Detecting anomalous methane emitters in oil/gas fields using satellite and surface observations

Daniel Cusworth

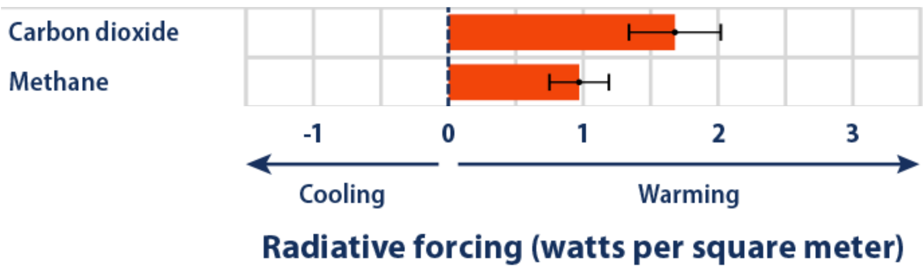
Thanks: Daniel Jacob, Alex Turner, Josh Benmergui, Cynthia Randles, Jeremy Brandman, Laurent White

12/20/17

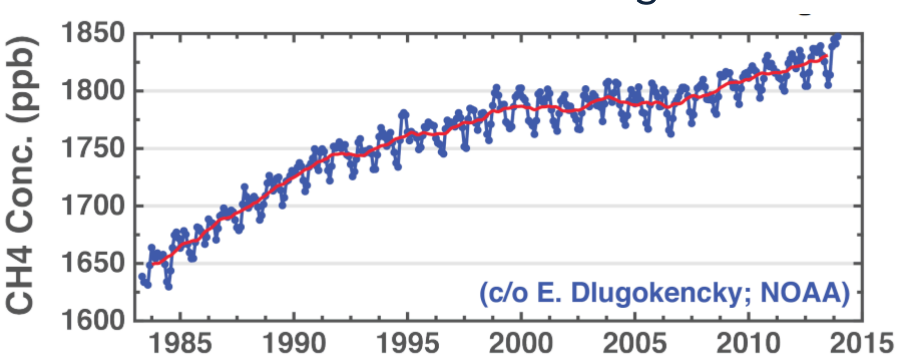
Methane is an important chemical from both an environmental and business standpoint.

Environment

Methane is a greenhouse gas



Methane has been increasing since ~2006



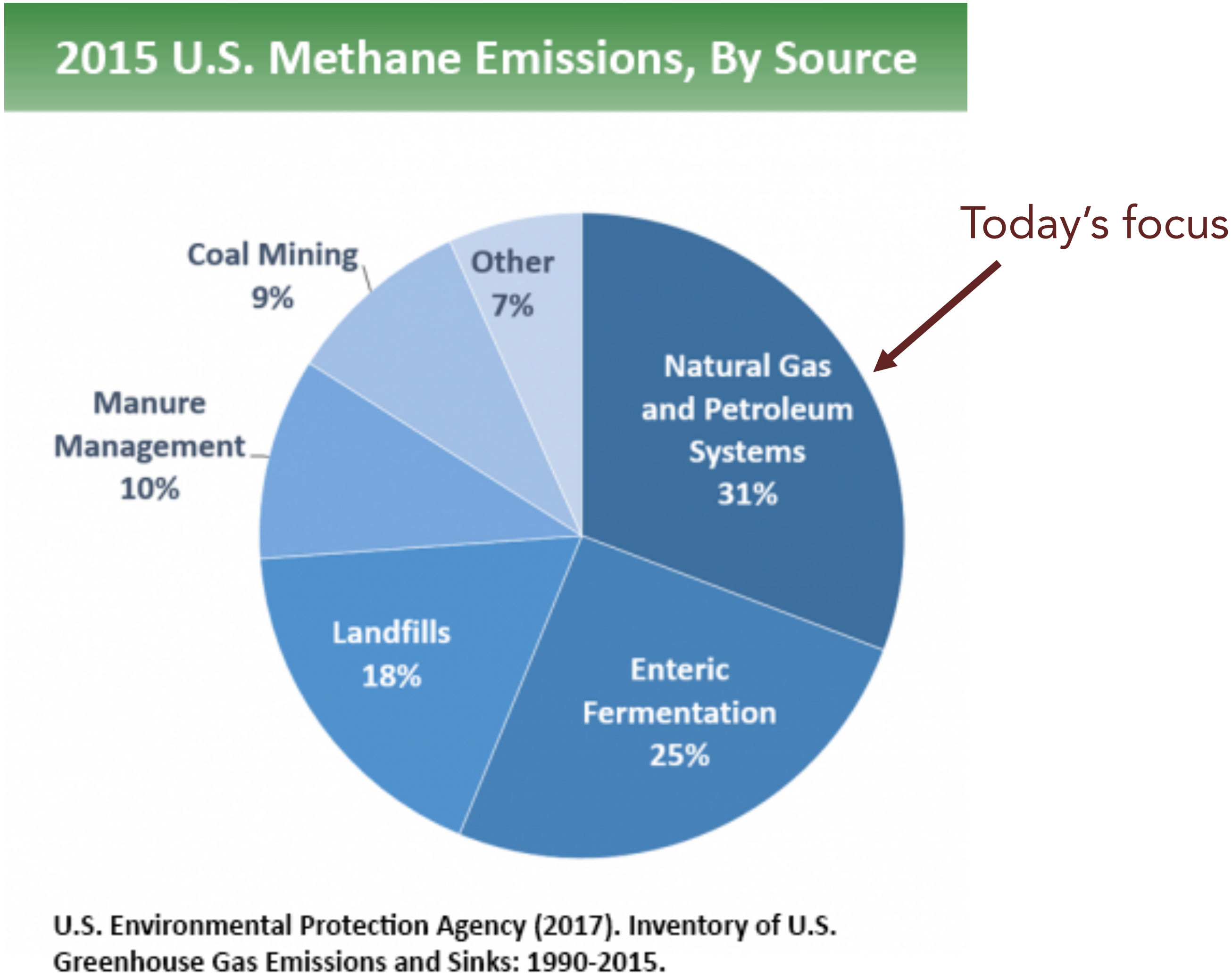
Business

Methane is a fuel

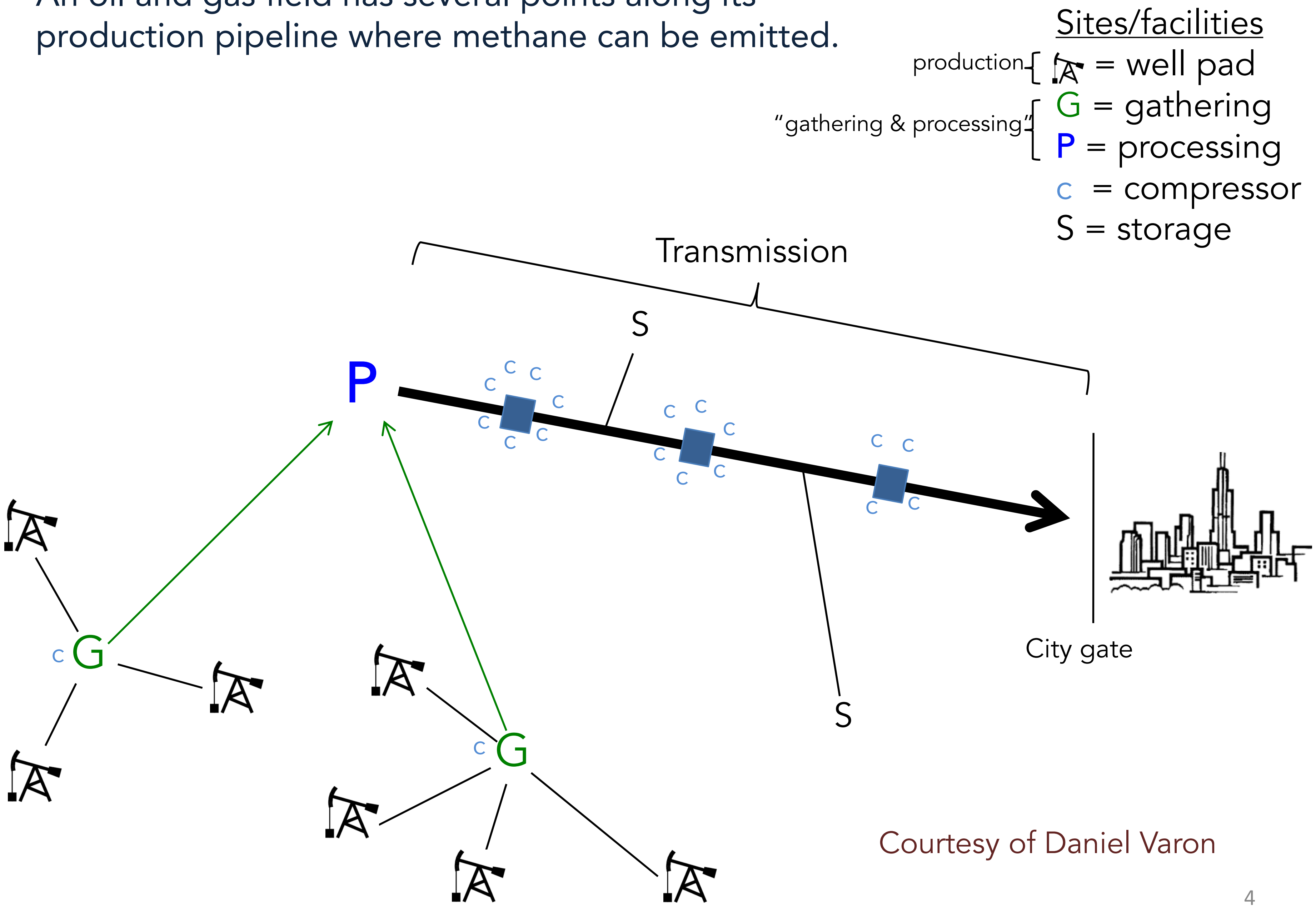
Lost/leaked methane can't be sold!

Reducing methane emissions could both mitigate global warming and boost profits.

Methane is emitted from a variety of sources.



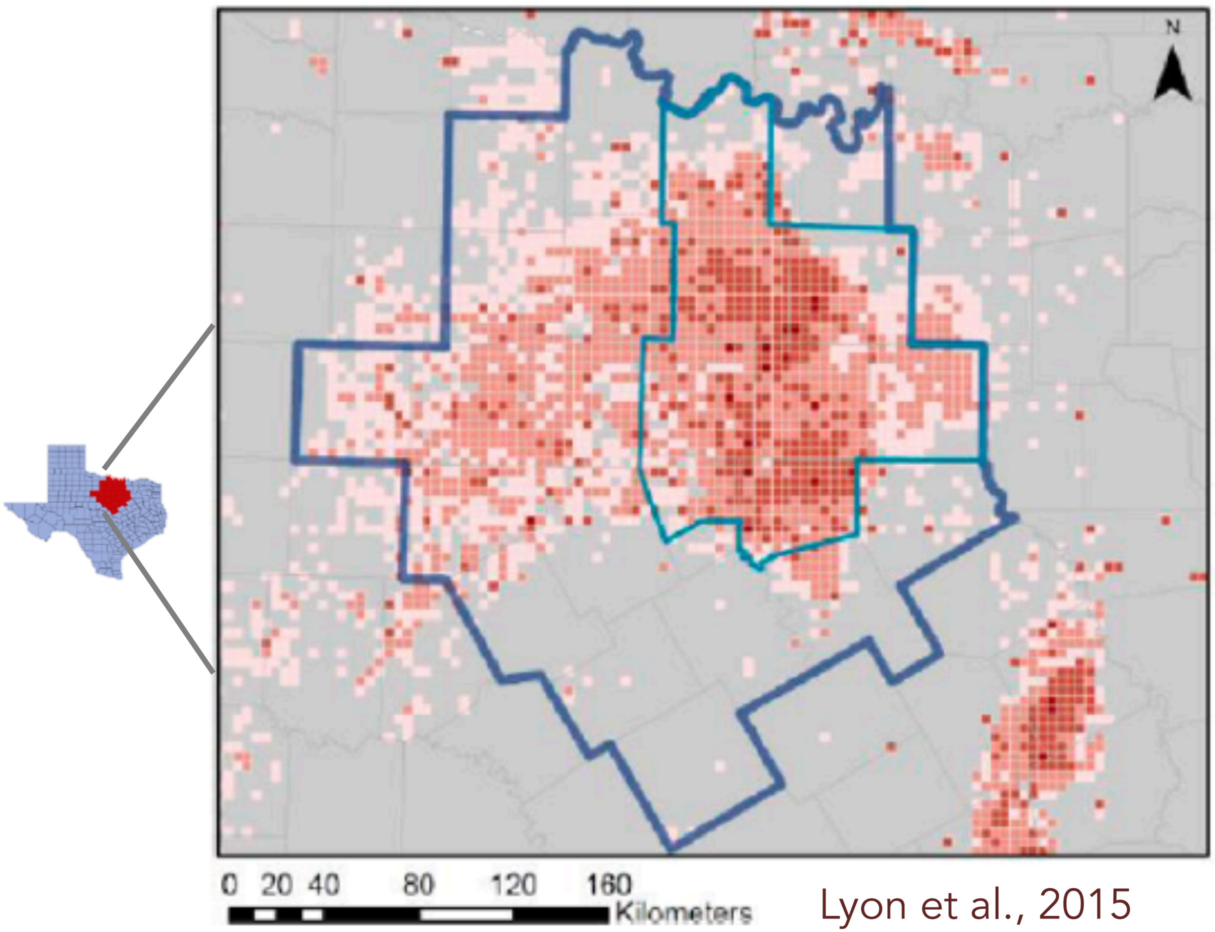
An oil and gas field has several points along its production pipeline where methane can be emitted.



Courtesy of Daniel Varon

In 2013, a coordinated field campaign among several research institutions was performed to quantify oil/gas emissions from the Barnett Shale region of Texas.

Barnett Shale thermogenic methane emissions



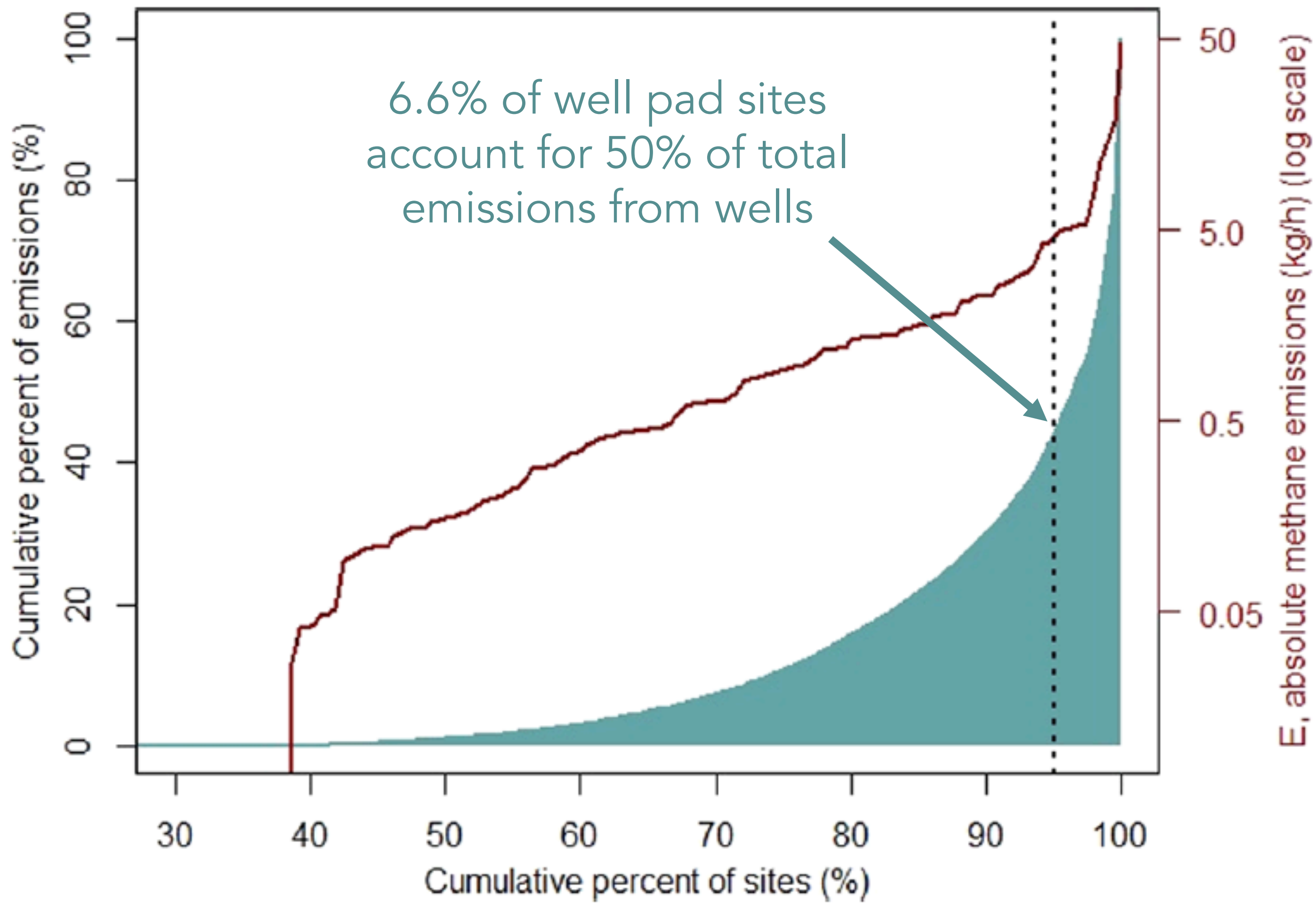
Lyon et al., 2015

15,044 gas well pads

5,842 oil well pads

Much of the region's emissions come from relatively few emitters – i.e., well-pads have "fat-tailed" probability distributions.

