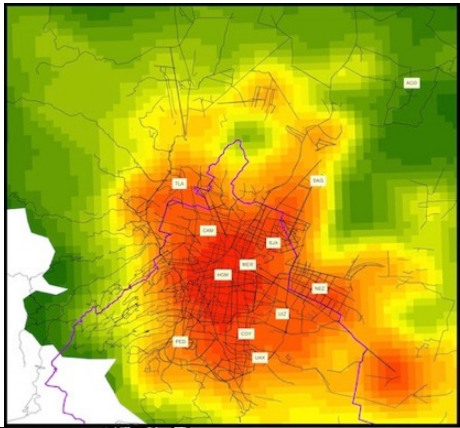
Leveraging models, monitors, and satellites for better environmental epidemiology:

exposure science matters for environmental health and justice



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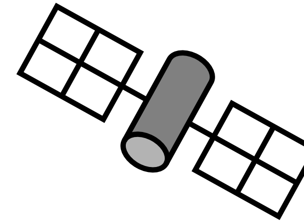
flickr.com/photos/gsfc/4386822005



Outline

- Advancing exposure science
- Implications of better models at the intersection of air pollution and heat
- Advancing climate~health epidemiology with Earth observations

Goal: leverage Earth observations to enhance exposure assessment for epidemiological analyses with cohorts and large health registries

Premise: *Getting exposures right matters*

Environmental exposures change dynamically over time and space

Example: substantial intra-urban temperature variation within urban heat archipelago

Accurate estimates required for epidemiological studies

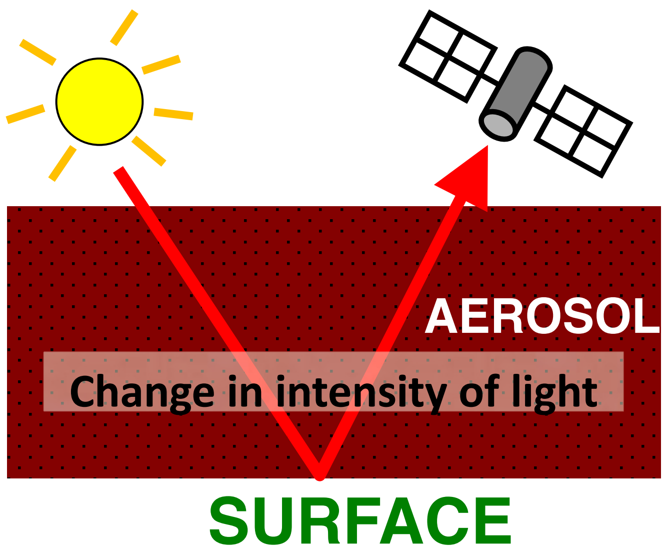
Our group builds geostatistical models with satellite data -- and investigates the implications of improvements

Combining satellite-derived predictors with meteorological, topographical & land use covariates

Satellite data

Aerosol Optical Depth (AOD) informs models for $PM_{2.5}$

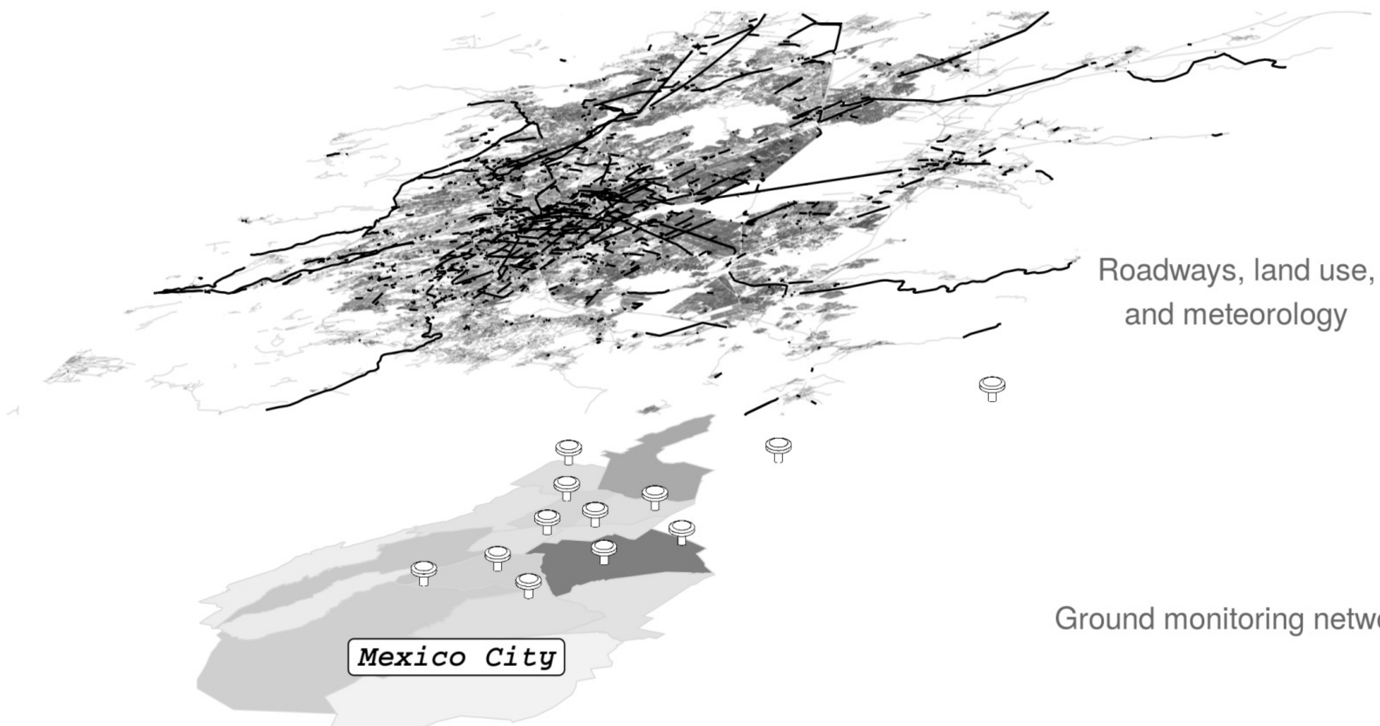
Land Surface Temperature (LST) informs models for air temperature



Layering information to estimate exposures

Ground monitoring network

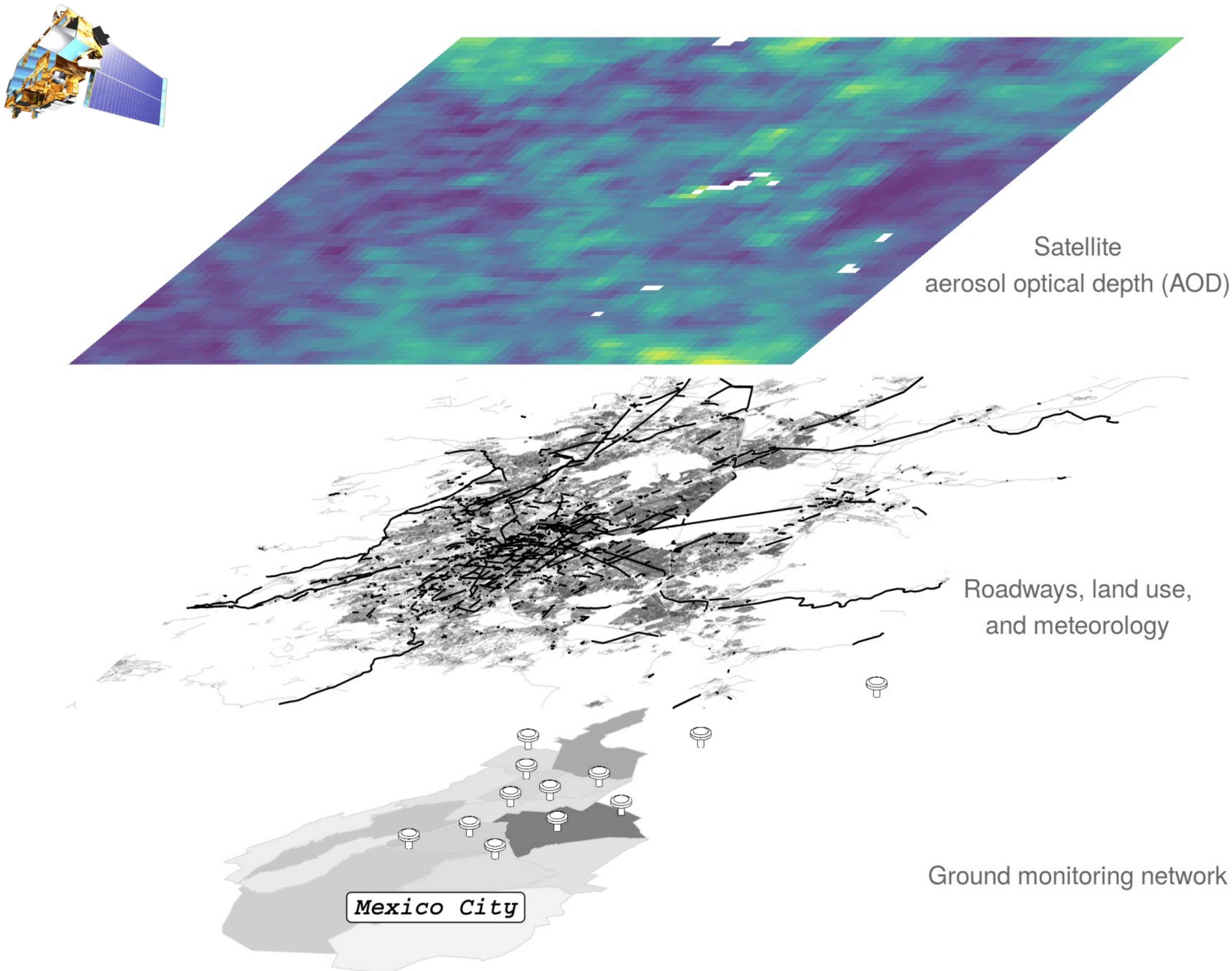
Layering information to estimate exposures



Roadways, land use, and meteorology

Ground monitoring network

Layering information to estimate exposures

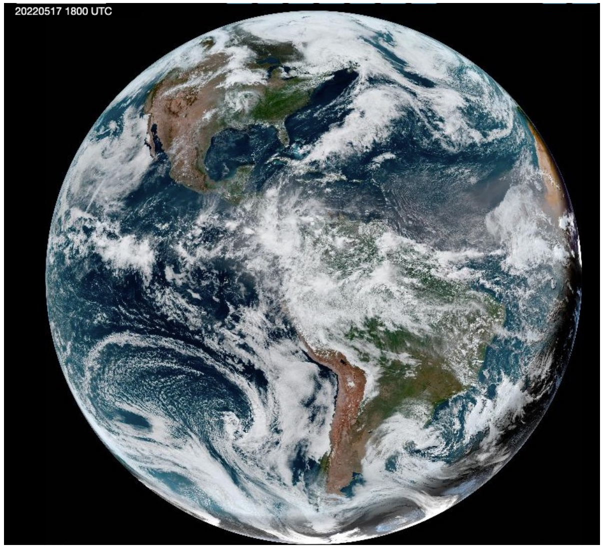


Technical challenges in applied remote sensing

Staggering data volume

Missing data (clouds, nighttime, indoors)

Measurement error (complex atmospheric effects)



Predictive models trained on ground stations

(Sub)Daily reconstruction with good spatial resolution

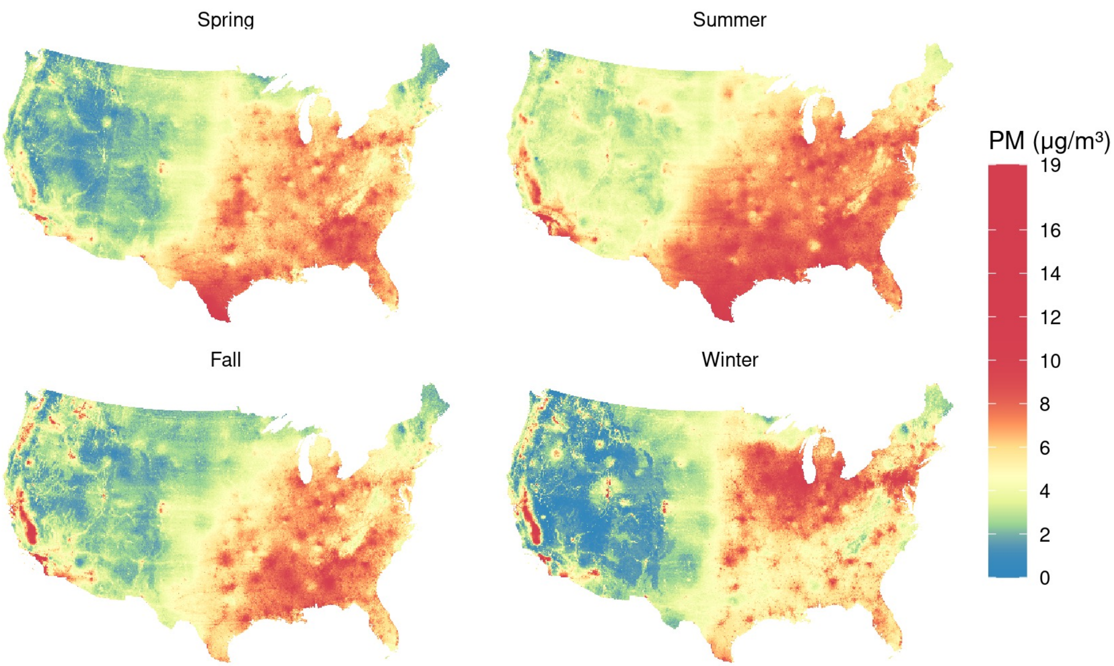
Flexible machine-learning models capture complex relations

But great care is needed to avoid overfitting!

