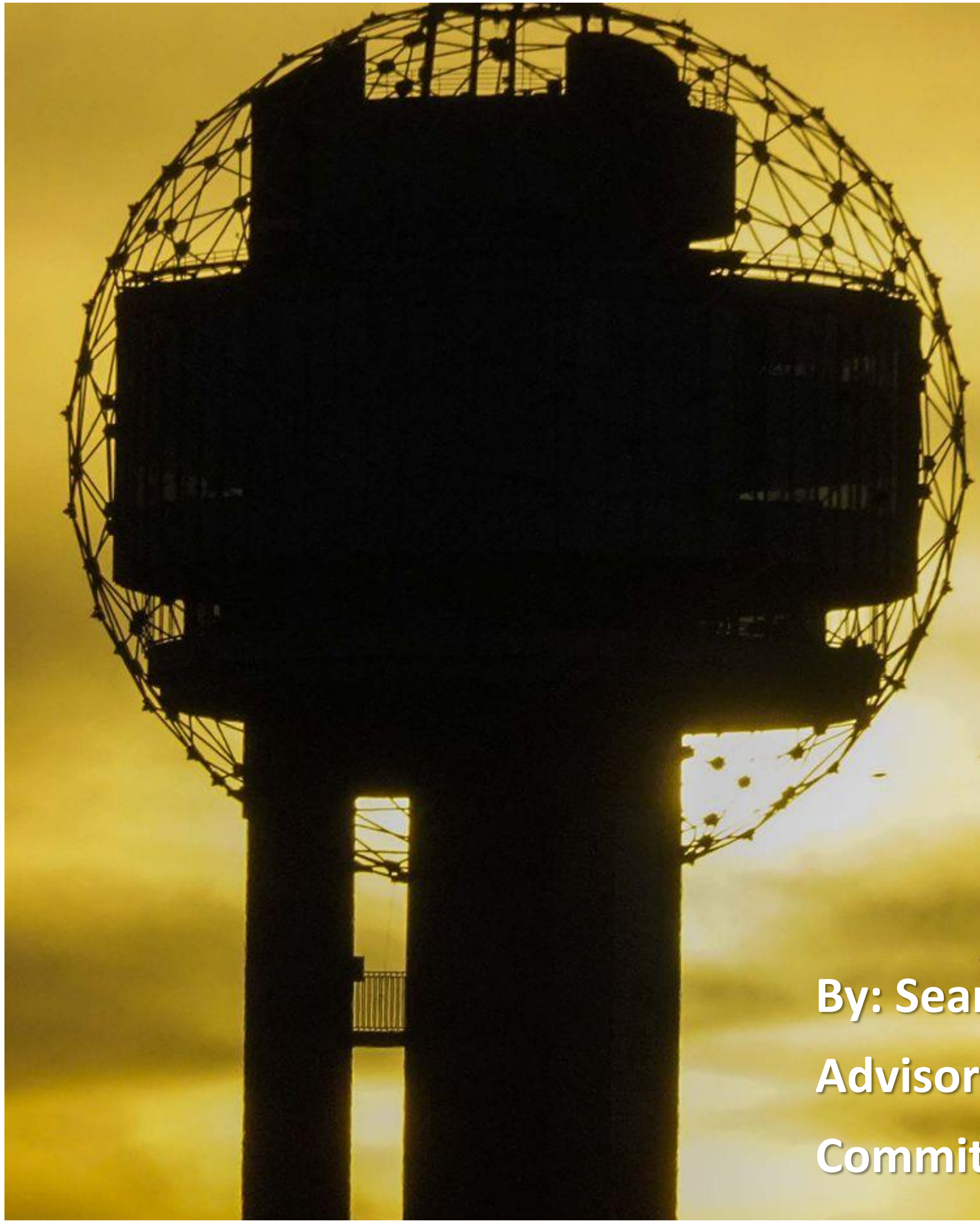
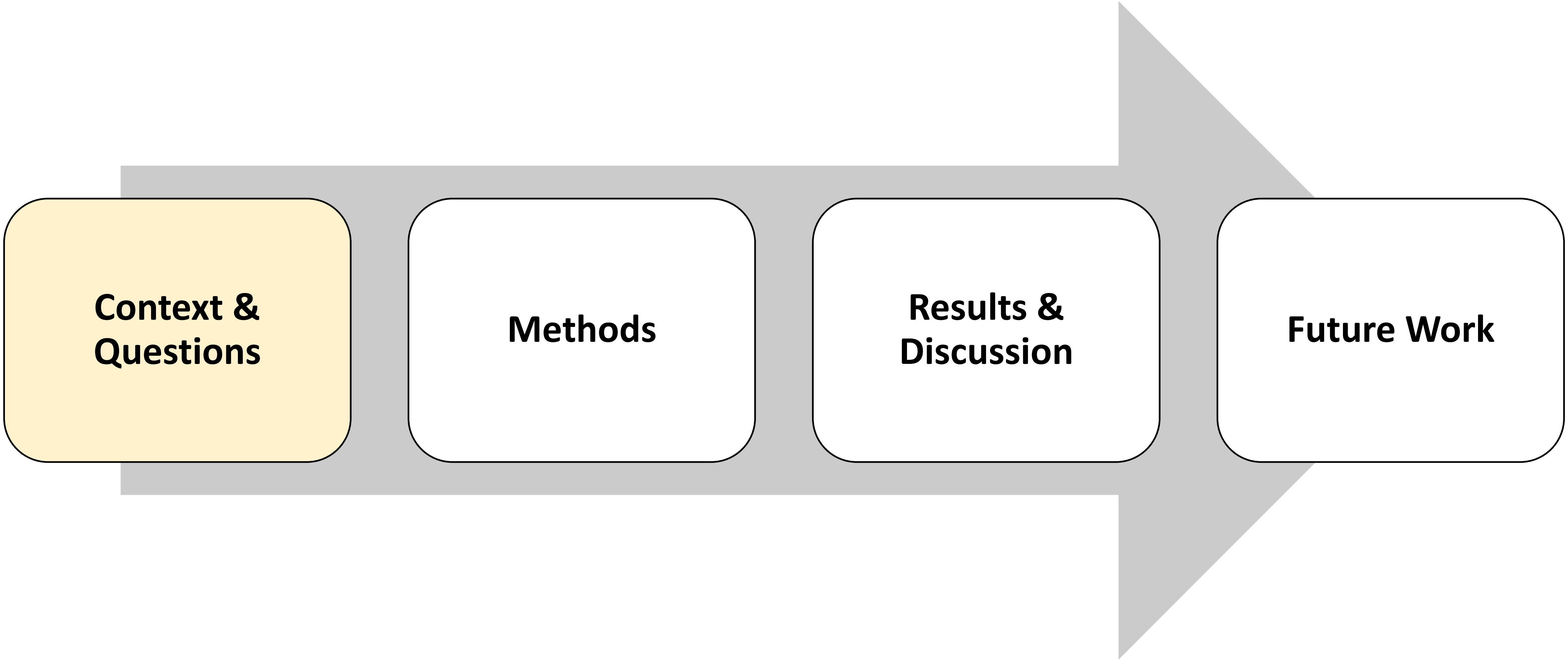


# Using Machine Learning to Develop a Calibration Model for Low-Cost Air Quality Sensors Deployed During a Dust Event

**By: Sean Hickey**

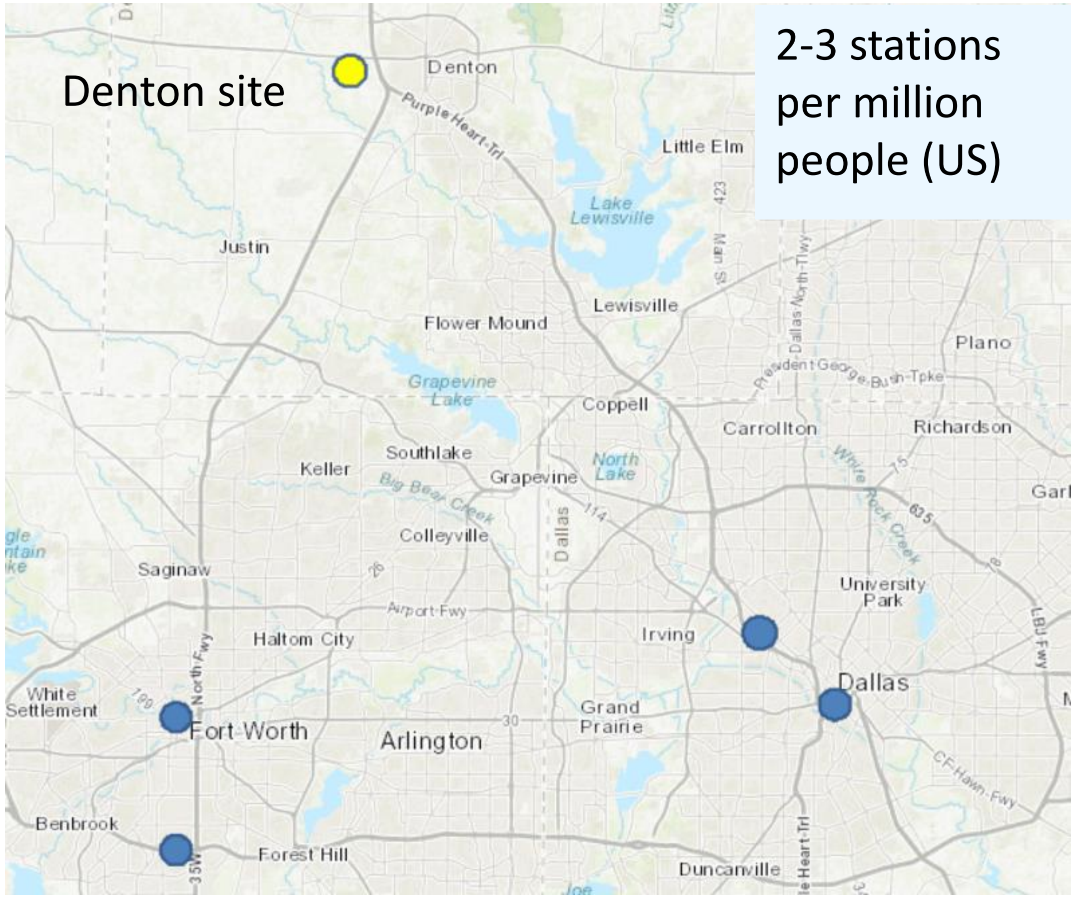
**Advisor: Dr. Lu Liang**

**Committee Members: Dr. Pinliang Dong, Dr. Chetan Tiwari**

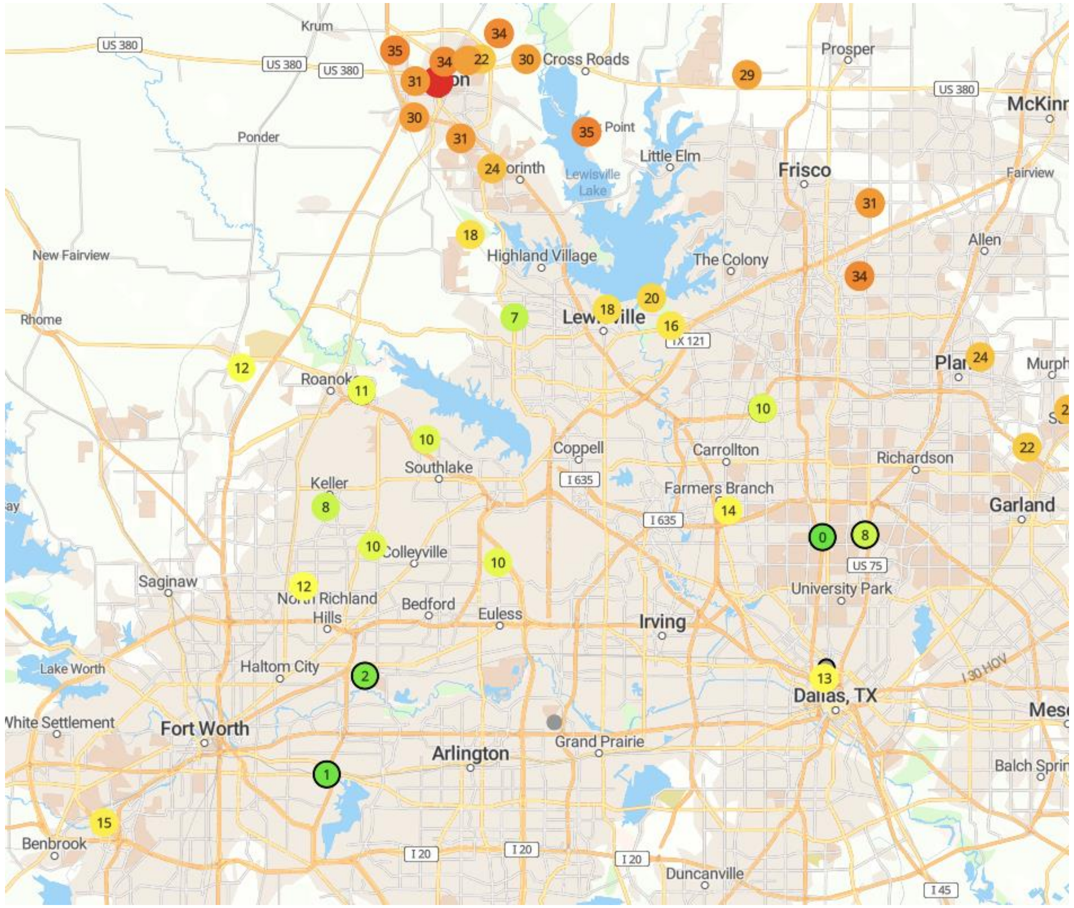

Context & Questions
Methods
Results & Discussion
Future Work

# Pollution is more variable than what we can currently capture

Dallas-Fort Worth Regulatory Monitoring Sites




Dallas-Fort Worth Low-Cost Sensor Sites



# Sensor Influences

| Variable | Effect |
|---|---|
| Relative Humidity | Water droplets binds to particles |
| | |
| | |

