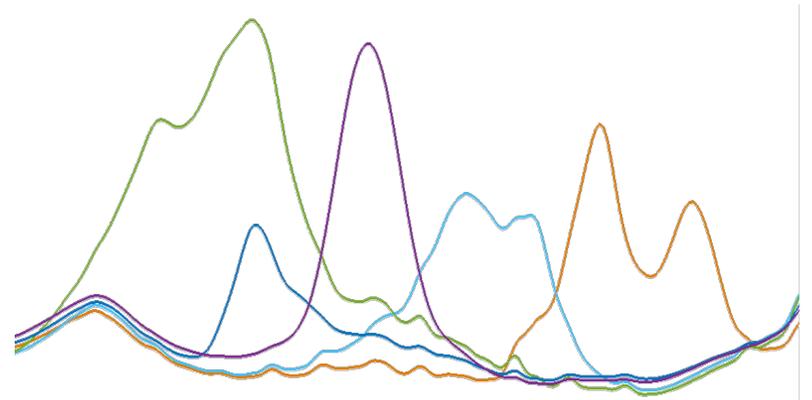


FT-IR OC AND EC: REEVALUATING BIASES AND CALIBRATION UPDATING



A.T. (Andy) Weakley
Ann M. Dillner
Air Quality Research Center
University of California, Davis

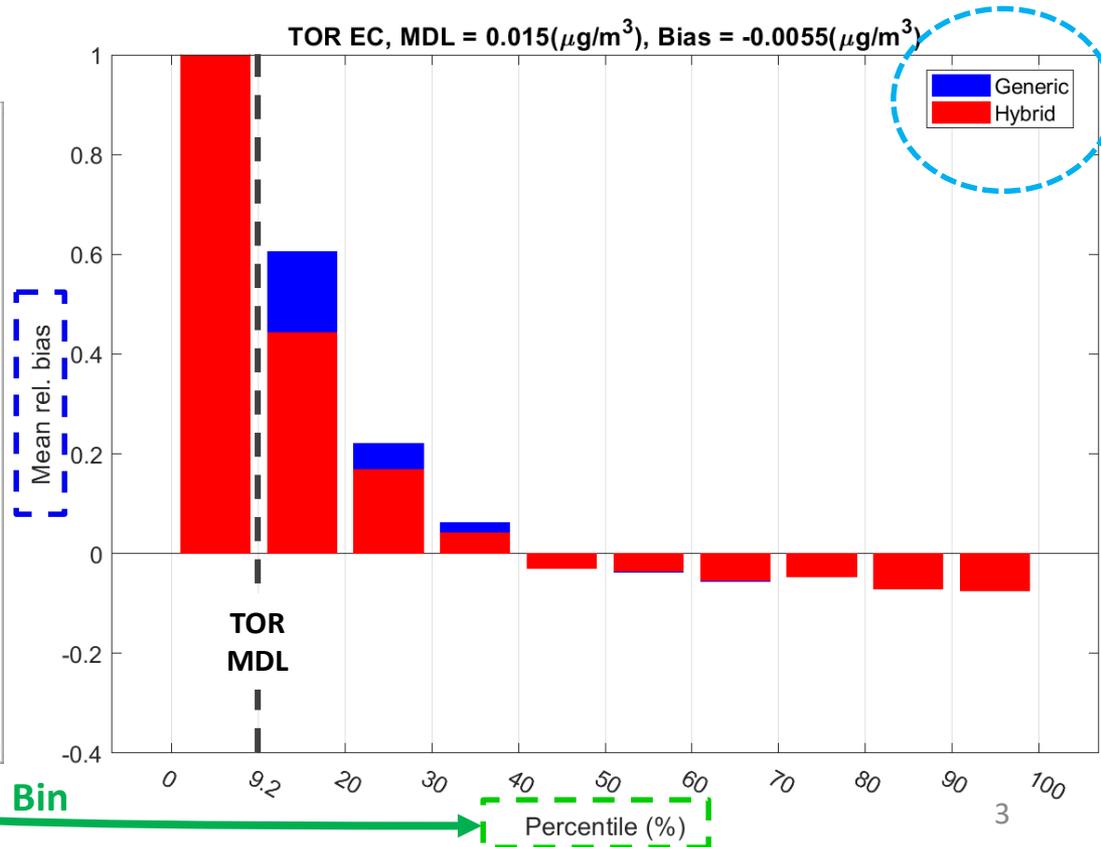
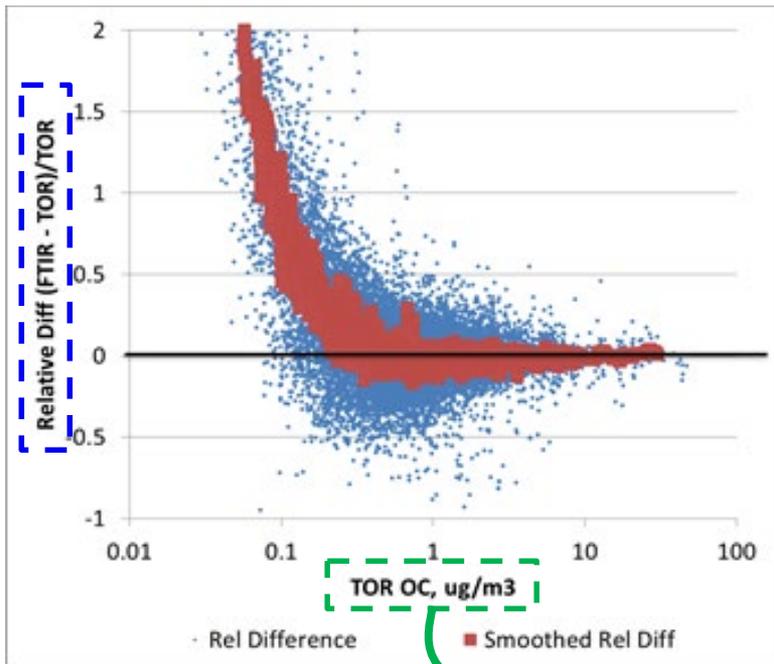
IMPROVE Steering Committee
Point Reyes National Park, CA
October 22, 2019

FT-IR Calibration: Outline

- Biases in FT-IR models
 - 2018 IMPROVE Steering Meeting **addressed FTIR bias**: $[\text{Bias}] = [\text{FTIR}] - [\text{TOR}]$
 - **Discovery**: Scatter plot of $[\text{Bias}]$ vs. $[\text{TOR}]$ *always* shows a (false) trend.*
 - Trend related to how the *geometry of how least squares works*
 - *Real measurement bias* found on $[\text{Bias}]$ vs. $[\text{FT-IR}]$ plots (or time series)
- Recalibration for (routine) OC and EC prediction
 - Propose a moving window method for calibration updating
 - AQRC database synchronization

FT-IR OC and EC “bias plots:” What you may have seen last year...

- **Presented with a problem...**
 - $[\text{rel. Bias}] = [\text{FTIR-TOR}]/[\text{TOR}]$
- **Led us to a diagnostic tool: the “mean relative bias plots”***
 - Bin samples using data percentiles
 - Calculate mean rel. bias within each bin
- **One objective for 2018 meeting:** presented *various ways to (try) to reduce* “the bias trend”



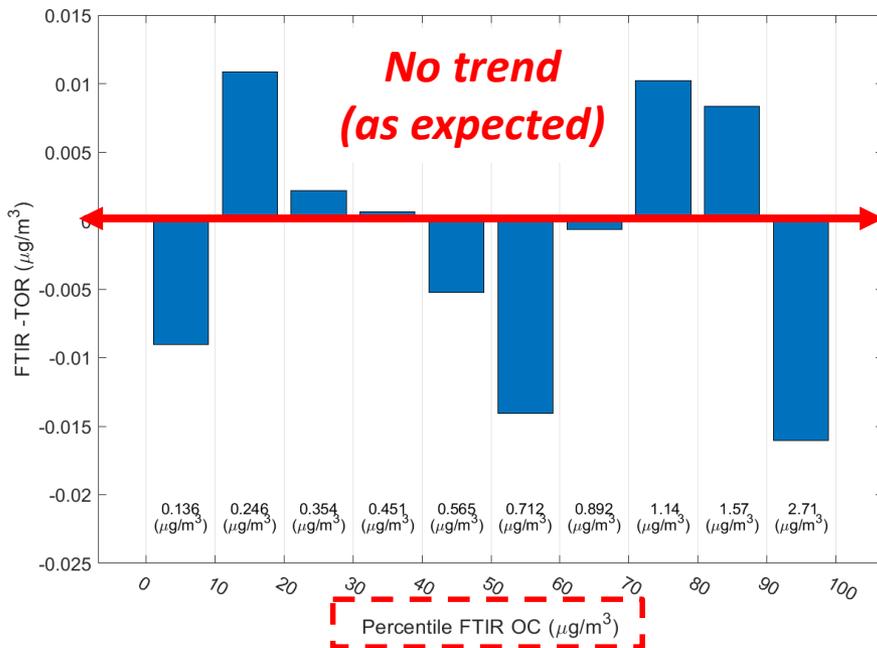
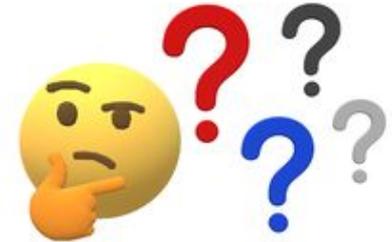
Figures adopted from “RE: FTIR OC and EC data for 2015” from Bret.Schichtel@colostate.edu

*- Taken directly from Dillner et al. 2018 IMPROVE STEERING presentation

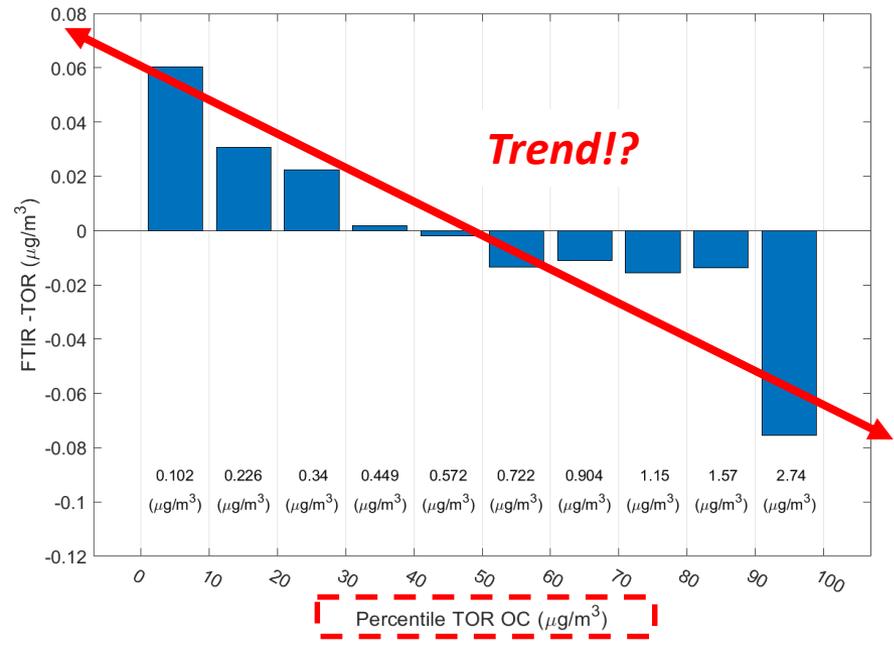
From Reality to Simulations...

Stranger Things with Least Squares

- Simulated simple “FT-IR OC calibration”– one X variable , one Y variable ($N=1,000,000$)
 - X =[one IR absorption measurement]
 - Y =[TOR]
 - $\hat{Y} = X * b$ =[FTIR]
- **No bias in this simulation!**



Plot bias **against FTIR**

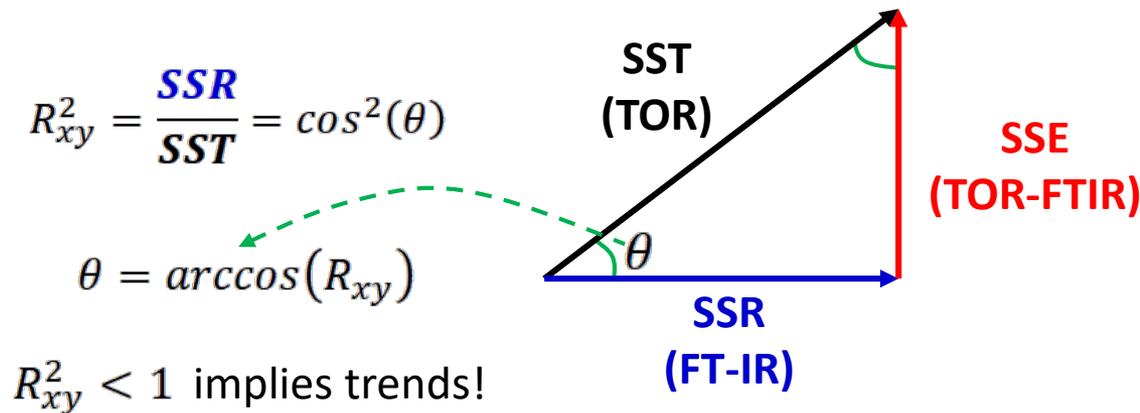


Plot bias **against TOR**

Why does this always happen with least squares?

- **Geometry.**

- Easiest way to understand: *sum-of-squares partitioning of Y (TOR)*



[Sum-of-squares in TOR] = [SS explained by FTIR calibration] + [SS error]

SST = SSR = SSE

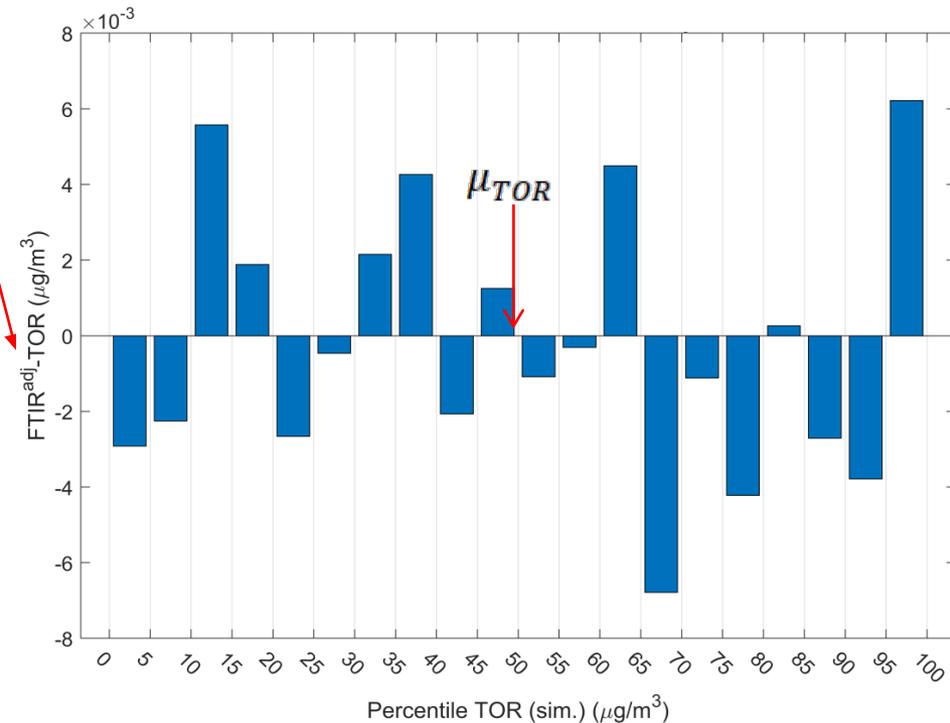
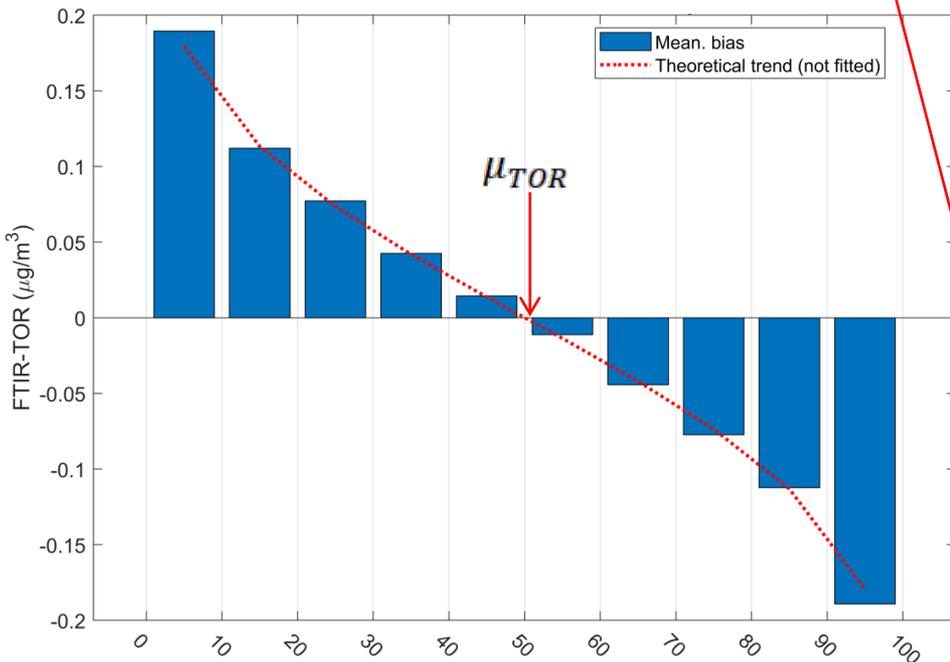
Attributes:

- **Oblique angles** imply dependence between sides
- Plotting dependent data (x,y) **implies trends** → hence our “bias” problem!
- Final note: **what’s the angle θ ?**

How to address geometry:*

Adjustment by Example

- Geometry **suggests...*** $[FTIR - TOR] = (1 - R_{xy}^2)\mu_{TOR} - (1 - R_{xy}^2)[TOR]$
Intercept (+) *Slope (-)*
- To adjust FTIR predictions to counter trend...
 - Rearrange and solve for TOR $[TOR]_i = \frac{1}{R_{xy}^2}([FTIR]_i - \mu_{TOR}) + \mu_{TOR}$
 - Rename TOR to **FTIR^{adj}** $[FTIR]_i^{adj} = \frac{1}{R_{xy}^2}([FTIR]_i - \mu_{TOR}) + \mu_{TOR}$



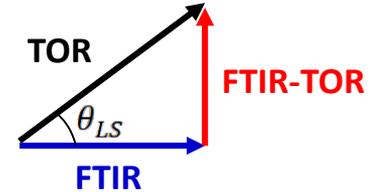
* Other solutions possible—this is a least squares soln

How to address geometry:*

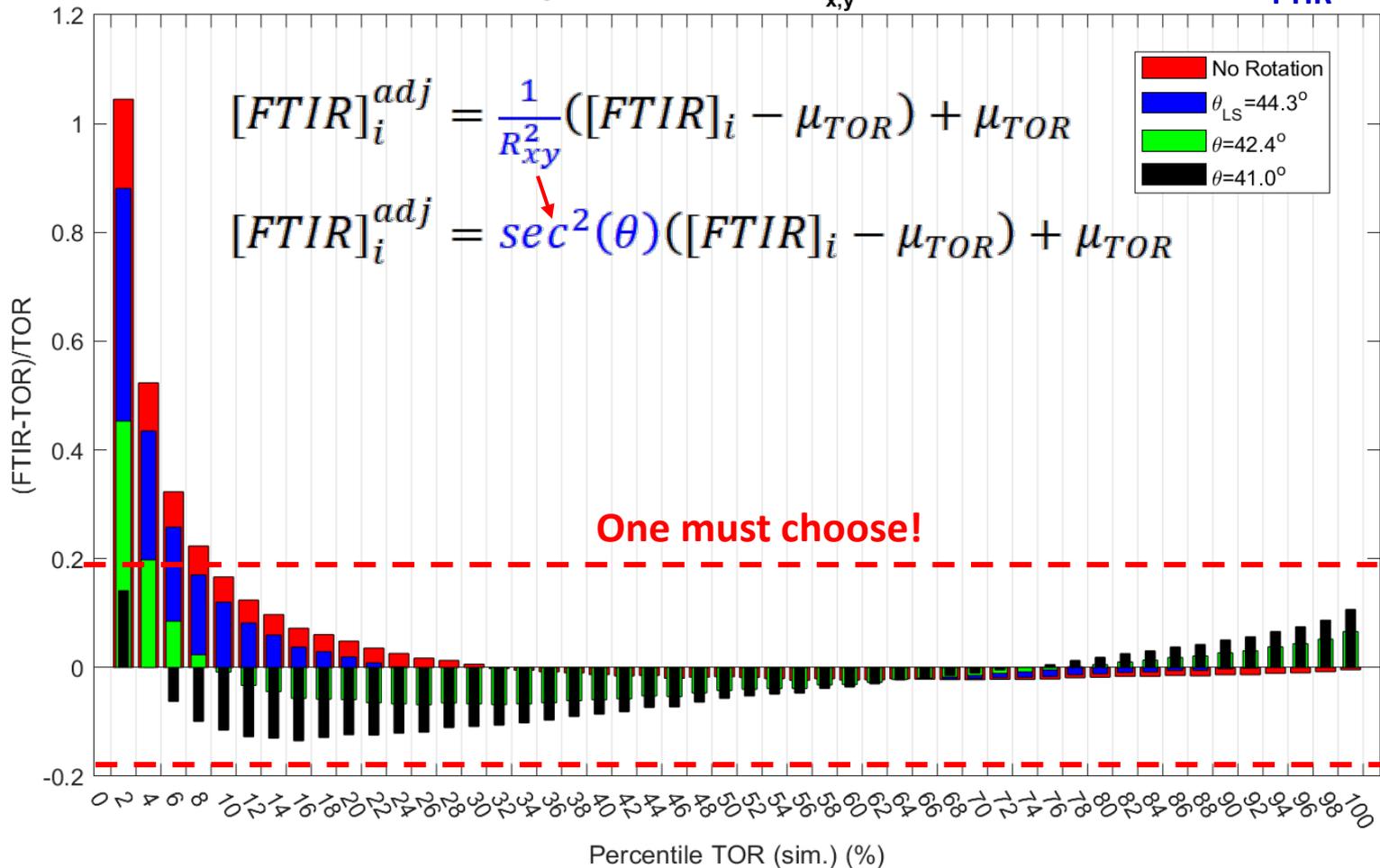
A General Framing

If data are **not normal** (e.g., lognormal), use **generic adjustment expression**

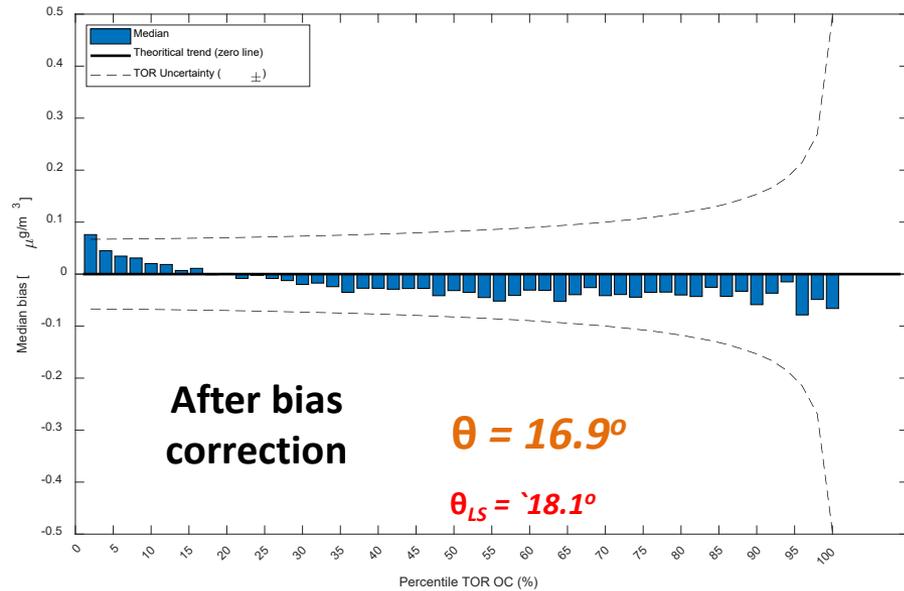
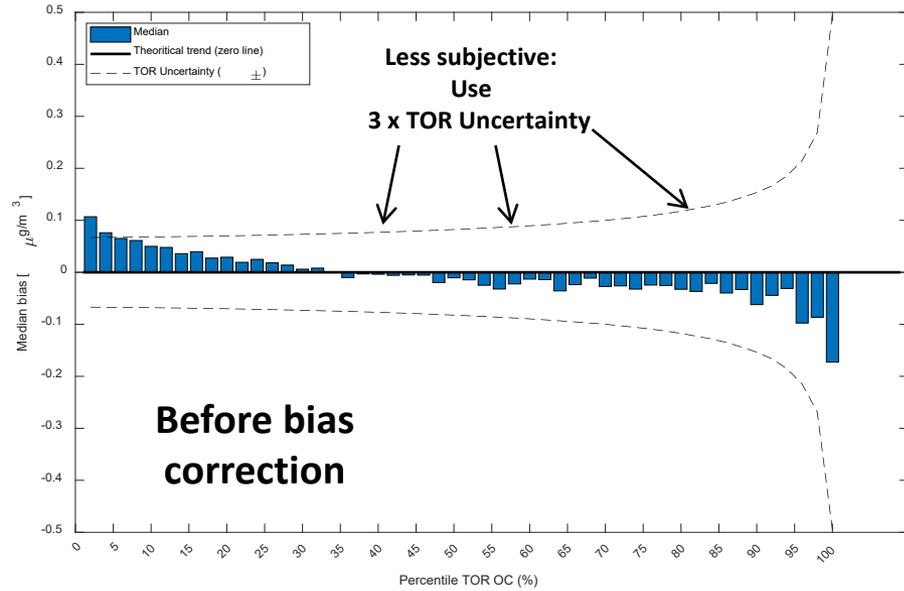
1. Calculate θ from the least squares solution $\rightarrow \theta_{LS} = \arccos(R_{xy})$
2. Adjust θ by trial-and-error



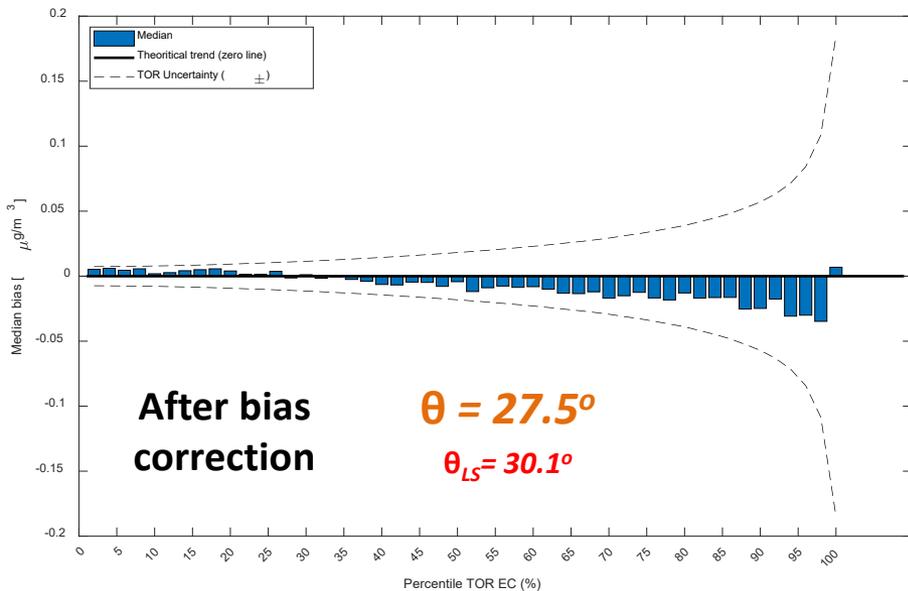
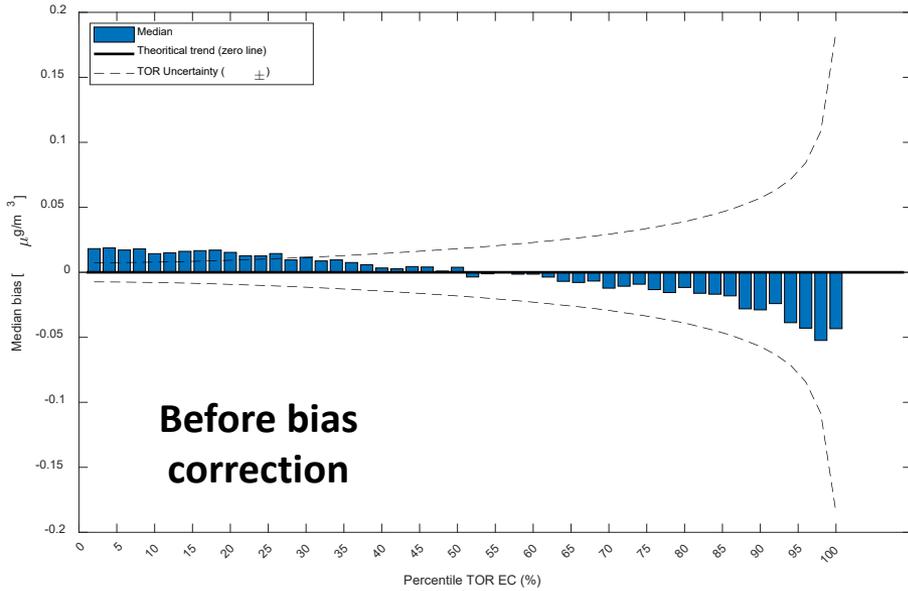
Lognormal, N=500000, $R_{x,y}^2 = 0.9663$



IMPROVE 2015 – Median bias OC

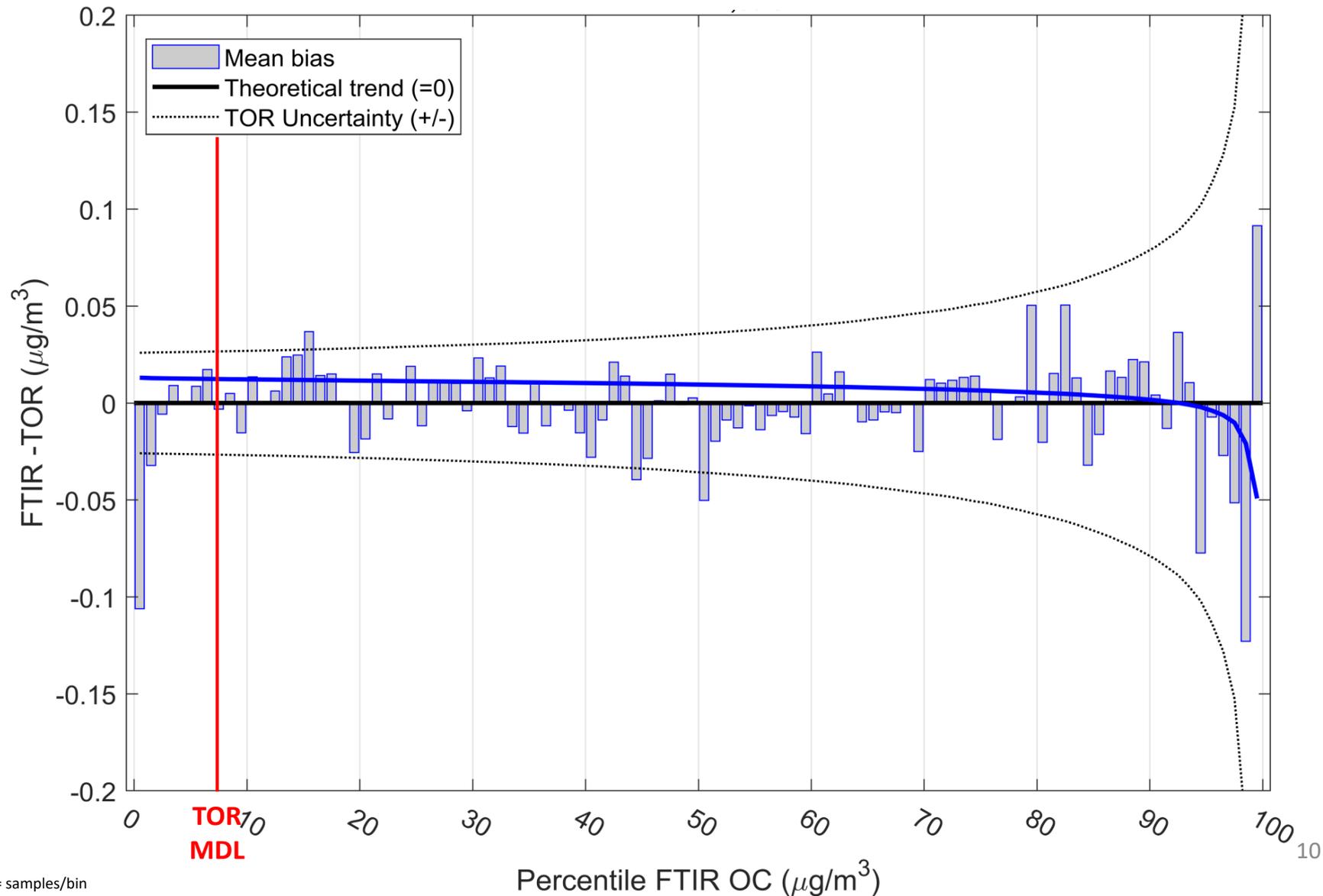
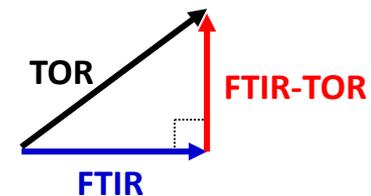


