HAQAST

The Air in Your Community: Estimating Surface $PM_{2.5}$ in California with a Fusion of Monitor Data, Satellite Observations and Downscale Modeling

Minghui Diao (PI), Frank Freedman, Sen Chiao, Isa Cruz
Department of Meteorology and Climate Sciences, San Jose State University
Co-I: **Mohammad Al-Hamdan**, USRA, NASA Marshall Space Flight Center
Co-I: **Akula Venkatram**, Department of Mechanical Engineering, University of California Riverside
Contact info: Minghui.Diao@sjsu.edu

HAQAST2020
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Motivation:

Satellite Regional $PM_{2.5}$ fields and Downscaling

Fine particulate is among the most harmful air pollutants for human health. There is ongoing interest in developing reliable methods to estimate PM2.5 concentrations 1) at unmonitored locations and 2) at finer horizontal resolution for improved health risk assessment and public health tracking.

We aim to develop an efficient system that can reliably estimate PM2.5 at unmonitored locations and at finer horizontal resolution at important locations.

- **MODIS aerosol optical depth (AOD)** provides an input for particulate levels at **unmonitored locations** in methods used to construct regional PM2.5 fields.
- **Dispersion model** fields can be fused into portions of these regional fields for **increased horizontal resolution** where high PM gradients can be anticipated, for example near major roadways.

Main methods of generating $PM_{2.5}$ datasets

1. Ground-based monitor data

EPA archived monitoring data can be accessed at the AirData website (https://www.epa.gov/outdoor-air-quality-data)

U.S. EPA initiated the Chemical Speciation Monitoring Network (CSN)

Temporary $PM_{2.5}$ monitors are deployed as a part of the Wildland Fire Air Quality Response Program (WFAQRP, https://wildlandfiresmoke.net/)

2. Ground-based monitor + model simulations

Atmospheric chemical transport models (CTMs)

EPA Fused Air Quality Surfaces Using Downscaling (FAQSD)

CDC National Environmental Public Health Tracking Network (EPHTN)

3. Ground-based monitor + satellite data

Linear regression models for estimating PM2.5 concentrations from remotely-sensed AOD; Adding meteorological parameters to develop multiple regression models or generalized additive models

4. Ground-based monitor + satellite data + model simulations

Example: van Donkelaar et al. (2015, 2016)

A survey on publicly available $PM_{2.5}$ exposure datasets

Table 1. A summary of the publicly available $PM_{2.5}$ exposure datasets.

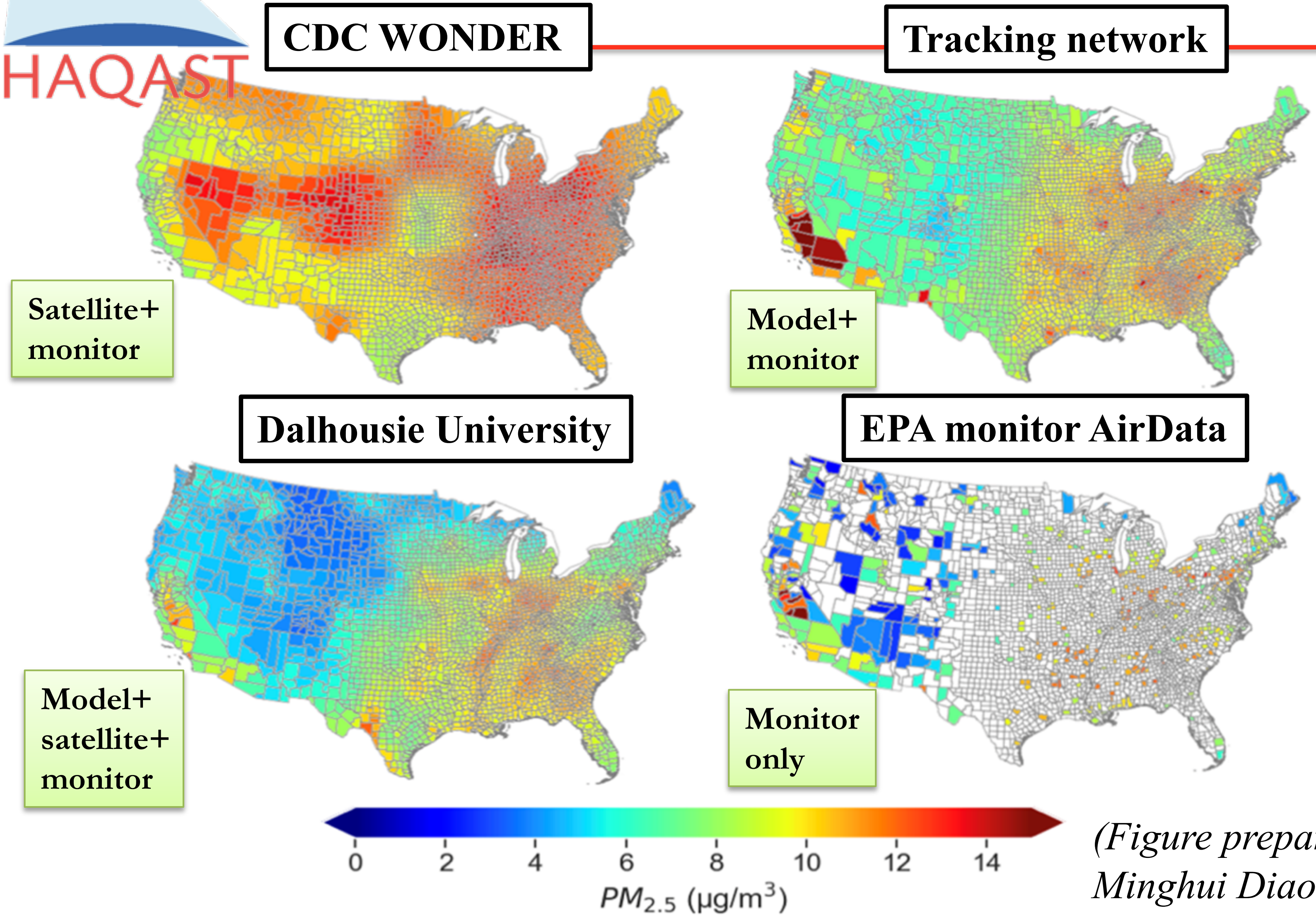
	Source of Dataset	Region	Time Period	Spatial Resolution	Temporal Resolution	Monitor	Model	Satellite	Reference
1	GBD	Global	1990–2013	*0.1°× 0.1°	Annual	X	X	X	Brauer et al. (2016)
2	Dalhousie Dataset V4. GL.02	Global	1998–2016	1 km^2	Annual	X	X	X	(1)
3	GBD	Global	2014	*0.1°× 0.1°	Annual	X	X	X	Shaddick et al. (2018a)
4	Berkeley Earth	Global	2016–2017	*0.1°× 0.1°	Daily	X	X		(2)
5	Dalhousie Dataset V4. NA.02	CONUS	2000–2016	1 km^2	Annual	X	X	X	(1)
6	EPA AirData	CONUS	1999–2018	Point data; also available when averaged on county scale	Daily	X			(3)
7	EST 2013	CONUS	2001–2006	8.9 km^2	Monthly	X	X	X	Beckerman et al. (2013)
8	CDC EPHTN	CONUS	2001–2015	County and census tract	Daily	X	X		(4)
9	EPA FAQSD	CONUS	2002–2015	12 km^2	Daily	X	X		(5)
10	CDC WONDER	CONUS	2003–2011	County	Daily	X		X	(6)
11	AQAH 2018	NC, USA	2006–2008	12 km^2	Monthly & Annual	X	X		Huang et al. (2018)

Notes. Table 1 shows spatially continuous $PM_{2.5}$ exposure datasets that are publicly available and free on individual websites or publications. The URLs of the datasets are listed below. *At mid-latitudes, 1° is approximately 100 km.

(1). Dalhousie University Datasets: http://fizz.phys.dal.ca/~atmos/martin/?page_id=140
(2). Berkeley Earth Air Quality Map: http://berkeleyearth.org/air-quality-real-time-map/
(3). AirData Dataset: https://www.epa.gov/outdoor-air-quality-data/download-daily-data
(4). CDC EPHTN: https://ephtracking.cdc.gov/DataExplorer/#/
(5). EPA FAQSD Dataset: https://www.epa.gov/hesc/rsig-related-downloadable-data-files
(6). CDC WONDER: https://wonder.cdc.gov/nasa-pm.html

(Diao, Holloway et al., JA&WMA review article, 2019)

Comparisons of three $PM_{2.5}$ datasets in the contiguous U.S.



(1) CDC WONDER exhibits higher $PM_{2.5}$ and a large regional maximum over the central U.S.

(2) For Southern California, EPHTN shows the highest $PM_{2.5}$ (over 14 μg/m3)

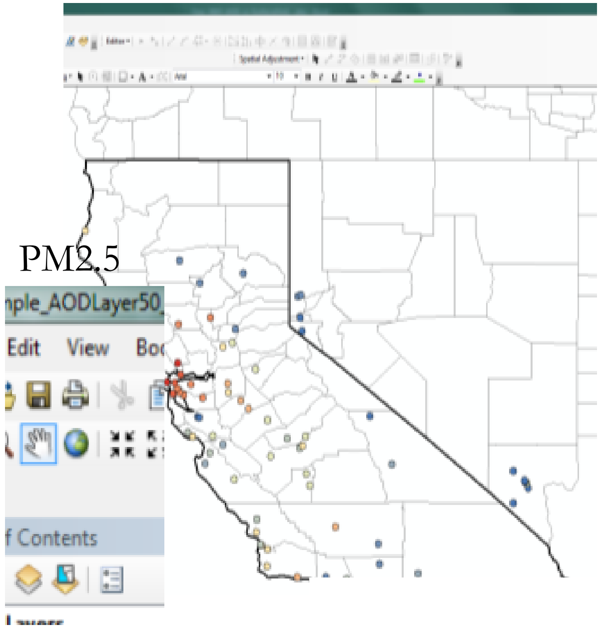
(3) Dalhousie exhibits lower $PM_{2.5}$ overall, and is more spatially homogeneous over the western U.S.

