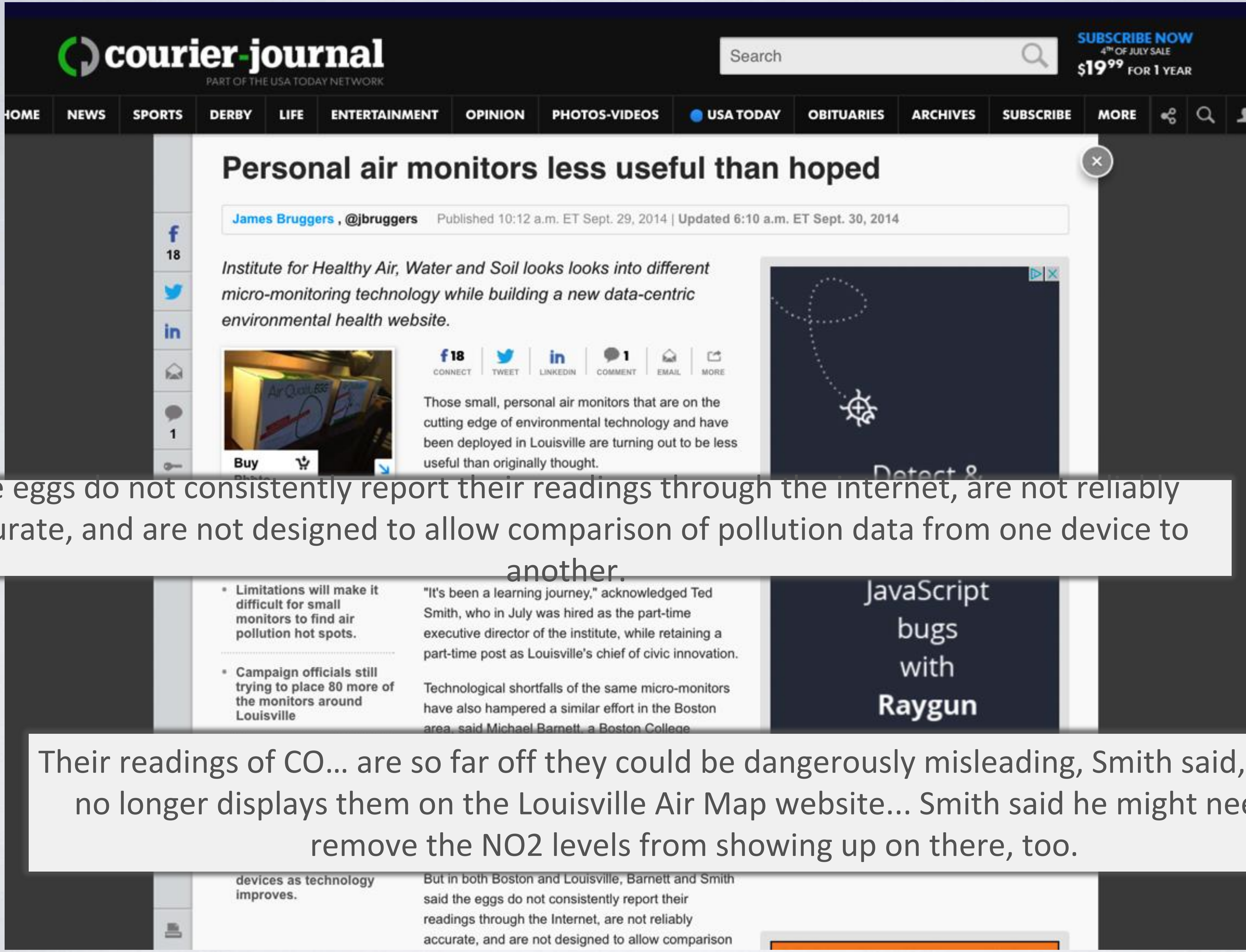
Automated Characterization of Consumer-Grade Sensor Accuracy from Supporting Data in Heterogeneous Air Quality Monitoring Networks

David Ramsay and Dr. Joe Paradiso

Responsive Environments, MIT Media Lab

mit
media
lab



courier-journal
PART OF THE USA TODAY NETWORK

Search

SUBSCRIBE NOW
4TH OF JULY SALE
$19.99 FOR 1 YEAR

HOME | NEWS | SPORTS | DERBY | LIFE | ENTERTAINMENT | OPINION | PHOTOS-VIDEOS | USA TODAY | OBITUARIES | ARCHIVES | SUBSCRIBE | MORE

Personal air monitors less useful than hoped

James Bruggers, @jbruggers Published 10:12 a.m. ET Sept. 29, 2014 | Updated 6:10 a.m. ET Sept. 30, 2014

Institute for Healthy Air, Water and Soil looks looks into different micro-monitoring technology while building a new data-centric environmental health website.

18 CONNECT | TWEET | LINKEDIN | 1 COMMENT | EMAIL | MORE

Buy Photo

Those small, personal air monitors that are on the cutting edge of environmental technology and have been deployed in Louisville are turning out to be less useful than originally thought.

- Limitations will make it difficult for small monitors to find air pollution hot spots.
- Campaign officials still trying to place 80 more of the monitors around Louisville

devices as technology improves.

"It's been a learning journey," acknowledged Ted Smith, who in July was hired as the part-time executive director of the institute, while retaining a part-time post as Louisville's chief of civic innovation.

Technological shortfalls of the same micro-monitors have also hampered a similar effort in the Boston area, said Michael Barnett, a Boston College

But in both Boston and Louisville, Barnett and Smith said the eggs do not consistently report their readings through the Internet, are not reliably accurate, and are not designed to allow comparison

The eggs do not consistently report their readings through the internet, are not reliably accurate, and are not designed to allow comparison of pollution data from one device to another.

Their readings of CO… are so far off they could be dangerously misleading, Smith said, and he no longer displays them on the Louisville Air Map website... Smith said he might need to remove the NO2 levels from showing up on there, too.

INTERNET OF NOTHING

~Pieter Franken, Safecast

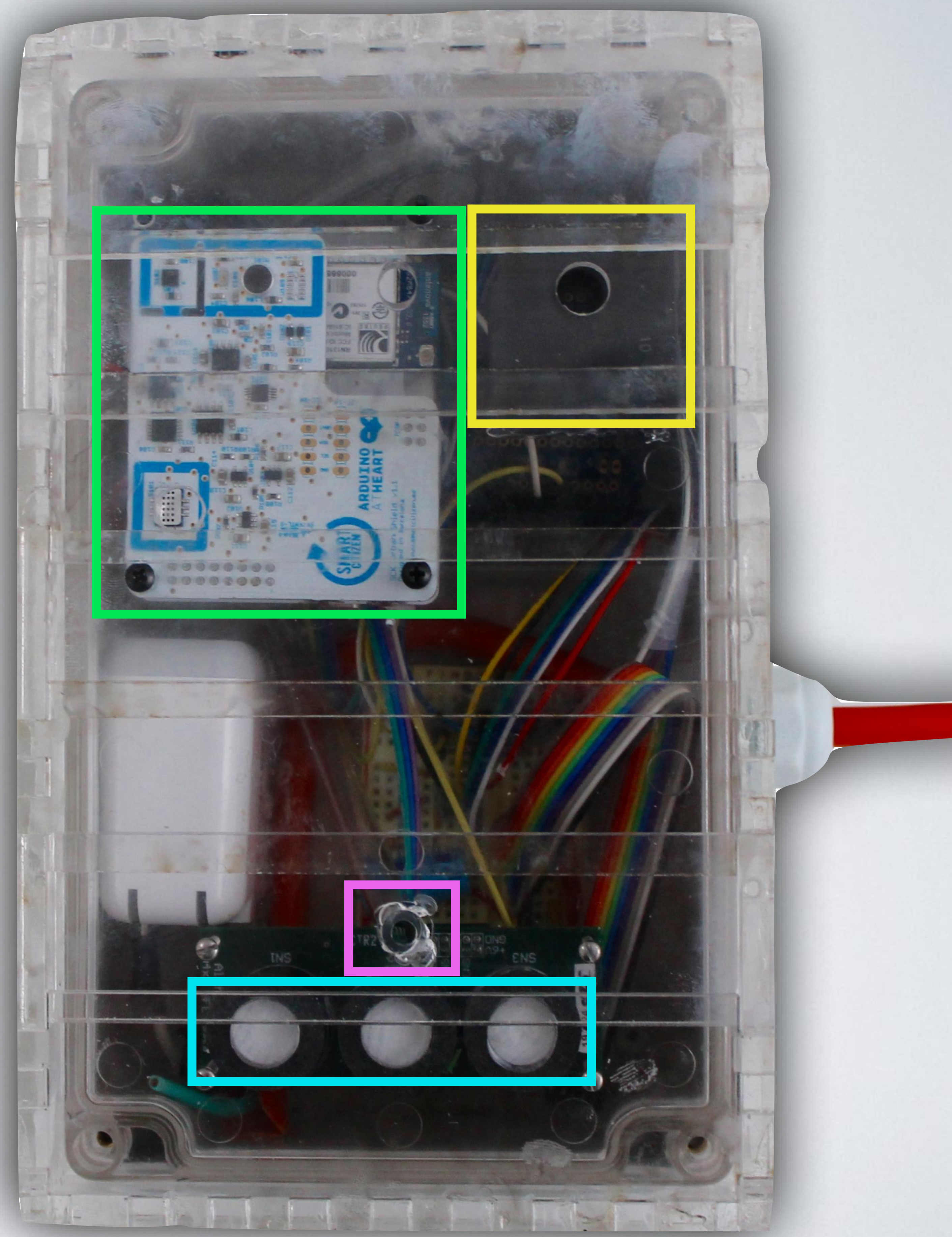
https://www.slideshare.net/safecast/owod-013pieter-franken-corporate-data


