



Health Impacts of Wildfire Smoke Exposure

Rocky Mountain Section of the Air &
Waste Management
July 20, 2021

Colleen E. Reid, PhD MPH
Department of Geography,
University of Colorado Boulder
Colleen.Reid@colorado.edu

HOTTER YEARS, MORE FIRES

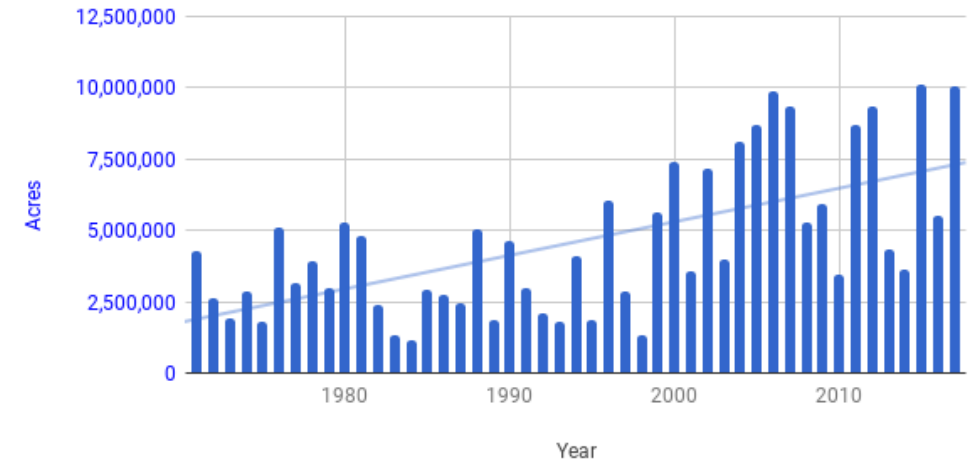
Number of Large Fires Across Western states



Wildfires greater than 1,000 acres reported to USFS. Prescribed burns excluded.
Aggregated average annual temperature of 11 western states (ccc-acis.org)
Source: U.S. Forest Service

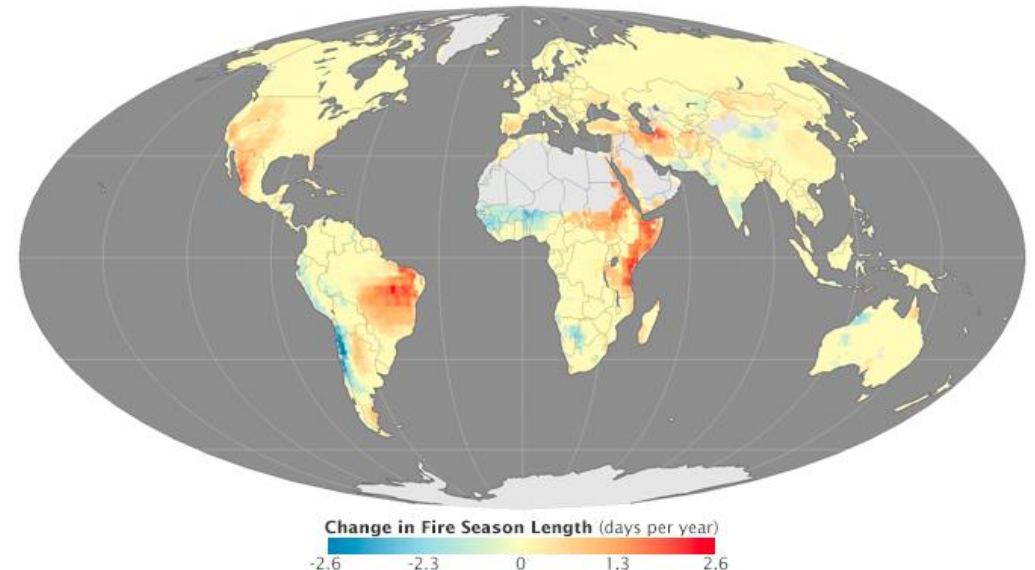
CLIMATE CENTRAL

Acres Burned per Year in the US (National Interagency Fire Center Data)



https://www.nifc.gov/fireInfo/fireInfo_stats_totalFires.html

<https://earthobservatory.nasa.gov/images/86268/longer-more-frequent-fire-seasons>





[Science](#) [Coronavirus](#) [Climate](#) [Earthquakes](#) [Deep Look Videos](#)

SCIENCE

California Wildfires Killed 106 People Two Years Ago. Researchers Say the Smoke Killed 3,652

By [Danielle Venton](#)

Dec 11, 2020

[Save Article](#)



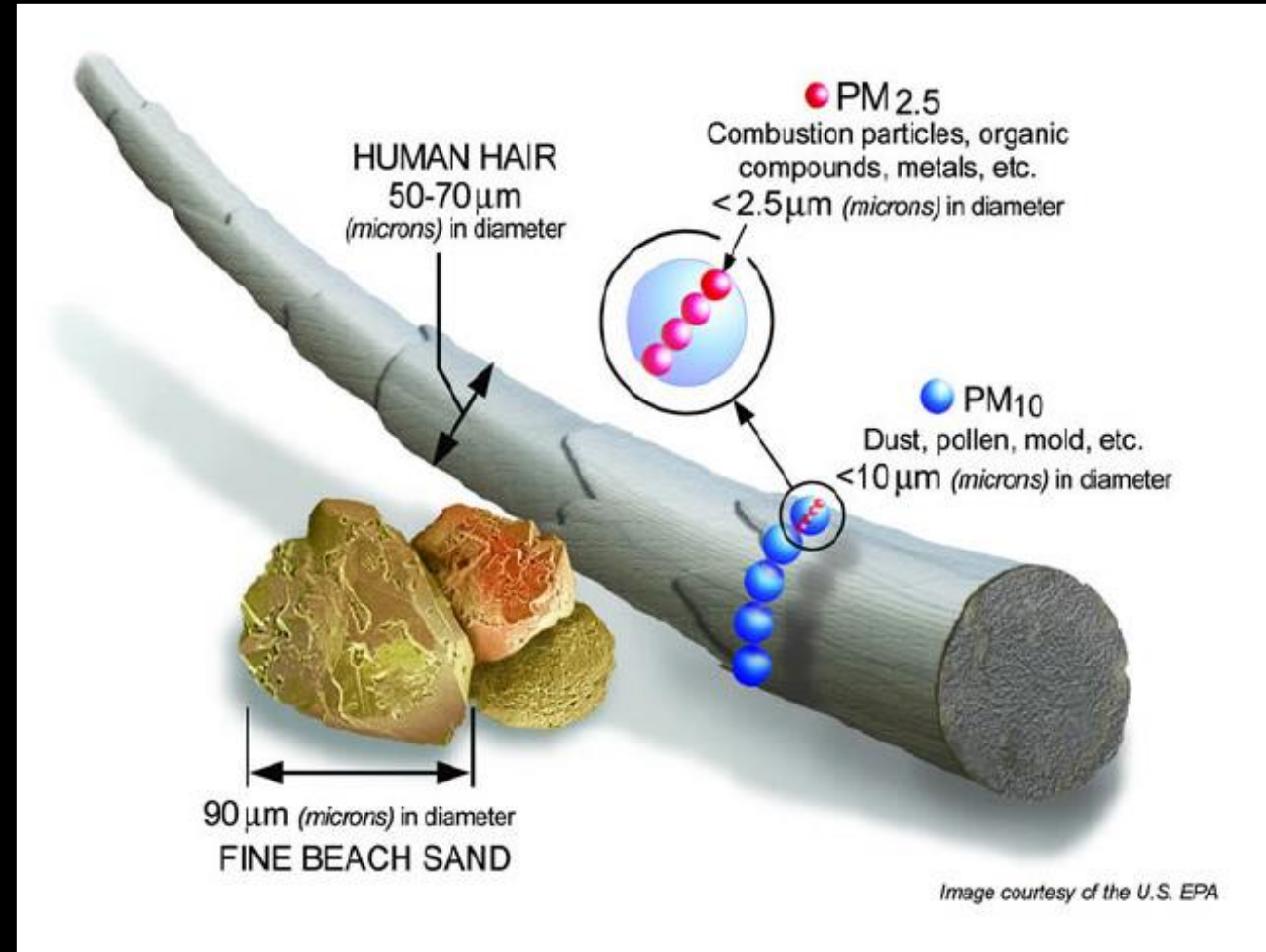
Emissions from Wildfires with Health Concerns

