Pollutant Spatial Fields to Characterize Exposure: Initial Work and Insights

AQAD Management Technical Meeting
18 December 2020

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Overview

1. Context from recent EJ coordination activity in the office

2. Presentation of results from spatial model intercomparison study

3. Discussion of programmatic needs and next steps

Ongoing EJ-related Discussions Across Office

- Interest in EJ raised earlier this year given national events
- Analytical discussions and engagement occuring across the office
  - EJ Analytics meetings hosted by Sara Terry (was OID now HEID)
  - Climate/EJ discussions hosted by Kevin Culligan
  - Air Toxics Strategy: Air Toxics Data Analytics Team led by Amy Vasu
  - Others?
- AQAD essential to analytics across office to inform and address EJ needs across multiple programs
  - Provide understanding of historical, current, and projected disparities in exposure
    - Provides context and insights across the office about trends, highest exposed communities, contributing sectors.
  - Provide capabilities to assess EJ impacts of policy options/control scenarios
- Need specifics from other divisions on what programmatic needs are?

Questions of Potential Relevance to EJ Programs

- What are the **most exposed groups** and how do exposures vary
  - spatially (nationally, urban, NAA),
  - temporally (past trends vs. projected, seasonally),
  - by pollutant (criteria, toxic), and
  - by metric (peak vs. mean, EJ metric)?
- What are the **key sources** that contribute to exposure within EJ communities, including emerging pollutants of concern (e.g., PFAS)?
- What **screening approaches** can be used to identify programmatically relevant areas of focus for EJ analyses?
- What **refined methods** and localized information can be used to understand EJ implications of actions early enough in the process to influence outcomes (e.g., Federal action, SIPs, permitting)?

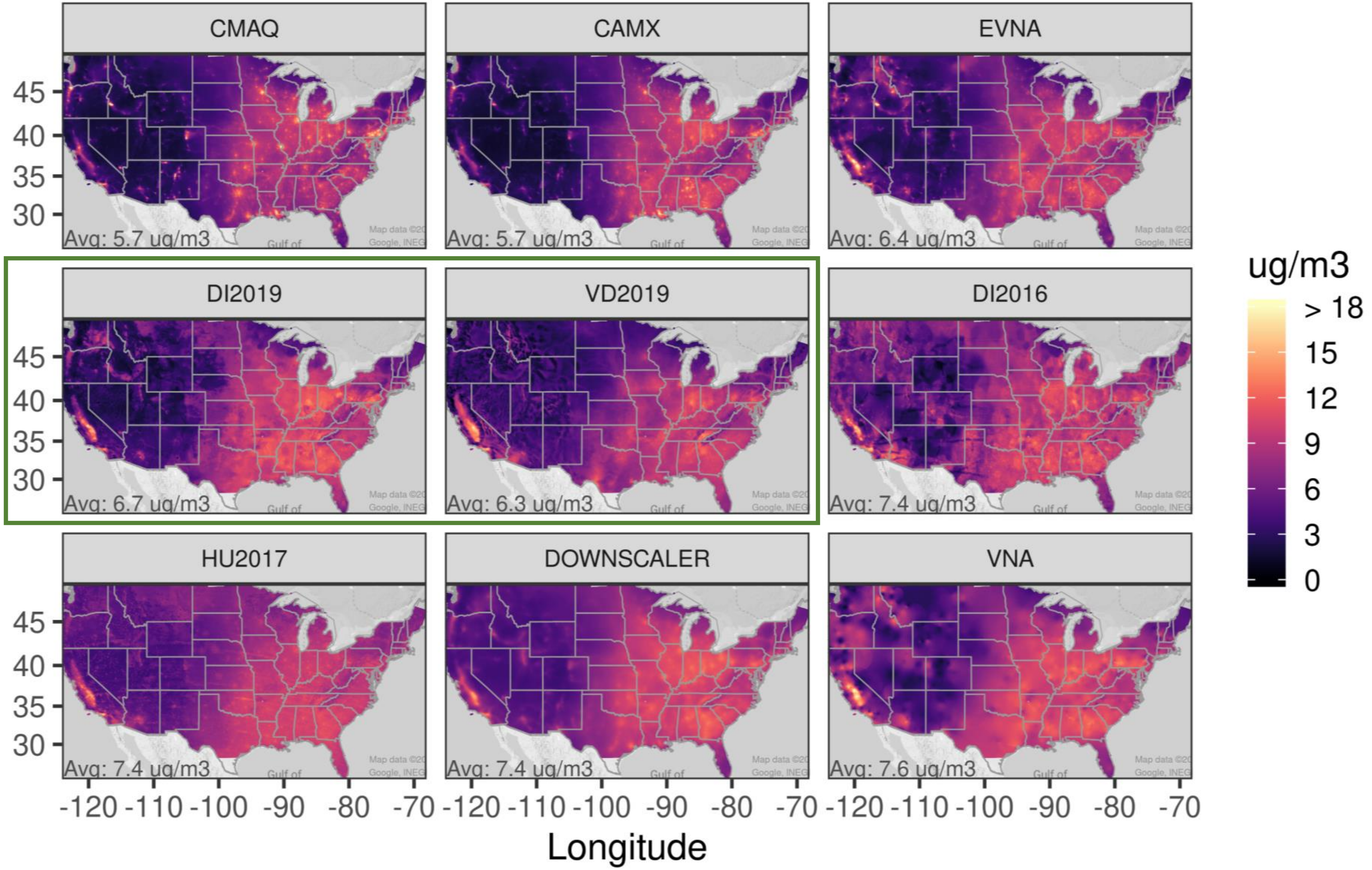
Introduction

- Earlier this year, we proposed a joint study with HEID examining the variability in health effects associated with different health functions and $PM_{2.5}$ spatial fields
- The proposal was redirected to an AQ intercomparison study that received approval to examine the variability in $PM_{2.5}$ concentrations, exposure, and changes over time associated with different $PM_{2.5}$ fields
- Analyses from the intercomparison study were then related to questions of interest from ongoing EJ discussions to provide preliminary insights as described below

Models in Intercomparison Study

Name	Method Description	Comments	Reference
CMAQ	Geophysical process model (v5.0.2)	Crucial for "what-if" scenarios, but not constrained with obs	US EPA (2015); Kelly et al. (2019a)
CAMx	Geophysical process model (v6.3.2)	Crucial for "what-if" scenarios, but not constrained with obs	US EPA (2017)
VNA	Interpolation of $PM_{2.5}$ observations	Accurate near monitors, but does not reflect unmonitored gradients	Abt (2012); Kelly et al. (2019b)
eVNA	Interpolation of obs w/ fusion of CTM results	Accurate near monitors, but unmonitored gradients sensitive to CTM performance	Abt (2012); Kelly et al. (2019b)
Downscaler	Bayesian statistical regression of CTM predictions and observations	Reasonable overall performance w/ limited data but tends to smooth out gradients	Berrocal et al. (2010); US EPA (2020)
VD2019	CTM scaling of satellite AOD to surface $PM_{2.5}$ w/ regression of residuals	Good performance at high resolution for long record; may not fully resolve gradients	van Donkelaar et al. (2019)
DI2016	Neural network model	Good performance at high resolution, but artifacts evident and now updated, DI2019	Di et al. (2016)
HU2017	Random forest model	Good performance, but limitations in resolution, availability and spatial features	Hu et al. (2017)
DI2019	Ensemble of random forest, gradient boosting, and neural network	Good performance at high resolution for long record; some non-intuitive hi-res	Di et al. (2019)

Model Selection for Today's Discussion



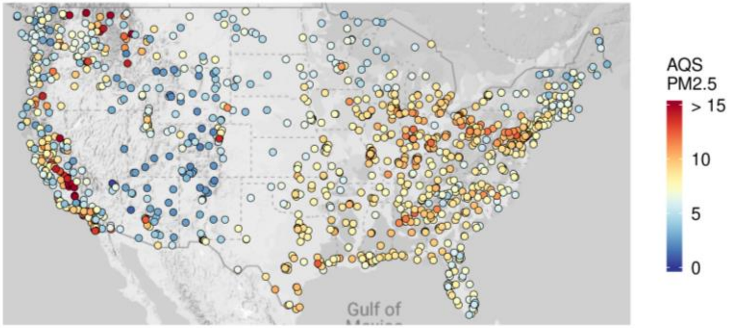
Here we use the satellite (VD2019) and machine learning (DI2019) methods

i. Good performance
ii. Multi-decade availability
iii. High resolution
iv. Contrasting algorithms
v. Scientific credibility

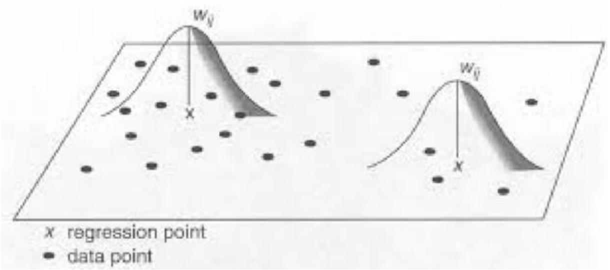
Satellite Method

- Satellite AOD is scaled to surface $PM_{2.5}$ using AQ model
- Surface $PM_{2.5}$ estimate is then fused with obs using regression

Monitoring

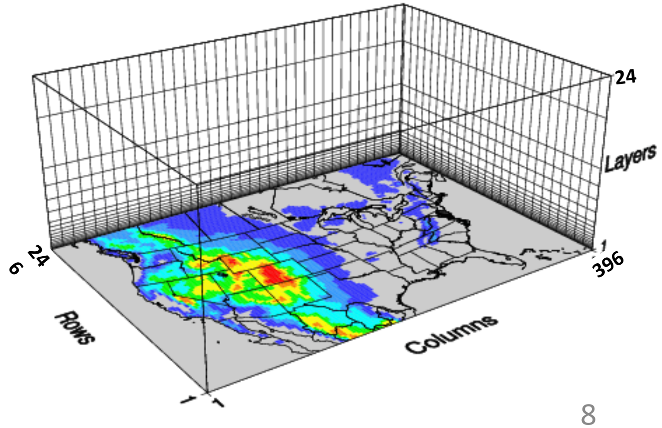


Statistical Fusion



Remote Sensing

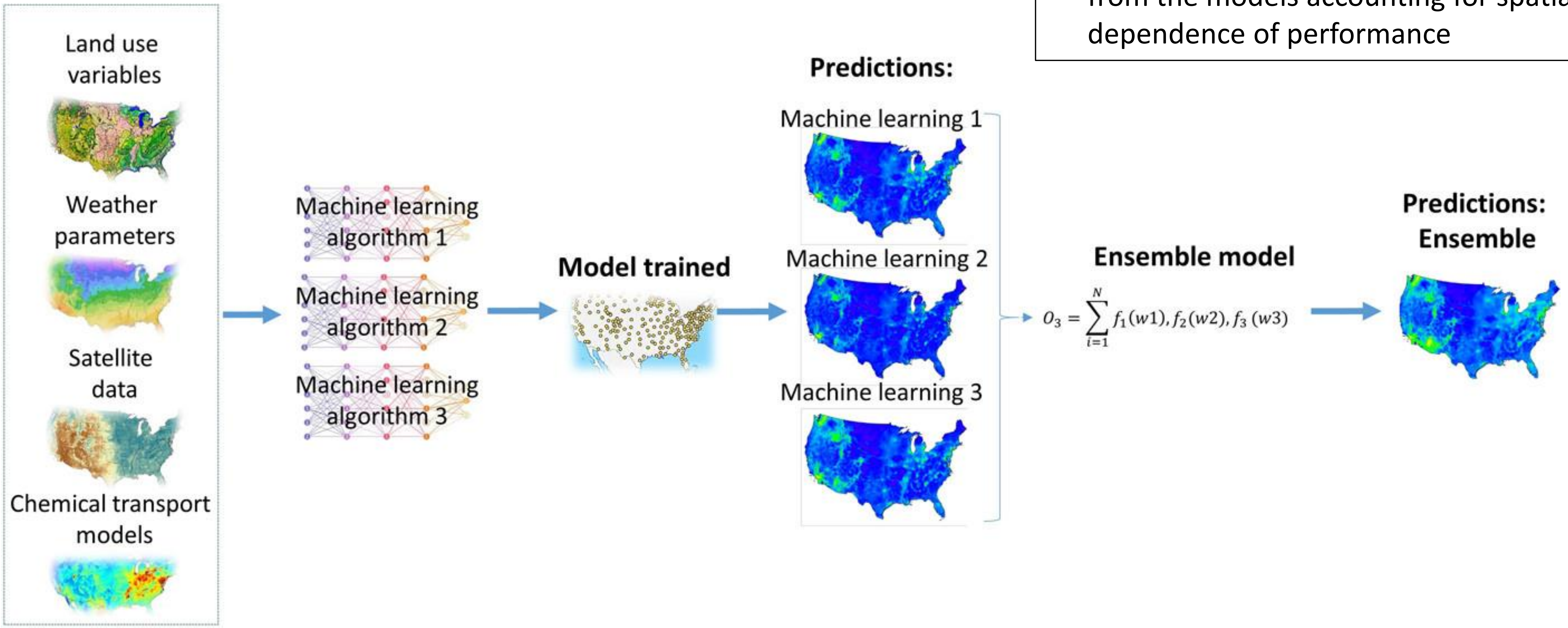
Chemical Transport Modeling



[van Donkelaar et al. (2019)]

