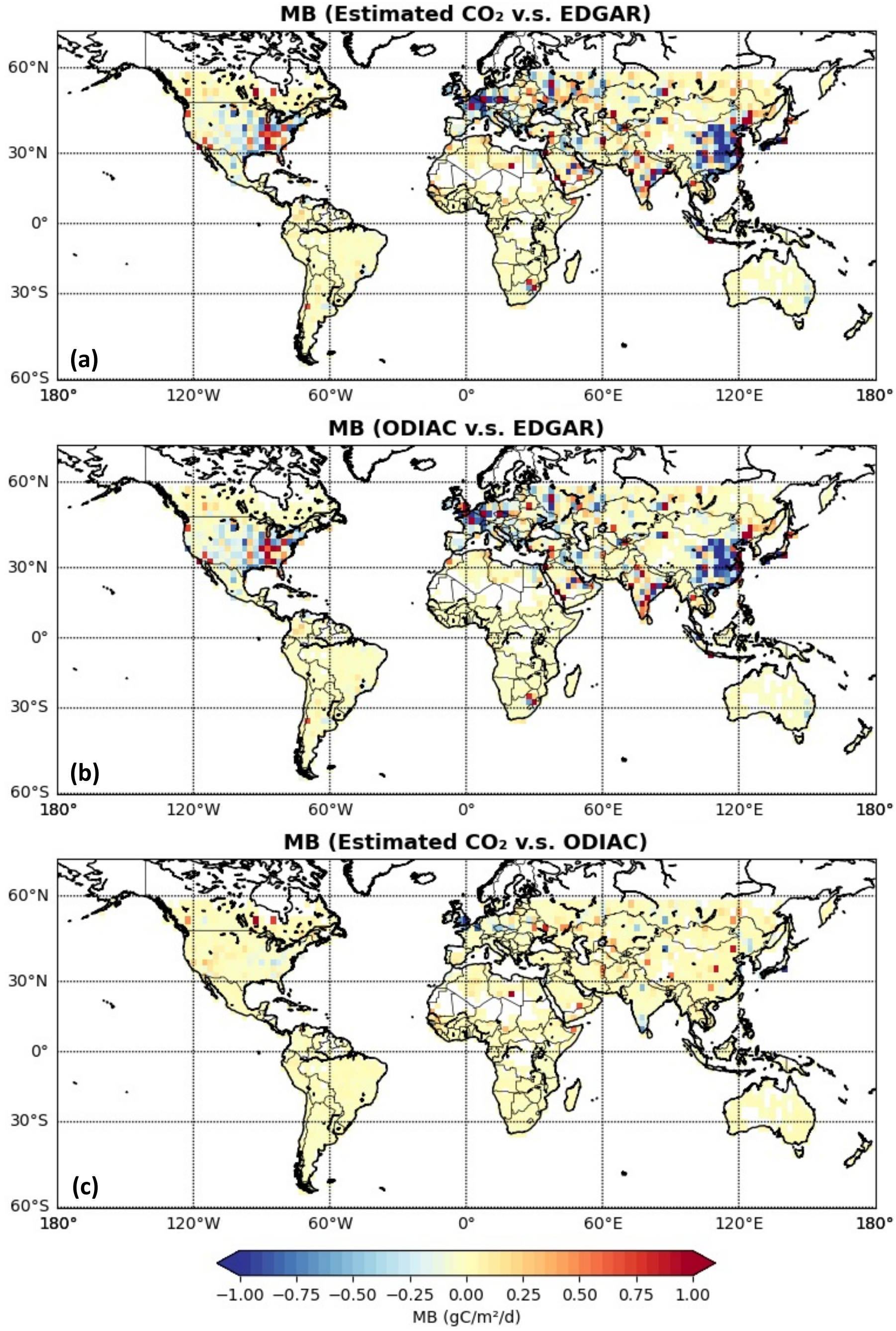


Figure 13: Distribution map of the mean bias in annual CO_2 emissions (a) satellite-based estimation and EDGAR; (b) ODIAC and EDGAR; (c) satellite-based estimation and ODIAC.

