Examining $PM_{2.5}$ concentrations and exposure using multiple models

19th Annual CMAS Conference, 26-30 October 2020, Virtual

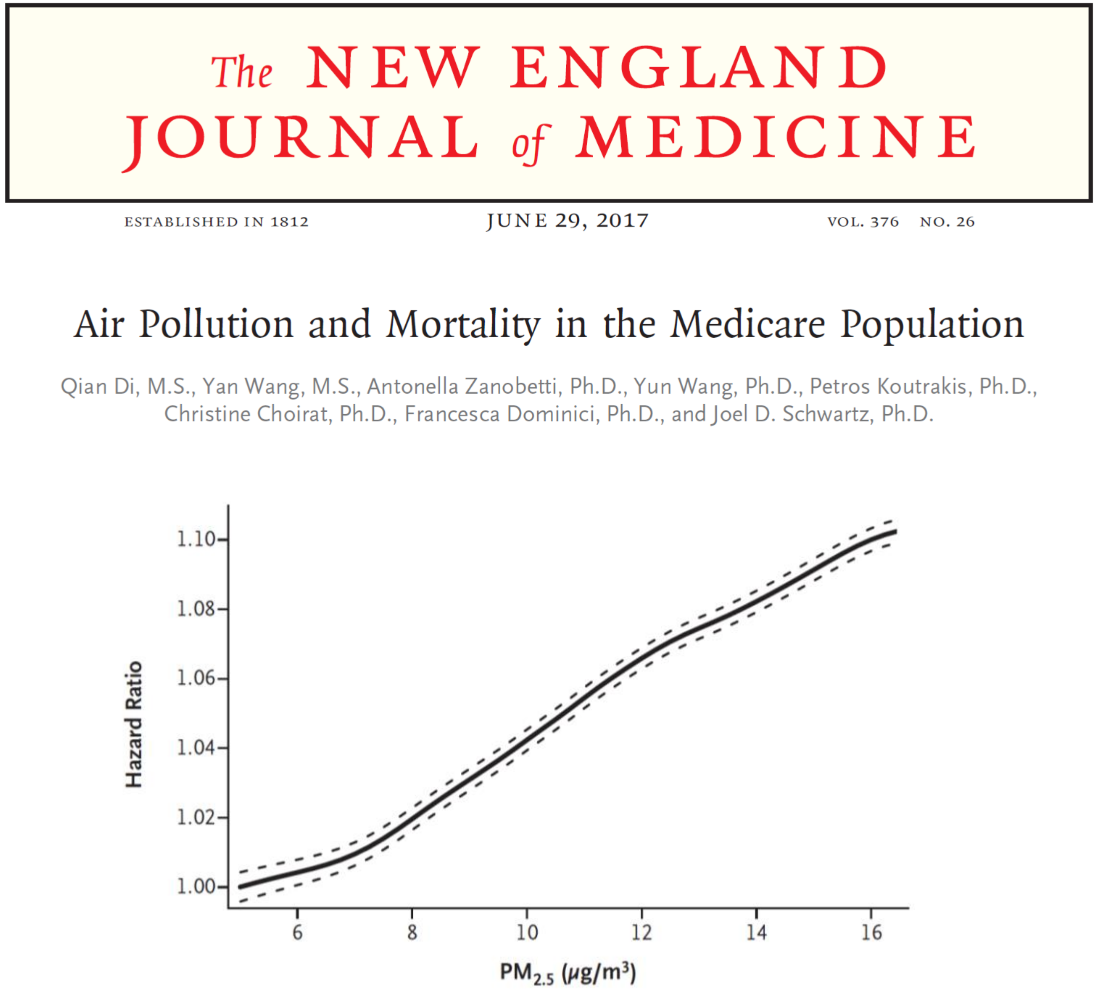
James T. Kelly[1], Carey Jang[1], Brian Timin[1], Qian Di[2], Joel Schwartz[3], Yang Liu[4], Aaron van Donkelaar[5,6], Randall V. Martin[5-7], Veronica Berrocal[8], and Michelle L. Bell[9]

[1]Office of Air Quality Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC
[2]Vanke School of Public Health, Tsinghua University, Beijing
[3]Department of Environmental Health, Harvard T.H. Chan School of Public Health, Boston, MA
[4]Gangarosa Department of Environmental Health, Rollins School of Public Health, Emory University, Atlanta, GA
[5]Department of Physics and Atmospheric Science, Dalhousie University, Halifax, Nova Scotia
[6]Department of Energy, Environmental & Chemical Engineering, Washington University, St. Louis, MO
[7]Harvard-Smithsonian Centre for Astrophysics, Cambridge, MA
[8]Donald Bren School of Information and Computer Sciences, University of California, Irvine, CA
[9]School of the Environment, Yale University, New Haven, CT

The views expressed in this presentation are those of the authors alone and do not necessarily reflect the views and policies of the U.S. Environmental Protection Agency

Background

- Associations between fine particulate matter ($PM_{2.5}$) exposure and adverse health effects have been reported, with 4.2 million deaths attributed in 2015
- Due to the limited coverage of monitoring, exposure assignments in health studies are increasingly based on modeled fields that incorporate available monitoring
- Continuous fields of $PM_{2.5}$ concentrations have facilitated epidemiologic studies with national coverage (e.g., Medicare cohort)