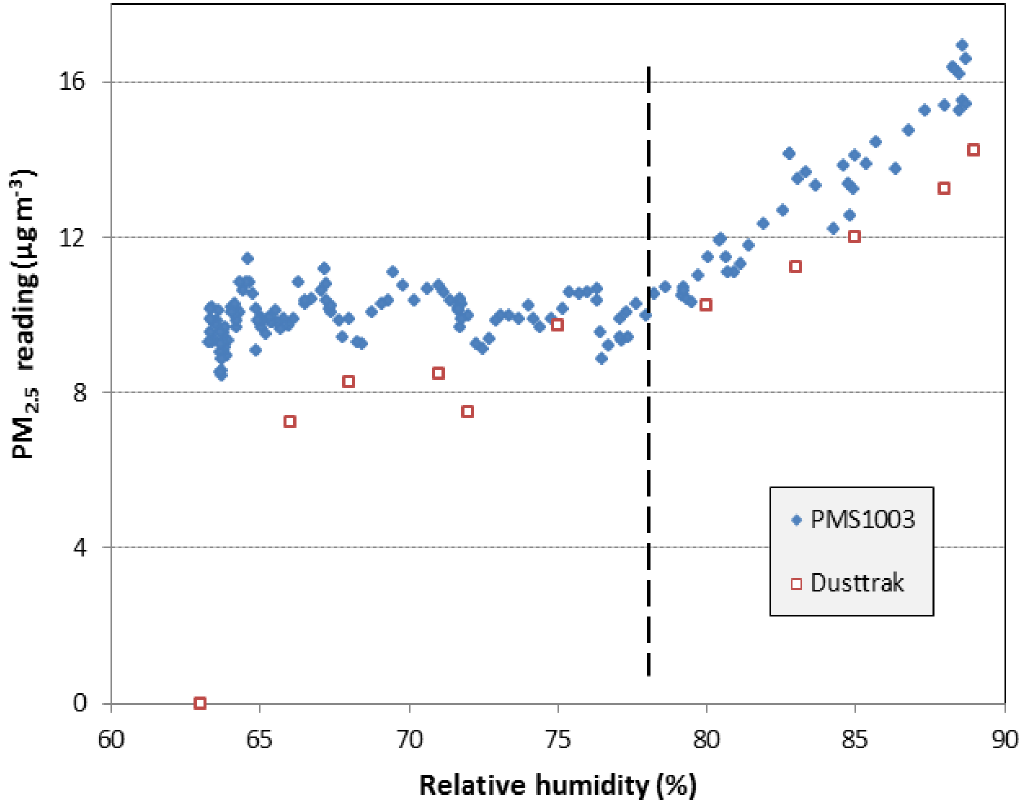
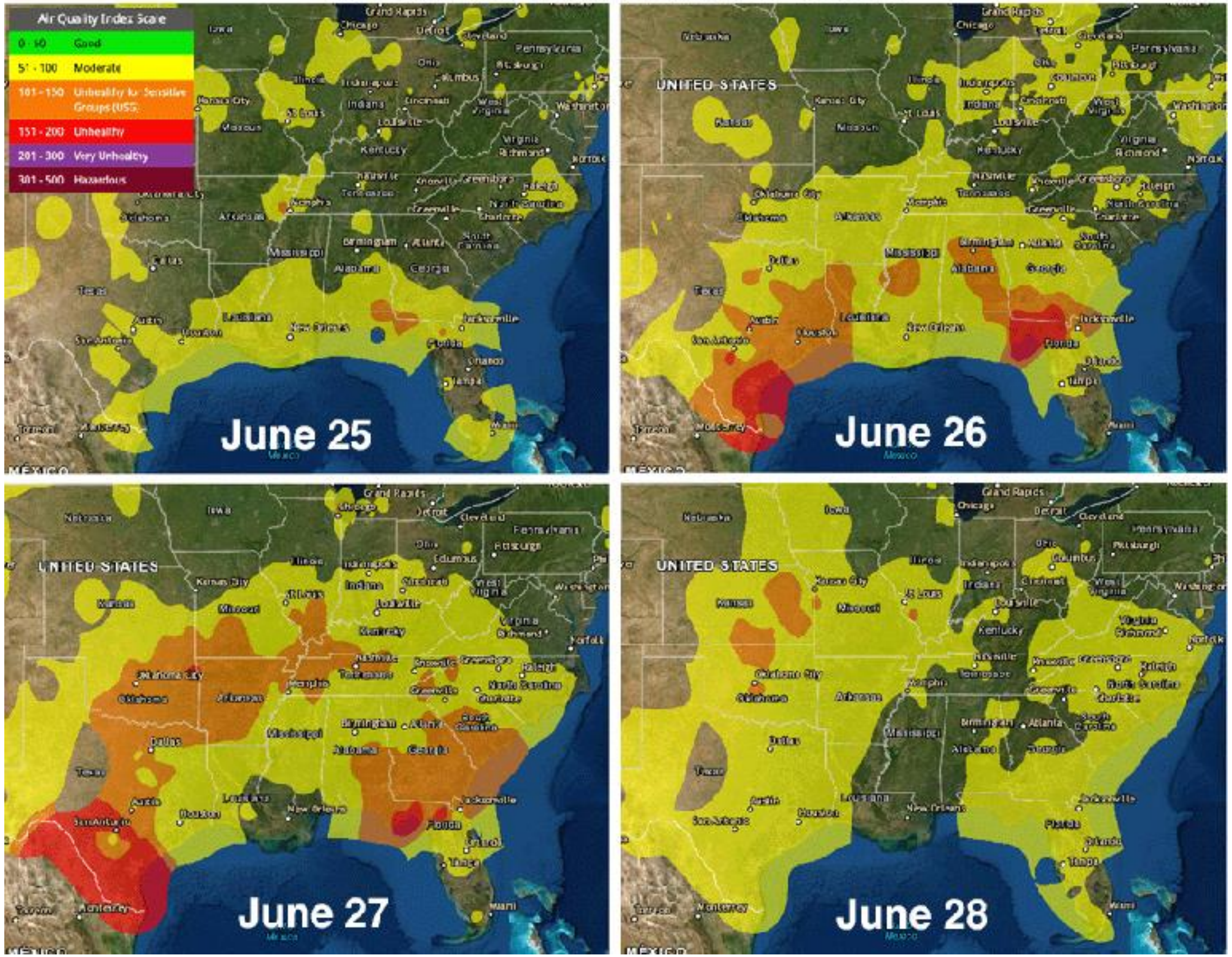



**Figure 1.** The $PM_{2.5}$ concentrations reported by two optical-based particle sensors as the relative humidity was systematically increased in a laboratory chamber (Jayarantne et al. 2018).

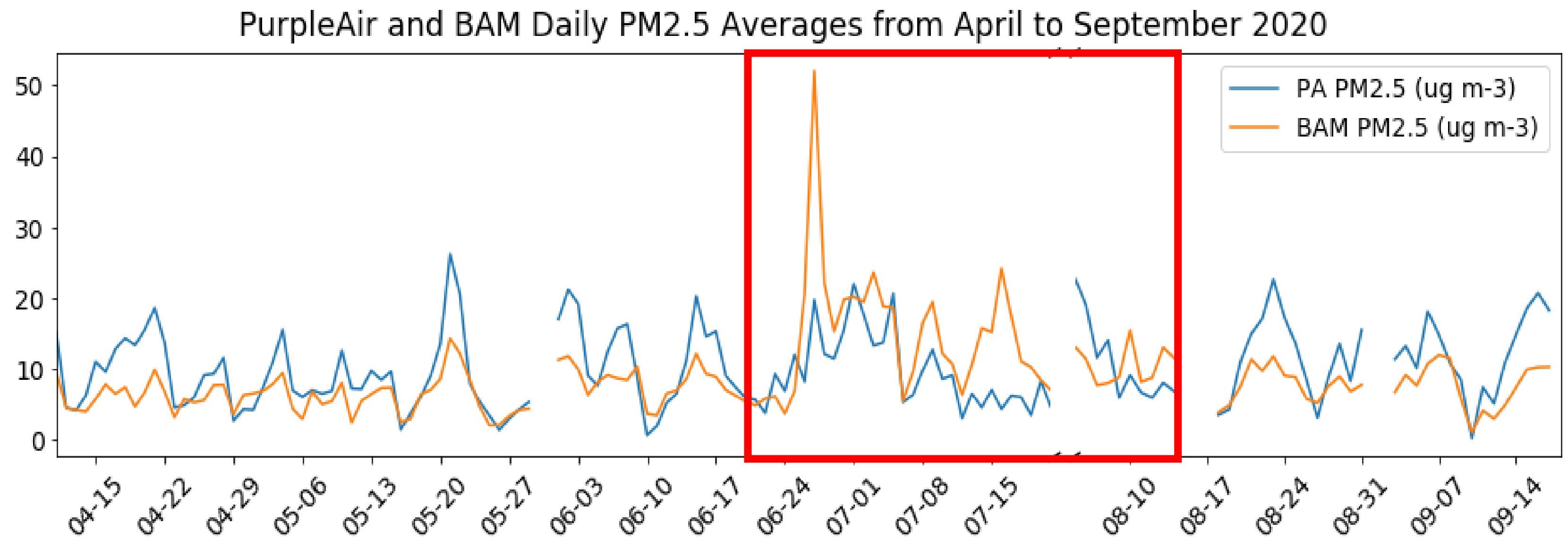
# Does dust affect sensor performance?

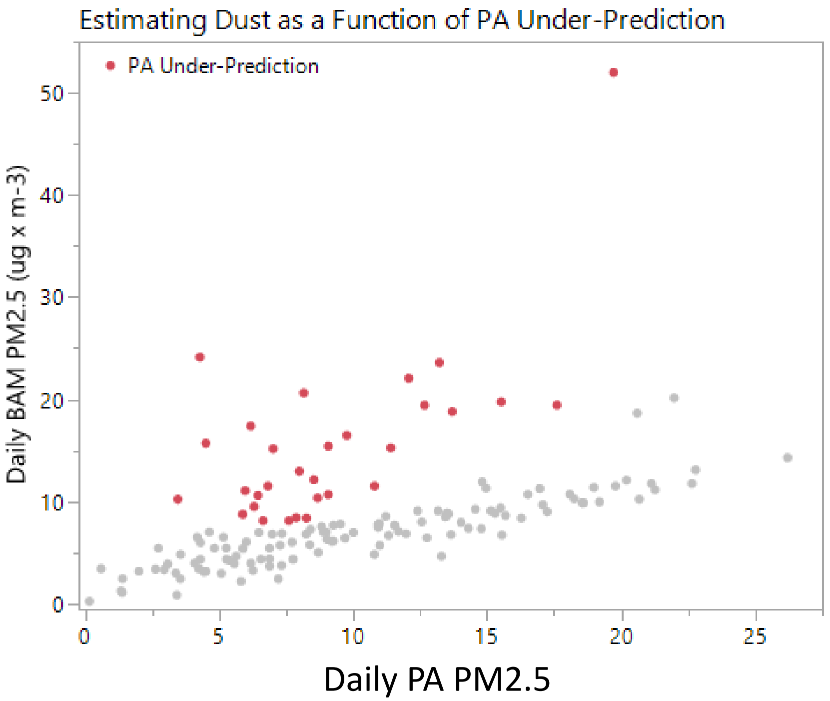
- A mass of hot, dry and dusty air forming over the Sahara
- It moves across the North Atlantic every 3-5 days in late spring to early fall
- Largest event in decades came this past summer from ~June - August

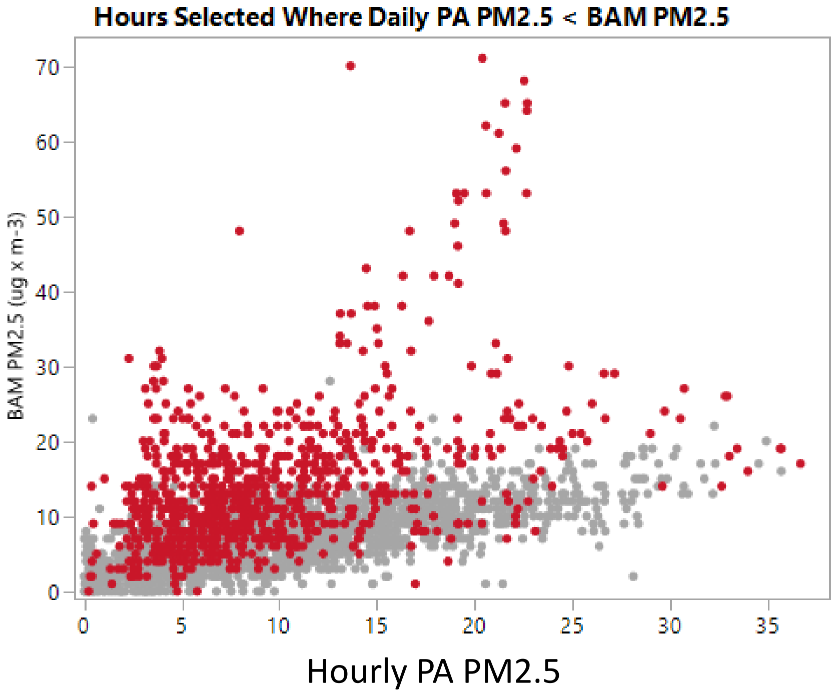
Air Quality Index for PM2.5, June 25 - 28, 2020



# Does dust affect sensor performance?



# What is calibration?

Co-locate sensors with more accurate instrument

Take data from one sensor and the reference instrument to build a model

**Training**

Low-cost sensors

Reference instrument

Apply the model to sensors not used for training and evaluate

**Validation**

Sensor Variables **Predict** → Actual PM2.5


Cost: \$280

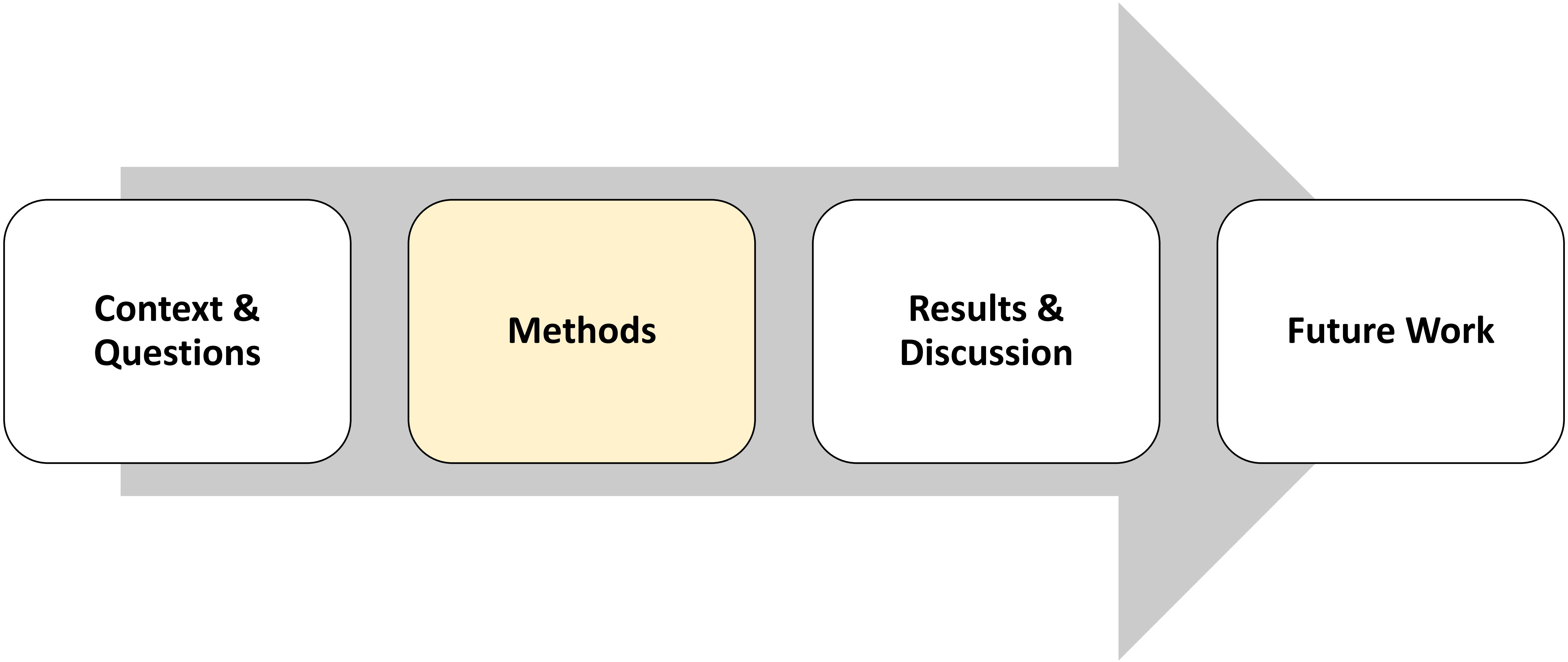
**PurpleAir Sensor**
- 2 PM sensors
  - $PM_1$, $PM_{2.5}$, $PM_{10}$
  - Particle Size Counts (P0.3, P0.5, … P10)
- RH, T sensors

**MetOne BAM 1020**
- Measures $PM_{2.5}$


Cost: >\$20,000

# Questions & Objectives:

- **Q1: Can a calibration model built from one sensor generalize to many sensors?**
  - Build a calibration model using ML algorithms
  - Test different variables
  - Use cross-validation to select the model that generalizes best
    - Best prediction accuracy
- **Q2: Can dust be identified from PurpleAir sensors?**
  - Create a filter to separate data from PurpleAir variables
- **Q3: Is partitioning data by dust, and subsequently building two models rather than one, a better strategy for calibrating low-cost sensors?**
  - Evaluate performance of split-model strategy vs. single model strategy