Optical Particle Counter OPC-N2 162270025
PM1 PM2.5 PM10
CAUTION-CLASS 3B LASER RADIATION
WHEN OPEN AVOID EXPOSURE TO BEAM

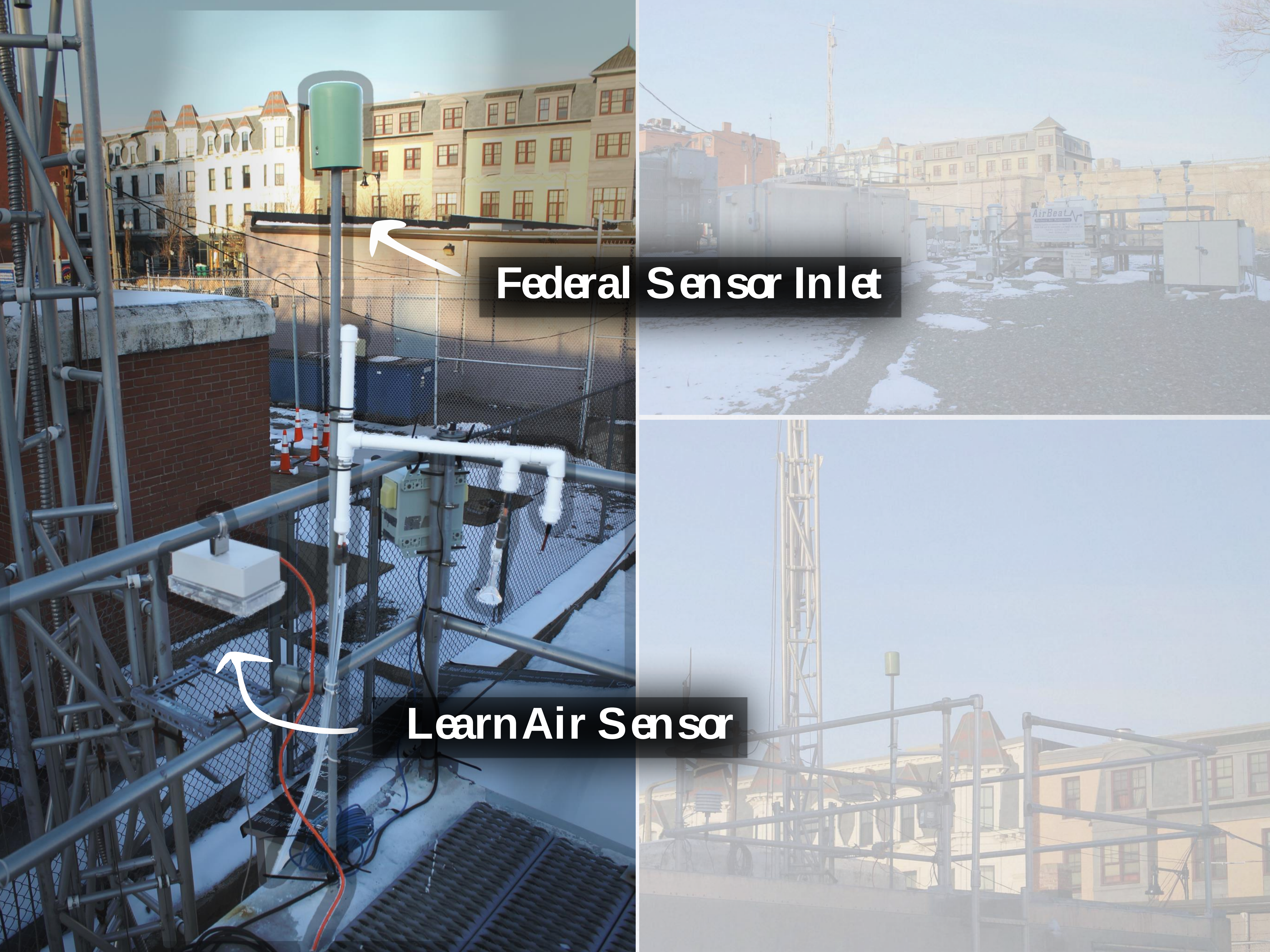

SULFUR DIOXIDE
SO2-B4 164511306
072
NO2-B4
082
CARBON MONOXIDE
CO-B4 162512433
072

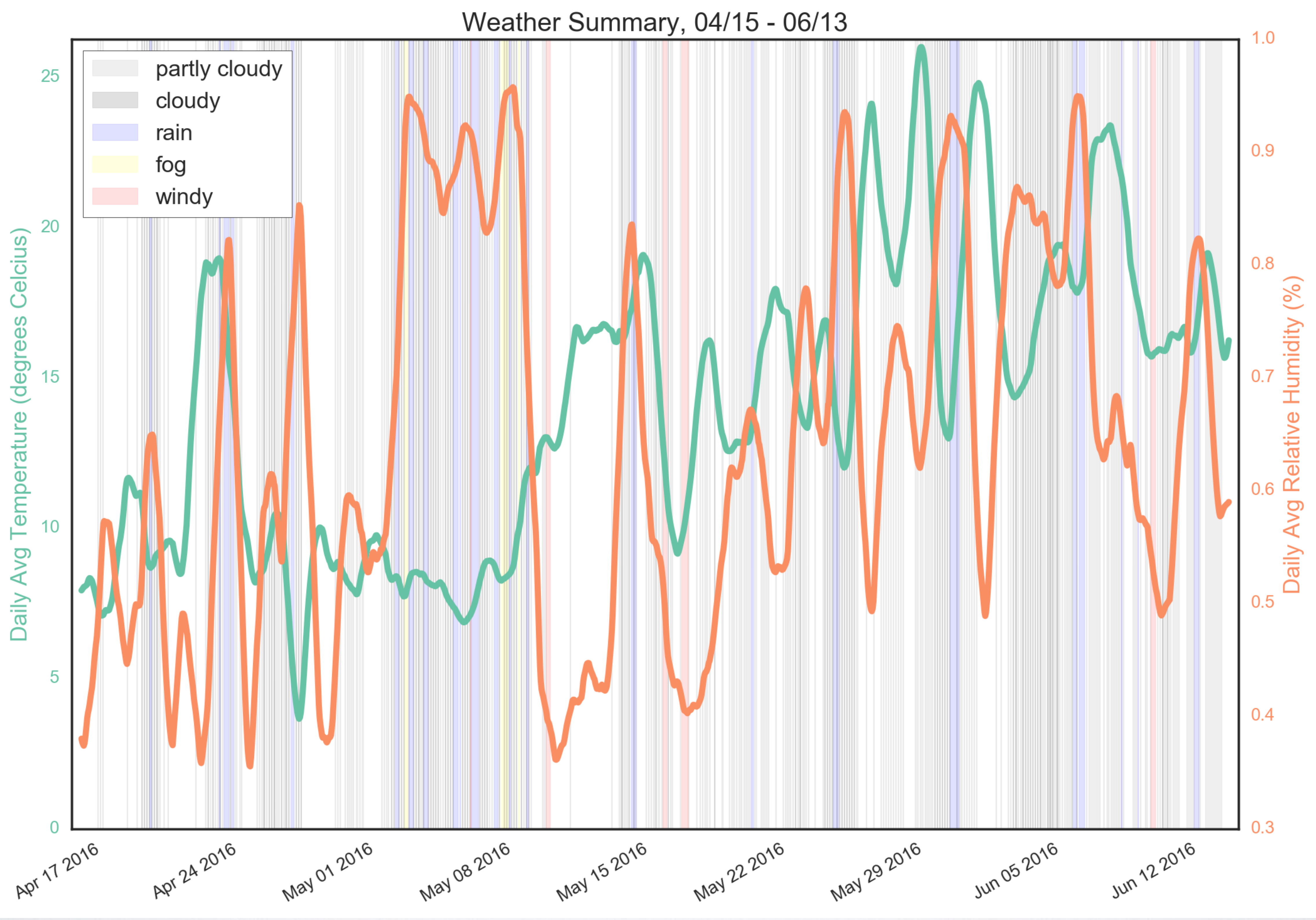
1 minute, timestamped:

- Temperature
- Humidity
- Light Level
- Wind
- cheap PM2.5
- cheap NO2
- cheap CO
- moderate CO
- moderate H2S
- moderate O3



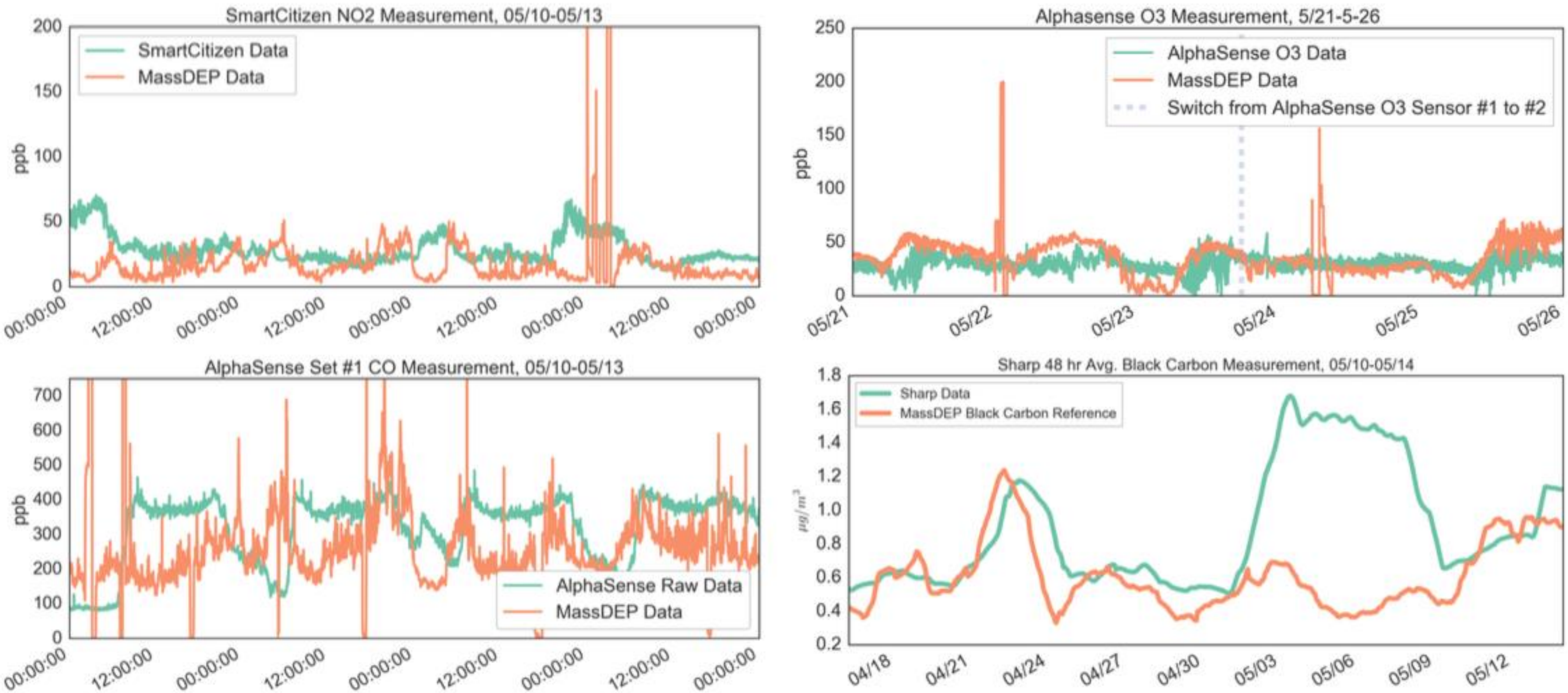

AirBeat

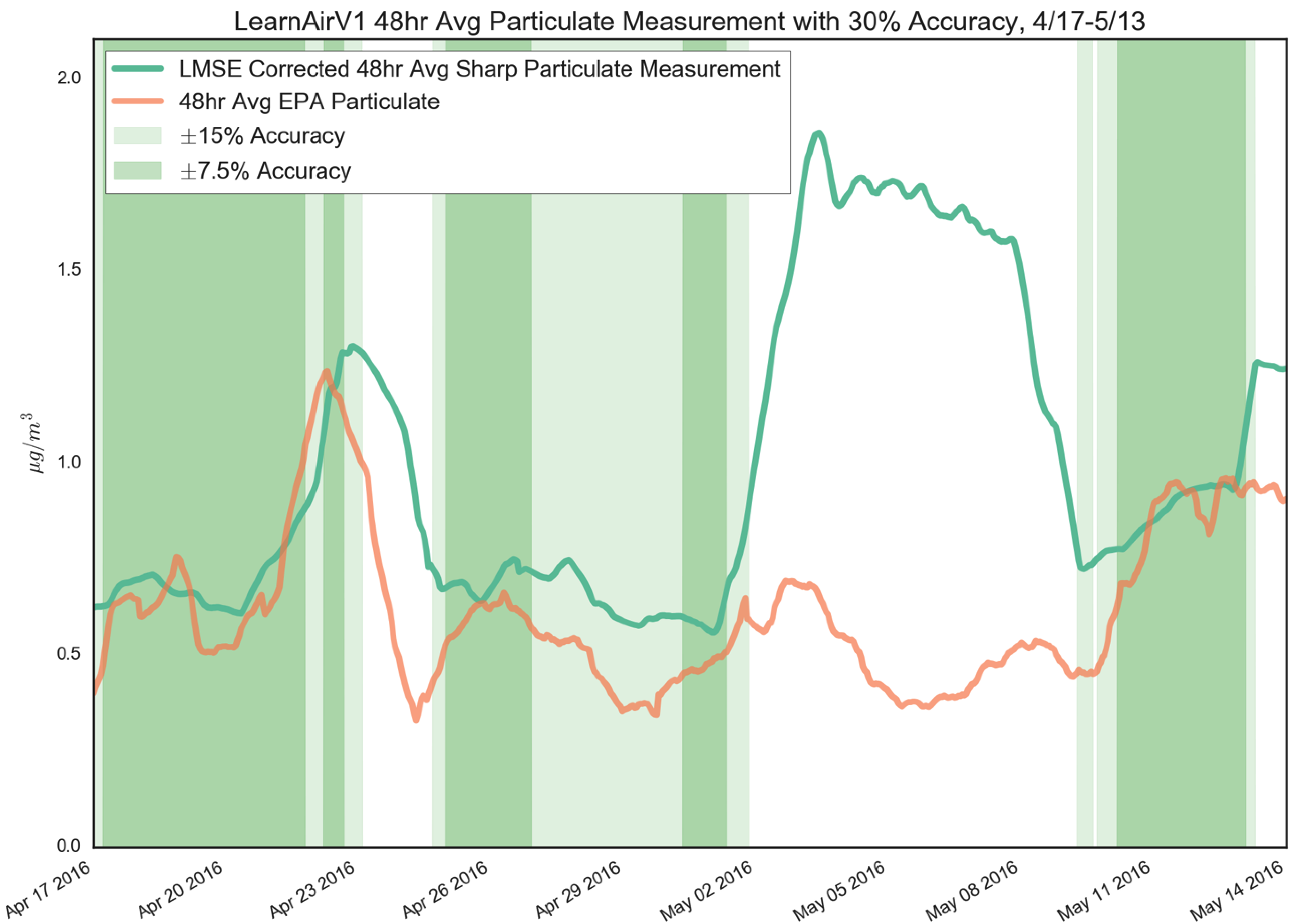

Federal Sensor Inlet
LearnAir Sensor



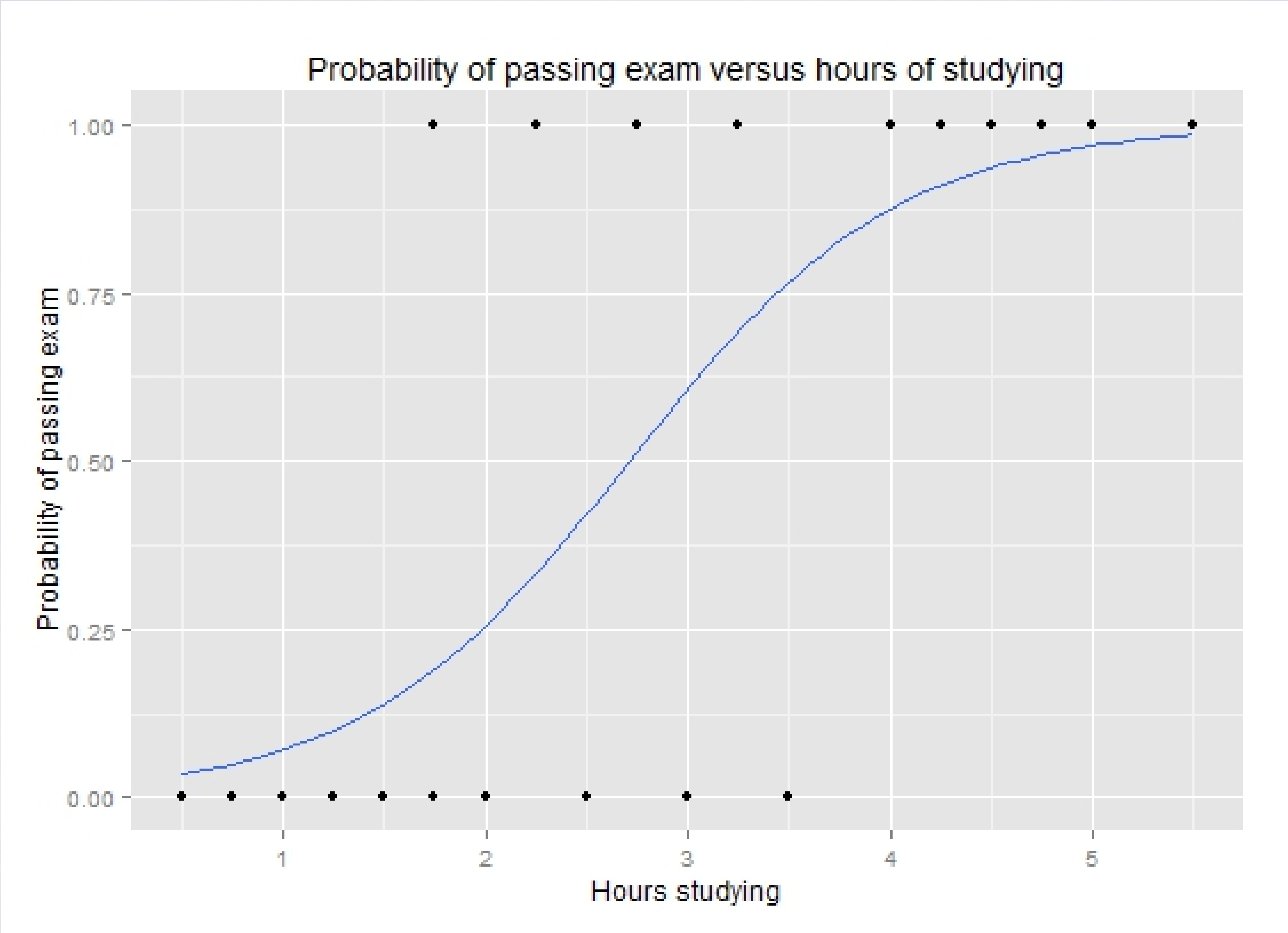
Weather Summary, 04/15 - 06/13
partly cloudy
cloudy
rain
fog
windy
Daily Avg Temperature (degrees Celcius)
Daily Avg Relative Humidity (%)
0
5
10
15
20
25
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0
Apr 17 2016
Apr 24 2016
May 01 2016
May 08 2016
May 15 2016
May 22 2016
May 29 2016
Jun 05 2016
Jun 12 2016

Conditions	Measurements
(from Sensor)	**(from Sensor)**
Temperature	PM2.5 (1 min resolution)
Humidity	Ozone (1 min resolution)
3-axis Motion	NO2 (1 min resolution)
3-axis Wind	CO (1 min resolution)
Visible Light	
UV Light	
(from Weather API and GPS)	**(from EPA/MassDEP Reference)**
Wind Speed/Direction	PM2.5 (1 hour resolution)
