Emissions from industry and how to automatically detect methane super-emitters

Machine learning for climate action
CS-E407519 Lecture 3

We will talk about ...

- Industry sector emissions
- Methane as greenhouse gas
- Automated detection and monitoring of methane super-emitters using satellite data (paper)
- Convolutional neural networks and support vector classifiers

What are industry emissions?

Industry emissions refer to the **greenhouse gases released during industrial processes** and manufacturing activities:

- steel, aluminium, and cement production: indispensable for our society
- chemical manufacturing

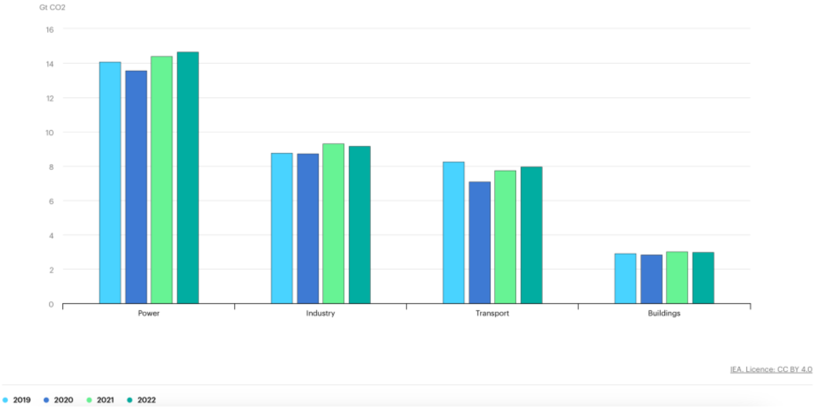
Emissions arise from:

- combustion of fuels for process heat
- chemical reactions necessary in industrial processes

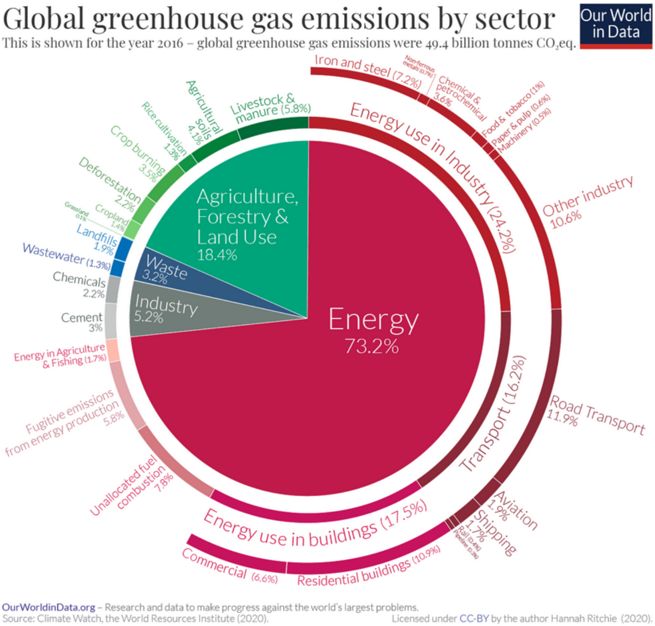
For example, the production of cement releases CO_2 as a byproduct of the chemical transformation of limestone into clinker.

From industrial emissions, 72% come from the manufacturing of 3 basic substances: steal, cement and chemicals.

Global emissions by sector



Global emissions by sector



Industry emissions

Main strategies to decarbonize industry sector (UNEP)

- Impose and strengthen **energy efficiency standards**. How? Modernize equipment, optimize processes, implement energy management systems. Efficient use of energy leads to lower fuel consumption and reduced emissions.
- **Price carbon**. (1) carbon tax: directly pricing each ton of emissions, or (2) a cap-and-trade system, which sets a total emissions limit and allows trading of emission allowances. This incentivizes businesses and individuals to decrease their carbon footprint and invest in cleaner alternatives.
- Promote the use of **efficient and renewable heating and cooling**.
- Incentivize and mandate less emissions of greenhouse gases, including **cutting methane leaks**.