Machine Learning Method

- ML models (neural network, random forest, and gradient boosting) are fit to obs using 50+ predictor variables
- An optimal ensemble prediction is made from the models accounting for spatial dependence of performance



Di et al. (2019); Di et al. (2020); Requia et al. (2020)

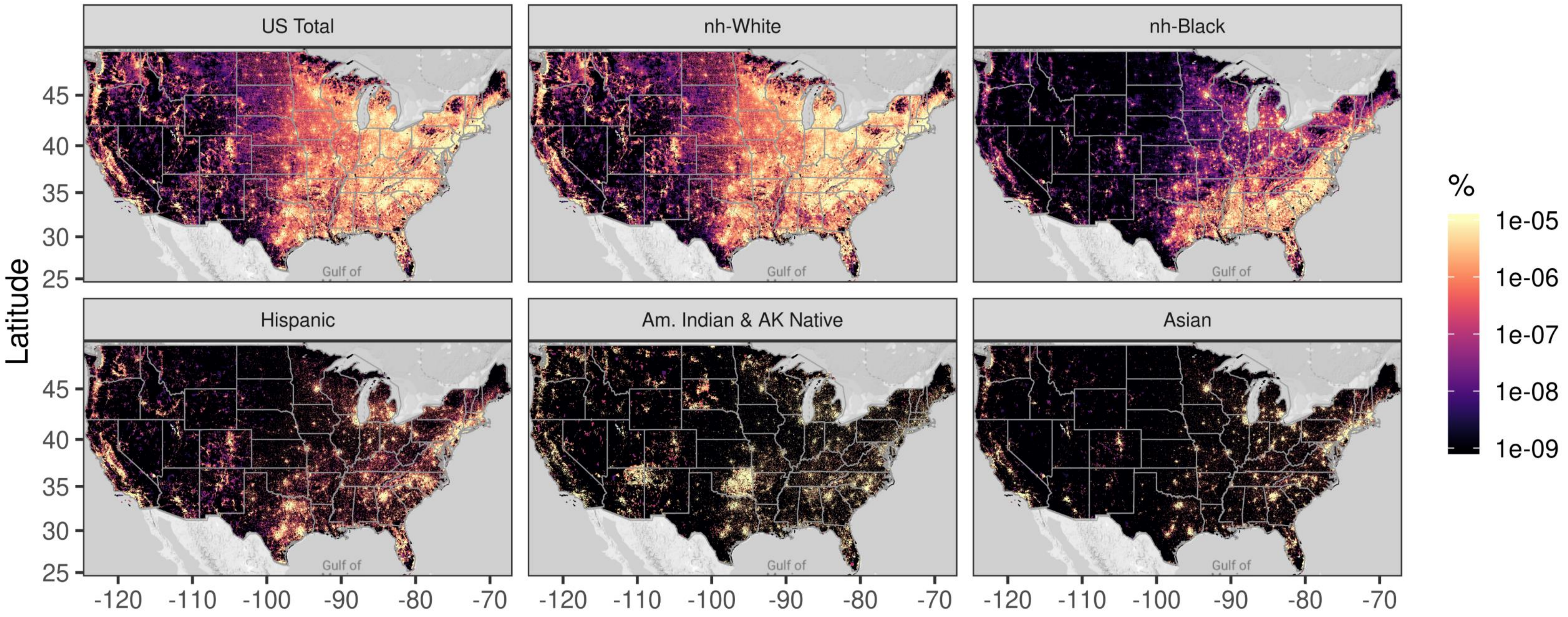
Air Quality Data

- $PM_{2.5}$
  - **Harvard Machine Learning**: 2000-2016, daily $PM_{2.5}$ at 1-km resolution based on ensemble machine learning (includes AQAD CMAQ data) (Di et al., 2019; DI2019)
  - **Dalhousie Satellite:** 2000-2018, annual $PM_{2.5}$ at 1-km resolution based on satellite AOD/GEOS-Chem/monitor approach (van Donkelaar et al., 2019; VD2019)
- O_3
  - **Harvard Machine Learning**: 2000-2016, daily MDA8 O_3 at 1-km resolution based on ensemble machine learning (includes AQAD CMAQ data) (Requia et al., 2020)
- NO_2
  - **Dalhousie Satellite**: 2019 annual average NO_2 at 2.8-km resolution based on TROPOMI/GEOS-Chem/monitor approach (Cooper et al., 2020)
  - **Harvard Machine Learning**: 2000-2016, daily max-hourly NO_2 at 1-km resolution based on ensemble machine learning (includes AQAD CMAQ data) (Di et al., 2019)

Population Data

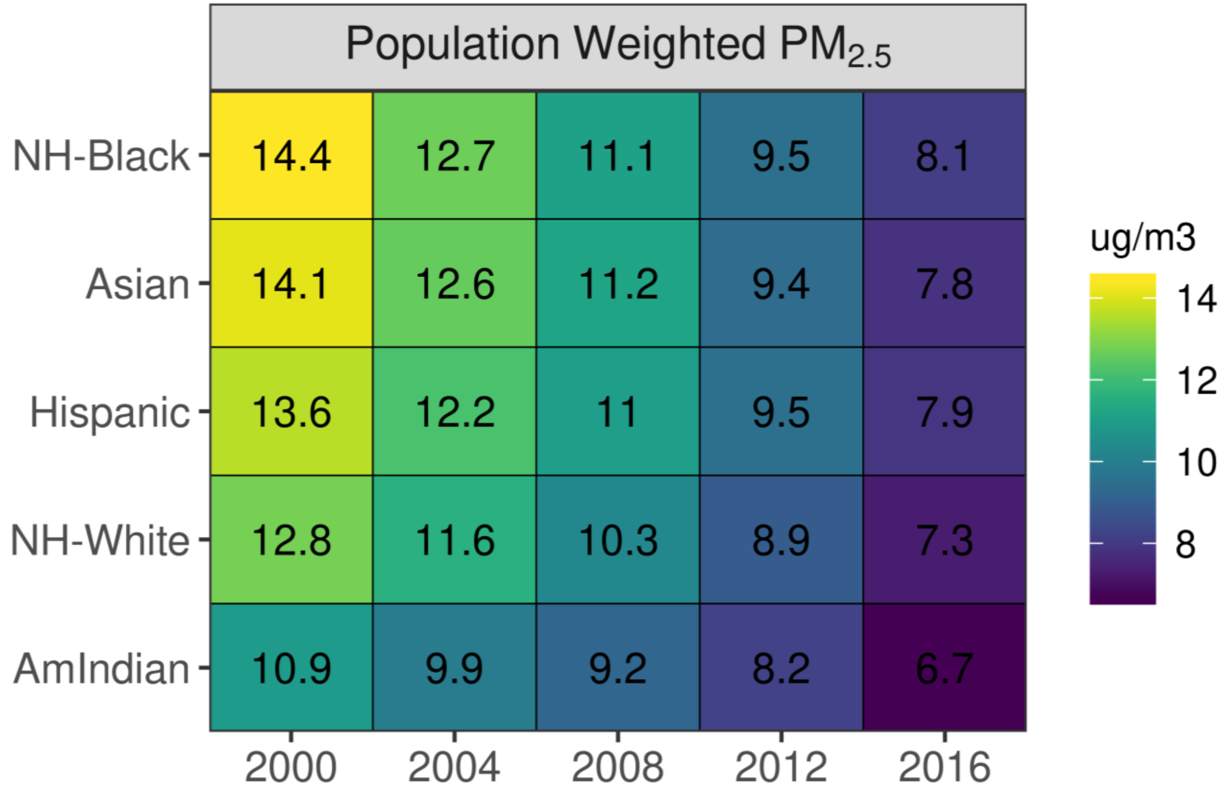
- 2010 Census block data aggregated to 1-km grid are used
- Exposure is estimated using population-weighted concentrations in terms of the following racial/ethnic groups:
  - Hispanic, non-Hispanic White (NH-White), non-Hispanic Black (NH-Black), Asian Alone (Asian), and American Indian & Alaskan Native (Am. Indian)
- We plan to develop a more comprehensive high-resolution population dataset in the future; however, previous studies have found that
  - Changes in population distributions (i.e., urbanization) have a small effect
  - Race/ethnicity is often the strongest indicator of exposure disparity

National Population Distributions: 2010



Differences in exposure result from the differences in population spatial distributions (e.g., NH-Black in south and urban areas; Hispanic in CA/TX/west; Asian in CA and urban areas; Am. Indian in rural areas)

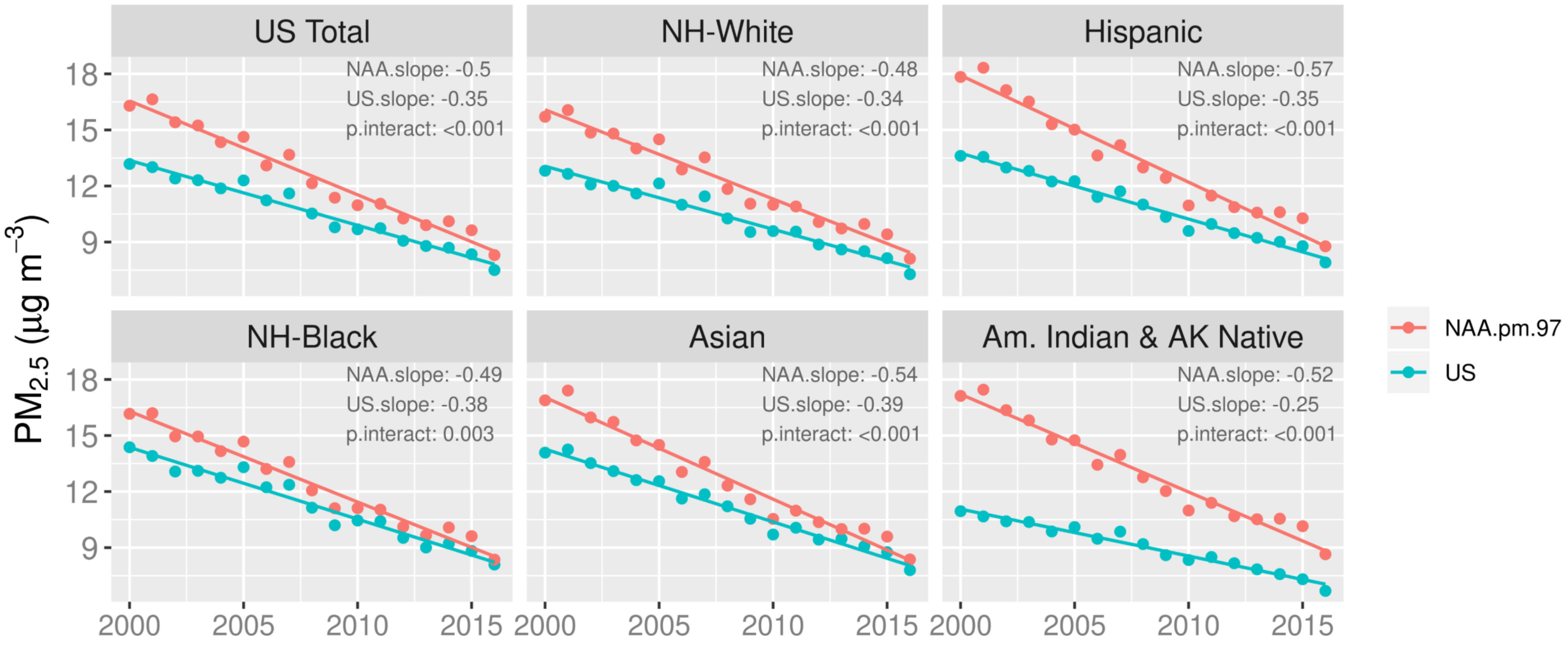
National Population-Weighted $PM_{2.5}$



- Exposure disparities (0.6 to 1.6 μg m^{-3}) exist between NH-Black and NH-White
- The gap between NH-Black and NH-White decreased by 50% from 2000 (1.6 μg m^{-3}) to 2016 (0.8 μg m^{-3}), but NH-Black is still most exposed

