GEOS-Chem-APM for (1) physics-guided machine learning parameterizations & (2) aerosol pollution exposure and health disparities assessment

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Research Tool

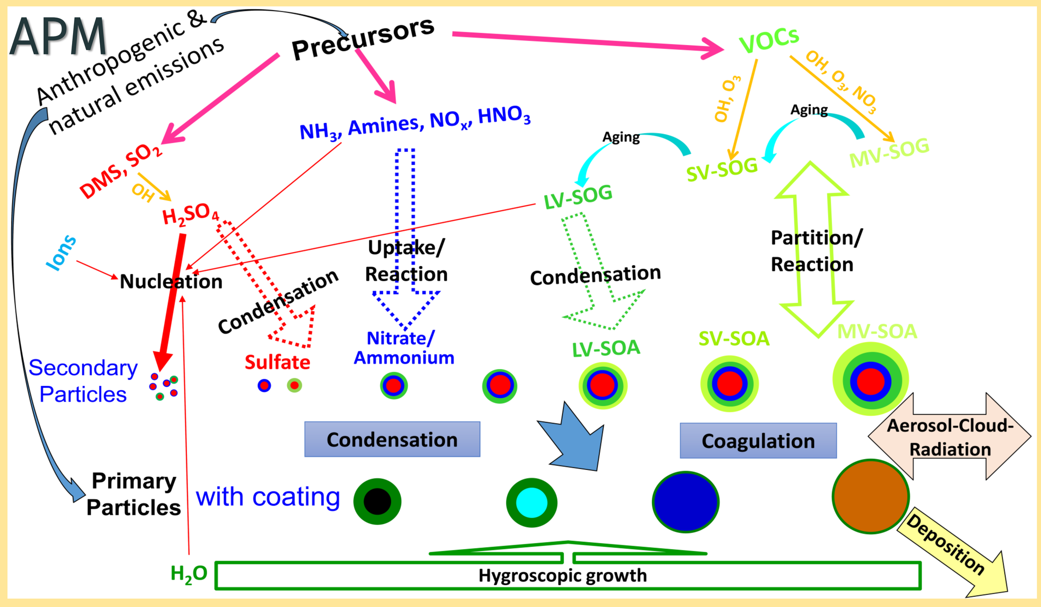
GEOS-Chem-APM

Full Chemistry

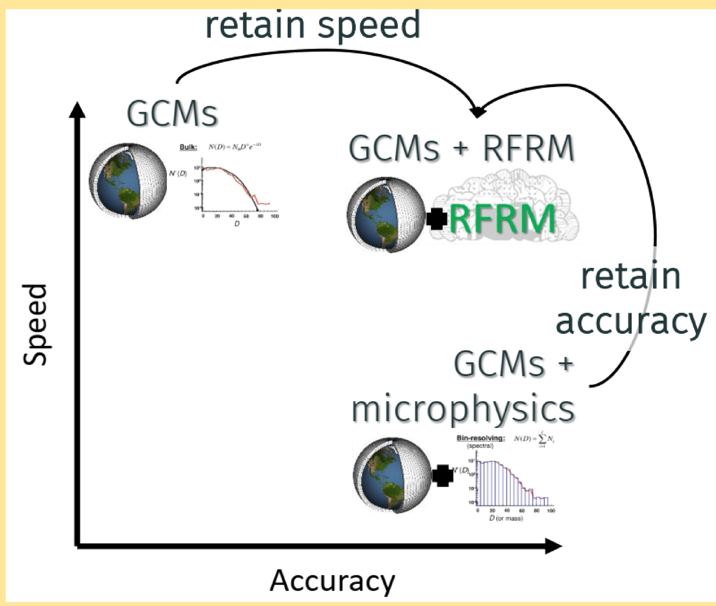
Size-resolved (bin) particle microphysics

Coating of primary particles by secondary particles

State-of-the-science nucleation mechanisms (Yu et al., GMD 2020)

