Improving Imaging Spectrometer Methane Plume Detection with Large Eddy Simulations

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Jet Propulsion Laboratory
California Institute of Technology

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Background and Motivation

1. Methane second most important anthropogenic greenhouse gas

2. Mitigation requires accurate quantification of stochastic and intermittent point-source emitters (Duren et. al., 2019)

Facility Level Observations from Space: Uncertain

In-situ Measurements: Sparse

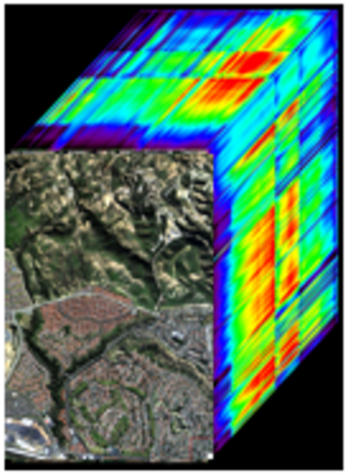
Consequence:

- Strength and Distribution of CH4 emissions poorly constrained
- Ambiguous regional budgets
- (Frankenberg et. al., 2016, Duren et. al., 2019) show strong emitters dominate regional budgets.

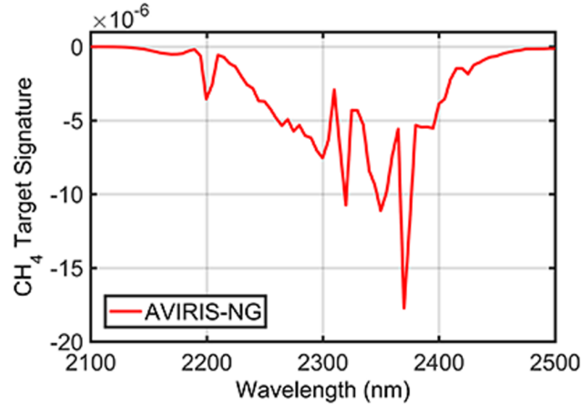
Solution: Airborne remote measurements with AVIRIS-NG, GAO at 1-5m ground resolution = rapid and repeated assessment of large areas.

AVIRIS-NG & GAO for CH_4 mapping

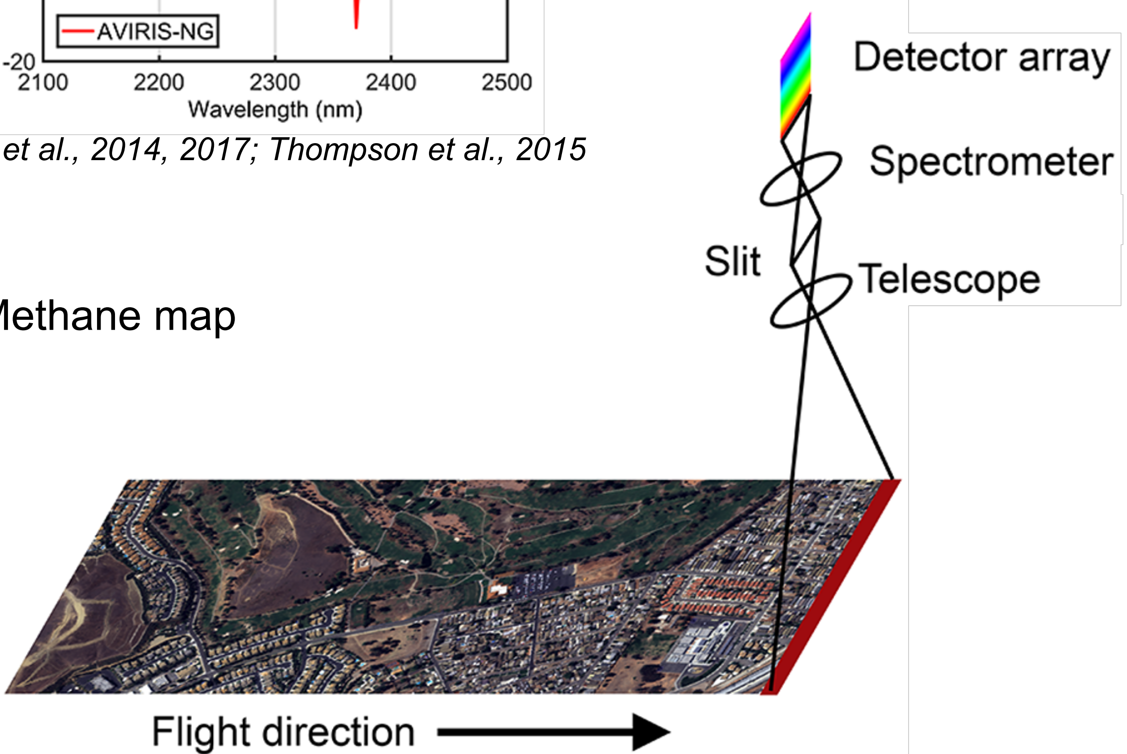
Calibrated radiance



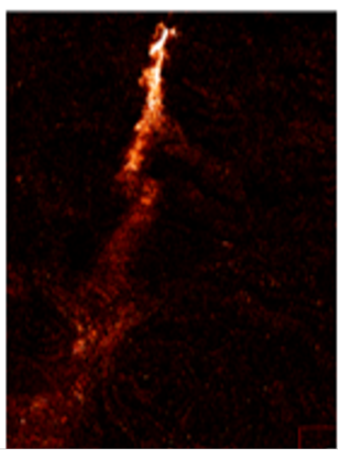
CH_4 retrieval



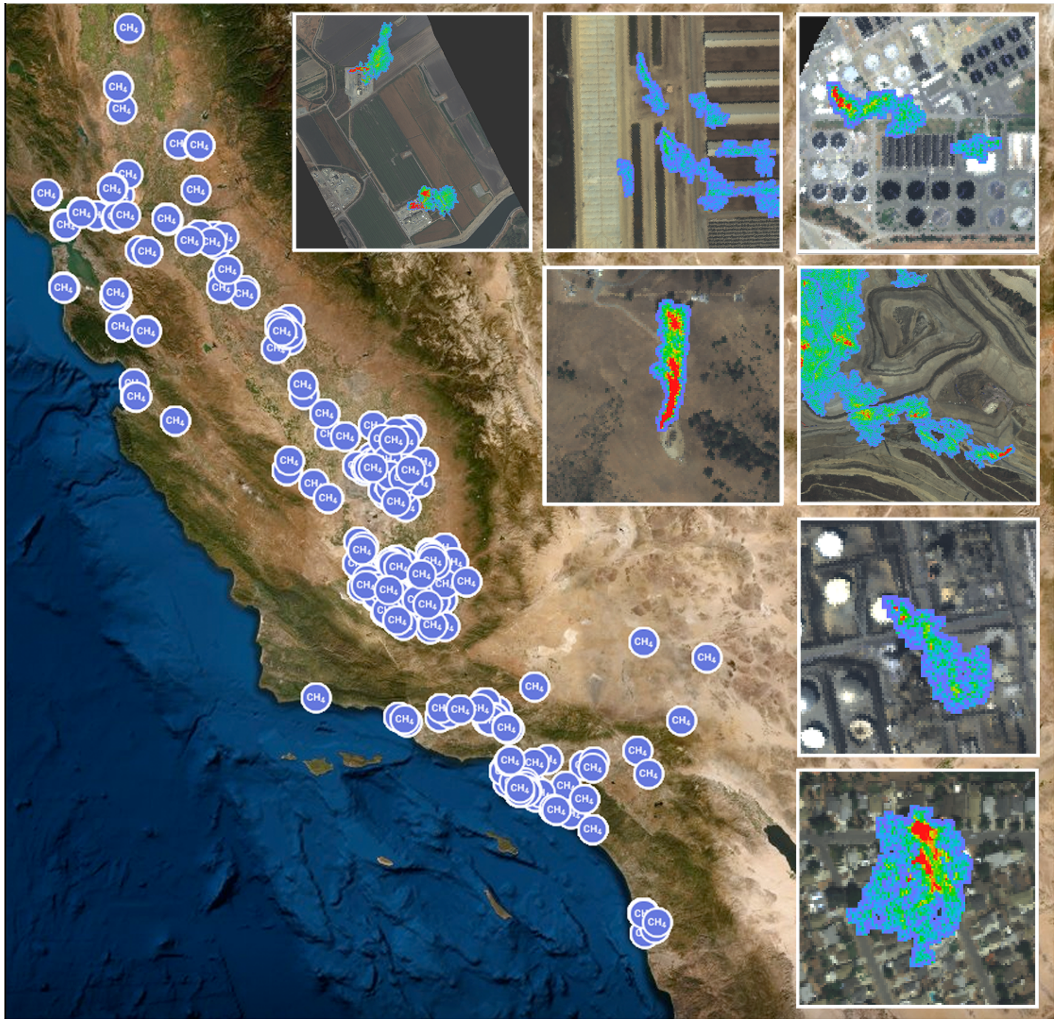
Thorpe et al., 2014, 2017; Thompson et al., 2015



Column-Matched Filter (CMF) Methane map



Duren et. al., 2019: 60% emissions from 10% point-source Emitters



Duren, R. M., Thorpe, A. K., Foster, K. T., Rafiq, T., Hopkins, F. M., Yadav, V., ... & Miller, C. E. (2019). California's methane super-emitters. Nature, 575(7781), 180-184.