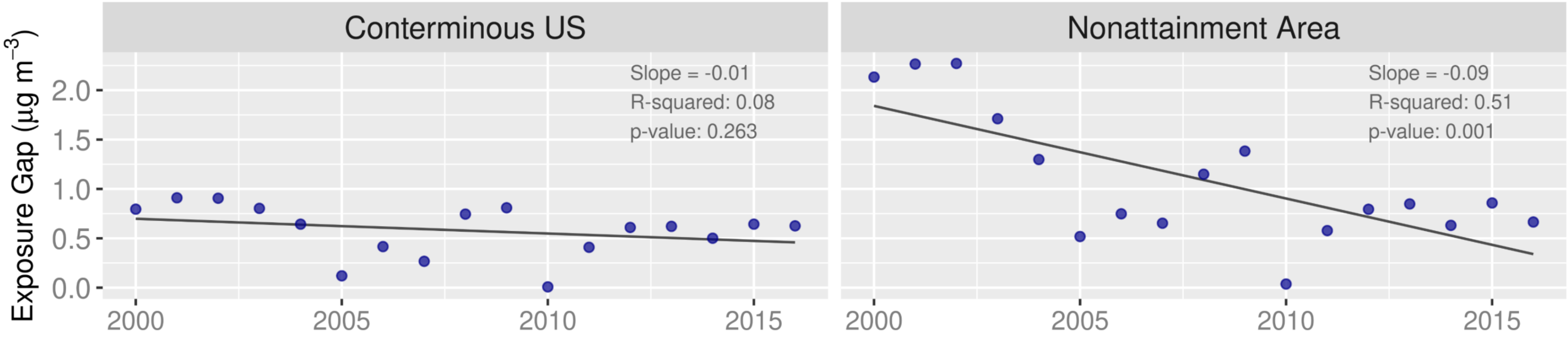
Absolute gap between NH-Black and NH-White is decreasing, but highest exposure for NH-Black group persists

National and Nonattainment Area $PM_{2.5}$ Trends: 2000-2016



Steeper decreases in NAAs vs. conterminous US; large difference between NAA and US for Am. Indian due to population distribution

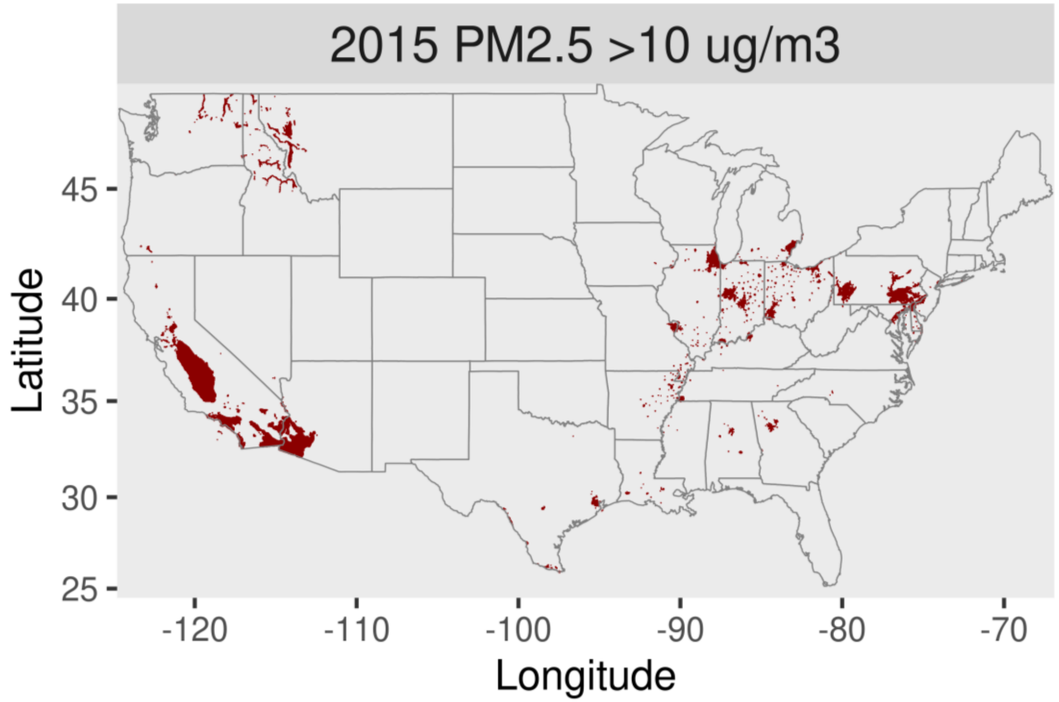
Trends in Hispanic-White $PM_{2.5}$ Gap: 2000-2016



- The difference in population-weighted concentration (Hispanic - NH-White) is shown by region (CONUS or 1997 $PM_{2.5}$ nonattainment areas)

In contrast to Black-White exposure gap, the Hispanic-White gap is stable over US but decreasing in NAAs (likely related to influence of California)

Population Above Threshold Concentration

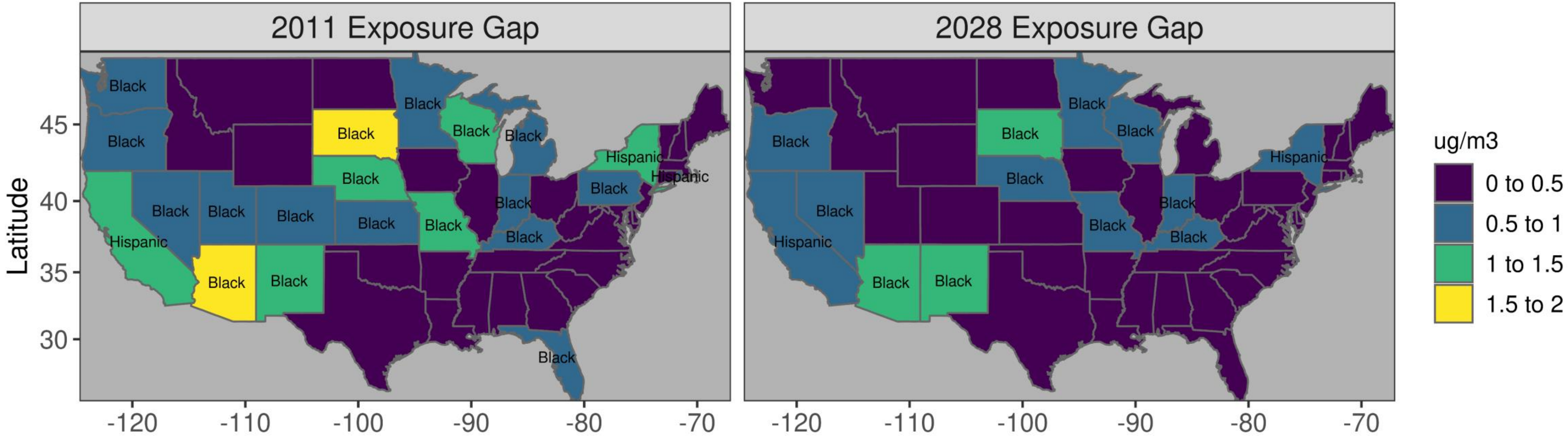


Group	% of Pop	% of Pop >10 ug/m³	Difference
NH-White	63.9	46.9	-17
Hispanic	16.4	28.1	+11.7
NH-Black	12.3	15.4	+3.1
Asian	4.6	7.2	+2.6
Am. Indian	0.9	0.6	-0.3

- Population proportions for Hispanic, NH-Black, and Asian groups are higher for areas with $PM_{2.5}$ >10 $\mu g\ m^{-3}$ than nationally

Targeting "urban increment" in relatively polluted areas provides opportunity for reducing disparities

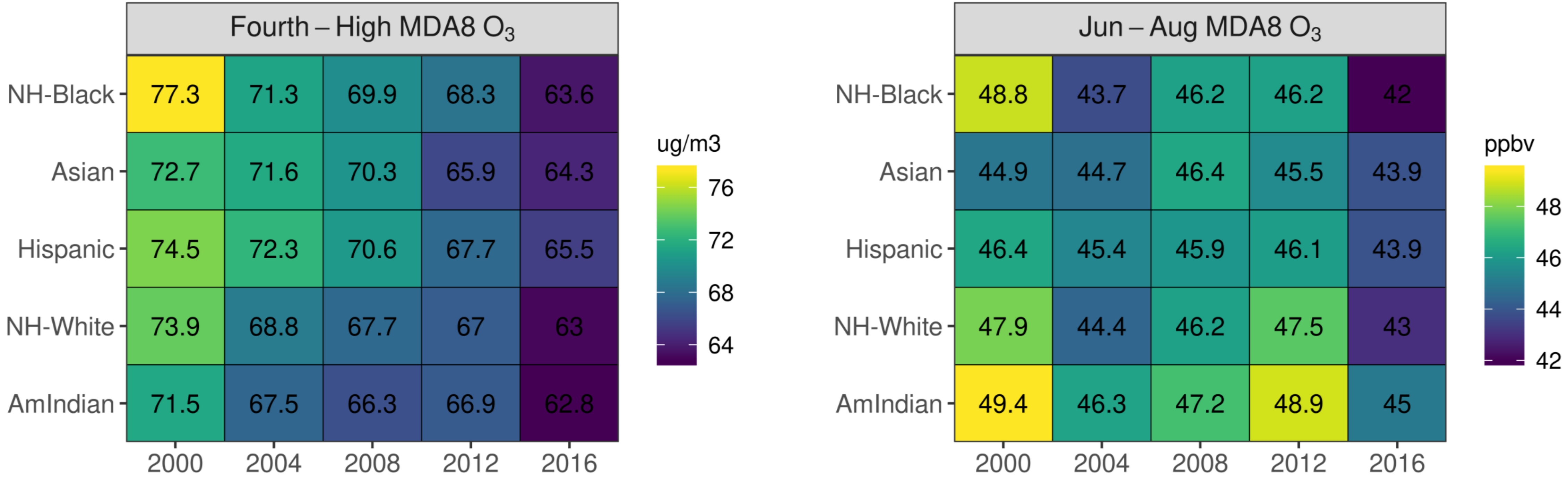
Future Projection of $PM_{2.5}$ Exposure Gap: 2011-2028



- The $PM_{2.5}$ gap between the most- and least-exposed groups is shown with labels for the most-exposed group
- Eight states have exposure gaps >1 μg/m^3 in 2011, but only three do in 2028