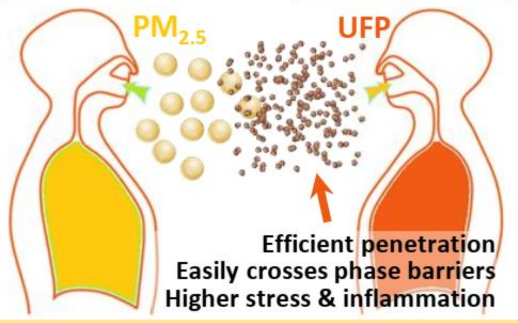


Objectives

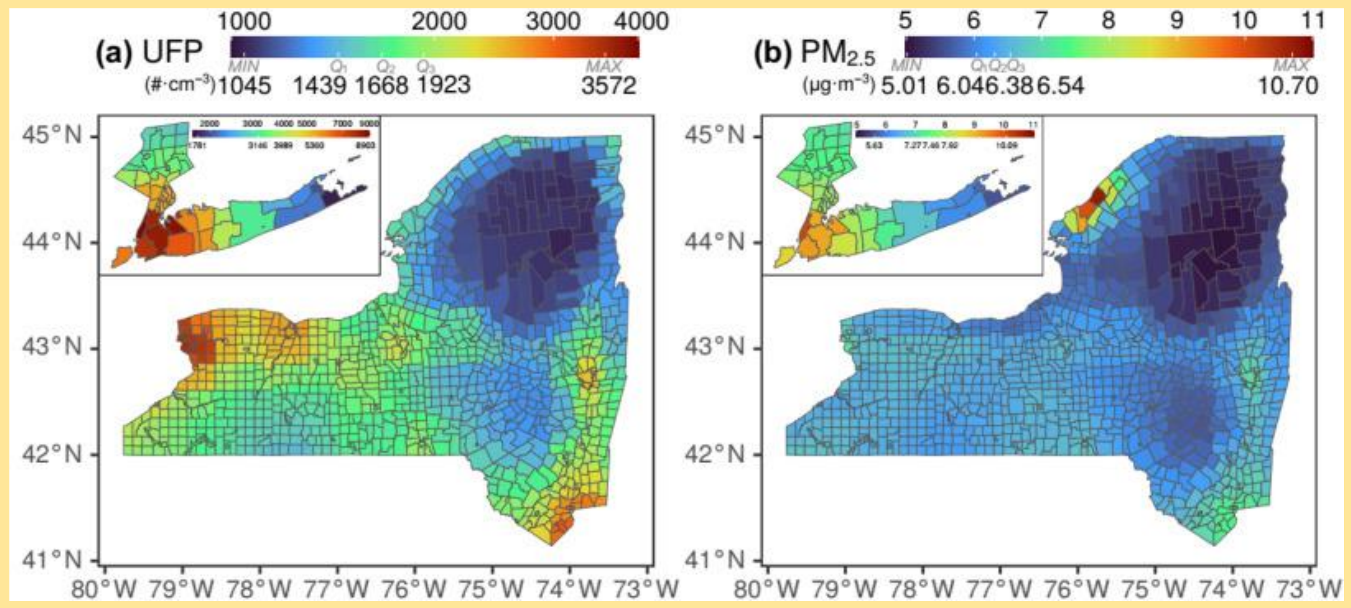


UFP potentially more deleterious than $PM_{2.5}$

	$PM_{2.5}$	UFP
Number	Small	Large
Size	Large	Small
Mass	Large	Small
Surface area: Volume ratio	Small	Large
Atmospheric lifetime	Short	Long
Regulated	Yes	No

