Discussion: Deep learning applied to CO_2 power plant emissions quantification using simulated satellite images

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In the following, the referees comments are in italics and in blue.

Report 2

We would like to thank the anonymous Referee 2 for her/his technical comments and suggestions on improving the manuscript.

The authors present a method to constrain power plant's CO2 emissions with a deep learning model. The model was trained and tested with simulated CO2 concentrations from SMARTCARB simulations. The analysis demonstrated the superior performance of the deep model to contain the low signal-to-noise ratio issue and is significantly better than the traditional CSF method. The topic is interesting, and the method is helpful for better inversion of CO2 emission in the future. However, there are still issues that need to be addressed before the paper can be published, particularly, an extended comparative analysis is suggested to provide a better understanding of the potential advantages and limitations of this method.

Main comments:

- *Line 42, the authors indicate that the purpose of this study is to address the second and third problems in the CO2 inversions: 2) the low signal-to-noise ratio and 3) the uncertainty in the transport and dispersion processes. I agree that the results demonstrated the remarkable ability to address the low signal-to-noise ratio issue, however, it is unclear how this analysis can address the issue of uncertainty in the transport and dispersion processes because the training and test are both based on SMARTCARB simulations by assuming no systematic errors in simulations.*

  The "uncertainty in transport and dispersion processes" refers to the challenge of accurately estimating emissions from a well-characterised plume. Traditional methods like cross-sectional fluxes are highly sensitive to small errors in wind assessment, which can lead to significant errors in emission estimates. Our Convolutional Neural Network (CNN) approach, however, appears to estimate emissions accurately even when there are potential errors in the wind fields used as inputs. These wind fields are not the same as those used to compute the SMARTCARB simulations, indicating robustness against such uncertainties.

We acknowledge the concern about potential systematic errors in the model, which could bias the training process. For instance, if real-world plumes are systematically different in some way not captured by the model (e.g., thinner due to lack of numerical dispersion), this could introduce bias. However, based on existing literature, we believe that such biases are not significant enough to make the SMARTCARB simulations fundamentally disconnected from reality. This is supported by publications like (Brunner et al., 2023), which suggest that mesoscale plume behaviours are generally well-represented in models.

Furthermore, classic inversion methods which rely on transport models typically compare the observed plume at time t with a model simulation at the same time. Should the model inaccurately represent the plume at this time, this can lead to substantial errors. However, the CNN model implicitly compares the observed plume at time t with a training dataset comprising multiple plume scenarios, thus providing a broader scope to mitigate errors that a single model simulation might introduce.

– *Sections 5.1-5.3: Here the model performance is demonstrated for Lippendorf, Turow, and Boxberg individually. It is suggested to demonstrate the performances of all PPs, including the city of Berlin, and provide a comparative discussion for the model performance over these PPs to investigate the possible consistency and discrepancy, which can provide a better understanding of the potential advantages and limitations of this method.*

  Implementing this suggestion would entail a significant amount of work. Choosing three target power plants represented a balance between adequate performance evaluation and computational efficiency. For each PP, we study three models: one with XCO2, winds; one with XCO2, winds, NO2; one with XCO2, winds, segmentation fields. For each model we need $\sim$10 CNN training runs (as the final model is an ensemble of models). So each study on a new PP requires near 30 CNN training runs. And therefore an extension of our work on the 5 other sources would represent 150 CNN training runs and other costs due to the constitution of the datasets, management of the results, etc. This would imply considerably more work and computation time.

  We knew about these costs and the limits. We therefore carefully selected the target power plants, based on several criteria.

  – a first criterion is that we wanted a variety of power plants, in terms of emissions (one low, one average, and one high emission power plant)
  – a second criterion is that we did not want power plants on the borders of the SMARTCARB domain. As you can see on Figure 1, Patnow or Opole are close to the borders and are subject to border conditions.
  – a third criterion was to not take into account power plants on the extrema in terms of emission rates (Boxberg was considered rather than Jänschwalde because Jänschwalde was the highest emission PP of our dataset and may fall "out-of-training" distribution).

