Replies to Reviewers' comments

Ms. Ref. No. : amt-2021-222

Title: Neural Network Based Estimation of Regional Scale Anthropogenic CO_2 Emissions Using OCO-2 Dataset Over East and West

We sincerely thank the Editor of the journal for reviewing our research paper and providing the list of comments/suggestions raised by the learned reviewers which in turn helped us in improving the quality of an earlier version of the manuscript. As per the suggestions of the reviewers, we have gone through the entire paper giving suitable answers to their queries and revised the whole paper. We have updated the figures following the suggestions of the reviewers. The authors wish to thank the Editor of the journal for his encouragement and support in contacting the reviewers to complete the peer-review process in time. The authors are also grateful to the anonymous reviewers for their constructive and useful comments, suggestions and critics which in turn improved the scientific content of an earlier version of the manuscript. All responses to the reviewers' comments in the revised manuscript are highlighted in RED, so that they may be easily identified.

Kind regards,
Farhan Mustafa & Co-authors

Response to Anonymous Referee 2 Comments

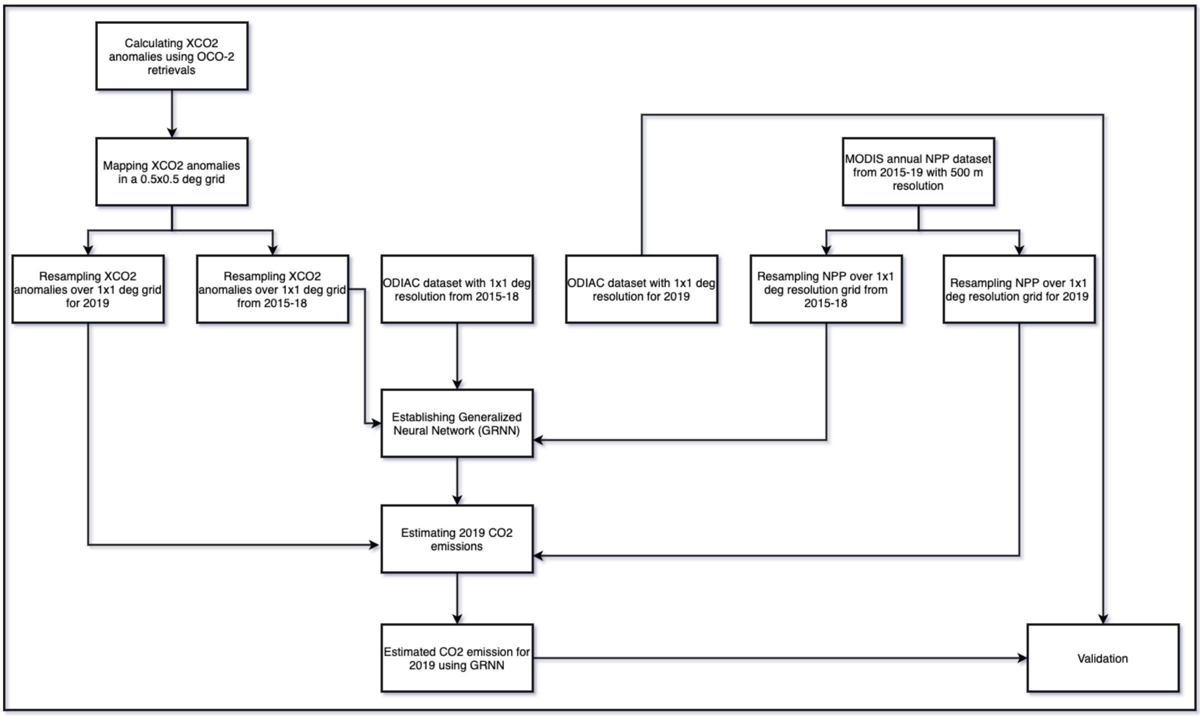
1. General Comments

Point 1: While the study is within the scope of AMT, it is extremely similar to paper by Yang et al. (2019) as also pointed out by the first reviewer. The authors uses the same method but applies it to OCO-2 instead of to GOSAT data and additional apply the method to West Asia. The method section is partly copying and partly paraphrasing Section 2.3 of Yang et al. (2019). Figures 1 and 2 are also extremely similar to Figures 2 and 3 in that paper without proper citations. Equations 2 and 3 are also identical. The results and conclusions sections have also some similarities with Yang et al. (2019) in the choice of analyses and figures. It is clearly necessary to rework the method and results section to make it better understandable as well as reduce similarities with and give proper credit to Yang et al. (2009). In addition, the authors need to clarify the novelty of their paper in comparison to previous studies.

