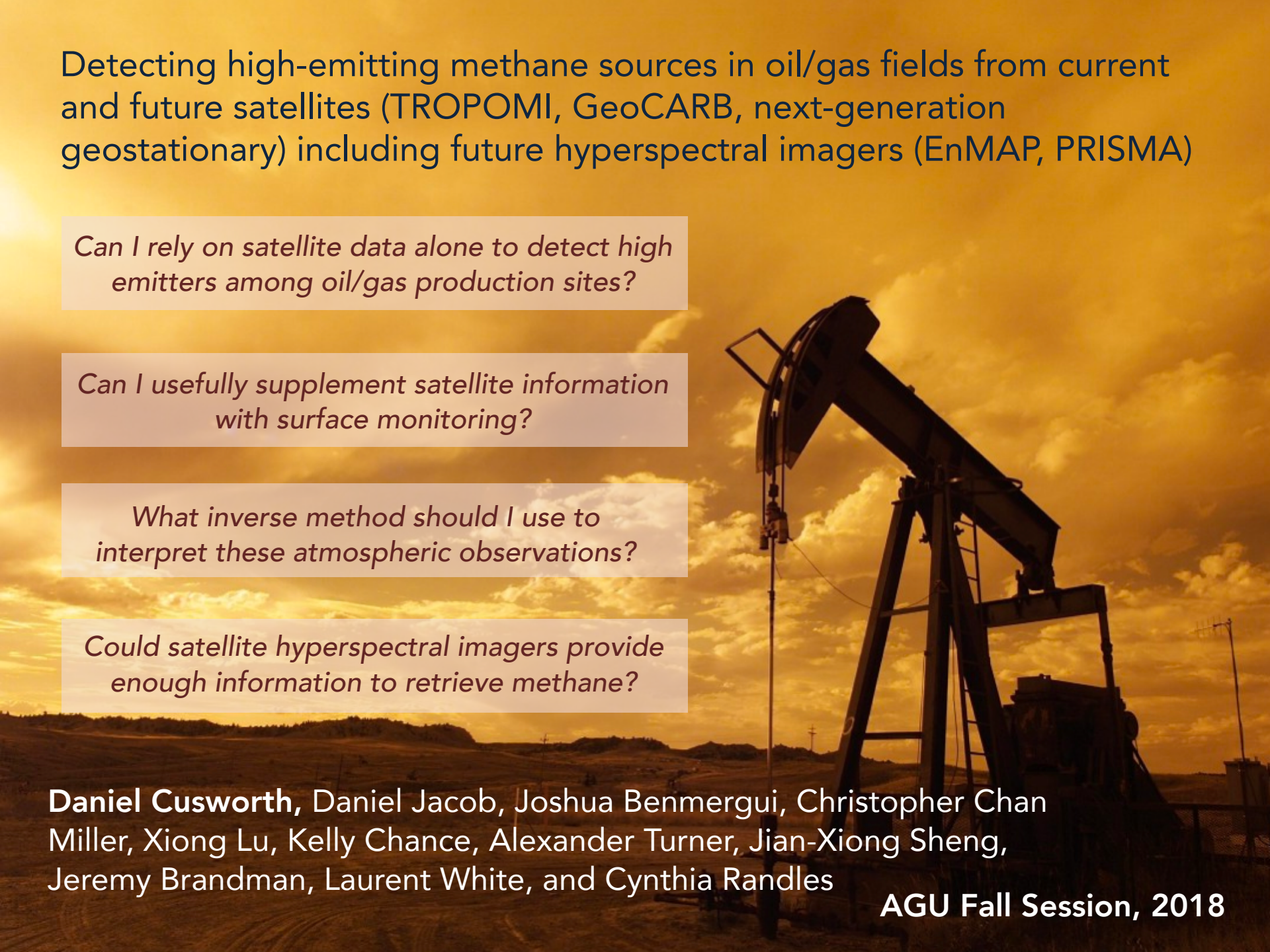
# Detecting high-emitting methane sources in oil/gas fields from current and future satellites (TROPOMI, GeoCARB, next-generation geostationary) including future hyperspectral imagers (EnMAP, PRISMA)

*Can I rely on satellite data alone to detect high emitters among oil/gas production sites?*

*Can I usefully supplement satellite information with surface monitoring?*

*What inverse method should I use to interpret these atmospheric observations?*

*Could satellite hyperspectral imagers provide enough information to retrieve methane?*



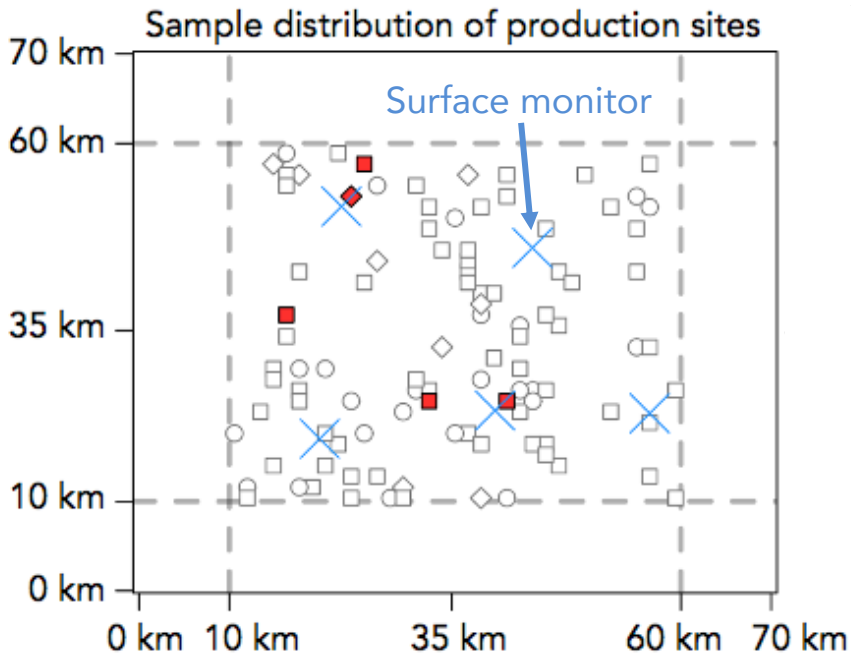
**Daniel Cusworth,** Daniel Jacob, Joshua Benmergui, Christopher Chan Miller, Xiong Lu, Kelly Chance, Alexander Turner, Jian-Xiong Sheng, Jeremy Brandman, Laurent White, and Cynthia Randles