Primary air pollutants

- CO
- NO₂
- PAHs – polycyclic aromatic hydrocarbons
- VOCs – volatile organic compounds
- Particulate Matter (PM)

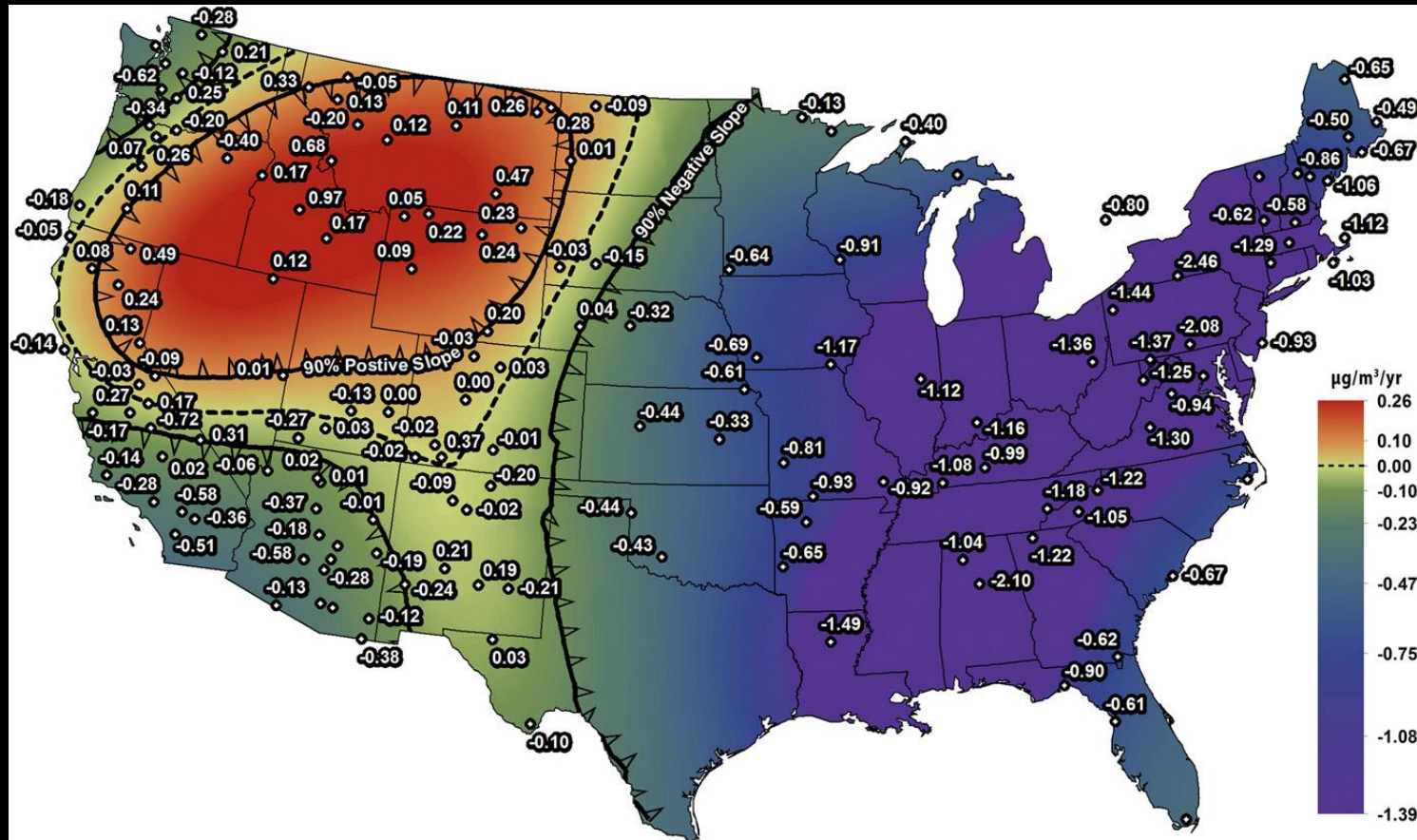
Secondary air pollutants

- Particulate Matter (PM)
- Ozone

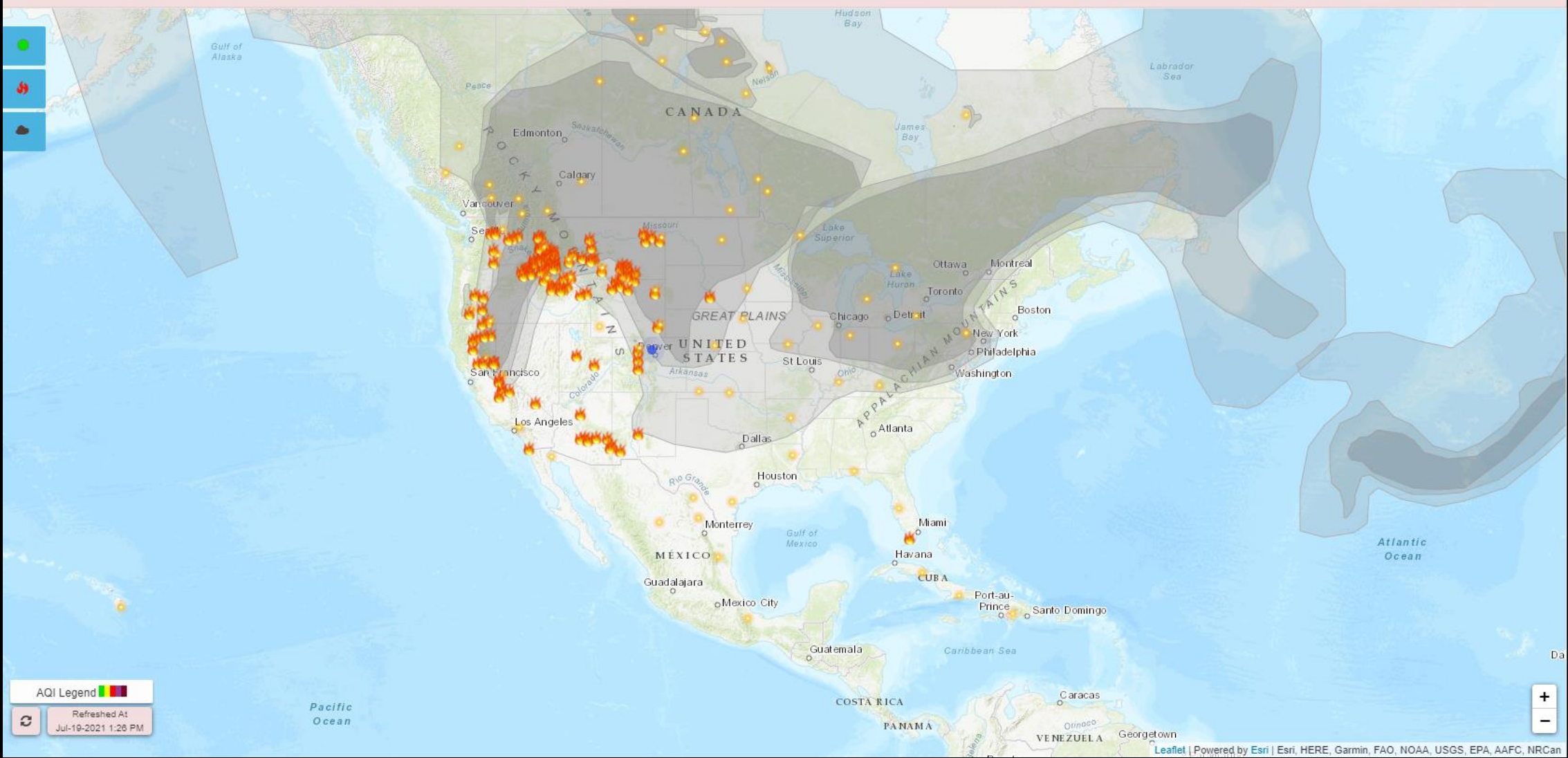


Why wildfires?

