Pollutant concentration mapping to support health impact assessment: global ozone concentrations, and PM from California wildfires

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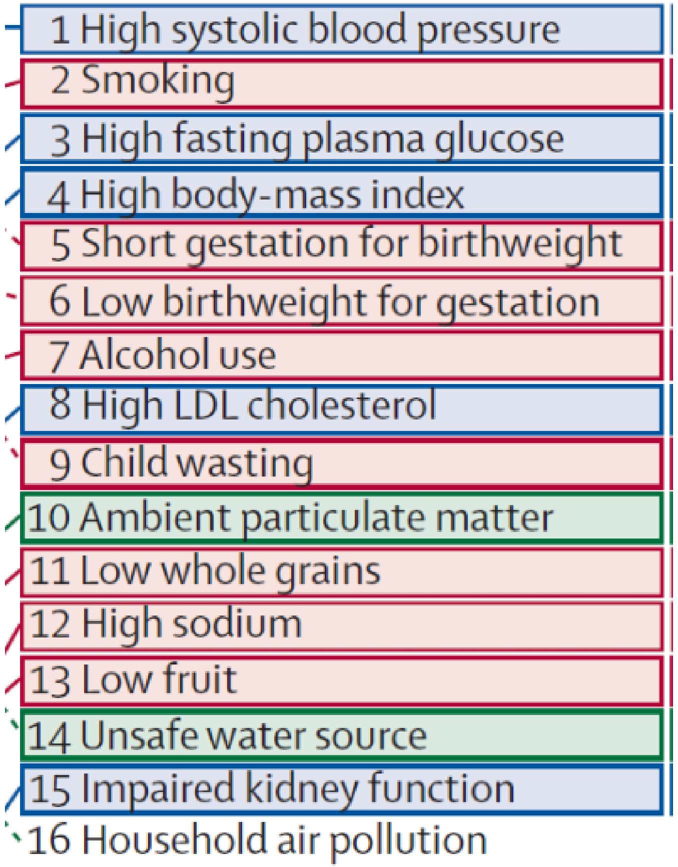
Global burden of disease of air pollution (2017)

Global Deaths per Year

Ambient $PM_{2.5}$ pollution:	**2.9 (2.5 – 3.4) million**	**1 in 19 deaths globally!**
Ambient ozone pollution:	**0.47 (0.18 – 0.77) million**	
Household air pollution from solid fuels:	**1.6 (1.4 – 1.9) million**	**1 in 45 deaths globally!**



Ambient $PM_{2.5}$ pollution is the 8^{th} leading risk factor for death globally.

Burnett et al. (PNAS, 2018) estimate 8.9 (7.5-10.3) million deaths from $PM_{2.5}$ in 2015.

GBD 2017 Team, *Lancet*, 2018

In the US, air pollution kills:

109,000 (2017 from GBD), 1 in 25 US deaths

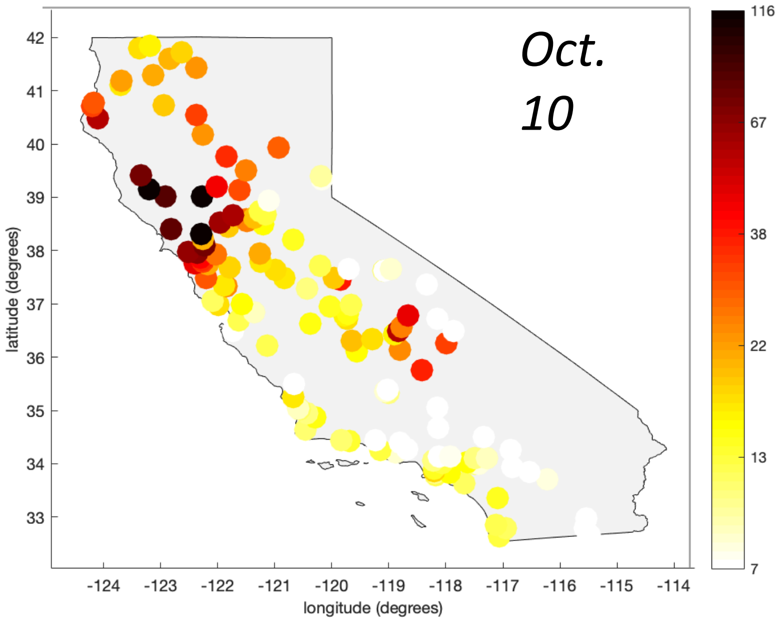
47,000 (2015 our work), 1 in 58 US deaths

Diabetes:	**80,000**
Influenza & pneumonia:	**52,000**
All suicides:	**45,000**
All transportation accidents:	**43,000**
Breast cancer:	**42,000**
All gun shootings:	**39,000**
Prostate cancer:	**30,000**
Parkinson's:	**30,000**
Leukemia:	**23,000**
HIV AIDS:	**6,000**

2016 data from CDC

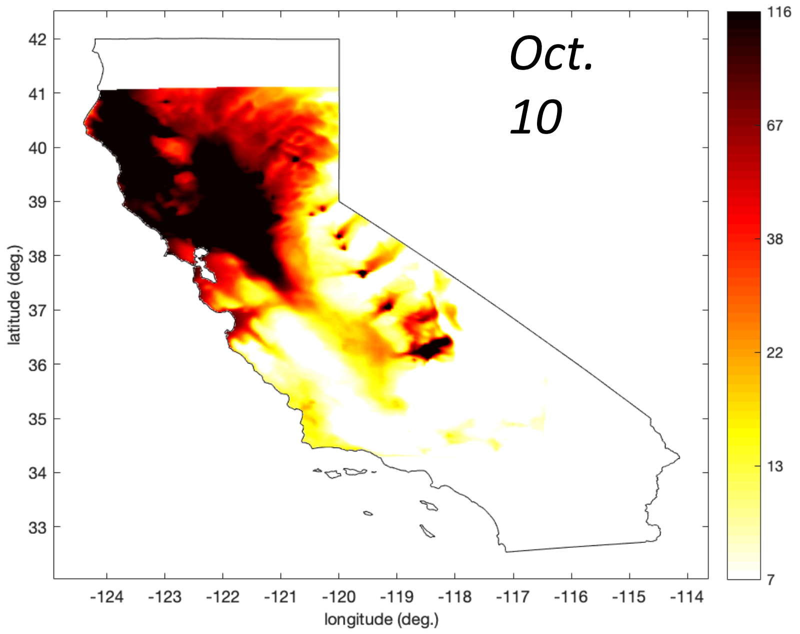
Available Data and Limitations

Monitoring Station $PM_{2.5}$



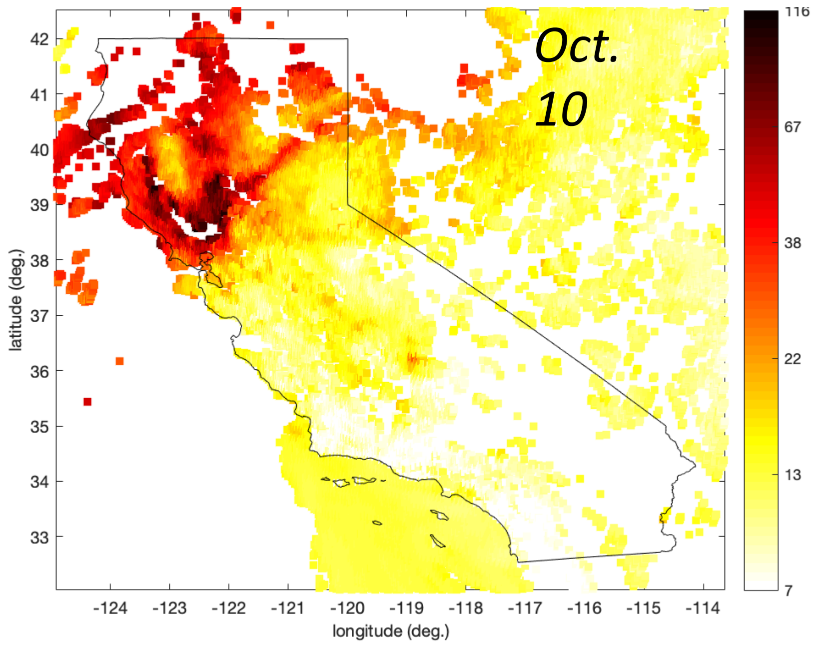
High-quality, accurate $PM_{2.5}$ measurements, readily available

CMAQ Model $PM_{2.5}$



Space/time coverage, knowledge of atmospheric physics and chemistry & fire emissions

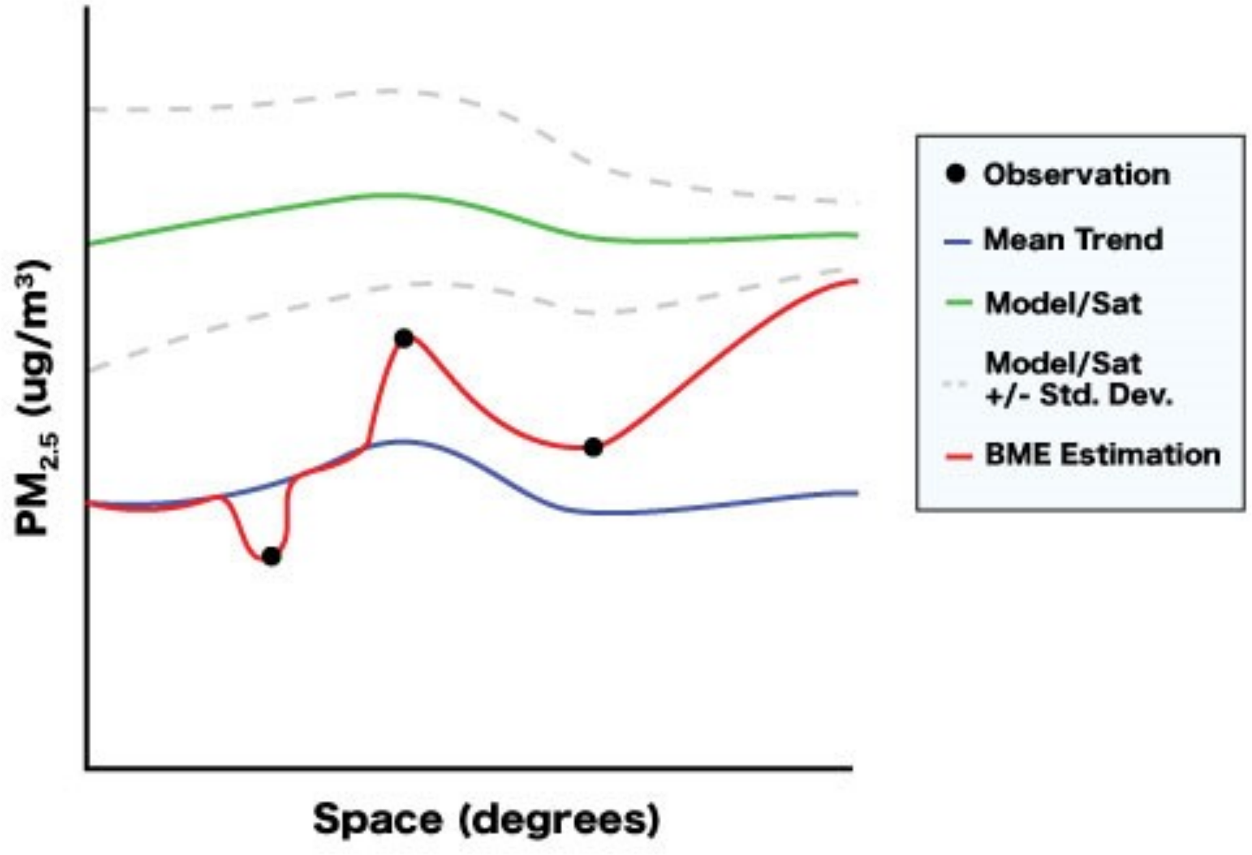
Satellite AOD-Derived $PM_{2.5}$



Space/time coverage, information on smoke plume location

Methods: Bayesian Maximum Entropy

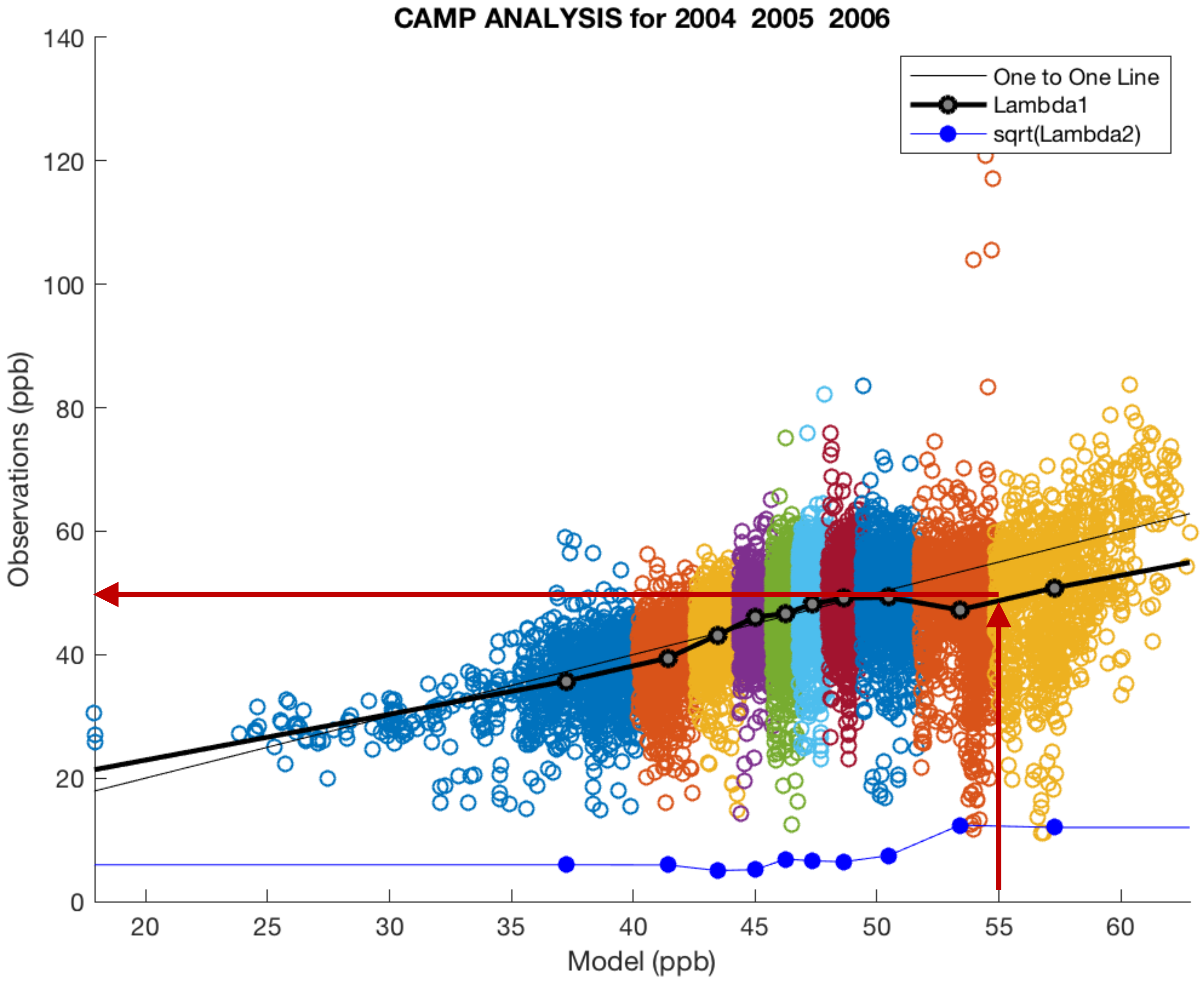
- Estimates concentrations at unmonitored locations using modern space/time geostatistics to combine site-specific and general knowledge
  - *Site-specific knowledge:* values at a known s/t location
  - *General knowledge:* mean trend, covariance, variance
- Treats observed values as hard or soft data
  - Influence of observations decreases with distance given s/t correlation.
- Treats models or satellites as soft data



Christakos and Serre (2000); Christakos et al. (2001)

Methods: CAMP correction

- Constant Analysis of Model Performance (CAMP)
- Corrects for model / satellite bias differentially over the range of modeled values



Reyes et al. (2017)

BME Data Fusion Applications

1) Global mapping of ozone concentrations, 1990-2017, at fine resolution to support the Global Burden of Disease Assessment

2) Mapping of $PM_{2.5}$ from the October 2017 California wildfires

Mapping Global Surface Ozone Concentrations

Goal: Estimate global surface ozone concentrations by statistically fusing global ozone observations and an ensemble of global models.

Stakeholder partners: Global Burden of Disease Assessment – Michael Brauer (UBC), Rick Burnett (Health Canada), Bryan Hubbell (EPA).