Oil and gas industry besides energy production

The oil and gas industry directly emits greenhouse gases through its own operations:

- extraction
- production
- refining
- processing of oil and natural gas

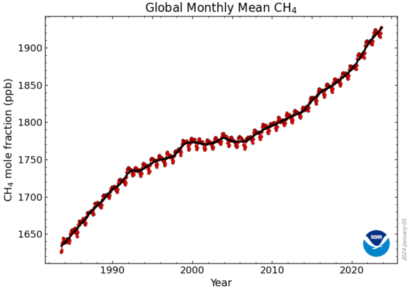
Activities like drilling, fracking, flaring, and venting of natural gas, and the operation of refineries contribute to these emissions.

The oil and gas industry is also involved in **methane emissions**, which is often released during the production and transportation of oil and natural gas.

Poll: Before the industrial era (pre-1750), what do you think were the primary sources of methane emissions?

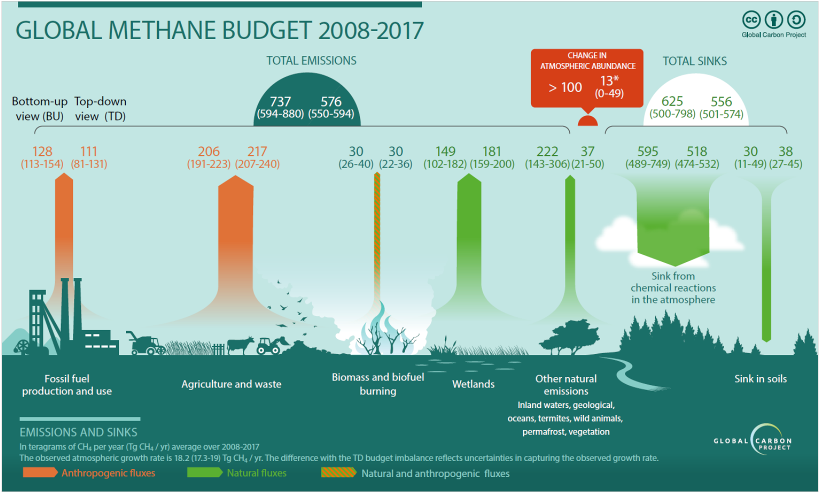
Methane in the atmosphere

- Human influence on atmospheric CH_4 may have begun thousands of years earlier than 1750.
- Growth and seasonal variability are affected by several factors; still ongoing research.
- Average atmospheric lifetime 9.1 years (IPCC AR5).
- Spatiotemporal variability in the order of tens of ppb's $\Rightarrow$ measurements need to be very accurate!

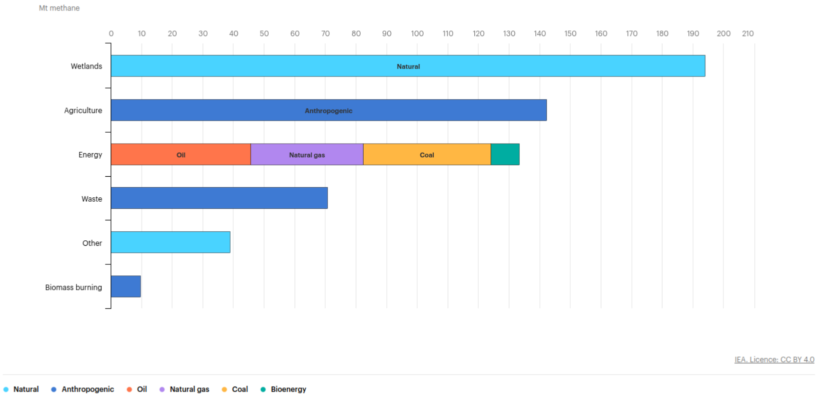


Average CH_4 mole fraction at marine surface sites started in 1983.
`https://www.esrl.noaa.gov/gmd/ccgg/trends_ch4/`

