Measuring progress under the Paris Agreement

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Stanford University
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A data-informed energy and climate policy analyst

The University of California Berkeley
Let There Be Light
1868

Carnegie Mellon University
Pittsburgh Pennsylvania 1900

Lumina
Decision Systems

CEDM

ML
Machine Learning
Carnegie Mellon University

Stanford | School of Earth, Energy & Environmental Sciences

What is the role of hydrocarbon fuels in a net-zero future?

Energy and climate decision-focused research

Methane emissions

Field trials
Region-scale surveys
Data science

Energy systems modeling

Techno-economic analysis
Systems dynamics modeling
Optimization
Projection uncertainty

Machine learning

Remote sensing
Data discovery
Community-building

The Paris Agreement aims to limit warming

- ≤ 2°C (preferably ≤1.5°C) above pre-industrial
- Legally binding treaty produced by Congress of Parties 21 in 2015 in Paris
- “countries aim to reach **global peaking of greenhouse gas emissions as soon as possible** to achieve a **climate neutral world by mid-century**.”

UNFCCC: https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement

How do we track progress?

Where do we need better tracking methods?

How can AI/ML help?

Poll: Which of the following are net greenhouse gases?

Ar

CO_2

F-gases

H_2O

O_3

H_2

CH_4

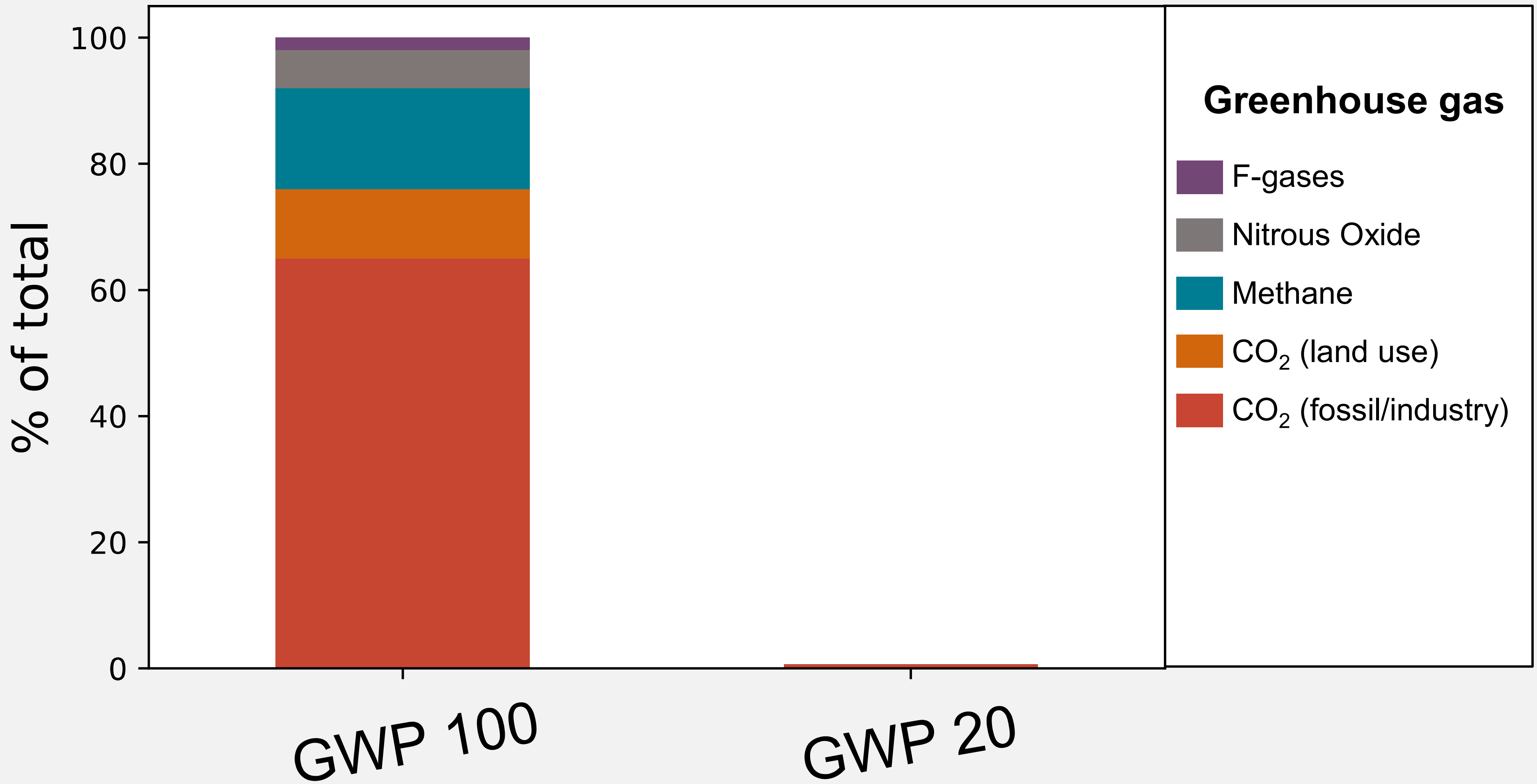
C_2-C_4

N_2O

N_2

O_2

CO_2 is most of the story, but far from all



EPA 2015, https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data

Key measurement and estimation methods

- Physics/chemistry first principles
- Direct measurements at all relevant facilities/assets
- Emission factor estimation
- Model-based simulation from atmospheric concentration measurements

Physics/chemistry first principles

We know what happens when hydrocarbons are combusted

$$CH_4 + 2O_2 \rightarrow 2H_2O + CO_2$$

Source: Wikimedia Commons

Direct measurements at all relevant facilities/assets

E.g. Continuous emissions monitoring systems at power plants

Great publicly available data in USA on CO_2 and health-damaging air pollutants

Not always feasible, especially for distributed infrastructure

Source: Wikimedia Commons

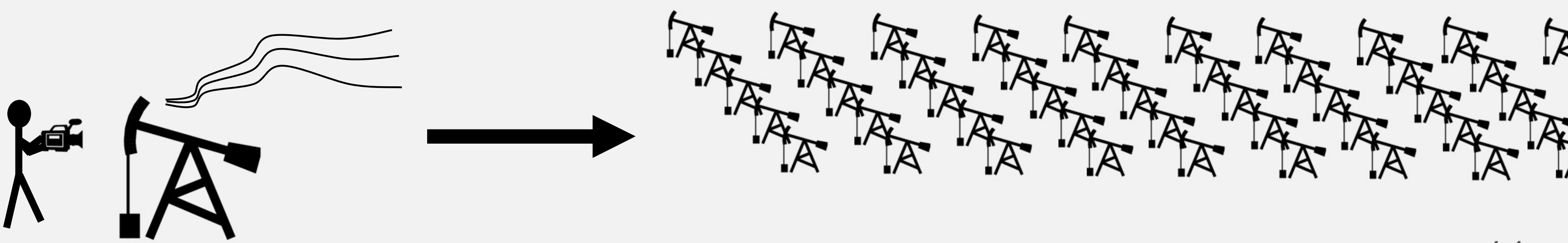
Emission factors (Sometimes called “bottom-up” estimation)

Take a small number of measurements

Assume they are representative of the population of assets

Scale those measurements up to estimate population emissions

E.g. Government methane emissions inventory estimates for key industries



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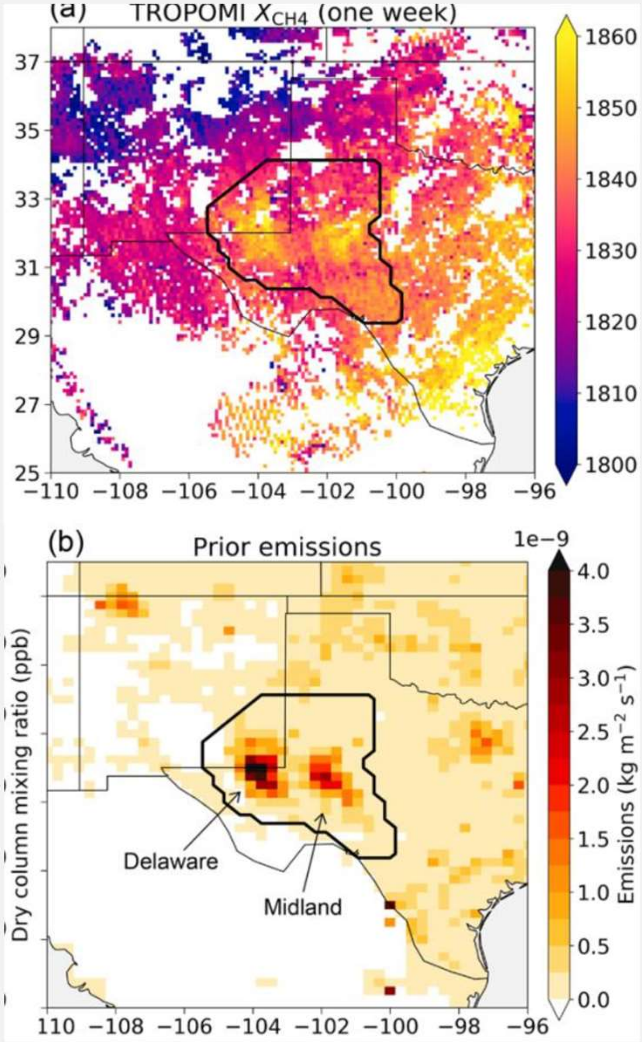
Model-based regional simulation from atmospheric concentration measurements