Team: Marissa Delang, Jacob Becker, Stephanie Cleland, Elyssa Collins, Marc Serre, Jason West (UNC), Owen Cooper, Kai-Lan Chang (U Colorado & NOAA), Martin Schultz, Sabine Schroder (Julich), CCMI and NASA modelers

TOAR
tropospheric ozone assessment report

ccmi
chemistry-climate model initiative

Geoscientific Model Development
Open Access
EGU

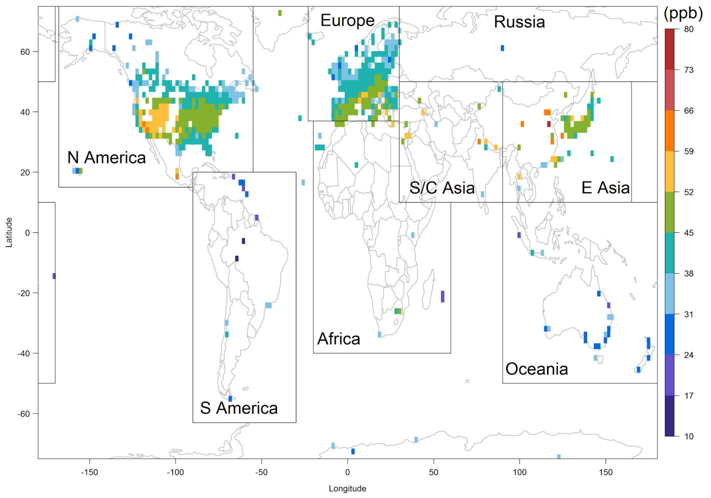
A new method (M^3Fusion v1) for combining observations and multiple model output for an improved estimate of the global surface ozone distribution

Kai-Lan Chang[1,2,3], Owen R. Cooper[2,3], J. Jason West[4], Marc L. Serre[4], Martin G. Schultz[5], Meiyun Lin[6,7], Virginie Marécal[8], Béatrice Josse[8], Makoto Deushi[9], Kengo Sudo[10,11], Junhua Liu[12,13], and Christoph A. Keller[12,13,14]

Ozone metric: 2008-2014 average of 6-month average 8-hr. daily maximum surface ozone concentration

Global Ozone Mapping for GBD 2017

TOAR
tropospheric ozone assessment report



ccmi
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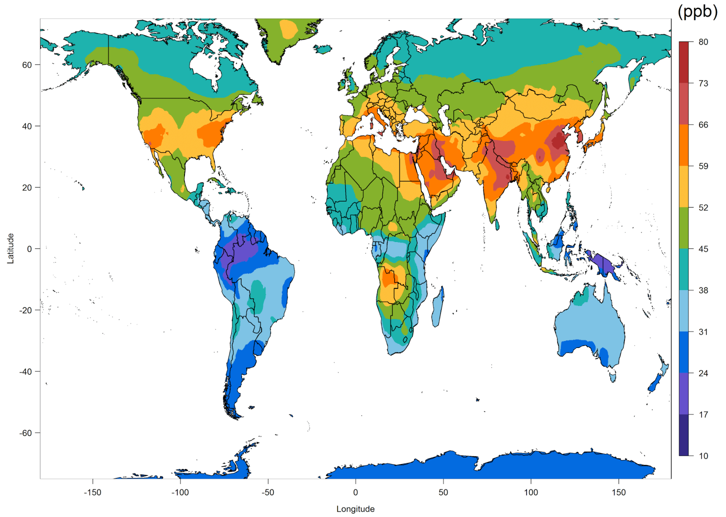
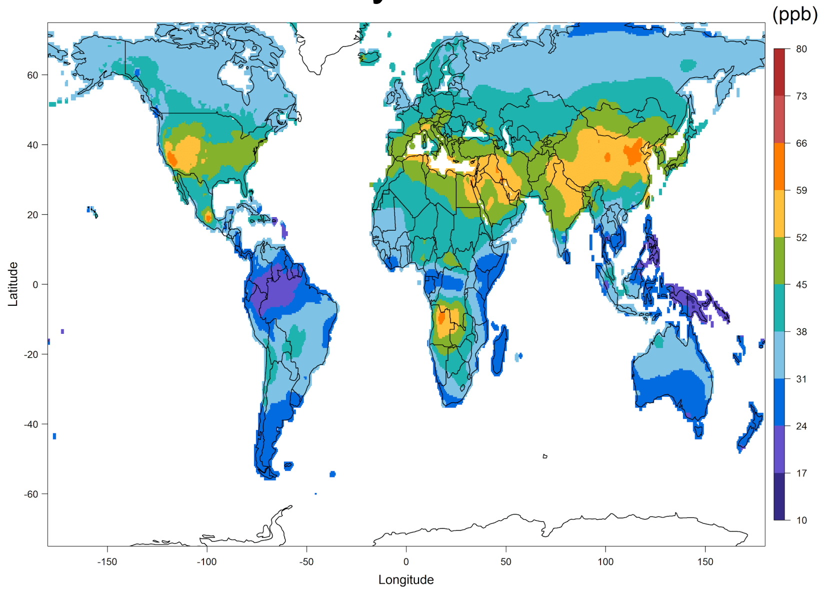


Fused ozone surface concentration used by GBD 2017



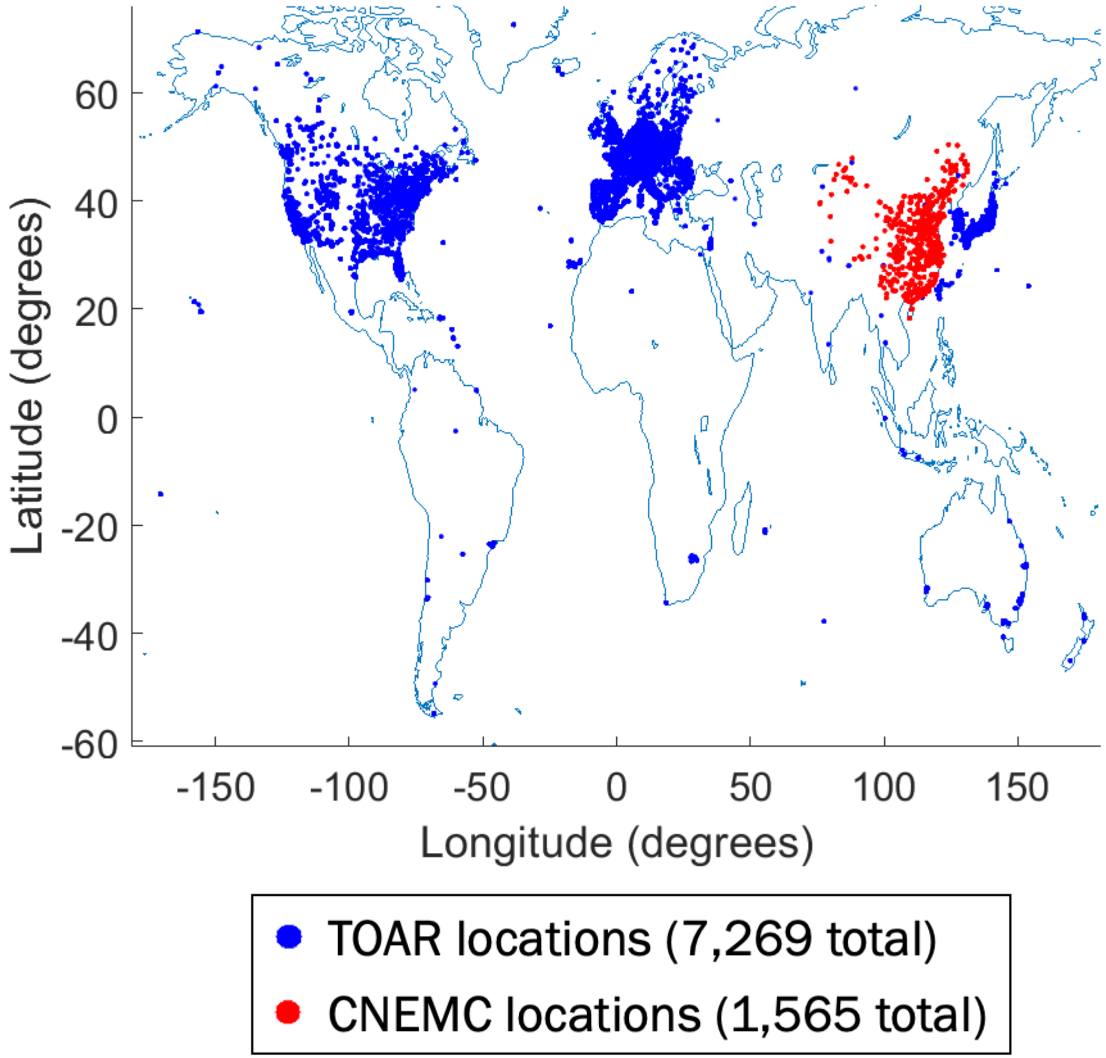
Chang et al. (GMD, 2019)

Improvements to M^{3}Fusion Method

1. Yearly output 1990 – 2017
2. Additional observations and models
3. Smooth weighting of observations across space (BME data fusion)
4. Time influence of observations (BME data fusion)
5. Spatial pattern from fine resolution model output

Data Sources

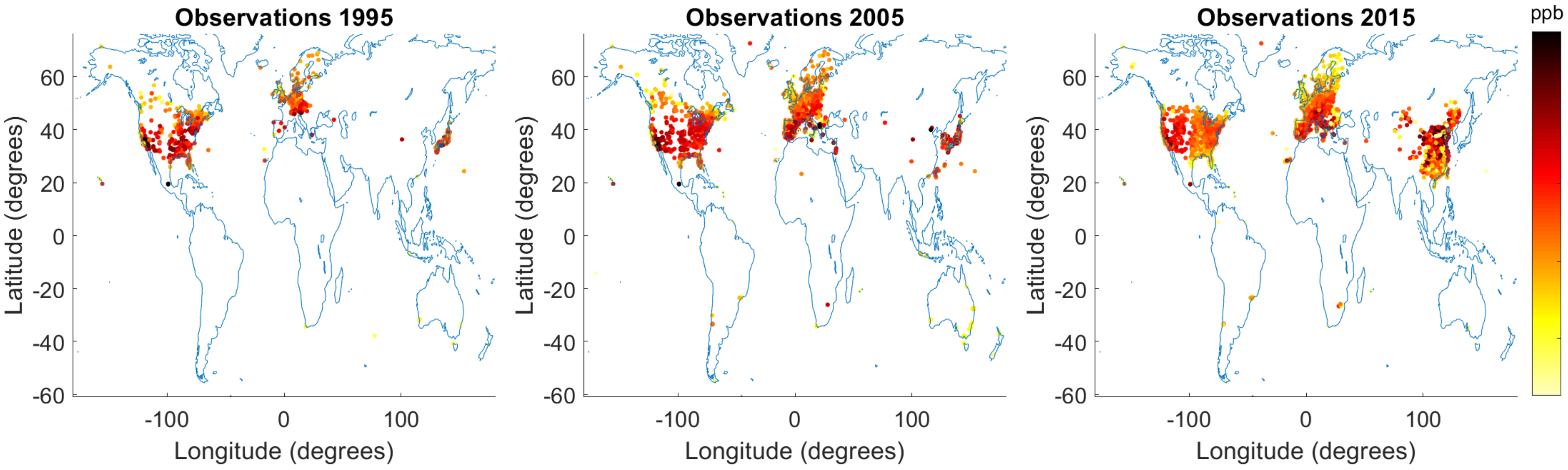
- Tropospheric Ozone Assessment Report (TOAR)
  - *1990 – 2017*
- Chinese National Environmental Monitoring Network (CNEMC)
  - *2013 – 2017*



Ground Level Observations

Ozone season daily maximum 8 hour mixing ratio (OSDMA8)

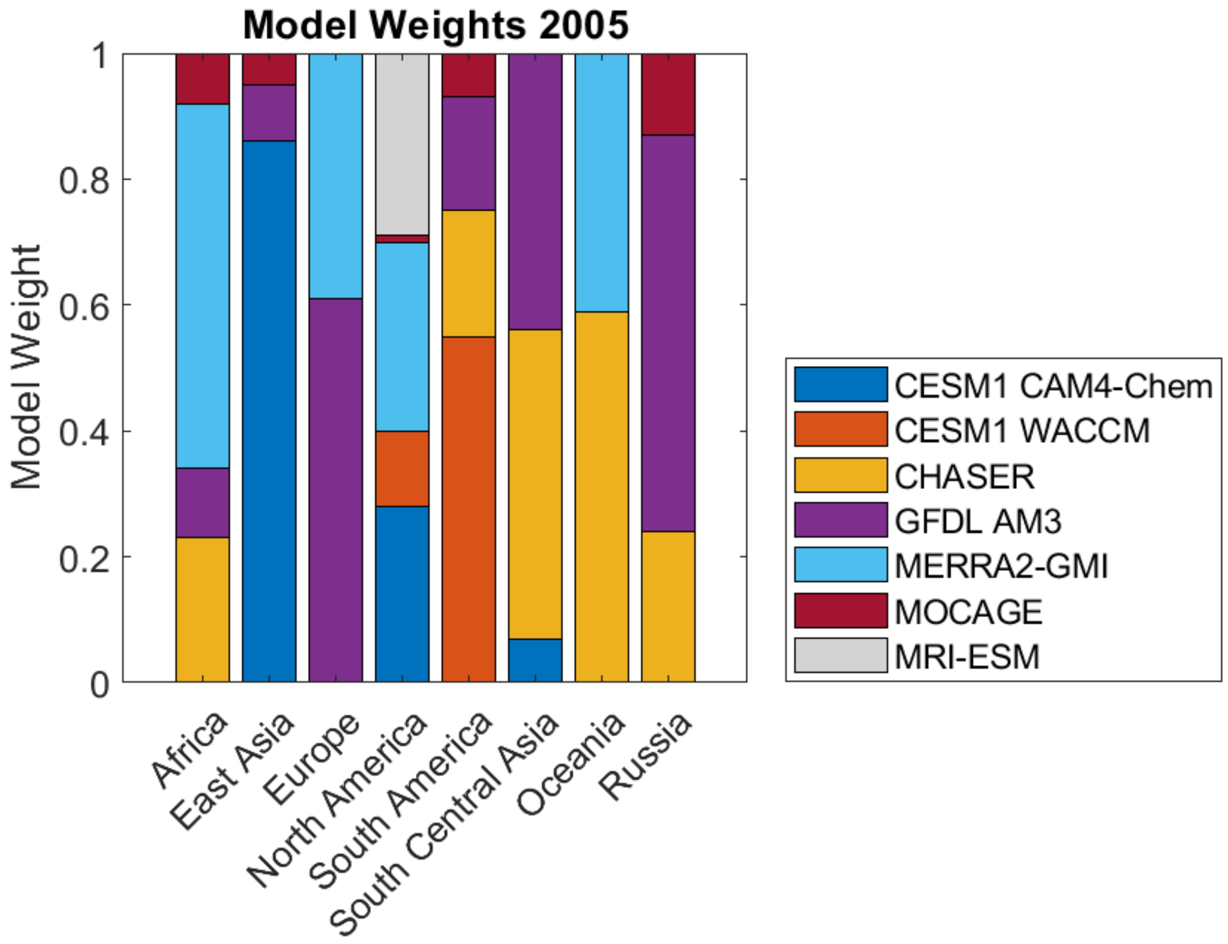
- Annual maximum of the 6-month running mean of the monthly average daily maximum 8-hour mixing ratio