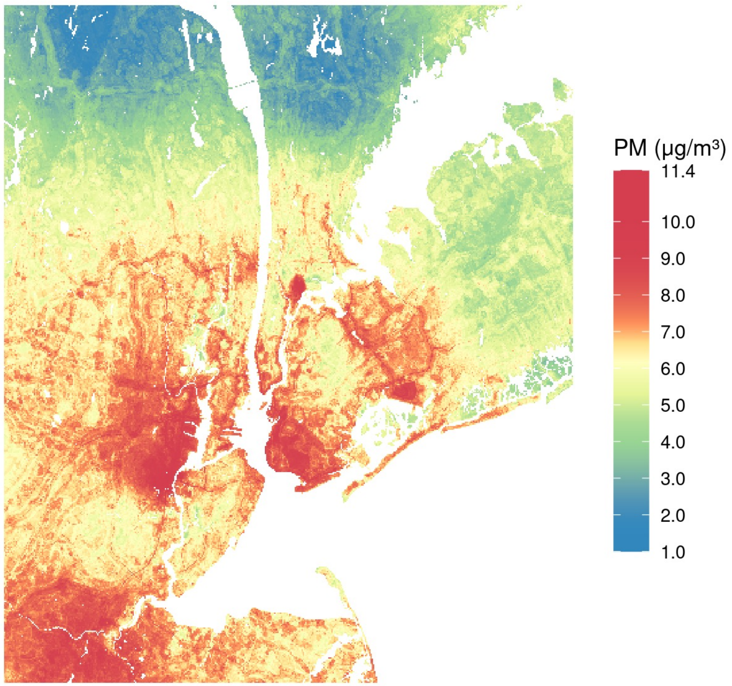
Just et al. Advancing methodologies for applying machine learning and evaluating spatiotemporal models of fine particulate matter ($PM_{2.5}$) using satellite data over large regions. *Atmos Env*. 2020;239:117649.

Daily high-resolution temperature and $PM_{2.5}$ across the Continental USA

(developed originally with support from NIH ECHO OIF)



Example: average 24-hour $PM_{2.5}$
Meteorologic seasons of 2019

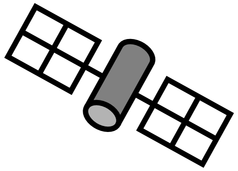


Example: 24-hour $PM_{2.5}$
July 10, 2021
(different color scale)

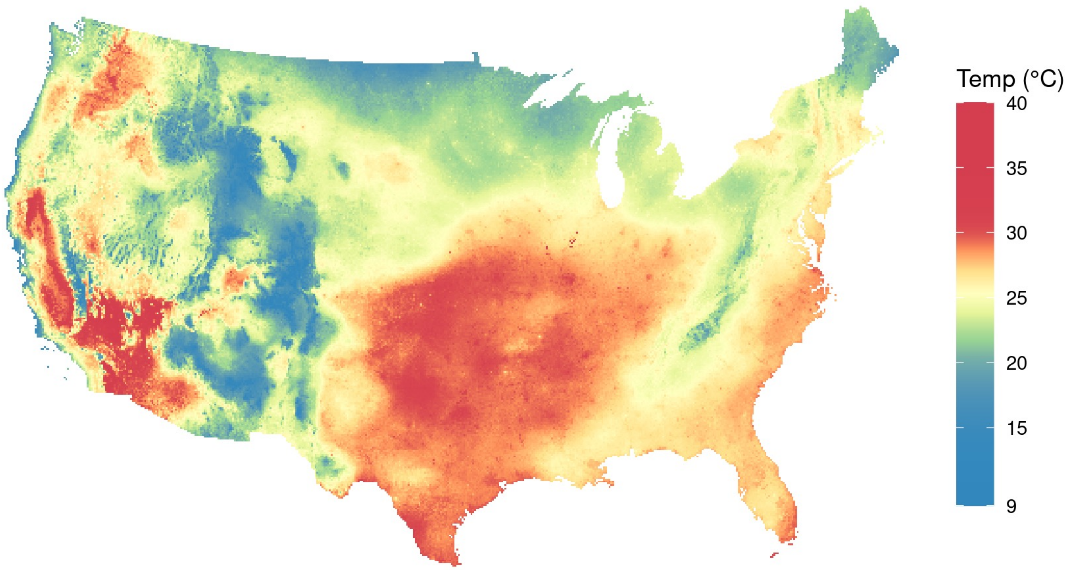
[Preprint]: Just et al. https://doi.org/10.1002/essoar.10512861.1

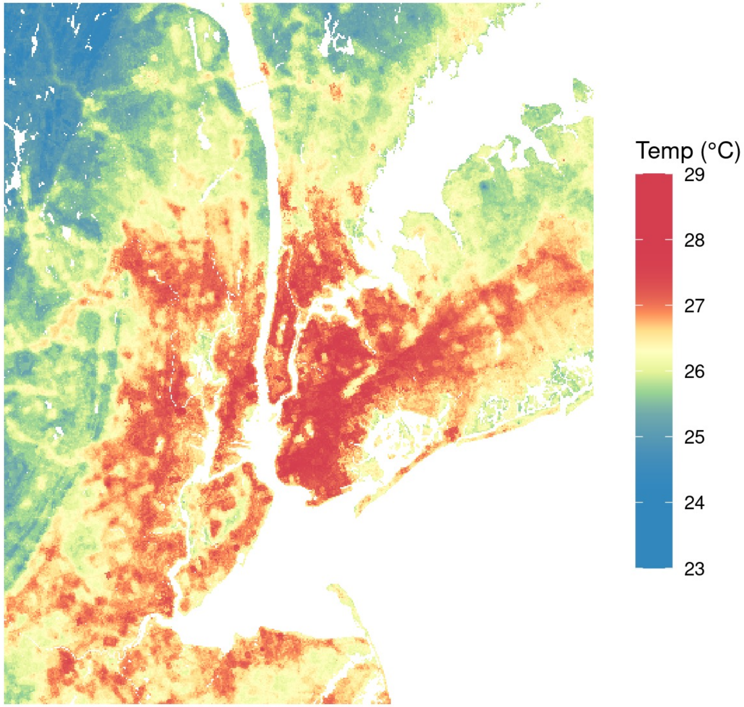
Daily high-resolution temperature and $PM_{2.5}$ across the Continental USA

(developed originally with support from NIH ECHO OIF)



Example: mean temperature August 11, 2021





(different color scale)

[Preprint]: Just et al. https://doi.org/10.22541/essoar.167591086.68441300/v1

XIS: XGBoost-**I**DW **S**ynthesis

Strengths of our geospatial prediction pipeline:

- **Performant**
- **Recent/Updatable**
- **Still improving**

Limitations of reconstruction:

- **Not a forecasting tool**
- **Not a digital twin (no simulation/manipulation)**

XIS Empirical comparisons with other models

XIS $PM_{2.5}$ comparison with EPA FAQSD

EPA produces daily tract-level $PM_{2.5}$ by fusing 12 km chemical transport model (CMAQ) with AQS site data

We compared models only with EPA AQS sites not used by either model (e.g., 310 sites with 76,220 days in 2018)

When we made predictions to the tract centroid, averaging across all years:

we have 16% lower Mean Absolute Error

Making predictions to exact monitor locations:

we have 22% lower Mean Absolute Error

[Preprint]: Just et al. https://doi.org/10.1002/essoar.10512861.1

XIS Temperature comparison with 3 gridded models

Our minimum temperature model has much lower prediction error across all station-days, all years 2014-2021 (e.g., in 2019 this was 2,702,679 observations):

28% of the MSE of PRISM (4 km)

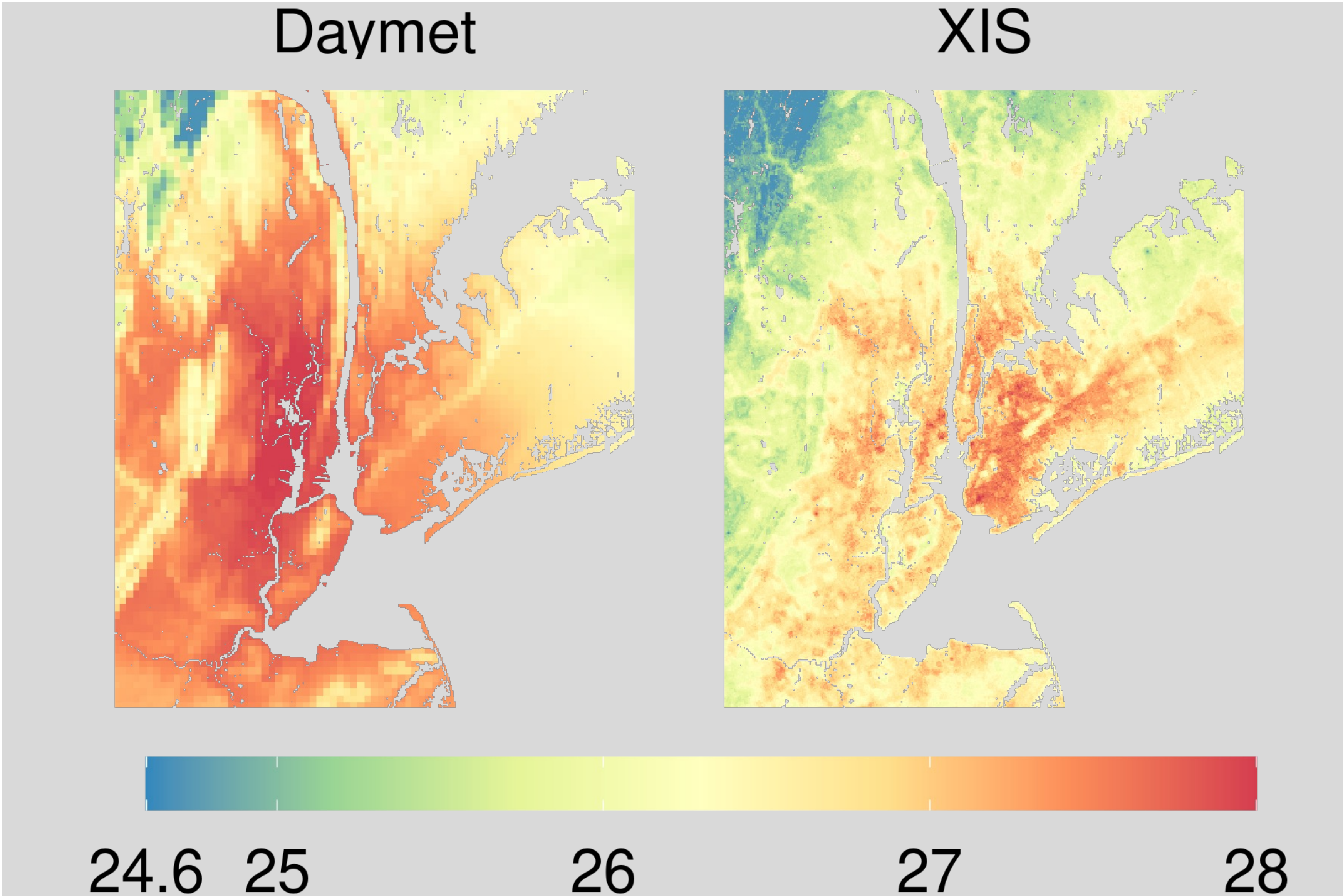
34% of the MSE of gridMET (4 km)

