Methane point source detection and quantification from high-resolution satellite observations and deep learning methods

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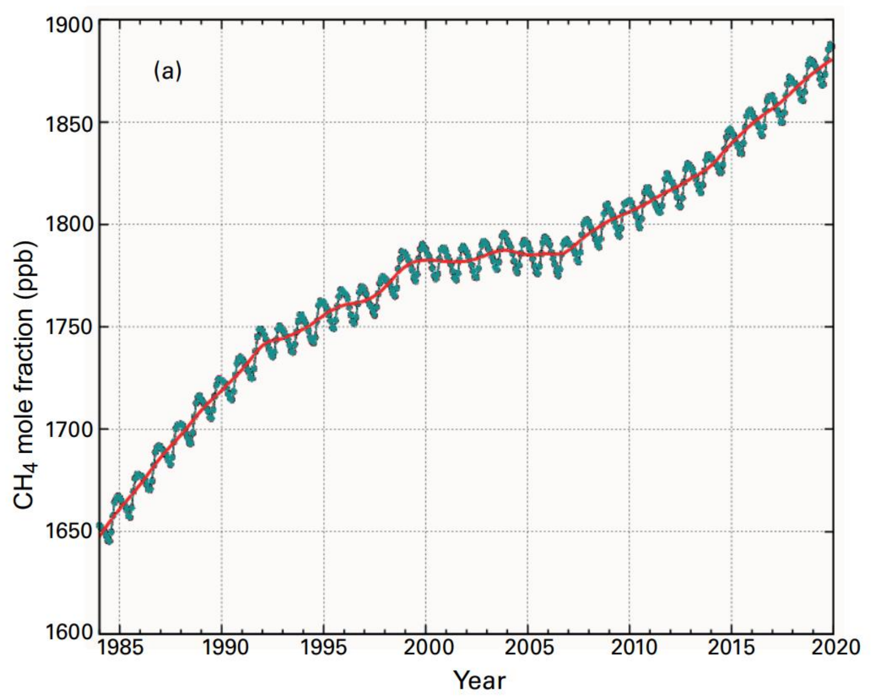
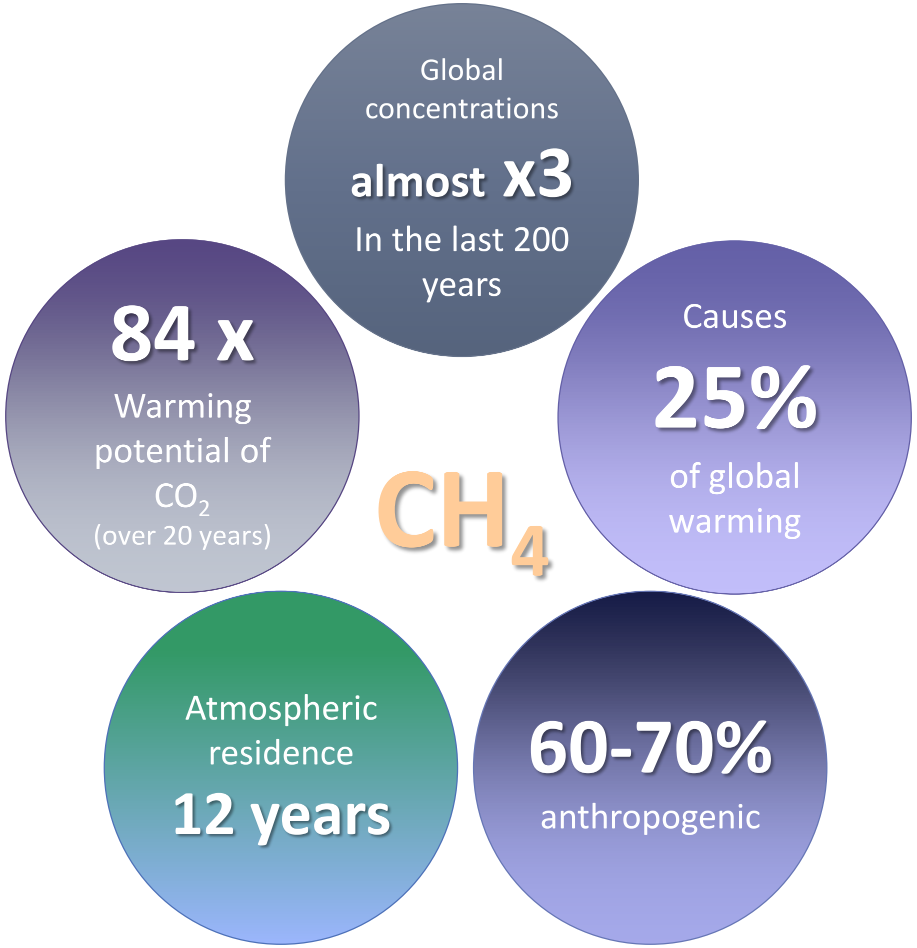
Motivation

