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METHANEMAPPER

Spectral Absorption Aware Hyperspectral Transformer for Methane Detection

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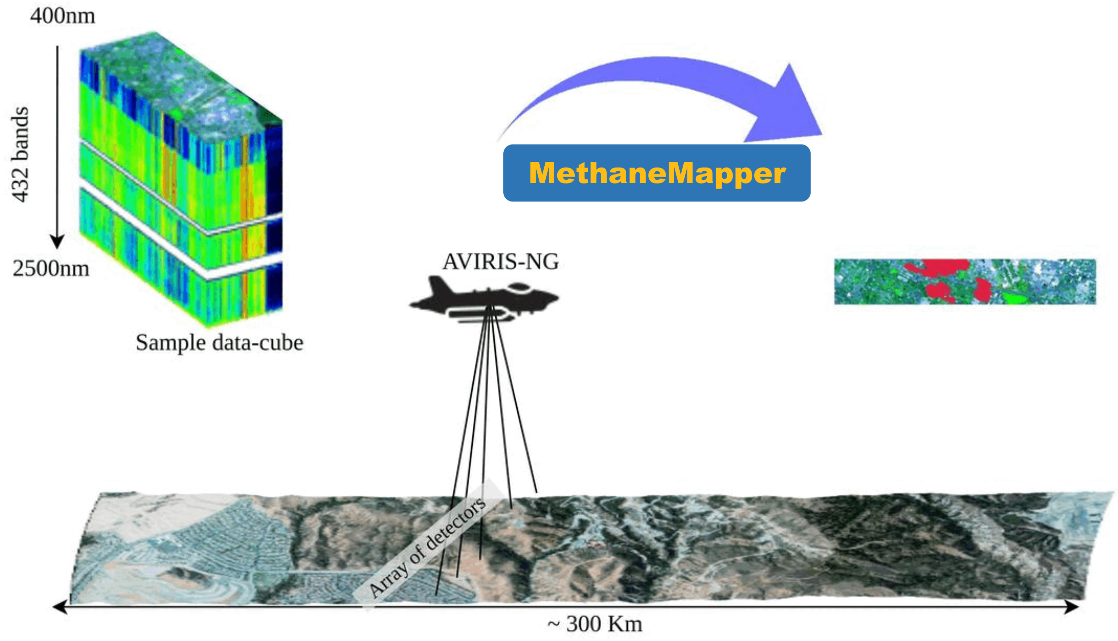
A S M Iftekhar, B S Manjunath

Istock Images

Summary:
Methane gas detection from Airborne Hyperspectral Imagery



Main Contributions:

- We introduce a novel single-stage end-to-end approach for methane plume detection using a hyperspectral transformer
- Largest public hyperspectral dataset → Methane HotSpot (MHS) dataset
    - Flightlines data from 6 different states over a time period of 8 years

Outline

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- Introduction
- Existing works and limitations
- Data collection pipeline and MHS Dataset Specifications
- **METHANEMAPPER**
- Conclusion

Motivation

- Greenhouse gas emissions are the invisible menace causing global warming
- Methane and Carbon Dioxide goes undetected because of invisibility
- Government is struggling to curb on these emissions
- US govt. set to pass $369 billions towards climate change

