

Fully-automated, machine learning-based, satellite methane detection algorithm applied to estimate offshore emissions

Pedro de Melo^{1,2}, Lori Bruhwiler¹

¹NOAA Global Monitoring Laboratory, Boulder, CO, USA, ²Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO, USA

pedro.demelo@noaa.gov



University of Colorado
Boulder



Goals of the project

- Data exploitation project to use high resolution satellite imagery to estimate methane emissions from leaking infrastructure.
- We first focus on the Gulf of Mexico – can we use glint data to estimate regional emissions? How accurate would it be?

Why study emissions in the Gulf of Mexico?

- Methane is a potent greenhouse gas and the second contributor to global warming, after carbon dioxide. Even though the methane atmospheric lifetime is relatively short (7–12 years), it traps 30 times more heat than carbon dioxide [1].
- Anthropogenic methane sources are known to be of significant contribution.
- Remote sensing of methane is a promising tool to monitor large areas with a high resolution and inform policy decisions, given its cost-effectiveness, low maintenance, and instantaneous results.
- Methane emissions in the Gulf of Mexico are likely underestimated, probably due to anomalous super emitters that are often neglected in scientific studies [2].



Figure 1: American oil platforms in the Gulf of Mexico. Data obtained from the BOEM database of oil and gas platforms in the Gulf. Our algorithm looks at available data at platforms to identify leaks.

Methodology

- Our main goal is to estimate regional emissions using remote sensing.
- In order to successfully detect plumes, we look for available data by checking available granules according to a list of coordinates of known platforms.
- If data is published, methane enhancement is calculated from whatever infrared signal is available (multispectral or hyperspectral).
- The methane enhancement image is fed to the image segmentation function.
- In case a plume has been detected, we check for false positives (calculating bounding box orientation, center of mass with respect to the platform, and comparing it to wind direction).
- After confirmation, emissions are estimated by IME, using GFS wind data.

