Identifying leaky wells in oil/gas fields by satellite observation of atmospheric methane

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

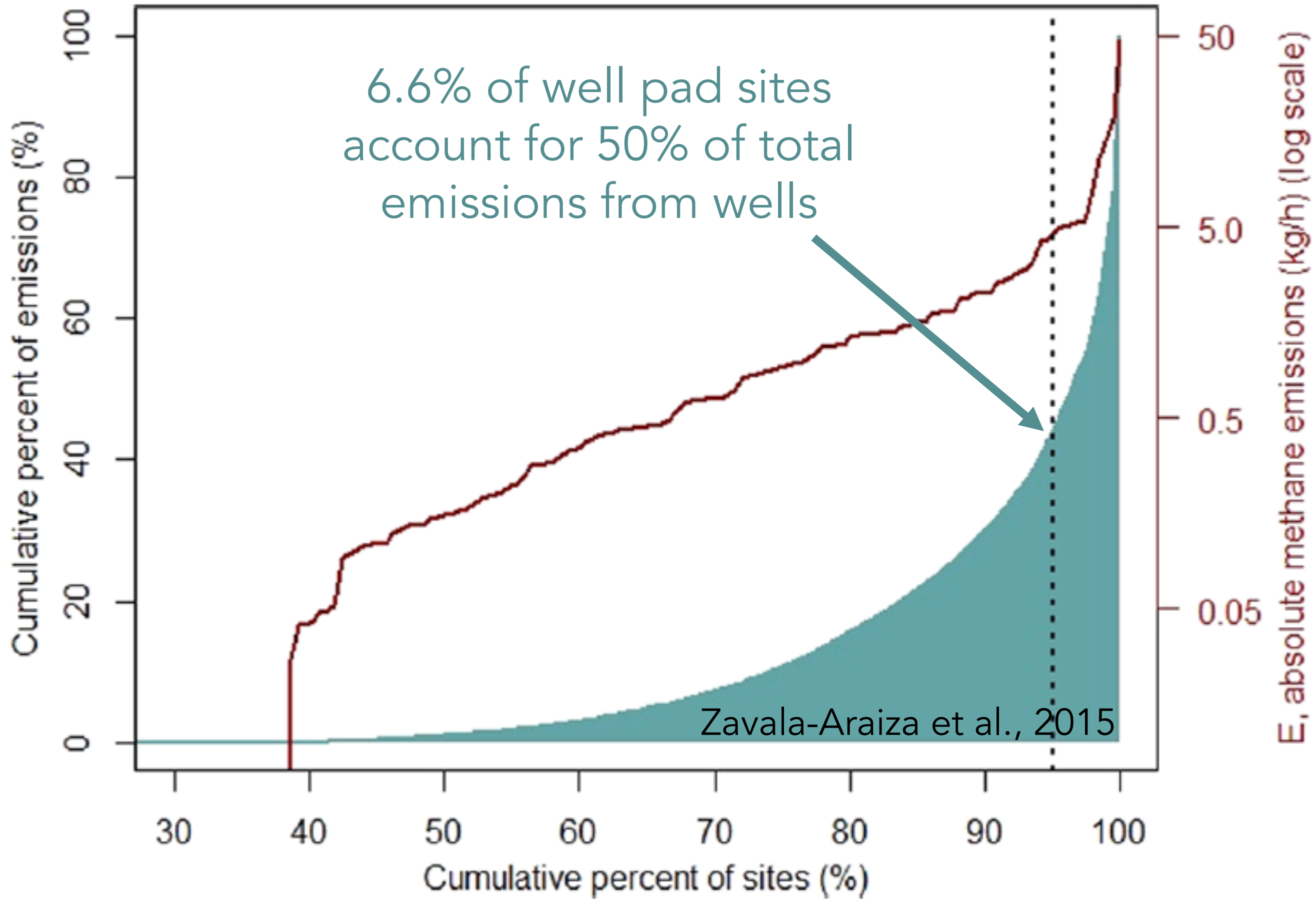
What inverse method should I use to interpret these atmospheric observations?

Can I usefully supplement satellite information with surface monitoring?

Thanks: Daniel Jacob, Alex Turner, Cynthia Randles, Jeremy Brandman, Laurent White

Most production emissions come from relatively few emitters – i.e., well-pads have "fat-tailed" or bimodal distributions.

Methane Emissions from oil/gas production sites (kg/h)



Can we locate sustained these anomalous emitters from space?

We set up observing system simulation experiments (OSSE) to test the feasibility of finding high-mode emitters using future satellite information.

Input:
Distribution of point emissions including outliers

Transport model to simulate "true" atmospheric methane concentrations

Create pseudo-observations with known satellite/surface noise characteristics and resolution

