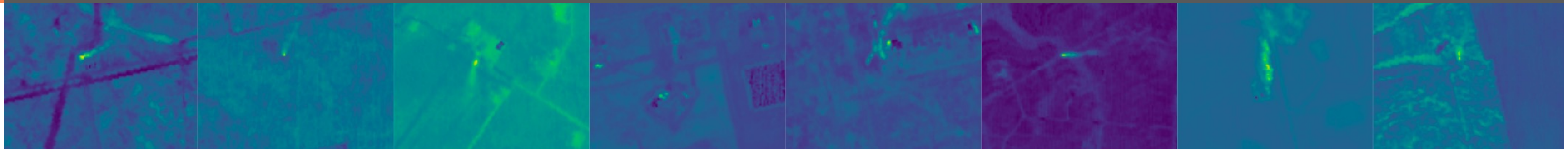
STARCOP: ML models for on-board detection of methane leaks in multispectral and hyperspectral sensors

ECMWF–ESA workshop 2022



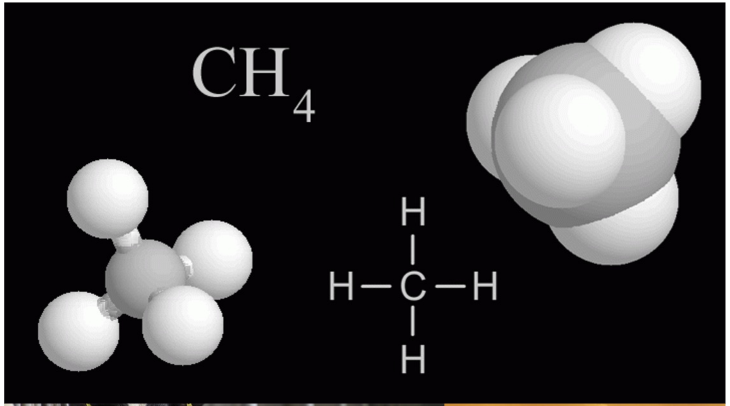
Vít Růžička, Gonzalo Mateo-García, Anna Vaughan,
Luis Gómez-Chova, Luis Guanter

Networked Intelligence in Orbit

esa Φ-Lab Partners · FDL · University of Oxford · Universitat de València · Universitat Politècnica de València · D-Orbit · Trillium Europe

Big picture

- *Reducing methane is one of the most easy pathways to limiting temperature growth to 1.5°C. Although other efforts also have to take place.*
- *Methane has **short atmospheric lifetime** = reducing it now will have actual and fast impact*
- *35% emissions made by humans are from **Oil and Gas industry, most of this is contributed from large leaks** (super-emitters).*
- *There is a need to precisely detect where do these leak originate from, to be able to attribute the leaks to companies / exact sources to fix them.*



- **The Problems:**
    - Methods working with **multi-spectral** data are **manual only**
    - **Hyper-spectral** methods produce **many false positives**
    - **No standardised ML-ready dataset** for methane detection

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    - Create a **testbed dataset** of manually verified plume events
    - Propose ML models working on multi- and hyper- spectral views of this data

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- **The Goal:** Reliable methane detection on-board of satellites using sensors with mixed capabilities

Can we detect methane on-board satellites?

