

Pollutant Spatial Fields to Characterize Exposure: Initial Work and Insights

*OAQPS Staff and GL Discussion
7 January 2021*

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Overview

1. Context from recent EJ coordination activity in the office
2. Illustration of analytical capabilities based on model intercomparison study
3. Future directions and connecting to programmatic needs

Ongoing EJ-related Discussions Across Office

- Interest in EJ raised earlier this year given national events
- Analytical discussions and engagement occurring across the office
 - EJ Analytics meetings hosted by Sara Terry
 - Climate/EJ discussions hosted by Kevin Culligan
 - Air Toxics Strategy: Air Toxics Data Analytics Team led by Amy Vasu/Patrick Lessard
- AQAD provides analytics across office to inform and address EJ needs across multiple programs
 1. Provide understanding of historical, current, and projected exposure disparities
 - Provides context and insights across our programs about trends, highest exposed communities, contributing sectors, etc.
 2. Provide capabilities to assess EJ impacts of policy options/control scenarios
- AQAD is most effect when specific programmatic needs are known early

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, toxics), and
 - by metric (peak vs. mean, EJ indicators)?
- What are the **key sources** that contribute to exposure within EJ communities, including emerging pollutants of concern (e.g., ETO, 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 inform and influence outcomes (e.g., Federal rule actions, SIPs, new source permitting)?

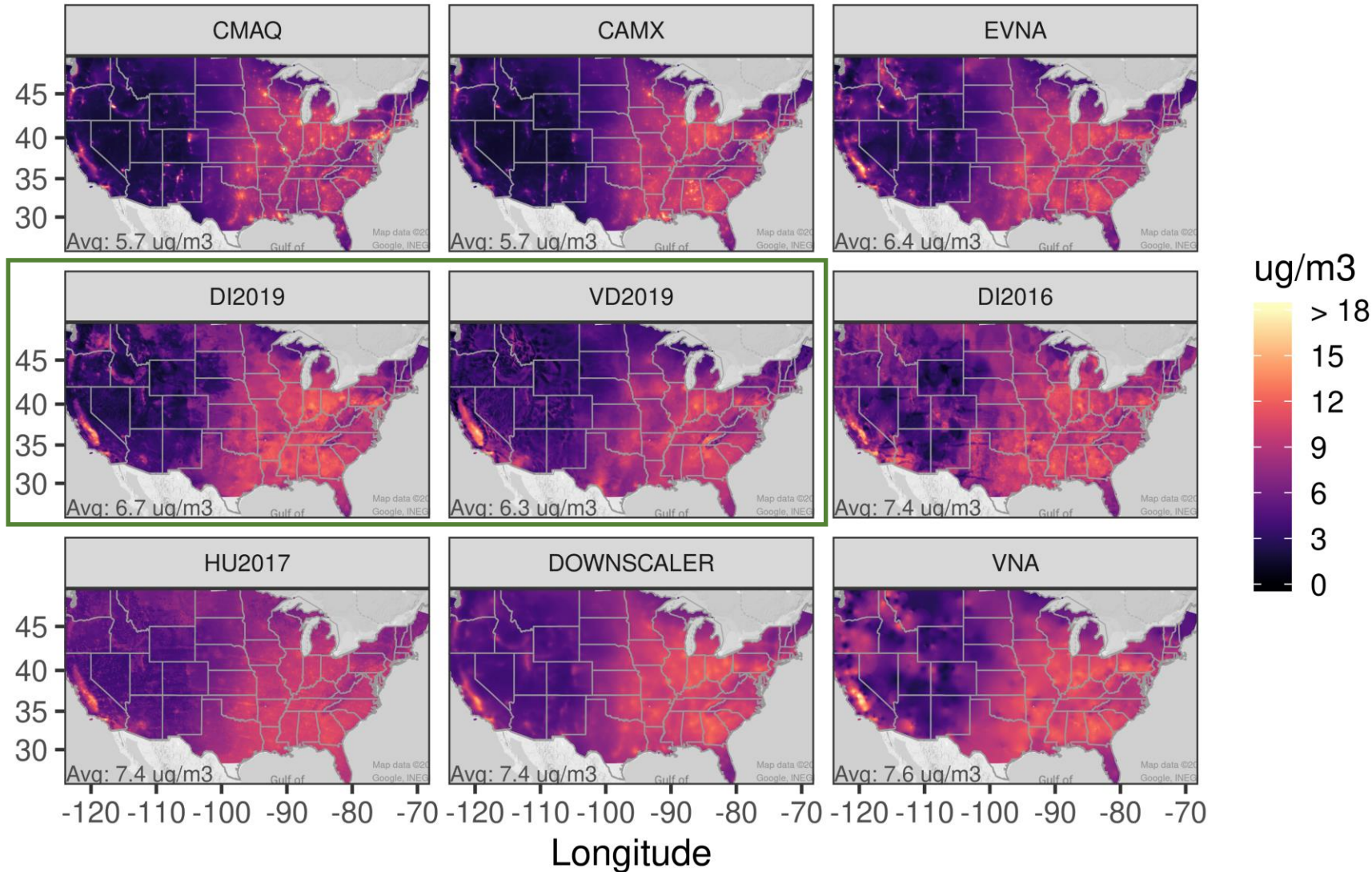
Background on AQ Intercomparison Study

- Early last 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 illustrate capabilities and 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