46% of the MSE of Daymet (1 km)

Evaluated at 10,000 randomly selected personal weather stations (of those not used by XIS)

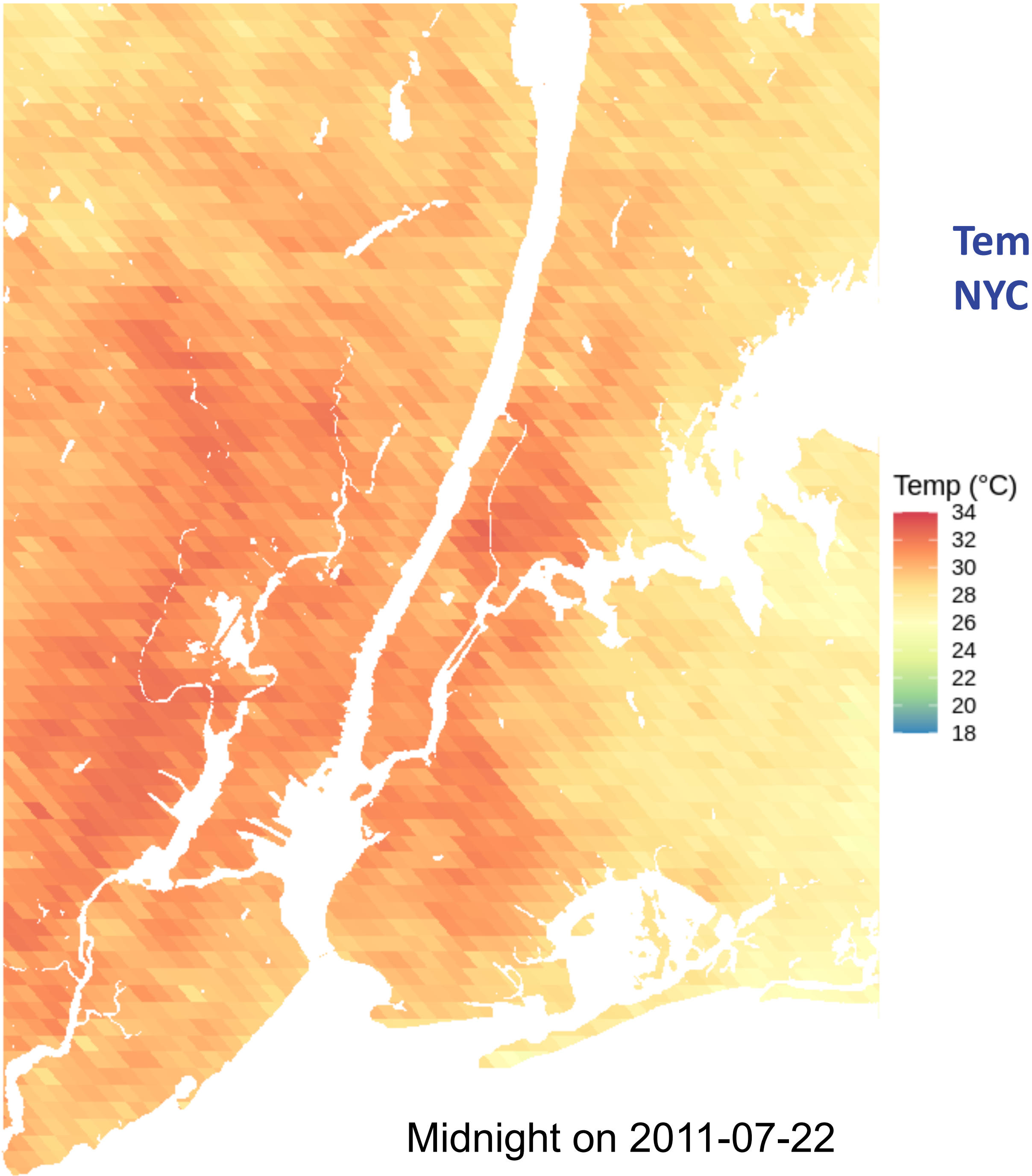
[Preprint]: Just et al. https://doi.org/10.22541/essoar.167591086.68441300/v1

Daily minimum temperature over NYC in a 2021 heatwave

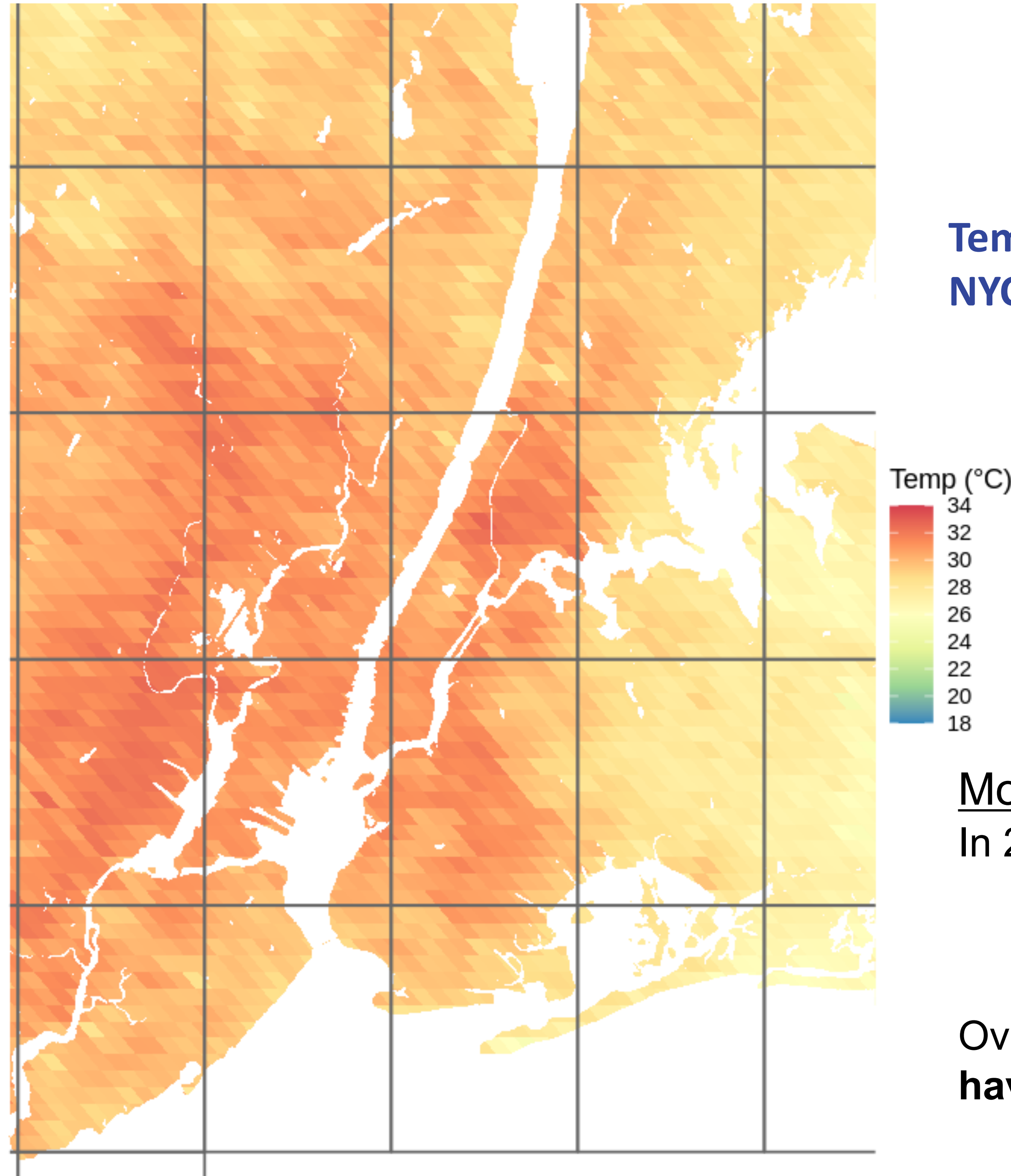


Implications of having better models

Temperature during a heatwave: NYC Metro Area



Midnight on 2011-07-22



Temperature during a heatwave: NYC Metro Area

<u>Model performance</u>

In 2019:

RMSE of XGBoost: 1.4 C

RMSE of NLDAS-2: 2.4 C

Overall: **our XGBoost predictions have 1/3 MSE of NLDAS-2 values**

Air temperature in a heatwave and social vulnerability

CDC's Social Vulnerability Index at Census Tracts

- 15 Census variables including SES, housing, transportation, language isolation, etc.
- Results in a proportional measure from 0 to 1

Mixed effects linear model:

- Dependent: Spatially-weighted air temperature prediction at Census Tract
- Independent:
  - Fixed: Intercept and the CDC SVI
  - Random: County-level intercepts, slopes of CDC SVI

Comparing slopes when using XGBoost model versus NLDAS-2 temperature

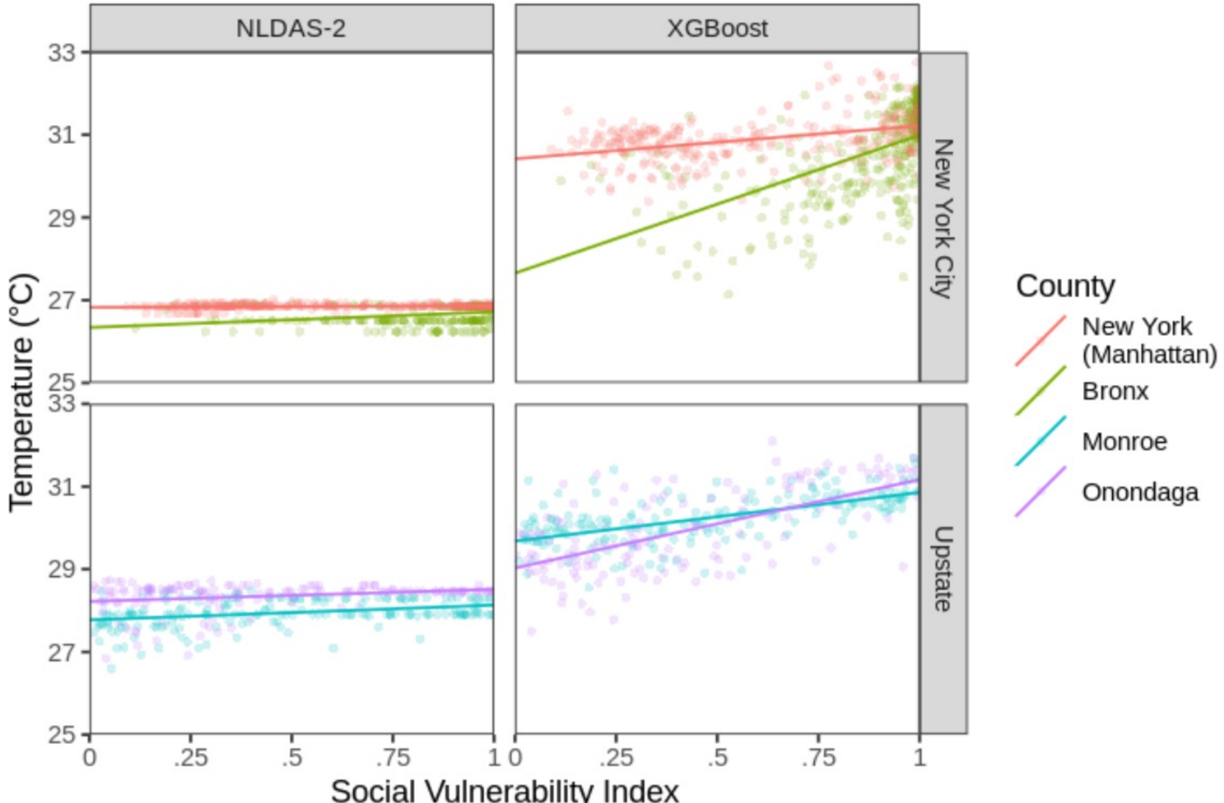
Air temperature in a heatwave and social vulnerability

Underestimated disparities?

