Assessment of Methane Mitigation Potential of Large Oil and Gas Leaks

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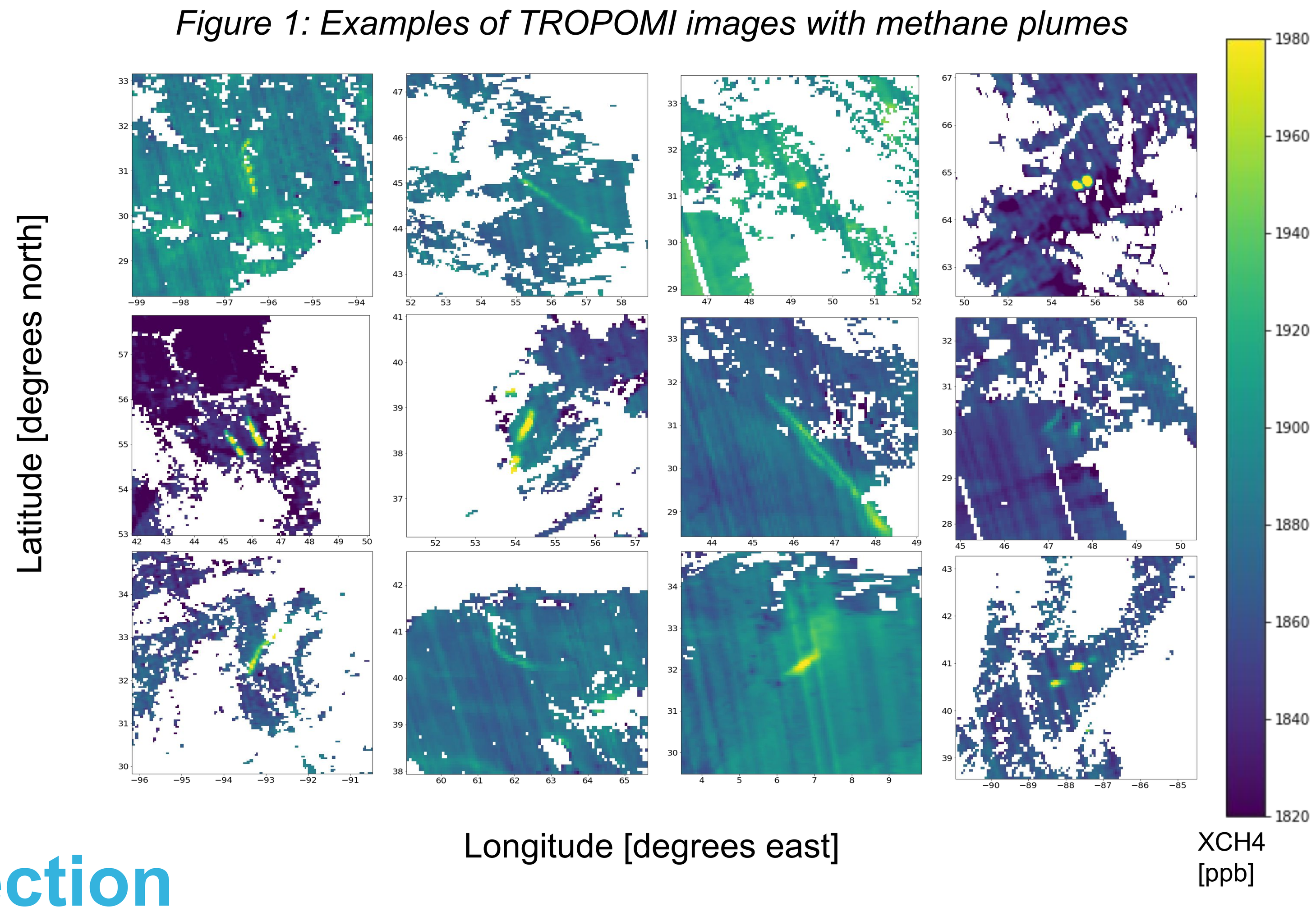
Global online detection and quantification system for methane ultra-emitters

