

# Fusing CMAQ with Observations to Estimate Air Quality & Health Impacts of Oct. 2017 CA Wildfires

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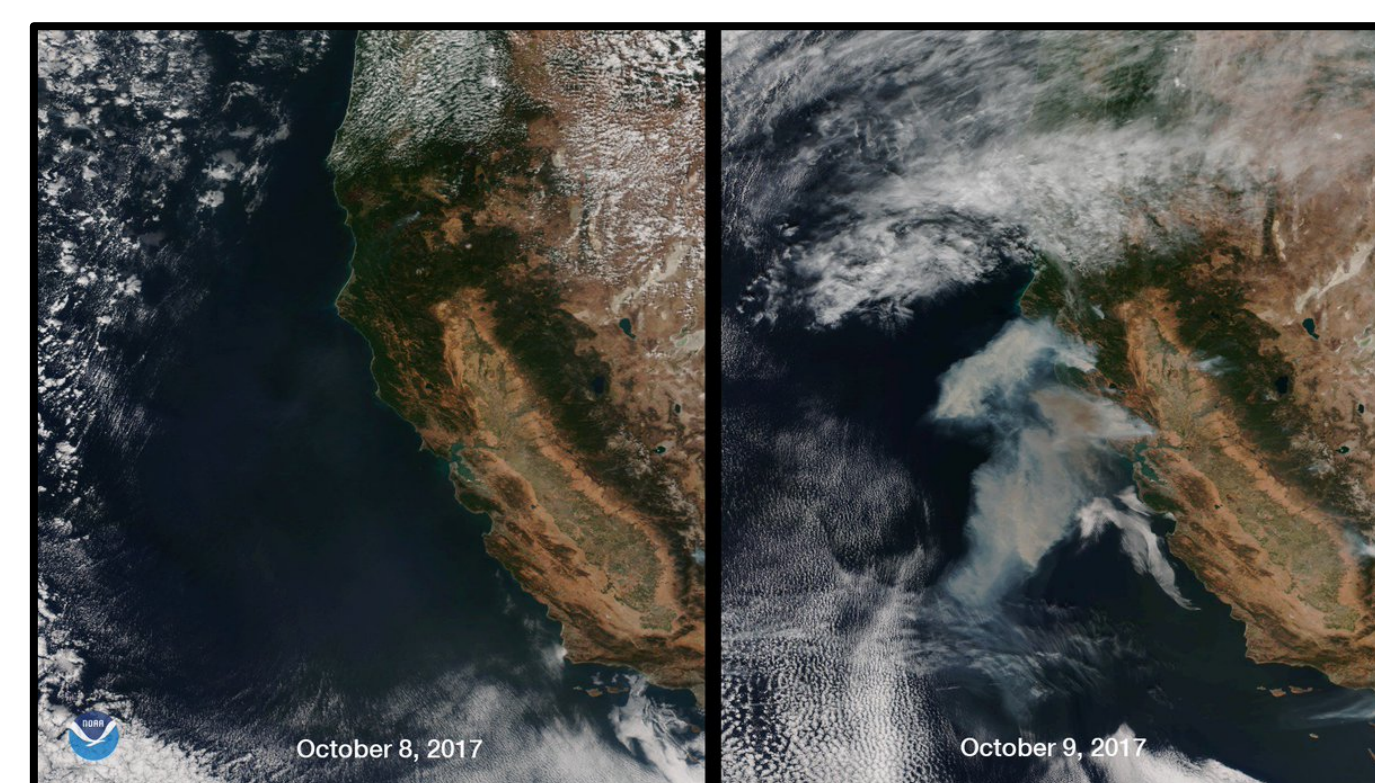


## INTRODUCTION

Beginning October 8-9, 2017, a series of wildfires in N. California resulted in:

- PM<sub>2.5</sub> concentrations reaching highest levels recorded to date in CA
- ~7.2 million people living in the Bay Area exposed to unhealthy air

Since smoke from this fire affected a large population, it is necessary to accurately estimate the extent of the air quality and health impacts of the fires. Geostatistical methods exist to correct and combine modeled and observed concentrations to estimate air quality<sup>3</sup>, but have not been applied to wildfires.



Img 1. Satellite imagery of the wildfire smoke on October 8 and 9, 2017 (source: NOAA)

This research has 2 primary goals:

1. Evaluate different methods for accurately **mapping PM<sub>2.5</sub> during the Oct. 2017 wildfires**, fusing together observed, modeled, and satellite AOD-estimated PM<sub>2.5</sub> concentrations
2. Use PM<sub>2.5</sub> estimates to **evaluate the acute health impact of the Oct. 2017 fires**, specifically the attributable respiratory and cardiovascular admissions

Future work will extend this approach to more health endpoints & pollutants.

## DATA

### PM<sub>2.5</sub> Data

To map air quality during the wildfires, 3 PM<sub>2.5</sub> datasets were used:

1. Surface observations from:
  - 114 EPA FRM/FEM monitoring stations across California, Oct. 1 – 31 (EPA's air quality database)
  - 49 temporary monitoring stations across California, Oct. 1 – 31 (US Forest Service)
2. Estimates from **Community Multiscale Air Quality (CMAQ) model** in the Central California region at a 4-km resolution from Oct. 3 – 20 (Bay Area Air Quality Management District (BAAQMD))
3. Satellite-based estimates from **Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Satellite Aerosol Optical Depth (AOD) data**, Oct. 1 – 31 (NASA)