NLDAS-2: **0.18 C**
(95% CI 0.12, 0.25)

– XGBoost: **0.71 C**
(95% CI 0.60, 0.82)

Tract-level analysis across 434 counties



(Carrión et al., 2021)

Social Vulnerability and $PM_{2.5}$ (*Nationwide, 2018 average*)

Mixed-effects model with a fixed effect for vulnerability, per-county random slopes and intercepts of vulnerability

Dependent variable was the 2018 average $PM_{2.5}$ concentration at the center of population of each tract (71,619 US Census tracts)

Our fixed effect of vulnerability was estimated as:

0.655 μg/m³ (95% CI 0.606, 0.703) with our model (XIS-$PM_{2.5}$)

Using the EPA FAQSD:

0.081 μg/m³ (95% CI [0.056, 0.105]) for FAQSD

Theme:
Better exposure models reveal previously under-estimated disparities and health impacts

Advancing climate and health epidemiology

Gene*Env study

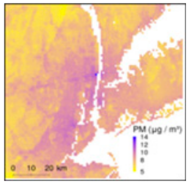
Ambient $PM_{2.5}$ and genetic risk allele interact in chronic kidney disease

A

Cohort

- 4,800 blacks enrolled from outpatient and inpatient clinical sites across the Mount Sinai Health System into the Bio*Me* biobank
- Urban environment including New York City and New Jersey
- No exclusion criteria
- All individuals linked to electronic health record (EHR)

- Individuals genotyped using Affymetrix 6.0 gene chip (909,600 SNPs)
- Extracted ***APOL1*** genotype and defined:
  - high-risk: G1/G1, G2/G2, or G1/G2
  - Low-risk: G1/G0, G0/G0, or G2/G0

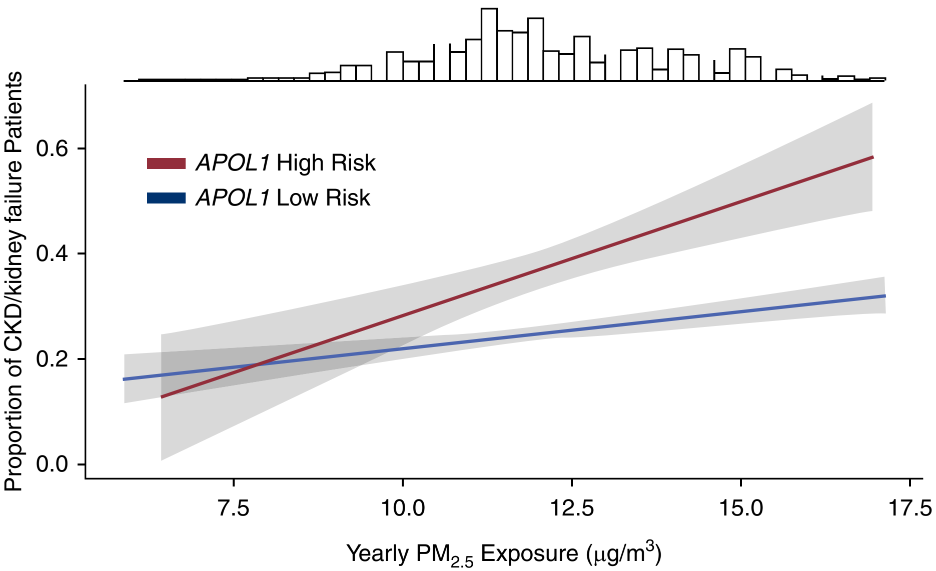


- For each patient, estimate average yearly $PM_{2.5}$ level at 1 x 1 km resolution using aerosol optical depth reported by NASA satellite

Statistical Analysis

- Logistic regression adjusted for age, sex, 10 genetic PCs, T2D, baseline eGFR, and Medicaid status
- Assess interaction effect of $PM_{2.5}$ and *APOL1* genotype on CKD risk

B



Paranje et al. CJASN 2020.

Daily exposure to $PM_{2.5}$ and 1.5 million deaths: A time-stratified case-crossover analysis in the Mexico City Metropolitan Area

Daily exposures for each of 586 sub-county regions from our satellite-based geostatistical model

1,479,950 non-accidental deaths (≥18 years-old) 2004-2019

Largest acute air pollution analysis in Central Mexico

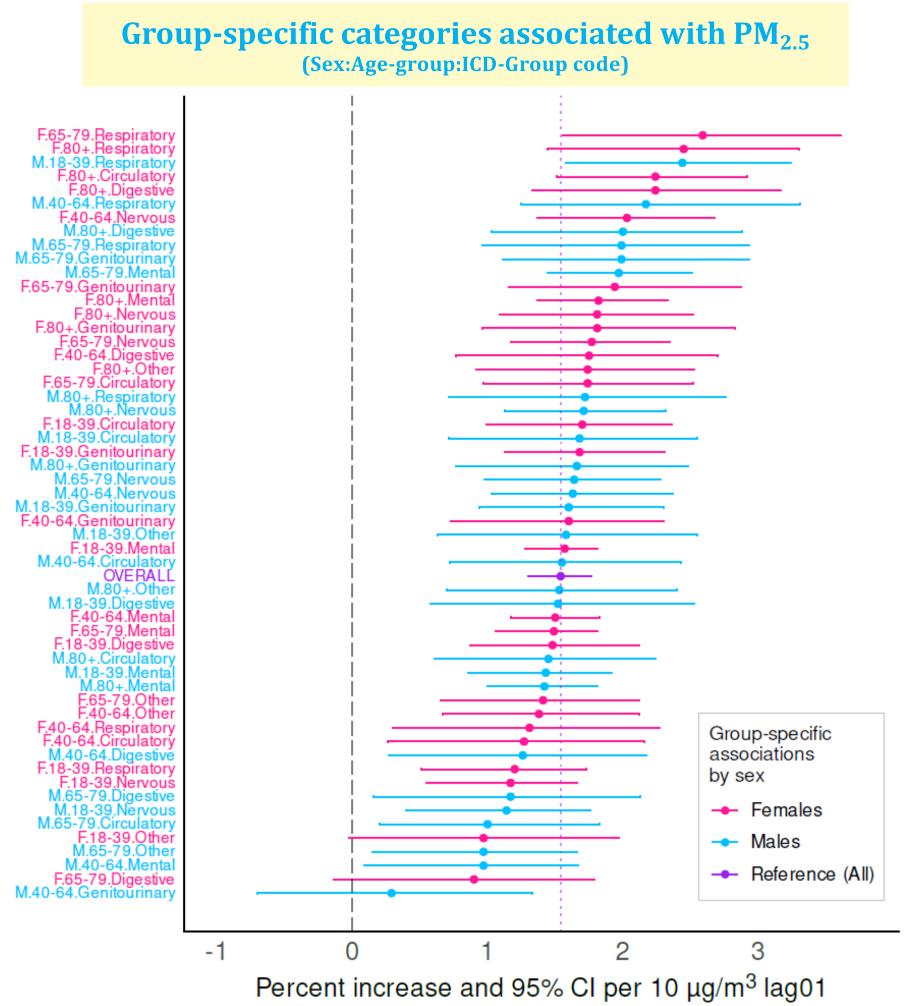
Cause-specific mortality, per 10μg/m^3 $PM_{2.5}$ (lag$_{06}$):

– hypertensive disease	2.28% (95%CI: 0.26%–4.33%)
– acute ischemic heart disease	1.61% (95%CI: 0.59%–2.64%)
– hemorrhagic stroke	3.63% (95%CI: 0.79%–6.55%)
– chronic respiratory disease	2.49% (95%CI: 0.71%–4.31%)
– influenza and pneumonia	4.91% (95%CI: 2.84%–7.02%)
– diseases of the liver	1.85% (95%CI: 0.31%–3.41%)
– renal failure	3.48% (95%CI: 0.79%–6.24%)

Gutiérrez Avila et al. Env Health 2023 https://doi.org/10.1186/s12940-023-01024-4

Identifying susceptible sub-populations

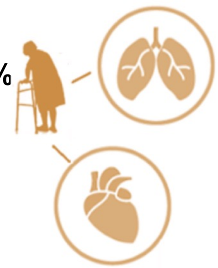
Using ridge regression in massive case-crossover analyses



Overall, a 10μg/m^3 higher lag$_{01}$ PM$_{2.5}$ associated with:

1.5% higher mortality (95%CI: 1.3% to 1.8%)

3 largest associations in Females for:



- **Respiratory mortality, 65-79 y/o: 2.6%** (95%CI: 1.6% to 3.6%)
- **Respiratory mortality, ≥80 y/o: 2.5%** (95%CI: 1.4% to 3.3%)
- **Circulatory mortality, ≥80 y/o: 2.2%** (95%CI: 1.5% to 2.9%)

3 largest associations in Males for:

- **Respiratory mortality, 18-39 y/o: 2.4%** (95%CI: 1.6% to 3.2%)
- **Respiratory mortality, 40-64 y/o: 2.2%** (95%CI: 1.3% to 3.3%)
- **Digestive mortality, 80+ y/o: 2.0%** (95%CI: 1.0% to 2.9%)