PBS Newshour

$1/3^{rd}$ of Gas Comes from Dairy Farms and Livestocks

$1/3^{rd}$ of Gas Comes from Oil and Gas Industry

Chief Contributors of Methane

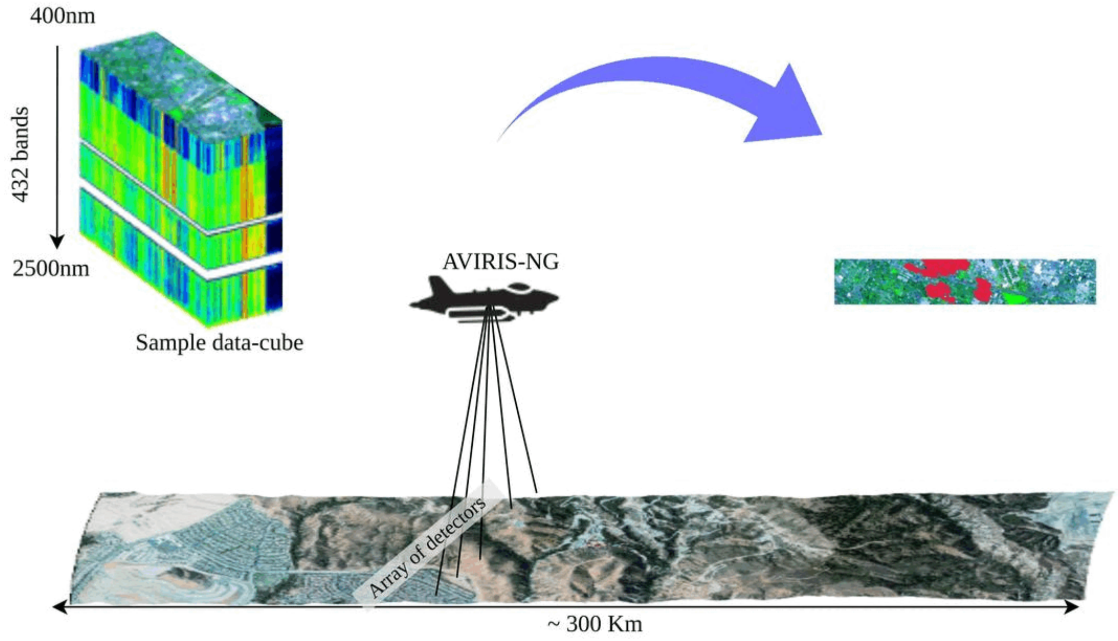
16% of Gas comes from Landfill sites

Example of invisibility in visible spectrum

Methane emission at the site

Outline

Methane gas detection from Airborne Hyperspectral Imagery

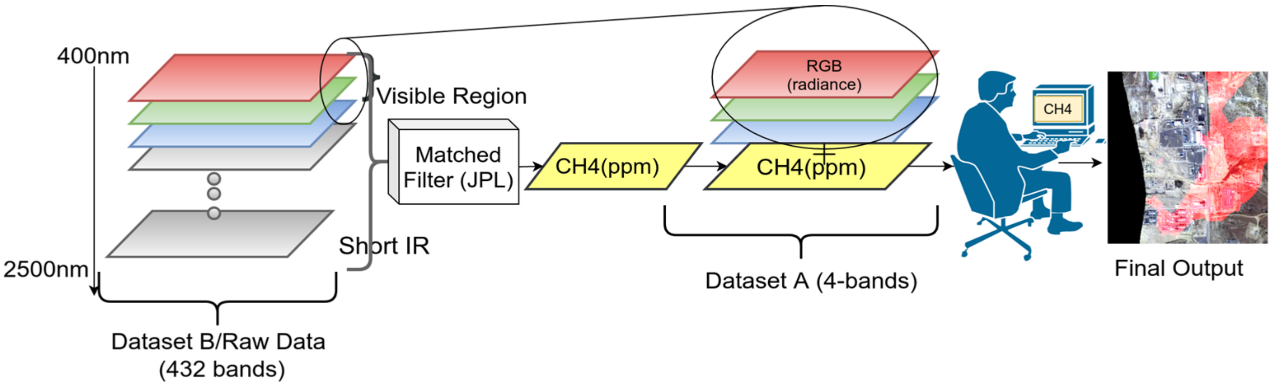


Conventional Detection Methods

- Iterative Maximum a Posterior Differential Optical Absorption Spectroscopy (IMAP-DOAS) algorithm
  - Uses Lambert-Beer law to model the absorption of solar radiation in the medium it is passing through
  - Highly dependent on pressure and temperature of the atmosphere
- Matched Filter
  - Uses background statistics to normalize the spectral signals and match with the methane spectral signature at every spatial location (pixel-wise)

Highly prone to false positives due to confusers on the ground such as hydrocarbon paints, roads, etc

Conventional Detection Methods



Needs Manual correction by an expert

Deep Learning based approach

- MethaNet An AI-driven approach to quantifying methane point-source emission from high-resolution 2-D plume imagery [6]
  - A shallow neural network with 4 layers for methane quantification

MethaNet only works with a corrected and clean methane enhancement output from matched filter

Very limited datasets available with ground truth

[5] **Kumar, Satish**, "Deep remote sensing methods for methane detection in overhead hyperspectral imagery." IEEE/CVF Winter Conference on Applications of Computer Vision. 2020 (WACV).
[6] "MethaNet–An AI-driven approach to quantifying methane point-source emission from high-resolution 2-D plume imagery." Remote Sensing of Environment 269 (2022): 112809.

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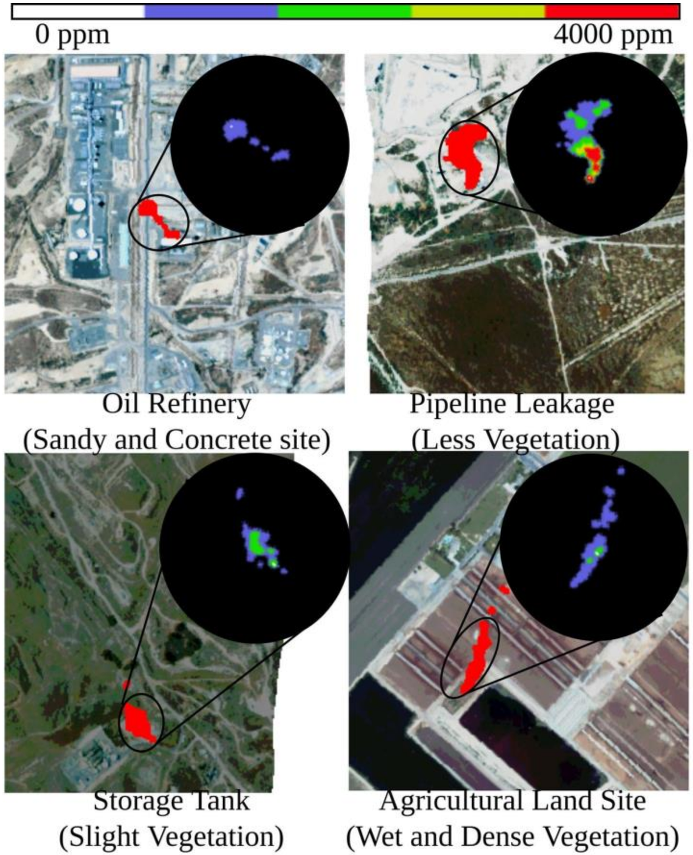
Methane HotSpot (MHS) Dataset

- Collected concentration patches from a non-profit entity
- Mapped all patches to AVIRIS-NG flightlines
- Created point source and diffused source plume sites
- The concentration patches verified by experts visiting the physical location



Dataset Statistics

Dataset	**MHS Dataset**	**JPL-CH4 detection-V1.0**
# plume sites	**3961**	161
# flightlines	**1185**	46
# point source	**3675**	114
# diffused source	**286**	57
Time period	**2015 - 2022 (8 years)**	2015 (1 year)
Segmentation Mask	**Yes**	**Yes**
Bonding box	**Yes**	No
Concentration map	**Yes**	No
Number of Regions	**6**	1