Problem Description

Current CNNs:

Low precision;

Poorly generalize to unseen campaigns.

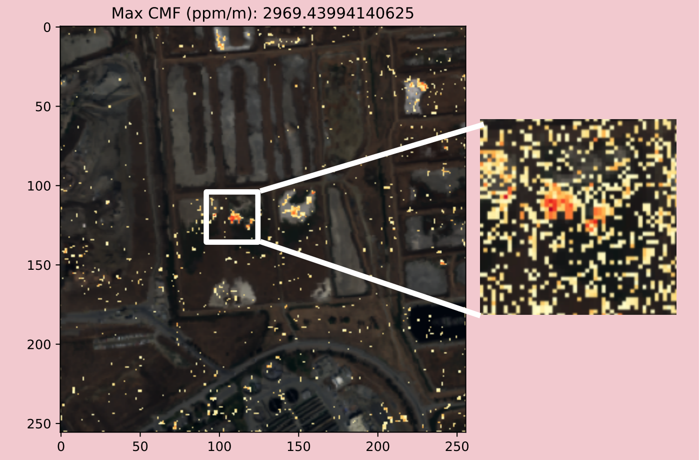
Why?

Lack of high quality training data

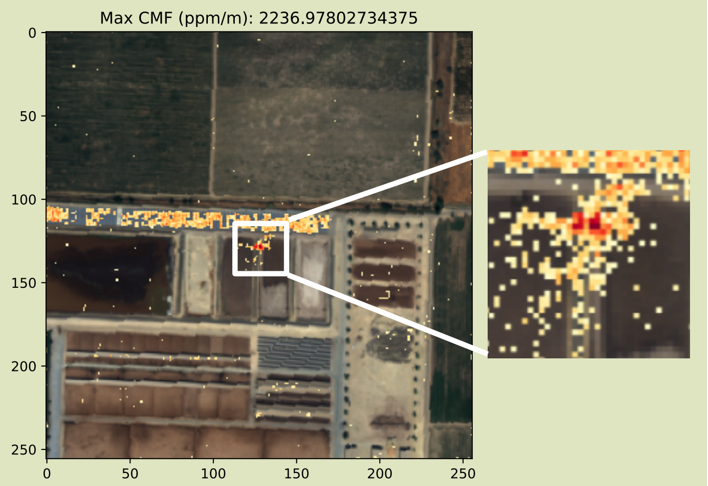
Large class imbalance observed during operational Deployment

Plume data availability restricted by field data

False Positive, P(Plume) = 0.95

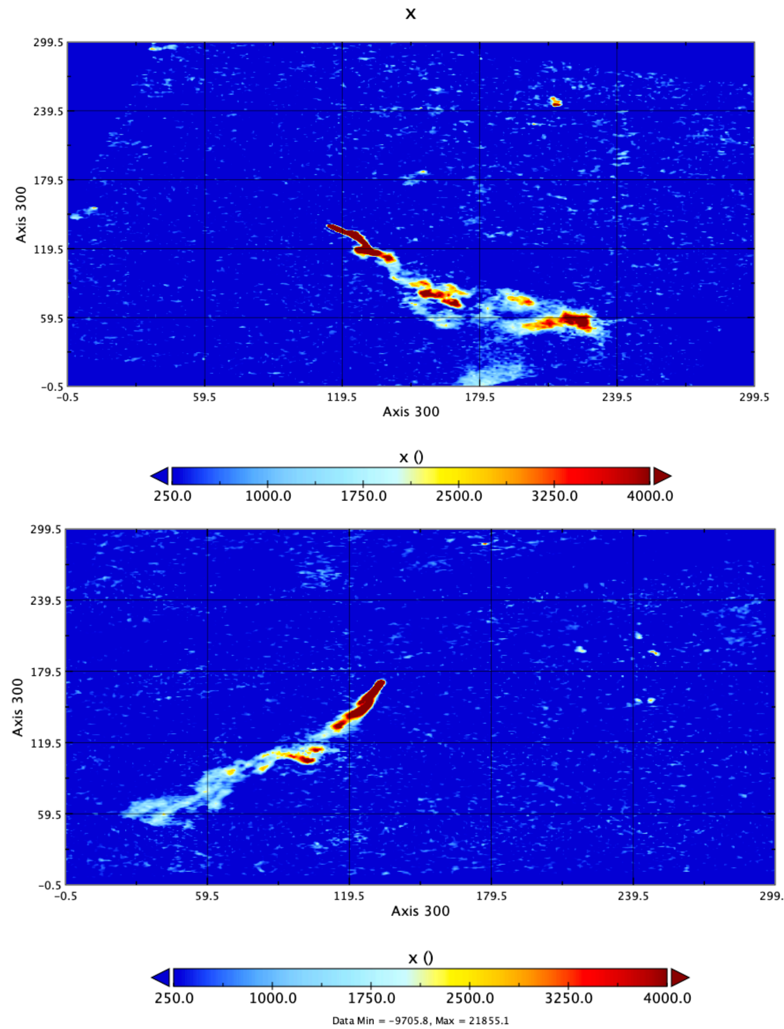


True Positive, P(Plume) = 0.94



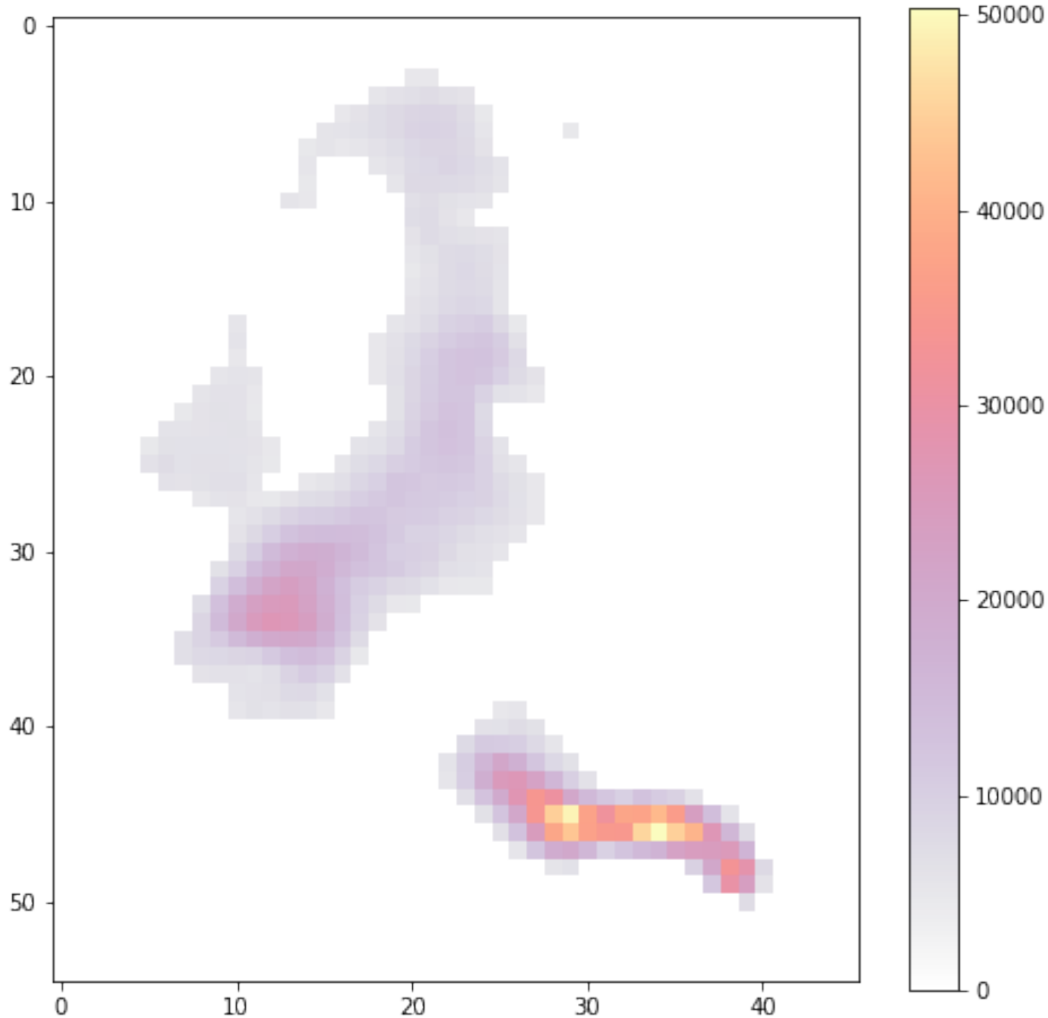
Research Question

Can synthetic CH_4 plumes generated with Large Eddy Simulations (LES) improve robustness of CNNs to false-positive plume detections and create cross-campaign generalizable classifiers?