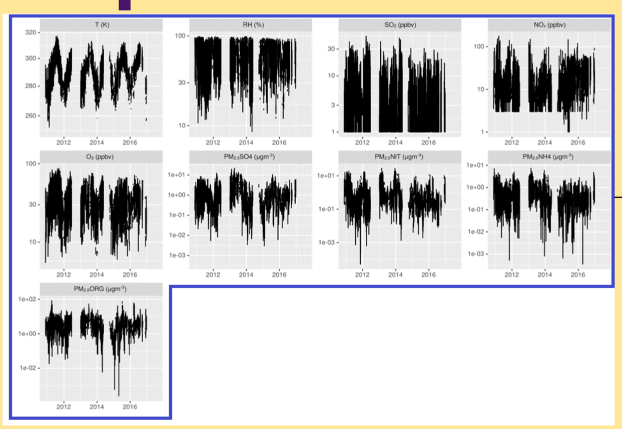


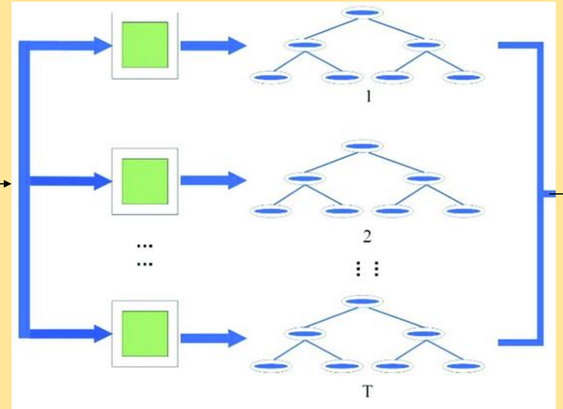
Domain for health-effects studies

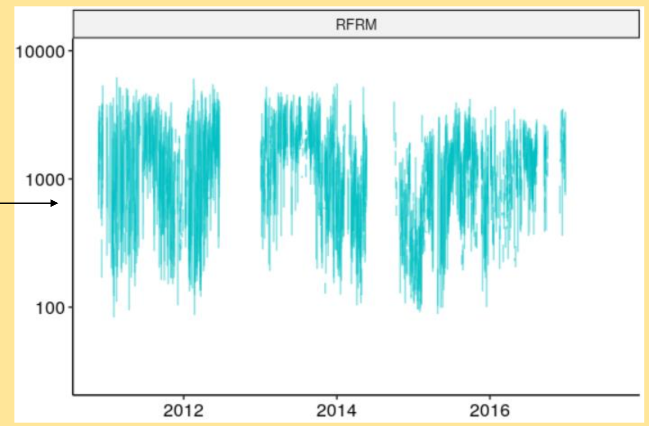


Machine Learning of Aerosol Properties

Input variables → Machine learning → Predictions







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Atmospheric Chemistry and Physics
EGU

Using machine learning to derive cloud condensation nuclei number concentrations from commonly available measurements

Arshad Arjunan Nair and Fangqun Yu
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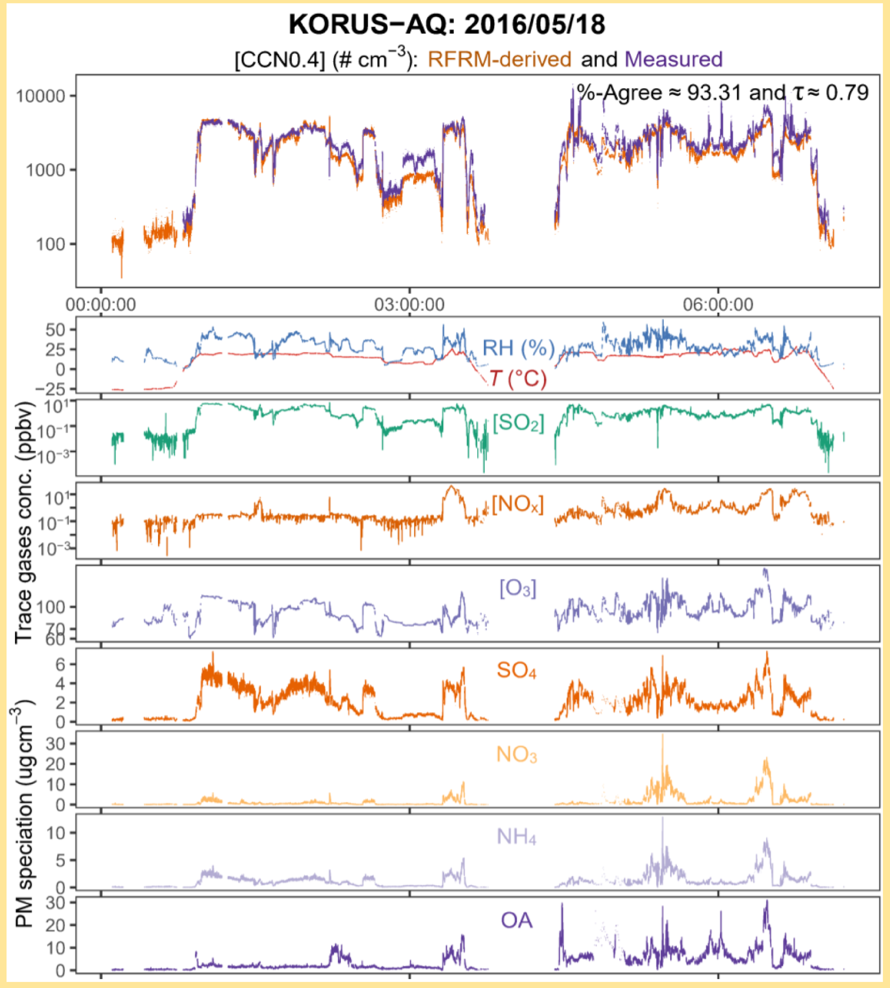
- ML trained on long-term GEOS-Chem-APM simulations
- Predictors: fractions of $PM_{2.5}$ (NH_4, SO_4, NO_3, SOA, BC, POC, dust, and salt), gaseous species (NO_x, NH_3, O_3, SO_2, OH, isoprene, and monoterpene), and meteorological variables (T, RH, precipitation, and solar radiation)
- Also captures [CCN0.4] variability & magnitude at ARM SGP