Common for regional methane and CO_2 estimation

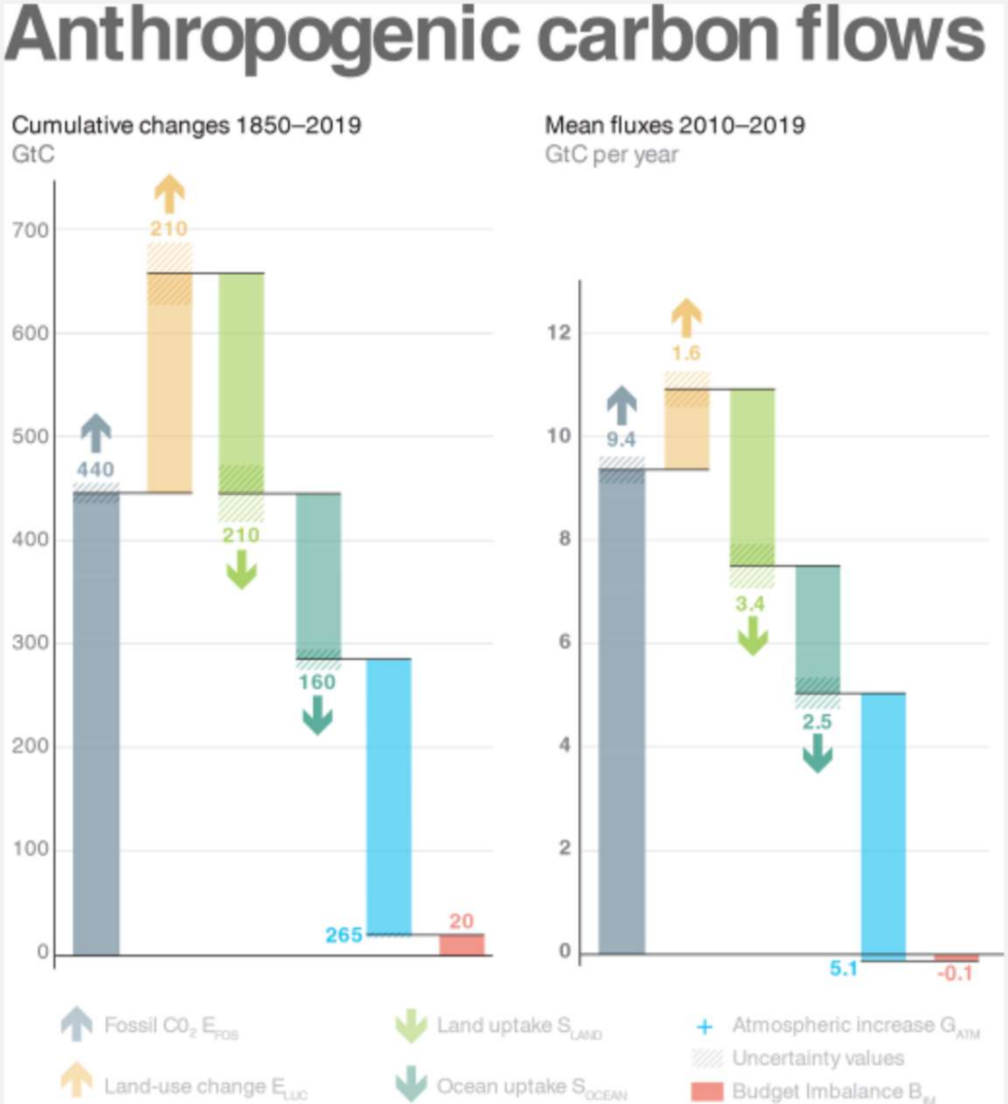
Can require sophisticated models with many underlying assumptions

Varon et al. 2022

What assumptions underlie these measurement methods?
What are their limitations?

Quick group brainstorm in the [Google Doc]
(~5 min)

Which methods do we use for which sources?



Friedlingstein et al. 2020

We have a pretty good understanding of CO_2 flows

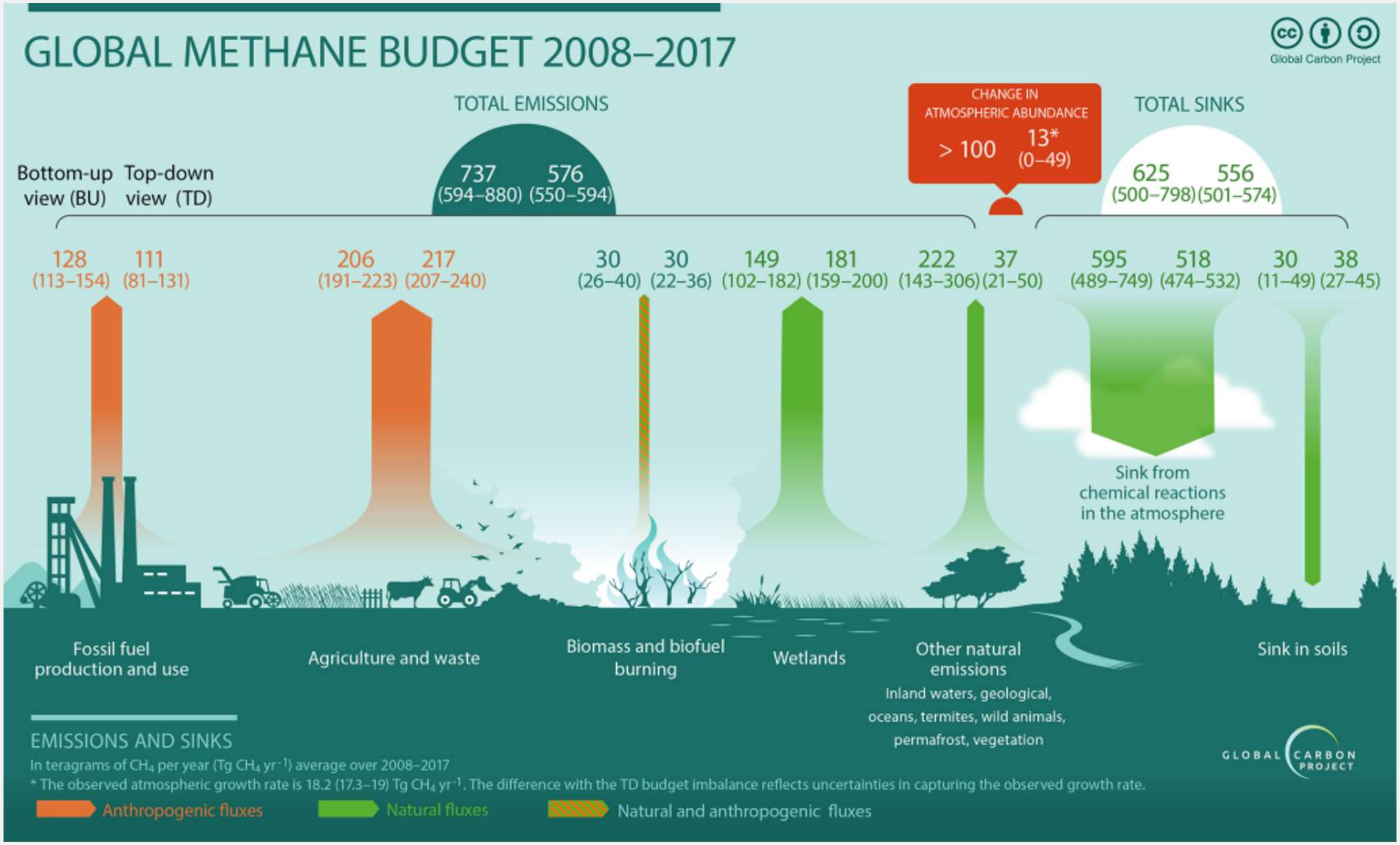
Burning x amount of coal/natural gas/oil emits y amount of CO_2

Similar for heavy industry, e.g. cement manufacturing

Some uncertainty in how much fossil fuel is being used

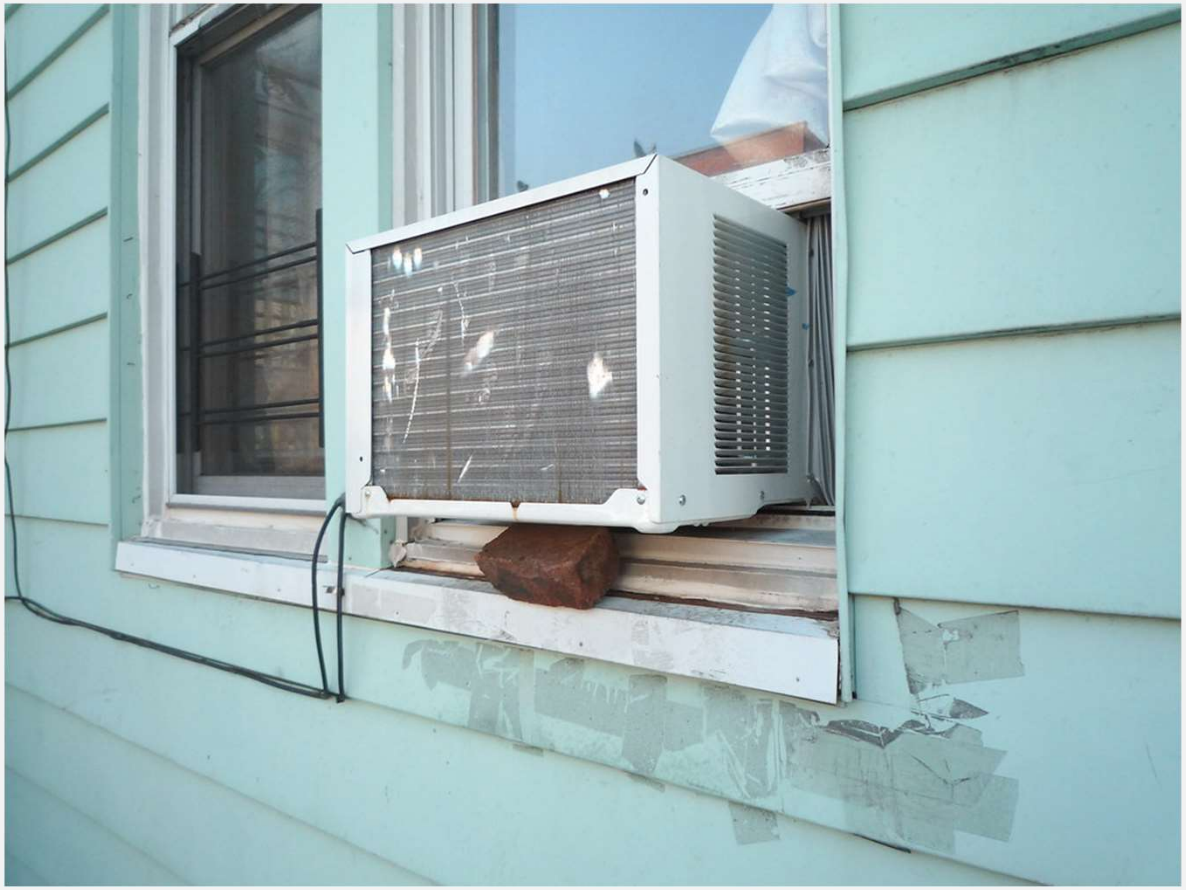
Some uncertainty in land use change and land and ocean uptake