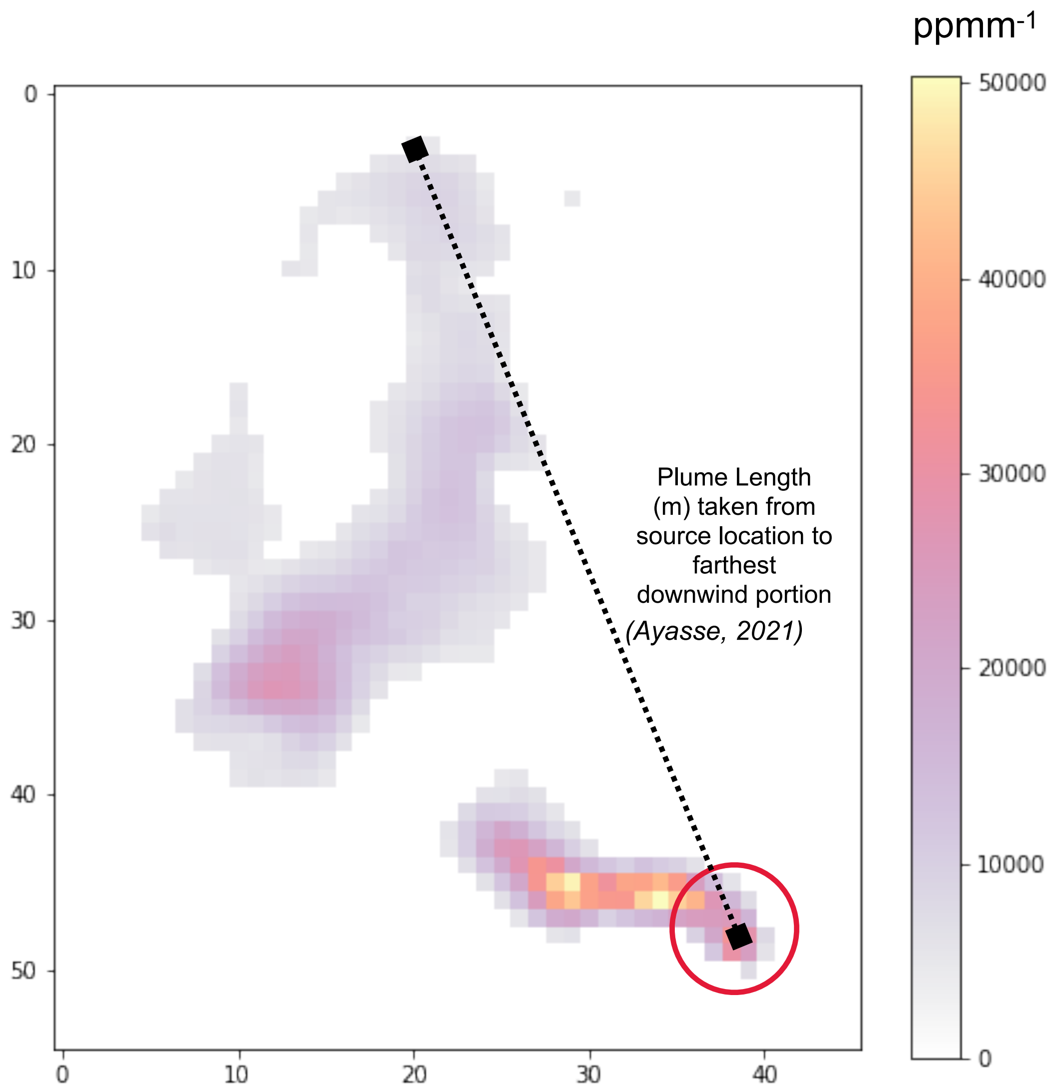
Source: LES

Preliminaries: Defining Plume Morphology



Source: LES (Jongaramrungruang et al., 2019)

Preliminaries: Ideal Plume Morphology

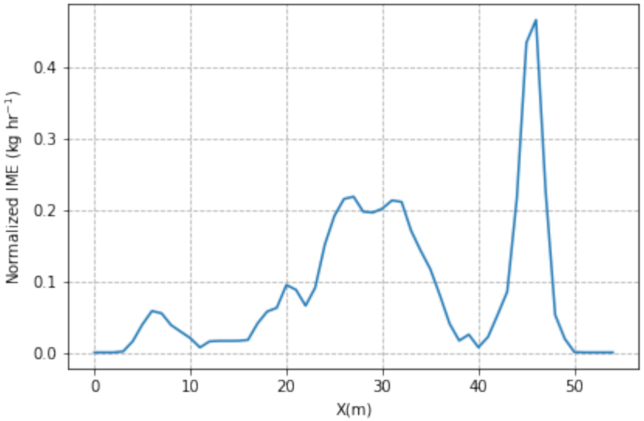


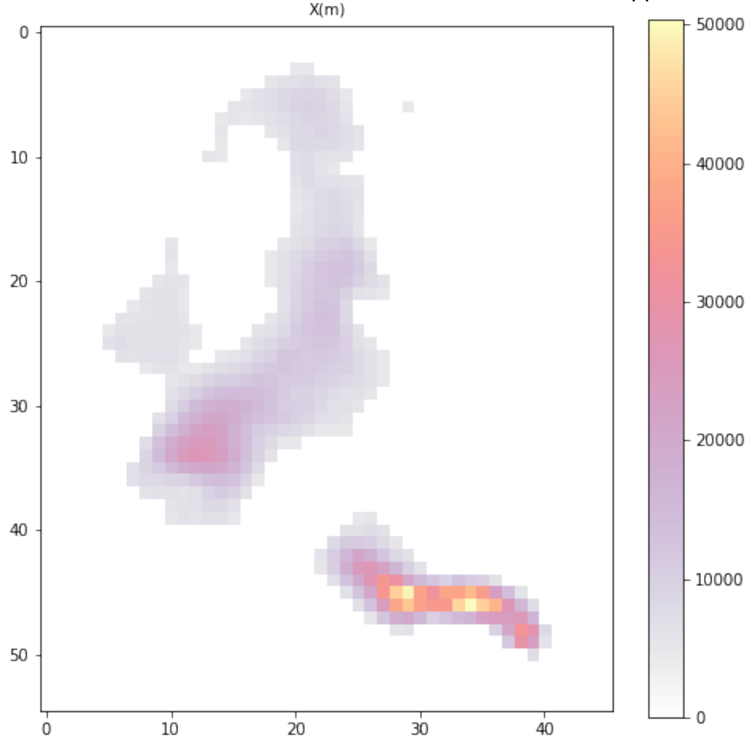
Temporally variable downwind portion; Dependent on geostrophic wind speed

Source Location

Source: LES (Jongaramrungruang et al., 2019)

Preliminaries: Ideal Plume Morphology





Source: *LES (Jongaramrungruang et al., 2019)*

Integrated Mass Enhancement

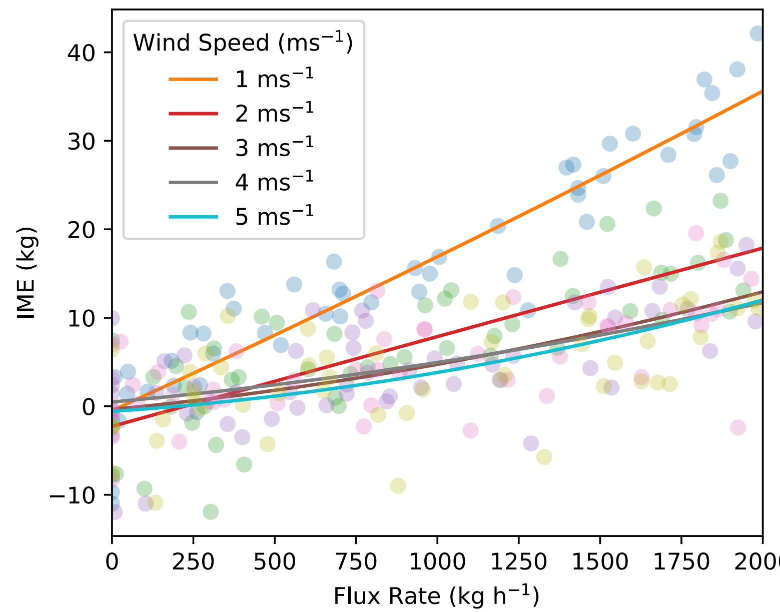
$$IME = k \cdot \sum_{i=1}^{N} CMF_i \times A_i$$

