MAPPING THE AIR QUALITY & HEALTH IMPACTS OF THE 2017 CALIFORNIA WILDFIRES

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INTRODUCTION

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

- 8,400 buildings destroyed, 100,000 people displaced, 185 hospitalized, 45 dead
- $PM_{2.5}$ concentrations reached highest levels recorded to date in the region
- ~7.2 million people living in the Bay Area exposed to unhealthy air

Exposure to wildfire smoke increases respiratory illness and symptoms and risk of hospital admission for respiratory disease[1,2]. Due to this health risk and an increased frequency of wildfires[3,4], it is important to develop accurate methods for estimating the air quality and health impacts of wildfires.

Geostatistical methods exist to combine modeled & observed concentrations to estimate air quality over a region[6], but these methods have not been applied to intense natural events like a wildfire. This research has two primary goals:

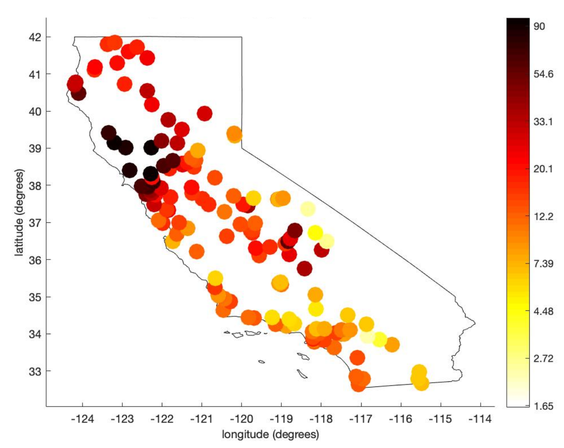
1. **Map $PM_{2.5}$ during the Oct. 2017 wildfires**, fusing together observed & modeled $PM_{2.5}$ concentrations
2. Use the $PM_{2.5}$ map to **estimate the acute health impact of the Oct. 2017 wildfires**, specifically the attributable respiratory hospital admissions

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

$PM_{2.5}$ DATA

To map air quality during the wildfires, 3 daily average $PM_{2.5}$ datasets were used:

1. Surface observations from 114 **EPA FRM/FEM monitoring stations** across California for Oct. 1 – 31, 2017 (EPA's air quality database)
2. Surface observations from 49 **temporary monitoring stations** across California for Oct. 1 – 31, 2017 (US Forest Service)
3. Estimates from **Community Multiscale Air Quality (CMAQ) model** in the Central California region at a 4-km resolution from Oct. 3 – 20, 2017 (Bay Area Air Quality Management District)



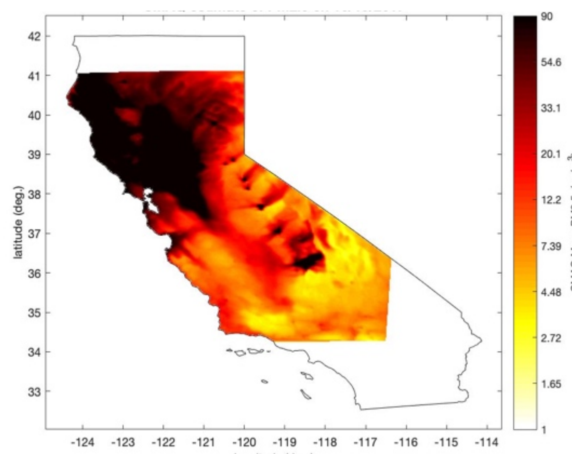


Fig. 1. (Top) Surface observations from FRM & temp stations, (Bottom) CMAQ model estimate, Oct.10

MAPPING METHODS

Four steps were used to fuse observed & modeled $PM_{2.5}$ over CA during the entire fire period:

1. Constant Air Quality Model Performance[5]-corrected CMAQ (CC-CMAQ) model
2. Simple space/time (s/t) kriging on log-$PM_{2.5}$ observations from FRM/FEM monitors – Flat Mean Trend (MT) removed
3. Simple s/t kriging on log-$PM_{2.5}$ observations from FRM/FEM & temporary monitors – Informed MT removed
4. Fusion of CC-CMAQ model & log-$PM_{2.5}$ observations from FRM/FEM & temporary monitors – Informed MT removed

Each step was evaluated through a leave-one-out cross-validation. The Mean Squared Error (MSE) and R^2 values were calculated using the 163 monitoring stations as the validation set.

