

# Improved Methane Plume Segmentation for Real-world Monitoring

## towards a more sustainable future

### Motivation

Monitoring and analysing methane emissions with sufficient accuracy is key to address the pollutant’s significant contribution to climate warming and respiratory illness death [1]. Current state of the art models suffer from high false positive rates, making practical deployment to inform and monitor sustainability policy in urban scenarios challenging, risking resource waste and inefficiency. We aim to develop and evaluate new machine learning architectures to reduce the FPR, without sacrificing detection accuracy to enable city-wide monitoring and targeted interventions. **The resulting system could empower cities worldwide to visualize, understand, and combat methane emissions, accelerating collective efforts toward a more sustainable future.**

### Background

State of the art model, “HyperStarcop,” is a UNet model, trained on hyper-spectral images to detect methane plumes [2]. While it demonstrates high sensitivity, it suffers from a false positive rate (FPR) of approximately 60%. We aim to improve this high FPR rate through implementing more refined UNet architectures.

### Assessed models overview

- ResUNet**
- MultiScale Context Retention: Uses hierarchical downsampling and upsampling while preserving fine details through skip connections, ensuring accurate segmentation of both small and large structures
  - Enhanced Feature Propagation with Residual Blocks: Integrates skip connections within each block to improve gradient flow, allowing for deeper networks without vanishing gradient issues [3]
- UNet ++**
- Dense Nested Skip Connections for Feature Enrichment: UNet++ introduces intermediate feature fusion at multiple levels, enabling gradual refinement of representations and reducing the semantic gap between encoder and decoder layers [4]
  - Enhanced Multi-Scale Learning with Deep Supervision: The nested structure improves segmentation accuracy by allowing the model to learn from multiple decoder pathways, enhancing feature reuse and improving fine-grained details [5]

- TransUNet**
- Hybrid CNN-Transformer Design: Combines convolutional feature extraction with a Transformer bottleneck, enabling both local spatial awareness and long-range dependencies for improved segmentation accuracy
  - Efficient Multi-Scale Learning: Uses hierarchical U-Net downsampling, a Transformer encoder for global context modeling, and skip connections to retain fine-grained details, ensuring robust segmentation of complex structures[6]

### Methodology

**Data sources**

**AVIRIS-NG (Airborne Visible/Infrared Imaging Spectrometer - Next Generation)** - High-resolution hyperspectral imaging system capturing 425 spectral bands (380–2510 nm)

**STARCOP AVIRIS ML Ready dataset** – Cleaned AVIRIS-NG; 1,878 labeled methane plumes and simulated multispectral products

**Sources of innovation**

**Added additional bands**

**Expanded Spectral Inputs for Enhanced Performance:**  
8 spectral wavelengths + Mag1C

**Applied a combined loss function**

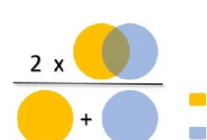
Combined the **cross-entropy** loss function with **Dice** loss function

**Performed Hyperparameter tuning**

- ResUNet** – Learning rate, optimiser, base channels, depth, dropout
- TransUNet** – Learning rate, optimiser, base channels, transformer embedding dimensions, number of heads, transformer depth