Crippa, M., Oreggioni, G., Guizzardi, D., Muntean, M., Schaaf, E., Lo Vullo, E., Solazzo, E., Monforti-Ferrario, F., Olivier, J. and Vignati, E., Fossil CO2 and GHG emissions of all world countries, EUR 29849 EN, Publications Office of the European Union, Luxembourg, 2019, ISBN 978-92-76-11100-9, doi:10.2760/687800, JRC117610.

Crippa, M., Solazzo, E., Huang, G., Guizzardi, D., Koffi, E., Muntean, M., Schieberle, C., Friedrich, R. and Janssens-Maenhout, G., 2020. High resolution temporal profiles in the Emissions Database for Global Atmospheric Research. Scientific data, 7(1), p.121.

Solazzo, E., Crippa, M., Guizzardi, D., Muntean, M., Choulga, M., and Janssens-Maenhout, G.: Uncertainties in the Emissions Database for Global Atmospheric Research (EDGAR) emission inventory of greenhouse gases, Atmos. Chem. Phys., 21, 5655–5683, https://doi.org/10.5194/acp-21-5655-2021, 2021.

Specific comments

Line 17: In this study, the regression model (i.e., GTWR) is developed using the ODIAC fossil fuel CO2 emissions data as inputs for the training and for model validation. In the big picture, how does this regression model contribute to our current capability of tracking fossil fuel CO2 emissions? Why should one rely on GTWR model emission estimates rather than ODIAC? From this manuscript, I don't see any evidence showing that the GTWR model estimates are closer to "true" emissions than ODIAC estimates, as section 4.1 "Validation of CO2 emissions," only shows how close the GTWR model estimates are to the ODIAC estimates.

Reply: We appreciate the reviewer for this comment. The primary objective of this research is to estimate CO_2 emissions from satellite-based measurements of CO_2 column amounts. The enhanced XCO_2 calculated from GOSAT XCO_2 product is used as the main indicator for estimation, while variables indicating atmospheric conditions are also included as independent variables to provide a more comprehensive understanding of the real-world emission system. As the relationships between variables are expected to vary across space and time due to local conditions and processes, the GTWR model is employed to analyze the spatiotemporal data. By using spatial and temporal weights, the GTWR model allows the regression coefficients to vary both spatially and temporally. Therefore, the GTWR model can provide more accurate and detailed insights into emission estimation.

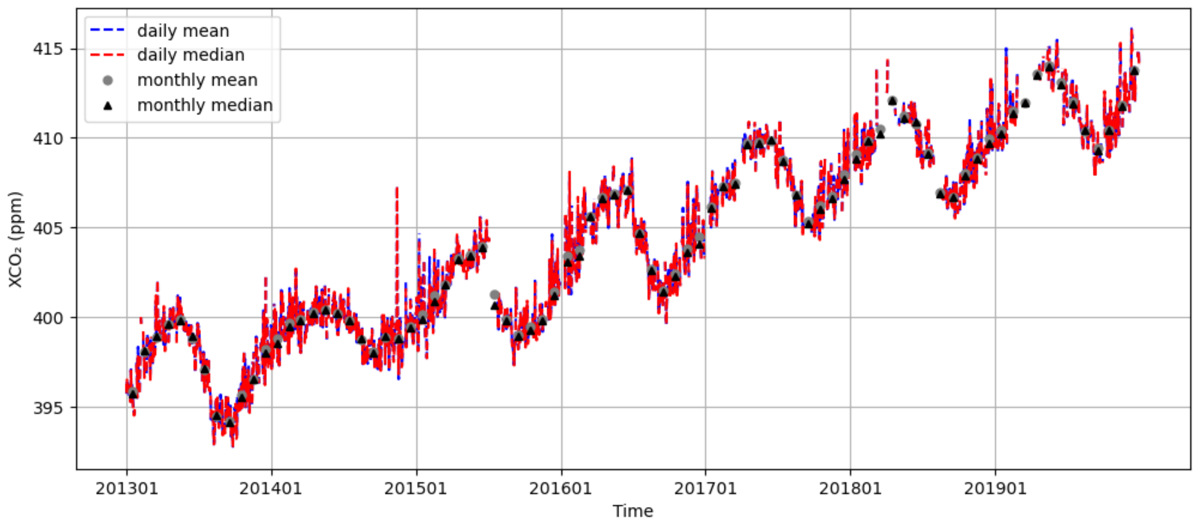
In principle, satellite-based measurements are objective and independent of any national or political interests, ensuring that the data is reliable and can be used to support international climate change negotiations and agreements. Due to the lack of physical measurements of CO_2 emissions, the ODIAC product was used as the reference data. While a high correlation between the model estimation and ODIAC data was observed, this study demonstrated the potential for monitoring emissions directly from space using satellite-based observations.