Context & Questions
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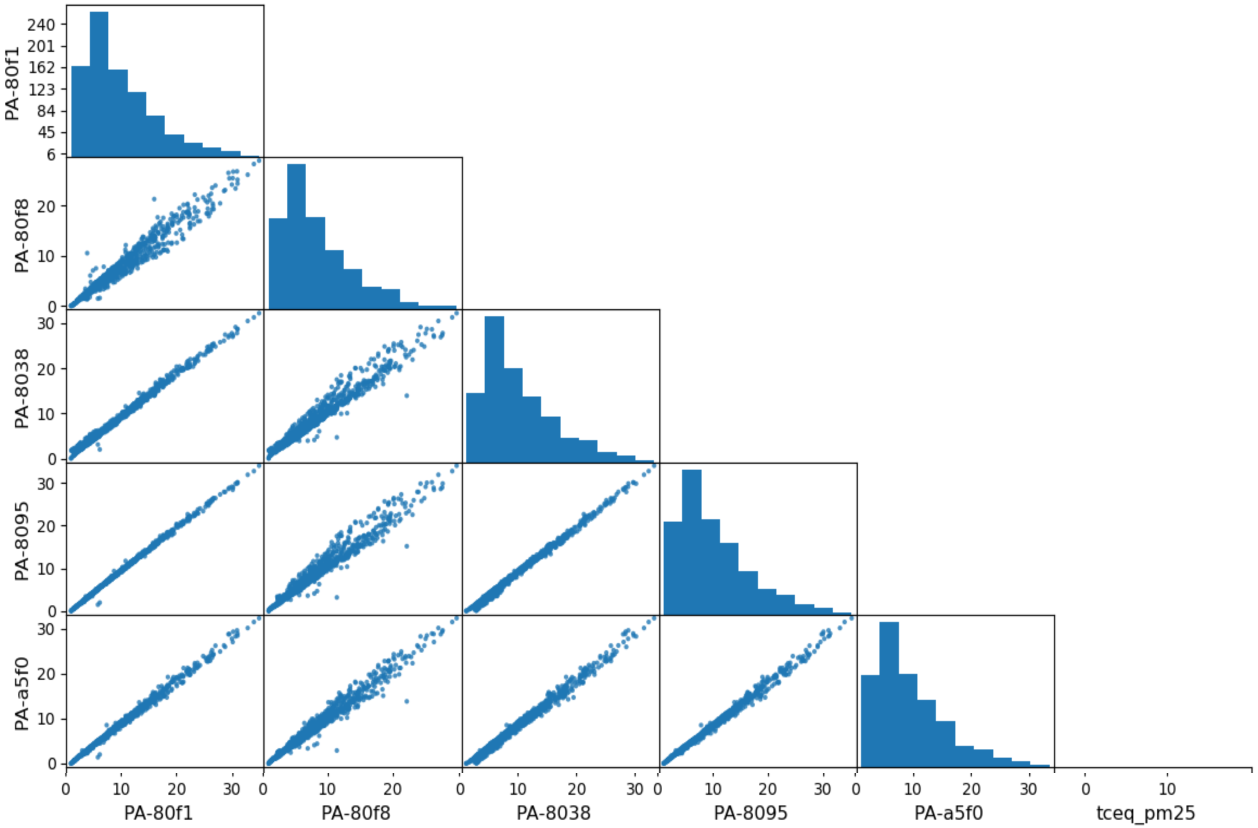
# Data Collection




| Deployment Period | Training Set 1 | Validation Set 2 | Validation Set 3 | Validation Set 4 |
|---|---|---|---|---|
| April - May | PA - Sensor | PA - Sensor | PA - Sensor | PA - Sensor |
| June | PA - Sensor | PA - Sensor | PA - Sensor | PA - Sensor |
| July | PA - Sensor | PA - Sensor | PA - Sensor | PA - Sensor |
| August - September | PA - Sensor | PA - Sensor | PA - Sensor | PA - Sensor |

# Objective: Build Calibration Models Using Two Strategies

**Build a Single Model**

**Build a Dust and Non-Dust Model**

**Split each dataset according to a dust filter to create "dust" and "non-dust" datasets**

**Train algorithms on training data**

Linear Regression & Random Forest

**Evaluate on 3 validation datasets**

Mean Absolute Error and Adj. R-Squared

# Objective: Evaluate Using Different Variables

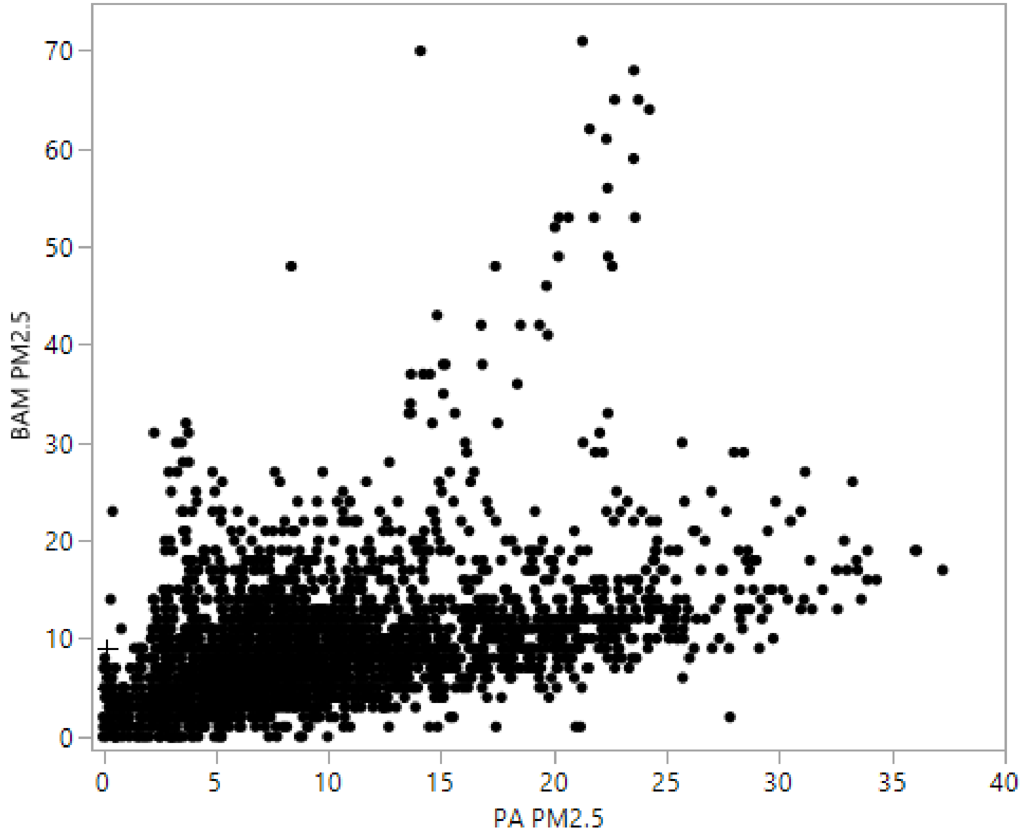
- PM: Mass concentration **(ug x m$^{-3}$)**
  - **PM2.5**, **PM1, PM10**
- Meteorological
  - **RH & T**
- New Variables: Ratios of PM
  - **PM1:PM2.5, PM2.5:PM10, PM1:PM10**
- P: Particle Size Count **(um)**
  - **P0.3, P0.5, P1.0, P2.5, P5.0, P10**

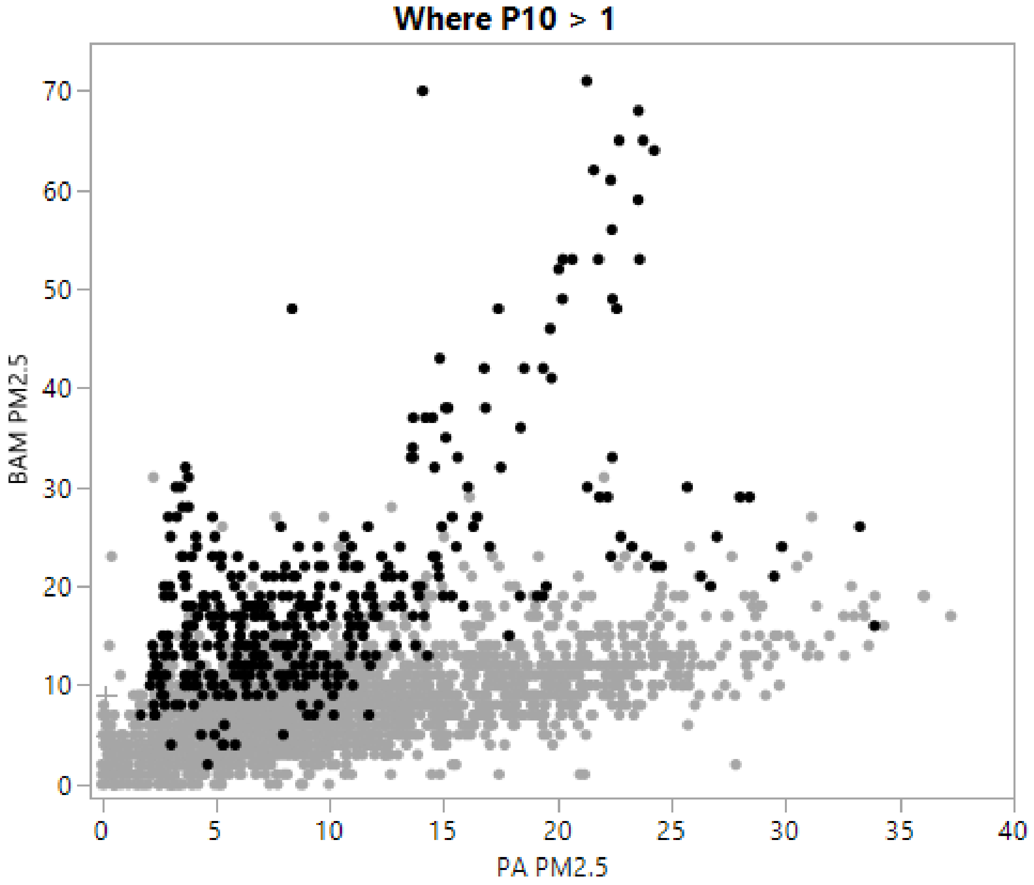
| | Number | Variables In Group |
|---|---|---|
| **VG1** | 1 | **PM2.5** |
| **VG2** | 3 | PM2.5<br>**RH, T** |
| **VG3** | 5 | PM2.5,<br>RH, T,<br>**PM1.0, PM10** |
| **VG4** | 8 | PM2.5,<br>RH, T,<br>PM1.0, PM10,<br>**PM1:PM2.5, PM2.5:PM10, PM1:PM10** |
| **VG5** | 14 | PM2.5,<br>RH, T,<br>PM1.0, PM10,<br>PM1:PM2.5, PM2.5:PM10, PM1:PM10,<br>**P0.3, P0.5, P1.0, P2.5, P5.0, P10.0** |

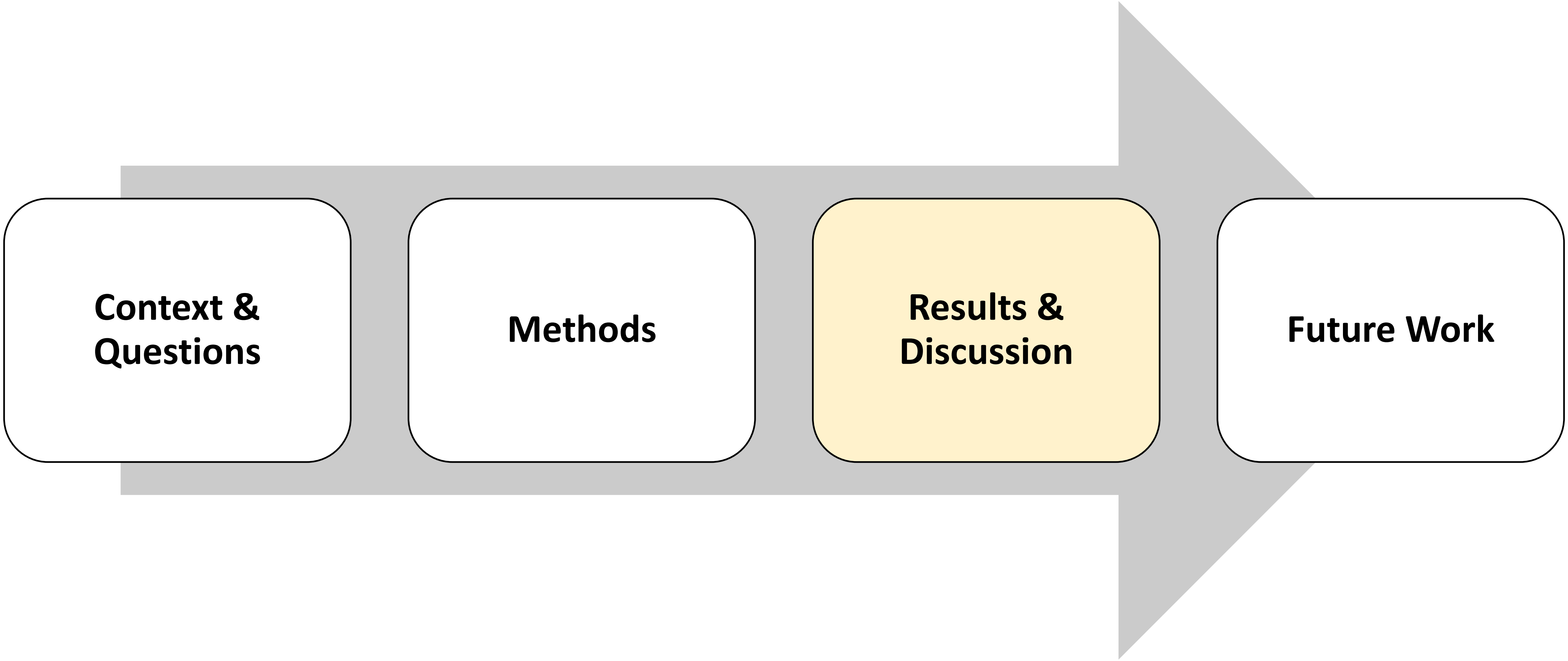
# Objective: Creating a Filter

Dust → WHERE **PM2.5:PM10** < Threshold

OR WHERE **P10** > Threshold




Context & Questions
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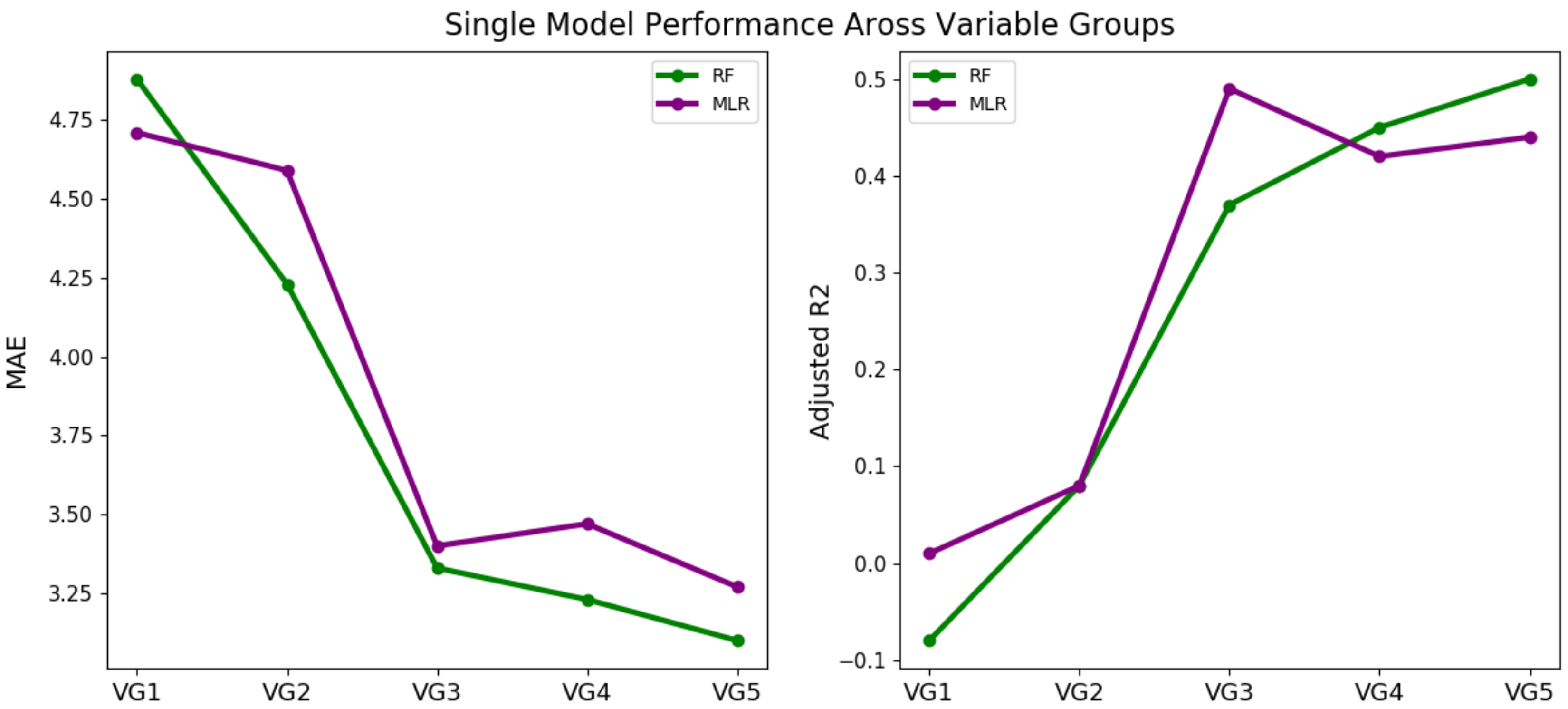
# Single Model