IMPROVE 2015 – Median Bias EC

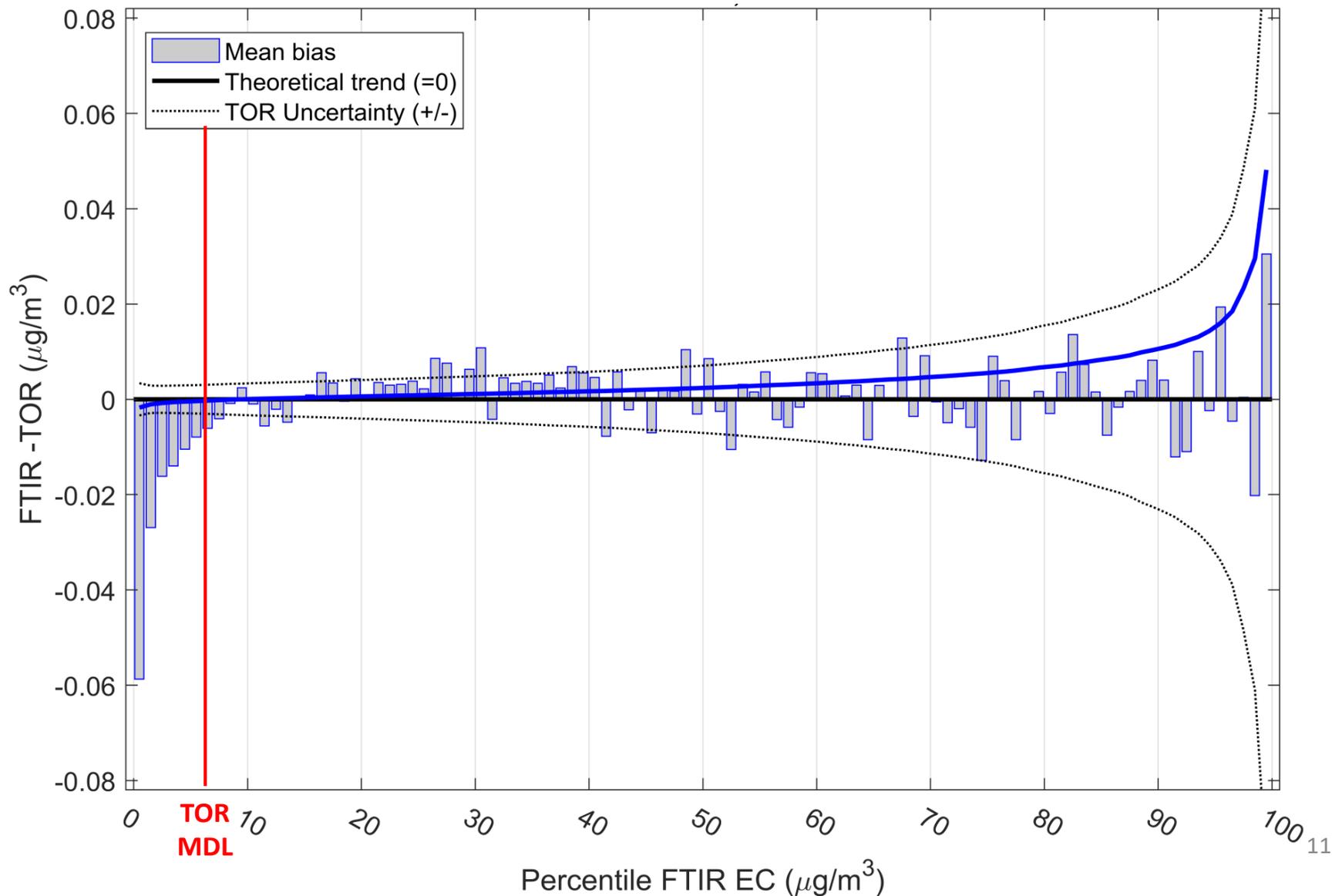




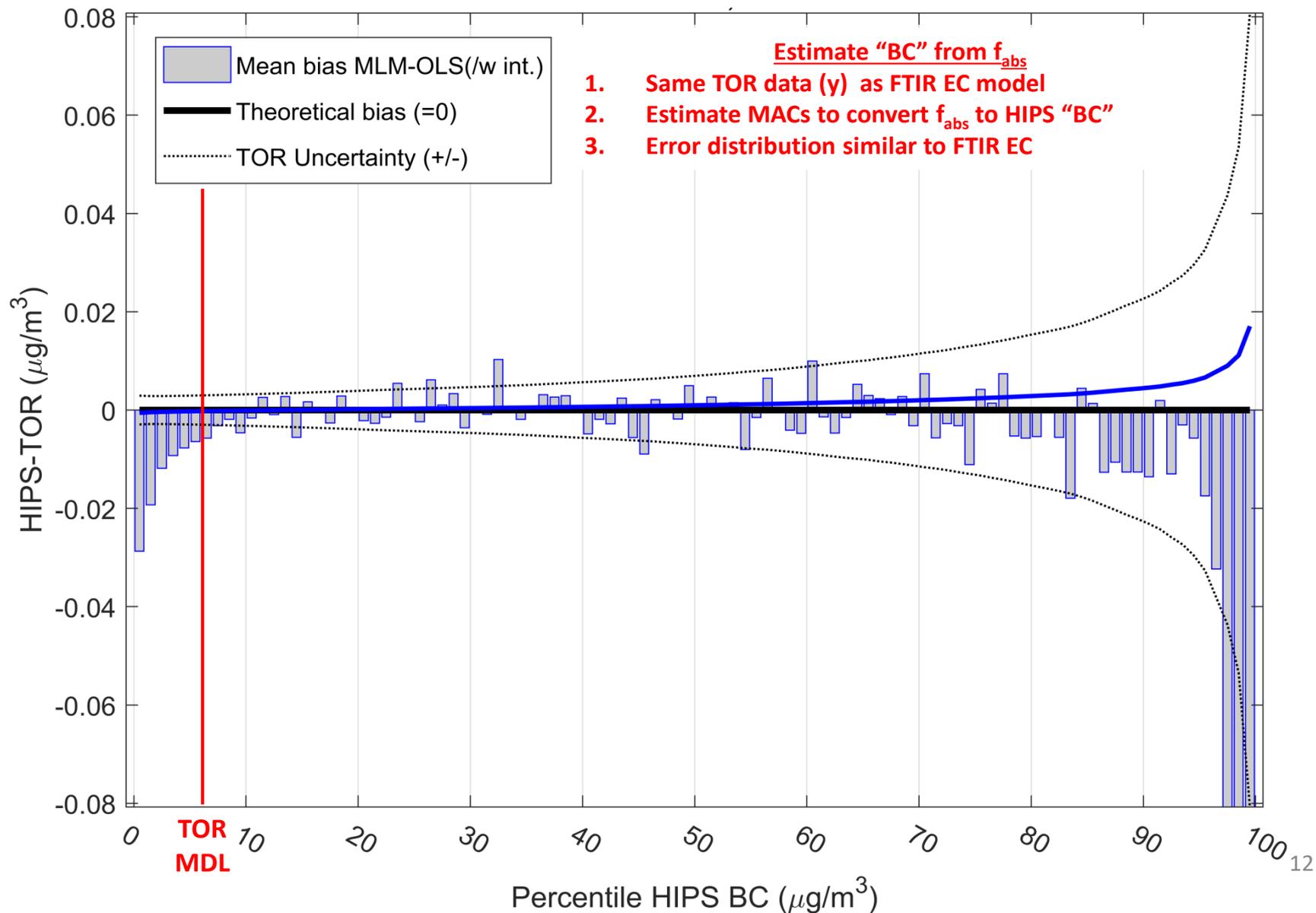
Real Measurement Bias in FTIR OC



Real Measurement bias in FT-IR EC



Real Measurement biases in HIPS “BC”: A non-FTIR example



Recalibration for Routine OC and EC Prediction

An Example

- Say we...
 - Develop an **FT-IR OC calibration** from *three months* of IMPROVE 2013 samples
 - Calibration spans: July 1, 2013 – Sept. 30, 2013
 - Reminder: “A calibration” = a set of coefficients, ***b***, that converts IR absorption into mass (OC or EC), i.e.,

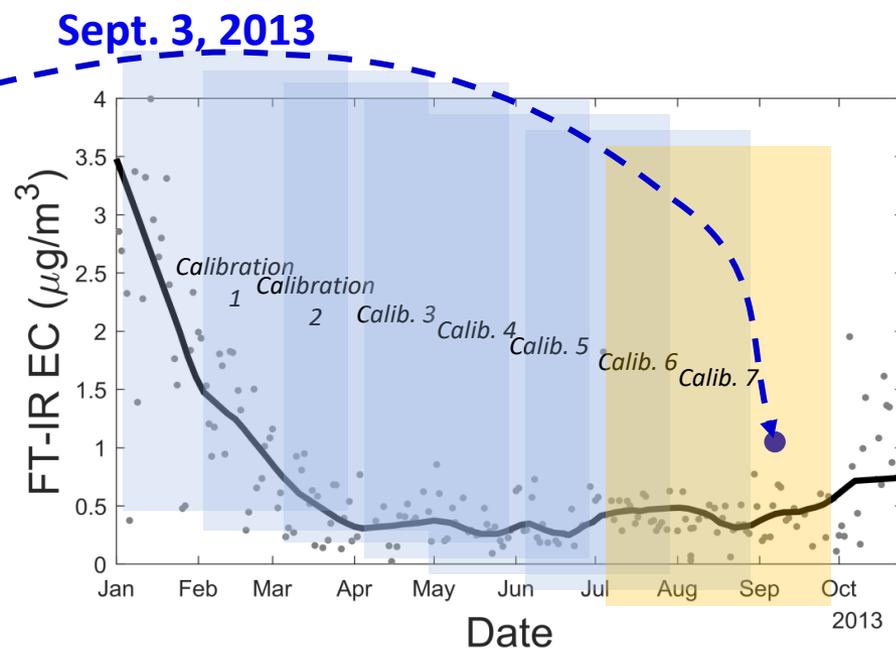
$$[OC] = [spectrum] * b$$

- Q: What’s an efficient way to regularly update the calibration to ensure robustness?
- A: Employ an **“moving window” type calibration**

How it works: A Three Month Moving Window Example

Potential Benefits

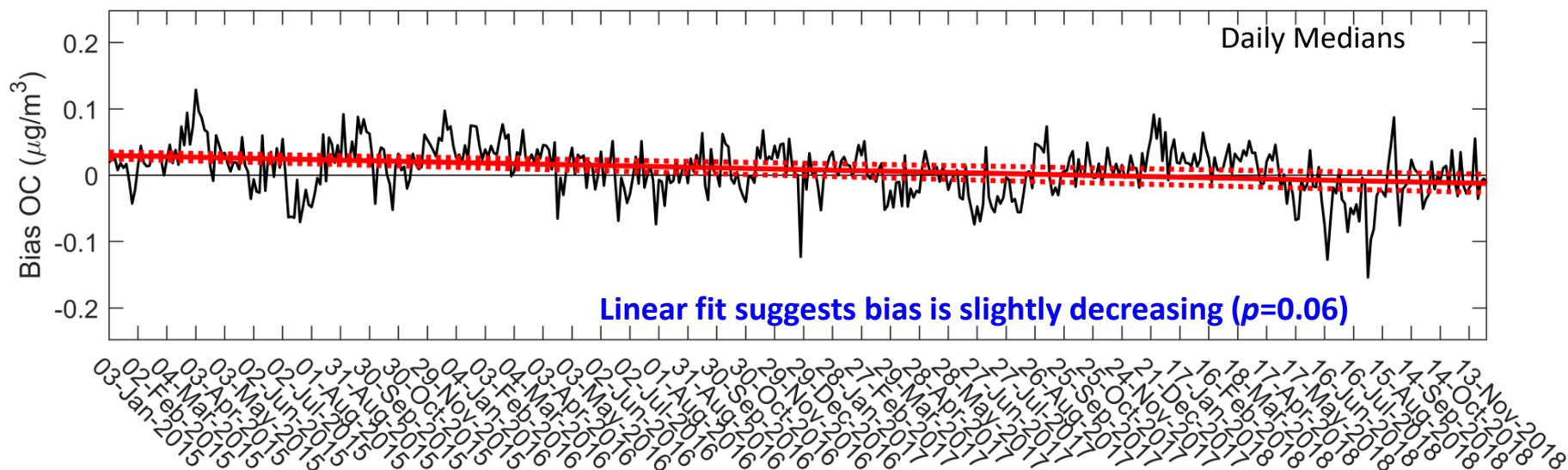
- Tunes the calibration to *instrument shifts/drifts (in FTIR and TOR instruments)*
- May adapt the calibration to *seasonality*



Moving Window Performance on IMPROVE 2015-2018 OC

Year	R ²	Bias (%)
2015	0.969	3.2
2016	0.877	2.2
2017	0.976	-0.2
2018	0.980	-0.3

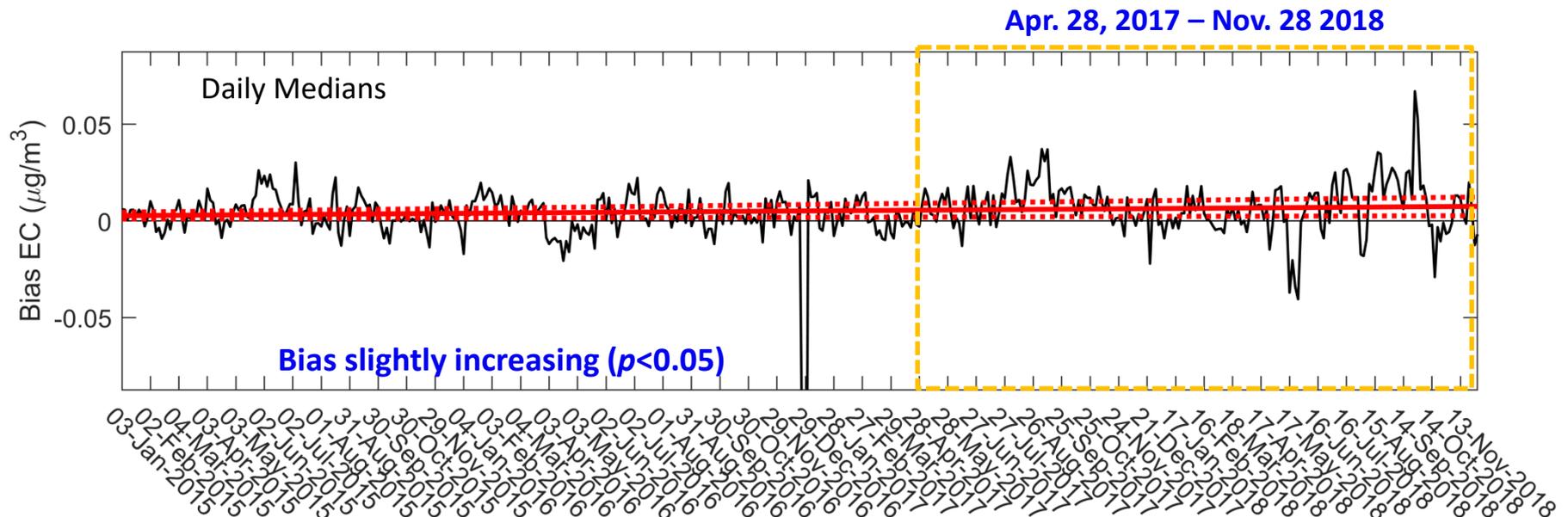
- **Twelve-month moving window** works best
 - Used 14% IMPROVE sites as per Bruno's analysis
 - Window shifts in one month increments
- Performance for four years of data...
 - *Roughly speaking: FT-IR OC bias appears to improve over time*



Moving Window Performance

IMPROVE 2015-2018 EC

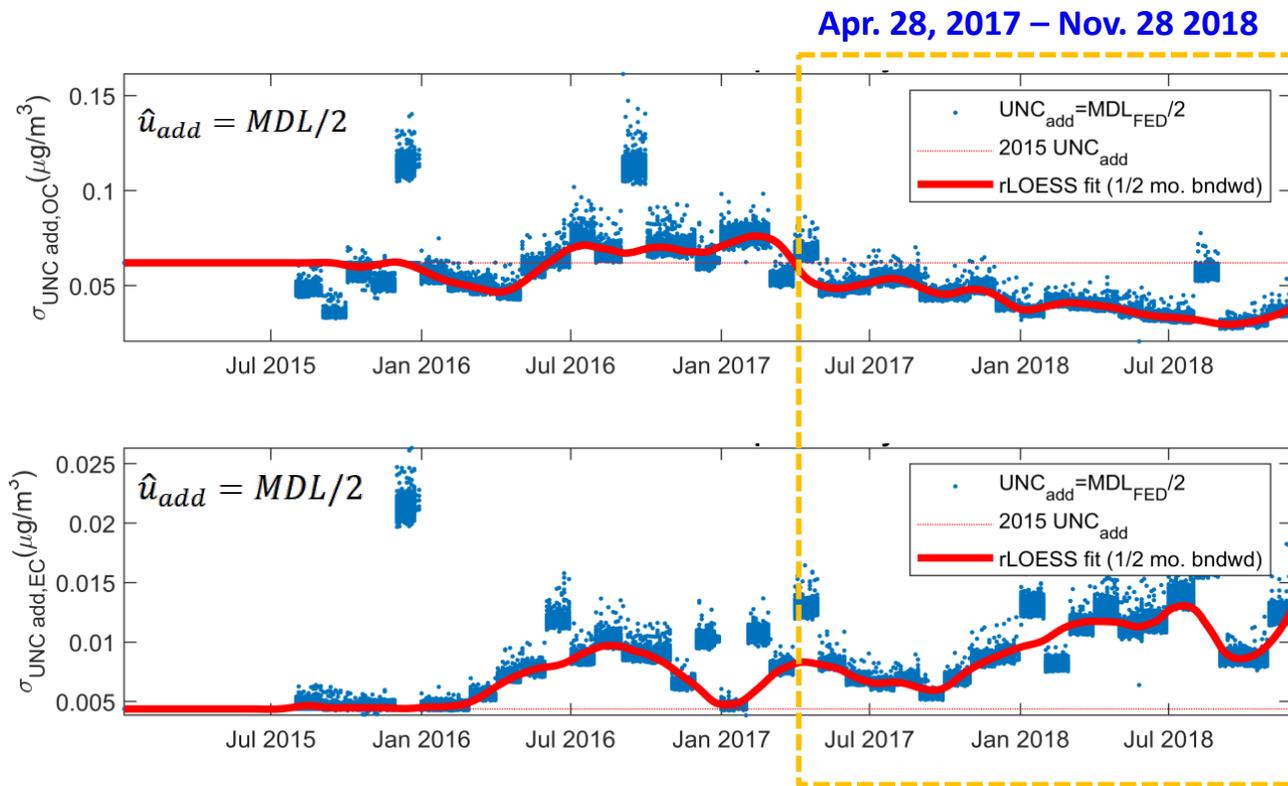
Year	R ²	Bias (%)
2015	0.879	5.1
2016	0.874	3.6
2017	0.871	6.5
2018	0.807	5.4



A Question on Drift: Where does it come from?