Global average CH4 concentrations

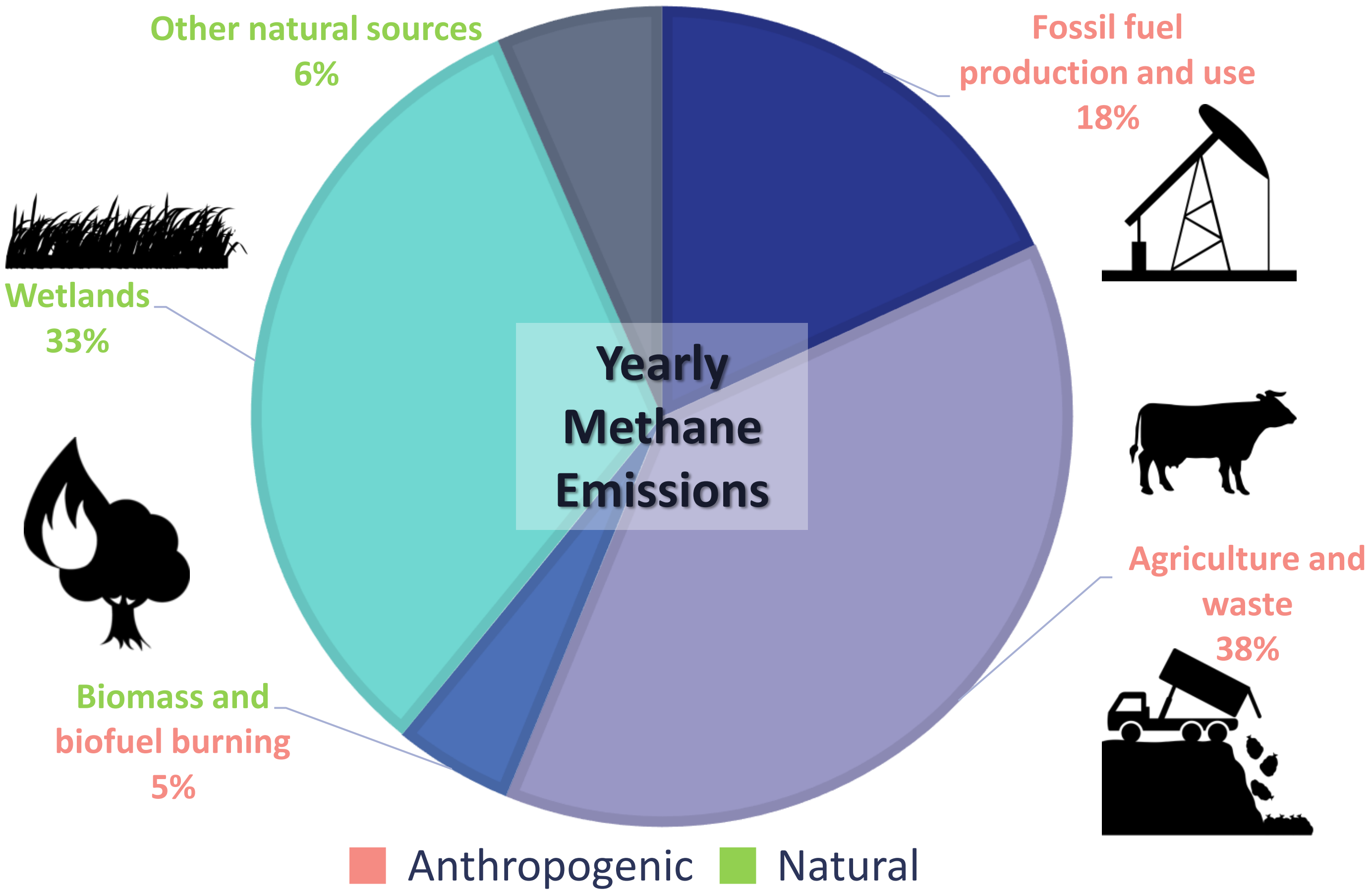


Source: World Meteorological Organisation (2020)

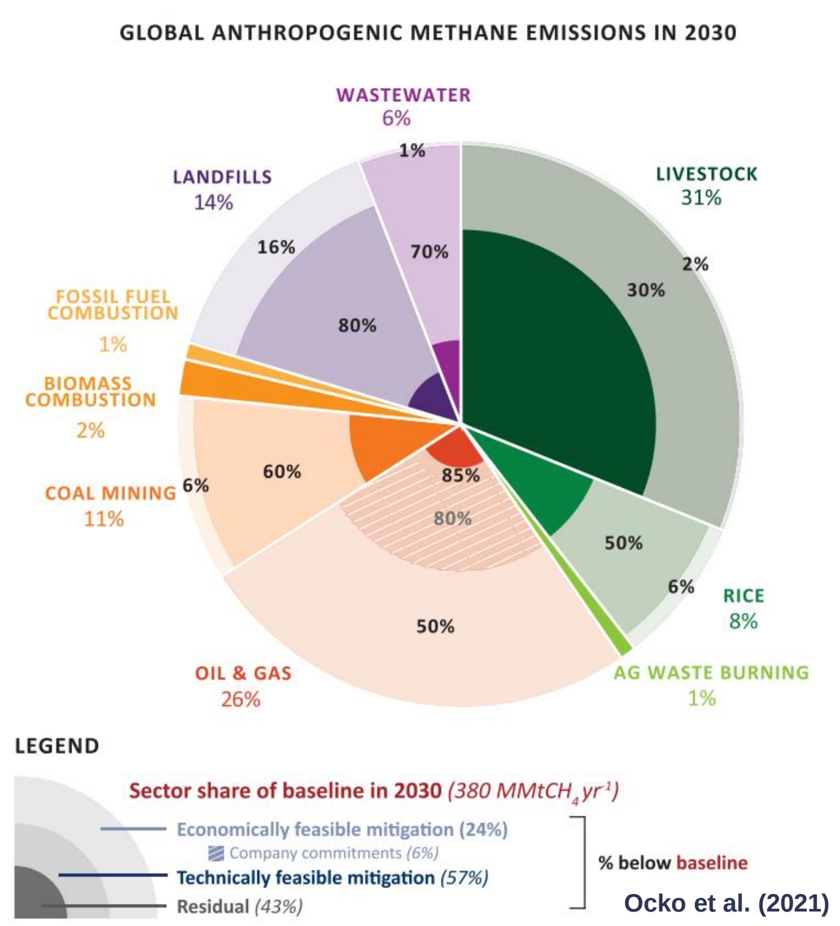
Methane is the second most important **greenhouse gas** and it plays an important role in climate change.