CH_4 → Mass Units

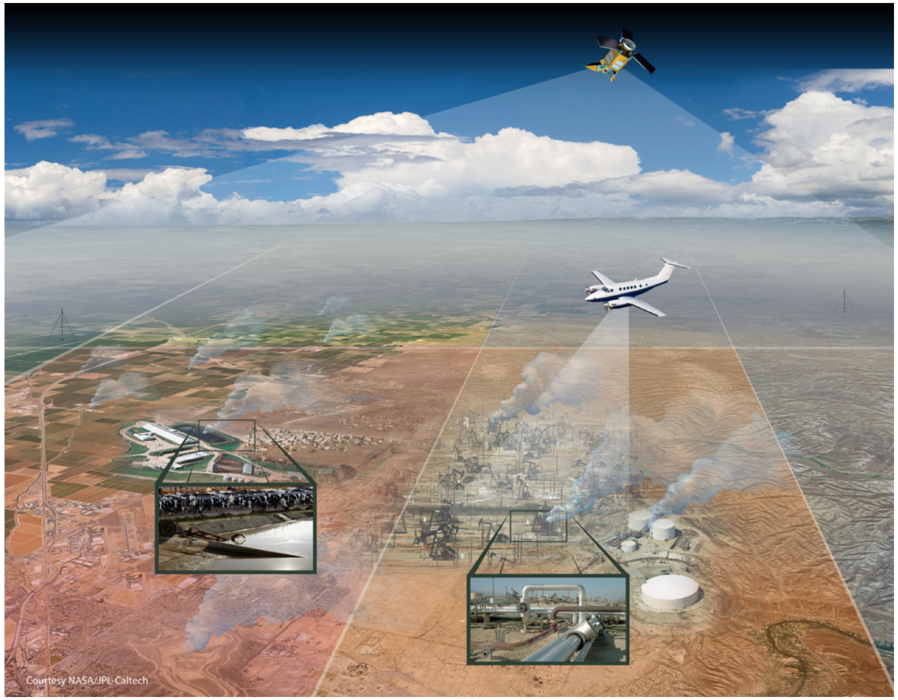
CH_4 2-D Enhancement

Plume Surface Area

IME is a good proxy for source emission rate

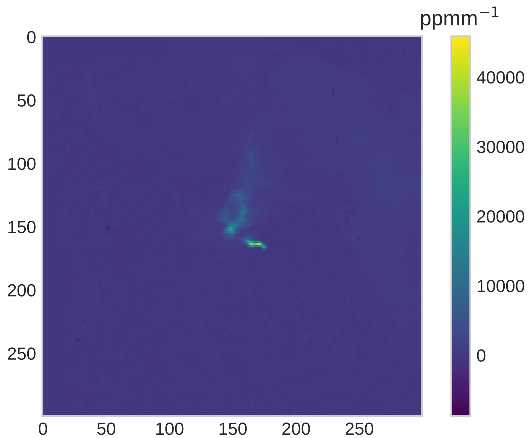


Contents



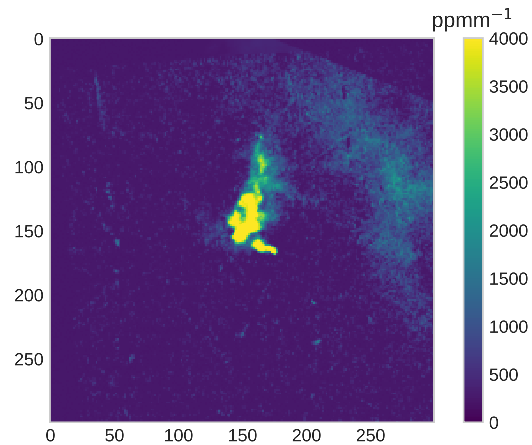
Directly Using LES Deteriorates Performance

LES flux rates linearly scaled from an LES run at flux = 20 kg/hr



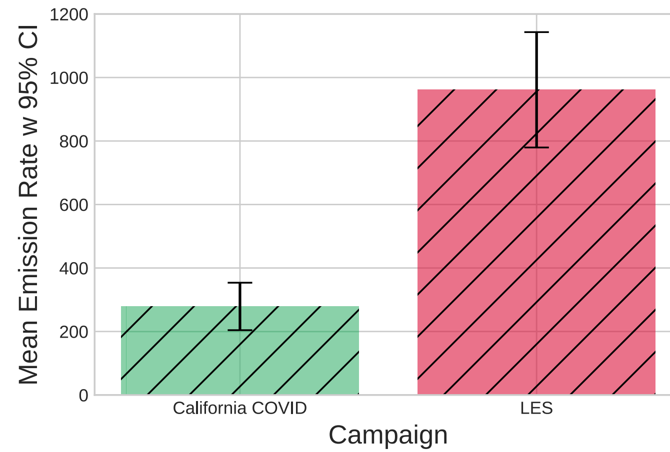
Original LES Plume

Plume Pixels = 138



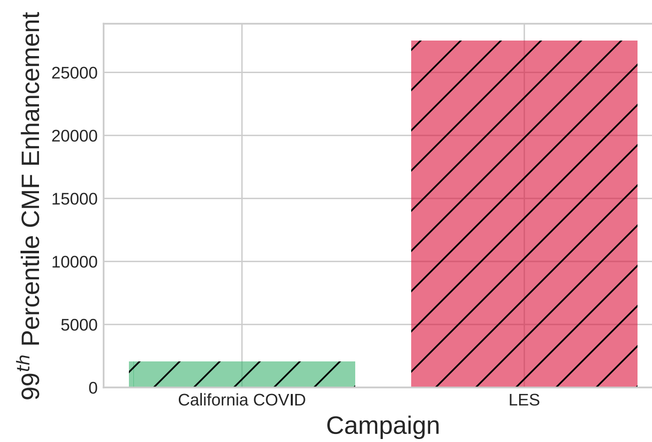
Clip CMF $\in [250{,}4000]$

 # Plume Pixels = 1003

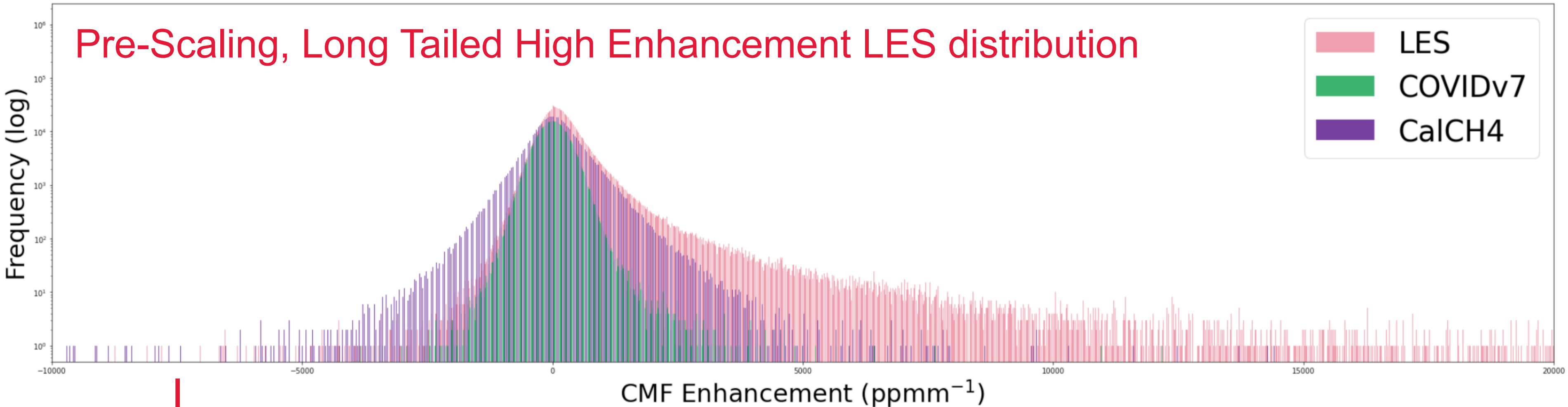


Clipped LES Plumes have:

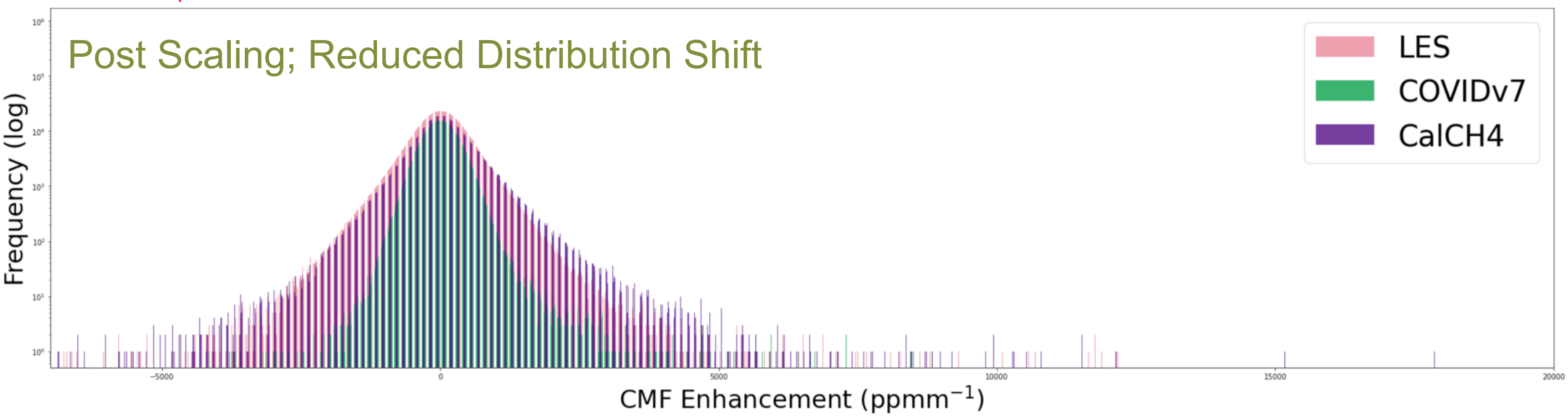
1) Large Plume Enhancements with Low BG Enhancements
2) No BG CMF artifacts (Ideal, smooth BG)
3) Large Surface area



Constraining Enhancement Differences



Scale by $\mu(\mu_{CalCH_4}, \mu_{COVID})$ + Overlay BGE randomly sampled from $CalCH_4$, COVID



Discriminator Network

Formulating Plume Filtering as a 2-Player Adversarial Game

Question: Can a trained Convolutional Neural Network distinguish Synthetic (LES) from Real-world (CalCH_4, COVID) Plumes?