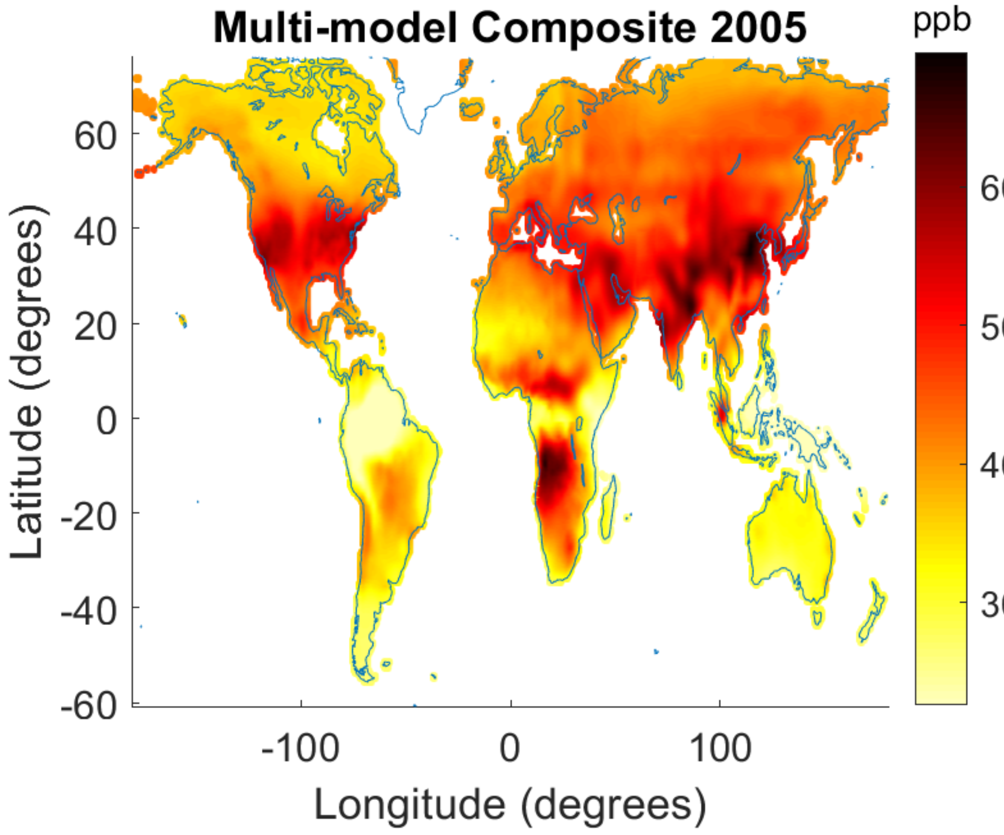


Atmospheric Model Output

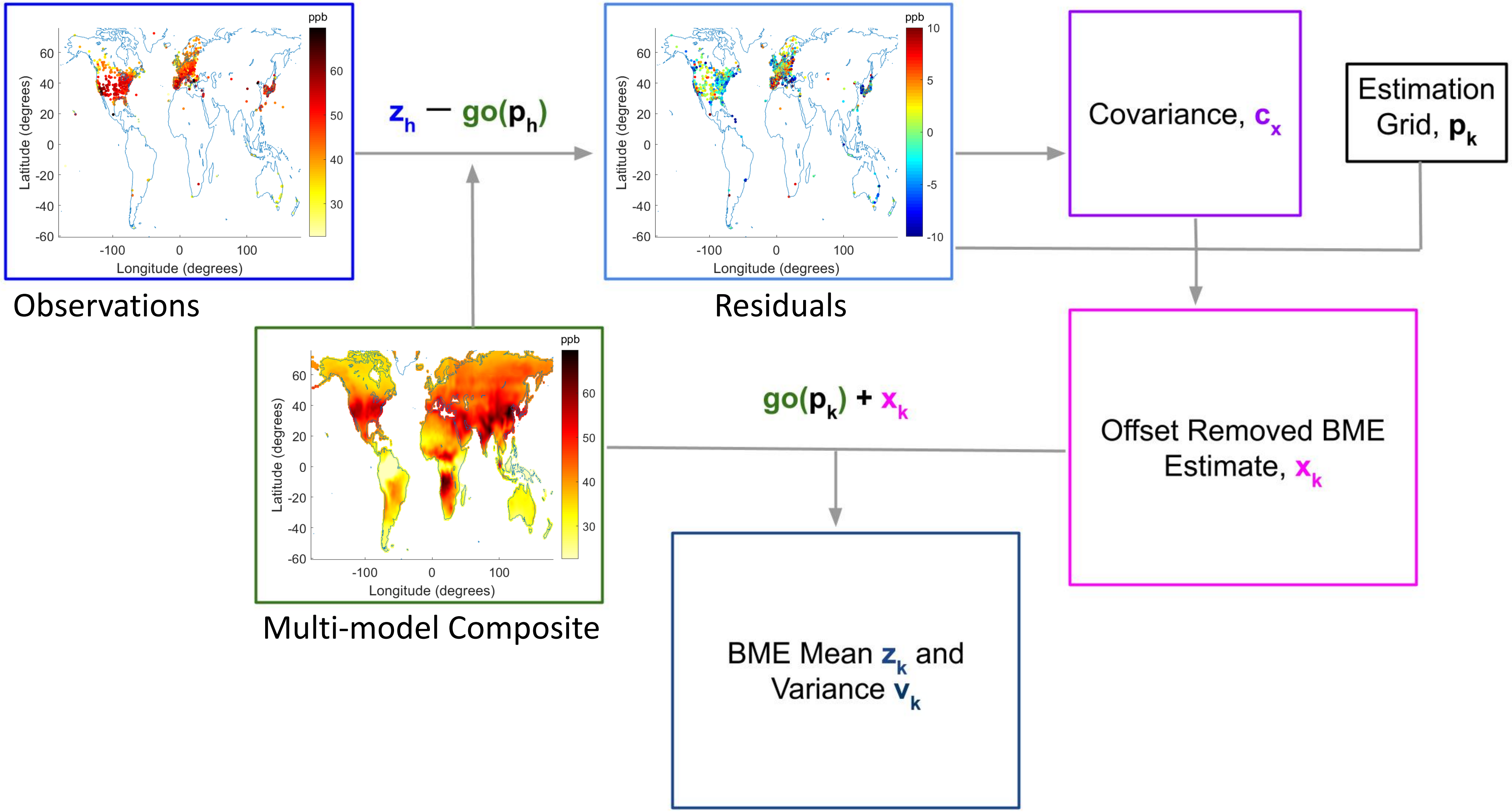
Model	Years	Resolution	Experiment
CESM1 CAM4-Chem	1990-2010	$1.9° \times 2.5°$	CCMI REF-C1SD
CESM1 WACCM	1990-2010	$1.9° \times 2.5°$	CCMI REF-C1SD
CHASER	1990-2010	$2.8° \times 2.8°$	CCMI REF-C1SD
GFDL-AM3	1990-2014	$2° \times 2.5°$	CCMI REF-C1SD
GFDL-AM4	2010-2016	$1° \times 1.25°$	CMIP6
MERRA2-GMI	1990-2017	$0.5° \times 0.625°$	CCMI REF-C1SD
MOCAGE	1990-2016	$2° \times 2°$	CCMI REF-C1SD
MRI-ESM	1990-2010	$2.8° \times 2.8°$	CCMI REF-C1SD
MRI-ESM2	2011-2017	$2.8° \times 2.8°$	CMIP6

M^3Fusion Model Composite





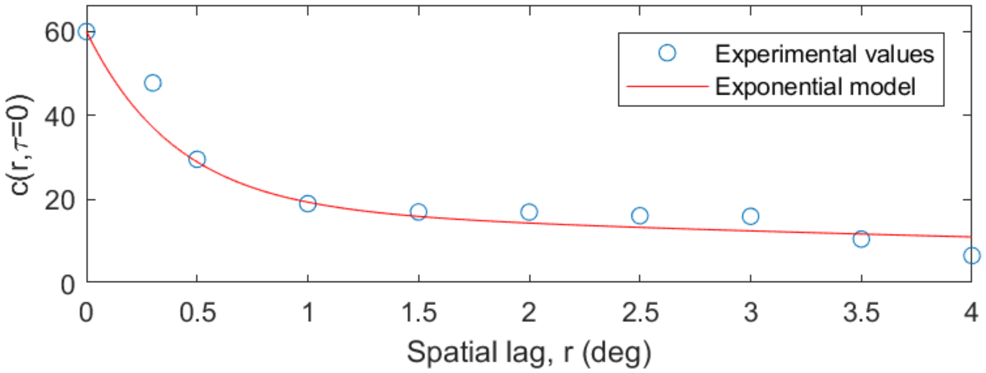
Bayesian Maximum Entropy (BME) Framework



Covariance

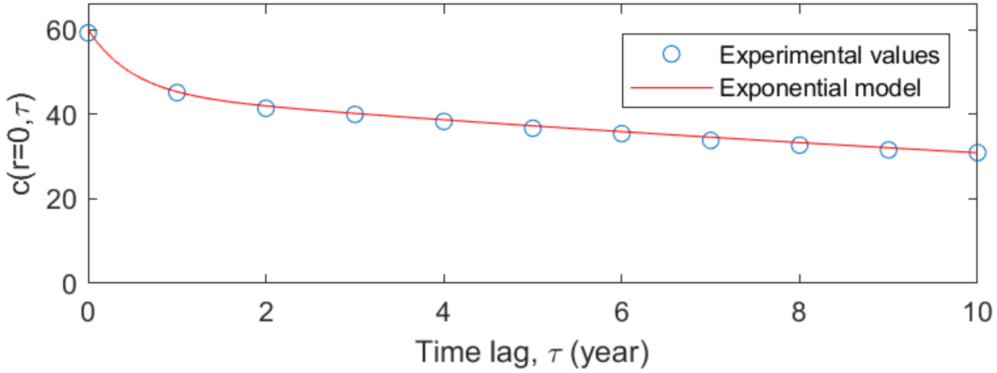
Range of influence of a measurement to predict other concentrations in space and time

Spatial Covariance



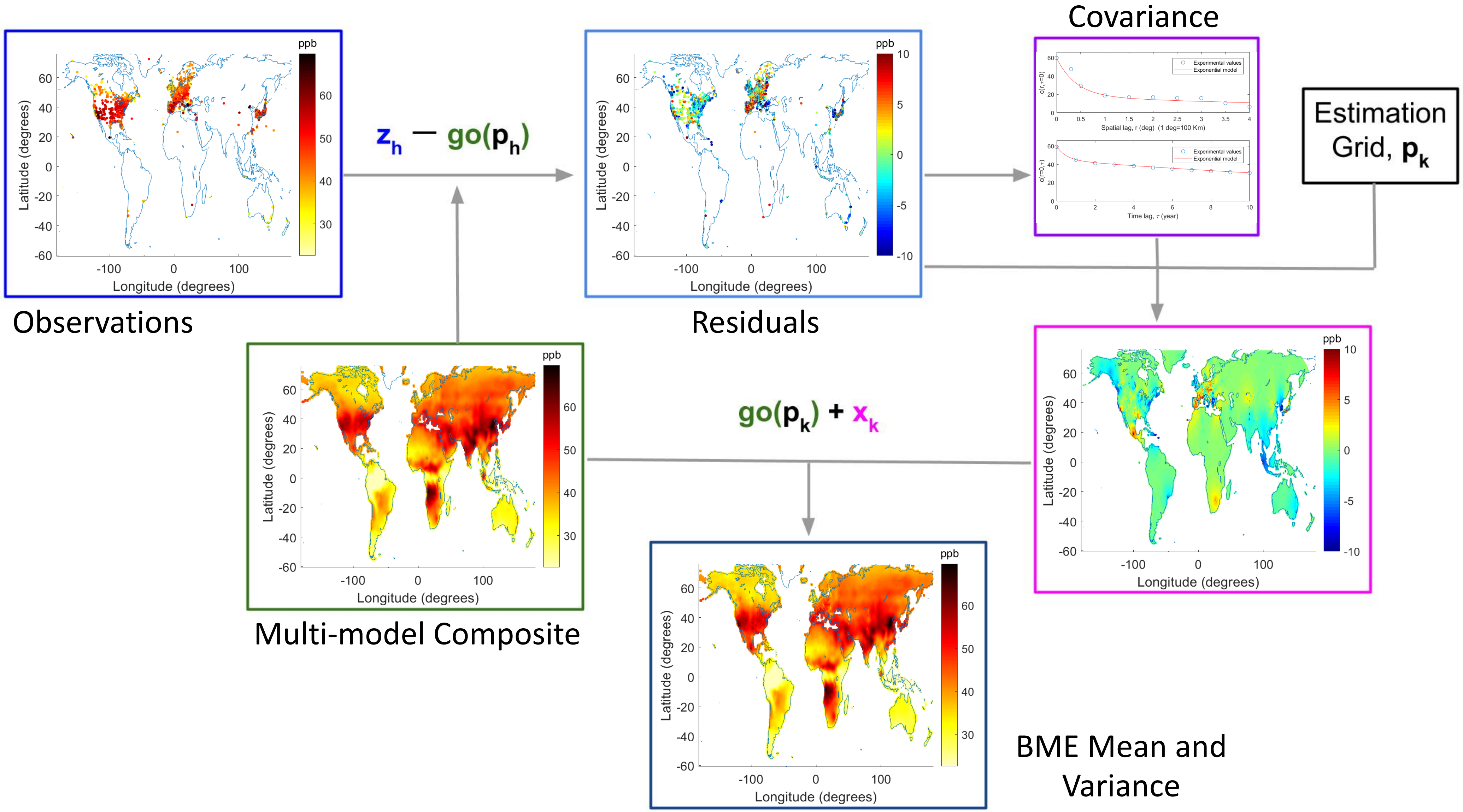
$$C_x(r, \tau = 0) = 60\left(0.7\exp\left(-\frac{3r}{1.2}\right) + 0.3\exp\left(-\frac{3r}{25}\right)\right)$$

Temporal Covariance



$$C_x(r = 0, \tau) = 60\left(0.75\exp\left(-\frac{3\tau}{80}\right) + 0.25\exp\left(-\frac{3\tau}{1.5}\right)\right)$$