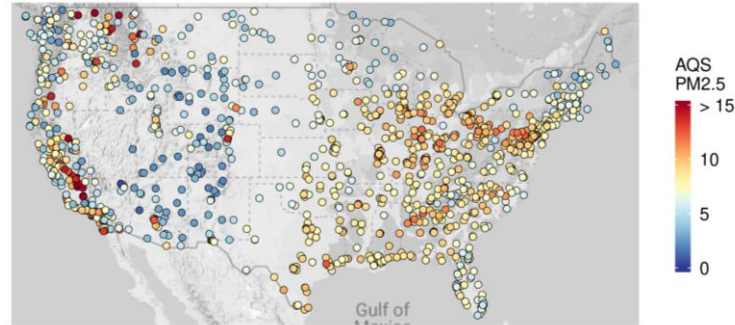
Satellite Method

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

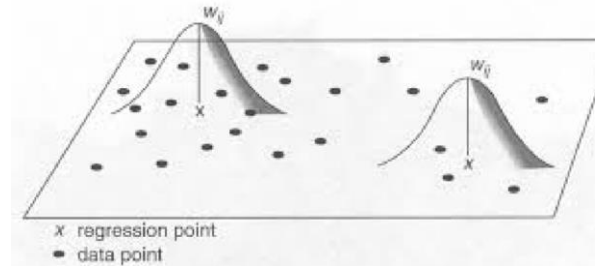
Remote Sensing



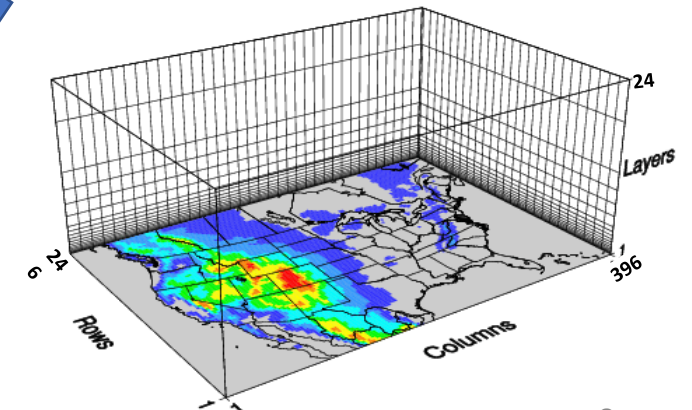
Monitoring



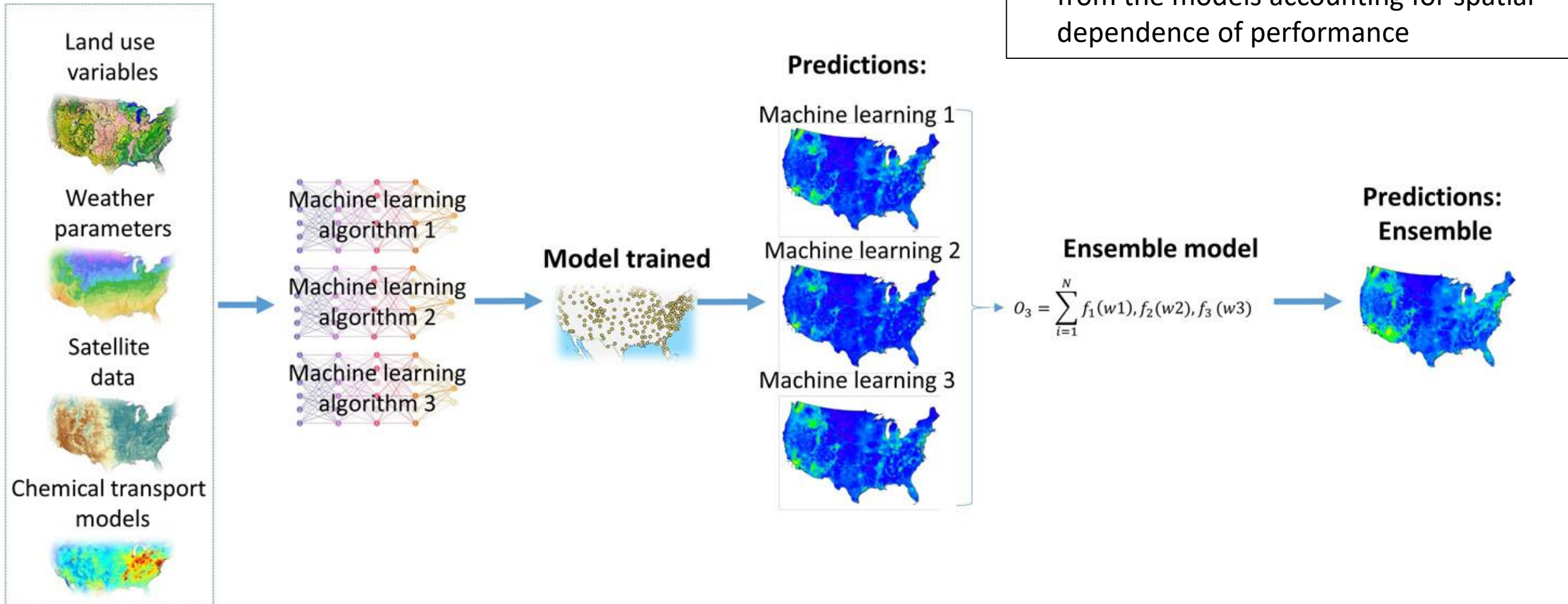
Statistical Fusion



Chemical Transport Modeling



Machine Learning Method



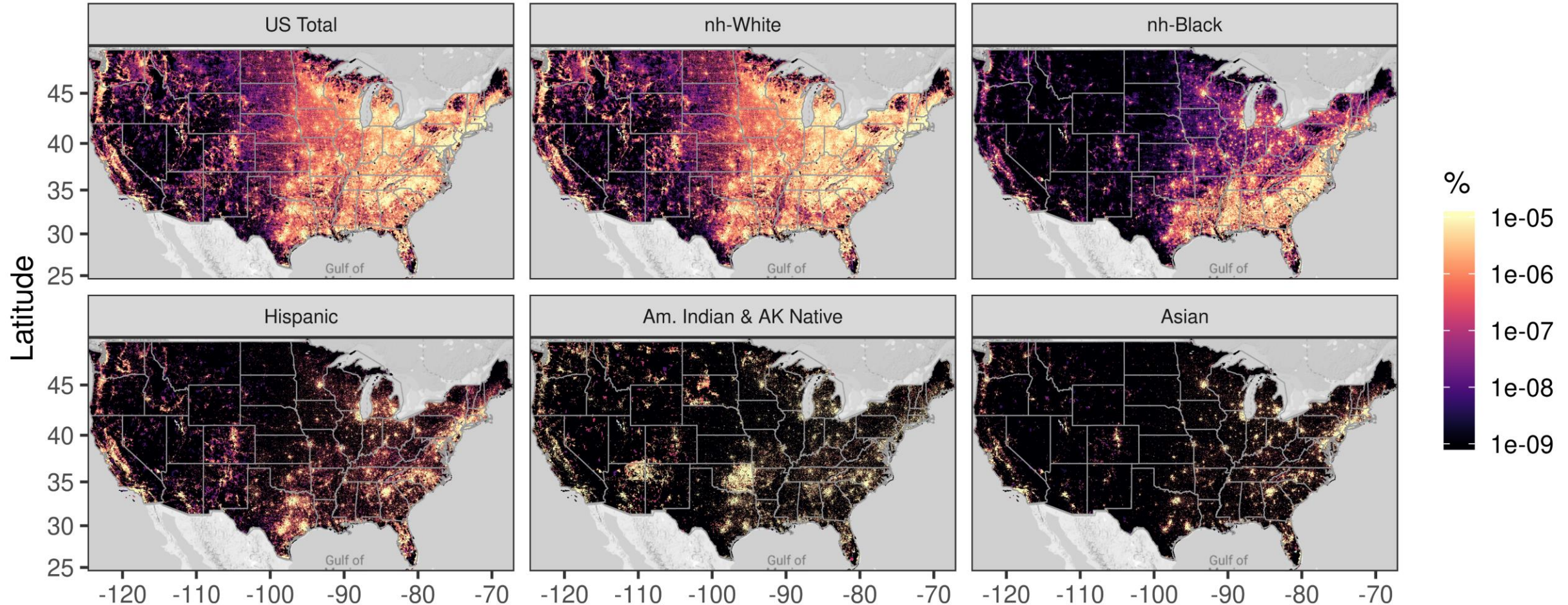
Air Quality Data

- $\text{PM}_{2.5}$
 - **Harvard Machine Learning:** 2000-2016, daily $\text{PM}_{2.5}$ at 1-km resolution based on ensemble machine learning (includes AQAD CMAQ data) ([Di et al., 2019; DI2019](#))
 - **Washington U. Satellite:** 2000-2018, annual $\text{PM}_{2.5}$ at 1-km resolution based on satellite AOD/GEOS-Chem/monitor approach ([van Donkelaar et al., 2019; VD2019](#))
- Ozone
 - **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
 - **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](#))
 - **Washington U. Satellite:** 2019 annual average NO_2 at 2.8-km resolution based on TROPOMI/GEOS-Chem/monitor approach ([Cooper et al., 2020](#))
- Ammonia
 - **Princeton Satellite Oversampling:** Long-term NH_3 at 2-km resolution based on oversampling of 2008-2017 of IASI columns (includes AQAD collaboration) ([Wang et al., 2021](#))

Population Data

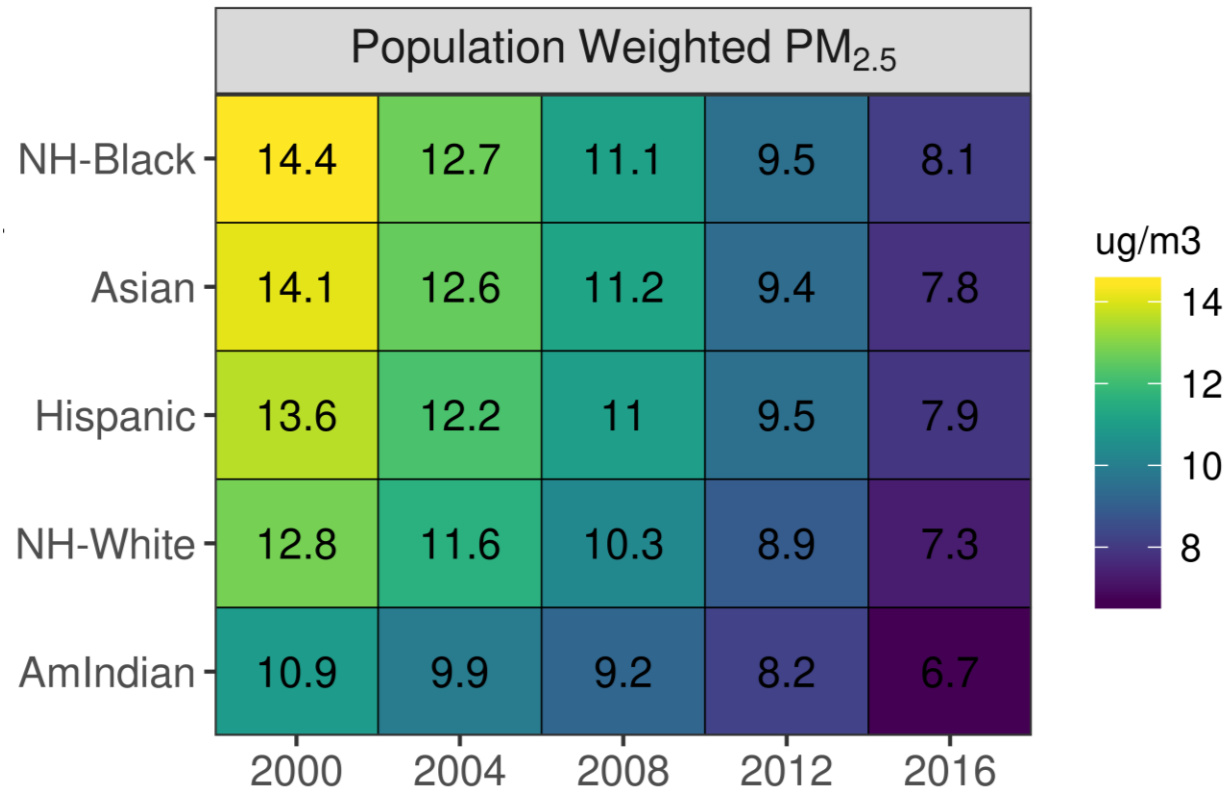
- 2010 Census block data aggregated to 1-km grid are used
- Exposure is estimated using population-weighted concentrations in terms of the following racial/ethnic groups:
 - Hispanic, non-Hispanic White (NH-White), non-Hispanic Black (NH-Black), Asian Alone (Asian), and American Indian & Alaskan Native (Am. Indian)
- We plan to consider time-varying population data and additional demographic indicators in the future, but previous studies have found that
 - Changes in population distributions (i.e., urbanization) have a small effect
 - Associations of race/ethnicity with high exposure remain after controlling for socioeconomic factors

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)