**Dice loss** + **Cross-entropy loss**

$$H = - \sum p(x) \log p(x)$$

2 x  Model prediction + Ground truth

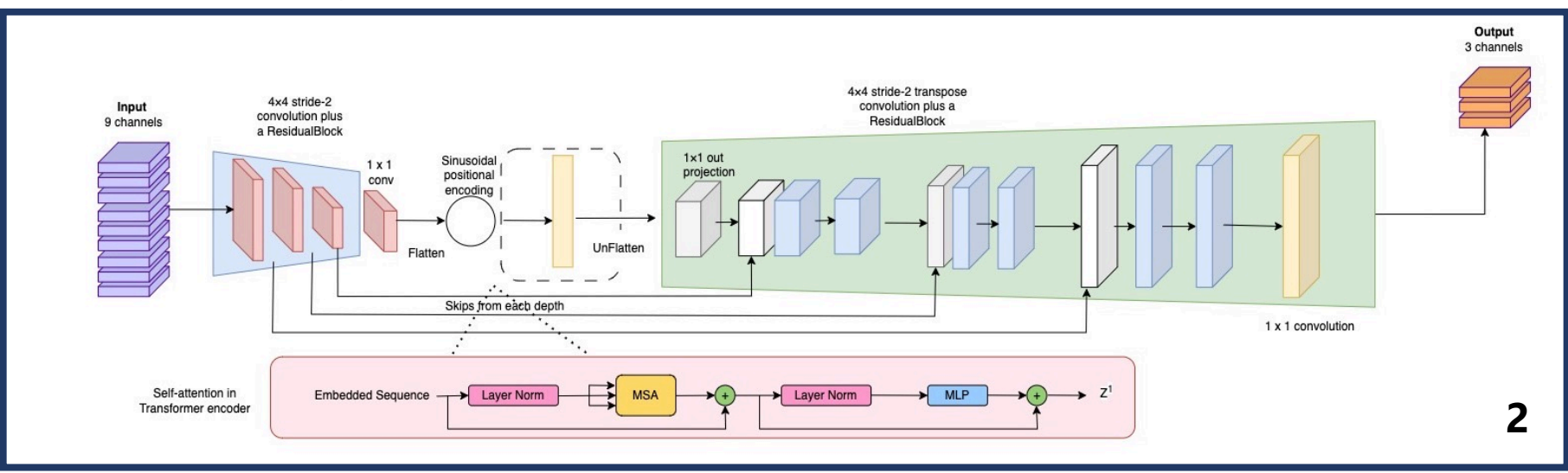
### Results

Comparative results across models

	FPR	F1 easy	F1 hard	Captured Plumes
UNet	c.0.1%	c.61.1%	c.29.4%	c.29.5%
TransUNet	c.0.3%	<b>c.82.3%</b>	c.15.0%	c.35.5%
Res UNet	<b>c.0.1%</b>	c.63.7%	c.25.0%	<b>c.50.3%</b>
UNet++	c.0.9%	c.33.9%	c.14.4%	c.7.7%