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



Zavala et al., 2015

Why do some well-pads sometimes have such high emissions?

Operation/emission modes of well-pads:

Expected low-mode emissions – associated with normal and expected operation of a well-pad

Expected high-mode emissions – associated with routine operations that produce high emissions (e.g., venting, maintenance, etc.)

Anomalous high-mode emissions – associated with instrument or other unknown malfunction at a well-pad.

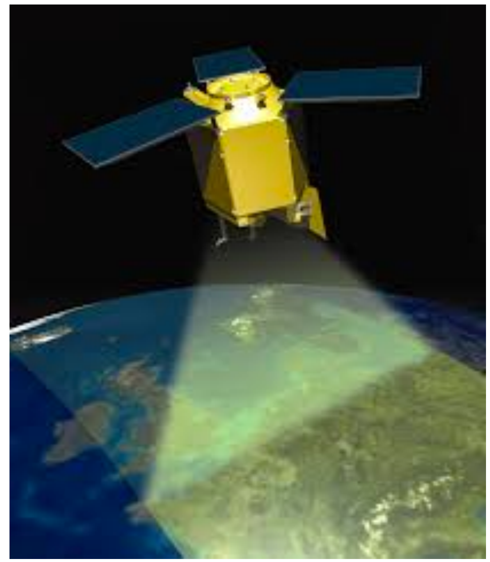
We want to be able to detect where and when these are occurring!

Our capacity to monitor methane from space for "free" is increasingly rapidly.

GOSAT (2009-)

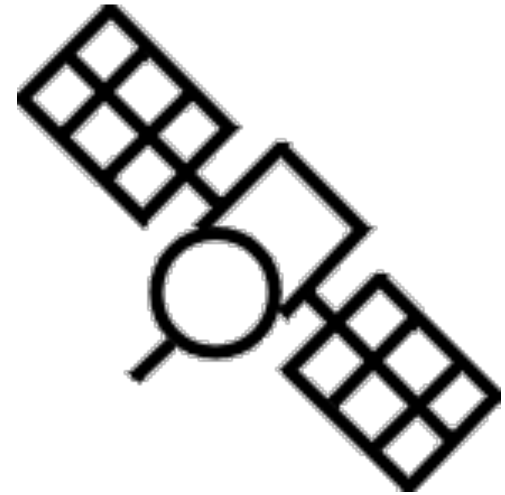
-10 km pixel
-0.7% precision
-3 day coverage
-sparse observations

TROPOMI (2017-)



-7 km pixel
-0.6% precision
-1 day coverage
-dense (gridded) observations

geoCARB (~2020)



-3 km pixel
-1.0% precision
-2-8 hr coverage
-dense (gridded) observations
-geostationary

Scientific question: Is the increasing coverage of satellite observations enough to detect anomalous emissions from well pads?

We can frame the scientific question in terms of joint interests of an oil/gas manager.

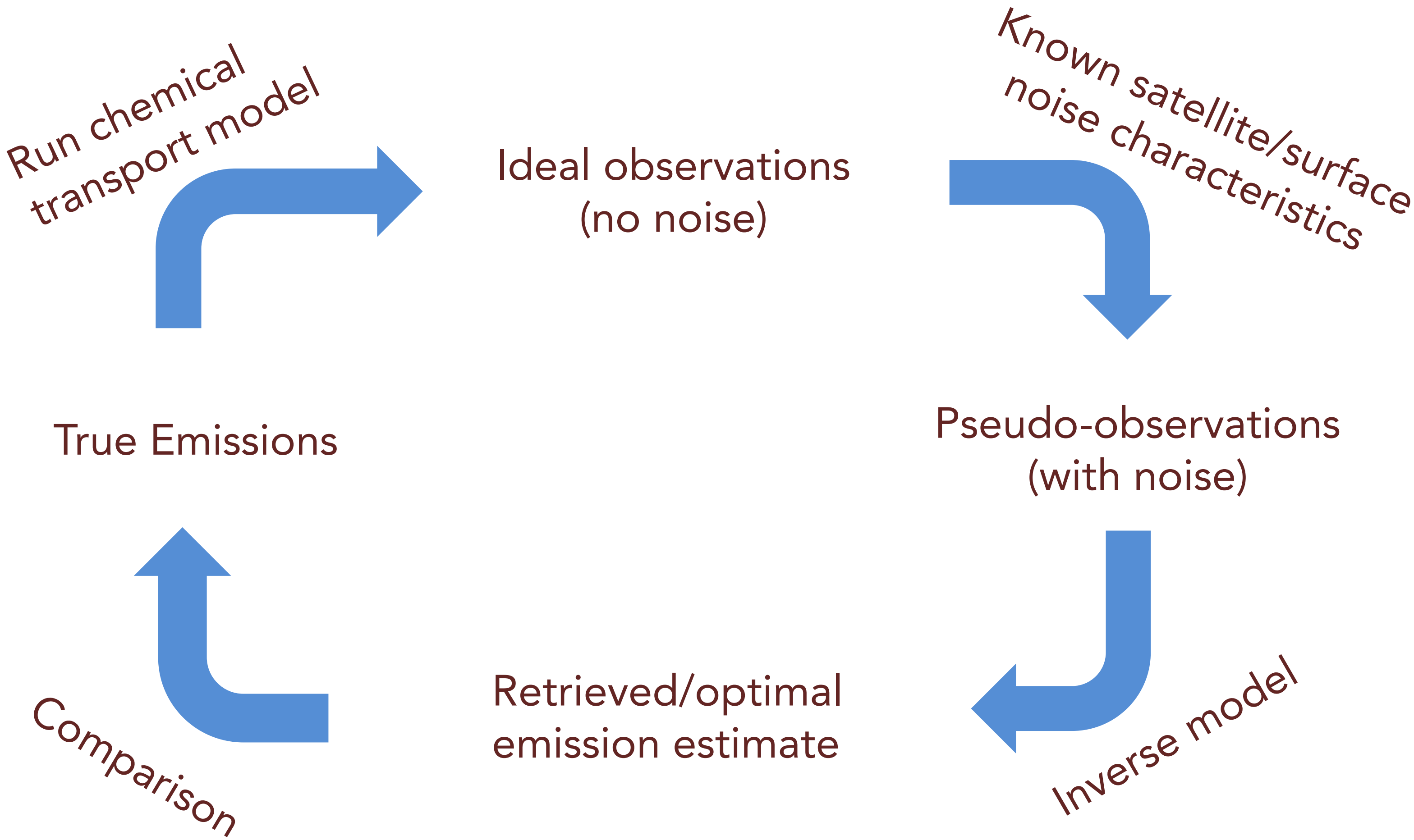
Can I use satellite data alone to determine if a facility has abnormally high emissions?

If not, where can I place surface monitors within my field to augment the information provided by satellites?

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

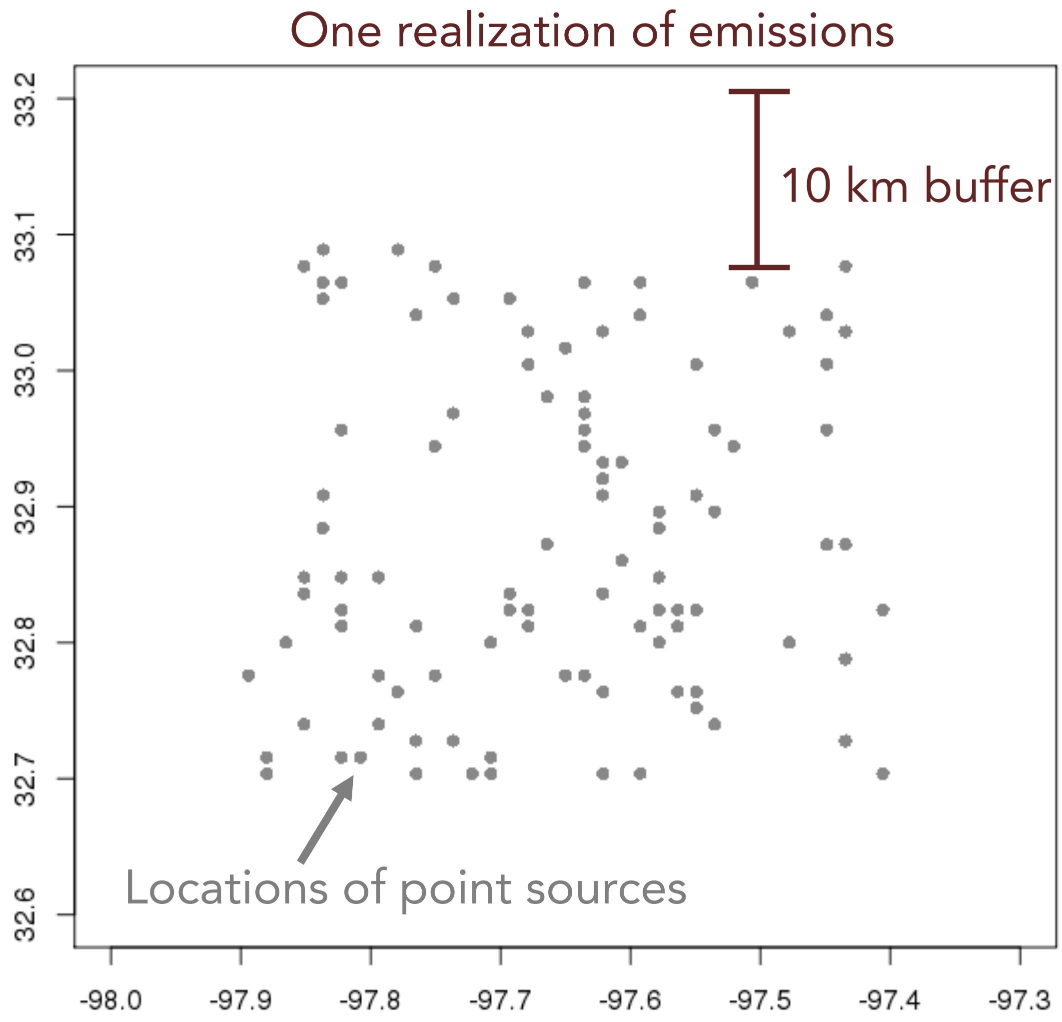
How can a combination of satellites and surface monitors pinpoint anomalous well-pad emission sources?

We set up an observing system simulation experiment (OSSE) to test the feasibility of detecting point sources with unexpectedly high emissions using various combinations of satellite and surface network measurements.



Part 1: Consider a hypothetical oil/gas field with a large number of point emitters that may operate in either low-emitting or anomalous high-emitting modes, generate a "true" emissions field by randomly sampling each mode.

We randomly scatter *n* point sources across a hypothetical 60x60 km^2 oil/gas field

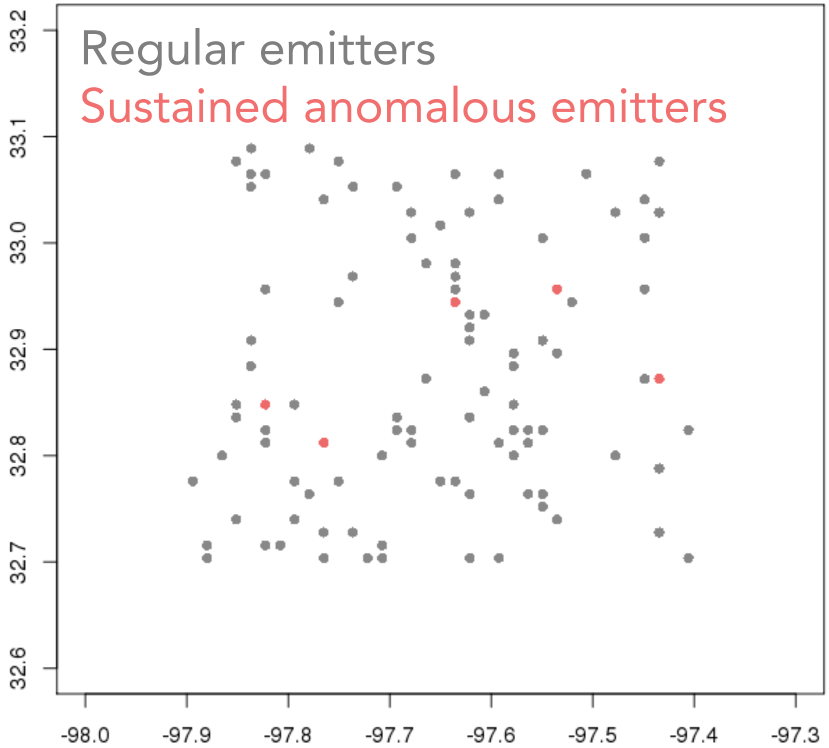


70x70 km^2 observation field

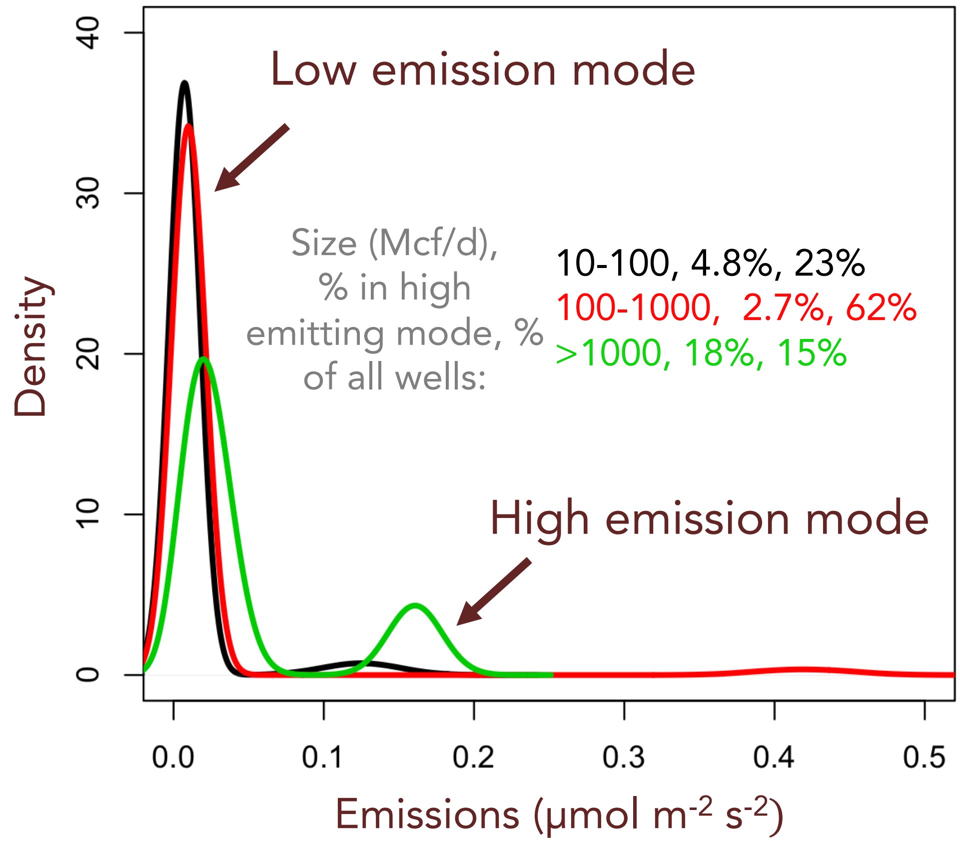
Randomly sample bimodal emission pdfs for each point source to obtain "true" emissions.