Wind Gusts	Ozone (1 hour online; 1 min)
UV Index	NO2 (1 hour online; 1 min)
Weather Description	CO (1 hour online; 1 min)
Precipitation	
Geography/Climate	
Temperature	
Humidity	
Barometric Pressure	


SmartCitizen NO2 Measurement, 05/10-05/13
SmartCitizen Data
MassDEP Data
ppb
Alphasense O3 Measurement, 5/21-5-26
AlphaSense O3 Data
MassDEP Data
Switch from AlphaSense O3 Sensor #1 to #2
ppb
AlphaSense Set #1 CO Measurement, 05/10-05/13
AlphaSense Raw Data
MassDEP Data
ppb
Sharp 48 hr Avg. Black Carbon Measurement, 05/10-05/14
Sharp Data
MassDEP Black Carbon Reference
$\mu g/m^3$

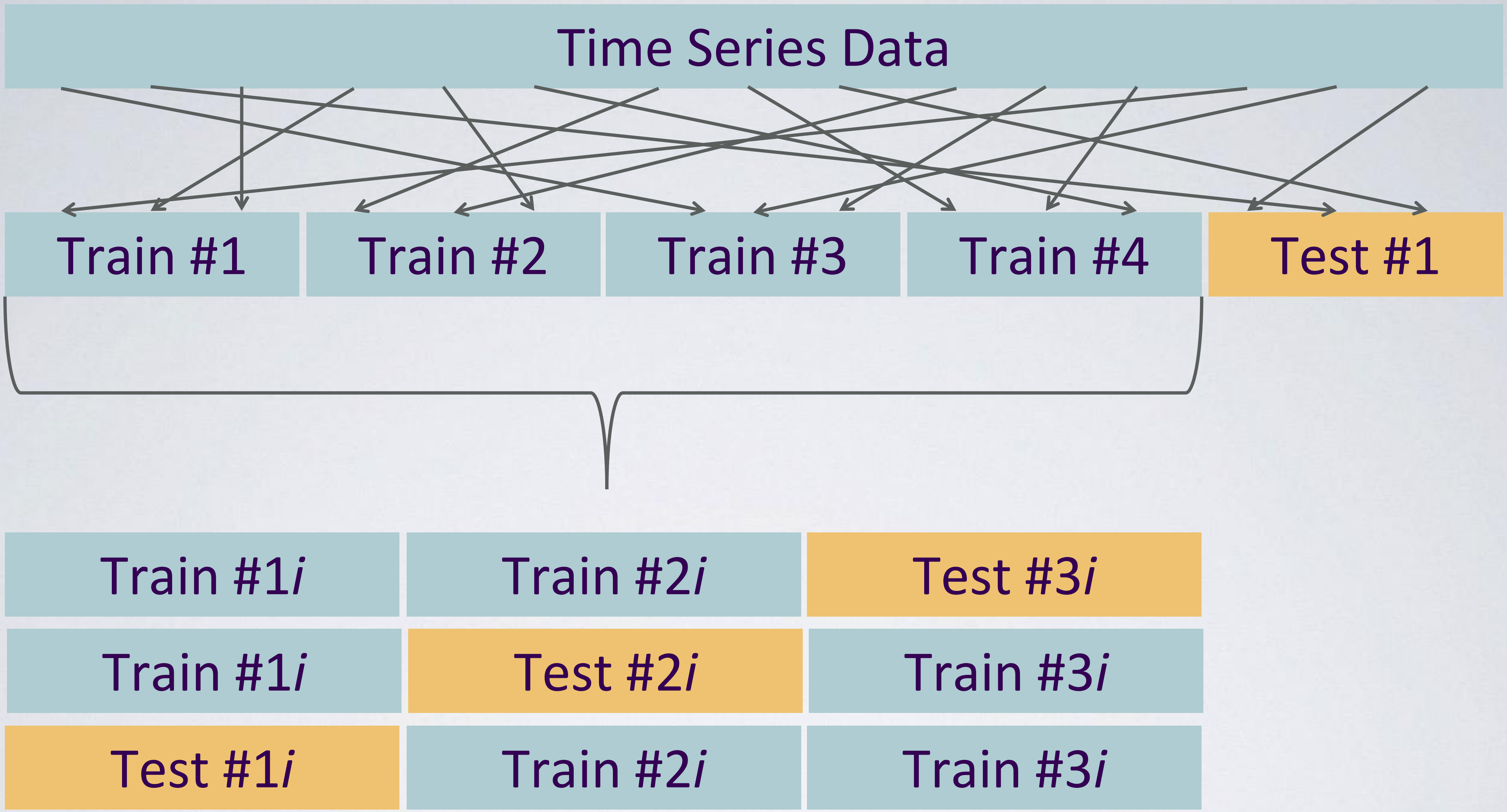

LearnAirV1 48hr Avg Particulate Measurement with 30% Accuracy, 4/17-5/13
LMSE Corrected 48hr Avg Sharp Particulate Measurement
48hr Avg EPA Particulate
±15% Accuracy
±7.5% Accuracy
$\mu g/m^3$
2.0
1.5
1.0
0.5
0.0
Apr 17 2016
Apr 20 2016
Apr 23 2016
Apr 26 2016
Apr 29 2016
May 02 2016
May 05 2016
May 08 2016
May 11 2016
May 14 2016