Slide courtesy of Dr. Iván Gutiérrez Avila

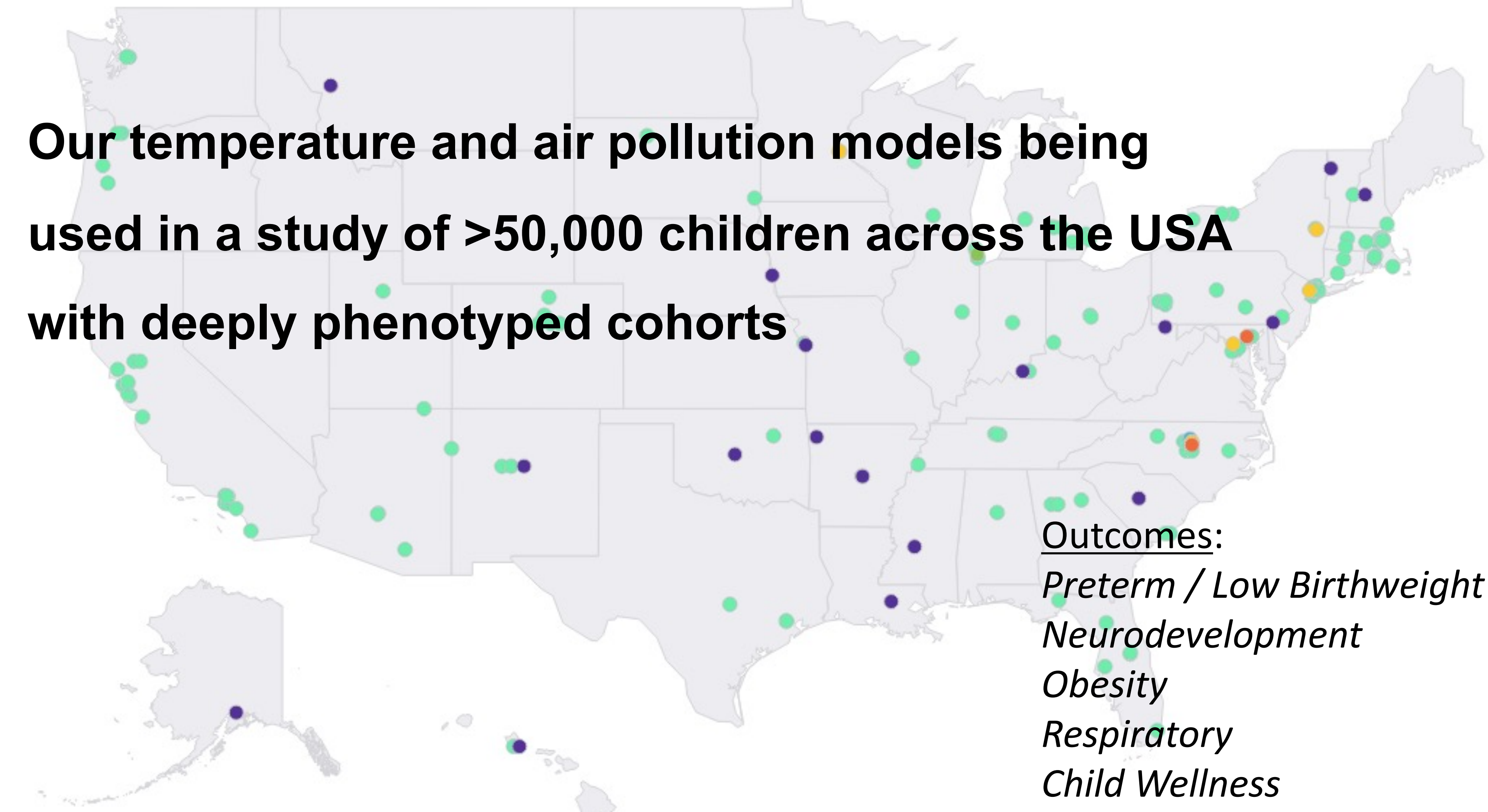
ECHO

Environmental influences on Child Health Outcomes

A program supported by the NIH

Opportunities and Infrastructure Fund (OIF) grant awarded April 2018

"ECHO-wide platform for studying air pollution, temperature, and greenness using satellite remote sensing with daily high-resolution national exposure estimates"



Our temperature and air pollution models being used in a study of >50,000 children across the USA with deeply phenotyped cohorts

<u>Outcomes</u>:

Preterm / Low Birthweight

Neurodevelopment

Obesity

Respiratory

Child Wellness

Linking to large registries

Comprehensive NYS hospitalization records with dates and exact residential addresses 2007-2023

Statewide Planning and Research Cooperative System (SPARCS)

Year 3 of 5-year R01 for the NIEHS Outstanding New Environmental Scientist (ONES) RFA:

"Extreme temperature, humidity, air pollution and spontaneous preterm birth"

Why study heat & air pollution together?

- Correlated episodic exposures
- Shared physiologic pathways
- Acute etiologic window

It’s all in the timing

“Why today?”

What is the relevant etiologic window?

Peak Exposures Matter!

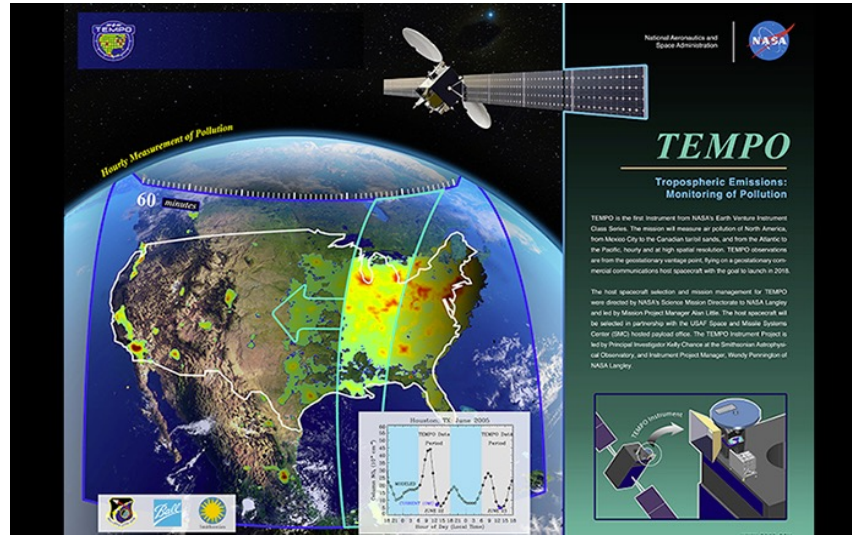
Epidemiologic approaches focused on timing and short-term exposure → response estimation

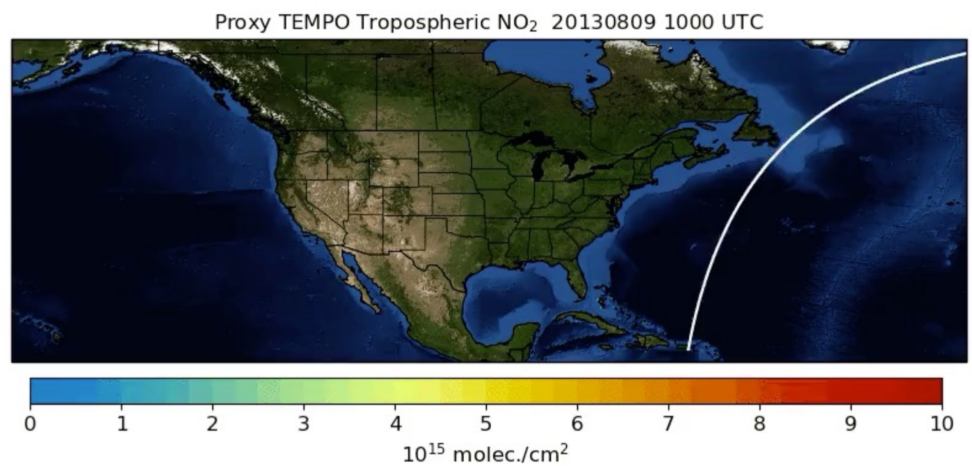
- Distributed Lag Nonlinear Modeling (DLNM)
- Case crossover modeling

No one breathes 24-hour averaged air

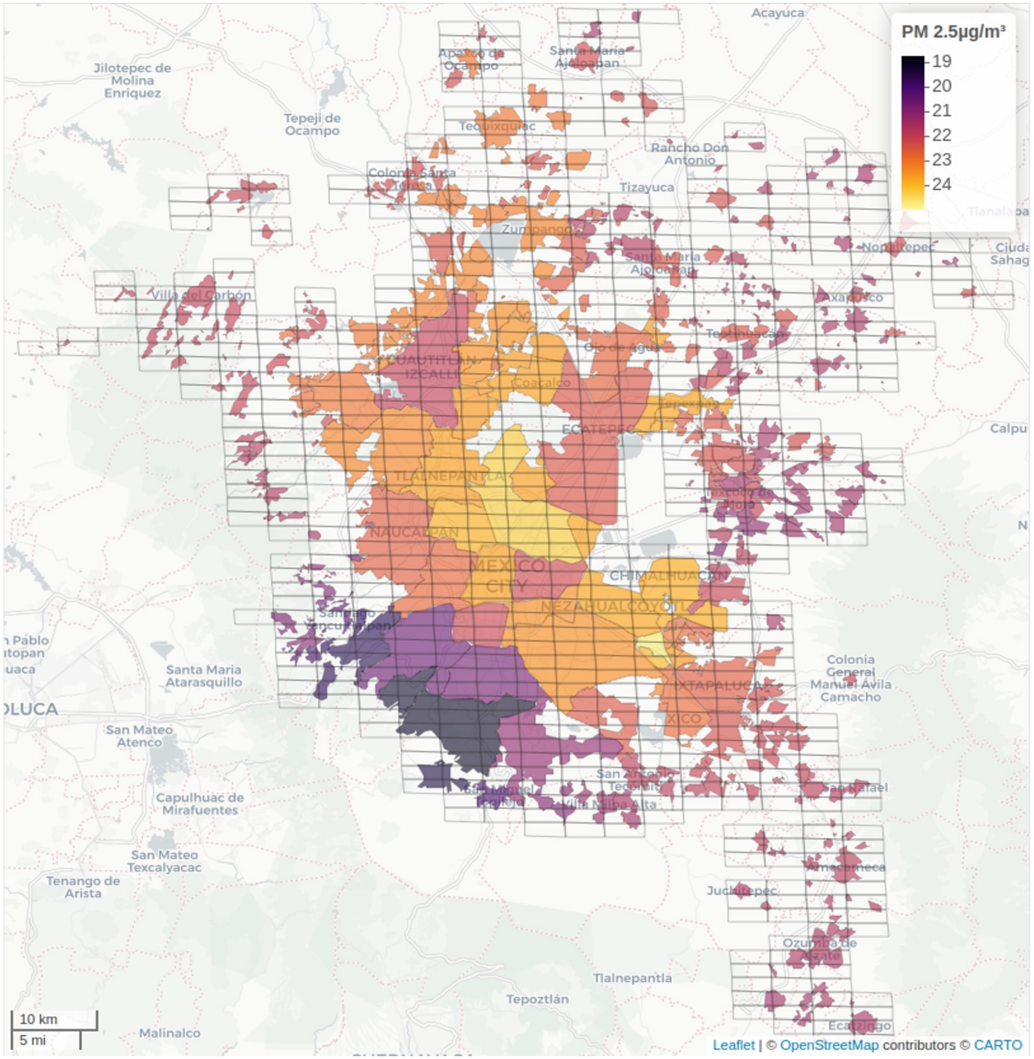
Adding gaseous air pollutants with *hourly* TEMPO instrument

(launched April 2023)





TEMPO's footprints ~1.6km * 4.5km



2019 modeled annual average $PM_{2.5}$ in 586 sub-county regions and 778 intersecting TEMPO cells

Short-term variation in air pollution and health is understudied

Exposure reconstruction:

Previous satellite-based estimates have relied on LEO single-overpass AOD

estimate 24-hour average $PM_{2.5}$ to reflect regulatory standards/methods?

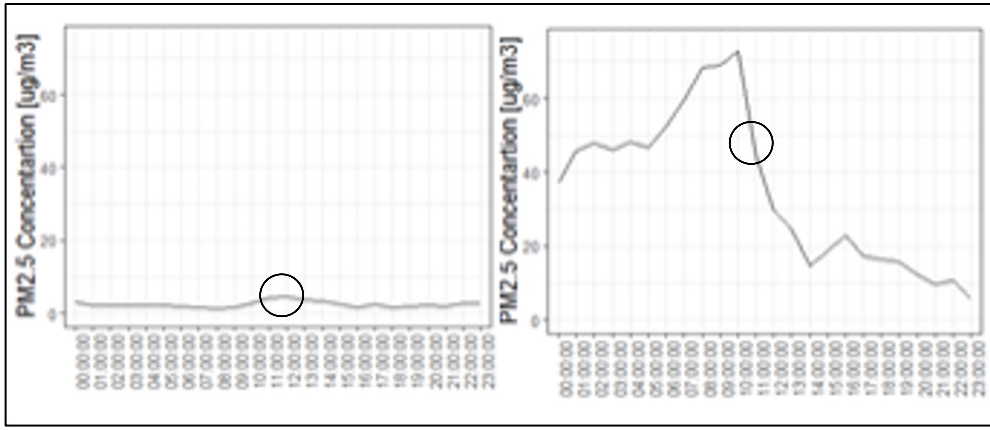
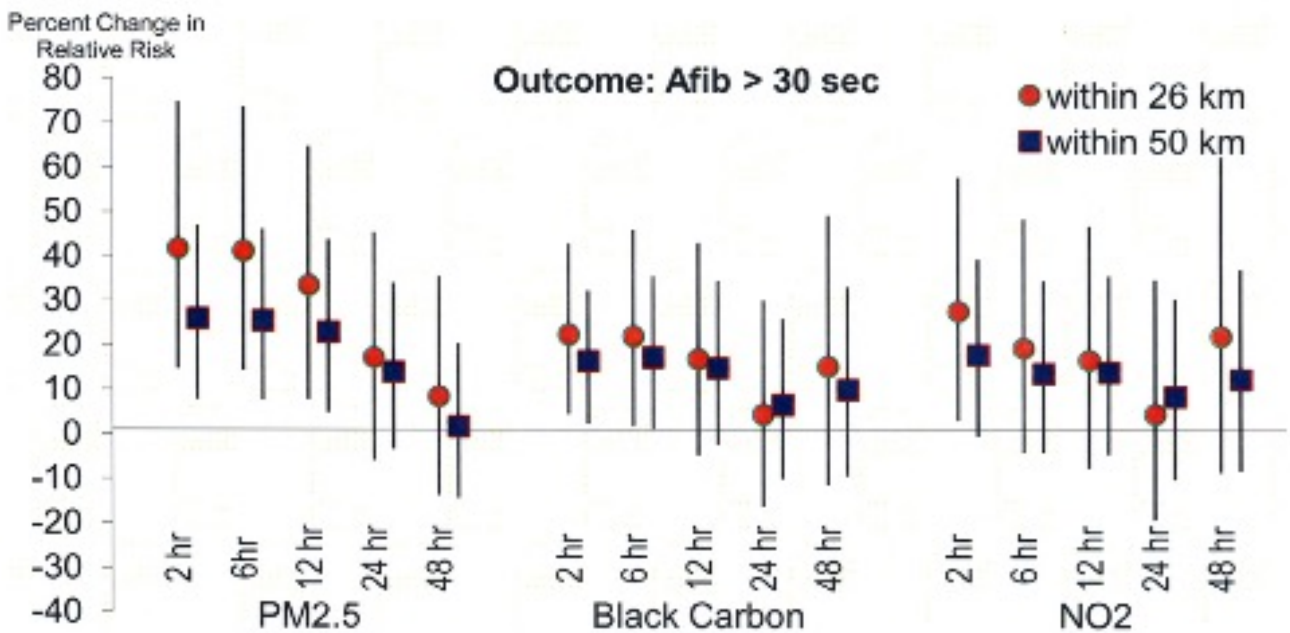