Assume EDF emission pdfs for gas wells of different size classes;
assumed to be temporally invariant (anomalous emitters are sustained)

One realization of emissions

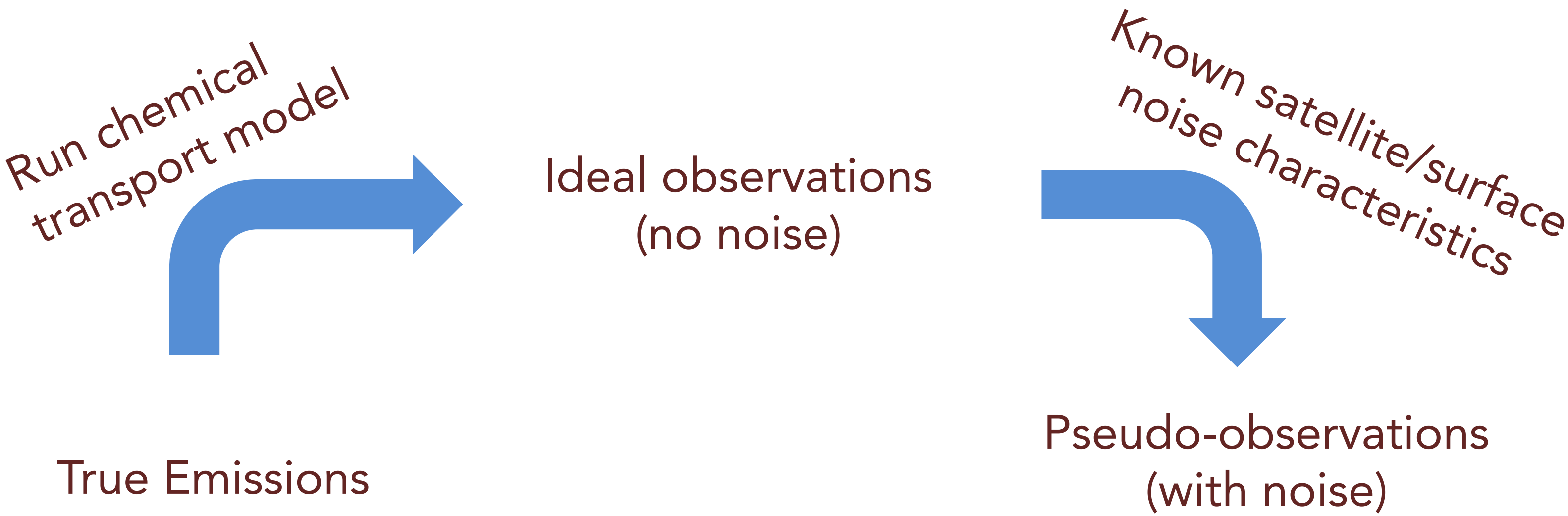


PDF of emission modes by source type



Emission pdfs taken from Zavala et al. (2015) and Rella et al. (2015)

Part 2: Postulate a surface/satellite observing network and create pseudo-observations given the "true" emissions and instrument noise.



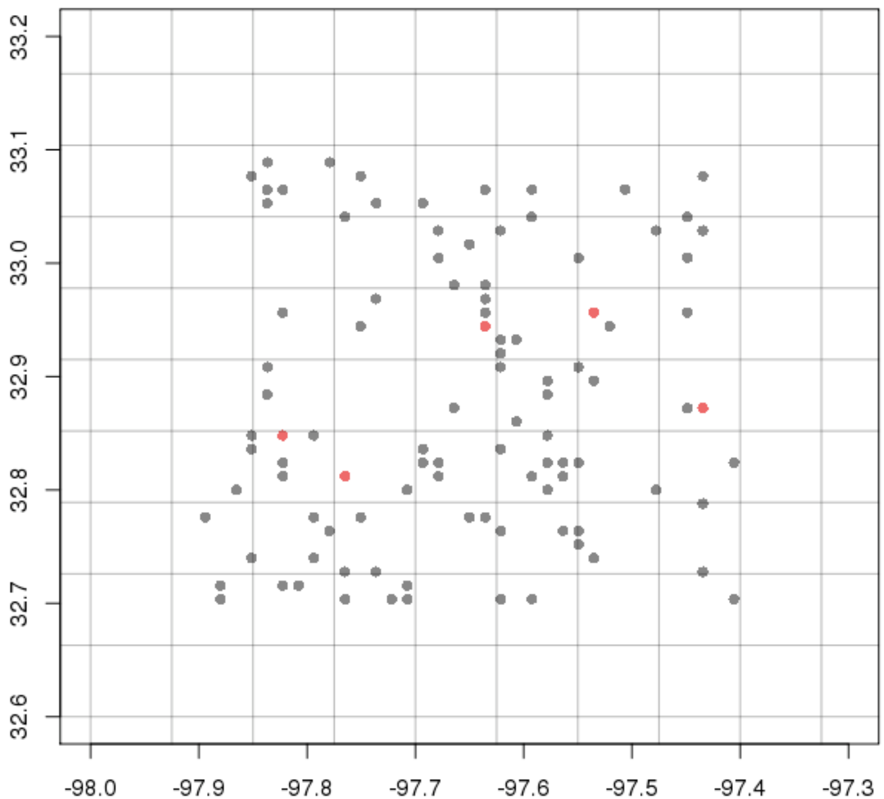
We perform inversions for several satellite/surface configurations over 70km subdomain of Barnett.

Satellite	Surface	State-vector
7km TROPOMI 1x daily 3km geoCARB 2x daily 3km geoCARB 4x daily	5, 10, 20, 30 Surface monitors placed using weighted k-means. Hourly observations, 24 hours a day	100, 500, 1000 emission sources of differing sizes

For each configuration, we run 100 realizations of "true emissions" – i.e., same spatial configuration with different realizations of large/uncertain emissions. This allows us to generalize the inversion characteristics

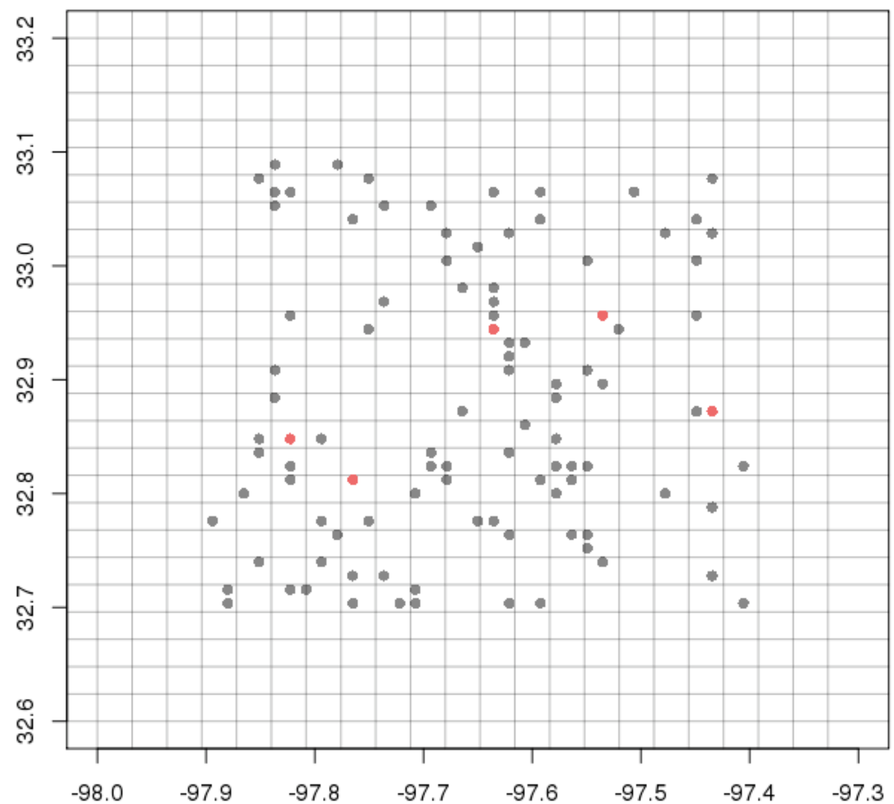
We examine Tropomi (1x daily) and geoCARB (2x, 4x daily) configurations.

Tropomi – 7x7km^2 pixels



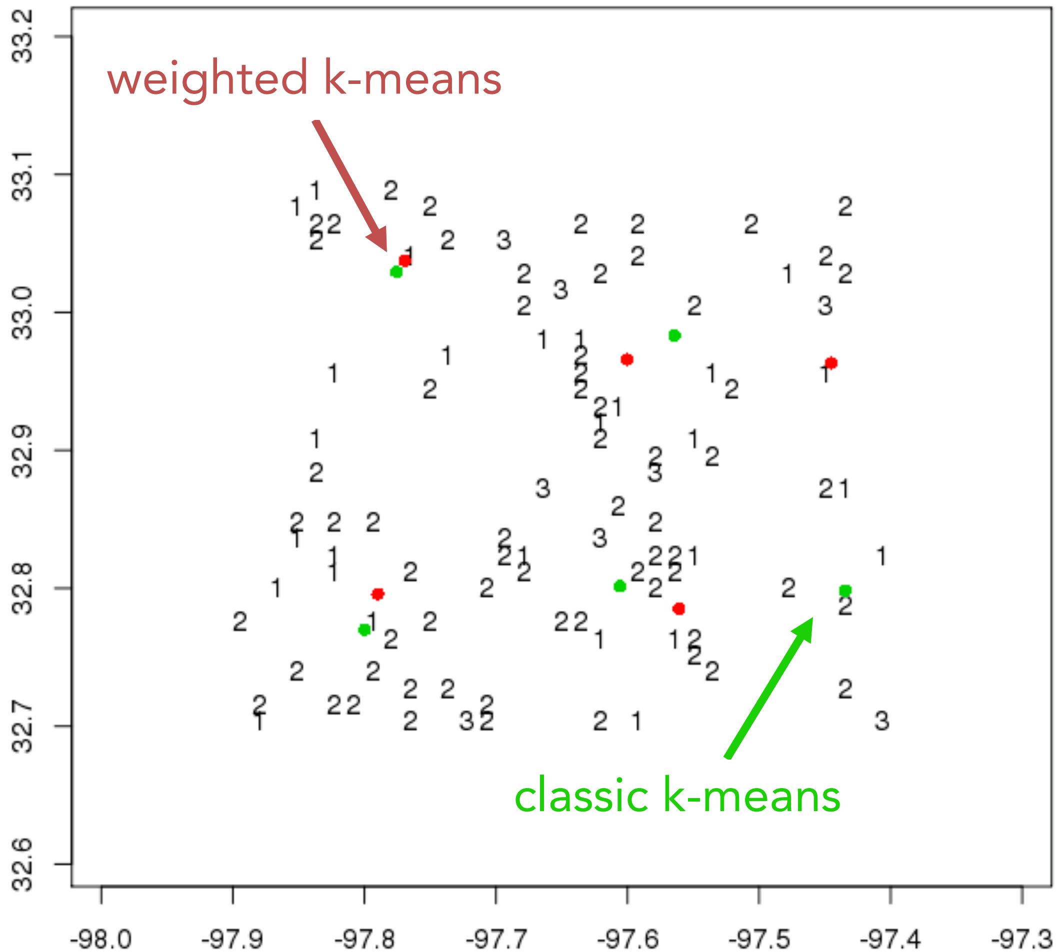
10.8 ppb instrument precision

geoCARB – 3x3 km^2 pixels



4 ppb instrument precision

We place *m* surface monitors via weighted k-means clustering that takes into account the size (and fat-tail probability) of the emitter.



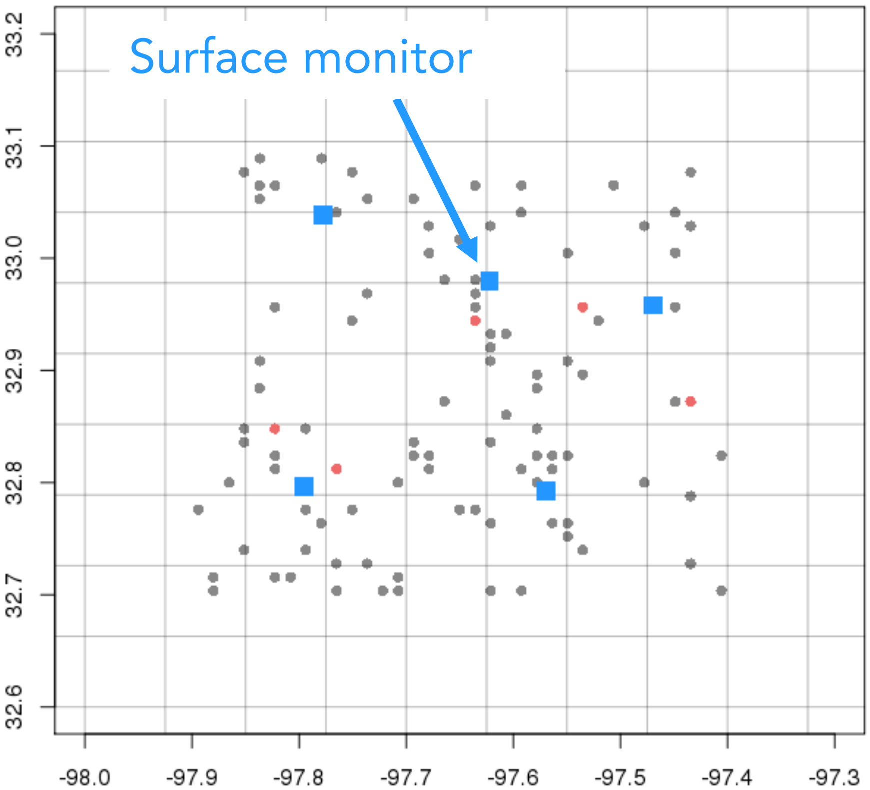
Numbers = size of emitter

1 = 10-100 Mcf/d
2 = 100-1000 Mcf/d
3 = >1000 Mcf/d

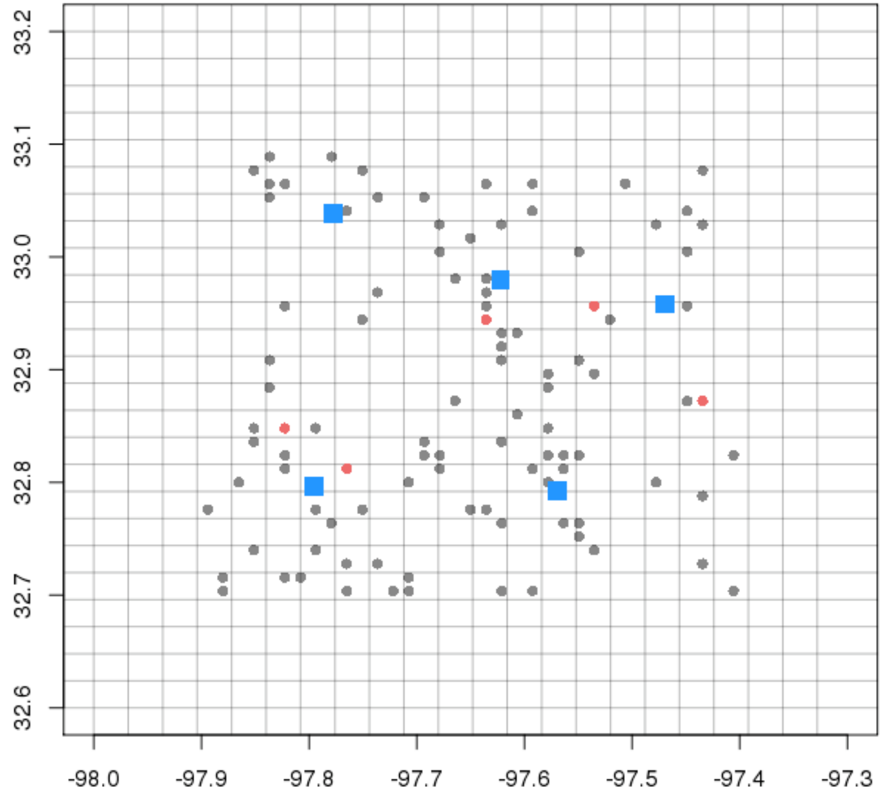
Here *m* = 5 monitors

We use these surface and satellite pseudo-observations for the OSSE.