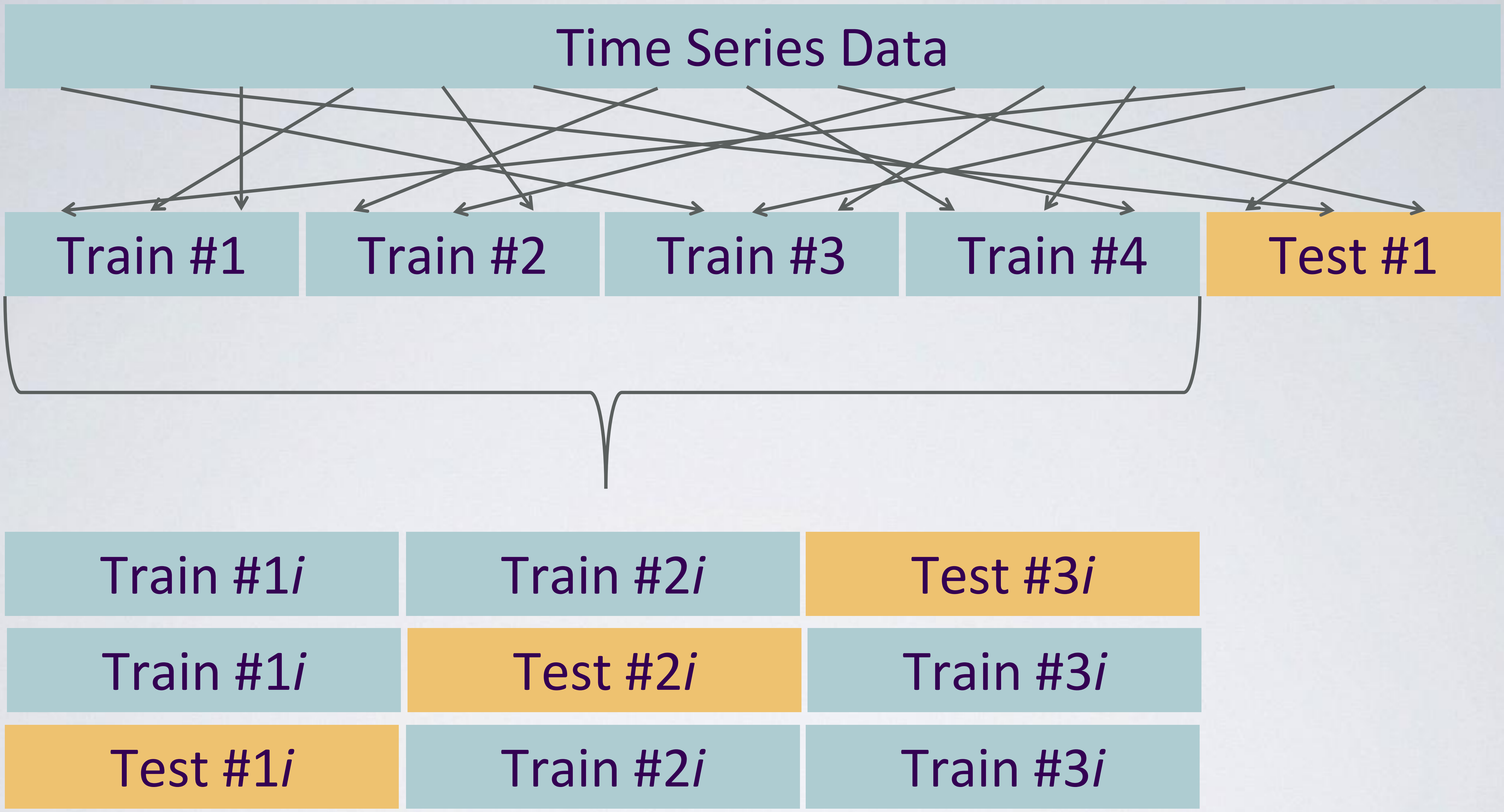
Logistic Regression



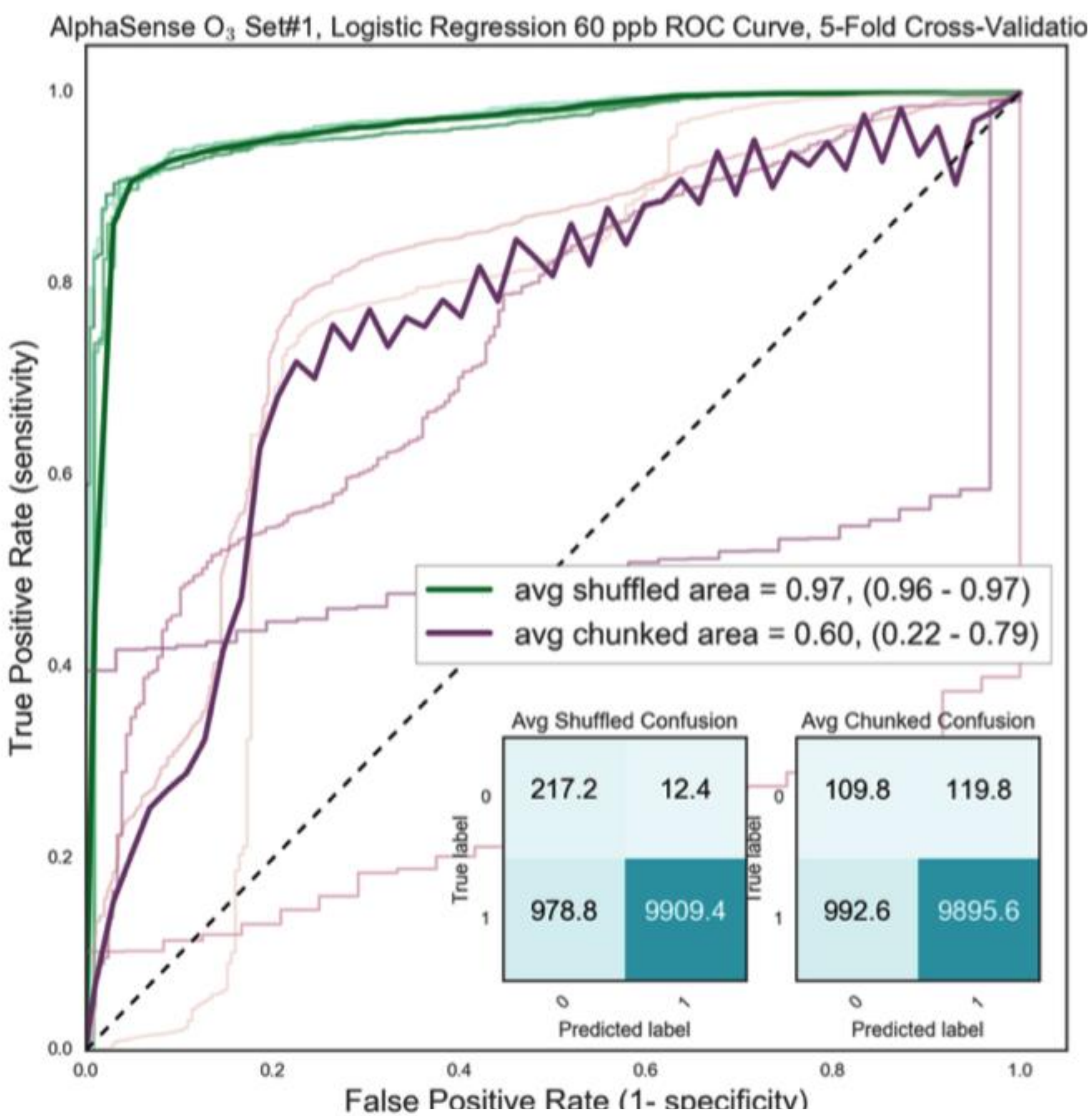
‘chunked’