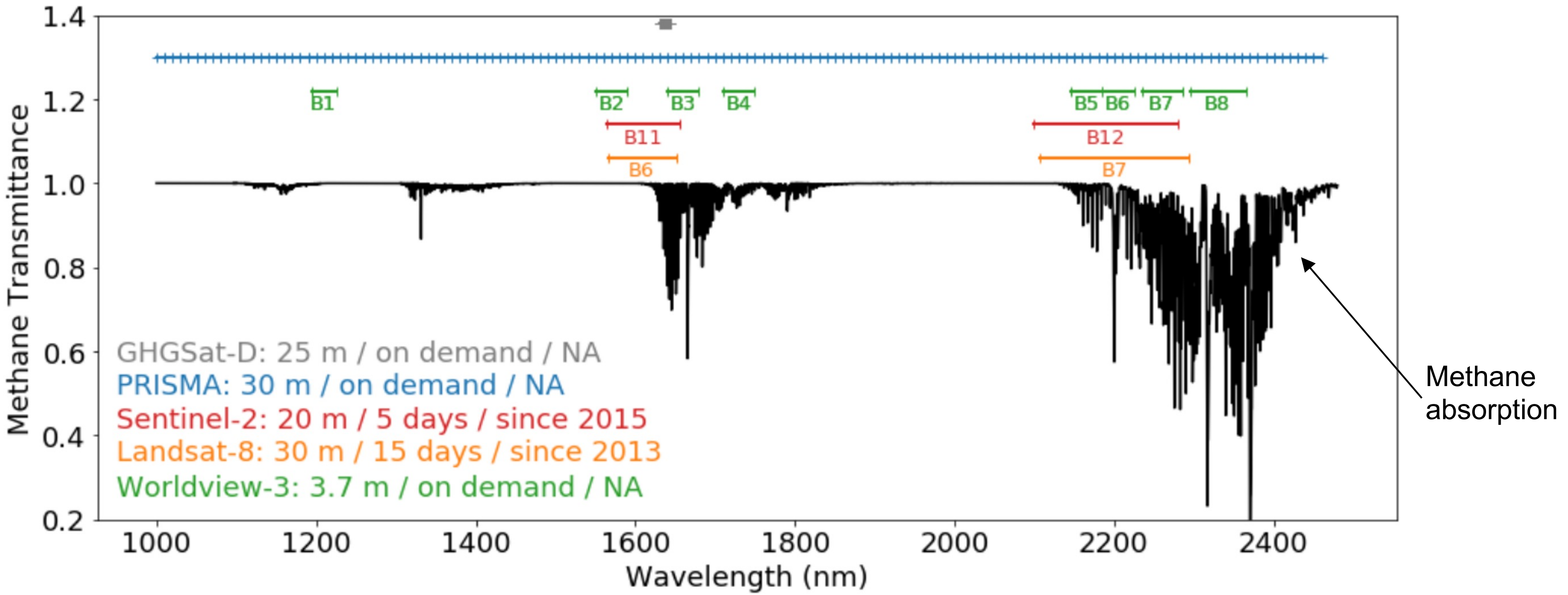
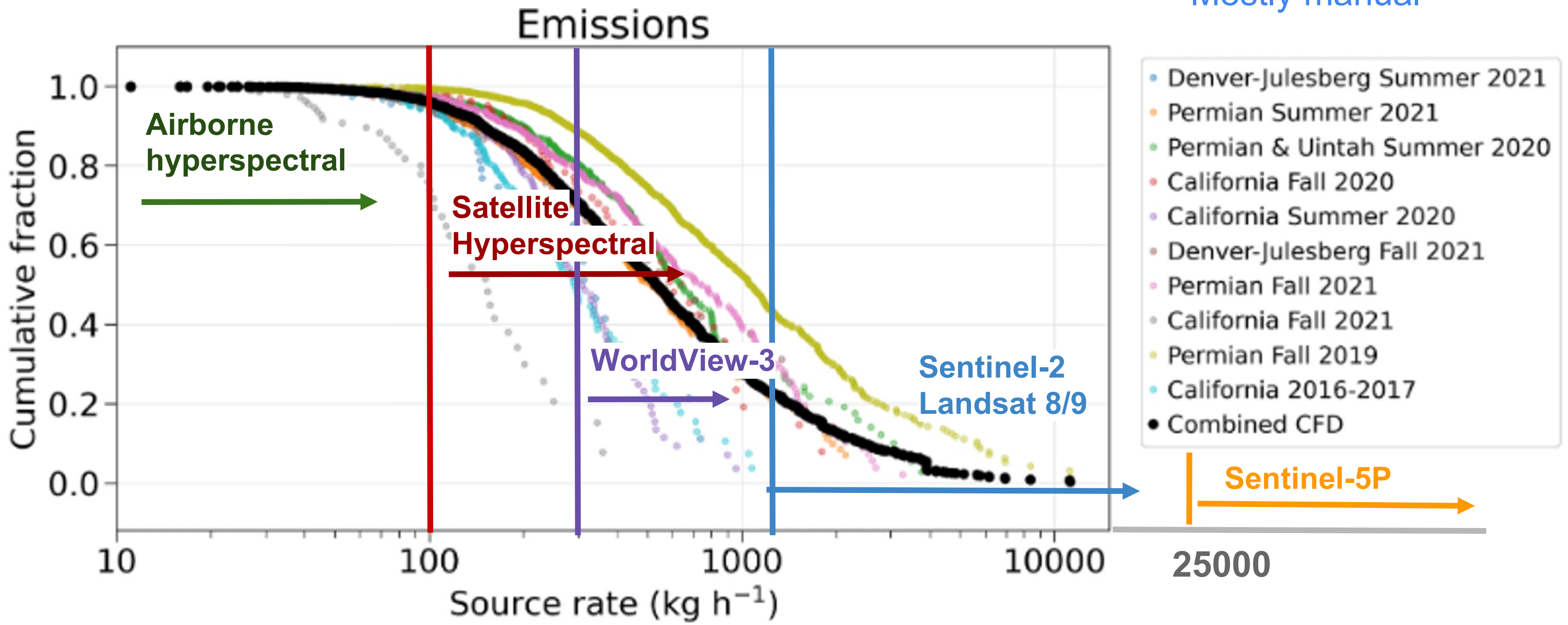


Figure taken from Sanchez-Garcia et al 2021: *Mapping methane plumes at very high spatial resolution with the WorldView-3 satellite*. Atmospheric Measurement Techniques Discussions 1–26. https://doi.org/10.5194/amt-2021-238

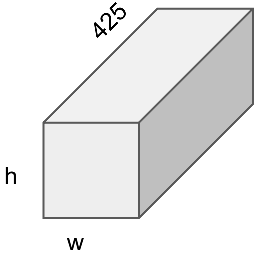
Detection limits (best cases)

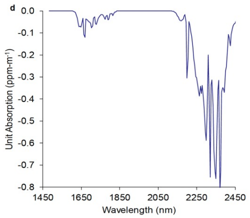
- Best cases, no systematic study of detection
- Mostly manual



[Jacob 2022] Quantifying methane emissions from the global scale down to point sources using satellite observations of atmospheric methane

Baseline methods for hyperspectral data

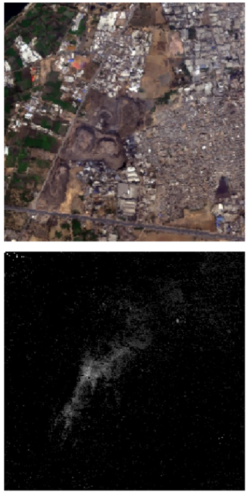




- Matched Filter approaches (example: **mag1c**) can be automated, but produce many false positives

- Processing large hyperspectral datasets is slow

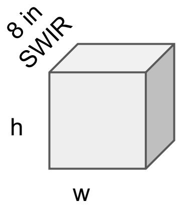
Plume:



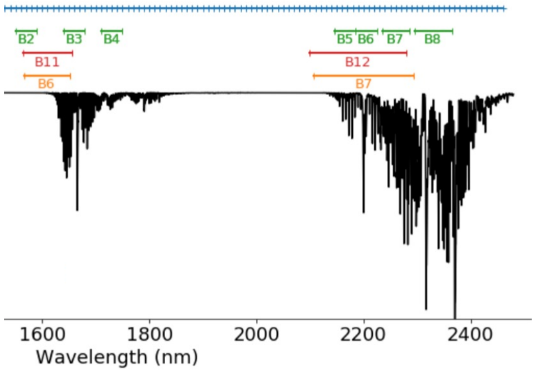
Known sources of false positives:

[M. D. Foote 2020] Fast and Accurate Retrieval of Methane Concentration From Imaging Spectrometer Data Using Sparsity Prior

Baseline methods for multispectral data



- Typically using **image differencing or ratios** between two channels (band inside and outside methane signature)



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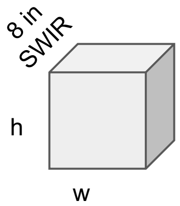

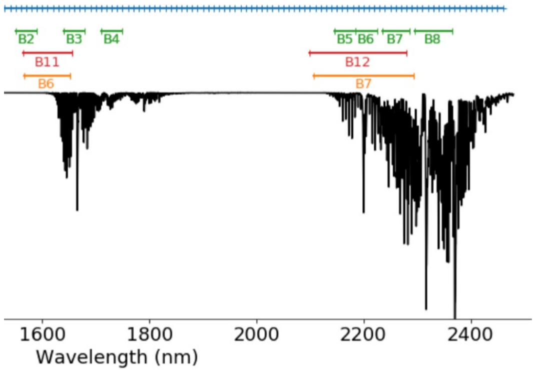

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Varon

$$\frac{\boldsymbol{c} * signal - bg}{bg + \varepsilon}$$

c ~ matched

Sánchez-García

From non-methane bands estimate the target methane band with **multiple linear regression**

[D.J. Varon et al., 2021] High-frequency monitoring of anomalous methane point sources with multispectral Sentinel-2 satellite observations
[Elena Sánchez-García et al. 2022] Mapping methane plumes at very high spatial resolution with the WorldView-3 satellite

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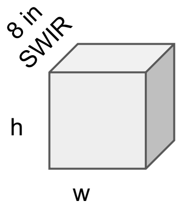

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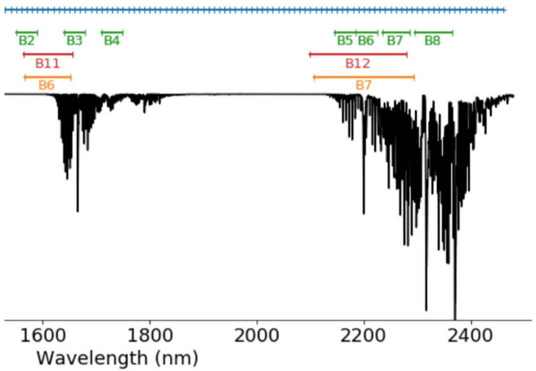

<u>Varon</u>

$$\frac{\boldsymbol{c} * signal - bg}{bg + \varepsilon}$$

c ~ matched

Example with WorldView3 bands:

$B_7 \Leftrightarrow B_5$

<u>Sánchez-García</u>

From non-methane bands estimate the target methane band with **multiple linear regression**

$$B_8' = MLR(B_{1\ldots6}, B_8)$$

$$B_8 \Leftrightarrow B_8'$$

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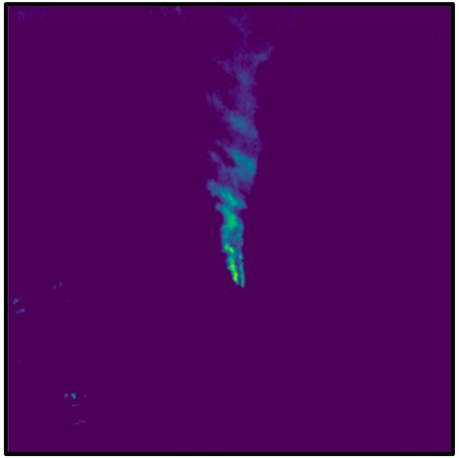
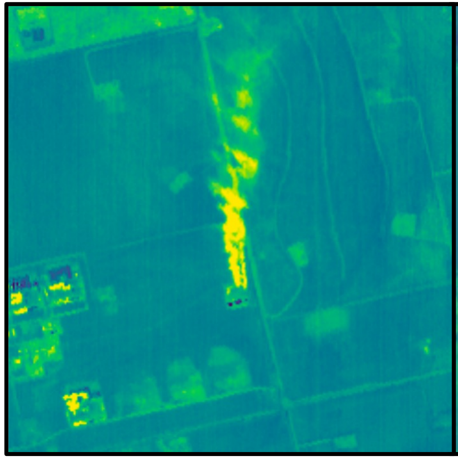
Detection capabilities using different sensors

Hyperspectral data:

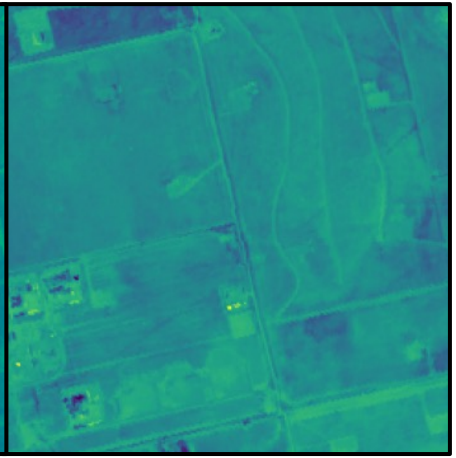
Multispectral data:



Matched filter approach (**mag1c**, uses bands between 2122-2488nm)



Simulated **WorldView3** SWIR bands B7 <> B5

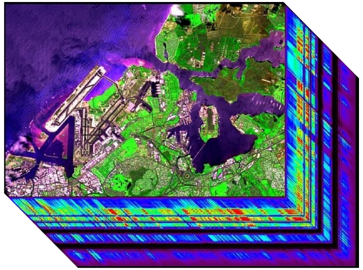


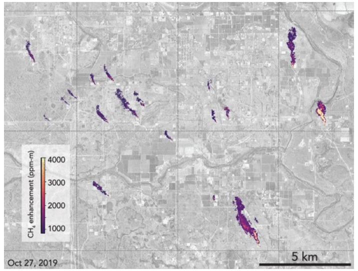
Simulated **Sentinel-2** bands B12 <> B11

Showing a very strong plume example!