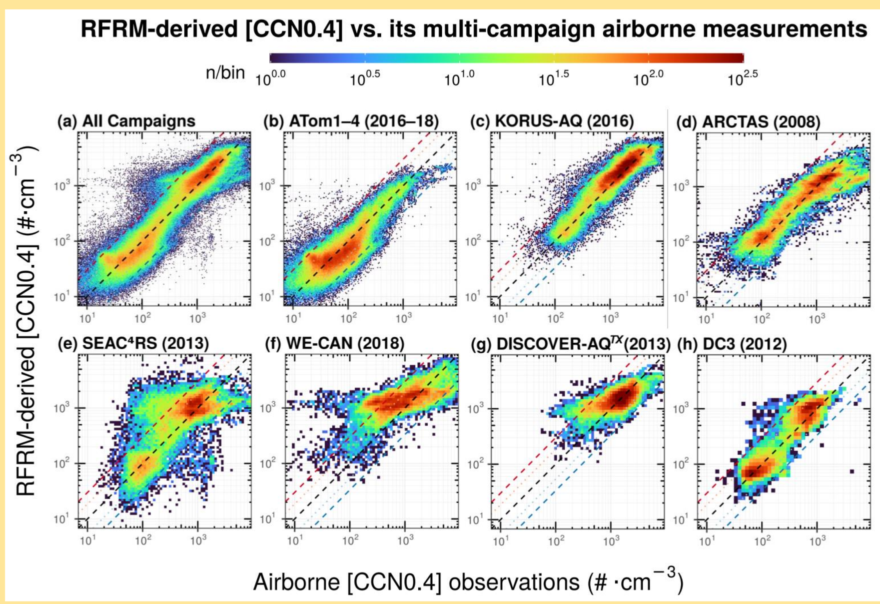


Geophysical Research Letters
AGU ADVANCING EARTH AND SPACE SCIENCE

Machine Learning Uncovers Aerosol Size Information From Chemistry and Meteorology to Quantify Potential Cloud-Forming Particles

Arshad Arjunan Nair[1], Fangqun Yu[1], Pedro Campuzano-Jost[2,3], Paul J. DeMott[4], Ezra J. T. Levin[4,5], Jose L. Jimenez[2,3], Jeff Peischl[2,6], Ilana B. Pollack[4], Carley D. Fredrickson[7], Andreas J. Beyersdorf[8,9], Benjamin A. Nault[2,3,10], Minsu Park[11], Seong Soo Yum[11], Brett B. Palm[7], Lu Xu[12,13], Ilann Bourgeois[2,6], Bruce E. Anderson[8], Athanasios Nenes[14,15,16], Luke D. Ziemba[8], Richard H. Moore[8], Taehyoung Lee[17], Taehyun Park[17], Chelsea R. Thompson[2,6], Frank Flocke[18], Lewis Gregory Huey[19], Michelle J. Kim[12], and Qiaoyun Peng[7]

- ML-derived CCN numbers in strong agreement with multi-campaign aircraft measurements
- Aerosol size information is contained in speciated aerosol mass, chemistry, and meteorology and is extractable by ML

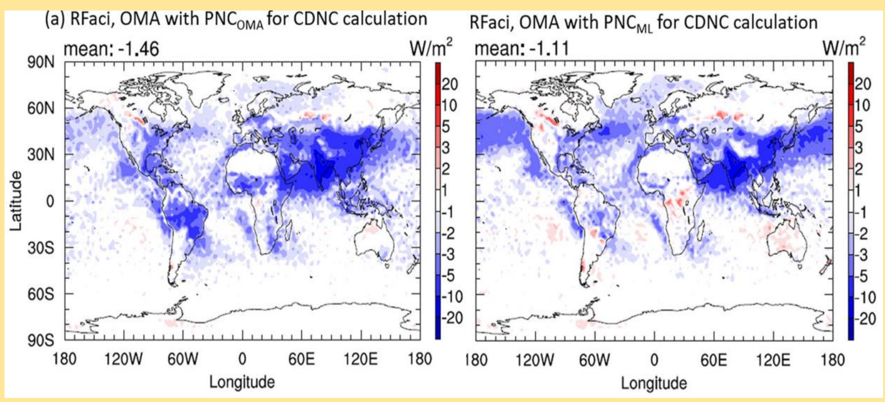


Geophysical Research Letters
AGU ADVANCING EARTH AND SPACE SCIENCE

Use of Machine Learning to Reduce Uncertainties in Particle Number Concentration and Aerosol Indirect Radiative Forcing Predicted by Climate Models