Methane spectral signature

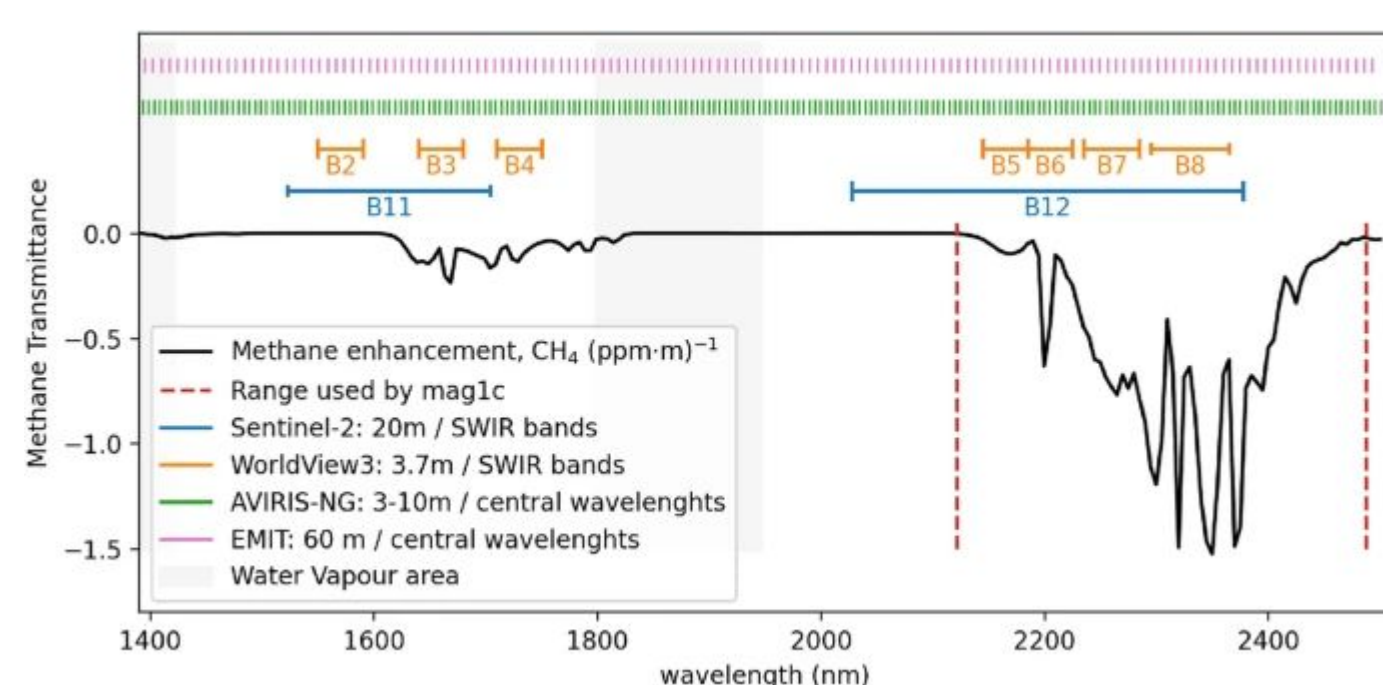
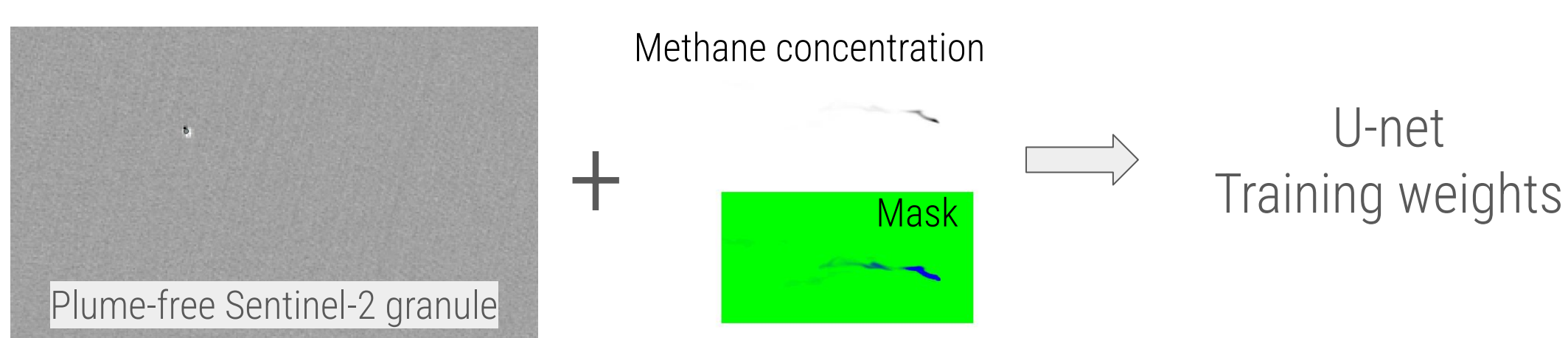


Figure 2: Methane spectral fingerprint, from [3]. Different instruments can detect chemical concentration in different ways. Some will be able to take advantage of using more spectral features compared to others. Here, we have the methane infrared spectrum and how select spectrometers can calculate methane enhancement.

Hyperspectral	Multispectral
High spectral resolution – cleaner signal	Noisy signal, not as clean as hyper
Low spatial resolution, narrow IFOV	High spatial resolution, large IFOV

Training weights



(WRF-LES plumes provided by Daniel Varon)

The process of obtaining training weights for plume detection here is similar to Bruno et al. [4]:

1. Generate artificial plumes (WRF-LES).
2. Convert/pixelate the plumes to the desired detector resolution and sensitivity.
3. Overlay the processed artificial plumes on plume-free backgrounds.
4. With a threshold mask and the image, we will have a training point.
5. Repeat steps 3-4, but rotating the plume to account for different possible wind directions.
6. After completing the steps above, the weights can be saved as a training data file, which can be imported to the program later.

Methane enhancement calculation to estimate emission rates

1. Determine the out-of-plume region from the plume mask.
2. Calculate the median signal of the background.
3. Subtract the value above from the entire image.
4. Integrate throughout all the in-plume pixels, taking into account the satellite resolution.

$$Q = \frac{(IME)U_{eff}}{L} \quad |\vec{w}_{10}| = ((u_{10})^2 + (v_{10})^2)^{1/2} \quad \text{Equations used to calculate emission source rates from satellite images and wind vectors}$$

$$U_{eff} = 0.7 + 0.23|\vec{w}_{10}| \quad \sigma_{Q,U} = \frac{0.23\sigma_U}{0.7 + 0.23U_{10}} [5].$$

Possible sources false positives

- Methane will have a overlapping spectral features with many objects and surface features if only a couple of bands are used to calculate a methane index.
- Some examples include wakes, clouds, smoke, oil leaks, etc.

