

Atmos. Meas. Tech. Discuss., referee comment RC2 https://doi.org/10.5194/amt-2021-222-RC2, 2021 © Author(s) 2021. This work is distributed under the Creative Commons Attribution 4.0 License.

Comment on amt-2021-222

Anonymous Referee #2

Referee comment on "Neural-network-based estimation of regional-scale anthropogenic CO_2 emissions using an Orbiting Carbon Observatory-2 (OCO-2) dataset over East and West Asia" by Farhan Mustafa et al., Atmos. Meas. Tech. Discuss., https://doi.org/10.5194/amt-2021-222-RC2, 2021

The authors setup a Generalized Regression Neural Network (GRNN) to predict CO₂ emissions over East and West Asia for 2019 using the ODIAC emission inventory (2015-2018) for training their model.

- 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.
- 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.

Specific/technical comments

- L72: Please clarify that this is not a new method.
- L111: life period -> life time

- L116ff: The paragraph is unclear. Please describe more clearly how the XCO2 anomaly is calculated.
- L175: Contributing a large fraction of global oil production does not necessarily imply high CO2 emissions.
- L176: "major fuel consumer" compared to whom?
- L179: "highest" compared to whom? Maybe just write "high" here?
- L201: The term "actual emissions" might refer to "true emissions", which are unknown. I would suggest to use "ODIAC inventory" here.
- 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.
- L214: What does "accounted for 80% of the total grids" mean?
- L215f: When comparing to Yang et al. (2019) it would useful using the same units.
- L239: "A previous study..." -> "Yang et al. (2019) ..."
- L236ff: Figure 6b shows some clear deviation from the linear relationship. Do you have an explanation for this behavior?
- L259: Please clarify that this approach was suggested already by Yang et al. (2019).
- L275ff: You could mention some current and future satellites here that could be used to improve the approach.
- 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.