The following paragraph has been added to the manuscript:

Line 151: The GTWR model is a statistical model that aims to capture the spatial and temporal relationships within the data to mathematically represent the real-world system. However, unlike traditional regression models that assume constant relationships, the GTWR model estimates localized parameters that can capture local variations, providing a more detailed understanding of spatiotemporal relationships. The physical basis of the GTWR model lies in the assumption that the relationships between the dependent and independent variables vary due to different local conditions, processes, and factors that influence the variables. It uses a distance-based kernel function (Gaussian) to weight observations based on both their spatial and temporal proximity to the location and period being modeled. It assigns higher weights to observations that are closer in space and time to the target location and time point. Therefore, the GTWR model can provide more accurate and detailed insights into emission estimation.

Lines 94-95: By definition, the XCO2 anomaly represents the column enhancement in atmospheric CO2 due to anthropogenic CO2 emissions. Correspondingly, background XCO2 is the XCO2 that would have been measured if there were no anthropogenic emissions. In this regard, how could the monthly median for each sub-region be used as the background XCO2? In a physical sense, the monthly median XCO2 is more like a representative XCO2 value that reflects both monthly fossil-fuel emissions and biogenic CO2 fluxes within the region. Therefore, the difference between the monthly mean XCO2 from each grid cell against the monthly median XCO2 from the region will represent the spatial differences in anthropogenic (i.e., fossil fuel) and biogenic CO2 fluxes between each grid cell vs. the whole sub-region. Such "spatial difference" cannot be interpreted as the anthropogenic CO2 emissions for the region. Also, the authors argue that using the monthly median value will de-trend the XCO2 data. However, using the monthly median, unlike the daily median used by Hakkarainen et al., 2016, is more likely to be affected by seasonality in XCO2, especially when there is a rapid shift and biospheric CO2 flux (i.e., growing season). Sensitivity analysis could be considered to test the impacts of the size of the temporal windows for averaging the satellite data (i.e., 1 day, 15 days, 1 month, etc.).

Reply: We thank the reviewer for this comment. The satellite-based measurements of total atmospheric CO_2 concentrations include both natural and human-caused sources of CO_2 emissions. To estimate CO_2 emissions, it is necessary to isolate the additional CO_2 emissions from human activities, which require the removal of background CO_2 levels. Hakkarainen et al. proposed subtracting the daily median at each grid cell to enhance the XCO_2 signal. Pan et al. adapted the background removal method and calculated the XCO_2 anomaly by subtracting the 16-day moving median XCO_2 observations across the study region. The time series analysis over the Caltech station during 2013 ~ 2019 (see Figure below) shows that both the daily and monthly data capture seasonal variation trends, while daily data exhibit strong fluctuations. Since GOSAT observations are much coarser in spatial resolution compared to OCO-2 observations, daily measurements are too sparse to statistically model the relationship between the enhanced XCO_2 and CO_2 emissions. To get sufficient global coverage for a stable calculation, the monthly mean XCO_2 was used in our study. Similarly, the monthly median XCO_2 could then be used to represent the 'background of CO_2 concentration' in the study area. By subtracting the monthly median, the XCO_2 signal could be enhanced and deseasonalized for further calculation.



