Deep Learning for Clouds, Cloud Shadow, and Plume Segmentation in Methane Satellite and Airborne Imaging Spectroscopy

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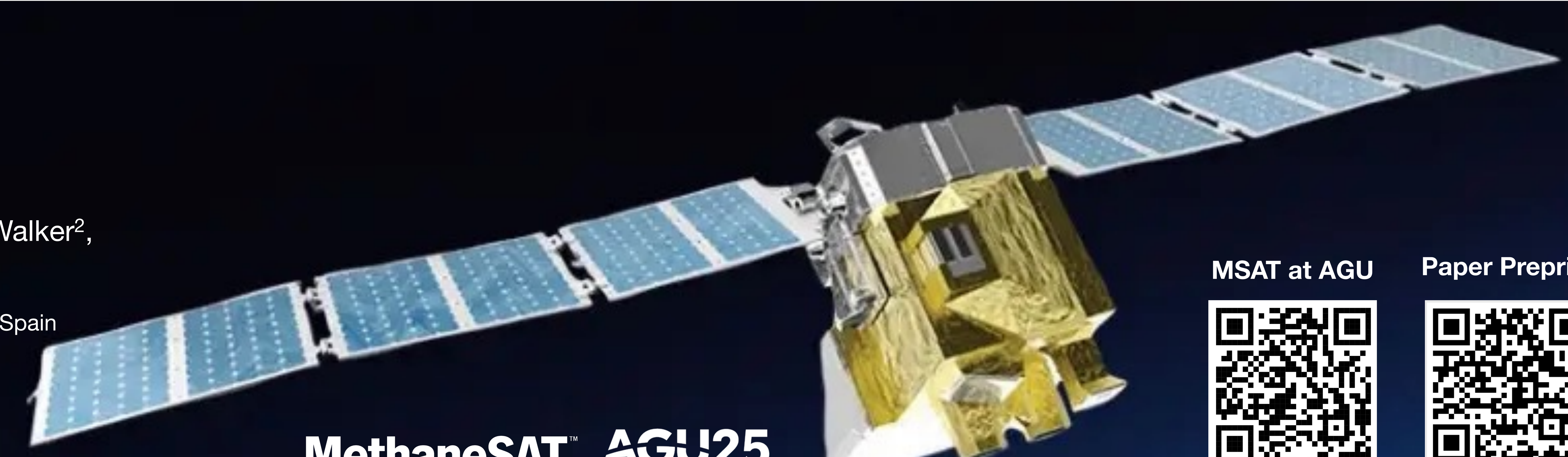


MethaneSAT AGU25

MSAT at AGU

Paper Preprint

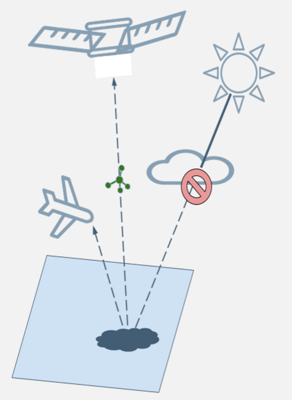
Cloud-Shadow Masking Using Hyperspectral Data

MOTIVATION

Methane is a potent greenhouse gas.

Cloud and Cloud shadows affects gas retrievals:

- **Clouds:** Occlude surface reflectance
- **Cloud Shadows:** Obscure solar illumination.



- **508** hyperspectral samples from CH_4 spectrometer
- **1592-1678 nm**, 1024 bins
- **~300×178** spatial soundings (along-track × across-track)
- **Cloud, shadows, dark surface** from L2 products

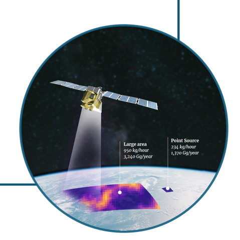
(Chan Miller et al., 2024)

MethaneAIR : Airborne precursor to MethaneSAT

- **262** hyperspectral samples from CH_4 spectrometer
- **1589-1686 nm**, 1080 bins
- **~2200×500** spatial soundings (along-track × across-track)
- **Cloud** and **cloud shadows** from L2 products