> **Baseline approach:** thresholding of the extracted feature map

Releasing: ML-Ready STARCOP Dataset

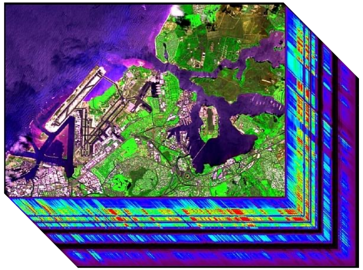


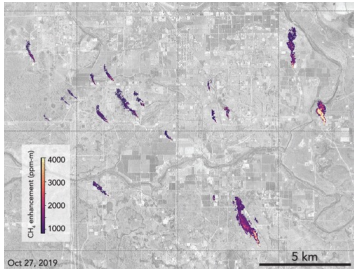


- Based on the **AVIRIS** aerial data collected in the **Permian Basin** area
- Large unwieldy dataset: **4.47 TB**
- Initial annotation available from [Cusworth 2021]

[D.H. Cusworth 2021] Intermittency of Large Methane Emitters in the Permian Basin

Releasing: ML-Ready STARCOP Dataset





- Based on the **AVIRIS** aerial data collected in the **Permian Basin** area
- Large unwieldy dataset: **4.47 TB**
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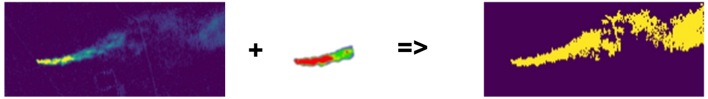
<u>**Augmented**</u> **with:**

- **Refined ground truth** annotations
- Predictions of other methods (**mag1c**)



Simulation of multi-spectral data:

- Existing: Sentinel-2 and WorldView3
- Future satellites:
    - Exploration: which bands to add?

Split into easy/hard plumes

[D.H. Cusworth 2021] Intermittency of Large Methane Emitters in the Permian Basin

Training dataset

From 1712 tiles with plumes and 1713 tiles without plumes, augmented with rotations, crops, …

Tile = 512x512 px

Test dataset

RGB | GT | mag1c | Ratios using simulated WV3 bands (Varon and Sánchez)

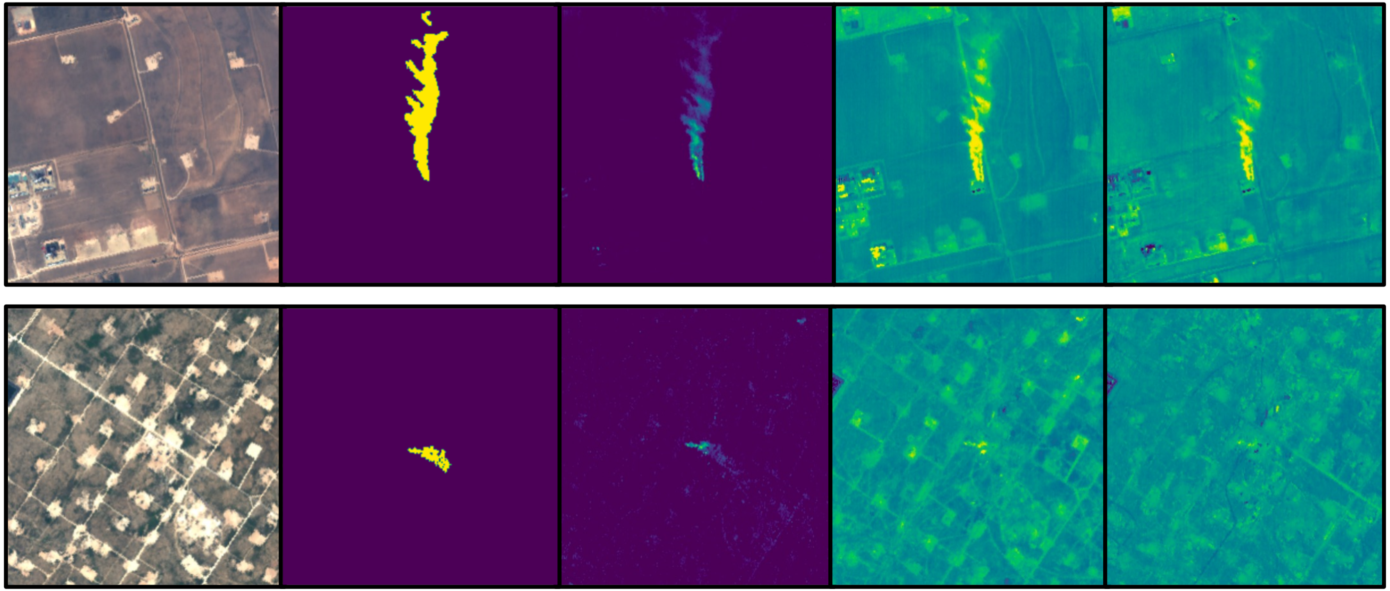
166 plumes

Easy

qplume > 1000

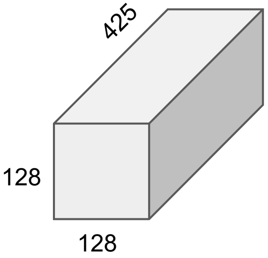
Hard

qplume < 1000

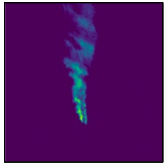


176 **No-plume** *From known confounders and random no-plume locations.*

HyperSTARCOP model



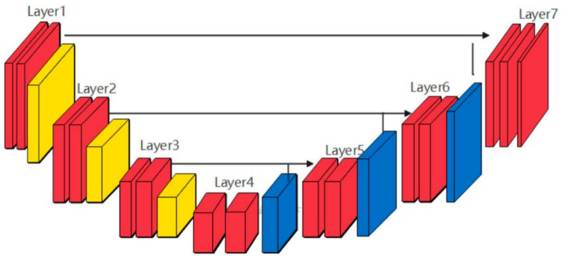
feature extraction:



Matched Filter (mag1c)

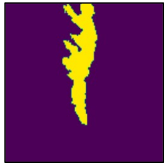
Selected bands (RGB)

U-Net



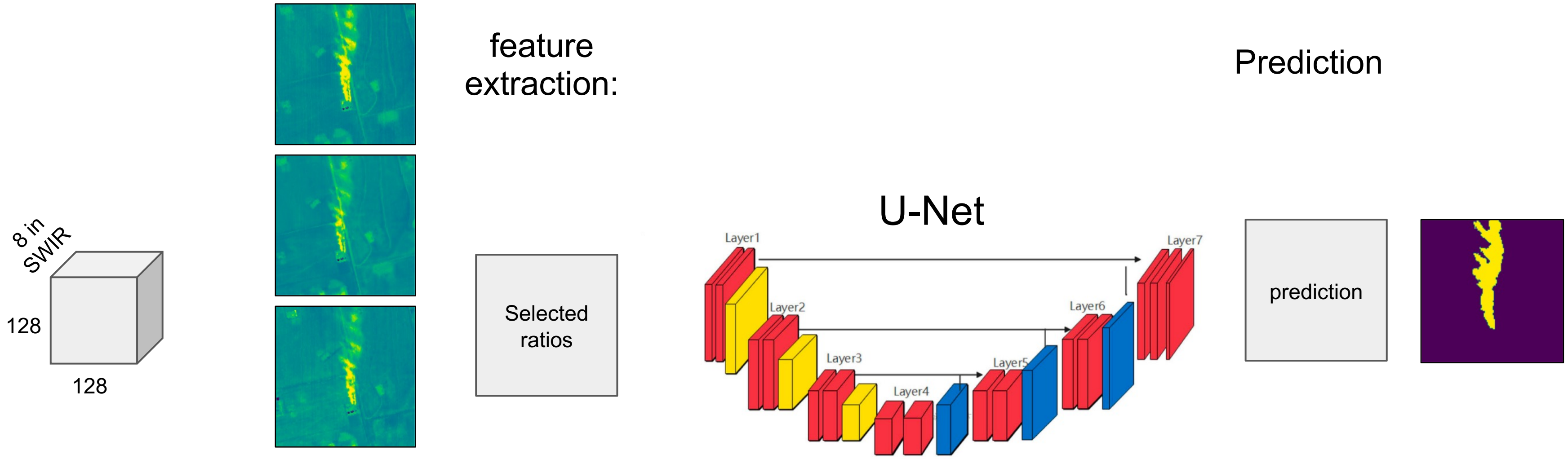
Prediction

prediction



- We use the output of mag1c with selected bands from the original hyperspectral sensor (RGB)
- To reduce the false positive detections in the predictions

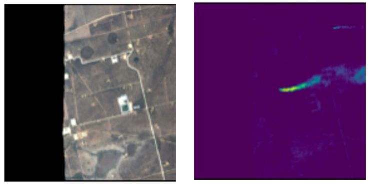
MultiSTARCOP model



- We test different **ratio products** used with multispectral data (Varon and/or Sánchez with different source bands)
- To achieve automated methane plume detection (current methods were manual)

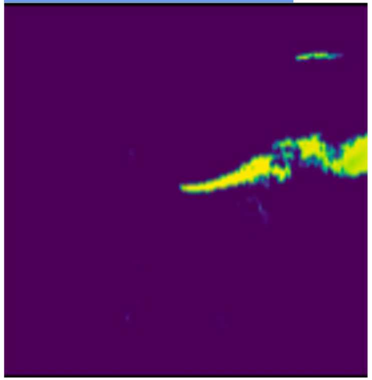
Prediction example:

Hyperspectral input:

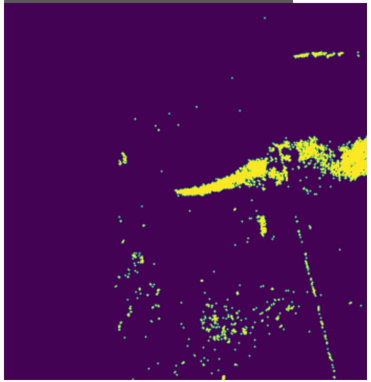


mag1c + rgb

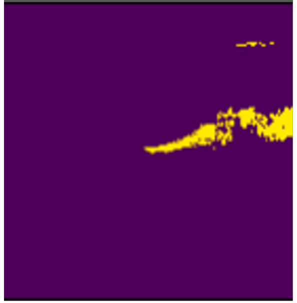
HyperSTARCOP



Baseline

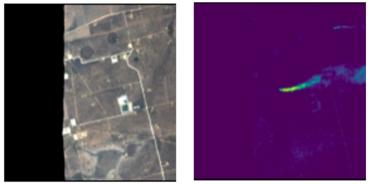


GT



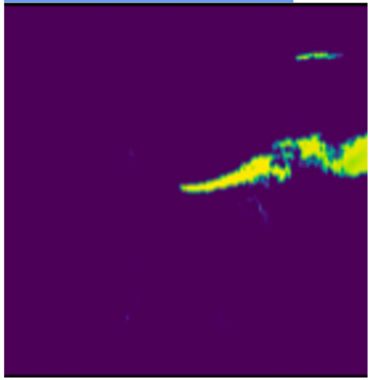
Prediction example:

Hyperspectral input:



mag1c + rgb

HyperSTARCOP



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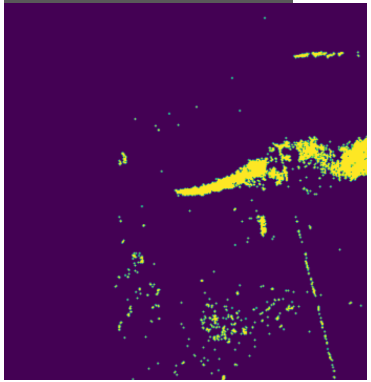