Tropomi – 7km

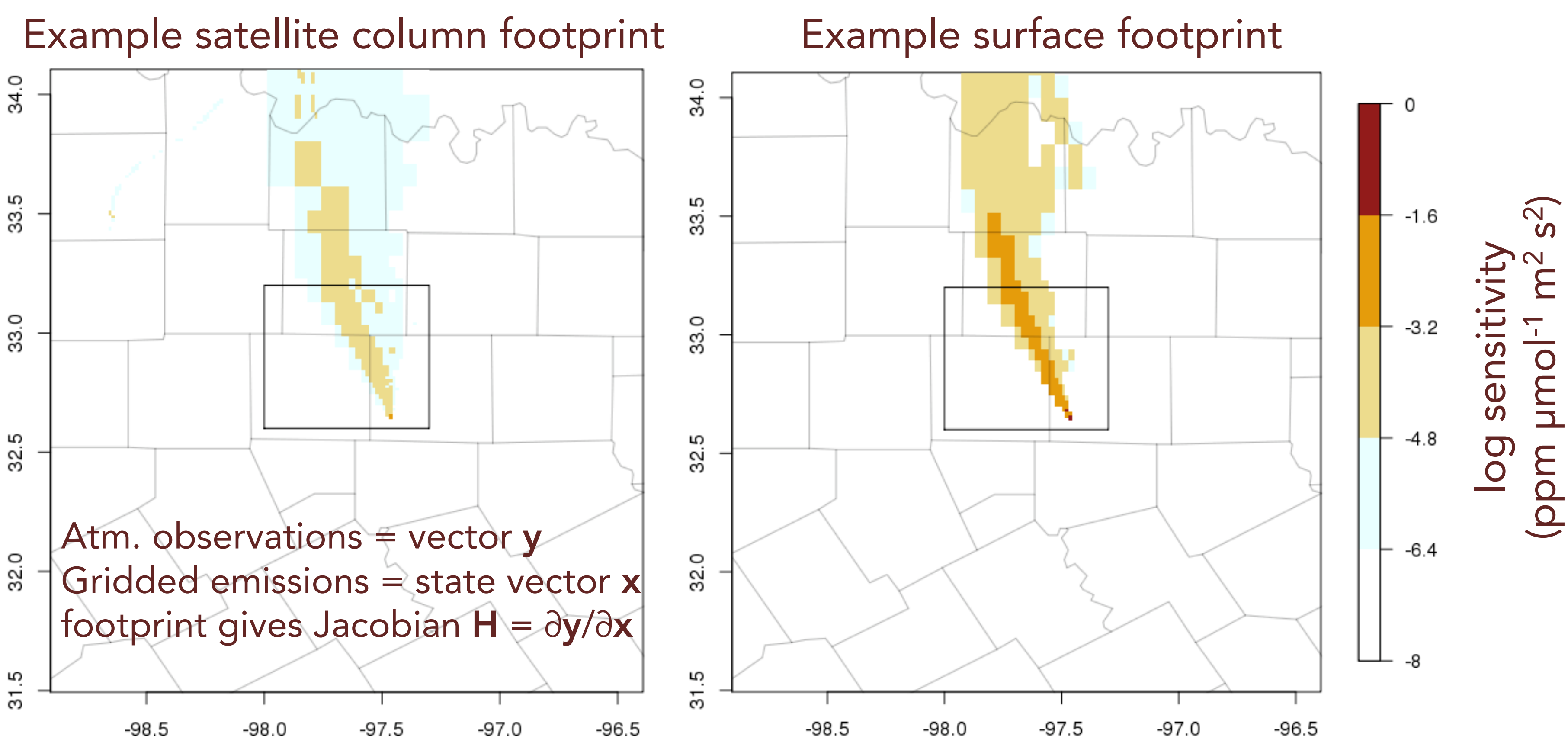


geoCARB – 3km



Assume one week of observations

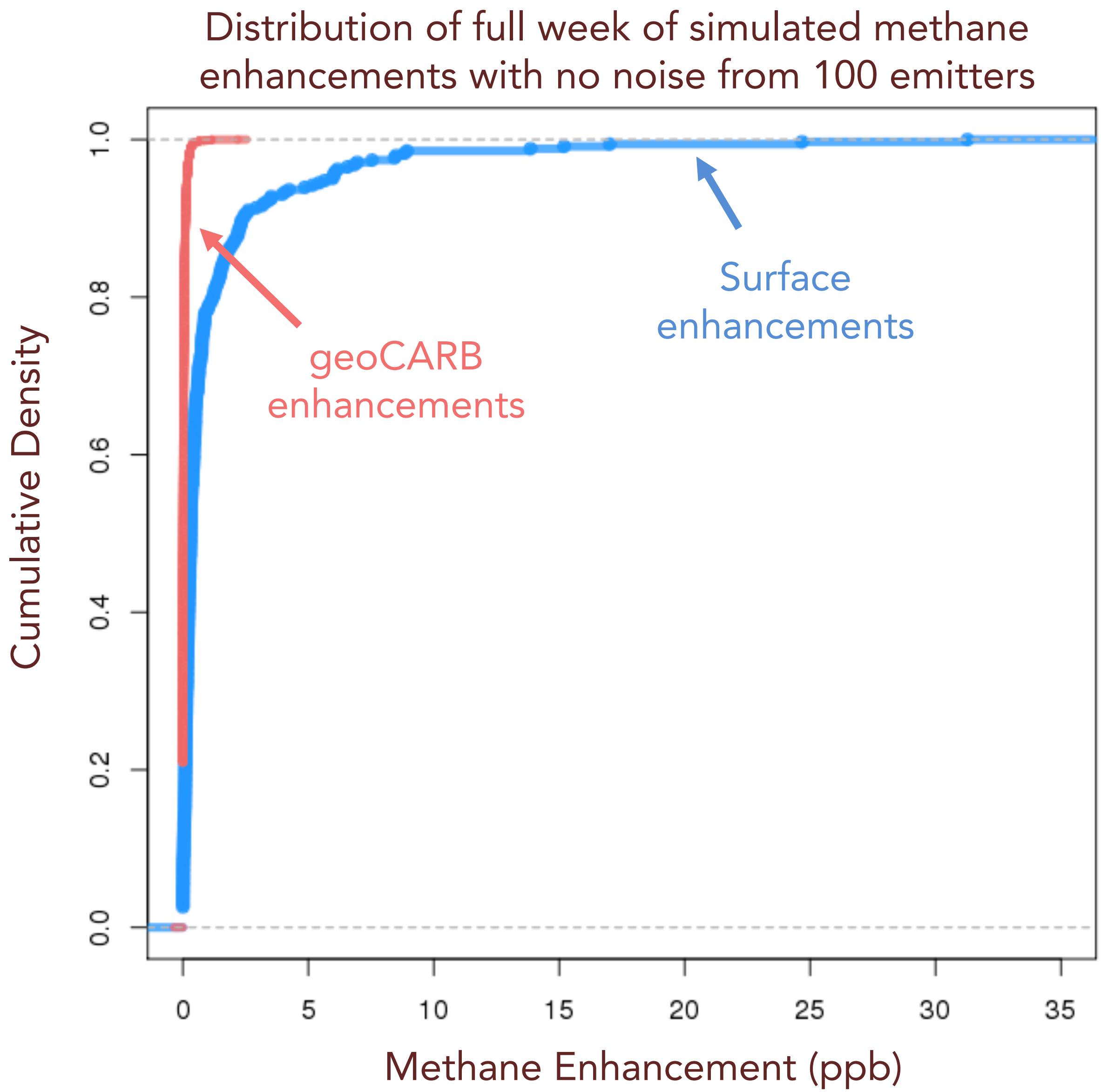
We use a 1-week (Oct 19-25, 2013) WRF meteorological model simulation for the Barnett Shale at 1.3x1.3 km^2 resolution to generate emission footprints for each individual atmospheric observation with the STILT backward Lagrangian model



WRF-STILT simulation assumes 4 ppb transport error (Turner et al., in prep):

1.3 km^2 resolution
50 vertical layers up to 100 hPa.
Mellor-Yamada-Janic boundary layer scheme
Initialized every 24 hours using North American Regional Reanalysis

The magnitude of methane enhancements seen from satellites is an order of magnitude smaller than surface enhancements.



Could be problematic given 4-10 ppb satellite instrument noise!

Part 3: Test different inverse methods to retrieve the abnormal emitters given the pseudo-observations and an atmospheric transport model.

True Emissions

Run chemical transport model

Ideal observations
(no noise)

Known satellite/surface noise characteristics

Pseudo-observations
(with noise)

Inverse model

Retrieved/optimal emission estimate

Each STILT sensitivity map corresponds to a row in the Jacobian matrix (**H**).

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

observations true emissions

Obs error sampled from gaussian distribution with mean = 0, sd = $\boldsymbol{\sigma}_{mod} + \boldsymbol{\sigma}_{instr}$

The model error is correlated among pseudo-observations

From Turner et al. (in prep):
L = 40 km (spatial correlation length scale)
$\boldsymbol{\tau}$ = 2 hrs (temporal correlation length scale)
$\boldsymbol{\sigma}^2_{mod}$ = 4 ppb

We account for spatial/temporal correlation using an observation error covariance matrix **R** = (r_{ij}), where r_{ij} is the error covariance between observations y_i and y_j separated by distance d and time Δt:

$$r_{ii} = \boldsymbol{\sigma}^2_{instr} + \boldsymbol{\sigma}^2_{mod}$$

$$r_{ij} = \boldsymbol{\sigma}^2_{mod} \times \exp\{-d/L\} \times \exp\{-\Delta t / \boldsymbol{\tau}\}$$

We look at different inverse methods to optimize emissions.

$\hat{\boldsymbol{x}}$, the optimal emission vector, is found through the following algorithm:

$$\min_{\boldsymbol{x}\in\mathbb{R}^{\boldsymbol{d}}}\{\boldsymbol{R}^{-1/2}\|\boldsymbol{Hx} - \boldsymbol{y}\|_2^2 + \lambda\|\boldsymbol{x}\|_{1\ or\ 2}\}$$

STILT footprints

pseudo-obs

regularization parameter

L-1 or L-2 norm

When λ = 0, we have the maximum likelihood or ordinary least-squares (OLS).

When λ > 0, we have Tikhonov regularization. This reduces overfitting by penalizing unphysically high emissions.

We look at different inverse methods to optimize emissions.

$\hat{\boldsymbol{x}}$, the optimal emission vector, is found through the following algorithm:

$$\min_{\boldsymbol{x}\in\mathbb{R}^{d}}\{\boldsymbol{R}^{-1/2}\|\boldsymbol{H}\boldsymbol{x}\ -\boldsymbol{y}\|_2^2+\lambda\|\boldsymbol{x}\|_{1\ or\ 2}\}$$