Methane sources

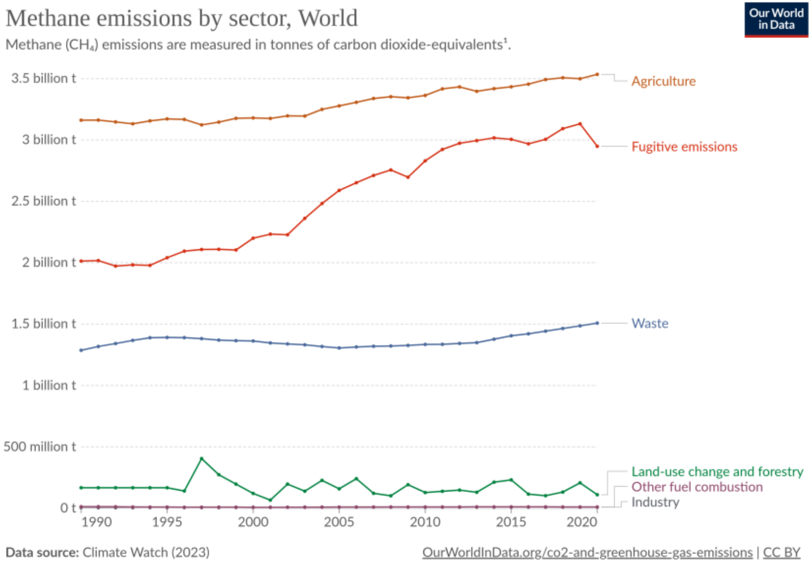


Methane sources

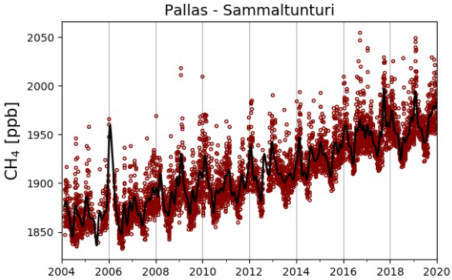


IEA, Sources of methane emissions, IEA, Paris https://www.iea.org/data-and-statistics/charts/sources-of-methane-emissions-4918, IEA. Licence: CC BY 4.0

Methane sources



Methane in the arctic



Measurements from Pallas-Sammaltunturi ICOS station. Location: On top of an Arctic hill in Muonio, Lapland, Finland. Measures CO_2, CH_4, CO and N_2O.

Take a look: Pallas-Sammaltunturi station!

- CH_4 concentration shows significant interannual variability and increase from 2008 onwards.
- Concentration peaks from autumn towards winter, and has a minimum in summer. **Note:** this depends on site much more than for CO_2.
- Arctic and boreal CH_4 exchange is likely under a rapid transformation in the warming climate.

Poll: How does methane compare to CO_2 in terms of its global warming potential over a 100-year period?

Automated detection and monitoring of methane super-emitters using satellite data[1]

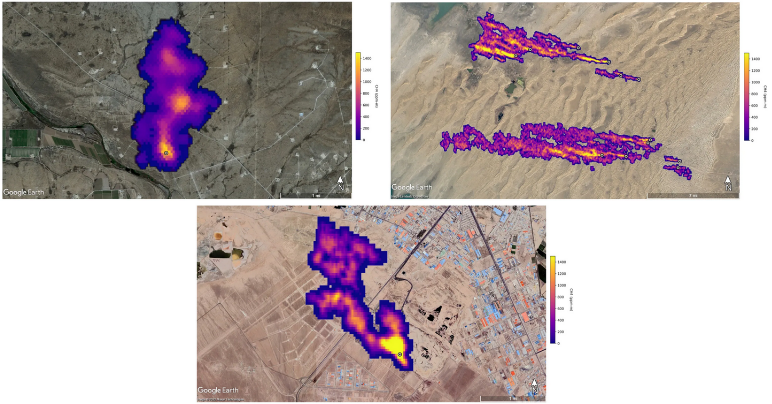
Steps:

1. Methane detection from TROPOMI (onboard Sentinel-5P)
2. Creation of methane plumes dataset
3. CNN
4. Feature engineering
5. SVC
6. Source rate quantification & plume characterization
7. Results

[1]Schuit, B. J., Maasakkers, J. D., Bijl, P., Mahapatra, G., van den Berg, A.-W., Pandey, S., Lorente, A., Borsdorff, T., Houweling, S., Varon, D. J., McKeever, J., Jervis, D., Girard, M., Irakulis-Loitxate, I., Gorroño, J., Guanter, L., Cusworth, D. H., and Aben, I. (2023). **Automated detection and monitoring of methane super-emitters using satellite data**. Atmospheric Chemistry and Physics, 23(16), 9071-9098. DOI: 10.5194/acp-23-9071-2023

Methane super-emitters

A small number of so-called **super-emitters** is responsible for a disproportionally large fraction of total methane emissions.