(Figure prepared by Grace Choi, Xiaomeng Jin, Minghui Diao, and Tracey Holloway)

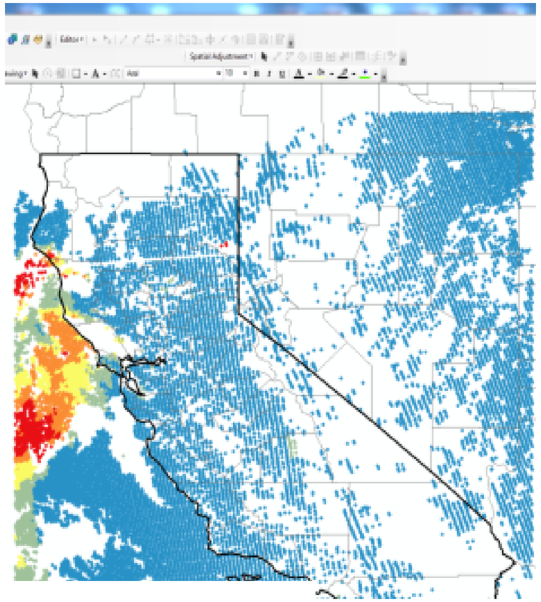
Diao M., T. Holloway, S. Choi, S.M. O'Neill, M.Z. Al-Hamdan, A.van Donkelaar, R.V. Martin, X. Jin, A.M. Fiore, D.K. Henze, F. Lacey, P.L. Kinney, F. Freedman, N.K. Larkin, Y. Zou, J. Kelly, A. Vaidyanathan. Methods, availability, and applications of $PM_{2.5}$ exposure estimates derived from ground measurements, models, and satellite datasets, *Journal of Air & Waste Management Association (JAMWA), 2019.*

Satellite data in analysis of California wildfire 2017

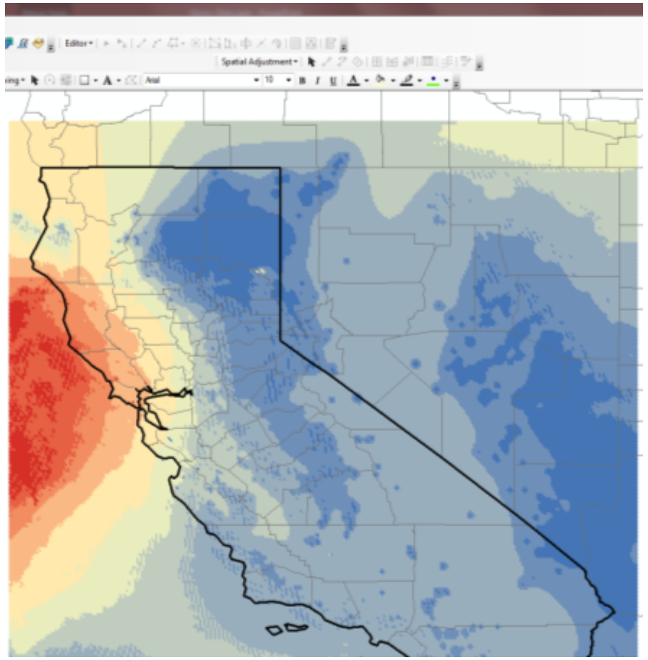
EPA/AQS PM2.5



NASA/MODIS AOD



AOD
- 0.0 - 0.44
- 0.45 - 1.04
- 1.05 - 1.67
- 1.68 - 2.39
- 2.40 - 3.99



PM2.5 (ug/m³)
- 0.0 - 8.4
- 8.5 - 12.4
- 12.5 - 15.5
- 15.6 - 18.5
- 18.6 - 22.6
- 22.7 - 28.2
- 28.3 - 36.0
- 36.1 - 45.6
- 45.7 - 54.7
- 54.8 - 75.7

Example of October 9, 2017

We used spatial/geostatistical surfacing algorithms, which combine data from 3-km, daily NASA Aqua MODIS satellite AOD data (Dark Target product) and EPA ground monitors to provide daily estimates of PM2.5 on a 3-km grid (surface). The surfacing and regression algorithms were explained in Al-Hamdan et al. (2009, *JAWMA*).

Figures prepared by:
Dr. Mohammad Al-Hamdan
USRA at NASA/MSFC
mohammad.alhamdan@nasa.gov

Publicly available satellite-derived $PM_{2.5}$ data

http://www.met.sjsu.edu/weather/HAQAST/home.html

Home | Core Project | Regional CA PM2.5 Fields | Dispersion Modeling | Tiger Teams | Data | Publications | Team Members

San José State Research: HAQAST Home Page

San José State University: NASA Health and Air Quality Applied Sciences Team

1. **Daily $PM_{2.5}$ Fields (2006 – 2017). Download csv files.**
2. **Daily Real-Time $PM_{2.5}$ Fields (Last 7 Days). Download netcdf files.**
3. **Daily Real-Time $PM_{2.5}$ Fields (East San Jose, CA)**

More satellite-based products on 2017 Cal Wildfires

Wildfire Tiger Team Website: http://bit.ly/haqasttiger

1. MAIAC Plume Injection Height (NASA)
Terra Tabular Data | Terra Maps
Aqua Tabular Data | Aqua Maps

2. MAIAC AOD maps
Terra Tabular Data | Terra Maps
Aqua Tabular Data | Aqua Maps

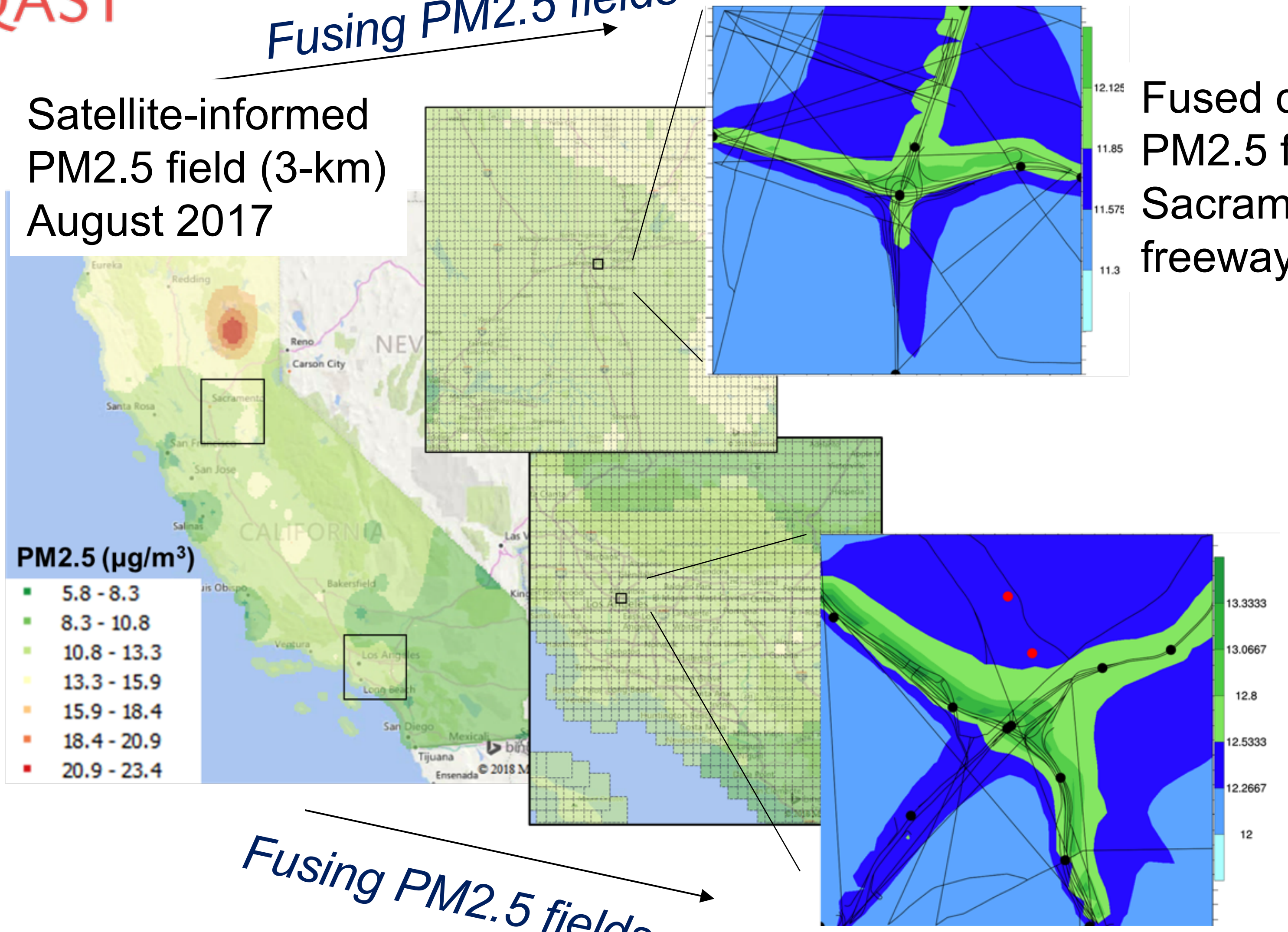
3. Data Fusion $PM_{2.5}$ Surfaces (MODIS, Surface Monitors) (NASA MSFC)
https://haze.airfire.org/webaccess/susan/HAQAST/Wildfires_TT/DataFusionPM2.5/

4. $PM_{2.5}$ and Wind Observations Analysis (SJSU, UCR)
Python code, observational data ($PM_{2.5}$, winds, fire perimeters), and hourly png figures at:
https://haze.airfire.org/webaccess/susan/HAQAST/Wildfires_TT/PM25_and_Wind_Obs/

Fusion of satellite-derived $PM_{2.5}$ and a downscale model

Fusing PM2.5 fields

Satellite-informed PM2.5 field (3-km) August 2017



Fused dispersion model PM2.5 field (~ 100 m) Sacramento area freeway interchange

Fused dispersion model PM2.5 field (~ 100 m) Los Angeles area freeway interchange

Fusing PM2.5 fields

~ 100 m resolution over 3 km regional grid

Figures prepared by: Frank Freedman, SJSU

Using Satellite Information And Measurements From Ground-Based Monitors During The October 2017 Fires In Northern California To Construct High Resolution $PM_{2.5}$ Maps

Yifan Ding[1]
Isa Cruz[2]
Frank Freedman[2]
Akula Venkatram[1]

1-University of California, Riverside, CA
2-San Jose State University, San Jose, CA