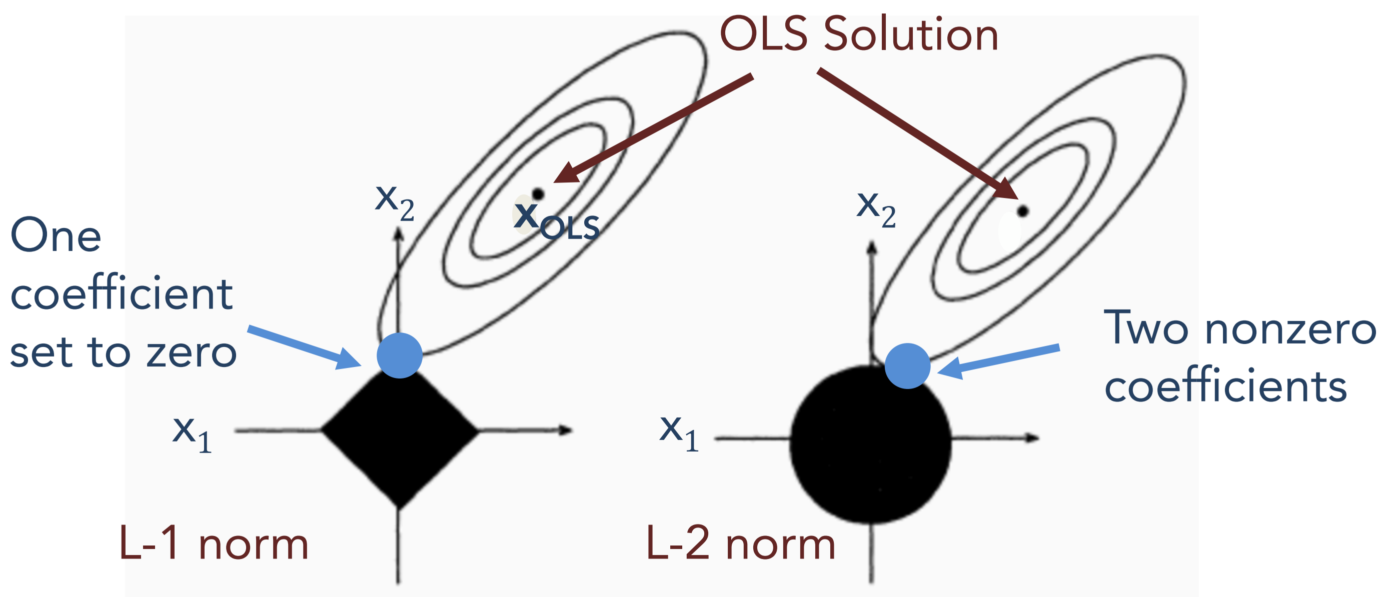
STILT footprints

pseudo-obs

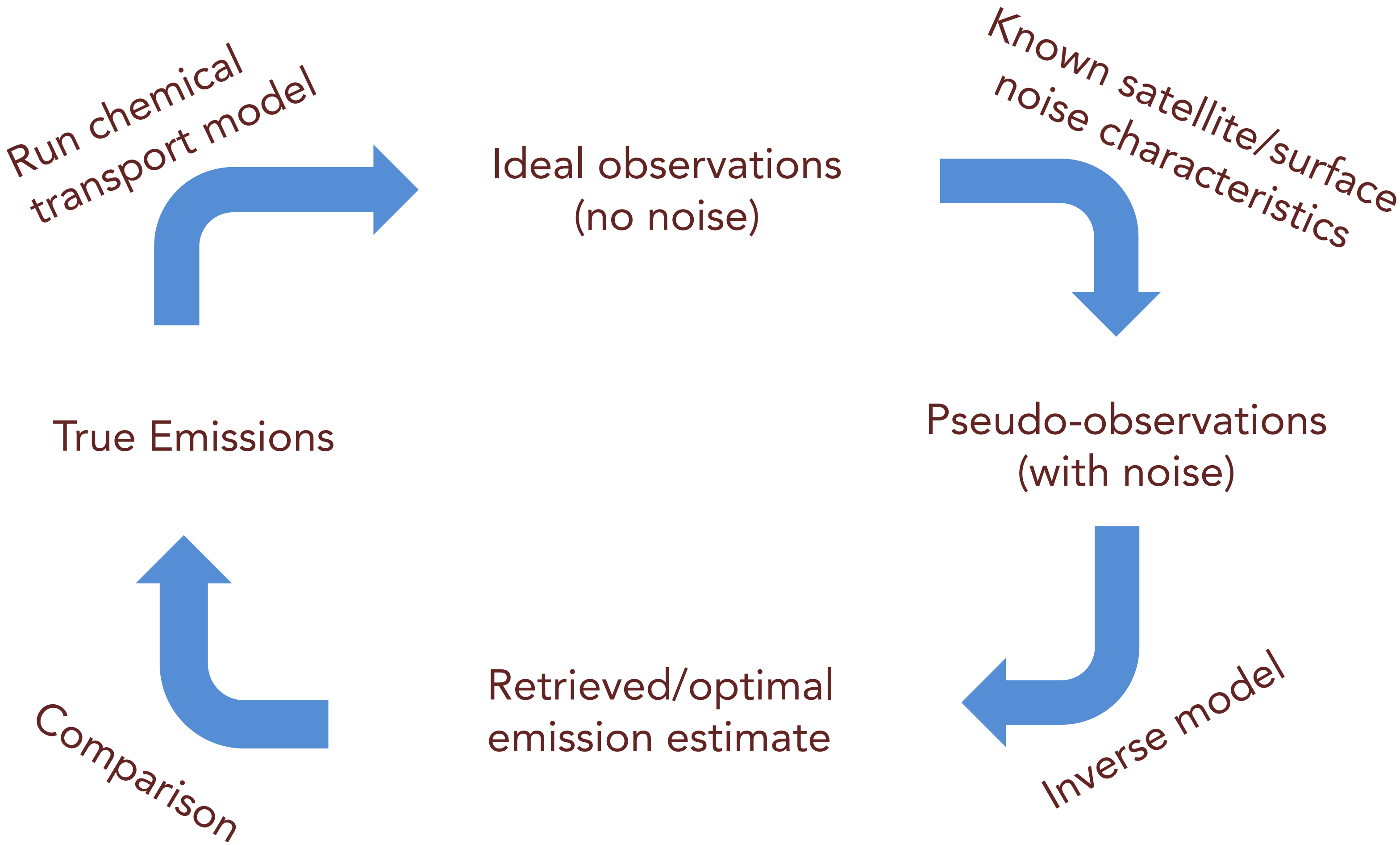
regularization parameter

L-1 or L-2 norm

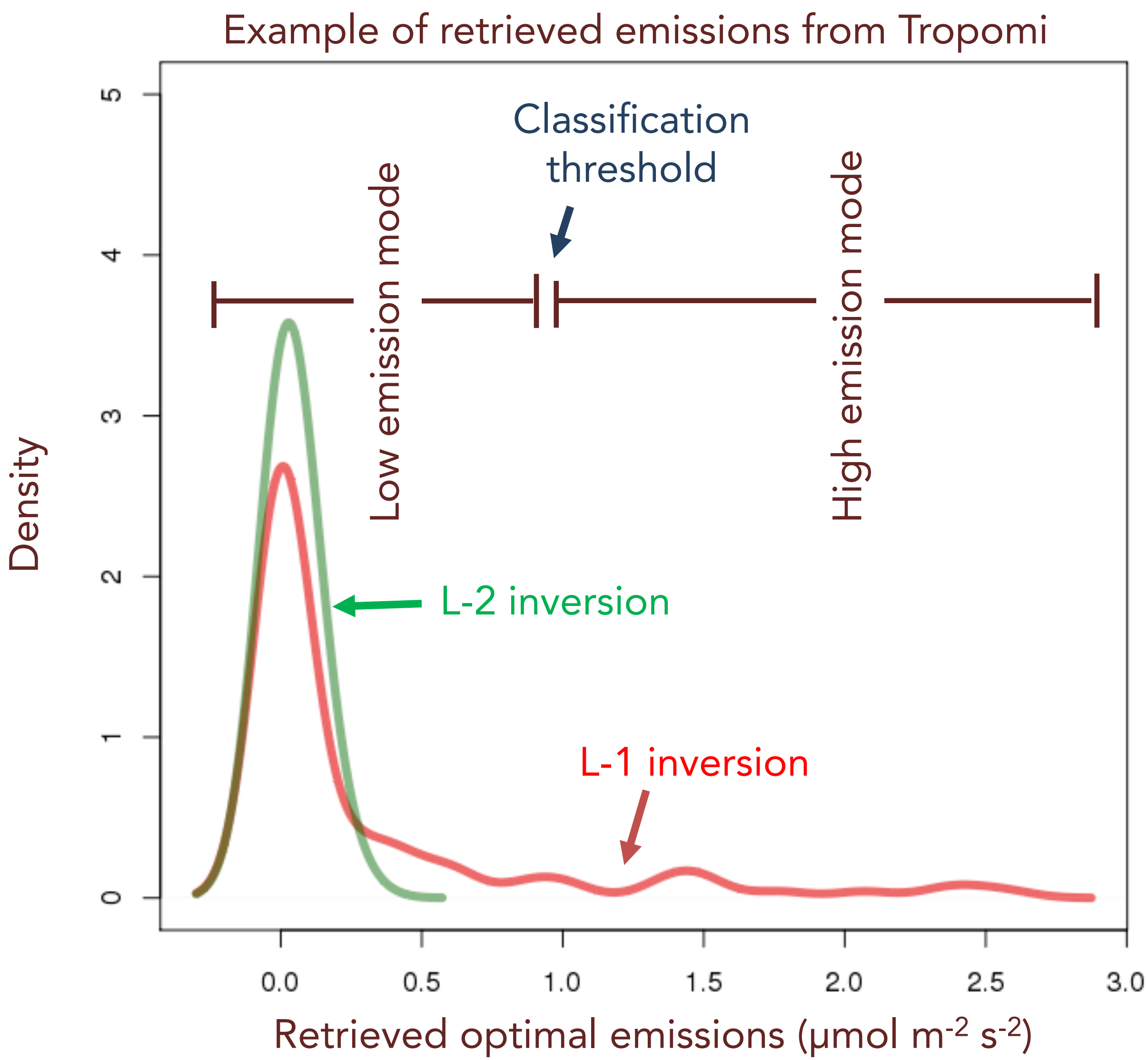
The L-1 norm (i.e., LASSO method) favors sparser solutions than the L-2 norm:



Part 4: Compare optimal emissions to true emissions. Devise metrics to determine the quality of the prediction.



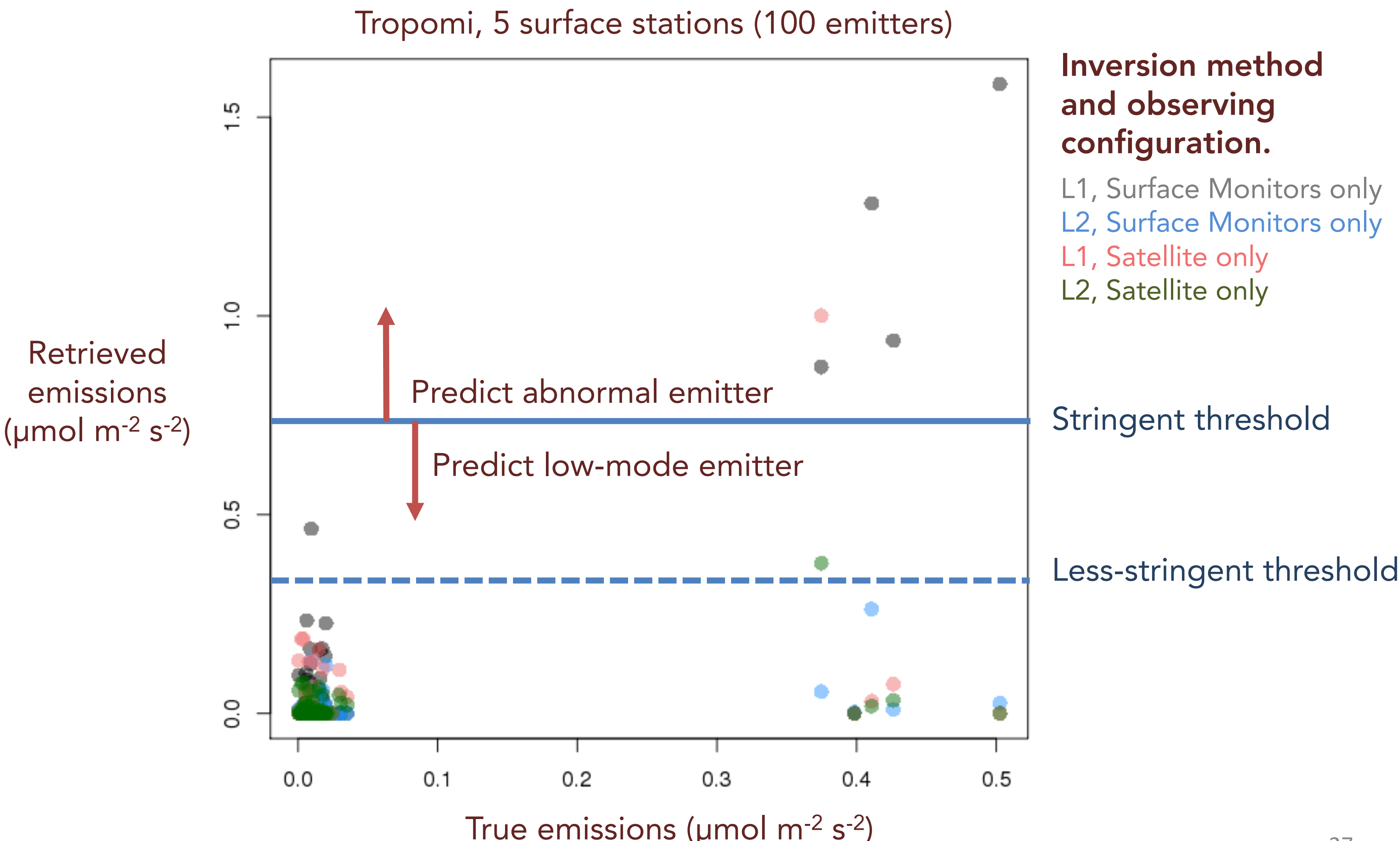
From the optimal set of emissions $\hat{\boldsymbol{x}}$, we wish to classify which are abnormally high emitters.



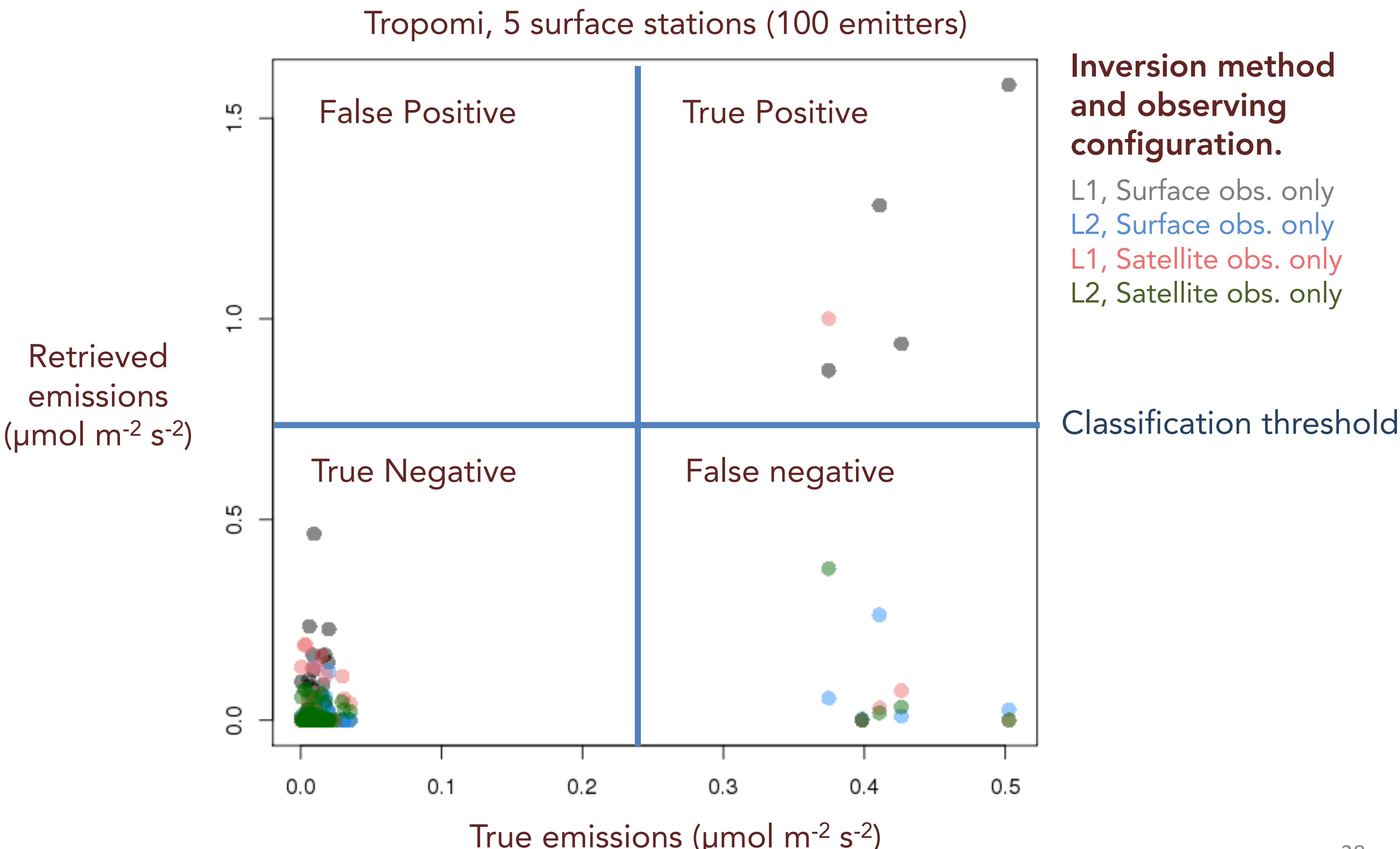
The classification threshold determines whether or not an optimal emission estimate should be classified as a low-emitter or high (i.e., abnormal) emitter

We determine the threshold by clustering the optimal emission estimates into two clusters using k-means.

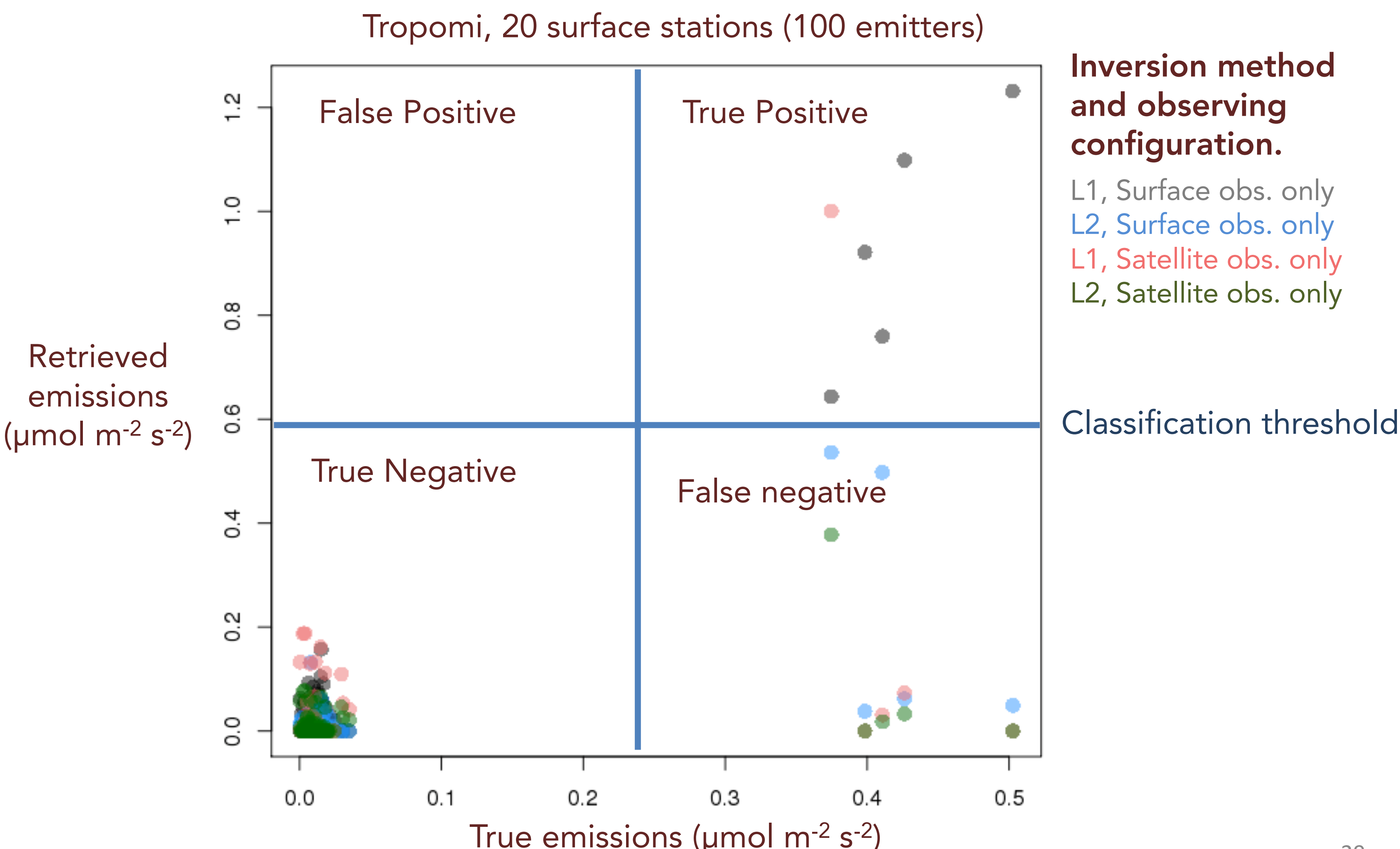
We compare the optimal emission estimates to the true emissions. The choice of threshold influences the classification between low and high emitting modes.