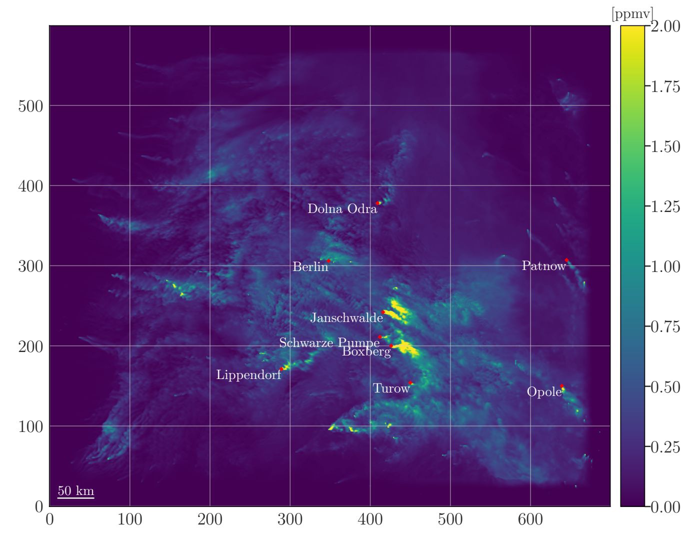

Figure 1. XCO_2 concentration map with the locations of Berlin and each considered PP within the complete SMARTCARB domain. The map consists only of the concentrations stemming from the major anthropogenic sources. Furthermore, to enhance plume visibility, as fluxes of power plants such as Jänschwalde are vastly superior to other fluxes, concentrations exceeding 2 ppmv have been capped at 2 ppmv.

- we also considered images with multiple power plants on the same image (such as Boxberg or Turow)

This discussion has been added in the manuscript (section: "Geographical separation between ...").

Finally, we can expect that the current CNN does not generalise well on Berlin for the following reason: we have no cities (apart from Berlin) in our dataset. A CNN used to predict the emissions of Berlin would be only trained on PPs which have very different plumes from those of a city.

- *Sections 5.1.1, 5.2.1 and 5.3.1 show the model performances, while Section 5.1.2 shows the effect of segmentation and NO2 fields and Section 5.3.2 shows overfitting investigation. The organization of these sections is orderless and needs to be improved.*

We have reorganised the manuscript following your comment. Now section 5.1 is about the model performances, 5.2 is about the two "investigations" (effect of segmentation/NO2 fields, and then overfitting). Thank you for this suggestion.

Technical comments:

- *Abstract: The abbreviations, such as CO2M, CO2 and NO2, should be defined.*

The abbreviations have been defined in the abstract.

– *It could be better to list the first, second and third problems more clearly, for example, 1); 2) and 3), otherwise, readers have to check Lines 34-41 carefully to determine which problems are the second and third.*

Your suggestion has been added to clarify what are the three problems. Thank you.

– *Figure 2: How is the targeted plume obtained?*

In the SMARTCARB dataset, the full CO2 field is made by summing up several components including the background and the major anthropogenic plumes. The targetted plume field is then obtained from the major anthropogenic plumes field after application of a pixel-wise weighting function described in (Dumont Le Brazidec et al., 2022).

– *Line 131: The title of Section 4 should be "Deep learning method for the inversion of XCO2".*

Thanks. We had missed this typo.

– *Table 1: It would be better to have a map to show the locations of these PPs.*

This has been added just next to Table 1. It was indeed missing, thank you.

– *Fig 3: The model input features are the XCO2 image, u-wind, v-wind and additional NO2 field or segregation model output contour. Figure 3 is not fully drawn and may be misinterpreted by the reader as inputting only the four features in the figure.*

It was indeed misleading. We have added the v-wind field in the figure and a note in the title to avoid misinterpretations.

– *Line 159-164: How was the range of these factors determined?*

Plume scaling factors (p and a) were chosen so that enhanced plumes are still in the range of "possible" plumes. a range is bigger than p range because the alternate anthropogenic fluxes field is supposed to be composed of lower plumes than the "major" anthropogenic fluxes field. Similarly, the background modifier b was chosen as the standard deviation of an average background so that enhanced background are still in the range of "possible" backgrounds. We have added a sentence about this in the manuscript.

– *Line 169: What kind of standardization is used?*

We use "Z-score normalization" (scaling the values of a feature to a mean of 0 and a std of 1). It is now precised in the manuscript.

– *It could be better to provide a brief explanation or definition for the kernel density (e.g., Fig. 6).*

The sentence: *"KDE is a non-parametric statistical technique that estimates the probability density function of a continuous random variable by smoothing its observed data points using a kernel function."* has been added in the manuscript. Here KDEs are preferred to histograms solely for visibility reasons.

Thank you very much for all these very clear and helpful remarks. We have added a note of thanks in the acknowledgments section of the paper.

Additionally, we have made available a cleaner version of the code on Zenodo and GitHub.

References

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