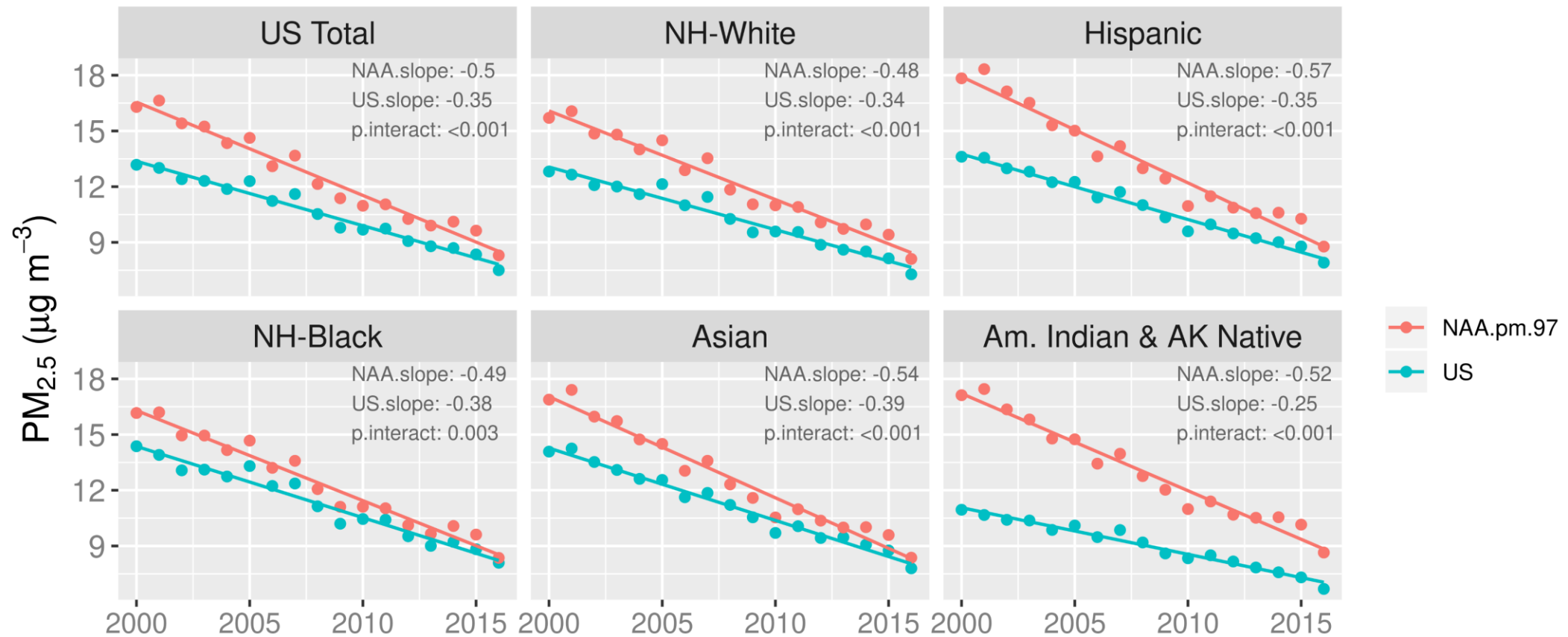
National Population-Weighted PM_{2.5}



- Exposure disparities (0.6 to 1.6 $\mu\text{g m}^{-3}$) exist between NH-Black and NH-White
- The gap between NH-Black and NH-White decreased by 50% from 2000 (1.6 $\mu\text{g m}^{-3}$) to 2016 (0.8 $\mu\text{g m}^{-3}$), 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

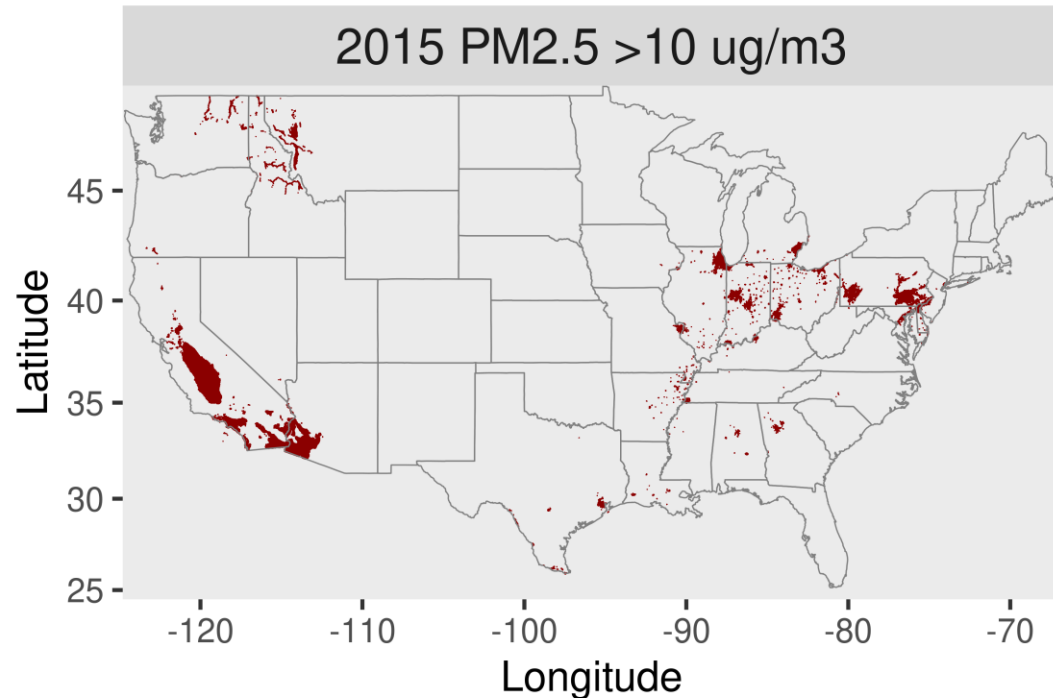
Trends in Hispanic-White PM_{2.5} Gap: 2000-2016



- 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

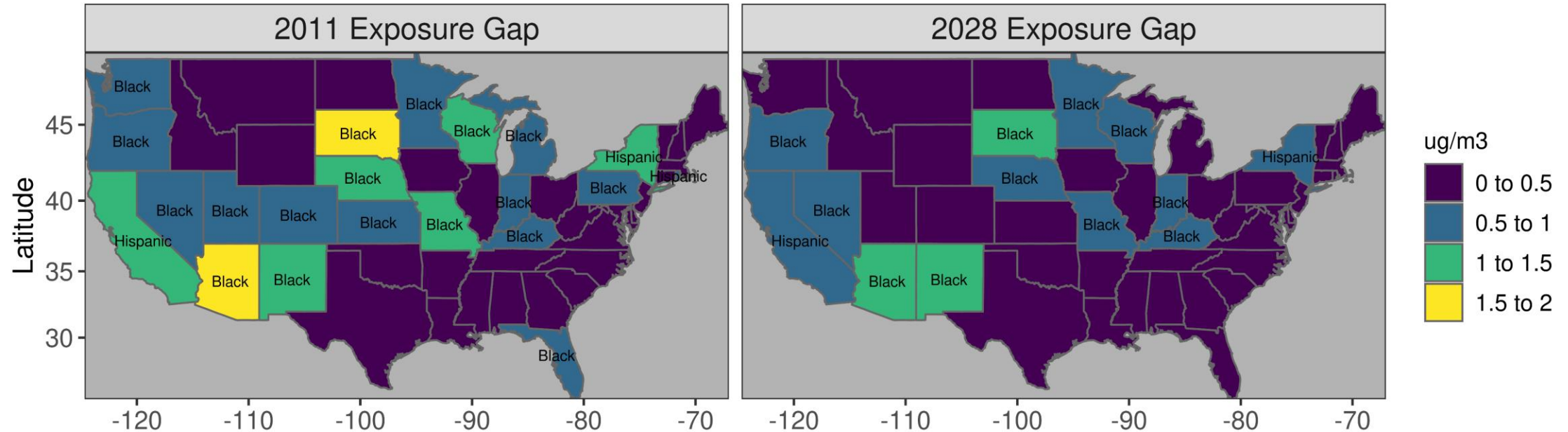


Group	% of Pop	% of Pop >10 $\mu\text{g}/\text{m}^3$	Difference
NH-White	63.9	46.9	-17
Hispanic	16.4	28.1	+11.7
NH-Black	12.3	15.4	+3.1
Asian	4.6	7.2	+2.6
Am. Indian	0.9	0.6	-0.3

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

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

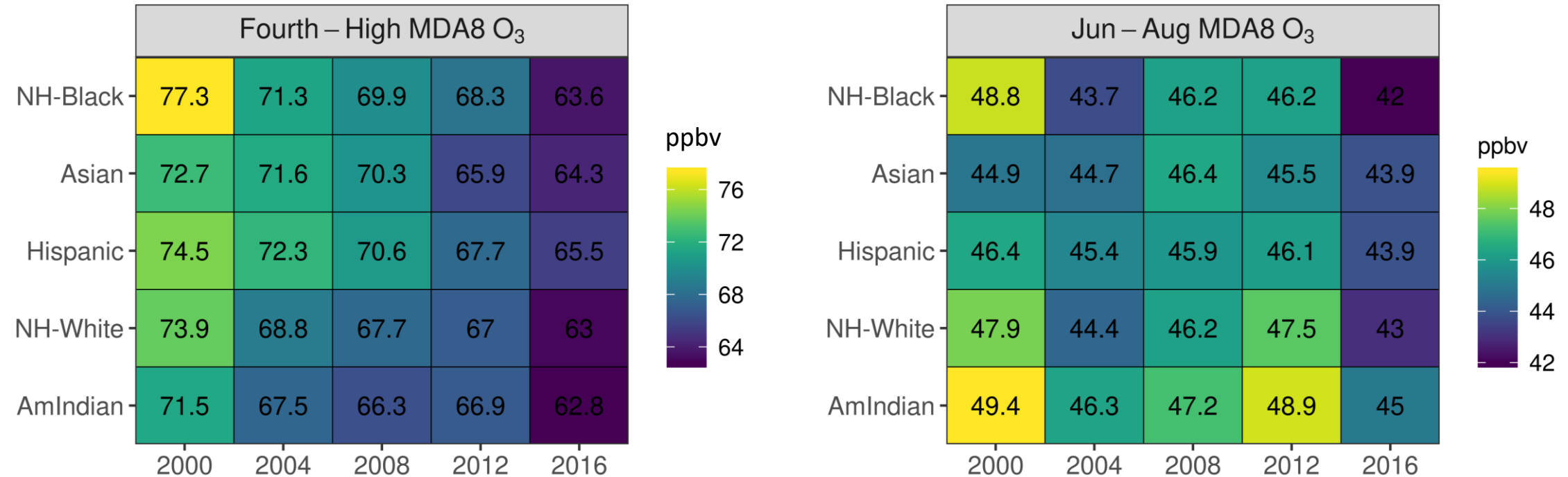
Future Projection of PM_{2.5} Exposure Gap: 2011-2028



- 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 $\mu\text{g}/\text{m}^3$ in 2011, but only three do in 2028