Sources of methane



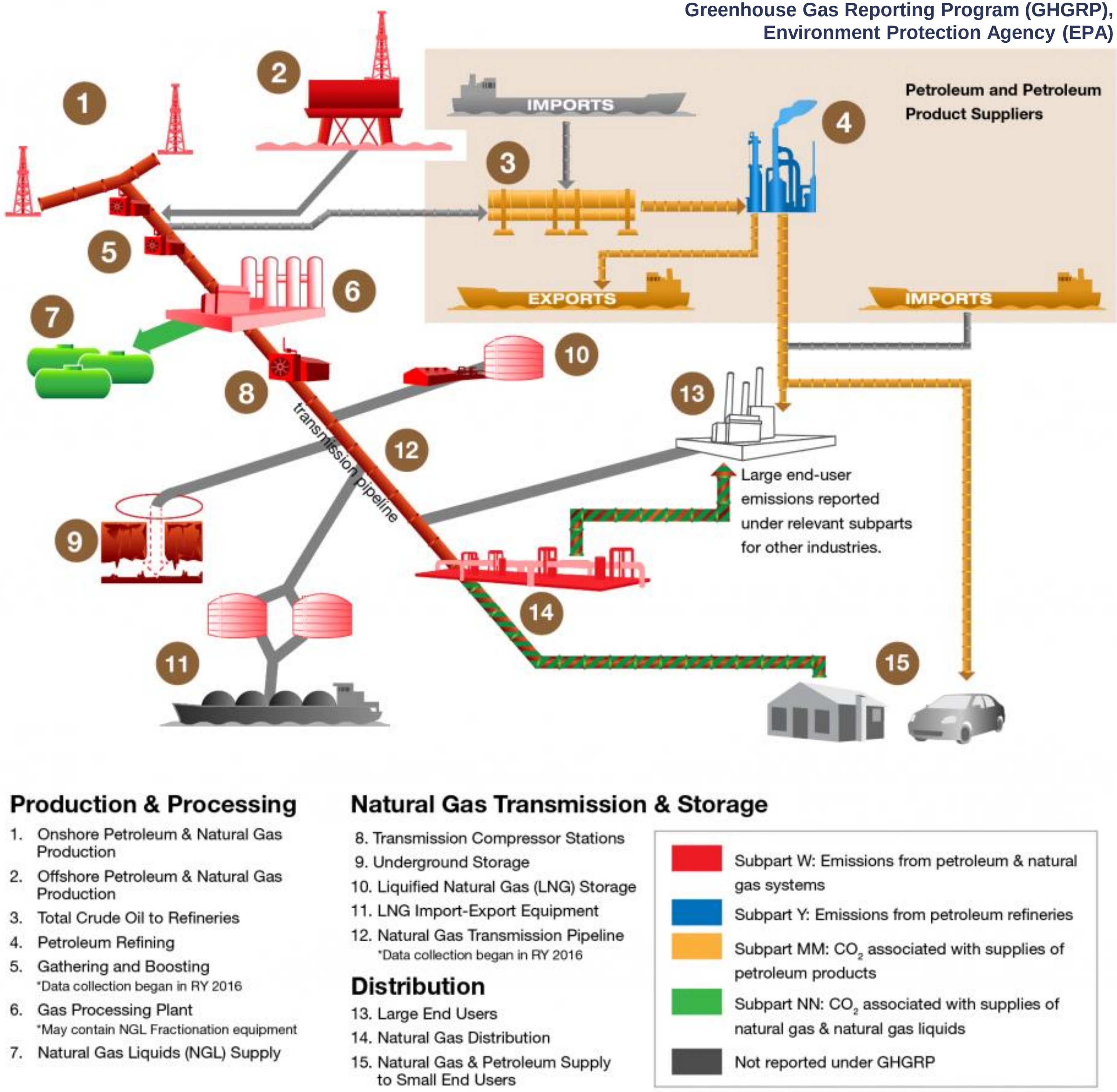
Data: Global Carbon Project (2020)



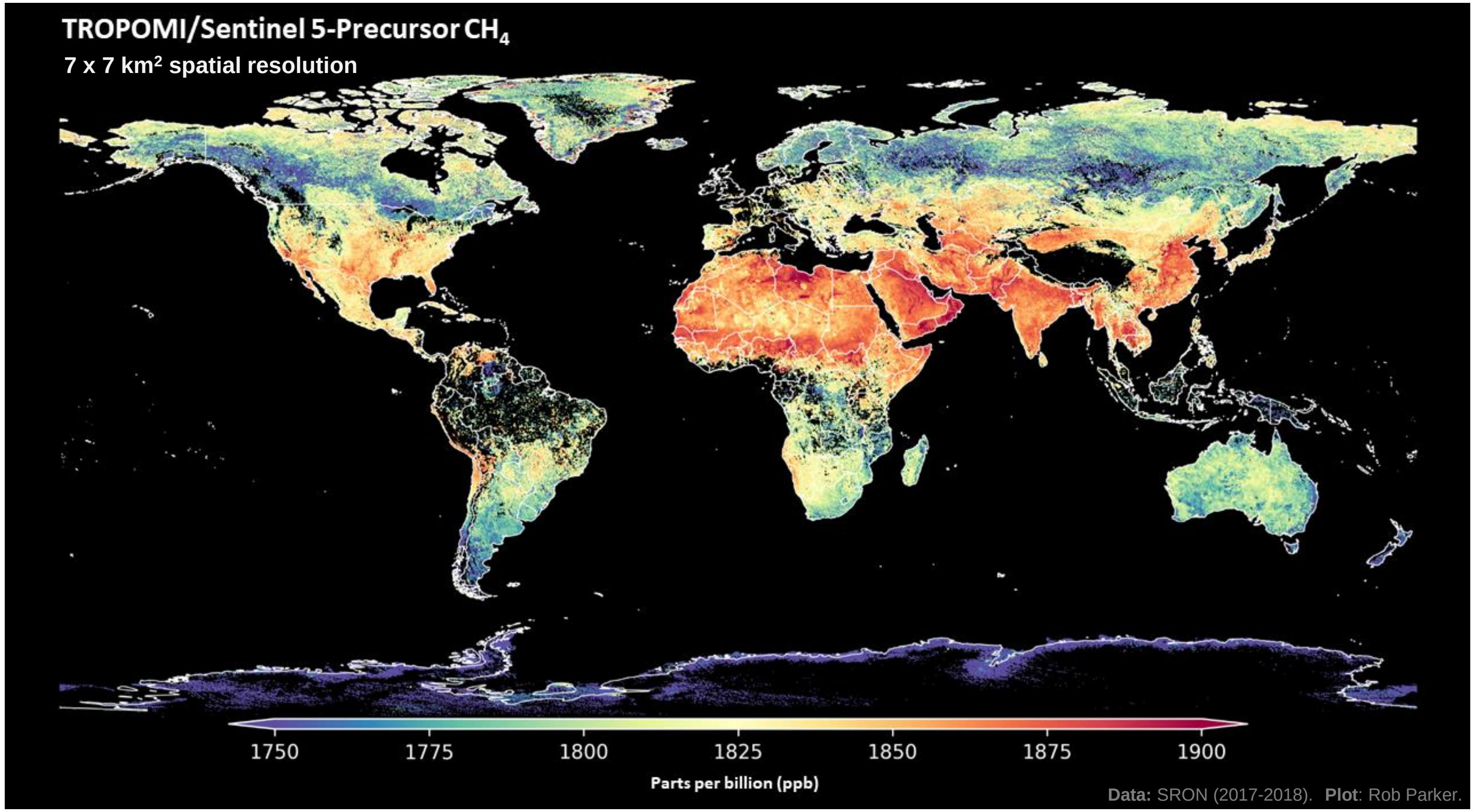
Oil and gas – great potential for mitigation

A small number of very strong sources (*super-emitters*) contribute a large fraction of total emissions.

Greenhouse Gas Reporting Program (GHGRP), Environment Protection Agency (EPA)



Synergy: global coverage vs high spatial resolution



Multispectral:

WorldView-3 (WV-3)
Pixel size: 4 x 4 m^2
8 broad SWIR bands
Spectral res.: 30-70 nm

Hyperspectral:

PRISMA
Pixel size: 30 x 30 m^2
Multiple SWIR bands
Spectral res.: 12 nm

Similar satellites:
- Multispectral: **Sentinel-2, Landsat-8**
- **GHGSat**

Methods for PRISMA and WV-3: retrieval and flux inversion

Data-driven retrieval

- Small number of singular vectors from the spectral Principal Component Analysis **(PCA)** describe background.
- Spectral CH_4 **Jacobian** describes radiance changes corresponding to methane enhancements.