Response 1: We are thankful to the anonymous referee for his/her constructive comments. The comments are very helpful in improving the quality of the manuscript and we have carefully used them to revise the manuscript.

We understand the concerns of the learned referee about the similarities between our manuscript and the article authored by (Yang et al., 2019). We extended the study following the suggestion given in the conclusion of the article written by (Yang et al., 2019). However, following the suggestion of the respected reviewer, the manuscript has been revised completely and substaintial changes have been made in the revised version of the manuscript.

- The prediction model has been changed/improved. A new dataset, MODIS net primary productivity (NPP) has been added to train the model and then predict the anthropogenic CO2 emission. The new flowchart of the model, updated in the revised manusctipt as, “Figure 1” is given in the following:



- More detail has been added to the section 2.2 of the revised manuscript at

L196-203 as, "OCO-2 XCO_2 dataset was downloaded from the Earthdata platform (https://earthdata.nasa.gov/) and to ensure the reliability of the data, screening and filtering of the dataset was carried out following the instructions given in the OCO-2 Data User Guide (DUG). Each sounding that is processed using the ACOS L2FP retrieval algorithm is assigned either a "good" (=0) or "bad" (=1) quality flag based on screening criteria derived from comparisons with TCCON and modelled CO_2 fields. It is generally advised that users should use the "good" quality soundings for regional and local scale studies because the soundings flagged as "bad" quality might include biases that compromise their utility for the application. In this study, the OCO-2 XCO_2 retrievals were included if: (i) they were flagged good (flag=0) and (ii) the standard deviation of the good soundings for the day was less than 2 ppm."

L245-256 as, "During the process of photosynthesis, the living plants convert the CO_2 into sugar molecules they use for food. In the process of making food, they also release the oxygen we breathe. Plant productivity plays a crucial role in the global carbon cycle by absorbing the CO_2 released by anthropogenic activities. The net primary productivity (NPP) shows how much CO_2 is absorbed by the plants during photosynthesis minus how much CO_2 is released during respiration. A negative value of NPP means that CO_2 is released into the atmosphere and a positive value represents the absorption of atmospheric CO_2. To improve the model results, an NPP dataset (MOD17A3HGF) provided by MODIS has also been used in this study. It provides information about annual NPP and is distributed by NASA's Land Processes Distributed Active Archive Center (LP DAAC). The NPP dataset with a spatial resolution of 500 meters (m) was downloaded from the LP DAAC website (https://lpdaac.usgs.gov/products/mod17a3hgfv006/). The annual NPP is derived from the sum of all 8-day Net Photosynthesis (PSN) products (MOD17A2H) from the given year. The MODIS NPP dataset was reprojected and resampled to the spatial resolution of 1°×1° Longitude/Latitude for each year and used along with the ODIAC and OCO-2 datasets to train the GRNN model and as well predicting the CO_2 emission."

- The sentence including, “we proposed a new method has been revised” and the author Yang et al., (2019) is given proper credit at various places of the manuscript. Such as,

At L105-107 as, “In this study, we have improved the model initially developed by (Yang et al., 2019) to estimate the regional scale anthropogenic CO_2 emissions using OCO-2 XCO_2 retrievals over East and West Asia. MODIS NPP, OCO-2 and ODIAC CO_2 datasets were obtained for a period of five years from January 2015 to December 2019.”

At L381-388 as, “(Yang et al., 2019) estimated the CO_2 emissions by a similar machine learning approach using GOSAT XCO_2 retrievals over China and differences between the estimated and the ODIAC CO_2 emissions were between $-5x10^9$ kg to $5x10^9$ kg. Moreover, the predicted results from the referenced study exhibited overall less CO_2 emissions relative to the ODIAC emissions contradicting our results. Our study showed better results and it might be due to several reasons; (i) we improved the prediction model with the addition of NPP dataset (Figure 4e), (ii) we utilized the higher resolution XCO2 retrievals provided by OCO-2, and (iii) we incorporated the OCO-2 XCO_2 retrievals processed using the latest version of the retrieval algorithm. The newer version of the ACOS L2FP retrieval algorithm has improved the quantity as well as the quality of the satellite-based observations (Taylor et al., 2021).”