Experiment:

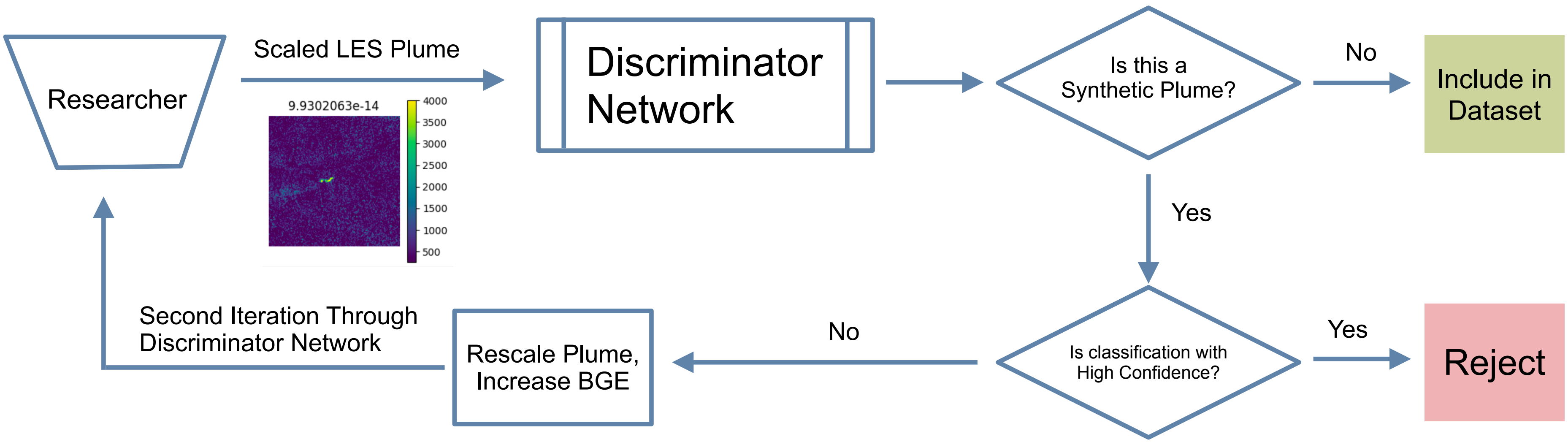
Discriminator Train Dataset

Positive Class (1)	***Negative Class (0)***
CalCH_4 Plumes + COVID Plumes + GAO Permian et al Plumes	Unscaled LES Plumes

Discriminator Test Dataset: Scaled LES Plumes

Discriminator Network

Formulating Plume Filtering as a 2-Player Adversarial Game



Test Dataset	Recall	Precision	F1
Plume, LES, Pre-Transform	1.00	0.94	0.97
Plume, LES, Post-Transform	0.10	0.75	0.21

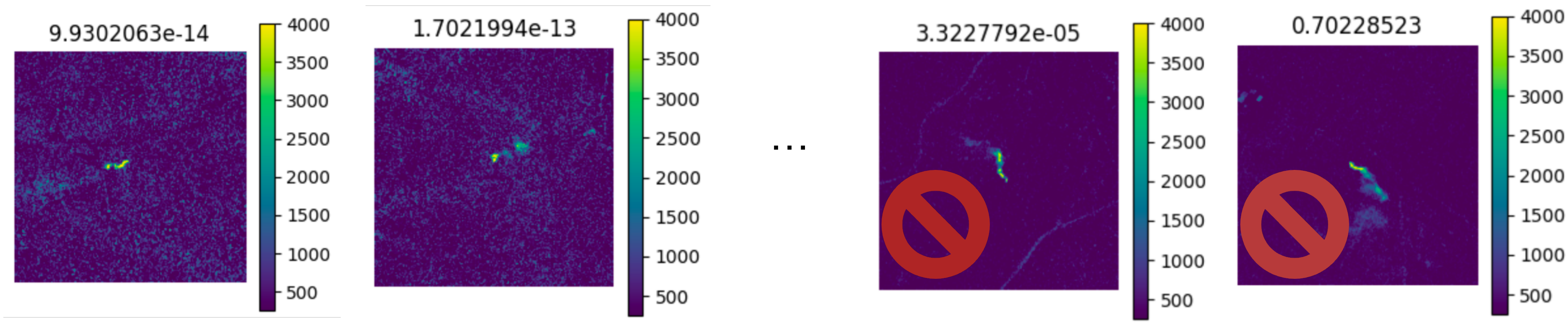
Note: Lower Precision → Scaled LES Plumes challenging to distinguish

Result: We now have a curated subset of high-quality LES plumes that closely resemble plumes from CalCH4 and COVID

Formulating Plume Filtering as a 2-Player Adversarial Game

Ranking LES Plumes by a ‘realism’ Metric

Most Resemblance to $CalCH_4$/ COVID Plumes ← Least Resemblance to $CalCH_4$/ COVID Plumes, Reject



Result: We now have a curated subset of high-quality LES plumes that closely resemble plumes from CalCH4 and COVID

Model and Training

Datasets:

(545 LES) + 179 COVID + 479 $CalCH_4$

+ ~7000 BG Tiles randomly sampled from COVID, $CalCH_4$

179 COVID + 479 $CalCH_4$

+ ~4000 BG Tiles randomly sampled from COVID, $CalCH_4$

Model: LES-CNN For 50 epochs @ LR = 10^{-2}, Decay by $\times 10$ on epochs 35, 45

Optimizer: SGD with Sharpness Aware Minimizer/ Stochastic Weight Perturbation (Foret et al., 2021)

Standard Plume Classification Loss

$$L_{plume} = \min_\theta \sum_{i=1}^{n} loss(x_i, \text{label}_i, \theta)$$

Sharpness-Aware Loss

$$min_\theta[max_{||\epsilon|| \leq \rho} L_{plume}(\theta + \epsilon)] + \lambda ||\theta||^2$$

Results

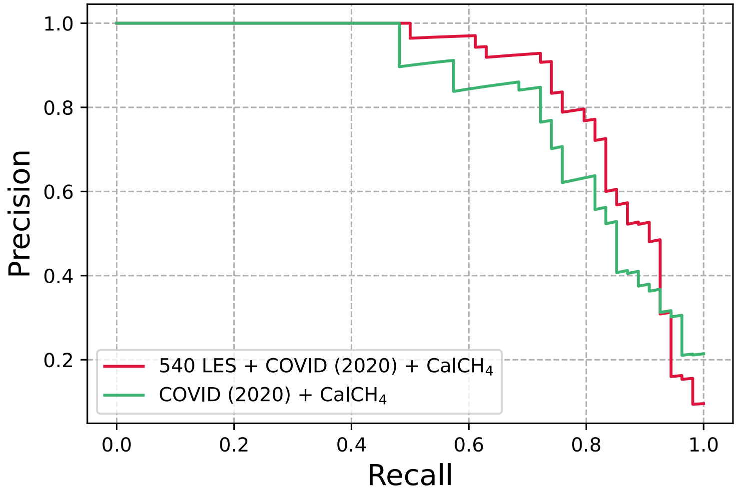
Single-Campaign Tests

Train Dataset	Test dataset	Precision	Recall	F1
LES + COVID + $CalCH_4$	COVIDv8 Test	0.80	0.85	0.82
COVID + $CalCH_4$	COVIDv8 Test	0.80	0.71	0.76
LES+ COVID + $CalCH_4$	$CalCH_4$ v8, Test	0.75	0.82	0.78
COVID + $CalCH_4$	$CalCH_4$ v8, Test	0.60	0.83	0.69

LES shows performance improvements, BUT

Plume:Background ratio of:

COVIDv8 Test = **1:26** $CalCH_4$v8 Test = **1:17**



Distant from Observed flight line ratios!

High Plume:Background Ratio ⟶ Unrealistic Result

Tile Sampling (Top)

Collect Representative sample of pos / background tiles.

Prevents class imbalanced-training

Sliding Window (Bottom)

Large number of Background tiles sampled

Operational Method!

An Example:

ang20180927t184652 (CalCH_4, 2018)

23 BG Tiles, 1 Plume Tile with Current Sampling Methodology

~3600 Tiles Sampled with 20-pixel-strided sliding window of size (256×256).