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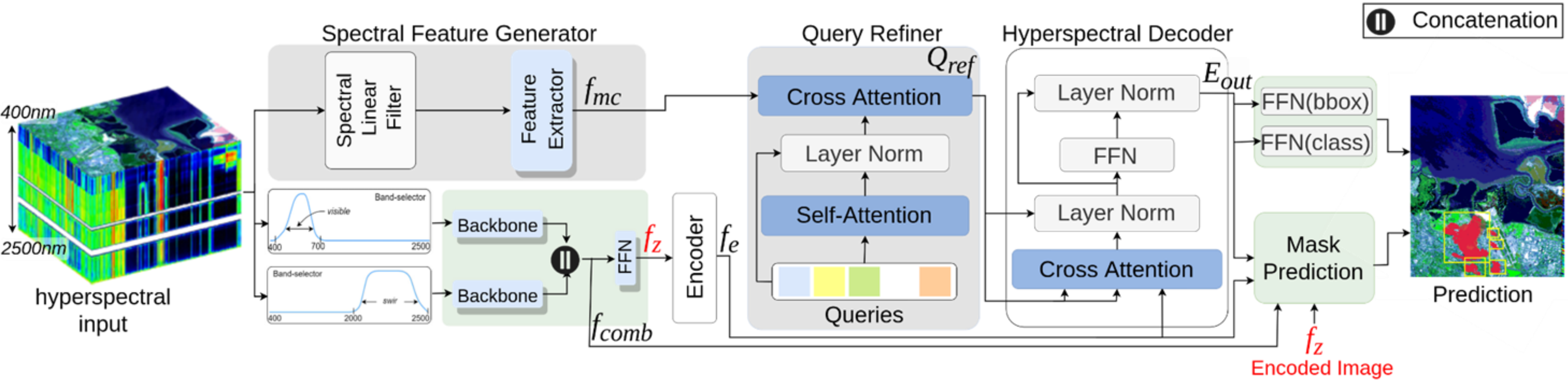
We built MethaneMapper

MethaneMapper

A spectral absorption aware hyperspectral transformer architecture for methane plume detection in hyperspectral imagery

We built MethaneMapper



A transformer-based methane detection architecture with Spectral Linear Filter

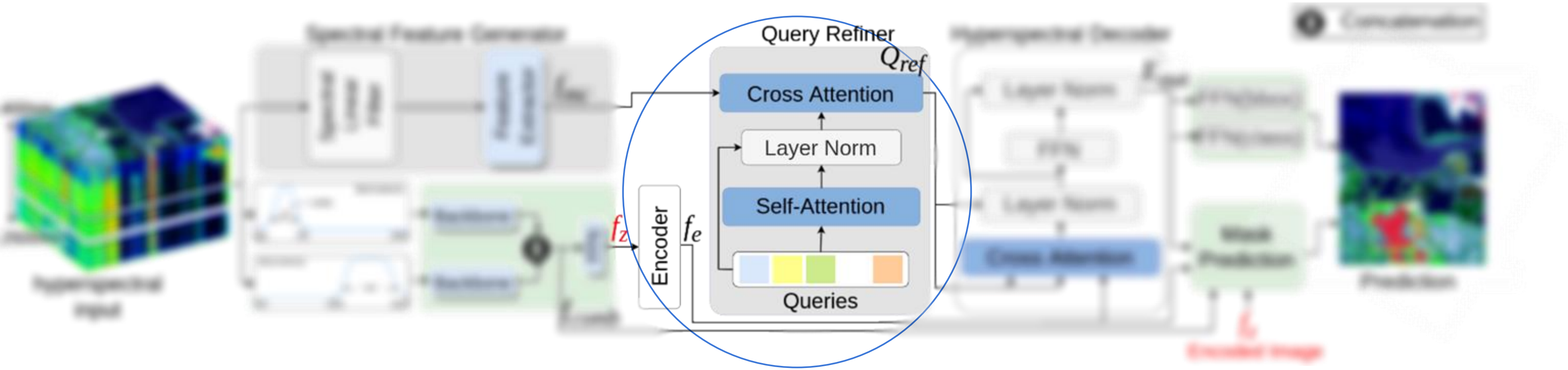
We built MethaneMapper

Takes in all 432 bands hyperspectral image

We built MethaneMapper

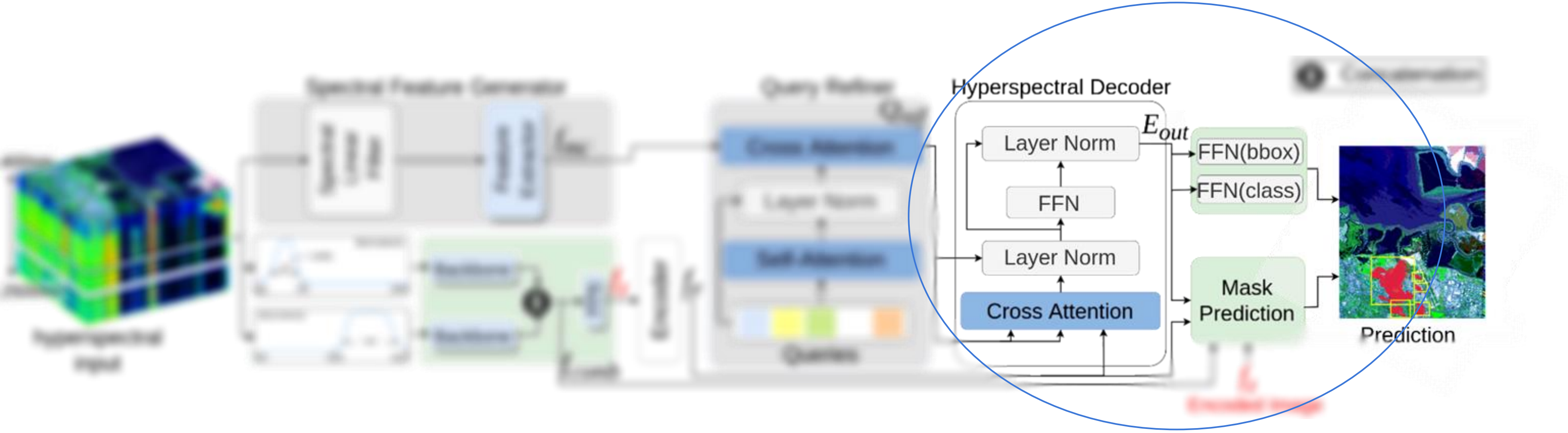
Processes the 432 bands hyperspectral image to generate methane candidate maps