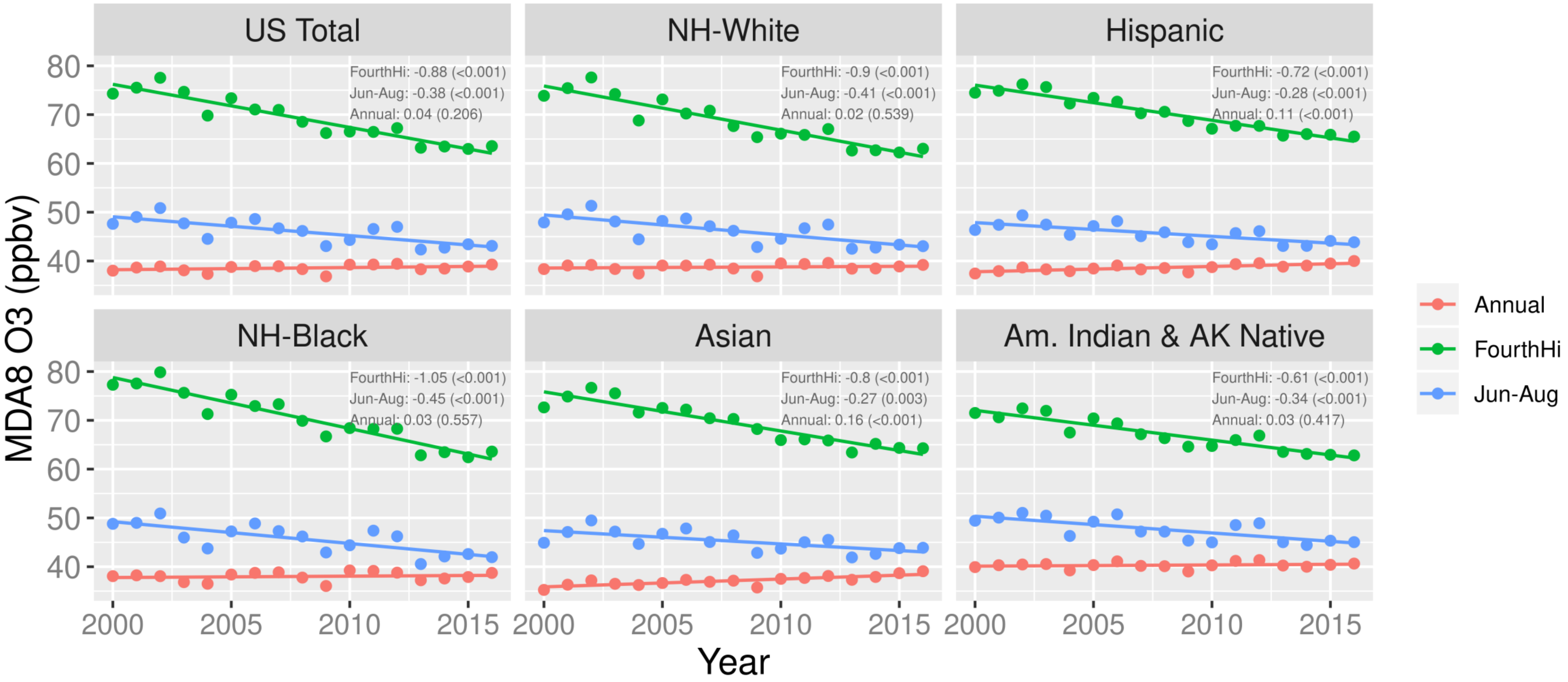
Projections from 2011 to 2028 continue the historical trend of reductions in the absolute exposure gap with persistence of most-exposed group

Population-Weighted MDA8 Ozone: 2000-2016



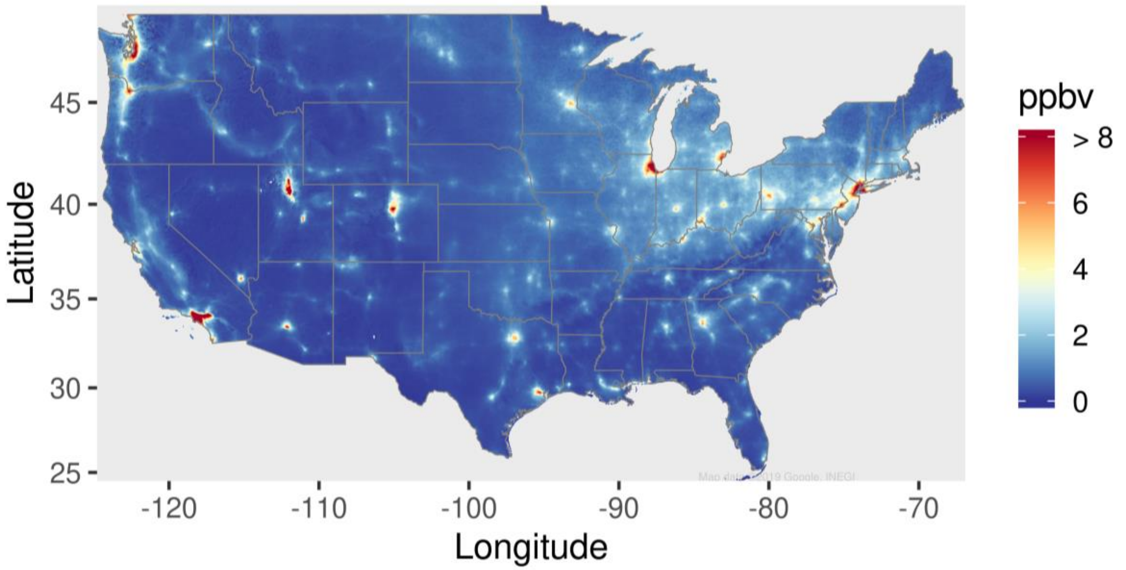
The most exposed group varies with metric (generally NH-Black for 4th high and Am. Indian for summer mean MDA8 O_3)

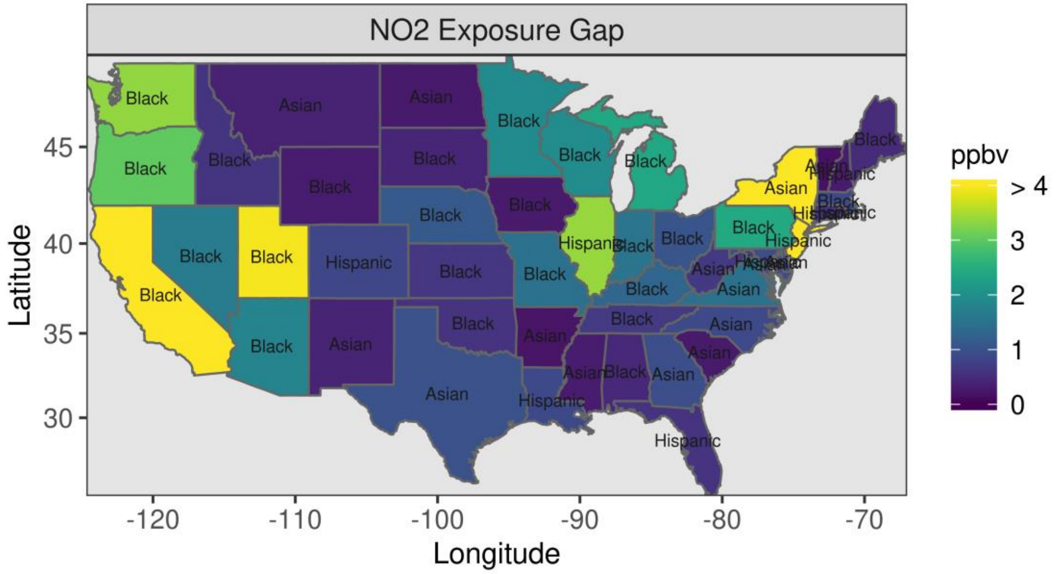
Trends in Three MDA8 Ozone Metrics: 2000-2016



Trends vary with metric (4th high decreasing, annual mean flat or increasing)

Nitrogen Dioxide (NO_2)



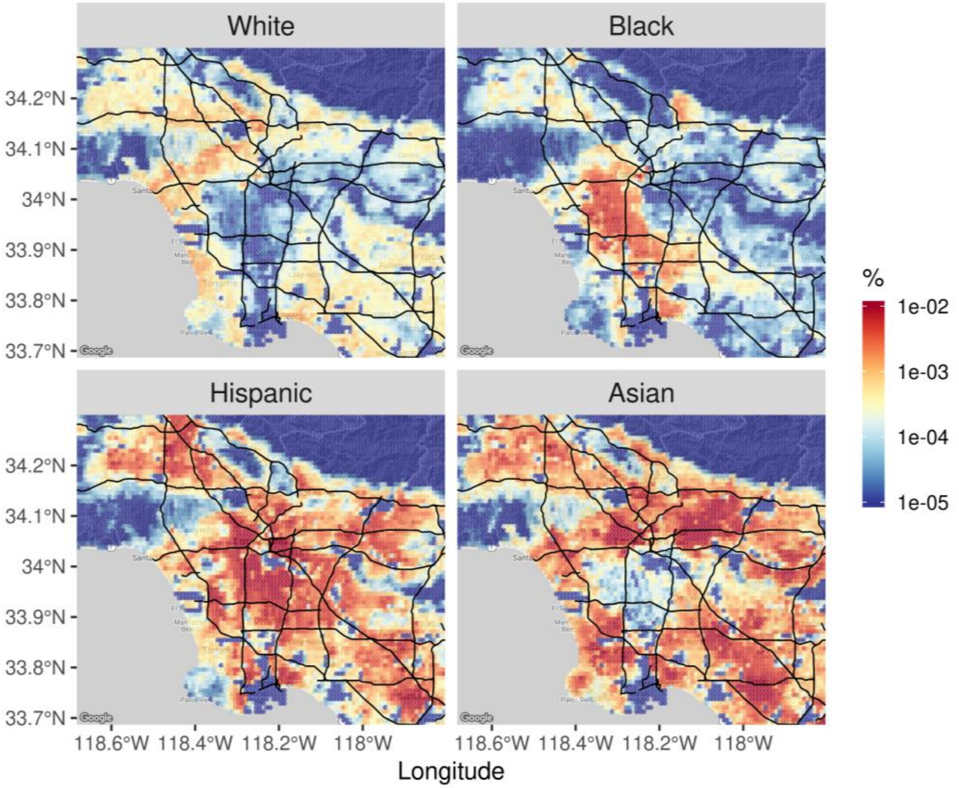


- NO_2 is more spatially heterogeneous than $PM_{2.5}$ yielding greater relative disparities (e.g., the Asian-White $PM_{2.5}$ gap is 7% of the national pop-wt $PM_{2.5}$, but the gap is 100% for NO_2)

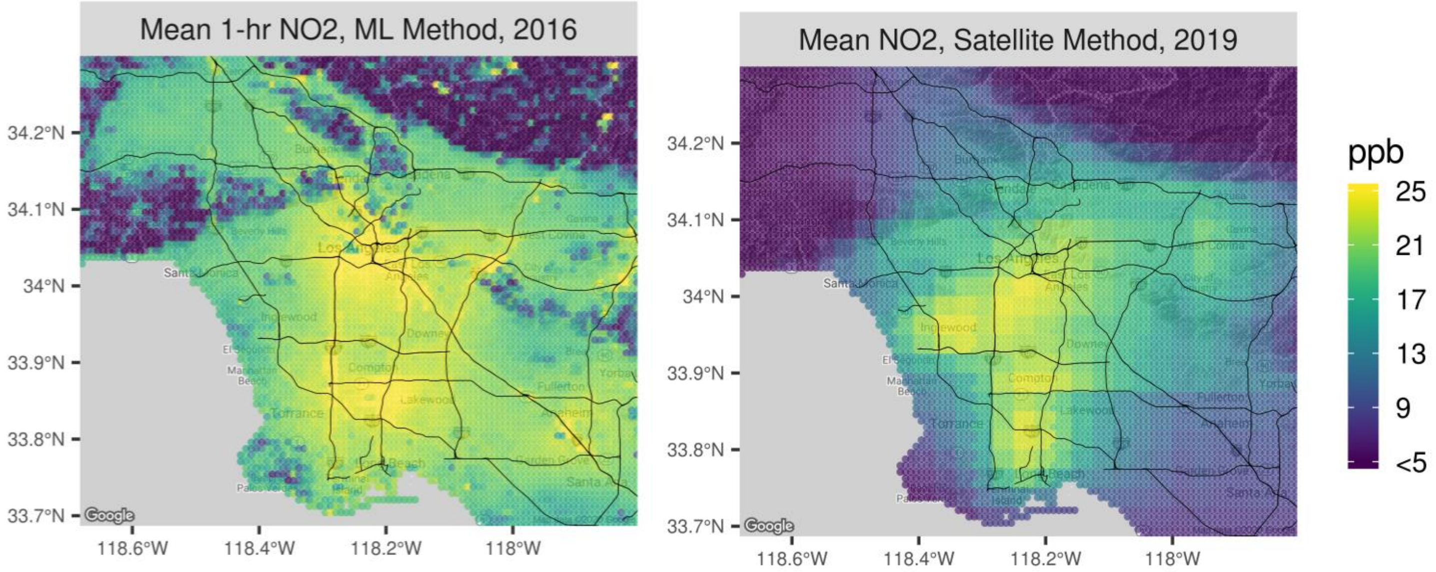
Spatially heterogeneous pollutants like NO_2, BC, diesel PM, UFP, and localized air toxics expected to have higher disparities than $PM_{2.5}$