The NEW ENGLAND JOURNAL of MEDICINE

ESTABLISHED IN 1812 JUNE 29, 2017 VOL. 376 NO. 26

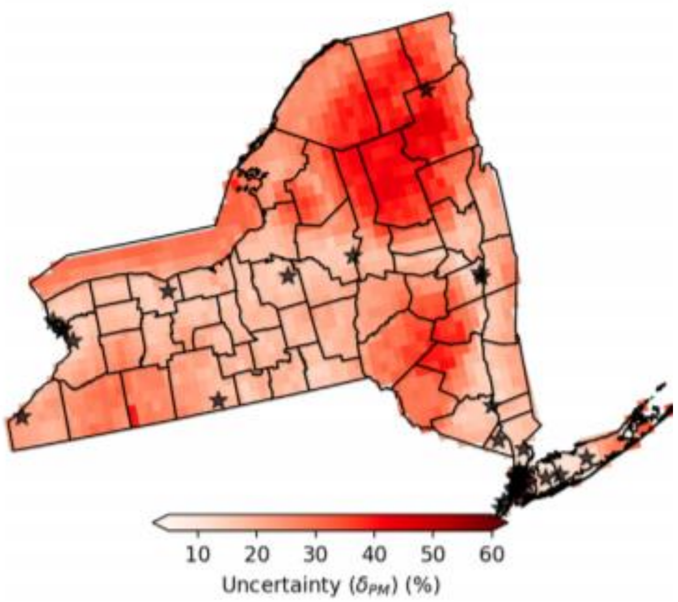
Air Pollution and Mortality in the Medicare Population

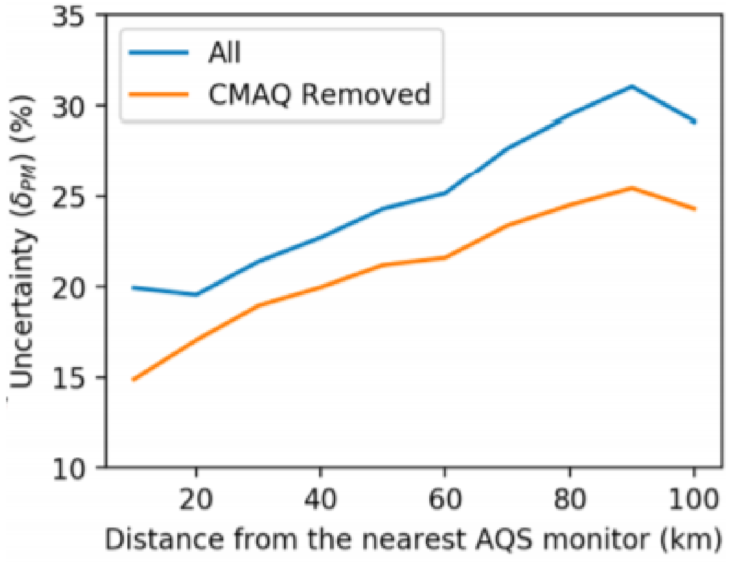
Qian Di, M.S., Yan Wang, M.S., Antonella Zanobetti, Ph.D., Yun Wang, Ph.D., Petros Koutrakis, Ph.D., Christine Choirat, Ph.D., Francesca Dominici, Ph.D., and Joel D. Schwartz, Ph.D.

Di et al. (2017) New England Journal of Medicine

Evaluation of $PM_{2.5}$ Fields

- Use of modeled $PM_{2.5}$ fields in policy-relevant health studies has raised questions about the reliability and consistency of exposure assignments
- Cross validation statistics can be excellent ($R^2 > 0.80$), but the relationship between such statistics and outcomes in specific health studies is unclear
- Moreover, studies have reported degradation in performance with distance to the nearest monitor (Figure, bottom)
- More work is needed to examine the influence of modeling approaches on outcomes in specific studies





[Jin et al. (2019)](#)

Objectives

- We use nine $PM_{2.5}$ concentration models (i.e., exposure models) that span a wide range of methods to assess

  i. $PM_{2.5}$ concentrations in 2011

  ii. Potential changes in $PM_{2.5}$ concentrations between 2011 and 2028 due to modeled emission changes

  iii. $PM_{2.5}$ exposure for the U.S. population and four racial/ethnic groups

The use of multiple models provides insights on current exposure modeling methods as well as a thorough characterization of $PM_{2.5}$ concentrations and exposure

Models

Case	Name	Method Description	Reference
1.	CMAQ	Geophysical process model (v5.0.2)	US EPA (2015); Kelly et al. (2019a)
2.	CAMx	Geophysical process model (v6.3.2)	US EPA (2017)
3.	VNA	Interpolation of $PM_{2.5}$ observations	Abt (2012); Kelly et al. (2019b)
4.	eVNA	Interpolation of obs w/ fusion of CTM results	Abt (2012); Kelly et al. (2019b)
5.	Downscaler	Bayesian statistical regression of CTM predictions and observations	Berrocal et al. (2010); US EPA (2020)
6.	VD2019	CTM scaling of satellite AOD to surface $PM_{2.5}$ with geographically-wt. regression of residuals	van Donkelaar et al. (2019), modified per V4.NA.02.MAPLE
7.	DI2016	Neural network model	Di et al. (2016)
8.	HU2017	Random forest model	Hu et al. (2017)
9.	DI2019	Ensemble of random forest, gradient boosting, and neural network learners	Di et al. (2019)