- Figure 1 (given above) has been changed as the model has been changed with the addition of new dataset.
- Figure 2 is a general structure of GRNN, however, the figure has been properly cited.
- The results section has been changed:

At L350-388 as, “The predicted CO_2 emission is overestimated over most of the regional parts; whereas, this overestimation is more significant over agricultural areas which are located near the high-density region, i.e., eastern China. Eastern China, Japan, and Korea are known to be among the regions with the highest CO_2 emissions and this underestimation over the agricultural areas might be caused by the nearby CO_2 emitting sources which raise the CO_2 concentration of the nearby areas through atmospheric transport. Previous studies demonstrated that the concentration of atmospheric CO_2 was influenced by atmospheric transport (Cao et al., 2017; Kumar et al., 2014). The areas where the predicted CO_2 emission is underestimated are covered by agriculture, forest and vegetation. This underestimation of the predicted CO_2 emissions over these areas indicate the presence of uncertainties in the XCO_2 anomalies that are likely to be produced by the CO_2 uptake of the biosphere which is still remaining in the XCO_2 anomalies. In addition, the areas where the estimated CO_2 emissions are overestimated have higher elevations. OCO-2 observations show larger uncertainties over elevated and mountainous areas, especially the Tibetan Plateau where the OCO-2 retrievals are significantly overestimated (Kong et al., 2019; Mustafa et al., 2020) and this might also have a contribution to the overestimation of estimated CO_2 emissions. The difference between the estimated and the ODIAC CO_2 emissions was ranging from $-0.06x10^9$ kg to $3.2x10^9$ kg and the magnitude of difference between $-1x10^9$ kg to $1x10^9$ kg accounted for 84% of the total number of grid cell. (Yang et al., 2019) estimated the CO_2 emissions by a similar machine learning approach using GOSAT XCO_2 retrievals over China and differences between the estimated and the ODIAC CO_2 emissions were between $-5x10^9$ kg to $5x10^9$ kg. Moreover, the predicted results from the referenced study exhibited overall less CO_2 emissions relative to the ODIAC emissions contradicting our results. Our study showed better results and it might be due to several reasons; (i) we improved the prediction model with the addition of NPP dataset (Figure 4e), (ii) we utilized the higher resolution XCO2 retrievals provided by OCO-2, and (iii) we incorporated the OCO-2 XCO_2 retrievals processed using the latest version of the retrieval algorithm. The newer version of the ACOS L2FP retrieval algorithm has improved the quantity as well as the quality of the satellite-based observations (Taylor et al., 2021)."

Point 2: I am also not convinced by the objective of the study: What is the advantage of the suggested approach over using the ODIAC inventory for 2019? The satellite-based product seems to be less accurate suffering from issues with XCO2 accuracy, not-accounted transport effects, and biospheric fluxes. In addition, a main objective of top-down emission estimates is the evaluation/validation of bottom-up inventories, but since the GRNN is trained with the ODIAC inventory, it is not able to identify systematic errors in the ODIAC dataset. I think it will be necessary to discuss these points in the paper.

Response 2: The suggested discussion has been added in the revised manuscript:

At L49-60 as, "Over the past few decades, significant work has been carried out to compile the regional as well as the global inventories of CO_2 emission from anthropogenic activities (Olivier et al., 2005; Janssens-Maenhout et al., 2015; Gurney et al., 2009; Oda and Maksyutov, 2015). Most of the emission inventories employ 'bottom-up' methods using available human activity data, emission factors and corresponding technologies. The bottom-up methods incorporate energy consumption datasets along with other information such as fuel purity, efficiency, etc. However, it is known that such information can be subject to errors and biases leading to considerable discrepancies and uncertainties in emission estimates, especially in the case of rapidly growing developing economies such as China and India (Guan et al., 2012; Korsbakken et al., 2016). These discrepancies can result in ~40% to ~100% uncertainty in emission estimations at the country and the local scales, respectively (Peylin et al., 2013; Wang et al., 2013). Moreover, the uncertainty in inventory datasets is also a challenging task and the intercomparisons of various inventories do not necessarily reveal all the uncertainties because different inventories are sometimes using common sources of information (Konovalov et al., 2016)."

