

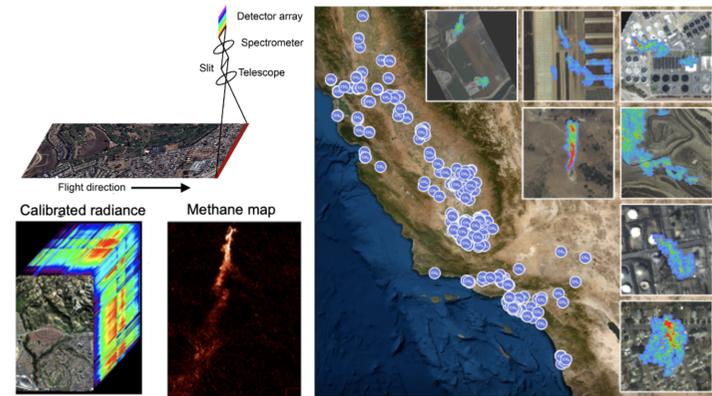
# Improving Imaging Spectrometer Methane Plume Detection with Large Eddy Simulations

Arjun Ashok Rao<sup>1</sup> Steffen Mauceri<sup>1</sup> Andrew K. Thorpe<sup>1</sup> Jake H. Lee<sup>1</sup> Brian D. Bue<sup>1</sup> Siraput Jongaramrungruang<sup>2</sup> Riley M. Duren<sup>4,3,1</sup>

<sup>1</sup>Jet Propulsion Laboratory, California Institute of Technology <sup>2</sup>California Institute of Technology <sup>3</sup>University of Arizona <sup>4</sup>CarbonMapper.org



## Background

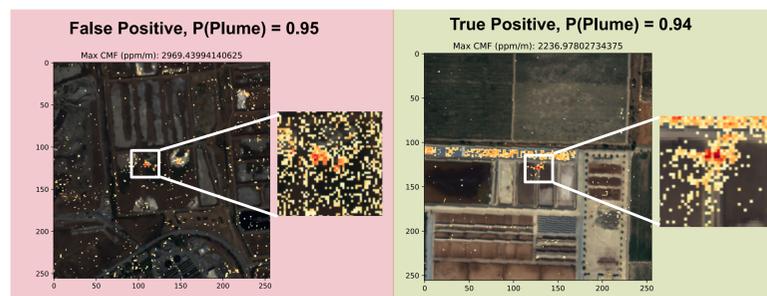


**Figure 1.** (Left) AVIRIS-NG 2D radiance cube is passed through a matched filter CH<sub>4</sub> retrieval to produce a CH<sub>4</sub> map. (Right) The California Methane Survey identified that 10% of point-source 'super-emitters' are responsible for 60% of emissions in California.

- Methane is the second most important anthropogenic greenhouse gas.
- Mitigation requires accurate quantification of stochastic and intermittent point-source emitters [1]

## Problem Description

- Current efforts to quantify emissions from point-source emitters at the space-borne level lack sufficient spatial resolution; In-situ measurements are sparse. This has led to **ambiguous regional budgets** [2]
- Airborne measurements with AVIRIS-NG and GAO maps CH<sub>4</sub> plumes at a high spatial resolution and allows **source attribution + emission quantification** (Figure 3).
- Convolutional Neural Networks (CNNs) can efficiently learn spatial information from hyperspectral imagery when trained to classify CH<sub>4</sub> plumes from AVIRIS-NG airborne data.
- **Problem:** Current CNNs trained on a plume-classification task have a high false-positivity rate and poorly generalize to new campaigns and ground terrain.