(1) A methane plume 3 km long in southeast of Carlsbad, New Mexico. (2) East of Hazar, Turkmenistan, a port city on the Caspian Sea, 12 plumes of methane stream westward. Some of them stretch for more than 32 km. (3) A methane plume at least 4.8 km long billows into the atmosphere south of Tehran, Iran. The plume comes from a major landfill, where methane is a byproduct of decomposition.
Plumes detected by NASA's Earth Surface Mineral Dust Source Investigation (EMIT) mission.
Credits: NASA/JPL-Caltech

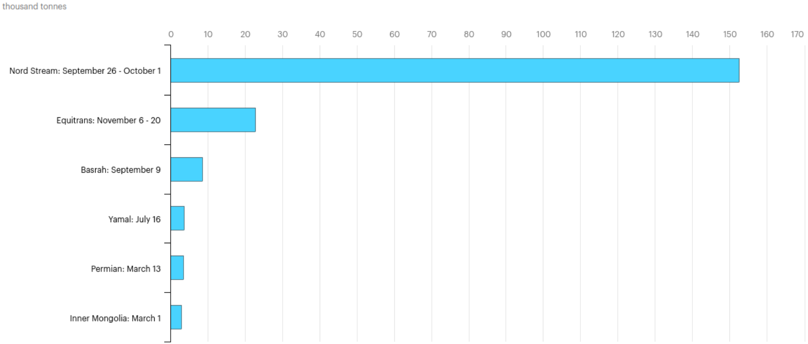
Methane super-emitters

Estimate flow rates of about 18 300 kg per hour at the Permian site, 50 400 kg per hour in total for the Turkmenistan sources, and 8 500 kg per hour at the Iran site.

The Turkmenistan sources have a similar flow rate to the 2015 Aliso Canyon gas leak, which exceeded 50 000 kg/h at times. The Los Angeles-area disaster was among the largest methane releases in U.S. history.

Nord stream leak There were at least three separate leaks. Up to 500 000 tons of methane were leaked from the pipelines. That's $\times 5$ more than Aliso Canyon gas leak.
There are different estimated amounts for the Nord Stream leak, ranging from 100 000 tons to almost 500 000 tons.

Methane super-emitters seen from space



IEA, Estimated methane emissions from single events detected by satellite, 2022, IEA, Paris https://www.iea.org/data-and-statistics/charts/estimated-methane-emissions-from-single-events-detected-by-satellite-2022, IEA. Licence: CC BY 4.0

Methane detection with TROPOMI (onboard Sentinel-5P)

TROPOMI (TROPOspheric MOnitoring Instrument) launched in October 2017 on board Sentinel-5 Precursor (Sentinel-5P). TROPOMI provides methane mixing ratios:

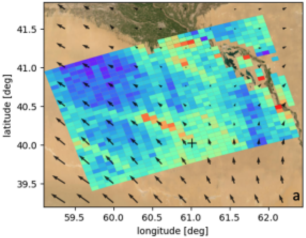
- pixel size 3.5/7 km $\times$7 km (in nadir)
- swatch of 2600 km
- daily coverage.

This enabling the detection of these super-emitters.

TROPOMI produces millions of observations each day, which together with the complexity of the methane data, makes manual inspection infeasible.

Step 1: Create a dataset of methane plumes

1. The authors created a dataset of scenes consisting of 32×32 pixels, both with and without methane plumes.
2. 32×32 pixels correspond roughly to an area of 176×232 km^2 at nadir and up to 176×448 km^2 for larger viewing angles.
3. For scenes with plumes, they use data over 60 persistently emitting locations.
4. After manual inspection, they have 828 images with plumes (from 2018 to 2020). 195 from coal mines, 203 from landfills or urban areas, and 430 from oil&gas infrastructure.



Step 1: Create a dataset of methane plumes

5. A set of 2242 scenes with no plume was obtained through manual inspection of six full orbits in different sections and meteorological conditions´.
6. Scenes with $< 20\%$ valid XCH_4 pixels were discarded.
7. The dataset contains 3070 scenes used for training, the difference in the number of positive (828) and negative (2242) scenes is corrected for later on using class weights.
8. For later: for each scene, they store 46 other channels of supporting information from the same TROPOMI Level 2 methane product (including co-retrieved atmospheric properties, meteorological parameters and geometric properties).

Step 1: Create a dataset of methane plumes

9. To correct for differences in local background concentrations (e.g. due to difference in latitude or surface altitude), each scene is normalized from 0 to 1.