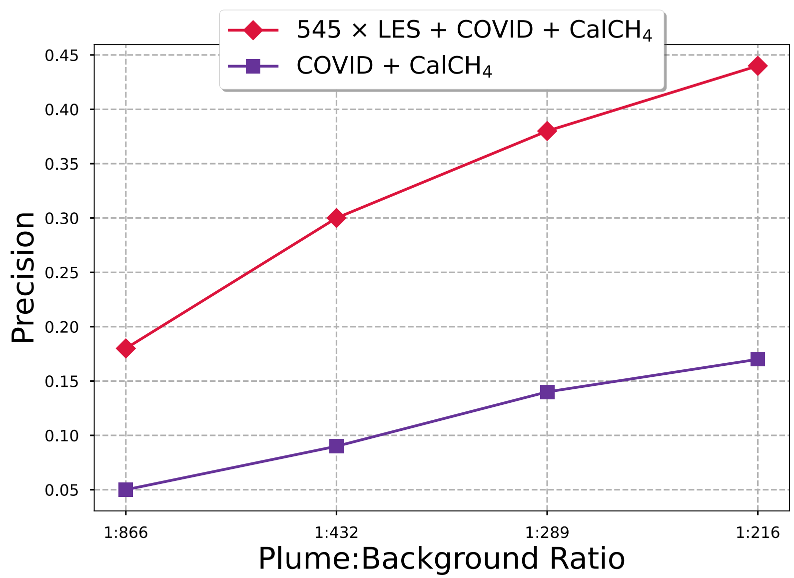
Results

Multi-Campaign, Imbalanced Test

Imbal

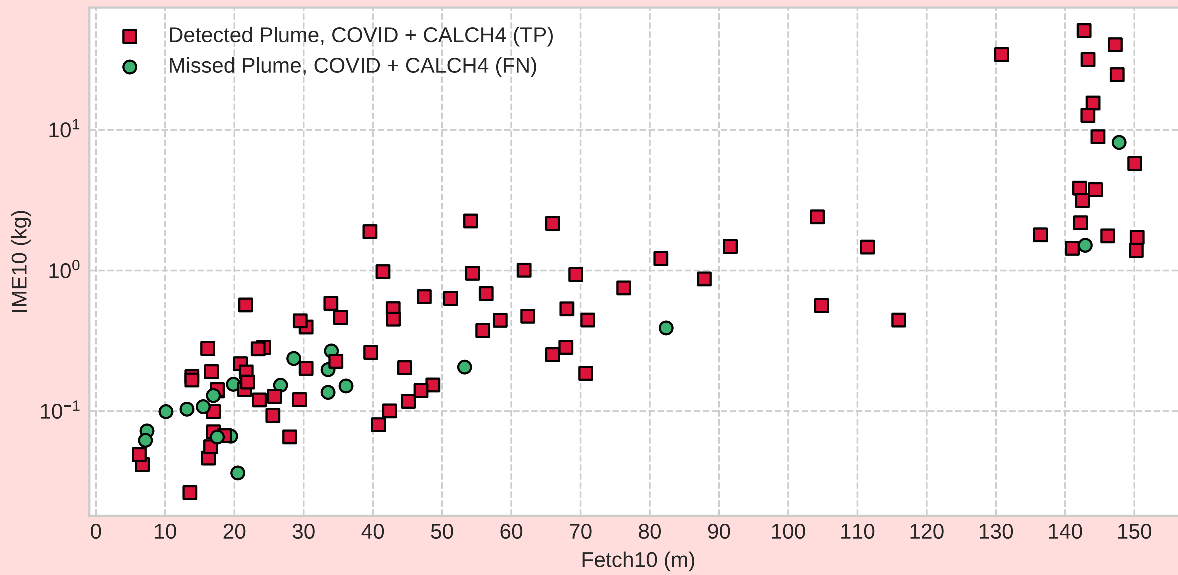
20 COVIDv8 Test Plumes
+ 20 $CalCH_4$v8 Test Plumes
+ 20 Permian et al. Test Plumes
+ 12,986 background tiles from COVIDv8, $CalCH_4$,Permian et al.

Train Dataset	Test dataset	Precision	Recall	F1
LES + COVID + $CalCH_4$	Imbal	0.32	0.90	0.47
COVID + $CalCH_4$	Imbal	0.20	0.85	0.34

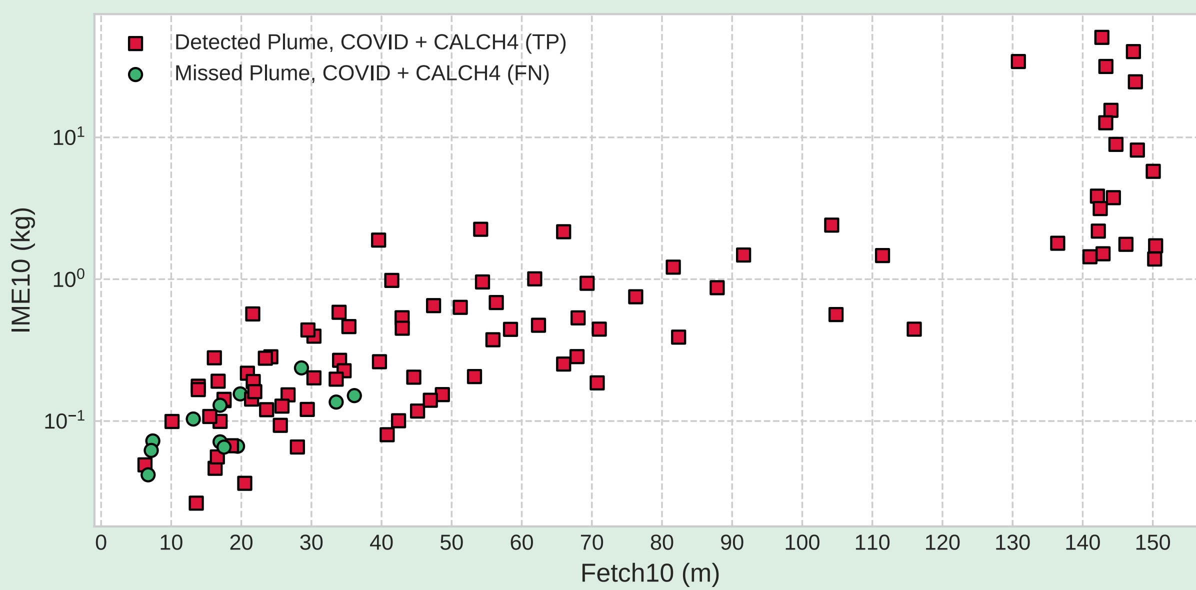


LES plumes show precision and recall improvement with large class imbalance, outperform real-world plume datasets.