NO_2 in Los Angeles

Normalized 2010 Population



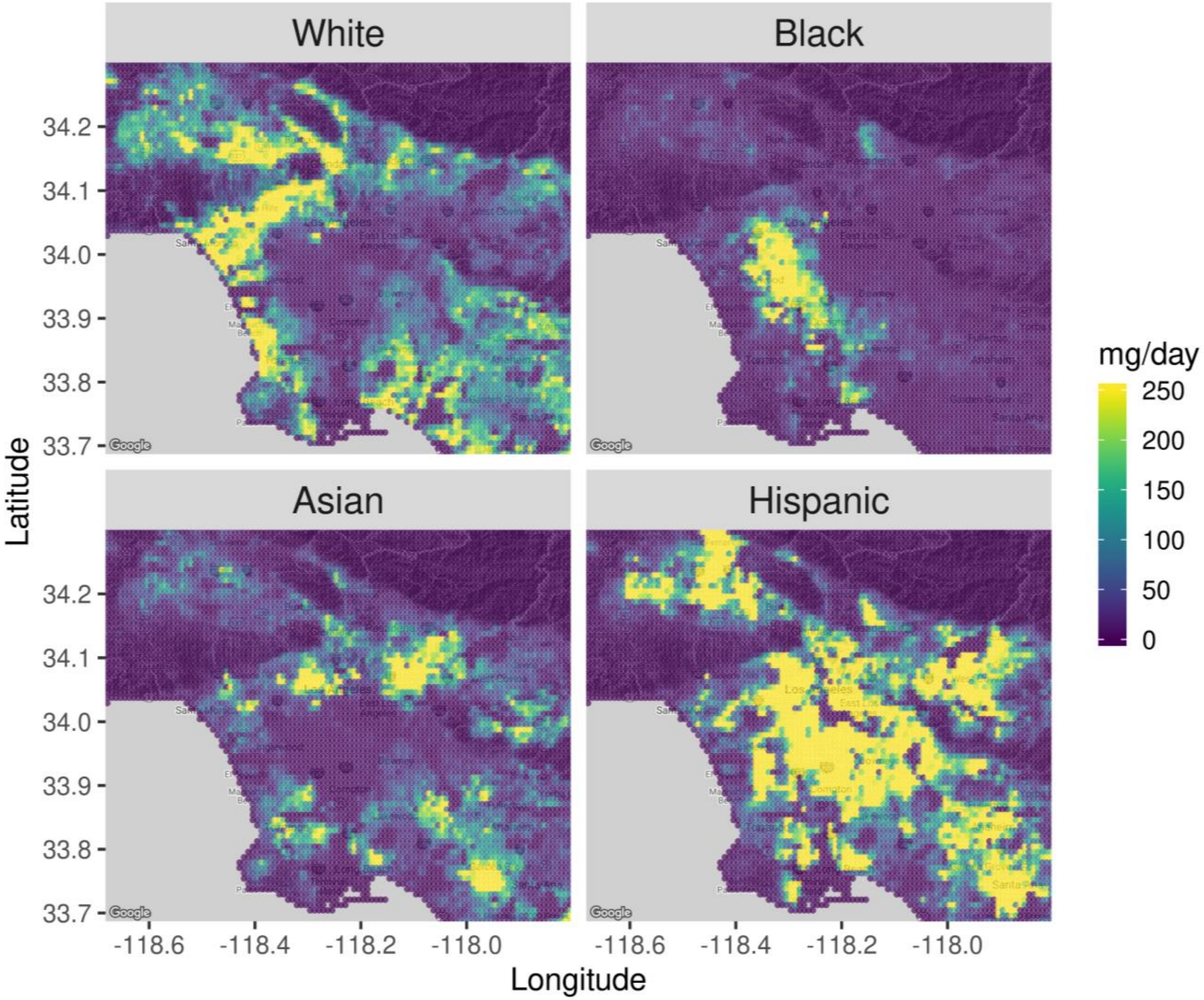
1-km NO_2 Predictions



- Gradients in terrain, concentration, and population demonstrate the value of high-resolution data
- Multiple models help mitigate limitations of using national models for urban areas, but fine-scale uncertainty remains

High concentrations and Black populations appear to overlap—joint metrics that combine concentration and population would be useful

Inhaled $PM_{2.5}$: Joint Concentration/Population Metric



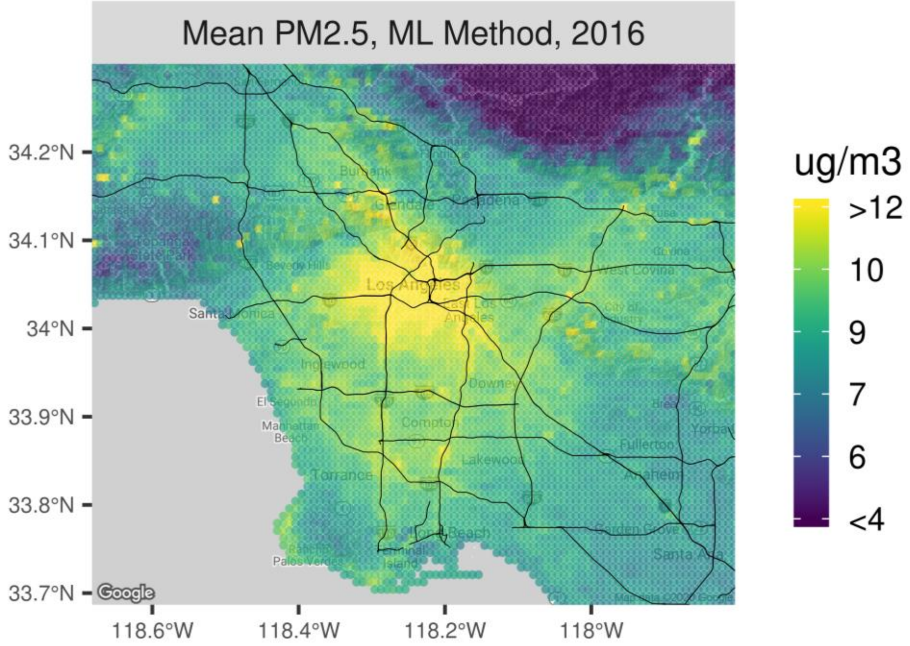
- Inhaled $PM_{2.5}$ (mg day^{-1}) in 2015 by group was calculated*
- Spatial segregation in urban areas provides opportunities for addressing disparities (ex., Rule 445 wrt Compton)

Future direction: calculate inhaled $PM_{2.5}$ by emission sector contribution to clearly show the sector burden by population group

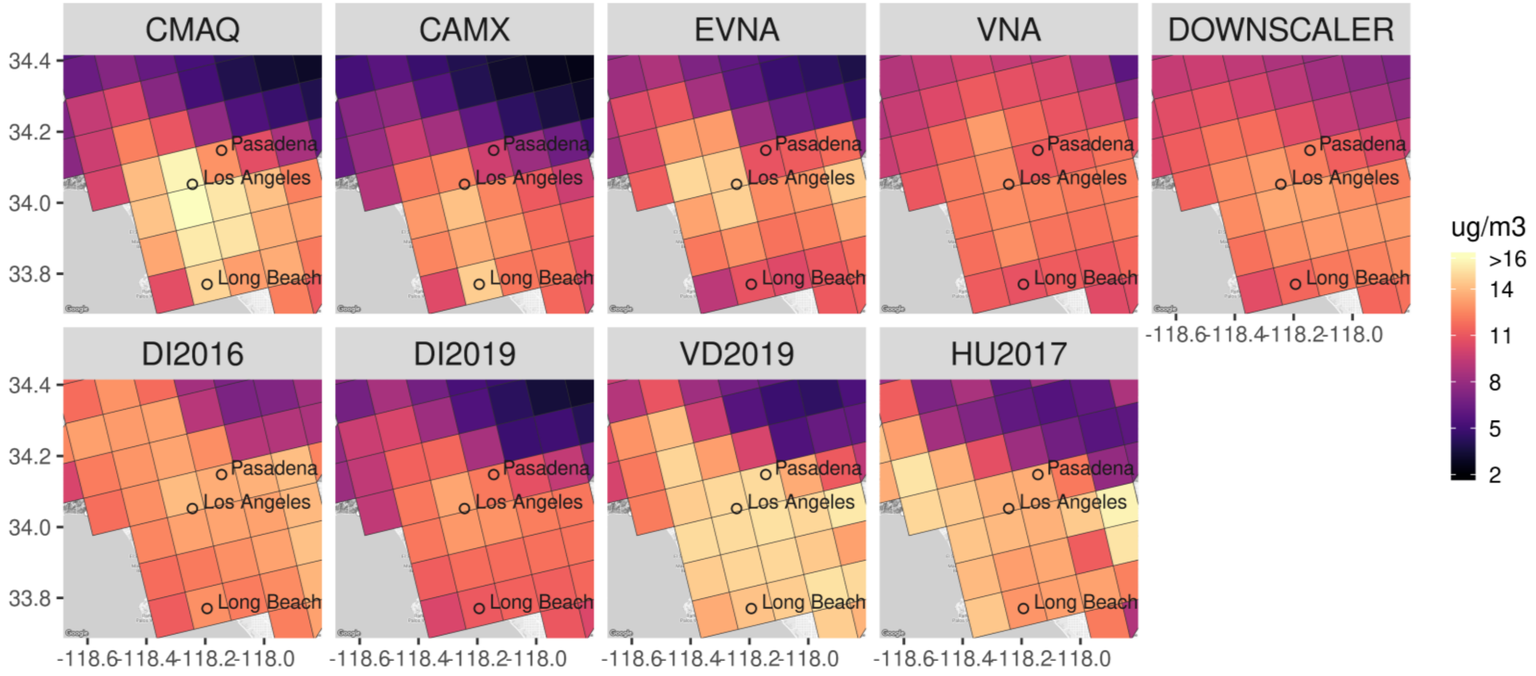
*Inhaled mass: $PM_{2.5}$ x breathing rate x population = ($\mu g/m^3$) (1 mg/1000 μg) x (m^3/person/day) x (# person) = mg/day