Constant Air Quality Model Performance (CAMP) Method

Step 1 - the CAMP Method, which evaluates and corrects the CMAQ model by:

- Accounting for the non-linear and non-homoscedastic relationship between CMAQ modeled and observed $PM_{2.5}$ data[5]
- Correcting errors in CMAQ model estimations by modeling the mean (λ_1) and variance (λ_2) of the observed value as a function of the given model value across the model domain[5]

Bayesian Maximum Entropy (BME) Framework

Step 2 - 4 - the BME framework uses modern spatiotemporal geostatistics to combine general knowledge with site-specific knowledge to create estimates of $PM_{2.5}$ at unmonitored locations[6].

A composite MT in space and time is removed from the data to characterize systematic structures and trends over space and time[6,7]. Two MTs are used:

- **Flat S/T Composite MT**– Assumes the MT of $PM_{2.5}$ observations is constant across space & time[6]
- **Informed S/T Composite MT**– Assumes that each s/t location has its own unique MT of $PM_{2.5}$ observations across space & time[7]

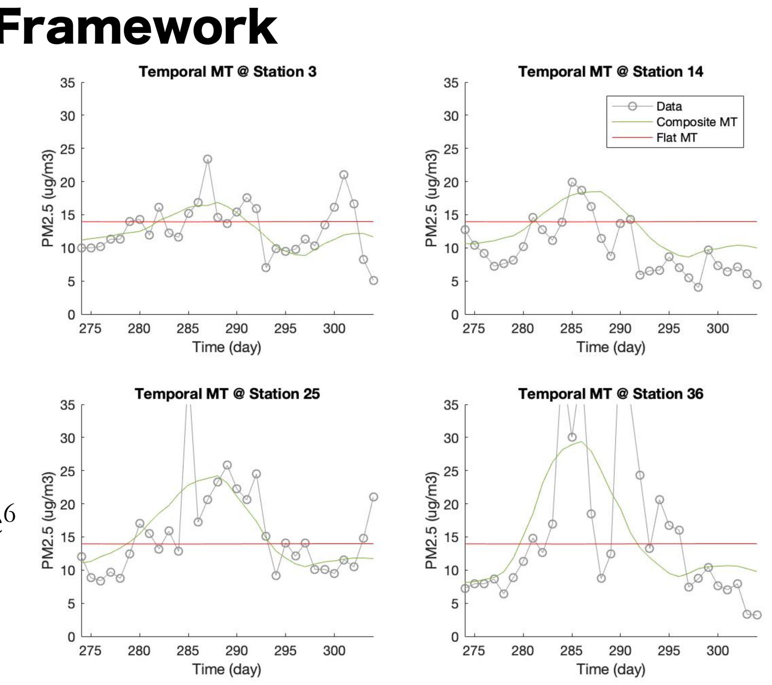


Fig. 2. Comparison between flat and informed s/t composite MT at 4 monitoring stations across CA during Oct. 2017

Step 4 - To fuse the CC-CMAQ model with the log-$PM_{2.5}$ data, the BME framework treats observed data as "hard" and model data as "soft"[6]. Unlike hard data, soft data:

- Influences only the site-specific knowledge[6]
- Includes a variance, where modeled $PM_{2.5}$ (λ_1) with lower variance (λ_2) have more influence[5,6]

The influence of a $PM_{2.5}$ measurement decreases with distance given the spatial correlations[6].

ACUTE HEALTH IMPACT

Objective

Conduct a health impact analysis of the Oct. 2017 wildfires for multiple acute health endpoints, using respiratory hospital admissions as an example.

Data & Methods

The rate of respiratory hospital admissions attributable to wildfire $PM_{2.5}$, given a log-linear relationship, is:

$$\Delta Y = Y(t) * (1 - e^{-\beta\,(X(s,t) - X_0(s,t))})$$

- $X(s,t)$ - mean $PM_{2.5}$ concentration at a s/t location, provided by the $PM_{2.5}$ estimations
- $X_0(s,t)$ - background concentration of $PM_{2.5}$ at a s/t location, the avg. $PM_{2.5}$ in CA in 2017: 9.9 $\mu g/m^3$
- $Y(t)$ - average admission rate, 6.5 hospital respiratory admissions per 100,000 people per day [8]
- $\beta = \frac{\ln(RR)}{10\ \mu g/m^3}$, RR - 2.07% increase in respiratory hospital admissions per 10 $\mu g/m^3$ increase in $PM_{2.5}$[9]

Monte-Carlo simulations of β were used to obtain ΔY estimates, then combined with population data estimate the daily respiratory hospital admissions.