Methane is much more uncertain



Saunois et al. 2020   Numbers in teragrams (million metric tons) of methane per year

Woefully understudied emissions : F-gasses, hydrogen, C_2-C_4



https://www.flickr.com/photos/jasoneppink/3840248708

Recap: Which methods do we use where?

Source	Greenhouse gas	First principles	Universal direct measurements	Emissions factors	Regional simulation
Electric power plants	CO_2	X	(In some countries)	X	
Oil and gas facilities	CH_4		(In select regions)	X	X
Wetlands	CH_4			X	X
Forests	CO_2, CH_4			X	X
Air conditioners, H_2 infrastructure	F-gases, H_2			(Just shy of guessing)	

Recap: AI/machine learning, at its core

Input + Output = Program

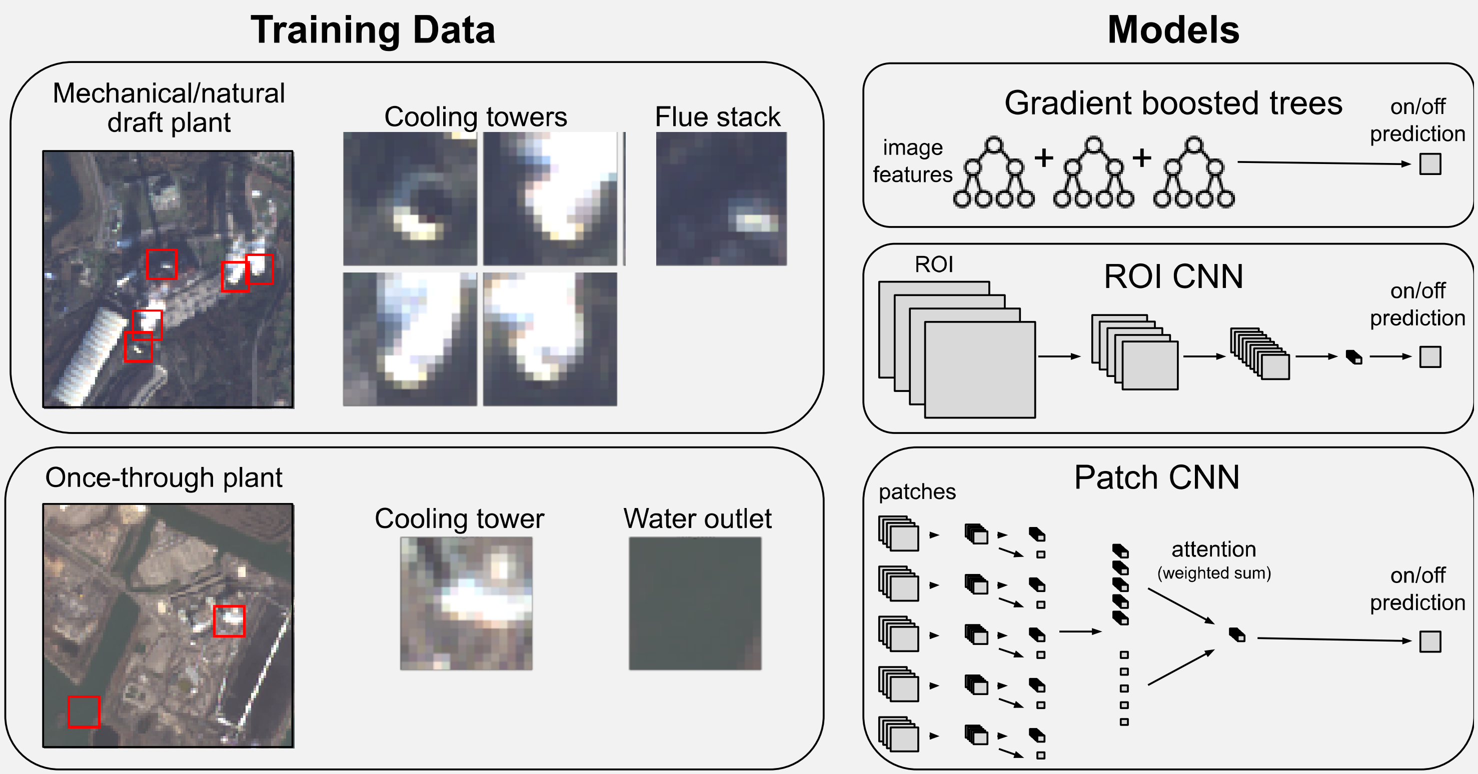
How can AI help improve GHG measurement?

Quick group brainstorm in the Google Doc
(~5 min)

Remote sensing to the rescue?

- Many of our estimates are based only loosely on measurements, high margin of error
- We don't know where many of the world's potentially emitting facilities are
- We also don't know what types of equipment are in use, e.g. in many of the world's oil and gas-producing facilities
- Can be hard, slow, and expensive to make measurements on the ground
- Satellites can see almost everywhere. Airplanes too, with permission.

Tracking every power plant on earth

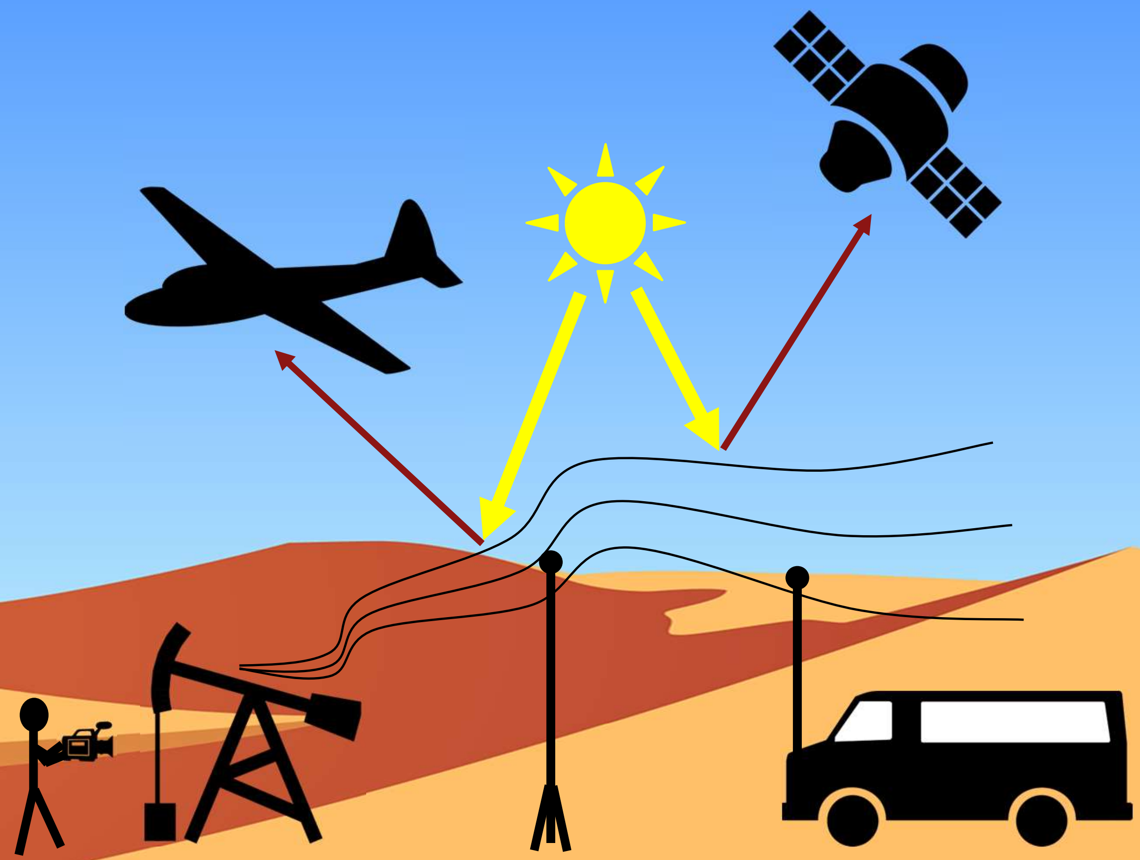


Steam plumes tell us when power plants are on.