Consideration of Grid Resolution for Los Angeles $PM_{2.5}$

2016 $PM_{2.5}$, 1-km Grid Spacing



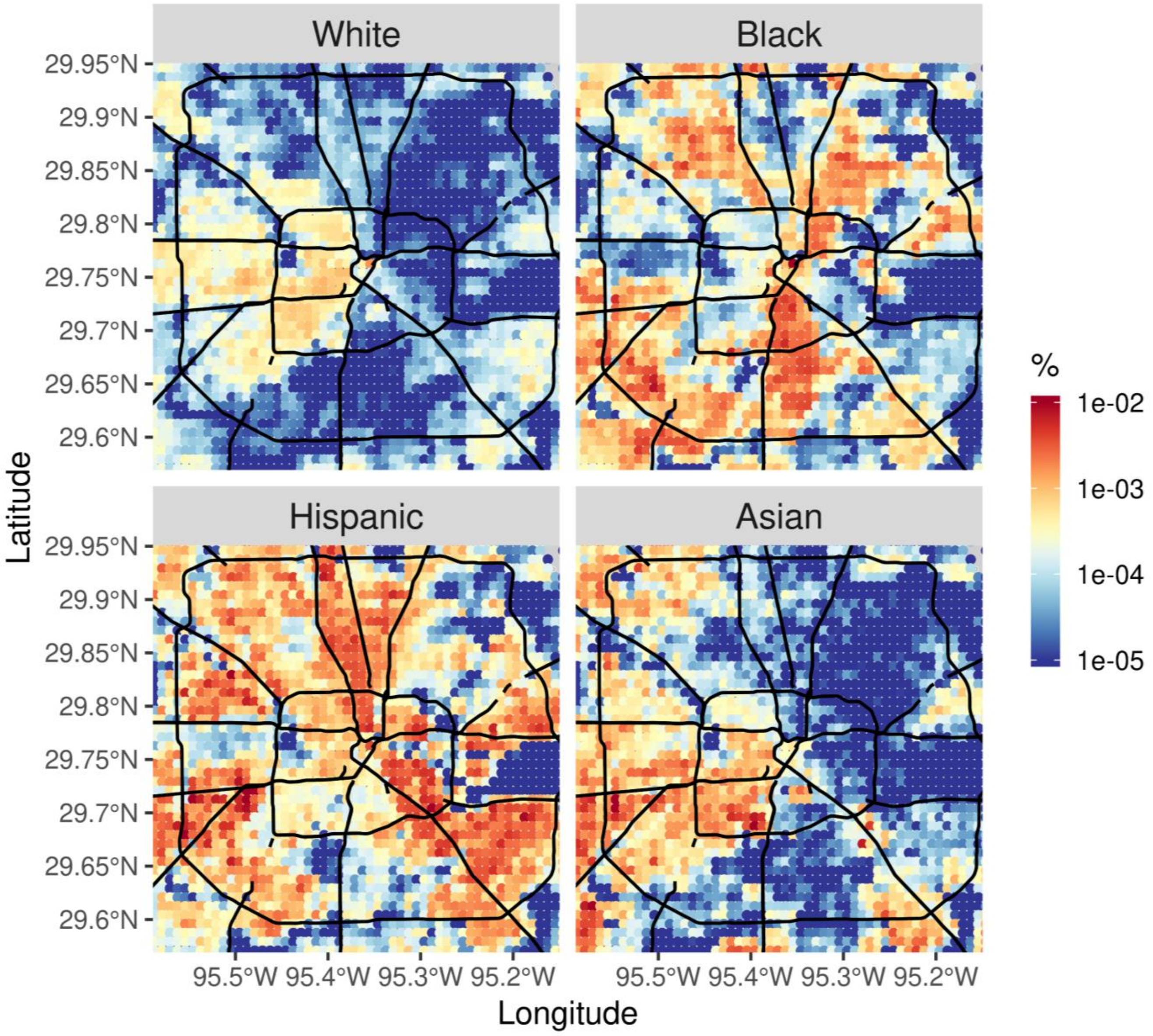
2011 $PM_{2.5}$, 12-km Grid Spacing



1-km grid spacing (left) is preferable to 12-km (right) for intra-urban analyses

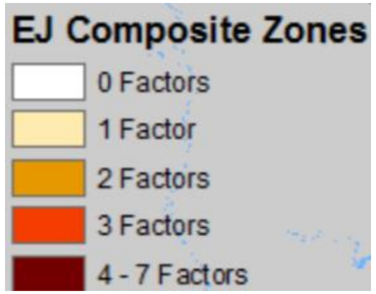
Normalized 2010 Population Distributions in Houston

Distributions of Black/White/Asian groups are moderately segregated in Houston (as in other US cities)—can cause exposure disparities



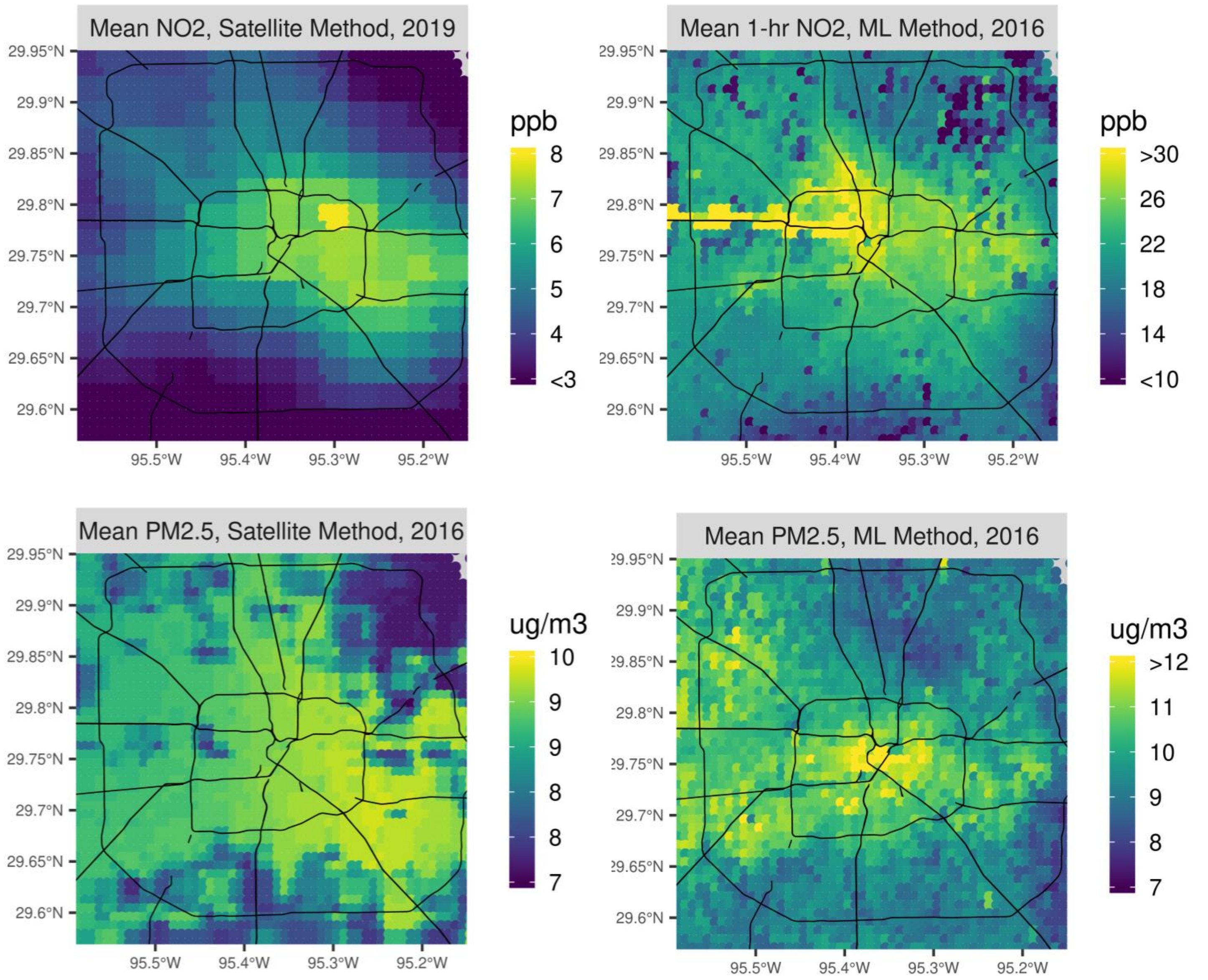
Houston NO_2 and $PM_{2.5}$

Zones of Composite Disadvantage



EJ Factors:

i. **Minority status**
ii. **Low-income status**
iii. Limited English proficiency
iv. Senior status
v. Limited educational attainment
vi. Carless households
vii. Female head of households



Urban mod-mod disagreements—need models based on local information for EJ case studies (e.g., next slide)

Note: Elevated cancer risk to the east of downtown Houston along ship channel has also been identified (e.g., see Appendix)

Non-Regulatory Measurements for "Neighborhood Scale" Air Quality

High Resolution $PM_{2.5}$ in NYC

A) NY Central Park, B) major roads between parks, C) JFK Airport.

[Huang et al. (2020)]

- Radom forest model trained with 150 NYCCAS monitors + 21 AQS monitors
- 100-m resolution model using satellite AOD, met, and landuse information
- Predictions >15% higher than AQS-only model in densely populated areas

Neighborhood-scale AQ is a new frontier in research with relevance to EJ

$PM_{2.5}$ Disparities Identified by Proximity to Emissions

AJPH ENVIRONMENTAL JUSTICE

Disparities in Distribution of Particulate Matter Emission Sources by Race and Poverty Status

Ihab Mikati, BS, Adam F. Benson, MSPH, Thomas J. Luben, PhD, MSPH, Jason D. Sacks, MPH, and Jennifer Richmond-Bryant, PhD

Objectives. To quantify nationwide disparities in the location of particulate matter (PM)-emitting facilities by the characteristics of the surrounding residential population and to illustrate various spatial scales at which to consider such disparities.

Methods. We assigned facilities emitting PM in the 2011 National Emissions Inventory to nearby block groups across the 2009 to 2013 American Community Survey population. We calculated the burden from these emissions for racial/ethnic groups and by poverty status. We quantified disparities nationally and for each state and county in the country.

Results. For PM of 2.5 micrometers in diameter or less, those in poverty had 1.35 times higher burden than did the overall population, and non-Whites had 1.28 times higher burden. Blacks, specifically, had 1.54 times higher burden than did the overall population. These patterns were relatively unaffected by sensitivity analyses, and disparities held not only nationally but within most states and counties as well.

Conclusions. Disparities in burden from PM-emitting facilities exist at multiple geographic scales. Disparities for Blacks are more pronounced than are disparities on the basis of poverty status. Strictly socioeconomic considerations may be insufficient to reduce PM burdens equitably across populations. (*Am J Public Health.* 2018;108:480–485. doi:10.2105/AJPH.2017.304297)

cardiovascular diseases as well as premature mortality.[6–8] Although proximity to facilities emitting PM is not a direct measure of exposure, it is a valuable metric. Unlike natural events that contribute to ambient PM, such as wildfires, the siting of a facility is the result of a decision-making process. Disparities in siting may indicate underlying disparities in the power to influence that process. For example, an Environmental Protection Agency (EPA) investigation in Flint, Michigan, found a direct link between racial discrimination and the permitting of a power station there, stating, "The preponderance of evidence supports a finding of discriminatory treatment of African Americans by [the Department of Environmental Quality] in the public participation process."[9]

We aimed to quantify nationwide disparities

ORD work suggests that emissions-based studies might be useful for screening or local areas analysis

Mikati et al. (2018)

Conclusions from Preliminary Work

- $PM_{2.5}$ disparities are evident, with highest exposure for NH-Black group
- Absolute $PM_{2.5}$ disparities have been decreasing and are projected to continue to decrease; however, highly-exposed groups persist
- For ozone, the highest exposed group and degree of disparity depends on the metric (e.g., 4^{th} high, summer mean, annual mean MDA8 O_3)
- Disparities are relatively high for NO_2 suggesting similar behavior for other pollutants with high spatial gradients (e.g., diesel PM, BC, UFP, toxics, etc.)
- For urban areas, accurate city-specific models based on local information are desired, but analyses based on emissions, multiple models, and other approaches could be useful until local modeling methods are mature