- Globally and regionally, wildfire risk is projected to increase under various potential future climate scenarios.
- The percent of our air pollution due to wildfires will likely increase, not just from climatic changes, but also because of declines in other sources of air pollution

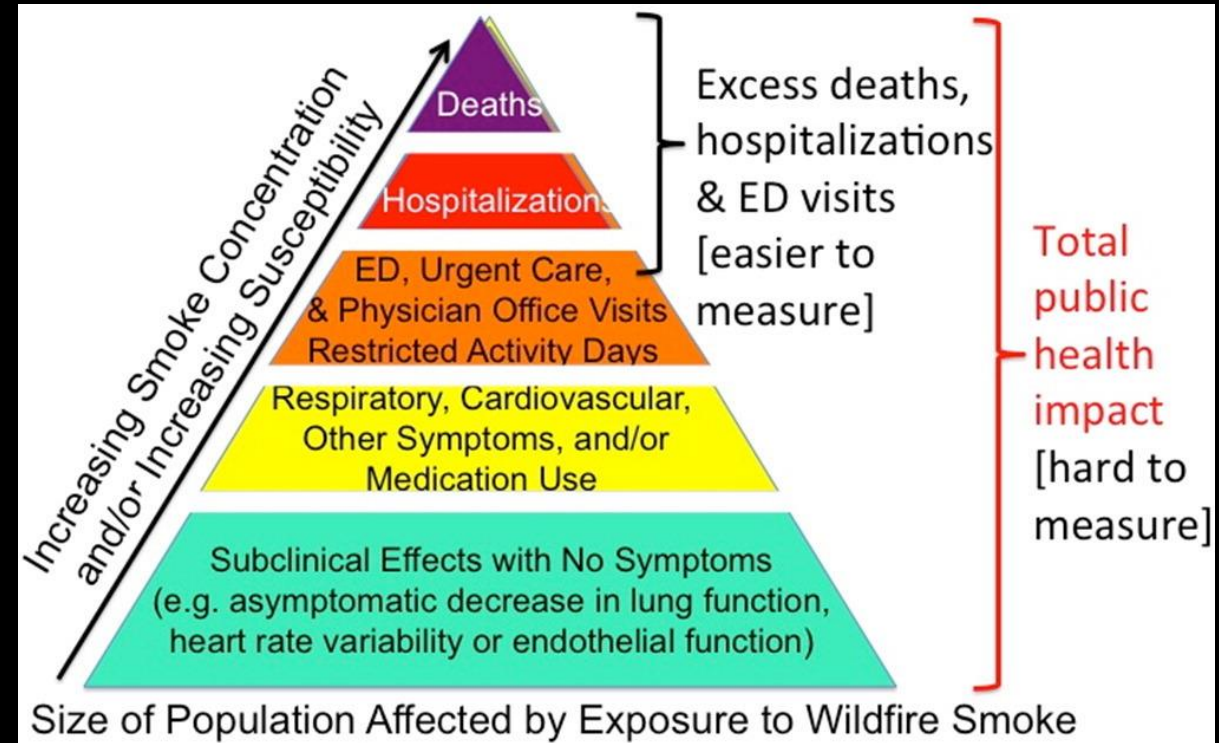


New Data May Be Available: Click to Refresh Data Layers



Epidemiological Difficulties in Studying Wildfires

- Studies are retrospective
 - → must use administrative health data
- “Tip of the Iceberg”



Cascio. (2017). Wildland fire smoke and human health. Science of the Total Environment.

Exposure Assessment Difficulties with Wildfires

Monitoring Data

- Some monitors only measure every third to sixth day

- Monitors miss a lot of spatial heterogeneity, particularly with fires

Satellite Data

- Temporal resolution issues

- Vertical resolution issues

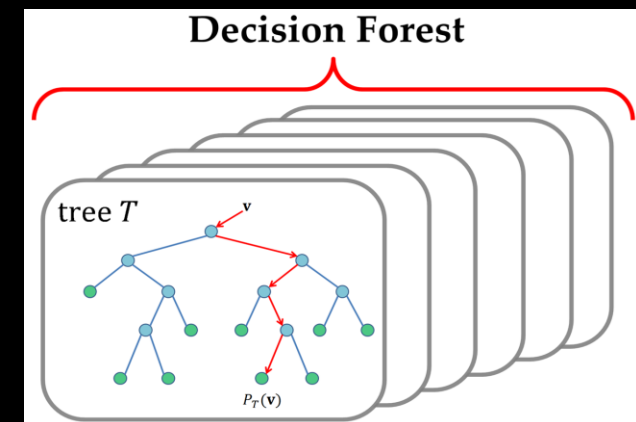
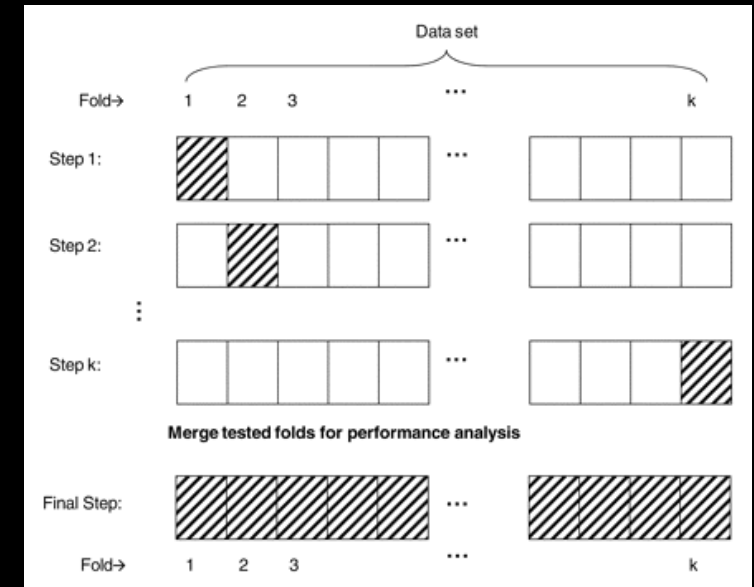
Chemical Transport Models