We can estimate how much fuel they are using from the size of the plume.

Couture et al. 2020

Finding invisible methane emissions



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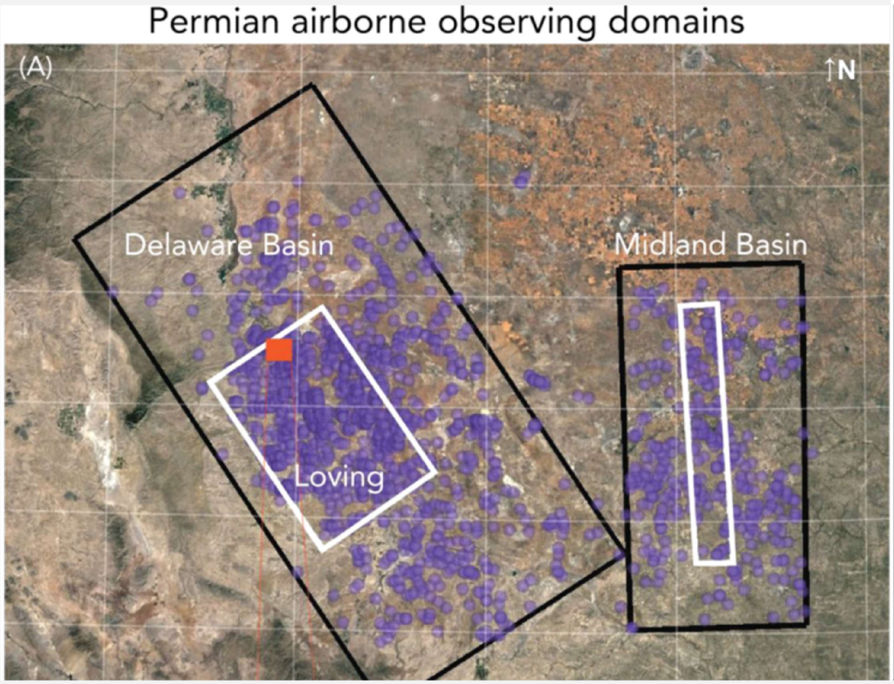
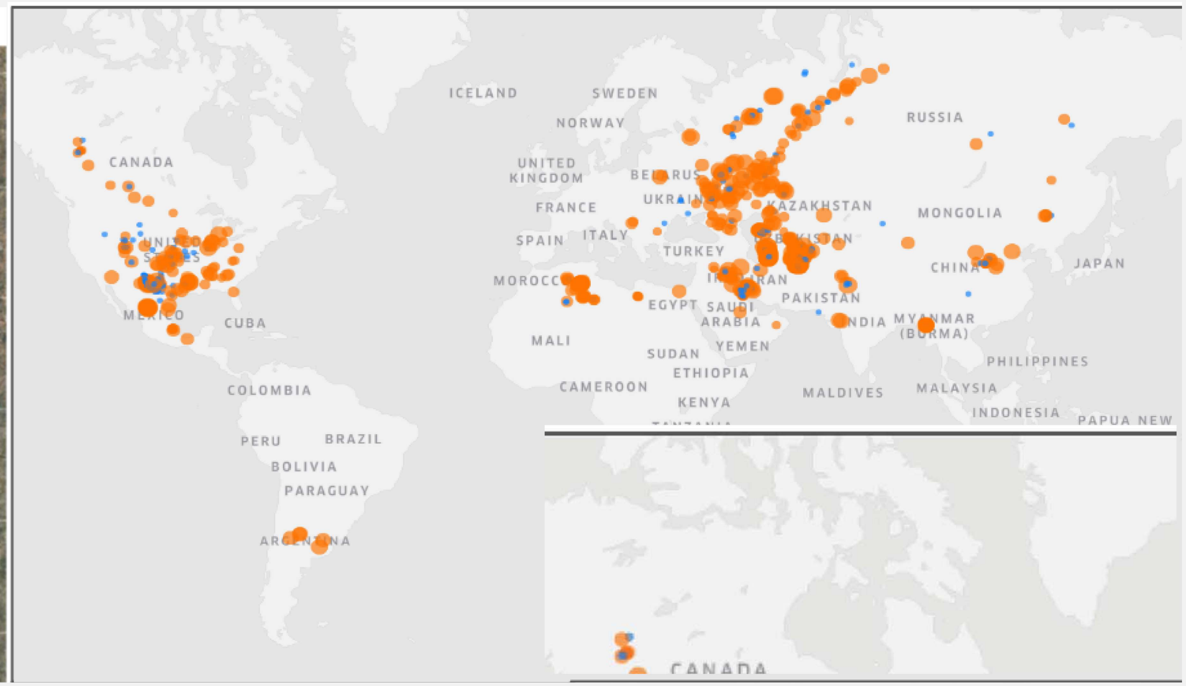
And oh, what methane emissions we've found…



By aircraft



By satellite

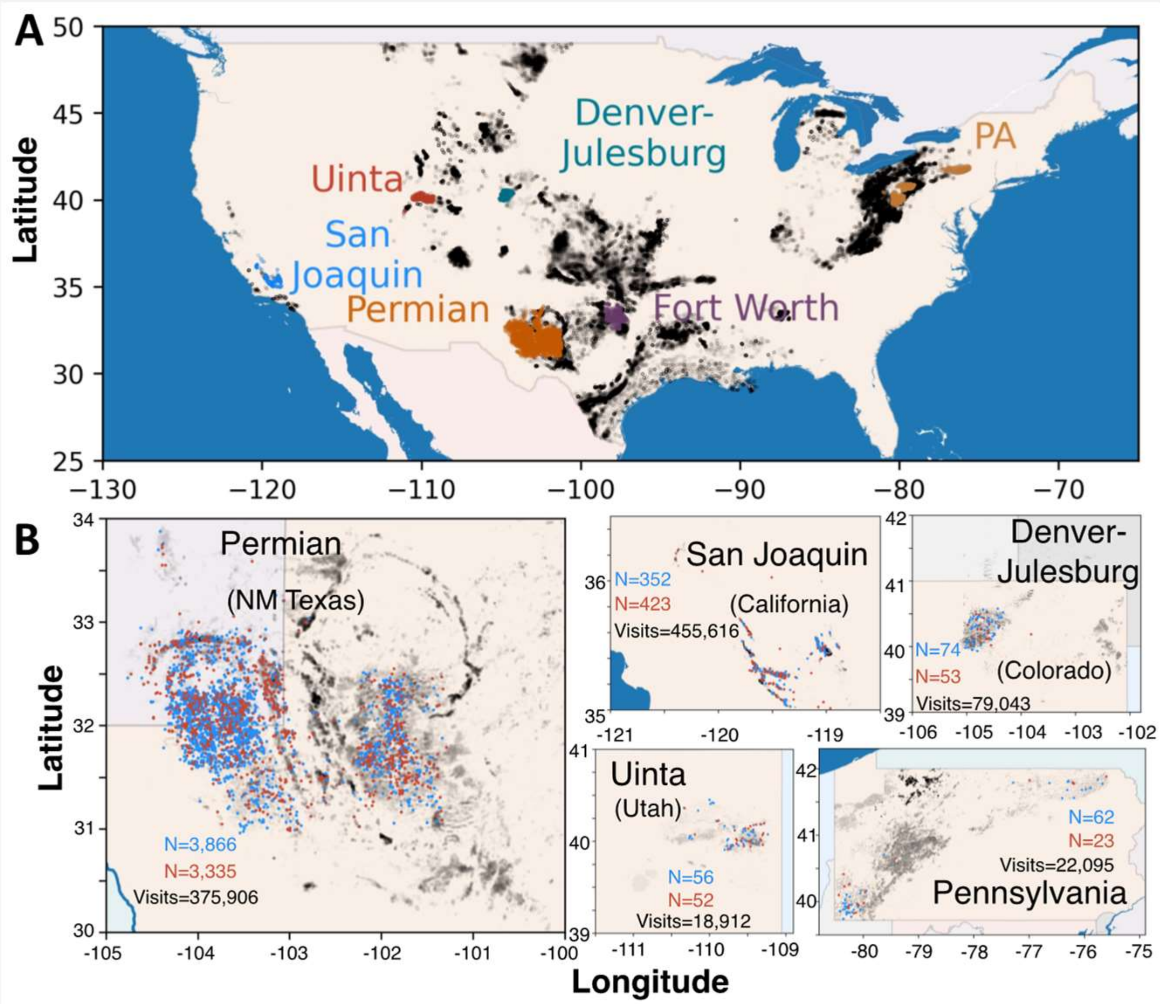
t/h is metric tons of methane per hour

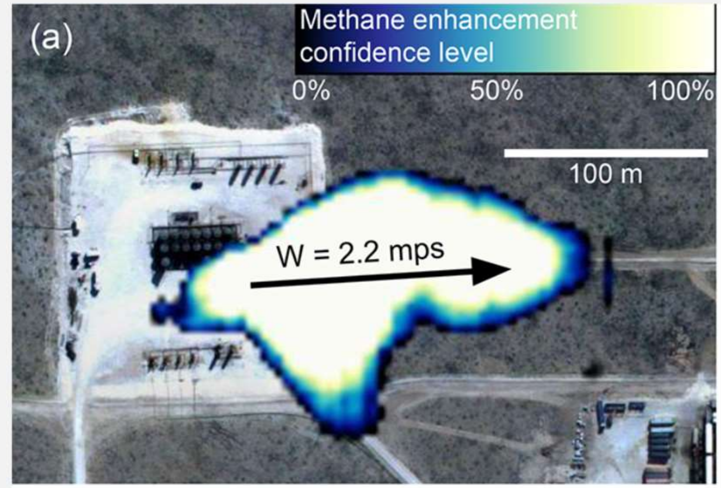
Cusworth et al. 2021, Lauvaux et al. 2022

Note on remote sensing of individual sources of other GHGs

- Remote sensing of individual carbon dioxide emissions is possible, but they need to be pretty big and we usually know where those sources are already
- F-gases are also detectable by remote sensing, but are often too small and diffuse to be measured
- Nitrous oxide emissions tend to be diffuse, hard to measure individually with remote sensing

Aerial surveys find huge emissions everywhere they look





Emission rates are as much as 7.7 times government estimates.