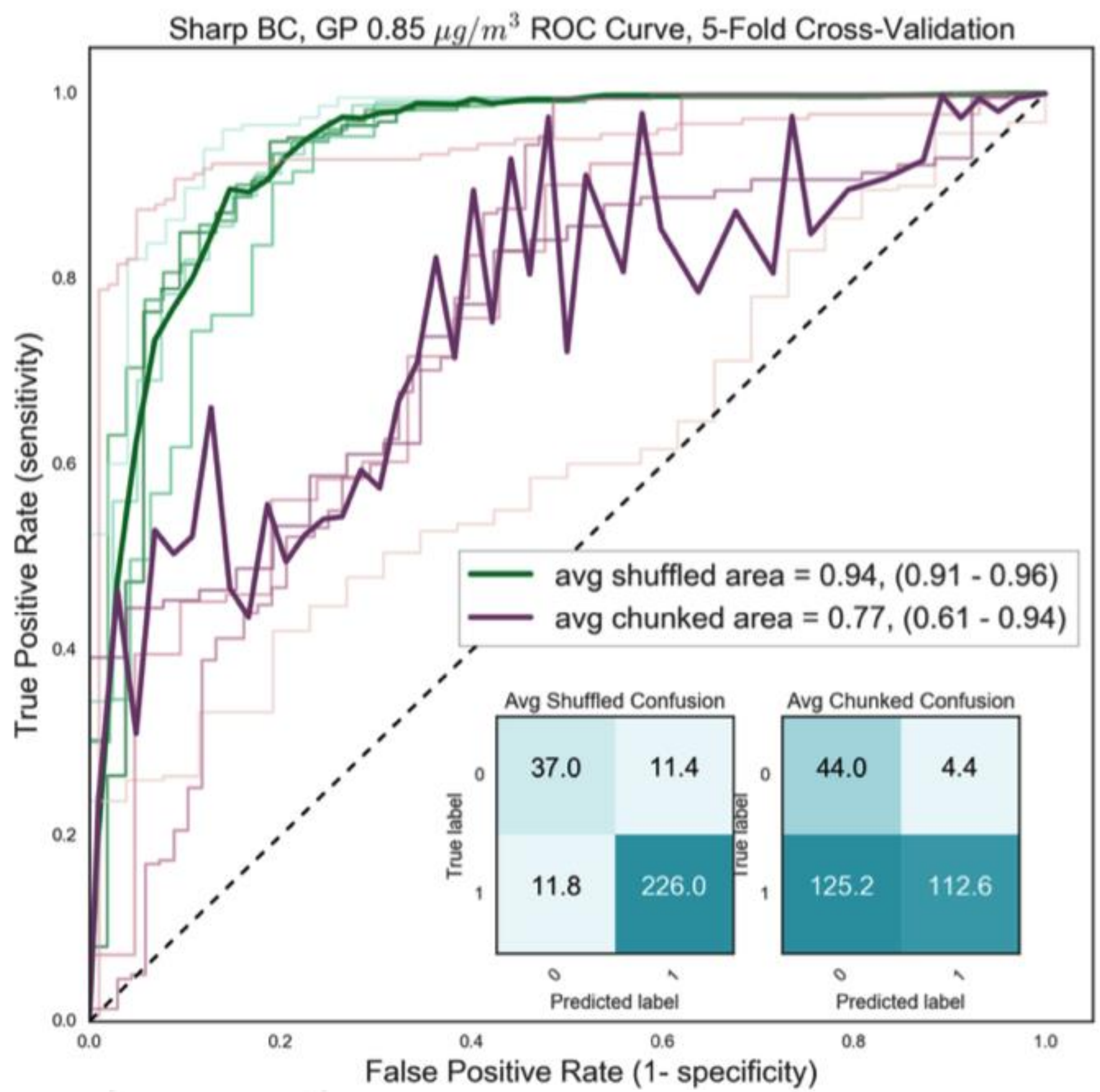
‘shuffled’

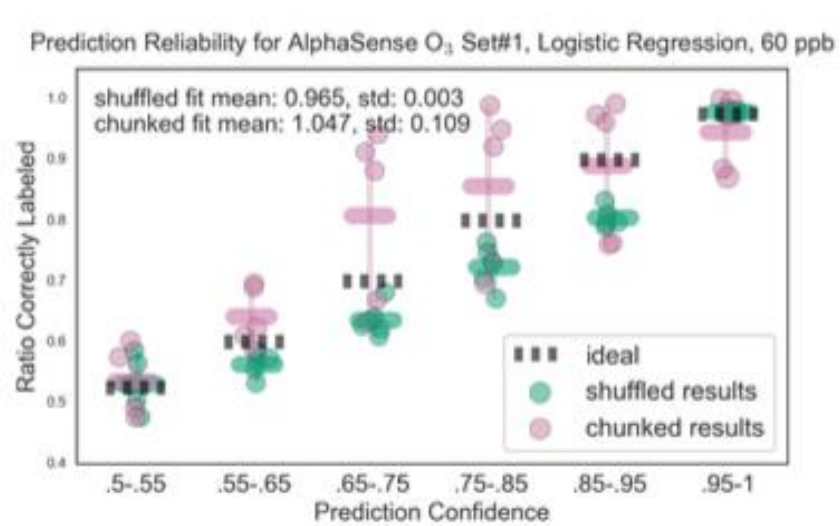

Time Series Data
Train #1
Train #2
Train #3
Train #4
Test #1
Train #1i
Train #2i
Test #3i
Train #1i
Test #2i
Train #3i
Test #1i
Train #2i
Train #3i

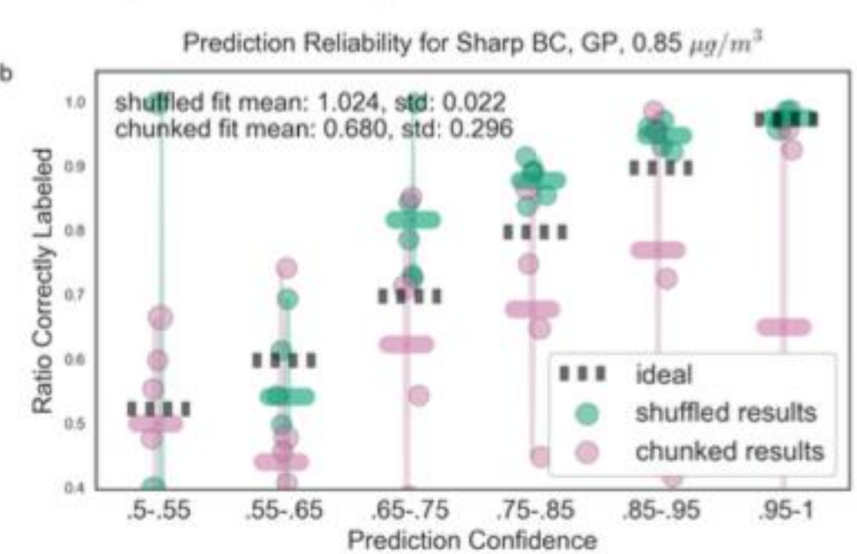


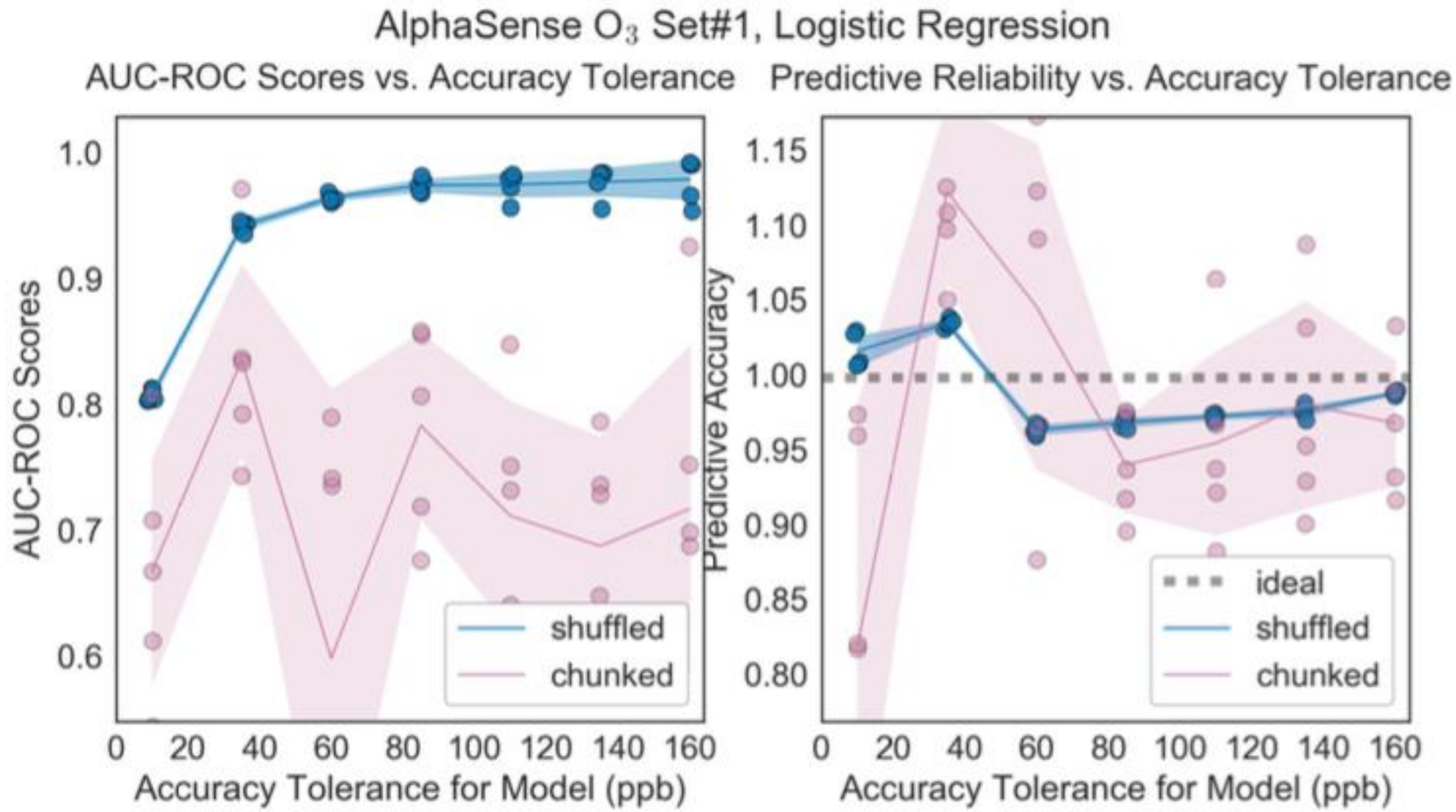
{ [L1, L2], [Regularization Strength], [SMOTE, Random Oversampling] }