- Can be inaccurate

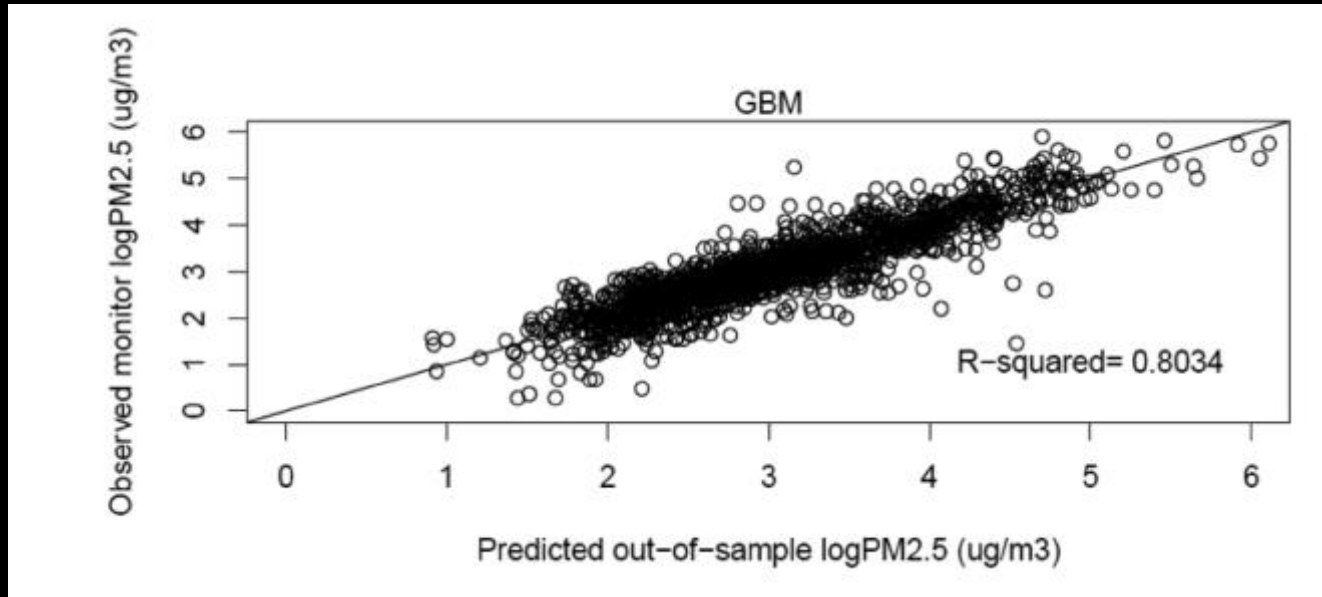


Exposure Assessment Methods Used in Wildfire Epidemiological Studies

- Blended Models
 - Statistically combine CTMs, satellite data, and monitoring data
 - Sometimes also auxiliary data
- My group uses machine learning to combine many auxiliary data set to create spatiotemporal estimates of air pollution concentrations

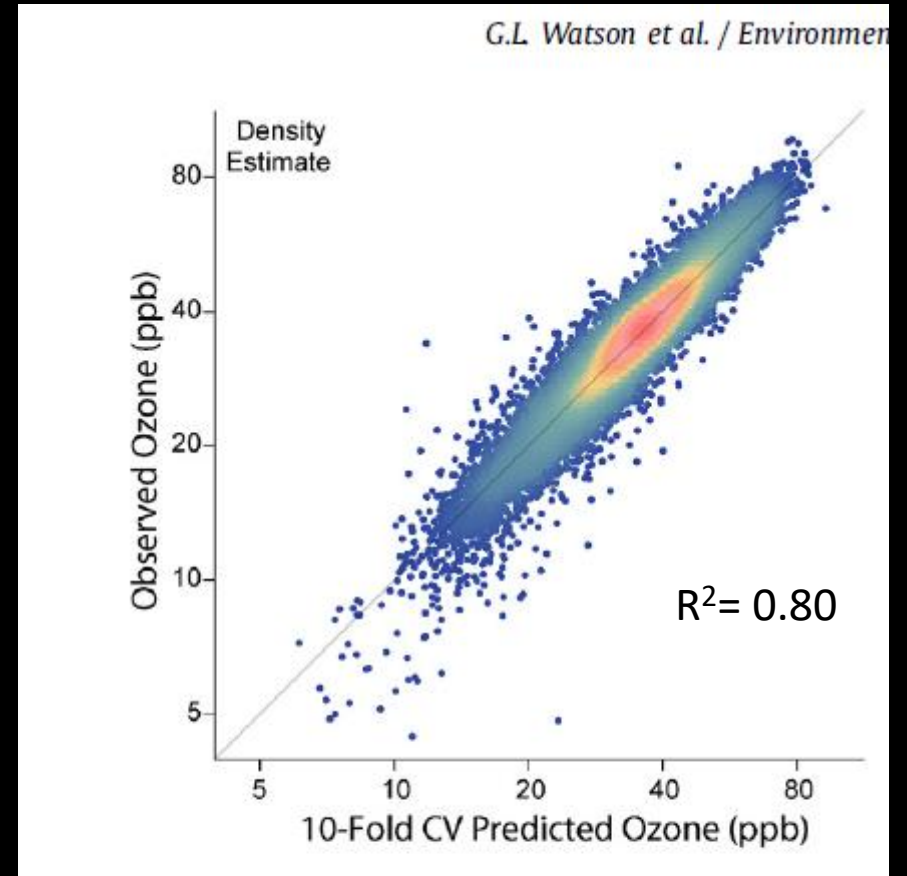


PM_{2.5} model



Reid et al. 2015. *Environmental Science & Technology*
Watson et al. 2019 *Environmental Pollution*

Ozone model



Relative risks of ED visits associated PM_{2.5} and ozone before, during, and after the 2008 northern California wildfires

Table 5
Relative risks (and 95% CIs) of ED visits associated with a 10 µg/m³ increase in PM_{2.5} before, during, and after the 2008 northern California wildfires.

Health outcome	Before fires	During fires	After fires
Combined respiratory	0.990 (0.953, 1.029)	1.035 (1.024, 1.045)	0.985 (0.943, 1.029)
Asthma	1.072 (0.980, 1.172)	1.115 (1.090, 1.140)	0.921 (0.845, 1.005)
COPD	0.953 (0.833, 1.091)	1.054 (1.023, 1.085)	1.110 (0.999, 1.235)
Pneumonia	0.907 (0.834, 0.988)	1.010 (0.985, 1.035)	1.013 (0.925, 1.110)
Acute bronchitis	1.132 (0.980, 1.307)	1.035 (0.997, 1.074)	1.066 (0.937, 1.213)
Acute respiratory infections	0.928 (0.870, 0.990)	0.997 (0.980, 1.015)	0.952 (0.889, 1.020)

Table 3
Relative risks (and 95% CIs) of ED visits associated with a 10 ppb increase in ozone before, during, and after the 2008 northern California wildfires.

Health outcome	Before fires	During fires	After fires
Combined respiratory	0.986 (0.968, 1.005)	1.013 (1.000, 1.027)	1.046 (1.029, 1.063)
Asthma	0.971 (0.934, 1.008)	1.050 (1.022, 1.078)	1.030 (0.997, 1.064)
COPD	0.985 (0.930, 1.043)	1.031 (0.998, 1.065)	1.010 (0.964, 1.058)
Pneumonia	0.984 (0.946, 1.023)	0.992 (0.965, 1.019)	1.011 (0.975, 1.048)
Acute bronchitis	0.945 (0.878, 1.017)	1.008 (0.966, 1.052)	1.006 (0.950, 1.065)
Acute respiratory infections	0.994 (0.962, 1.026)	0.998 (0.976, 1.020)	1.083 (1.057, 1.109)

All models are for the two-day moving average controlling for time trend, day of week, heat index, median income, percent of the population over 65, smoking prevalence, and ozone
Take from paper under revisions at Environment International.