Background   Methane (KCH_4)

$$F(W,J) = \sum_{k=1}^{c} J_k \cdot W_k + J_{c+1} \cdot W_{c+1}$$

1. Forward model

$$\|y - F(J,W)\|^2 = 0$$

2. Least-squares fit

Based on Thorpe et al. (2014)

Integrated Mass Enhancement (IME) flux inversion

- Source rate estimated from total **plume mass**, **wind speed**, and **plume length**.
- Generating the **plume mask** is one of the critical and most challenging steps.

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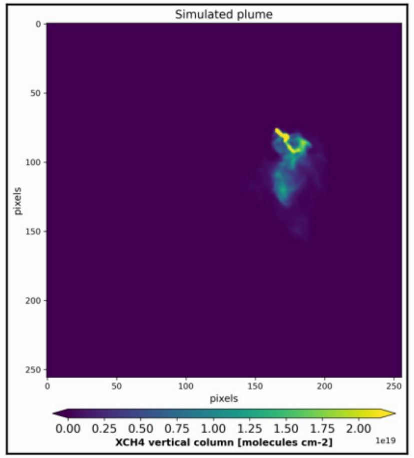
Testing our methods with PRISMA WRF-LES simulations

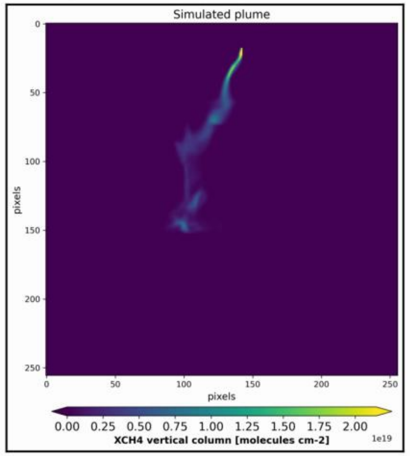
Example 1

Q simulated: 7813.0



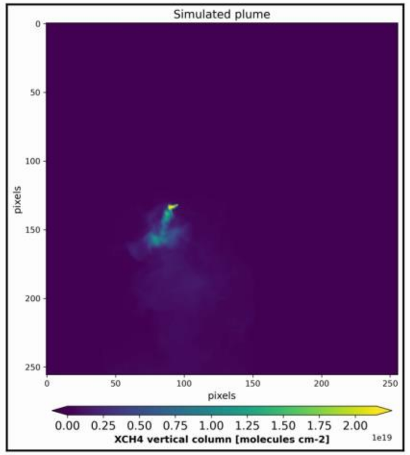
Example 2

Q simulated: 8359.0

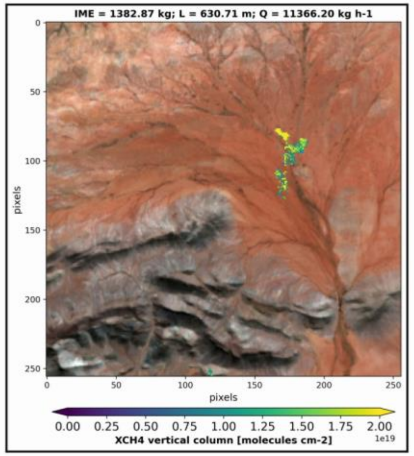