Inverse model

Output:
Locations of high-mode (outlier) emitters

Compare

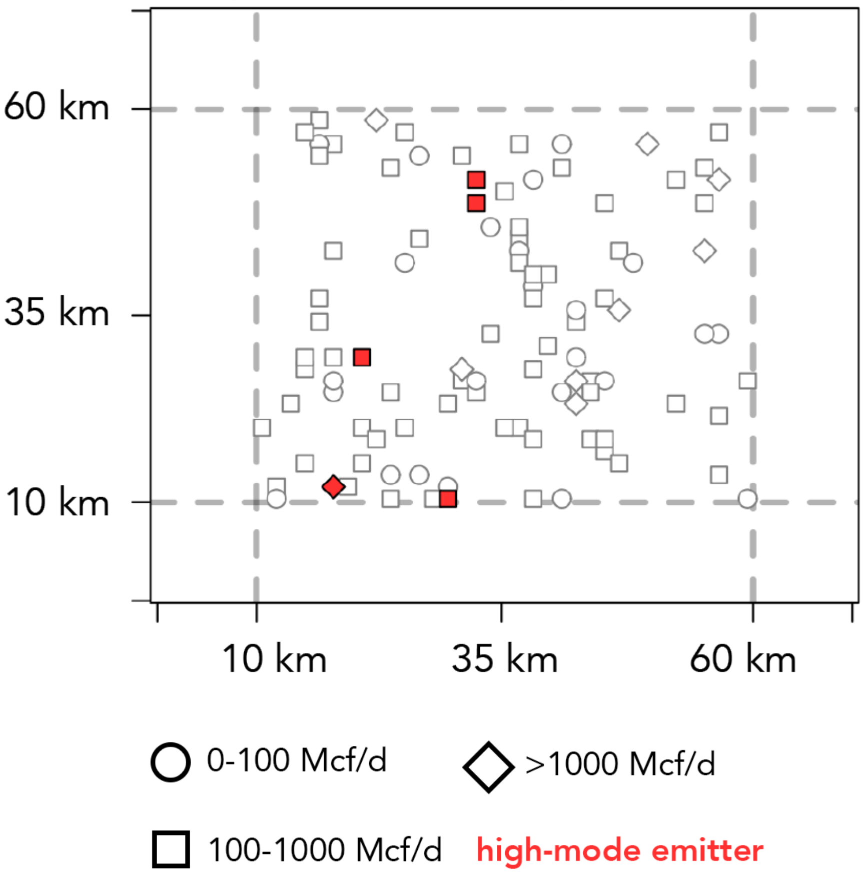
We want the inversion to find the **locations** of high-mode emitters. We don't care as much about quantifying the magnitude of emitter through the inversion.

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

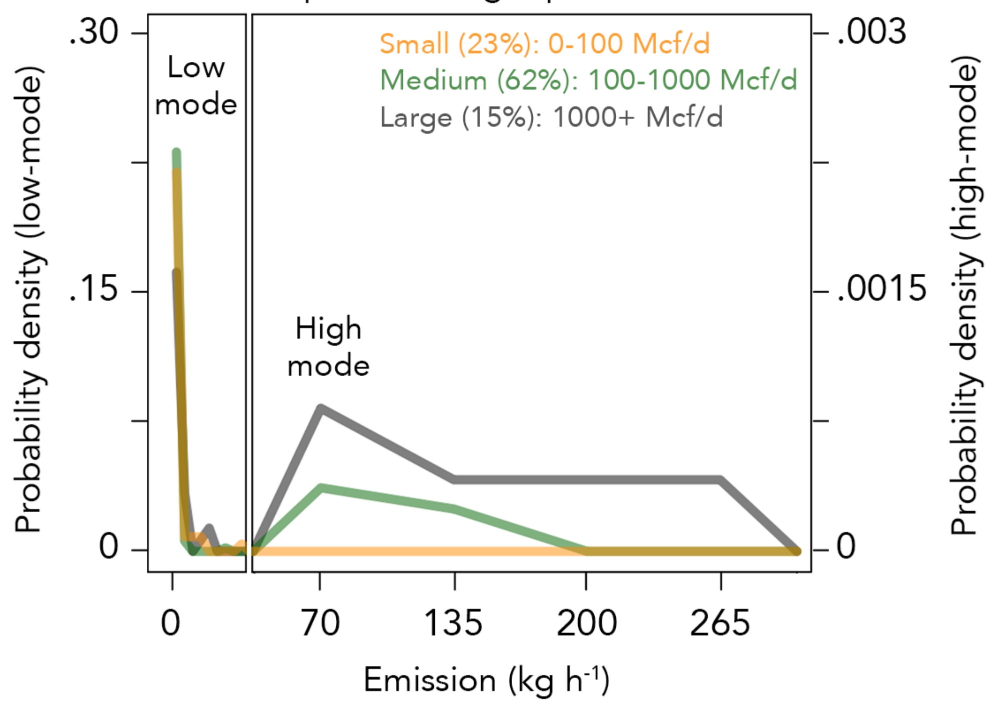
Randomly distribute N emitters in a 50 km² subdomain

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

Sample distribution of production sites

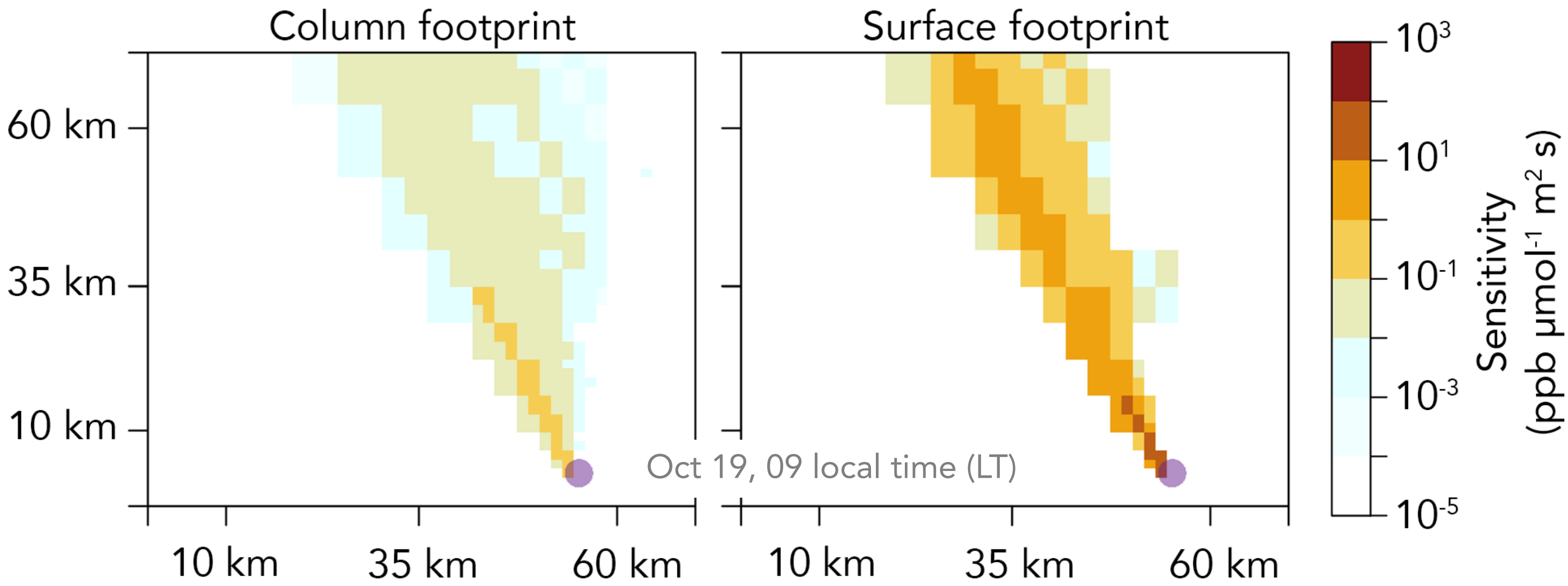


Emission pdfs for oil/gas production sites



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

Atmospheric methane concentrations are simulated using WRF-STILT.