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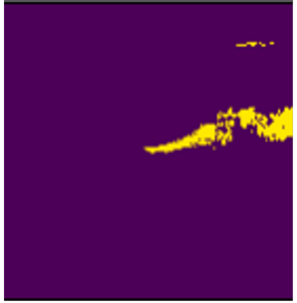
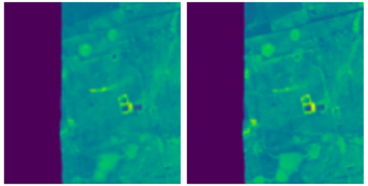
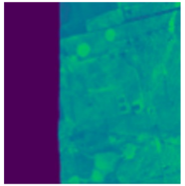


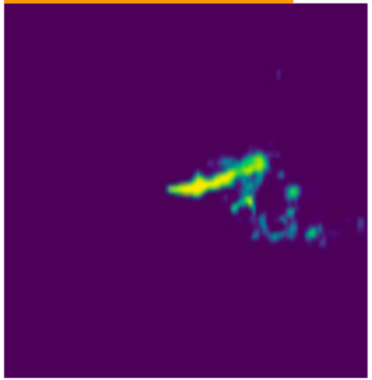
Multispectral input:



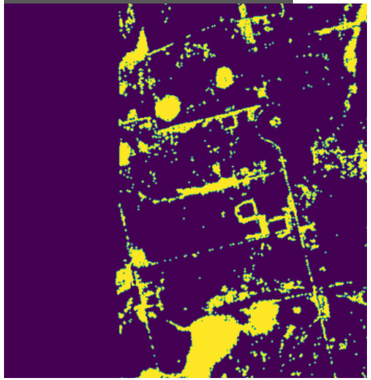


ratios

MultiSTARCOP



Baseline



Results

F1 score shown in percentage (averaged over 3 runs)
for legibility ±std shown only for hyperspectral

segmentation
classification

Hyperspectral (AVIRIS)	F1 (easy)	F1 (hard)	FPR	Captured plumes
Baseline, mag1c + morpho.	67.4	39.9	75.4	**96.4**
HyperSTARCOP	**83.6±1.5**	**39.8±1.9**	**45.7±5.4**	91.0±2.6

Multispectral (WV3)	F1 (easy)	F1 (hard)	FPR	Captured plumes
Baseline, ratios + morpho.	7.4	0.5	100.0	100.0
Our (Varon)	**32.3**	10.6	85.9	**63.6**
Our (Sanchez)	24.9	**11.5**	**68.5**	35.0
Our (Varon+Sanchez)	30.5	9.5	**67.8**	37.3

- *Our proposed methods **outperform the baselines in both scenarios.***

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+24%   -39%   - 5%

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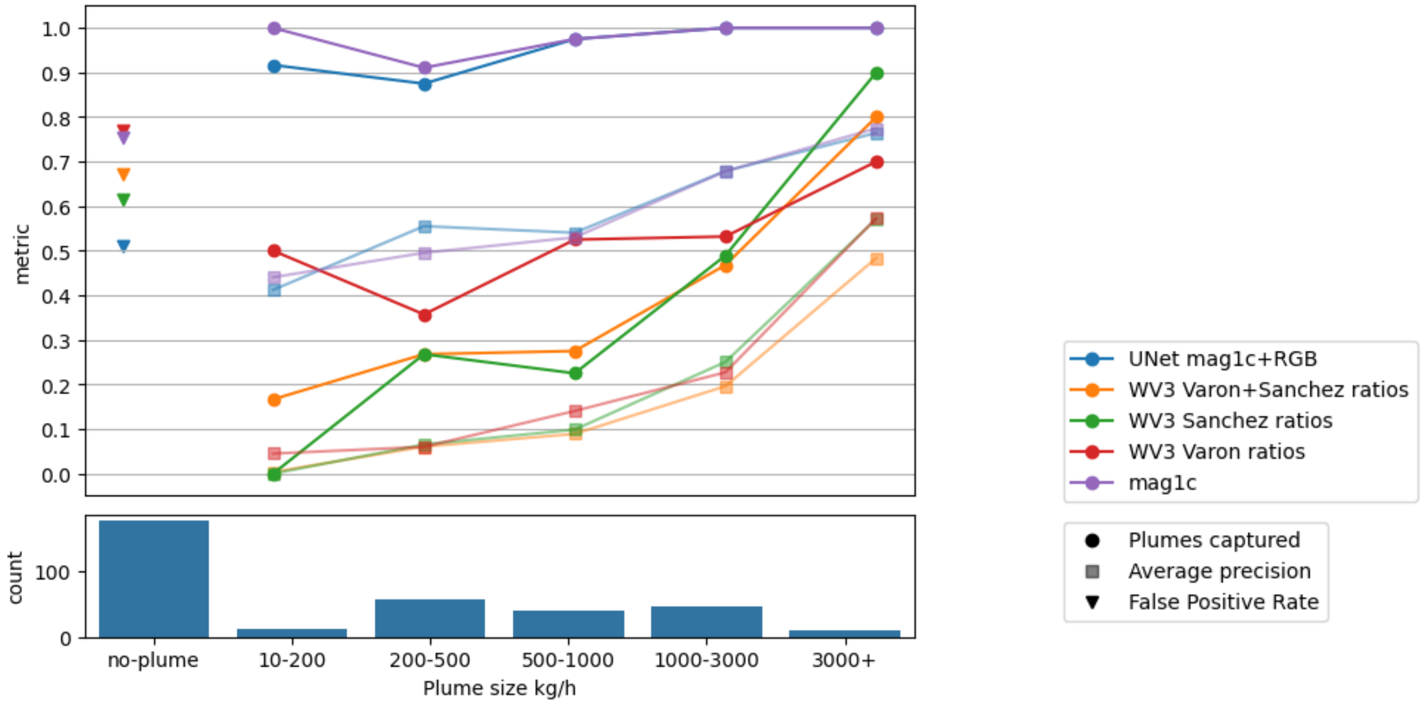
by plume size