Future Directions (1): Connecting to Other AQAD Capabilities

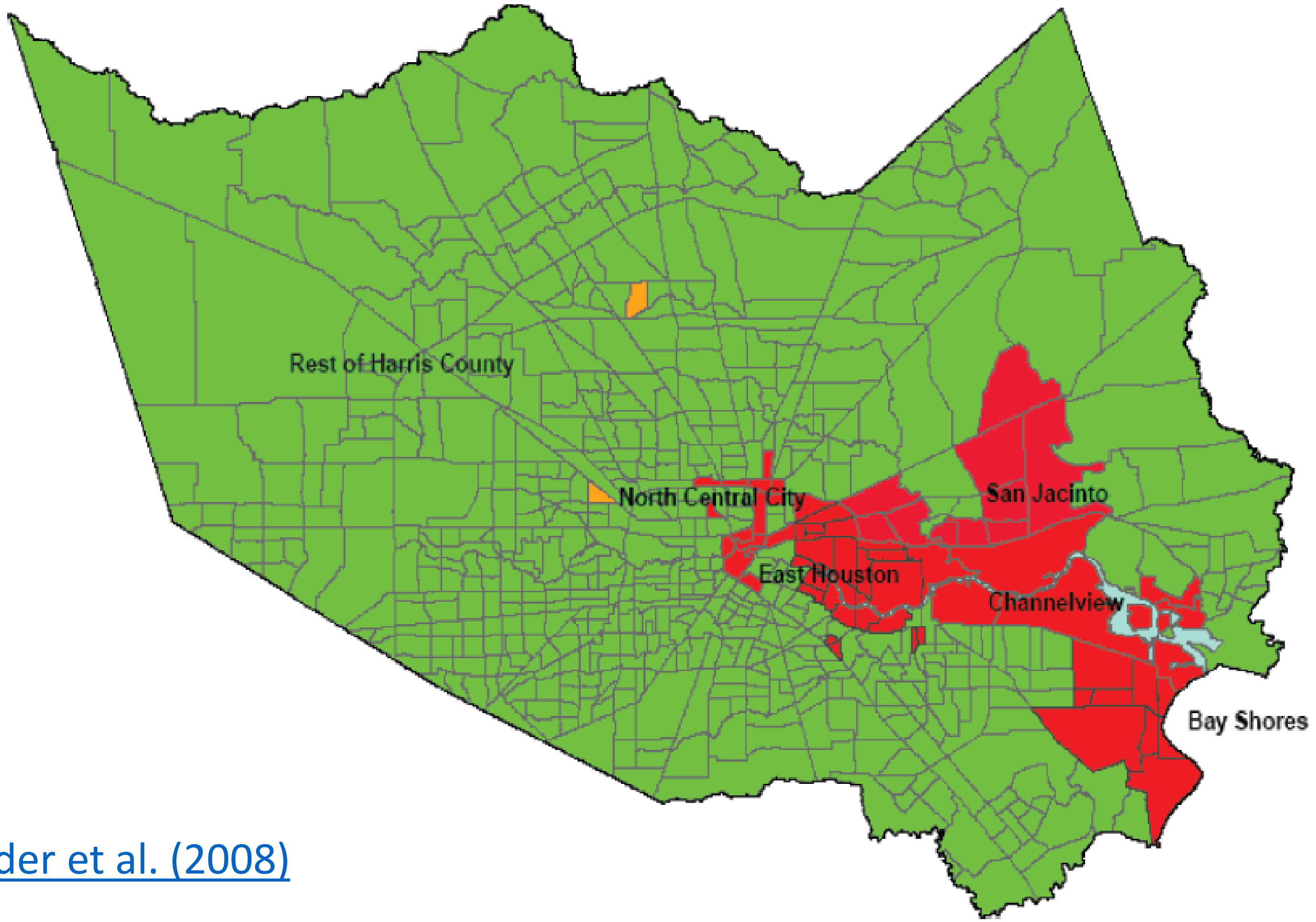
- Identify case study areas with potential EJ issues using screening analyses (e.g., NEXUS tool, Proximity-based analysis)
- Use source apportionment or other methods to understand source/sector contributions to disparities in case study areas
- Characterize multipollutant exposures for areas of interest using information on toxics or from the multipollutant modeling platform
- Understand tradeoffs and opportunities related to potential climate initiatives, Federal rules, or state actions
- Others?

Future Directions (2): Connecting to OAQPS Programmatic Needs

- Specific applications need to be identified through cross-office coordination; likely applications include the following:
  - Implementation: SIPs, permitting, exceptional events
  - NAAQS reviews: RIAs, REAs
  - Federal rules: EGU rules/policies, sector rules, OTAQ mobile source rules
  - Outreach: Advance program, Tribal areas, EJ communities, Multi-pollutant efforts
  - Others?

Additional Slides

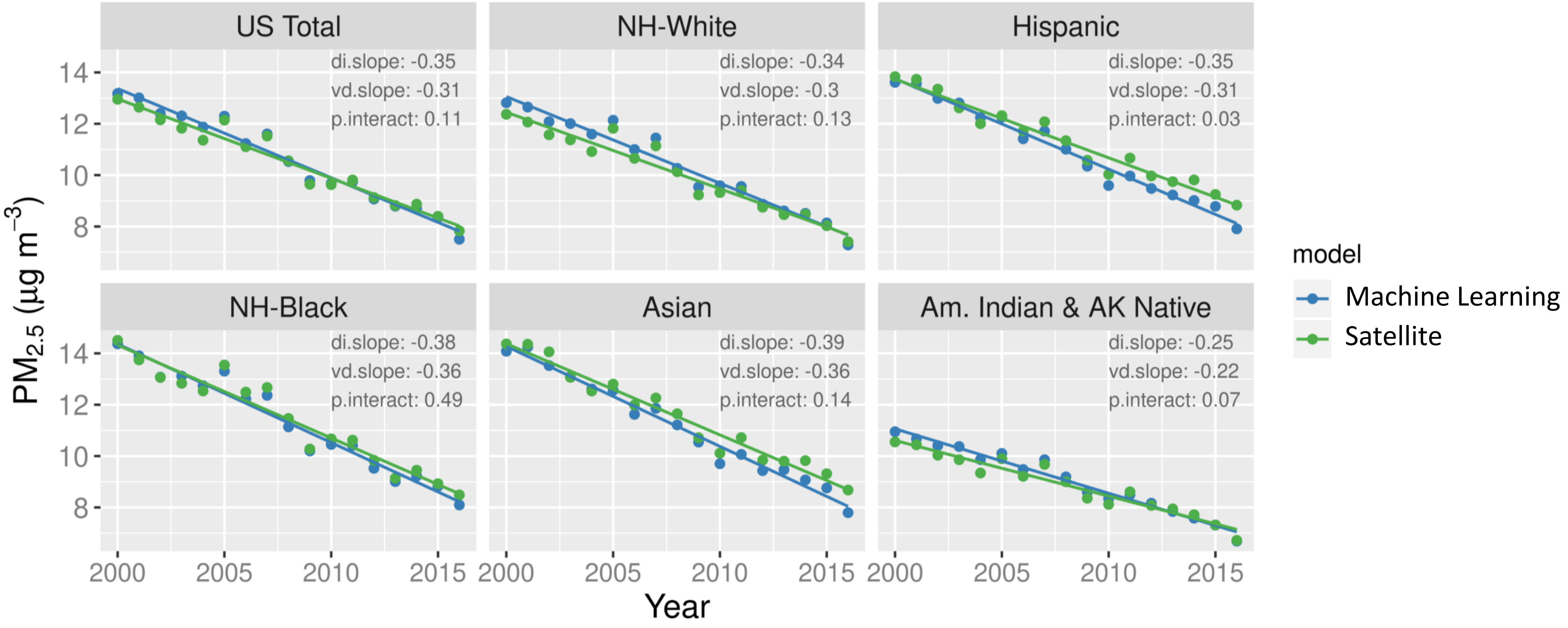
Cancer Risk In Houston



[Linder et al. (2008)]

FIGURE 3. Individual cancer risk > 90th percentile by area, Harris County, 1999.

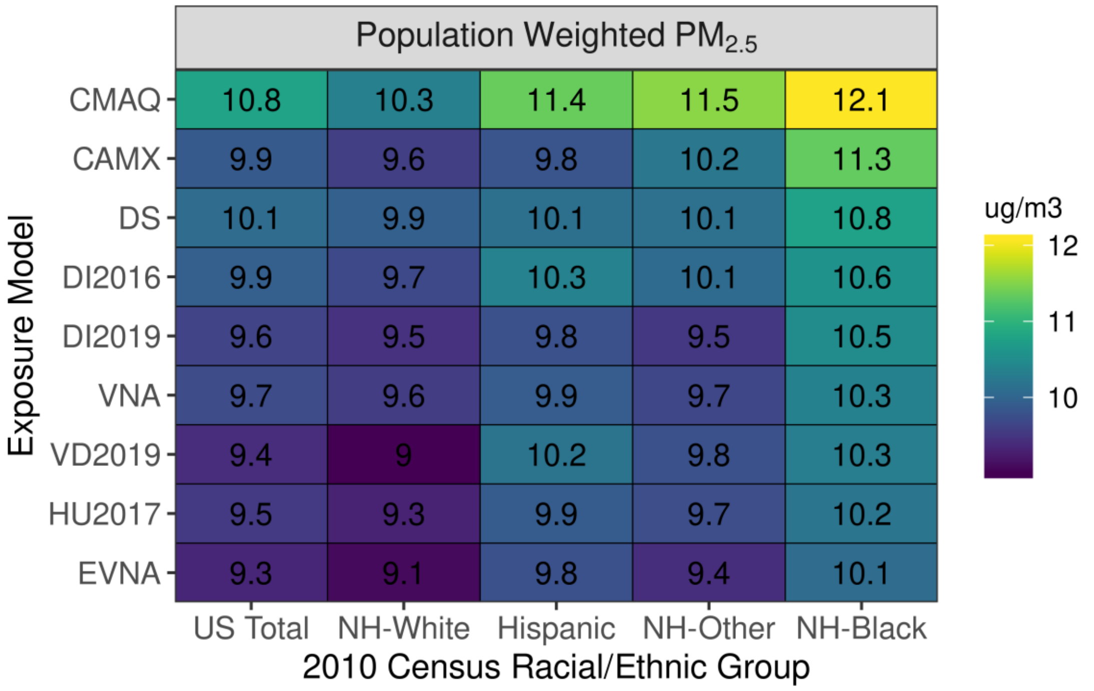
National $PM_{2.5}$ Trends from Two Models



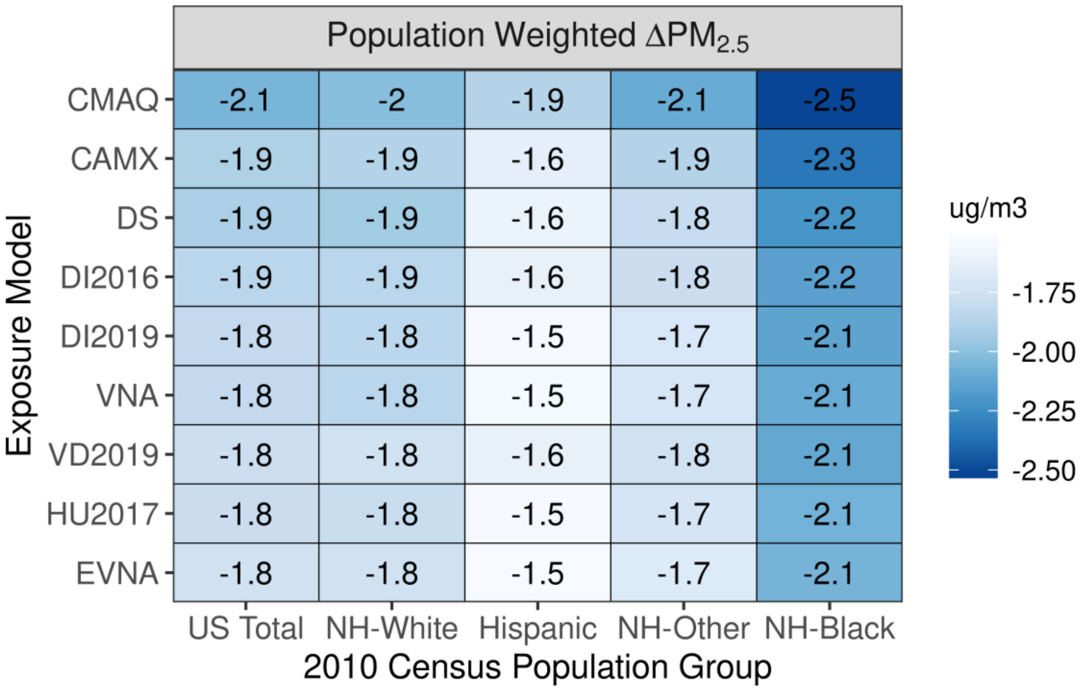
Similar national trends based on two different models build confidence