To generate pseudo-observations (constant background):

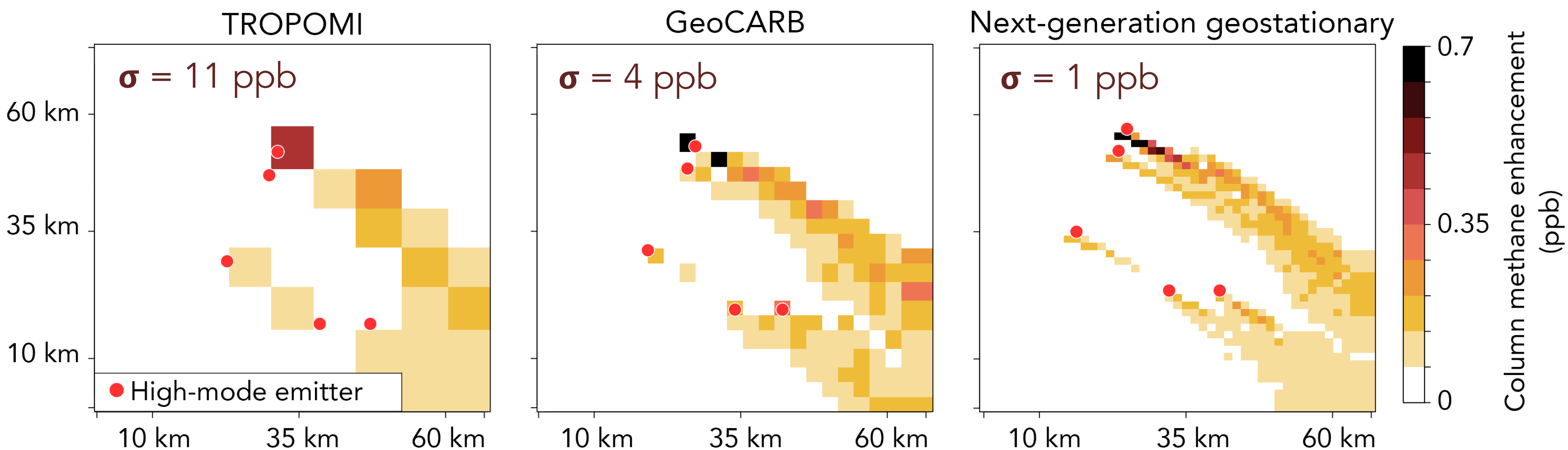
$$\mathbf{y} = \mathbf{Hx} + \boldsymbol{\sigma\varepsilon} + \mathbf{b}$$

H = ∂**y**/∂**x** : Jacobian matrix derived from WRF-STILT (Turner et al. 2018)
x: emission state vector

σ: instrument precision
ε ~ *N*(0,1)

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

Simulated **noiseless** concentrations of column methane for single pass of different satellite configurations



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

Repeat sampling and inverse methods are needed to constrain locations of emitters.

We explore sparse and non-sparse inversion solutions.

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

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

STILT footprints

Pseudo observations

Observational error covariance

Regularization parameter

L-1 or L-2 norm

Observational error covariance **R** constructed using error correlation length scales:

$$r_{ii} = \sigma_m^2 + \sigma_i^2$$

$$r_{ij} = \sigma_m^2 \times \exp\left\{-\frac{d}{\ell}\right\} \exp\left\{-\frac{t}{\tau}\right\} \quad \text{for } i \neq j$$

ℓ = 40 km (spatial length scale)

τ = 2 hrs (temporal length scale)