Study Methods

- 2011 $PM_{2.5}$ concentrations are averaged to the annual period on a common to 12-km grid
- Exposure is estimated with population-weighted average concentrations using 2010 Census data*
- Projection from 2011 to 2028 is based on relative response factors from previous CAMx modeling:

$$RRF_{species} = \frac{C_{2028,species}}{C_{2011,species}} \quad (1)$$

$$RRF_{Tot,PM2.5} = \frac{\sum C_{Obs,species} RRF_{species}}{\sum C_{Obs,species}} \quad (2)$$

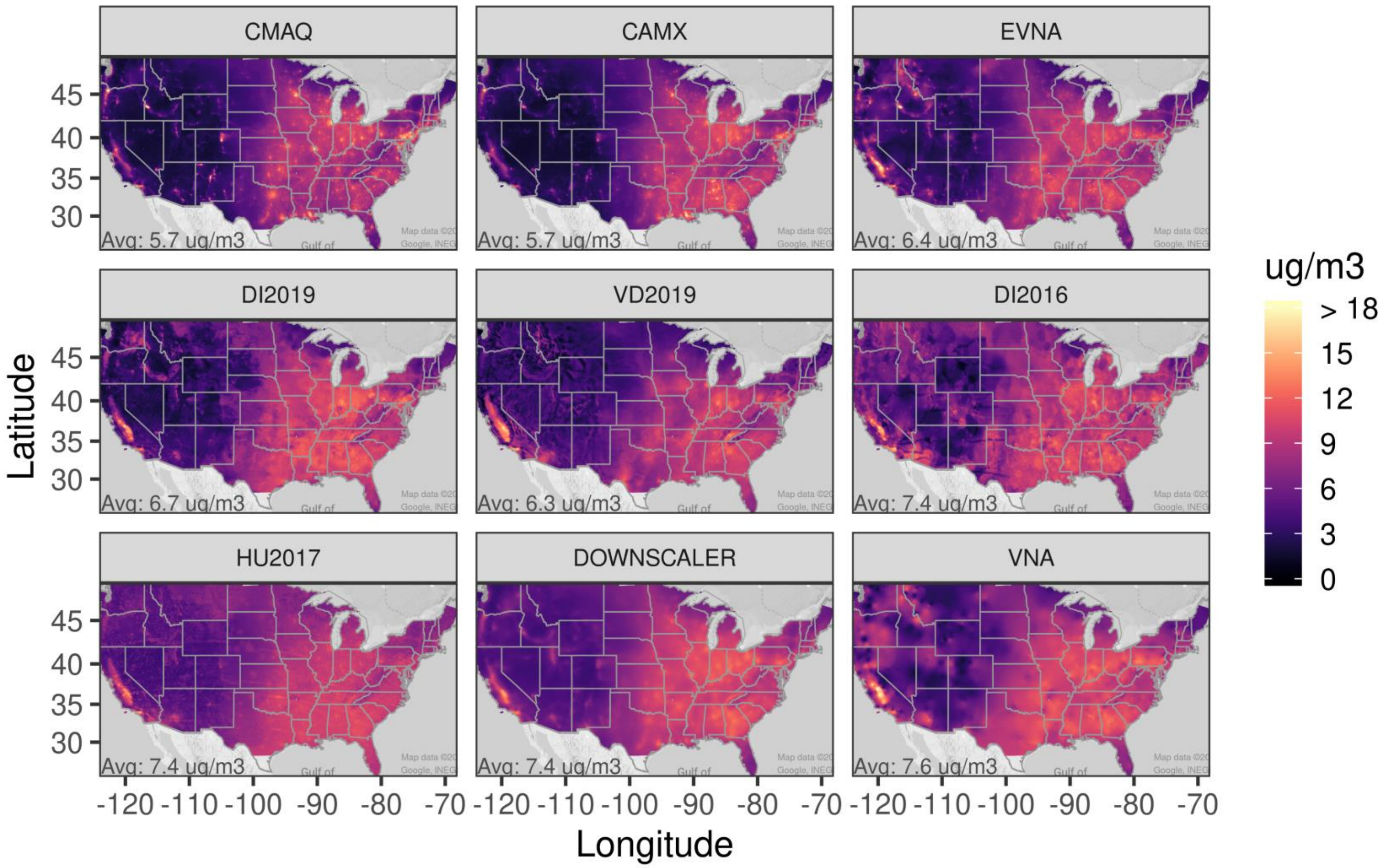
$$PM2.5_{Mod,2028} = RRF_{Tot,PM2.5} PM2.5_{Mod,2011} \quad (3)$$

Emission Change: 2011 to 2028

Pollutant	Emission Change
SO_2	-63%
NO_x	-50%
VOC	-20%
$PM_{2.5}$	-4%

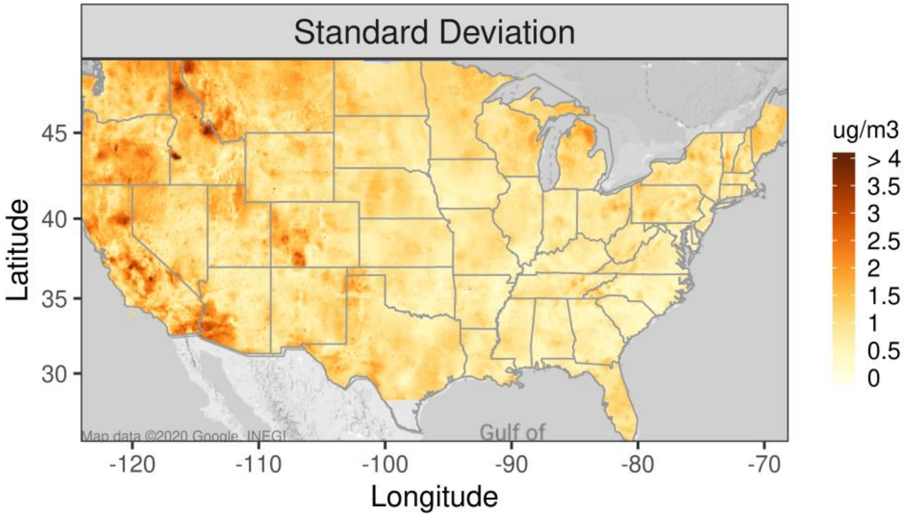
*Based on census block data aggregated to 1- or 12-km grid, https://doi.org/10.7927/H40Z716C