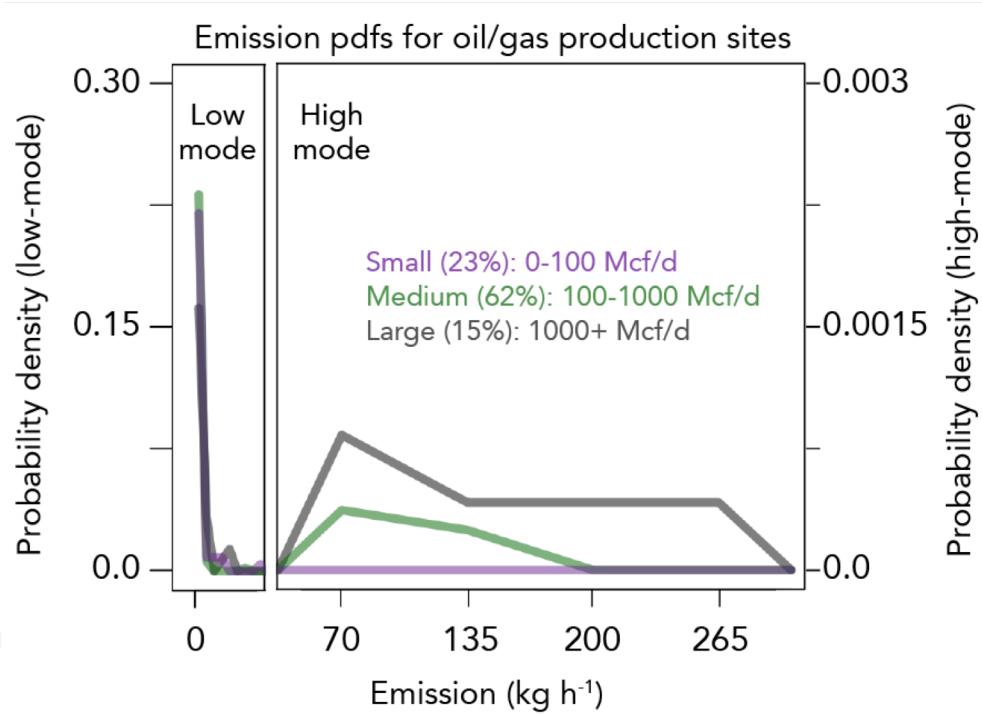
**AGU Fall Session, 2018**

We construct an ensemble of emission fields using the emission characteristics of of production sites.

Randomly distribute N emitters in a 50 km$^2$ subdomain

For each emitter, get true emission rate by sampling emission probability density functions (pdfs) – Generate 500 ensembles



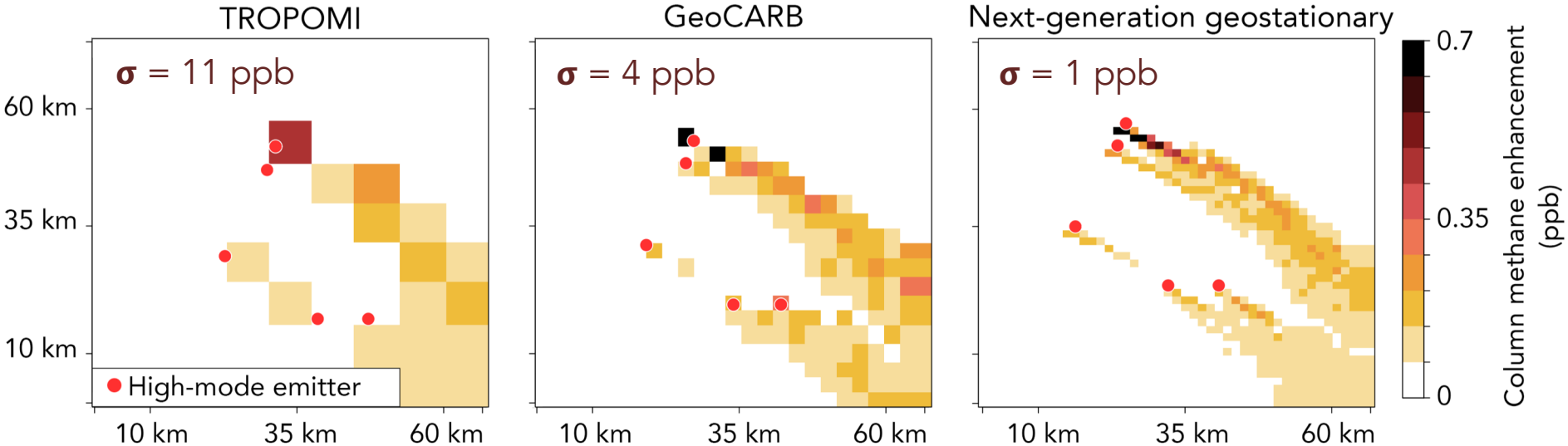

○ 0-100 Mcf/d ◇ >1000 Mcf/d

□ 100-1000 Mcf/d **high-mode emitter**

pdfs from field measurements
(Lan et al., 2015; Rella et al., 2015; Yacovitch et al., 2015)

We generate methane columns for TROPOMI, GeoCARB (2-4 passes/day), and a next-generation geostationary (10 passes/day) satellite.