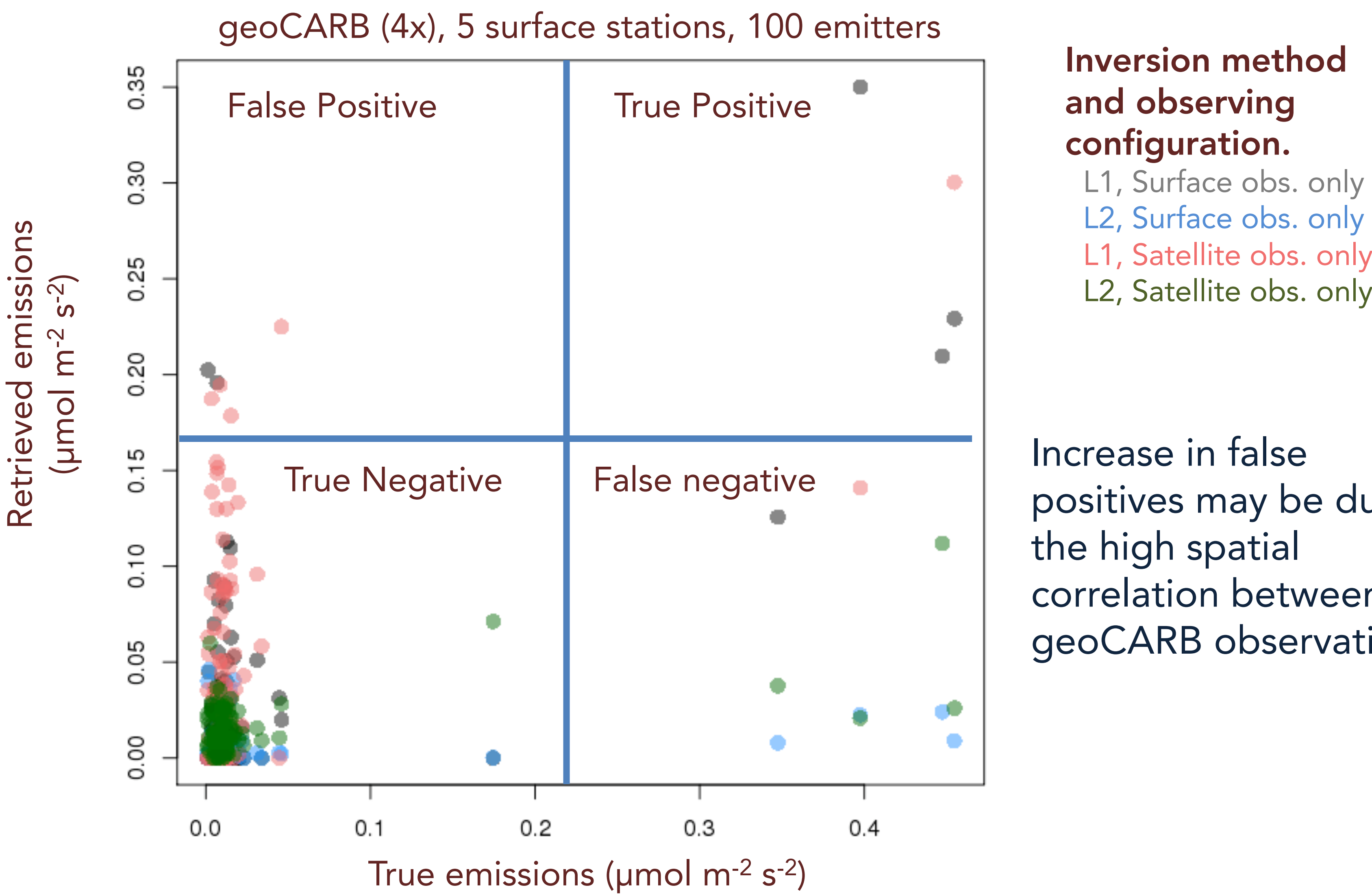
We separate the inversion vs. truth comparison into four quadrants (true/false positive/negative) to assess the classification’s strength.



When we perform the inversion with more surface monitors, the true positive rate increases.



Going to higher spatial and temporal resolution increases the rate of false positives.



Increase in false positives may be due to the high spatial correlation between geoCARB observations.

We introduce two metrics to determine the quality of prediction:

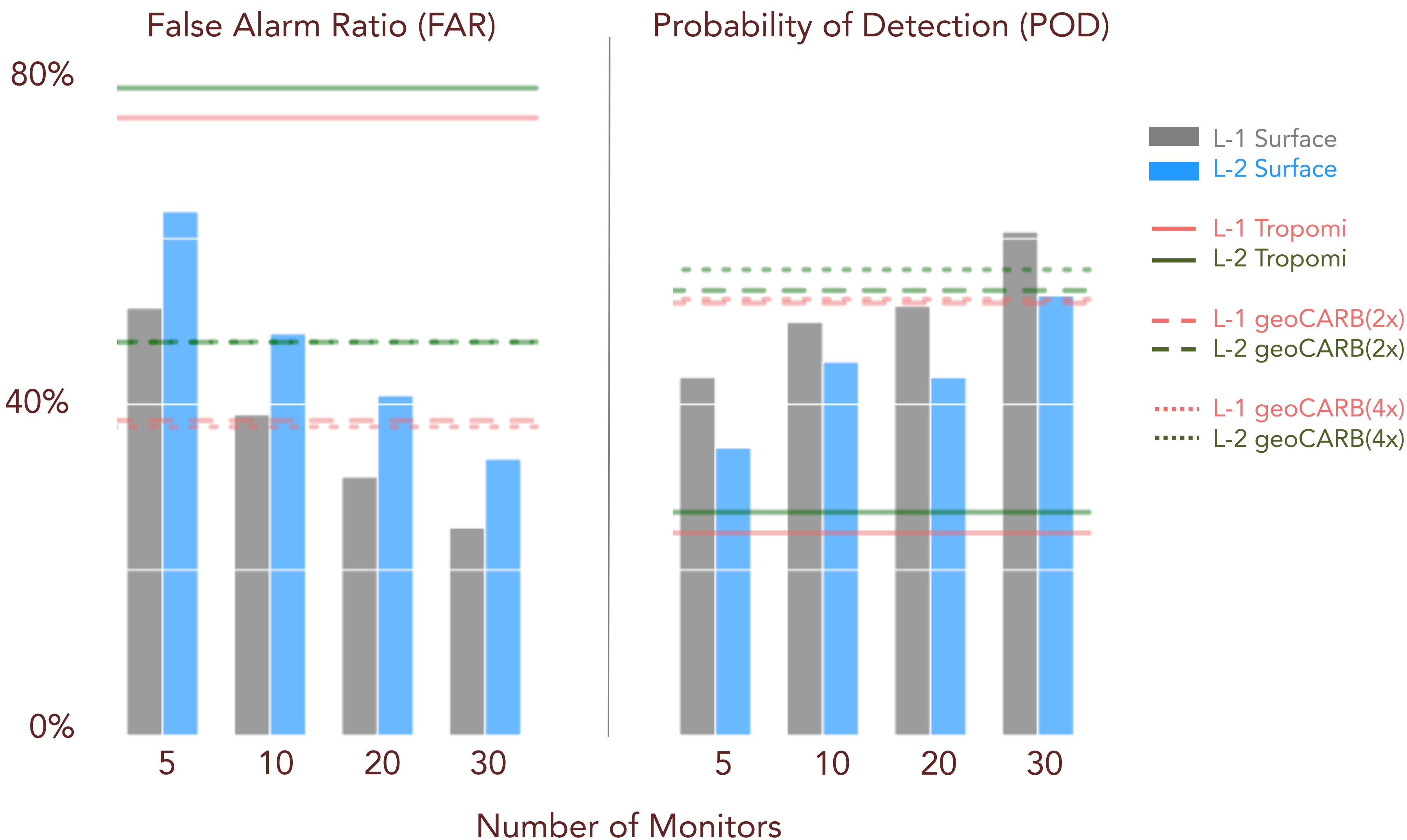
Probability of Detection: 100 * (True Positives) / (True Positives + False Negatives)

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

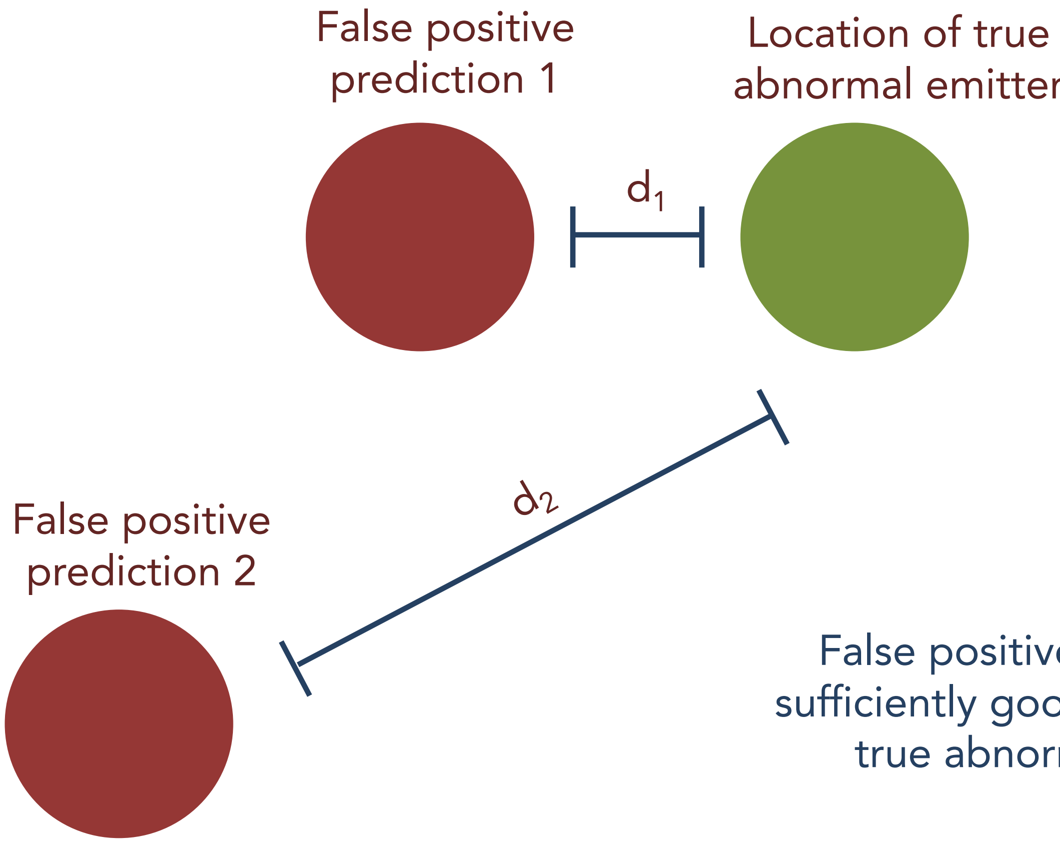
False Alarm Ratio: 100 * (False Positives) / (True Positives + False Positives)

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

geoCARB gives similar results to 10-20 surface monitors. L-1 outperforms L-2 for FAR and L-2 slightly outperforms L-1 for POD.

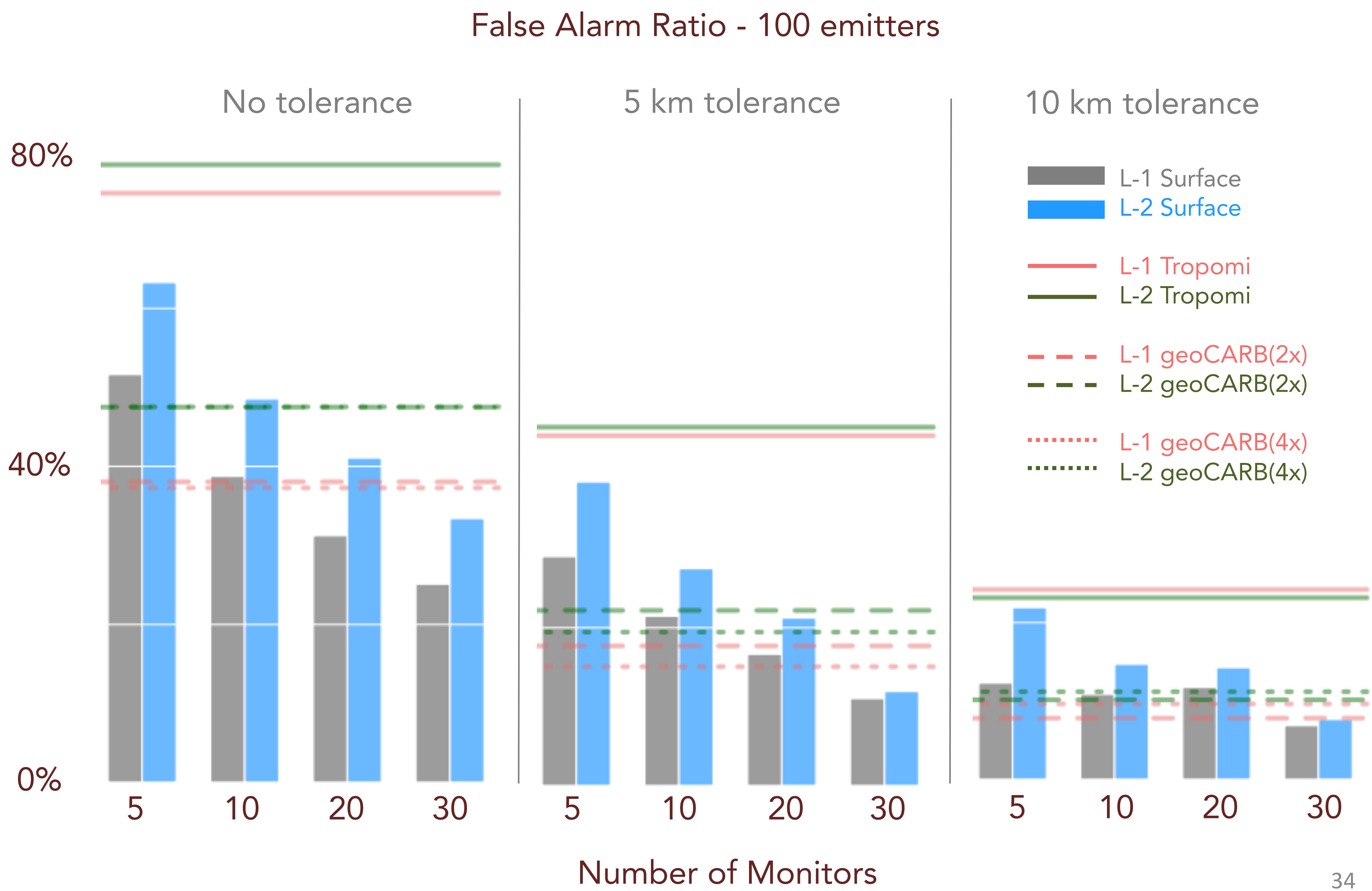


How bad are false positive predictions? If predictions are spatially close to true anomalous high-mode emitter, perhaps the prediction is still useful.

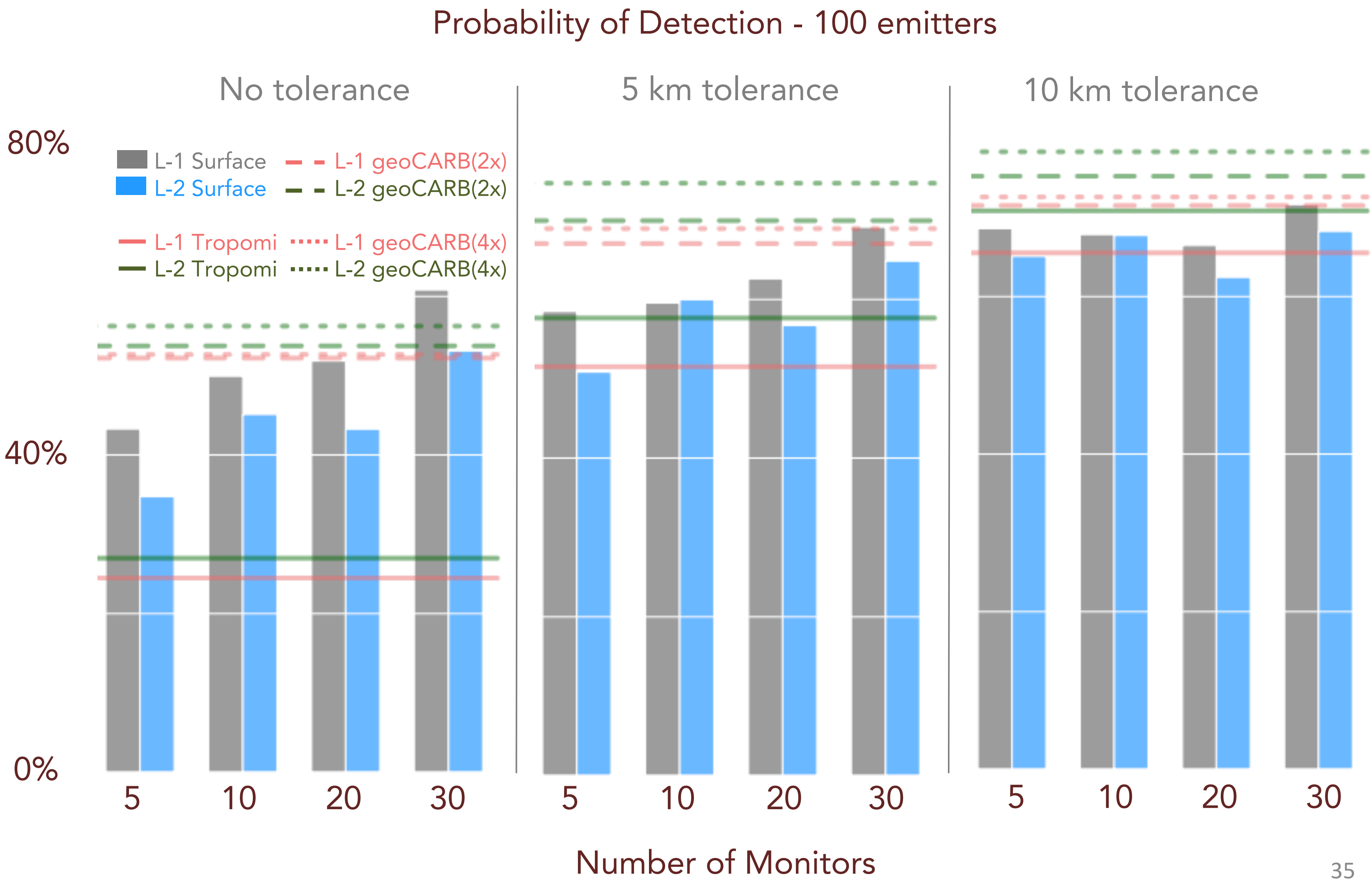


False positive prediction 1 may be sufficiently good as the distance to the true abnormal emitter is small.