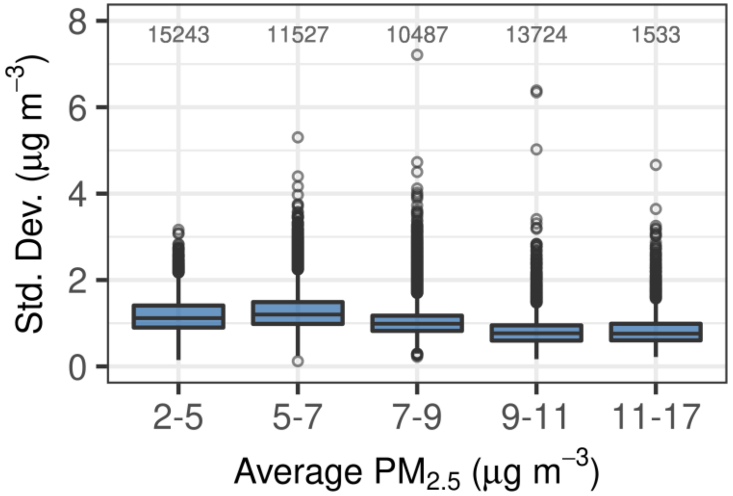
2011 $PM_{2.5}$ Concentrations

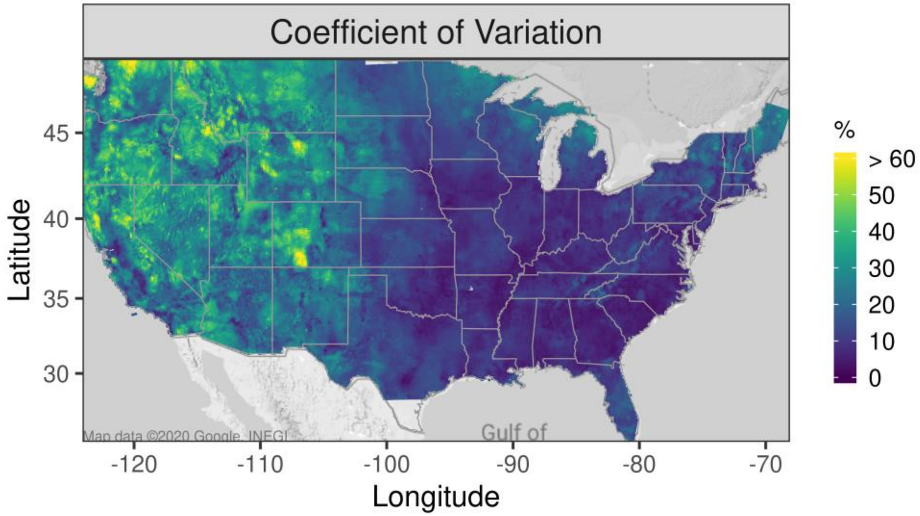


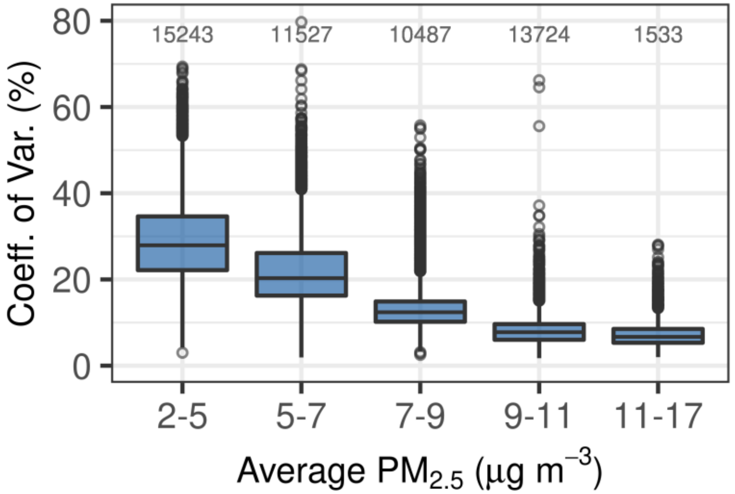
- Broad agreement in $PM_{2.5}$ spatial variation among models
- CMAQ and CAMx have the lowest national average, but high $PM_{2.5}$ in cities
- The relatively smooth fields (VNA and Downscaler) have the highest national average