Example 3

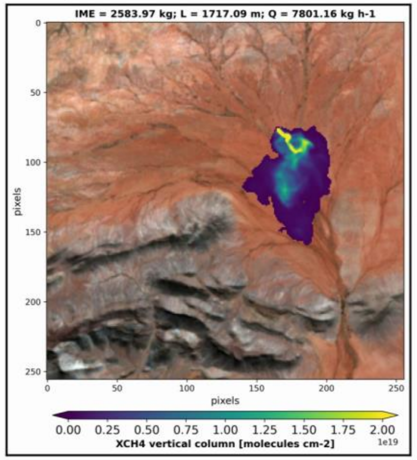
Q simulated: 2290.0



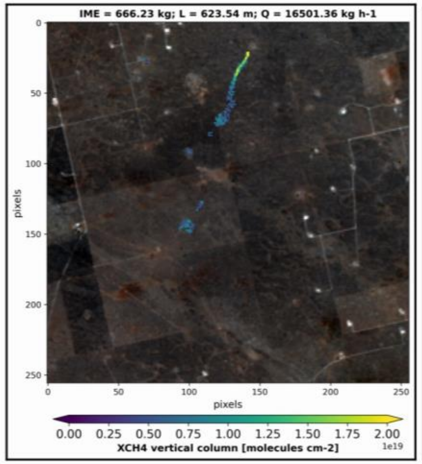
Q retrieved: 11366.0



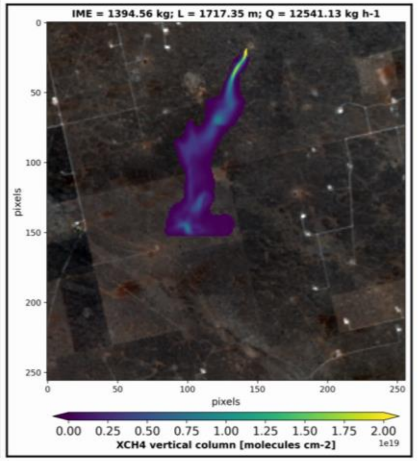
Q sim plume: 7801.16



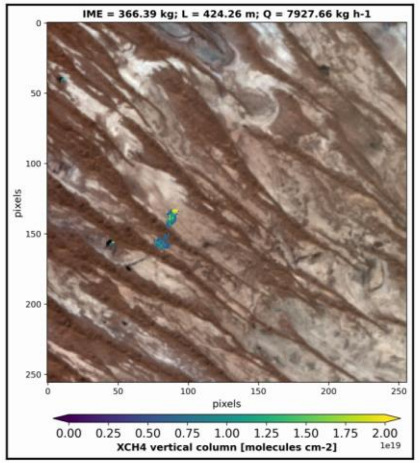
Q retrieved: 16501.0



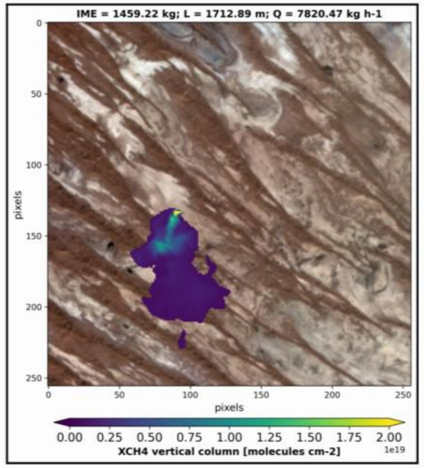
Q sim plume: 12541.13



Q retrieved: 7928.0



Q sim plume: 7820.47



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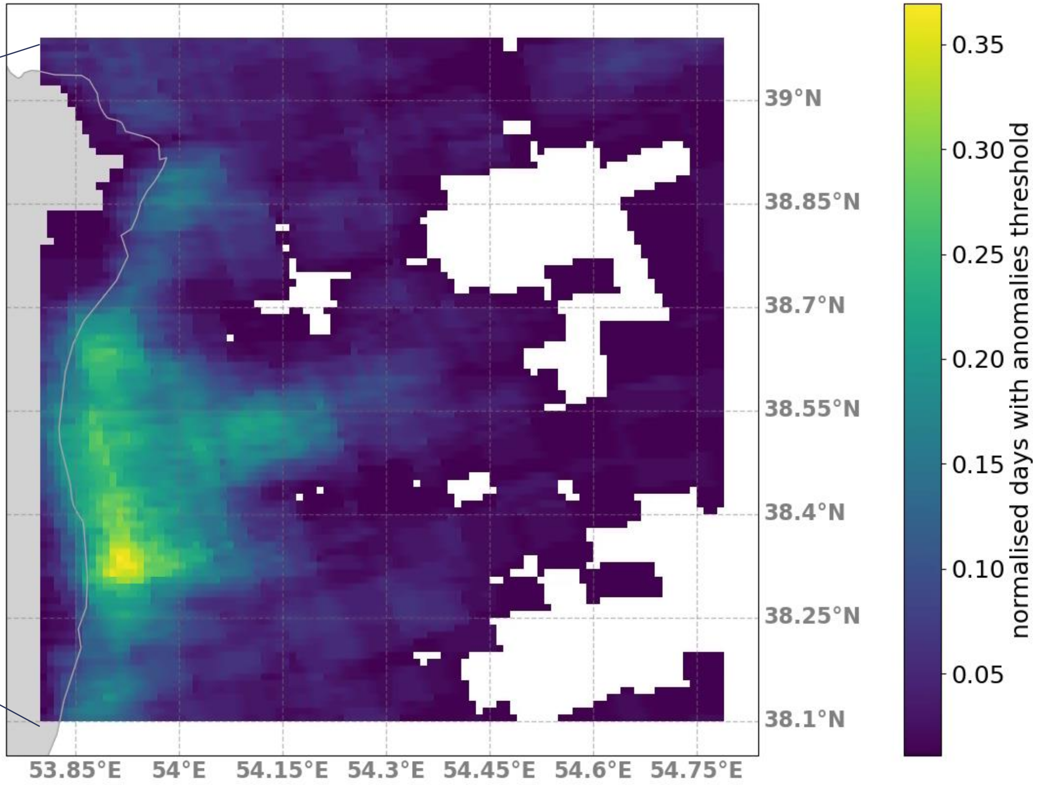
Case study 1: TROPOMI anomalies Turkmenistan

We calculate anomalies using Bremen XCH4 v1.5 **2020** data.



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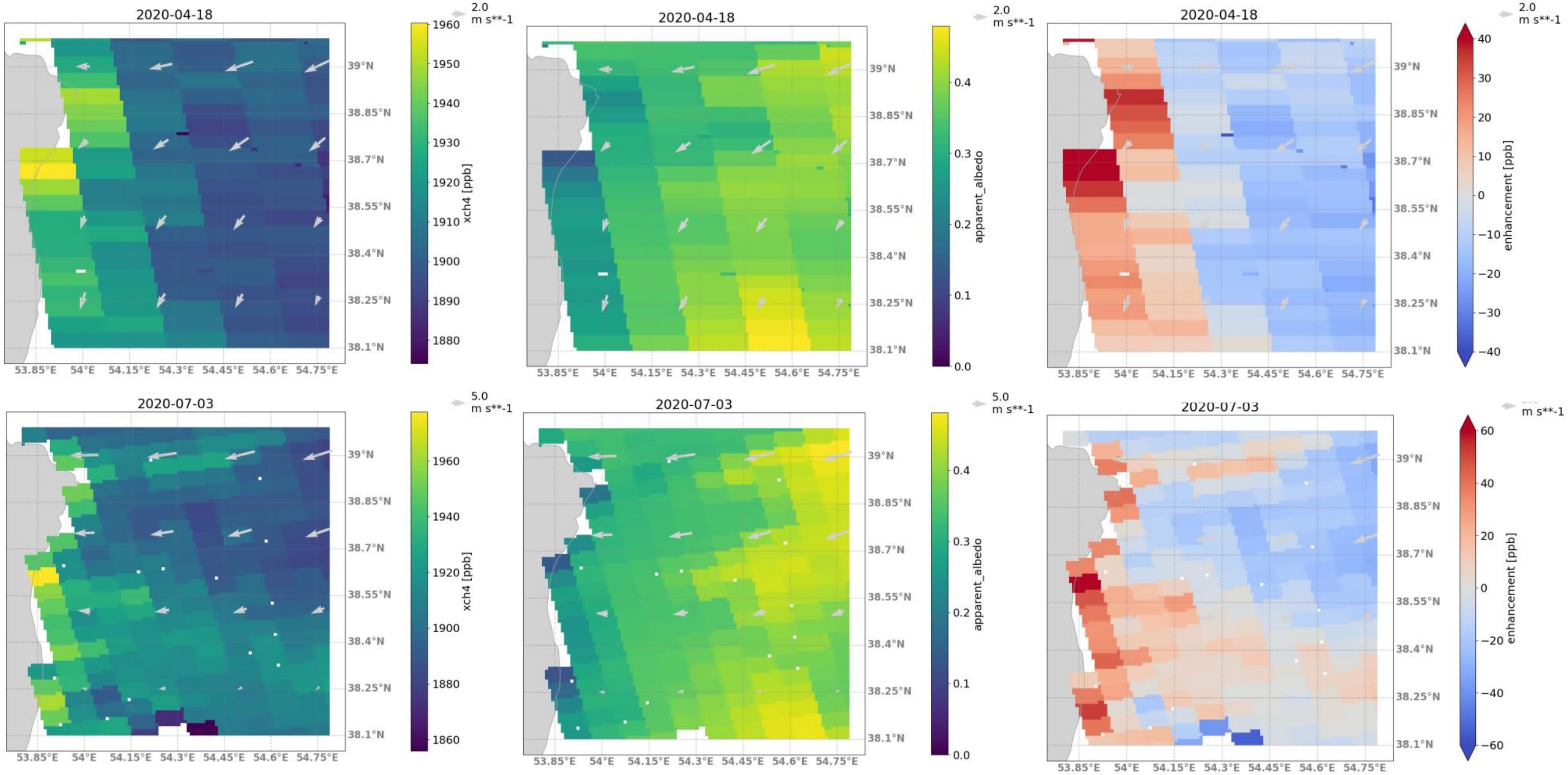
Case study 1: TROPOMI anomalies Turkmenistan