σ_m = 4 ppb

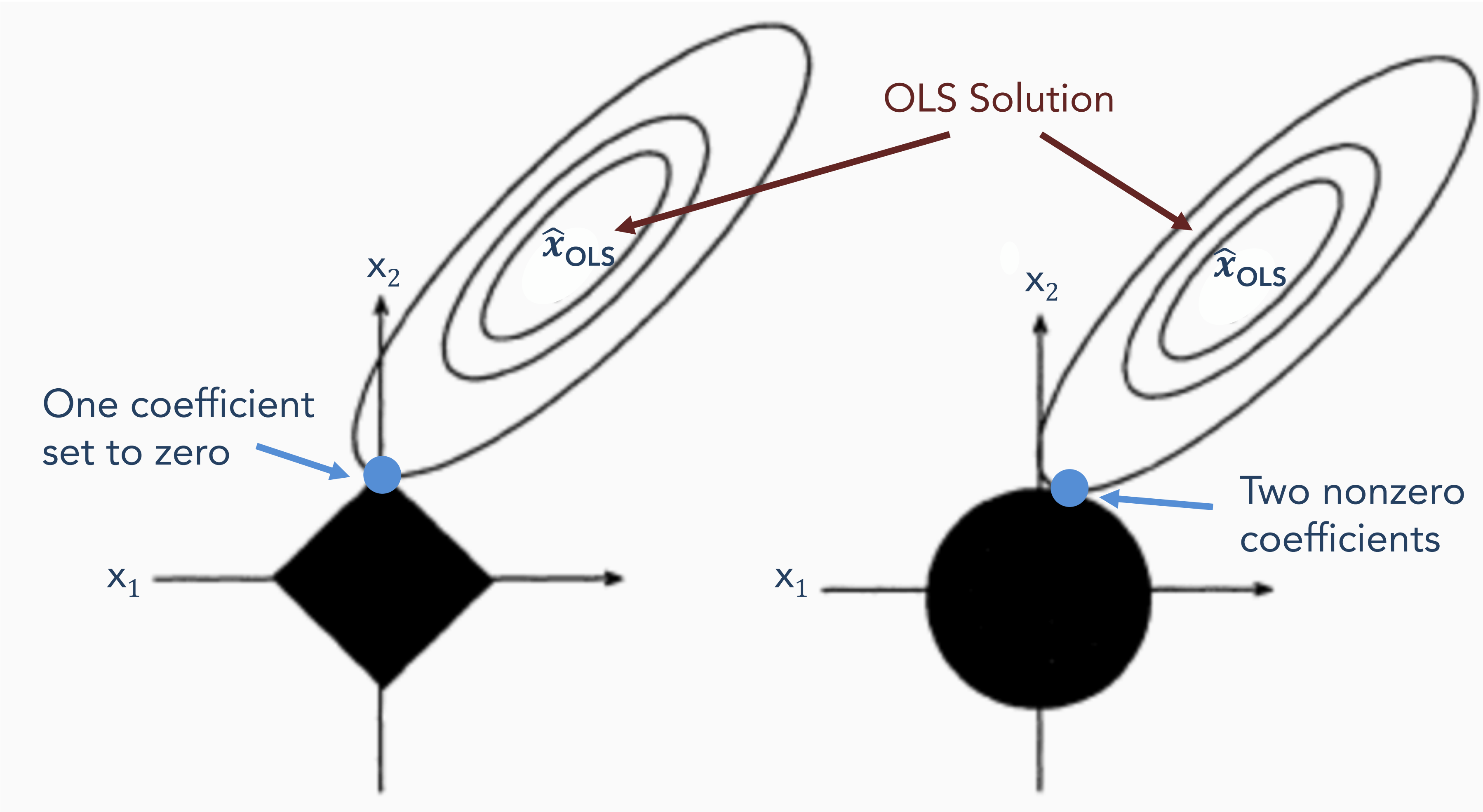
For combined satellite + surface inversion:

$$cor(i,j) = 0.65$$

$$r_{ij} = cor(i,j) \times \sigma_m^2 \exp\left\{-\frac{d}{\ell}\right\} \exp\left\{-\frac{t}{\tau}\right\} \quad \text{for } i \neq j$$

Sheng et al. (2018)

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



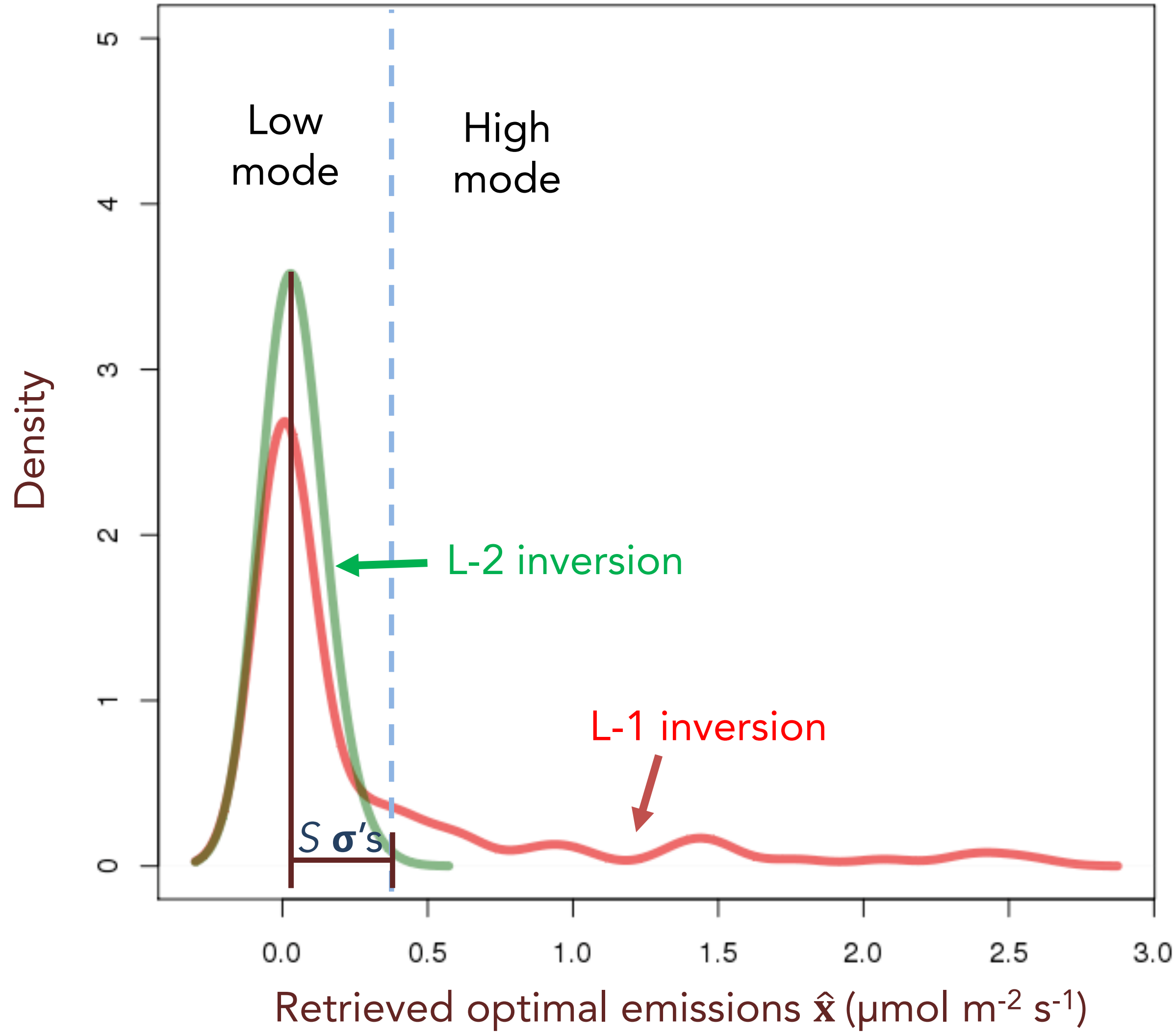
L-1 norm

L-2 norm (Gaussian)

Our emitter field is quasi-sparse, so L-1 may be preferable

L-1 sparse solutions may be more suited for fat-tailed emission distributions.

