Author's Response to Reviewers #1: GHGPSE-Net: A method towards spaceborne automated extraction of greenhouse-gas point sources using point-object-detection deep neural network

Yiguo Pang^{1,2}, Denghui Hu¹, Longfei Tian¹, Shuang Gao¹, and Guohua Liu^{1,2}

¹Innovation Academy for Microsatellites of Chinese Academy of Sciences, Shanghai, China ²University of Chinese Academy of Sciences, Beijing, China

Contact author: Yiguo Pang (pangyiguo21@mails.ucas.ac.cn)
Corresponding author: Guohua Liu (liugh@microsate.com)

October 20, 2025

We sincerely thank the editor and reviewers for the valuable comments and suggestions. Our detailed point-by-point responses to review #1 are given as follows, where the reviewer's comments are in *blue italics* and our responses are in normal text.

Point-by-point Response

The manuscript "GHGPSE-Net: A method towards spaceborne automated extraction of greenhousegas point sources using point-object-detection deep neural network" presents a novel deep learning framework and a large dataset for detecting and quantifying greenhouse gas (GHG) point sources from satellite imagery.

We appreciate your positive feedback on our manuscript. We are glad that you found our deep learning framework and dataset to be novel and valuable.

The authors are the first to introduce the point object detection approach in this domain, which is very valuable and insightful for the GHG point source monitoring community, as it has the potential to integrate and simplify the processing complexity largely. The authors also demonstrate the feasibility of the model by evaluating it on two datasets, including authentic satellite observations.

That is a very precise summary of our work. We are grateful for your recognition of our contribution to GHG point source monitoring.

Though I anticipate more evaluations may be required on the upcoming moderate-resolution carbon monitoring satellites (e.g., CO2M and TanSat-2) to fully explore the potential. This

work marks an important step towards automated GHG point source monitoring and has the potential to make a significant contribution to the GHG remote sensing community.

Thank you for your valuable suggestion. We agree that further evaluations on real satellite data are required. Currently, there are limited available observations from such satellites with moderate resolution specifically designed for GHG monitoring. We are currently testing our methods on more high-resolution satellite data, such as EMIT, and we plan to evaluate our model on the upcoming missions. However, in this study, we focused on developing and validating the methodology using synthetic data and available satellite observations to demonstrate its feasibility. Further evaluations may be out of the scope of this initial study. Future work will continue to fully explore the potential of our approach on both moderate-resolution and high-resolution satellite data.

Minor suggestions:

(1-1) The dataset construction process, including WRF-GHG simulation, XCO2 construction and data augmentation, involves multiple scenarios, especially it seems that the model is trained on the synthetic dataset and evaluated using independent datasets. It may be better clarified using a diagram.

We appreciate your suggestion. We agree that the current description of the dataset construction process is rather complex. We will improve the clarity of this section to better illustrate the workflow. Here is a summary of the dataset construction process:

- WRF-GHG Simulation: We use the WRF-GHG model to simulate greenhouse gas plumes.
- **Pseudo-observation:** We generate pseudo-observations of XCO2 for each instrument scenarios (HGET, HGET-3ppm, UCPI, etc.) based on the WRF-GHG outputs.
- Data augmentation: Based on the pseudo-observations, we apply various data augmentation techniques (e.g., rotation, scaling, noise addition) to enhance the diversity of the dataset. The data augmentation is performed separately for each instrument scenario. Although the augmentation processes can be applied in the training process, we perform them beforehand for simplicity and efficiency. There are 3,144 snapshots generated from WRF-GHG simulations and there are 24,000 samples for each instrument scenario after augmentation. If not specifically mentioned, the data augmentation is applied to all the datasets.

(1-2) The authors summarized GHGPSE-Net in Figure 3. However, the overall methodology, including simulation, simulation evaluation, training dataset preparation, and deep learning evaluation, is quite complex and somewhat difficult to follow. The authors may consider summarizing the entire methodology in Section 2.

We appreciate the detailed and constructive suggestion. We will consider better summarizing the entire methodology in Section 2. The construction of the datasets is described earlier in our response to comment (1-1). Here, we summarize the evaluation process as follows:

Experiment	Trainning	Evaluation	GKF?	σ [km]
Sect. 3.2 (Fig. 6)	HGET	HGET	•	0.25
	HGET	HGET	•	0.50
	HGET	HGET	•	0.75
	HGET	HGET	•	1.50
	HGET	HGET		0.25
	HGET	HGET		0.50
	HGET	HGET		0.75
	HGET	HGET		1.50
Sect. 3.2 (Fig. 7)	HGET	HGET	•	0.25
	HGET	HGET	•	0.50
	HGET	HGET	•	0.75
	HGET	HGET	•	1.50
	HGET	HGET	•	3.00
	HGET	HGET		0.25
	HGET	HGET		0.50
	HGET	HGET		0.75
	HGET	HGET		1.50
	HGET	HGET		3.00
Sect. 3.3 (Tab. 3)	HGET	HGET	•	0.50
	HGET-3ppm	HGET-3ppm	•	0.50
	UCPI	UCPI	•	2.00
	UCPI-3ppm	UCPI-3ppm	•	2.00
	$OCO-3^1$	OCO-3	•	2.25
Sect. 3.4 (paragraph 1)	HGET	HGET	•	0.50
	HGET (no-aug)	HGET	•	0.50
Sect. 3.4 (SMARTCARB)	UCPI-0.7ppm	SMARTCARB ²	•	2.00
Sect. 3.4 (OCO-3)	OCO-3	$OCO-3 (obs)^3$	•	2.25

¹ It's worth noting that the OCO-3 dataset is constructed based on synthetic data.

Table 1: Summary of the experiment configurations conducted in the "Results" secion.

(1-3) In some related GHG plume detection studies, deep learning models usually require wind as an input. Does GHGPSE-Net not require the 2D wind field as input?

Currently, GHGPSE-Net does not require the 2D wind field as input and performs source extraction solely using XCO2 observations. Indeed, additional input to the model, such as wind field, NO_2 concentration, will enhance the model performance, as demonstrated by Kuhlmann et al. [2019a], Kuhlmann et al. [2020] and Dumont Le Brazidec et al. [2024]. Additional input, such as cloud cover, surface type and land-ocean mask, may be helpful to perform quality control. However, the inclusion of additional input will increase the model complexity and make the analysis more difficult. In this initial study, we focus on developing a basic framework for GHG point source extraction using only XCO2 observations. Future work will explore the

² The SMARTCARB dataset is constructed based on Kuhlmann et al. [2019b].

³ The OCO-3 (obs) dataset is constructed based on real OCO-3 satellite observations [OCO-2/OCO-3 Science Team et al., 2022].

inclusion of additional inputs and improve its real-world applications. We will further clarify this point in the "Discussions and Conclusion" section.

(1-4) According to the result (e.g., Table 3), it seems the "2 km \times 2 km" in L10 should be 0.5 km \times 0.5km.

Thank you for pointing out this inconsistency. You are correct that the case referred in the abstract should be HGET, which is $0.5 \, \text{km} \times 0.5 \, \text{km}$. We will correct this in the revision.

Technical comments: (2-1) Typo in L59 and L137.

Thank you for your careful review. It should be "further" in L59 and L137 should be "... the concentration map can be expressed as: ...".

(2-2) It should be "mean squared error" instead of "mean square error" in L10, L208, and L223.

Thank you for your suggestion and we will make the correction in the revision.

References

References

Joffrey Dumont Le Brazidec, Pierre Vanderbecken, Alban Farchi, Grégoire Broquet, Gerrit Kuhlmann, and Marc Bocquet. Deep learning applied to CO₂ power plant emissions quantification using simulated satellite images. *Geoscientific Model Development*, 17(5):1995–2014, March 2024. ISSN 1991-959X. doi: 10.5194/gmd-17-1995-2024.

Gerrit Kuhlmann, Grégoire Broquet, Julia Marshall, Valentin Clément, Armin Löscher, Yasjka Meijer, and Dominik Brunner. Detectability of CO₂ emission plumes of cities and power plants with the Copernicus Anthropogenic CO₂ Monitoring (CO2M) mission. *Atmospheric Measurement Techniques*, 12(12):6695–6719, December 2019a. ISSN 1867-1381. doi: 10. 5194/amt-12-6695-2019.

Gerrit Kuhlmann, Valentin Clément, Julia Marshall, Oliver Fuhrer, Grégoire Broquet, Christina Schnadt-Poberaj, Armin Löscher, Yasjka Meijer, and Dominik Brunner. SMARTCARB – Use of satellite measurements of auxiliary reactive trace gases for fossil fuel carbon dioxide emission estimation. Technical report, Zenodo, January 2019b.

Gerrit Kuhlmann, Dominik Brunner, Gregoire Broquet, and Yasjka Meijer. Quantifying CO2 emissions of a city with the Copernicus Anthropogenic CO2 Monitoring satellite mission. *Atmospheric Measurement Techniques*, 13(12):6733–6754, December 2020. ISSN 1867-1381. doi: 10.5194/amt-13-6733-2020.

OCO-2/OCO-3 Science Team, Abhishek Chatterjee, and Vivienne Payne. OCO-3 Level 2 biascorrected XCO2 and other select fields from the full-physics retrieval aggregated as daily files, Retrospective processing v10.4r, 2022.