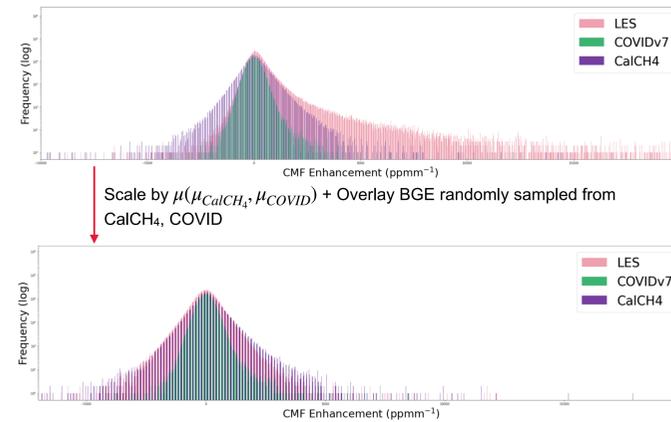
## Problem

Lack of High Quality Training Data; Availability of Diverse Plumes Restricted to Field-Collected Datasets

## Research Question

Can synthetic CH<sub>4</sub> plumes generated with **Large Eddy Simulations (LES)** [3] improve **robustness** of CNNs to false-positive plume detections and create **cross-campaign generalizable** classifiers?

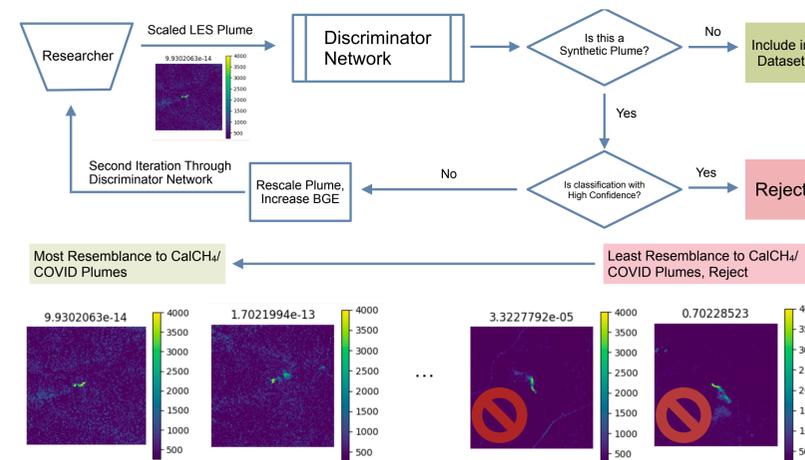
## Methodology – Constraining Enhancement Distributions



**Figure 2.** Long-Tailed, high enhancement distribution of Synthetic LES plumes constrained by mean-scaling and overlaying Background Enhancements randomly sampled from California COVID Campaign (2020), and Cal-CH<sub>4</sub> Campaign (2019).

Synthetic LES plumes had a significantly higher mean enhancement with a long tailed enhancement distribution. CNNs easily distinguish synthetic plumes from real data captured in the California COVID campaign (2020), and the Cal-Methane Campaign (2019).

## Methodology – Synthetic Data Filtering as a 2-Player Adversarial Game



**Figure 3.** (Top) Filtering for realistic plumes is reformulated as a 2-player adversarial game. Scaled LES plumes are posed to a discriminator network that classifies the plume as **synthetic** or **real**. LES Plumes successfully classified as a real-campaign plume are included in training datasets, while LES-identified plumes are re-scaled/ rejected based on a CNN confidence output. (Bottom) Selected LES plumes are ranked according to a 'realism' metric; Top *N* most realistic plumes are selected for training.

## References

[1] R. M. Duren, A. K. Thorpe, K. T. Foster, T. Rafiq, F. M. Hopkins, V. Yadav, B. D. Bue, D. R. Thompson, S. Conley, N. K. Colombi *et al.*, "California's methane super-emitters," *Nature*, vol. 575, no. 7781, pp. 180–184, 2019.

[2] C. Frankenberg, A. K. Thorpe, D. R. Thompson, G. Hulley, E. A. Kort, N. Vance, J. Borchardt, T. Krings, K. Gerilowski, C. Sweeney *et al.*, "Airborne methane remote measurements reveal heavy-tail flux distribution in four corners region," *Proceedings of the national academy of sciences*, vol. 113, no. 35, pp. 9734–9739, 2016.