Example classification of high-mode emitters using posterior emission estimate $\hat{\mathbf{x}}$



High-mode classification:

S $\boldsymbol{\sigma}$'s above the mean

Vary S between 1.65-2.5

We grade the inversion/classification using three performance metrics:

Probability of Detection (POD):

100 * True Positives (TP) / [True Positives + False Negatives (FN)]

Tells you how many anomalous emitters you predicted compared to how many exist in reality.

False Alarm Ratio (FAR):

100 * False Positives (FP) / [True Positives + False Positives]

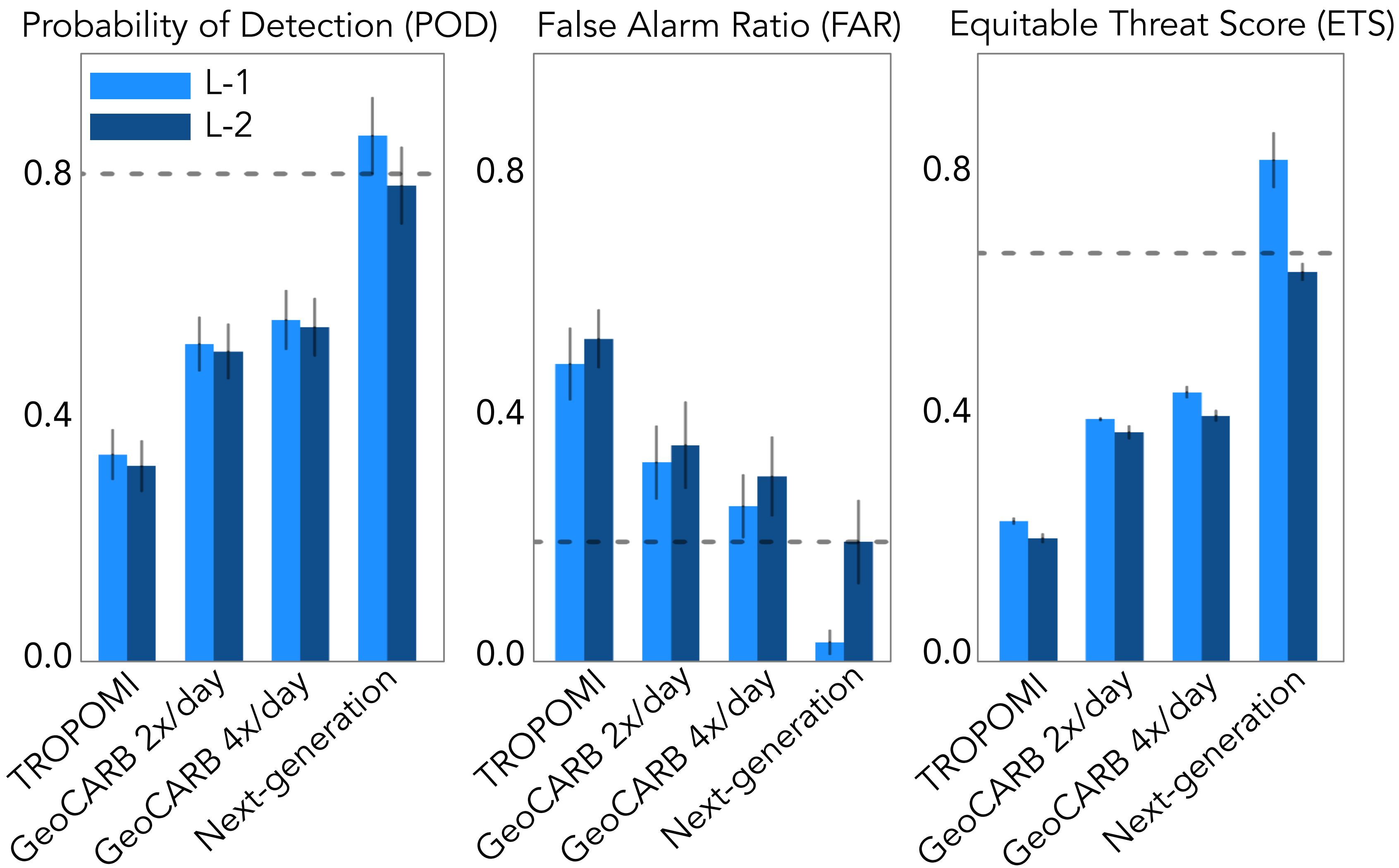
Tells you how often you cause a false alarm by predicting an anomalous emitter that didn't exist in reality.

Equitable Threat Score (ETS):

[FP – Random Hits] / [TP + FP + FN – Random Hits]

Combines POD and FAR to give an overall prediction metric.