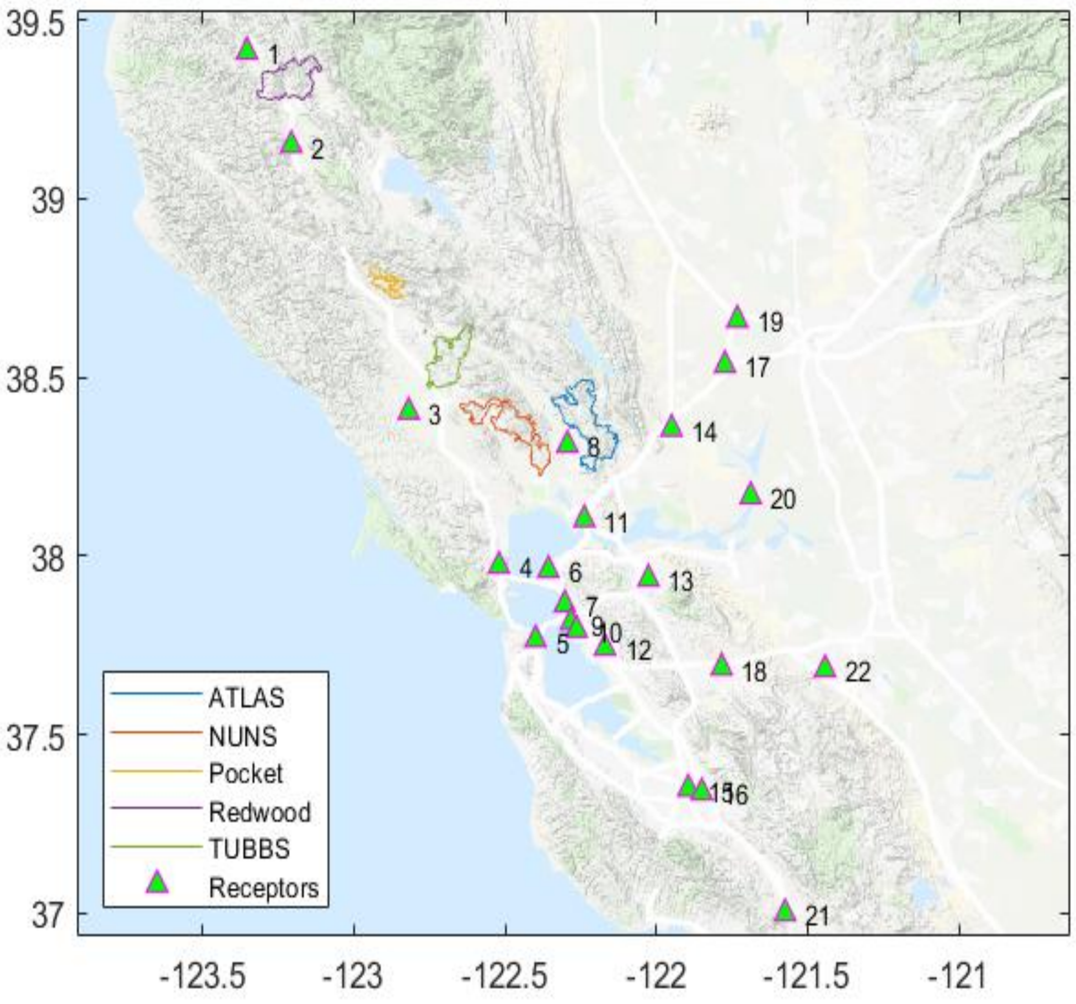
UNIVERSITY OF CALIFORNIA, RIVERSIDE

Motivation

- Surface monitors have limited spatial resolution
- Remote sensing has limited temporal resolution

Need methods to improve spatial and temporal resolution of available information

PM2.5 Ground Monitors Spatial Distribution

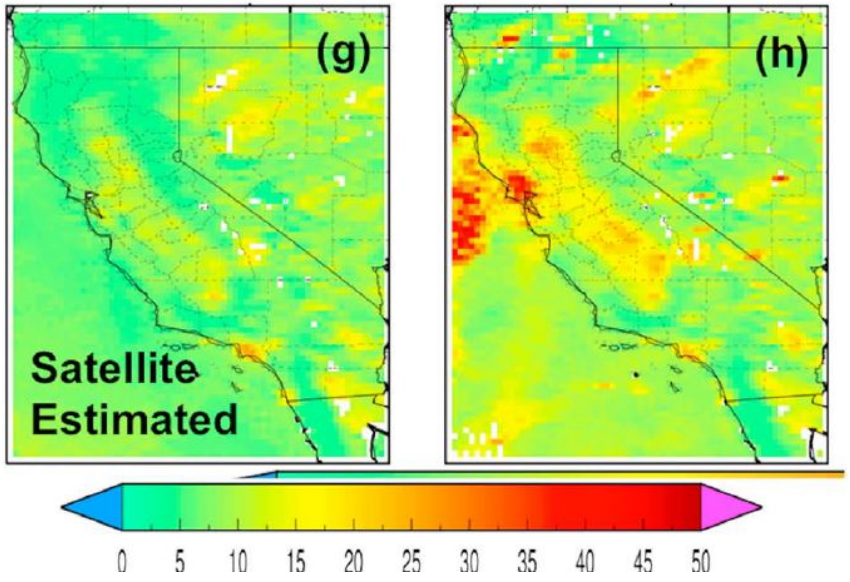


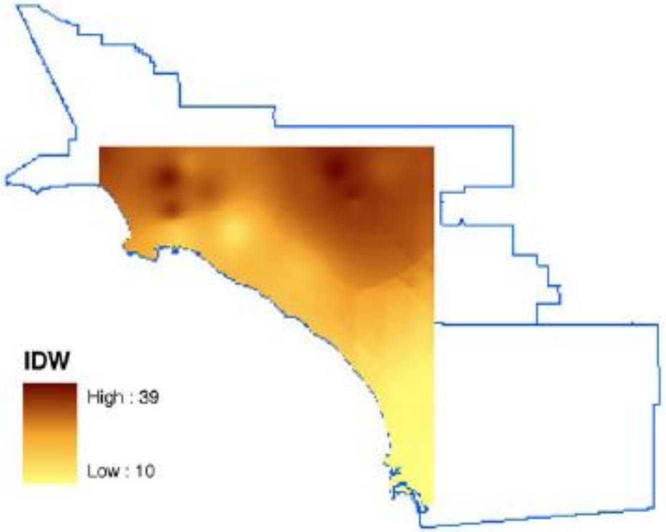
Some Relevant Studies

- Gupta et al. (2018) estimated spatial distribution of $PM_{2.5}$ during 2017 fires using satellite and data from LCAQMs

- Wu et al. (2006) estimated daily PM10 and $PM_{2.5}$ at a zip-code level using satellite and ground-based information during the 2003 fires

These studies used statistical interpolation methods to create maps





Objective and Approach

UCR

Improve upon purely statistical interpolation approaches

- Use dispersion models to capture the structure of fire plumes in available information
- Apply statistical methods to residuals left over after structure has been removed

Approach

1. Fit concentration estimates from dispersion model to measured concentrations to obtain fire emissions
   - $C_{ok} = \sum T_j E_{jk} + \varepsilon$
2. Fit AOD to the measured concentrations to construct empirical AOD model
3. Combine dispersion model with AOD model
4. Interpolate residuals between measured concentrations and combined model using Kriging at these receptors to construct high resolution maps
   - $C_o^e = C_p + Kriged(\varepsilon)$

