Spectral Channel Attention Network: A Method for Hyperspectral Semantic Segmentation of Cloud and Shadows

M. Pérez-Carrasco[1 2], M. Nasr[2 3], S. Roche[3 4], C. C. Miller[3 4], Z. Zhang[3 4], C. F. Park[3], E. Walker[4] , C. Garraffo[2], D. Finkbeiner[3], R. Gautam[4], S. Wofsy[3]

[1]Center for Data and AI, Universidad de Concepción
[2] Center for Astrophysics | Harvard & Smithsonian
[3] Harvard University
[4] Environmental Defense Fund

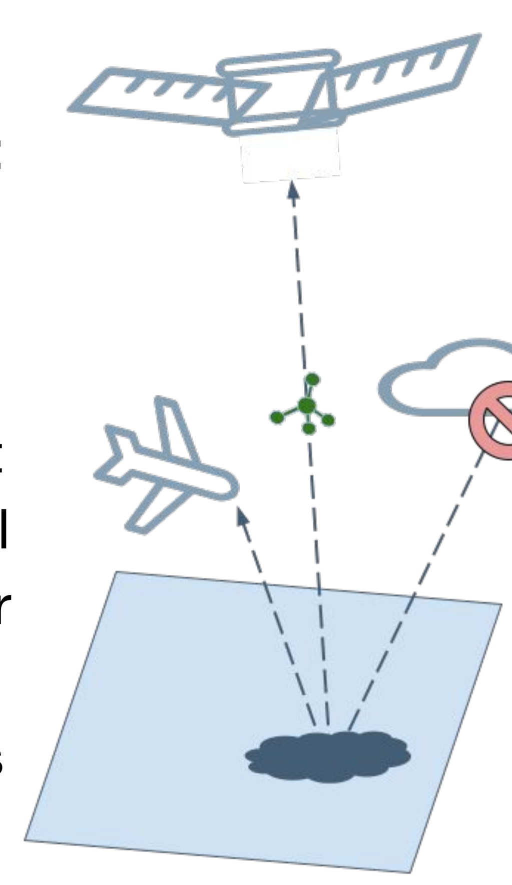
MOTIVATION

- **Methane** is a potent greenhouse gas.
- **Cloud and Cloud shadows** affects gas retrievals:

Clouds: Occlude surface reflectance

Cloud Shadows: Obscure solar illumination.

- **SCAN** is simple deep learning architecture that perform band selection by weighting spectral channels based on their discriminative power for semantic segmentation of cloud and shadows
- **SCAN** can be effectively combined with U-Net's spatial strengths.



DATA

MethaneAIR: Airborne precursor to MethaneSAT

- 508 hyperspectral samples from CH_4 spectrometer [1]
- Spectral range: 1592-1678 nm, 1024 spectral bins
- ~300×178 spatial soundings (along-track × across-track)
- Cloud, shadows and dark surface from L2 products [2]

MethaneSAT: Satellite mission launched April 2024

- 262 hyperspectral samples from CH_4 spectrometer [1]
- Spectral range: 1589-1686 nm, 1080 spectral bins
- ~2200×500 spatial soundings (along-track × across-track)
- Cloud and cloud shadows from L2 products [2]

SPECTRAL CHANNEL ATTENTION NETWORK (SCAN)