- Perhaps TOR?

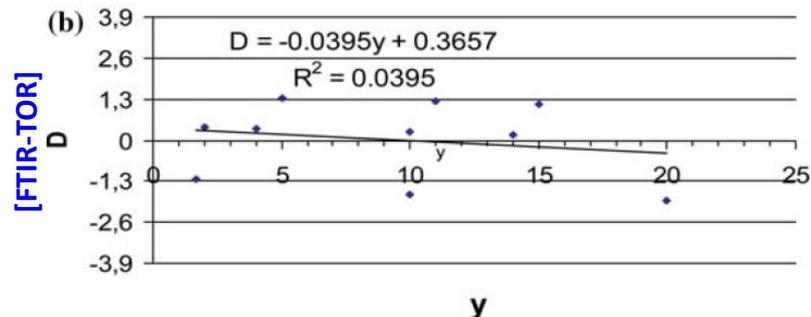
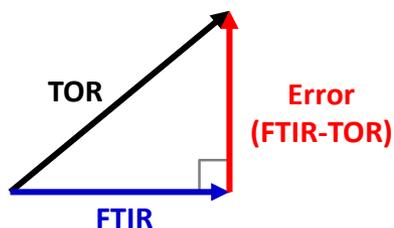
- Downloaded MDL data from the FED wizard (August 25, 2019) $\hat{u}_{add} = MDL/2$



Conclusions: Biases

1. Geometry of least squares guarantees

- A linear trend on [Bias] vs. [TOR] plot
- **Occasionally revisited in the literature**



Besalú, E., et al., *An overlooked property of plot methods.*
Journal of Mathematical Chemistry, 2006. **39(3)**: p. 475-484.

2. May adjust geometric bias on [FT-IR]-[TOR] vs. [TOR] plot

- Neither revisited nor mentioned in the literature...

3. True measurement biases found on...

- [FT-IR]-[TOR] vs. [FT-IR] plot
- [FT-IR]-[TOR] vs. time plot
- **Use these plots for diagnostic purposes before θ adjustment!**

Practical Conclusions: Routine Calibration Updating

1. Upload(ed) spectra into AQRC database
 - IMPROVE 2017 through present in IMPROVE database
 - 2015 and 2016 to be added within a month
 - All CSN spectra (2017-present) are in CSN database
2. Database: connects collocated TOR data with FTIR spectra
 - For **14% of IMPROVE sites** and **13% of CSN sites** that retain TOR
3. Update calibration: ***moving window, monthly shifts***
 - Determine FTIR OC and EC in all samples ***from all IMPROVE sites***
4. Future work:
 - Assess ability to handle drift in FTIR and TOR measurements
 - Assess impacts of aerosol sources on predictions (and drifts)

Acknowledgements

- Funding for this project:
 - EPA and IMPROVE (NPS Cooperative Agreement P11AC91045)
 - EPRI (Agreement 10003745 and 10005355)
 - Swiss Polytechnic University-Lausanne (EPFL)
- Collaborators, post-docs and graduate students (and many undergraduate students):
 - Satoshi Takahama
 - Andy Weakley
 - Bruno Debus
 - Alexandra Boris
 - Mohammed Kamruzzaman
 - Charlotte Burki
 - Jenny Hand
 - Amir Yadzani
 - Travis Ruthenburg
 - Matteo Reggente
 - Brian Trout
 - Katie George
 - Charity Coury
 - Kelsey Seibert
 - Sean Raffuse
 - Tony Wexler
- CSN, FRM, IMPROVE, SEARCH programs and site/state personnel
- Joann Rice, Mike Hays, Emily Li, EPA
- Bret Schichtel and Scott Copeland, IMPROVE
- Stephanie Shaw and Eric Edgerton, EPRI/ARA
- Randall Martin and the SPARTAN personnel, SPARTAN and Washington University
- Dave Diner and MAIA team members, MAIA and JPL

Supporting Analysis

S1: Geometry of least squares: More Advanced
Presentation material

S2: Addl. Moving Window Material, Uncertainty
Calculations

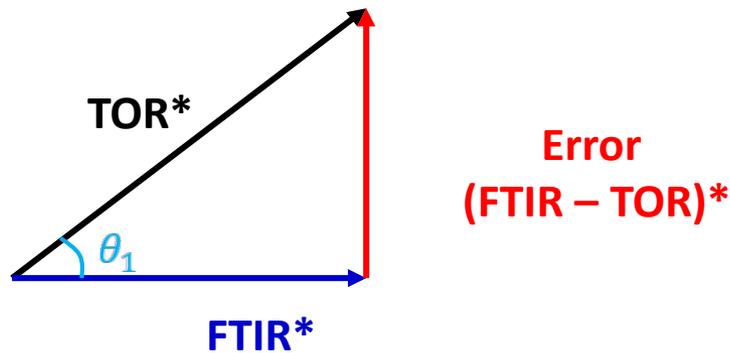
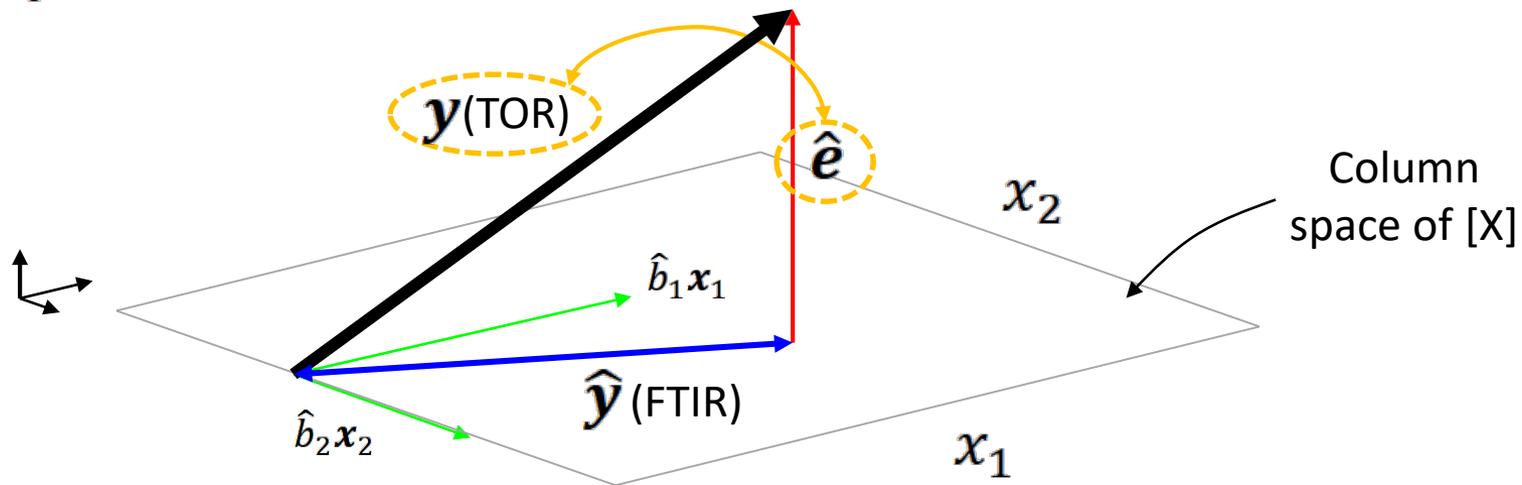
S3: An attenuation model for EC and OP

Section 1: Back to School...

Vector geometry of least squares

$$\mathbf{y} = \hat{b}_1 \mathbf{x}_1 + \hat{b}_2 \mathbf{x}_2 + \hat{\mathbf{e}}$$

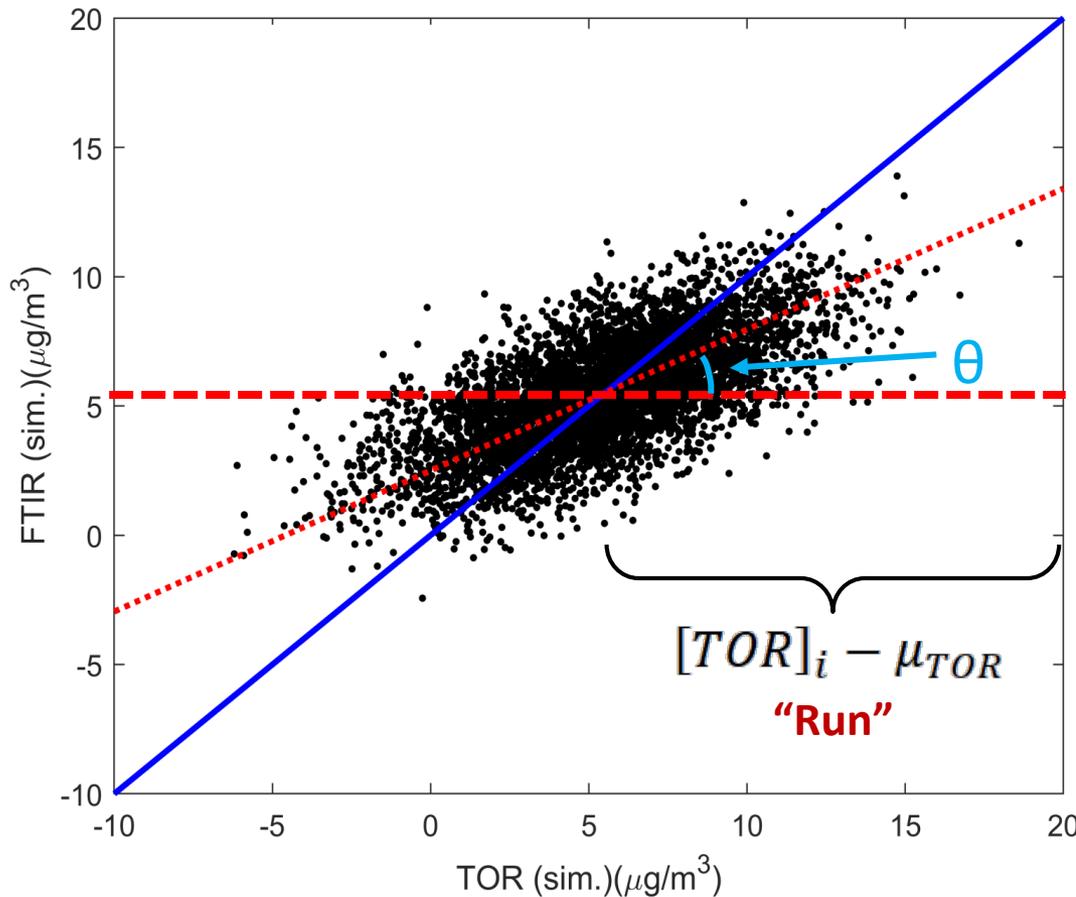
$$\mathbf{y} = \hat{\mathbf{y}} + \hat{\mathbf{e}}$$



* Vector length = sum-of-squares

S1: An Adjustment Formula (ATW thinks this is correct)

Trying to **completely eliminate the bias is a fools errand...**
Nevertheless, it may be addressed.



$$[FTIR]_i - \mu_{TOR}$$

$$\frac{[FTIR]_i - \mu_{TOR}}{[TOR]_i - \mu_{TOR}} = \tan(\theta)$$

Adjustment method

Choose θ by trial and error
until plots “look good”*

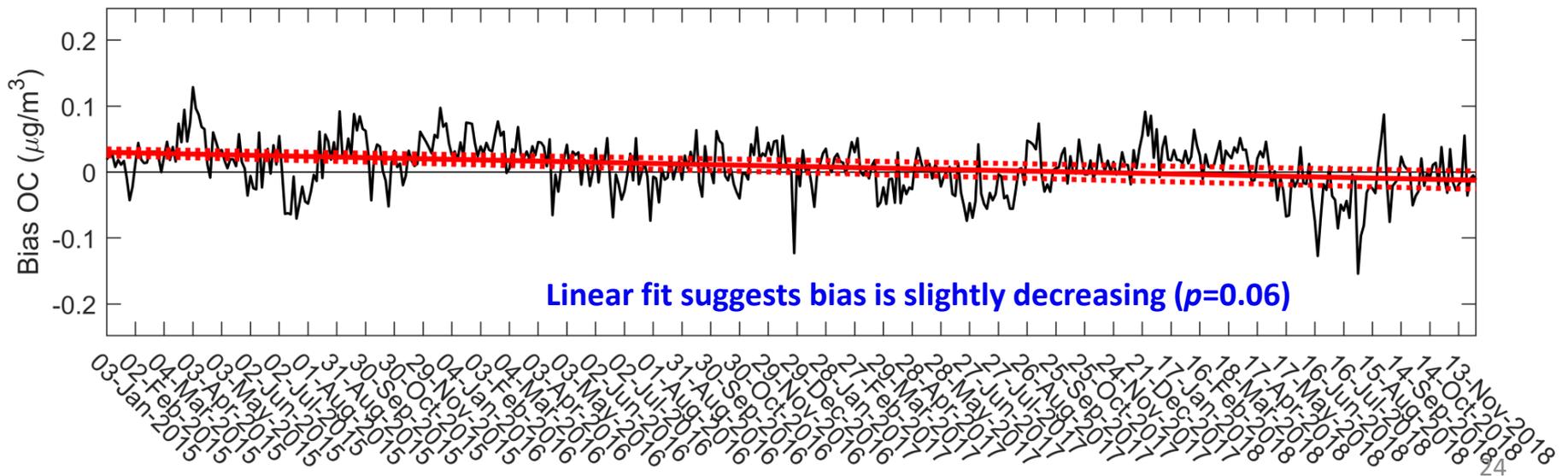
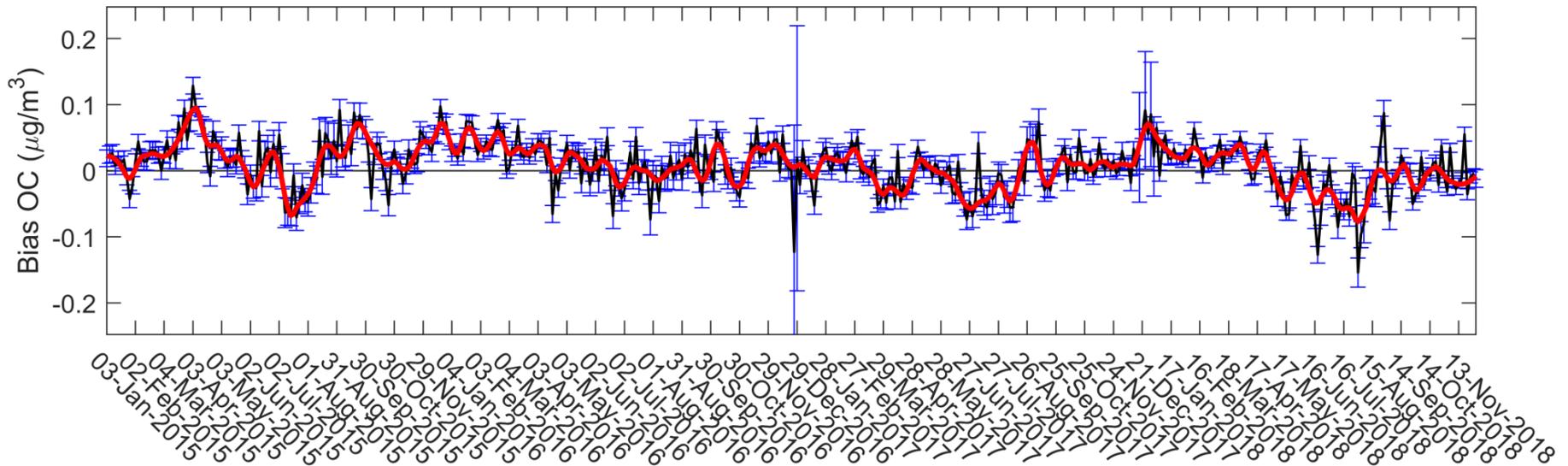
Adjustment equation $[FTIR]_i^{adj} = [TOR]_i = \cot(\theta)([FTIR]_i - \mu_{TOR}) + \mu_{TOR}$

