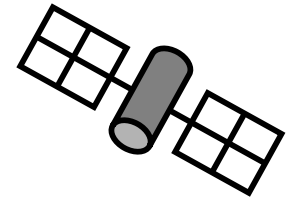


Air pollution and temperature as spatial factors impacting child health



Allan C. Just PhD

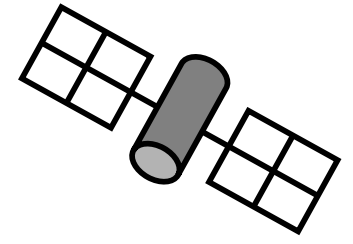
Nazareth-Ferguson Family University Associate Professor of Public Health in the Department of Epidemiology and Institute at Brown for Environment and Society

allan_just@brown.edu



School of
Public Health
BROWN UNIVERSITY



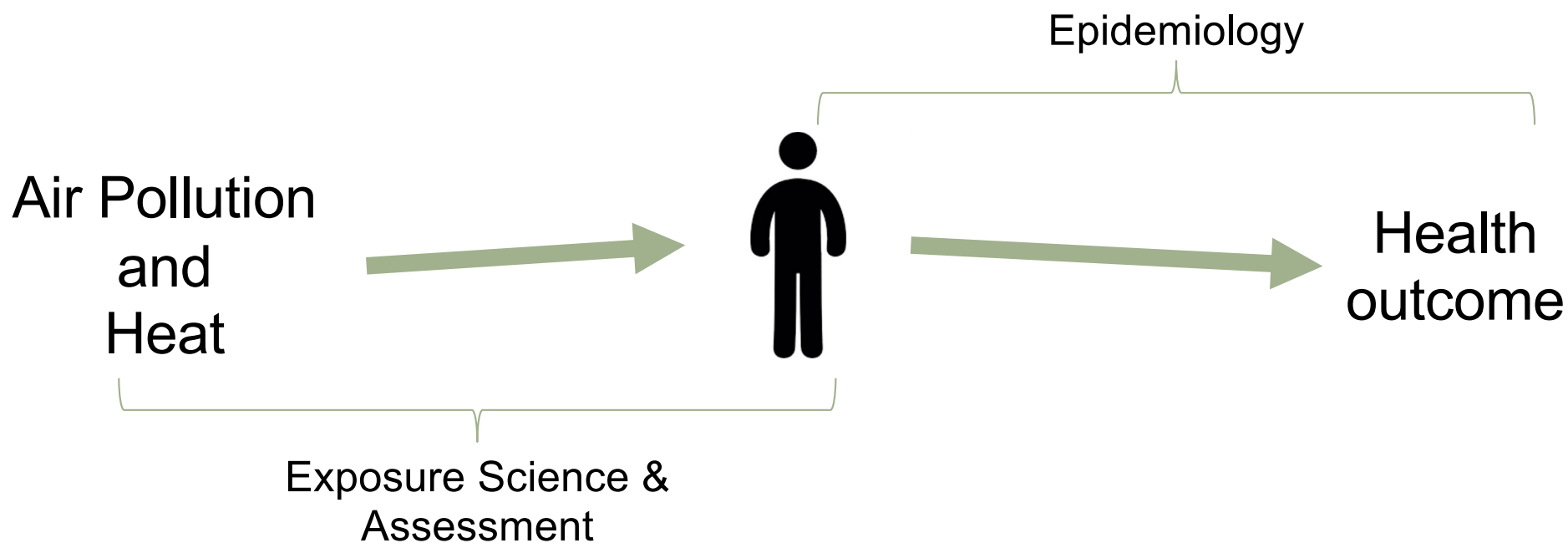


Outline

- Advanced exposure modeling for air pollution, temperature, and humidity
- Unique opportunities for ECHO
- What are we missing and what could solutions look like?