At L111-117 as, "Atmospheric CO_2 monitoring satellites can detect and analyze the anthropogenic CO_2 signatures and the satellite-based estimation of anthropogenic CO_2 emissions can be helpful in investigating the carbon emissions as a data-driven method, which is different to the conventional method in calculating emission inventory. Although estimation of anthropogenic CO_2 emission using satellite datasets is a challenging task because some other factors such as the atmospheric transport and the terrestrial ecosystem play notable roles in controlling the spatial distribution of atmospheric CO_2 (Cao et al., 2017) but still this data-driven method can provide a meaningful help in quantifying anthropogenic CO_2 emissions that will be important for evaluating the effects for anthropogenic CO_2 emissions reduction at regional as well as global scales."

2. SSpecific/technical comments

L72: Please clarify that this is not a new method.
Response : It has been cleared in the revised manuscript:
At 105-107 as, "In this study, we have improved the model initially developed by (Yang et al., 2019) to estimate the regional scale anthropogenic CO_2 emissions using OCO-2 XCO_2 retrievals over East and West Asia."

L111: life period -> life time

Response : The mistake is corrected.

L116ff: The paragraph is unclear. Please describe more clearly how the XCO2 anomaly is calculated.

Response : We are thankful to the reviewer for valuable suggestion. The description has been simplied in the revised manuscript:

At L208-210 as, "To highlight the areas associated with the anthropogenic CO_2 emission, XCO_2 anomalies were calculated by subtracting the daily XCO_2 median (daily background) from the individual XCO_2 observation, a method suggested by previous studies (Hakkarainen et al., 2019, 2016)."

L175: Contributing a large fraction of global oil production does not necessarily imply high CO2 emissions.

Response : The sentence has been removed.

L176: "major fuel consumer" compared to whom?

Response : Compared to other countries in the region. The sentence has been revised as, "In addition, Iran, Saudi Arabia, and Iraq are the major fuel consumers of the region and contribute more than 60% of the region's total fossil fuel CO_2 emissions."

L179: "highest" compared to whom? Maybe just write "high" here?

Response : The mistake has been corrected.

L201: The term "actual emissions" might refer to "true emissions", which are unknown. I would suggest to use "ODIAC inventory" here.

Response : We are thankful to the reviewer for valuable suggestion. The term "actual emission" has been revised throughout the manuscript.

L213f: It quite unclear what the "difference" and "magnitude of difference" refer to. Instead of stating exponential values here, it would more interesting what are the absolute and relative deviations depending, for example, on land cover.

Response : We are grateful to the learned reviewer for constructive comment. The manuscript has been revised following the given suggestion.

L214: What does "accounted for 80% of the total grids" mean?

Response : It mean the 80% of the toal number of grid cells. The sentence has been simplied as, "the magnitude of difference between $-1x10^9$ kg to $1x10^9$ kg accounted for 84% of the total number of grid cells."

L215f: When comparing to Yang et al. (2019) it would useful using the same units.

Response : Same units have been used for comparions in the revised manscript:

At L379-388 as, "The difference between the estimated and the ODIAC CO_2 emissions was ranging from $-0.06x10^9$ kg to $3.2x10^9$ kg and the magnitude of difference between $-1x10^9$ kg to $1x10^9$ kg accounted for 84% of the total number of grid cells. (Yang et al., 2019) estimated the CO_2 emissions by a similar machine learning approach using GOSAT XCO_2 retrievals over China and differences between the estimated and the ODIAC CO_2 emissions were between $-5x10^9$ kg to $5x10^9$ kg. Moreover, the predicted results from the referenced study exhibited overall less CO_2 emissions relative to the ODIAC emissions contradicting our results. Our study showed better results and it might be due to several reasons; (i) we improved the prediction model with the addition of NPP dataset (Figure 4e), (ii) we utilized the higher resolution XCO2 retrievals provided by OCO-2, and (iii) we incorporated the OCO-2 XCO_2 retrievals processed using the latest version of the retrieval algorithm. The newer version of the ACOS L2FP retrieval algorithm has improved the quantity as well as the quality of the satellite-based observations (Taylor et al., 2021)."