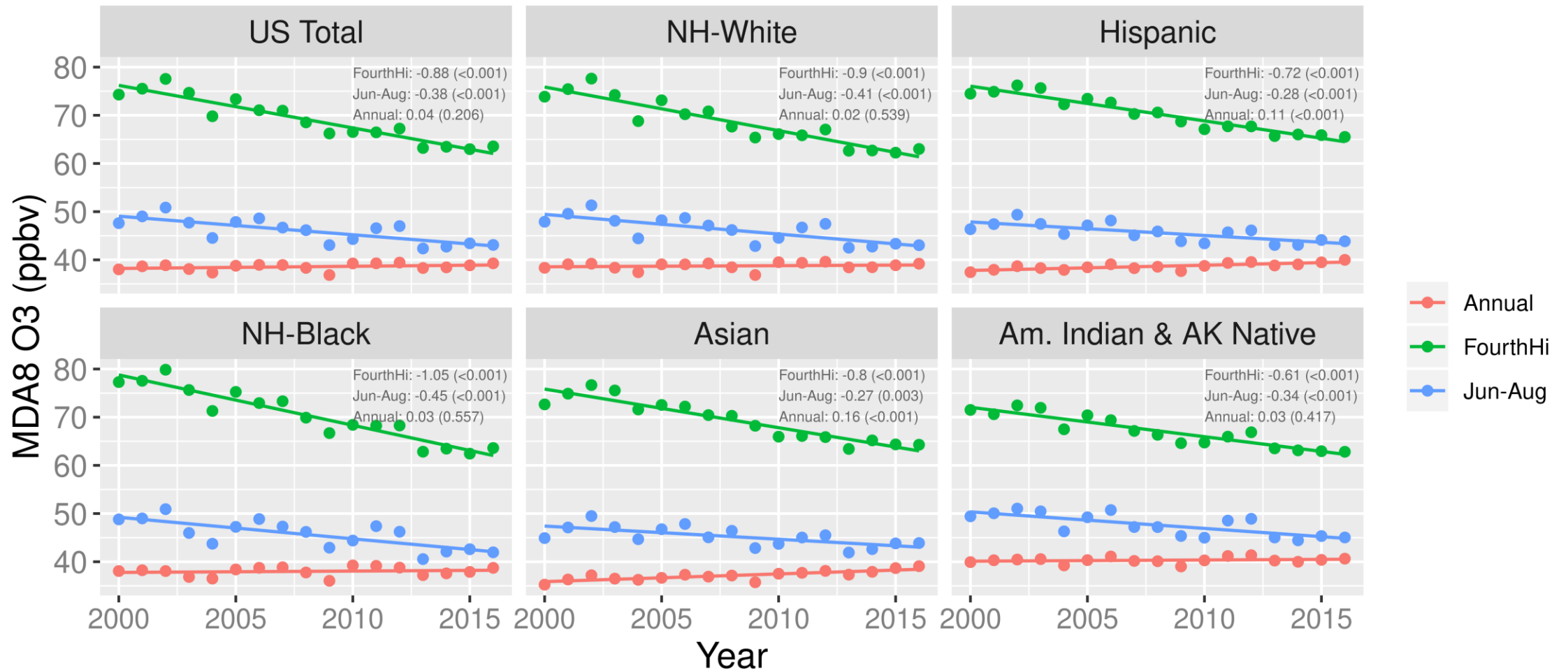
Projections from 2011 to 2028 continue the historical trend of reductions in the absolute exposure gap with persistence of most-exposed group

Population-Weighted MDA8 Ozone: 2000-2016



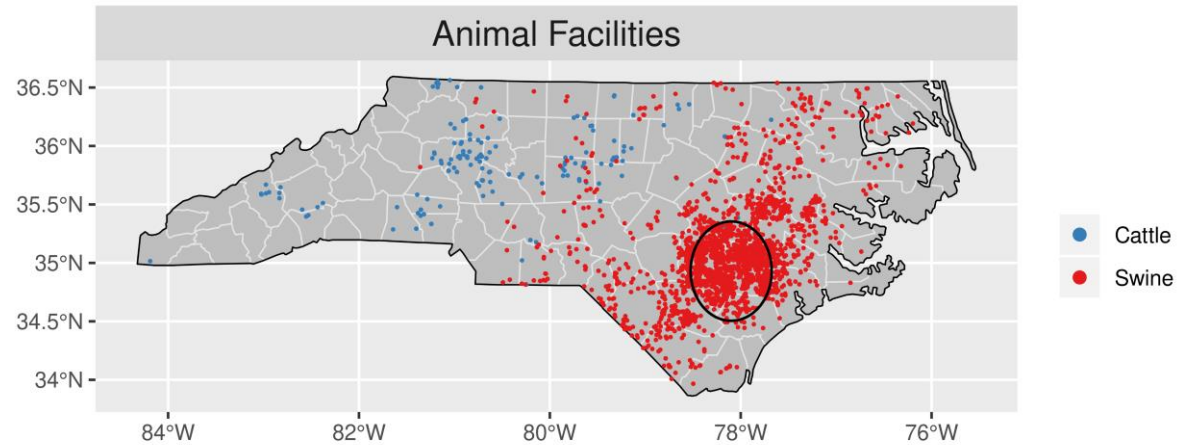
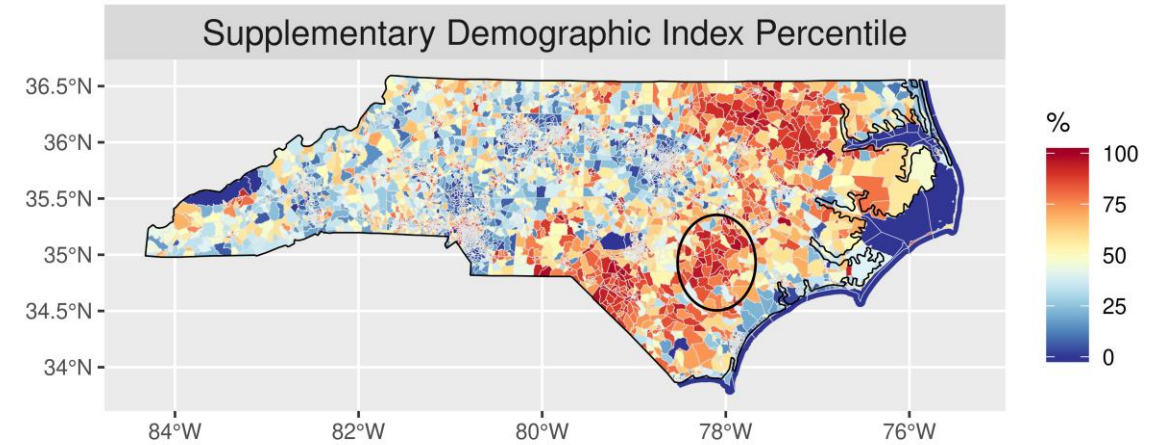
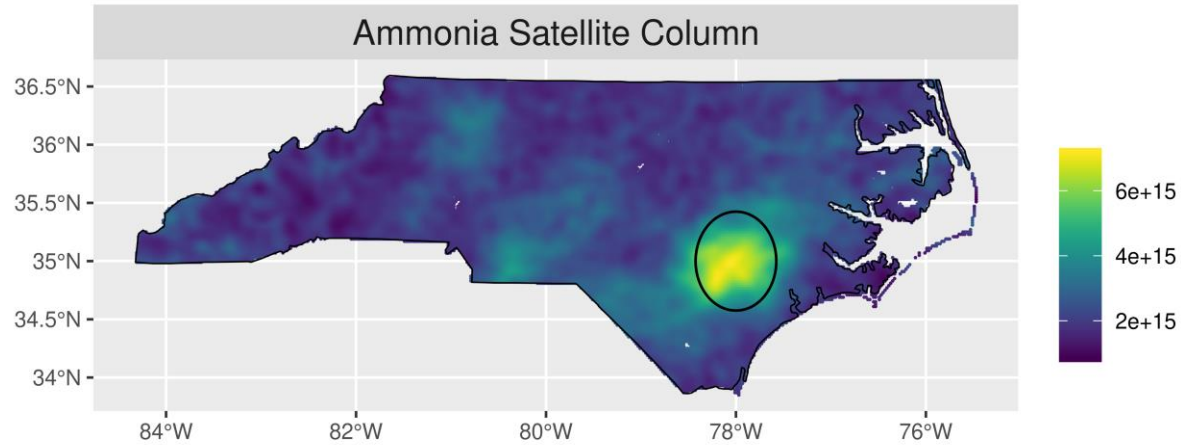
The most exposed group varies with metric (generally NH-Black for 4th high and Am. Indian for summer mean MDA8 O₃)