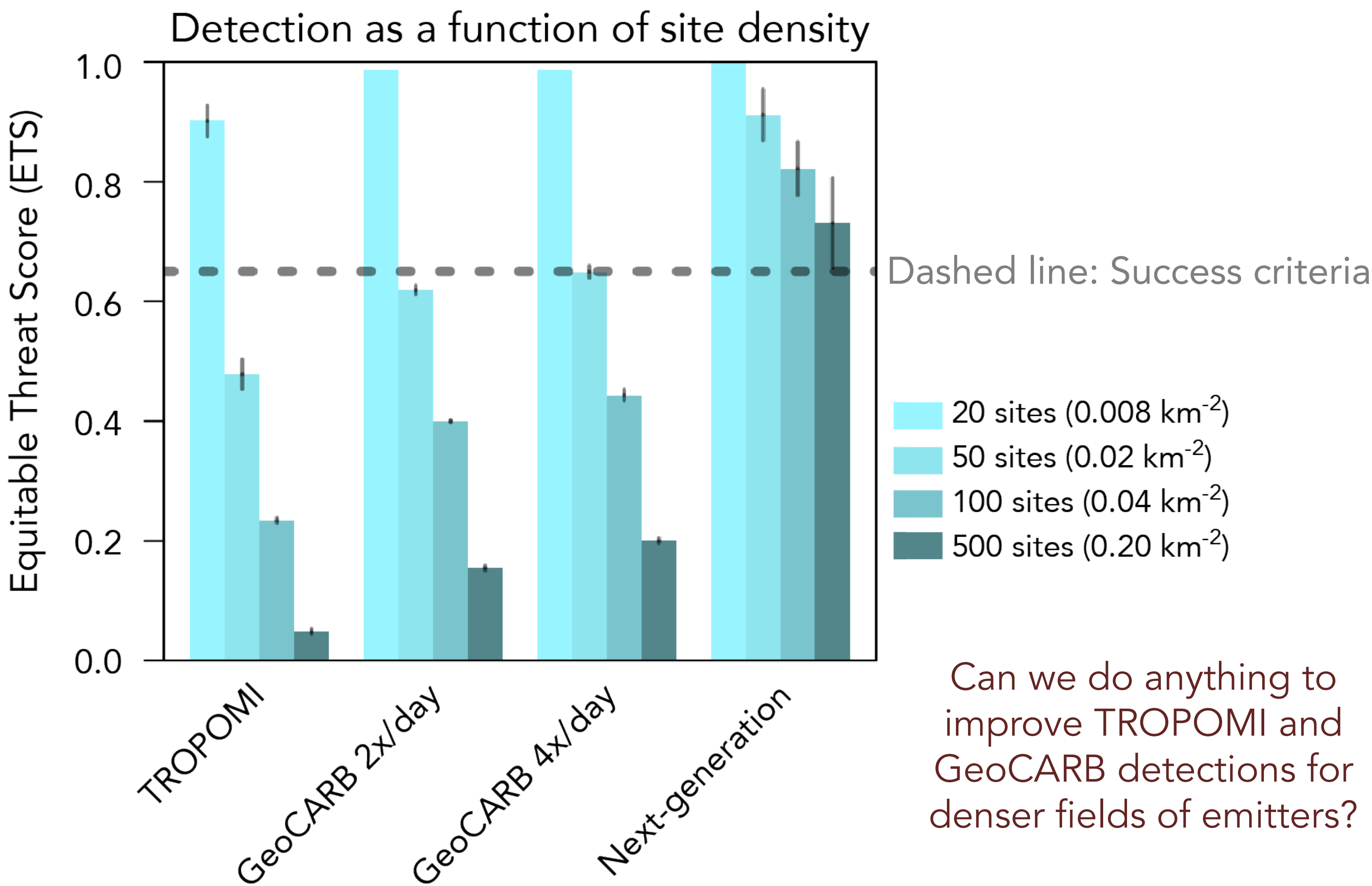
L-1 inversion consistently produces results. Consistent with sparse nature of emission distribution.



For a field of 100 emitters

Dashed line: Success criteria

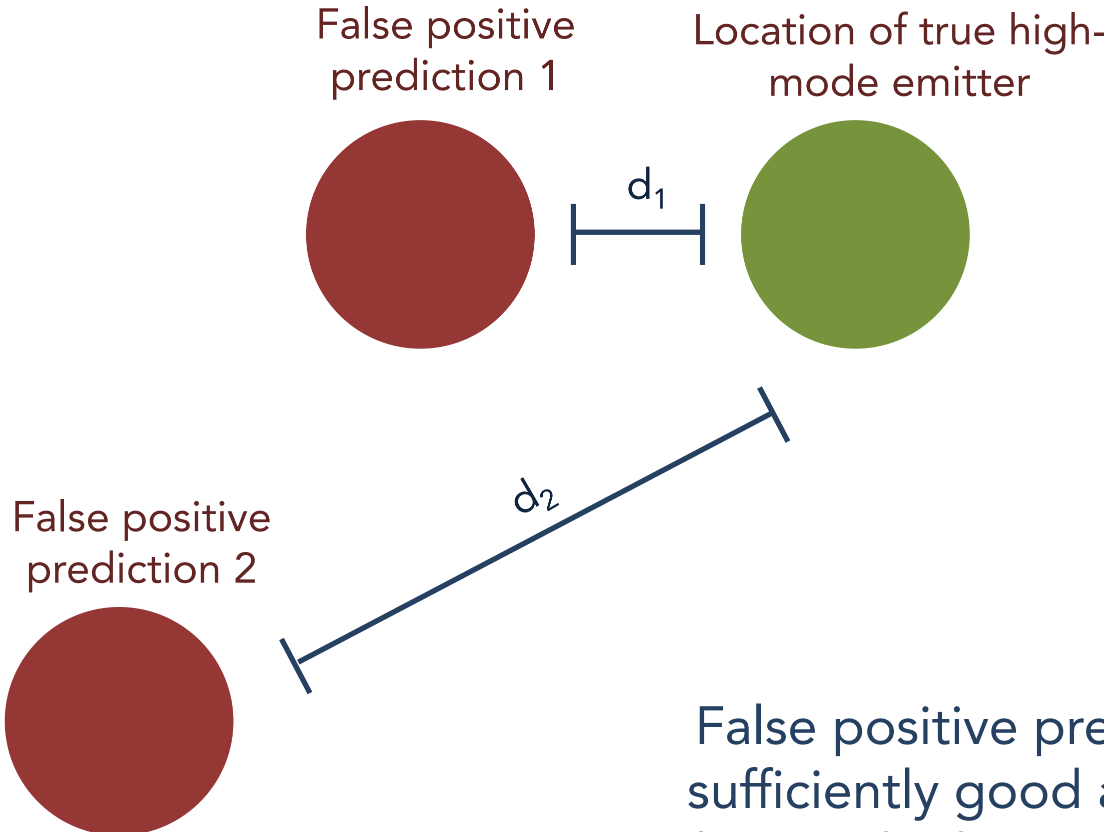
Observing systems are more successful at constraining fields of fewer emitters.