Lines 172-174: What is the physical basis of the found correlation between the anthropogenic CO2 emissions and other ancillary variables, such as air temperature and tcwv, wind speed? I

could see how the air surface temperature is (non-linearly) correlated to the fossil fuel CO2 emissions: Higher energy demand for spatial heating/cooling during the winter/summer periods leads to higher fossil fuel combustion and corresponding CO2 emissions. However, I do not see any physical relationship between CO2 emissions and other variables such as wind speed and tcwv. I do not think the larger amount of water vapor in the atmospheric column is related to the surface CO2 emissions. When there is no physical relationship between the regressor and predictors, the regression model is hard to justify, and the result (even when it's showing good R2) is likely to be overfitting of the input parameters.

Reply: We appreciate the reviewer's comment. Atmospheric conditions affect the distribution, transport, and measurement of CO_2 emissions. For instance, wind can carry CO_2 away from the source, leading to a more widespread distribution of emissions over a large area. Strong vertical motion promotes the dispersal of CO_2 emissions throughout the troposphere. Water vapor and air temperature are related to the solubility of CO_2, as well as vegetation photosynthesis, respiration, etc. Understanding the relationships between atmospheric conditions and CO_2 emissions is essential for accurately estimating emissions. It is important to note that the GTWR model can adapt to local variations in the data and capture complex spatial patterns. The cross-validation results show that the model has consistent performance on both the training and testing subsets. To further examine the input parameters in the model, a series of analysis were conducted with multiple combinations of input variables in the tropical area (training subset), the verification results (details in the following table) prove that the model is not overfitting.

Input variables	R^2
ΔXCO_2	0.769
ΔXCO_2, WS, $\omega 500$	0.877
ΔXCO_2, WS, $\omega 500$, WV, AT	0.971
ΔXCO_2, WS, $\omega 500$, WV, AT, GFED	0.972

Line 175: How can the strong subsiding motion be associated with significant CO2 emissions? I could understand how these ancillary variables are physically related to XCO2 data, not emissions. If that's what the author originally intended, then the regression model should be constructed around XCO2, not emissions.

Reply: Thank you for the comment. The primary goal of this research is to estimate anthropogenic CO_2 emission using the total amount of CO_2 (XCO_2) observed from remote sensing satellite. The relationship between CO_2 emissions and XCO_2 is direct: as human activities release more CO_2 into the atmosphere, the XCO_2 levels increase. To accurately estimate CO_2 emissions, atmospheric conditions must be considered, as they can influence the distribution and concentration of CO_2 emissions.

The relationship between CO_2 emissions and atmospheric conditions is complex and interconnected. Large-scale atmospheric circulation is responsible for redistributing the CO_2 emissions around the globe. For instance, the subsiding motion can lead to the accumulation of CO_2 near the Earth's surface by reducing vertical mixing and dispersion. Higher CO_2 concentrations can influence regional climate patterns and potentially affect biospheric CO_2 flux. Understanding the complex interactions between the atmospheric movement and CO_2 concentrations is essential for developing effective estimates of anthropogenic emissions.

Line 187: AE is the ODIAC CO2 emissions for the regression model training, correct? If so, AE is not the "anthropogenic" emissions but CO2 emissions from fossil fuel combustion and cement production. Therefore, having fire CO2 emissions as a regressor in the model doesn't have a physical basis.

Reply: Thanks for the observation. We have revised the sentence for clarification purpose:

where AE_i are the ODIAC CO_2 emissions of sample i at location (μ_i, ν_i) at time t_i.