Note that $\theta = \frac{7\pi}{4}\theta_1 \pm \frac{\pi}{4}$ from triangle slide— as far as I can see

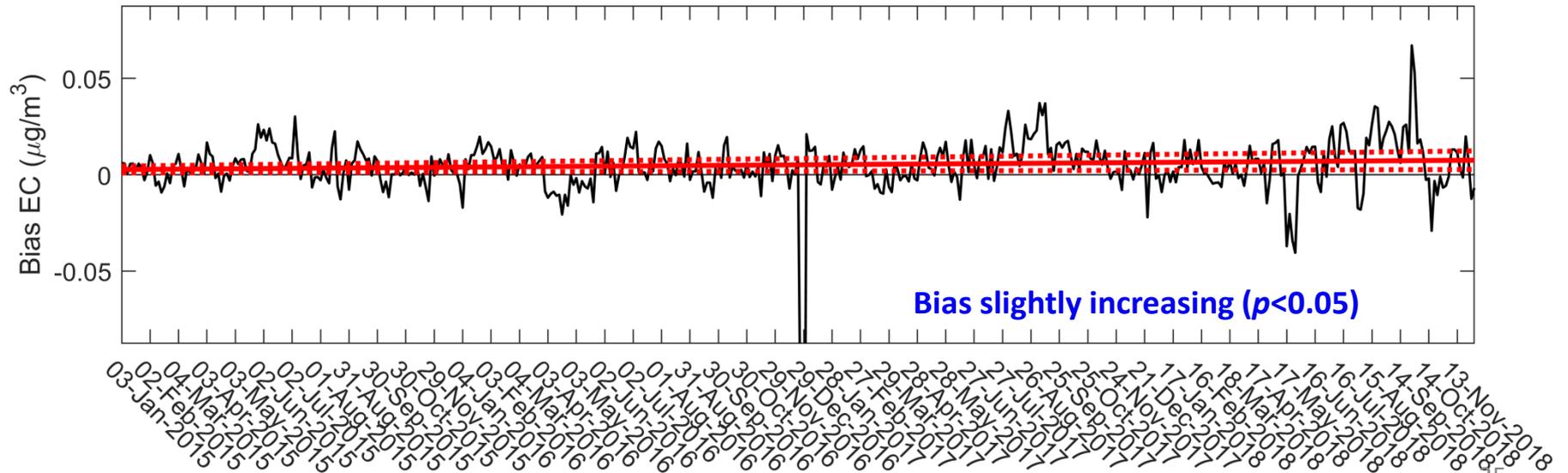
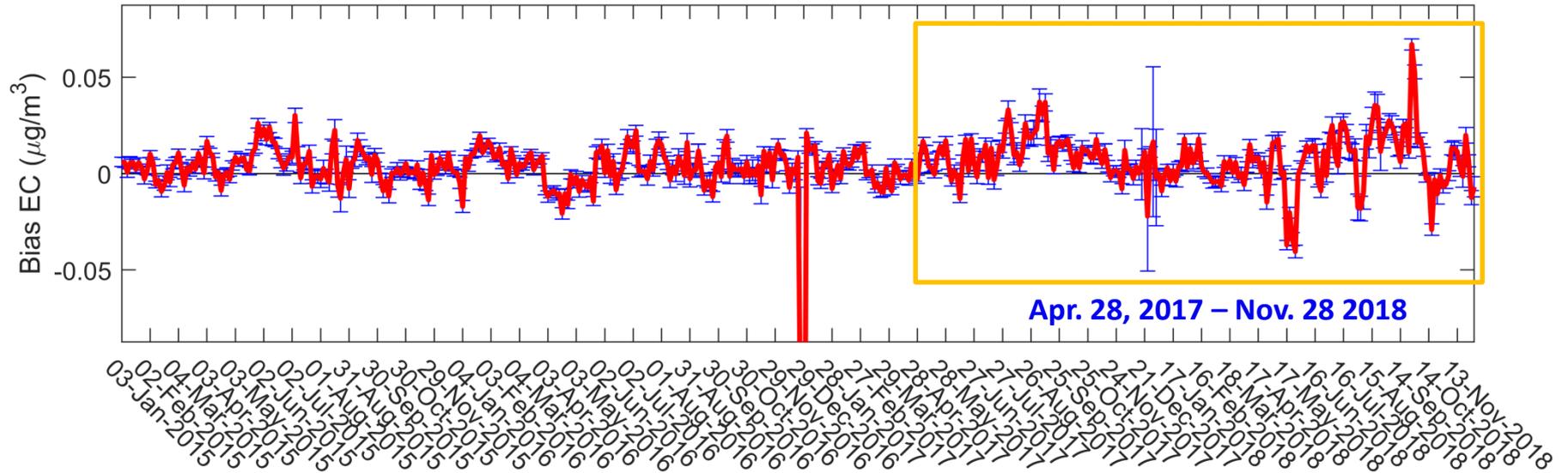
*- There are several solutions that work exactly for normally distributed samples— including a rearrangement of the eqn on the previous slide

Section 2: Moving Window Results

Temporal OC (real) Bias: Daily Medians



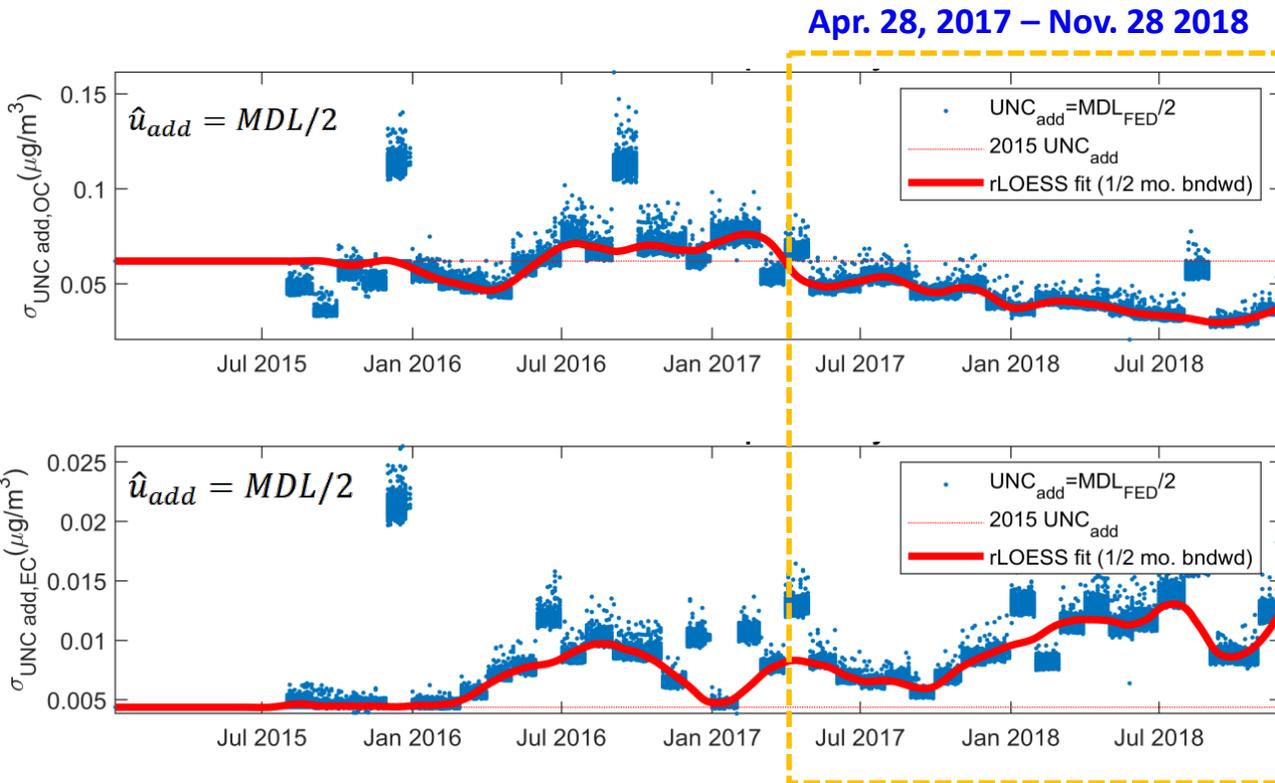
S2 :Temporal EC (real) Bias: Daily Medians



S2: A Question on Drift: Where does it come from?

- Perhaps TOR?

- Downloaded MDL data from the FED wizard (August 25, 2019) $\hat{u}_{add} = MDL/2$



- Notice that OC uncertainty drops and EC uncertainty consequently rises

- Changes track with real FT-IR OC, EC biases through time

S2: Models for Measurement Error and Uncertainty (Restated)

Observations:

- Using standard methods to estimate sample uncertainty in TOR, we see that FT-IR OC errors are approximately on the order of TOR OC (field) errors

– Simply:

$$\hat{u}_{ik} = \sqrt{\hat{u}_{k,add}^2 + \hat{u}_{k,rel}^2 C_{ik}^2}$$

- \hat{u}_i = uncertainty of sample i , species k (e.g., OC)
- $\hat{u}_{k,add}$ = additive uncertainty for species k
- $\hat{u}_{k,rel}$ = relative/multiplicative uncertainty for species k
- C_{ik} = mass concentration of sample i , species k

Other details on metric calculations

Additive uncertainty (u_{add} ; C_{FB} = field blank conc.)

$$\hat{u}_{k,add} = \frac{P_{95}(C_{i,FB}) - P_{50}(C_{i,FB})}{\Phi^{-1}(1 - \frac{\alpha}{2})} \approx \frac{P_{95}(C_{i,FB}) - P_{50}(C_{i,FB})}{2}$$

Robust standard deviation
(normal, $\alpha=0.05$)

MDL (k=2) is a rearrangement of the expression

$$MDL = 2\hat{u}_{k,add}$$

Relative uncertainty (u_{rel})

$$\hat{u}_{k,rel} = \frac{P_{84}(D_i) - P_{16}(D_i)}{2} \leftarrow D_i = \frac{C_{i1} - C_{i2}/\sqrt{2}}{\bar{C}_i} \leftarrow \bar{C}_i = \frac{C_{i1} + C_{i2}}{2}$$

Current Approach:

Fed Download, fit, interpolate (round 1)

- According to IMPROVE (DRI) SOPS we can use...

- Therefore, as we showed on previous slide...

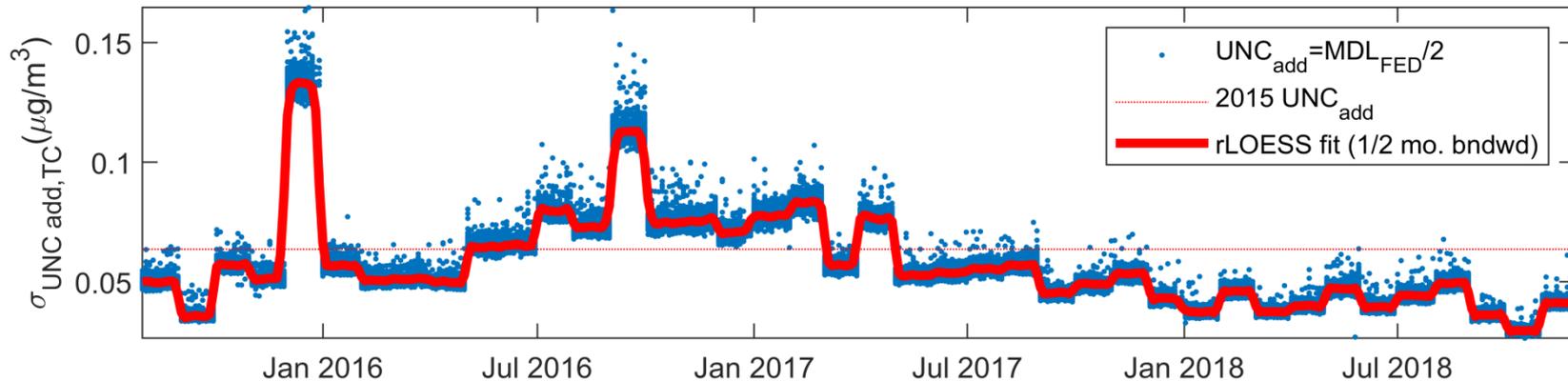
$$\hat{u}_{add} = MDL/2$$

- Since MDLs are not associated with each sample, let's fit a function (smoother) to the time series and then **find uncertainty for each sample via interpolation**

- First, used a robust smoother with an 1/2 month bandwidth to eliminate (false) jumps in uncertainty (red line)

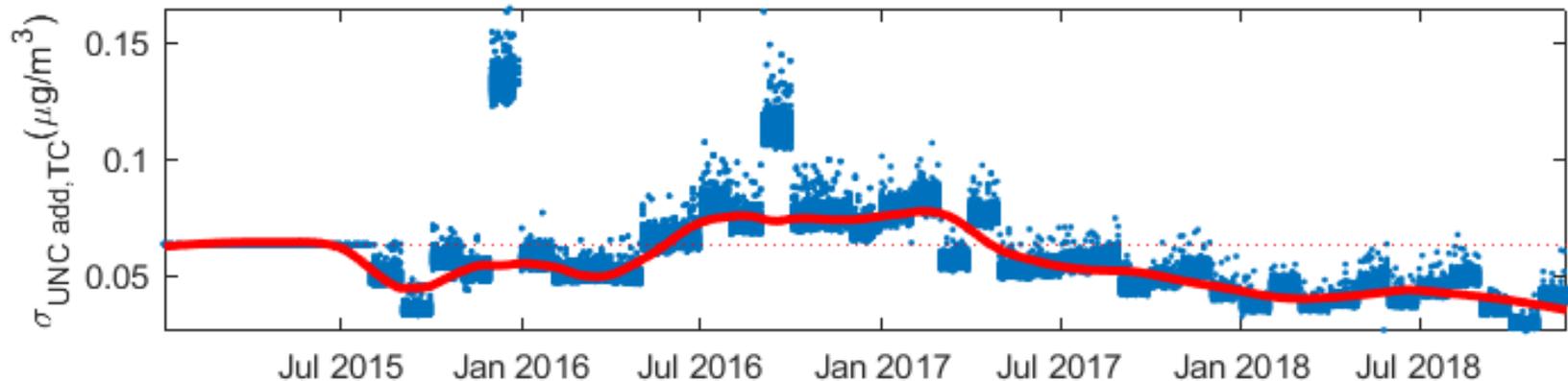
- Nice piecewise behavior—probably not physically realistic

- MDLs were not available for OC,EC,TC from Jan.-Aug. 2015 → used a constant value (not shown) from our database over this range (red dashes)