Photo credit: archive.epa.gov

“In fact, prior to recent EPA regulatory proposals for tightening the NAAQS for PM and O_3, the EPA's Clean Air Science Advisory Committee advised the EPA to give a scientific rationale for the 24hr PM_{10} averaging time in the NAAQS” – Delfino et al. *EHP* 1998

Examples of short-term cardiovascular exposure-response in air pollution epidemiology

Case-crossover matched on hour and day of week in 176 patients with implantable cardioverter-defibrillators with 328 episodes of atrial fibrillation

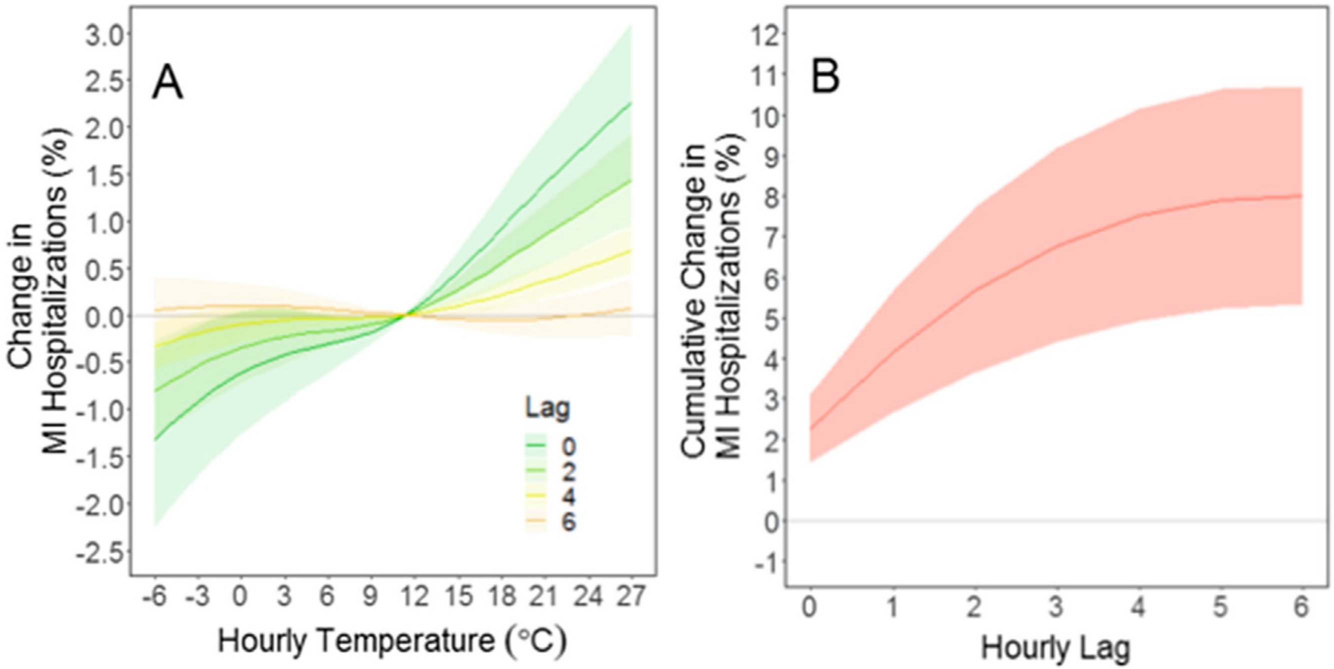


Risk of atrial fibrillation with Air Pollution in Patients Living Within 26 km of the Air Pollution Monitoring Site

(Link et al., *JACC* 2013)

Exposure-response curves from hourly exposures with hourly outcomes!

Dataset: Linked hourly NLDAS-2 temperature by zipcode of residence for **791,695 primary MI hospital admissions** (lag 0 = admit hour minus 3)

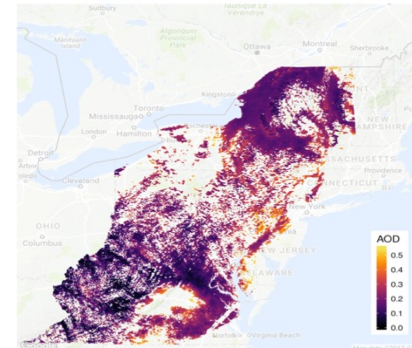


Panel B illustrates the cumulative association for an increase from median temperature (11 °C) to the 95th percentile (27 °C) for lags 0–6.

Can ultra short-term changes in ambient temperature trigger myocardial infarction?

2020. Rowland et al. Env Int.

Machine-learning to refine AOD



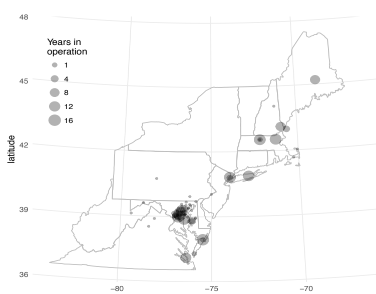
remote sensing

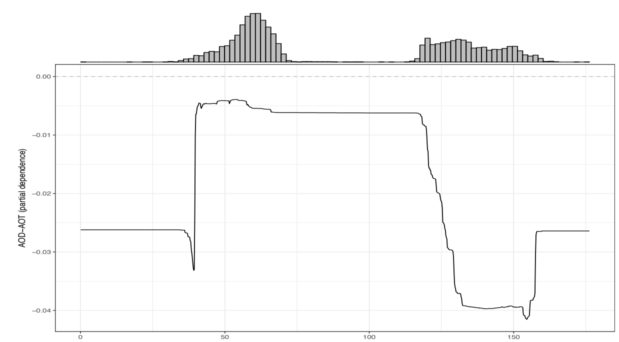
Article

Correcting Measurement Error in Satellite Aerosol Optical Depth with Machine Learning for Modeling $PM_{2.5}$ in the Northeastern USA

Allan C. Just [1,*], Margherita M. De Carli [1], Alexandra Shtein [2], Michael Dorman [2], Alexei Lyapustin [3] and Itai Kloog [2]

- Match up satellite AOD with ground-based AOD from AERONET
- train XGBoost on the difference using endogenous predictors of retrieval error (no assimilation of outside info)
- Construct a correction factor

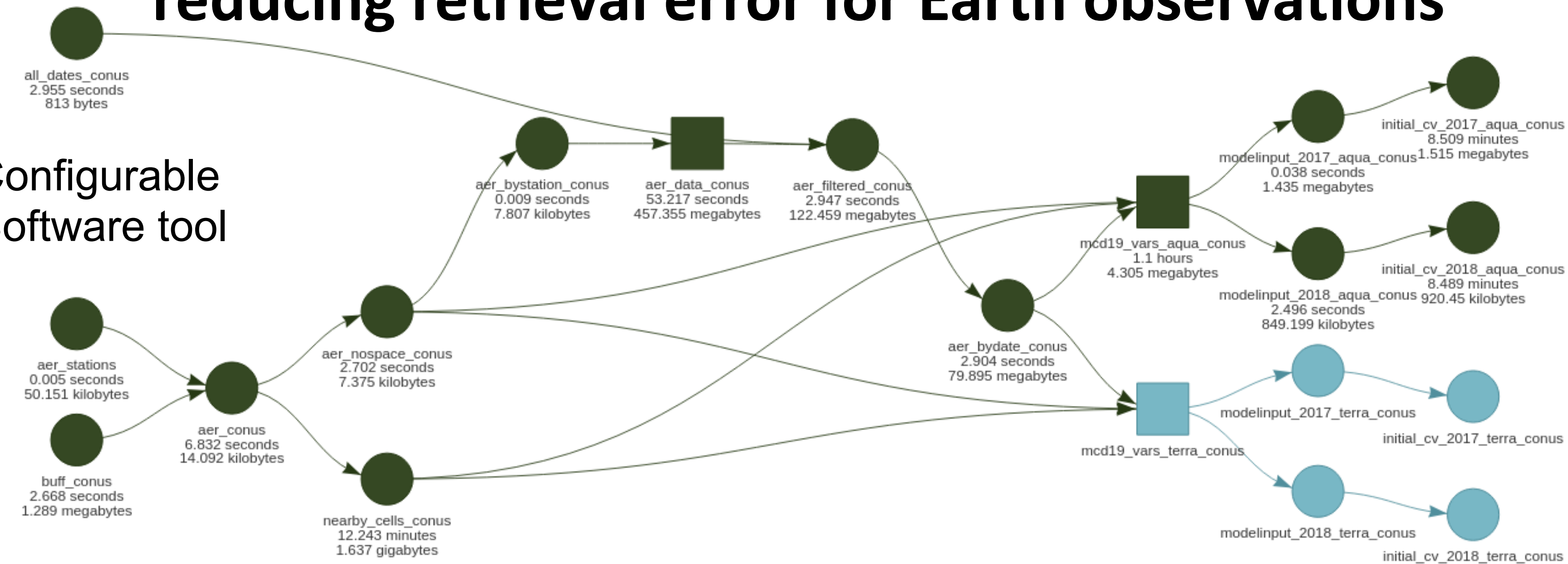




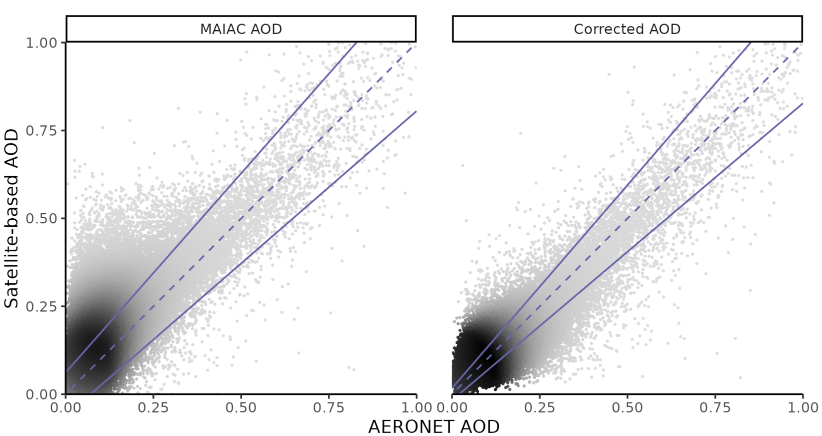
Just et al. *Remote Sens*. 2018, 10(5), 803 https://doi.org/10.3390/rs10050803