- TROPOMI: near-polar sun-synchronous orbit, 13 to 14 orbits per day, covers ~95% of the earth surface everyday
- Data product: ***methane_mixing_ratio_bias_corrected*** offline, processed within 24h after release (2 to 5 days after sensing)
- Processing pipeline:
  1. ***Detect anomalous methane concentrations*** automatically, estimate source location
  2. Human or ML-based labelling/checking, false positives removal
  3. ***Quantify flow rates*** using HYSPLIT [1]
  4. Human check, spurious quantifications removal
  5. Estimate ***total emissions from ultra-emitters*** per country
  6. ***Mitigation costs/benefits*** analysis at country-level

Figure 1: Examples of TROPOMI images with methane plumes

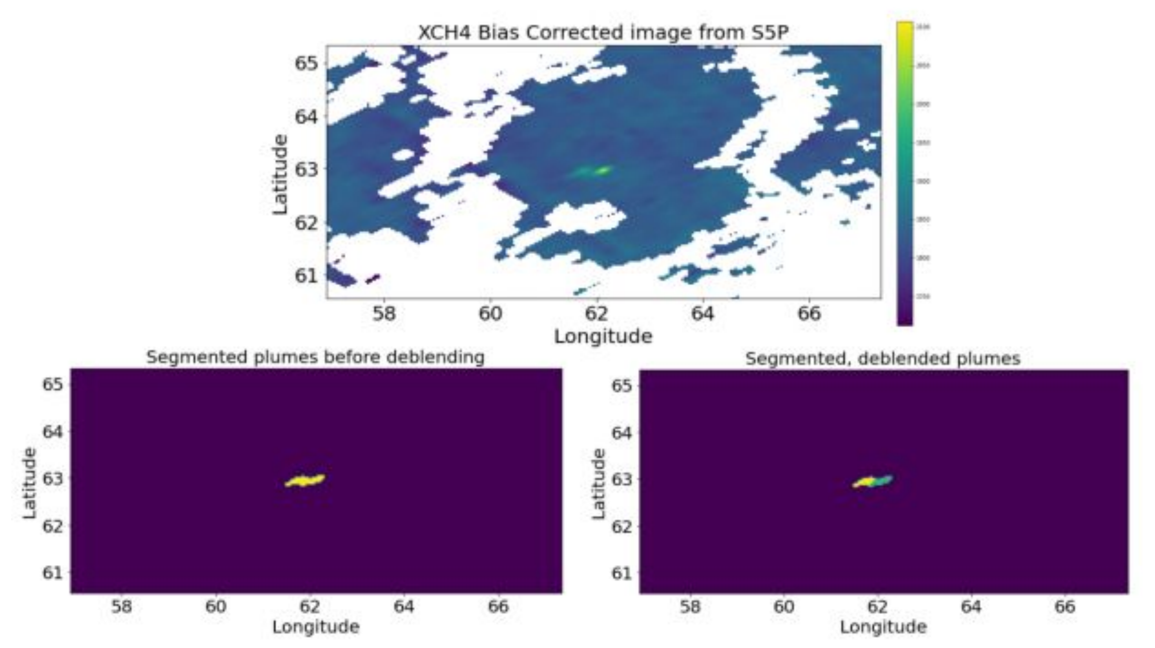


Methane plumes detection

Main steps:

1. ***Denoising*** using Gaussian convolutional filters
2. ***Local background computation*** based on a patch in the neighborhood of each pixel
3. ***Background subtraction***:
   $$AnomalyMap = Image - Background - k \times StandardDeviation$$
   and selection of ***contiguous anomalous pixels*** [2]
4. ***Deblending***: sharpening convolution kernel and watershed segmentation
   → At this step, candidate plumes are detected using pure computer-vision techniques on TROPOMI XCH4 images only. At step 7, we use auxiliary TROPOMI data (e.g. SWIR albedo) and external data (e.g. wind and infrastructure data) to filter out false positive detections using supervised ML.
5. Automatic checks (methane intensity, number of pixels, QA value) and manual checks (wind direction, albedo, ground infrastructure)
6. ***Source location inference*** (upwind direction from plume centroid)
7. **Feature extraction** and **filter false positives** using either **supervised learning** or human labelling
   → Features depict the data quality, sensitivity of the XCH4 retrieval to the scene albedo, plume direction relative to wind direction, intensity of the detected plume, proximity to a well-known set of potential emitters (fossil fuel production and transportation infrastructure)
   → Bootstrap train set to balance labels (the pure computer vision procedure produces a lot of false positives because we want to avoid missing out detections)
   → Use a gradient boosting classifier
   → Test set composed of 4210 negative and 594 positive labels; metrics on the right →