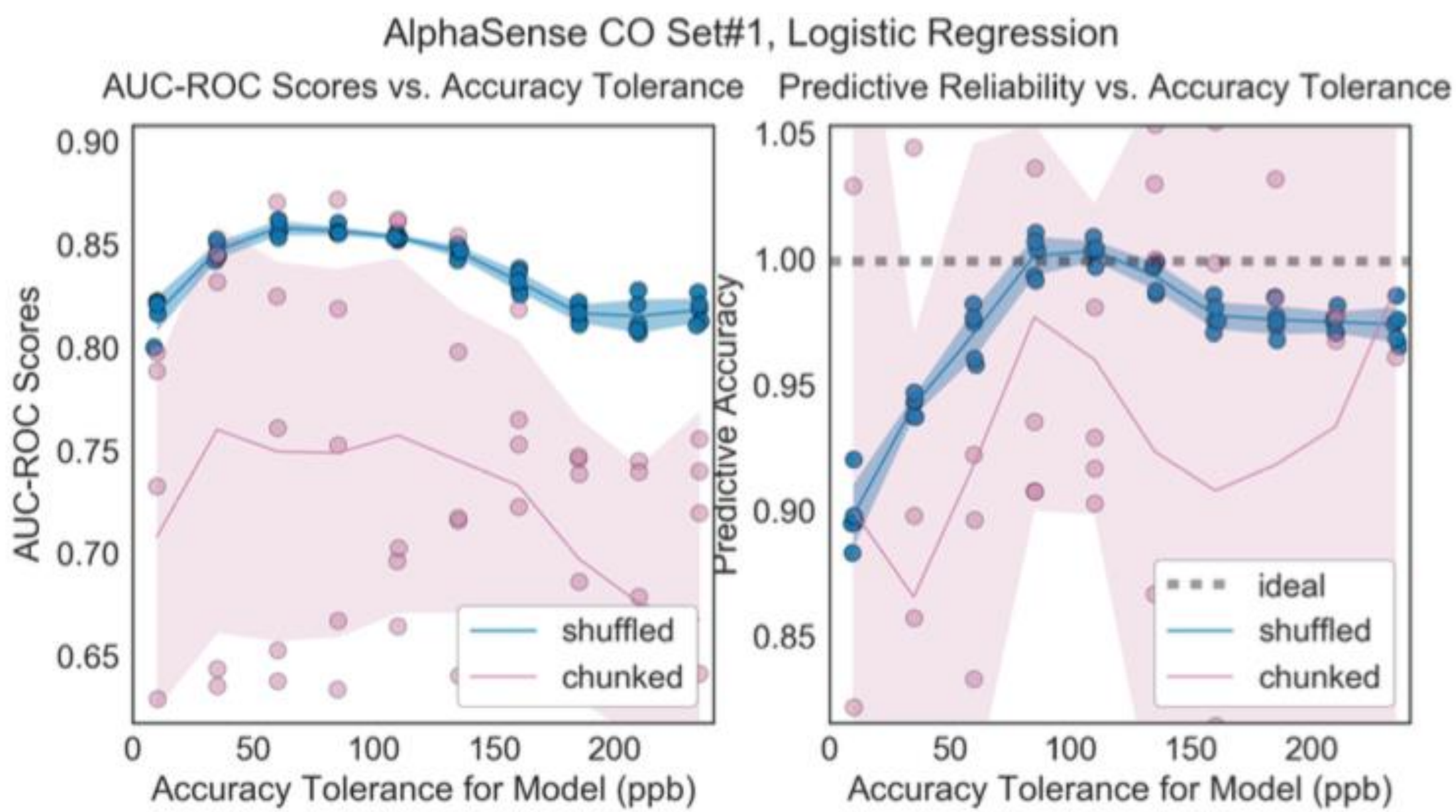

AlphaSense O3 Set#1, Logistic Regression 60 ppb ROC Curve, 5-Fold Cross-Validatio
True Positive Rate (sensitivity)
False Positive Rate (1- specificity)
avg shuffled area = 0.97, (0.96 - 0.97)
avg chunked area = 0.60, (0.22 - 0.79)
Avg Shuffled Confusion
217.2
12.4
978.8
9909.4
Avg Chunked Confusion
109.8
119.8
992.6
9895.6
True label
Predicted label


Sharp BC, GP 0.85 μg/m3 ROC Curve, 5-Fold Cross-Validation
True Positive Rate (sensitivity)
False Positive Rate (1- specificity)
avg shuffled area = 0.94, (0.91 - 0.96)
avg chunked area = 0.77, (0.61 - 0.94)
Avg Shuffled Confusion
37.0
11.4
11.8
226.0
Avg Chunked Confusion
44.0
4.4
125.2
112.6
True label
Predicted label


Prediction Reliability for AlphaSense O3 Set#1, Logistic Regression, 60 ppb
shuffled fit mean: 0.965, std: 0.003
chunked fit mean: 1.047, std: 0.109
Ratio Correctly Labeled
Prediction Confidence
.5-.55
.55-.65
.65-.75
.75-.85
.85-.95
.95-1
ideal
shuffled results
chunked results


Prediction Reliability for Sharp BC, GP, 0.85 μg/m3
shuffled fit mean: 1.024, std: 0.022
chunked fit mean: 0.680, std: 0.296
Ratio Correctly Labeled
Prediction Confidence
.5-.55
.55-.65
.65-.75
.75-.85
.85-.95
.95-1
ideal
shuffled results
chunked results


AlphaSense O_3 Set#1, Logistic Regression
AUC-ROC Scores vs. Accuracy Tolerance
Predictive Reliability vs. Accuracy Tolerance
AUC-ROC Scores
Predictive Accuracy
Accuracy Tolerance for Model (ppb)
Accuracy Tolerance for Model (ppb)
ideal
shuffled
chunked
shuffled
chunked


AlphaSense CO Set#1, Logistic Regression
AUC-ROC Scores vs. Accuracy Tolerance
Predictive Reliability vs. Accuracy Tolerance
AUC-ROC Scores
Predictive Accuracy
Accuracy Tolerance for Model (ppb)
Accuracy Tolerance for Model (ppb)
ideal
shuffled
chunked
shuffled
chunked

	Tolerance	Shuffled ROC-AUC (mean±std)	fit (mean±std)	ΔPPV
AlphaSense CO #1 Logistic	85 ppb	0.86±0.00	1.002±0.008	0.28
AlphaSense CO #2 Logistic	85 ppb	0.90±0.00	1.004±0.006	0.26
AlphaSense CO All Logistic	85 ppb	0.86±0.00	0.997±0.003	0.26
AlphaSense O_3 #1 Logistic	35 ppb	0.94±0.00	1.036±0.002	0.07
AlphaSense O_3 #2 Logistic	60 ppb	1.00±0.00	0.996±0.001	0.00
AlphaSense O_3 All Logistic	60 ppb	0.95±0.00	0.961±0.004	0.01
AlphaSense NO_2 Logistic	10 ppb	0.89±0.00	0.995±0.008	0.21
SmartCitizen NO_2 Logistic	10 ppb	0.81±0.00	1.022±0.003	0.17
SmartCitizen CO Logistic	60 ppb	0.75±0.00	1.016±0.002	0.18
Sharp Logistic	0.85 $\mu g/m^3$	0.94±0.02	1.040±0.020	0.13
Sharp 48 hr Avg Logistic	0.35 $\mu g/m^3$	0.98±0.00	1.012±0.060	0.32