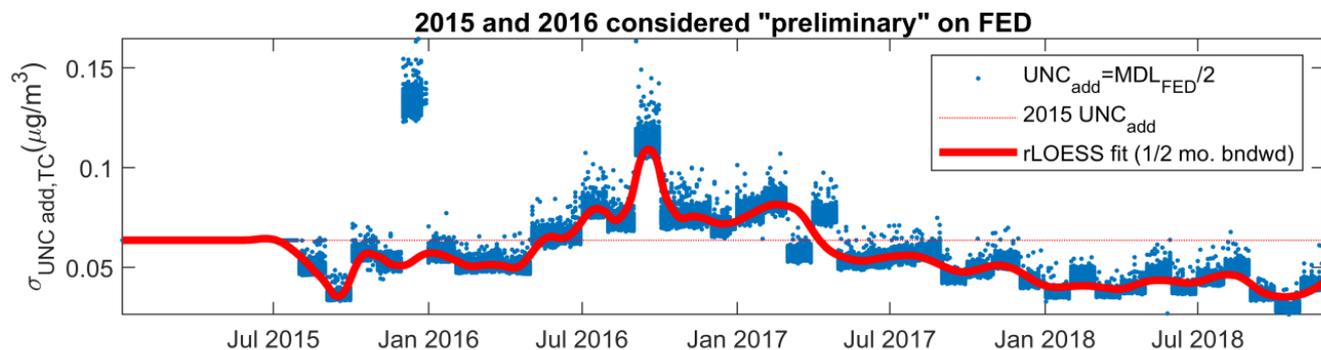
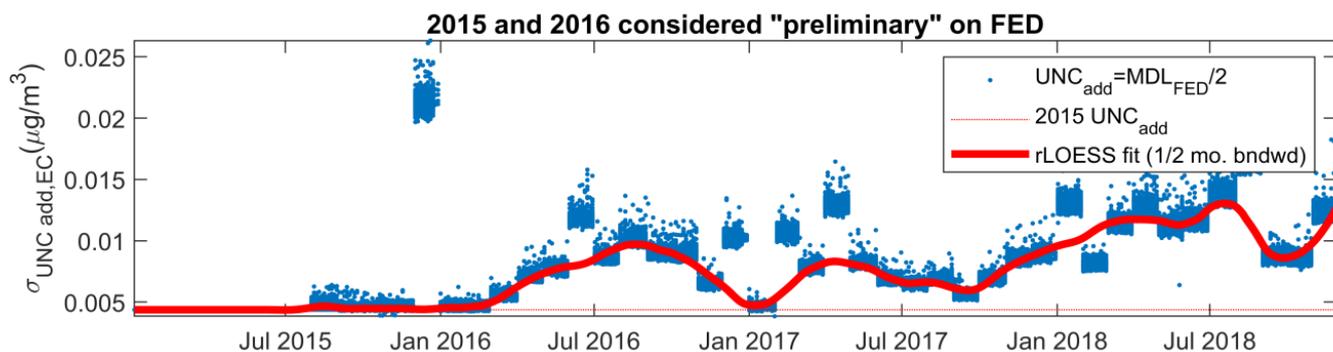
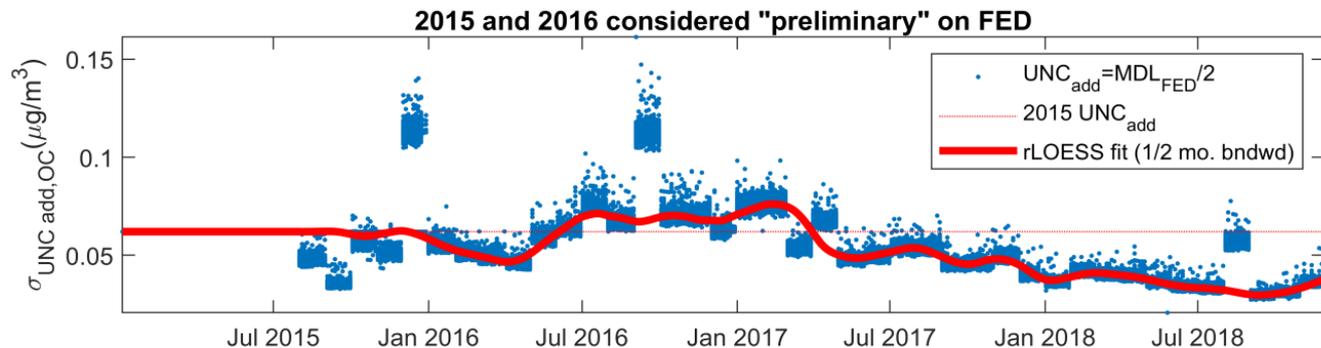


Better approach: 8mo bandwidth

- Certainly appears more reasonable to assume a smoother series
 - ***Downward trend in uncertainty starting ~Jan. 2017***
 - DRI changed FID to IR detector
- But does that seem reasonable?
 - Is this the real life, or is this just fantasy?*



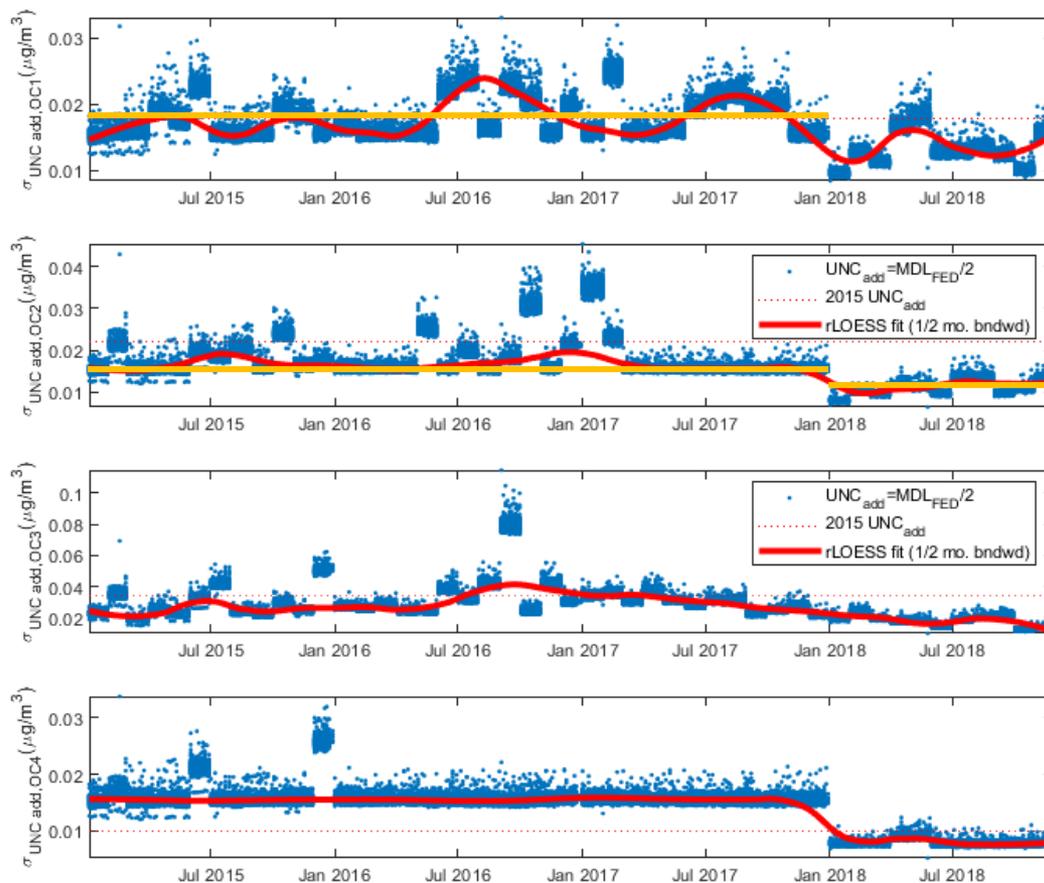
Looking at OC, EC, and TC



- OC additive uncertainty *decreases*
- EC additive uncertainty correspondingly *increases*
- Interesting since these uncertainties probably should not be *physically* coupled, perhaps?
- Furthermore, what explains an increase in EC additive error?
- **Review sources of additive error in TOR**

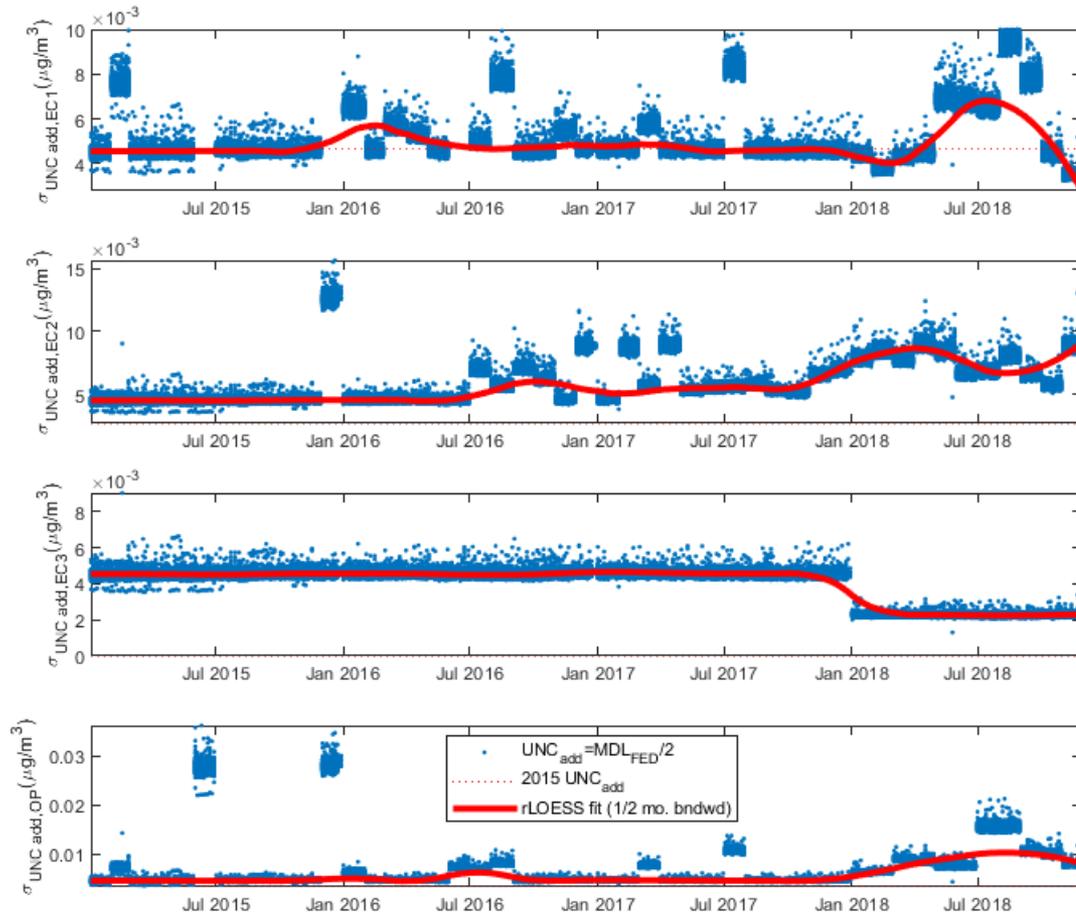
Additive Uncertainty in OC fractions

- Some calculation methodology probably changed in 2018— according to OC4
- Could explain some or all of the downward “trend”



Additive Uncertainty EC Fractions

- Calculation methodology probably changed in 2018— clearest in EC3
 - Could explain some or all of the upward “trend”



Section 3:

A Model for EC and OP Attenuation?

- Chow et al. (2004) presents the following (simple) model of attenuation whereby EC and OP may be determined from He-Ne transmittance— in the TOR oven— according to the following governing equation...

$$[\text{Carbon}]_{\text{after } O_2} = [\text{EC}] + [\text{OP}] = \frac{\tau_{\text{attn,EC}}}{E_{a,\text{EC}}} + \frac{\tau_{\text{attn,OP}}}{E_{a,\text{OP}}}$$

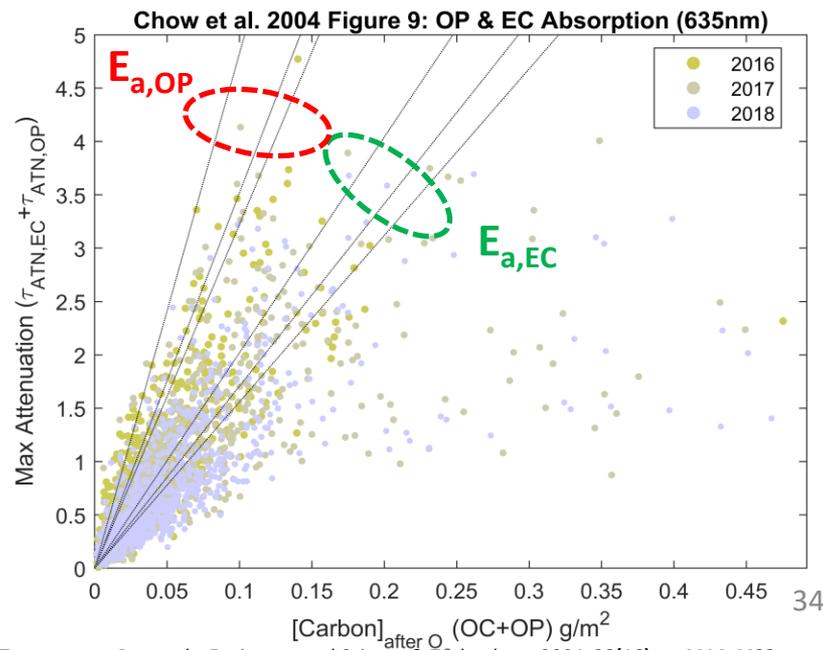
$$\tau_{\text{attn,EC}} = -\ln\left(\frac{T_i}{T_f}\right) \quad \tau_{\text{attn,OP}} = -\ln\left(\frac{T_{\text{min}}}{T_i}\right)$$

- Perform a linear regression as...

$$y = [\text{EC}] + [\text{OP}]$$

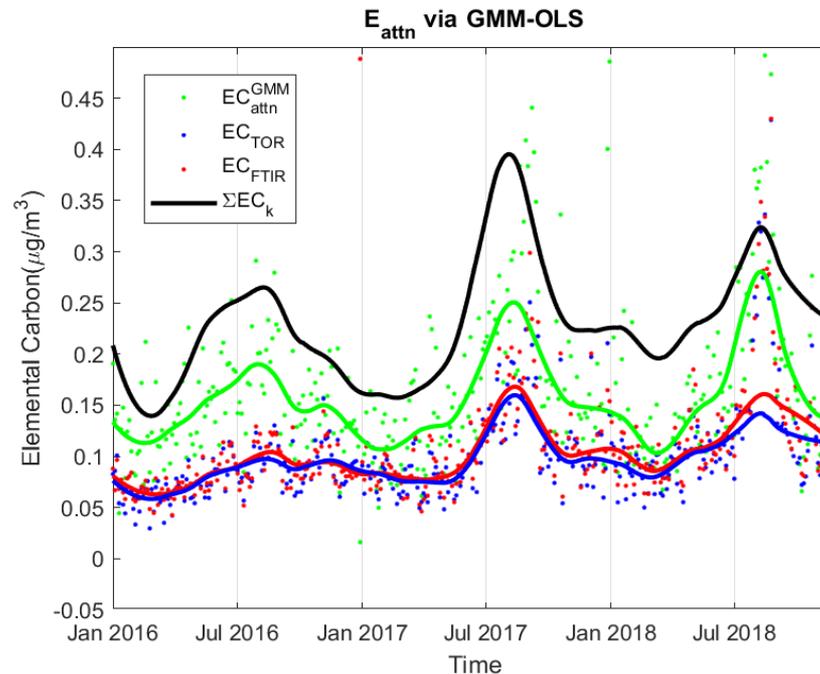
$$[X] = [\tau_{\text{attn,EC}} \quad \tau_{\text{attn,OP}}]$$

$$b = \begin{bmatrix} 1 & 1 \\ E_{a,\text{EC}} & E_{a,\text{OP}} \end{bmatrix} \quad \text{“MAC” (m}^2\text{/g)}$$



A Final Question: FT-IR and TOR Stability

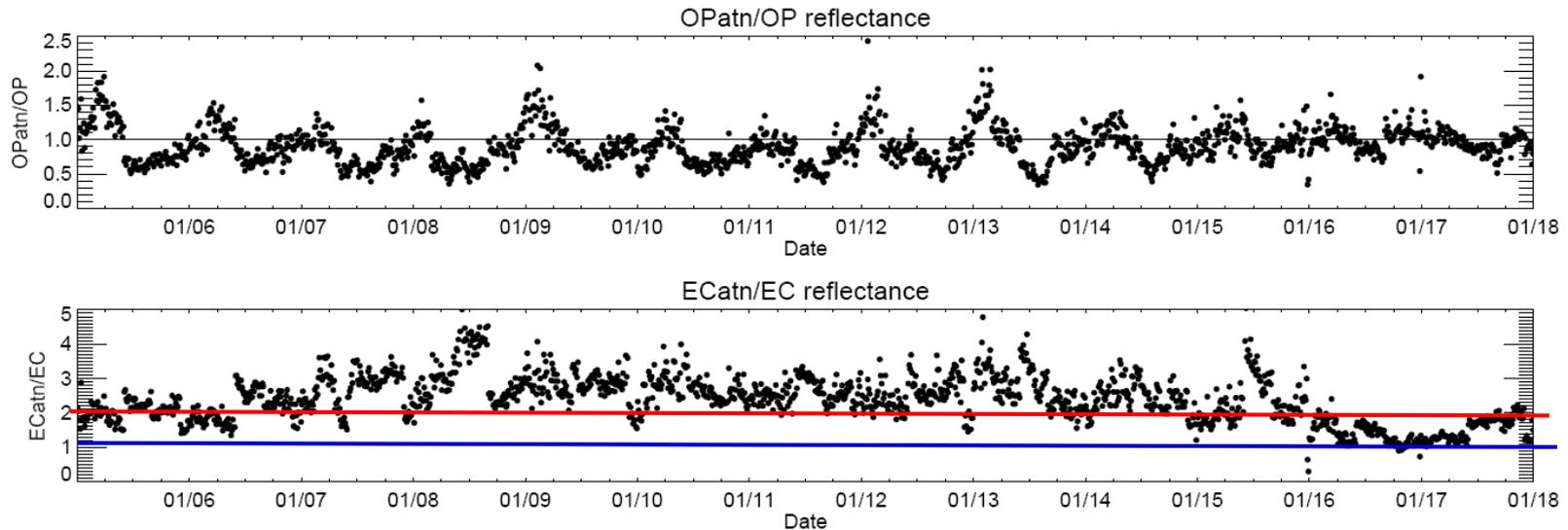
- Will **FT-IR** affect long-term trends if *substituted* for **TOR** relative to *possible* uncertainties in **OP estimates**?
 - Daily medians plotted
- **Estimated EC** using oven laser transmittance (= EC_{attn})
 - ...via methods developed in Chow et al. 2004.
 - Details in Section S3 for Supp. Mat.