Simulated **noiseless** concentrations of xCH4




To generate pseudo-observations (constant background):

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \boldsymbol{\sigma}\boldsymbol{\varepsilon} + b$$

**H** = ∂**y**/∂**x** : WRF-STILT footprints
**x:** emission state vector
**σ:** instrument precision
**ε** ~ *N*(0,1)

Even high-resolution enhancements are small compared to instrument precision!

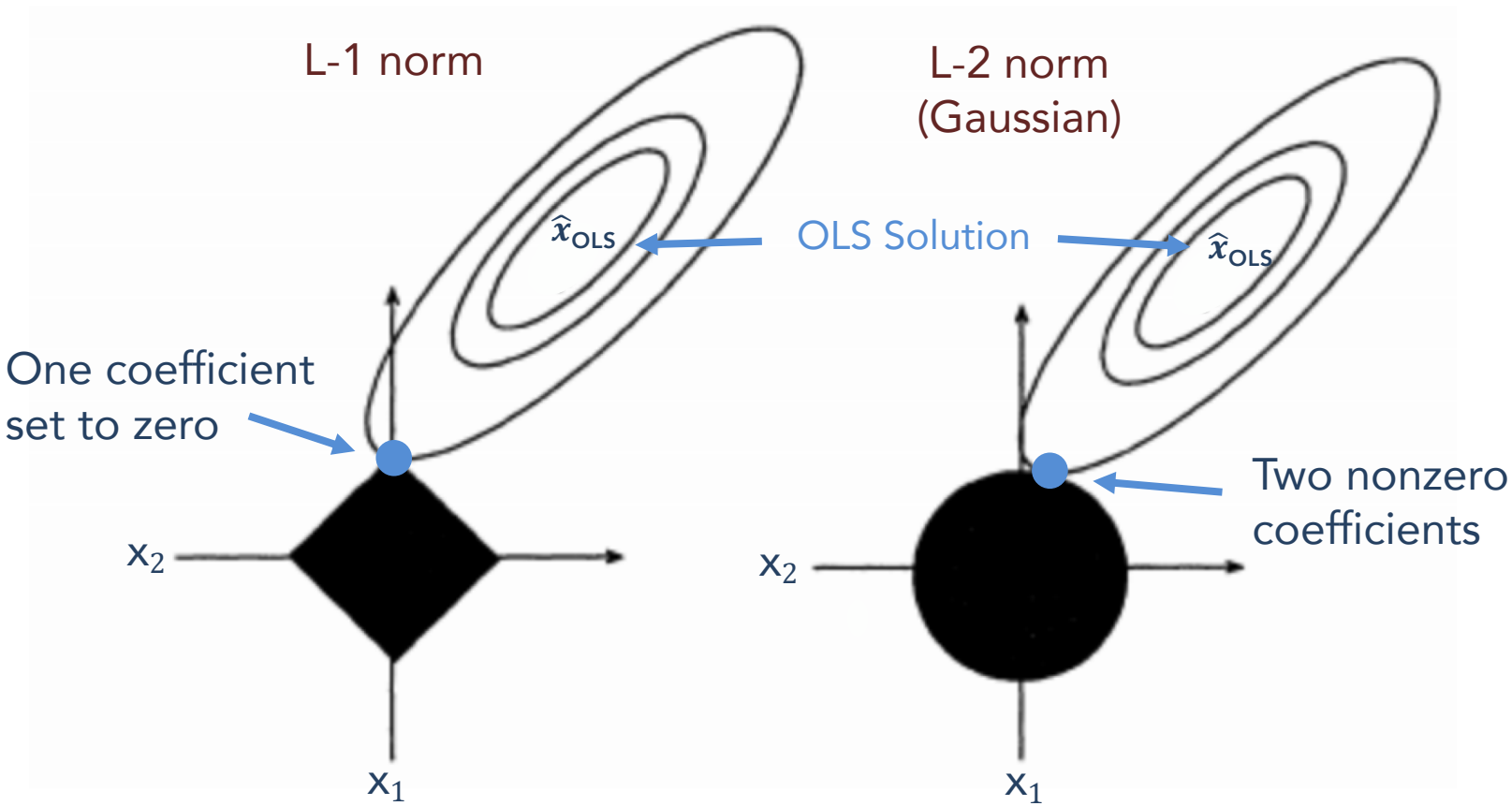
We explore sparse and non-sparse inversion solutions.

$\hat{\boldsymbol{x}}$ , the optimal emission vector, is found by minimizing the cost function $J(\mathbf{x})$:

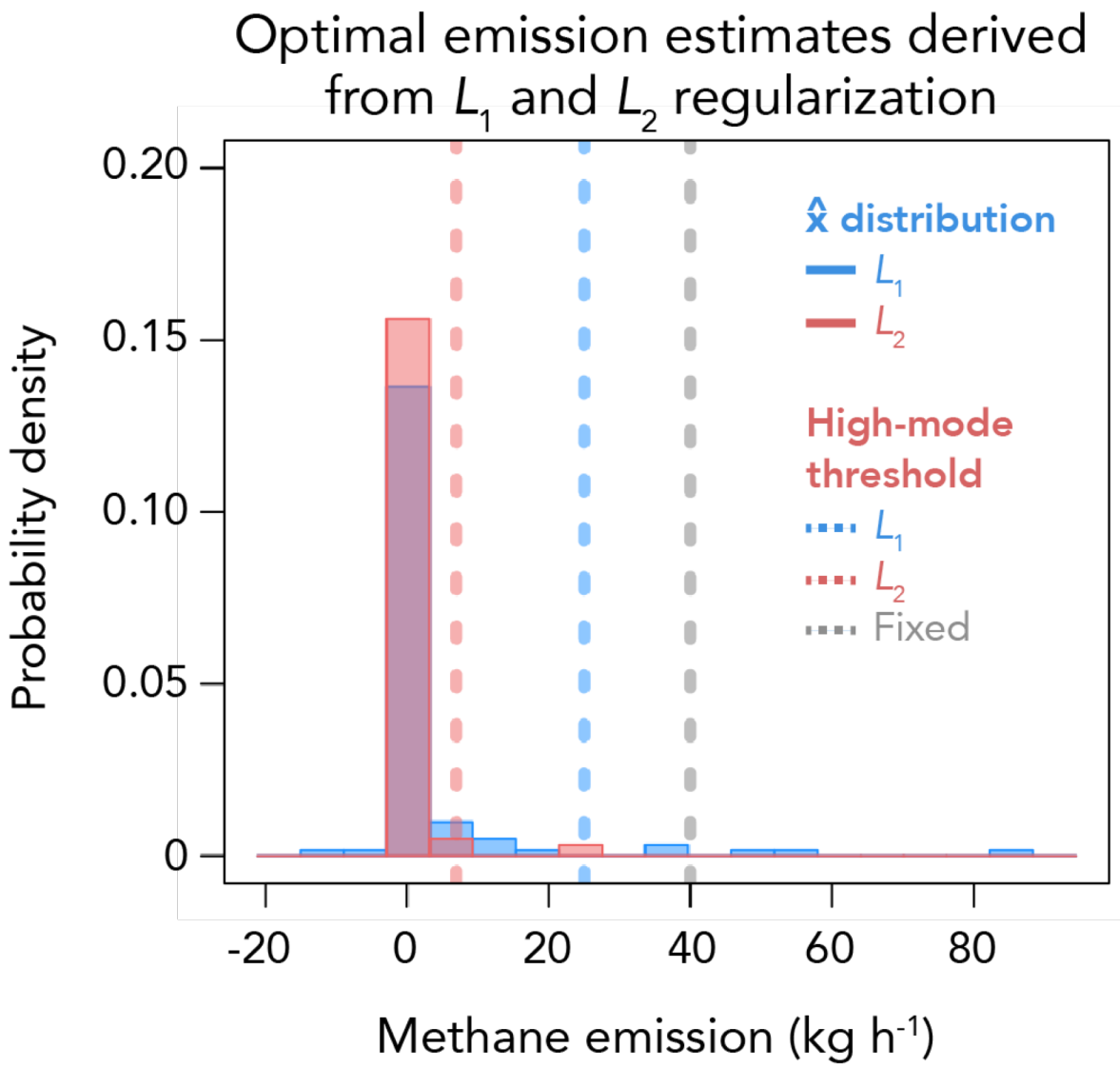
$$\boldsymbol{J}(\mathbf{x}) = (\mathbf{Hx} - \boldsymbol{y})^T \mathbf{R}^{-1} (\mathbf{Hx} - \boldsymbol{y}) + \lambda \|\mathbf{x}\|_L$$

L-1 or L-2 norm

L-1 regularization favors sparser solutions than L-2:



High-mode emitters are classified as outliers from the distribution of $\hat{\mathbf{x}}$.