Variability Among Non-CTM Models

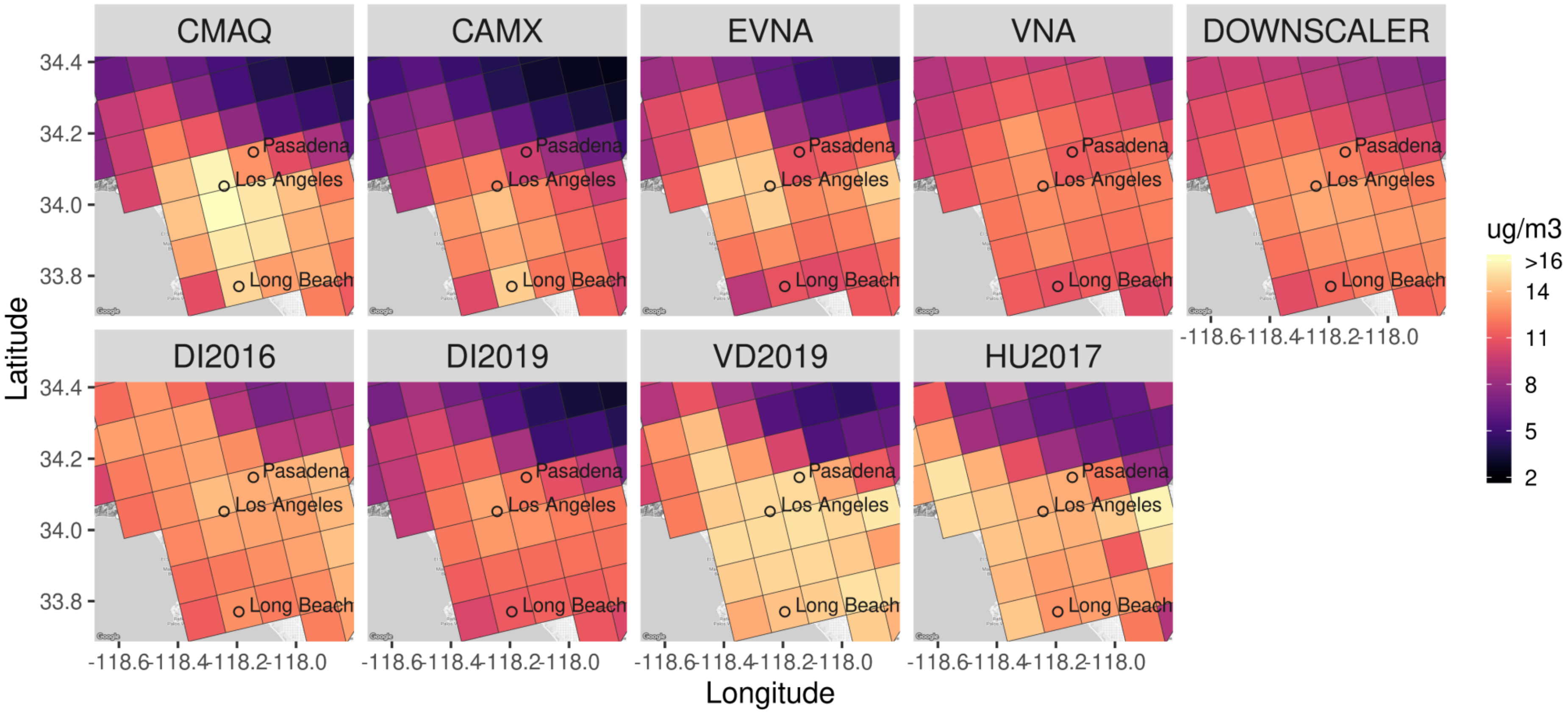




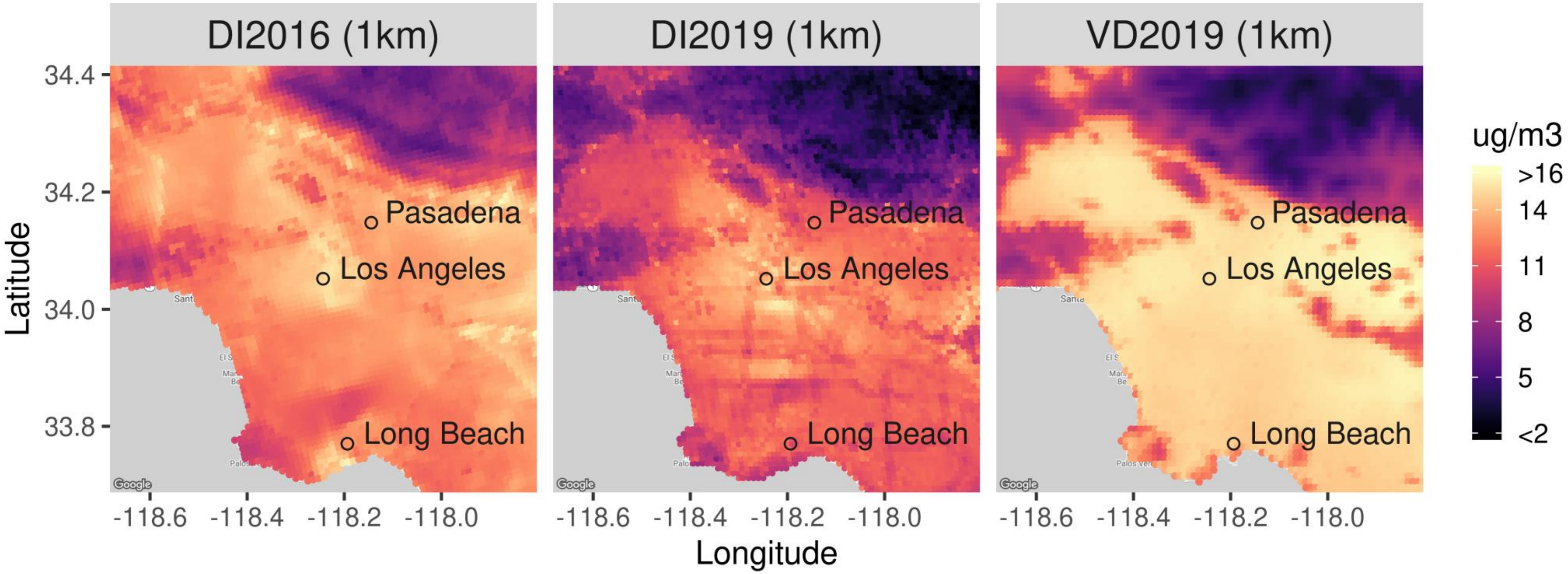