Fangqun Yu[1], Gan Luo[1], Arshad Arjunan Nair[1], Kostas Tsigaridis[2,3], and Susanne E. Bauer[2]
[1]Atmospheric Sciences Research Center, State University of New York, Albany, NY, USA, [2]NASA Goddard Institute for Space Studies, New York, NY, USA, [3]Center for Climate Systems Research, New York, NY, USA

- Trained using GEOS-Chem-APM, the ML model adds only ~3.1% overhead to GEOS-Chem Classic
- Also implemented in GISS-ModelE2.1-OMA with PNC now agreeing better with measurements

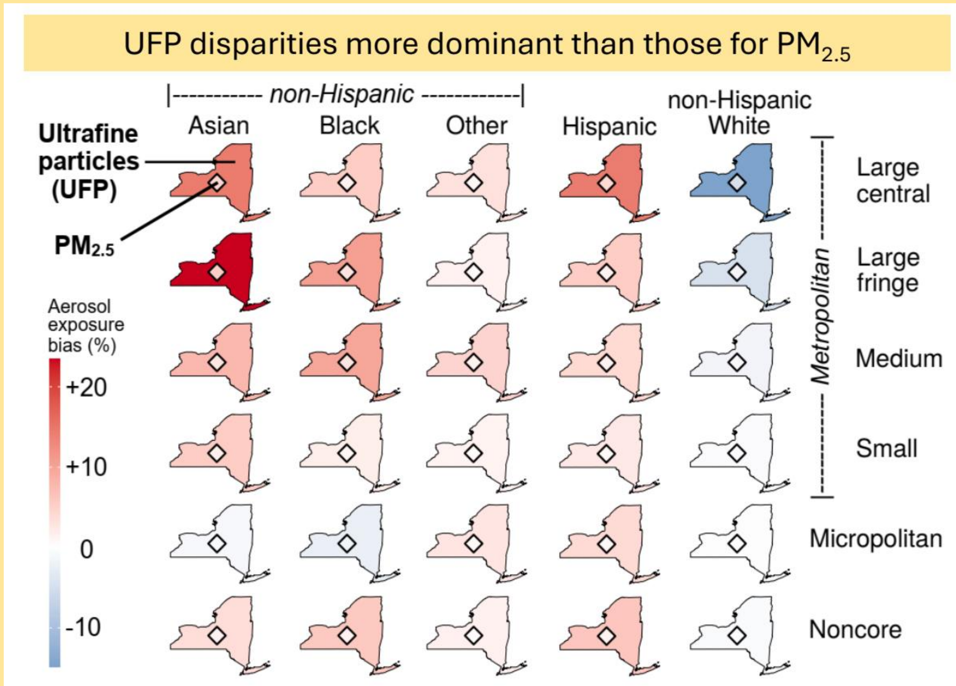


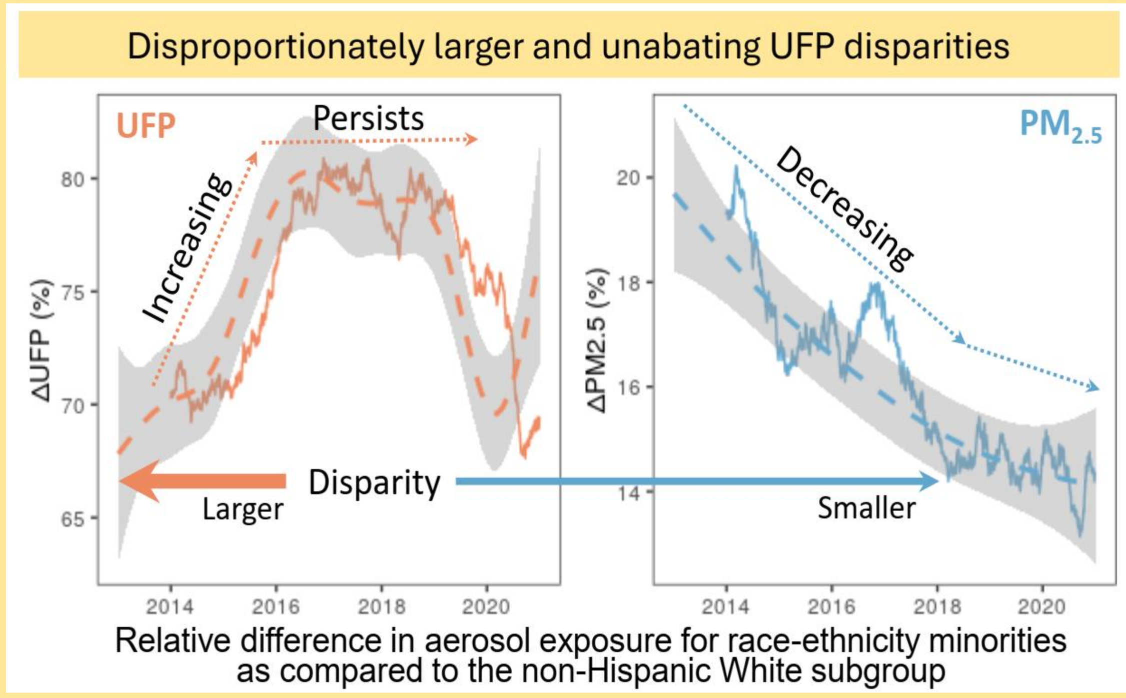
- RF_{aci} changes from −1.46 to −1.11 W·m^{-2}; closer to median IPCC value and GISS-ModelE2.1-MATRIX
- Highlights need to account for the particle size changes from PI to PD in PNC and CDNC calculations