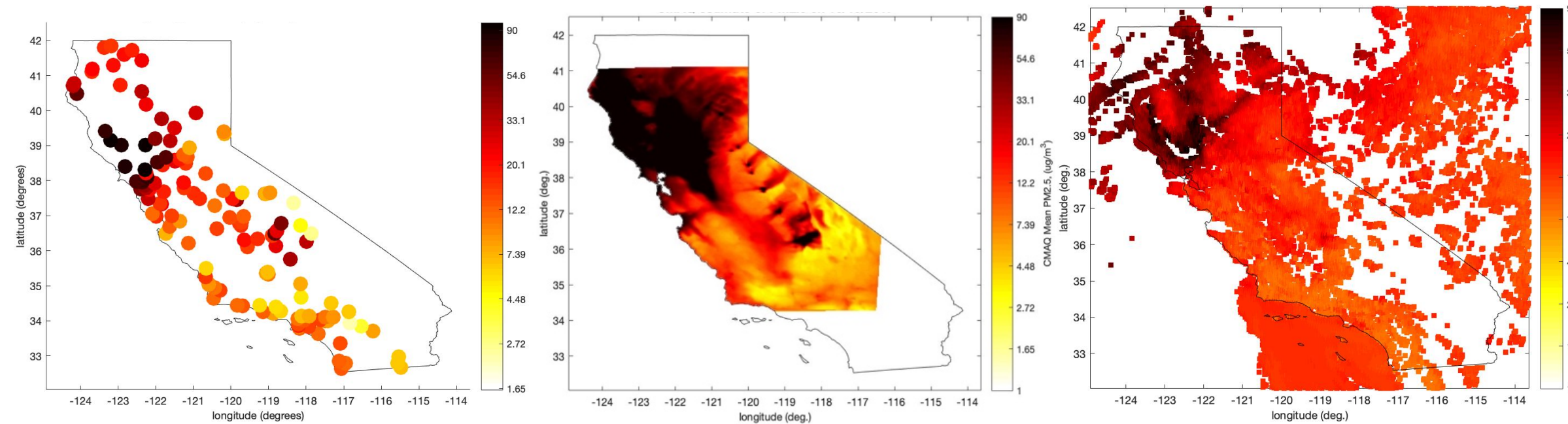


Fig. 1. Estimates of PM<sub>2.5</sub> surface concentrations on Oct. 10 from (Left) FRM & temporary stations, (Middle) BAAQMD CMAQ model, and (Right) MODIS Terra Satellite AOD Data

### Hospital Admission Data

To estimate attributable hospital admissions, the following data were used:

1. **Concentration-response functions** for health endpoints:
  - 2.07% (95% CI, 1.20% - 2.95%) ↑ in respiratory, 1.89% (95% CI, 1.34% - 2.45%) ↑ in cardiovascular hospital admissions per 10 μg/m<sup>3</sup> ↑ in PM<sub>2.5</sub><sup>1</sup>
2. **County-level hospital admission rates** for respiratory illness & cardiac causes across CA for 2017 (EPA Benefits Mapping and Analysis Program)
3. **Percent PM<sub>2.5</sub> attributable to fires**, used to estimate background PM<sub>2.5</sub> concentration, from CMAQ model w/ and w/o fire emissions (BAAQMD)

## MAPPING PM<sub>2.5</sub>

### Objective

Evaluate the accuracy of four different methods for mapping daily average PM<sub>2.5</sub> during the Oct. 2017 wildfires using available data: observed, modeled, & satellite AOD-estimated PM<sub>2.5</sub> concentrations

### Methods

2 steps were used to prepare the modeled and AOD-estimated PM<sub>2.5</sub> concentrations:

1. Conversion of MODIS AOD to PM<sub>2.5</sub> using a simple linear regression<sup>2</sup>
2. Constant Air Quality Model Performance (CAMP)<sup>5</sup>-correct CMAQ (CC-CMAQ) model & AOD-estimated PM<sub>2.5</sub> (CC-Sat)

*CAMP Method:* corrects errors in estimations by modeling the mean ( $\lambda_1$ ) and variance ( $\lambda_2$ ) of observed value as a function of estimated value, accounting for nonlinearity and heteroscedasticity<sup>3</sup>

Using the Bayesian Maximum Entropy (BME) Framework, 4 mapping methods were evaluated & compared using Mean Squared Error (MSE) and R<sup>2</sup> values from cross-validations:

1. Space/time (s/t) BME kriging on log-PM<sub>2.5</sub> obs
2. Fusion of CC-CMAQ & log-PM<sub>2.5</sub> obs
3. Fusion of CC-Sat & log-PM<sub>2.5</sub> obs
4. Fusion of CC-CMAQ, CC-Sat, & log-PM<sub>2.5</sub> obs

*BME Framework:* estimates PM<sub>2.5</sub> at unmonitored locations, using geostatistics to combine site-specific and general knowledge<sup>4,5</sup>. Treats observed PM<sub>2.5</sub> data as hard, CMAQ/AOD data as soft<sup>4</sup>. Soft data ( $\lambda_1$ ) with lower variance ( $\lambda_2$ ) have more influence. Influence of hard data decreases with distance given s/t correlation<sup>4</sup>.