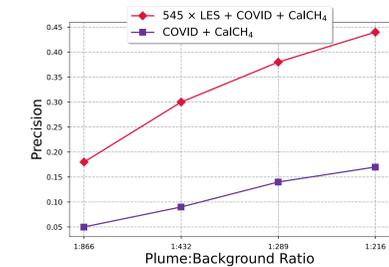
[3] S. Jongaramrungruang, C. Frankenberg, G. Matheou, A. K. Thorpe, D. R. Thompson, L. Kuai, and R. M. Duren, "Towards accurate methane point-source quantification from high-resolution 2-d plume imagery," *Atmospheric Measurement Techniques*, vol. 12, no. 12, pp. 6667–6681, 2019.

## Results

### Multi-Campaign Tests

To simulate flightline-level test-time imbalance, we sample a total of 60 plumes evenly distributed over 3 campaigns and append 13000 background tiles, creating a plume:background ratio of 1:217.

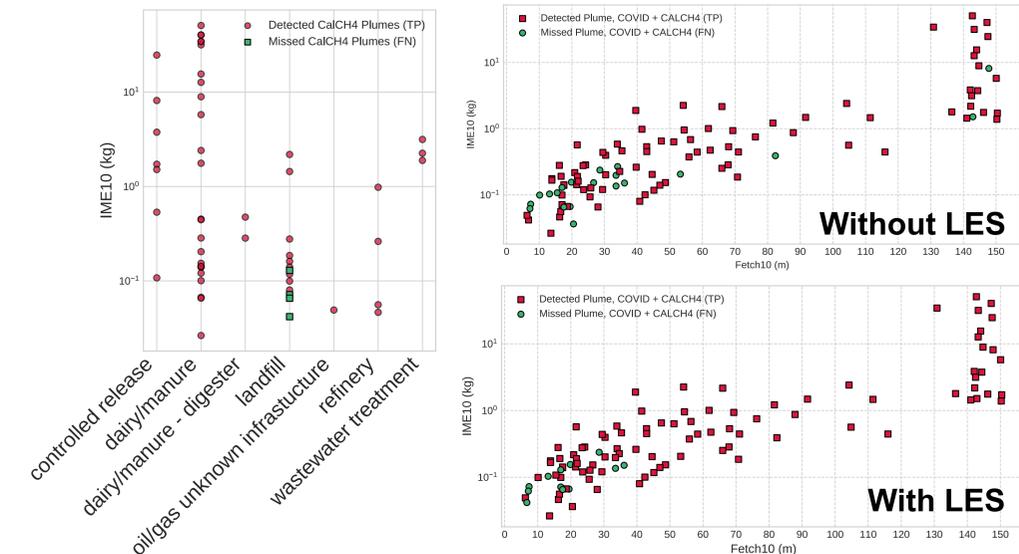
Train Dataset	Test dataset	Precision	Recall	F1
LES + COVID + CalCH <sub>4</sub>	Imbal	0.32	0.90	0.47
COVID + CalCH <sub>4</sub>	Imbal	0.20	0.85	0.34



**Figure 4.** Plume classification precision vs Dataset Imbalance (Higher = More Realistic)

LES-aided CNNs exhibit a lower false-positivity rate when trained on realistic datasets spanning multiple campaigns.

## Analysis



**Figure 5.** Missed Plume Analysis: (Left) Source-Type vs Integrated Methane Enhancement (IME) for LES-aided CNNs. (Right) Fetch-IME plot for LES (Bottom) and non-LES-aided (Top) CNNs.

## Conclusion

- LES-trained CNNs show improved precision and recall performances and classify plumed previously missed by traditional models.
- LES plumes show significant precision and recall improvements with **large class imbalance**, outperform real-world plume datasets.
- However, LES-trained CNNs predict small, weak plumes as background with near-certainty.
- LES plumes are not equipped to replace weak, diffused plume data such as those found near landfills (Figure 5).