Perhaps FT-IR biases— relative to TOR— are much smaller than differences in measured EC compared to true atmospheric EC?

Context II: Daily network median ratios of OP_{atn}/OP and EC_{atn}/EC (from “TOR Optical Analysis”, J. Hand, 8/30/19)

$$EC_{\text{atn}} = x_1 b_1 = \frac{\tau_{\text{attn,EC}}}{E_{a,EC}} \quad OP_{\text{atn}} = x_2 b_2 = \frac{\tau_{\text{attn,OP}}}{E_{a,OP}}$$



- Jenny Hand shows...
 - EC is slightly overpredicted in 2016-2018 (~10-100%, perhaps): 1 is ideal on bottom fig
 - Jenny performed OLS regressions by first grouping samples by season and region

Section 3:

Cluster Analysis and then Regression for MACs?

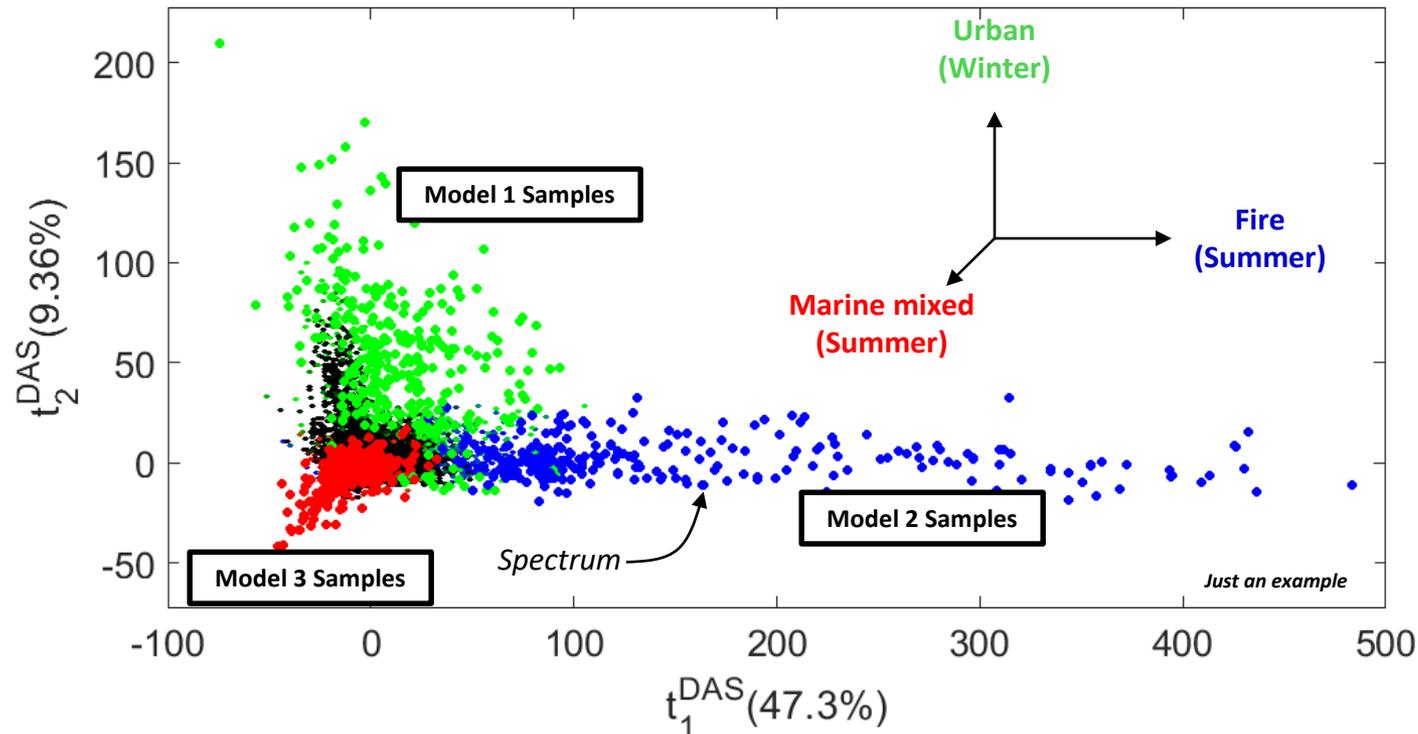
Thoughts:

- Perhaps we can bring something similar to the table with our Gaussian Mixture Model (GMM) cluster analysis

Gaussian Mixture Modeling (GMM): Basically clustering before regression

Big point: use source attribution(ish) information to homogenize EC_{attn} , OP_{attn} regressions

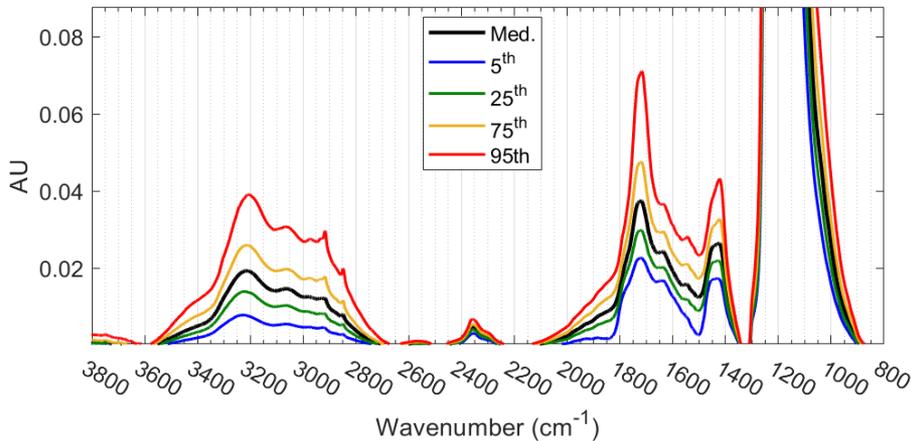
1. GMM already developed from IMPROVE 2015 FT-IR spectra (**21 clusters**)
2. Apply GMM to 2016-2018 spectra → place samples into clusters
3. Develop a regression for each cluster (**21 models**) using OLS, WLS, IRLS in turn
4. Check out the estimated MACs, time series, etc.



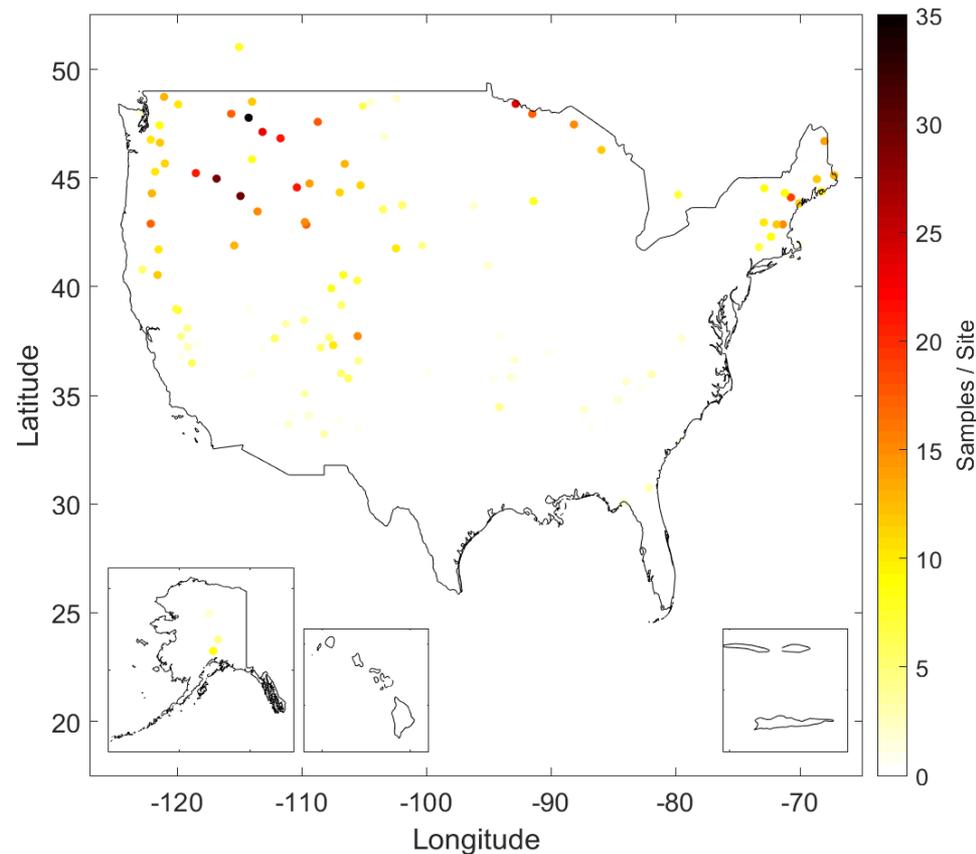
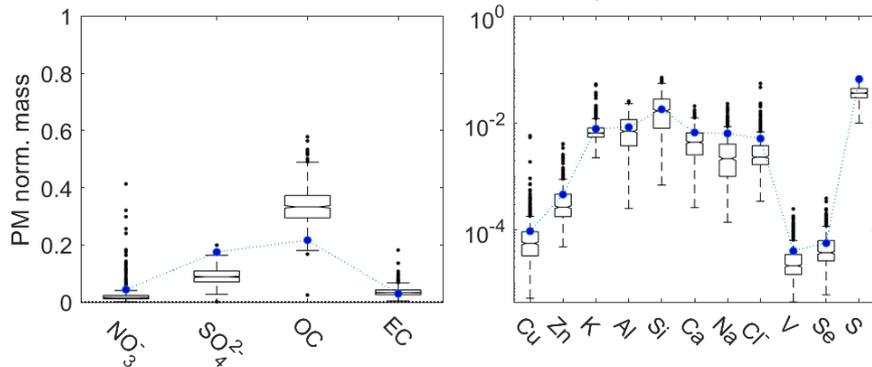
Refresher: A Typical GMM Cluster

Essentially Region + Season Dependence

NW Wildfire (Summer dom.), N(FB) = 977(0)

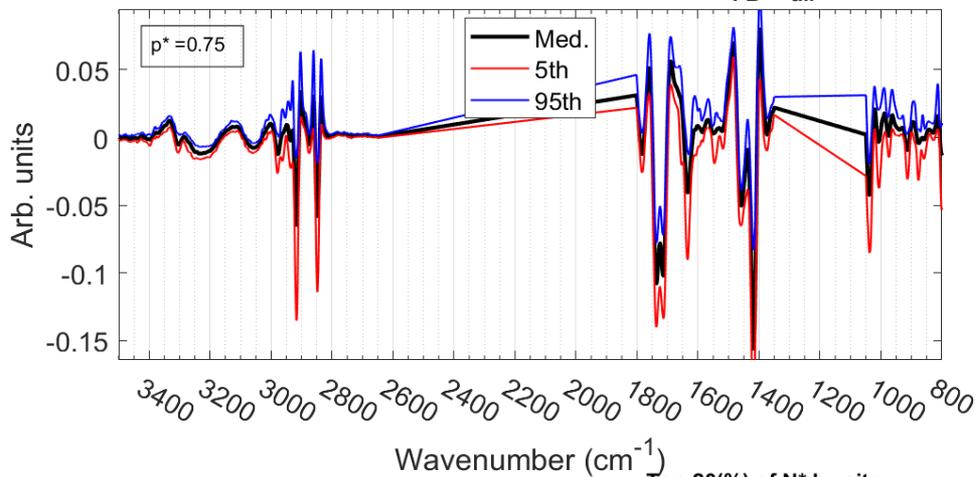


Ion, Carbon, Elemental Composition

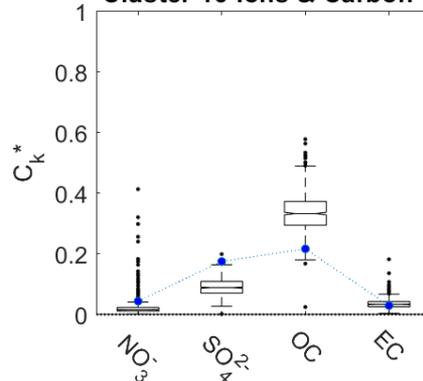


Update 10/10: More Details about NW Wildfire Cluster

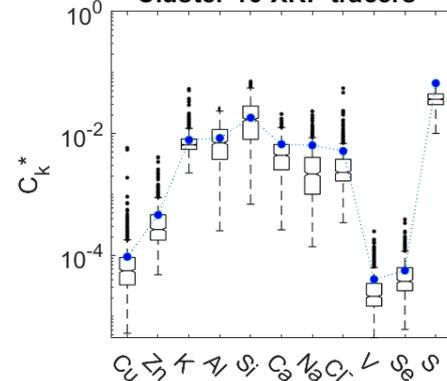
NW Wildfire (Summer dom.) 16 FBC spectra ($N^*, N_{FB}, N_{all} = 824, 0, 977$)



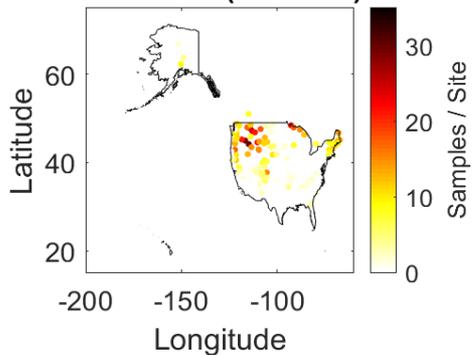
Cluster 16 Ions & Carbon*



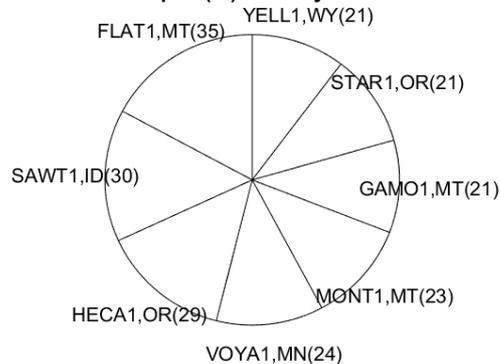
Cluster 16 XRF tracers*



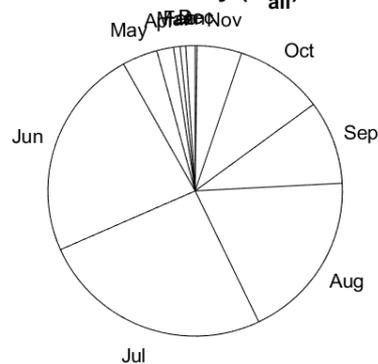
Geo. Dist. ($N^* = 824$)



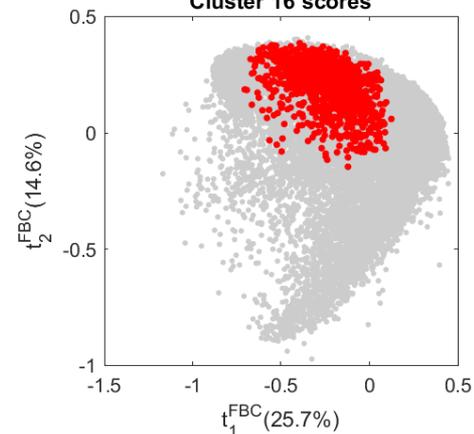
Top 20(%) of N^* by site



Seasonality (N_{all})