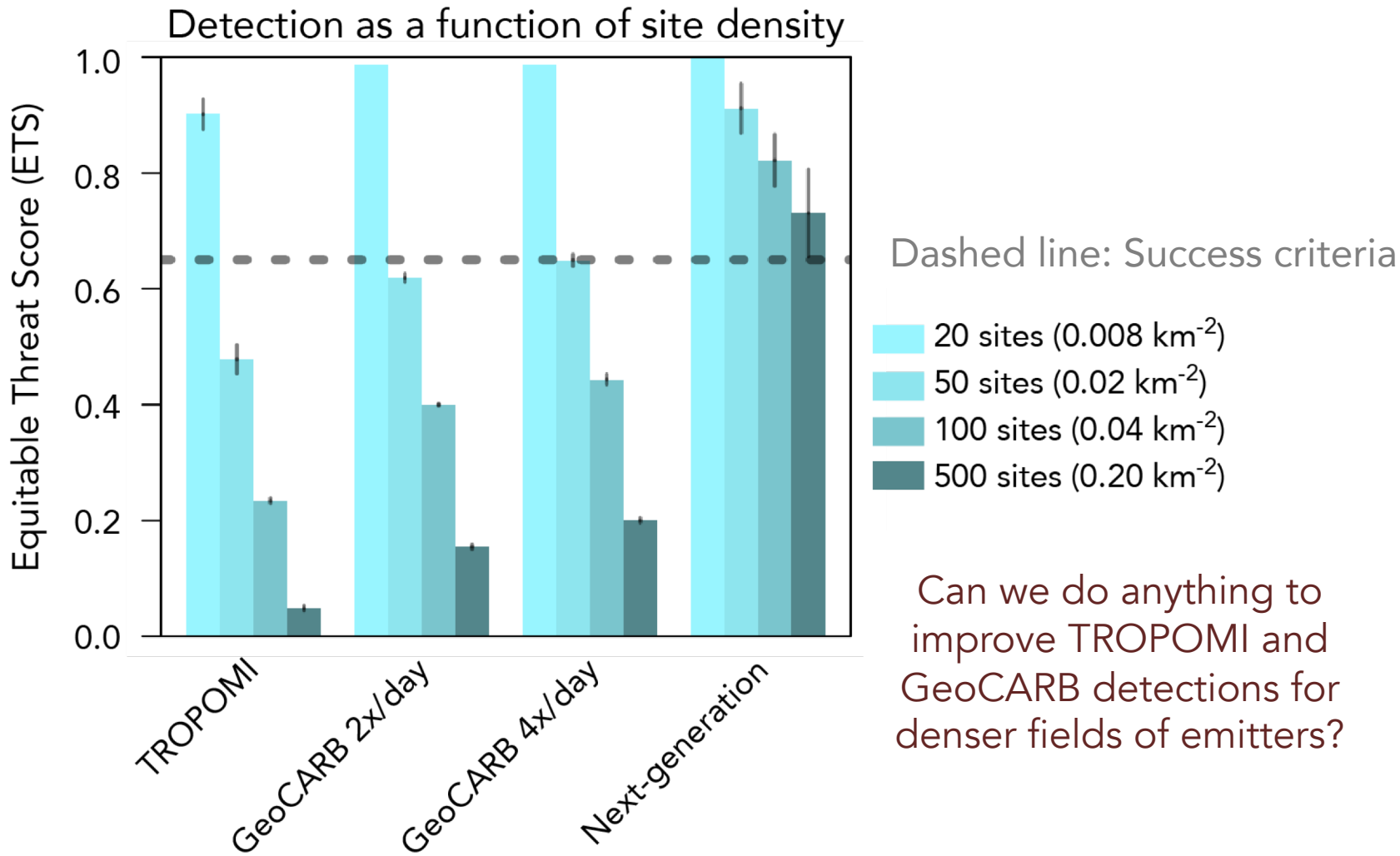

**High-mode classification:**

*S* **σ**'s above the mean

Vary *S* between 1.65-2.5

**We choose L-1 regularization in the results that follow.**

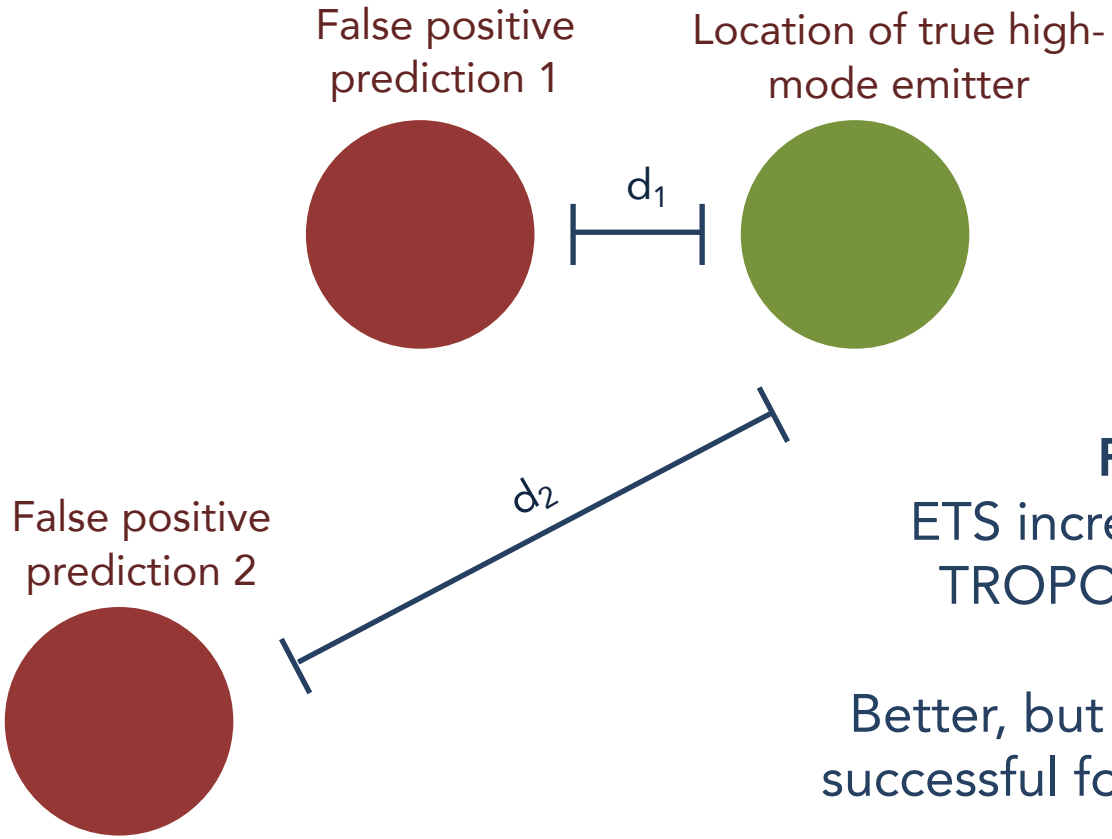
# Observing systems are more successful at constraining fields of fewer emitters.




Can we do anything to improve TROPOMI and GeoCARB detections for denser fields of emitters?

**Equitable Threat Score (ETS):**
[False Positives – Random Hits] / [True Positives + False Positives + False Negatives – Random Hits]

Are all false positives created equal? What if introduce a spatial tolerance?