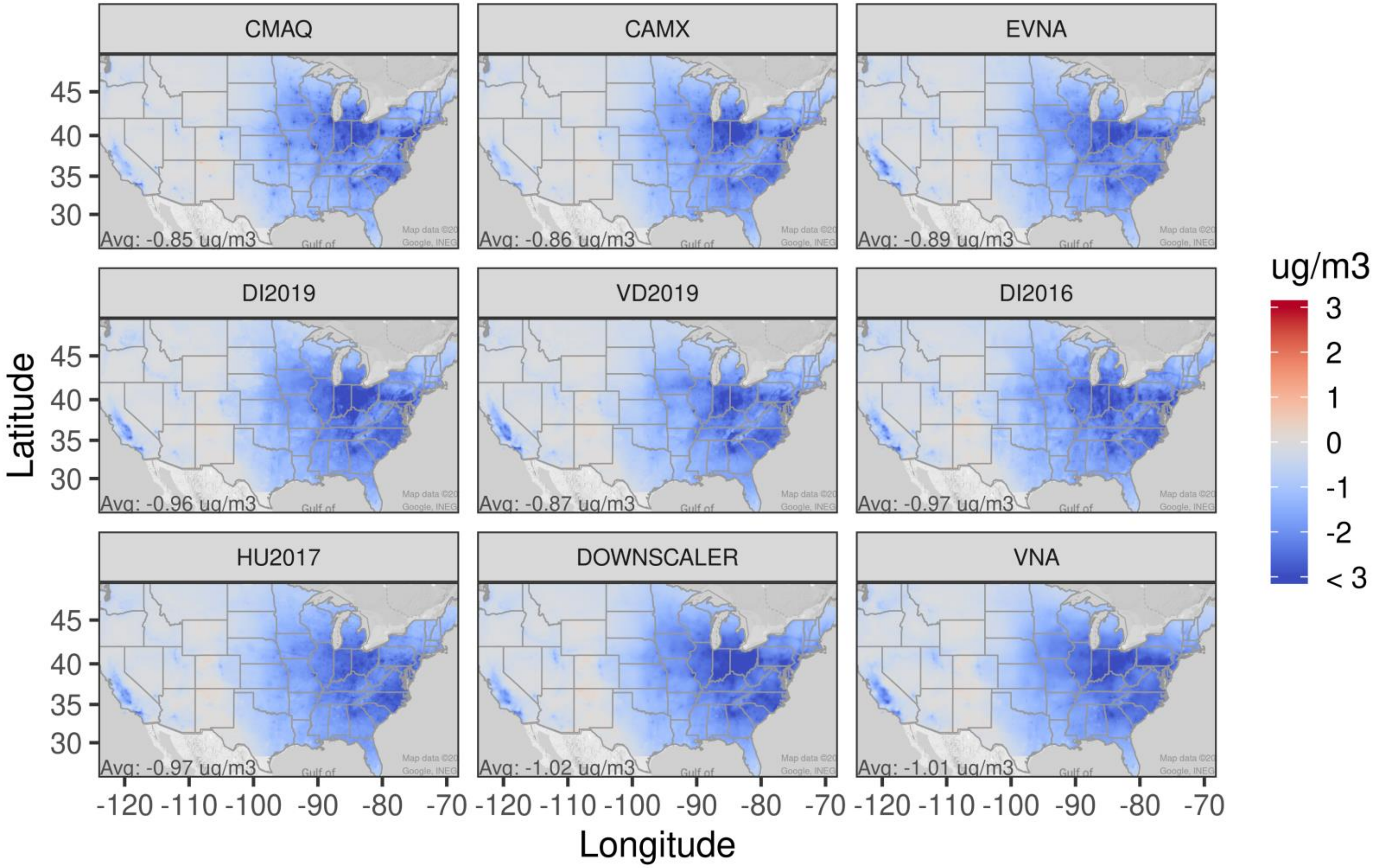
Los Angeles (12-km)



Los Angeles (1-km)