Study Area and Time Period in 2017

Oct-8

Oct-9

Oct-10

Oct-11

Oct-12

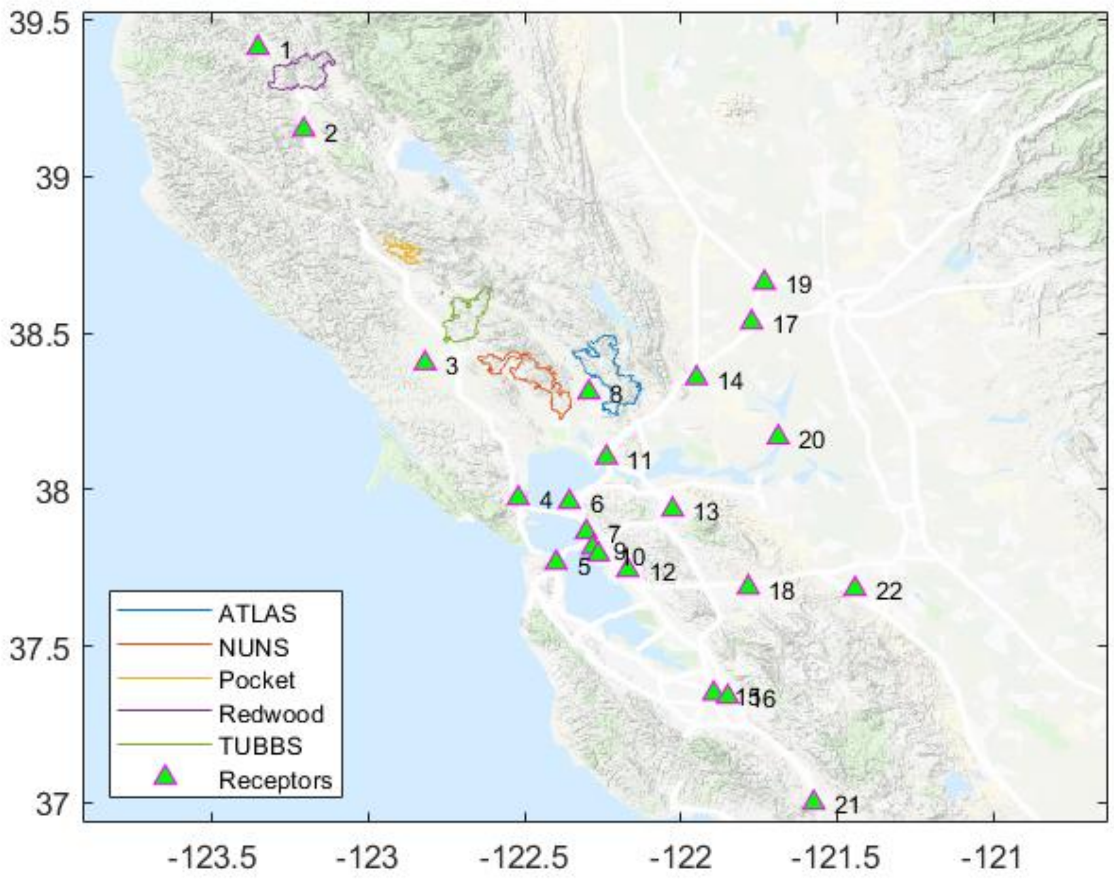
Oct-13

Oct-14

Oct-15

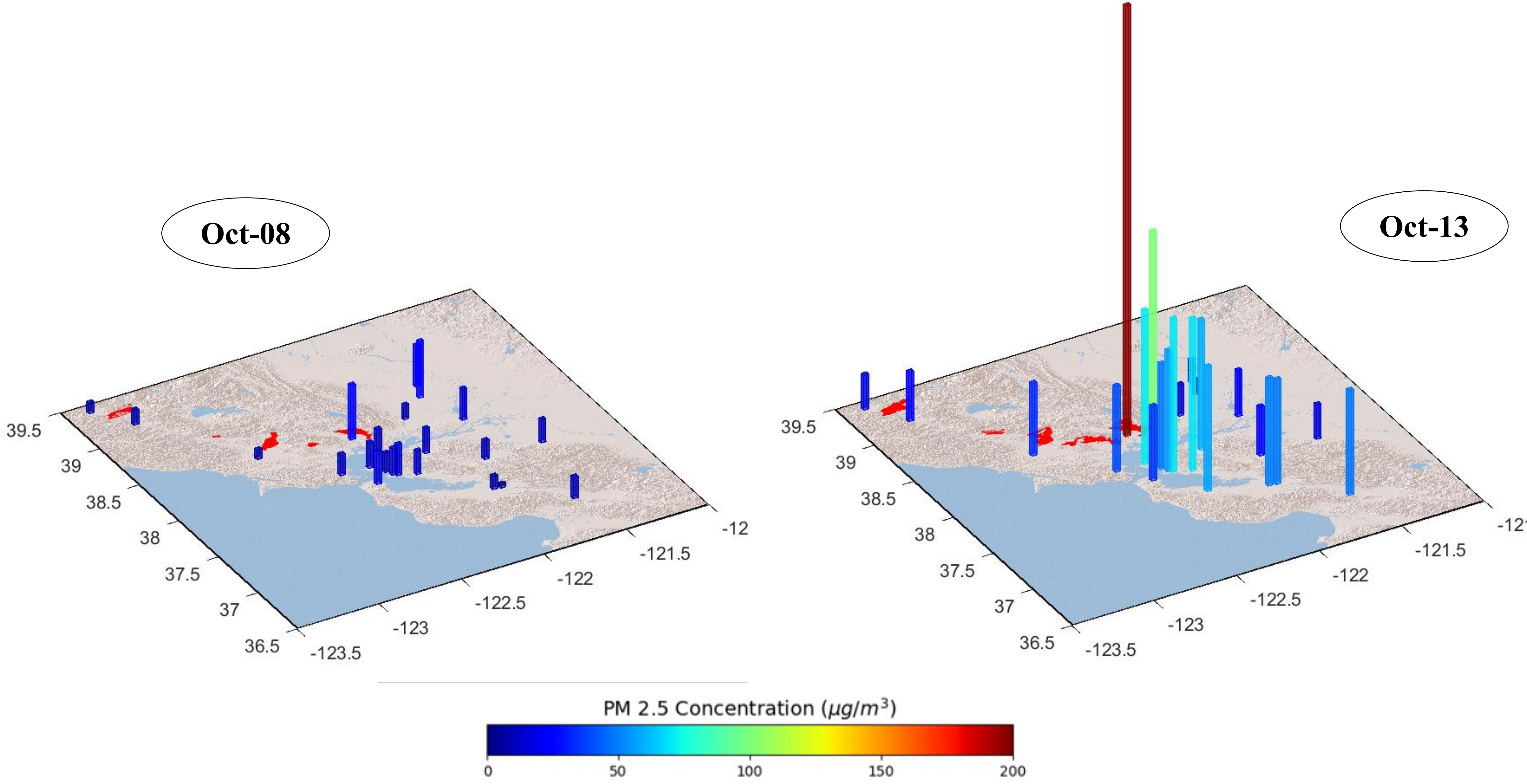
Image taken from:
worldview.earthdata.nasa.gov

Air Quality Management Information System (AQMIS) Surface Monitors



Date	24 hours Averaged Measured Concentration($\mu g/m^3$)	Standard deviation of Measured Concentration($\mu g/m^3$)
Oct-8	11	6
Oct-9	29	19
Oct-10	55	43
Oct-11	44	27
Oct-12	42	24
Oct-13	49	41
Oct-14	21	9
Oct-15	16	14

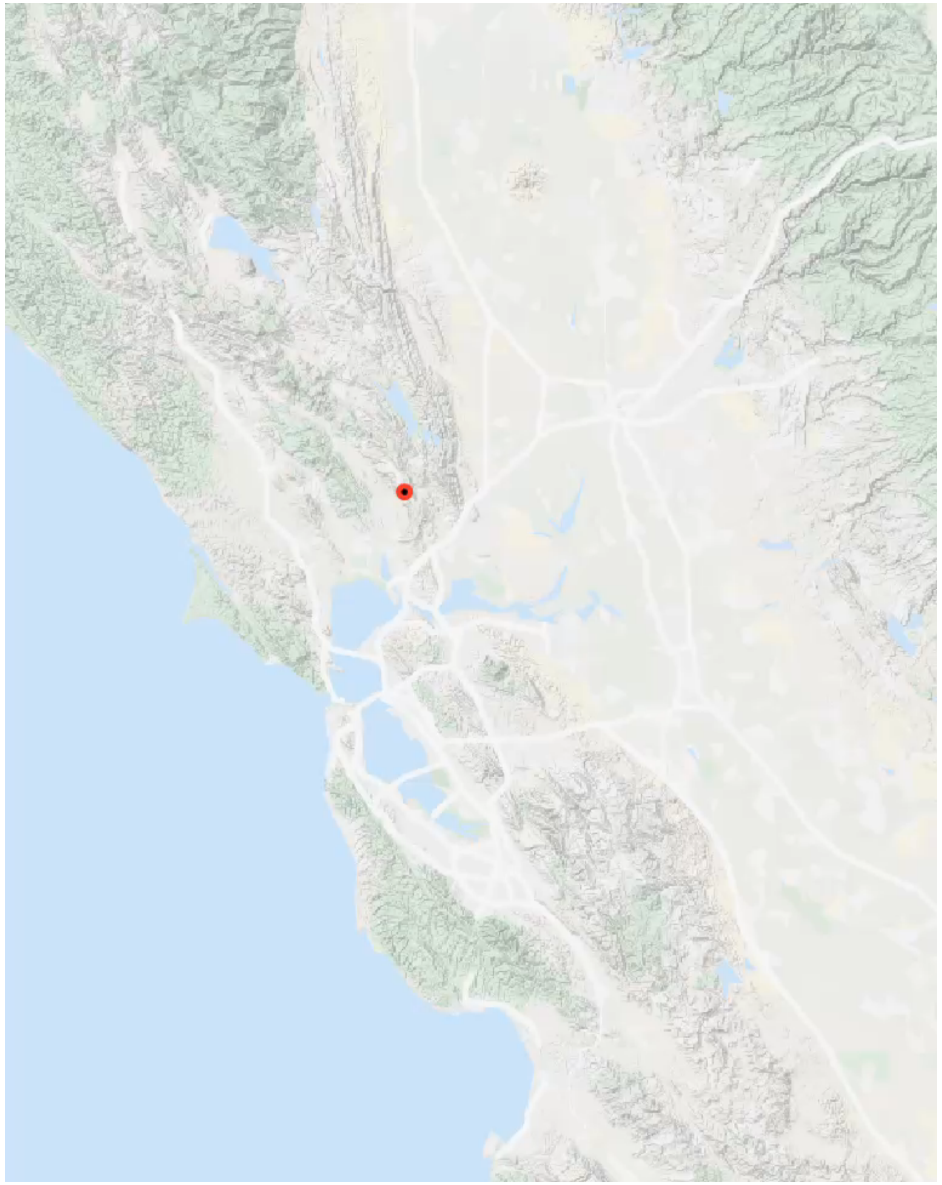
$PM_{2.5}$ Surface Concentrations



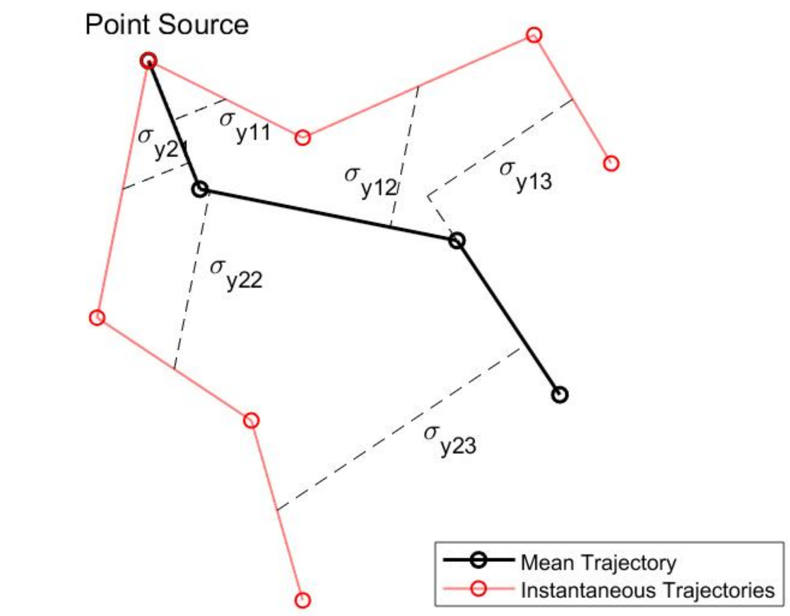
Dispersion Models Use Trajectories

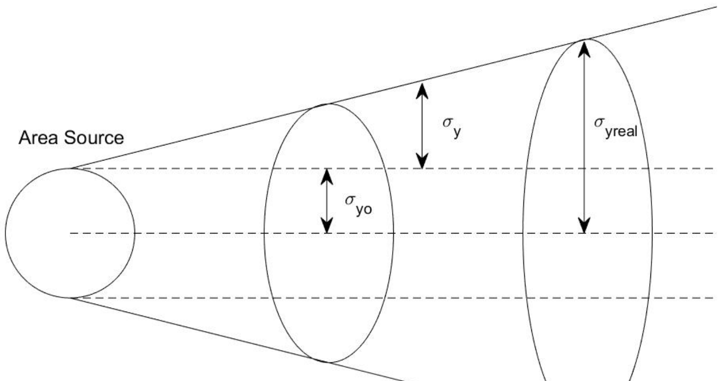
- Segmented Plume Model
- Lagrangian Backward Trajectory Model