Bayesian Maximum Entropy (BME) Framework



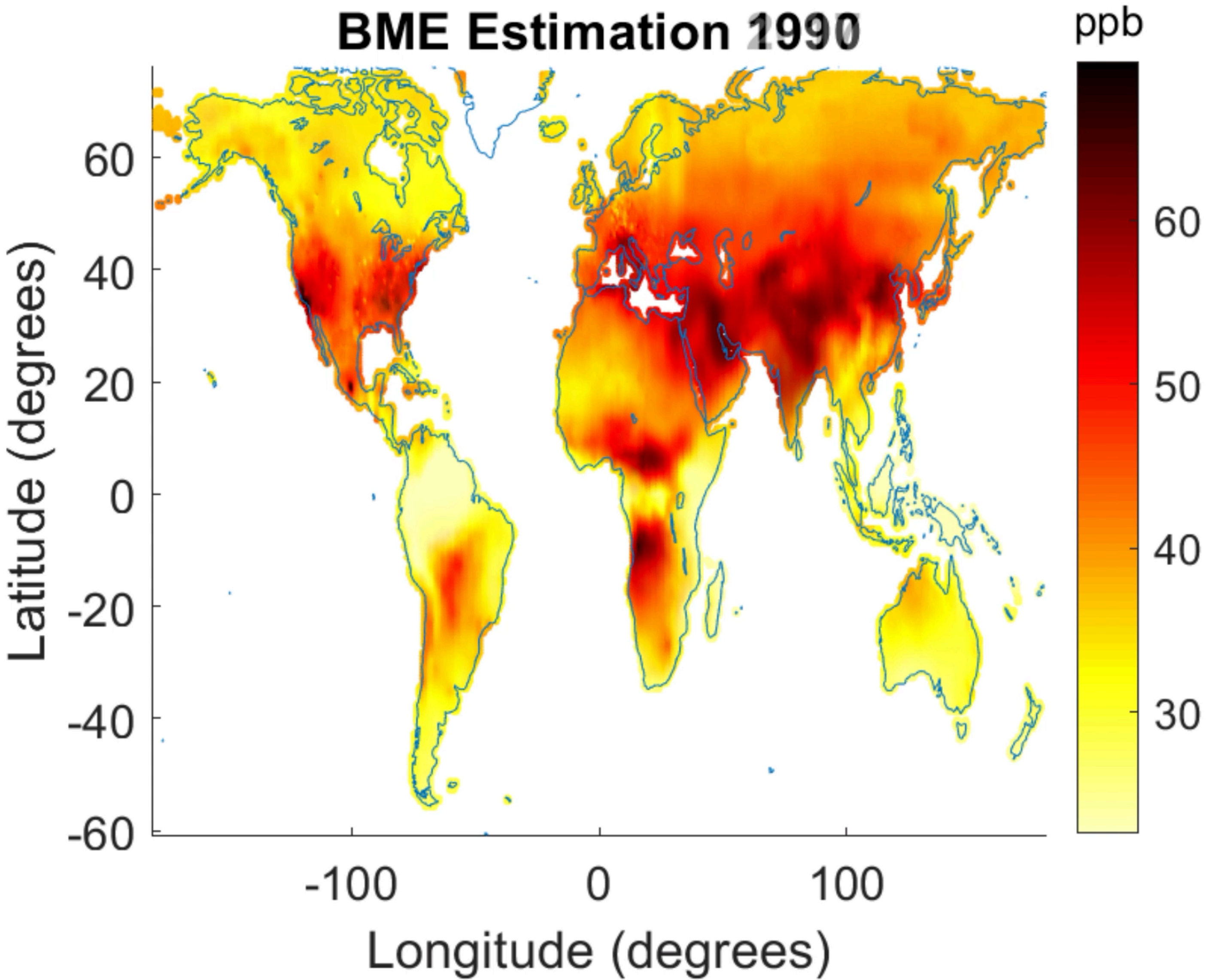
BME Output

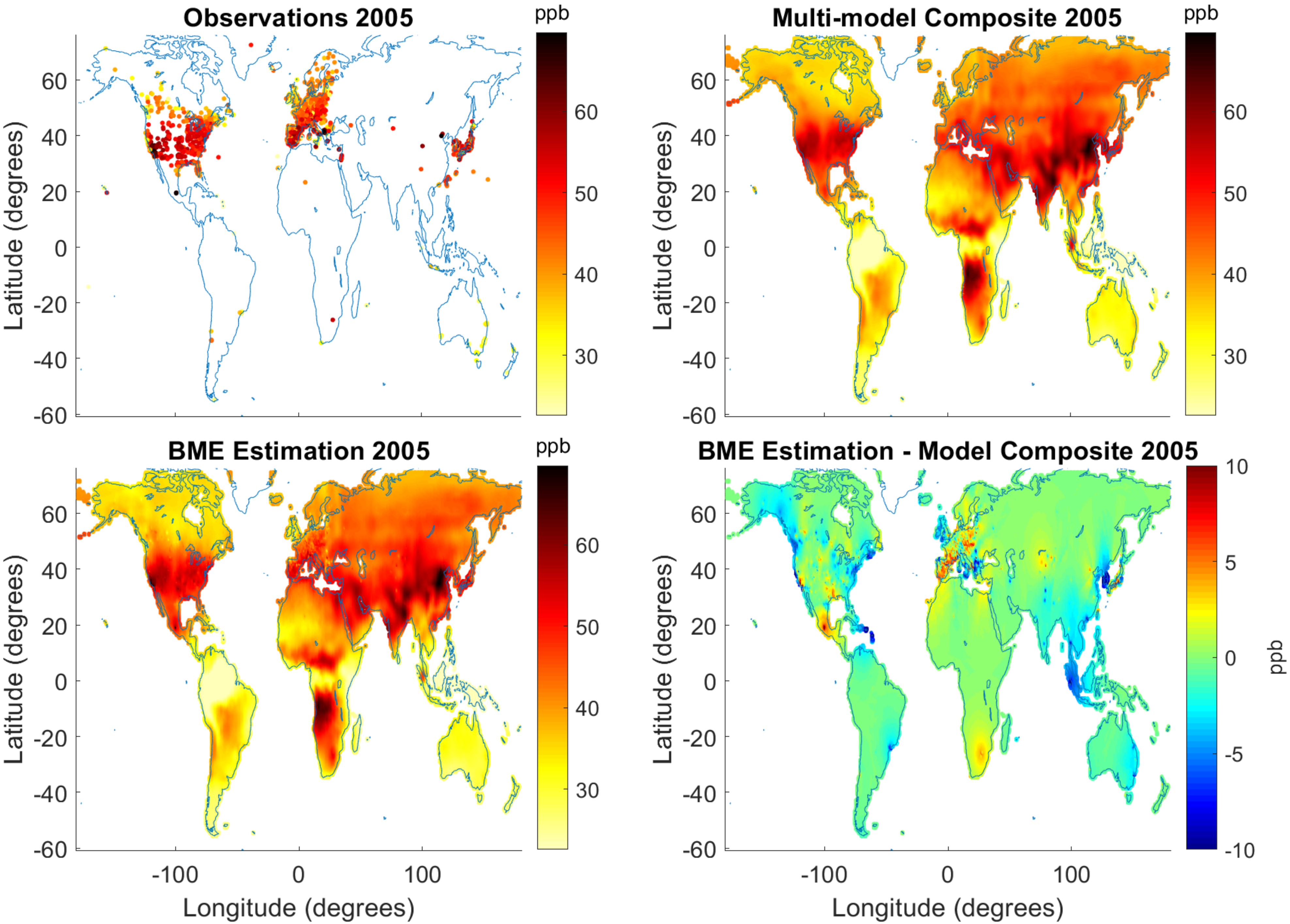
BME Mean

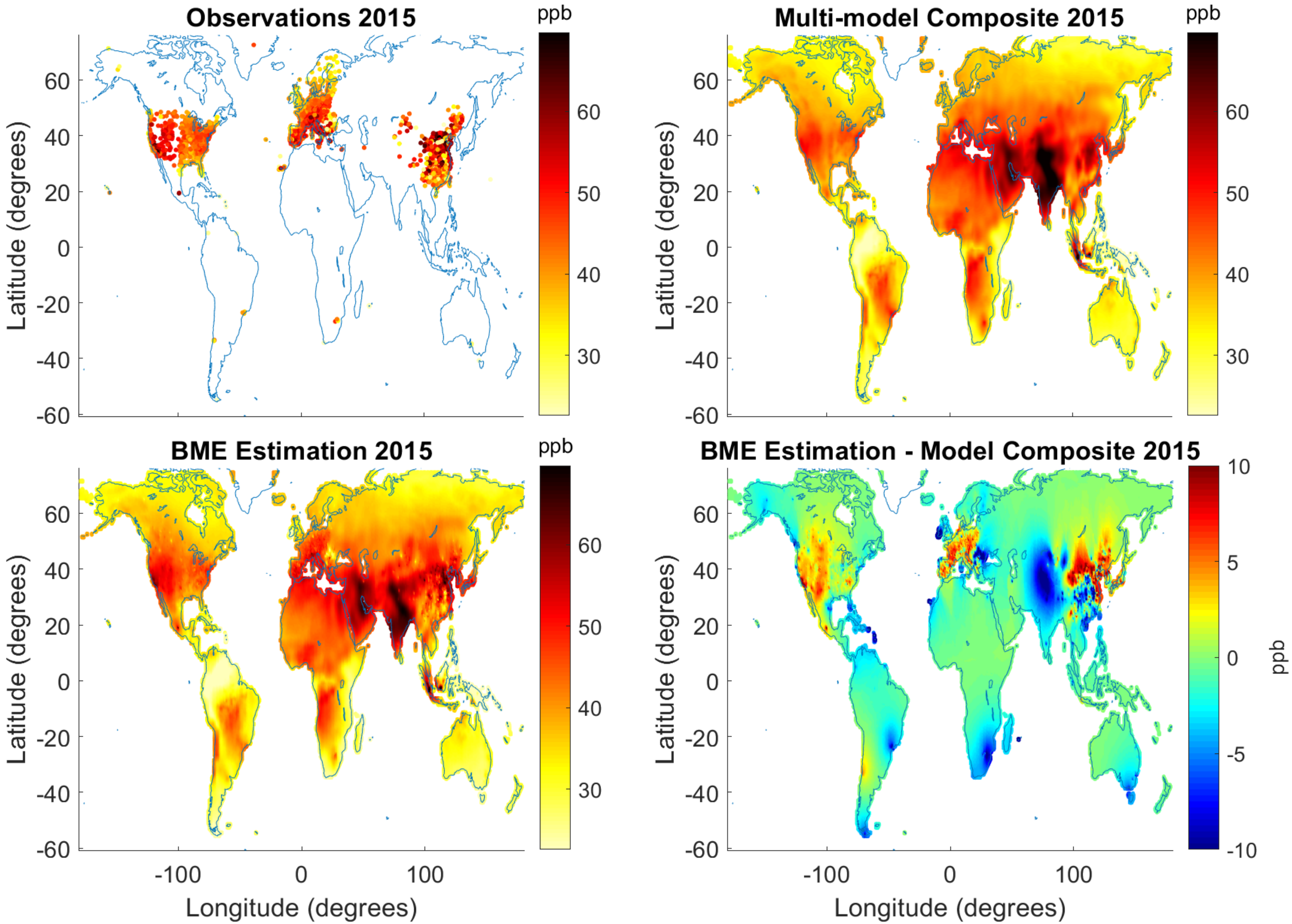
- Matches observation at monitoring stations
- Influence of observation drops off according to space/time covariance
- Away from observations, output is multi-model composite

BME Variance

- Low near observations

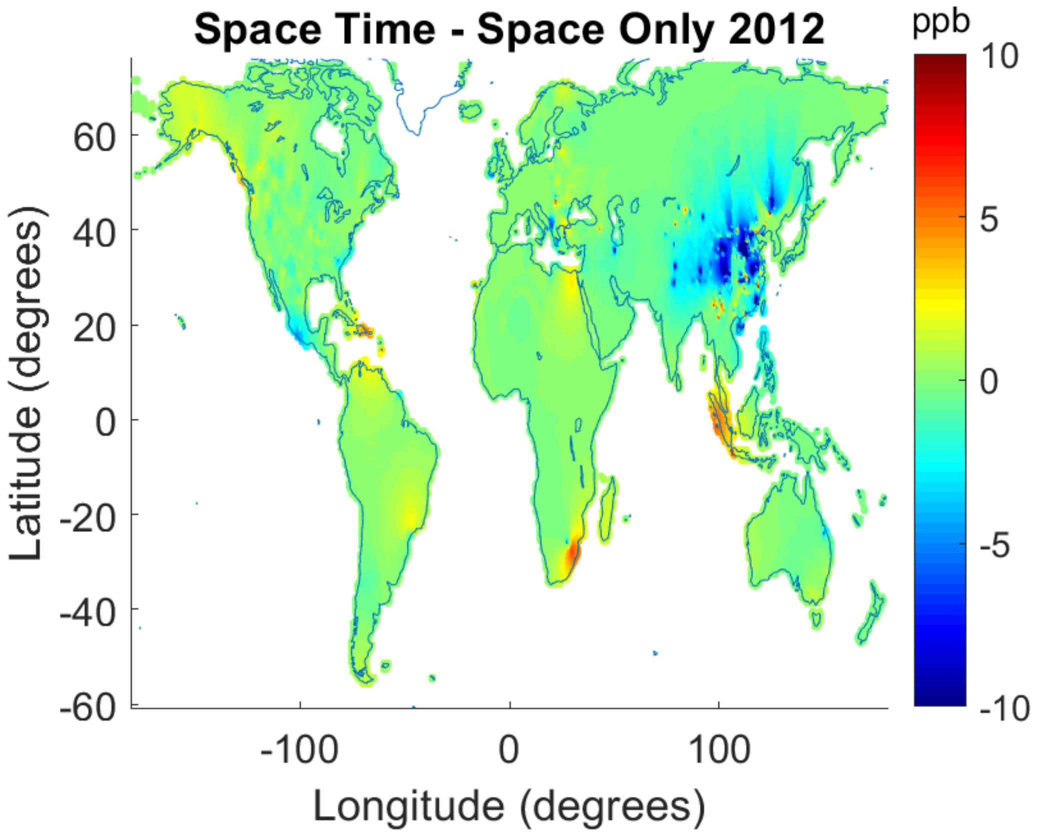


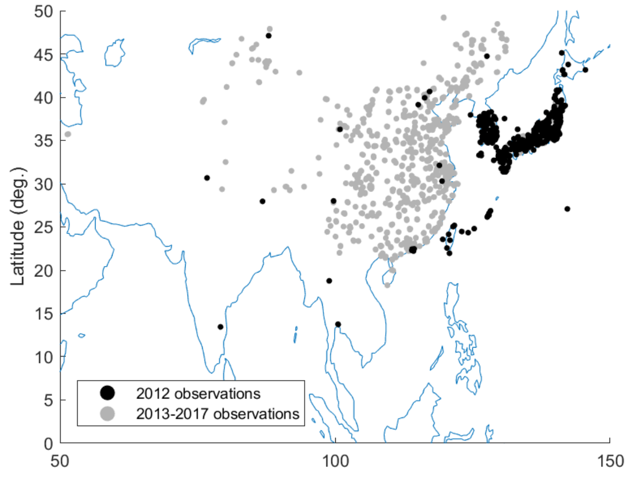

Observations 2005
Multi-model Composite 2005
BME Estimation 2005
BME Estimation - Model Composite 2005
ppb
Latitude (degrees)
Longitude (degrees)
60
40
20
0
-20
-40
-60
-100
0
100
50
30
10
5
-5
-10

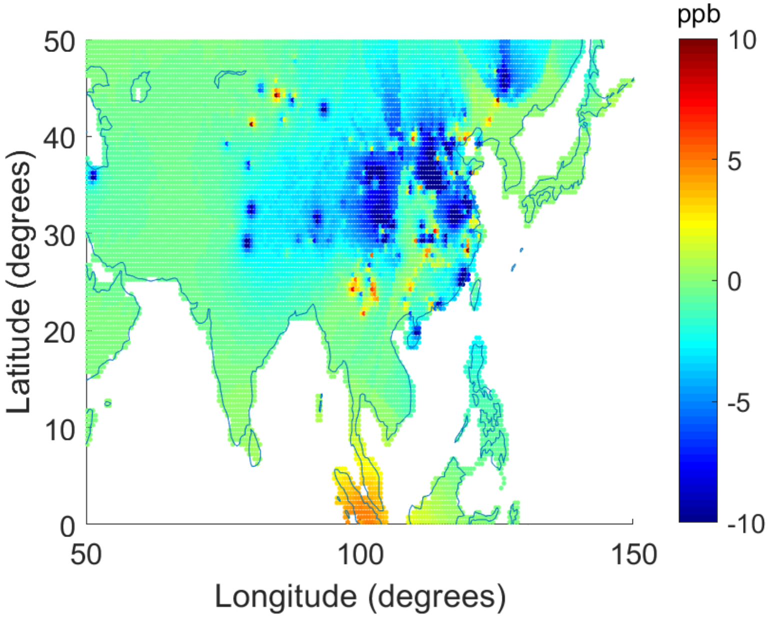


Observations 2015
Multi-model Composite 2015
BME Estimation 2015
BME Estimation - Model Composite 2015
ppb
Latitude (degrees)
Longitude (degrees)
-60
-40
-20
0
20
40
60
-100
0
100
30
40
50
60
10
5
0
-5
-10

Influence of Observations Across Time



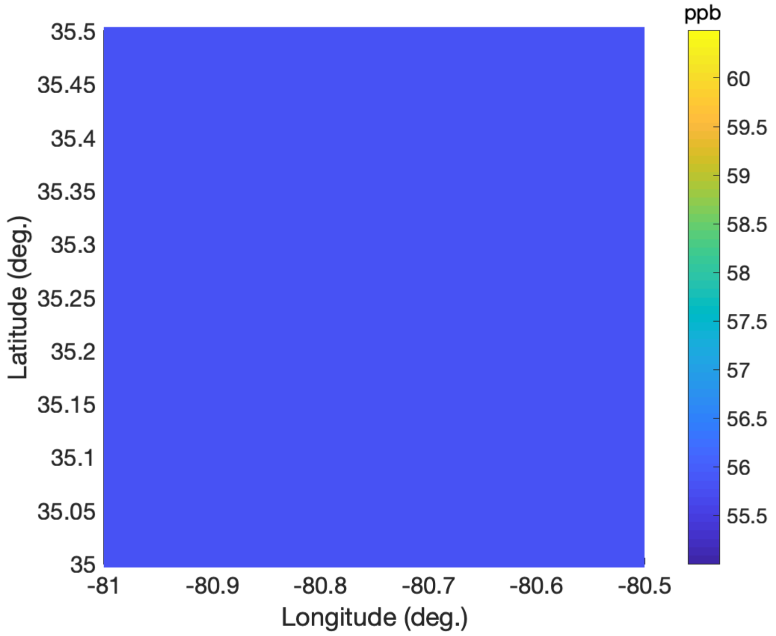




Fine Resolution Addition

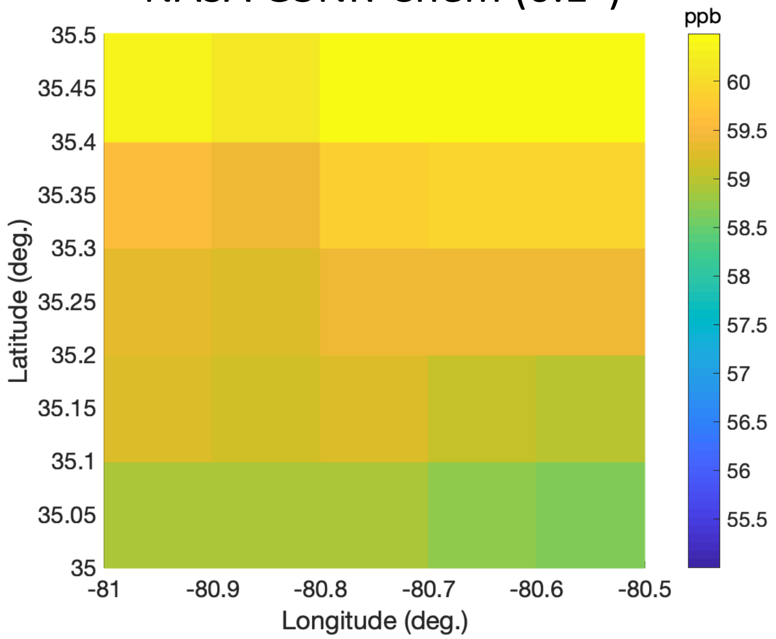
NASA G5NR-Chem model: 0.125° July 2013 - June 2014

BME Coarse Resolution (0.5°)



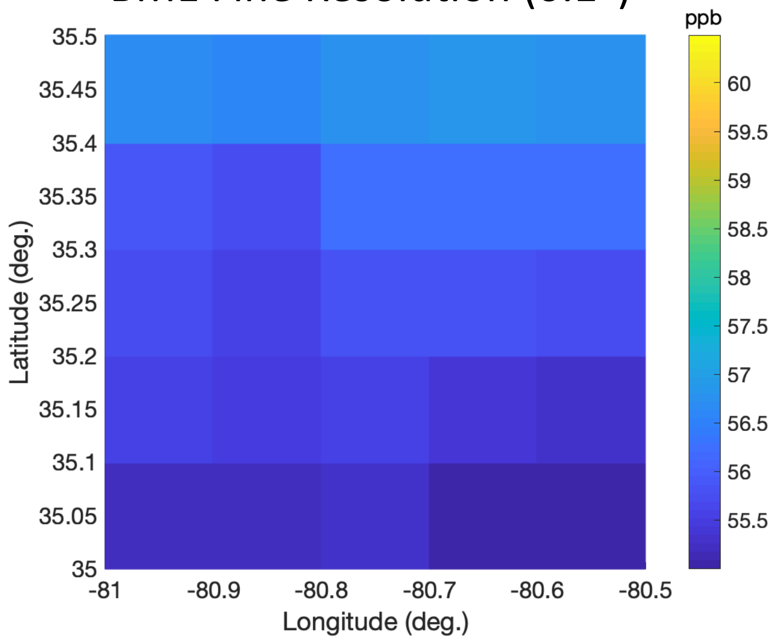
Average = 55.832 ppb

NASA G5NR-Chem (0.1°)



Average = 59.487 ppb

BME Fine Resolution (0.1°)



Average = 55.832 ppb

0.5° grid cell over Charlotte, North Carolina in 2005

Method Evaluation

Scenario	RMSE (ppb)	MSE (ppb^2)	ME (ppb)	R^2
Multi-model Mean	13.76	189.23	-11.00	0.28
Multi-model Composite	7.82	61.14	-1.07	0.30
Space Only Corrected	5.61	31.50	0.17	0.63
Space Time Corrected	3.99	15.94	-0.01	0.81
Fine Resolution	5.50	30.21	-0.22	0.64

Key Features

- Yearly ozone distribution (1990-2017)
- Incorporates observations and model output
- Observations influence both space and time
- Fine resolution (0.1 degree) according to fine resolution model

- Annual ozone maps were provided to the GBD team and will be used for GBD 2019

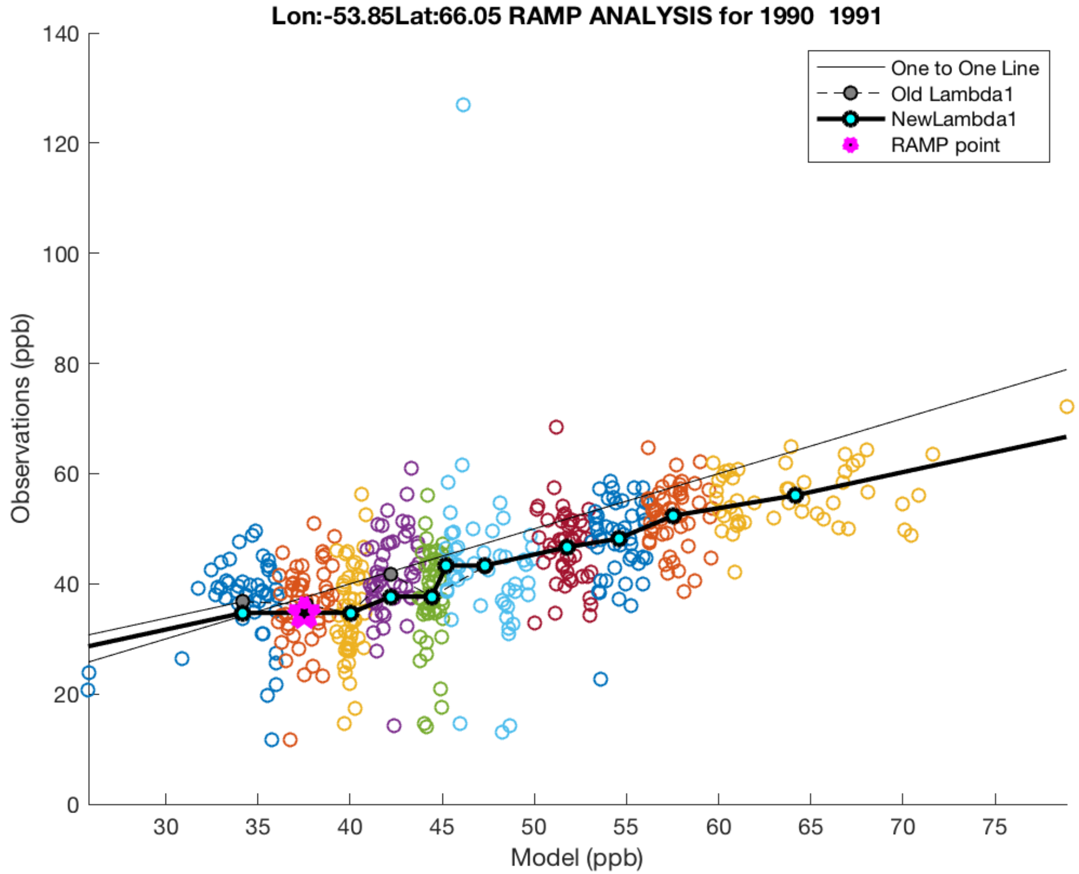
Regional Air Model Performance (RAMP)

Just like CAMP, but each estimation point uses only the nearest n observations to correct the model

Still uses 3 years of data
(except first and last year)