Figure 2: Main step of the plume detection and segmentation process



Tables 1 and 2: Metrics and confusion matrix of the supervised ML filter (against human labels)

Accuracy	0.94
Precision	0.80
Recall	0.82
F1-score	0.81

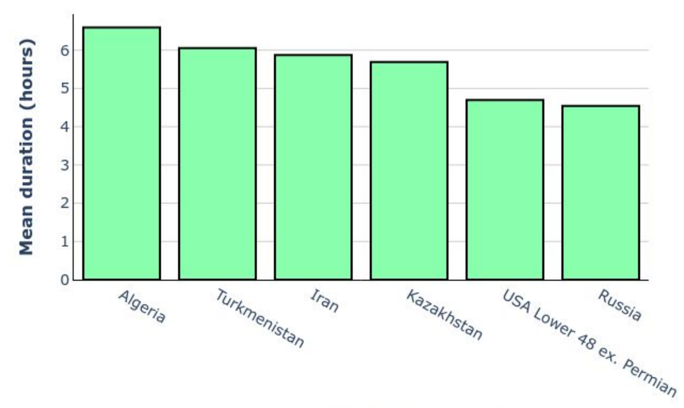
	Prediction: true	Prediction: false
Label: true	3091	119
Label: false	107	487

Assessment of methane emissions from large releases

Due to **TROPOMI's partial coverage** (missing data due to cloud cover, rough terrain, high SZA, aerosols,...), it is necessary to **estimate the large methane releases that cannot be detected by TROPOMI**. For that purpose, we use statistical learning to estimate the coverage of TROPOMI over some polygon (= the number of valid readings provided by TROPOMI over a polygon during a selected time interval)

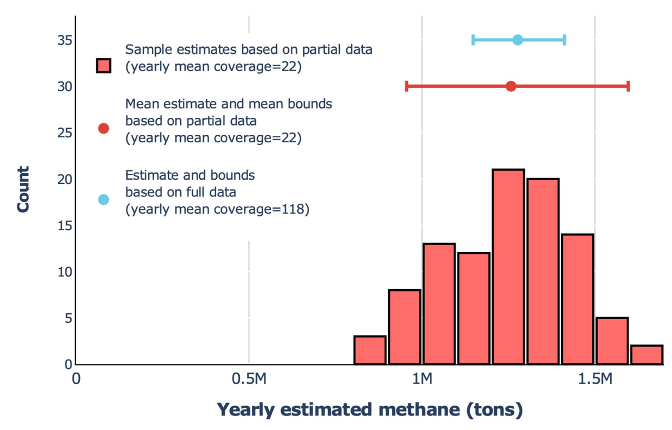
1. **Compute coverage *c*** for the polygon during the given period (ML-based)
   → Split the polygon 120*120km into patches
   → For each patch, apply a logistic regression model (output 1 if the quality of the patch is good enough for the detection algorithm to detect a methane plume, 0 otherwise); the logistic regression takes as input the histogram of pixel QA values within the patch
   → For a polygon, daily coverage = number of valid patches divided by total number of patches
   → For a given period, coverage = sum of daily coverages for the period
2. **Estimate the number of leaks that would have been detected given full coverage** during this period, as
   $$n_{est} \sim NB(n_{obs}, p)$$
   With n_{est} the estimated number of leaks, n_{obs} the observed number of leaks, $p = c / n_{days}$ where n_{days} is the number of days, *c* is the coverage in the period, and *NB* stands for the negative binomial law
3. Repeatedly sample n_{est} to **estimate the total amount of methane emitted by large releases along with confidence bounds** (this estimate is μ * H where μ is the mean of the NB distribution and H is the average amount of methane emitted in the detected events).

Figure 3: Estimated duration of the detected emissions



From TROPOMI images, we can only estimate the flow rate of the methane releases. To derive an amount of methane emitted, we have to estimate the release duration. We consider 3 scenarii, estimating the release duration by dispersion modelling and making assumption on the intermittency of the sources.