Reproducible machine-learning framework for reducing retrieval error for Earth observations

Configurable Software tool

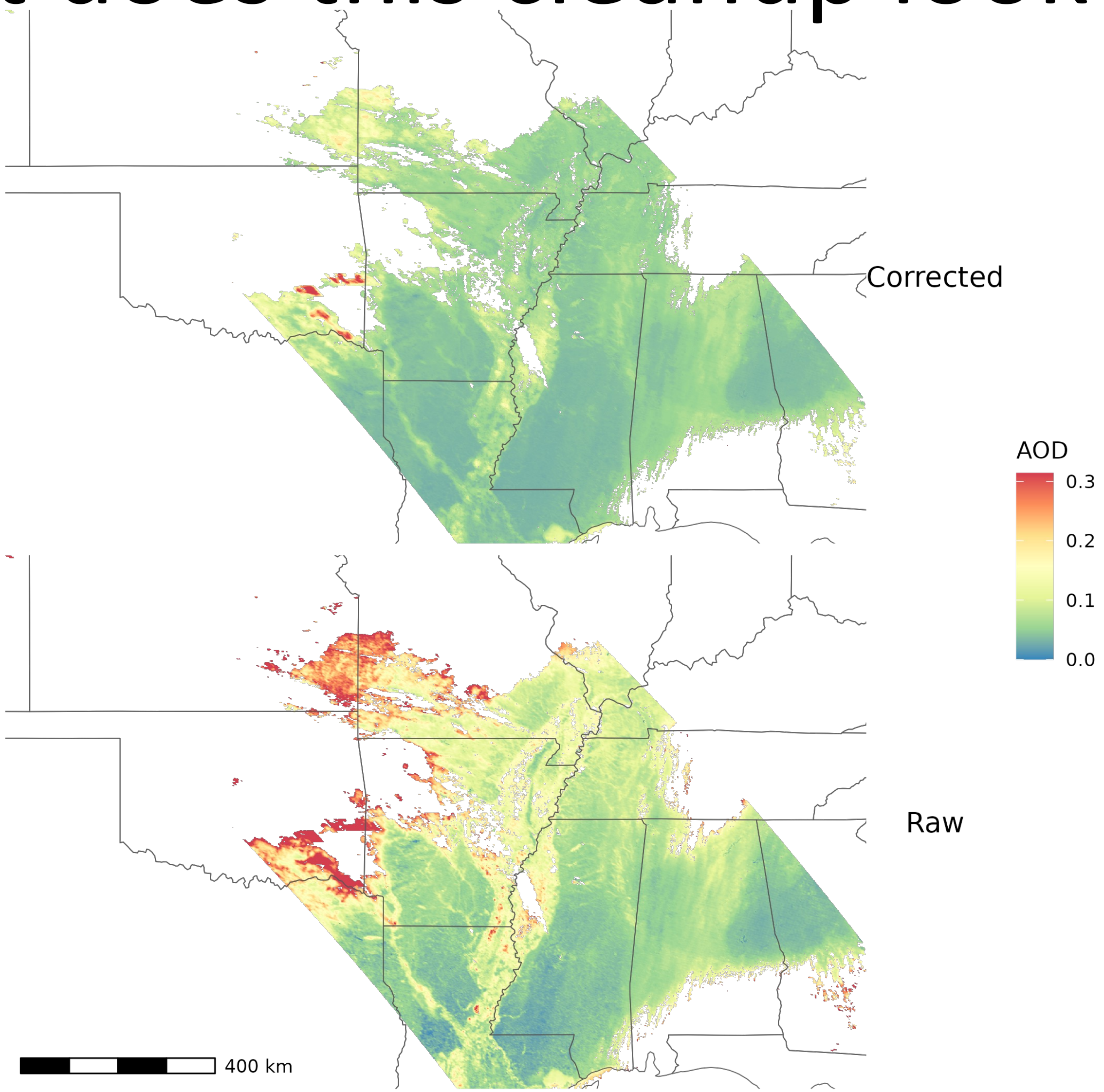


Cases	Sites	RMSE, raw	RMSE, corrected	Proportion of raw MSE	Median, ground	Bias, raw	Bias, corrected
109,386	337	0.102	0.061	0.354	0.078	+0.054	+0.001



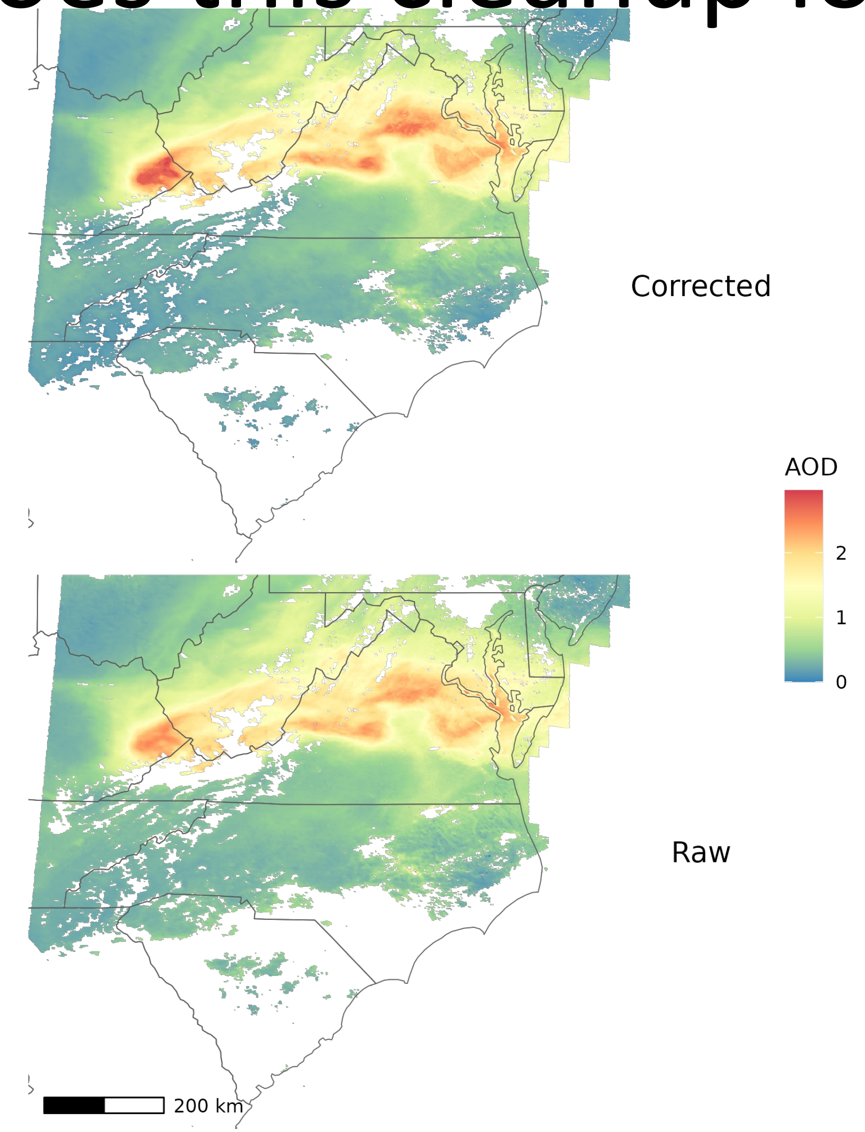
ML cleanup decreases 1km MAIAC AOD error by 65% in k-fold site-level cross validation across CONUS (2000-2022)

What does this cleanup look like?



Maps of typical MAIAC and Corrected AOD. Day selected as having the median improvement in MSE at AERONET sites (2005-01-14). The map is centered on Arkansas.

What does this cleanup look like?



Maps of MAIAC and Corrected AOD over the Mid-Atlantic US during a documented exceedance event with downmixing of long-range transported smoke from Canadian wildfires (June 10, 2015).

Does cleanup improve agreement with AQS $PM_{2.5}$?

- We examined 1,642,701 observations of AQS $PM_{2.5}$ on 1,436,978 cell-days with AOD. ***The correlation of the observations with the original satellite values was 0.440, compared to 0.495 with our corrected values.***

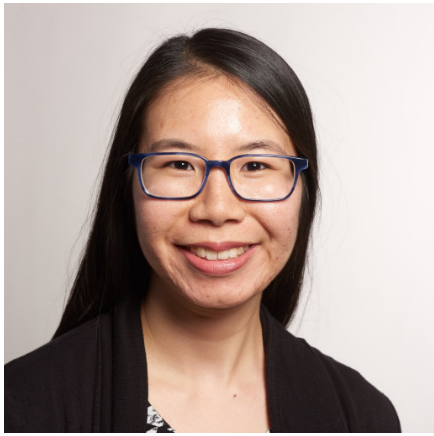
- In a year-level comparison, we took cell-years with at least 100 days of AQS observations and 10 days per month of satellite observations for at least 12 months. Obtaining 911 cell-years, we compared official AQS annual means to the yearly means of satellite observations, computed with daily means weighted according to how many days of the year to which each day was closest. ***The result was a correlation with the original satellite values of 0.329, compared to 0.549 with our corrected values.***

Former Postdoctoral Mentees

Dr. Iván Gutiérrez Avila
(ISMMS)

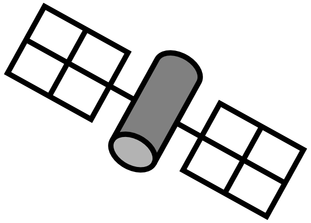
Dr. Daniel Carrión
(Yale SPH)

Dr. Sandy Wong
(Ohio State)



Dr. Jonathan Heiss
(GRAIL)

Acknowledgments



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Children's Hospital of Philadelphia/UPenn

Heather Burris

NASA Goddard Space Flight Center

Alexei Lyapustin
Yujie Wang

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Discussion!

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Informing public health & policy

Improved epidemiological models can:

- Be combined with climate projections to estimate long-term impacts of climate change

- Be incorporated in health impact analyses to compare policy scenarios

- Inform current medical and health-based decision-making (e.g., ***ProAire*** – Mexico's air quality planning)

Satellites are a key tool for monitoring the consequences of climate change

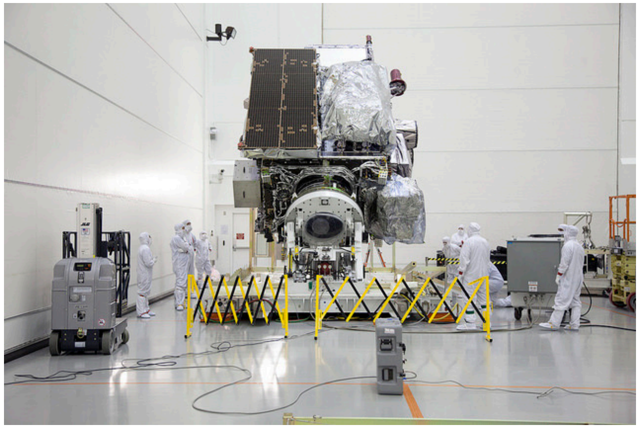
New sensors, new opportunities!