Each year the n closest points are used

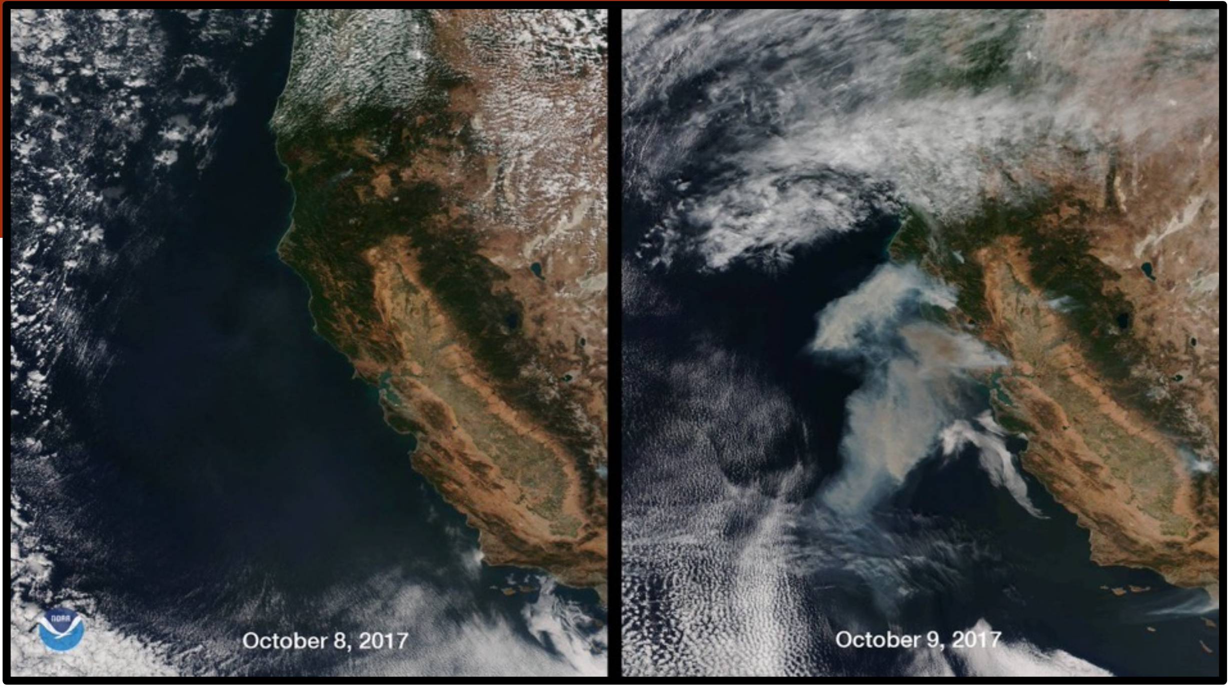
Restrict slope of correction ≥ 0



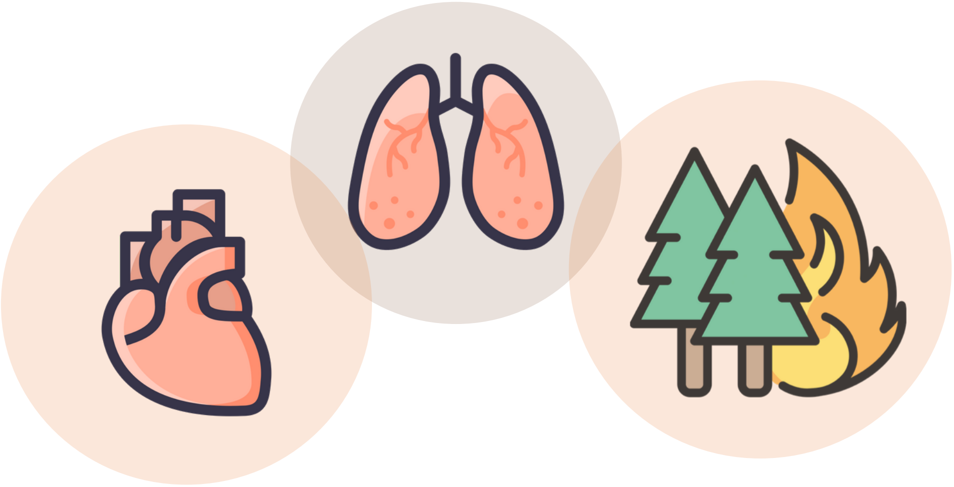
ESTIMATING WILDFIRE SMOKE CONCENTRATIONS DURING THE OCTOBER 2017 CALIFORNIA FIRES THROUGH BME SPACE/TIME DATA FUSION

Stephanie Cleland, Jason West, Marc Serre • UNC-Chapel Hill • HAQAST Webinar 3/5

INTRODUCTION
2017 N. CALIFORNIA FIRES



- Beginning October 8-9, 2017, a series of wildfires in N. California resulted in:
  - Highest $PM_{2.5}$ concentrations ever recorded in Bay Area
  - 8,400 buildings destroyed, 100,000 people displaced, >185 hospitalized, 45 dead
  - ~7.2 million people exposed to unhealthy air
- Wildfires are occurring with increased **frequency**, **intensity**, and **severity** due to climate change
- Smoke exposure increases respiratory and cardiovascular morbidity and mortality



INTRODUCTION

ESTIMATING SMOKE CONCENTRATIONS

Three primary datasets are used to characterize population-level exposure to wildfire emissions:

1. Monitoring Station Observations

2. Chemical Transport Models

3. Satellite-Based Measurements

INTRODUCTION
ESTIMATING SMOKE CONCENTRATIONS

Previous methods for estimating ground-level wildfire smoke concentrations:

- Spatial interpolation of observations
- Chemical transport models
  - Occasionally adjusted by monitoring data, satellite remote sensing data or post-processing statistical techniques
- Geostatistical methods combining observations with modeled and/or satellite-derived concentrations
  - Data fusion, regression modeling, and machine learning methods

Combining multiple $PM_{2.5}$ datasets often leads to improvements in $PM_{2.5}$ estimations during a wildfire

GOALS

Produce accurate estimates of daily average ground-level $PM_{2.5}$ concentrations during the Oct. 2017 fires by:

1. Using the Constant Air Quality Model Performance (CAMP) correction method to bias-correct CMAQ (CC-CMAQ) and AOD-estimated $PM_{2.5}$ (CC-Sat) concentrations

2. Using the Bayesian Maximum Entropy (BME) framework to fuse monitoring station observations with CC-CMAQ and/or CC-Sat output across space and time

3. Evaluating the accuracy of four different BME s/t kriging and data fusion methods to identify the BME methods and combination of $PM_{2.5}$ data sources that best estimate ground-level $PM_{2.5}$ concentrations during the fires

No prior study has evaluated the accuracy of combining all three datasets to estimate wildfire-related $PM_{2.5}$ while correcting for the bias present in satellite and CTM data

METHODS
DATA

To estimate smoke concentrations during the wildfires, three $PM_{2.5}$ datasets were used:

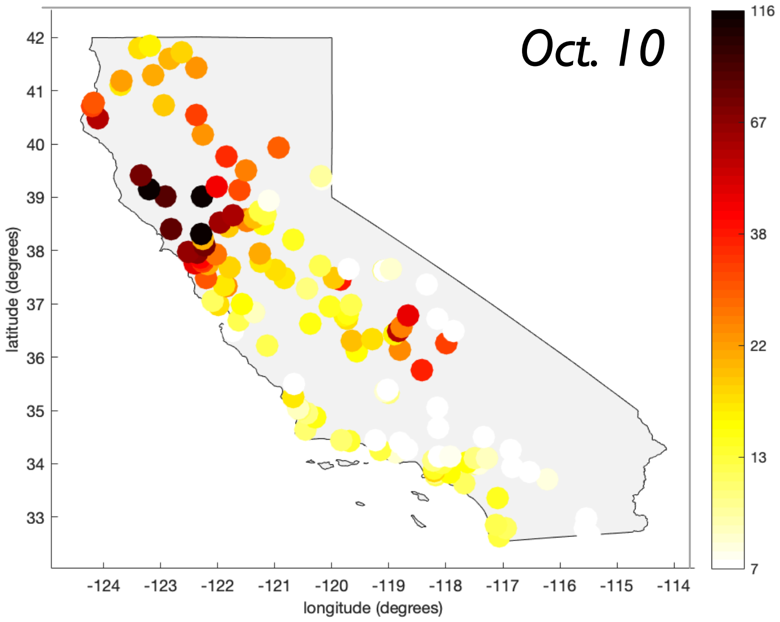
1. Surface observations from:
   - 114 **EPA FRM/FEM monitoring stations** across California, Oct. 1 – 31 (EPA's air quality database)
   - 49 **temporary monitoring stations** across California, Oct. 1 – 31 (US Forest Service)

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)

3. Satellite-derived estimates from **Moderate Resolution Imaging Spectroradiometer (MODIS) Terra Satellite** Aerosol Optical Depth (AOD) data, Oct. 1 – 31 (NASA)

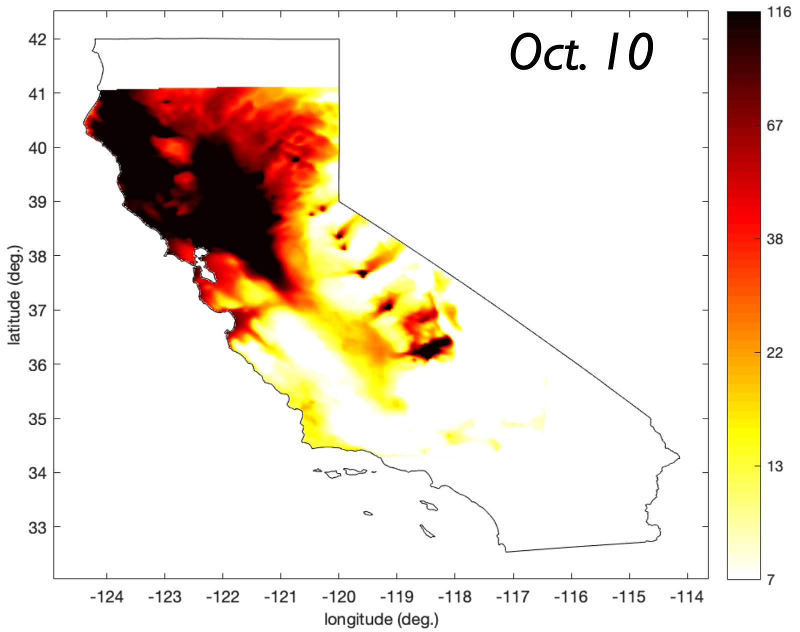
METHODS
DATA

Monitoring Station $PM_{2.5}$



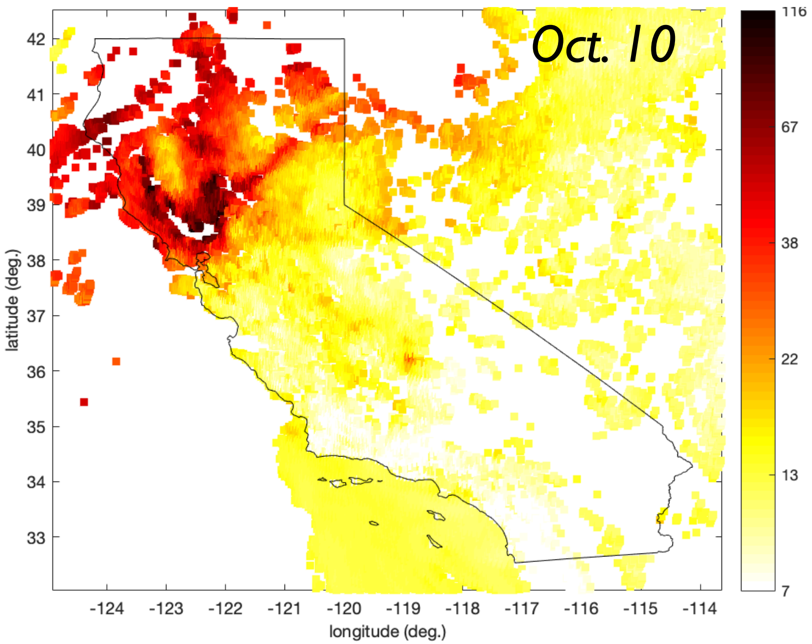
High-quality, accurate $PM_{2.5}$ measurements, readily available

CMAQ Model $PM_{2.5}$



Space/time coverage, knowledge of atmospheric physics and chemistry and fire emissions

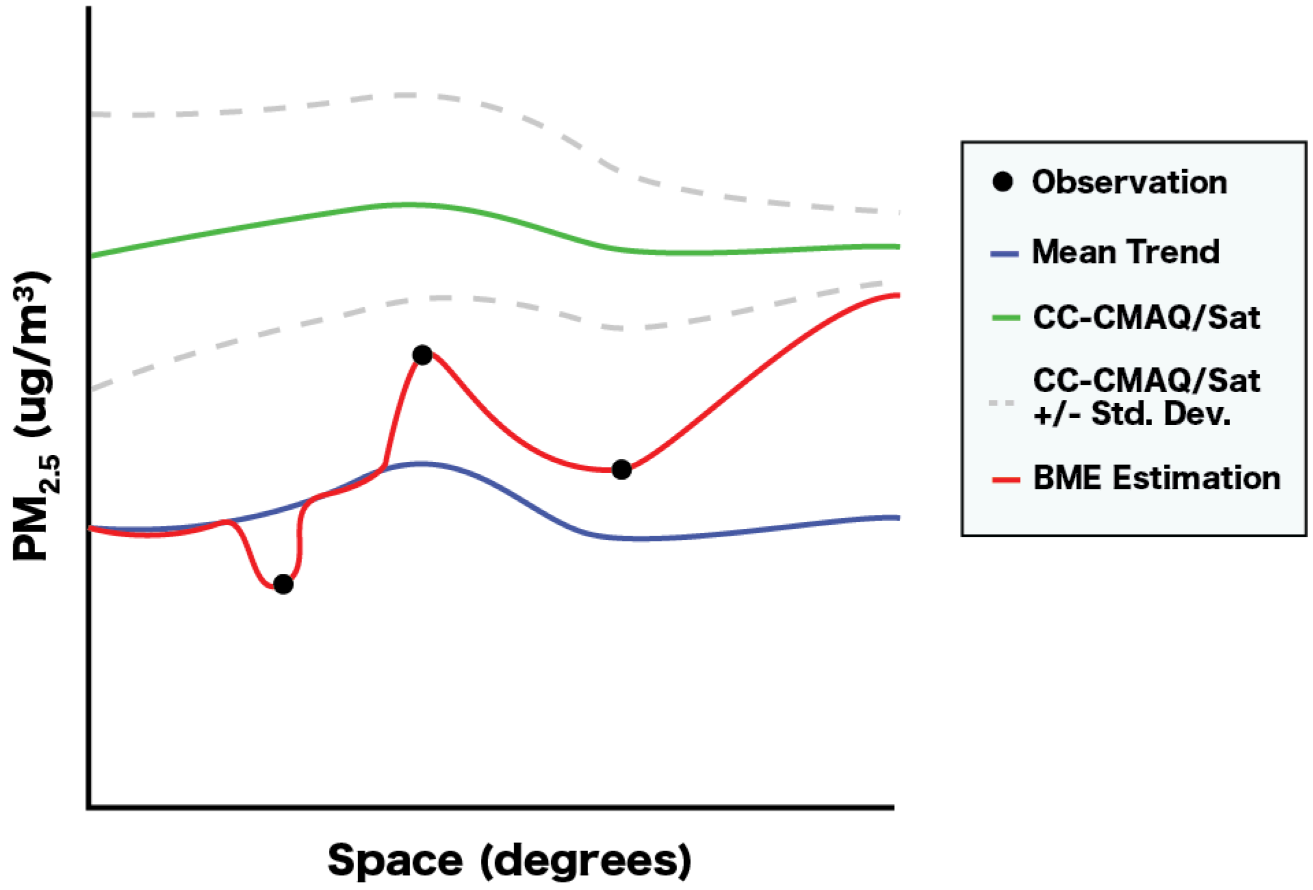
Satellite AOD-Derived $PM_{2.5}$



Space/time coverage, information on smoke plume location

METHODS
BME FRAMEWORK

- Estimates $PM_{2.5}$ at unmonitored locations using modern s/t geostatistics to combine site-specific and general knowledge
  - *Site-specific knowledge:* $PM_{2.5}$ at a known s/t location
  - *General knowledge:* mean trend, covariance, variance
- Treats observed $PM_{2.5}$ as hard data
- Treats CC-CMAQ, CC-Sat $PM_{2.5}$ as soft data



METHODS
SOFT DATA CREATION

2 steps were used to prepare the modeled and satellite AOD-estimated $PM_{2.5}$ concentrations for BME data fusion:

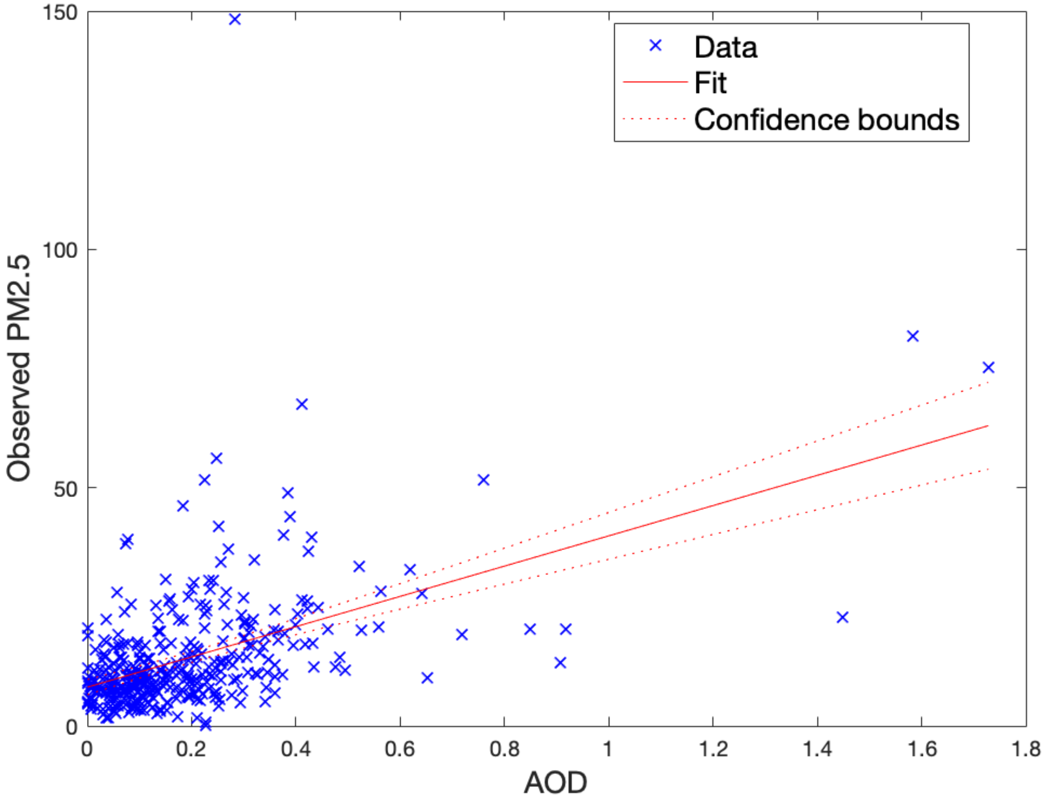
1. Conversion of MODIS AOD to $PM_{2.5}$ using a simple linear regression
2. CAMP-correct CMAQ (CC-CMAQ) model and AOD-estimated $PM_{2.5}$ (CC-Sat)