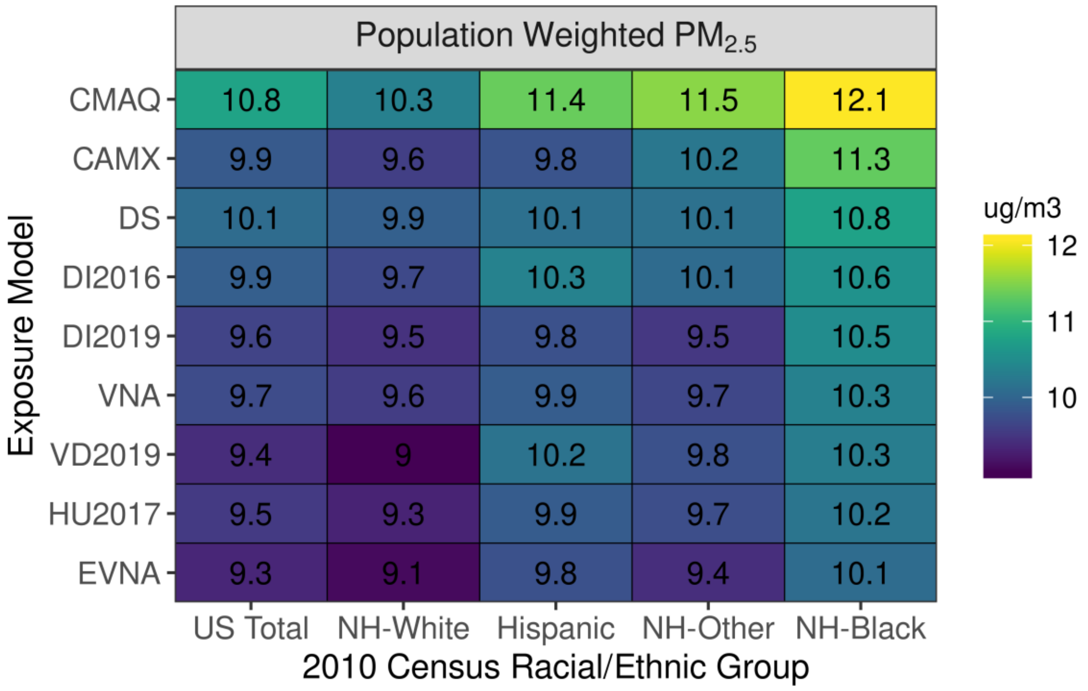
$\Delta PM_{2.5}$ Concentrations (2028 – 2011)



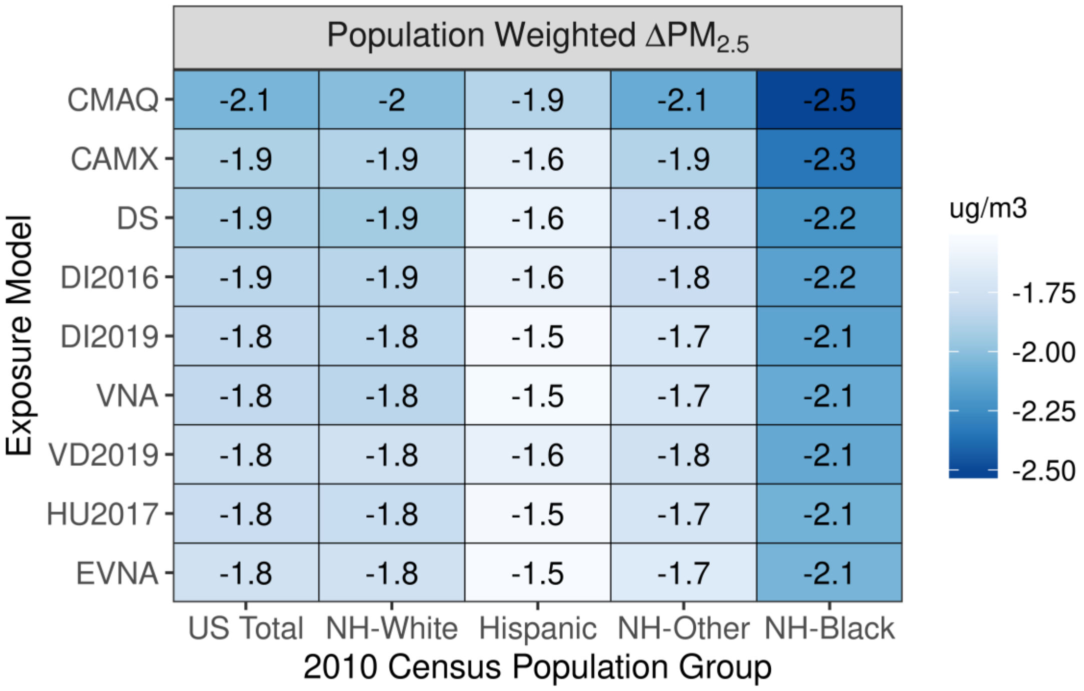
- Large (>3 $\mu g\ m^{-3}$) decreases in $PM_{2.5}$ in parts of the east with reduced SO_2 emissions
- Broad agreement in $\Delta PM_{2.5}$ spatial variation among models
- Differences in spatial variations follow 2011 fields due to use of same RRFs in all cases