We built MethaneMapper



Our Query refiner block takes the methane candidate maps and refine the random queries

We built MethaneMapper



The refined queries narrow down the search space of the transformer decoder to locate the methane plumes and help to remove the false positives

MethaneMapper: Spectral Linear Filter (SLF)

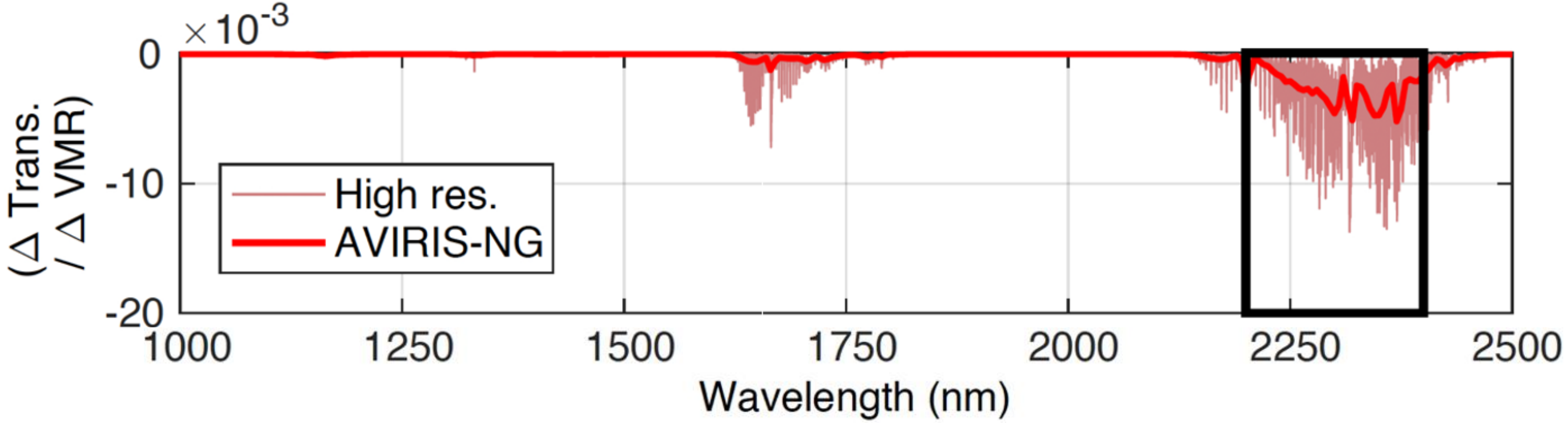
SLF filters' out the background noise based on the spectral absorption properties of reflected solar radiations by methane gas

Absorption of solar reflected radiation by methane is modeled as additive perturbation: $$\mathbf{x}_i = \mathbf{r}_i + \mathbf{t}$$

where $\mathbf{r}_i$ is the i^{th} pixel in the hyperspectral image representing ground terrain, and $\mathbf{t}$ is the methane absorption pattern

MethaneMapper: Spectral Linear Filter (SLF)

The methane absorption pattern “**t**” is shown below



MethaneMapper: Spectral Linear Filter (SLF)

Since our signature of interest is very weak in the $\mathbf{x}_i$, we do a dot product with vector $\boldsymbol{\alpha}$. This vector $\boldsymbol{\alpha}$ is called "matched filter" :

$$\alpha = \frac{\mathbf{Cov}^{-1}\mathbf{t}}{\sqrt{\mathbf{t}^T\mathbf{Cov}^{-1}\mathbf{t}}}$$