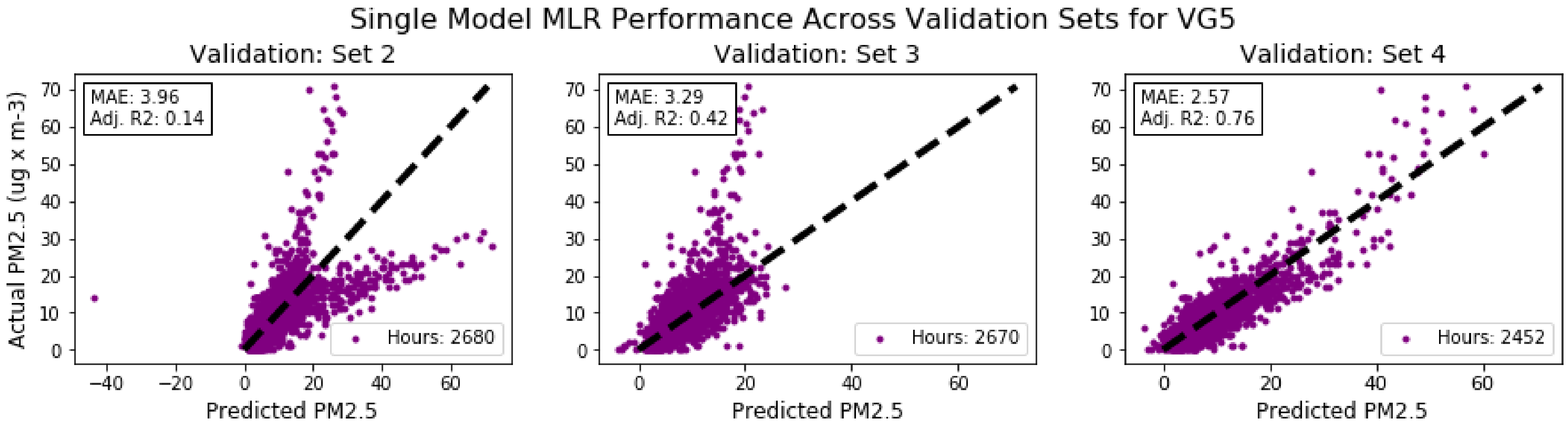
Average Performance Across 3 Sets

**RF** MAE = 3.1, R2 = 0.5

**MLR** MAE = 3.27, R2 = 0.44

| | Variables Added |
|---|---|
| **VG1** | PM2.5 |
| **VG2** | +RH, T |
| **VG3** | +PM1.0, PM10 |
| **VG4** | +Ratios (PM2.5:PM10, …) |
| **VG5** | +Particle Size Counts (P0.3, …) |

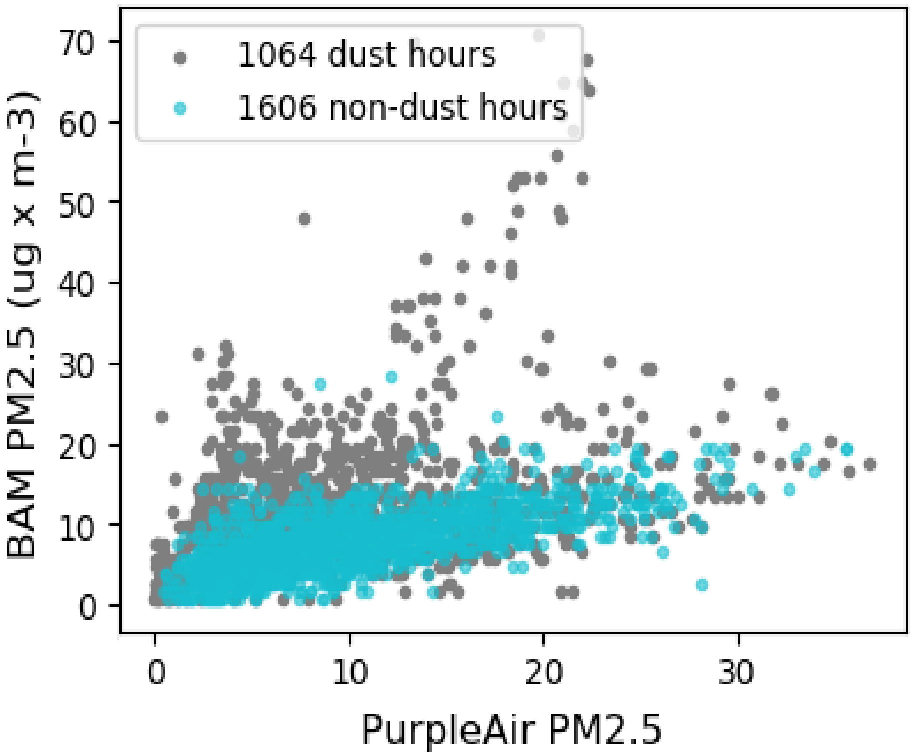


# Separating the Data by Filter

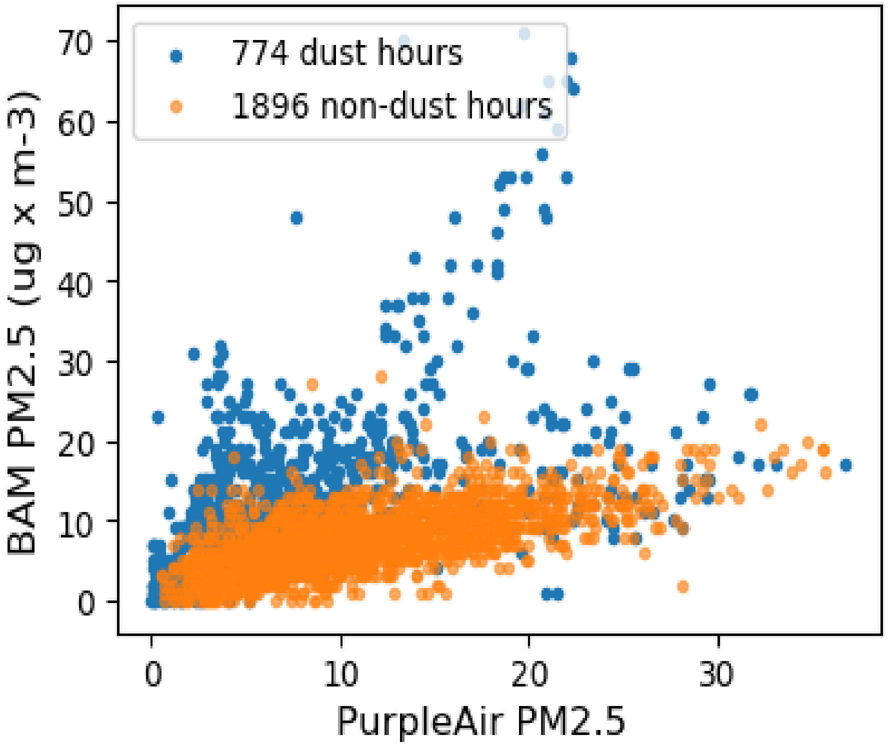
**Random Forest**

Dust WHERE PM2.5:PM10 < **0.84** OR P10 > **0.4**




**Multiple Linear Regression**

Dust WHERE PM2.5:PM10 < **0.86** OR P10 > **0.8**

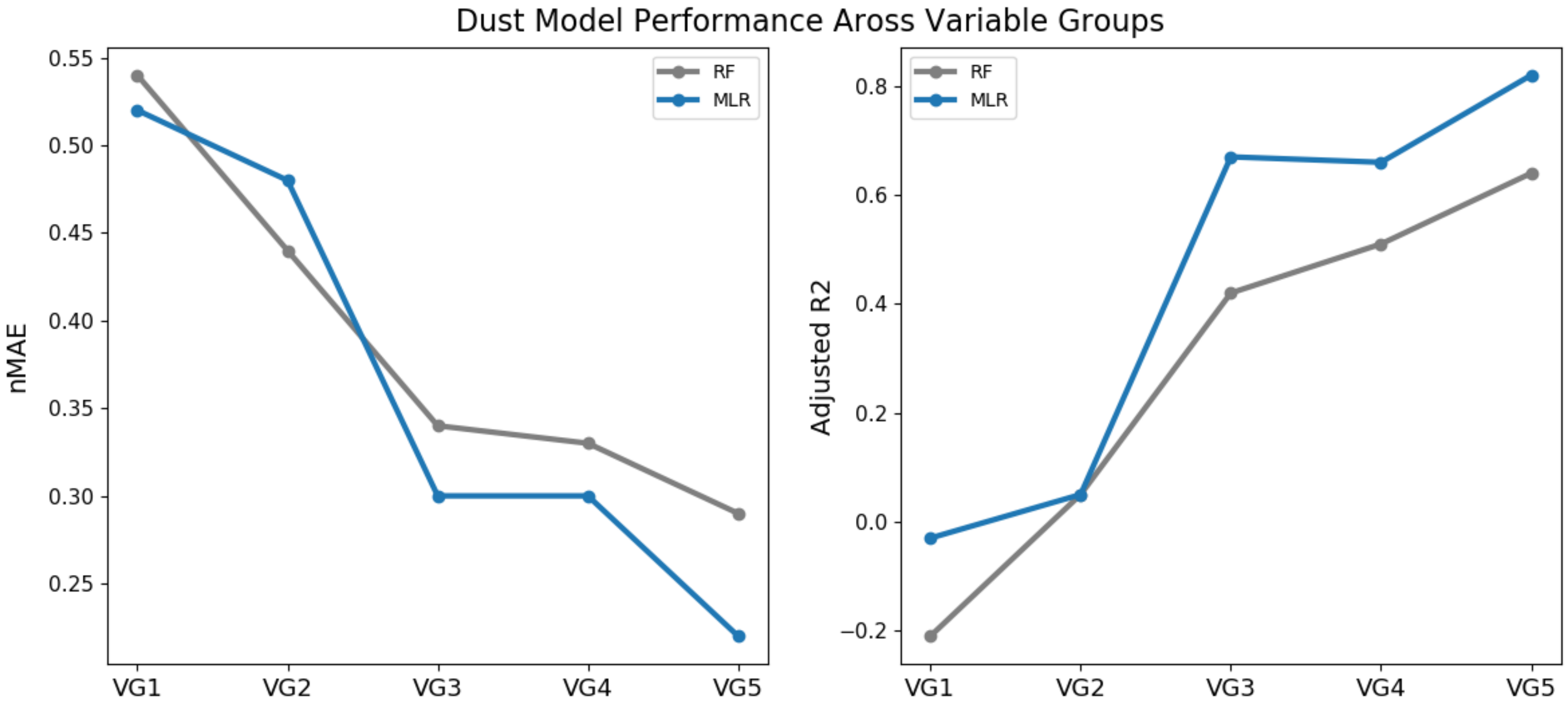


# Split-Model: Dust

## Average Performance Across 3 Sets

| | | | |
|---|---|---|---|
| **RF** | nMAE = 0.29<br>R2 = 0.64 | **MLR** | nMAE = 0.22<br>R2 = 0.82 |

| | Variables Added |
|---|---|
| **VG1** | PM2.5 |
| **VG2** | +RH, T |
| **VG3** | +PM1.0, PM10 |
| **VG4** | +Ratios (PM2.5:PM10, …) |
| **VG5** | +Particle Size Counts (P0.3, …) |