National Population-Weighted $PM_{2.5}$

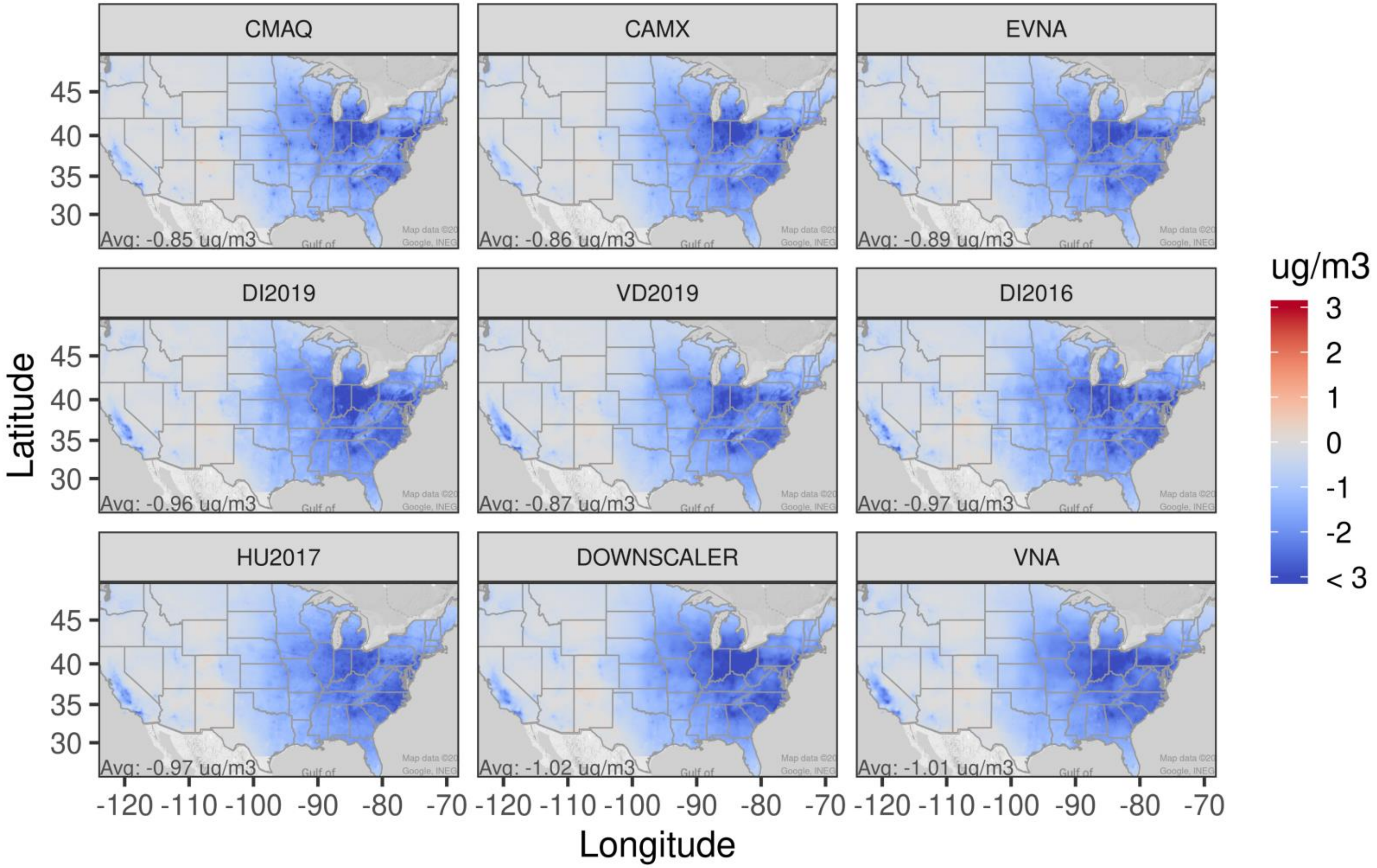
2011 $PM_{2.5}$



$\Delta PM_{2.5}$ (2028 – 2011)

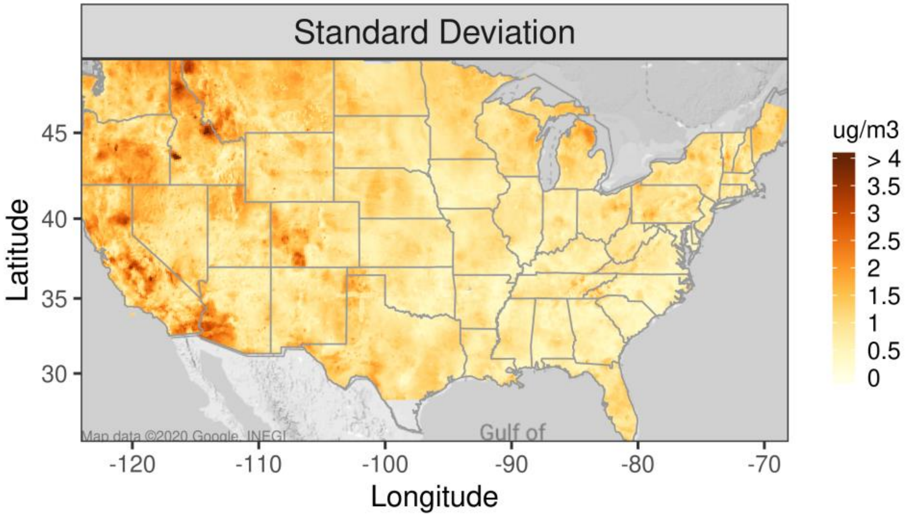


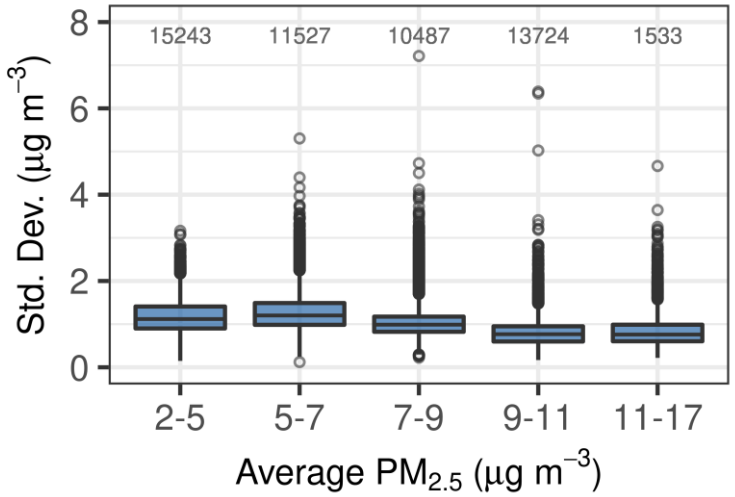
$\Delta PM_{2.5}$ Concentrations (2028 – 2011)

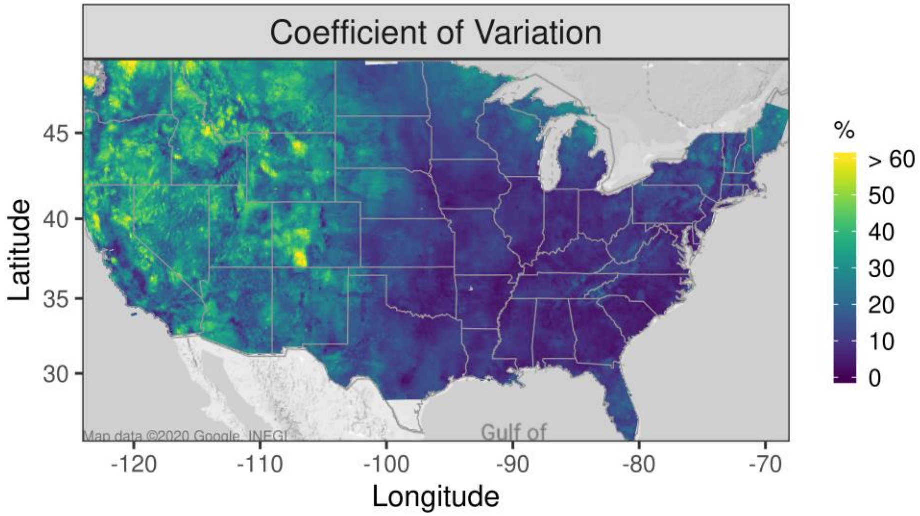


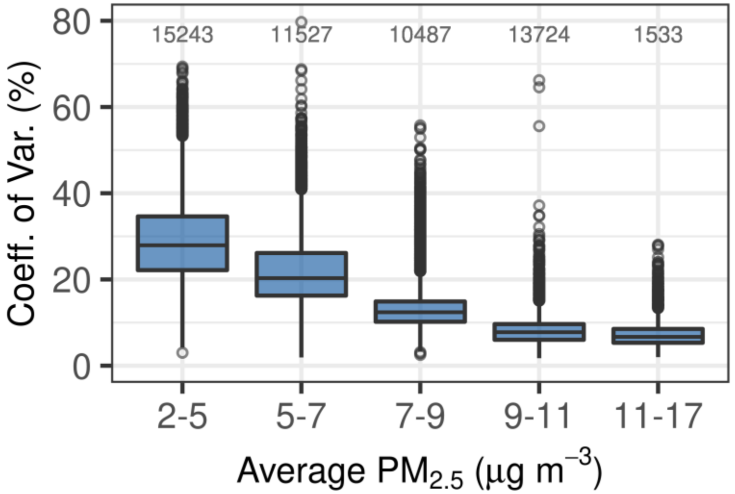
- Large (>3 $\mu g\ m^{-3}$) decreases in $PM_{2.5}$ in parts of the east with reduced SO_2 emissions
- Broad agreement in $\Delta PM_{2.5}$ spatial variation among models
- Differences in spatial variations follow 2011 fields due to use of same RRFs in all cases

Variability Among Non-CTM Models

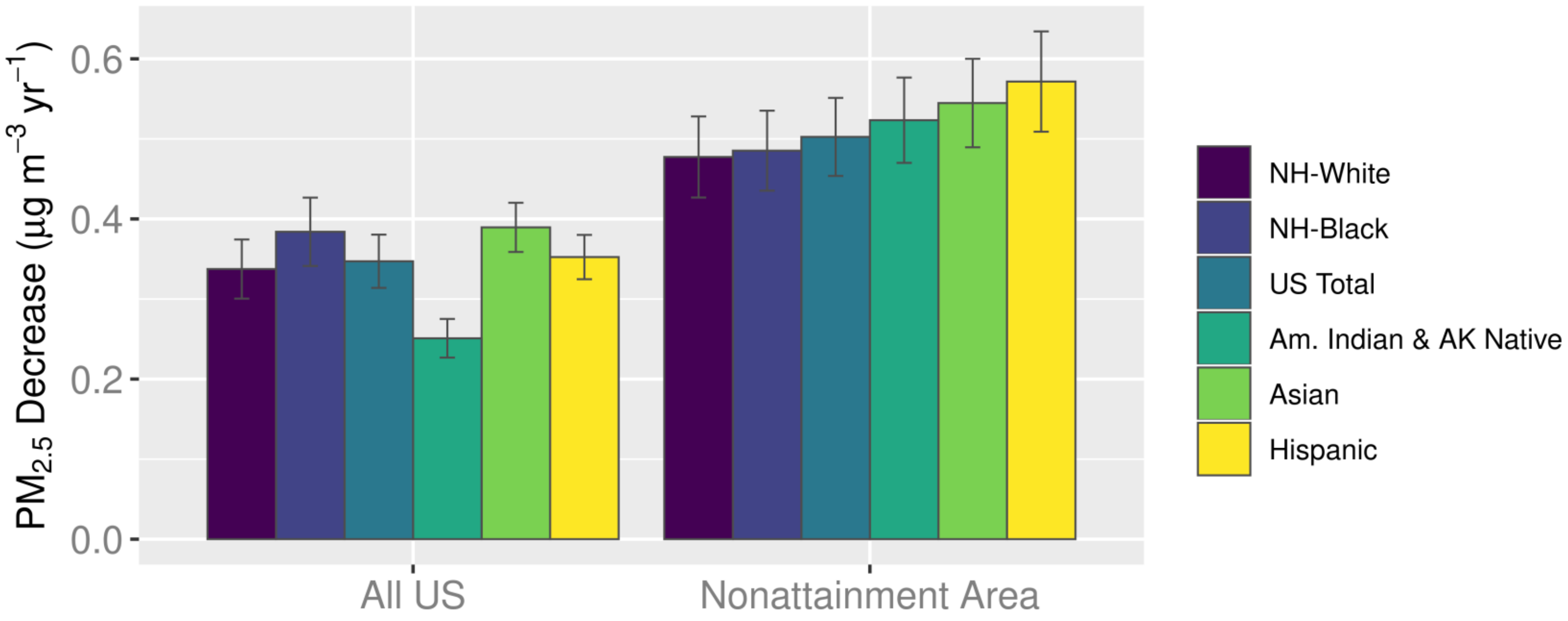








Comparing $PM_{2.5}$ Trends for US and NAAs: 2000-2016



The relative ranking of groups differs between areas (e.g., the Am. Indian trend is weakest for "All US" but third highest in NAAs)