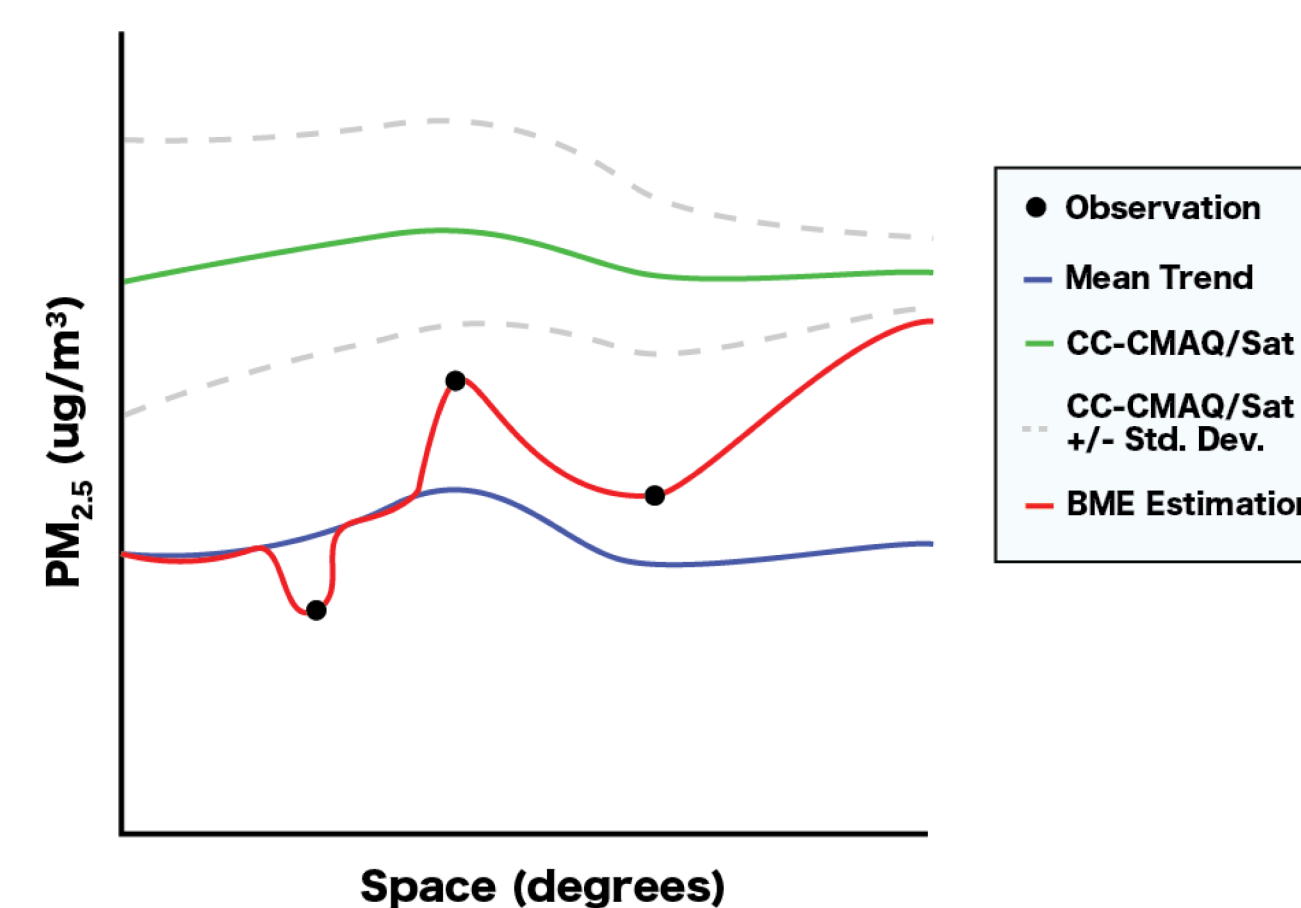


Fig. 2. Example of the BME Method