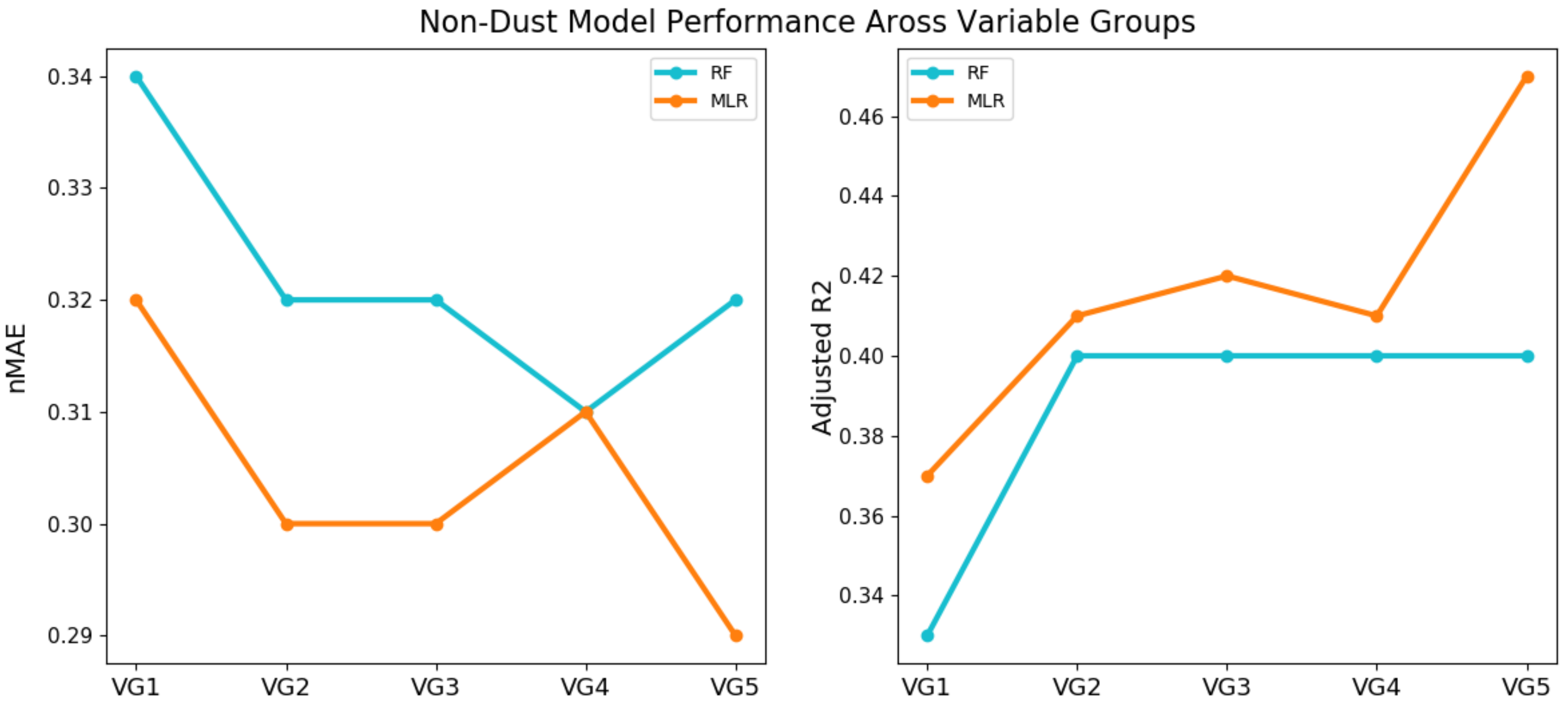


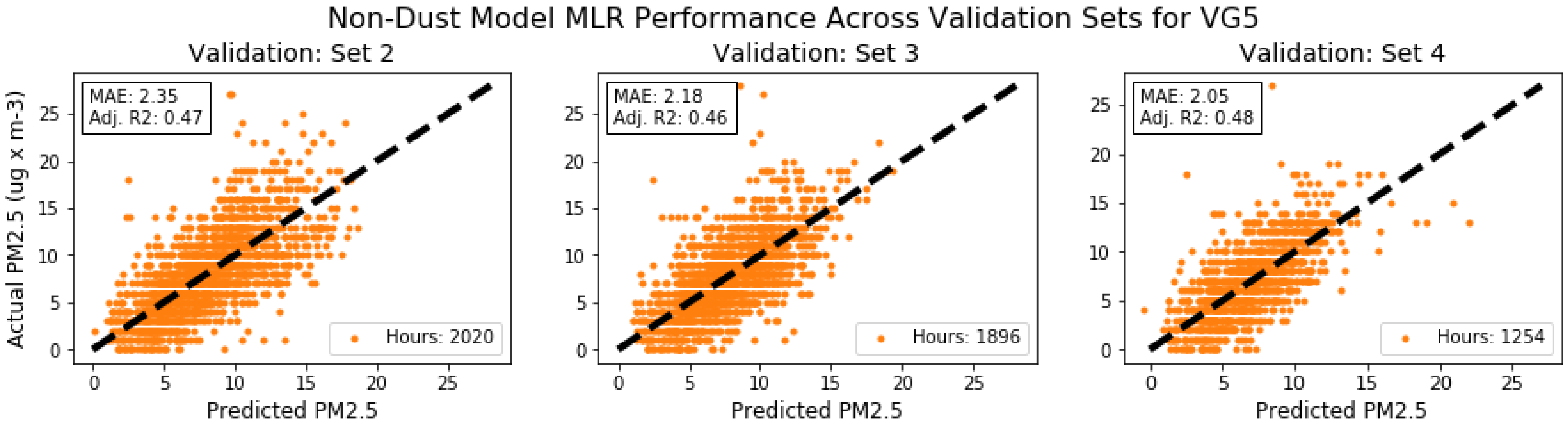
# Split-Model: No dust

Average Performance Across 3 Sets

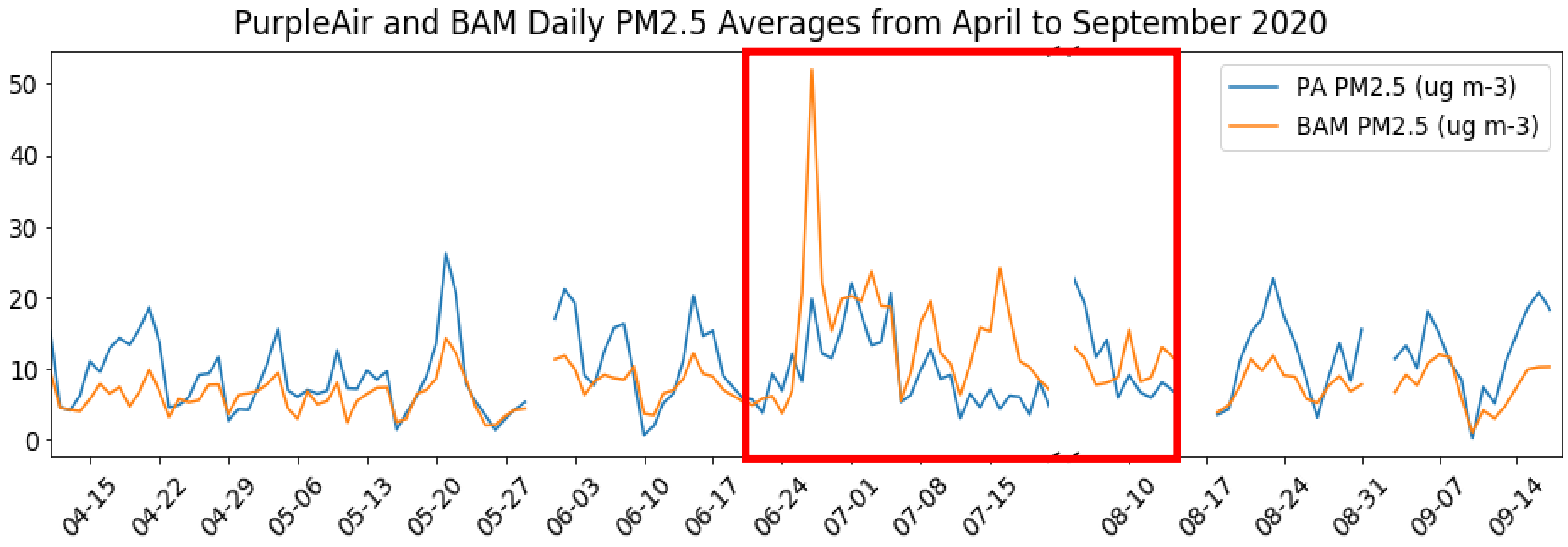
| | | | |
|---|---|---|---|
| **RF** | nMAE = 0.32<br>R2 = 0.4 | **MLR** | nMAE = 0.29<br>R2 = 0.47 |

| | **Variables Added** |
|---|---|
| **VG1** | PM2.5 |
| **VG2** | +RH, T |
| **VG3** | +PM1.0, PM10 |
| **VG4** | +Ratios (PM2.5:PM10, …) |
| **VG5** | +Particle Size Counts (P0.3, …) |

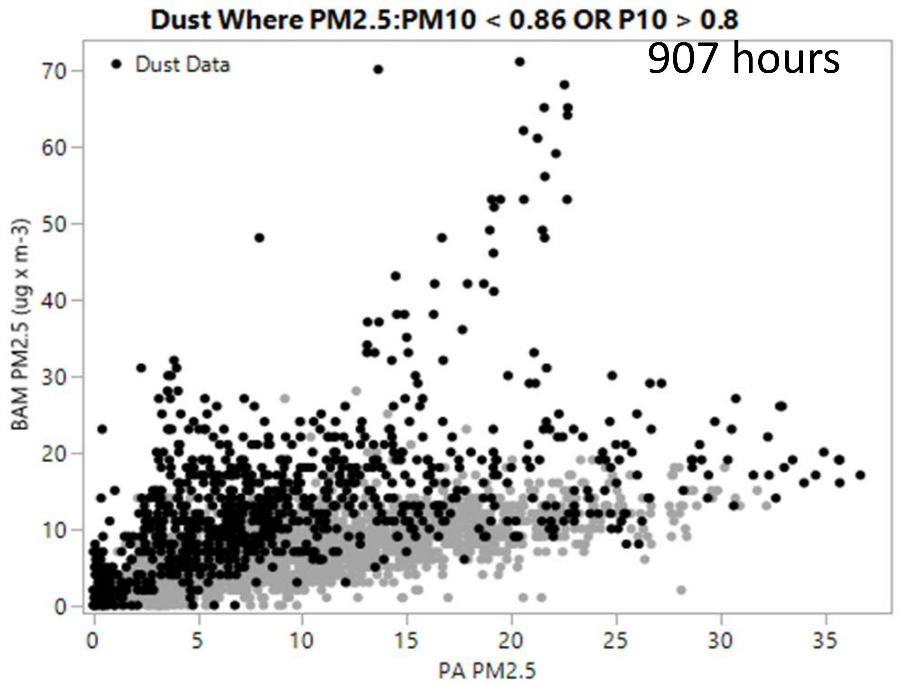


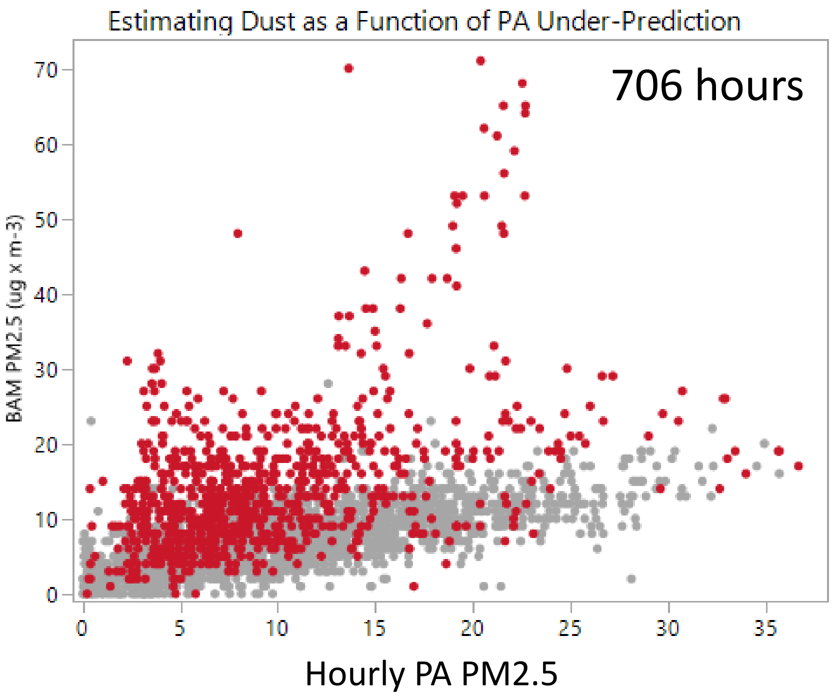



# The split-model approach looks good, but does the filter make sense?




**The filter selected 584 hrs of under-predicted hours as dust (83%)**



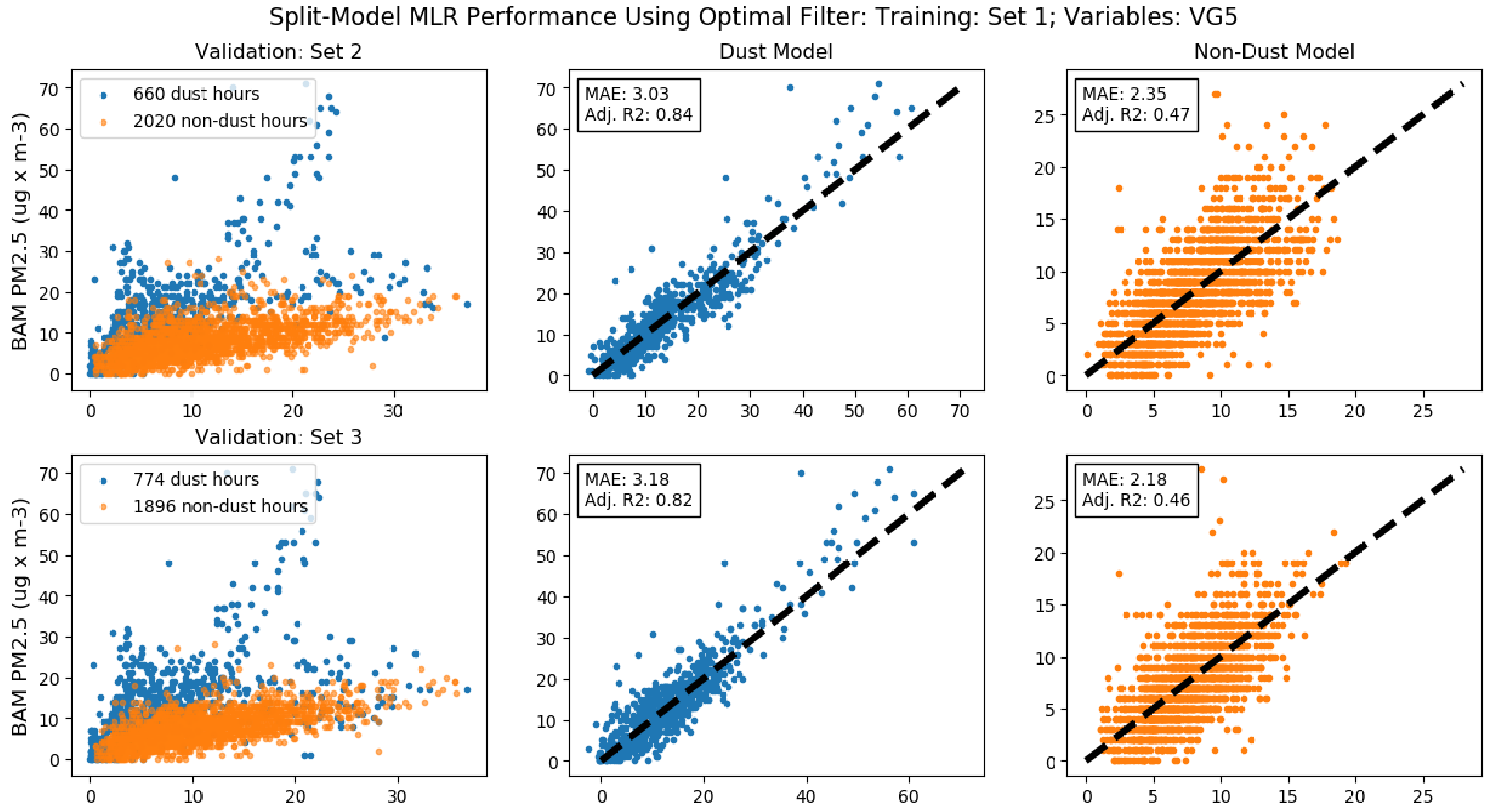
# Key Takeaways: The Best Approach

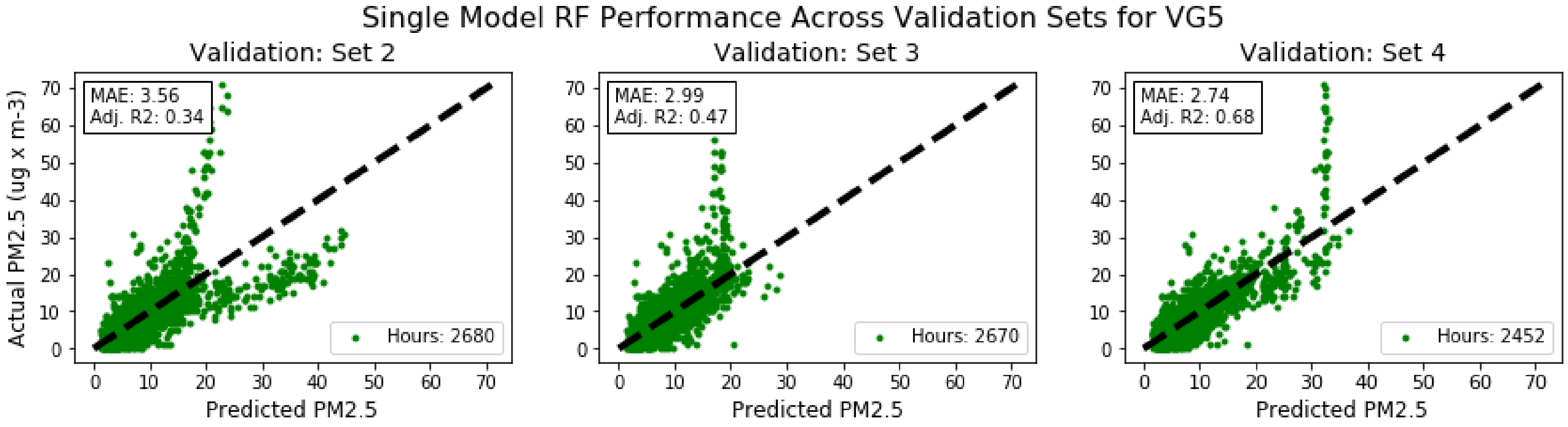
**Split MLR**
nMAE = 0.27
Adj. R2 = 0.65

**Single-Model RF**
nMAE = 0.32
Adj. R2 = 0.49

The split method does not hurt predictive performance. In fact, it improves it.