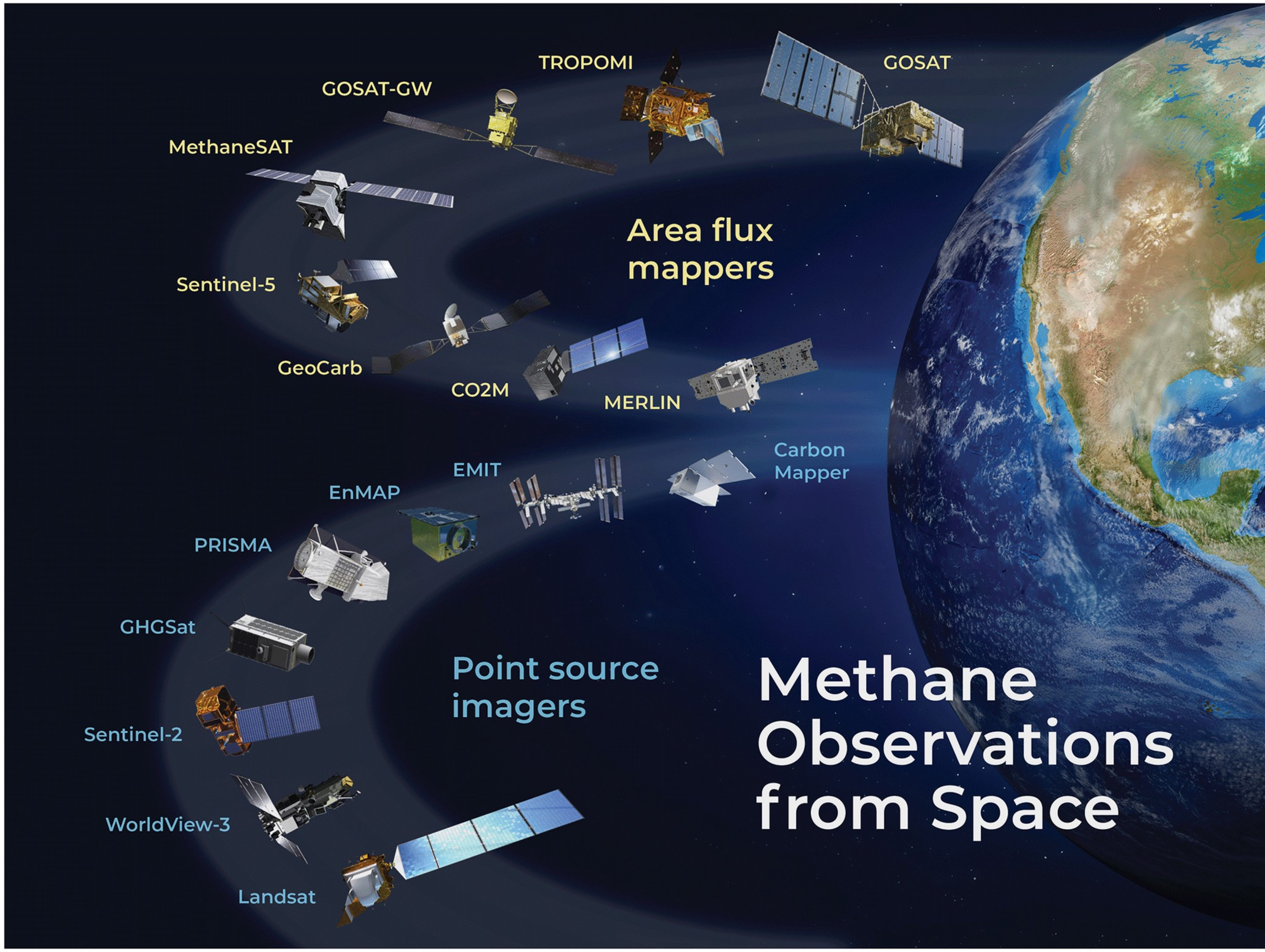
~0.01-1.7% of sites often contribute 50-80% of total emissions

Sherwin et al. 2023; Chen, Sherwin et al. 2022

Satellites can look anywhere on Earth

But do they work?

Jacob et al. 2022

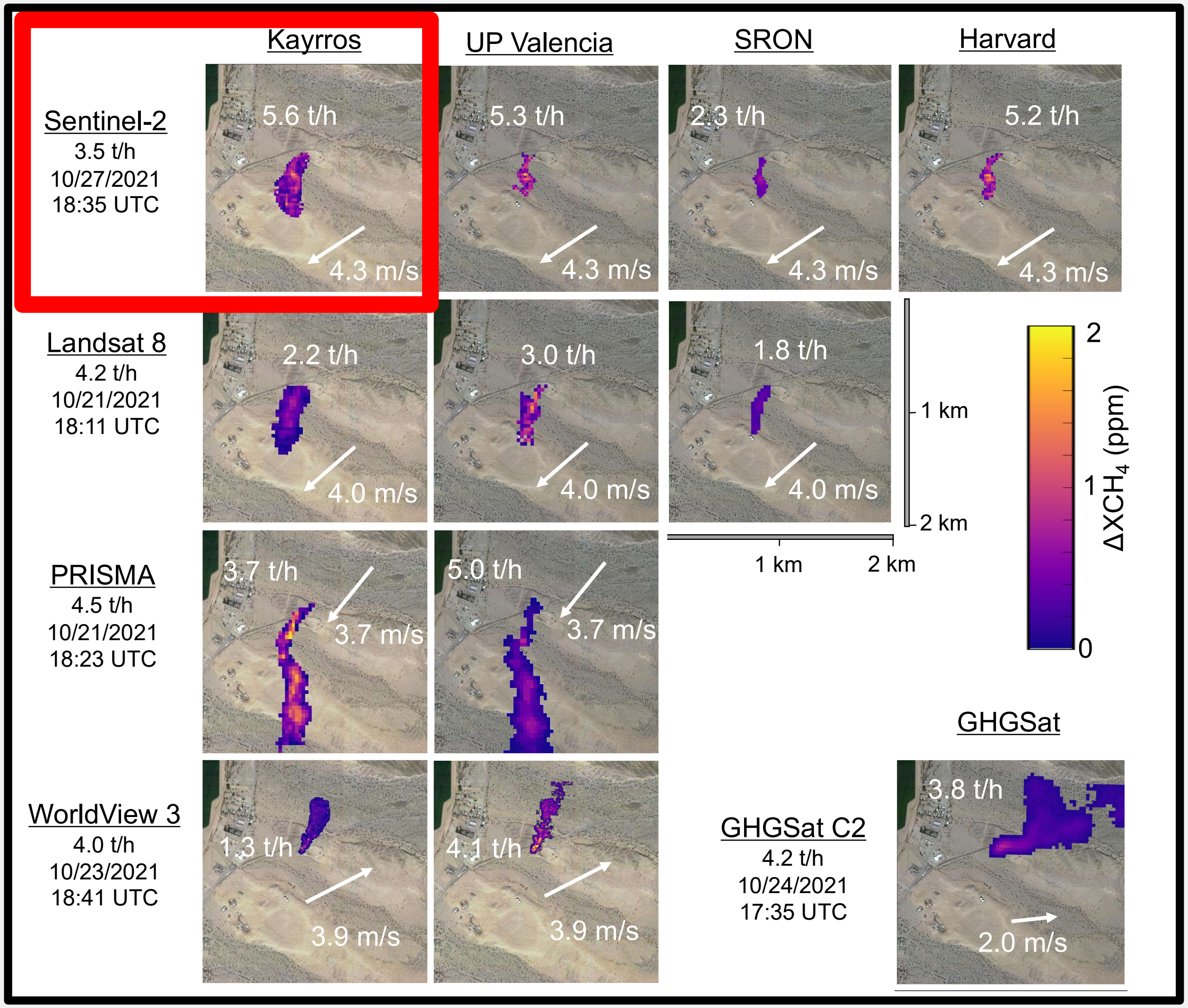


Ground truthing remote sensing: Controlled methane releases, a real-life test set