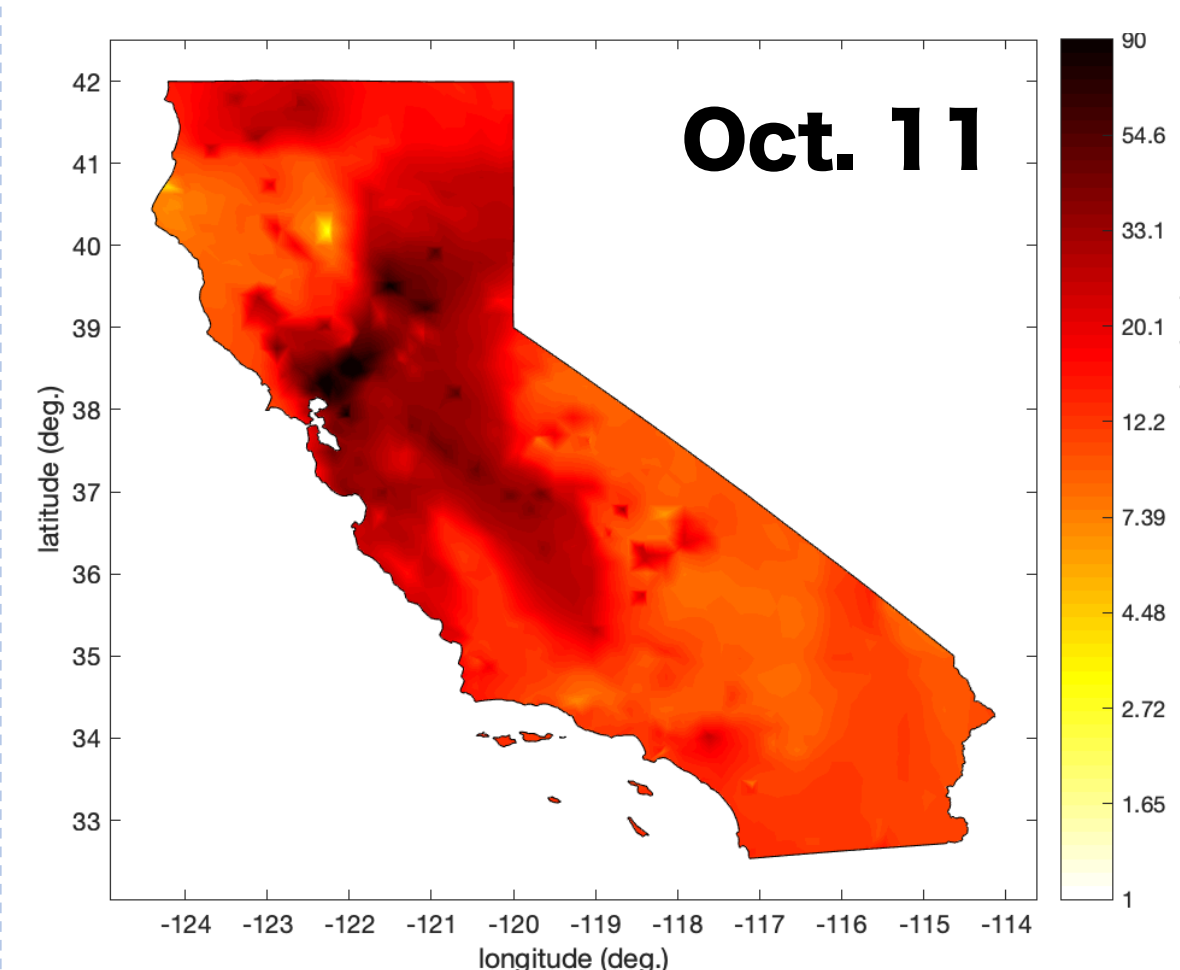
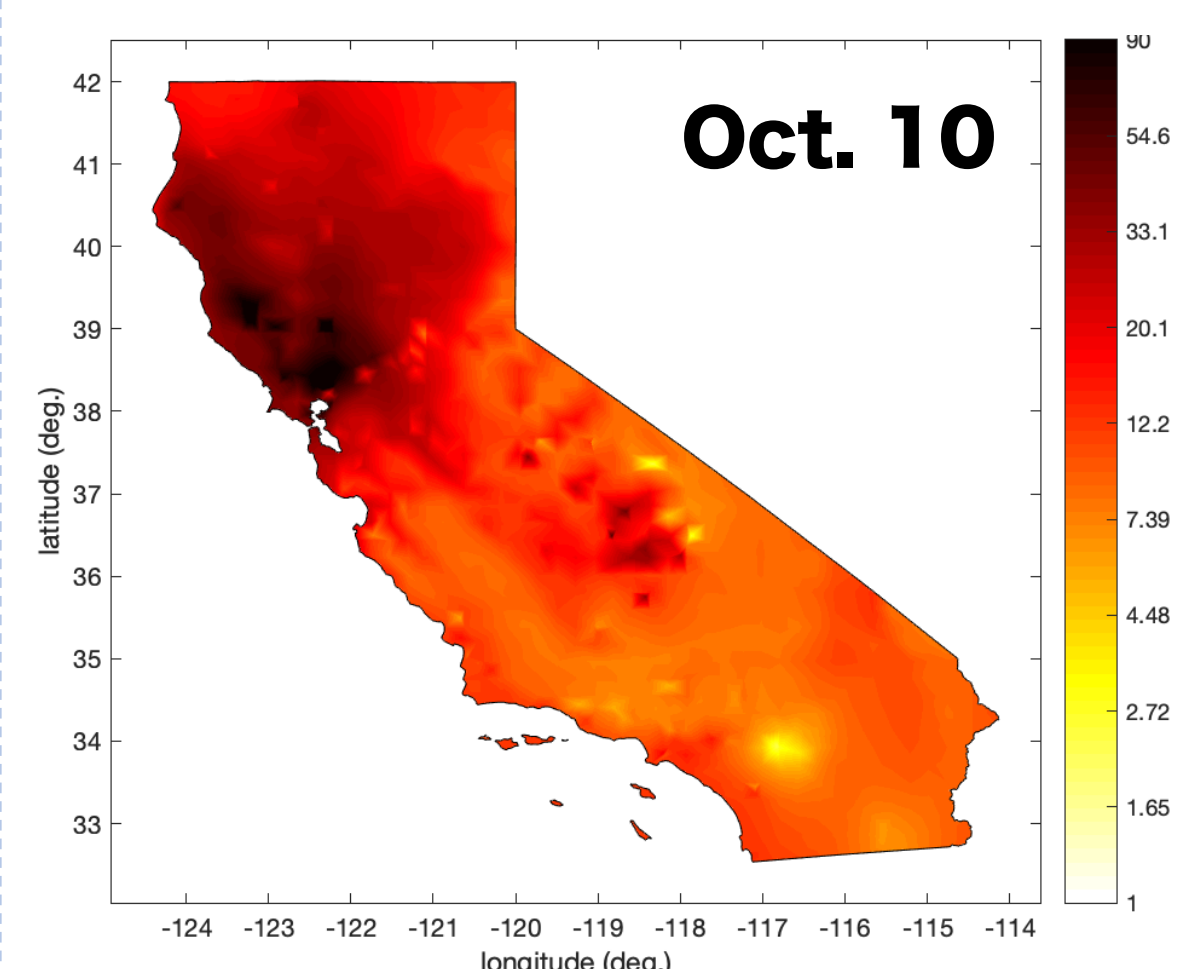