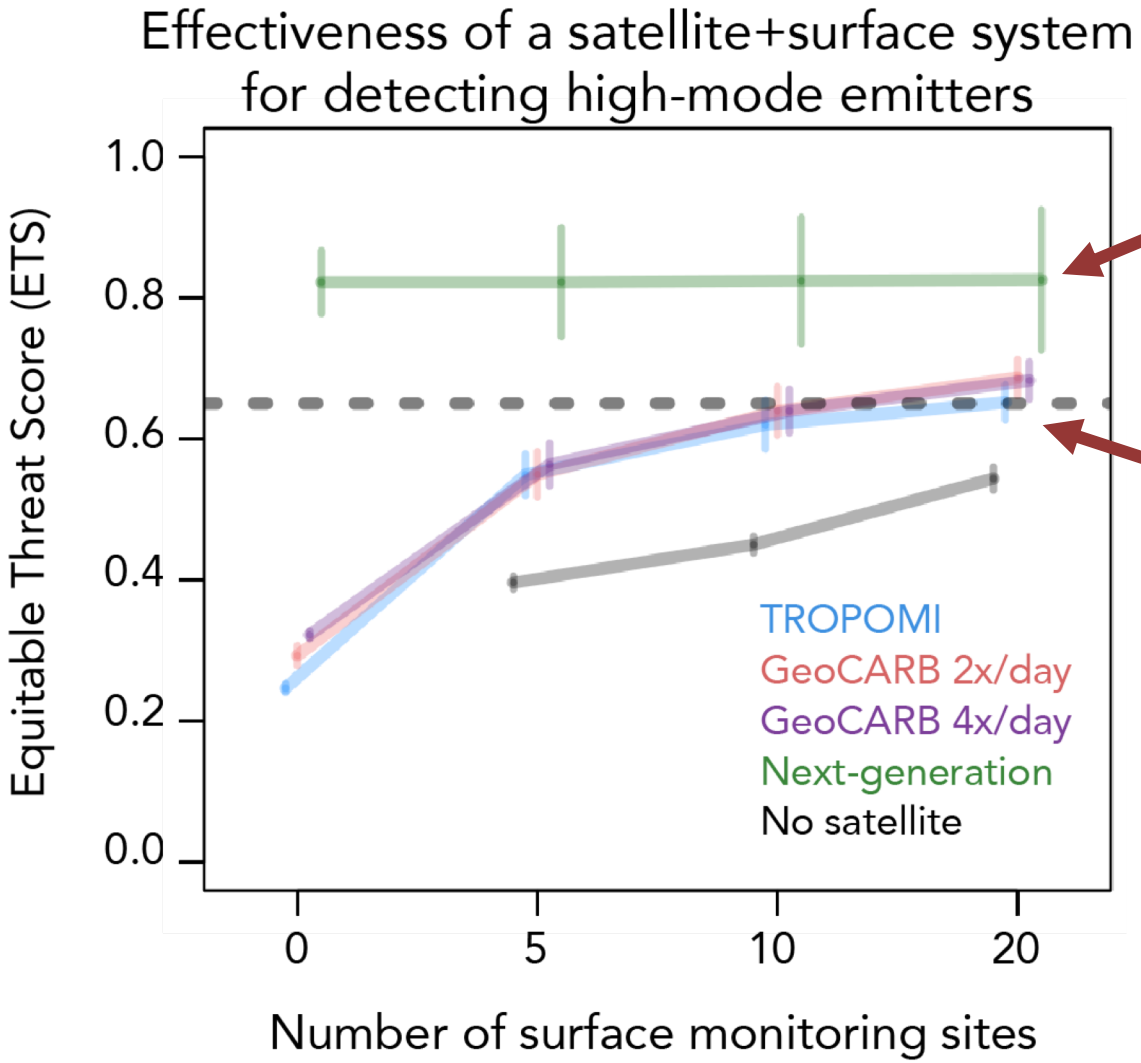



**Results:**
ETS increases by 0.2 for TROPOMI/GeoCARB

Better, but not enough to be successful for 100 emitter field.

**What about adding surface monitors to the prediction?**

Combining satellite information with surface monitors via a joint inversion provides successful detection capability.



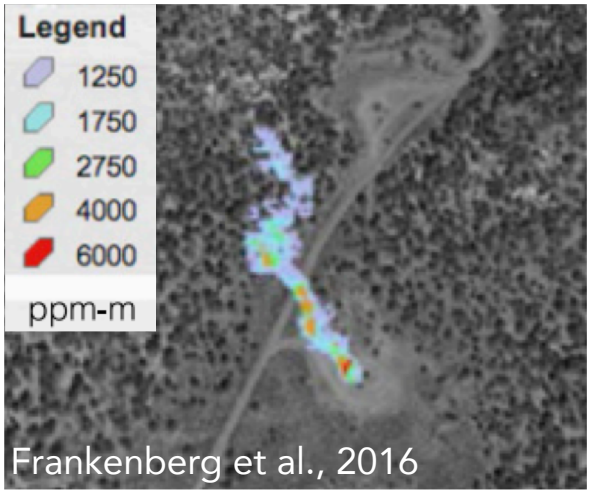

Next-generation doesn't improve with surface monitoring. Can do it all from space!

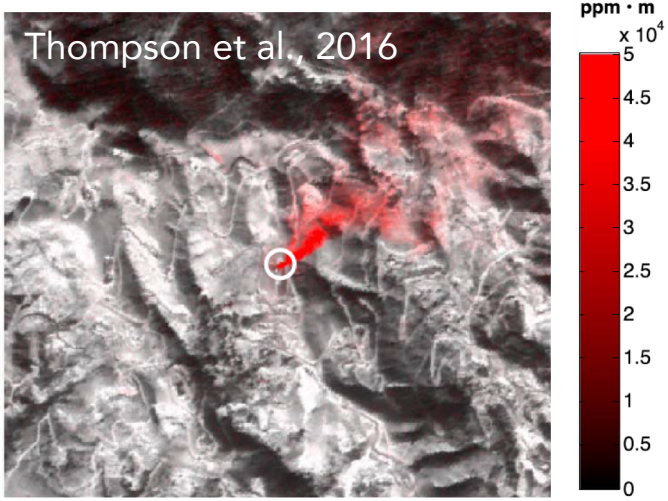
10-20 monitor combination with TROPOMI or GeoCARB are successful!

100 emitter field

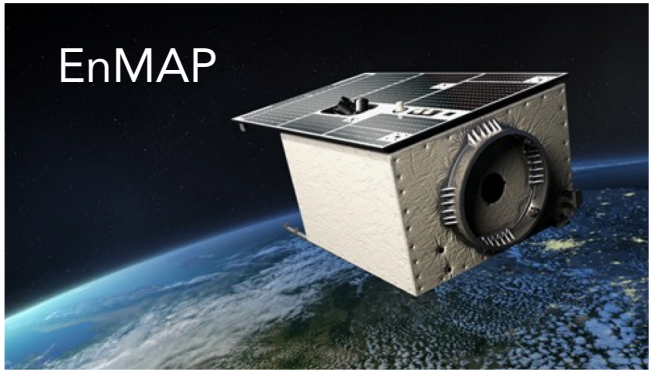
# Different approach:

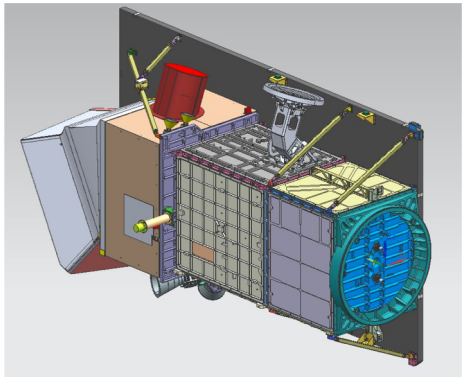
Hyperspectral imagers onboard aircraft can detect methane plumes.