PM_{2.5} and ozone exposure estimates by ZIP code by day for the 2008 northern California wildfires

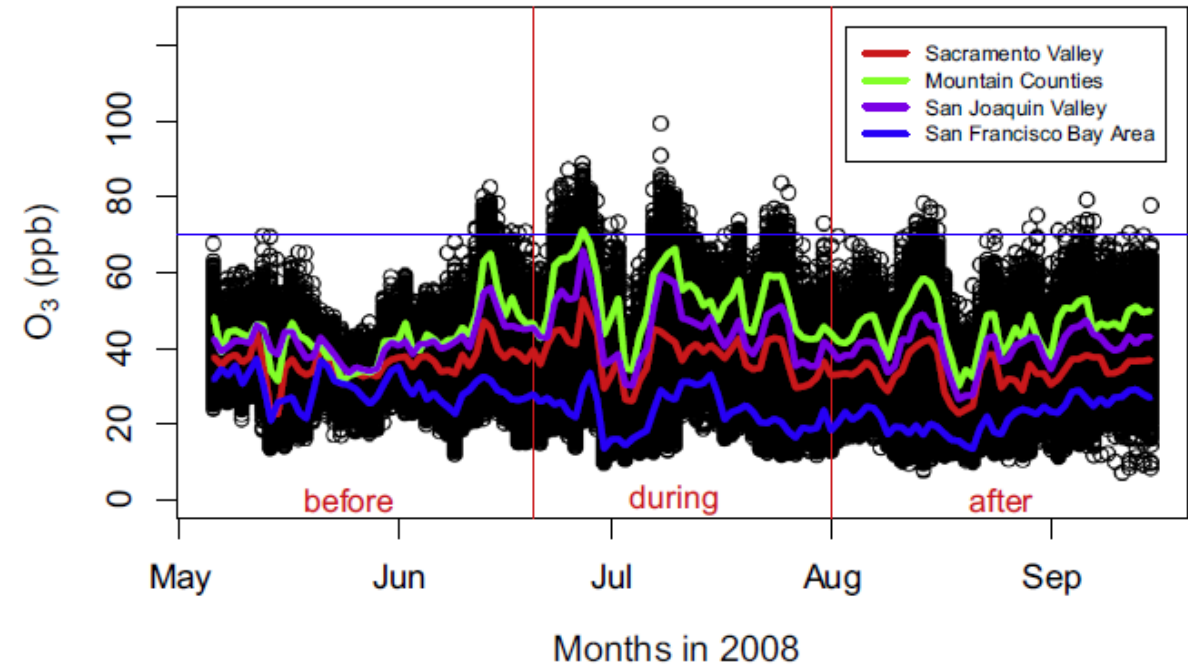
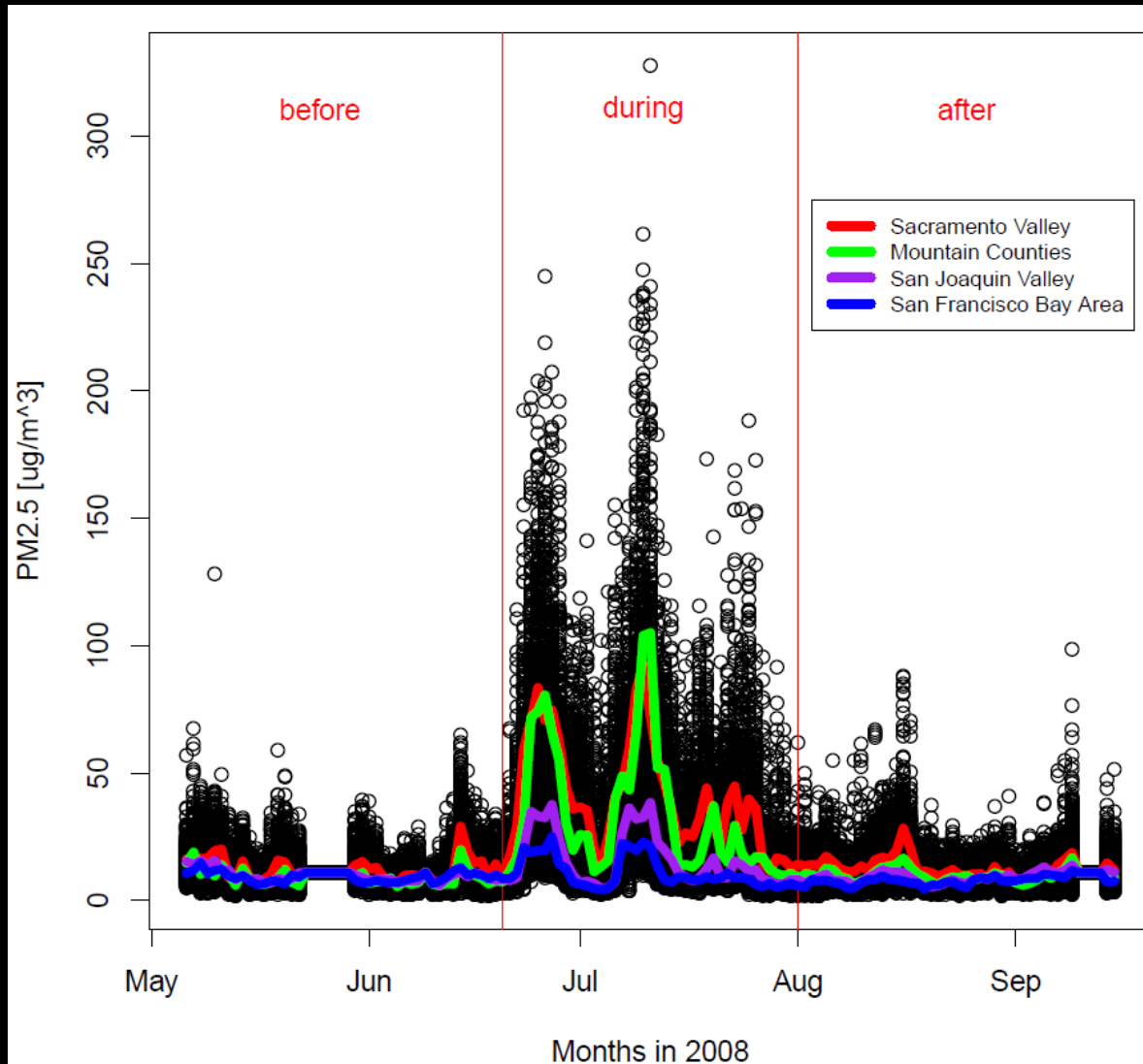


Fig. 3. Ozone levels by ZIP-code day during the study period with averages for some air basins.