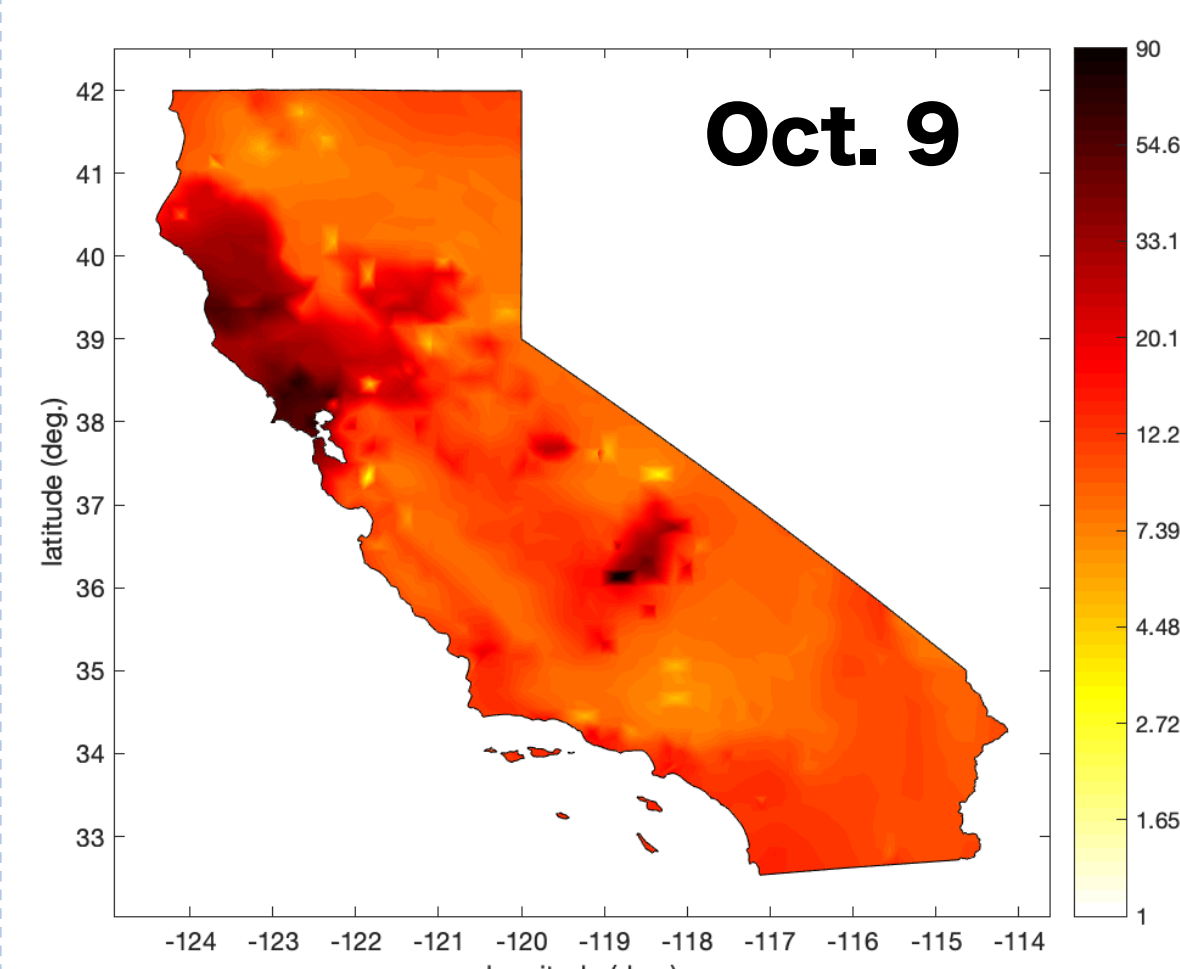
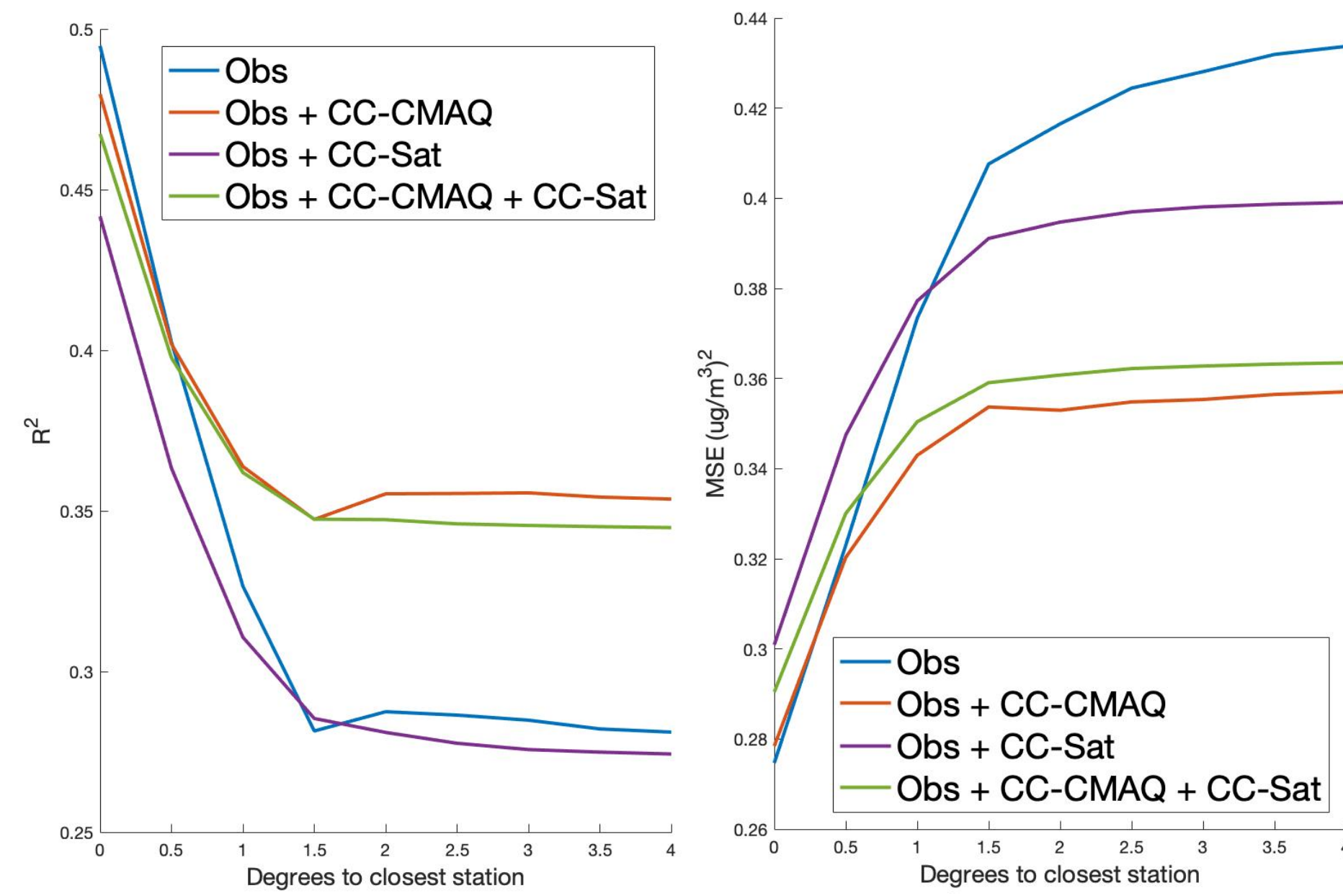