(NASA, 2019)

METHODS

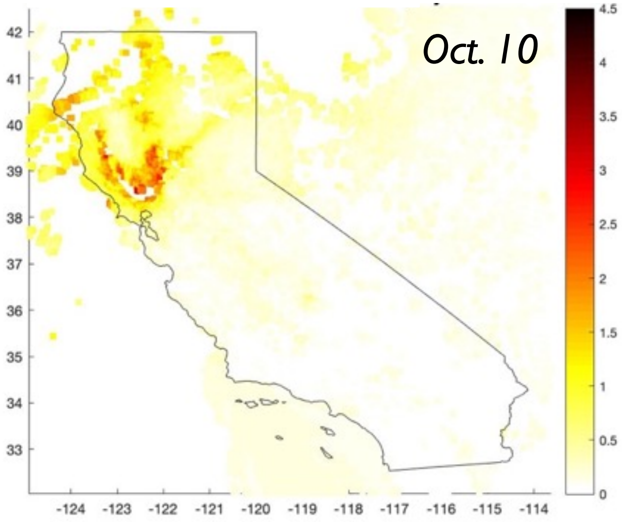
AOD→$PM_{2.5}$ CONVERSION

1. Conversion of MODIS AOD to $PM_{2.5}$ using a simple linear regression
   - MODIS AOD paired with collocated daily avg. $PM_{2.5}$ observations
   - Simple linear regression trained on 75% of paired data to obtain formula → 25% of data used to validate

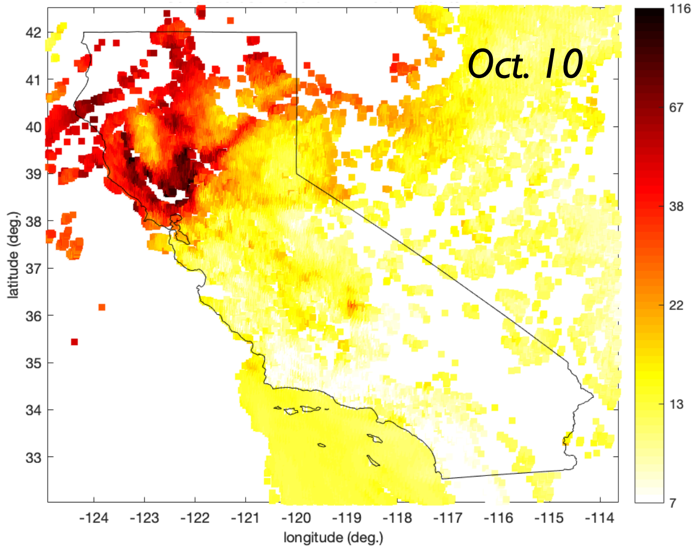


$PM_{2.5}$ Estimation = Slope * AOD + Intercept

AOD



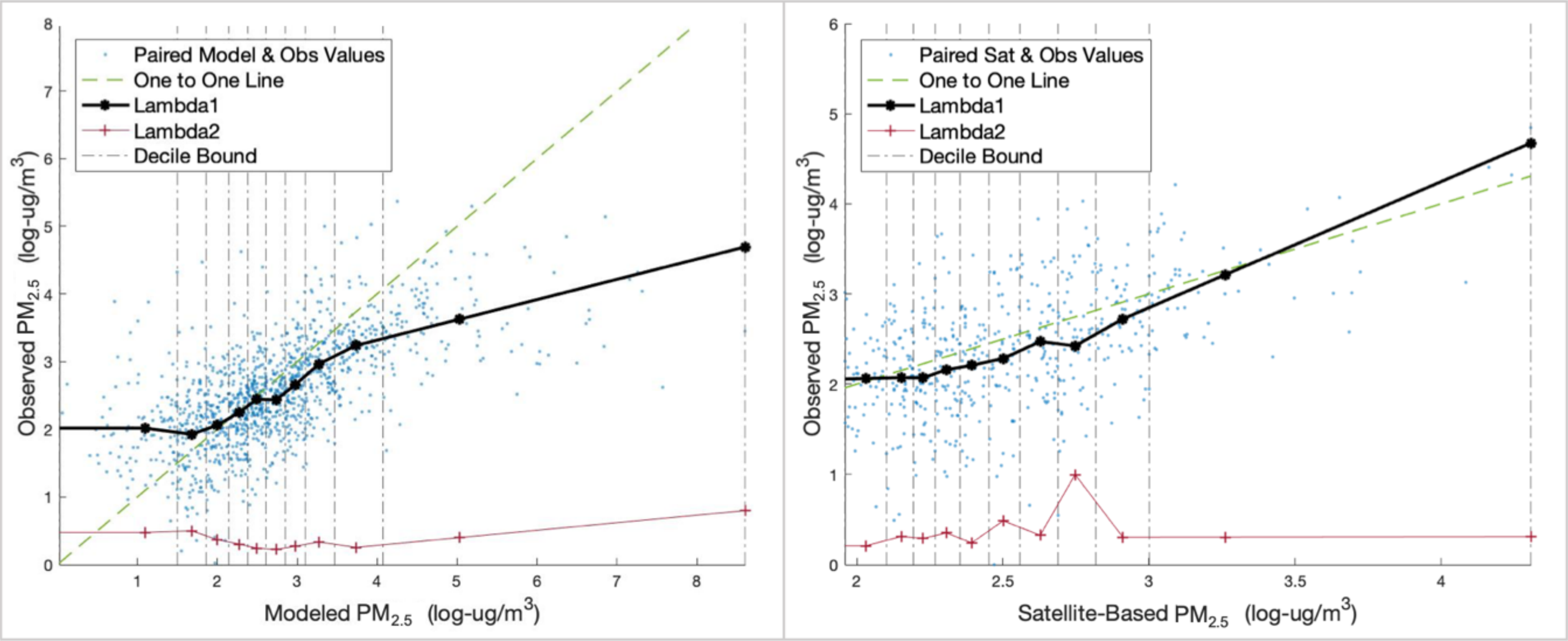
AOD-Derived $PM_{2.5}$



METHODS
CAMP

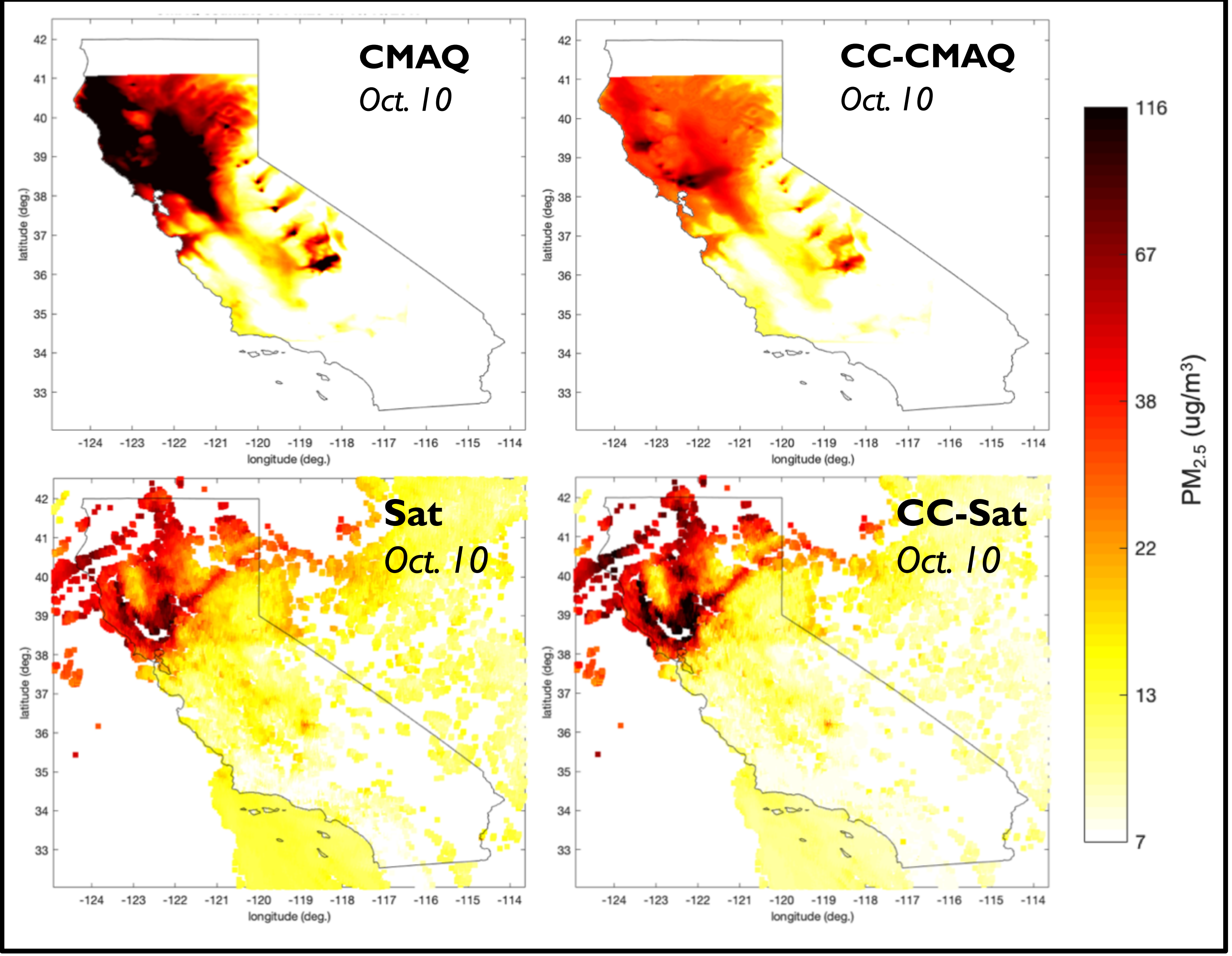
2. CAMP-correct CMAQ (CC-CMAQ) model and AOD-derived $PM_{2.5}$ (CC-Sat)

- Model the mean (λ_1) and variance (λ_2) of observed value as a function of estimated value, accounting for the non-linear and non-homoscedastic relationship between estimated and observed $PM_{2.5}$ data



METHODS
CAMP

	MSE (log-(μg/m³)²)	R^2 (log-space)
CMAQ	0.703	0.410
CC-CMAQ	0.331	0.452
Sat	0.406	0.237
CC-Sat	0.389	0.229



METHODS
EVALUATING 4 APPROACHES

Using the BME Framework, 4 mapping methods were evaluated, using Mean Squared Error (MSE) and R^2 values from cross-validations:

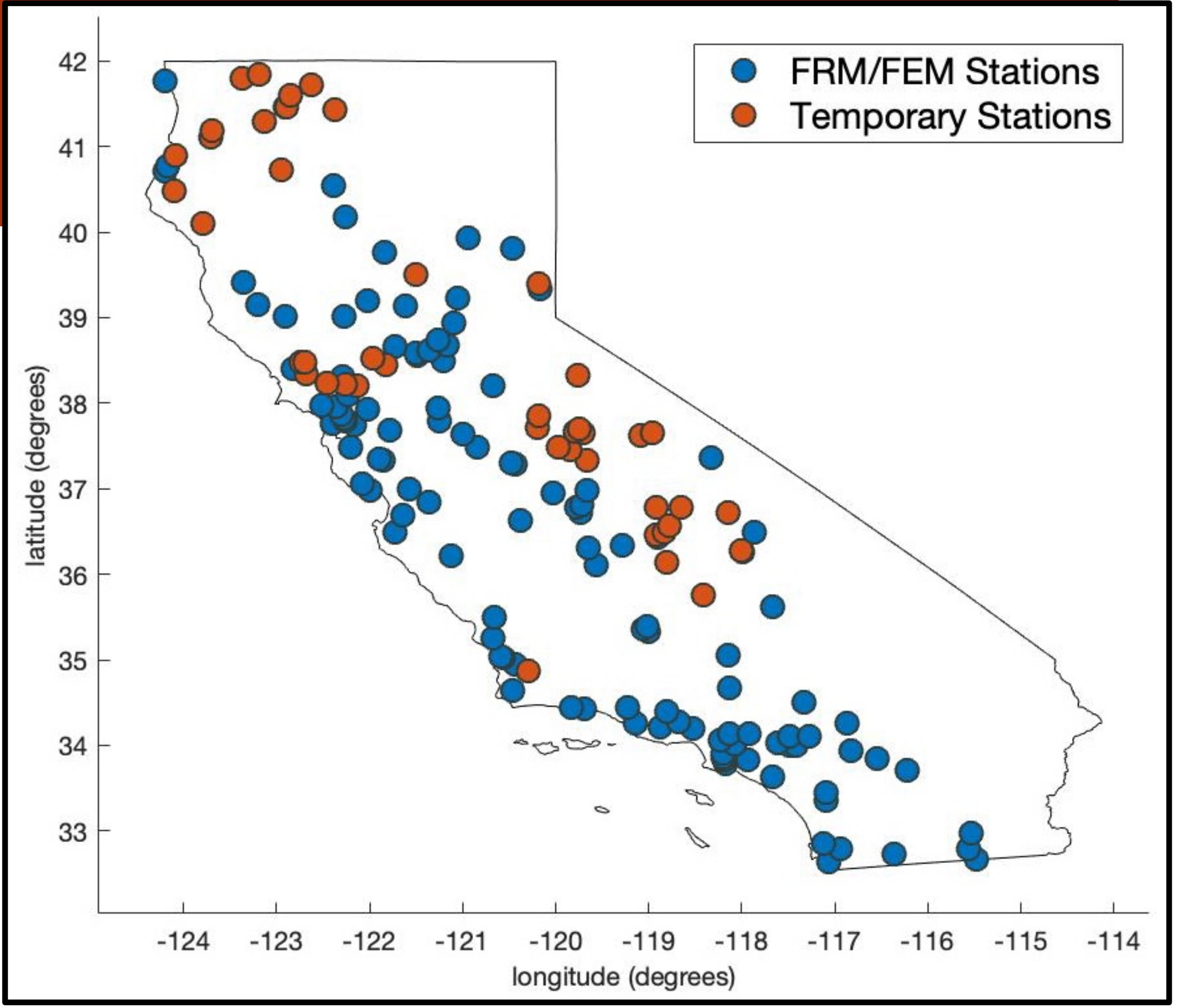
1. Space/time BME kriging on log-$PM_{2.5}$ observations
   - With and without temporary station data
2. BME data fusion of CC-CMAQ & log-$PM_{2.5}$ observations
3. BME data fusion of CC-Sat & log-$PM_{2.5}$ observations
4. BME data fusion of CC-CMAQ, CC-Sat, & log-$PM_{2.5}$ observations

RESULTS
TEMPORARY STATIONS

- Use of temporary station data, while not FRM/FEM, improves accuracy of $PM_{2.5}$ estimates by increasing the coverage of surface observations
  - 114 stations → 163 stations
  - 2670 s/t observations → 3621 s/t observations

Leave-one-out cross-validation results

Method	MSE (log-(μg/m³)²)	R^2 (log-space)
S/T BME Kriging on Obs FRM Only	0.249	0.546
S/T BME Kriging on Obs FRM + TEMP	0.139	0.740

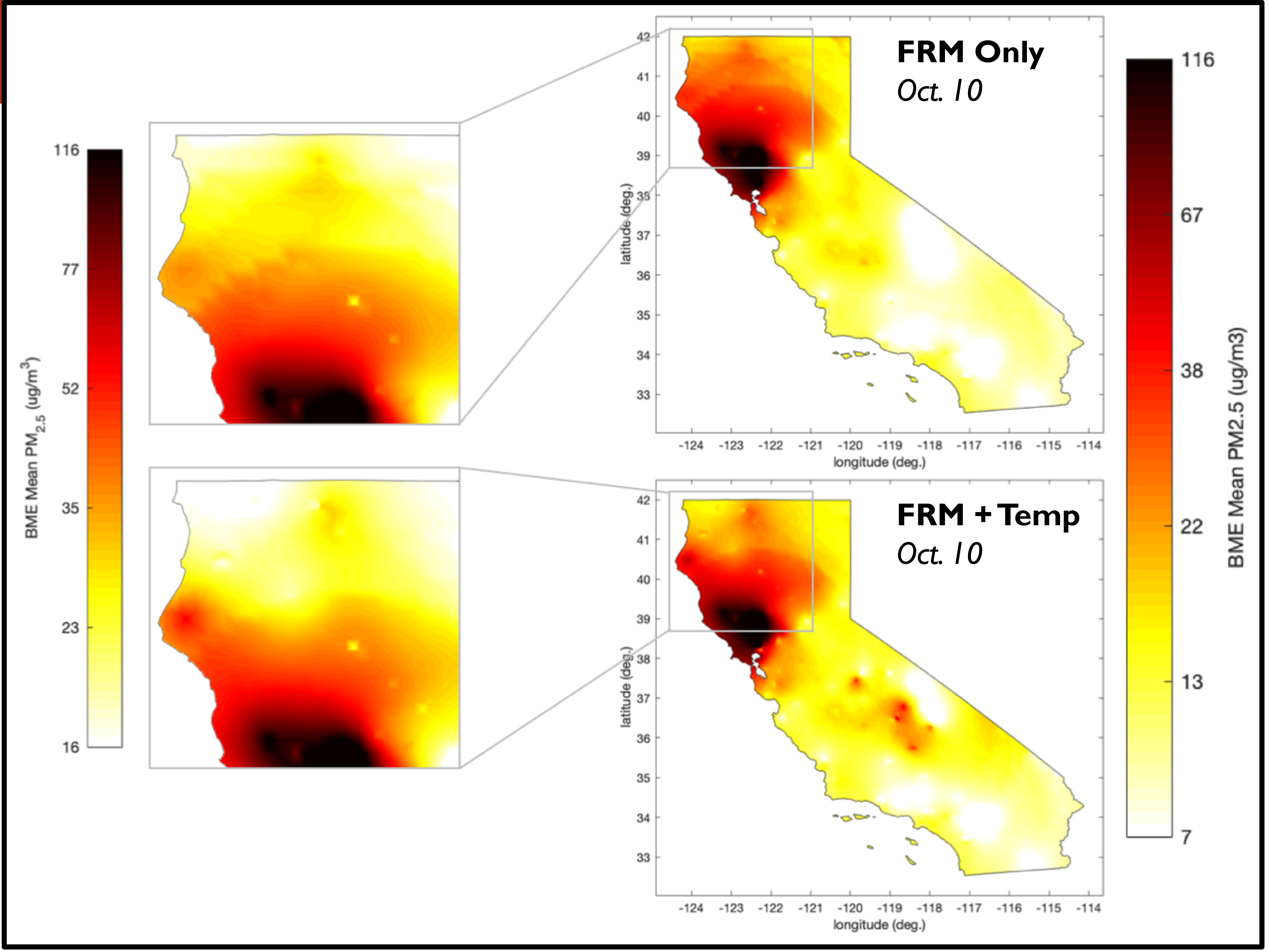


RESULTS

TEMPORARY STATIONS

- Use of temporary station data, while not FRM/FEM, improves accuracy of $PM_{2.5}$ estimates by increasing the coverage of surface observations
  - 114 stations → 163 stations
  - 2670 s/t observations → 3621 s/t observations