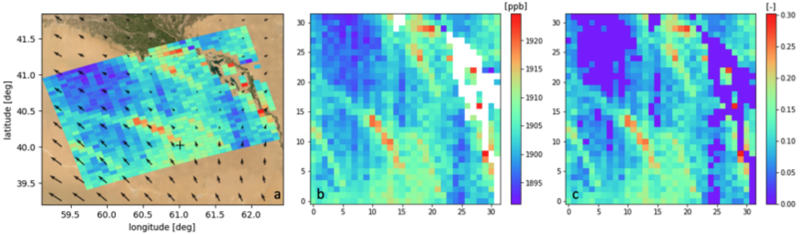


Figure 1. Atmospheric methane mixing ratios of a 32x32 pixel scene containing a methane plume originating from a known persistent source (indicated by the +) as observed by TROPOMI on 2021-12-05 at 08:47 UTC (not included in the training data). (a) Mercator projection of the scene over ESRI World Imagery (Esri, Maxar, Earthstar Geographics, and the GIS User Community, 2022), arrows show the local GEOS-FP 10m windfield (Molod et al., 2012). (b) 32x32 pixel scene in along-orbit vs across-orbit direction, indicating filtered pixels. (c) the same scene after pre-processing as used by the CNN.

Step 2: Train a convolutional neural network (CNN)

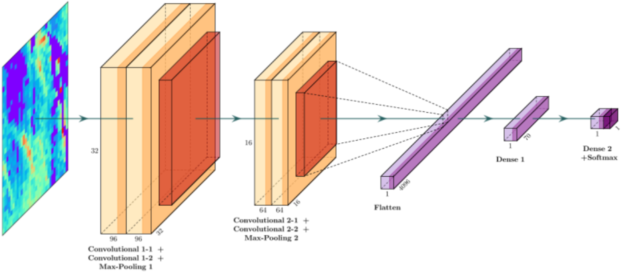
Main advantages of CNN over other algorithms:

- No need to indicate where the plume is within the image. the CNN learns to localize interesting features during training.
- CNN is capable of retaining spatial information.
- The same convolutional kernel scans the entire image, which is computationally efficient.
- The model is rotational and translational invariant **when properly trained**.

This last model property is essential for the automated detection of plumes, as those can be located anywhere within a scene and the wind can be in any direction.

Step 2: Train a convolutional neural network (CNN)

- The CNN outputs a prediction between 0 and 1 indicating the confidence ofthe model about the presence of a plume-like structure.
- Scenes with prediction scores > 0.5 are classified as plumes.
- CNN architecture: 2 convolutional blocks followed by 2 fully-connected layers and an output node.
- **NOTE:** They found that deeper networks (e.g. Resnet or VGG-16) did not yield an improvement in performance for this problem with relatively low resolution.



CNN structure

Step 2: Train a convolutional neural network (CNN)

Some technical aspects:

1. Scenes contain mostly clear positives and clear negatives to effectively learn distinguishing features.
2. Training 60%, validation 20% and test 20%.
3. **Data augmentation:** 90° rotations and flipped $\Rightarrow \times 8$ data images.
4. Train CNN with augmented dataset, 19 648 images.
5. CNN designed and trained with Keras, first with default hyperparameters (number of layers, dimensions of layers, number of filters, learning rate,...).
6. Model trained with a maximum of 100 epochs, optimizing the validation loss, using binary cross-entropy as the loss function and ADAM as the optimizer.
7. To make model more robust, 0.4 dropout layer in the first fully-connected layer during training.
8. ReLU (rectified linear unit) activation function in all layers except for the final layer. Softmax activation function for last layer.

Step 2: Train a convolutional neural network (CNN)

9. To force the model to focus on plume-like signatures, the loss weight of plume scenes is set to double that of negatives scenes.
10. After training, the model performance is evaluated by classifying the labeled test set.
11. Hyperparameters are further optimized using KerasTuner.
12. Top 10 performing models are inspected and optimal hyperparameters are selected by combining this optimization with expert judgement on this particular problem.
14. The trained CNN is applied to all year 2020 data, a total of 5193 orbits resulting in 752 890 scenes (only scenes with $> 20\%$ valid pixels), of which 25 626 scenes (3.4%) are identified as containing plumes.
15. A subset of these scenes is used to train the second step of the machine learning pipeline.