The equation formulates the GTWR model for emission estimation. In principle, ΔXCO_2 refers to the total release of CO_2 into the atmosphere, primary from the burning of fossil fuels, deforestation, and other human activities. CO_2 released by fires contributes to the overall increase in atmospheric CO_2 concentration, although this contribution is generally smaller compared to emissions from fossil fuel combustion. However, during years with extensive wildfires, the contribution of fire emissions can be more substantial and should be taken into account. By incorporating GFED data, which is available at a global scale, as an input parameter in the model, it is possible to further improve the performance of CO_2 emission estimations.

Lines 235-237: Because the regression model presented in this study relies heavily on ODIAC emission data, spatiotemporally disaggregated bottom-up emission inventory, the emission estimates from this study are not entirely independent from the conventional "bottom-up" method.

Reply: The following comments has been added to the manuscript to address this point:

Line 249: In principle, satellite-based measurements are objective and independent of any national or political interests, ensuring that the data is reliable and can be used to support international climate change negotiations and agreements. Due to the lack of physical measurements of CO_2 emissions, the ODIAC product was used as the reference data. It is important to note that the satellite-based estimation does not account for potential confounding factors in the ODIAC product. While a high correlation between the model estimation and ODIAC data is observed, this study demonstrates the potential for monitoring emissions directly from space using satellite-based observations.

Lines 244-246: How does the MB value of 0.05 gC/m^2/month translate into a policy-relevant scale? For example, what are the MB values when the grid pixels are aggregated for annual emissions from large emitting countries (i.e., United States, China, India)? Also, what are the correlation coefficients at each sub-region?

Reply: We appreciate your comment. The unit for the emission was consistent with the ODIAC product, therefore, the correct unit for satellite-based estimation and MB should be gC/m^2/d. We have revised the manuscript accordingly. The gC/m^2/d stands for grams of carbon per square meter per day. It is a standardized, area-normalized, and time-resolved unit in grided carbon emission datasets. We appreciate your suggestion to aggregate emissions by administrative aeras. However, aggregating emissions by administration will introduce errors and uncertainties that are beyond the context and scope of the analysis in this research. Instead, an additional grided EI from EDGAR was added in this research for intercomparison analysis.

The correlation coefficients at each subregion were summarized in the following table.

Sub-region	Slope	Intercept	R^2
Tropical (35,802)	1.007	-0.001	0.880
North America (19,071)	1.002	-0.001	0.933
Mediterranean (18,316)	1.004	-0.002	0.875
East Asia (26,229)	1.001	-0.001	0.947
South America (6,357)	1.000	0	0.999
Africa (2,979)	1.000	0	0.999
Oceania (4,806)	1.002	0	0.988

Technical corrections

Lines 11-12: Within the atmospheric science/satellite observation research community, the "top-down" approach usually indicates the emission estimation method using the direct atmospheric observations of trace gas (i.e., Inversion analysis, mass balance analysis).

Reply: We appreciate your comment. We have revised the following sentence as follows:

This paper proposes a direct estimation method using GTWR model to infer the spatiotemporal relationship between satellite-based atmospheric measurements of CO_2 concentrations and CO_2 emissions.

Line 16: The term enhanced XCO2 seems vague. Please use more specific terms (i.e., enhanced XCO2 relative to the regional background).