- Consistent across validation sets
- Higher accuracy
- Contextualizes the data by adding dust component



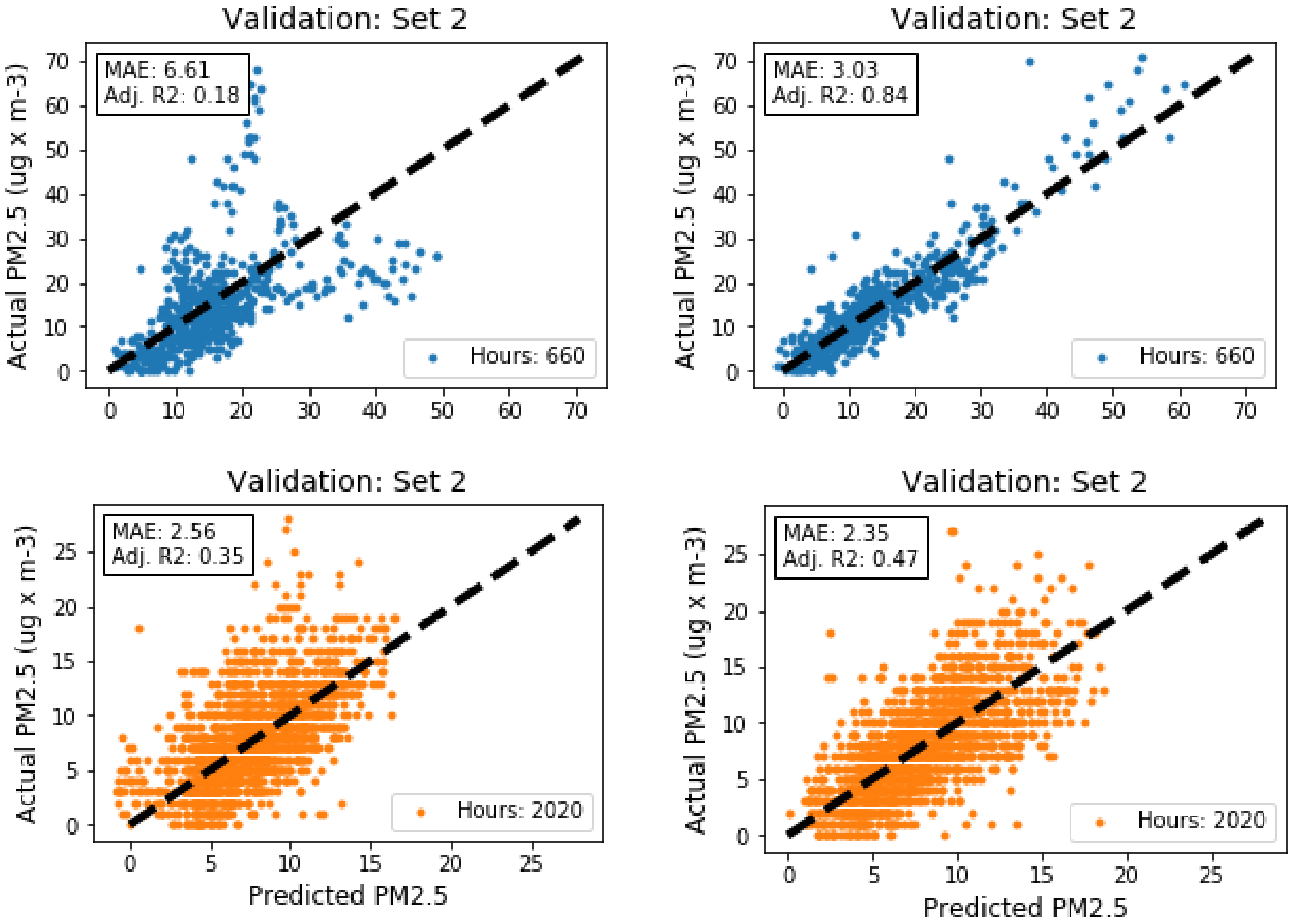



# Key Takeaways: Model complexity

Relationships between sensors and actual $PM_{2.5}$ more complex during the presence of dust

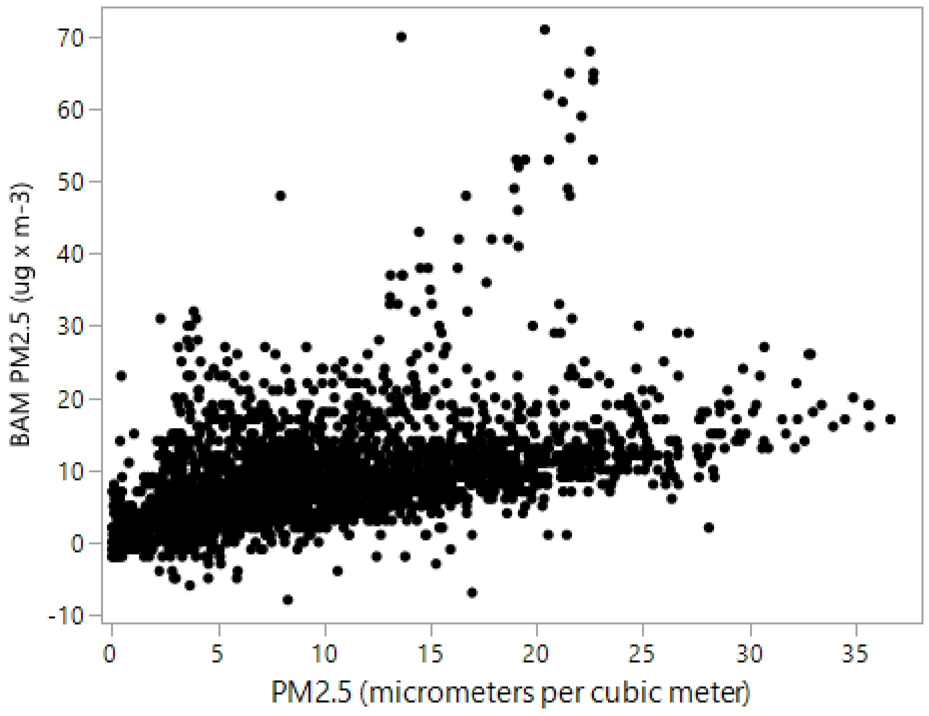
VG2: PM2.5, RH, T

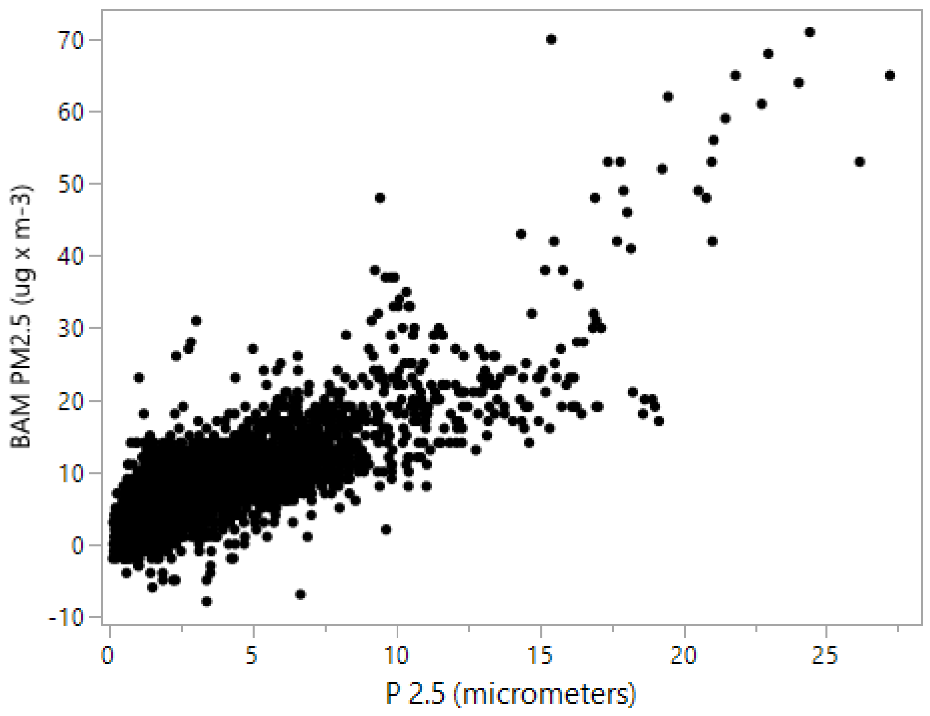
VG5: All variables



# Key Takeaways: PM vs. P

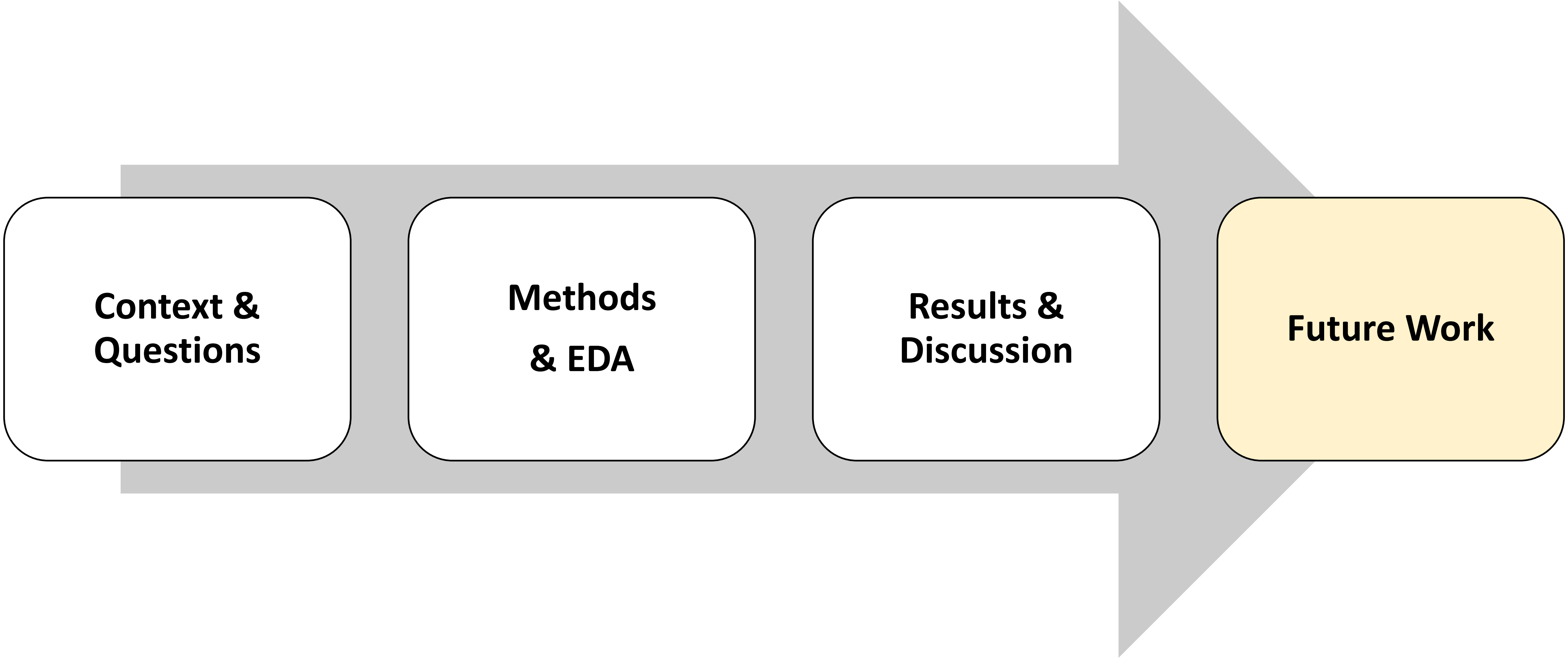
Particle size counts may be better predictors of actual PM2.5 than sensor PM concentrations in some environments




# Why is this significant?

PA-sensors convert particle size counts into mass concentrations according to factory calibration


Context & Questions
Methods & EDA
Results & Discussion
Future Work

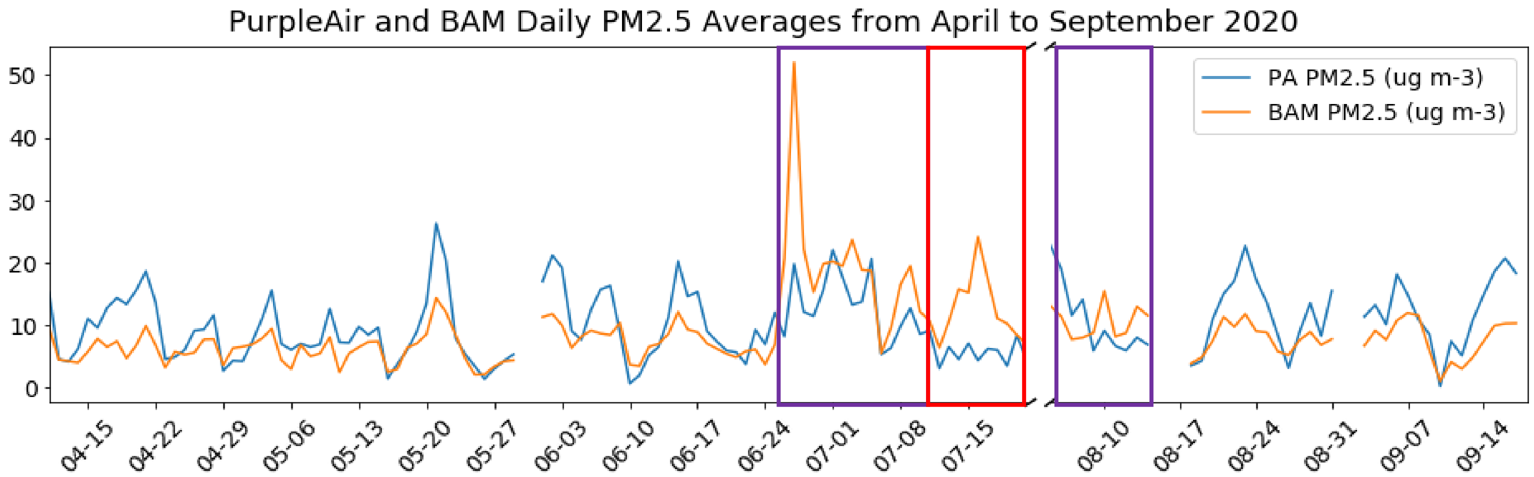
# Future Work

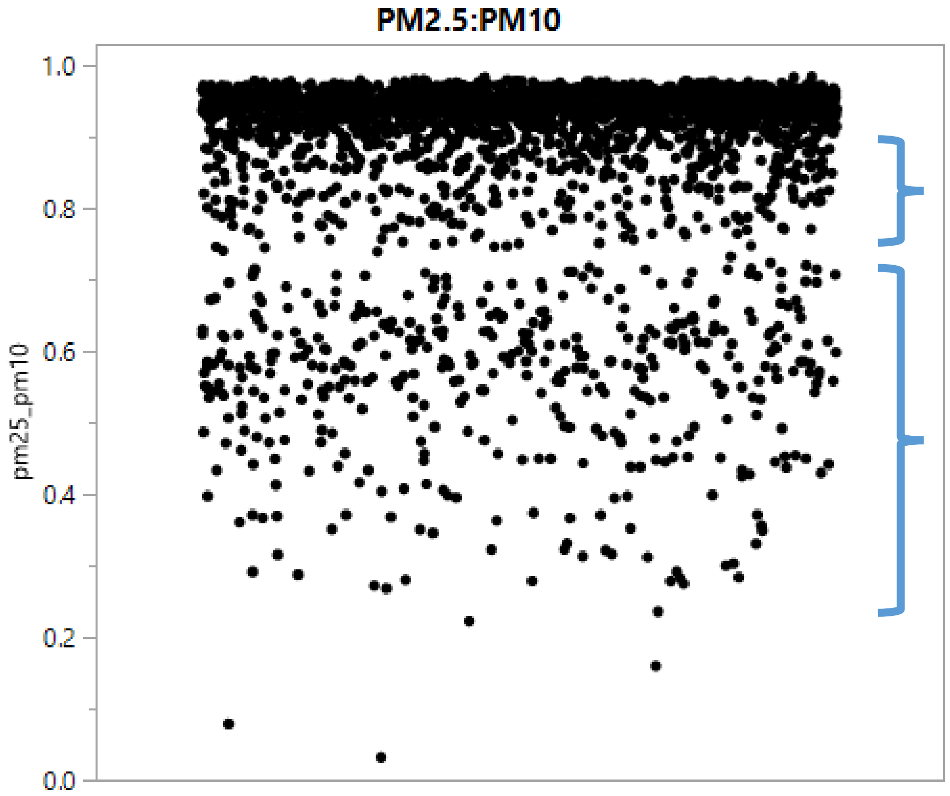
1. Apply correction model to other sensors deployed to locations in Denton to perform spatial and temporal analyses.

2. Validate model at another site and at future times.

3. Validate filter using another data source.

4. Can PA PM2.5:PM10 ratio tell us about the source of the Saharan dust?




158/261 hours:
06/26 – 06/29
07/03 – 07/04
08/09 – 08/14

366/420 hours:
07/06 – 07/21

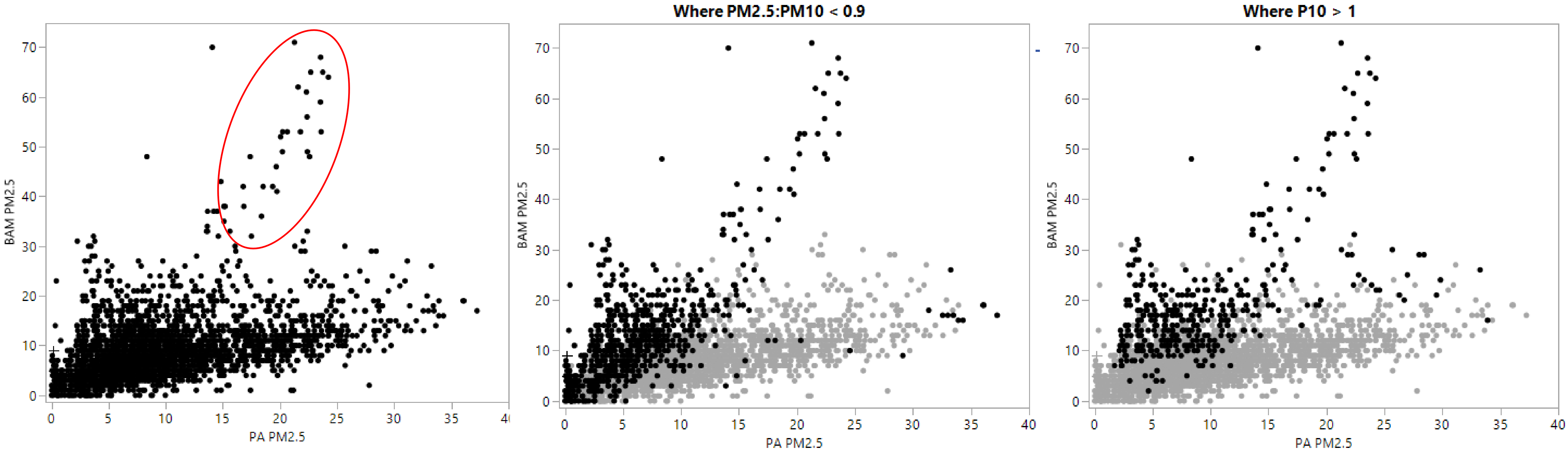
# Thank you for listening!
# Questions?