Step 3: CNN model evaluation

The performance of the CNN is evaluated using common performance evaluation metrics based on **true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN)**:

$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \quad \text{precision} = \frac{TP}{TP + FP},$$

$$\text{recall} = \frac{TP}{TP + FN}, \quad F_1 = 2 \cdot \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}.$$

- The **precision** indicates which fraction of scenes identified as plumes are actually a plume.
- The **recall** indicates which fraction of plumes present in the testset are correctly identified.
- The **F1-score** incorporates both into a single metric.

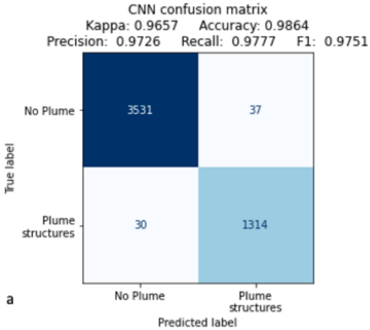
They also use **Cohen's kappa coefficient**, but we won't go into details.

Poll: In some scenarios, you might have to choose between improving either precision or recall. What could be the implications of prioritizing one over the other in methane plume detection?

Step 3: CNN model evaluation

More technical aspects

1. Model with optimized hyper-parameters was trained 50 times with different splits of the training and test datasets. The model is relatively insensitive to different splits. This shows that the model is robust and well generalized.
2. Recall is prefferd over precision because the key focus is to have as few potential plumes as possible go undetected.



Confusion matrix showing the performance of the CNN on test dataset.

3. Manual inspection of the misclassified scenes (30 FN and 37 FP, out of 4912 augmented test scenes) indicates these are borderline cases with difficult to discern morphological structures that are even challenging to a human expert.

Step 4: Feature engineering

Some known facts about methan retrievals:

1. Methane is difficult to retrieve from satellite measurements. Earth surface type, atmospheric or meteorological conditions are known to affect the retrieval. This means that not every plume-like structure in the XCH_4 observation is an actual methane plume.
2. If retrieval parameters such as surface albedo or aerosol scattering coefficient are high, then the methane enhancement might be a retrieval artefact.
3. Other common artefacts appear on the borders of clouds or coastlines.

Feature engineering is the process of using domain knowledge to create or modify features from data that make machine learning algorithms work better. It can significantly improve the performance of predictive models.

Feature vectors are constructed, they consist of features based on the corresponding scene. These vectors are then used to train the second model of the machine learning pipeline, the **suport vector classifier (SVC)**.

Step 5: Support vector classifier (SVC)

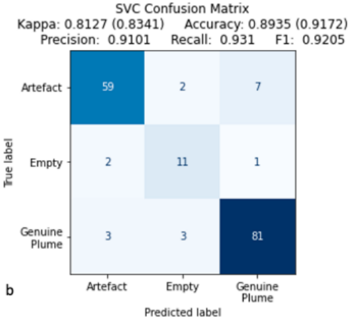
A **support vector classifier (SVC)** works by finding the best way to separate different classes of data points in a given dataset.

SVC is particularly effective when the groups can be clearly divided, and it can handle complex scenarios where the groups are not linearly separable by projecting the data into a space where they can be.

1. Training dataset: 843 labeled scenes from year 2020 classified by the CNN to contain plumes.
2. Scenes are labeled as **plume** (444), **artefact** (341) or **empty** (58), indicating there is not a clear plume or artefact.
3. They train the SVC on a vector of 41 features per scene, including: correlations with retrieval parameters for different plume masks, the angle between the wind and elongated direction of the plume, the elongation ratio of the plume, the source rate, and several statistical properties.

Step 5: Support vector classifier (SVC)

4. **Model evaluation:** The binary **Cohen's Kappa score** is 0.83. (considered good if > 0.8). The **recall** is 0.93 (i.e. 93% of the scenes with plumes in the test set are successfully identified).
5. **Feature importance:** the most important features are: correlation of XCH4 with aerosol optical thickness, CNN score, albedo correlation the enhancement of the plume, the fraction of valid pixels, the angle with the local wind, and the average quality flag of plume pixels. These correspond to what is important to a human expert labeler.



Further steps

Extra 1: Source rate quantification
They go further than plume identification and quantify the amount of emissions from each identified source.

There are several methods to do this, they use one called **integrated mass enhancement**. This method relates the emission rate to the observed methane enhancement in the plume and the local windfield.