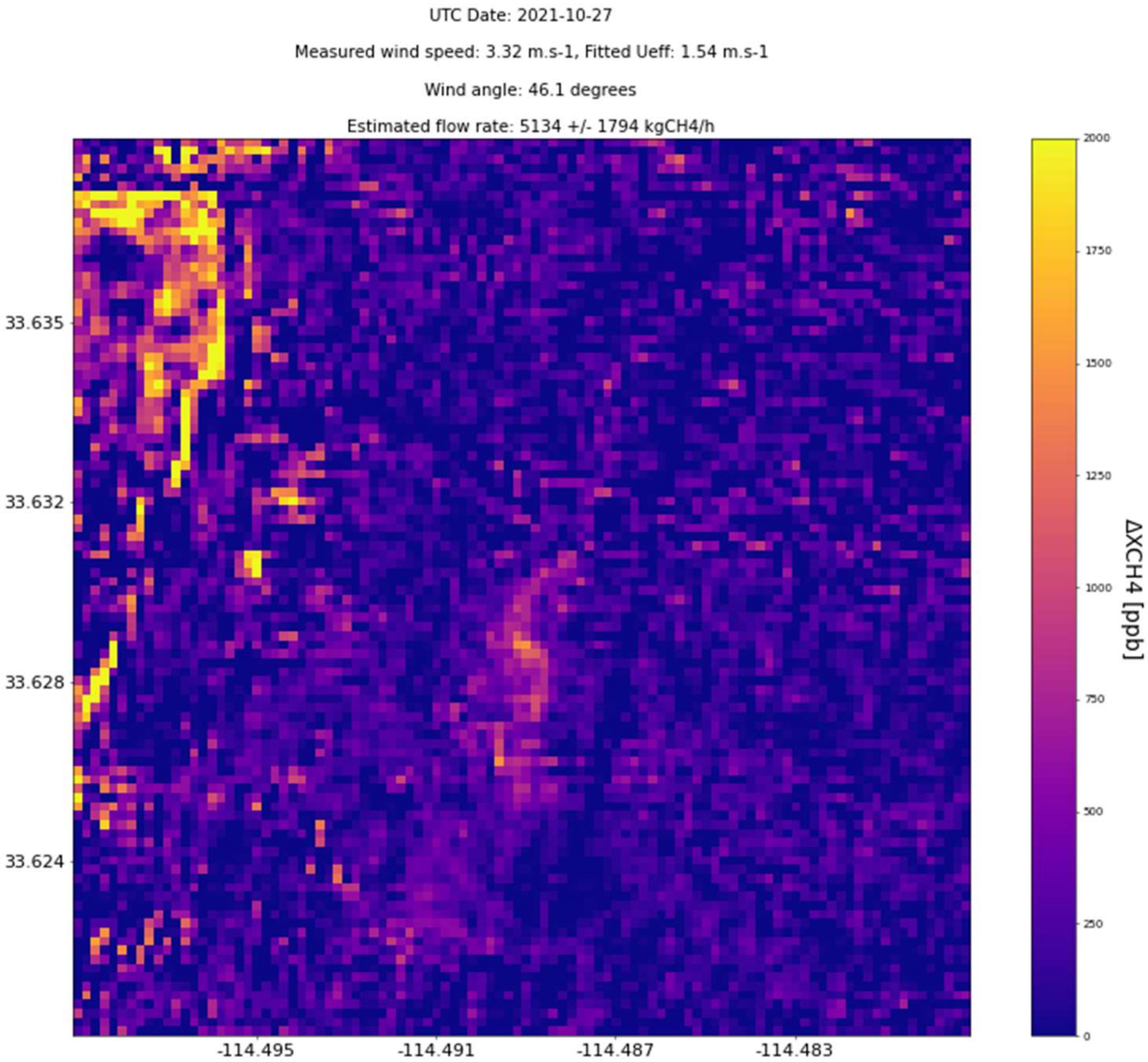
We tested satellites and aircraft by releasing methane into the atmosphere

Sherwin et al. 2023

Participating satellite teams did well



Sherwin et al. 2023



What is a plume and what is an artifact?

Raw methane concentration enhancement estimate
from Kayrros

Sherwin et al. 2023

AI for automatic plume finding?

If you're not careful, you can see methane that isn't there

Current remote sensing methods use human review

Can we reliably automate that?

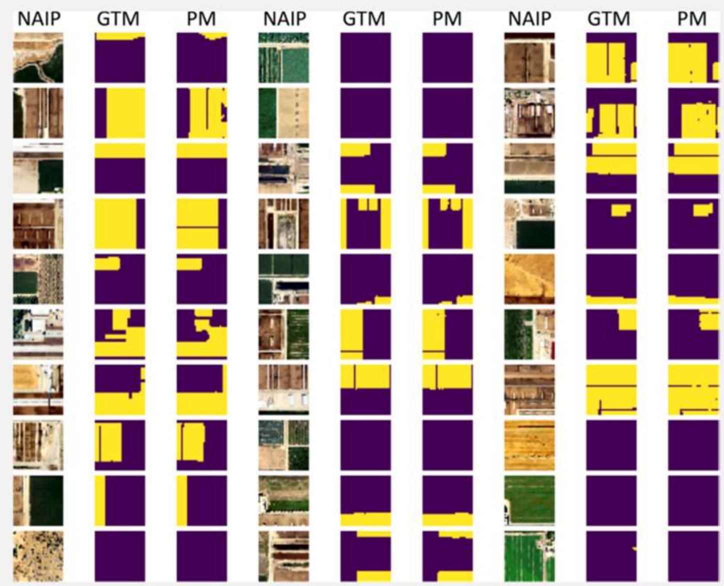
11/01/2021
(False positive)

Zhang et al. 2022

Remote infrastructure mapping: Knowing where to look

Where are the potentially emitting facilities?

AI can help us find them worldwide.

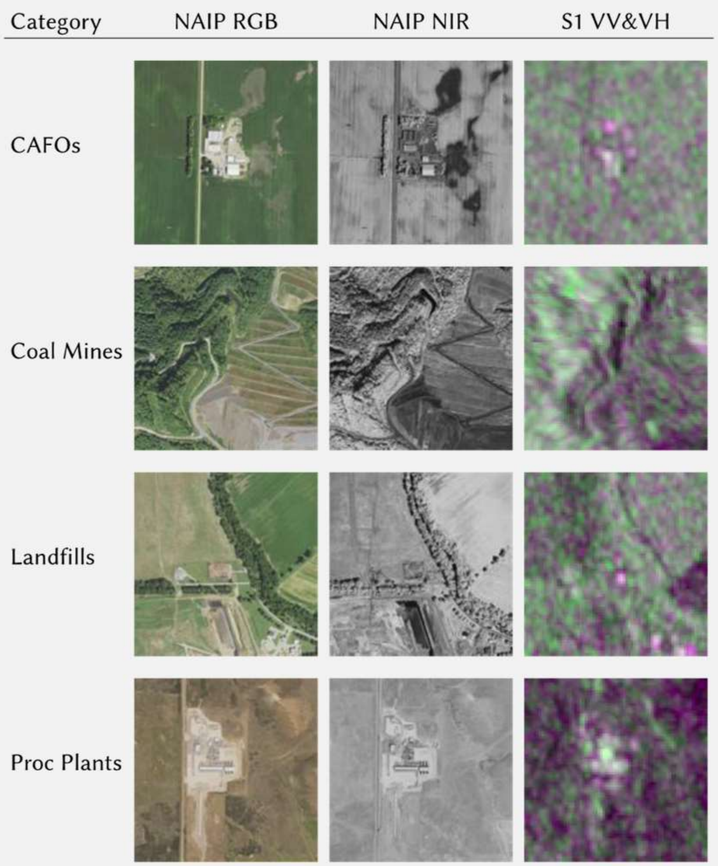


Sheng et al. 2020, Dileep et al 2020, Jeong et al. 2022

Coming soon:

METER-ML: A Multi-sensor Earth Observation Benchmark for Automated Methane Source Mapping

Bryan Zhu *, Nicholas Lui *, Jeremy Irvin *, Jimmy Le, Sahil Tadwalkar, Chenghao Wang, Zutao Ouyang, Frankie Y. Liu, Andrew Y. Ng, Robert B. Jackson