Fetch-IME Plot to Identify Weak False Negatives

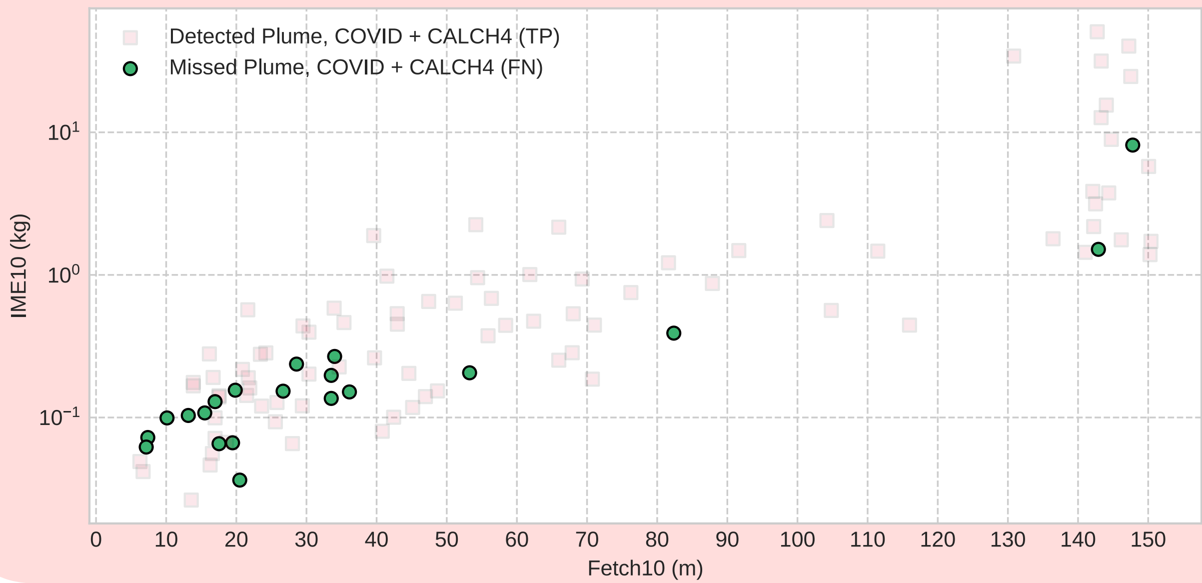


Without LES

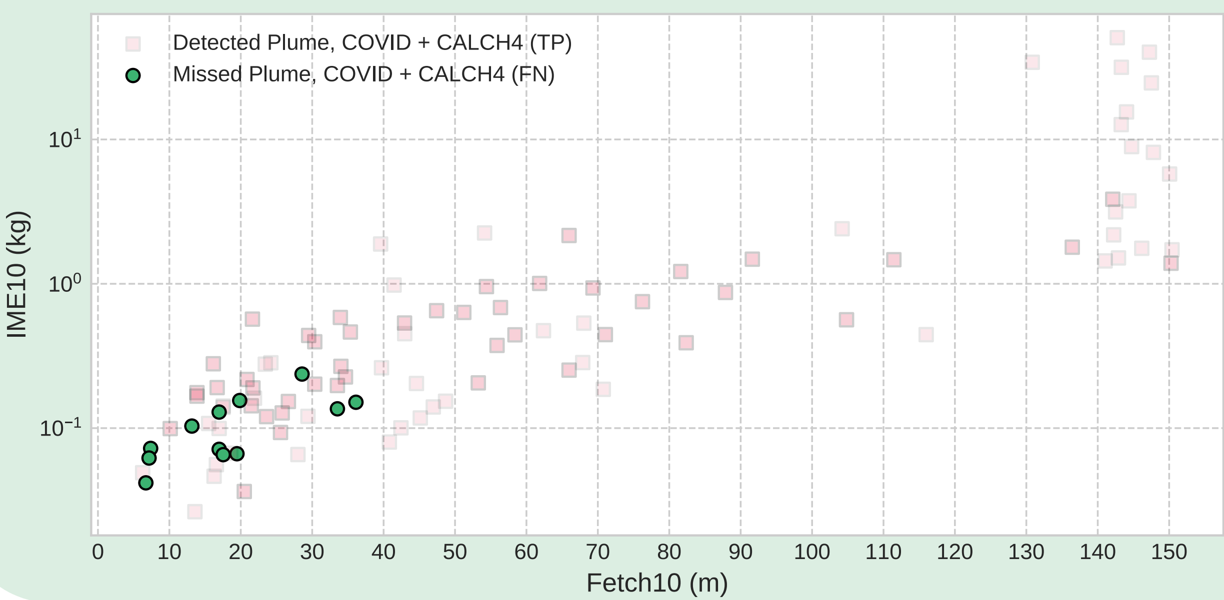


With LES

LES-aided CNNs capture Fetch > 40m Plumes

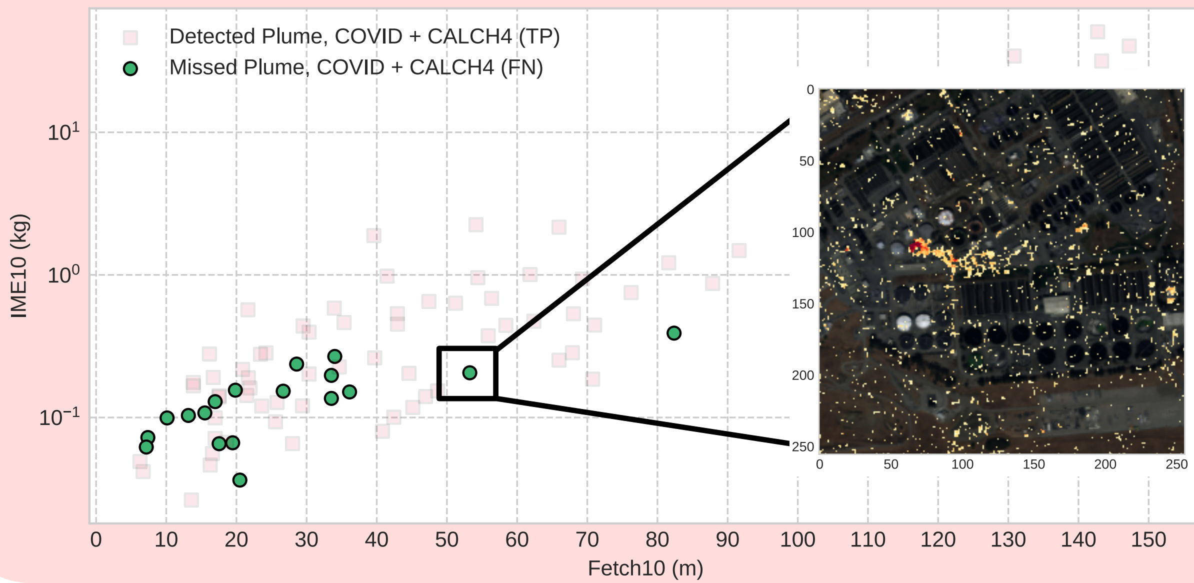


Without LES

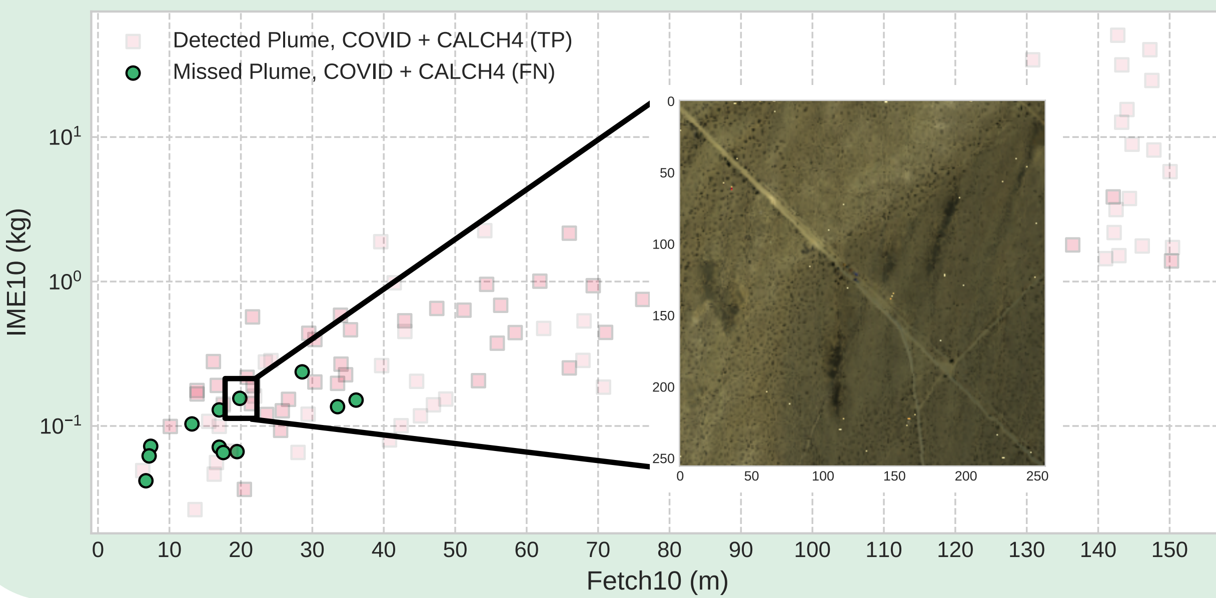


With LES

< 40m Fetch, < 0.5 kg IME Undetectable



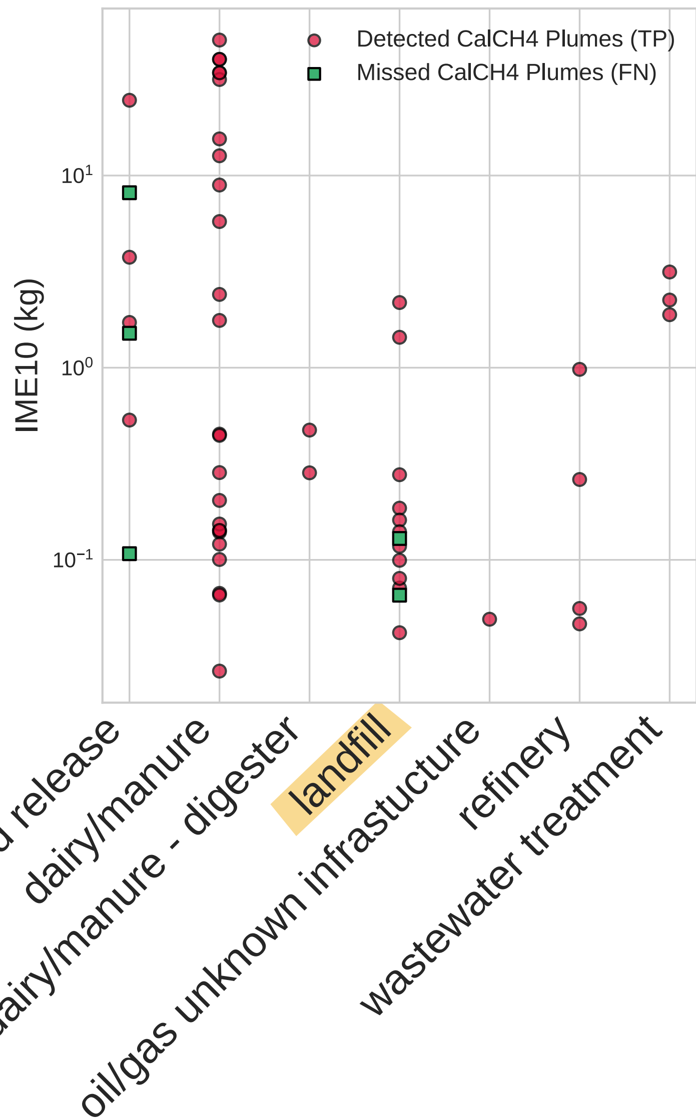
Without LES



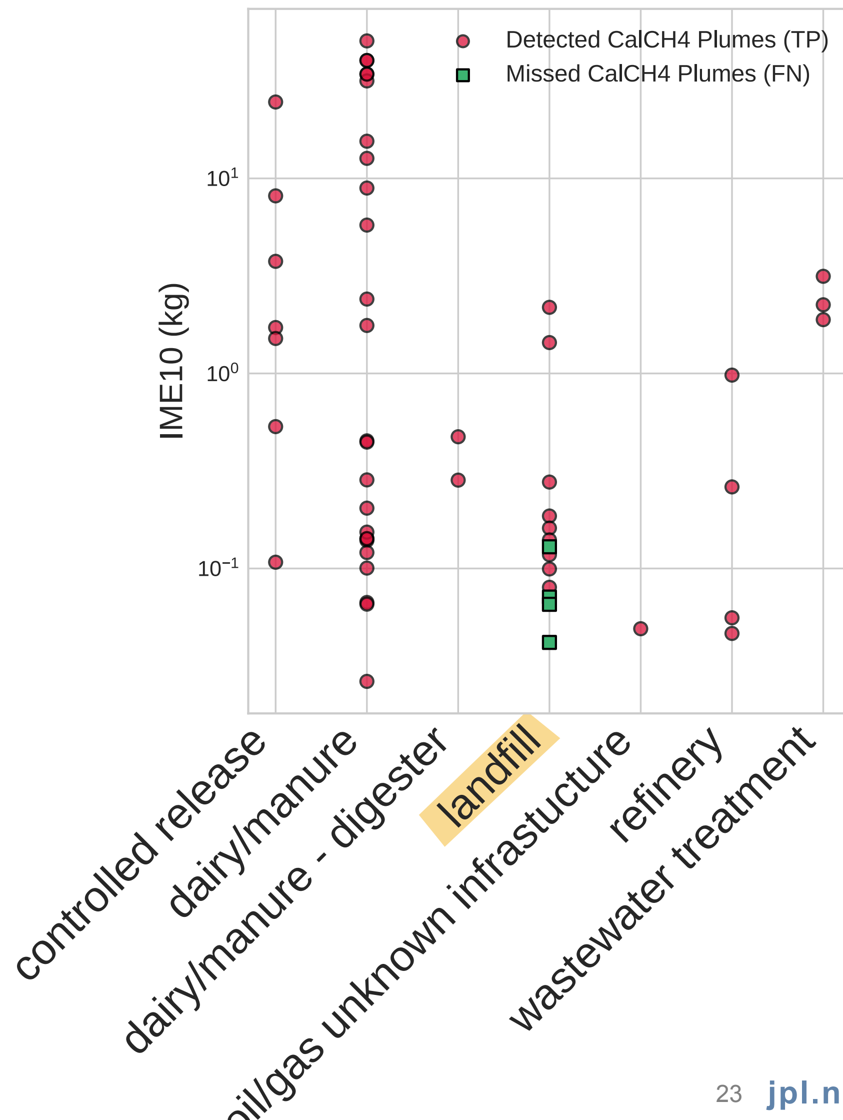
With LES

Source Attribution for $CalCH_4$ 2018

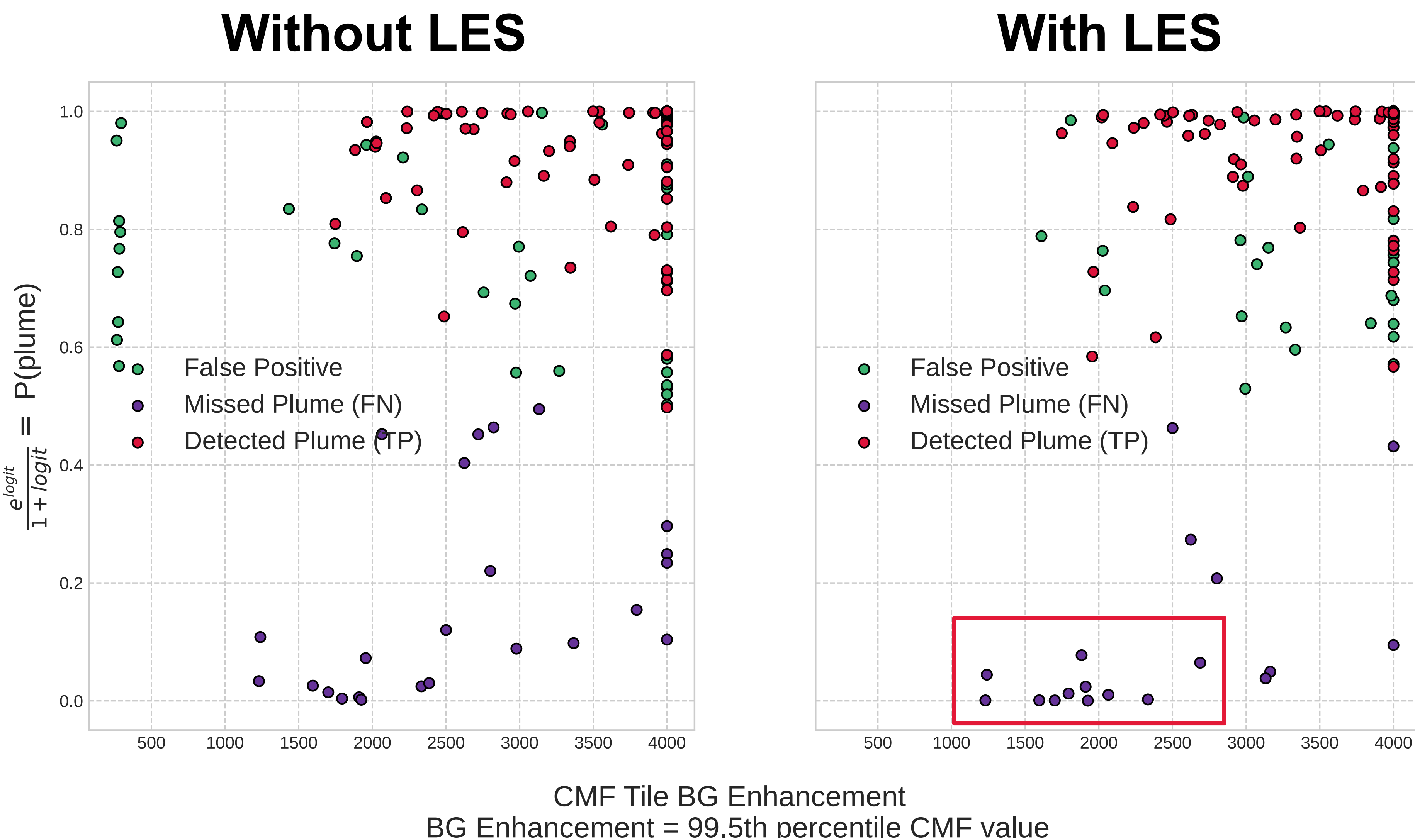
Without LES



With LES



Incorrect Plume Detections By CNN Confidence



Summary

LES plumes are transformed and filtered to closely resemble CalCH_4 (2018) and COVID (2020) plumes

LES Plumes significantly improve precision and recall with additional improvements on multi-campaign, imbalanced datasets with high background oversampling

However, most CNNs fail to distinguish < 40m Fetch, < 0.5 kg IME plumes and classify them as background with near-certainty.

Next Steps

Analysis stage noted several FPs distant from any surface infrastructure/ sub-facility.

↓

Connecting plume classification to Carbon Mapper sub-facility detection (Lawrence, 2021).

Downsample LES Plumes for 30m Plume Detection (Jake Lee, Steffen Mauceri)

LES Work @ AGU Fall Meeting ’21

Ashok, A., Mauceri, S., Thorpe, A., et al, (submitted), “Improving Imaging Spectrometer Methane Plume Detection with Large Eddy Simulations”, *AGU Fall Meeting 2021*

GC003. Addressing Global and Regional Sustainability Challenges with Satellite Data and Machine Learning

Lee, J., Mauceri, S., Dey, S., **Ashok, A.**, et al, (submitted), “Methane Plume Detection with Future Orbital Imaging Spectrometers”, *AGU Fall Meeting 2021*

GC012. Advancing Global Imaging Spectroscopy and Thermal Infrared Measurements

Thank You!

- Andrew Thorpe, Steffen Mauceri
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- MLIA and 2021 SURF@JPL Interns
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- Carbon Mapper Team!
- analysis and paralysis, EMIT clusters

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