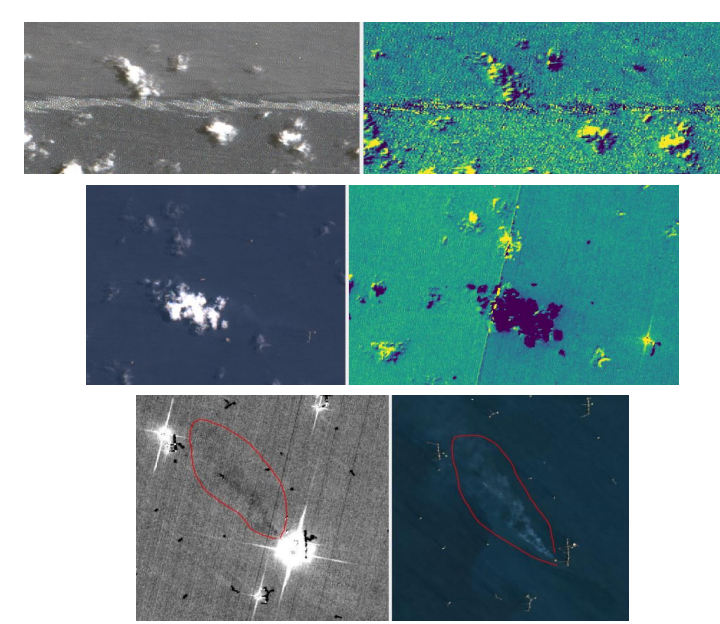


Figure 4: False positives are a problem when using multispectral imaging to detect plumes. You can see here how oil leaks, clouds, and thick smoke look when calculating a normalized methane index $(SWIR2-SWIR1)/(SWIR2+SWIR1)$.

Breaking down our algorithm

1. Retrieve satellite data (Sentinel-2, EMIT, EnMAP).
2. Plume image segmentation using U-Net (tensorflow, keras) with training weights.
3. Import Global Forecast System (GFS) wind vector fields.
4. Interpolate wind to find the vector at the platform.
5. Analyze plume mask orientation and center of mass (python cv2), check how it compares to wind at the platform.
6. Attribute a confidence value depending on how the vectors diverge.
7. If likely to be a plume, calculate IME.
8. Save result to our plume database.