XCH4 column | **Apparent albedo** | **XCH4 Enhancement**



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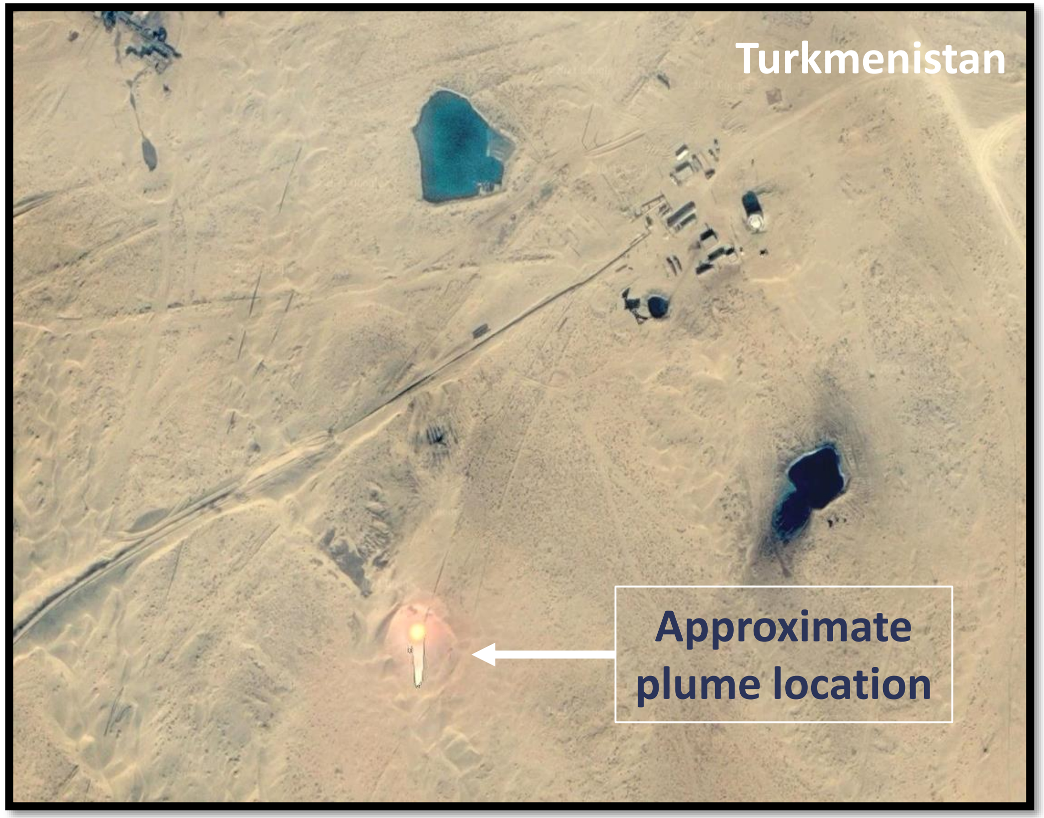
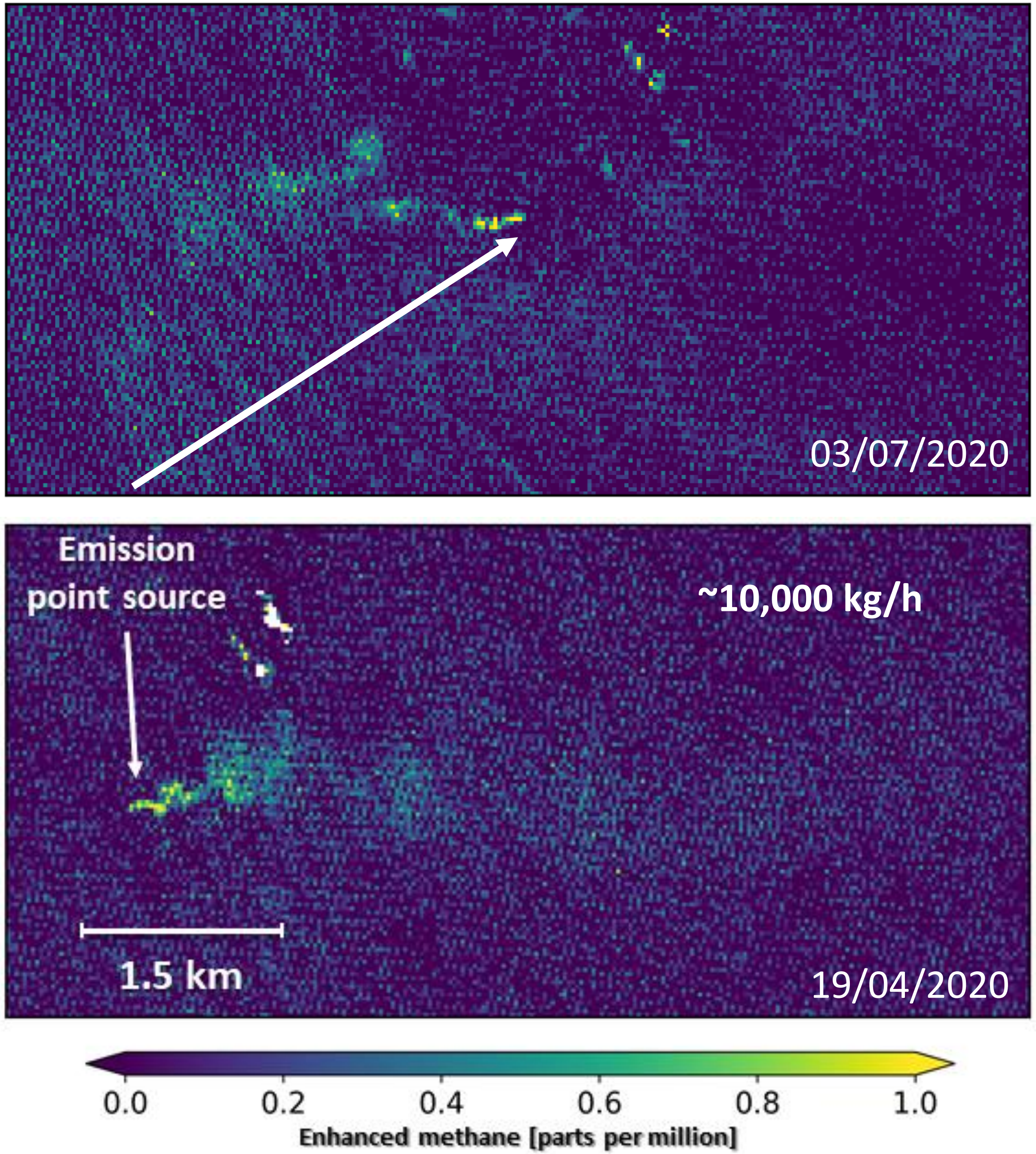
Case study 1: PRISMA