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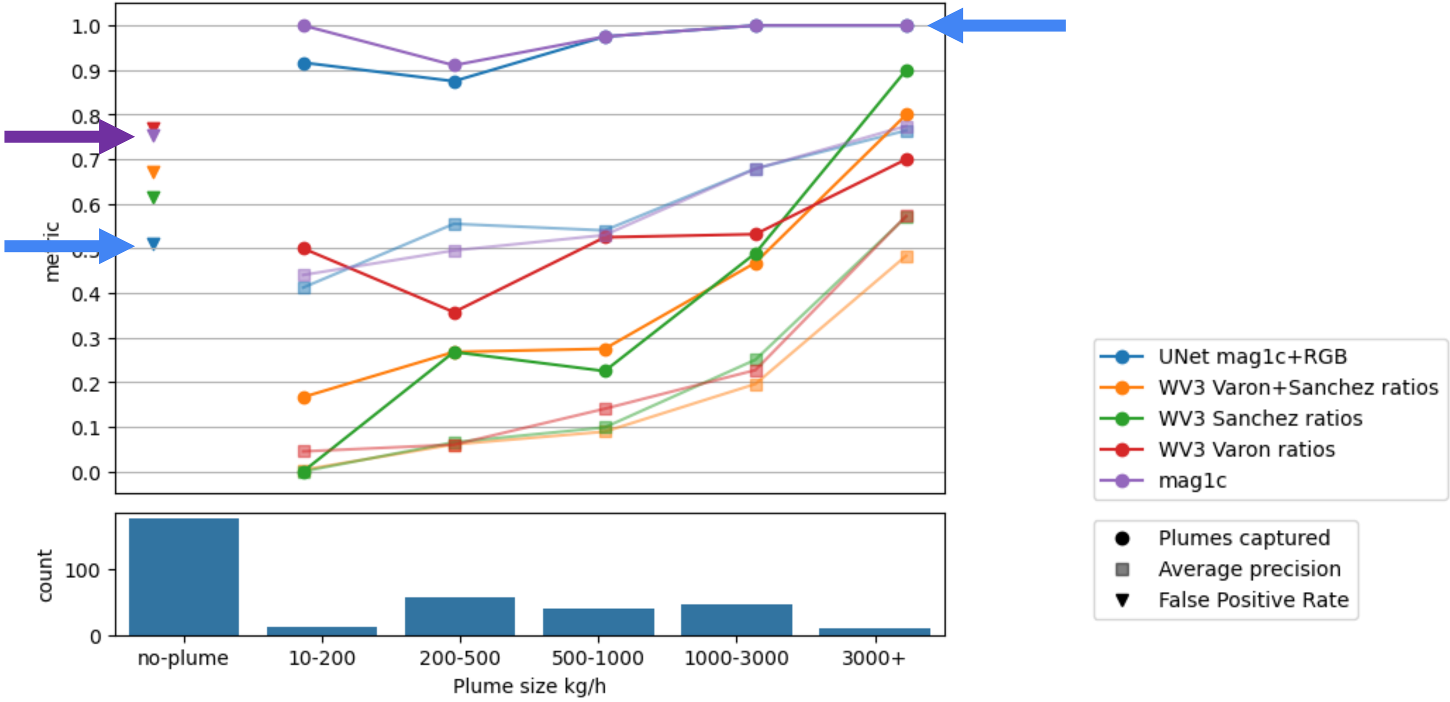

- While maintaining the **same performance for larger plumes** (> 200), our **hyperspectral method achieves 32% drop of FPR** on no-plume data.

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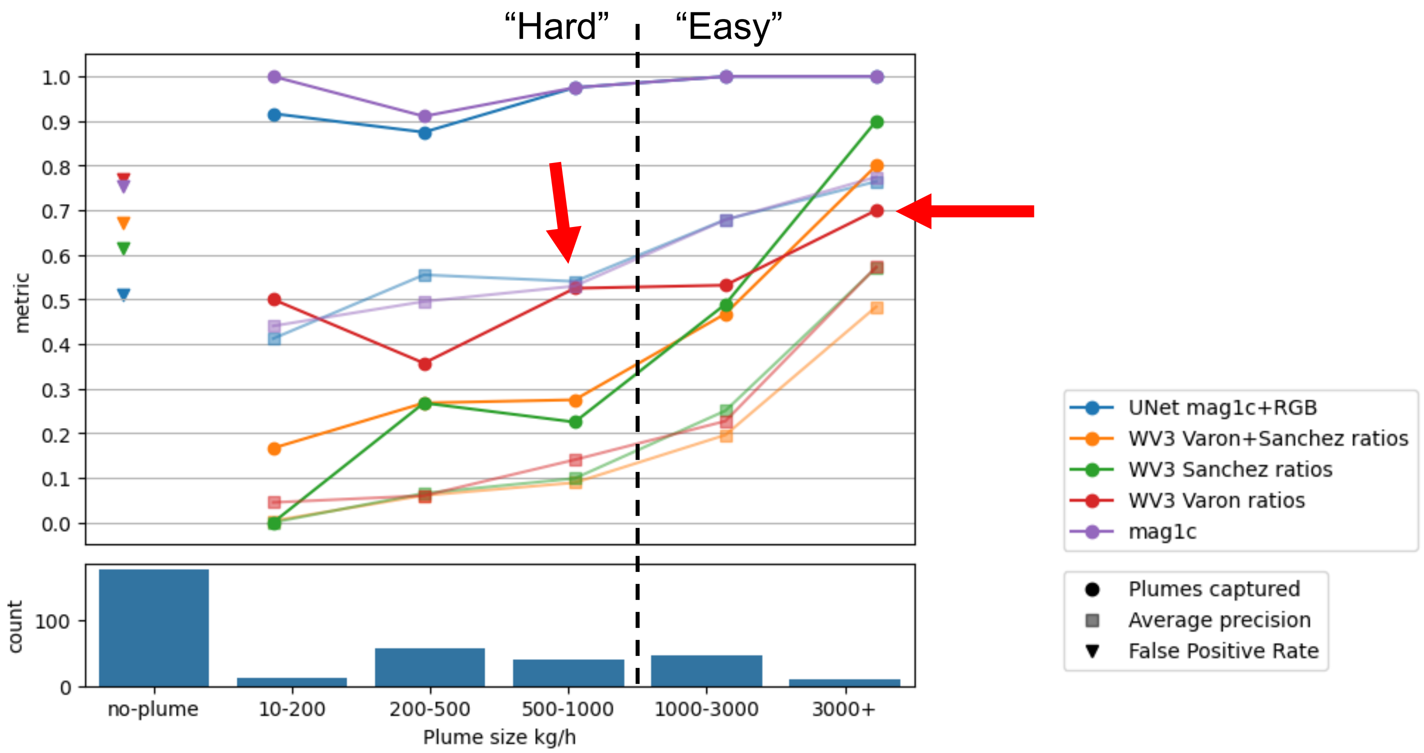