GEOS-Chem-APM for pollutant exposure & health impacts

Environmental exposure disparities in ultrafine particles and $PM_{2.5}$ by urbanicity and socio-demographics in New York state, 2013–2020

Arshad Arjunan Nair[a,*], Shao Lin[b,c], Gan Luo[a], Ian Ryan[c], Quan Qi[d], Xinlei Deng[c], Fangqun Yu[a,*]





Relative difference in aerosol exposure for race-ethnicity minorities as compared to the non-Hispanic White subgroup

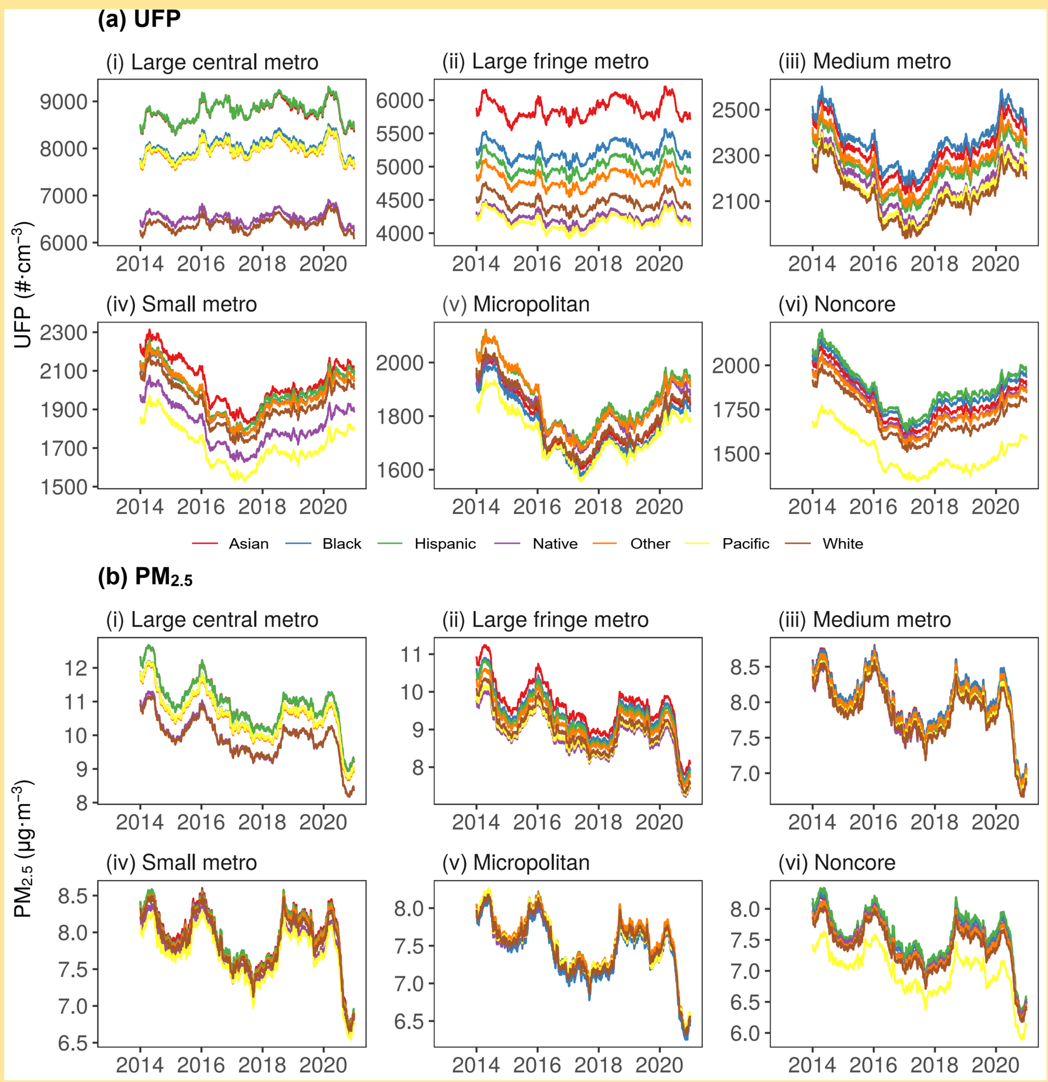


Figure. Population-weighted exposure at the county subdivision level in NYS during 2013–2020.