Could satellites with similar instrument characteristics do the same?

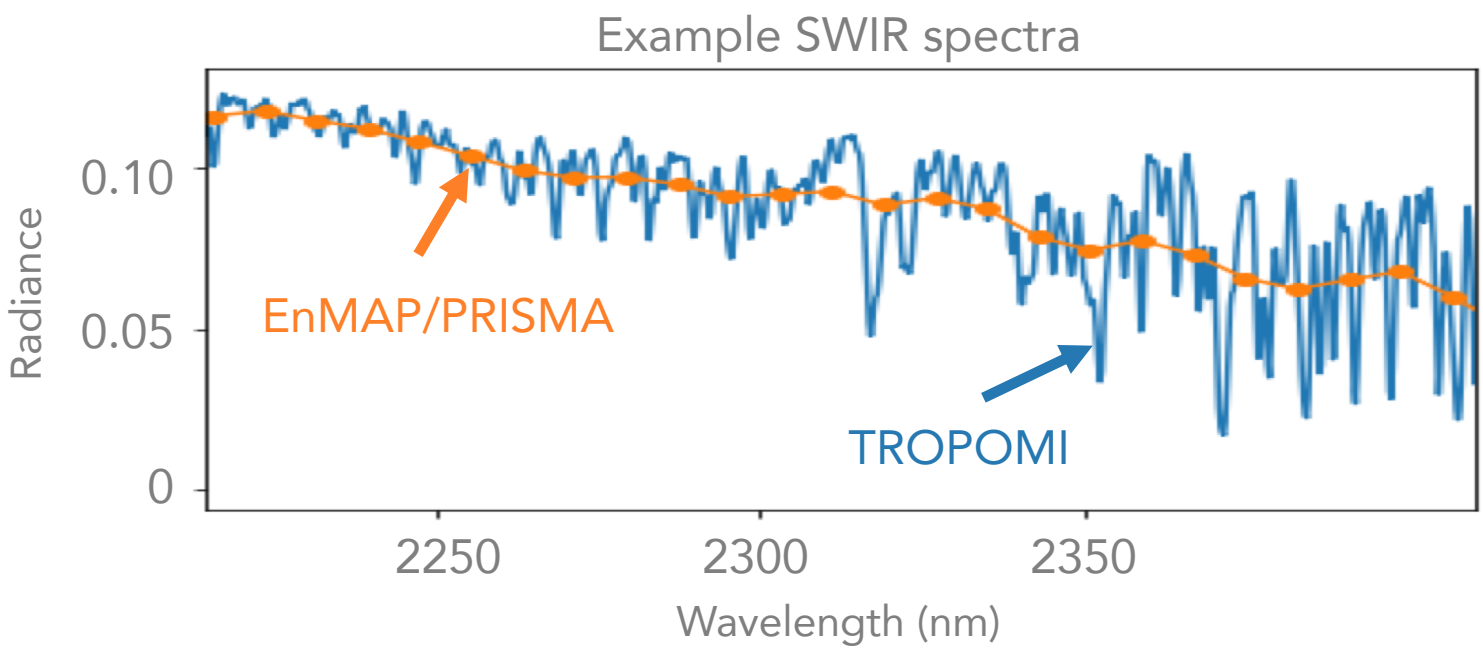


PRISMA

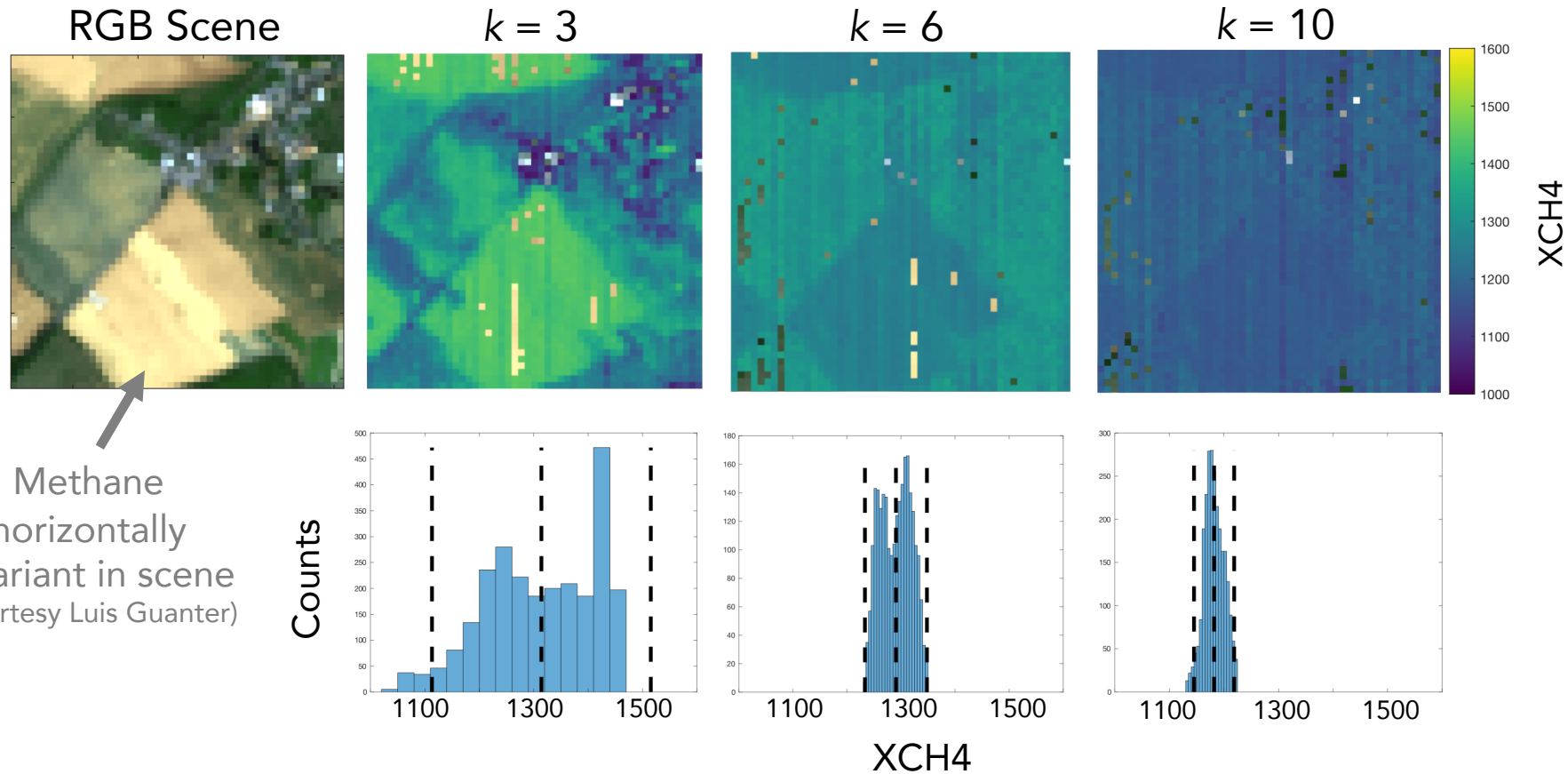
# Hyperspectral imagers trade spectral resolution for spatial resolution.