  Wind speed and direction at 80 m
  from HRRR model



Segmented Plume Model





$$\sigma_{yreal}^2 = \sigma_y^2 + \sigma_{yo}^2$$

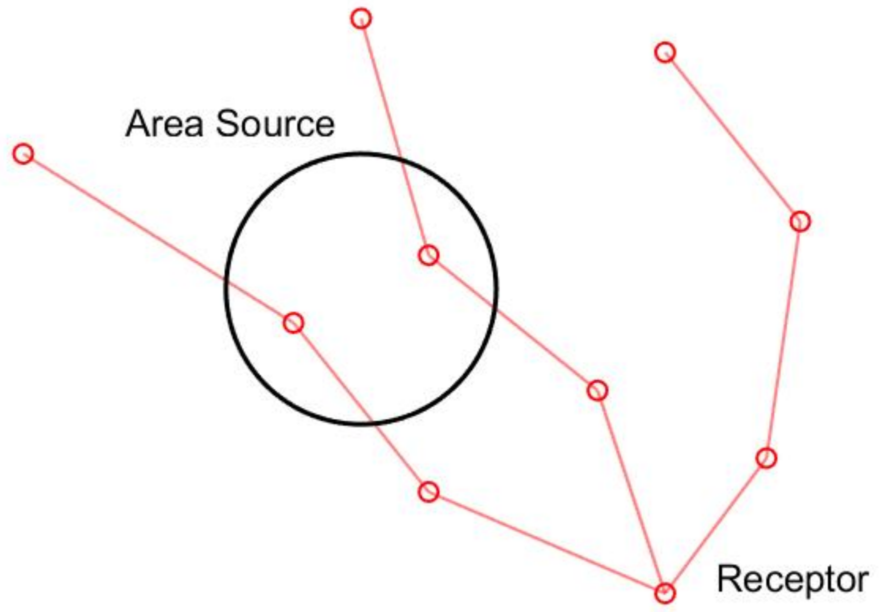
$$T_{jk} = \frac{1}{\sqrt{2\pi}\sigma_y < hU >} \exp\left[-\frac{1}{2}\left(\frac{y}{\sigma_y}\right)^2\right]$$

$$C_{ok} = \sum_j T_j E_{jk} + c_b$$

- Assume particles are well mixed over the boundary layer height *h*
- The total horizontal spread consists of standard deviation of the horizontal distances and initial radius of the fire

Lagrangian Model

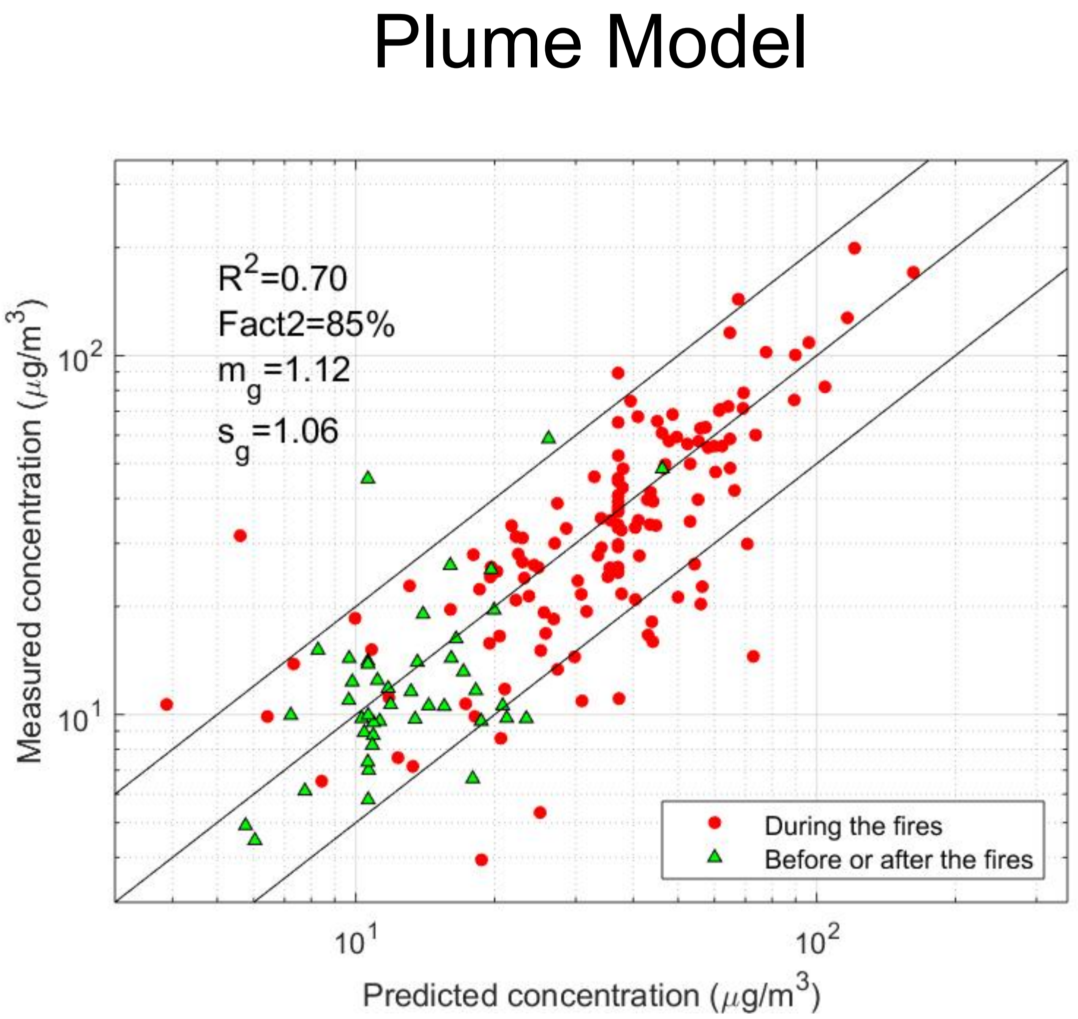
- Each backward trajectory is extended backward in time for 12h using 0.25h time steps
- The transport coefficient for each trajectory is computed by taking $q_i = 1\frac{\mathrm{g}}{\mathrm{m}^2}/s$ over the area of the fire of interest

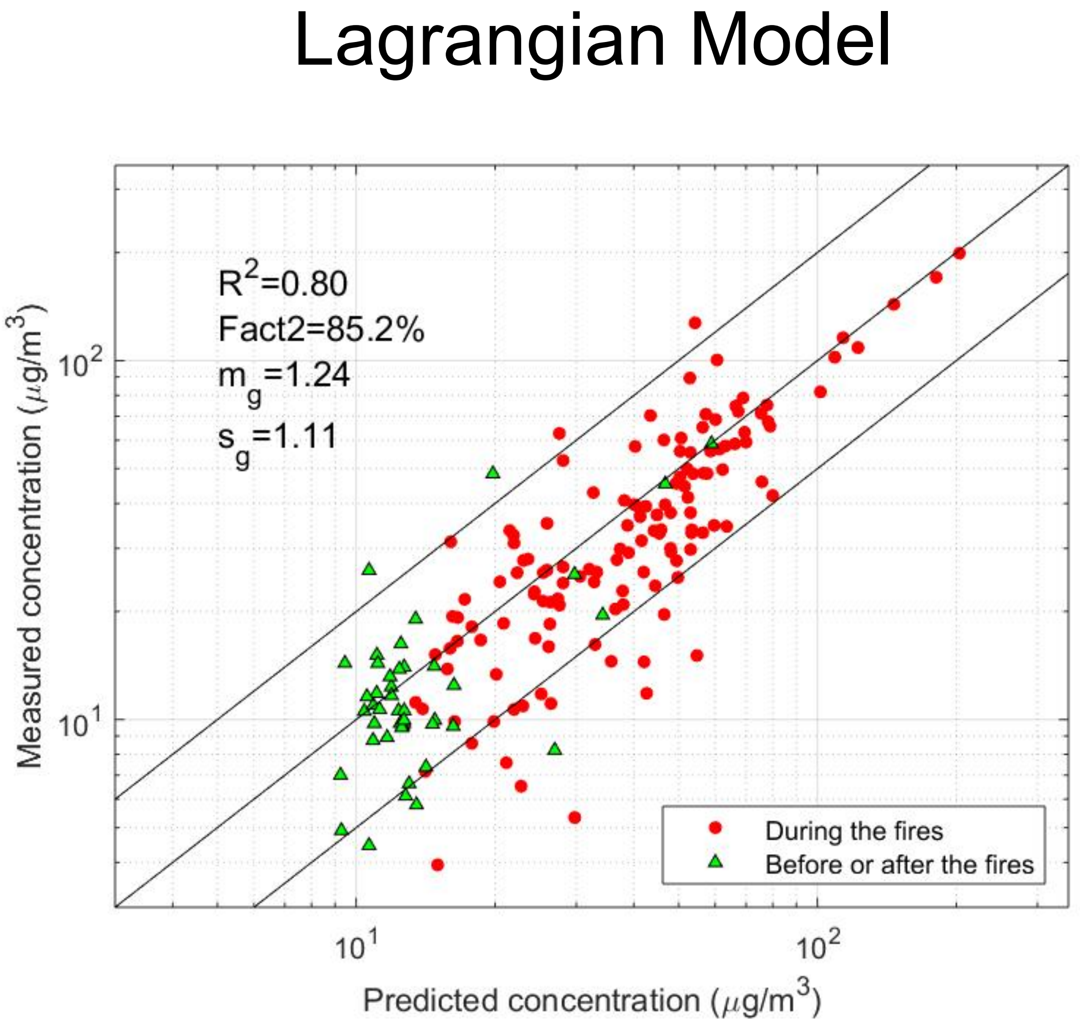


$$T_i = T_{i-1} \cdot \min\left(\frac{h_{i-1}}{h_i}, 1\right) + \frac{q_i \cdot \Delta t}{h_i}$$