(Chan Miller et al., 2024)

MethaneSAT: Satellite mission launched April 2024



METHODOLOGY

Six semantic segmentation models for cloud and shadow detection:

Iterative Logistic Regression (ILR): Baseline that learns a compact spectral basis through iterative dimensionality reduction. (Park et al, 2023)
Multilayer Perceptron (MLP): Processes each pixel's spectral signature independently.
U-Net: Encoder-decoder architecture with skip connections for spatial context. (Ronneberger et al, 2015)
Spectral Channel Attention Network (SCAN): Model incorporating spectral attention mechanisms.
Combined MLP: Ensemble approach using MLP to fuse U-Net & SCAN.
Combined CNN: Ensemble approach using CNN to preserve spatial context during fusion.

Training: Weighted cross-entropy loss, Adam optimizer, data augmentation with random flips and rotations.

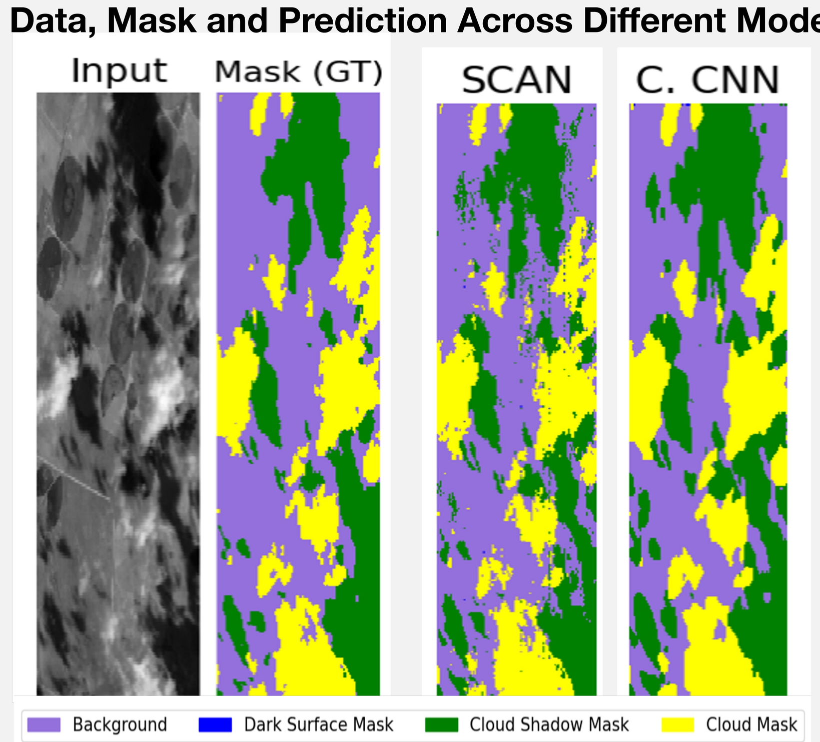
(Pérez-Carrasco et al., 2025a)

CLOUD-SHADOW RESULTS

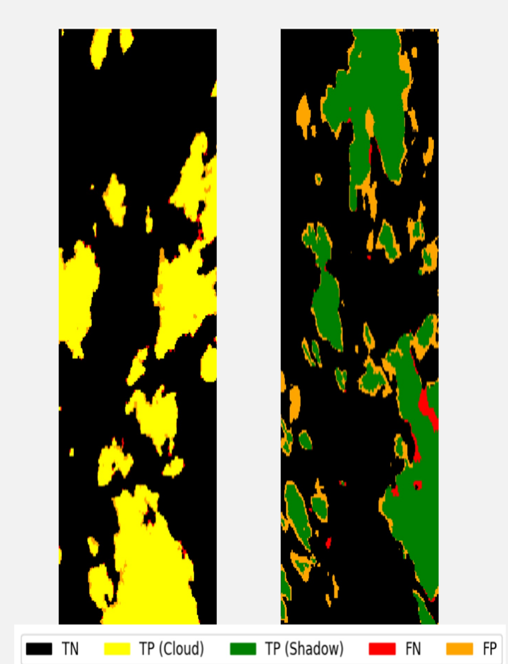
We evaluated models using accuracy and F1-score metrics with macro-averaging across classes. (Pérez-Carrasco et al., 2025b)