Trends in Three MDA8 Ozone Metrics: 2000-2016



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

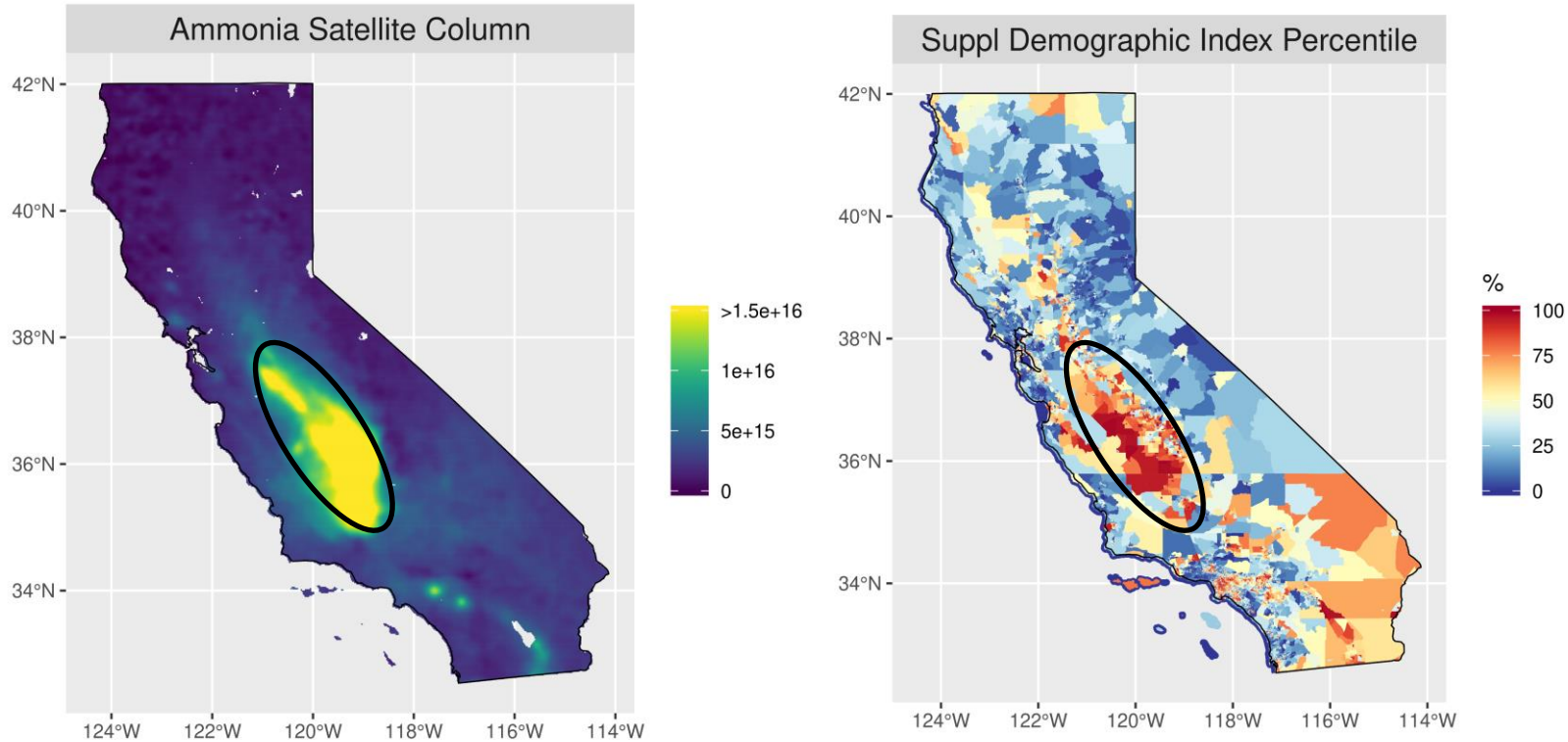
Ammonia in North Carolina



In eastern NC, ammonia is elevated near hog farms where Demographic Index Percentile* is elevated

*Suppl. Dem. Index Percentile: The percentile (% of the US population lives in a block group with a lower value) of the Supplementary Demographic Index (the average of percent minority, percent low income, percent less than high school education, percent linguistically isolated, percent kids, and percent elderly in the block group)

Ammonia in California

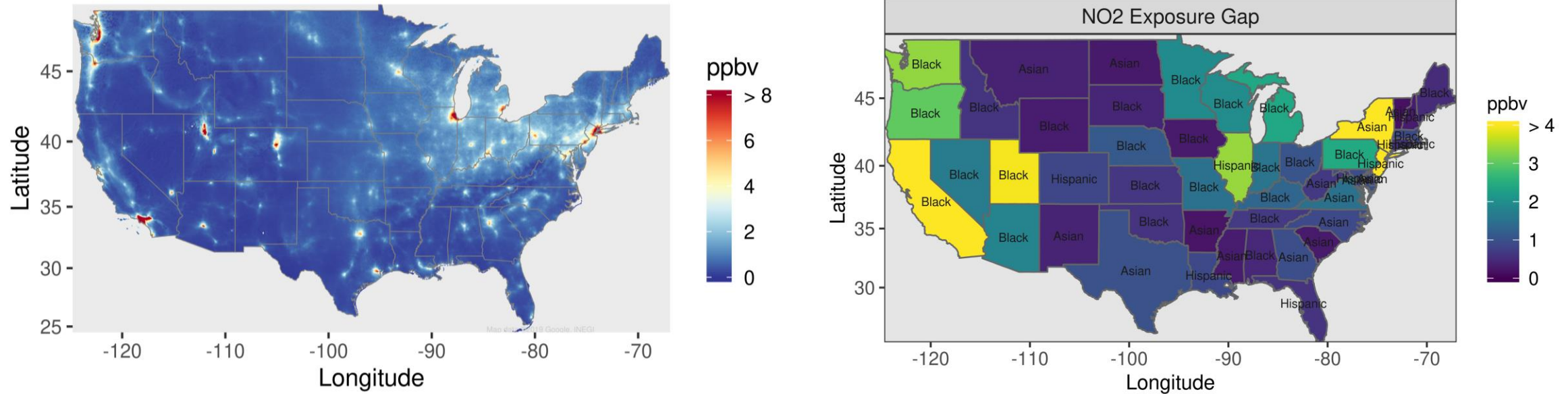


In San Joaquin Valley, ammonia is elevated near dairy farms and agricultural activity where Demographic Index Percentile* is elevated

- Statewide, ammonia exposure is 30% higher for Hispanic than NH-White based on satellite columns

*Suppl. Dem. Index Percentile: The percentile (% of the US population lives in a block group with a lower value) of the Supplementary Demographic Index (the average of percent minority, percent low income, percent less than high school education, percent linguistically isolated, percent kids, and percent elderly in the block group)

Nitrogen Dioxide (NO₂)

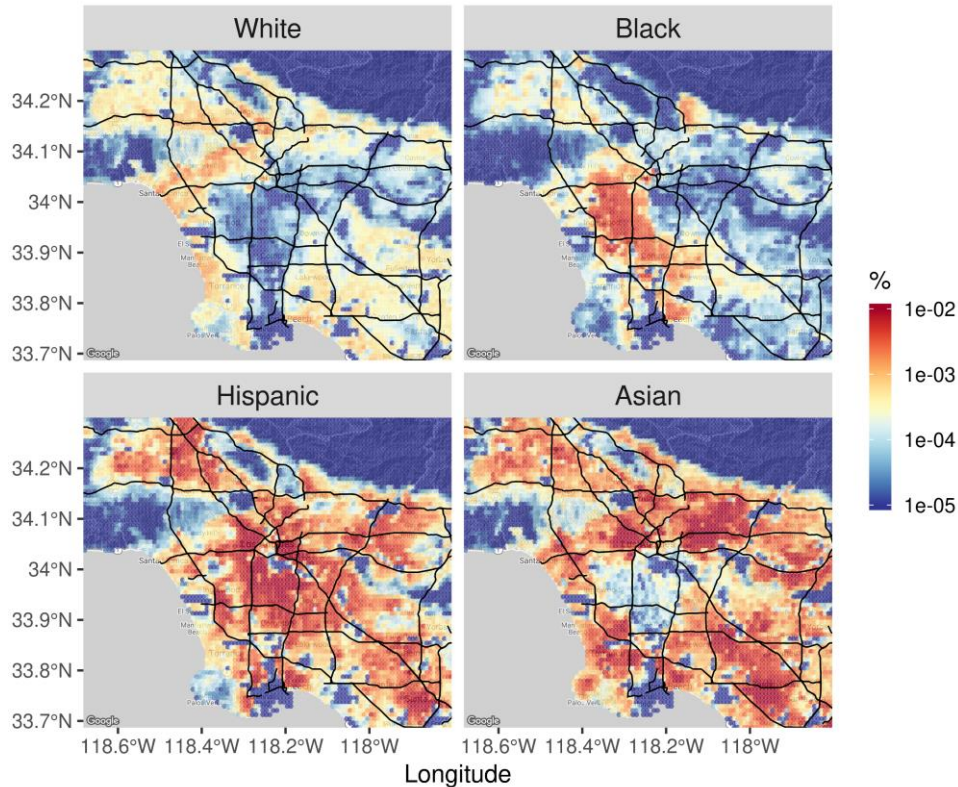


- NO₂ is more spatially heterogeneous than PM_{2.5} yielding greater relative disparities (e.g., the Asian-White PM_{2.5} gap is 7% of the national pop-wt PM_{2.5}, but the gap is 100% for NO₂)

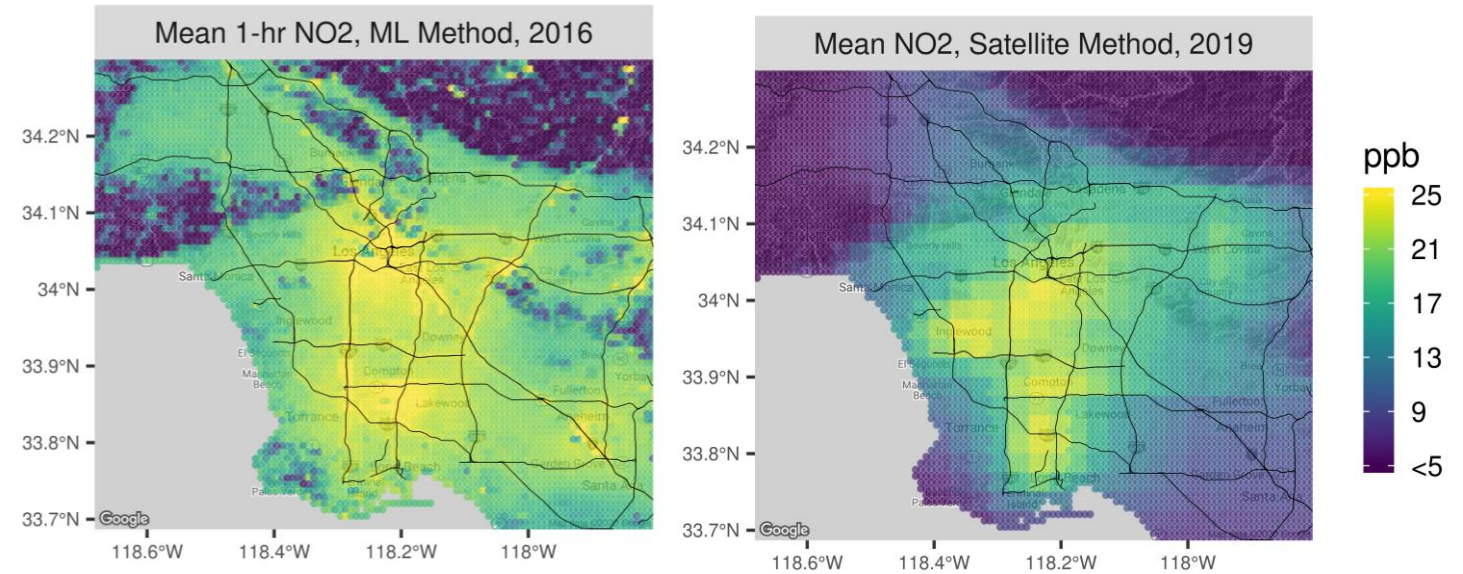
Spatially heterogeneous pollutants like NO₂, BC, diesel PM, UFP, and localized air toxics expected to have higher disparities than PM_{2.5}