Fig. 3 PM<sub>2.5</sub> estimates, Oct. 10-12, using the fusion of CC-CMAQ and observations

### Results

- **Fusing observations with CC-CMAQ provides most accurate PM<sub>2.5</sub> estimate** – used for acute health impact

- Adds knowledge of atmospheric chemistry & physics
- Better estimates PM<sub>2.5</sub> if >35 miles from a station
- Fusing CC-Sat with observations and CC-CMAQ performs similarly but slightly worse
- May require better AOD → PM<sub>2.5</sub> conversion
- Space/time BME kriging on observations produces most accurate estimates at monitoring station locations
- Fires had clear impact on air quality reaching PM<sub>2.5</sub> levels dangerous to human health (daily avg. PM<sub>2.5</sub> >165 μg/m<sup>3</sup>)



Method	MSE (log-μg/m <sup>3</sup> ) <sup>2</sup>	R <sup>2</sup> (log-space)
S/T BME Kriging on Obs	0.139	0.740
Fusion, Obs + CC-CMAQ	0.144	0.730
Fusion, Obs + CC-Sat	0.156	0.710
Fusion, Obs + CC-CMAQ + CC-Sat	0.155	0.717

Table 1. Results from leave-one-out cross validation

## ESTIMATING ACUTE HEALTH IMPACT

### Objective

Using PM<sub>2.5</sub> observations fused with CC-CMAQ, estimate the respiratory and cardiovascular hospital admissions attributable to PM<sub>2.5</sub> from the Oct. 2017 fires

### Methods

The rate of respiratory and cardiovascular hospital admissions attributable to PM<sub>2.5</sub> from the fires, given a log-linear relationship, is:  $\Delta Y = Y(t) * (1 - e^{-\beta(X(s,t) - X_0(s,t))})$

- $Y(t)$  - baseline county-level cardiovascular/respiratory admission rate
- $(1 - e^{-\beta(X(s,t) - X_0(s,t))})$  - attributable fraction
- $X(s, t)$  - mean PM<sub>2.5</sub> concentration at a s/t location
- $X_0(s, t)$  - background concentration of PM<sub>2.5</sub> at a s/t location
- $\beta = \frac{\ln(RR)}{10 \mu g/m^3}$ , RR - hospital admission-PM<sub>2.5</sub> concentration-response functions

Monte-Carlo simulations of  $\beta$  were used to obtain  $\Delta Y$  estimates. The  $\Delta Y$  estimates were combined with census tract-level population data to estimate the daily respiratory and cardiovascular hospital admissions.

### Results

- Between Oct. 6 - 20, we estimate **234 people** were admitted to the hospital for **respiratory illness** and **214 people** for **cardiac causes** due to the fires

- Highest rates of admission occurred in densely populated areas with high PM<sub>2.5</sub> levels from the fires; cardiovascular admissions were more concentrated north of Bay Area
- Our estimated 105 total cardiovascular and respiratory hospital admissions by Oct. 10 are comparable to the 185 admissions reported by local news at 3 hospitals by Oct. 10<sup>6</sup>