Goal: building spatiotemporal exposure models to aid epidemiological analyses with cohorts (started for ECHO!) and large health registries

Improving Exposure Science to Improve our Environmental Epidemiology



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



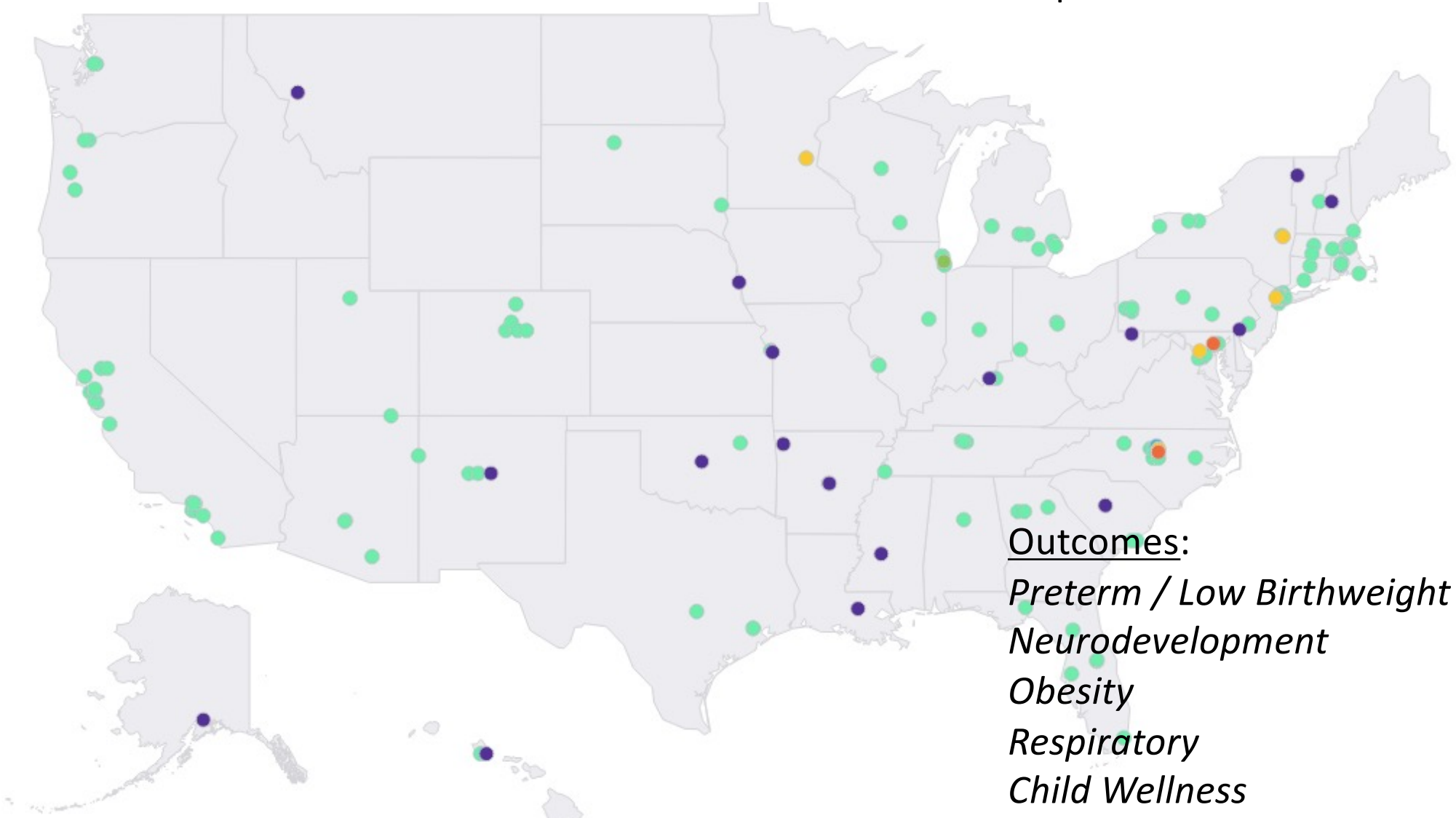
ECHO

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“



Outcomes:

*Preterm / Low Birthweight
Neurodevelopment
Obesity
Respiratory
Child Wellness*

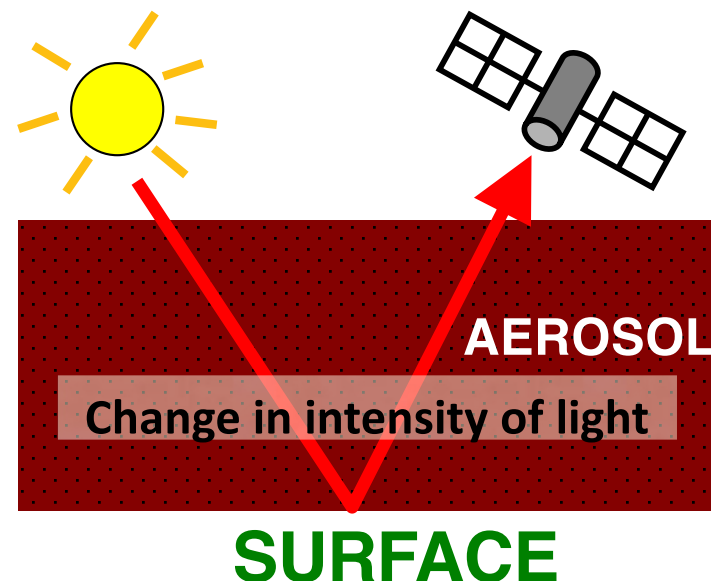
Combining satellite-derived predictors with meteorological, topographical & land use covariates

Satellite data

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

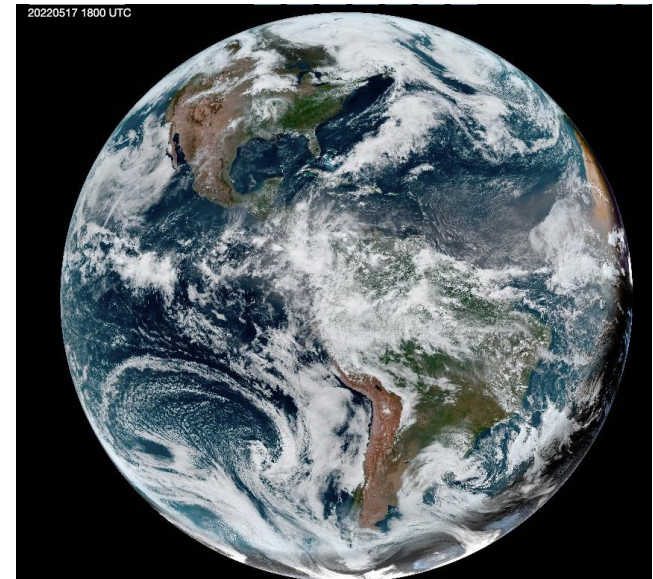
Land Surface Temperature (LST) informs models for air temperature

Column Water Vapor (CWV) informs models for dew point (humidity)



Technical challenges in applied remote sensing

- Staggering data volume
- Missing data (clouds, nighttime, indoors)
- Measurement error (complex atmospheric effects)



XIS: XGBoost-IDW Synthesis

- 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)

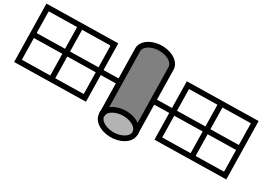
Predictive models trained on ground stations

- (Sub) Daily reconstruction with good spatial resolution
- Flexible machine-learning models capture complex relations
- But great care is needed to avoid overfitting!