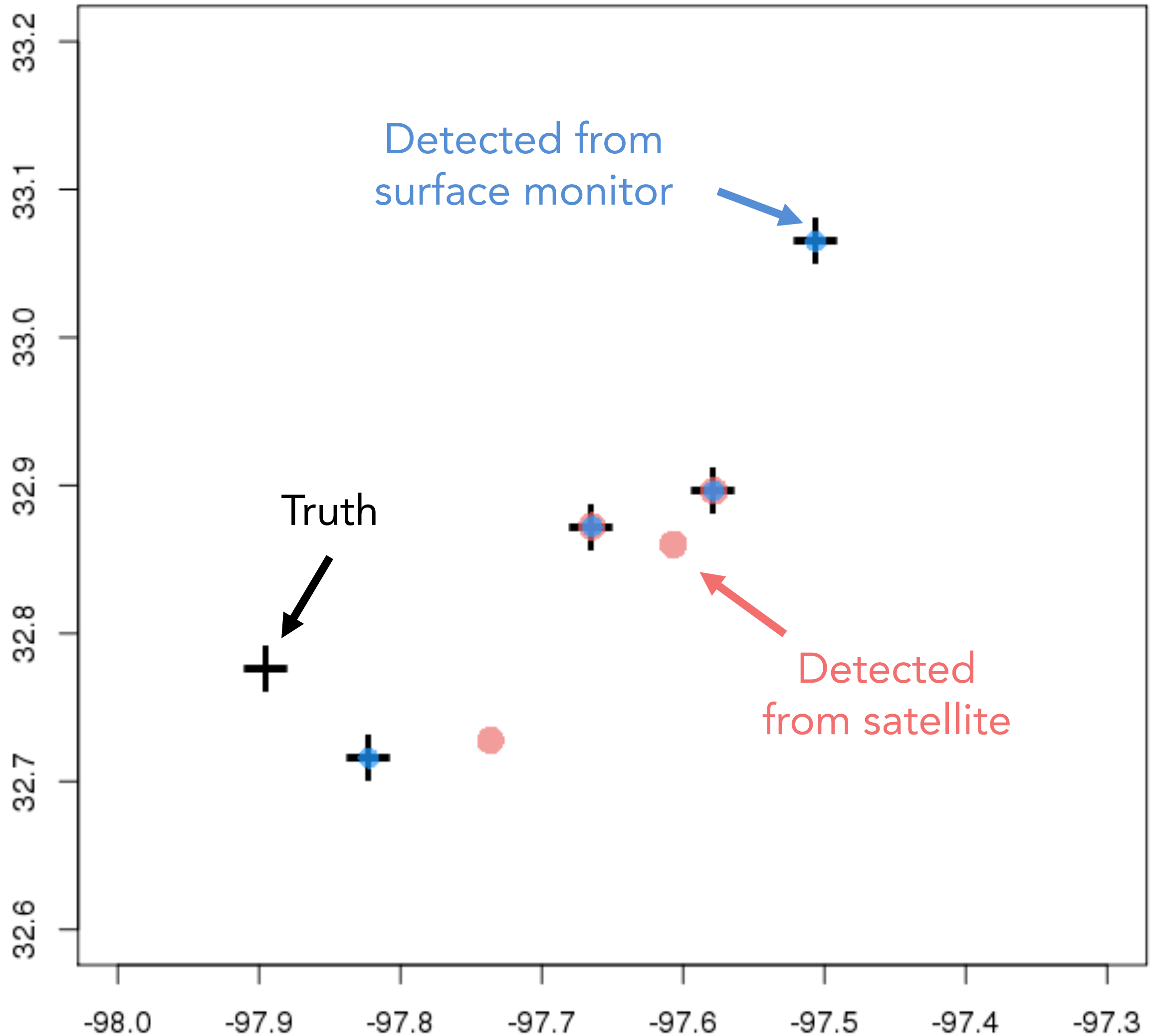
A 5km tolerance reduces FAR to ~20% for both surface and geoCARB. Tropomi requires a 10 km tolerance to get similar results.



geoCARB gives better POD at 5km tolerance than surface monitors. Expected result given that satellites prone to higher FAR.



How should we combine surface and satellite detections of anomalous high-mode emitters.



Approach 1:

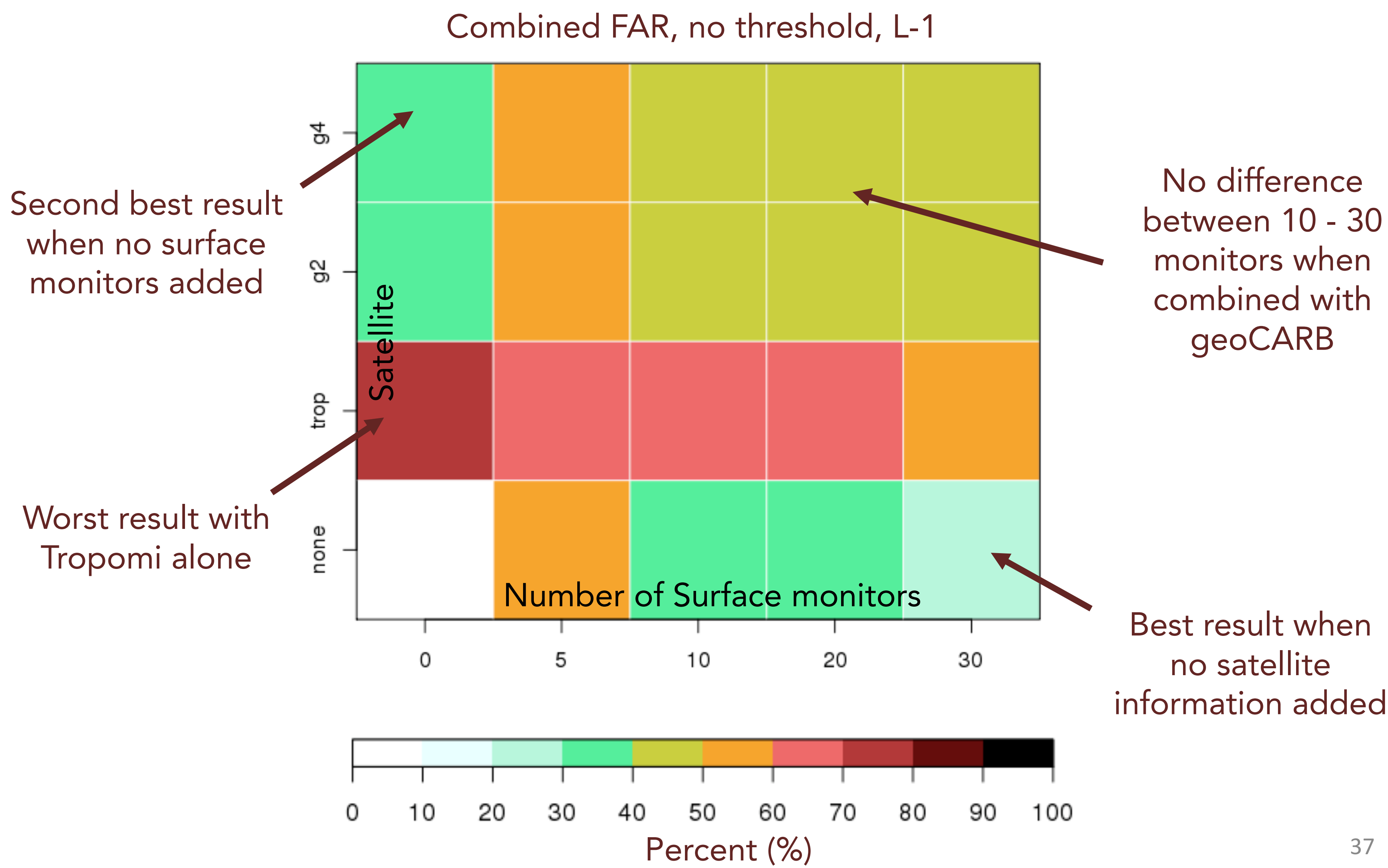
Take the union of satellite and surface detections.

This example:

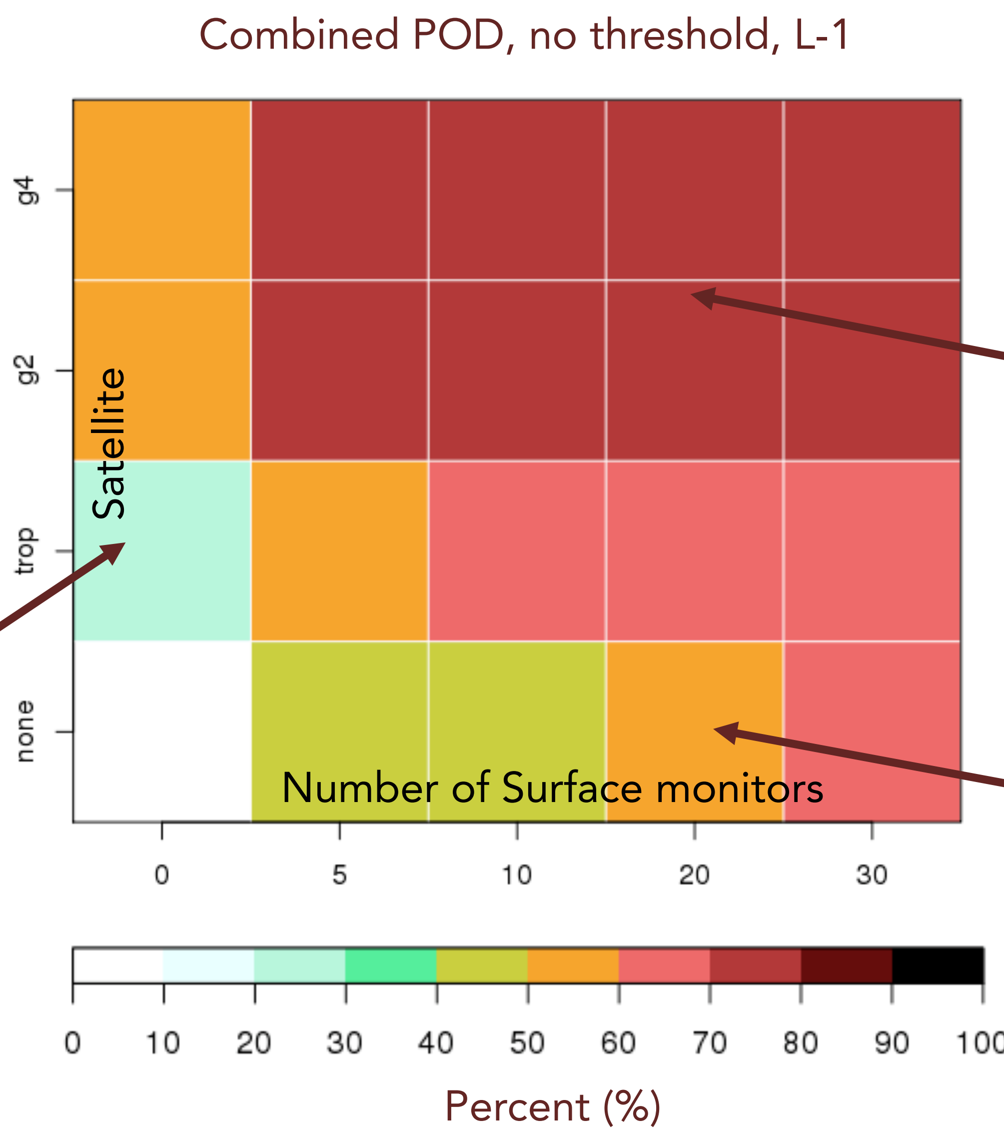
Satellite – 2 TP, 2 FP, 1 FN
Surface – 4 TP, 0 FP, 1 FN

Combined – 4 TP, 2 FP, 1FN

Combining satellite detections to surface detection increases the rate of false positives.



The best POD comes when satellite and surface detections are combined, though adding more than 5 monitors adds little additional gain.

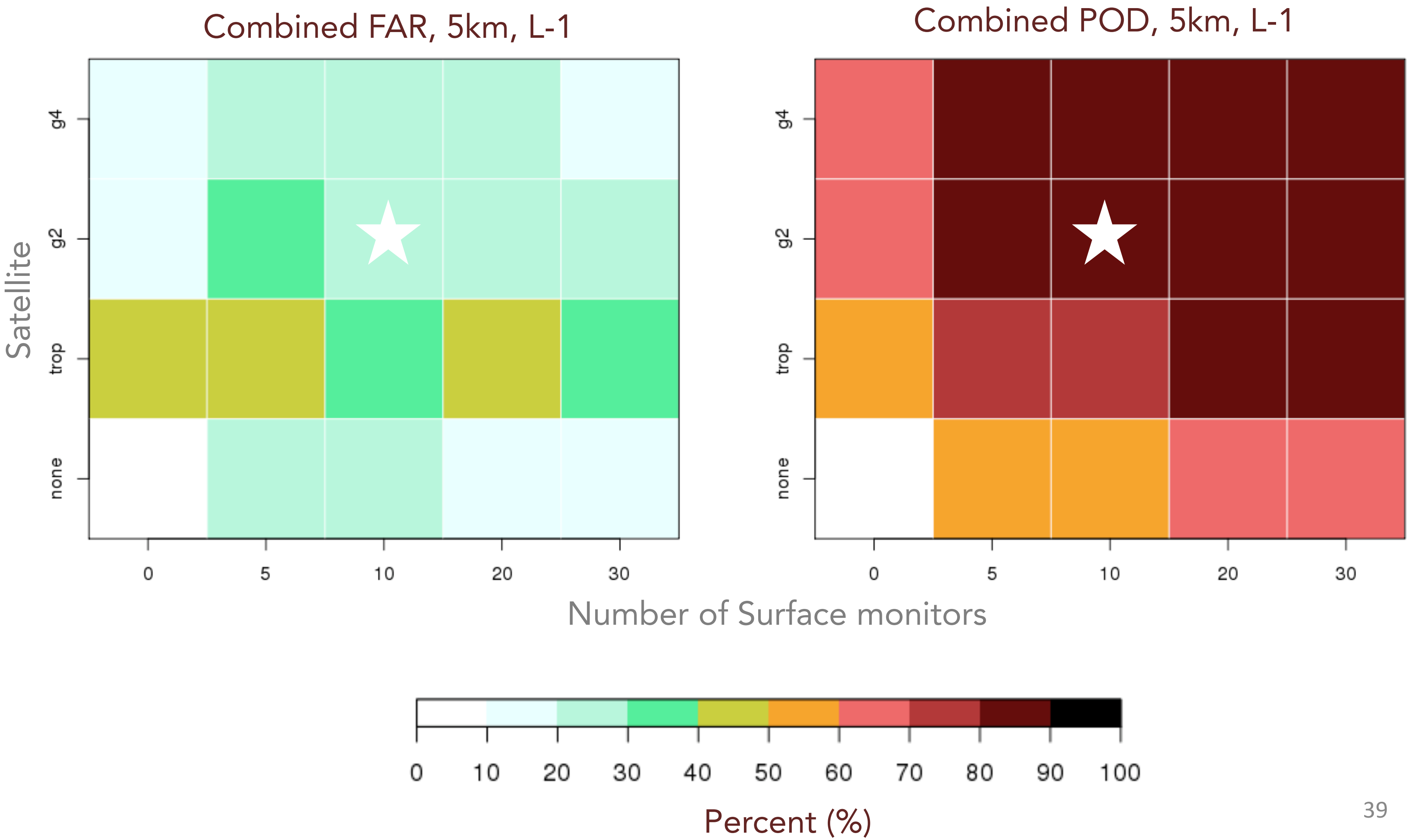


Best result is a combination. No difference between 5 - 30 monitors when combined with geoCARB