# Extra

# Objective: Creating a Filter

Dust → WHERE **PM2.5:PM10** < Threshold

OR WHERE **P10** > Threshold



# Average validation metrics for MLR Split

**Dust**

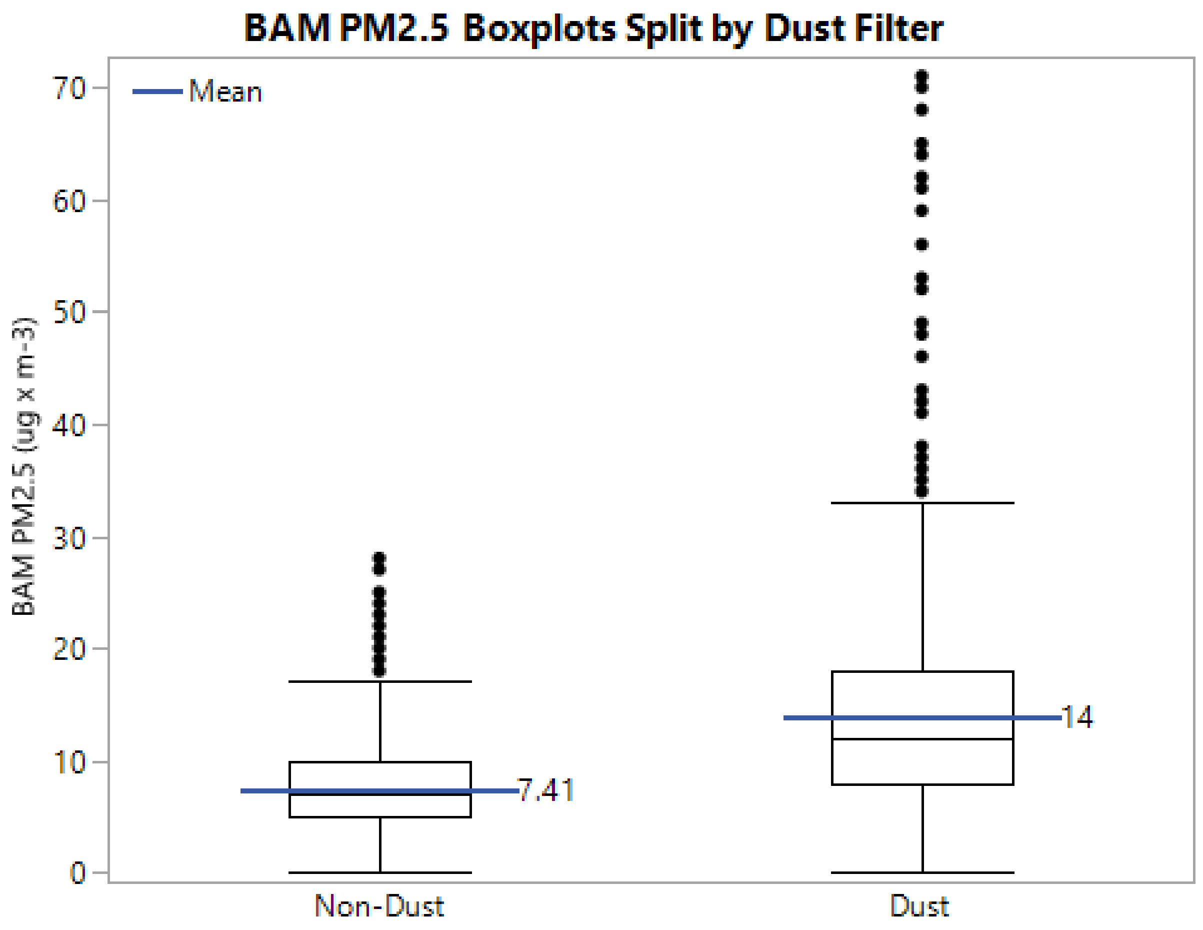
MAE = 3.01; Adj. R2 = 0.82

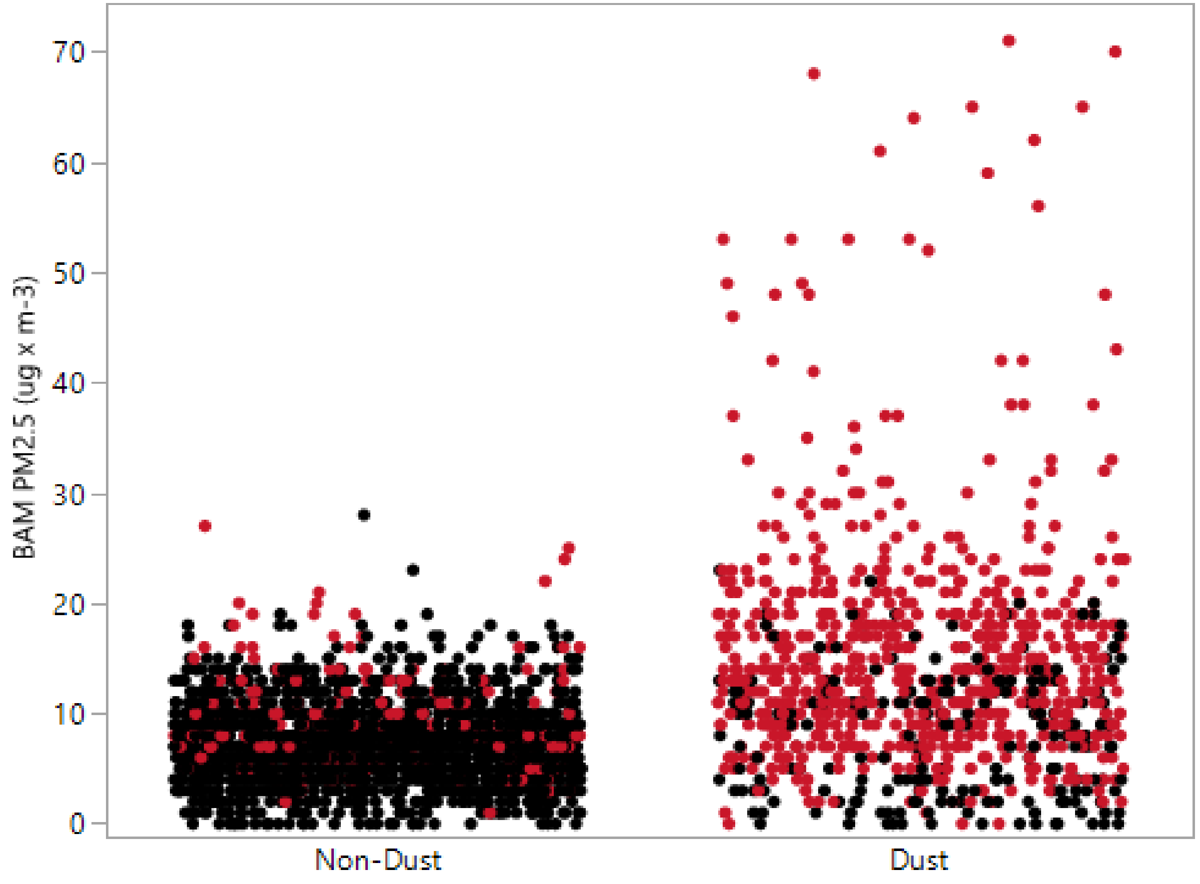
**Non-Dust**

MAE = 2.19; Adj. R2 = 0.47

# The split-model results look good, but what about the filter?

**584 hrs of overlap with under-prediction hours (83%)**



# Particle Size Counts vs All Variables

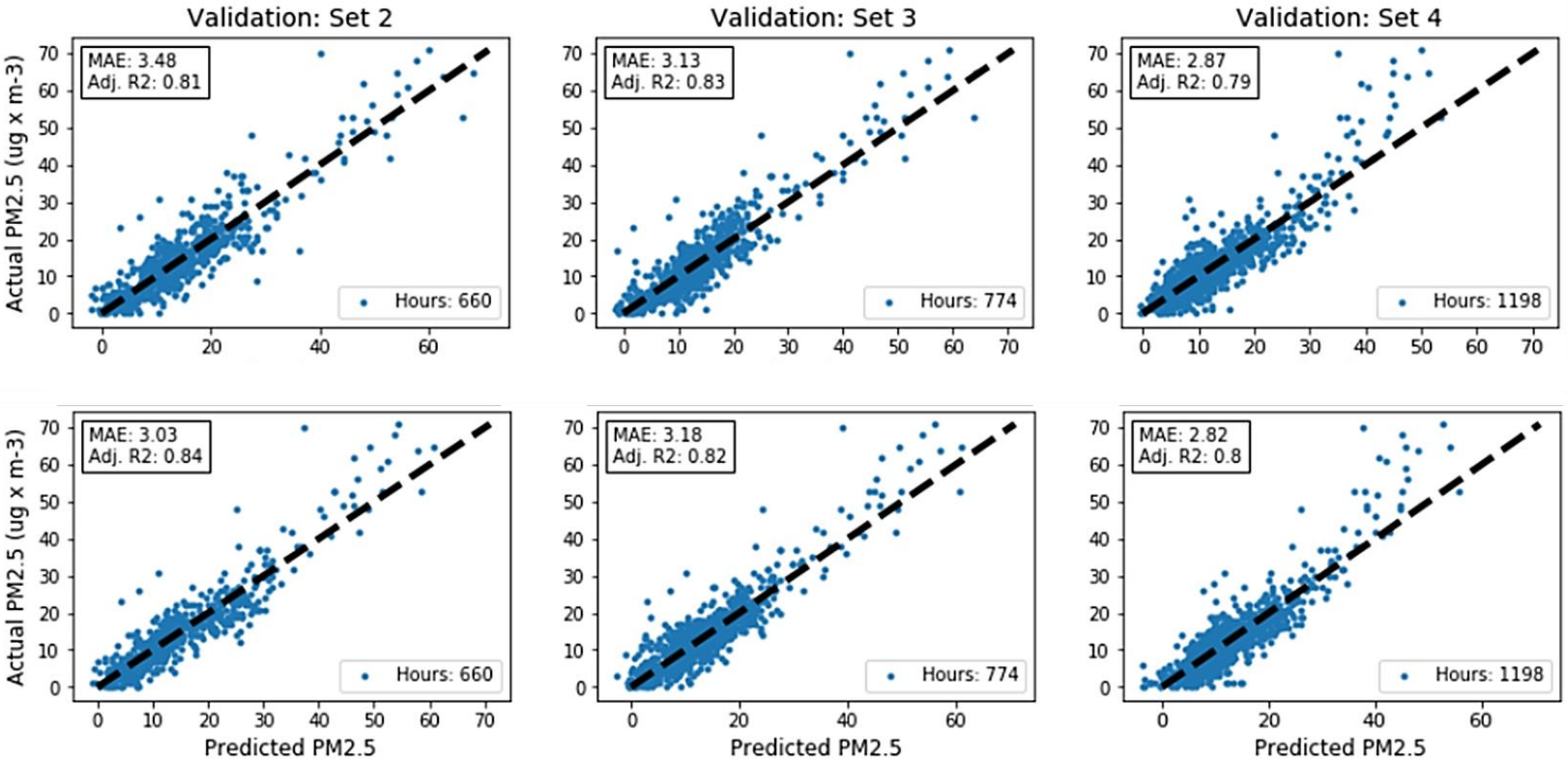
| | Variables Added |
|---|---|
| **VG1** | PM2.5 |
| **VG2** | +RH, T |
| **VG3** | +PM1.0, PM10 |
| **VG4** | +Ratios (PM2.5:PM10, …) |
| **VG5** | +Particle Size Counts (P0.3, …) |

| | **Dust MAE** | **Non-Dust MAE** | **Dust R2** | **Non-Dust R2** |
|---|---|---|---|---|
| P Count + RH, T | 3.16 | 2.21 | 0.81 | 0.46 |
| VG5 | 3.01 | 2.19 | 0.82 | 0.47 |

# Using particle size counts + RH & T almost as strong as using all possible variables

RH, T + Particle Size Counts

VG5: All Variables (adding PM variables)



# Particle Size Count Might Be a Better (or at least good of a) Predictor as Manufacturer Derived PM

- Dust
  - 9/14 significant at 99% level
  - 1 significant at the 95% level
  - Complex model needed
- Non-Dust
  - 5/14 significant at 99% level
  - 4 significant at the 95% level
  - Less complex model needed

| Dust |
|---|
| T |
| RH |
| P0.3 |
| P0.5 |
| P1 |
| P2.5 |
| P5 |
| P10 |
| PM2.5 |
| PM1 |
| PM10 |
| PM1:PM2.5 |
| PM2.5:PM10 |
| PM1:PM10 |

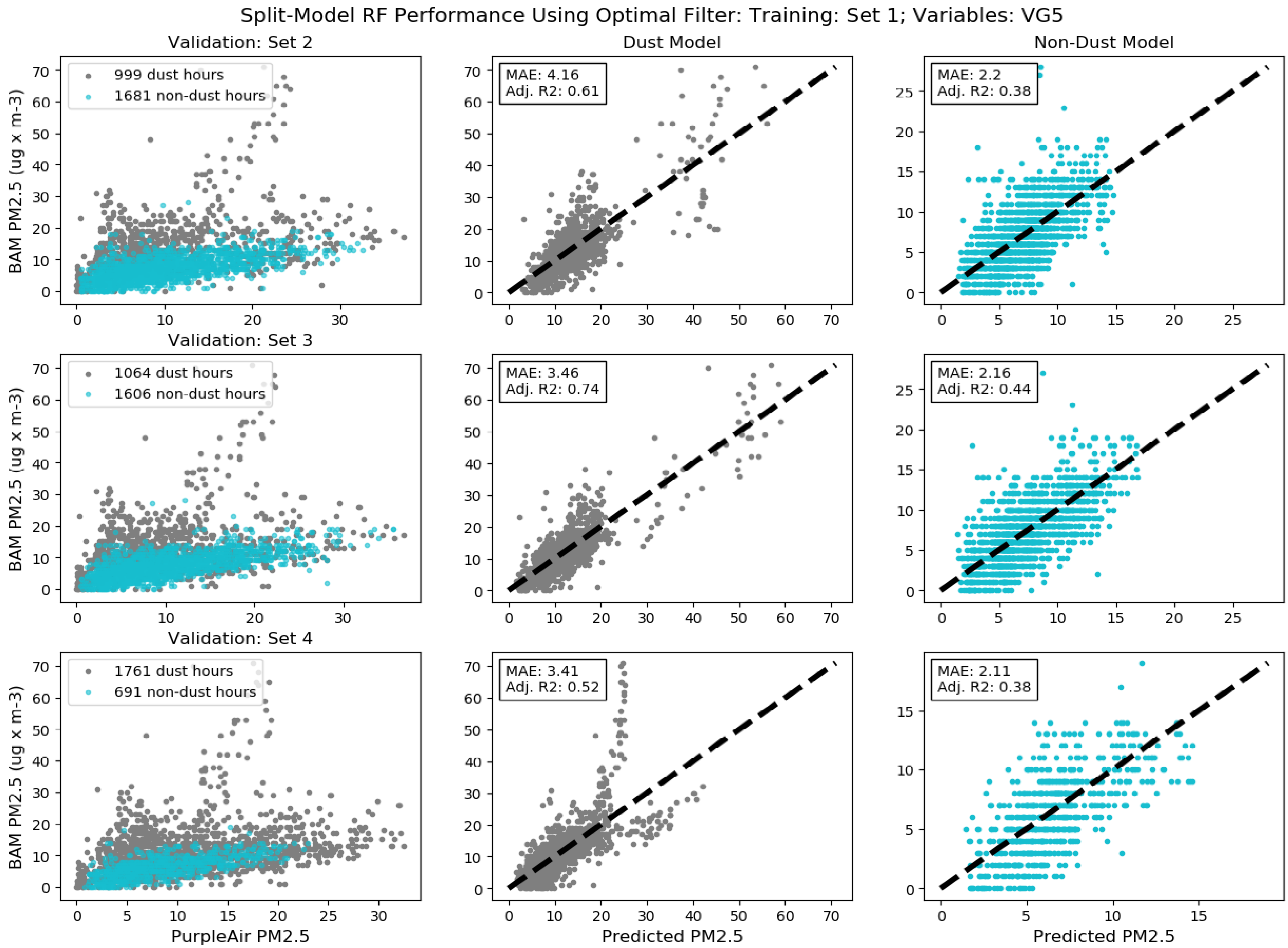
| Legend | |
|---|---|
| p>0.1 | |
| p<0.1 | * |
| p< 0.05 | ** |
| p<0.01 | *** |