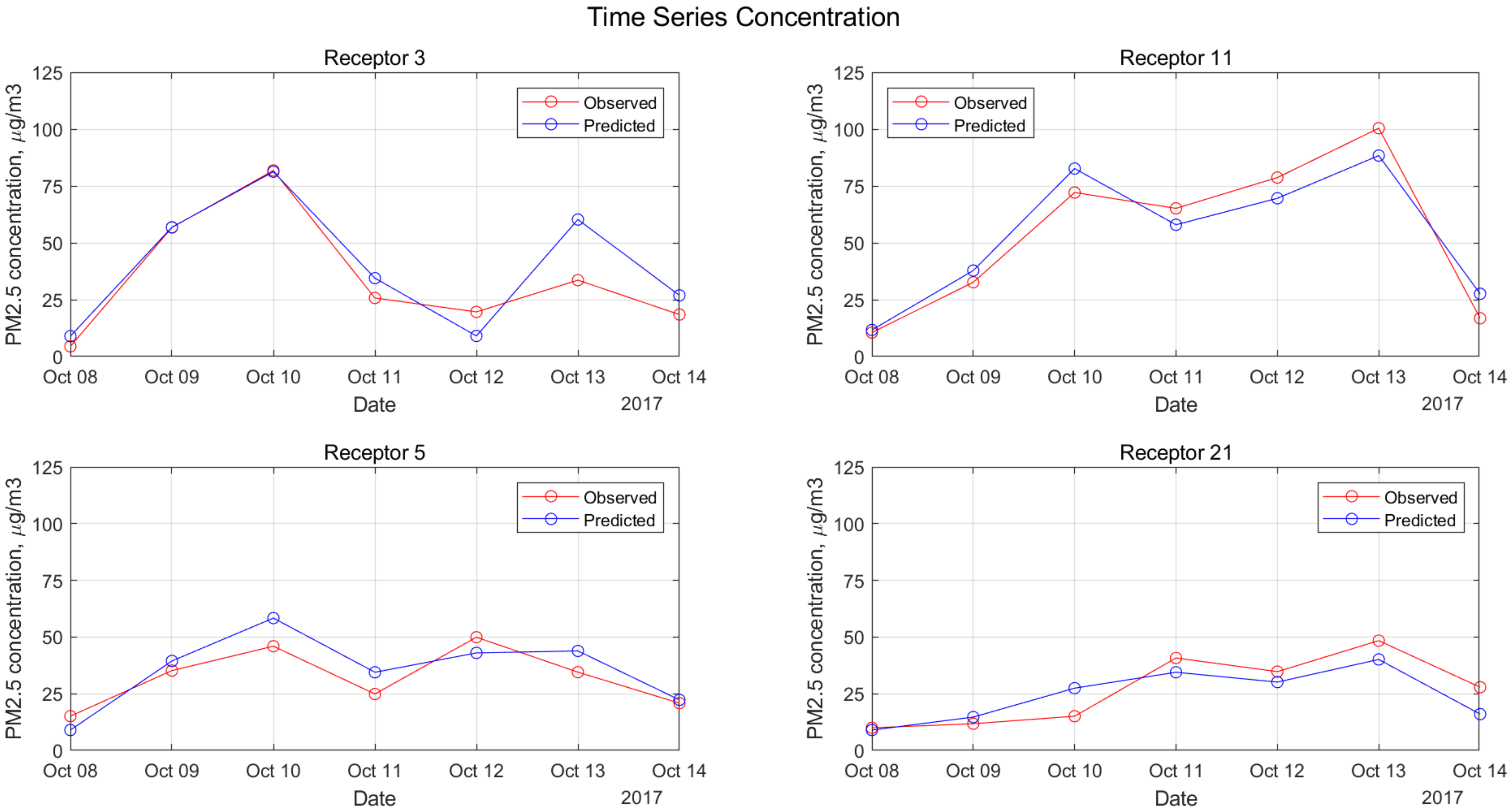
$$C_{ok} = \sum_j T_{jk} E_j + q_b \tau \left\langle \frac{1}{h} \right\rangle$$

Performance





The Plume Model



$PM_{2.5}$ Emissions Inferred from Fitting

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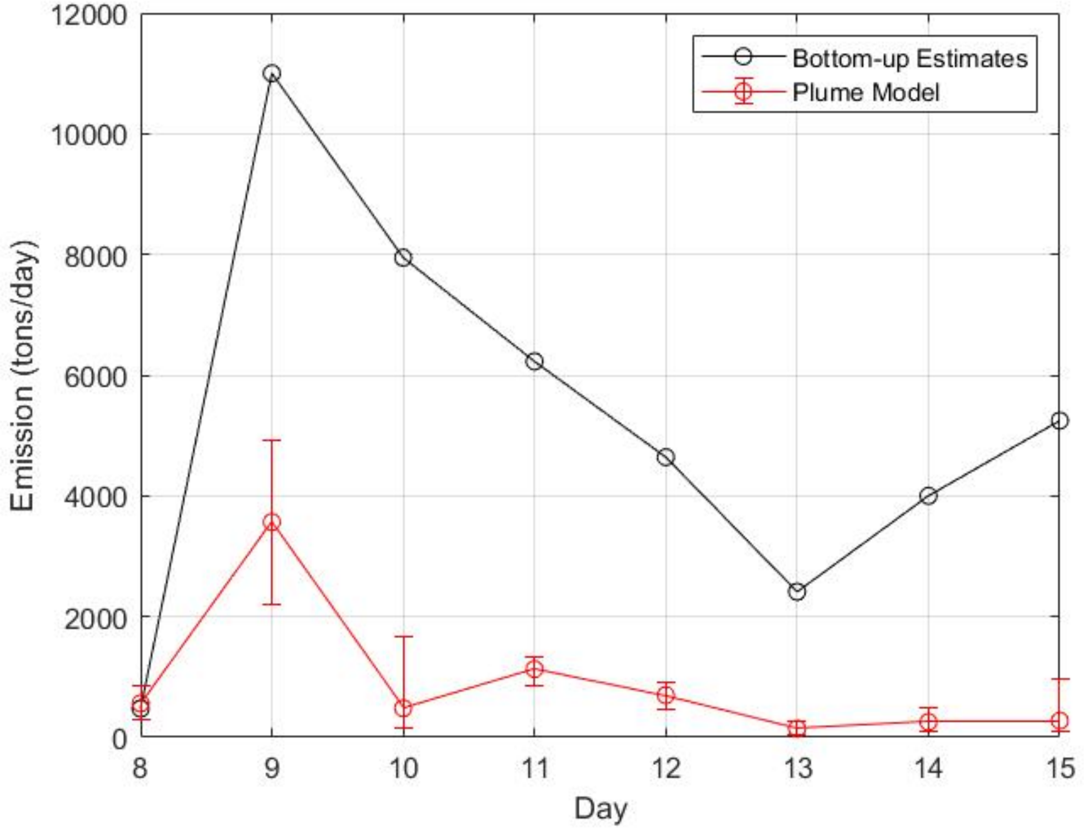
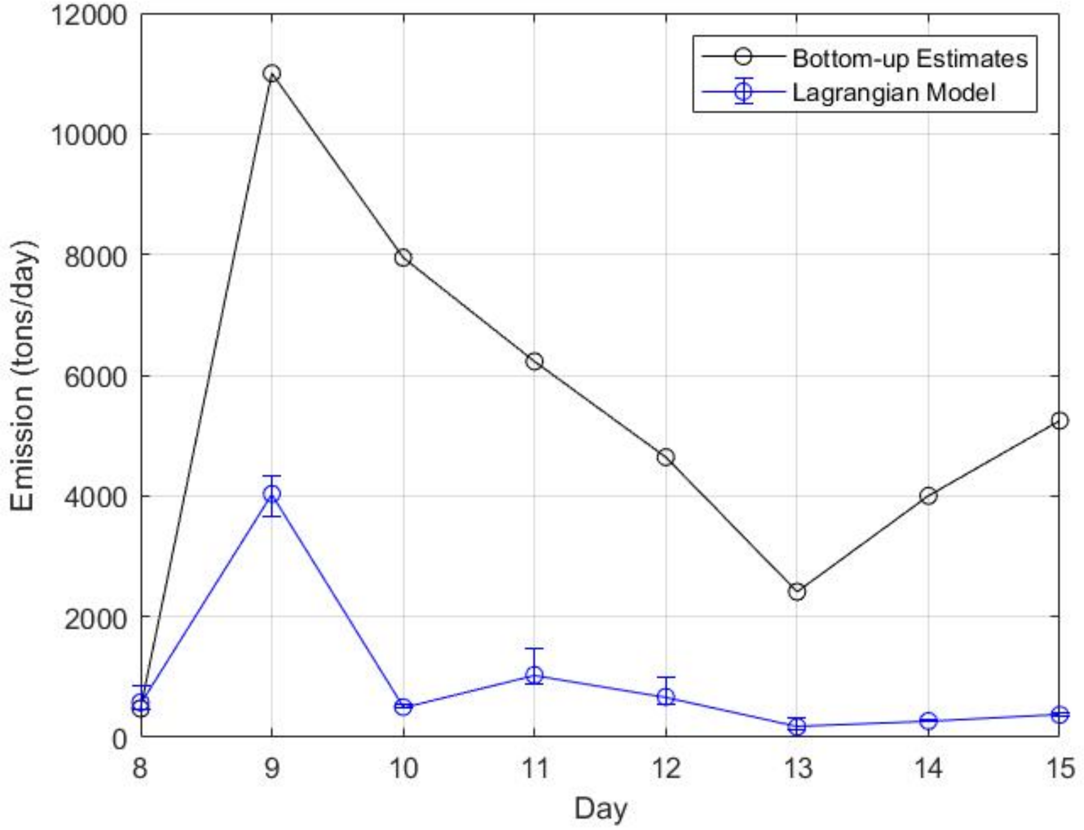
Plume Model



Lagrangian Model



Model inferred emissions are smaller than bottom-up estimates because they only account for emissions entrained into boundary layer