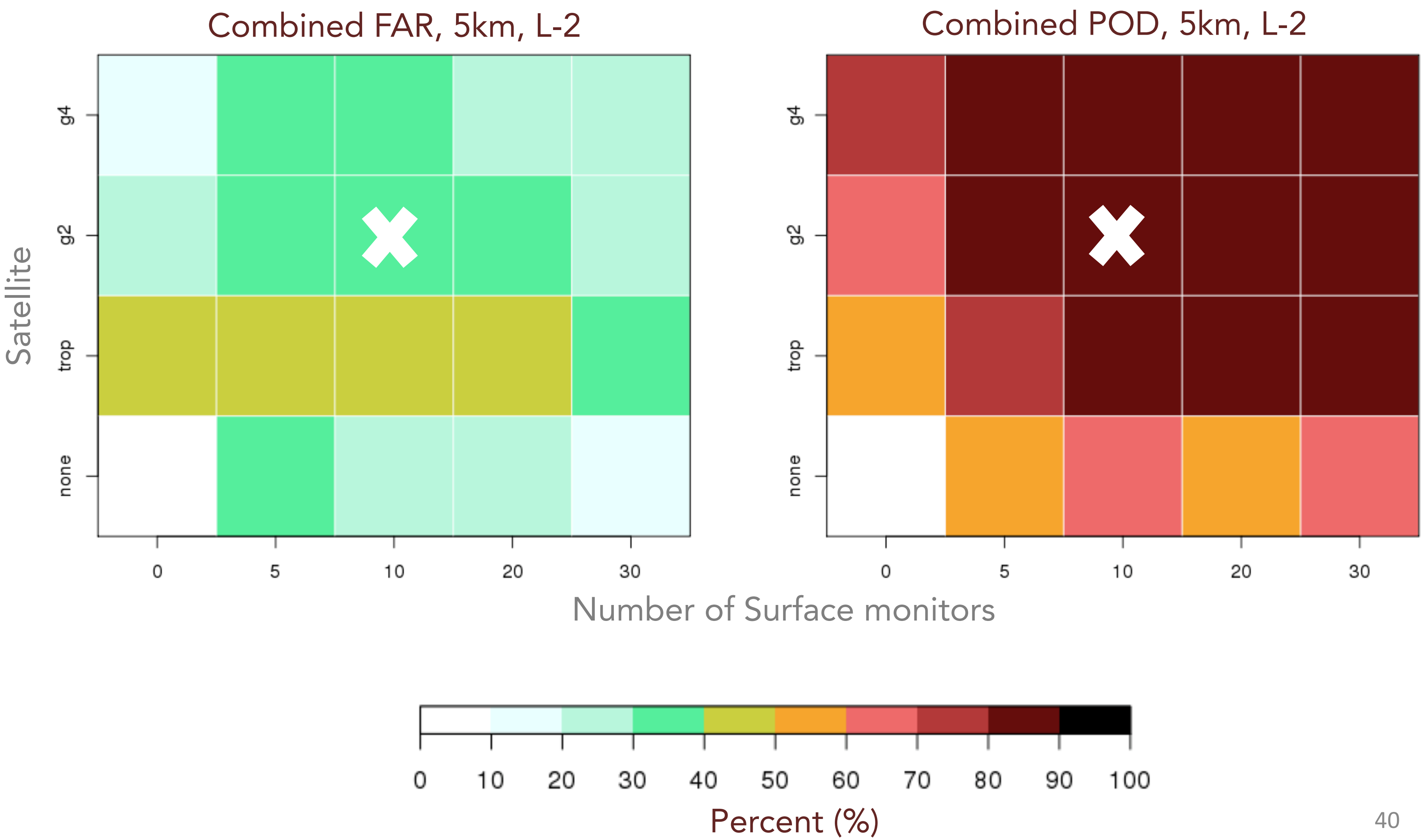
Worst result with Tropomi alone

20 surface monitors alone produces a similar result as geoCARB alone

A 5km threshold shows an "optimal" observing system of geoCARB 2x/day with 10 surface monitors.



Combined L-2 methods do not show enough of a POD enhancement to justify the worse FAR results.



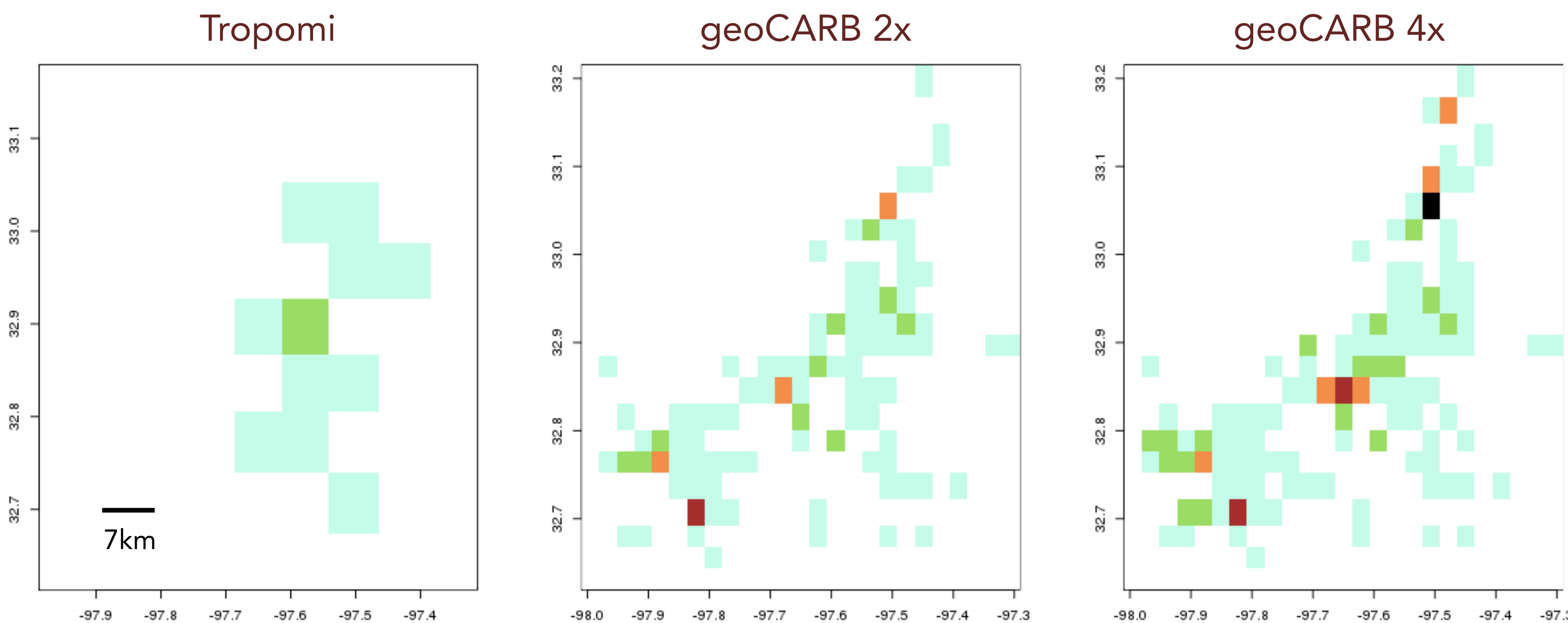
Some other questions for thought:

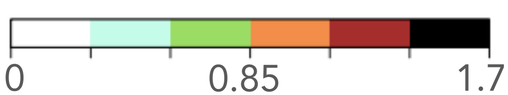
Do we have to use an inverse method, STILT, etc. in order to predict anomalous emitters?

Could we just use observations to detect anomalous emissions?

Could we have done this all without an inversion?

Maximum xCH4 "observed" over Oct. 19-25 – **no noise added**



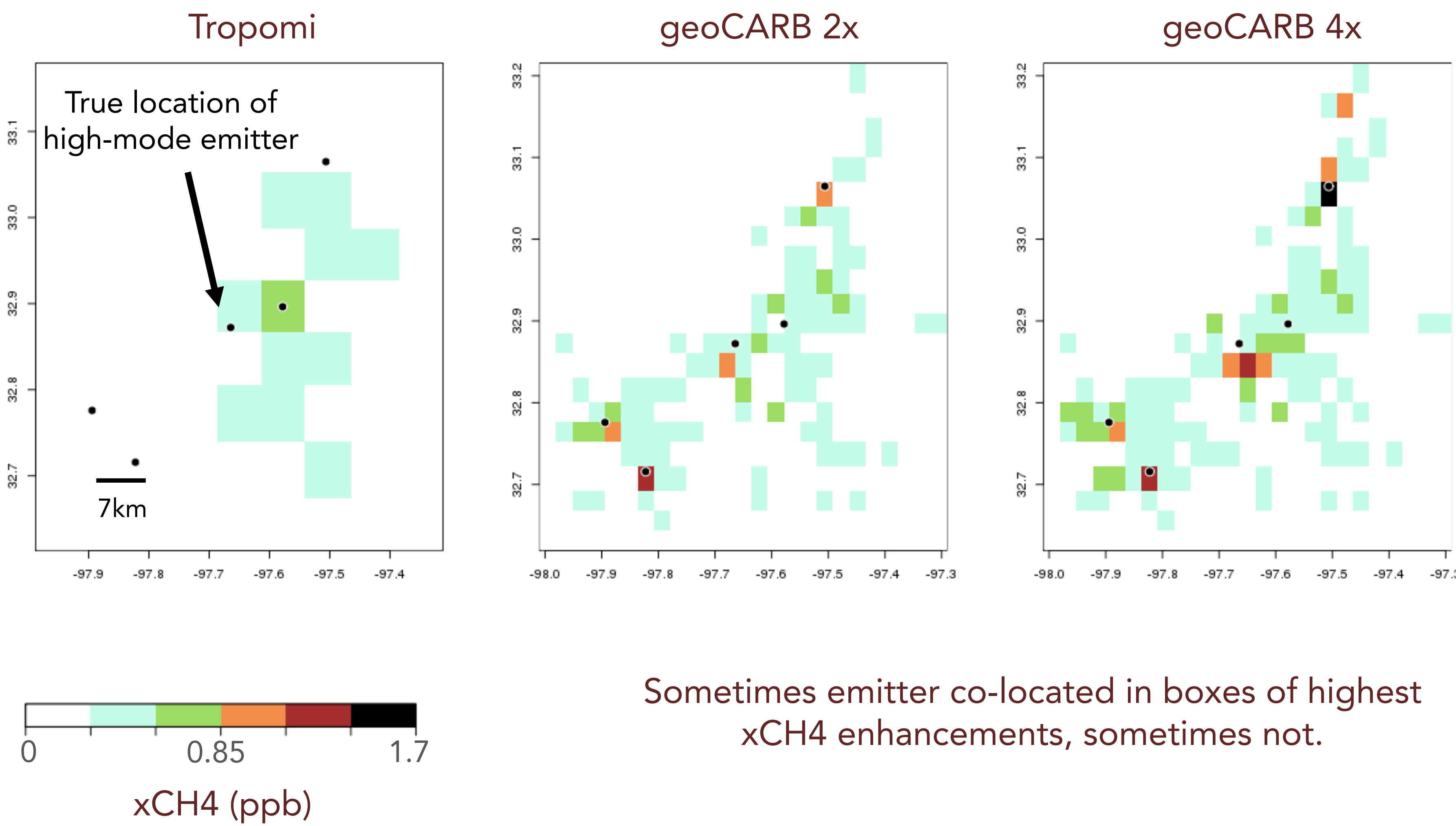


xCH4 (ppb)

How many grid cells do you need to drive around to find the high-mode emitter?

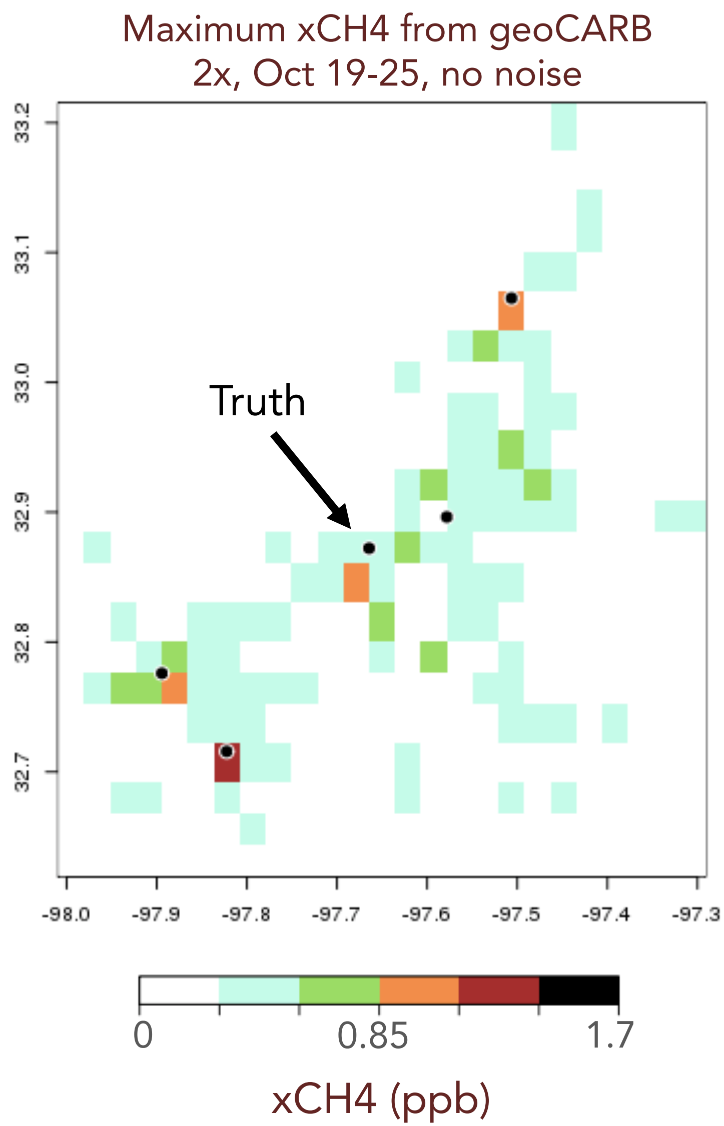
Will still run into many false negatives if you do not determine a threshold.

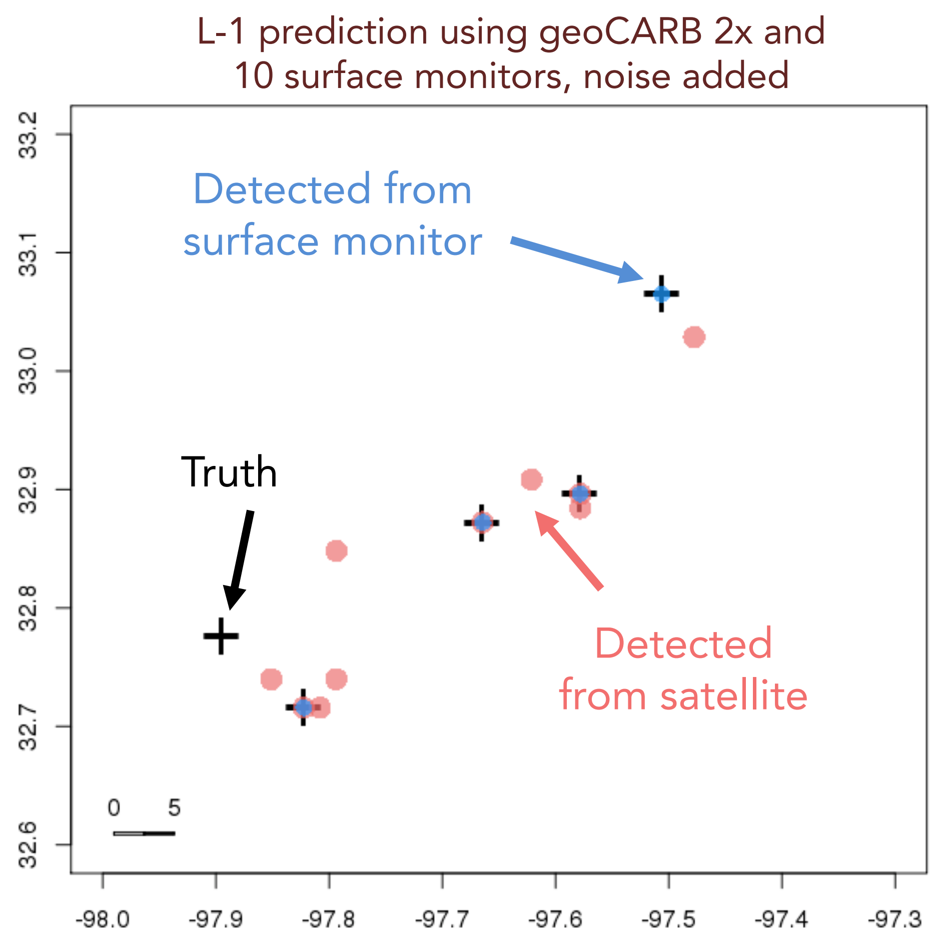
Maximum xCH4 "observed" over Oct. 19-25



Sometimes emitter co-located in boxes of highest xCH4 enhancements, sometimes not.

For some realizations, geoCARB/satellite detections get within 5km of all high-mode emitters, though at the expense of potential false positives.





Current Status, Moving Forward

geoCARB shows promising potential to be able to detect anomalous high-mode emissions from well-pads or other fat-tailed methane sources.

Adding tolerance to a prediction greatly improves its true-positive probability.

For a 100-emitter field, we find that geoCARB twice daily coupled with 10 surface monitors provides the best balance between false-positive and false-negative predictions.

We are currently setting up an inversion for a combined satellite/surface Jacobian. This requires understanding the error-covariance between surface and satellite footprints.

We are analyzing optimal surface configurations for 500 and 1000 emitters.