$PM_{2.5}$, temperature, humidity

Ozone, NO_2, SO_2

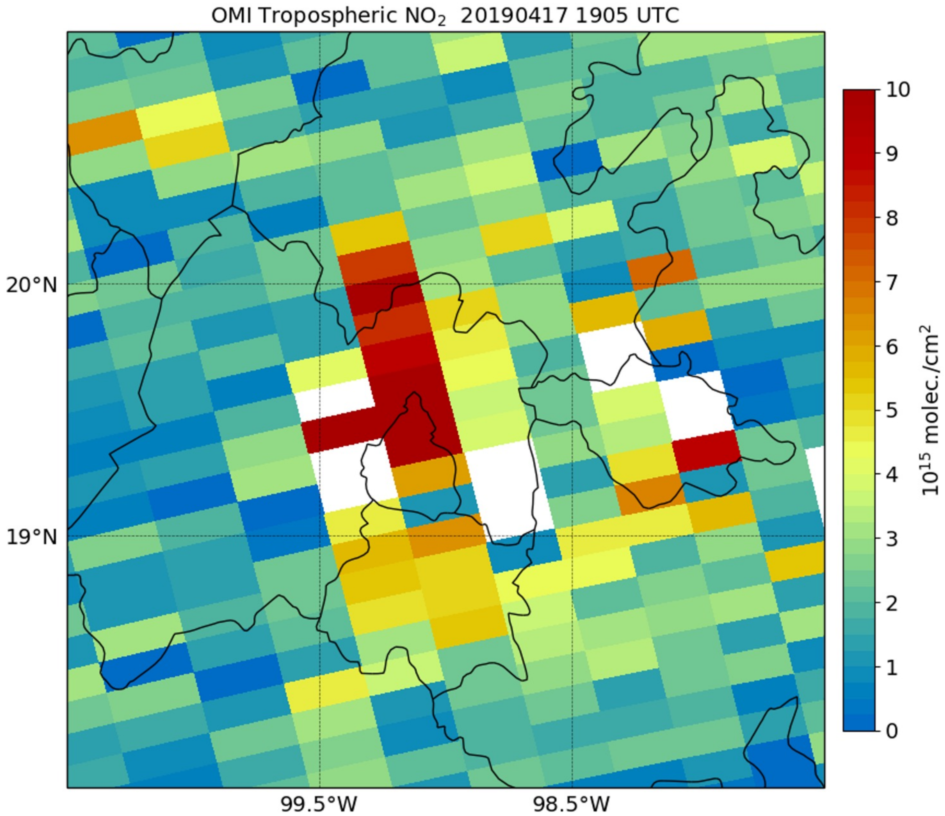
Vegetation/Greenness

Wildfires and flaring

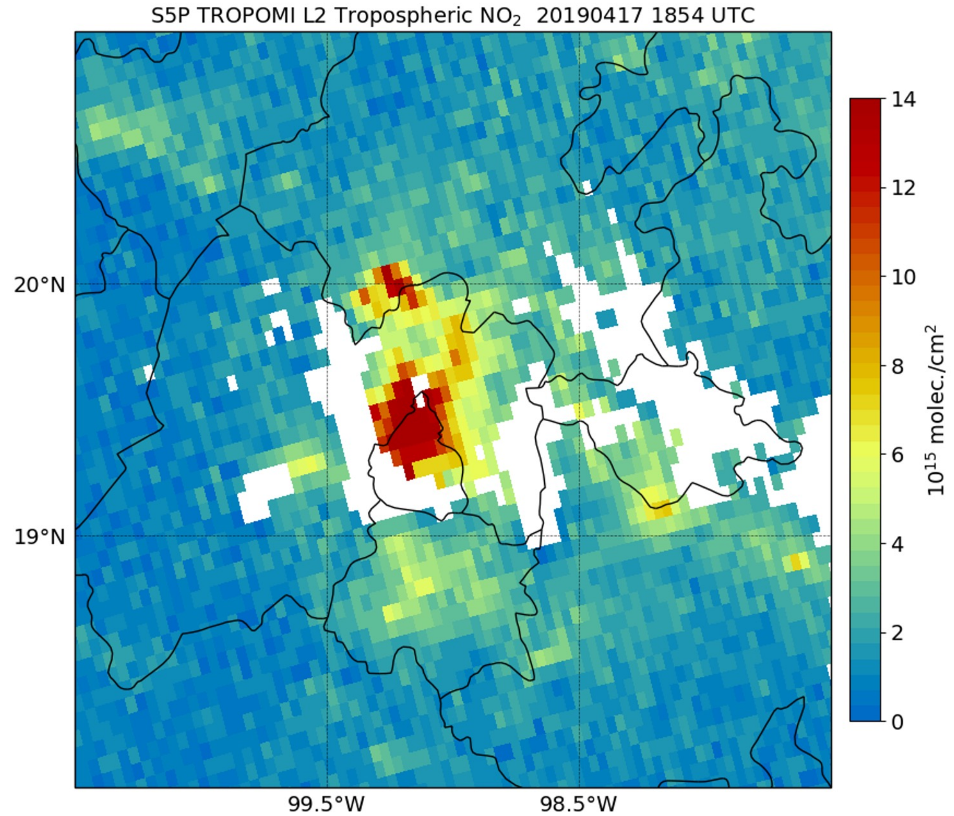


Newer satellites – better products

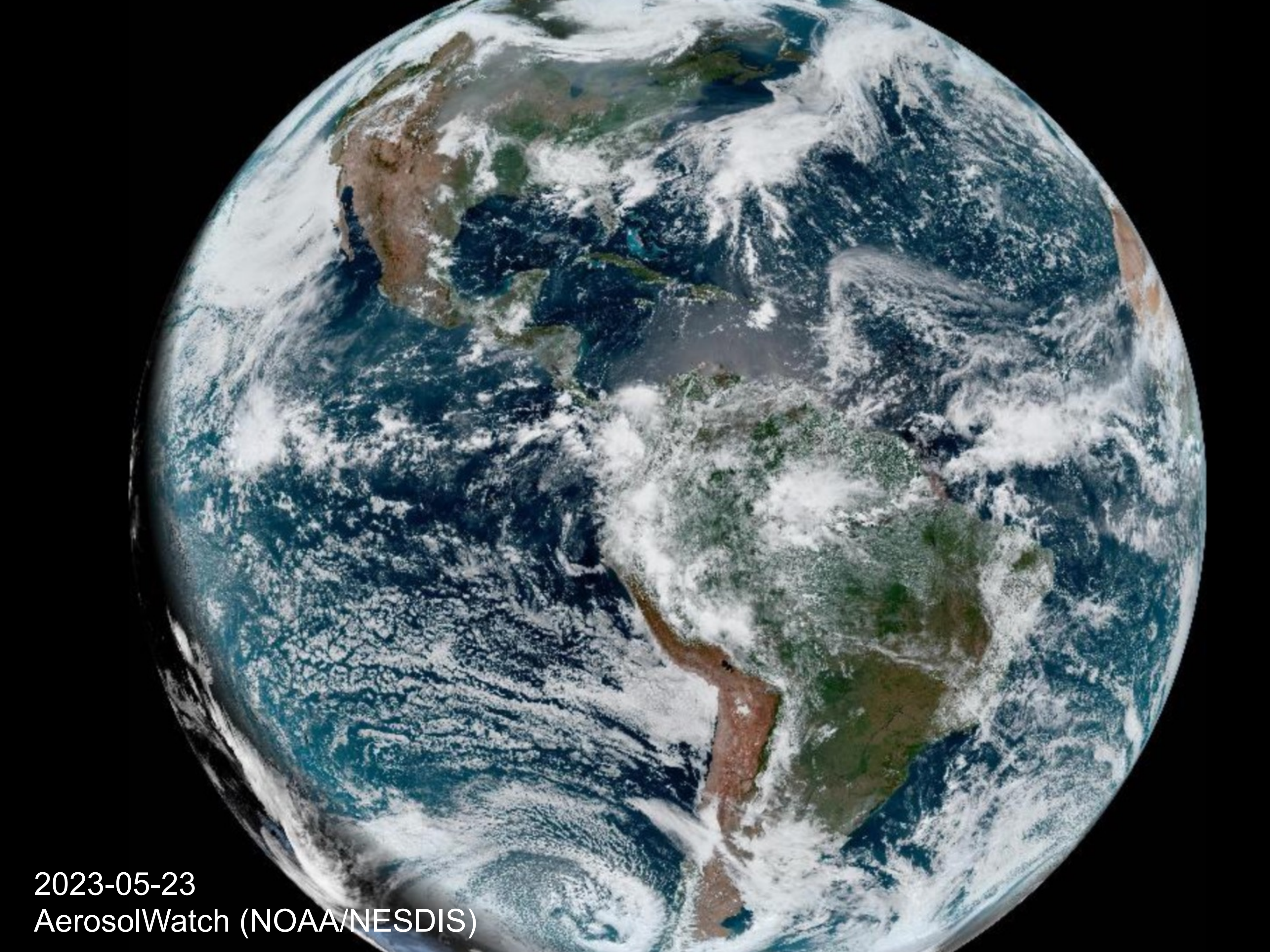
Higher-resolution satellite products reveal patterns

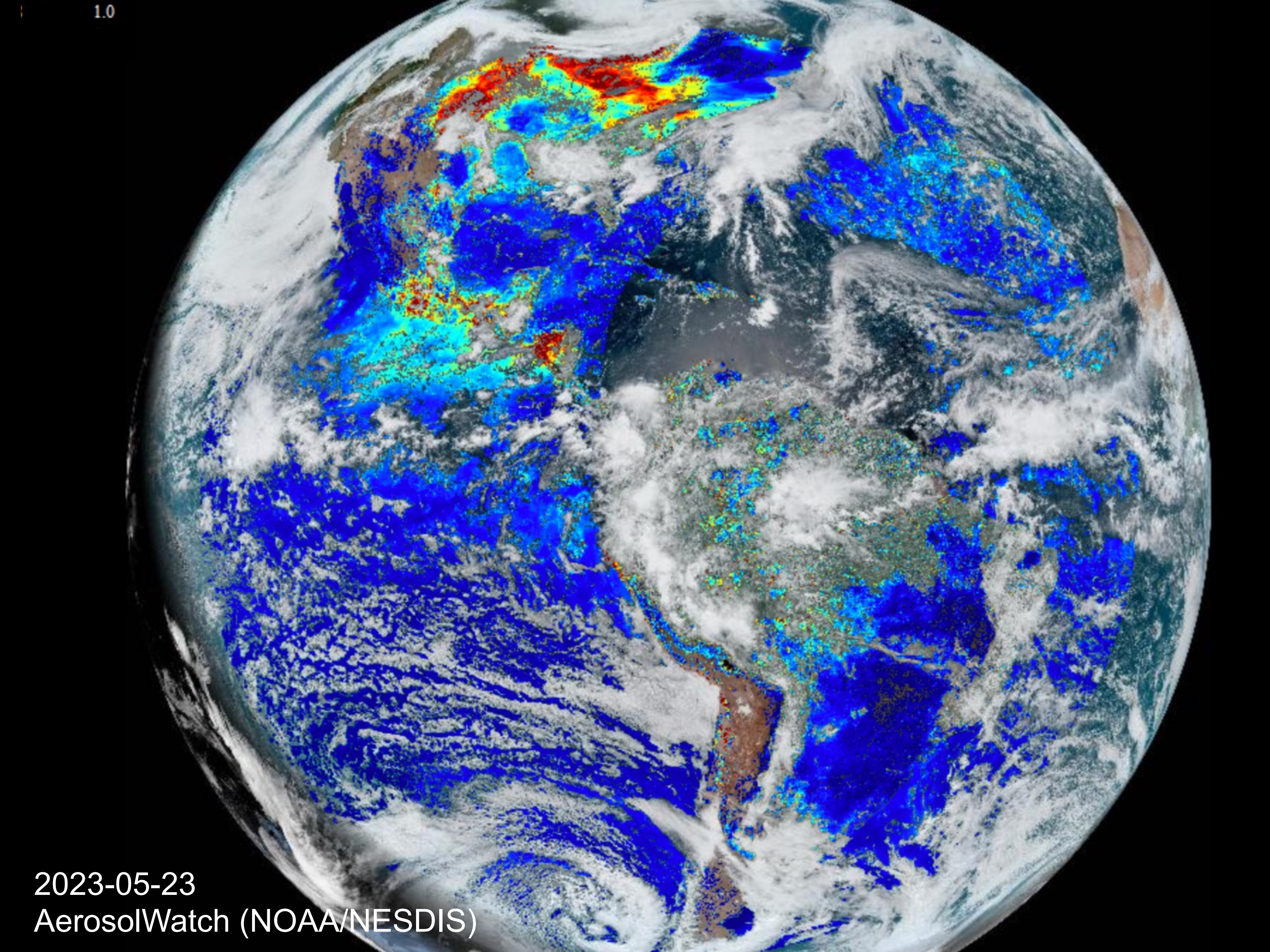


OMI retrieval over Mexico City (launched 2004)



TROPOMI retrieval over Mexico City (launched 2017)


2023-05-23
AerosolWatch (NOAA/NESDIS)



2023-05-23
AerosolWatch (NOAA/NESDIS)