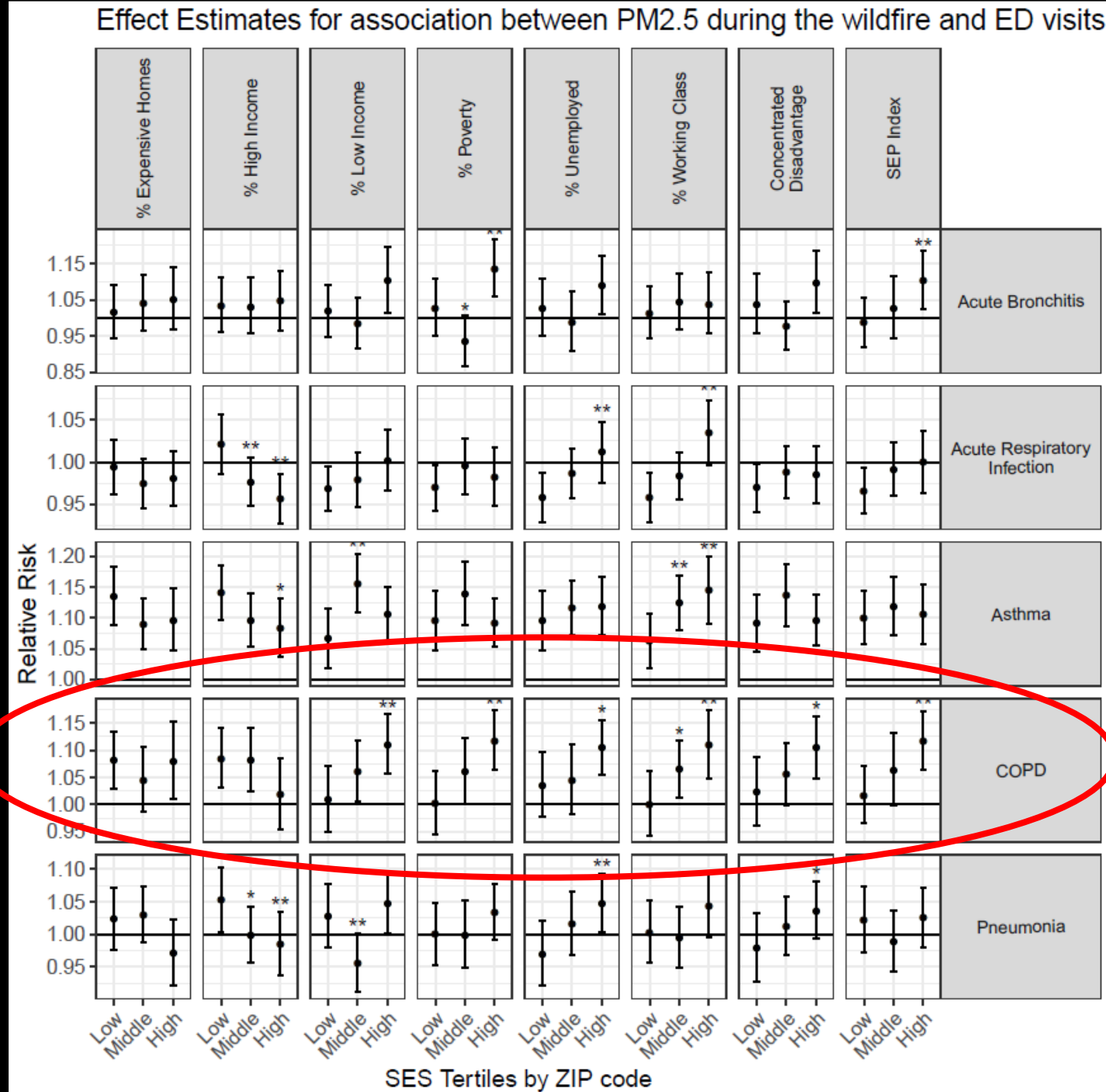
Effect estimates for association between PM_{2.5} and respiratory ED visits modified by SES

All models are for the two-day moving average controlling for time trend, day of week, heat index, median income, percent of the population over 65, smoking prevalence, and ozone
Not yet published.

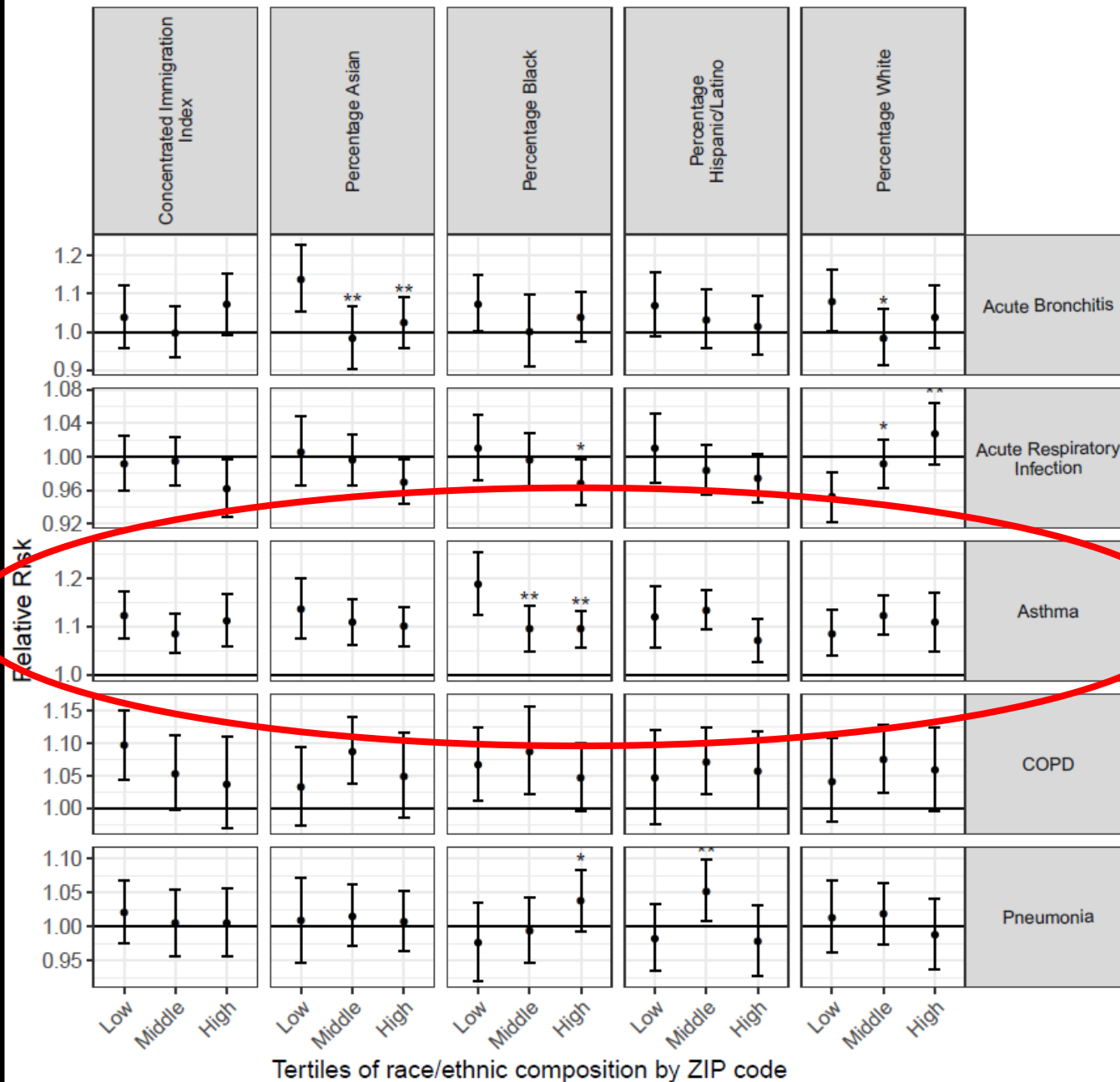


Effect estimates for association between PM_{2.5} and respiratory ED visits modified by SES

All models are for the two-day moving average controlling for time trend, day of week, heat index, median income, percent of the population over 65, smoking prevalence, and ozone
Not yet published.