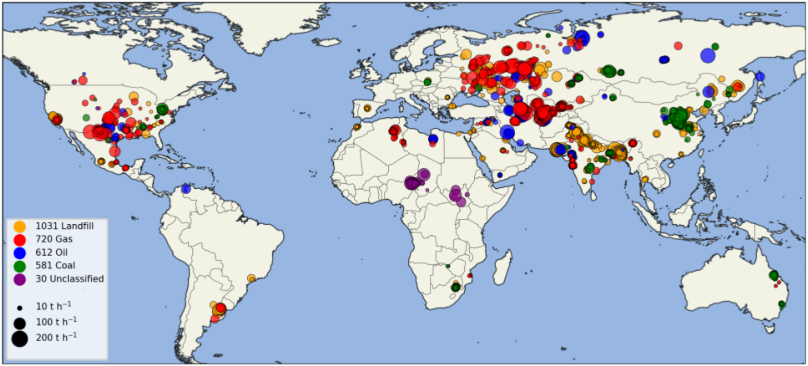
Extra 2: Plume characterization
To assess which anthropogenic activity might underlie a detected plume, they use the estimated source location to find the local dominant source type in bottom-up inventories.

Results

1. The trained models are applied to all 2021 TROPOMI XCH_4 data.
2. Analysing the full year with the ML pipeline takes approximately three hours on a single core.
3. From 794 395 scences, the CNN identifies 26 444 (3.3%) as containing plume-like structures.
4. The SVC classifies 10 430 of these scenes as plumes.
5. After duplicate removal, 4869 scenes are identified as unique. These are manually checked to assess performance.
6. 2974 are confident plumes, 745 are labelled as potential plumes.
7. Accepting these scenes as plumes results in a precision of 76% for the full pipeline. These potential plumes could not readily be verified as real methane plumes, but are valuable for further inspection.

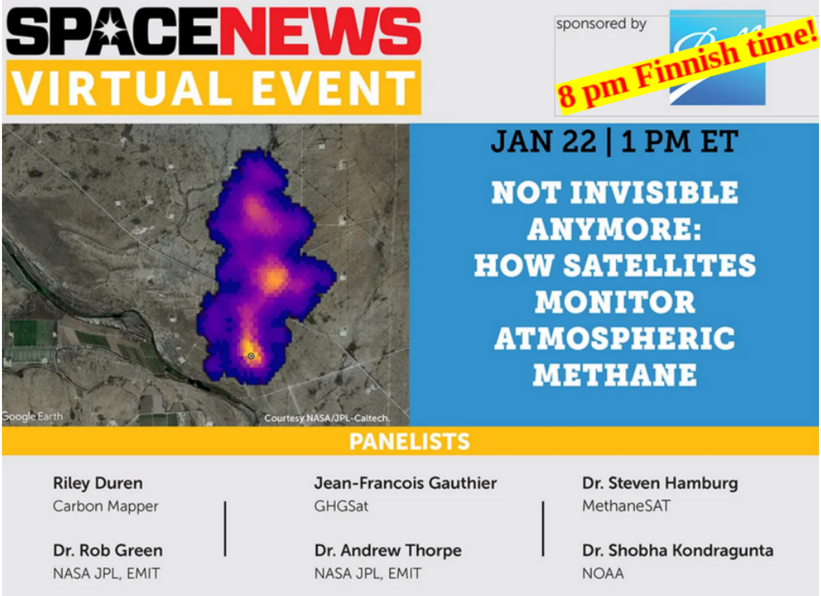
Poll: If a CNN model shows high accuracy in detecting methane plumes, does it necessarily mean it's the best model for this task? Why or why not?

Results



All 2974 confident plume detections for 2021, grouped into one of the four dominant anthropogenic source types and sized by source rate. 30 detections in central Africa are labeled as unclassified.

Ad 1: Related event



Ad 2: Summer job at FMI?

Greenhouse Gases and Satellite Methods group at FMI seeks

- a seasonal worker for data handling, scientific instrumentation development and instrument operation at the Sodankylä research station.
- a seasonal worker for scientific research work either at Helsinki office or Sodankylä research station.
- a seasonal worker for scientific instrumentation development work at the Sodankylä research station.

The Atmospheric Remote Sensing group seeks a trainee for a summer job in analysing space-borne Sentinel-5P/TROPOMI observations of nitrogen dioxide at the FMI Helsinki office.

Check `https://valtiolle.fi/`