Model	MethaneAIR Acc (%)	MethaneAIR F1 (%)	MethaneSAT Acc (%)	MethaneSAT F1 (%)
Individual Methods				
ILR	73.81±4.05	62.07±0.86	71.82±4.02	64.35±3.56
MLP	82.49±2.24	71.29±1.02	74.03±3.72	67.11±2.06
U-Net	**88.26±0.45**	**76.24±1.90**	78.73±3.23	68.56±0.36
SCAN	86.51±2.90	74.96±0.96	**80.33±3.43**	**71.53±0.75**
Ensemble Methods				
Combined MLP	88.92±1.80	76.99±6.78	81.32±1.28	78.10±1.72
Combined CNN	**89.42±1.20**	**78.50±3.08**	**81.96±1.45**	**78.80±1.28**

Data, Mask and Prediction Across Different Models



Classification Errors C. CNN



Sample, mask and predictions from MethaneAIR dataset, and shadows classification errors for combined CNN (C. CNN). SCAN method generates great boundary delineation. When combined with UNet, generates both spatial coherence and boundary precision in C. CNN

Key Findings:

- **ML model ability to mask clouds shadows with high accuracy.**
- SCAN is better for shadows and dark surfaces. U-Net is better for clouds.
- SCAN outperforms U-Net on MethaneSAT data, suggesting the value of spectral attention for specific sensor characteristics.
- Combined CNN model achieved superior performance in both datasets.

Plume Masking Using XCH4 Data

INITIAL EXPLORATORY PLUME DATASET

MethaneAIR: 43 scenes with corresponding L3 XCH4 imagery and masks derived from wavelet method (~300 methane plumes).

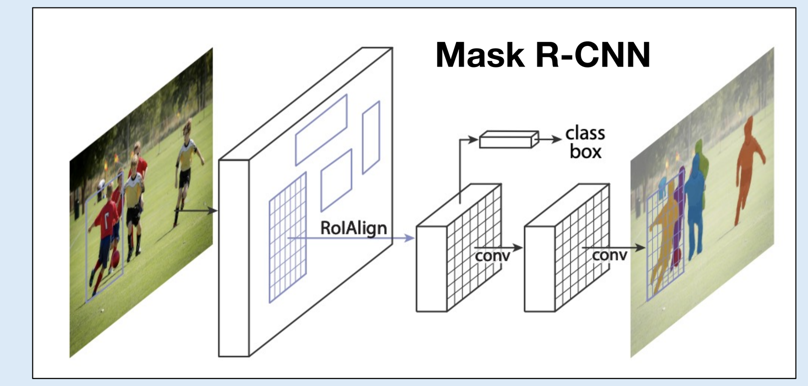
MethaneSAT: 11 scenes with corresponding L3 XCH4 imagery and masks (58 methane plumes).

(Zhang et al. 2024)

METHODOLOGY

Semantic Segmentation
U-Net

Instance Segmentation
Mask R-CNN



He et al. 2018

We compared different backbones for Mask R-CNN:

- **ResNet-50**, Vision Transformer (ViT), Masked Autoencoder (MAE)

INITIAL PLUME RESULTS

Model	MethaneAIR Accuracy (%)	MethaneAIR F1 (%)	MethaneSAT* Accuracy (%)	MethaneSAT* F1 (%)
U-Net	93.12	72.90	96.79	61.65
Mask R-CNN ResNet	**98.46**	**94.16**	**72.95**	**72.21**
Mask R-CNN ViT	77.69	64.37	65.39	64.62
Mask R-CNN MAE	88.77	66.30	65.95	63.93

Results averaged over the best 3 cross-validated folds measured on test set.