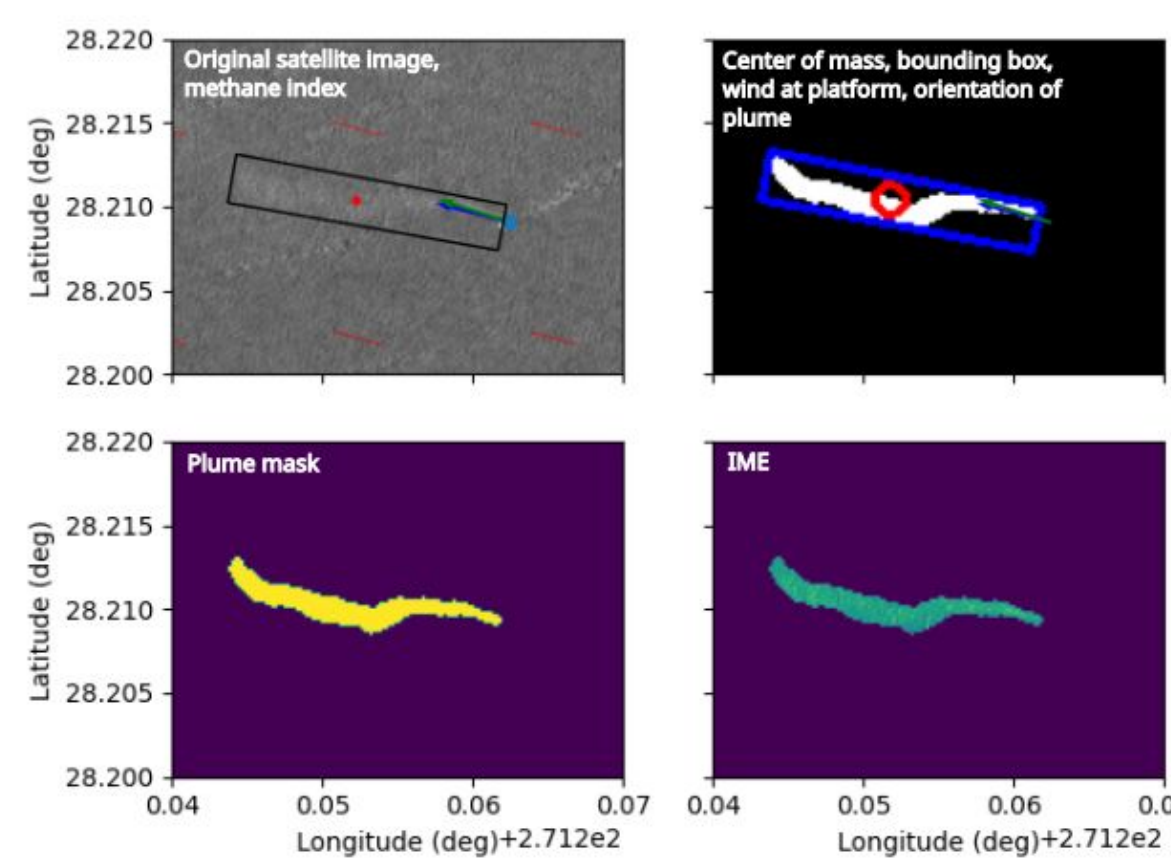


Figure 5: Sample output of our program. The algorithm downloads granules following a coordinate and date input (BOEM database) and tries to detect a plume using U-net segmentation. If using multispectral, the program checks for false positives by calculating bounding box orientation and center of mass. If a plume is confirmed, emissions are estimated using IME.

Questions to answer

- How accurate do our input parameters need to be to simulate artificial plumes that train our model well enough to detect real emissions?
- Do we need to reproduce all (or most) types of plume under different circumstances to incorporate to our training dataset?
- Is a large eddy simulation necessary? Do we need real WRF or idealized would suffice? How to keep computational costs down?
- Can we estimate regional emissions based on the available remote sensing data? Is the wind data accurate enough? What portion of emissions are missed by satellites?
- Is it feasible to monitor emissions over a full glint season? How much is emitted when sun glint is not available?
- Would it be cost-effective to use commercial satellites to monitor platforms?
- What do we gain with new satellites and detectors being launched?

References

- [1] <https://climate.nasa.gov/vital-signs/methane/>, last accessed May 23rd, 2024.
- [2] Alan M. Gorchov Negron, Eric A. Kort, Yuanlei Chen et al. *Excess methane emissions from shallow water platforms elevate the carbon intensity of US Gulf of Mexico oil and gas production*. PNAS 120 (15) e2215275120 (2023) <https://doi.org/10.1073/pnas.2215275120>
- [3] Růžička, V., Mateo-Garcia, G., Gómez-Chova, L. et al. *Semantic segmentation of methane plumes with hyperspectral machine learning models*. Sci Rep 13, 19999 (2023). <https://doi.org/10.1038/s41598-023-44918-6>
- [4] Bruno, J. H., Jervis, D., Varon, D. J., and Jacob, D. J.: *U-Plume: automated algorithm for plume detection and source quantification by satellite point-source imagers*, Atmos. Meas. Tech., 17, 2625–2636, <https://doi.org/10.5194/amt-17-2625-2024>, 2024.
- [5] Varon, D. J., Jacob, D. J., McKeever, J., Jervis, D., Durak, B. O. A., Xia, Y., and Huang, Y.: *Quantifying methane point sources from fine-scale satellite observations of atmospheric methane plumes*, Atmos. Meas. Tech., 11, 5673–5686, <https://doi.org/10.5194/amt-11-5673-2018>, 2018.
- [6] Yuzhong Zhang et al. *Quantifying methane emissions from the largest oil-producing basin in the United States from space*. Sci. Adv. 6, eaaz5120 (2020). <https://doi.org/10.1126/sciadv.aaz5120>