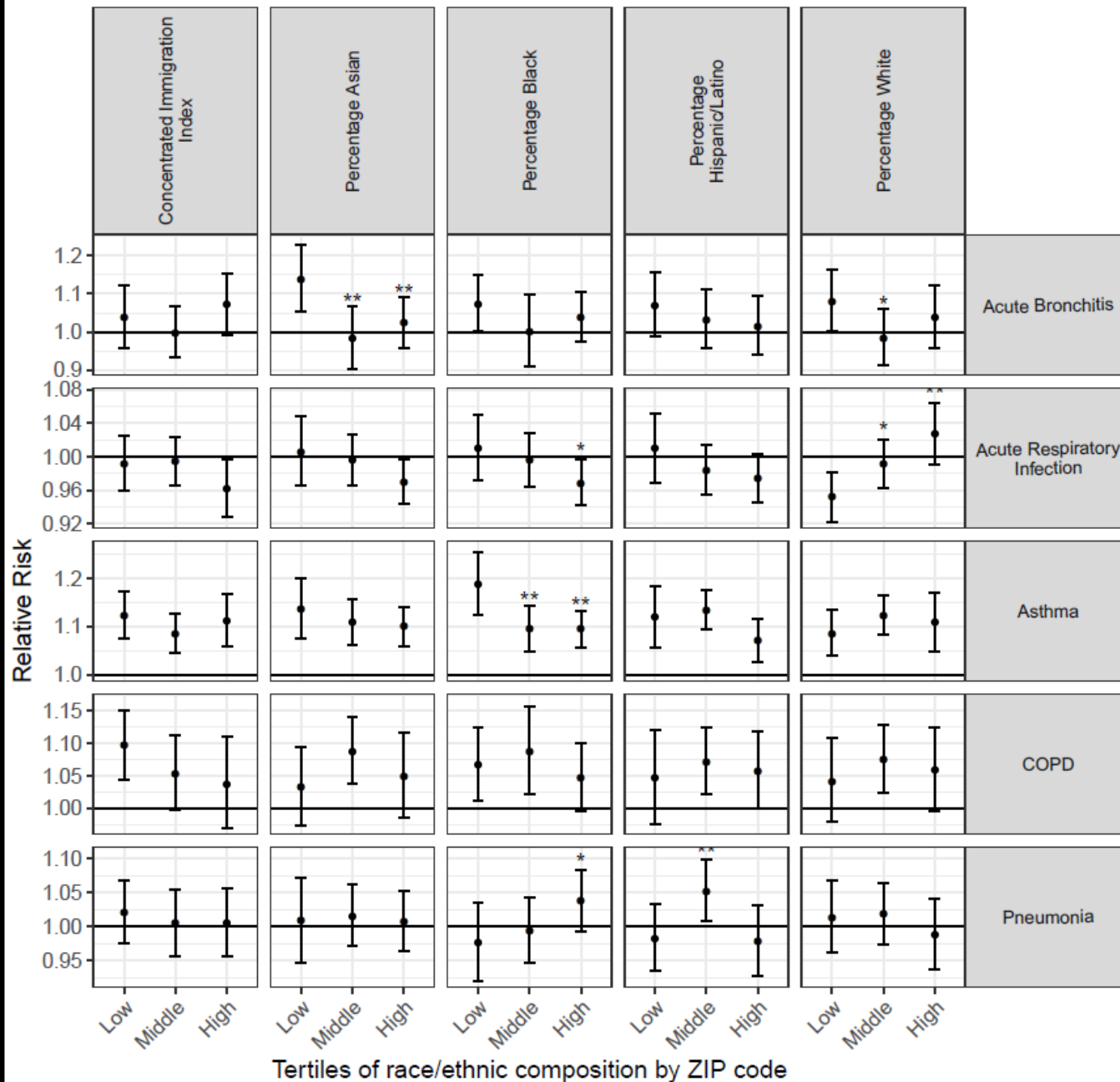
Effect Estimates for association between PM_{2.5} during the wildfire and ED visits



Effect estimates
for association
between PM_{2.5}
and respiratory
ED visits
modified by
racial/ethnic
composition

All models are for the two-day moving average controlling for time trend, day of week, heat index, median income, percent of the population over 65, smoking prevalence, and ozone
Not yet published.

Effect Estimates for association between PM_{2.5} during the wildfire and ED visits



Effect estimates
for association
between PM_{2.5}
and respiratory
ED visits
modified by
racial/ethnic
composition

All models are for the two-day moving average controlling for time trend, day of week, heat index, median income, percent of the population over 65, smoking prevalence, and ozone
Not yet published.

Why are lower SES communities more affected by wildfire smoke?

- In air pollution research from other sources, this is also found
- The differential findings could be due to:
 - Higher exposure to air pollution in lower SES communities
 - The role of the social determinants of health interacting with the environmental determinants of health
 - Or a combination of the two
- With wildfires, though, we wouldn't expect that the patterning of exposure to match the patterning of SES...

Fires effect on birth weight

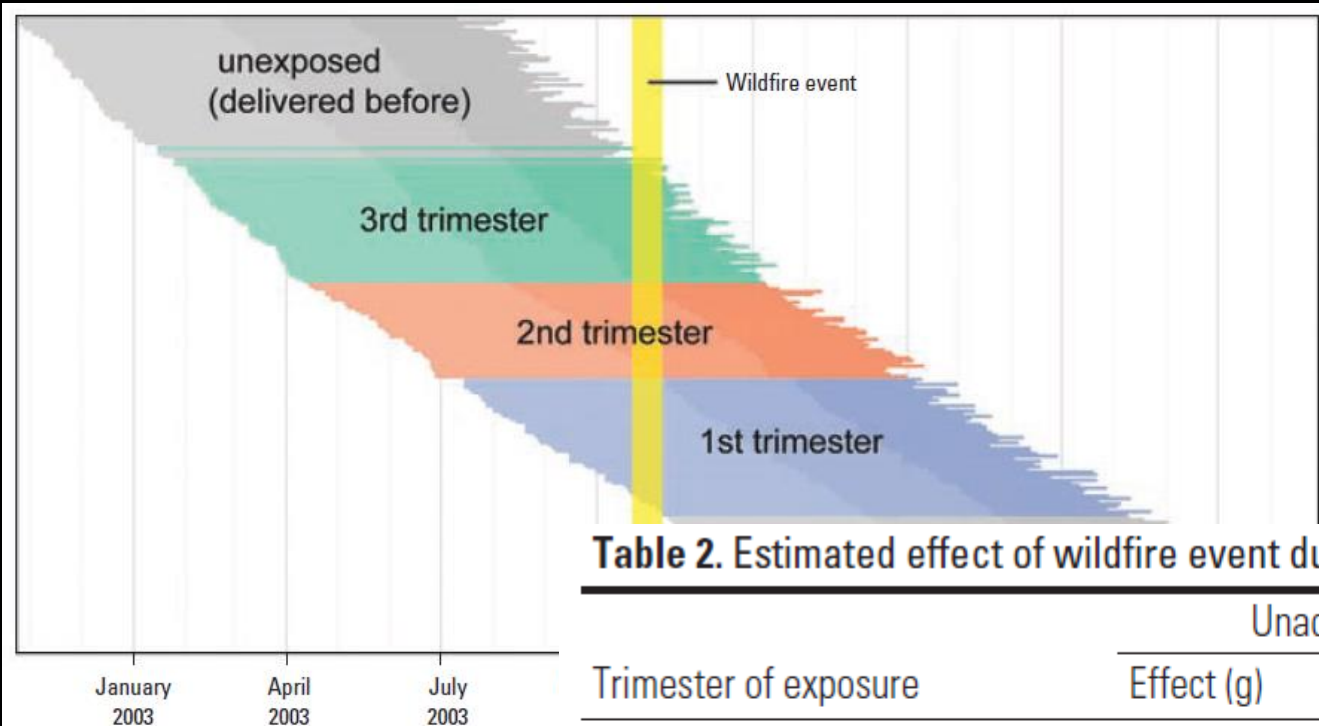
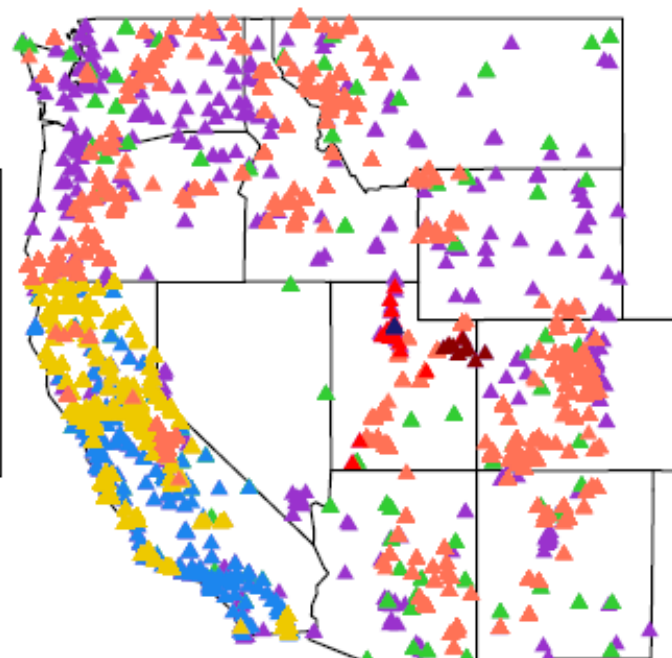
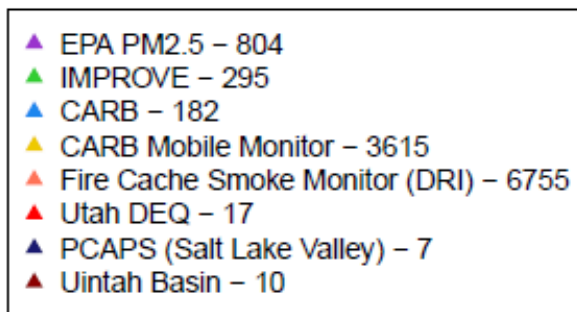