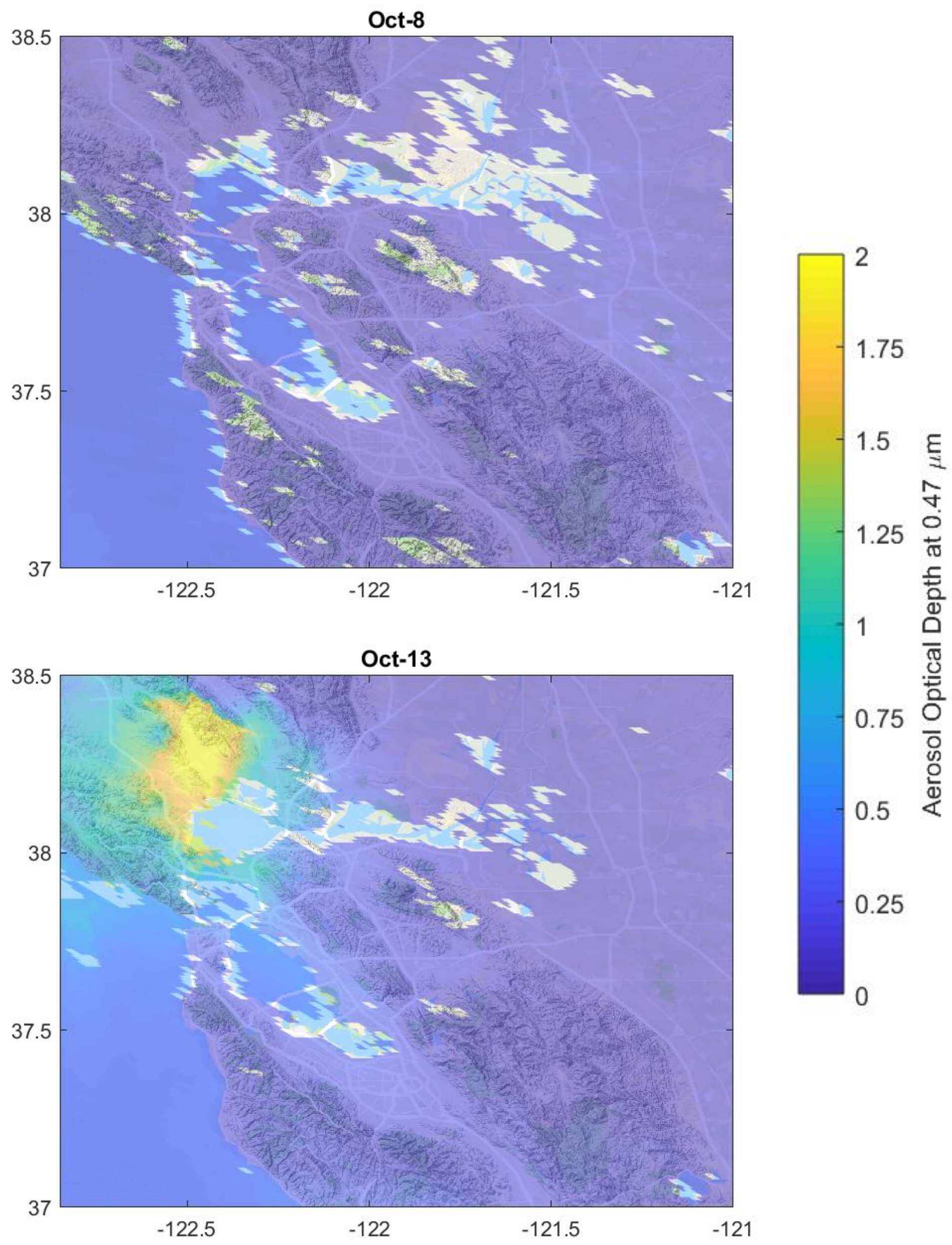
Emissions Inferred from Model

Date	Plume Model			Lagrangian Model		
	Mean sum (tons/day)	LL	UL	Mean sum (tons/day)	LL	UL
Oct-8	563	0.51	1.49	578	0.81	1.50
Oct-9	3566	0.62	1.38	4032	0.91	1.07
Oct-10	481	0.31	3.49	501	0.96	1.06
Oct-11	1129	0.76	1.17	1032	0.86	1.42
Oct-12	698	0.64	1.30	670	0.83	1.47
Oct-13	144	0.39	1.84	173	0.71	1.89
Oct-14	254	0.43	1.89	270	0.96	1.12
Oct-15	275	0.31	3.47	372	0.93	1.07

95% confidence intervals for emissions obtained by bootstrapping residuals between model estimates and measured concentrations

Observations From MCD19A2

- Moderate Resolution Imaging Spectroradiometer (MODIS)
- Multi-Angle Implementation of Atmospheric Correction (MAIAC)
- Contains multiple orbit overpasses daily
- 1 km resolution of Aerosol Optical Depth (AOD)



AOD Model

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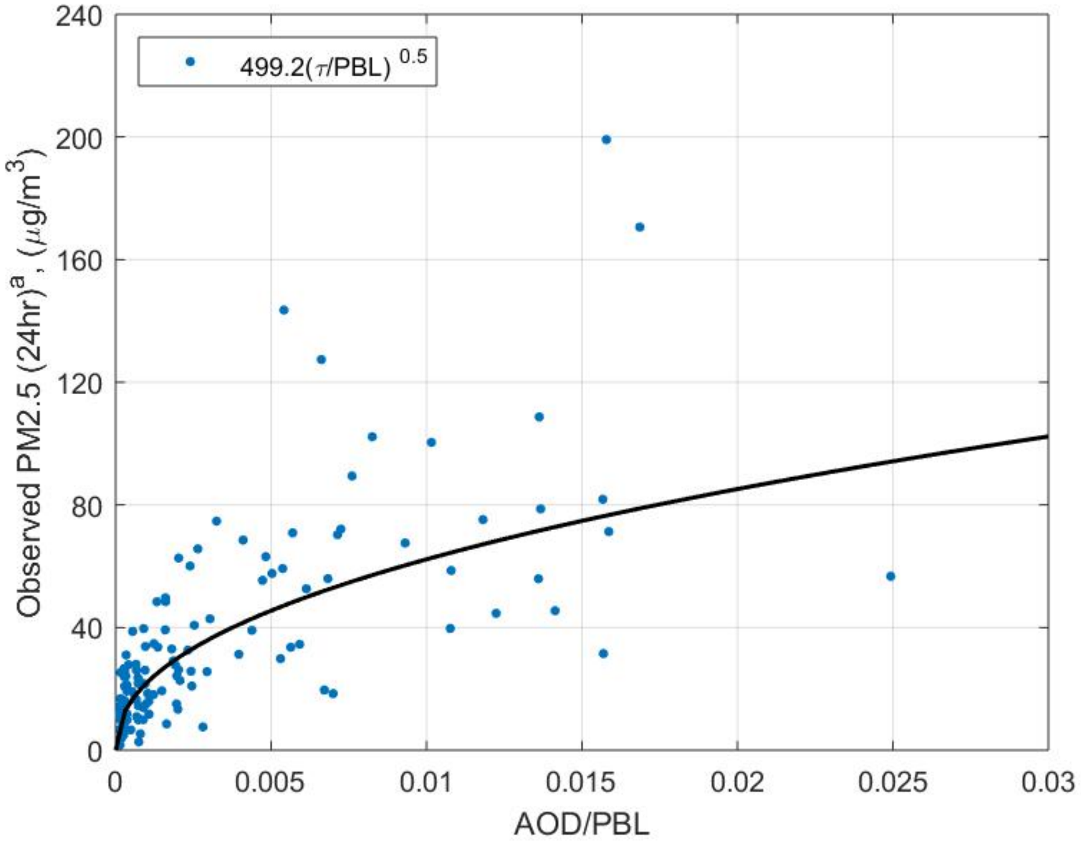
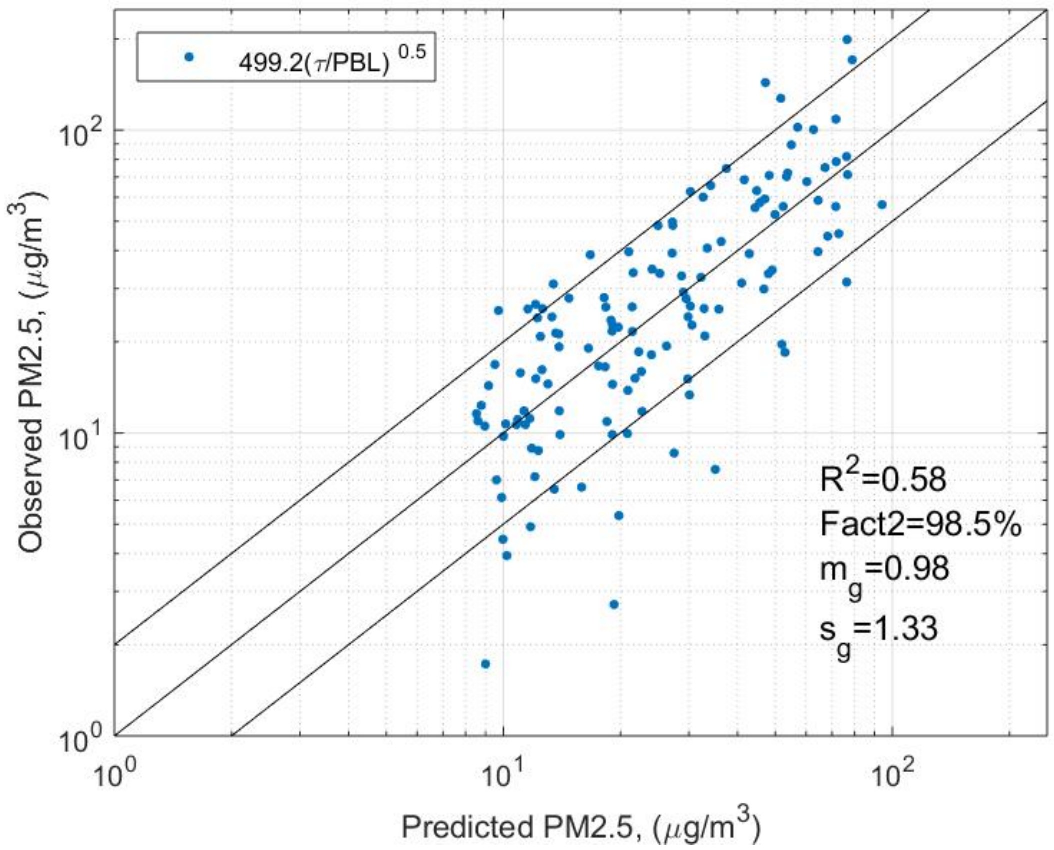
Surface $PM_{2.5}$ concentration fitted to the ratio of AOD to planetary boundary layer (PBL) height using a power curve





The Combined Model

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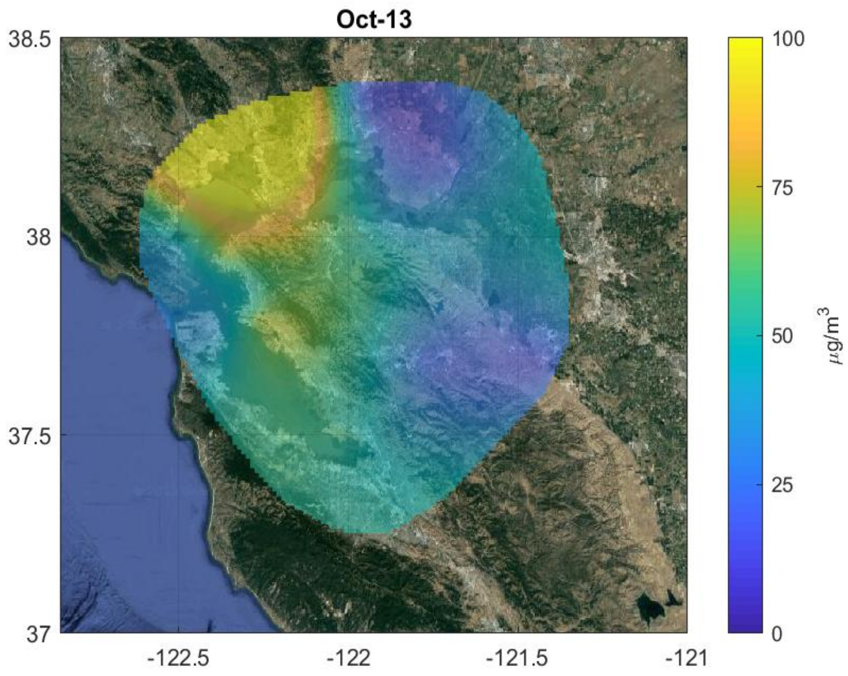
- $C_o = AC_{plume} + BC_{AOD} + C_b + \varepsilon$
- $C_o^e = C_p + Kriged(\varepsilon)$