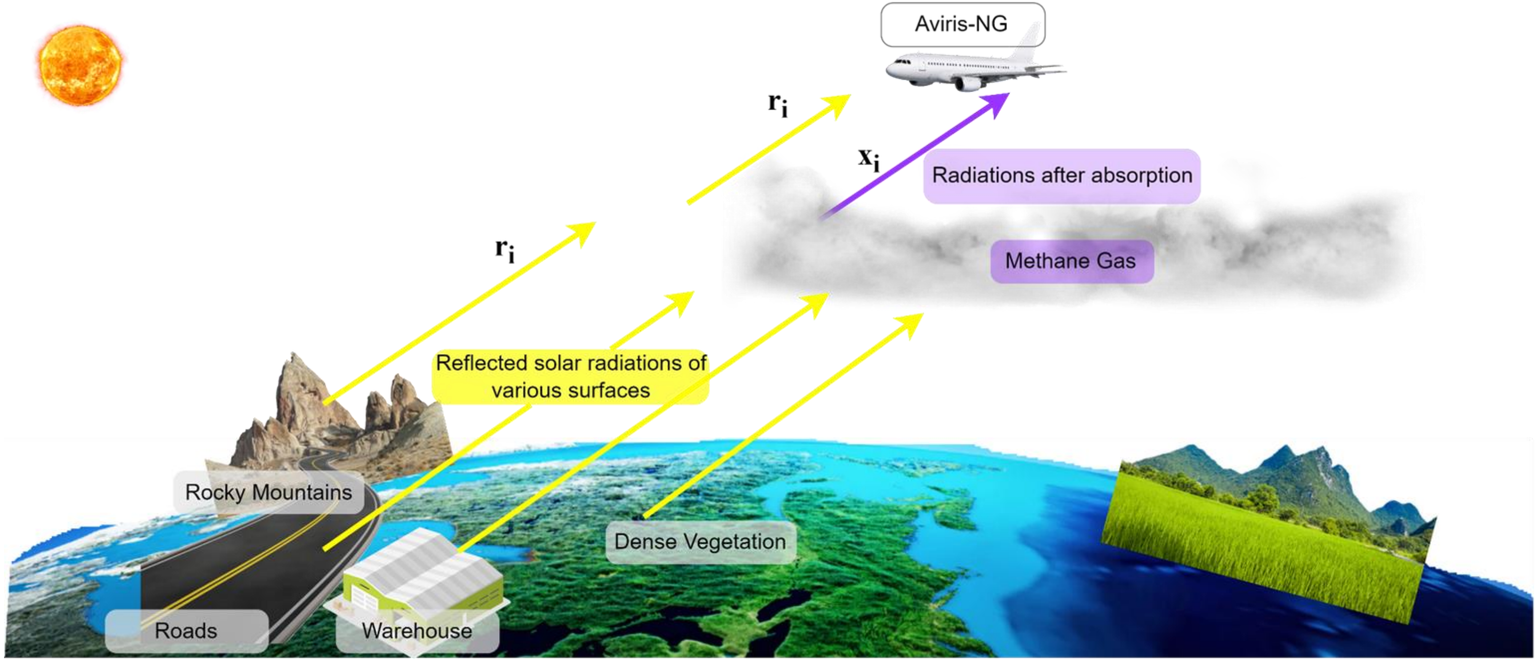
where $\mathbf{Cov}^{-1}$ is the inverse of covariance of the background when no methane is present. The methane enhancement per pixel is computed as:

$$\hat{\alpha}(\mathbf{x}_i) = \frac{(\mathbf{x}_i - \mu)^T\mathbf{Cov}^{-1}\mathbf{t}}{\sqrt{\mathbf{t}^T\mathbf{Cov}^{-1}\mathbf{t}}};$$

where $\hat{\alpha}(\mathbf{x}_i)$ is the per pixel estimation of methane

MethaneMapper: Spectral Linear Filter (SLF)

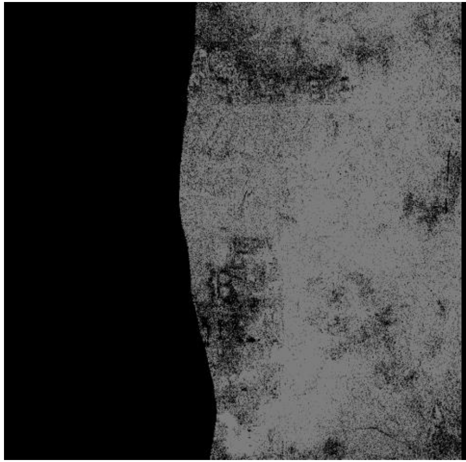
The $\mathbf{Cov}^{-1}$ in previous step is computed with an underlying assumption that the ground terrain does not change much, BUT it is not the case,

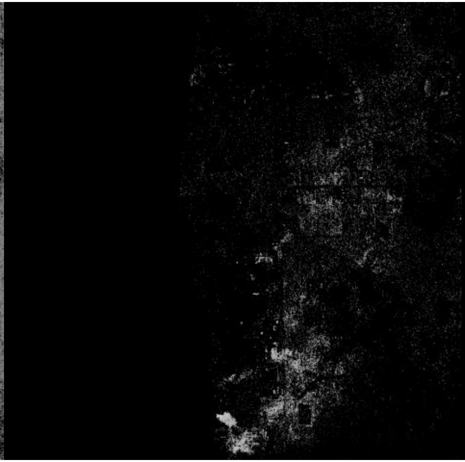


MethaneMapper: Spectral Linear Filter (SLF)

We did a simple land cover classification of the ground terrain and then compute $\mathbf{Cov}_k^{-1}$ for each class k.

$$\mathbf{SLF}(\mathbf{x}_i) = \frac{(\mathbf{x}_i - \mu_k)^T \mathbf{Cov}_k^{-1} t}{\sqrt{t^T \mathbf{Cov}_k^{-1} t}} \; \forall \, (i) \in \text{class } k$$


Traditional Matched Filter


Spectral Linear Filter


Ground Mask


Ground Terrain

MethaneMapper: Quantitative Performance

Method MHS (Ours) data)	mAP	mIOU
SpectralFormer [9]	0.33	0.41
UPSnet (stuff) [10]	0.32	0.38
UPSnet (things+stuff)[10]	0.29	0.35
U-net [11]	0.35	0.46
DETR-R18 [12]	0.37	0.56
DETR-R50 [12]	0.44	0.59
MM-R18 + Matched Filter	0.45	0.60
MM-R18 + Spectral Linear Filter	0.52	0.63
MM-R50 + Spectral Linear Filter	**0.59**	**0.68**