Findings

- On Oct. 10, an estimated 96 people were admitted for respiratory illness due to exposure to wildfire $PM_{2.5}$, with an estimated 164 people admitted Oct. 8 - 10
- The highest rate of admissions occurred in densely populated areas with high $PM_{2.5}$ levels from the smoke

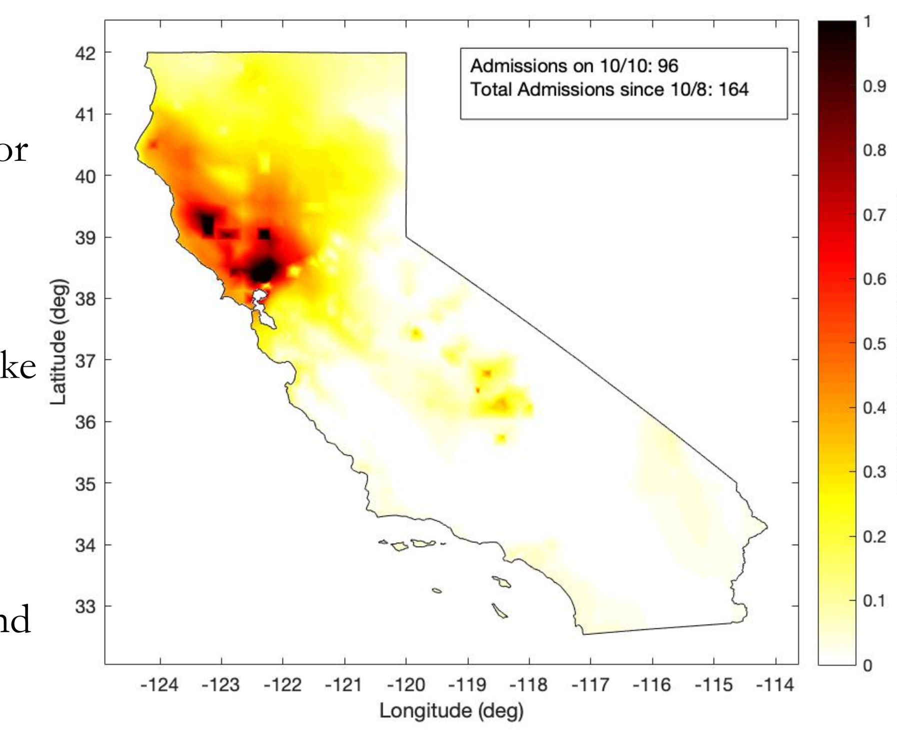


Fig. 3. Estimate of rate of hospital respiratory admissions attributable to $PM_{2.5}$ from the wildfires, Oct. 10

Future Work

- Conduct risk assessment in BenMAP to leverage the county-level $Y(t)$ values and validate findings
- Improve $X_0(s,t)$ to be an informed $PM_{2.5}$ background concentration that varies geographically across CA
- Perform impact analysis on additional acute health outcomes over entire fire period