Google maps



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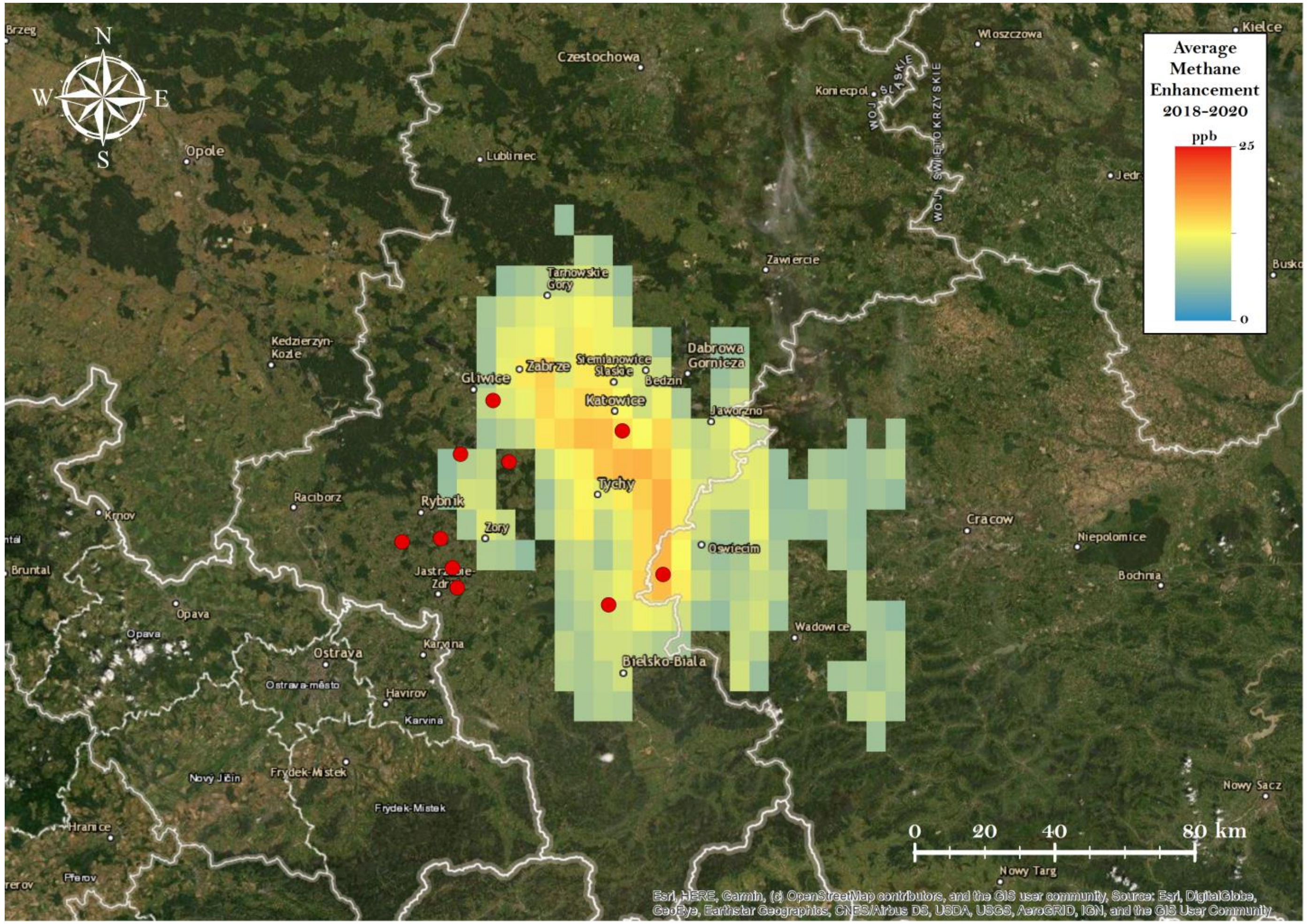
Case study 2: TROPOMI Poland coal mines

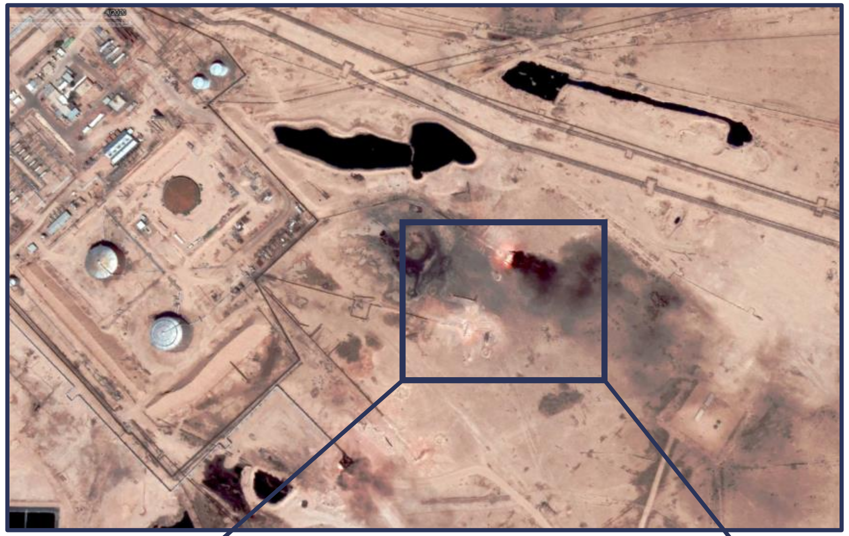
Average, wind-rotated methane enhancement over Polish coal region 2018-2020.