- Use of temporary station data also refines smoke plume shape in Northern California



COMPARISON OF 4 BME METHODS

- CAMP improves the accuracy of the CMAQ and satellite-derived products

Leave-one-out cross-validation results

Method	MSE (log-(µg/m³)²)	R^2 (log-space)
Satellite-Derived $PM_{2.5}$ (Sat)	0.406	0.237
CMAQ Model	0.703	0.410
CAMP-Corrected (CC)-Sat	0.389	0.229
CC-CMAQ	0.331	0.452
1. BME S/T Kriging on Obs	0.139	0.740
2. BME Fusion, Obs + CC-CMAQ	0.144	0.730
3. BME Fusion, Obs + CC-Sat	0.162	0.699
4. BME Fusion, Obs + CC-CMAQ + CC-Sat	0.159	0.708

RESULTS

COMPARISON OF 4 BME METHODS

- CAMP improves the accuracy of the CMAQ and satellite-derived products
- All BME s/t kriging and data fusion methods performed better than either of the standalone CMAQ and satellite-derived products

Leave-one-out cross-validation results

Method	MSE (log-(μg/m³)²)	R^2 (log-space)
Satellite-Derived $PM_{2.5}$ (Sat)	0.406	0.237
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RESULTS

COMPARISON OF 4 BME METHODS

- CAMP improves the accuracy of the CMAQ and satellite-derived products
- All BME s/t kriging and data fusion methods performed better than either of the standalone CMAQ and satellite-derived products
- BME s/t kriging on observations produces most accurate estimates at monitoring station locations

Leave-one-out cross-validation results

Method	MSE (log-(μg/m³)²)	R^2 (log-space)
Satellite-Derived $PM_{2.5}$ (Sat)	0.406	0.237
CMAQ Model	0.703	0.410
CAMP-Corrected (CC)-Sat	0.389	0.229
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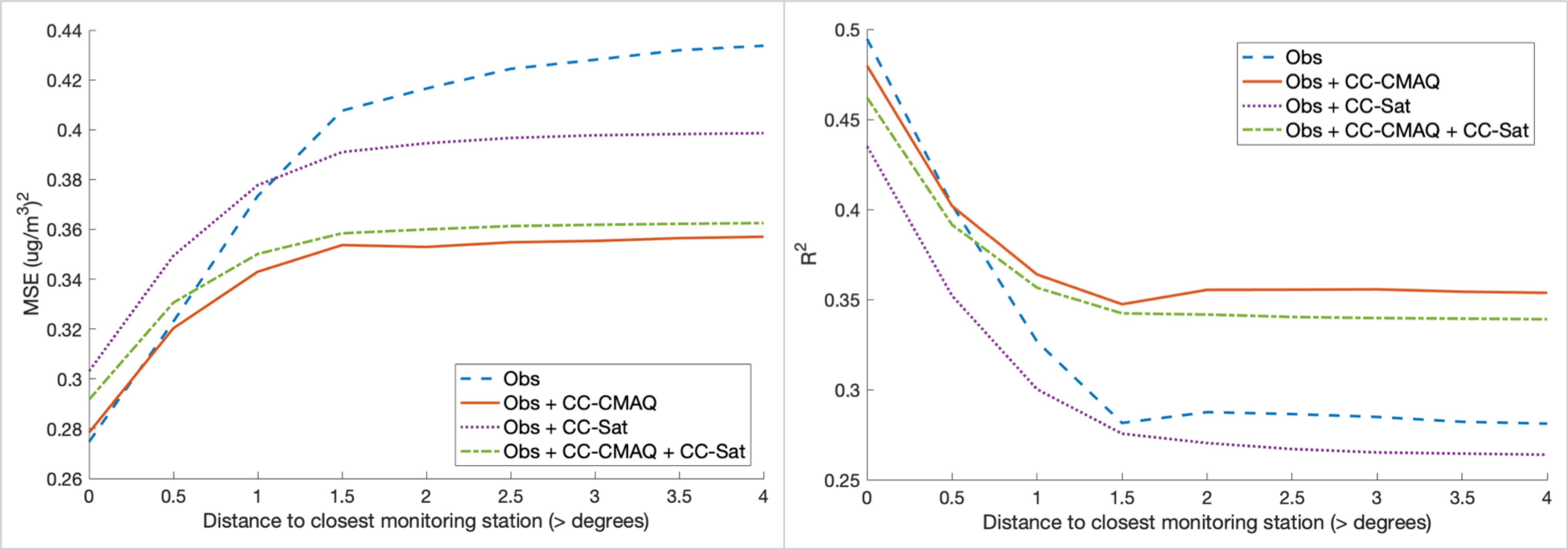
3. BME Fusion, Obs + CC-Sat	0.162	0.699
4. BME Fusion, Obs + CC-CMAQ + CC-Sat	0.159	0.708

RESULTS

COMPARISON OF 4 BME METHODS

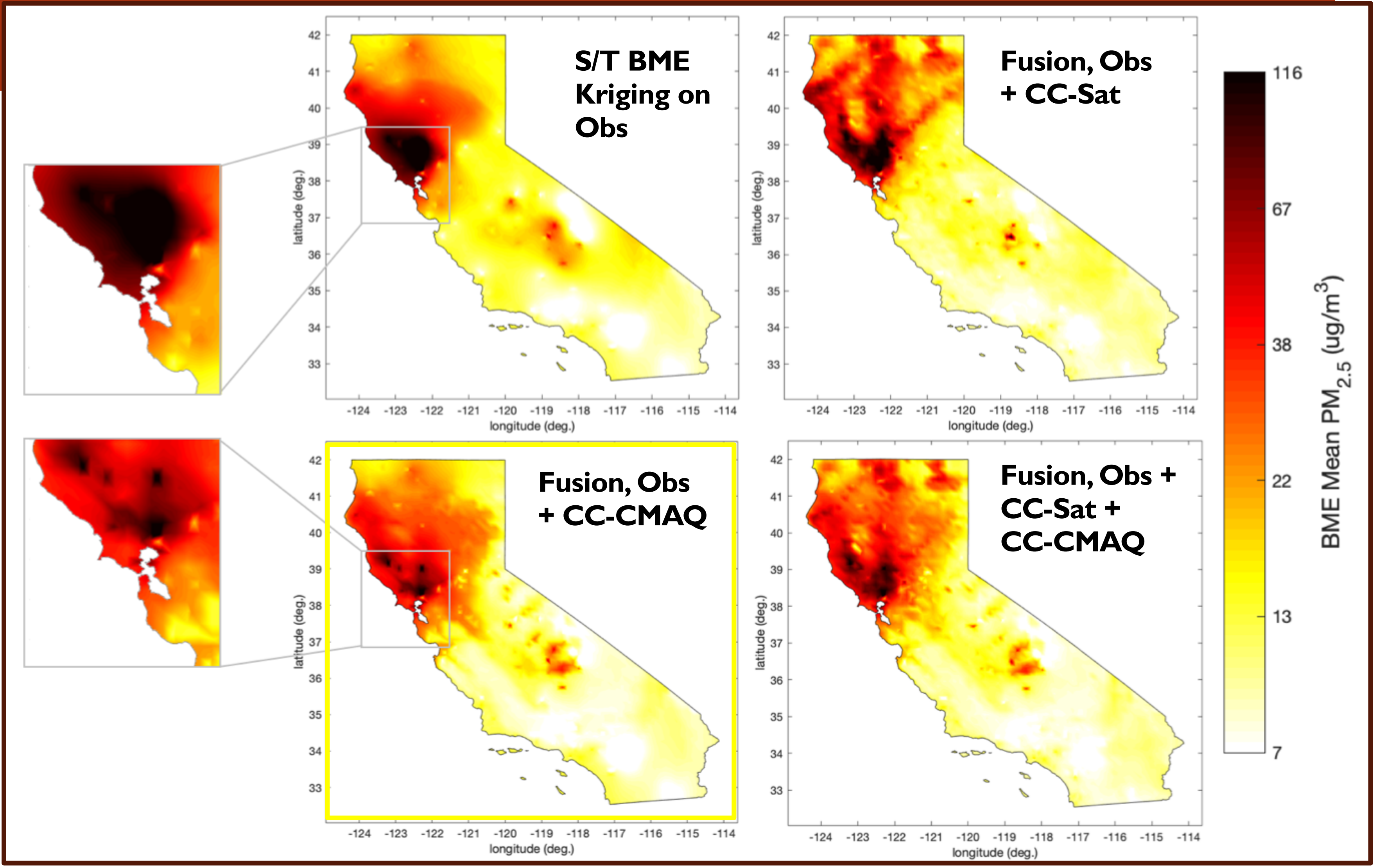
- Fusing observations with CC-CMAQ provides best overall $PM_{2.5}$ estimate
  - Better estimates $PM_{2.5}$ if > ~35 miles from a station

Radius cross-validation results



RESULTS
COMPARISON

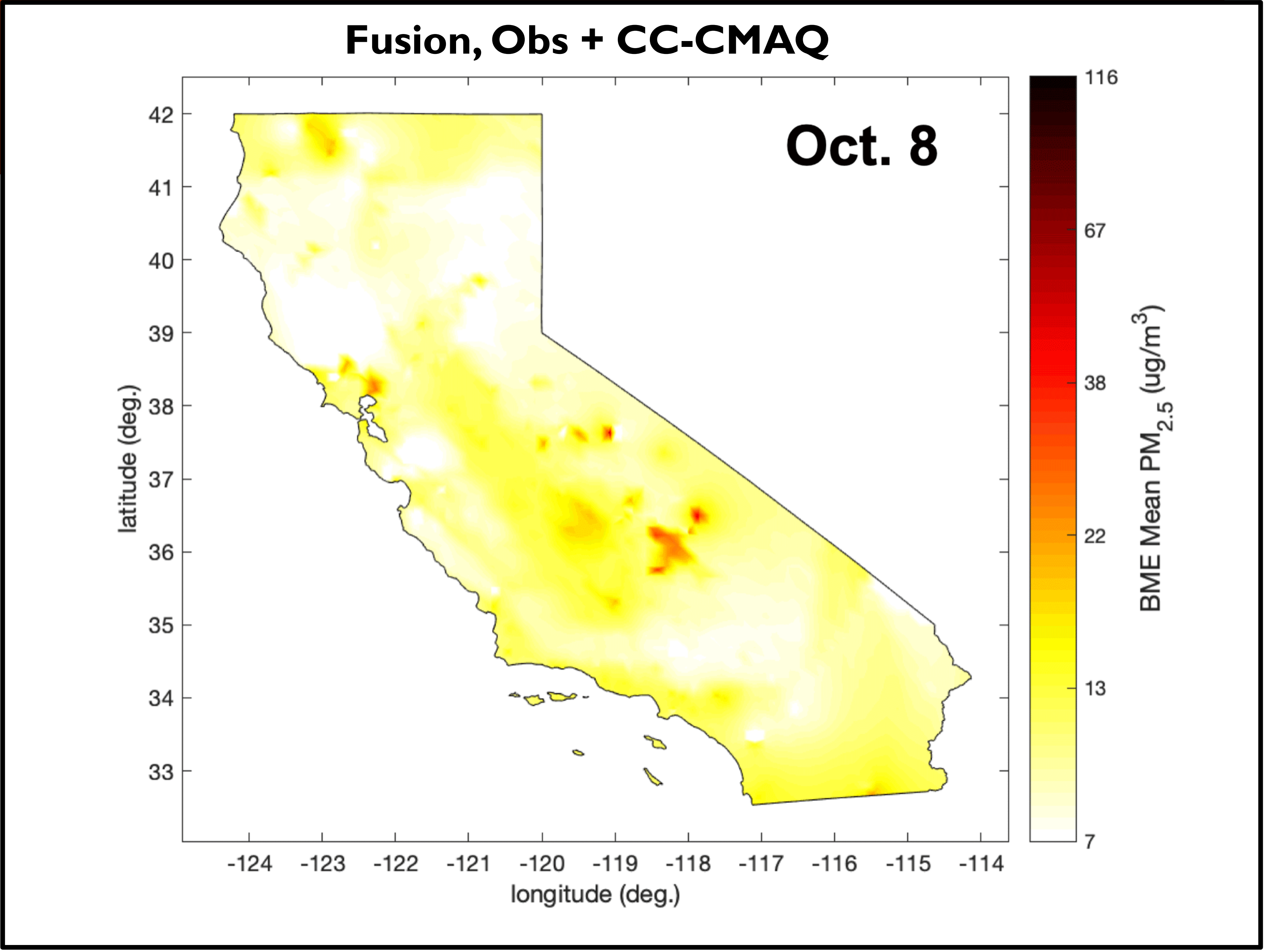
- Fusing observations with CC-CMAQ provides best overall $PM_{2.5}$ estimate
  - Adds knowledge of atmospheric chemistry and physics and fire emissions



RESULTS

$PM_{2.5}$ MAPS

- Fires had clear impact on air quality, with daily avg. $PM_{2.5}$ >190 µg/m^3
- EPA identifies 24-hour average $PM_{2.5}$ concentrations >150.5 µg/m^3 as very unhealthy
  - During the fires, an estimated **60,371** individuals were exposed to daily avg. $PM_{2.5}$ >150.5 µg/m^3
  - On Oct. 13, an estimated **57,013** individuals were exposed to daily avg. $PM_{2.5}$ >150.5 µg/m^3



AIR QUALITY MAPPING
RESULTS

- CAMP improves the accuracy of the CMAQ and satellite-derived products
- Use of temporary station data improves accuracy of $PM_{2.5}$ estimates and refines smoke plume shape
- All four BME s/t kriging and data fusion methods performed better than either of the standalone CMAQ and satellite-derived products
- BME s/t kriging on observations produces most accurate estimates at monitoring station locations
- Fusing observations with CC-CMAQ provides best overall $PM_{2.5}$ estimate, especially in smoke-impacted, station-scarce regions
- Fires had clear impact on air quality, reaching $PM_{2.5}$ levels dangerous to human health

BME Data Fusion

- Our datasets are available for others to use upon request, for health impact assessment and epidemiology.
- Fusing data from multiple sources usually performs better than single datasets.
- Flexible methods that are adaptable to a wide range of applications and input data.

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- Multiple global modeling teams including at CCMI and NASA

HAQAST FIRES TIGER TEAM

- Susan O'Neill & Minghui Diao for leading
- BAAQMD for CMAQ model runs
- USFS for temporary station data
- Rest of team for collaboration & support

HAQAST INDICATORS TIGER TEAM

- Susan Anenberg for leading

QUESTIONS?