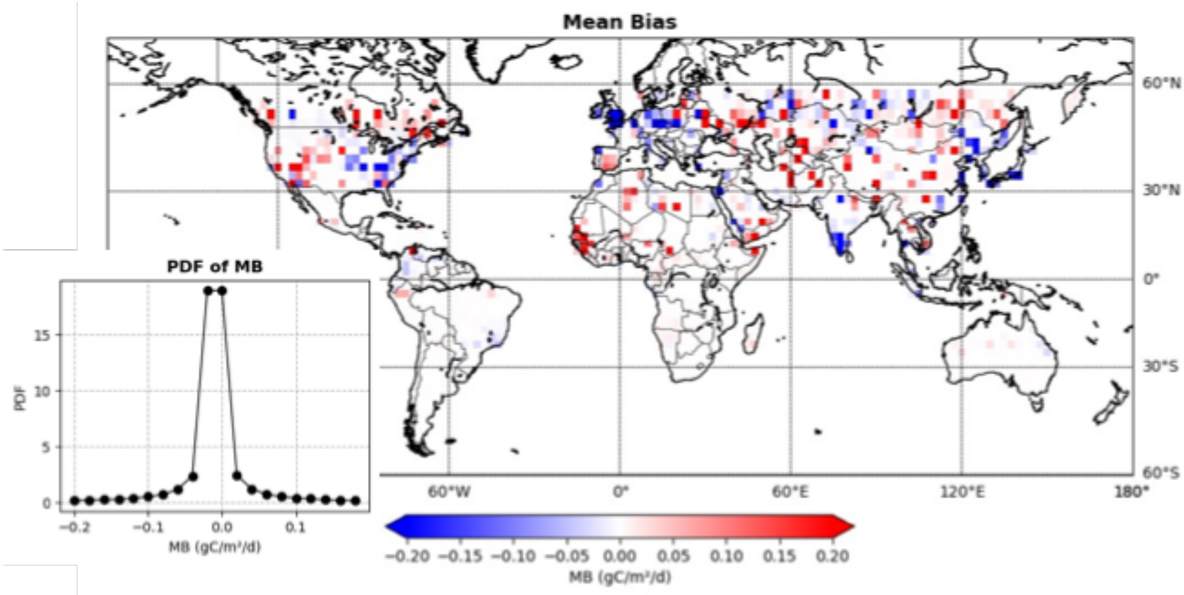
Reply: We have revised the manuscript to address this point.

Line 27: The words "and removal" seem unnecessary in this sentence.

Reply: We have revised the manuscript as suggested.

Figure 9: Map is too small to see some regional features in the mean bias. Increasing the map size or zooming in to -60 to 60 degrees will make the map legible.

Reply: We have revised the figure as suggested.



RC2

I second what Anonymous Referee #1 discussed. As discussed by Referee #1, this study developed a method to reasonably replicate ODIAC estimates, but the study did not demonstrate its scientific significance. As presented in many previous studies, ODIAC should/does have its own errors like other emission products. For example, Oda et al. (2019) characterized modeling errors in ODIAC. There are many other papers that studied potential errors in ODIAC. ODIAC has a data policy. While users can freely use the product for research purposes, users should read papers suggested before using it mainly to reasonably understand the limitation of the data product. In the manuscript, the potential errors in ODIAC were not discussed at all. Why? Does it not matter?

Reply: Thank you for the comment. It is important to note that our focus is on estimating CO_2 emissions using satellite-based measurements of CO_2 column amounts. The GTWR model was adopted for the first time to mathematically represent the spatiotemporal relationship between satellite-based measurements of CO_2 concentrations in the atmosphere and CO_2 emissions. In principle, satellite-based measurements are objective and independent of any national or political interests, ensuring that the data is reliable and can be used to support international climate change negotiations and agreements. Due to the lack of physical measurements of CO_2 emissions, the ODIAC product was used as the reference data as it is the only global, spatially explicit EI data product that meets the requirements of Ciais et al. (2015) and has been intensively used for global and regional atmospheric inversion (e.g. Thompson et al. 2016). We acknowledge that there are potential emission modeling errors and uncertainties associated with the ODIAC grided product. This study assumes that those errors and uncertainties are minor when compared with other grided emission inventories. While high correlation between the model estimation and ODIAC data is observed, this study demonstrates the potential for monitoring emissions directly from space using satellite-based observations.

I also do not see support for the policy relevance of this study. As clearly stated in our papers, ODIAC is primarily designed and developed for accurately prescribing atmospheric CO2 simulations, rather than informing policy. What climate policy do you mean? Sector? How can you possibly inform sectoral emission differences independently just using CO2? I failed to find the relevance of this study to climate mitigation policy.