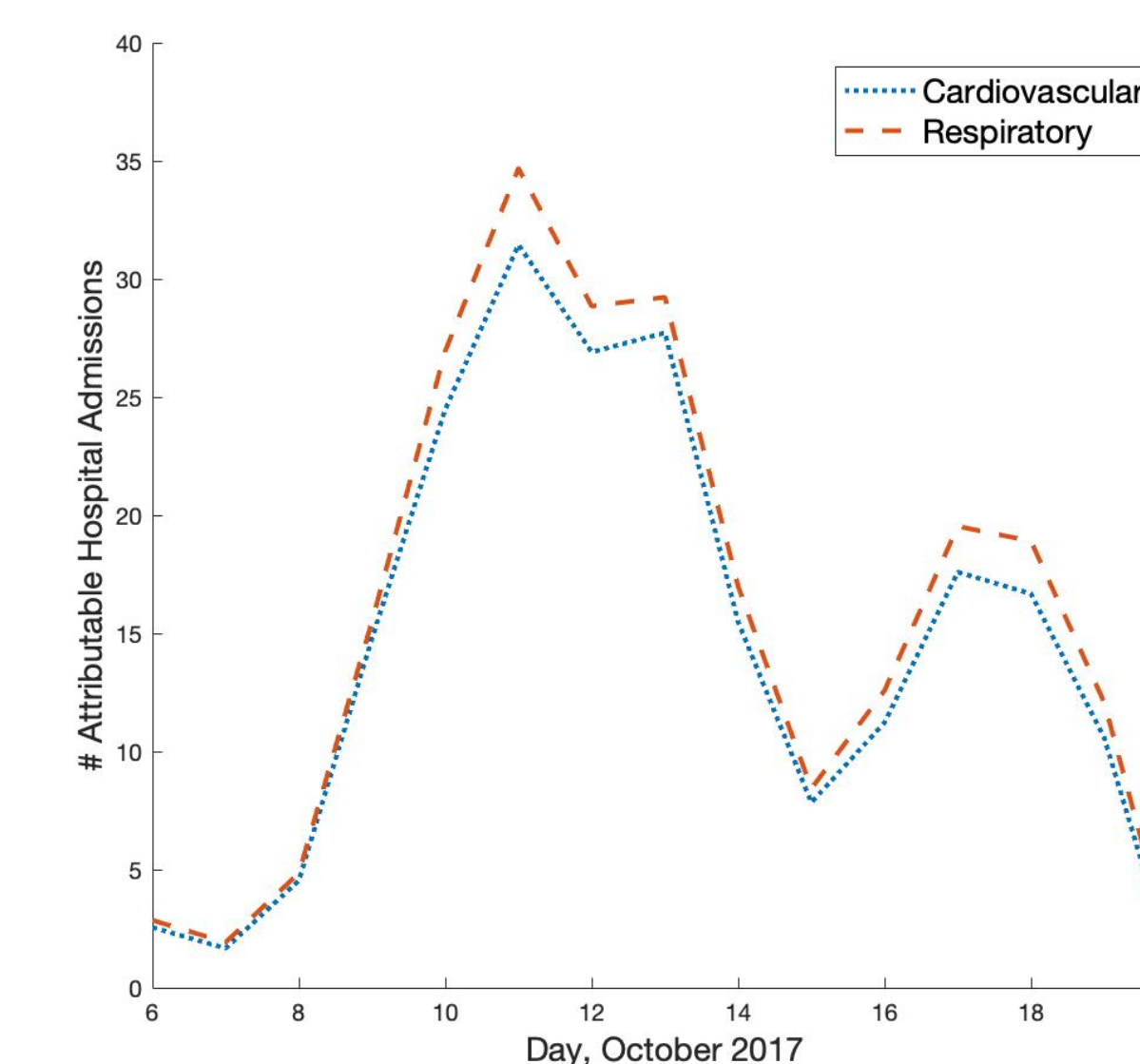
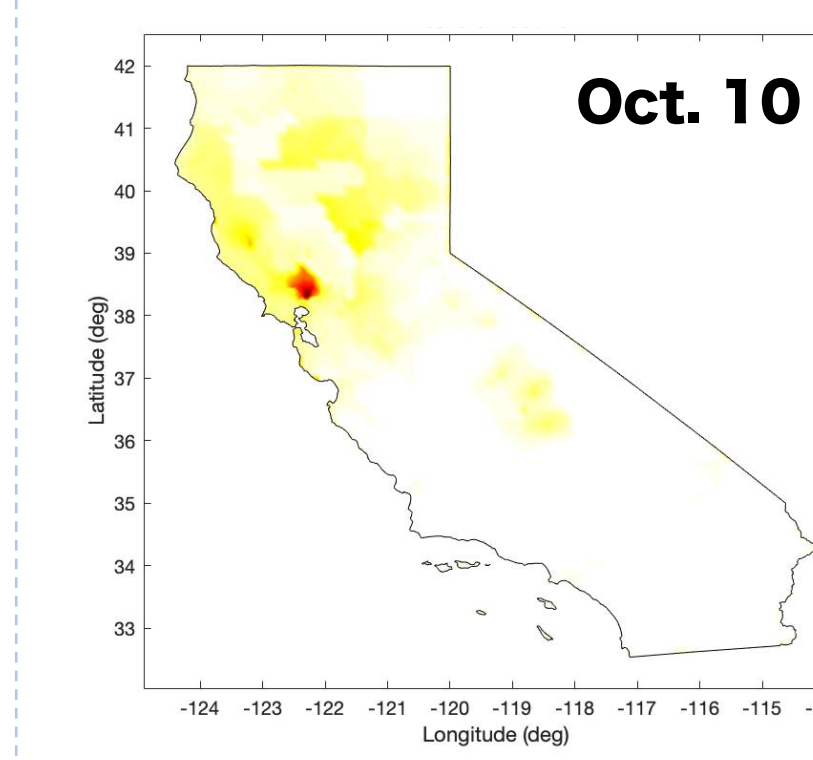
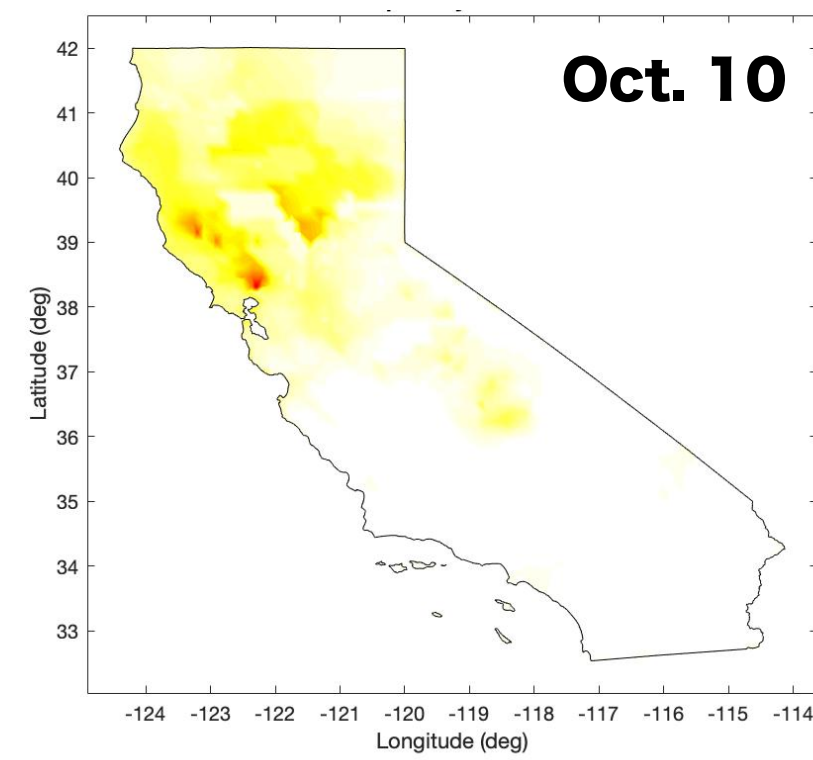