**MethaneSAT results were pretrained on MethaneAIR data*

Initial Findings:

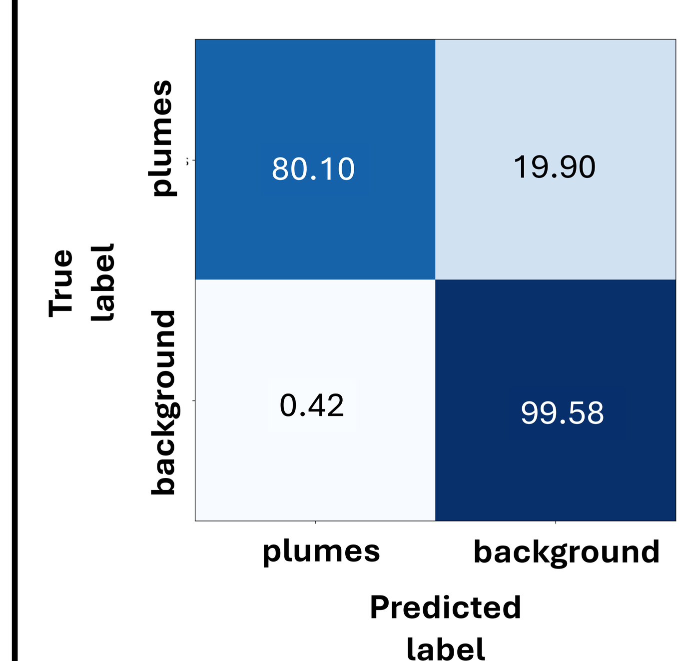
- Mask R-CNN ResNet seems a suitable option for plume detection.

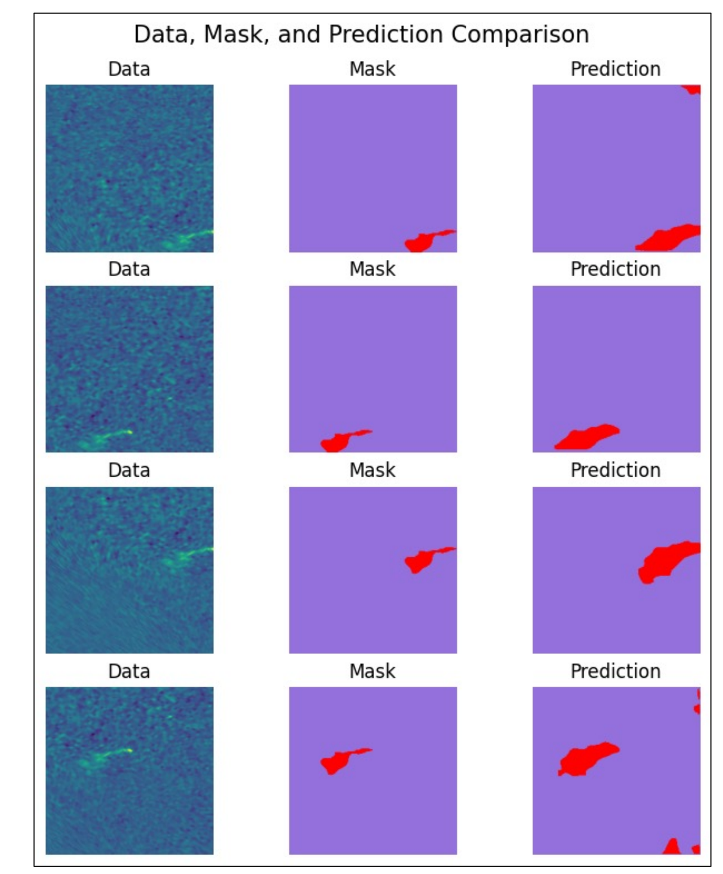
Next steps:

- Integrate additional simulated plumes and MethaneAIR data.
- Optimize performance for diffuse plumes and in noisy scenes.
- Explore plumes segmentation directly from L1B radiance data.

Mask R-CNN + ResNet Example for MethaneAIR

	precision	recall	f1-score
Background	0.99	1.00	1.00
Plumes	0.85	0.80	0.82
accuracy			0.99
macro avg	0.92	0.90	0.91
weighted avg	0.99	0.99	0.99





Acknowledgements: https://www.methanesat.org

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