[8] **Kumar, Satish, "MethaneMapper:** Spectral Absorption aware Hyperspectral Transformer for Methane Detection", IEEE/CVF (CVPR 2023)
[7] **Kumar, Satish,** "Deep remote sensing methods for methane detection in overhead hyperspectral imagery." IEEE/CVF Winter Conference on Applications of Computer Vision. 2020 (WACV 2020).
[9] "SpectralFormer: Rethinking hyperspectral image classification with transformers." IEEE Transactions on Geoscience and Remote Sensing 60 (2021):
[10] "Upsnet: A unified panoptic segmentation network." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.
[11] U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich
[12] Carion, Nicolas, et al. "End-to-end object detection with transformers." Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020

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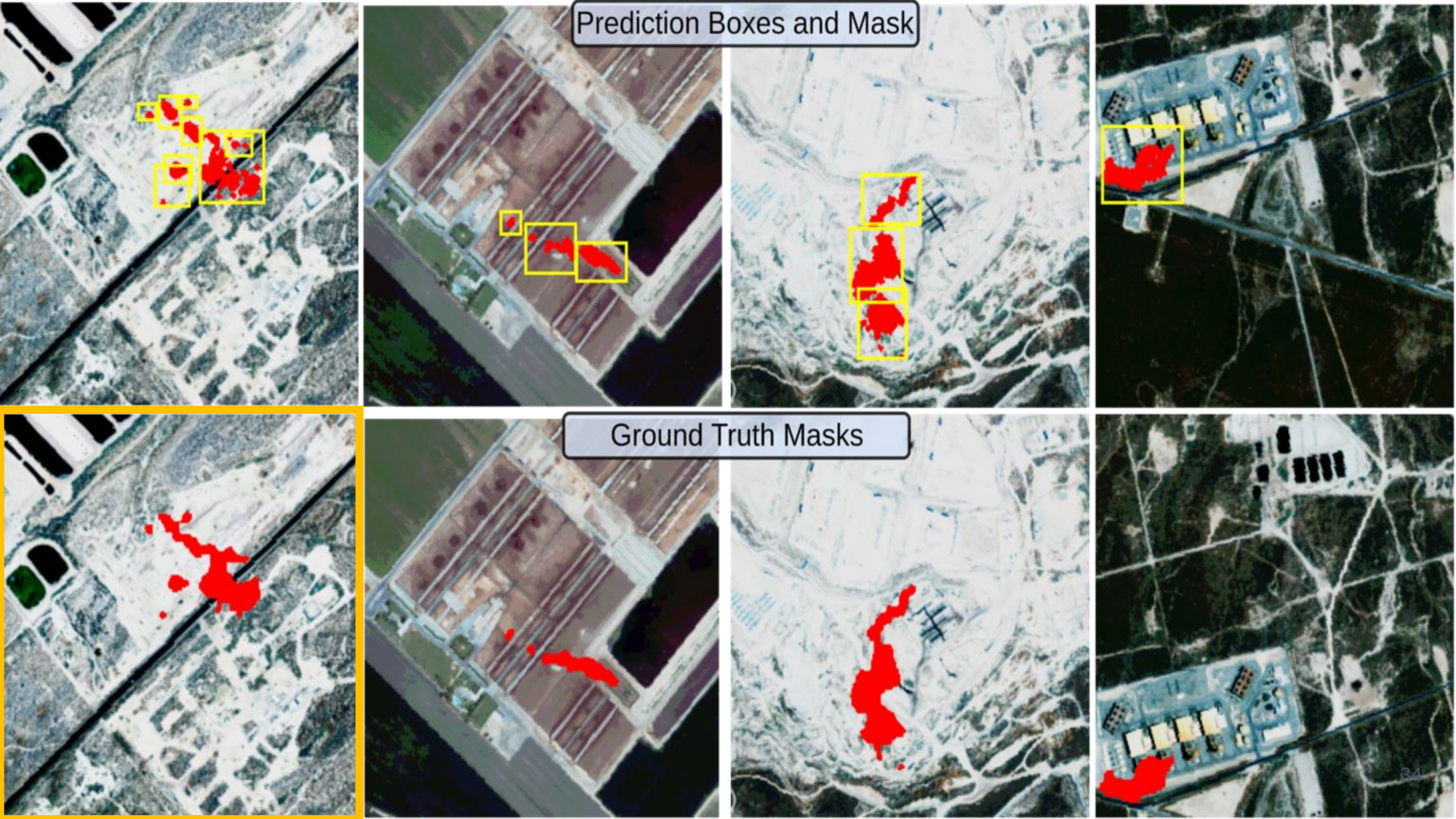
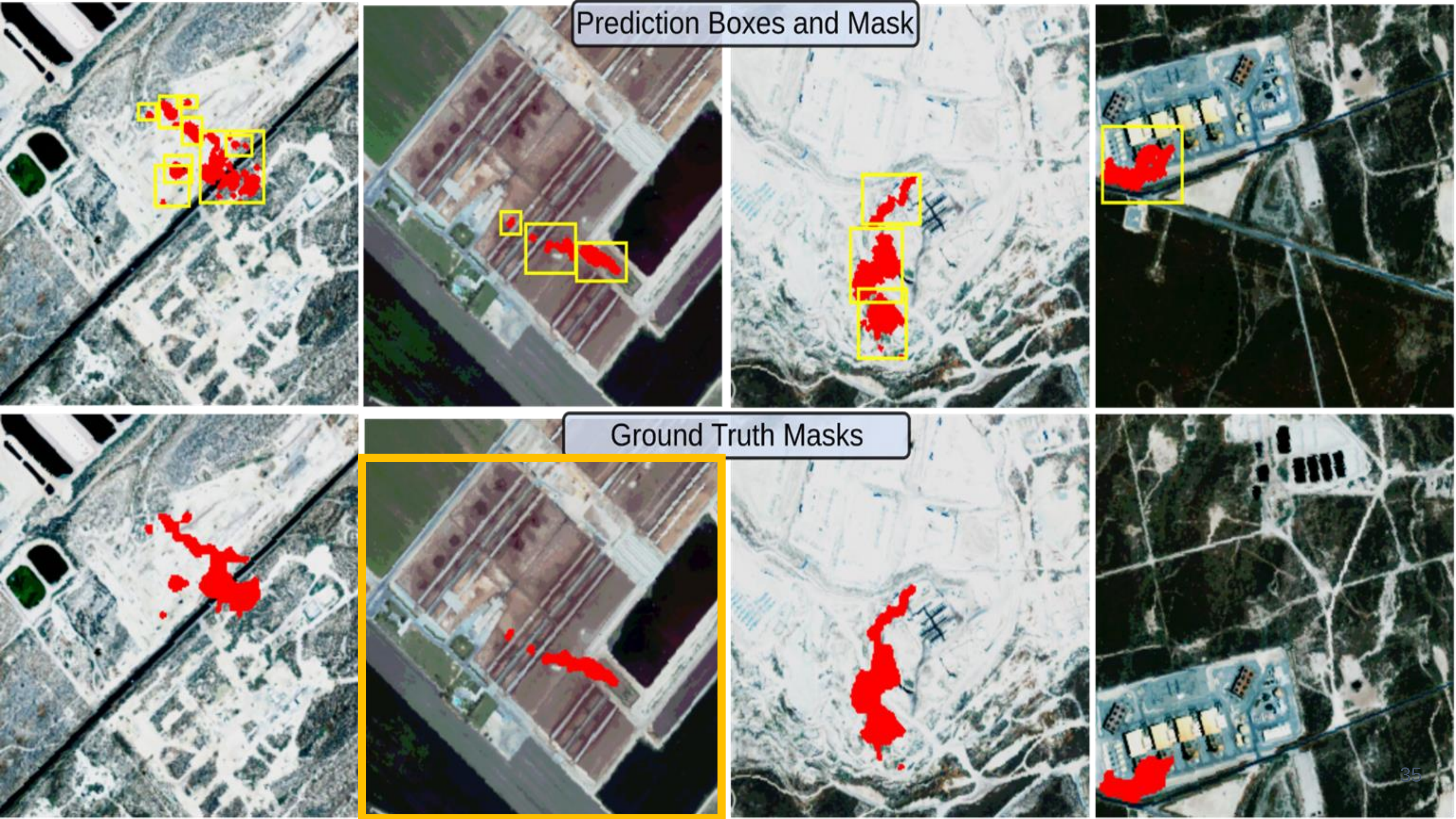