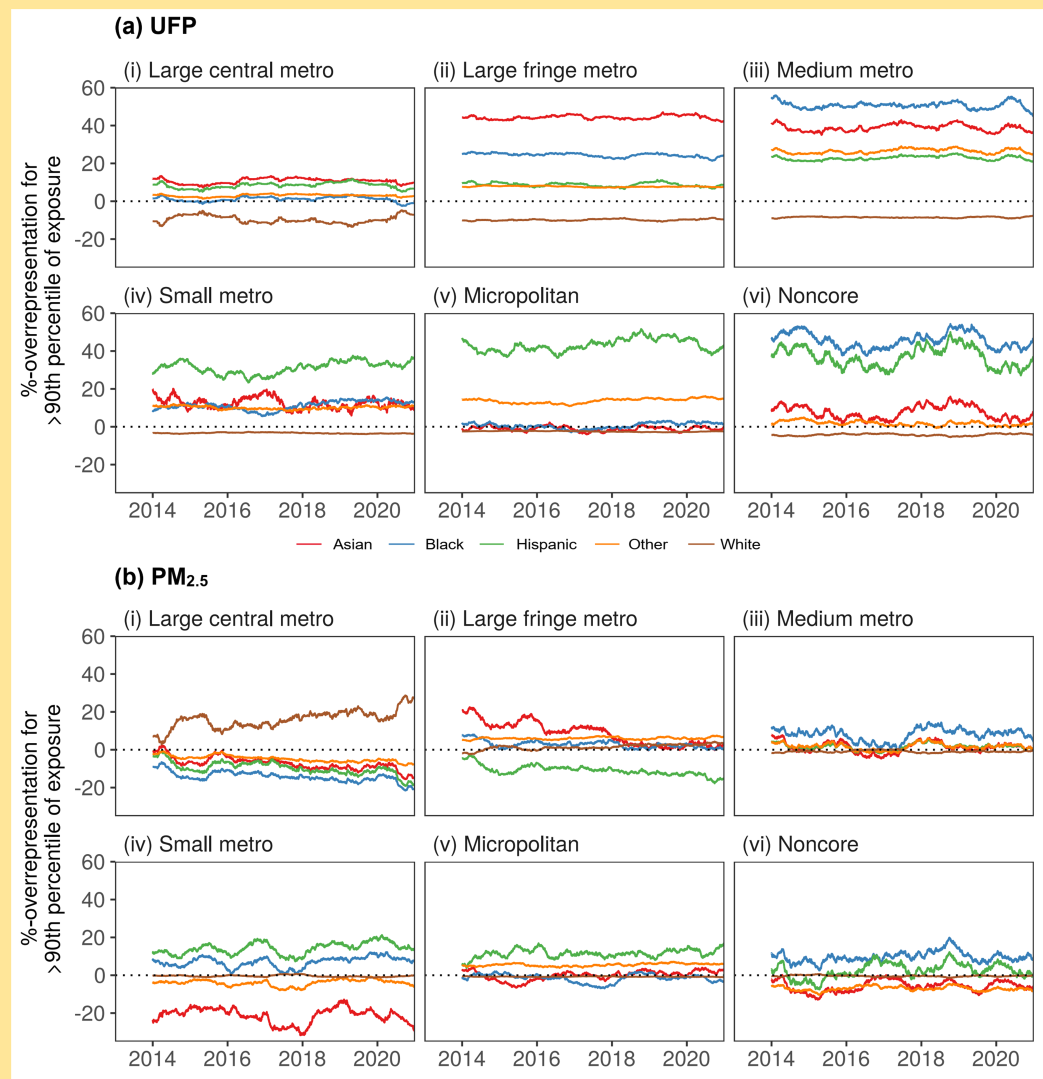
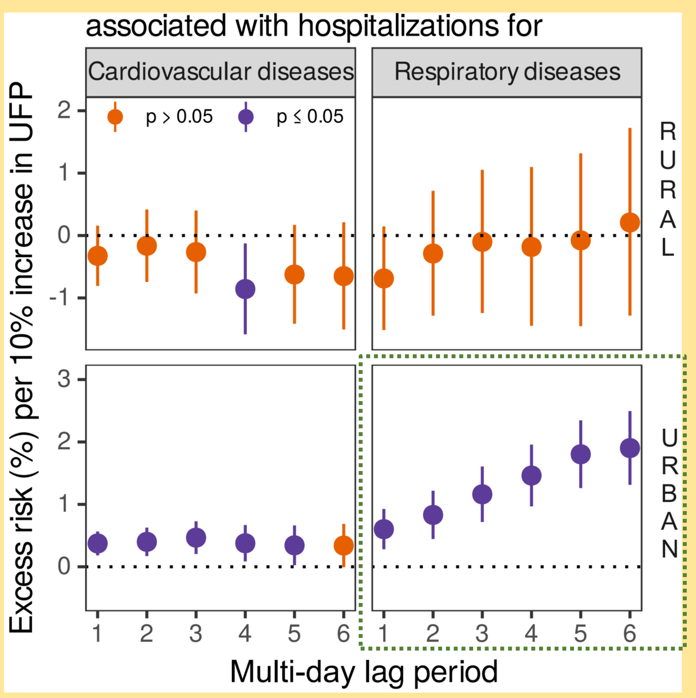
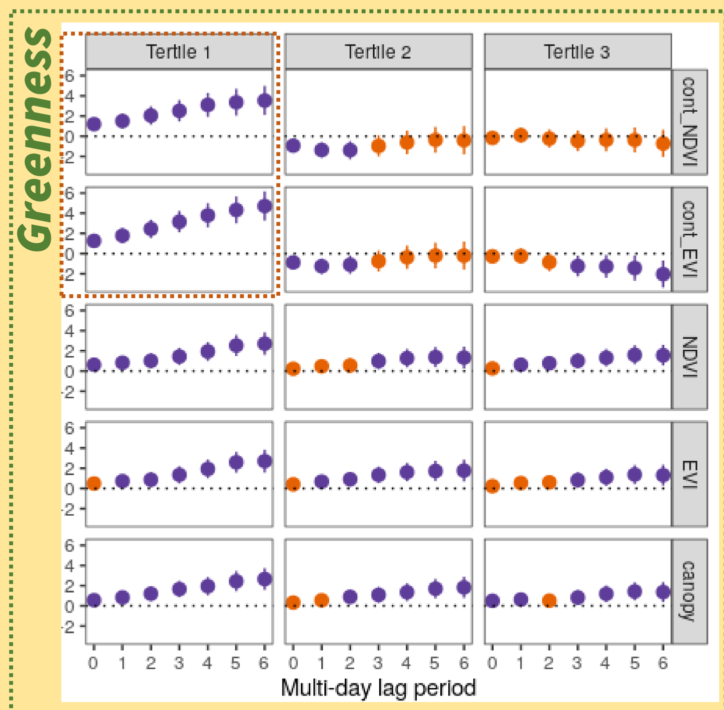
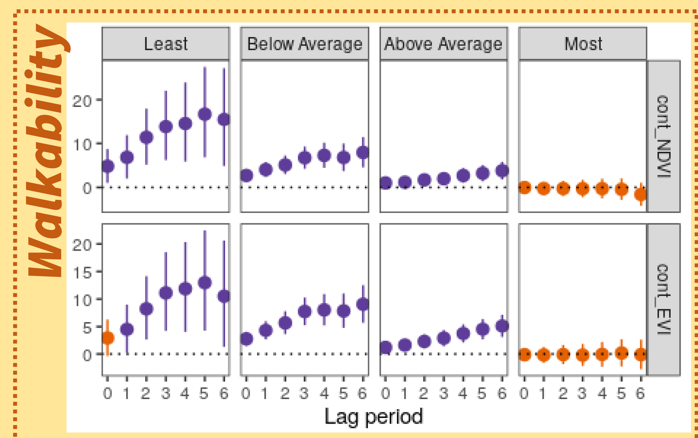


Figure. Race-ethnicity representation bias in the worst 10% exposure jurisdictions.







Largest excess risks of hospitalization (cardiovascular: 9.4–10.6% & respiratory: 13–16.7%) associated with UFP exposure for least green and least walkable jurisdictions