NO₂ in Los Angeles

Normalized 2010 Population



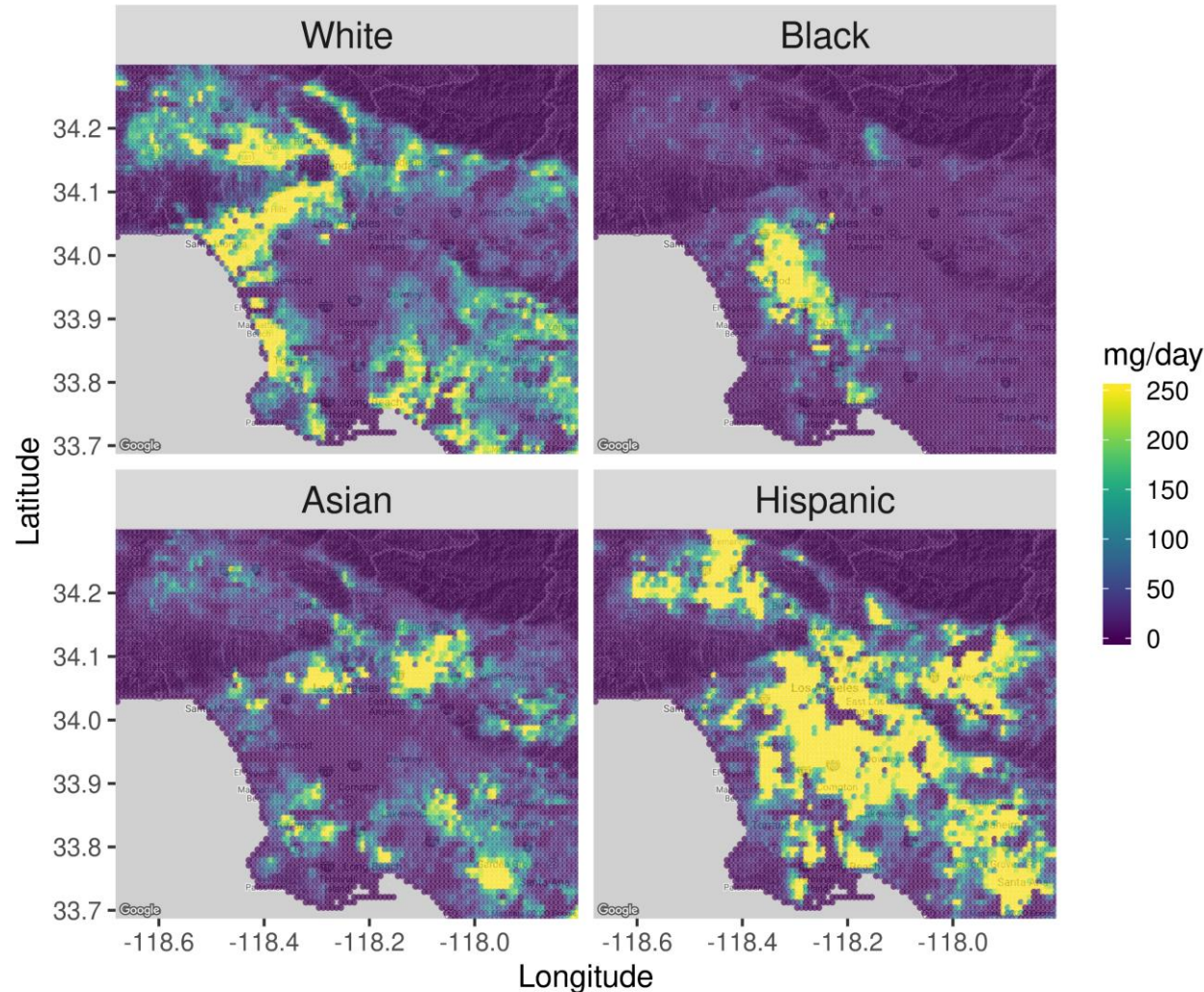
NO₂ Predictions



- 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



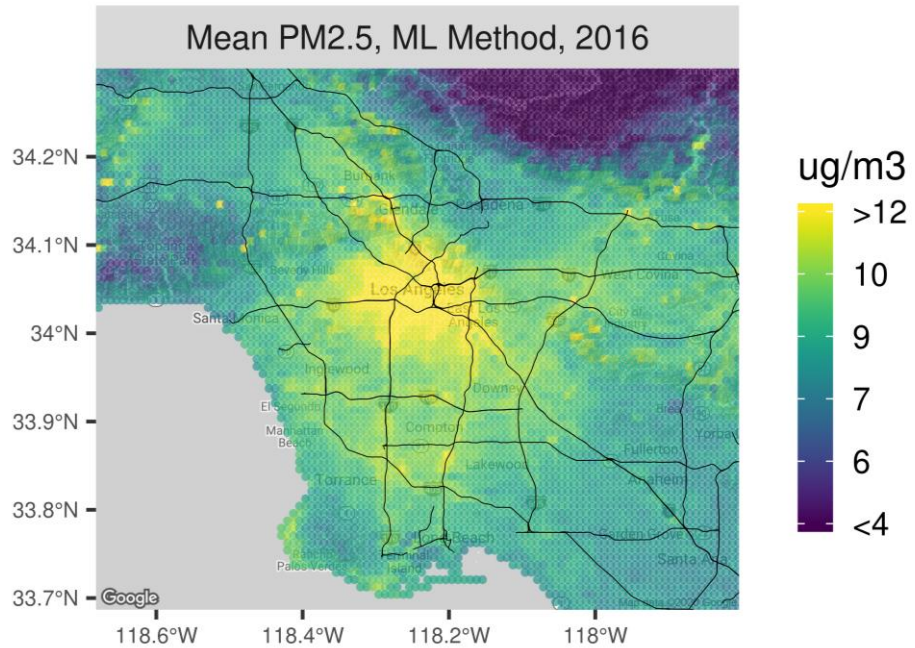
- Inhaled PM_{2.5} (mg day⁻¹) in 2015 by group was calculated*
- Spatial segregation in urban areas provides opportunities for addressing disparities (ex., Rule 445 wrt Compton)

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

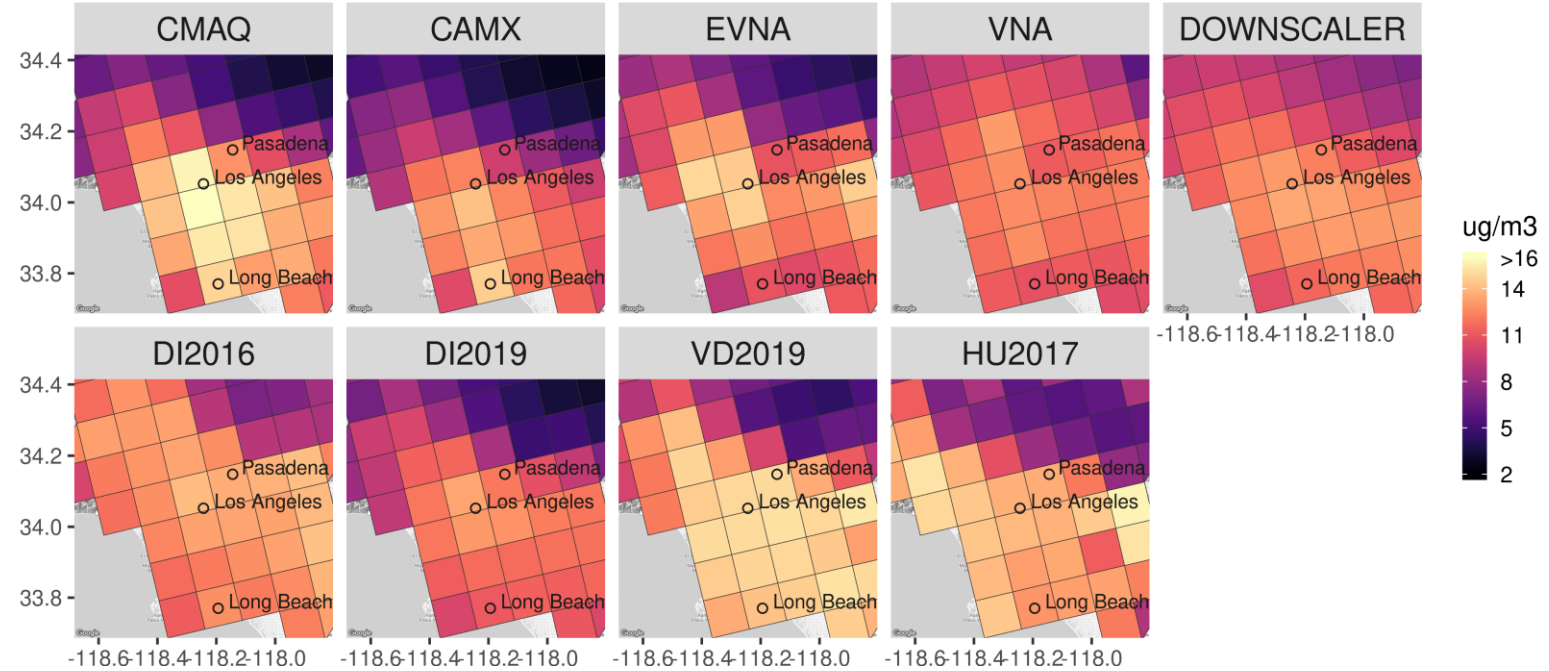
*Inhaled mass: PM_{2.5} x breathing rate x population = (μg/m³) (1 mg/1000 μg) x (m³/person/day) x (# person) = mg/day