Prediction Boxes and Mask
Ground Truth Masks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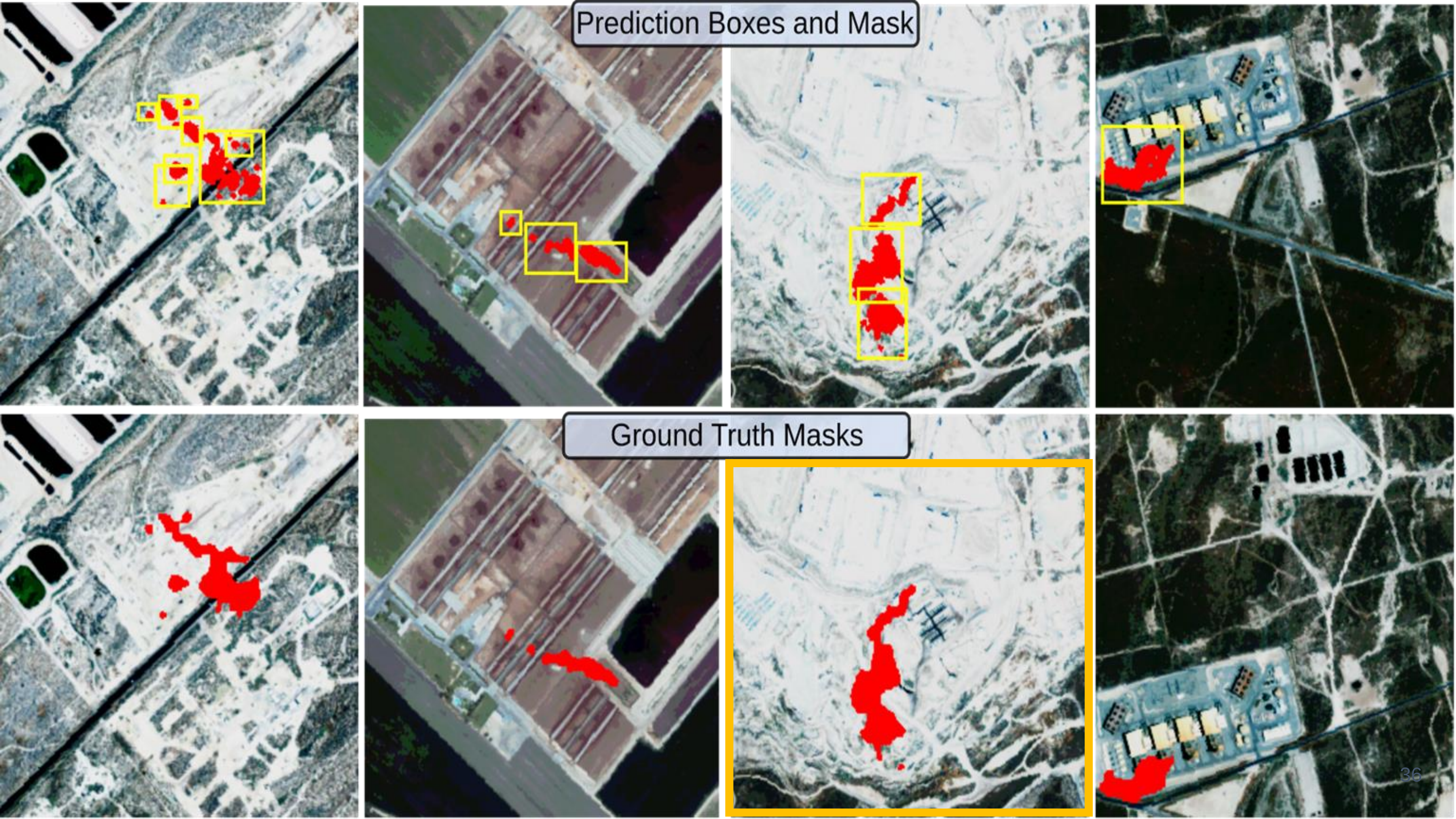
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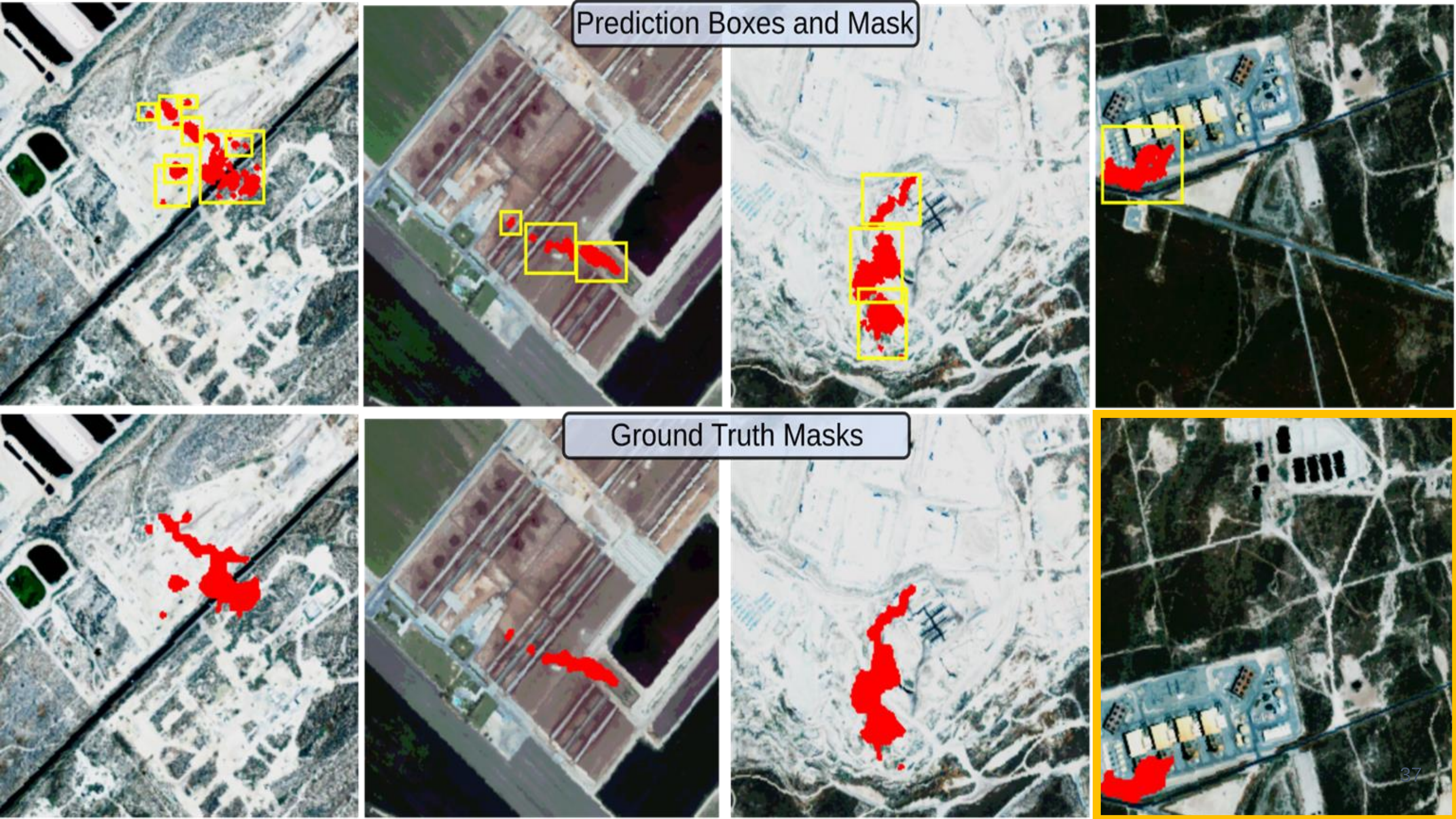
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MethaneMapper: Conclusion

We provide an end-to-end approach with **high quality methane plume detection** and provide the computer vision community with **largest hyperspectral dataset** to promote research in this field

MethaneMapper

Spectral Absorption Aware Hyperspectral Transformer for Methane Detection

By: Satish Kumar

Dataset and Source code:

Thank you for Listening