National Population-Weighted $PM_{2.5}$

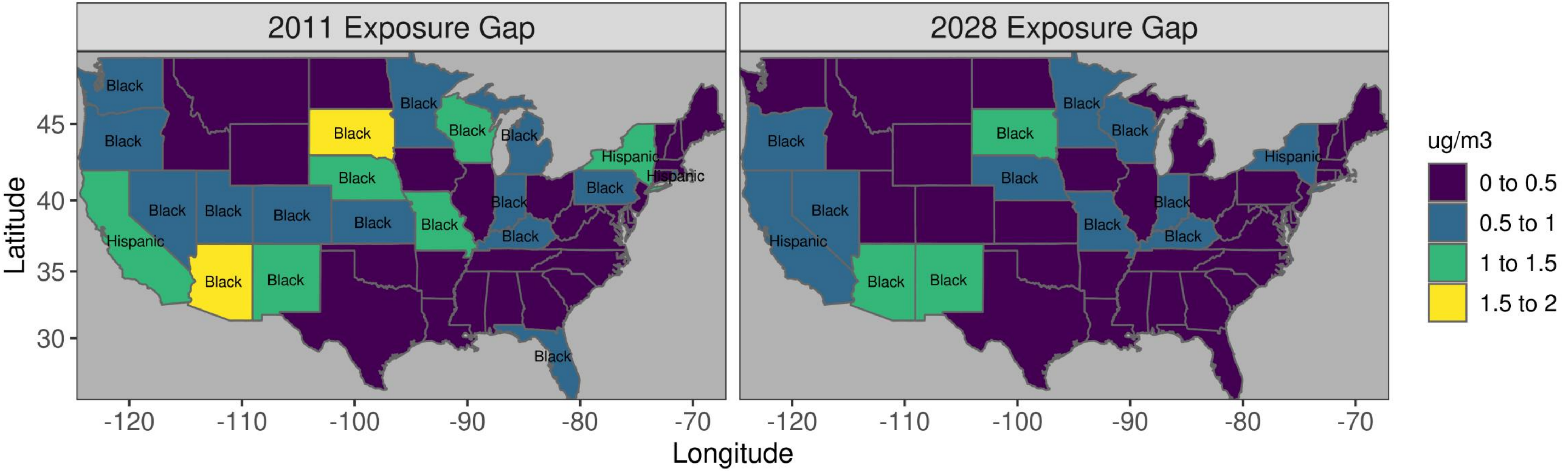
2011 $PM_{2.5}$



$\Delta PM_{2.5}$ (2028 – 2011)



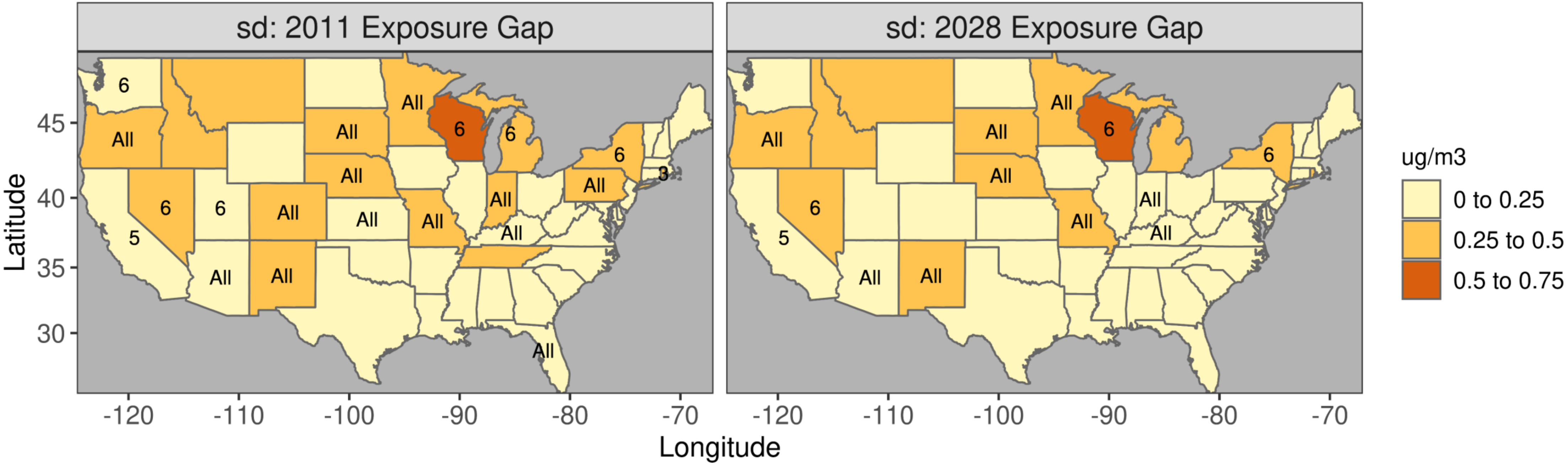
Exposure Gap



- The exposure gap* between the highest- and lowest-exposure group is shown with labels for the highest-exposed group when $\Delta PM_{2.5} > 0.5\ \mu g\ m^{-3}$
- Modeled emission reductions from 2011 to 2028 reduce the absolute exposure gap

*Based on average concentration field across the seven non-CTM models

Standard Deviation in Exposure Gap Among Models



- The standard deviation in exposure gap from the seven non-CTM models is shown with a label for the number of models predicting the same most-exposed group
- Standard deviations are generally <0.5 $\mu g\ m^{-3}$ and models generally agree on the most exposed group

Conclusions

- $PM_{2.5}$ predictions for 2011 are in broad agreement among the non-CTM models at regional and national scales, although differences in intra-urban spatial variations are evident
- Agreement among models is closer for population-weighted $PM_{2.5}$ than uniformly weighted $PM_{2.5}$ due to relatively large differences in sparsely populated and monitored western regions
- Reductions in $PM_{2.5}$ concentrations were predicted broadly over the eastern U.S. and parts of the west for modeled emission changes between 2011 and 2028; $\Delta PM_{2.5}$ was not very sensitive to the selection of 2011 $PM_{2.5}$ field
- The absolute exposure gap across four racial/ethnic groups is predicted to decrease based on modeled emission changes between 2011 and 2028