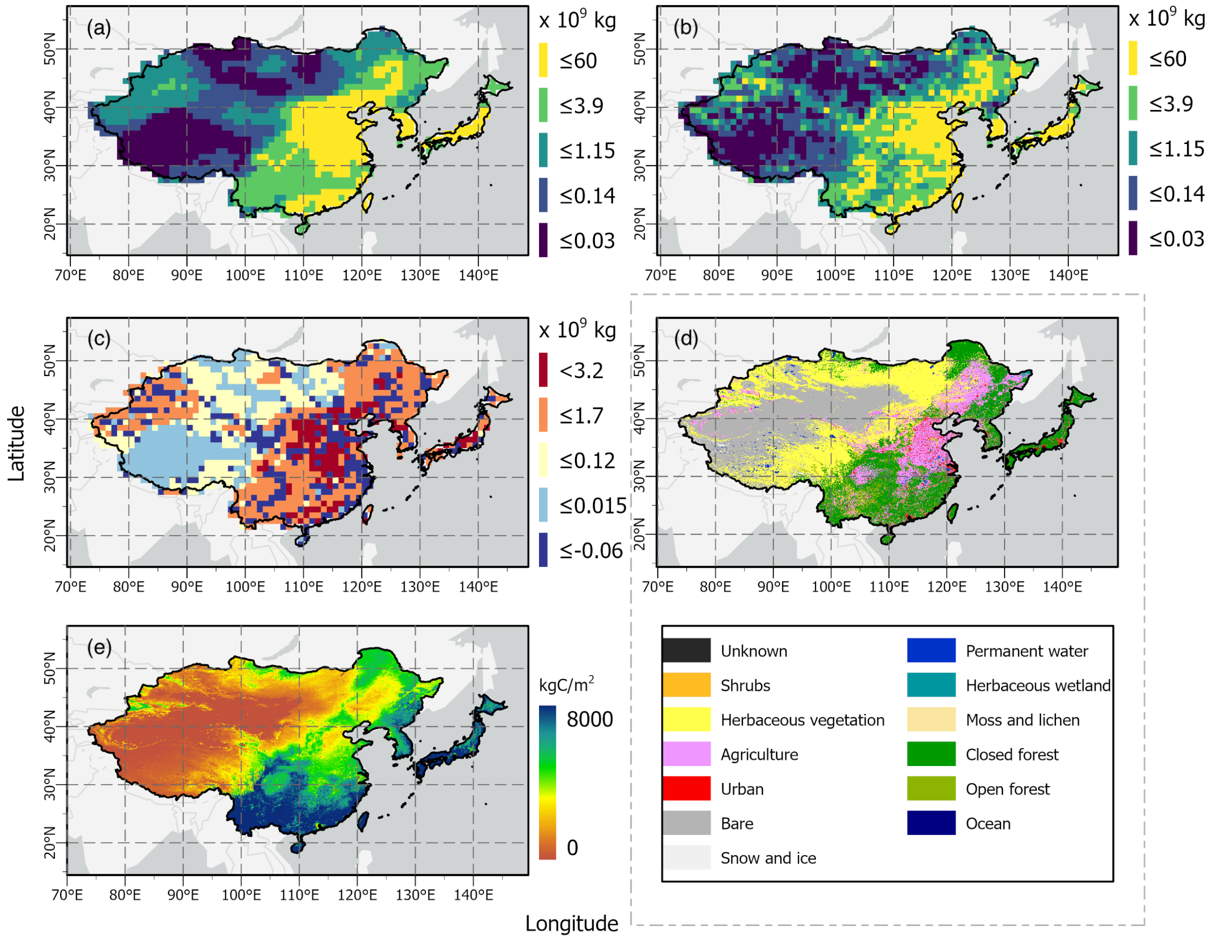
L239: "A previous study…" -> "Yang et al. (2019) …"
Response : Change has been made in the revised manuscript.

L236ff: Figure 6b shows some clear deviation from the linear relationship. Do you have an explanation for this behavior?
Response : This behaviour is due to the reason that XCO2 anomalies show strong correlation with the higher values of ODIAC emissions, however, this correlation is weak with the smaller values of ODIAC inventory.

L259: Please clarify that this approach was suggested already by Yang et al. (2019).
Response : It has been clarified in the Introduction section and this misleading sentence in the Summary and Conclusions section has been removed in the revised manuscript.

L275ff: You could mention some current and future satellites here that could be used to improve the approach.
Response : The suggestion has been improved and the manuscript has been revised:
At L630-631 as, "Joint utilization of the observations from the old and the latest satellites such as OCO-3, GOSAT-2, and TanSAT might reduce the spatiotemporal gaps and uncertainties."

Figs. 3-6: You use blue or bright colors for high emissions and red or dark colors for low emissions, which is somewhat counterintuitive because most people would expect the opposite.
Response : We are thankful to the learned reviewer for constructive comment. We have updated the maps following the colour pallets used by most of the CO2 community, i.e., Perceptually Uniform Sequential color pallete, "Viridis" for emissions and diverging colour pallete "RdYlBu" for maps showing differences.



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