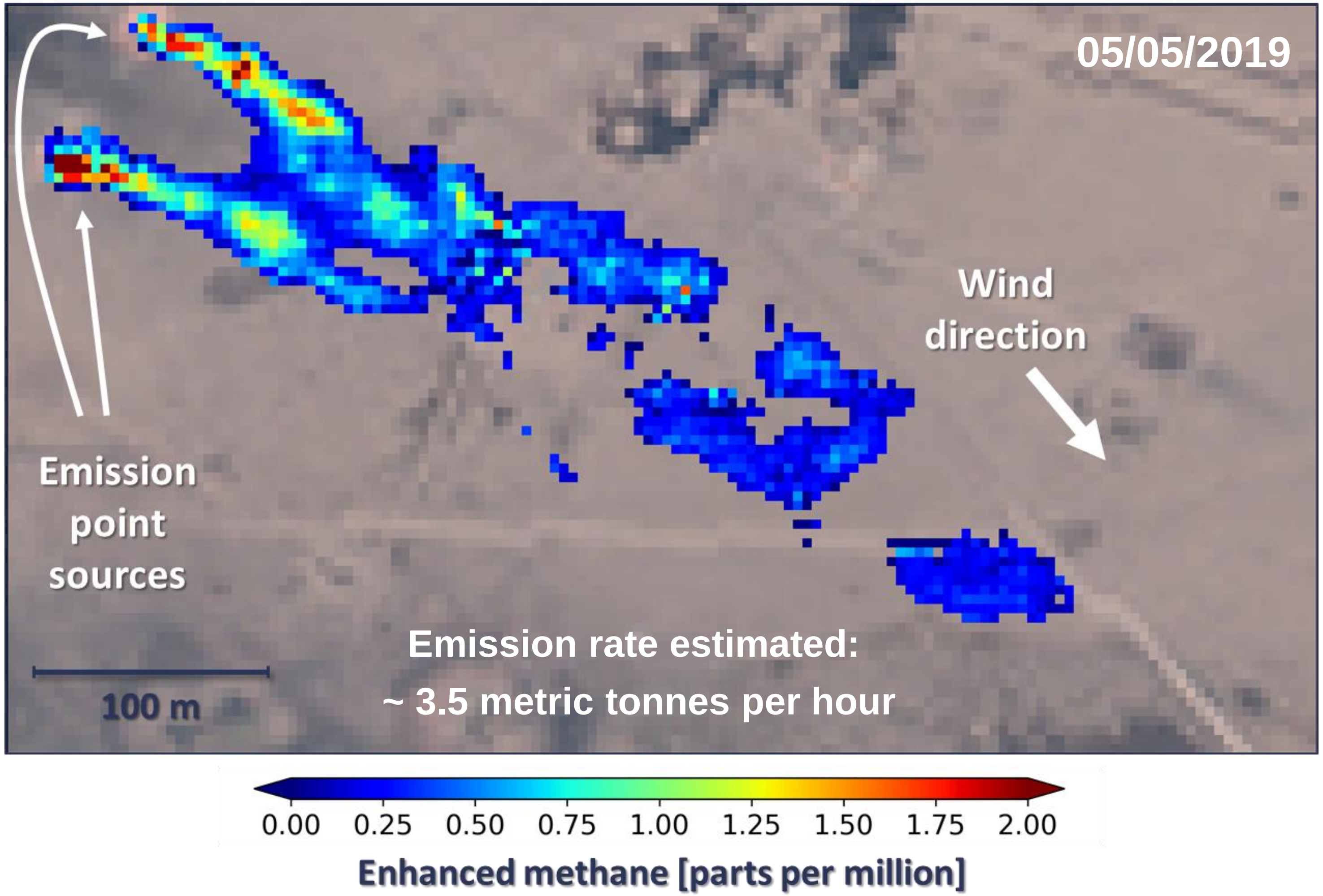
Some of the highest emitting coal mines in Poland

Finding PRISMA data over the region proved challenging and no plumes were found.

Case study 3: WV-3 Middle East oil/gas facility



Google maps
(04/2020)



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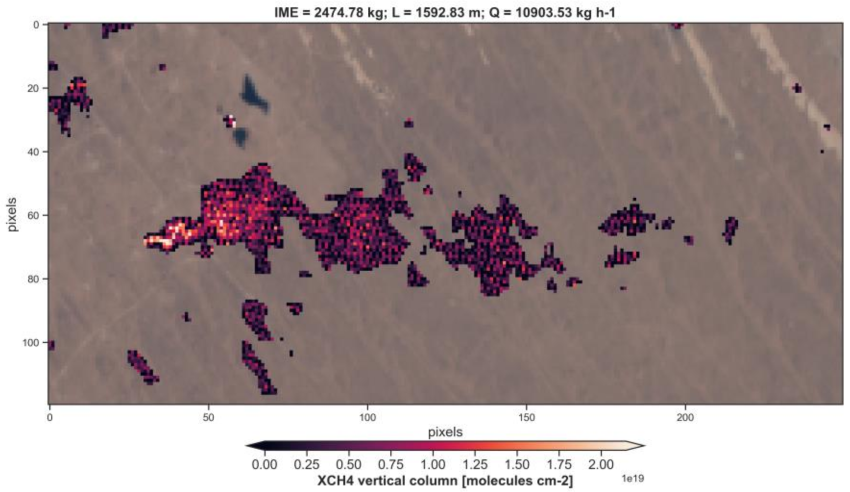
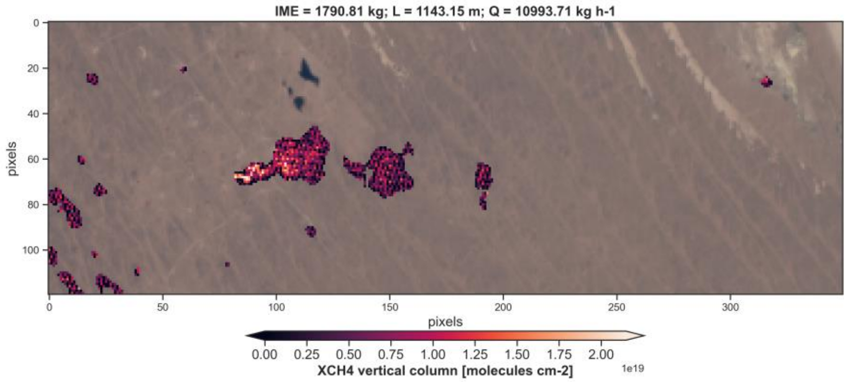
Advanced methods: Machine Learning





Traditional methods for isolating plumes have high **uncertainties** and are inconsistent for different scenes.

We are developing **machine-learning** models to improve plume detection and quantification using **WRF-LES simulated plumes for training**

Note: confidential, non-published material has been removed from this presentation.

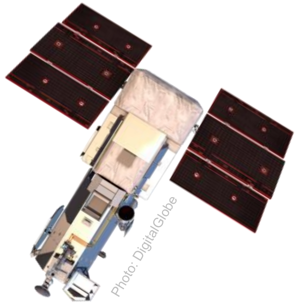
Take home messages

Anthropogenic methane emissions from oil and gas have large contributions to the methane budget but are often easily fixable.

We can use various **satellite observations** at different resolutions in **synergy** to find and quantify these emissions.

Machine learning can help us better find and isolate plumes. We have developed **deep learning** models to isolate and quantify emissions, with promising results.

Upcoming high-res satellites such as MethaneSat and CarbonMapper will add to the current capabilities.



Thank you!

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