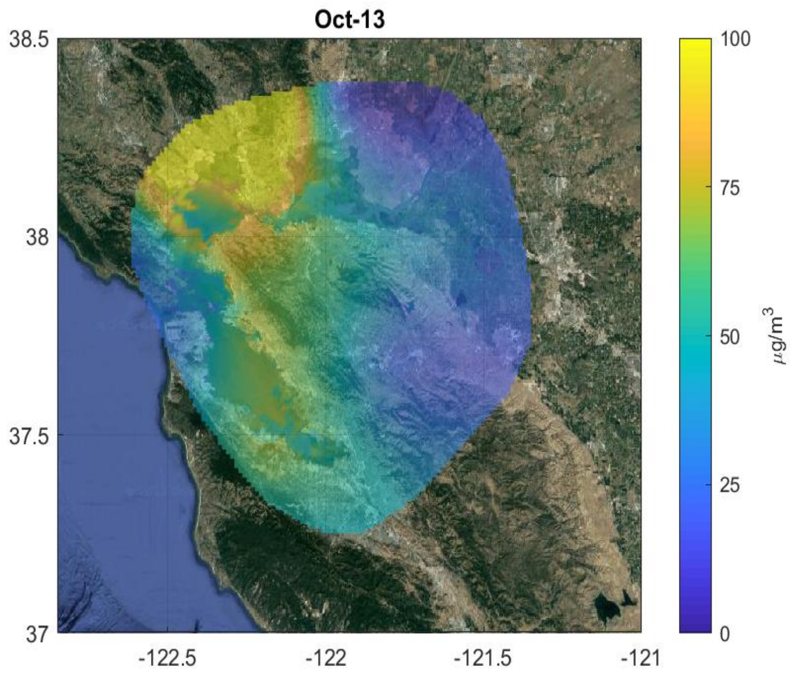
Date	A	B	Background	Plume Model R^2	Combined Model R^2
Oct-8	0.86	0.16	0	0.40	0.43
Oct-9	0.65	0.35	0	0.41	0.59
Oct-10	0.82	0.32	0	0.70	0.71
Oct-11	0.92	0.16	0.55	0.34	0.36
Oct-12	0.97	0.05	0	0.83	0.83
Oct-13	0.74	0.42	0	0.61	0.66
Oct-14	1.00	0.00	0	0.28	0.28
Oct-15	0.72	0.20	0	0.33	0.39

Concentration Maps

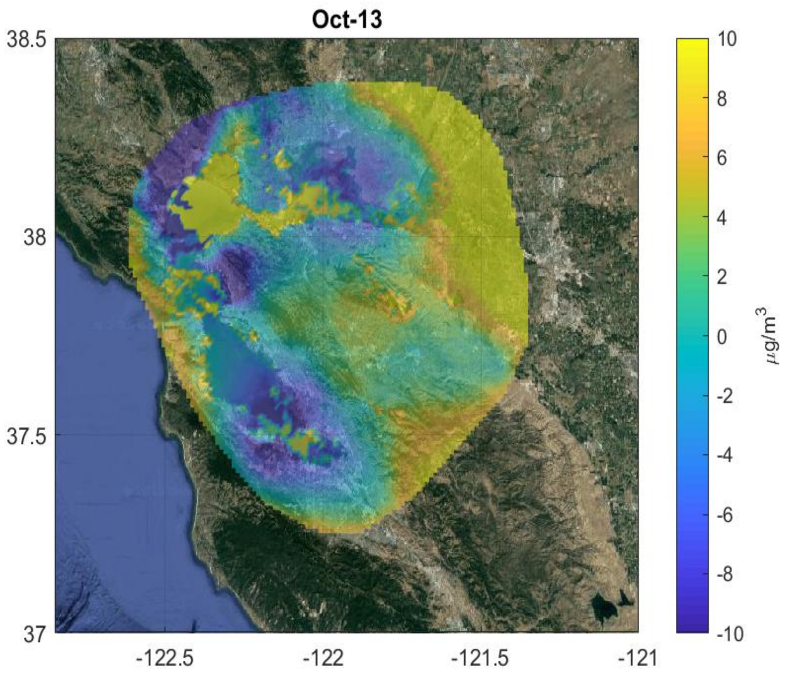
Kriged Observation



Combined Model

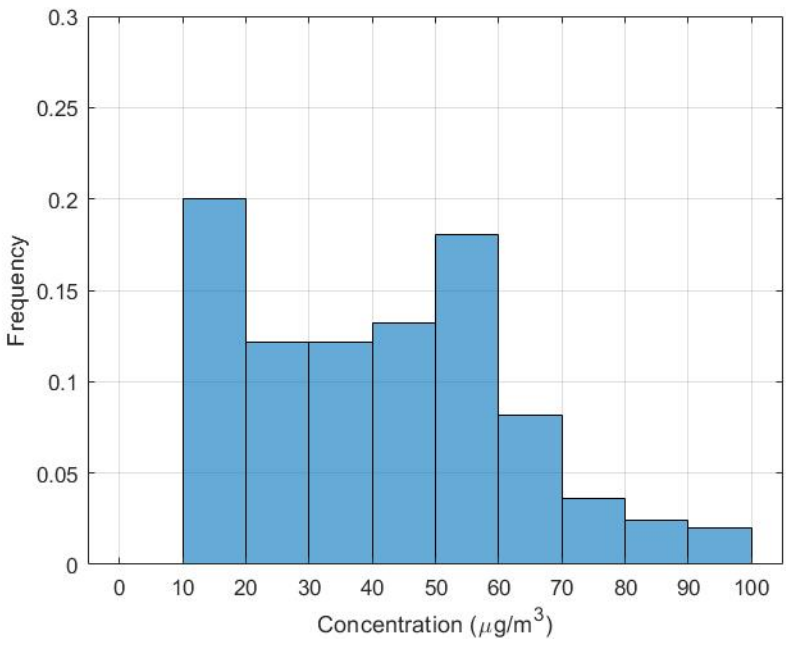


Differences

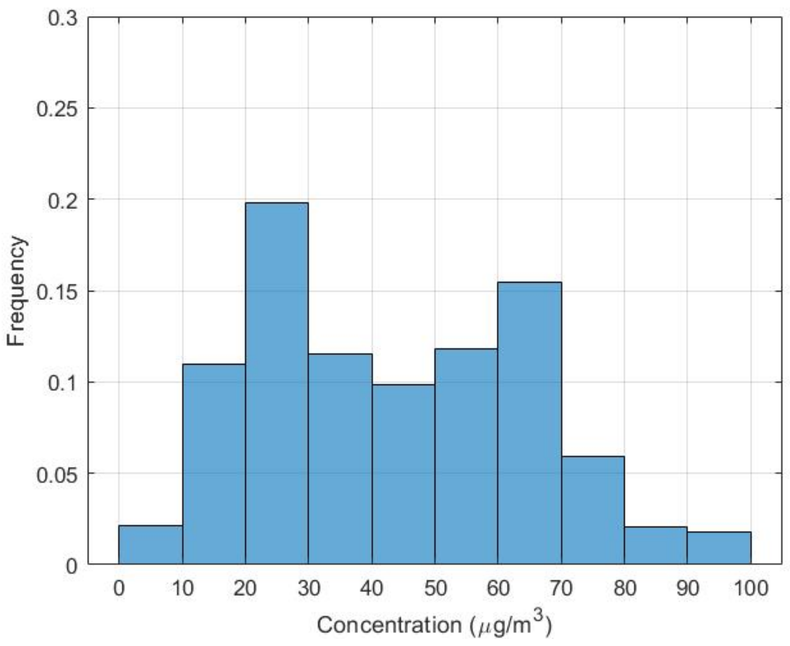


Histograms

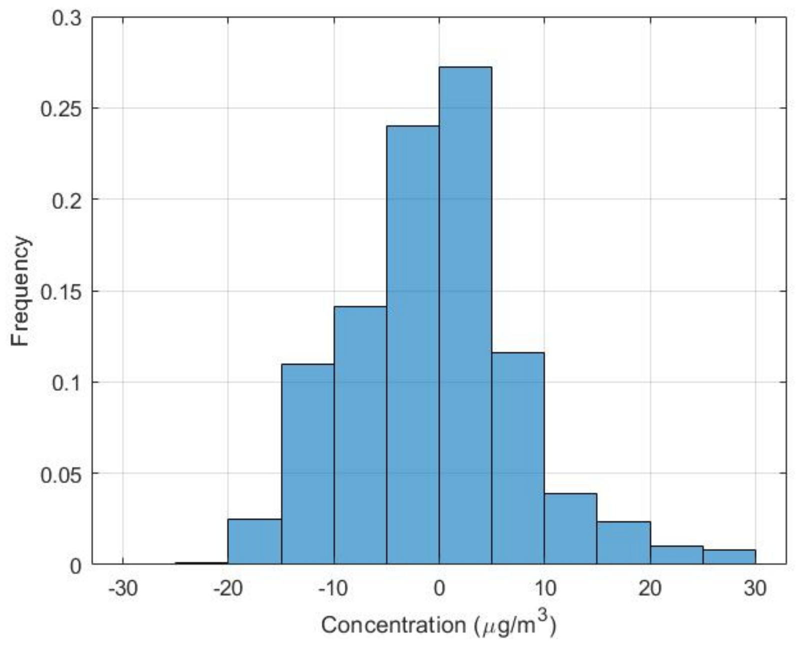
Kriged Observation



Combined Model



Differences



Summary and Conclusion

- Dispersion models provide useful descriptions of surface $PM_{2.5}$ concentration patterns caused by fires
- The AOD model is a useful complement to the dispersion model
- Model based residual Kriging yields more variance in the spatial distribution than Simple Kriging can

Dispersion models in combination with satellite derived AOD can improve upon the spatial/temporal resolution of ground based monitoring