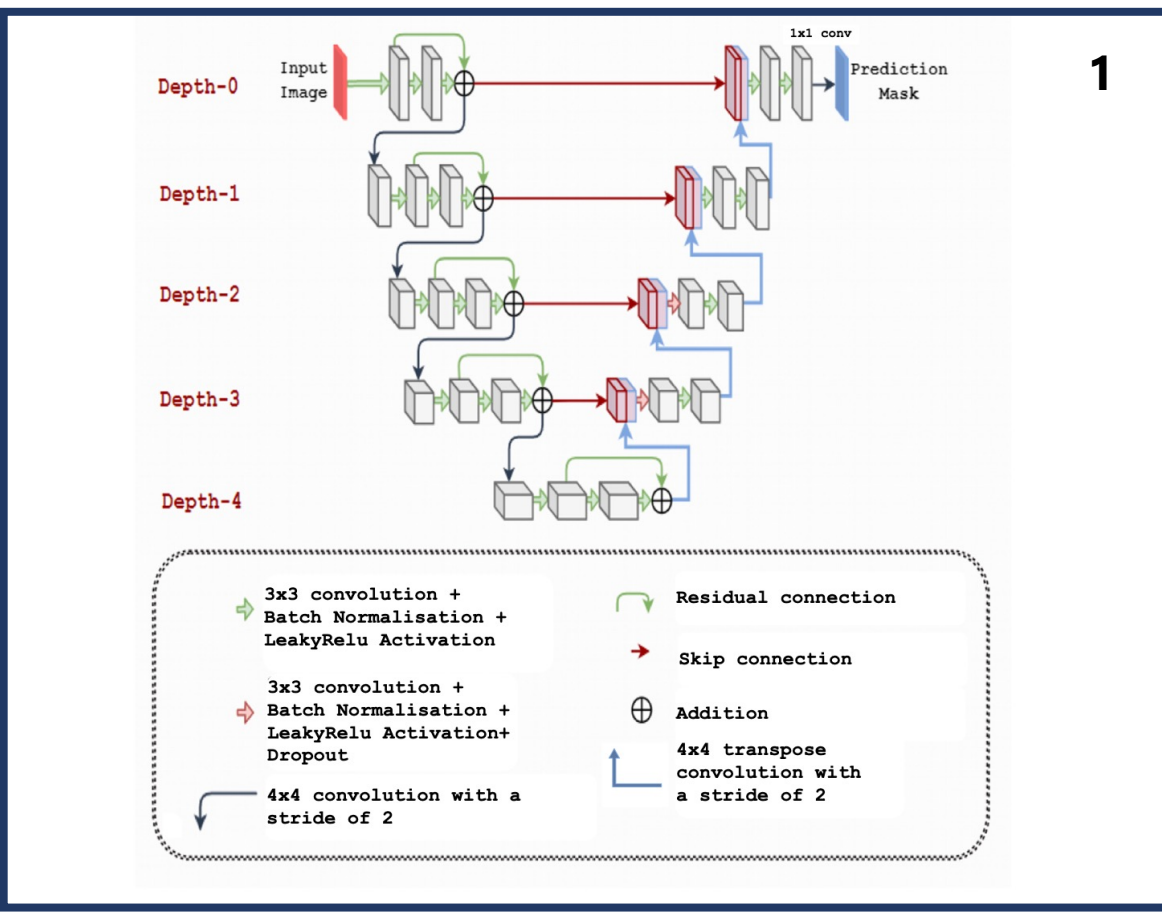
Baseline model

**Top performing model architecture**



1. Residual UNet (ResUNet)

2. Transformer UNet (TransUNet)



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Models were trained on a smaller dataset of samples due to resource constraints, continued training will lead to improved performance

**TransUNet** shows good performance on plumes that are relatively larger or clearer.

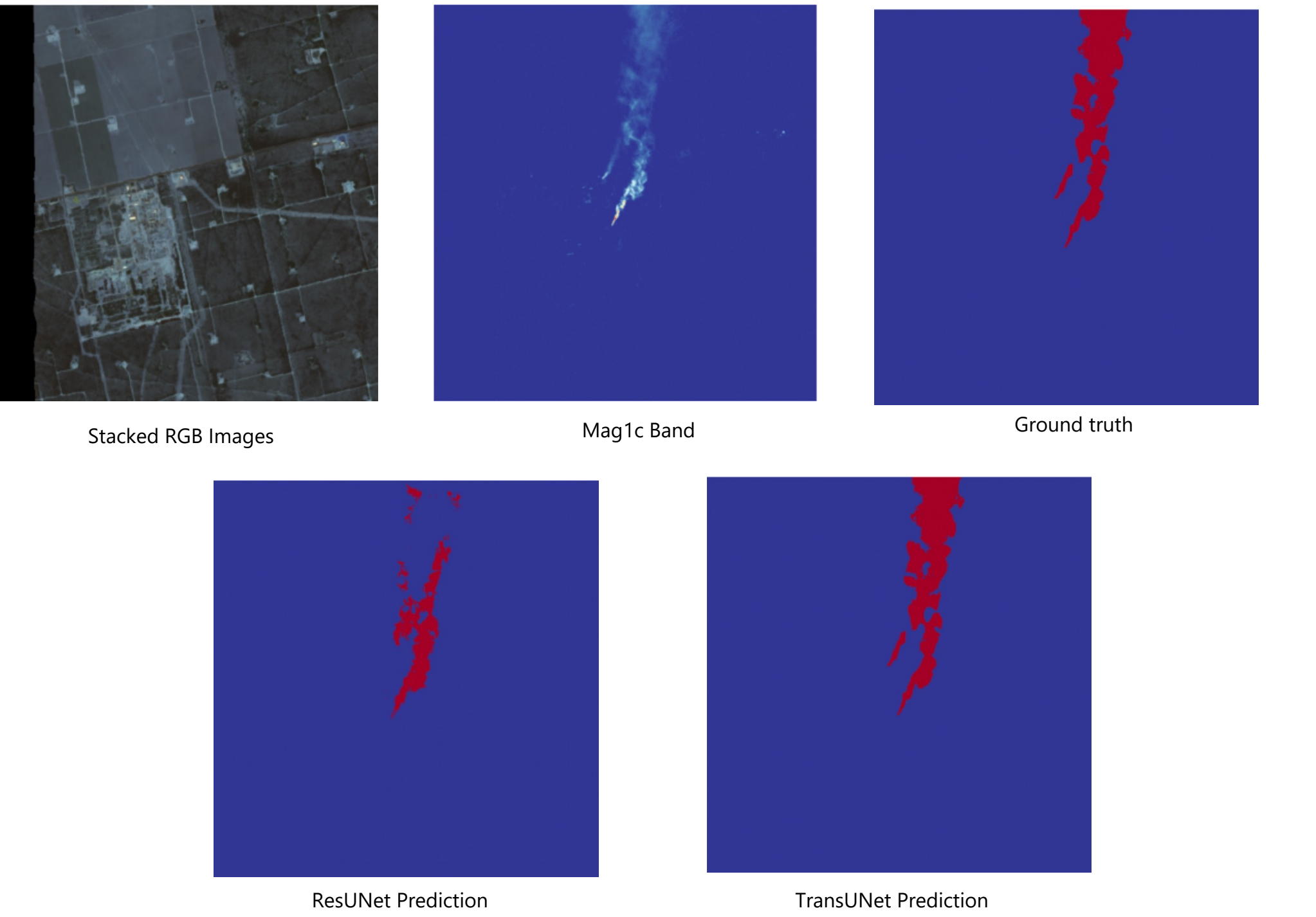
**ResUNet** captures more total plumes but with a lower F1 easy, indicating it may over-segment or produce partial detections that inflate the captured plumes count