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Acknowledgements

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RESULTS: AIR QUALITY MAPS

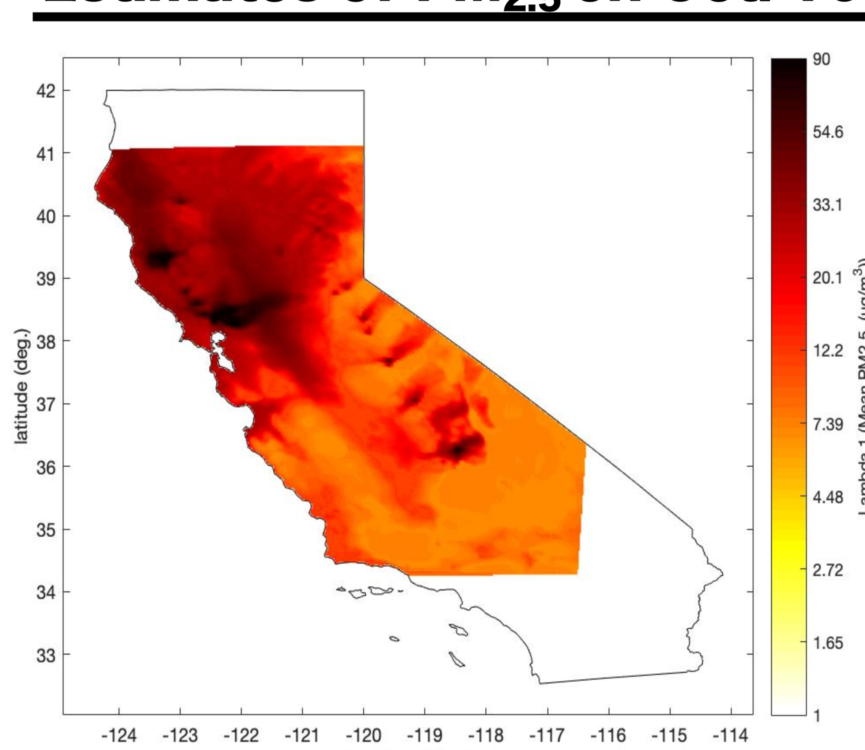
Findings

- CC-CMAQ leverages benefits of CMAQ's knowledge of atmospheric physics and chemistry while correcting for errors in modeled $PM_{2.5}$
  - Reduction in CMAQ MSE (0.703 to 0.331 (log-$\mu g/m^3)^2$)
  - Increase in CMAQ R^2 (0.410 to 0.452 (log-$\mu g/m^3)^2$)
- Use of temporary station data, while not FRM/FEM, improves accuracy of $PM_{2.5}$ estimates by increasing the coverage of surface observations
- Removing an informed MT improves accuracy of the $PM_{2.5}$ estimate, using knowledge that each location had a unique $PM_{2.5}$ trend during the fires
- The final fusion of the CC-CMAQ model with log-PM2.5 observations reduces the MSE and R2 of PM2.5 estimate, creating a map that is both accurate and more physically meaningful

Limitations & Future Work

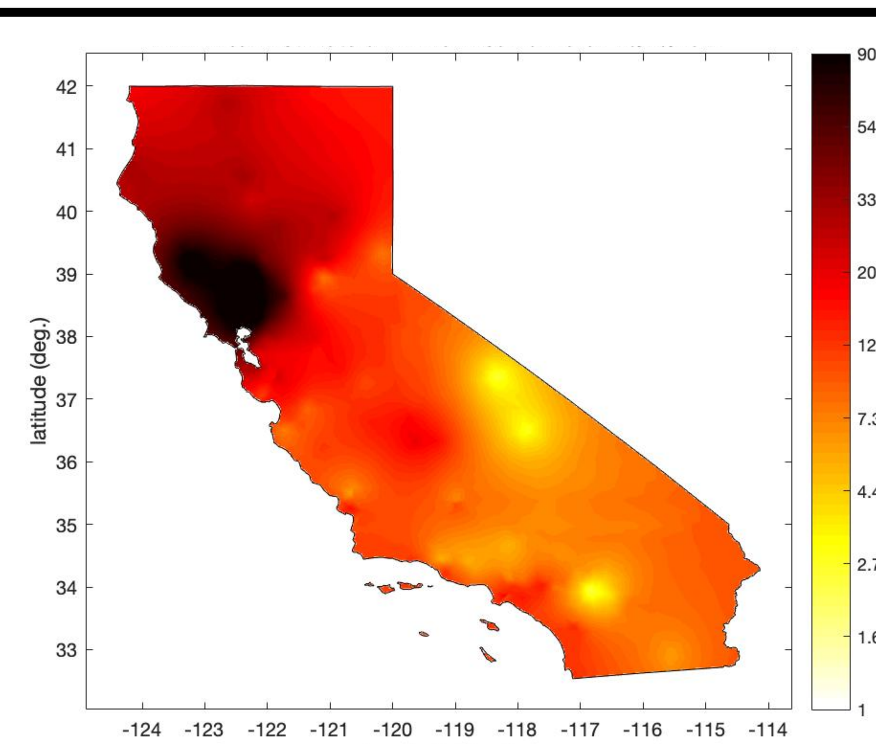
- Validation set for cross-validation MSE and R^2 is limited to observed data
- Investigate inclusion of satellite data to further improve $PM_{2.5}$ estimate
- Create maps for additional wildfire smoke pollutants (O_3, NO_2) for the entire fire period