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

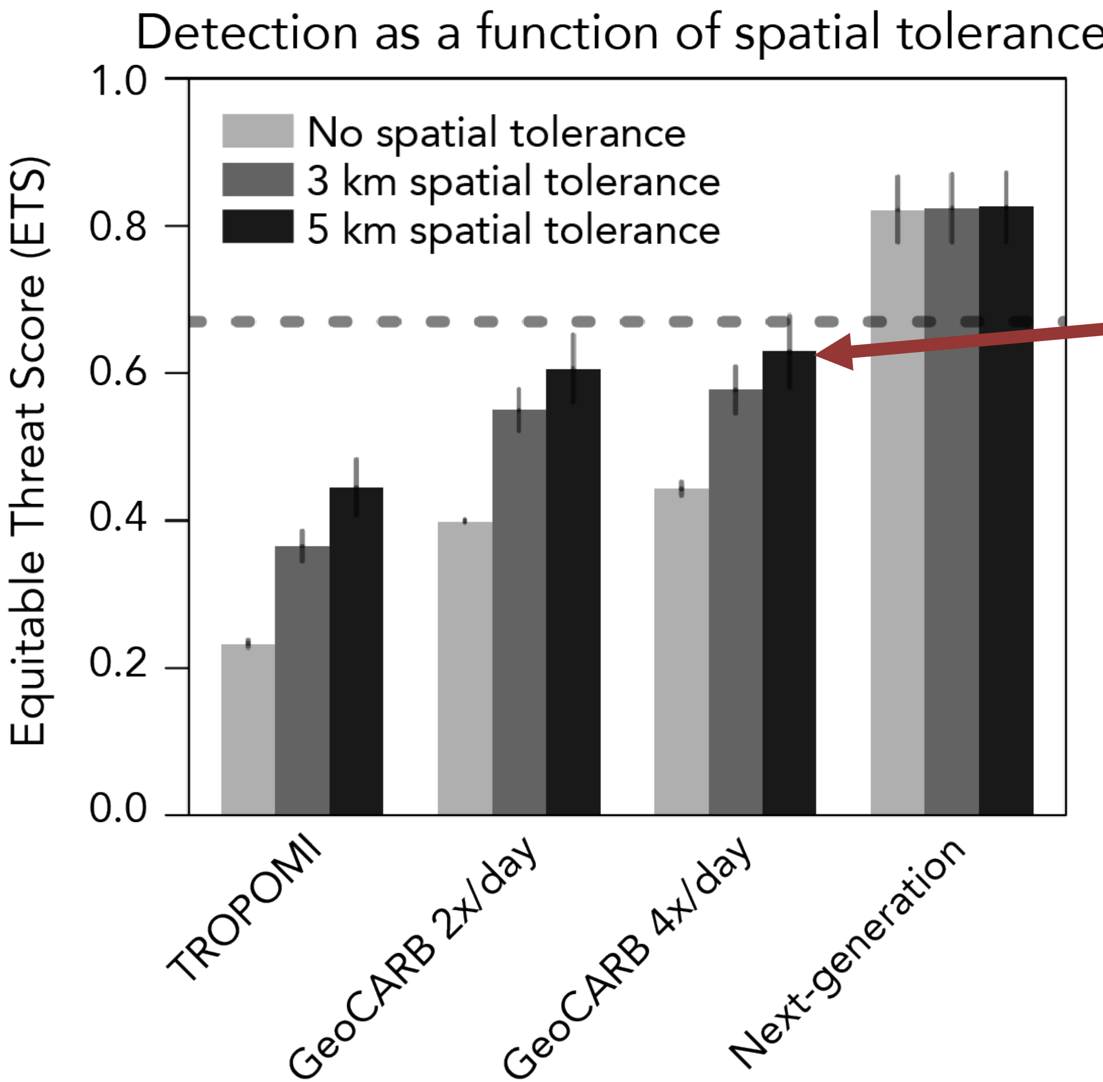
Using L-1 inversion

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



False positive prediction 1 may be sufficiently good as the distance to the true high-mode emitter is small.

Spatial tolerance improves satellite detections.