	Tolerance	Chunked ROC-AUC (mean±std)	fit (mean±std)	ΔPPV
AlphaSense CO #1 Logistic	85 ppb	0.75±0.09	0.978±0.076	0.21
AlphaSense CO #2 Logistic	85 ppb	0.83±0.05	0.997±0.040	0.19
AlphaSense CO All Logistic	85 ppb	0.72±0.08	0.895±0.047	0.17
AlphaSense O_3 #1 Logistic	35 ppb	0.84±0.08	1.124±0.060	0.06
AlphaSense O_3 #2 Logistic	60 ppb	0.88±0.09	0.971±0.073	0.00
AlphaSense O_3 All Logistic	60 ppb	0.81±0.08	0.961±0.142	0.01
AlphaSense NO_2 Logistic	10 ppb	0.73±0.10	1.060±0.188	0.14
SmartCitizen NO_2 Logistic	10 ppb	0.66±0.04	0.851±0.090	0.09
SmartCitizen CO Logistic	60 ppb	0.54±0.10	0.797±0.142	0.03
Sharp Logistic	0.85 $\mu g/m^3$	0.88±0.06	1.037±0.115	0.11
Sharp 48 hr Avg Logistic	0.35 $\mu g/m^3$	0.88±0.11	0.917±0.125	0.22

			Shuffled			
			Thresh = 0.5		Thresh = 0.9	
		Base PPV	PPV	%Removed	PPV	%Removed
CO AS#1 Logistic	10 ppb	0.05	0.12	0.67	0.17	0.99
	35 ppb	0.17	0.38	0.62	0.56	0.97
	60 ppb	0.30	0.57	0.57	0.79	0.93
	85 ppb	0.45	0.73	0.51	0.88	0.90
	110 ppb	0.59	0.84	0.45	0.93	0.86
	135 ppb	0.74	0.91	0.39	0.98	0.81
CO AS#1 GP	10 ppb	0.05	0.07	0.52	nan	1.00
	35 ppb	0.17	0.29	0.53	0.68	0.99
	60 ppb	0.30	0.52	0.54	0.77	0.96
	85 ppb	0.45	0.71	0.50	0.82	0.91
	110 ppb	0.59	0.83	0.47	0.92	0.96
	135 ppb	0.74	0.91	0.46	0.95	1.00

			Chunked			
			Thresh = 0.5		Thresh = 0.9	
		Base PPV	PPV	%Removed	PPV	%Removed
CO AS#1 Logistic	10 ppb	0.05	0.09	0.65	0.11	0.96
	35 ppb	0.17	0.32	0.59	0.38	0.94
	60 ppb	0.30	0.49	0.53	0.65	0.92
	85 ppb	0.45	0.65	0.46	0.74	0.93
	110 ppb	0.59	0.81	0.47	0.89	0.89
	135 ppb	0.74	0.89	0.44	0.95	0.85
CO AS#1 GP	10 ppb	0.05	0.05	0.07	0.04	0.50
	35 ppb	0.17	0.18	0.11	0.17	0.66
	60 ppb	0.30	0.33	0.14	0.45	0.72
	85 ppb	0.45	0.59	0.36	0.67	0.87
	110 ppb	0.59	0.83	0.60	0.87	0.97
	135 ppb	0.74	0.90	0.75	0.94	0.99

			Shuffled				Chunked			
			Thresh = 0.5		Thresh = 0.9		Thresh = 0.5		Thresh = 0.9	
		Base PPV	PPV	%Removed	PPV	%Removed	PPV	%Removed	PPV	%Removed
CO AS#1 Logistic	10 ppb	0.05	0.12	0.67	0.17	0.99	0.09	0.65	0.11	0.96
	35 ppb	0.17	0.38	0.62	0.56	0.97	0.32	0.59	0.38	0.94
	60 ppb	0.30	0.57	0.57	0.79	0.93	0.49	0.53	0.65	0.92
	85 ppb	0.45	0.73	0.51	0.88	0.90	0.65	0.46	0.74	0.93
	110 ppb	0.59	0.84	0.45	0.93	0.86	0.81	0.47	0.89	0.89
	135 ppb	0.74	0.91	0.39	0.98	0.81	0.89	0.44	0.95	0.85
CO AS#1 GP	10 ppb	0.05	0.07	0.52	nan	1.00	0.05	0.07	0.04	0.50
	35 ppb	0.17	0.29	0.53	0.68	0.99	0.18	0.11	0.17	0.66
	60 ppb	0.30	0.52	0.54	0.77	0.96	0.33	0.14	0.45	0.72
	85 ppb	0.45	0.71	0.50	0.82	0.91	0.59	0.36	0.67	0.87
	110 ppb	0.59	0.83	0.47	0.92	0.96	0.83	0.60	0.87	0.97
	135 ppb	0.74	0.91	0.46	0.95	1.00	0.90	0.75	0.94	0.99
CO SCK Logistic	10 ppb	0.10	0.15	0.56	nan	1.00	0.11	0.37	0.07	0.96
	35 ppb	0.32	0.47	0.52	0.73	1.00	0.36	0.38	0.24	0.96
	60 ppb	0.51	0.69	0.48	0.86	0.99	0.54	0.36	0.35	0.92
	85 ppb	0.66	0.82	0.44	0.93	0.97	0.66	0.36	0.53	0.87
	110 ppb	0.78	0.90	0.41	0.96	0.96	0.78	0.34	0.68	0.83
	135 ppb	0.87	0.94	0.37	0.98	0.93	0.88	0.32	0.83	0.78
CO SCK GP	10 ppb	0.10	0.12	0.55	nan	1.00	0.10	0.10	0.15	0.81
	35 ppb	0.32	0.44	0.47	0.85	1.00	0.36	0.24	0.33	0.91
	60 ppb	0.51	0.66	0.47	0.76	0.99	0.54	0.49	0.00	1.00
	85 ppb	0.66	0.79	0.47	0.96	1.00	0.68	0.67	0.00	1.00
	110 ppb	0.78	0.86	0.48	1.00	1.00	0.76	0.80	1.00	1.00
	135 ppb	0.87	0.91	0.49	nan	1.00	0.84	0.87	0.33	1.00
SHARP Logistic	0.1 $\mu g/m^3$	0.14	0.21	0.55	0.15	0.98	0.18	0.56	0.25	0.99
	0.35 $\mu g/m^3$	0.47	0.67	0.49	0.88	0.88	0.63	0.54	0.96	0.98
	0.6 $\mu g/m^3$	0.70	0.86	0.32	0.97	0.79	0.83	0.38	0.88	0.78
	0.85 $\mu g/m^3$	0.83	0.96	0.22	1.00	0.56	0.95	0.28	0.94	0.72
	1.1 $\mu g/m^3$	0.87	0.97	0.18	1.00	0.48	0.97	0.25	0.97	0.69
	1.35 $\mu g/m^3$	0.90	0.98	0.17	0.99	0.51	0.98	0.35	1.00	0.87
SHARP GP	0.1 $\mu g/m^3$	0.14	0.20	0.99	0.20	1.00	0.13	0.11	0.11	0.75
	0.35 $\mu g/m^3$	0.47	0.67	0.45	0.94	0.92	0.58	0.34	0.66	0.72
	0.6 $\mu g/m^3$	0.70	0.86	0.25	0.96	0.69	0.87	0.56	0.86	0.87
	0.85 $\mu g/m^3$	0.83	0.95	0.17	0.98	0.46	0.96	0.59	0.97	0.83
	1.1 $\mu g/m^3$	0.87	0.97	0.16	0.98	0.49	0.98	0.78	0.95	0.97
	1.35 $\mu g/m^3$	0.90	0.97	0.10	0.98	0.34	0.97	0.56	0.98	0.82

Shuffled vs Chunked – quantify seasonal characterization

Arbitrary PPV – trade off quality vs. quantity

Insights into Sensor Limits and Design

Building it into a Network and Automating it

dramsay@media.mit.edu

This work was supported by the **Environmental Defense Fund**.

Thanks to Safecast and the Civic Media group for input, guidance, and inspiration.
Special thanks to readers Dr. Steven Hamburg and Professor Ethan Zuckerman.

Thesis available here:
https://www.davidbramsay.com/public/RamsayMastersThesis.pdf

More information is available here:
https://media.mit.edu/projects/wearable-ble-platform-for-citizen-monitoring