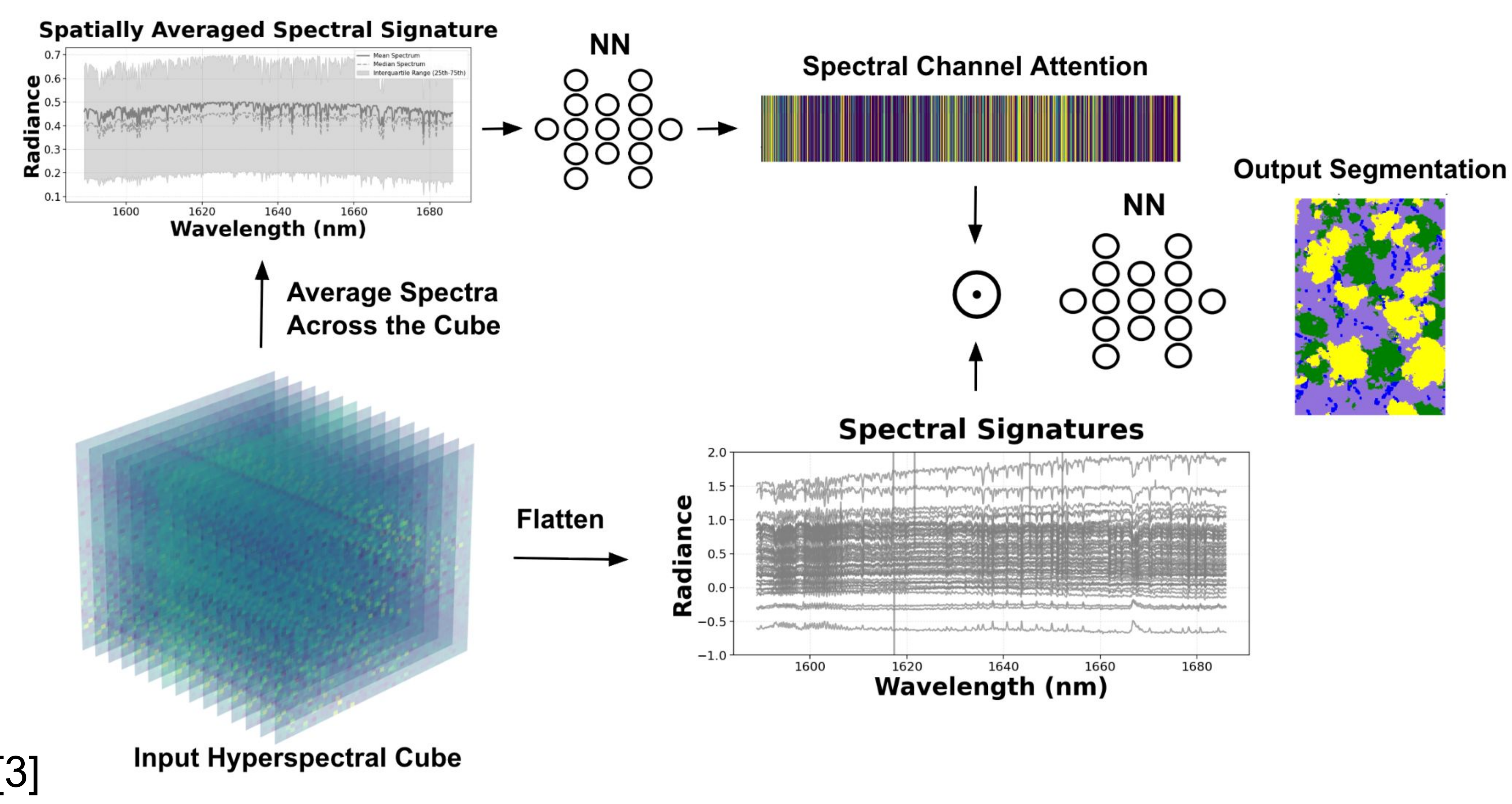
SCAN emphasize informative wavelengths.

Method:

- Input: $X \in R^{(B\times H\times W\times C)}$ hyperspectral data
- Attention weights: $\alpha = \sigma(W_2 \mathrm{ReLU}(W_1\bar{x}))$, where $\bar{x}$ is spatially averaged input data.
- Attended features: $X\_att = X \odot \alpha$
- Classification: $P(y|X) = \mathrm{Softmax}(f\_MLP(X\_att))$

Benefits:

- Adaptive spectral band weighting
- Enhanced discriminative features
- Can be easily combined with other methods such as U-Net [3]