Reply: We appreciate your comment. The satellite-based measurements of total atmospheric CO_2 concentrations include both natural and human-caused sources of CO_2 emissions. We adapted the background removal method proposed by Hakkarainen et al. (2016), by subtracting the monthly median, the XCO_2 signal could be enhanced and deseasonalized for further calculation. In principle, ΔXCO_2 refers to the total release of CO_2 into the atmosphere, primary from the burning of fossil fuels, deforestation, and other human activities. As the ODIAC was adopted for model development, the satellite-based estimation is expected to represent the fossil fuel combustion.

It is important to note that the GTWR model can adapt to local variations in the data and capture complex spatial patterns. As the relationships between variables are expected to vary across space and time due to local conditions and processes, the GTWR model is employed to analyzing the spatiotemporal data. By using spatial and temporal weights, the GTWR model allows the regression coefficients to vary both spatially and temporally. We agree that there are potential limitations in using the ODIAC product for model development. We have added comments on the limitation in the manuscript. Nevertheless, the observed positive correlation among EDGAR, ODIAC, and satellite-based estimation has implications for understanding global emission patterns, and the high correlation demonstrates the potential for monitoring emissions directly from space using satellite-based observations.

I also don't think the correlation coefficient is a great metric for emission estimation. You need to know the accuracy of emission estimates if you truly wanted to do emission monitoring.

Reply: The model uncertainty is estimated through cross-validation. The data was split into training (~70%) and testing (~30%) subsets using the bootstrap method for model development and validation. The results showed that satellite-based estimations are highly consistent with the ODIAC product, with R^2 of 0.951 and 0.929, respectively. In addition, a comprehensive intercomparison with an additional EI (EDGAR) was added in the manuscript. While we agree that understanding the "accuracy" of the emissions is a fundamental limitation due to technical difficulties, this question extends beyond the scope of the current study. We will consider it for future research projects.

This study has a fundamental design flaw, and the conclusion is not supported. While Referee #1 kindly provided their detailed feedback, I do not believe the review process is for correcting fundamental errors or addressing knowledge gaps in the authors to make the manuscript something publishable. Our role as a referee is only to evaluate what is presented. I suggest Editor to reject the manuscript. I failed to see any chance for this study to be published in ACP and contribute to the high level science of ACP.

Reply: We appreciate the reviewer's concern regarding the potential design flaw and the assertion that our conclusions are not supported by the findings. However, we believe that our research design is appropriate for addressing the research questions and that our conclusions are well-grounded in the results.

The key novelty of our research is using satellite-based observation on CO_2 column amounts to estimate CO_2 emissions. The statistical model, GTWR model, was adopted for the first time to account for the spatiotemporal relationship between satellite-based measurements of CO_2

concentrations in the atmosphere and CO_2 emissions. Upon revisiting our methodology and findings, we have taking into account the points raised by the reviewer and added comments on the ODIAC limitations and included a comprehensive intercomparison with an additional emission inventory, EDGAR. We have ensured that the methodology is in line with established practices.

Our conclusions are drawn from a careful analysis of the data. We have made efforts to take into account any limitations and potential confounding factors. While we acknowledge that using ODIAC data for model development has its limitations, we believe that our conclusions contribute valuable insights and advance the understanding of global CO_2 emission patterns.

Lastly, the authors should respectfully use the data provided. Where possible, the authors should show original data sources and acknowledge the data properly (e.g. GOSAT). For TCCON data, did you follow the data license policy? https://tccon-wiki.caltech.edu/Main/DataLicense

Reply: we appreciate the reviewer's concerns regarding compliance with the data license policy. We have thoroughly reviewed the data sources and licensing requirements for our study to ensure full adherence to all relevant policies. We would like to clarify that all data used in our research have been used in accordance with their respective licensing agreements. We have added the appropriate citations and provided the necessary acknowledgements to give credit to the data providers.