| Instrument | Launch | Spatial Resolution | Spectral Resolution (SWIR) |
|---|---|---|---|
| LandSAT-8 | 2013 | 30 m | 100+ nm |
| AVIRIS-NG (aircraft) | 2012 | 0.3-4m | 5 nm |
| PRISMA | 2019 | 30 m | 10 nm |
| EnMAP | 2020 | 30 m | 10 nm |
| EMIT | 2022 | 33 m | 7-10 nm |
| TROPOMI | 2017 | 7 km | 0.25 nm |



The IMAP-DOAS (Thorpe et al., 2014) retrieval algorithm has been used to infer methane concentrations from hyperspectral imagers.

IMAP-DOAS has polynomial (order *k*) representation of surface:

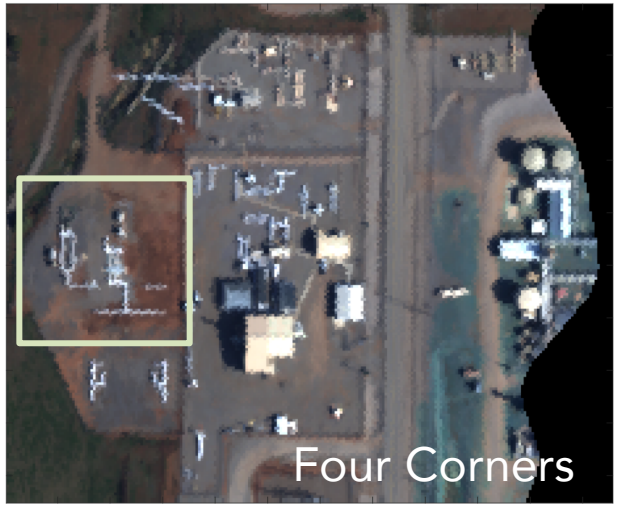



Methane horizontally invariant in scene
(Courtesy Luis Guanter)

The surface parameterization strongly influences the methane retrieval

We modify an AVIRIS-NG image over a variable methane field to assess the capability of EnMAP to detect hotspots.

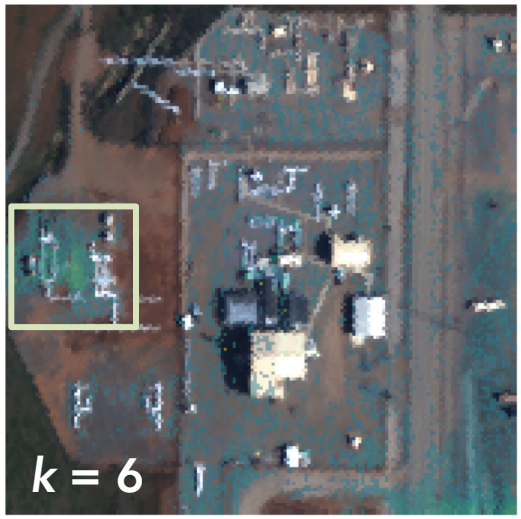
AVIRIS-NG RGB image

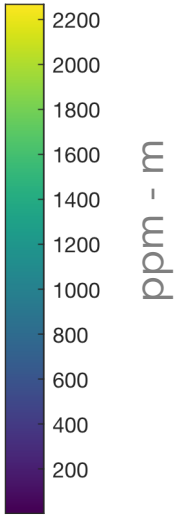



Spectral & spatial resampling

EnMAP equivalent retrieval


AVIRIS-NG retrieval




Both "EnMAP" and AVIRIS-NG agree on the location of the largest methane enhancement (the boxed subscene).

## Answers to our initial questions:

***Can I rely on satellite data alone to detect anomalous high-mode emitters among the production sites in an oil/gas field?***

For fields of few emitters, yes! As you increase the density of emitters, TROPOMI and GeoCARB need to be supplemented with surface monitors and/or a spatial tolerance needs to be allowed.

***What inverse method should I use to interpret these atmospheric observations?***

We find that sparse/L-1 methods are better suited for this problem due to the fact that the oil/gas field is essentially sparse in its emission characteristics.

***Can I usefully supplement satellite information with surface monitoring?***

Adding surface monitors shows the potential to improve predictions via a combined inversion. The next-generation satellite alone is sufficient for successful detection.

***Could future satellite hyperspectral imagers provide enough information to retrieve methane?***

Our preliminary results show that it is possible, but care needs to be taken in assessing surface properties.