Fig. 6. Daily respiratory and cardiovascular admissions during the fires, Oct. 6 - 20

### Cardiovascular Admissions



### Respiratory Admissions



### Future Work

- Integrate finer resolution health data into assessment, using a temporally-specific baseline admission rate,  $Y(t)$
- Further improve accuracy of background concentration estimate outside bounds of CMAQ model
- Perform impact assessment on additional health outcomes over entire fire period

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6. Associated Press. (2017). Hospitals say at least 185 treated for injuries. Retrieved from <https://www.wibw.com/>

### Acknowledgements

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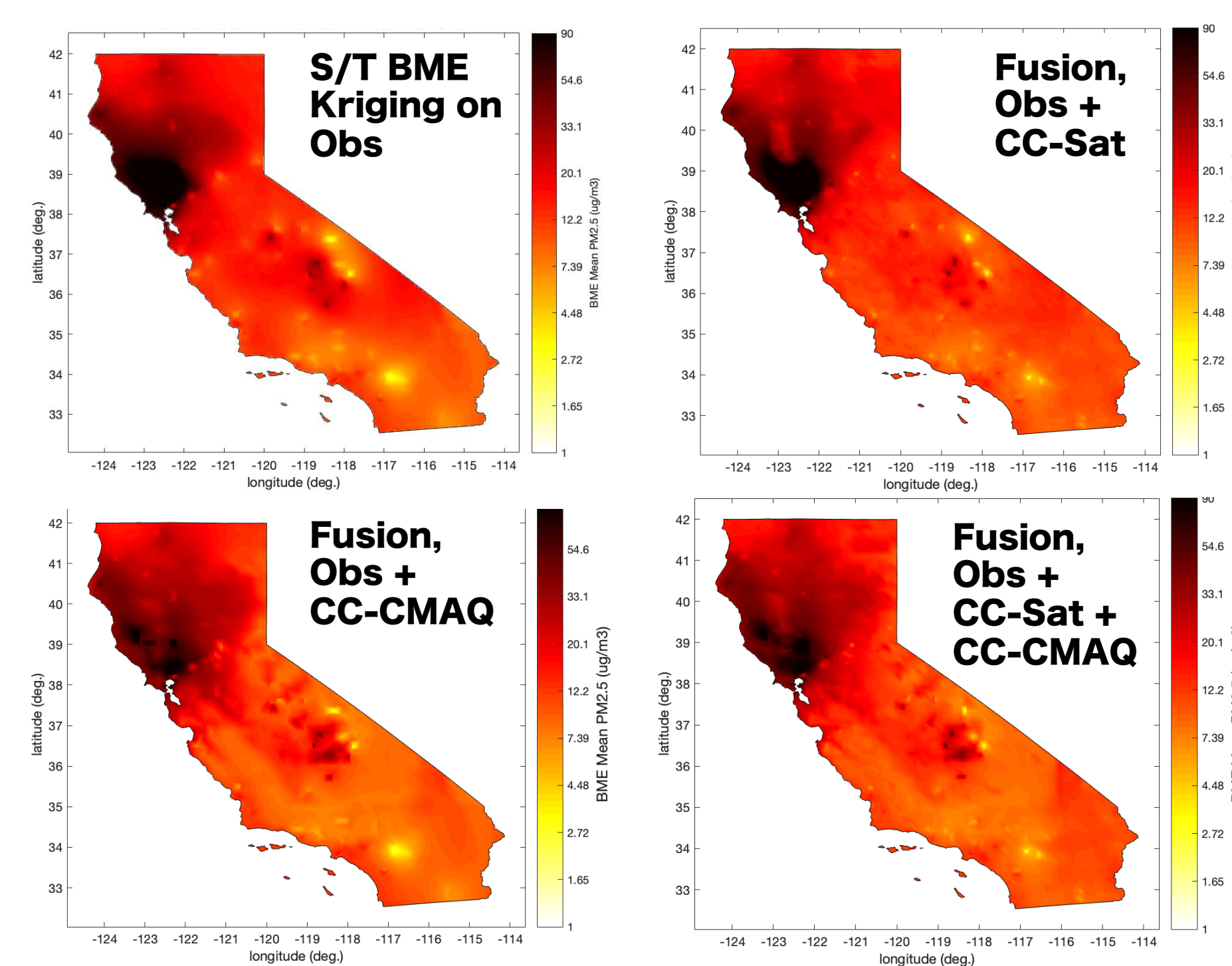


Fig. 5. Comparison of 4 PM<sub>2.5</sub> estimation methods, Oct. 10, 2017