### Climate action application

The improved performance facilitates model application to **real-world monitoring scenarios in urban settings**, facilitating accurate methane emission monitoring and informing policy strategies towards more sustainable cities.

### Case study for model application: London

Like many cities, London has ambitious sustainability plans, including the “Accelerated Green” pathway to achieve a net-zero carbon target by 2030 [9]. However, research highlights the city’s current methane monitoring systems are inaccurate and inconsistent [2,3]. Methane emissions in London are primarily contributed by natural gas leaks [8], **hence our model can be implemented to identify such leaks so as to inform policy rollout and solution prioritisation, as well as monitor policy efficacy over time.**



**Improved models lead to more effective adaption, enabling informed policy decisions and sustainable climate action**

[1] J. Tauschinski and A. Mooney, *Financial Times*, Nov. 12, 2024. [Online]. Available: [ft.com](https://www.ft.com/content/1048550/arXiv.2102.04306). [2] spaceml-org/STARCOP, *Jupyter Notebook*, Mar. 11, 2025. [GitHub](https://github.com/spaceml-org/STARCOP). [3] Z. Zhang et al., *IEEE Geosci. Remote Sens. Lett.*, vol. 15, no. 5, pp. 749–753, May 2018. doi: 10.1109/LGRS.2018.2802944. [4] Z. Zhou et al., *arXiv*, Jul. 18, 2018. doi: 10.48550/arXiv.1807.10165. [5] S. Hesaraki, *Medium*, Mar. 18, 2025. [Online](https://medium.com/@s_hesaraki/1048550-arXiv.2102.04306). [6] J. Chen et al., *arXiv*, Feb. 08, 2021. doi: 10.48550/arXiv.2102.04306. [7] C. Helfter et al., *Atmos. Chem. Phys.*, vol. 16, no. 16, pp. 10543–10557, Aug. 2016. doi: 10.5194/acp-16-10543-2016. [8] E. Saboya et al., *Atmos. Chem. Phys.*, vol. 22, no. 5, pp. 3595–3613, Mar. 2022. doi: 10.5194/acp-22-3595-2022. [9] *London City Hall*, Mar. 15, 2025. [Online](https://www.london.gov.uk/press-releases/major/london-city-hall/2025/03/15/accelerated-green). [10] *Imperial News*, Mar. 16, 2025. [Online](https://www.imperial.ac.uk/news/2025/03/16/accelerated-green/). [11] *London City Hall*, Mar. 15, 2025. [Online](https://www.london.gov.uk/press-releases/major/london-city-hall/2025/03/15/accelerated-green/).