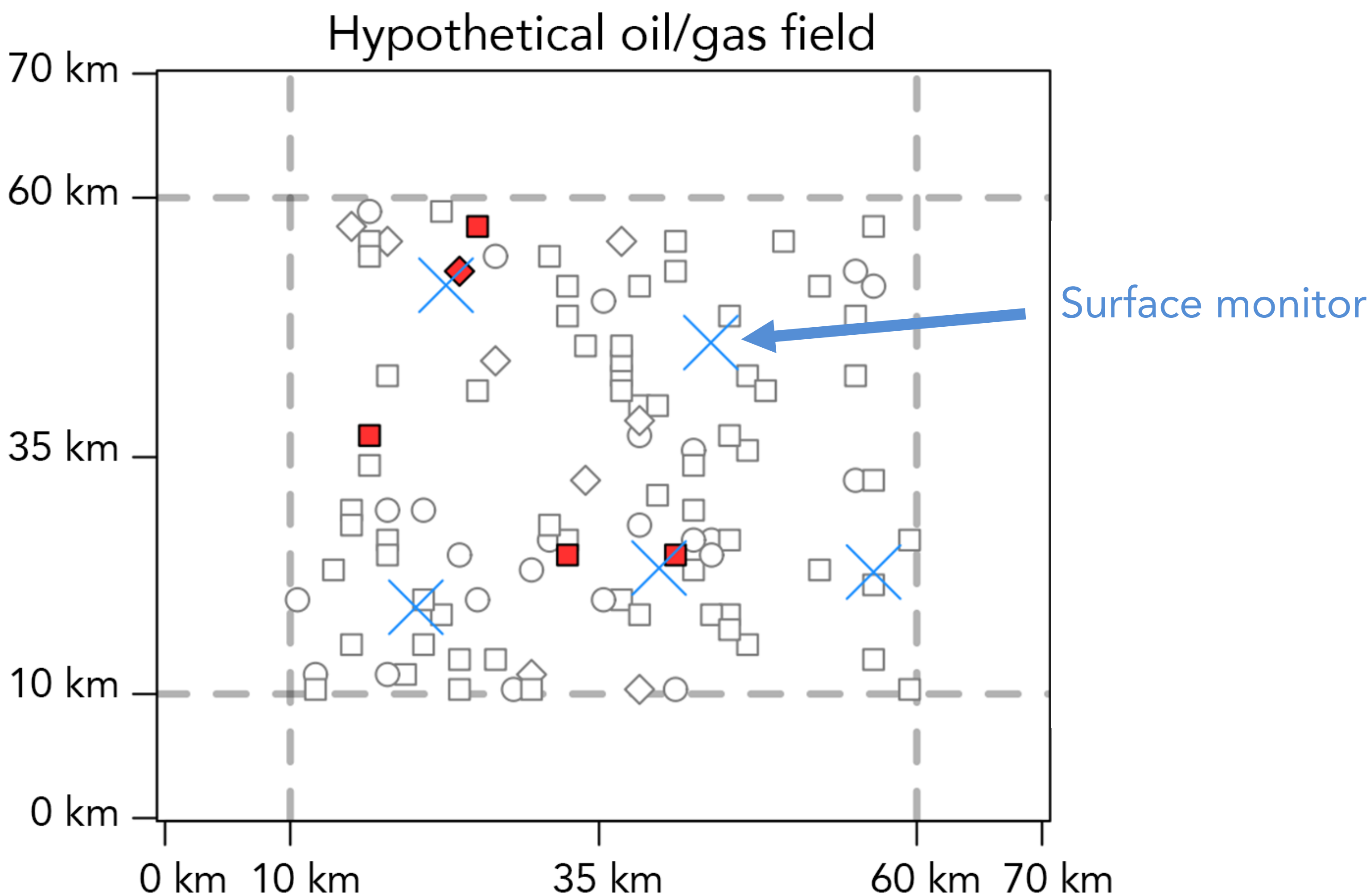


For 5km tolerance, GeoCARB gets closer but is still not quite successful.

What about adding surface monitors to the prediction?

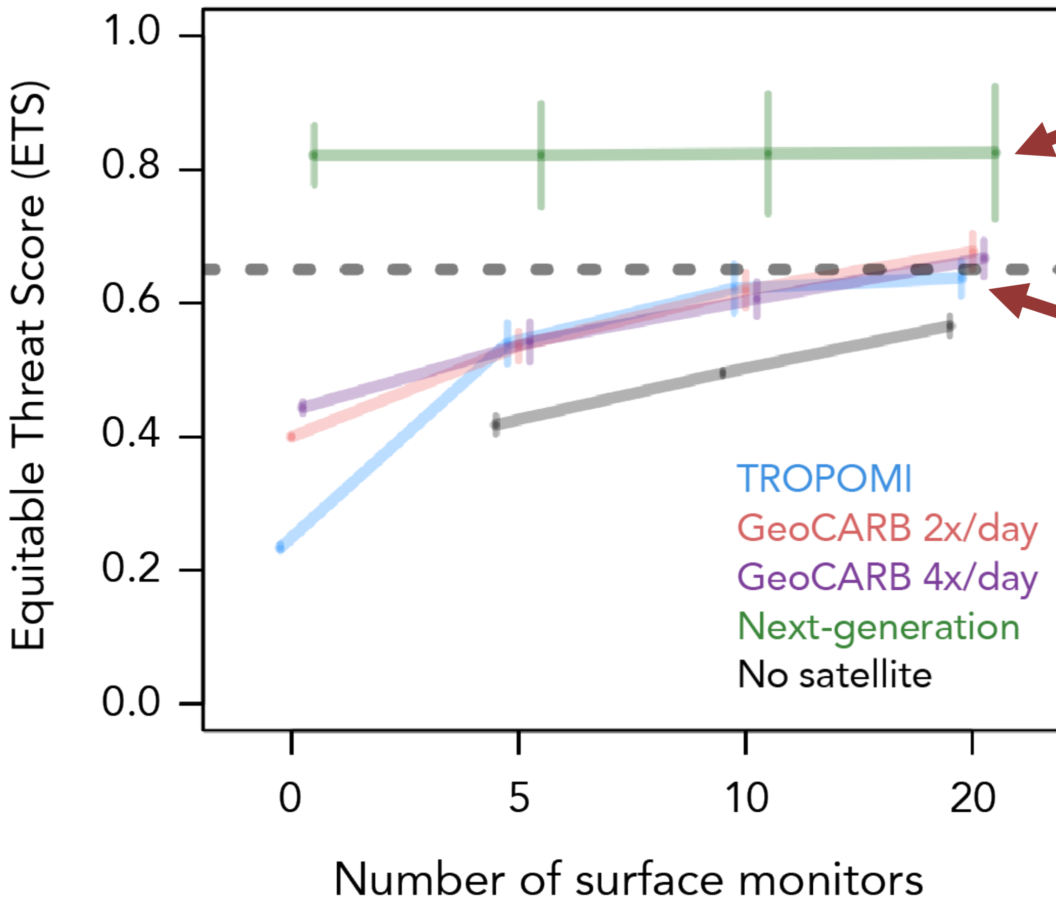
Using L-1 inversion, 100 emitter field

Surface monitors are placed using the k-means algorithm.
Average distance between emitter and monitor is minimized.



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

Effectiveness of a satellite+surface system for detecting high-mode emitters



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

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

Using L-1 inversion, 100 emitter field

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.