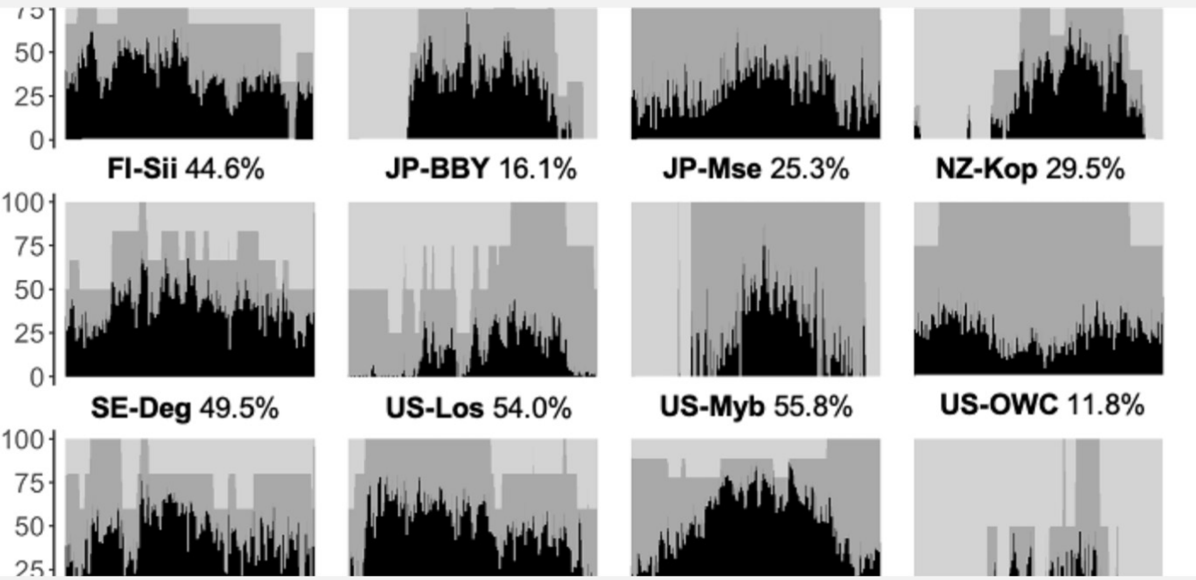


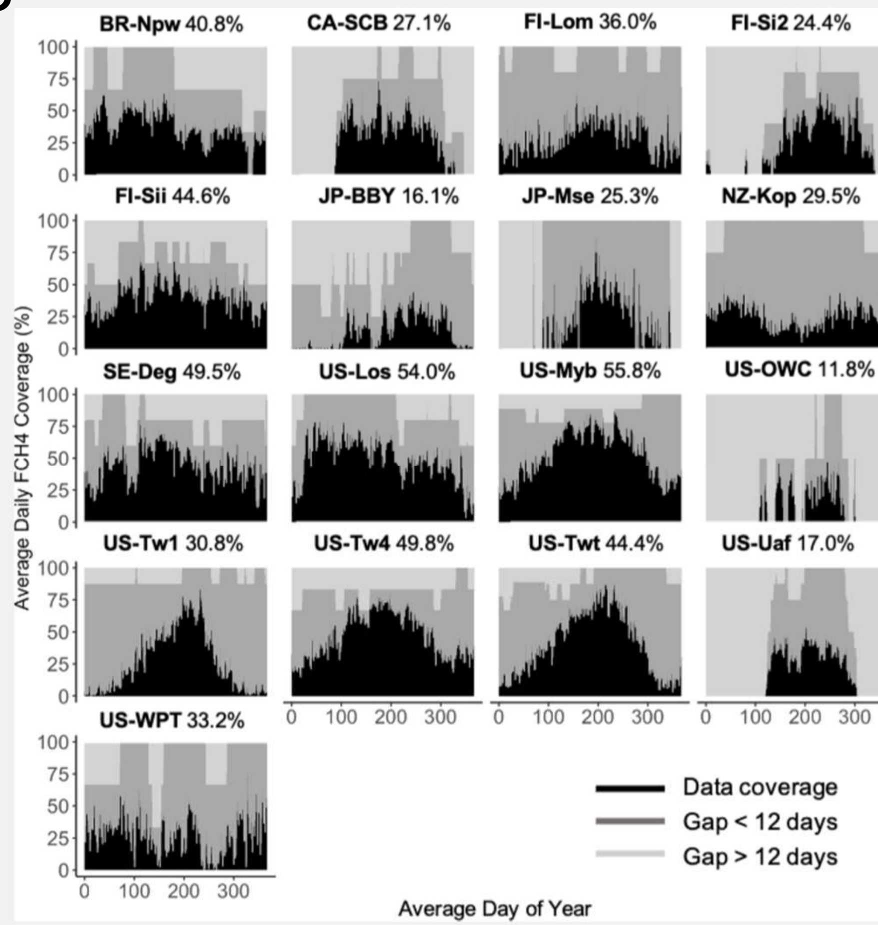
Global database of infrastructure that might emit methane

Created through computer vision applied to remote sensing

Zhu, Liu, Irvin et al. 2022

How can AI help?
Filling in missing data





Wetland methane measurement towers can't collect valid data all the time.

How can we estimate these missing data to conduct valid analysis?

Irvin et al. 2021

There is lots of room for improvement in emissions tracking

- We need to track a lot of emissions sources across the globe
- Remote sensing can help us:
  - Find potential emitters
  - Detect active emissions
- Machine learning can help automate greenhouse gas remote sensing
  - Can also help fill gaps in existing emissions datasets
- Under-studied greenhouse gases could use some extra attention
  - F-gases
  - N_2O
  - C_{2+} hydrocarbons

Acknowledgments

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Strategic Energy Alliance

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Rawhide

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Philippine Burdeau

Richard Chen

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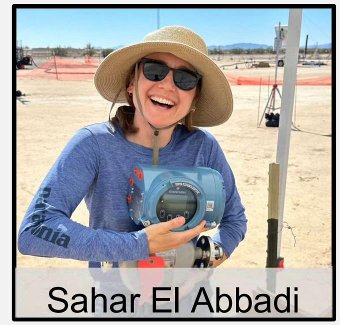
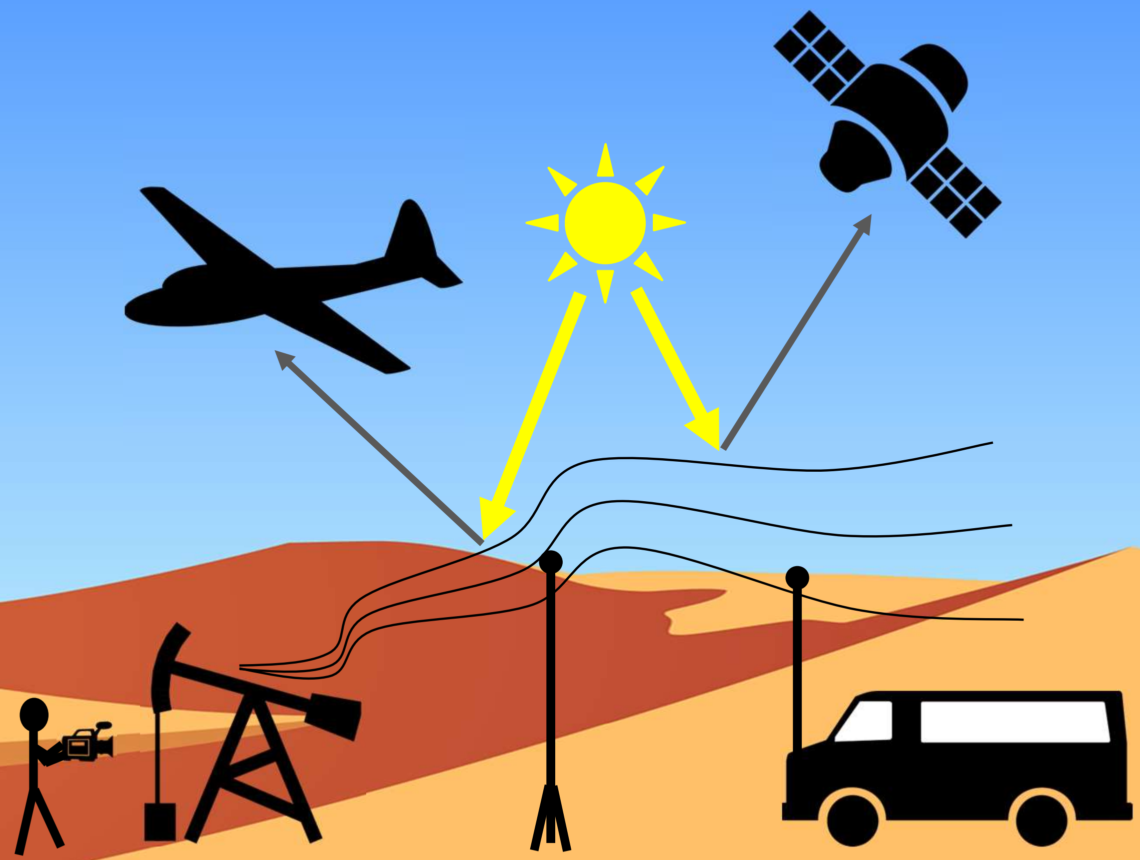


Sahar El Abbadi

Jeff Rutherford

Zhan Zhang

Q&A



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Works cited

(1) Varon, D. J.; Jacob, D. J.; Hmiel, B.; Gautam, R.; Lyon, D. R.; Omara, M.; Sulprizio, M.; Shen, L.; Pendergrass, D.; Nesser, H.; Qu, Z.; Barkley, Z. R.; Miles, N. L.; Richardson, S. J.; Davis, K. J.; Pandey, S.; Lu, X.; Lorente, A.; Borsdorff, T.; Maasakkers, J. D.; Aben, I. Continuous Weekly Monitoring of Methane Emissions from the Permian Basin by Inversion of TROPOMI Satellite Observations; preprint; Gases/Atmospheric Modelling/Troposphere/Chemistry (chemical composition and reactions), 2022. https://doi.org/10.5194/acp-2022-749.

(2) Friedlingstein, P.; O'Sullivan, M.; Jones, M. W.; Andrew, R. M.; Hauck, J.; Olsen, A.; Peters, G. P.; Peters, W.; Pongratz, J.; Sitch, S.; Le Quéré, C.; Canadell, J. G.; Ciais, P.; Jackson, R. B.; Alin, S.; Aragão, L. E. O. C.; Arneth, A.; Arora, V.; Bates, N. R.; Becker, M.; Benoit-Cattin, A.; Bittig, H. C.; Bopp, L.; Bultan, S.; Chandra, N.; Chevallier, F.; Chini, L. P.; Evans, W.; Florentie, L.; Forster, P. M.; Gasser, T.; Gehlen, M.; Gilfillan, D.; Gkritzalis, T.; Gregor, L.; Gruber, N.; Harris, I.; Hartung, K.; Haverd, V.; Houghton, R. A.; Ilyina, T.; Jain, A. K.; Joetzjer, E.; Kadono, K.; Kato, E.; Kitidis, V.; Korsbakken, J. I.; Landschützer, P.; Lefèvre, N.; Lenton, A.; Lienert, S.; Liu, Z.; Lombardozzi, D.; Marland, G.; Metzl, N.; Munro, D. R.; Nabel, J. E. M. S.; Nakaoka, S.-I.; Niwa, Y.; O'Brien, K.; Ono, T.; Palmer, P. I.; Pierrot, D.; Poulter, B.; Resplandy, L.; Robertson, E.; Rödenbeck, C.; Schwinger, J.; Séférian, R.; Skjelvan, I.; Smith, A. J. P.; Sutton, A. J.; Tanhua, T.; Tans, P. P.; Tian, H.; Tilbrook, B.; van der Werf, G.; Vuichard, N.; Walker, A. P.; Wanninkhof, R.; Watson, A. J.; Willis, D.; Wiltshire, A. J.; Yuan, W.; Yue, X.; Zaehle, S. Global Carbon Budget 2020. Earth Syst. Sci. Data 2020, 12 (4), 3269–3340. https://doi.org/10.5194/essd-12-3269-2020.