Figure 2. Schematic illustrating exposure as lap between the wildfire event (yellow) and clarity, gestational intervals are shown order from 2002–2004 is shown. Dates on the x-axis seasonality.

Table 2. Estimated effect of wildfire event during gestation on birth weight (g), by trimester.

Trimester of exposure	Unadjusted model		Adjusted model	
	Effect (g)	95% CI	Effect (g)	95% CI
Third (≥ 29 weeks)	–7.9	(–12.8, –3.1)	–7.0	(–11.8, –2.2)
Second (17–28 weeks)	–17.1	(–21.9, –12.3)	–9.7	(–14.5, –4.8)
First (1–16 weeks)	–3.9	(–7.8, 0.0)	–3.3	(–7.2, 0.6)
Any trimester	–8.8	(–11.5, –6.1)	–6.1	(–8.7, –3.5)

Adjusted model includes terms for fetal sex, gestational age, parity, maternal age, maternal education, maternal race/ethnicity, secular trend, and season.



Machine learning derived daily PM_{2.5} concentration estimates from by County, ZIP code, and census tract in 11 western states 2008-2018

[Cite](#)
[Download all \(2.82 GB\)](#)
[Share](#)
[Embed](#)
[+ Collect](#)
[...](#)
 27 views 25 downloads 0 citations

Dataset posted on 04.02.2021, 10:11 by Colleen Reid, Melissa Maestas, Ellen Considine, Gina Li

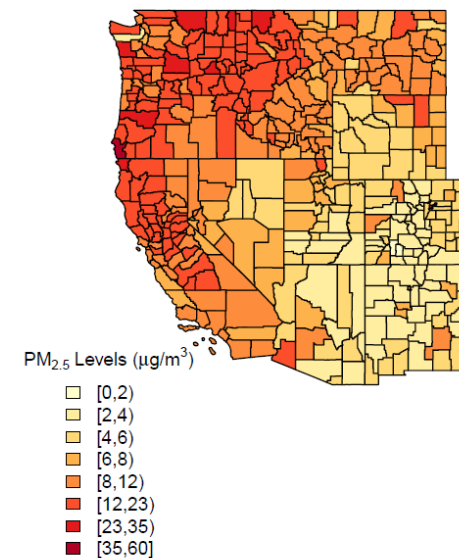
We created daily concentration estimates for fine particulate matter (PM_{2.5}) at the centroids of each county, ZIP code, and census tract across the western US, from 2008-2018. These estimates are predictions from ensemble machine learning models trained on 24-hour PM_{2.5} measurements from monitoring station data across 11 states in the western US. Predictor variables were derived from satellite, land cover, chemical transport model (just for the 2008-2016 model), and meteorological data. Ten-fold spatial and random CV R² were 0.66 and 0.73, respectively, for the 2008-2016 model and 0.58 and 0.72, respectively for the 2008-2018 model. Comparing areal predictions to nearby monitored observations demonstrated overall R² of 0.68 for the 2008-2016 model and 0.58 for the 2008-2018 model, but we observed higher R² (> 0.80) in many urban areas. These data can be used to understand spatiotemporal patterns of exposures to and health impacts of PM_{2.5} in the western US where PM_{2.5} levels have been heavily impacted by wildfire smoke over this time period.

CATEGORIES
 • Environmental and Occupational Health and Safety
 • Atmospheric Aerosols
 • Geography
 • Environmental Science

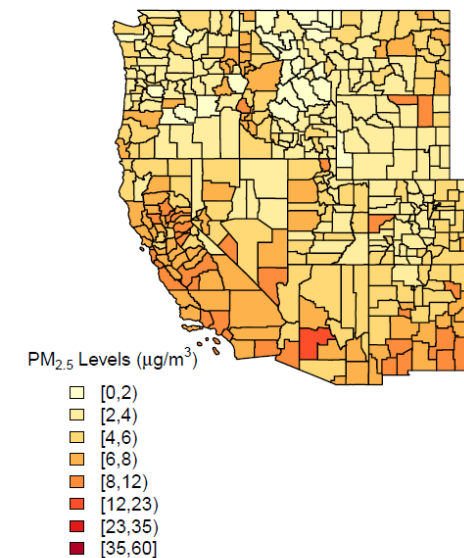
KEYWORDS
 air pollution
 fine particulate matter
 machine learning PM2.5

LICENCE

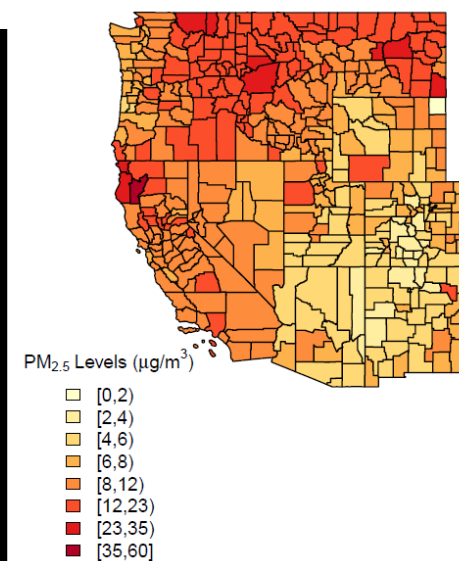
Fall 2017



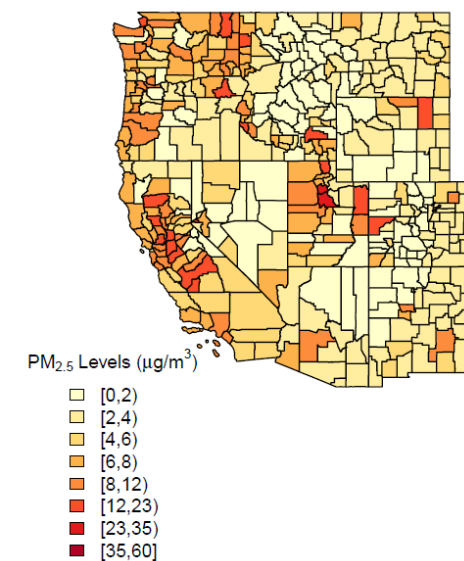
Spring 2011



Summer 2015



Winter 2013



Thank You!!

Colleen E. Reid, PhD MPH
Assistant Professor of Geography
University of Colorado Boulder
Colleen.Reid@Colorado.edu