Consideration of Grid Resolution for Los Angeles PM_{2.5}

2016 PM_{2.5}, 1-km Grid Spacing



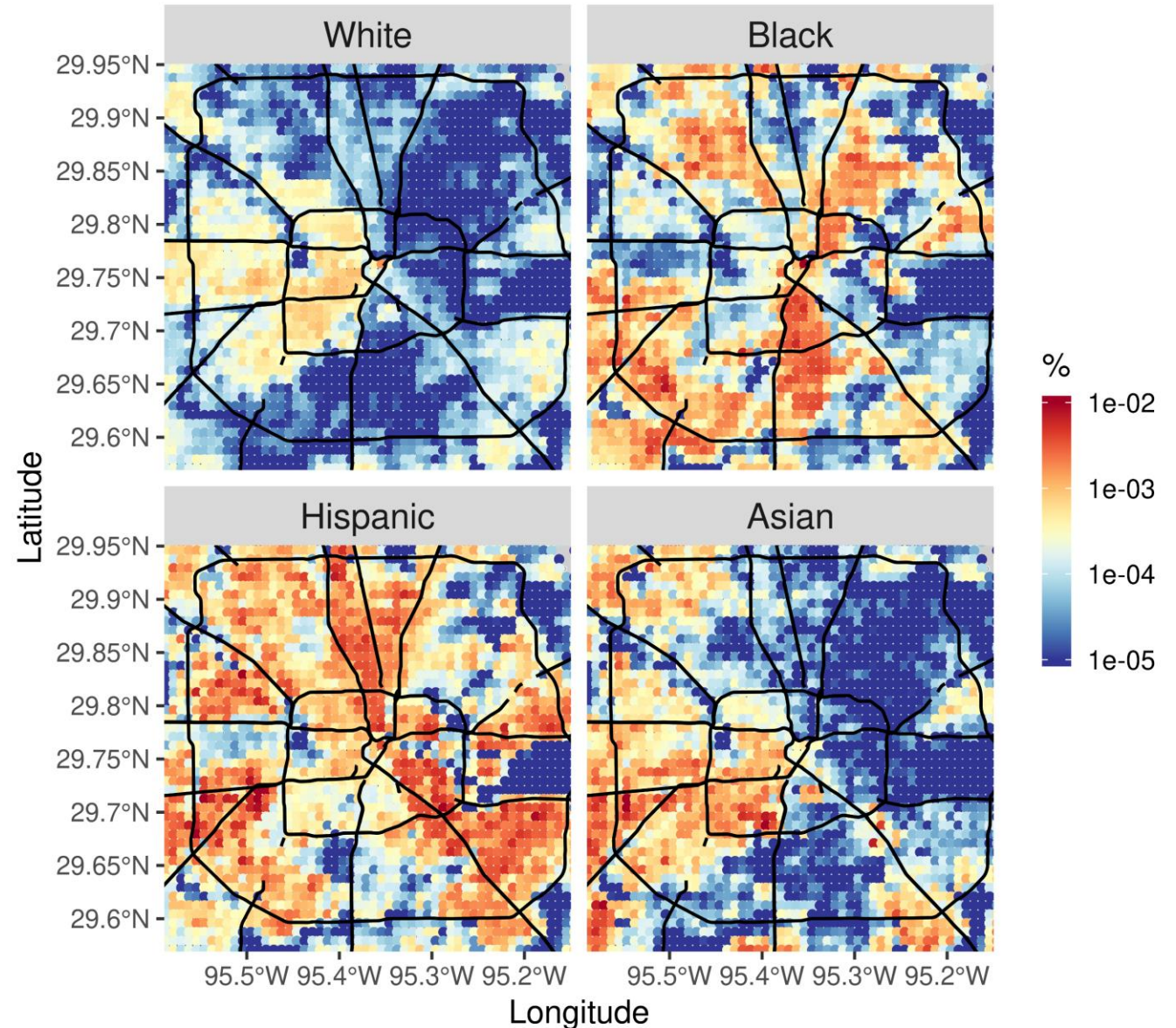
2011 PM_{2.5}, 12-km Grid Spacing



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

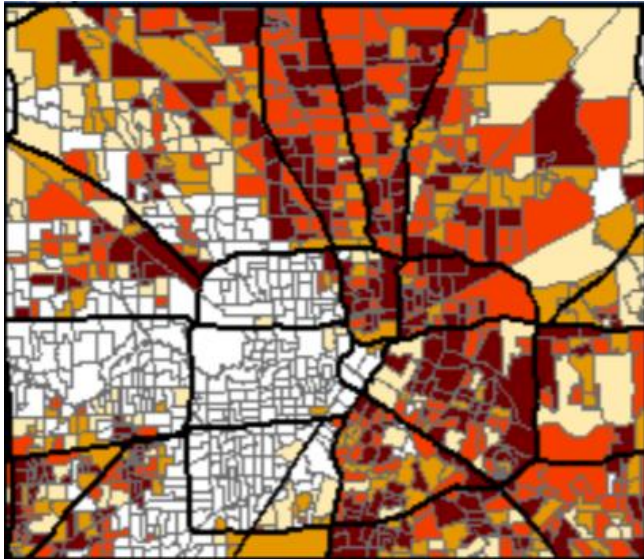
Normalized 2010 Population Distributions in Houston

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

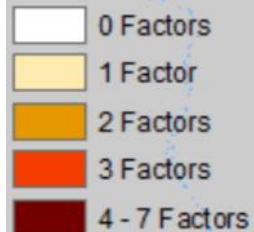


Houston NO₂ and PM_{2.5}

Zones of Composite Disadvantage



EJ Composite Zones

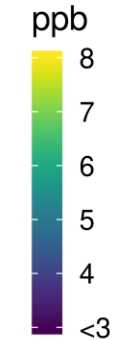
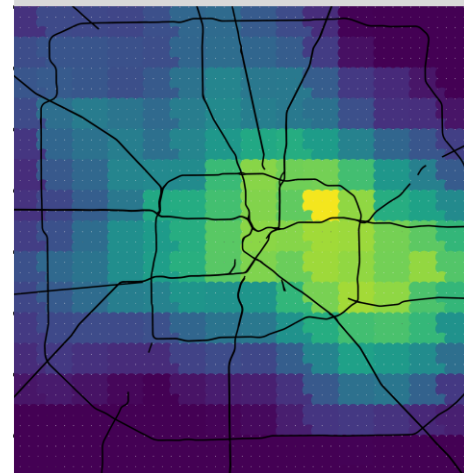


EJ Factors:

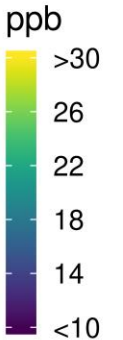
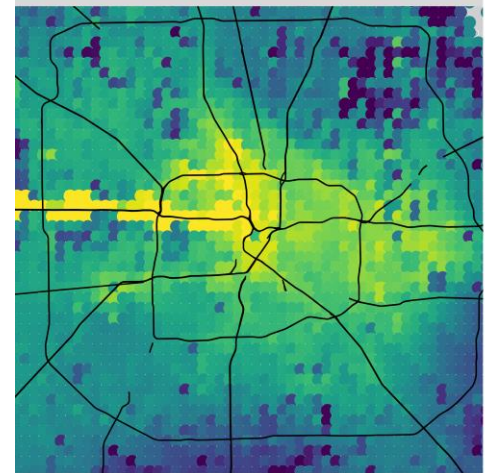
- i. **Minority status**
- ii. **Low-income status**
- iii. Limited English proficiency
- iv. Senior status
- v. Limited educational attainment
- vi. Carless households
- vii. Female head of households

NO₂ Predictions

Mean NO₂, Satellite Method, 2019

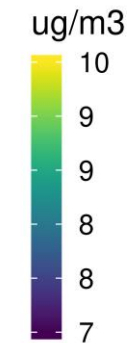
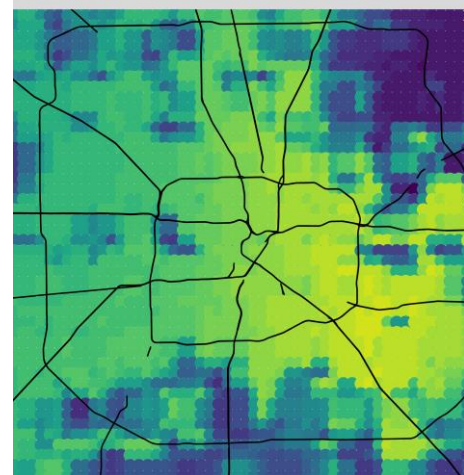


Mean 1-hr NO₂, ML Method, 2016

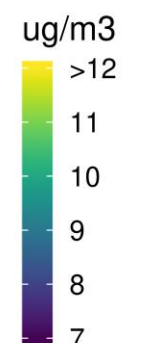
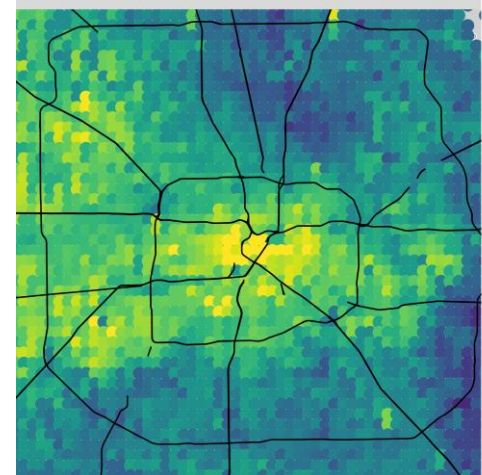