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APPENDIX

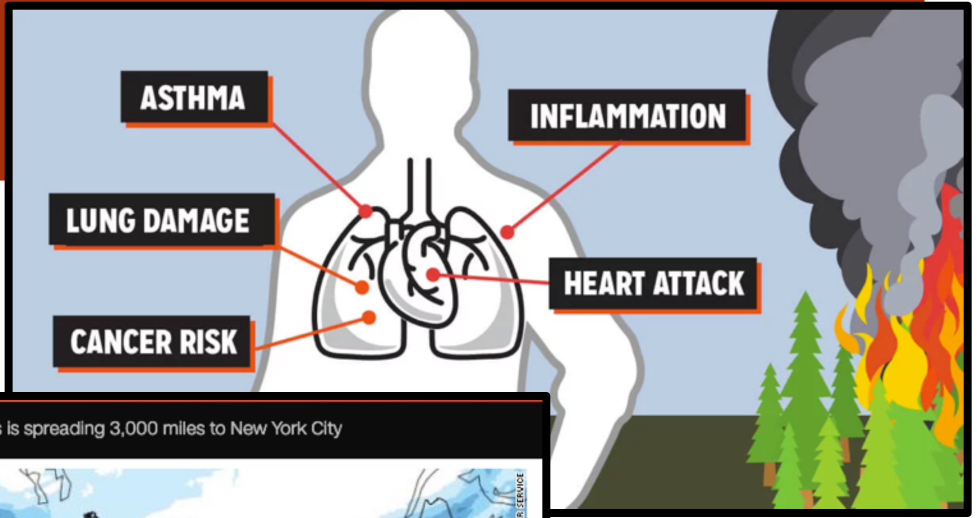
INTRODUCTION
WILDFIRES & CLIMATE CHANGE

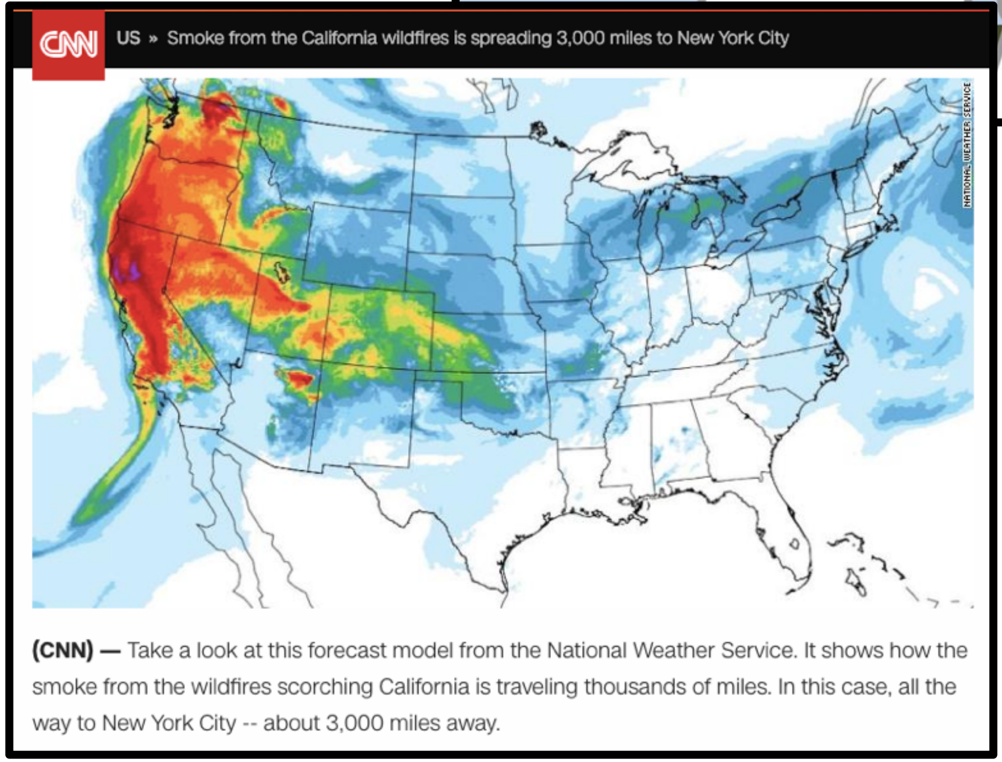
- Wildfires are occurring with increased **frequency**, **intensity**, and **severity** due to climate change, with larger burn areas and longer season
  - October 2018 wildfires (Camp Fire) were deadliest and most destructive wildfire season ever recorded in California
  - Recent Kincade Fire in N. California → 77,000+ acres burned, 180,000 people displaced, 1 million without power

(Reid et al, 2016; Durán et al, 2014)

INTRODUCTION
IMPACT OF WILDFIRES

- Increased respiratory and cardiovascular morbidity and mortality
  - Exacerbation of COPD and asthma
  - Increased risk of respiratory infection and CHF
  - Increased hospital and ED admissions
- $PM_{2.5}$ from wildfire smoke remains in the air for extended periods and can be transported over large distances
- Need a framework to better understand the impacts of these fires



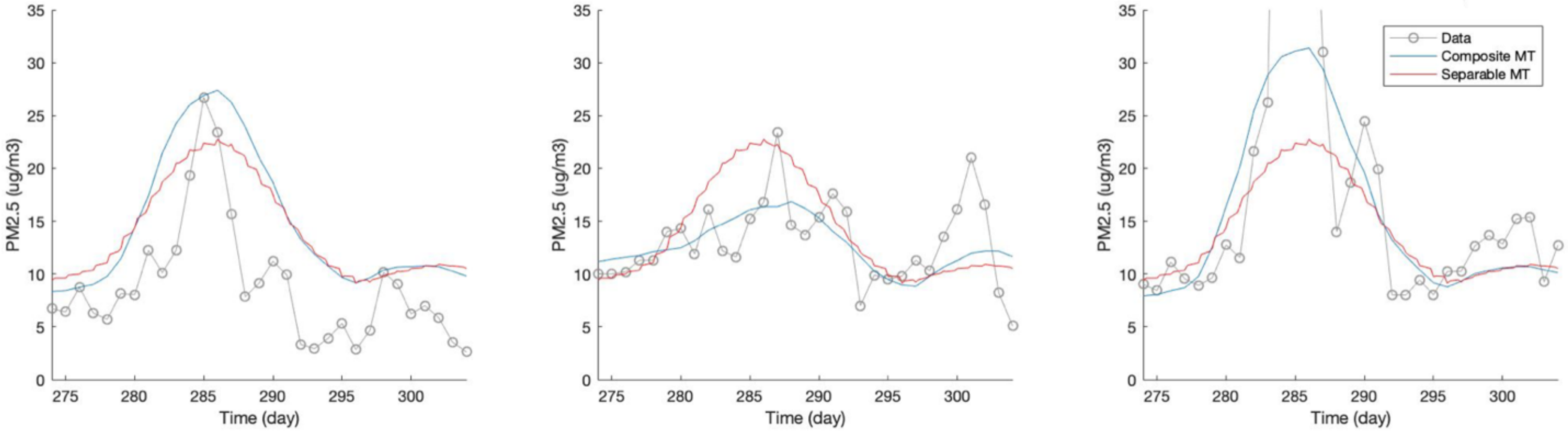


(Christakos et al, 2000; Lee et al, 2012)

METHODS
MEAN TREND

An informed composite mean trend (MT) in space and time is removed from the data to characterize systematic structures and trends over space and time

- *Informed Separable s/t MT* – Assumes that the MT of $PM_{2.5}$ is a combination of a purely spatial and temporal MT
- ***Informed s/t Composite MT***– Assumes that each s/t location has its own unique MT of $PM_{2.5}$ observations across space & time



METHODS

COVARIANCE

$$c_x(r,t) = c_{01}\exp\left(\frac{-3r}{a_{r1}}\right)\exp\left(\frac{-3t}{a_{t1}}\right) + c_{02}\exp\left(\frac{-3r}{a_{r2}}\right)\exp\left(\frac{-3t}{a_{t2}}\right) + c_{03}\exp\left(\frac{-3r}{a_{r3}}\right)\exp\left(\frac{-3t}{a_{t3}}\right)$$

Human Activities

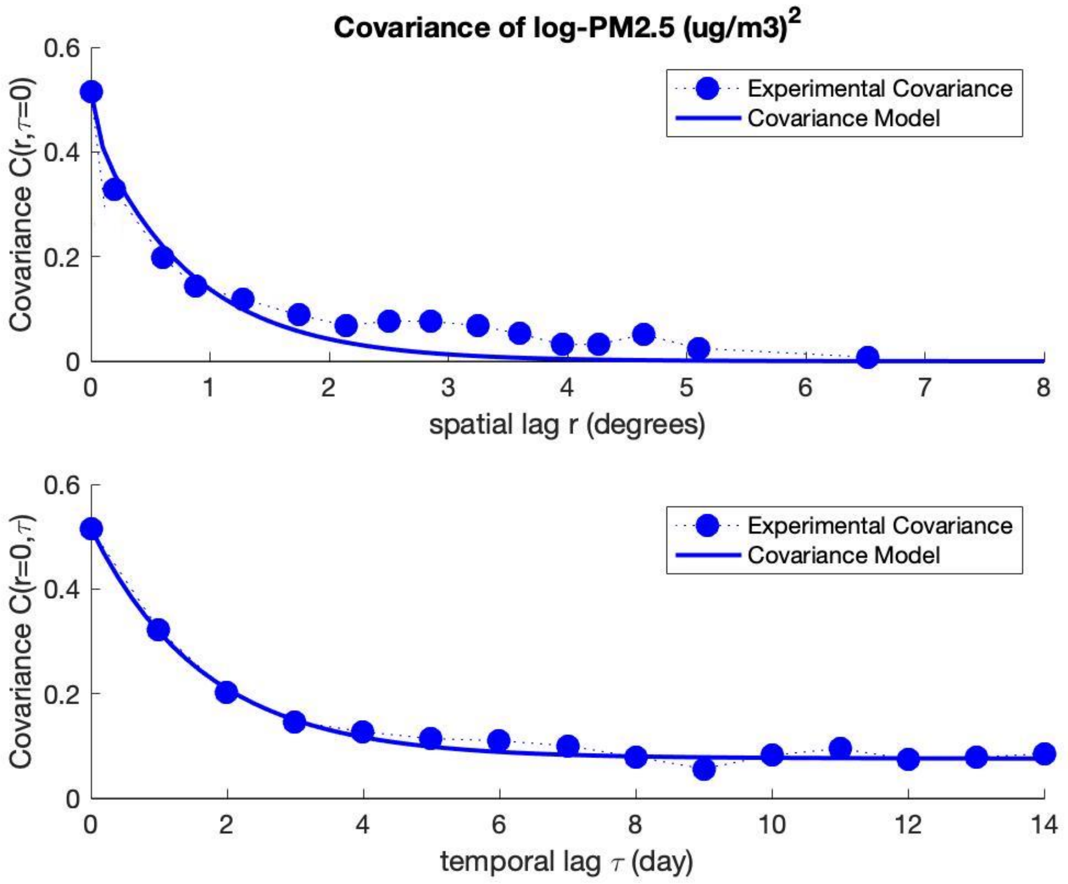
a_{r1} = 0.15 degrees, a_{t1} = 16,425 days, c_{01} = 0.0636 (log-ug/m^3)^2

Weather-Related

a_{r2} = 4 degrees, a_{t2} =365 days, c_{02} = 0.0142 (log-ug/m^3)^2

Wildfire-Related

a_{r3} = 2.5 degrees, a_{t3} = 5 days, c_{03} = 0.441 (log-ug/m^3)^2



METHODS
BME FRAMEWORK

Use of BME for mapping & assessing health risk of PM:

- Estimates of mortality risk differed among exposure models → using the BME framework to map $PM_{2.5}$ resulted in better Cox proportional hazard model fit and larger effect size *(Jerrett et al, 2017)*
- Incorporating land-use regression (LUR) into BME framework to map $PM_{2.5}$ across the United States resulted in a 22% reduction in MSE over simple kriging *(Reyes & Serre, 2014)*
- Using a moving-window BME approach to map $PM_{2.5}$ across the United States led to a significant reduction in estimation error → recommended for epidemiological studies investigating the effect of long-term exposure to $PM_{2.5}$ *(Akita, Chen, & Serre, 2012)*
- BME led to improved, more meaningful estimates of the annual PM_{10} in the state of California, compared to traditional techniques of spatial kriging → the advantages of BME are particularly valuable when assessing health risks *(Christakos et al, 2001)*

METHODS
BME FRAMEWORK - CITATIONS

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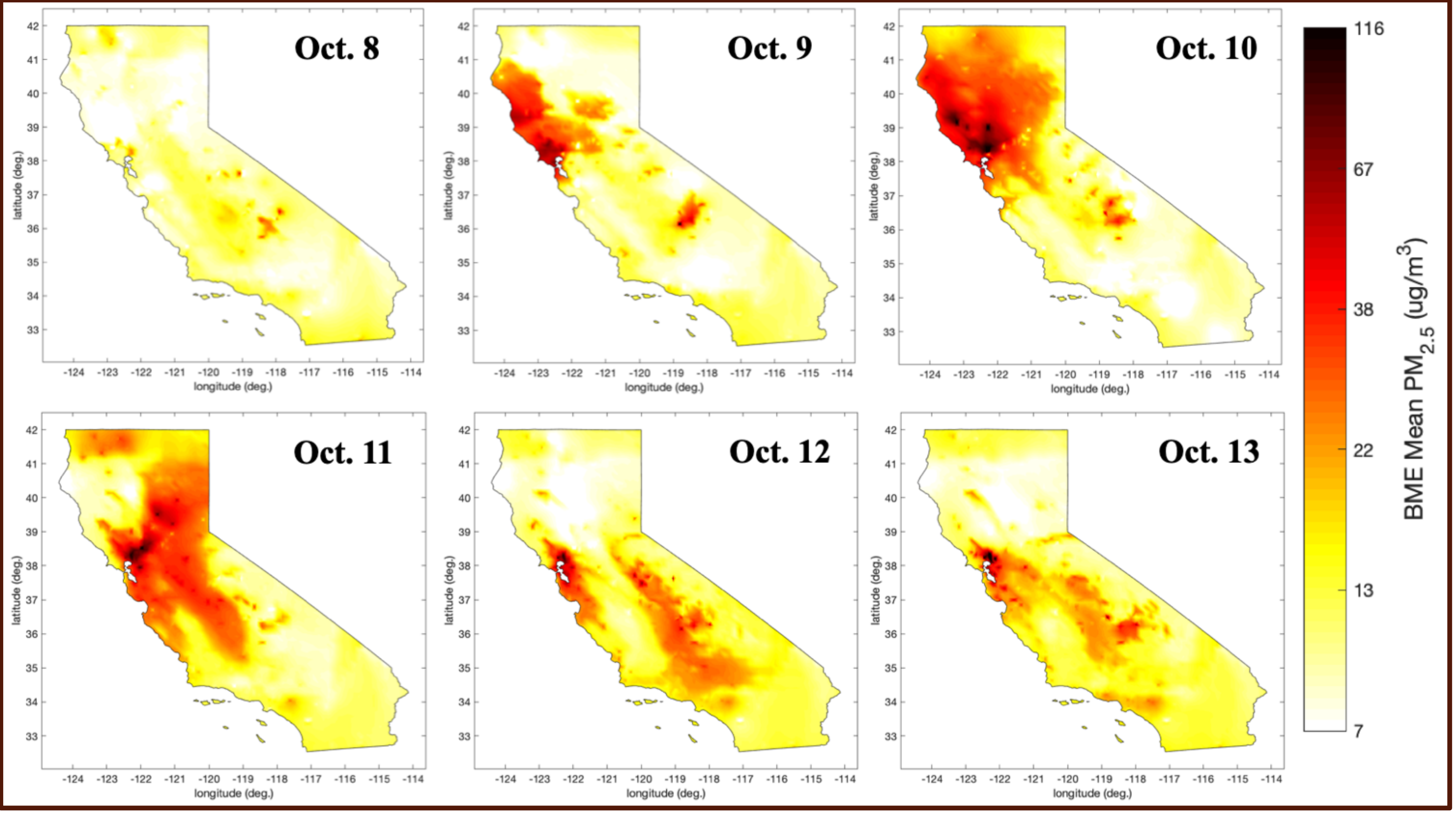
RESULTS

$PM_{2.5}$ MAPS

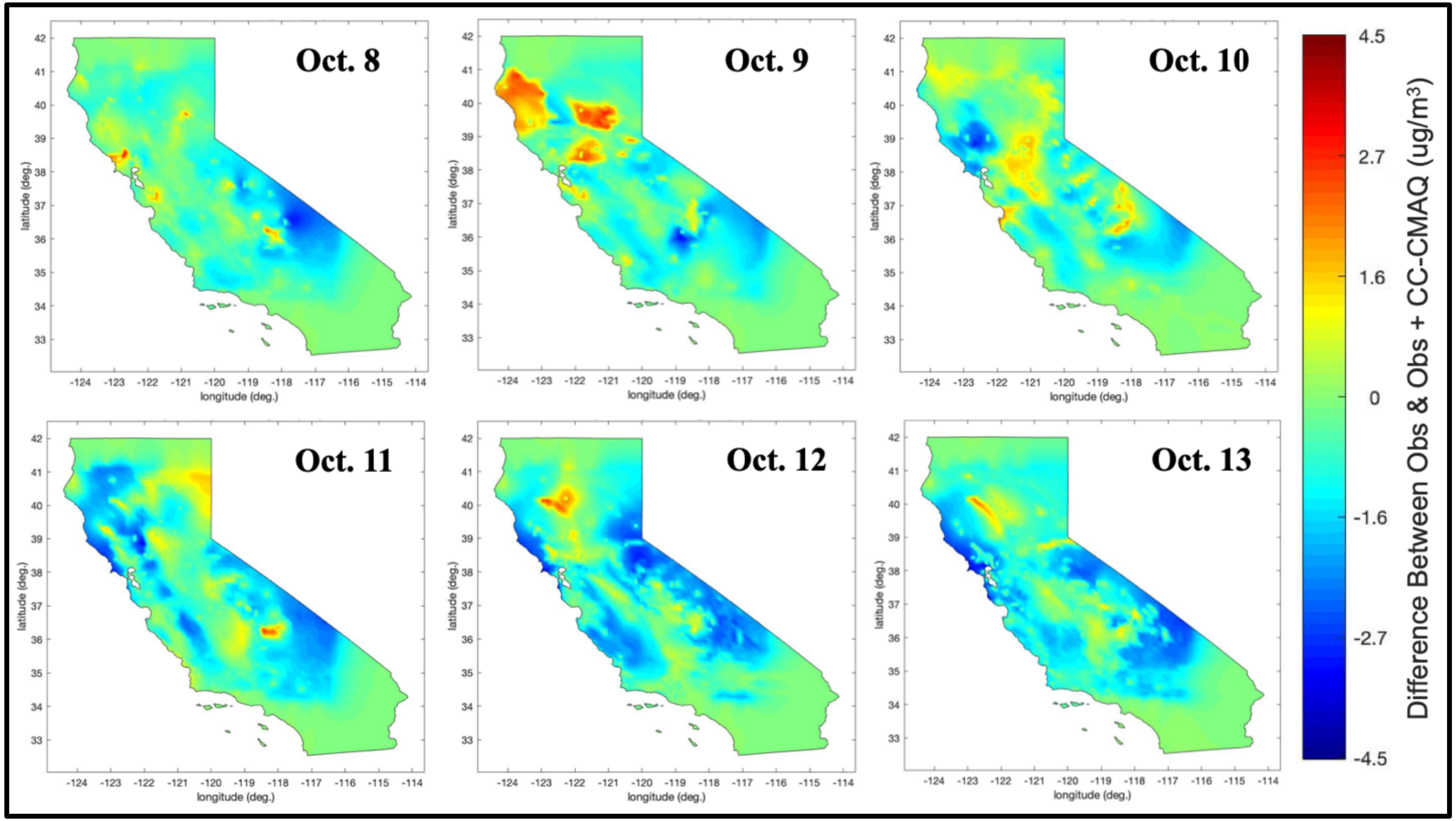
- Fires had clear impact on air quality, reaching $PM_{2.5}$ levels dangerous to human health → Daily avg. $PM_{2.5}$ >150.5 µg/m^3
- EPA identifies 24-hour average $PM_{2.5}$ concentrations >150.5 µg/m^3 as very unhealthy
  - On Oct. 13, an estimated **57,013** individuals were exposed to daily avg. $PM_{2.5}$ >150.5 µg/m^3

Fusion, Obs + CC-CMAQ



RESULTS
COMPARISON BETWEEN KRIGING & FUSION

- Difference between $PM_{2.5}$ estimations produced by BME s/t kriging on observations and BME data fusion of observations and CC-CMAQ



RESULTS

BME VARIANCE