Estimates of $PM_{2.5}$ on Oct. 10, 2017



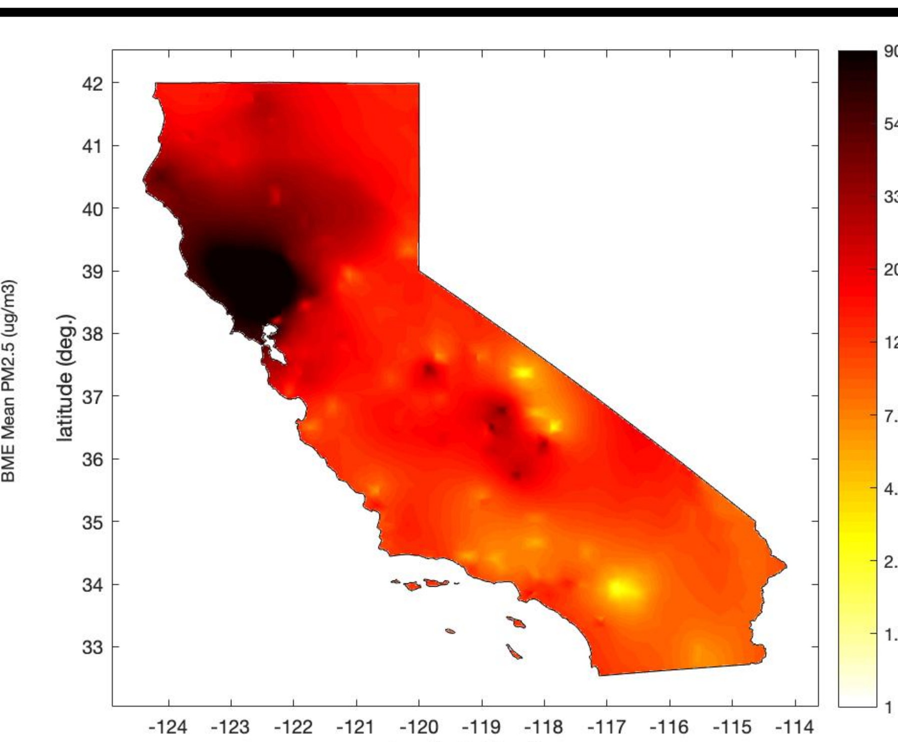
1. CC-CMAQ Model

MSE: **0.331** (log-$\mu g/m^3)^2$
R^2: **0.452** (log concentration)



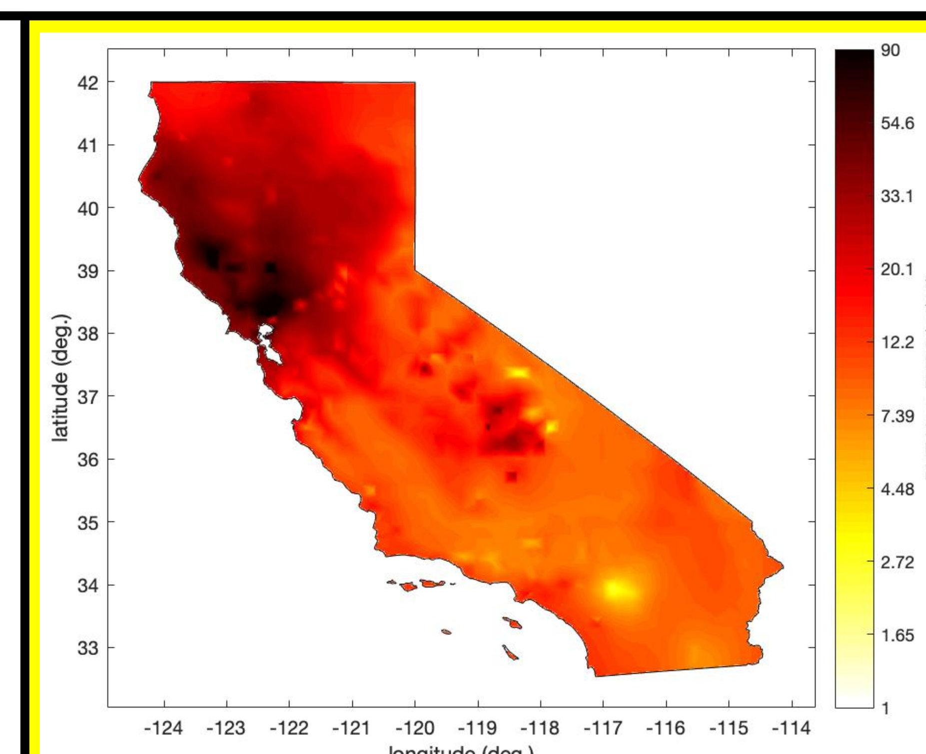
2. S/T kriging, FRM/FEM Obs, Flat MT

MSE: **0.182** (log-$\mu g/m^3)^2$
R^2: **0.661** (log concentration)



3. S/T kriging, FRM/FEM & Temp Obs, Informed MT

MSE: **0.139** (log-$\mu g/m^3)^2$
R^2: **0.740** (log concentration)



4. Fused CC-CMAQ + FRM/FEM & Temp Obs, Informed MT

MSE: **0.144** (log-$\mu g/m^3)^2$
R^2: **0.730** (log concentration)