Figure 4: Validation of the Negative-Binomial extrapolation



To validate the extrapolation of observed methane emissions into a country-level assessment, we sub-sampled the country with the highest coverage (yearly coverage=118) to the country with the smallest one (yearly coverage = 22). The results show consistency of both the estimate of methane emitted and the confidence interval.

Assessment of methane mitigation potential

- Evaluate the spending required to eliminate these methane ultra-emitters, based on methodology from the EPA [3], IEA [4], IIASA [5]
- ***Net spending appears to be negative*** for most of the countries
- When incorporating the **societal cost of methane** [6]**, net benefits are worth billions of 2018 US dollars**.

Figure 5: Net spending and benefits for ultra-emissions mitigation

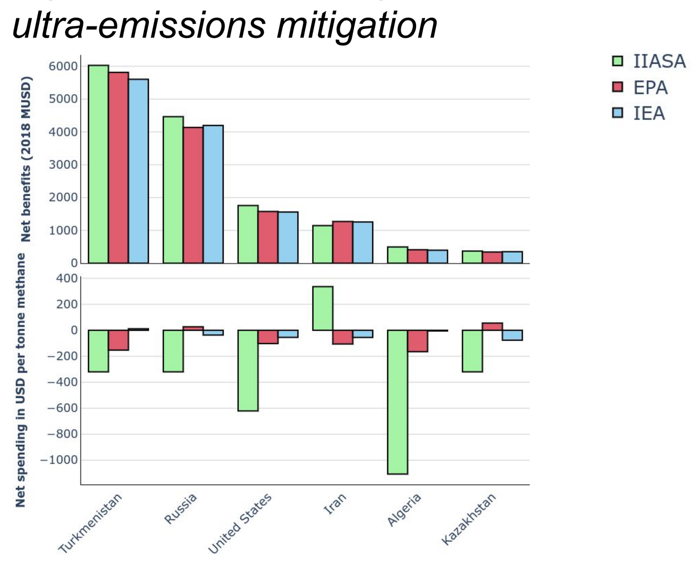
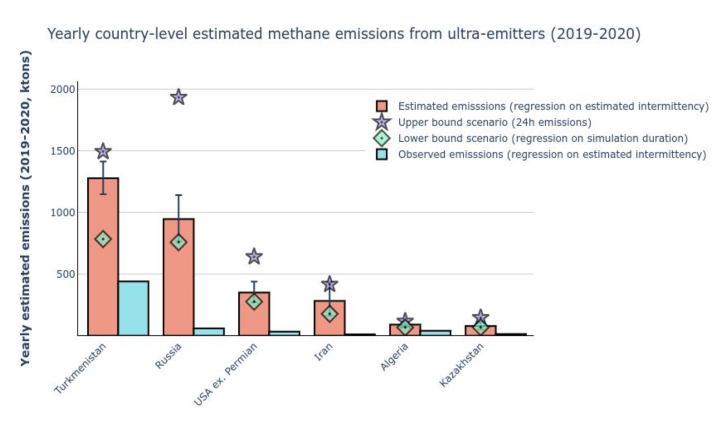


Figure 6: Estimated methane emissions from ultra-emitters, at country-level



References

[1] Price-Whelan, A. M. et al. The Astropy project: Building an open-science project and status 951 of the v2. 0 core package. The Astronomical Journal 156, 123 (2018).
[2] Stein, A. et al. NOAA's HYSPLIT atmospheric transport and dispersion modeling system. 265 Bulletin of the American Meteorological Society 96, 2059–2077 (2015).
[3] EPA. Global Non-CO2 Greenhouse Gas Emission Projections & Mitigation Potential: 2015-2050. United States Environmental Protection Agency (2019).
[4] IEA. Methane Tracker. International Energy Agency (2021)
[5] Höglund-Isaksson, L., Gómez-Sanabria, A., Klimont, Z., Rafaj, P. & Schöpp, W. Technical potentials and costs for reducing global anthropogenic methane emissions in the 2050 timeframe–results from the GAINS model. Environmental Research Communications 2, 025004 (2020).
[6] UNEP/CCAC. Global Methane Assessment: Benefits and Costs of Mitigating Methane Emissions. United Nations Environment Programme and Climate and Clean Air Coalition
283 (2021).