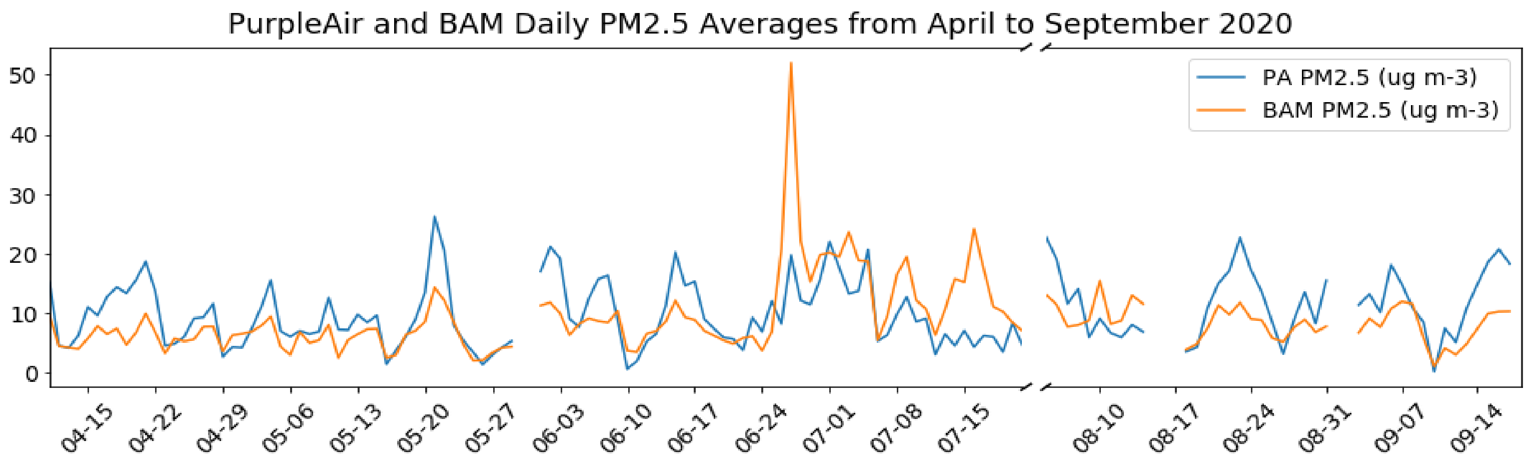
| Deployment Period | Training Set 1 | Validation Set 2 | Validation Set 3 | Validation Set 4 |
|---|---|---|---|---|
| **April - May** | PA-a5f0 | PA-80f1 | PA-8095 | PA-8038 B |
| **June** | PA-c074 | PA-8079 | PA-adb9 | PA-8d18 |
| **July** | PA-d5ec | PA-d147 | PA-16a0* A | PA-38da* A |
| **August - September** | PA-e4f6 | PA-198 | PA-e396 | PA-8060 |

# Evaluating the Dust Filter

- Performance varied according to the parameters of the filter used
- A filter that optimized the dust data did not necessarily optimize the non-dust data
- A filter that optimized MAE did not necessarily optimize R2
- Filters were ranked according to MAE and R2 for both dust and non-dust models
- The ranks were summed to find

| P10 Count | PM2.5:PM10 Ratio | Dust MAE | Dust R2 | Non-Dust MAE | Non-Dust R2 | Sum of Ranks |
|---|---|---|---|---|---|---|
| 0.8 | 0.86 | 4 | 6 | 55 | 5 | 70 |
| 0.8 | 0.85 | 18 | 16 | 71 | 17 | 122 |
| 0.8 | 0.75 | 11 | 4 | 87 | 23 | 125 |
| 0.8 | 0.88 | 0 | 0 | 59 | 67 | 126 |
| 0.8 | 0.74 | 17 | 5 | 80 | 25 | 127 |
| ... | ... | ... | ... | ... | ... | ... |
| 0.8 | 0.94 | 80 | 93 | 63 | 101 | 337 |
| 0.6 | 0.94 | 95 | 99 | 52 | 102 | 348 |
| 0.9 | 0.94 | 88 | 96 | 66 | 100 | 350 |
| 0.7 | 0.94 | 89 | 97 | 67 | 104 | 357 |
| 0.5 | 0.94 | 101 | 104 | 49 | 103 | 357 |

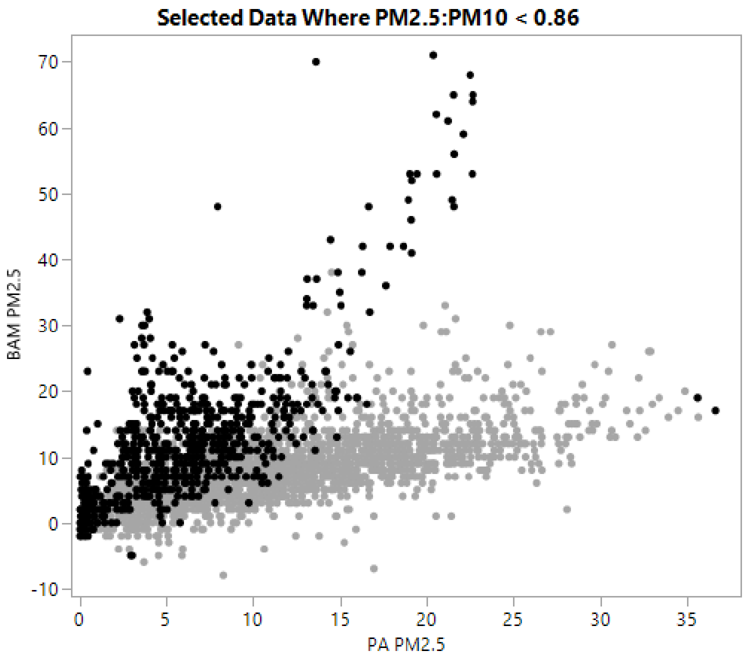

Split-Model RF Performance Using Optimal Filter: Training: Set 1; Variables: VG5
Validation: Set 2
Dust Model
Non-Dust Model
999 dust hours
1681 non-dust hours
MAE: 4.16
Adj. R2: 0.61
MAE: 2.2
Adj. R2: 0.38
Validation: Set 3
1064 dust hours
1606 non-dust hours
MAE: 3.46
Adj. R2: 0.74
MAE: 2.16
Adj. R2: 0.44
Validation: Set 4
1761 dust hours
691 non-dust hours
MAE: 3.41
Adj. R2: 0.52
MAE: 2.11
Adj. R2: 0.38
BAM PM2.5 (ug x m-3)
PurpleAir PM2.5
Predicted PM2.5

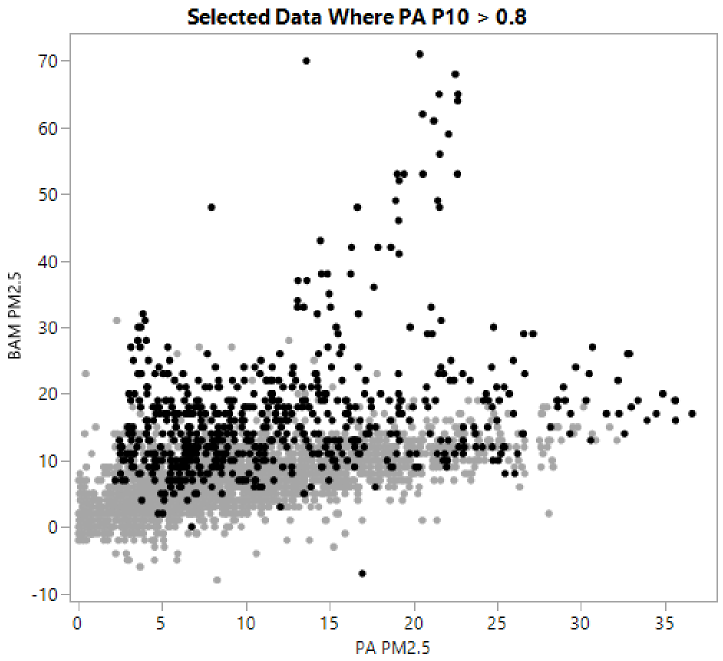


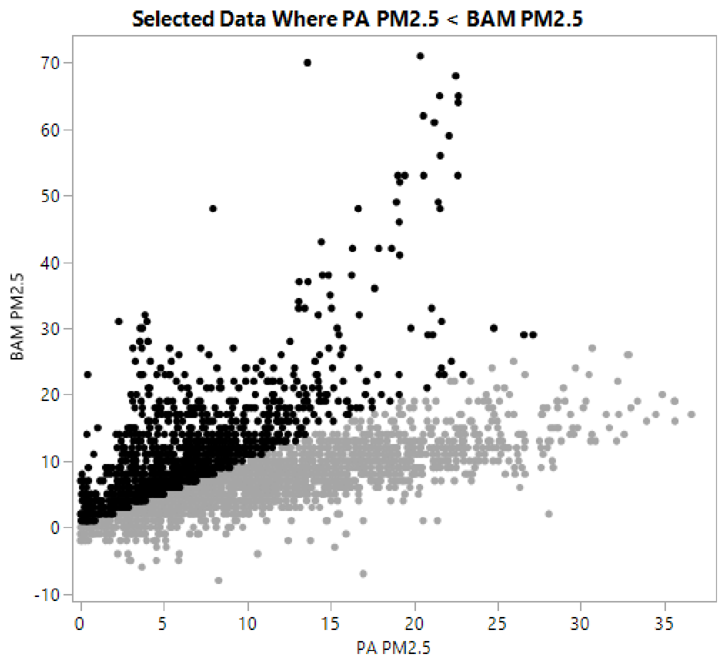

666 hours

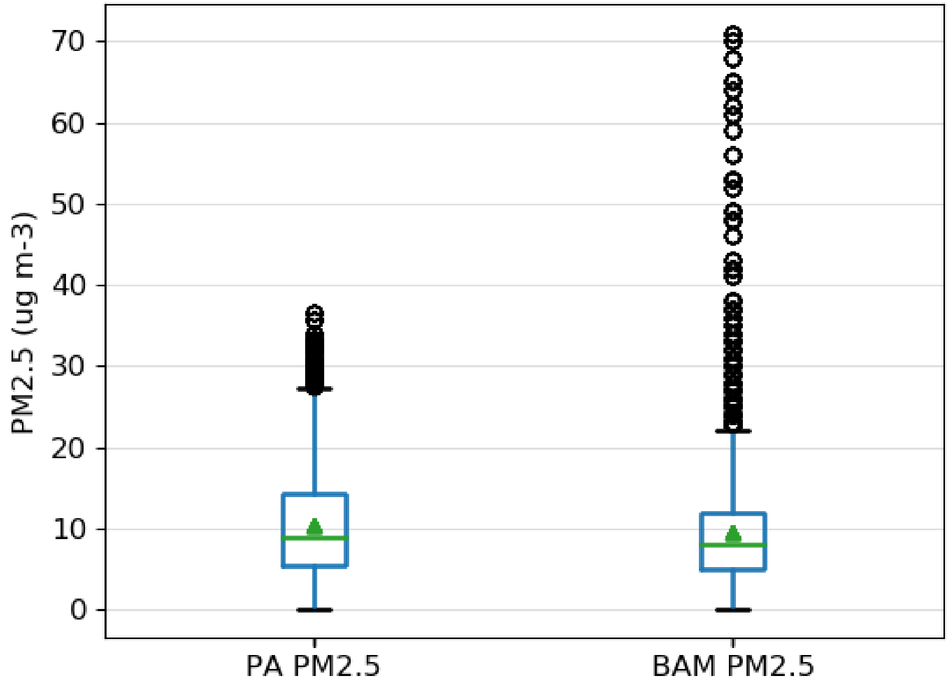
625 hours

1108 hours

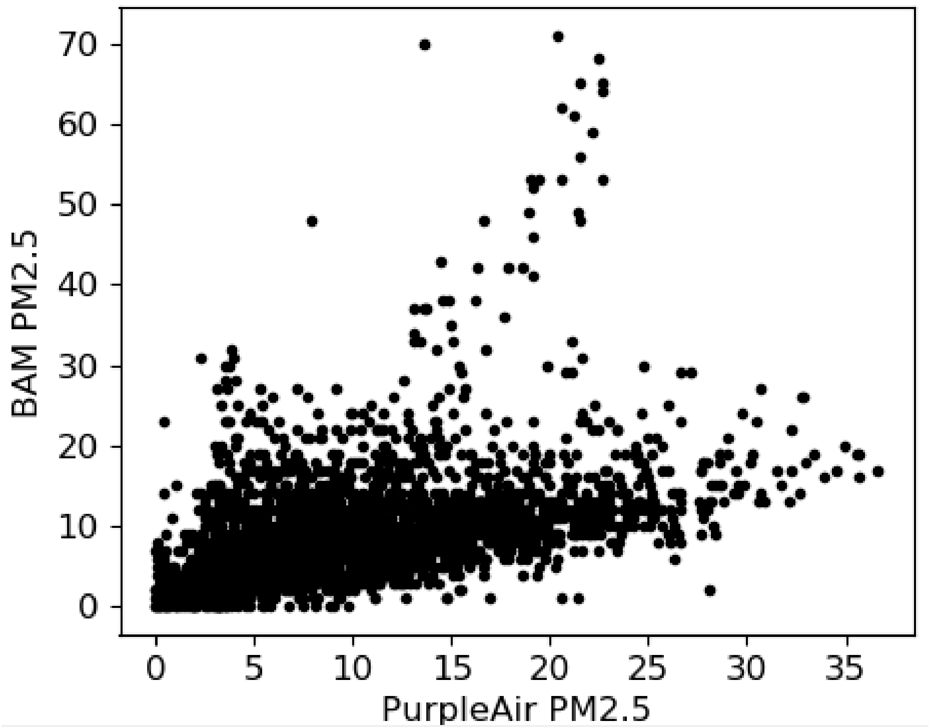




PM2.5 (ug m-3)
0
10
20
30
40
50
60
70
PA PM2.5
BAM PM2.5

BAM PM2.5
0
10
20
30
40
50
60
70
0
5
10
15
20
25
30
35
PurpleAir PM2.5

| Abbreviation | Number | Variable Type | Variables In Group |
|---|---|---|---|
| **VG1** | 1 | PM: | PM2.5 |
| **VG2** | 3 | PM:<br>Meteorological: | PM2.5<br>RH, T |
| **VG3** | 5 | PM:<br>Meteorological: | PM2.5, PM1.0, PM10<br>RH, T |
| **VG4** | 8 | PM:<br>Meteorological:<br>PM Ratio: | PM2.5, PM1.0, PM10<br>RH, T<br>PM1:PM2.5, PM2.5:PM10, PM1:PM10 |
| **VG5** | 14 | PM:<br>Meteorological:<br>PM Ratio:<br>Particle Size Count: | PM2.5, PM1.0, PM10<br>RH, T<br>PM1:PM2.5, PM2.5:PM10, PM1:PM10<br>P0.3, P0.5, P1.0, P2.5, P5.0, P10.0 |

# A New Approach: Calibrating Low-Cost Air Quality Sensors According to Pollutant Source

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