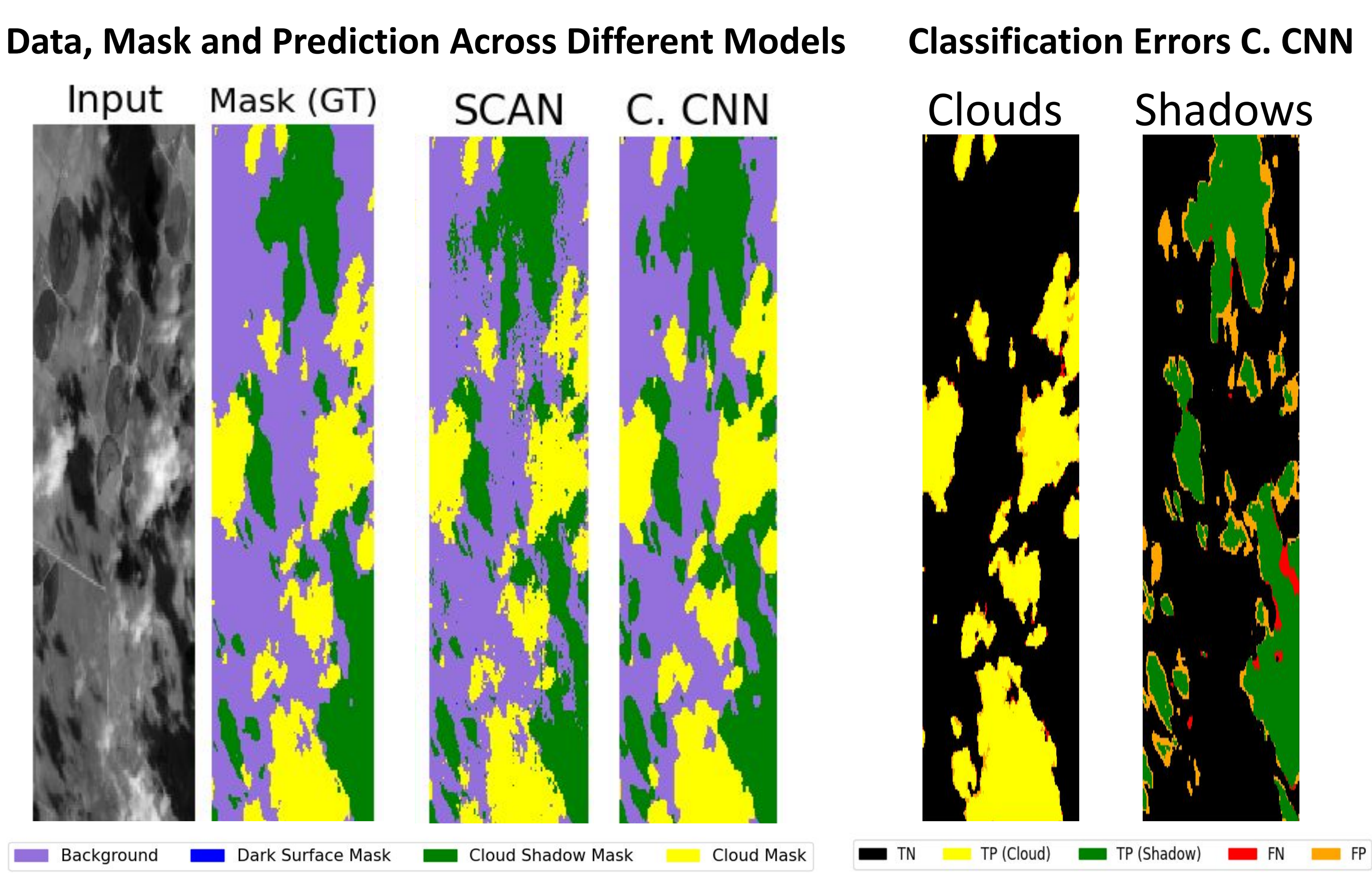
RESULTS

We evaluated models using accuracy and F1-score metrics with macro-averaging across classes. We compare our method with Iterative Logistic Regression [4] (ILR), Multilayer Perceptron (MLP), UNet [3] and the ensemble methods Combined MLP and Combined CNN.

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**

Key Findings:

- 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.



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

Acknowledgements Funding for MethaneSAT and MethaneAIR activities was provided in part by Anonymous, Arnold Ventures, The Audacious Project, Ballmer Group, Bezos Earth Fund, The Children's Investment Fund Foundation, Heising-Simons Family Fund, King Philanthropies, Robertson Foundation, Skyline Foundation and Valhalla Foundation. We thank the AstroAI and EarthAI institutes at the Center for Astrophysics | Harvard & Smithsonian.

Citations

[1] E. K. Conway et al. *Level0 to level1b processor for methaneair.* ATM, 17(4), 2024.
[2] C. Chan Miller et al. *Methane retrieval from methaneair using the co2 proxy approach: a demonstration for the upcoming methanesat mission.* ATM, 17(18), 2024.
[3] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015* (pp. 234–241).
[4] Park, C.F., et al. (2023). Hyperspectral shadow removal with Iterative Logistic Regression and latent Parametric Linear Combination of Gaussians.

Corr. Auth: manuel.perez_carrasco@cfa.harvard.edu