- While maintaining the **same performance for larger plumes** (> 200), our **hyperspectral method achieves 32% drop of FPR** on no-plume data.
- We introduce **automated multispectral models** which are capable of **detection of >70% of very large plumes and >50% or large plumes.**

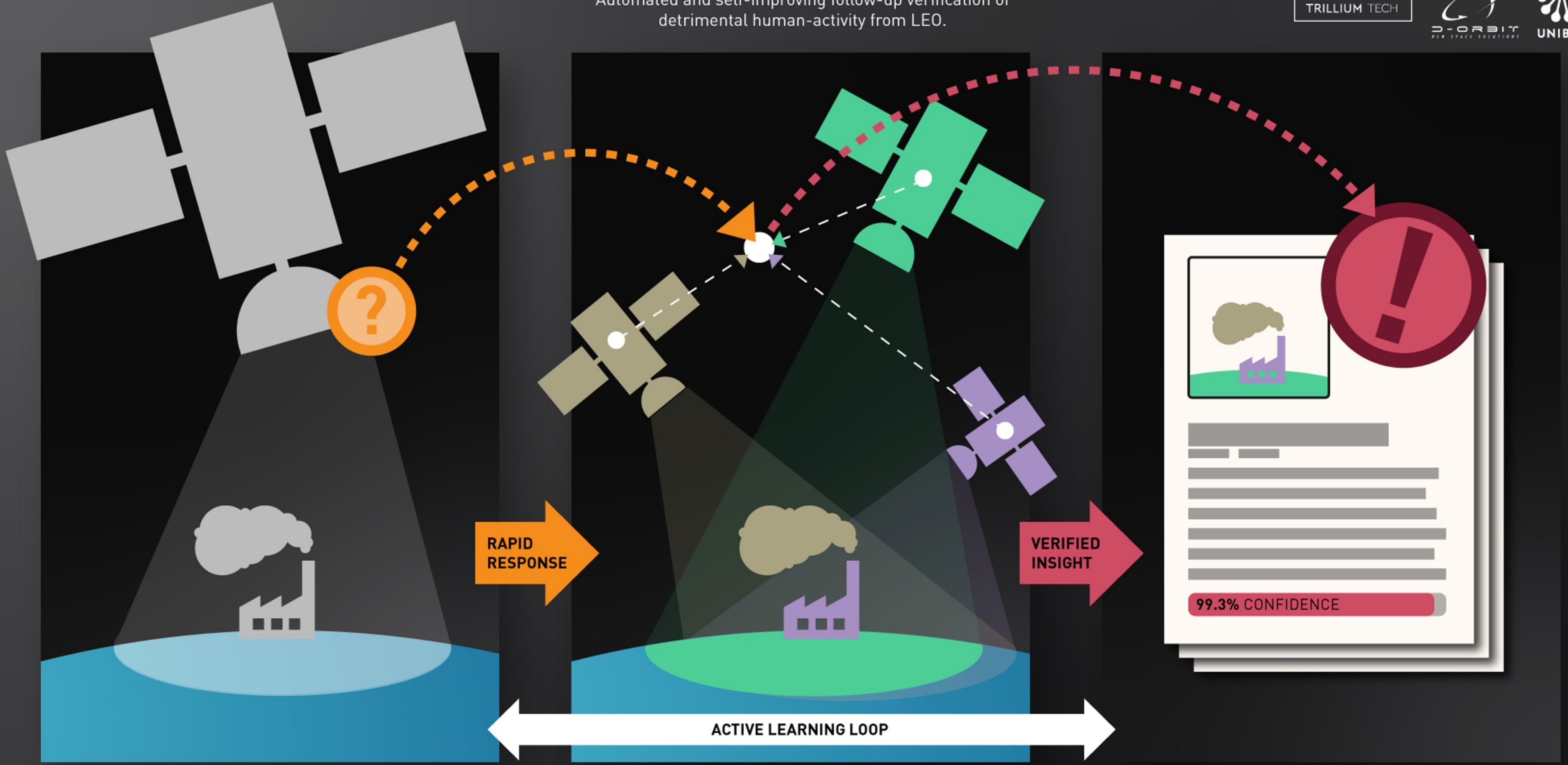
STARCOP

Automated and self-improving follow-up verification of detrimental human-activity from LEO.

TRILLIUM TECH

D-ORBIT

UNIBAP



'Tip-off' signal [redacted]

Follow up with (1) third party verification [redacted]

Insight, returned rapidly to the ground.

Conclusions:

- **<u>STARCOP models</u>**: U-Net based model for plume detection
- Hyperspectral model **reduces the FPR of the baseline by 39%** while maintaining its performance on most plumes
- **Automated multispectral model** capable of **detecting 50% of large and 70% of very large plumes**
- **Dataset:** release of **challenging ML-ready dataset testbed** for plume detection

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Thank you for your attention!

Any questions?