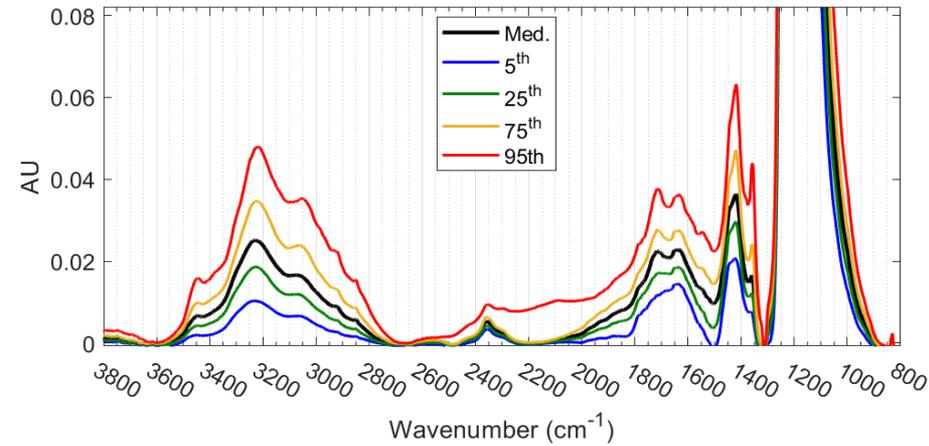
Cluster 16 scores



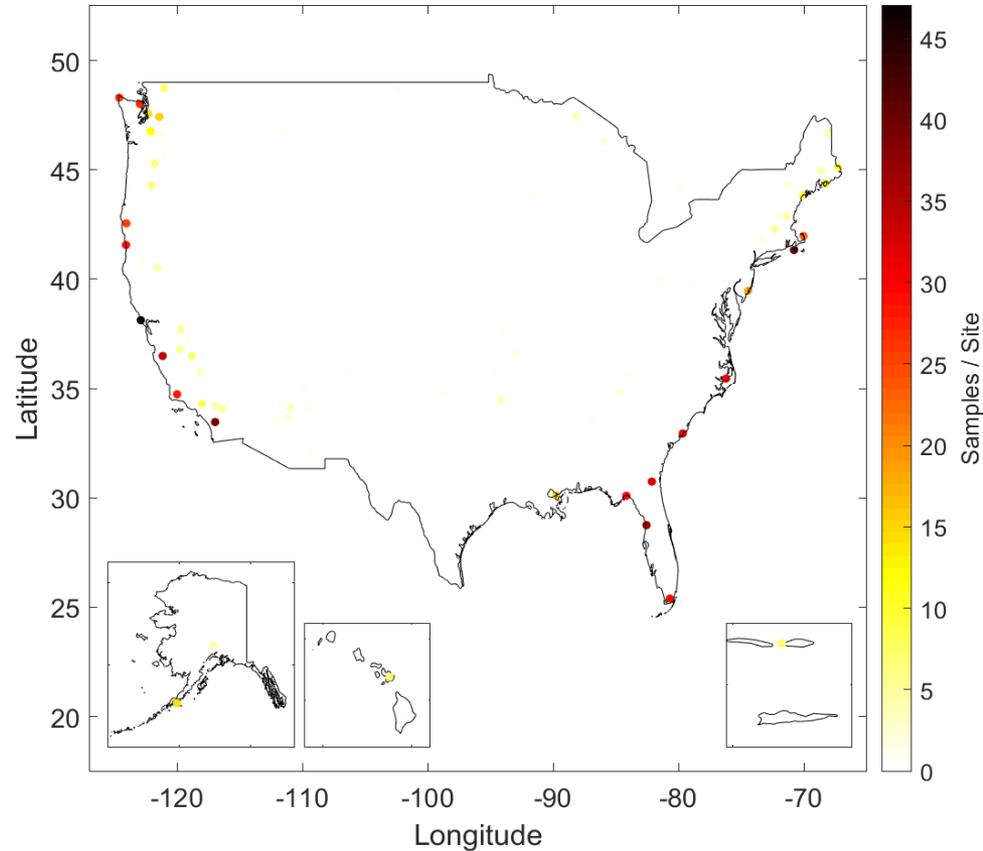
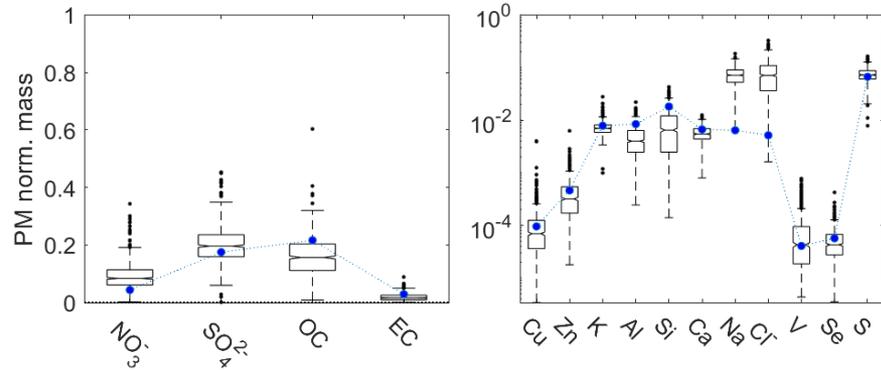
Asterisk *- denotes samples with at least a 75% chance of being in this cluster over any other cluster

Refresher: Atypical Non-regional/seasonal Cluster

Marine, N(FB) = 810(0)

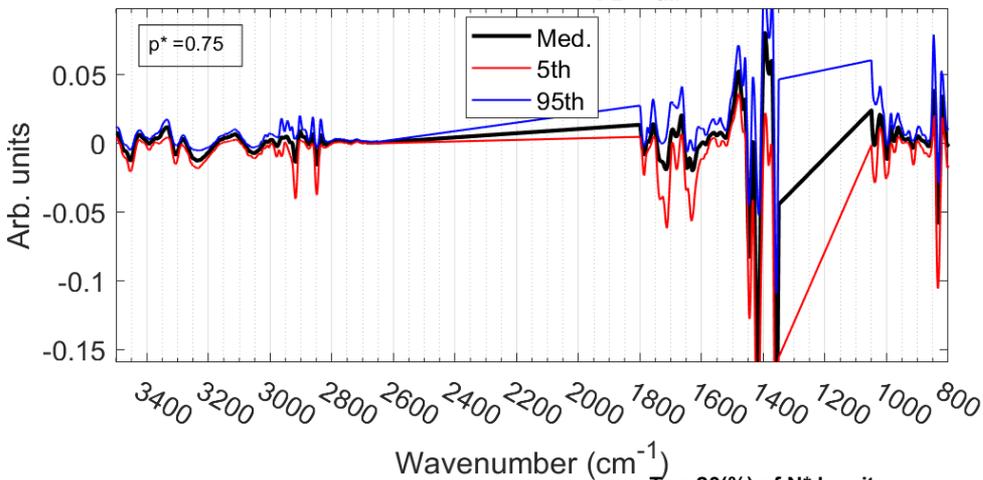


Ion, Carbon, Elemental Composition

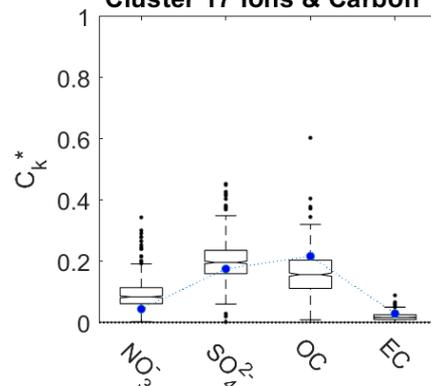


Update 10/10: More Details about Marine Cluster

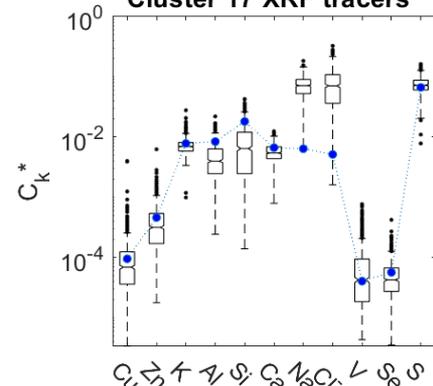
Marine 17 FBC spectra ($N^*, N_{FB}, N_{all} = 720, 0, 810$)



Cluster 17 Ions & Carbon*

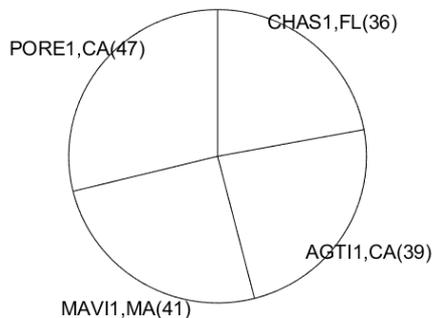
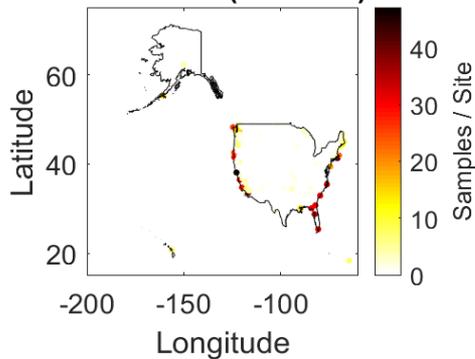


Cluster 17 XRF tracers*

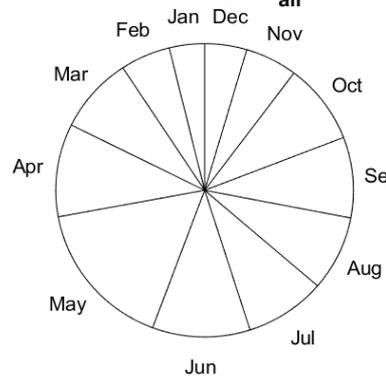


Top 20(%) of N^* by site

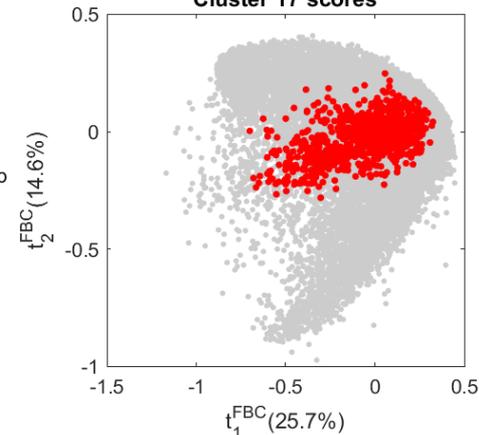
Geo. Dist. ($N^* = 720$)



Seasonality (N_{all})



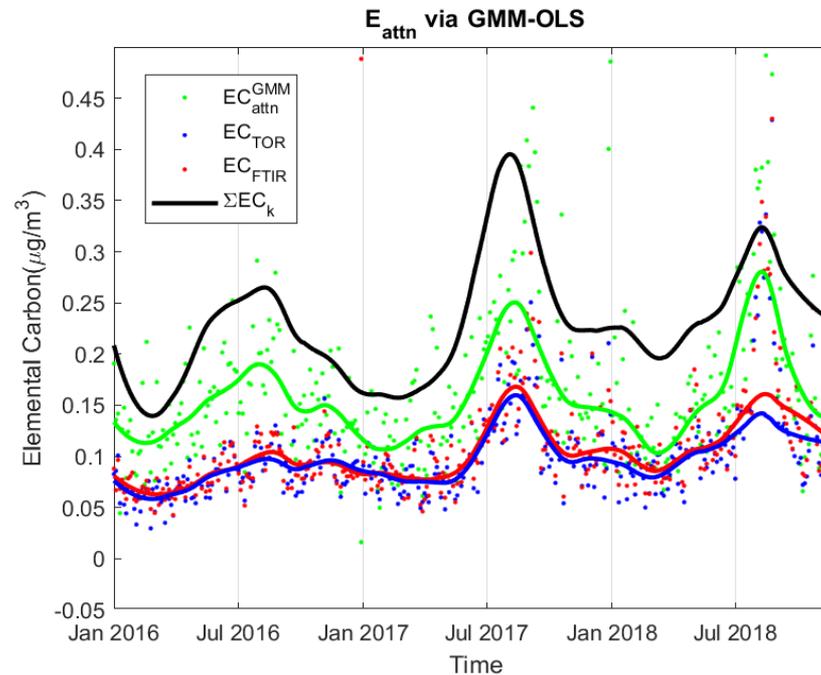
Cluster 17 scores



Asterisk *- denotes samples with at least a 75% chance of being in this cluster over any other cluster

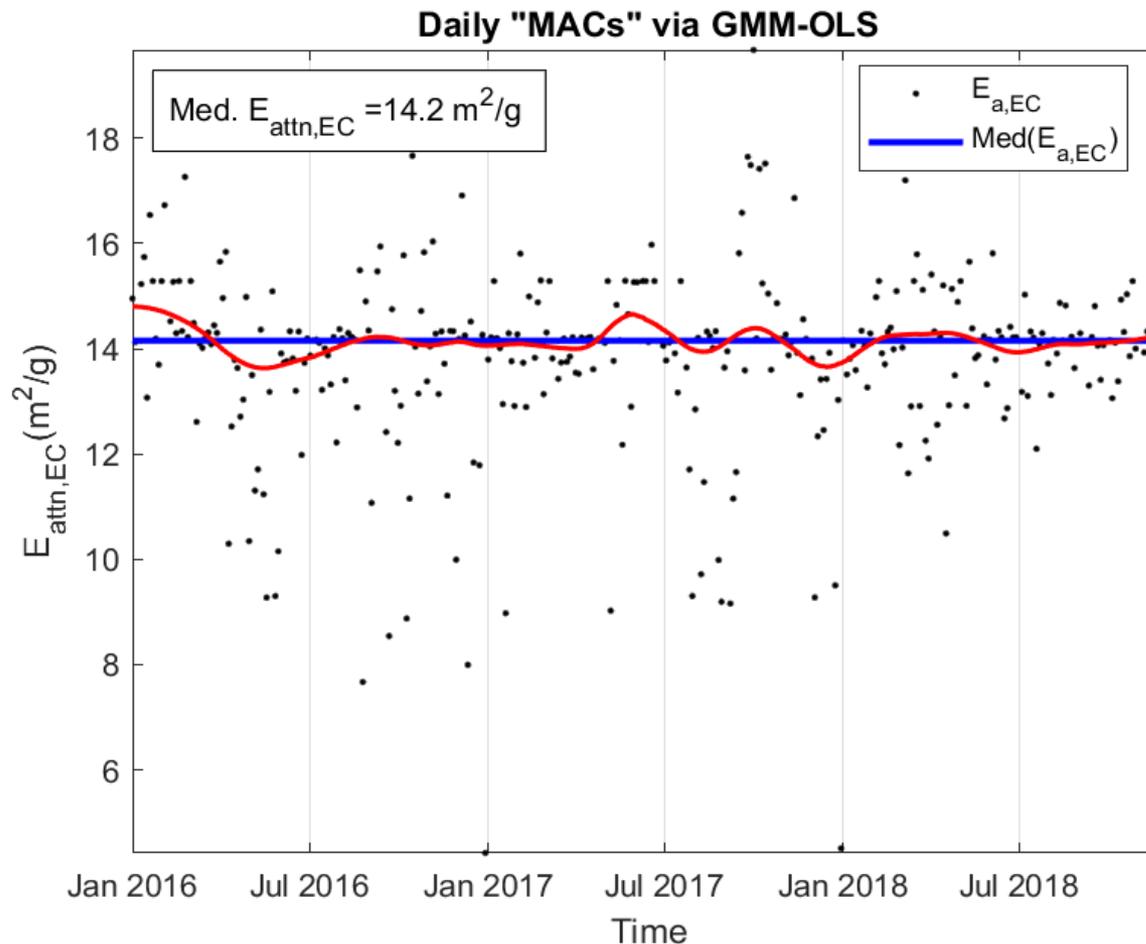
GMM-OLS Regressions

- Does the GMM route matter to trends?
 - Certainly follows general shape of TOR and FTIR OC series more closely
 - Best to do GMM-OLS over OLS (time only)



GMM-OLS: Return of the MACs?

- I could show you 21 “MACs”... one for each cluster
- Instead, **GMMs** allows calculation of “MACs” ($E_{a,EC}$) on a per sample basis using a weighted average scheme



How can you get a “MAC” for each sample from a GMM?

Gist: Use GMM to *average* the cluster-model MACs to give a MAC for each sample

First: Predict EC for a sample (i) using all K cluster models

- Each IMPROVE sample therefore has 21 EC predictions given $K=21$ clusters calculated
 - Let’s also call Chow’s “ $E_{a,EC}$ ” = “MAC”

$$EC_{attn,(i,k)} = \frac{\tau_{i,EC}}{MAC_k}$$

$\tau_{attn,EC} = -\ln \left(\frac{T_i}{T_f} \right)$
Dropped “attn”
Indexed on sample i

- Example: EC_{attn} predicted from cluster 1 model for sample i is given as...

$$EC_{attn,(i,1)} = \frac{\tau_{i,EC}}{MAC_1}$$

For cluster 10 model...

$$EC_{attn,(i,10)} = \frac{\tau_{i,EC}}{MAC_{10}}$$

And so on...

How to get a “MAC” for each sample

Second:

- Find (posterior) probabilities, $p(k)$, of belong to cluster
- Use to calculate ***a weighted average of EC predictions***

$$EC_{attn,i} = p_1 \frac{\tau_{i,EC}}{MAC_1} + \dots + p_{21} \frac{\tau_{i,EC}}{MAC_{21}}$$

$$EC_{attn,i} = \sum_{k=1}^{21} p_k \frac{\tau_{i,EC}}{MAC_k}$$

Comments:

1. What's nice about probabilities: they live between 0 and 1
2. Formula makes intuitive sense: the “closer” a sample is to a cluster, the higher the likelihood ($p(k)$) it has the mass attenuation associated with that cluster
3. Alternatively, if a sample is close to several clusters it's MAC may be a sort of “simple average” of those MACs
 - Causal point: the clusters themselves should make sense from a chem. phys. standpoint for the model to be more than an exercise in linear algebra. ☺

How to get a “MAC” for each sample

Third: Separate k and i terms and reduce to find sample specific MAC (MAC_i)

Starting with...

$$EC_{attn,i} = \sum_{k=1}^{21} p_k \frac{\tau_{i,EC}}{MAC_k}$$

Sample MAC is therefore...

$$MAC_i = \left(\sum_{k=1}^K \frac{p_k}{MAC_k} \right)^{-1}$$

Pull tau from the sum...

$$EC_{attn,i} = \tau_{i,EC} \sum_{k=1}^K p_k \frac{1}{MAC_k}$$

Let the following be the MAC for sample i

$$(MAC_i)^{-1} = \sum_{k=1}^K \frac{p_k}{MAC_k}$$