Works cited

(3) Saunois, M.; Stavert, A. R.; Poulter, B.; Bousquet, P.; Canadell, J. G.; Jackson, R. B.; Raymond, P. A.; Dlugokencky, E. J.; Houweling, S.; Patra, P. K.; Ciais, P.; Arora, V. K.; Bastviken, D.; Bergamaschi, P.; Blake, D. R.; Brailsford, G.; Bruhwiler, L.; Carlson, K. M.; Carrol, M.; Castaldi, S.; Chandra, N.; Crevoisier, C.; Crill, P. M.; Covey, K.; Curry, C. L.; Etiope, G.; Frankenberg, C.; Gedney, N.; Hegglin, M. I.; Höglund-Isaksson, L.; Hugelius, G.; Ishizawa, M.; Ito, A.; Janssens-Maenhout, G.; Jensen, K. M.; Joos, F.; Kleinen, T.; Krummel, P. B.; Langenfelds, R. L.; Laruelle, G. G.; Liu, L.; Machida, T.; Maksyutov, S.; McDonald, K. C.; McNorton, J.; Miller, P. A.; Melton, J. R.; Morino, I.; Müller, J.; Murguia-Flores, F.; Naik, V.; Niwa, Y.; Noce, S.; O’Doherty, S.; Parker, R. J.; Peng, C.; Peng, S.; Peters, G. P.; Prigent, C.; Prinn, R.; Ramonet, M.; Regnier, P.; Riley, W. J.; Rosentreter, J. A.; Segers, A.; Simpson, I. J.; Shi, H.; Smith, S. J.; Steele, L. P.; Thornton, B. F.; Tian, H.; Tohjima, Y.; Tubiello, F. N.; Tsuruta, A.; Viovy, N.; Voulgarakis, A.; Weber, T. S.; van Weele, M.; van der Werf, G. R.; Weiss, R. F.; Worthy, D.; Wunch, D.; Yin, Y.; Yoshida, Y.; Zhang, W.; Zhang, Z.; Zhao, Y.; Zheng, B.; Zhu, Q.; Zhu, Q.; Zhuang, Q. The Global Methane Budget 2000–2017. Earth Syst. Sci. Data 2020, 12 (3), 1561–1623. https://doi.org/10.5194/essd-12-1561-2020.

(4) Couture, H. D.; O’Connor, J.; Mitchell, G.; Söldner-Rembold, I.; D’souza, D.; Karra, K.; Zhang, K. D.; Kargar, A. R.; Kassel, T.; Goldman, B. W.; Tyrrell, D.; Czerwinski, W.; Talekar, A.; McCormick, C. Towards Tracking the Emissions of Every Power Plant on the Planet. In Tackling Climate Change with Machine Learning; Virtual, 2020; p 9.

Works cited

(5) Cusworth, D. H.; Duren, R. M.; Thorpe, A. K.; Olson-Duvall, W.; Heckler, J.; Chapman, J. W.; Eastwood, M. L.; Helmlinger, M. C.; Green, R. O.; Asner, G. P.; Dennison, P. E.; Miller, C. E. Intermittency of Large Methane Emitters in the Permian Basin. Environ. Sci. Technol. Lett. 2021, 8 (7), 567–573. https://doi.org/10.1021/acs.estlett.1c00173.

(6) Lauvaux, T.; Giron, C.; Mazzolini, M.; d’Aspremont, A.; Duren, R.; Cusworth, D.; Shindell, D.; Ciais, P. Global Assessment of Oil and Gas Methane Ultra-Emitters. Science 2022, 375 (6580), 557–561. https://doi.org/10.31223/X5NS54.

(7) Sherwin, E.; Rutherford, J.; Zhang, Z.; Chen, Y.; Wetherley, E.; Yakovlev, P.; Berman, E.; Jones, B.; Thorpe, A.; Ayasse, A.; Duren, R.; Brandt, A.; Cusworth, D. Quantifying Oil and Natural Gas System Emissions Using One Million Aerial Site Measurements; preprint; In Review, 2023. https://doi.org/10.21203/rs.3.rs-2406848/v1.

(8) Chen, Y.; Sherwin, E. D.; Berman, E. S. F.; Jones, B. B.; Gordon, M. P.; Wetherley, E. B.; Kort, E. A.; Brandt, A. R. Quantifying Regional Methane Emissions in the New Mexico Permian Basin with a Comprehensive Aerial Survey. Environ. Sci. Technol. 2022, 56 (7), 4317–4323. https://doi.org/10.1021/acs.est.1c06458.

Works cited

(9) Jacob, D. J.; Varon, D. J.; Cusworth, D. H.; Dennison, P. E.; Frankenberg, C.; Gautam, R.; Guanter, L.; Kelley, J.; McKeever, J.; Ott, L. E.; Poulter, B.; Qu, Z.; Thorpe, A. K.; Worden, J. R.; Duren, R. M. Quantifying Methane Emissions from the Global Scale down to Point Sources Using Satellite Observations of Atmospheric Methane. Atmos. Chem. Phys. 2022, 22 (14), 9617–9646. https://doi.org/10.5194/acp-22-9617-2022.

(10) Sherwin, E. D. Single-Blind Validation of Space-Based Point-Source Detection and Quantification of Onshore Methane Emissions. Scientific Reports 2023. https://doi.org/10.1038/s41598-023-30761-2.

(11) Zhang, Z.; Sherwin, E. D.; Varon, D. J.; Brandt, A. R. Detecting and Quantifying Methane Emissions from Oil and Gas Production: Algorithm Development with Ground-Truth Calibration Based on Sentinel-2 Satellite Imagery. Atmos. Meas. Tech. 2022, 15 (23), 7155–7169. https://doi.org/10.5194/amt-15-7155-2022.

(12) Sheng, H.; Irvin, J.; Munukutla, S.; Zhang, S.; Cross, C.; Story, K.; Rustowicz, R.; Elsworth, C.; Yang, Z.; Omara, M.; Gautam, R.; Jackson, R. B.; Ng, A. Y. OGNet: Towards a Global Oil and Gas Infrastructure Database Using Deep Learning on Remotely Sensed Imagery; p 8.

Works cited

(13) Dileep, S.; Zimmerle, D.; Beveridge, J. R.; Vaughn, T. Automated Identification of Oil Field Features Using CNNs. In Tackling Climate Change with Machine Learning; Virtual, 20; p 6.

(14) Jeong, S.; Fischer, M. L.; Breunig, H.; Marklein, A. R.; Hopkins, F. M.; Biraud, S. C. Artificial Intelligence Approach for Estimating Dairy Methane Emissions. Environ. Sci. Technol. 2022, 56 (8), 4849–4858. https://doi.org/10.1021/acs.est.1c08802.

(15) Zhu, B.; Lui, N.; Irvin, J.; Le, J.; Tadwalkar, S.; Wang, C.; Ouyang, Z.; Liu, F. Y.; Ng, A. Y.; Jackson, R. B. METER-ML: A Multi-Sensor Earth Observation Benchmark for Automated Methane Source Mapping. arXiv August 15, 2022. http://arxiv.org/abs/2207.11166 (accessed 2023-05-05).

Works cited

(16) Irvin, J.; Zhou, S.; McNicol, G.; Lu, F.; Liu, V.; Fluet-Chouinard, E.; Ouyang, Z.; Knox, S. H.; Lucas-Moffat, A.; Trotta, C.; Papale, D.; Vitale, D.; Mammarella, I.; Alekseychik, P.; Aurela, M.; Avati, A.; Baldocchi, D.; Bansal, S.; Bohrer, G.; Campbell, D. I.; Chen, J.; Chu, H.; Dalmagro, H. J.; Delwiche, K. B.; Desai, A. R.; Euskirchen, E.; Feron, S.; Goeckede, M.; Heimann, M.; Helbig, M.; Helfter, C.; Hemes, K. S.; Hirano, T.; Iwata, H.; Jurasinski, G.; Kalhori, A.; Kondrich, A.; Lai, D. Y.; Lohila, A.; Malhotra, A.; Merbold, L.; Mitra, B.; Ng, A.; Nilsson, M. B.; Noormets, A.; Peichl, M.; Rey-Sanchez, A. C.; Richardson, A. D.; Runkle, B. R.; Schäfer, K. V.; Sonnentag, O.; Stuart-Haëntjens, E.; Sturtevant, C.; Ueyama, M.; Valach, A. C.; Vargas, R.; Vourlitis, G. L.; Ward, E. J.; Wong, G. X.; Zona, D.; Alberto, Ma. C. R.; Billesbach, D. P.; Celis, G.; Dolman, H.; Friborg, T.; Fuchs, K.; Gogo, S.; Gondwe, M. J.; Goodrich, J. P.; Gottschalk, P.; Hörtnagl, L.; Jacotot, A.; Koebsch, F.; Kasak, K.; Maier, R.; Morin, T. H.; Nemitz, E.; Oechel, W. C.; Oikawa, P. Y.; Ono, K.; Sachs, T.; Sakabe, A.; Schuur, E. A.; Shortt, R.; Sullivan, R. C.; Szutu, D. J.; Tuittila, E.-S.; Varlagin, A.; Verfaillie, J. G.; Wille, C.; Windham-Myers, L.; Poulter, B.; Jackson, R. B. Gap-Filling Eddy Covariance Methane Fluxes: Comparison of Machine Learning Model Predictions and Uncertainties at FLUXNET-CH4 Wetlands. Agricultural and Forest Meteorology 2021, 308–309, 108528. https://doi.org/10.1016/j.agrformet.2021.108528.