PM_{2.5} Predictions

Mean PM_{2.5}, Satellite Method, 2016



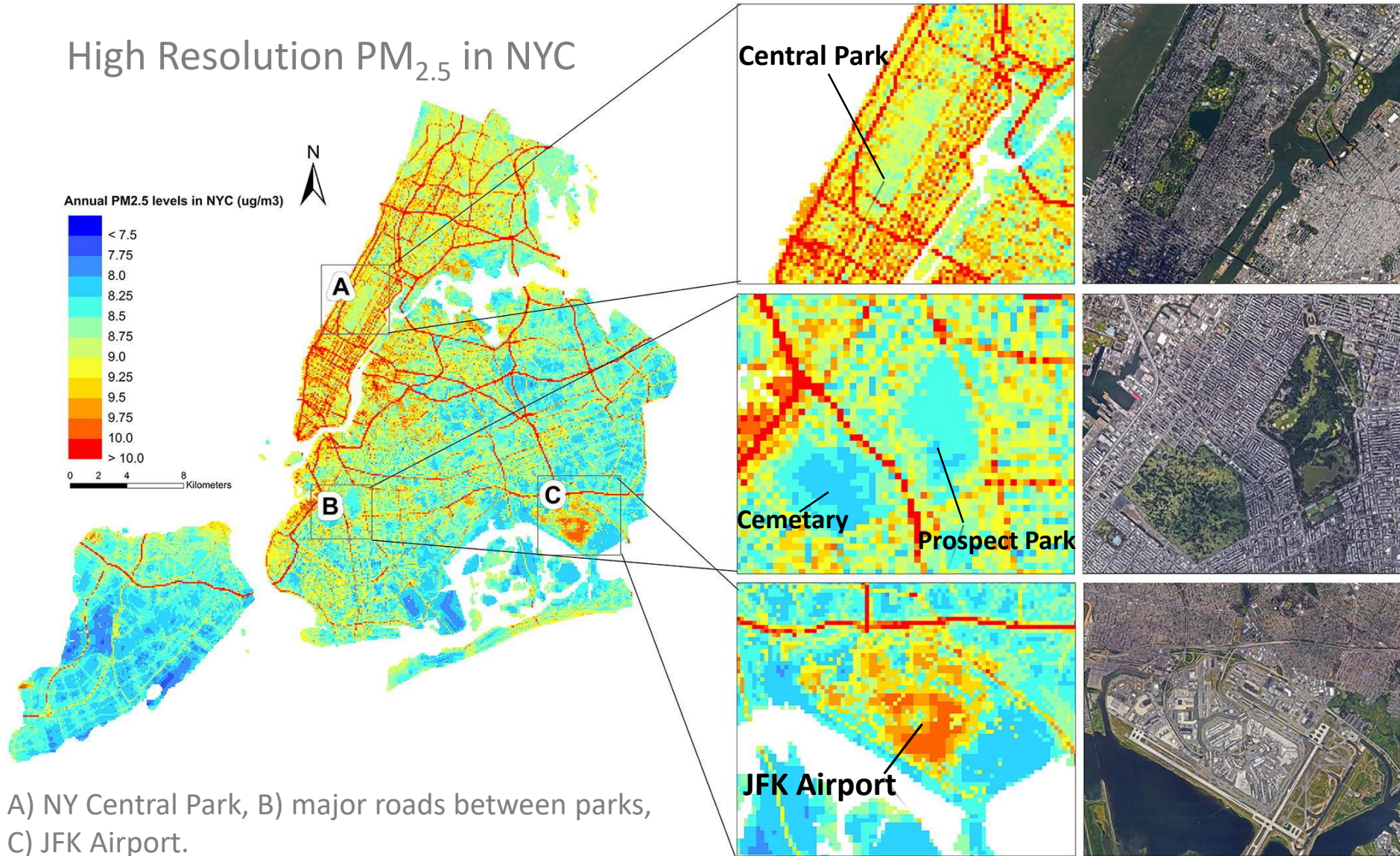
Mean PM_{2.5}, ML Method, 2016



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

Non-Regulatory Measurements for “Neighborhood Scale” Air Quality

High Resolution PM_{2.5} in NYC



- Random 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.

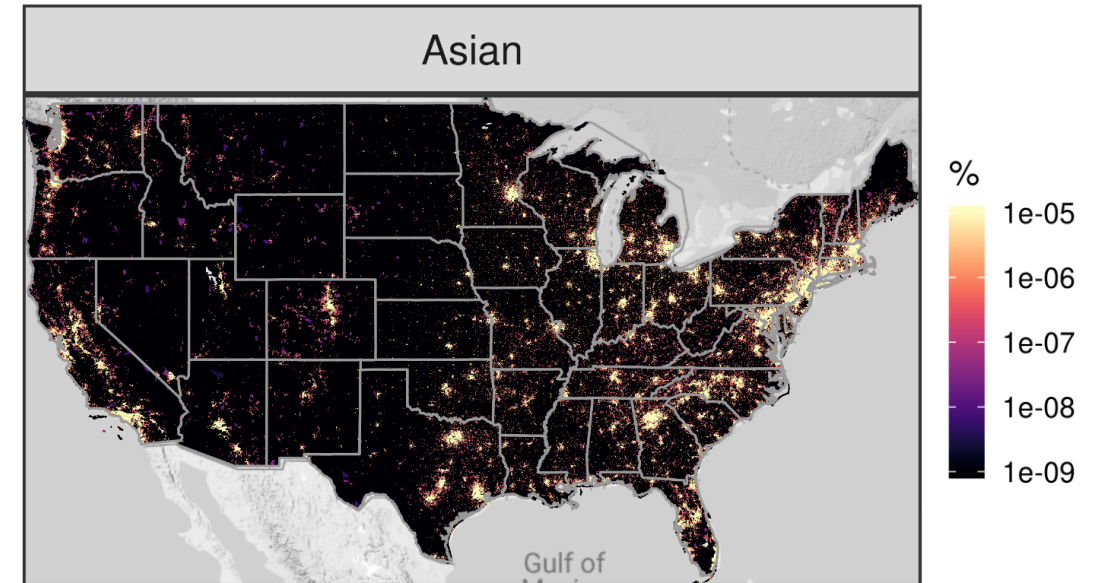
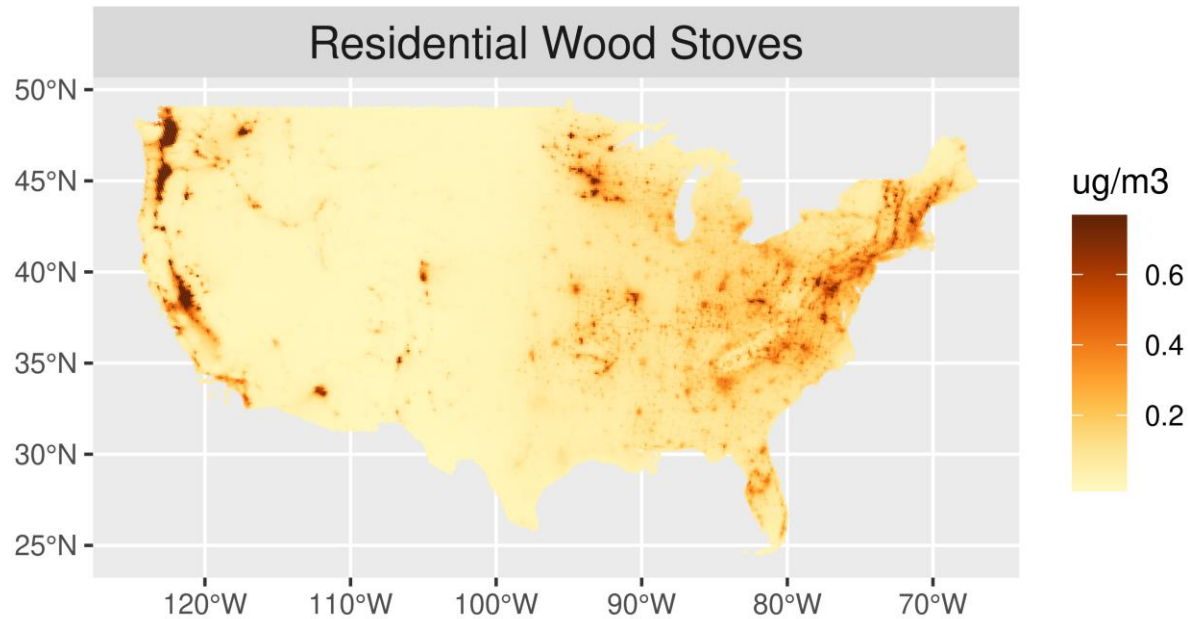
Conclusions. Disparities in burden from PM-emitting facilities exist at multiple geographic scales. Disparities for Blacks are more pronounced than are disparities on the basis of poverty status. Strictly socioeconomic considerations may be insufficient to reduce PM burdens equitably across populations. (*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

Preliminary Consideration of 2017 Sector Modeling



2017 Sector Modeling from Kirk Baker

- Nationally, exposure to PM_{2.5} from residential wood stoves is 30% higher for Asian than NH-White based on 2017 CAMx sector modeling

Future work will examine sector contributions to exposure in more detail

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., 4th high, summer mean, annual mean MDA8 O₃)
- Disparities are relatively high for NO₂ 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 Analytic 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
- Others?

Future Directions (2): Connecting to OAQPS Programmatic Needs

- Specific applications to be identified through cross-office coordination but could 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?