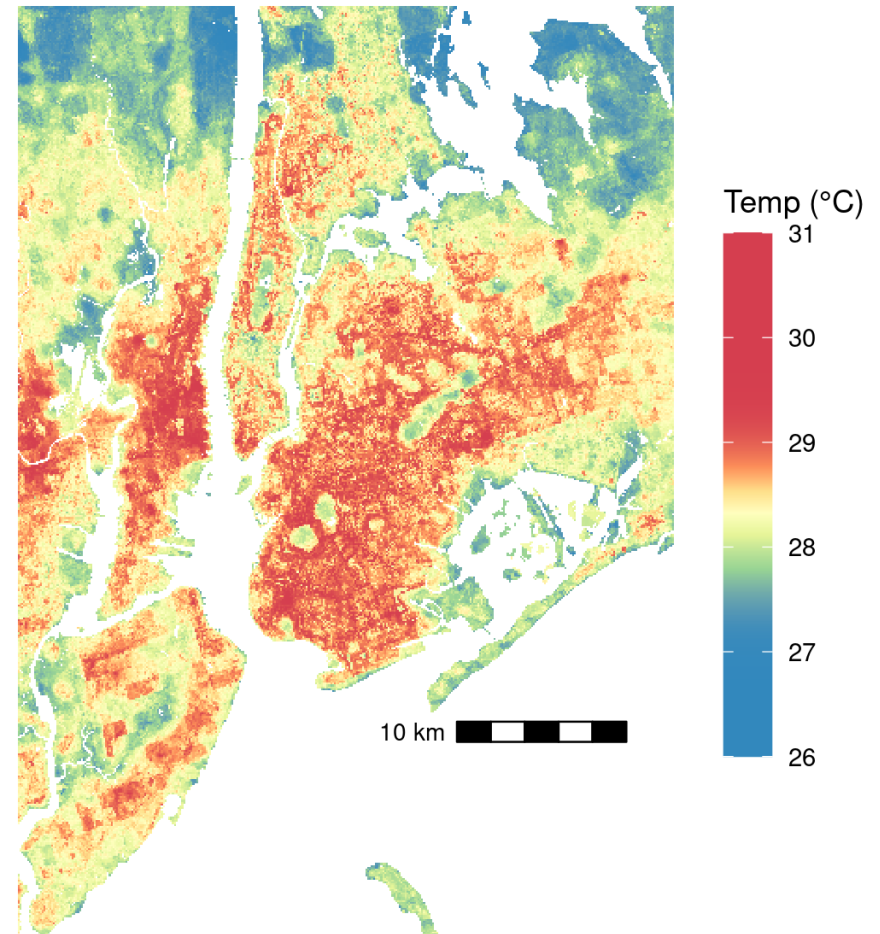
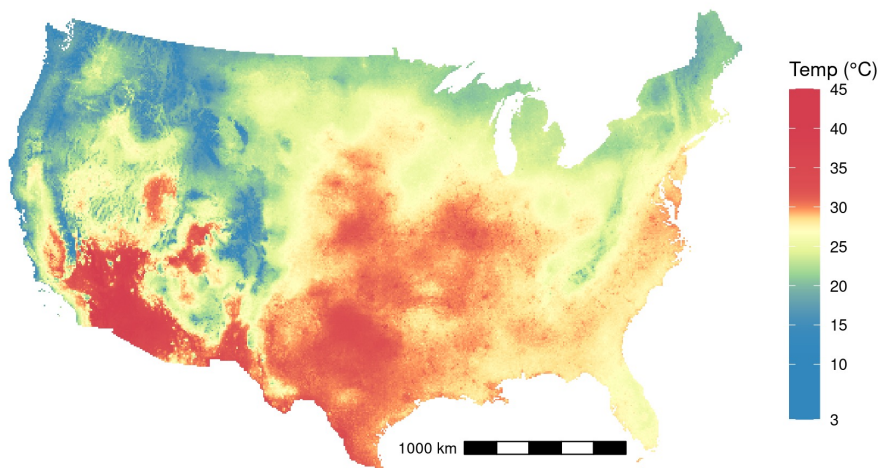
Just et al. Advancing methodologies for applying machine learning and evaluating spatiotemporal models of fine particulate matter (PM_{2.5}) using satellite data over large regions. *Atmos Env.* 2020;239:117649.



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



Example: mean temperature July 27, 2023



(different color scale)

Just et al. *Env Research* 2025 (temperature model)

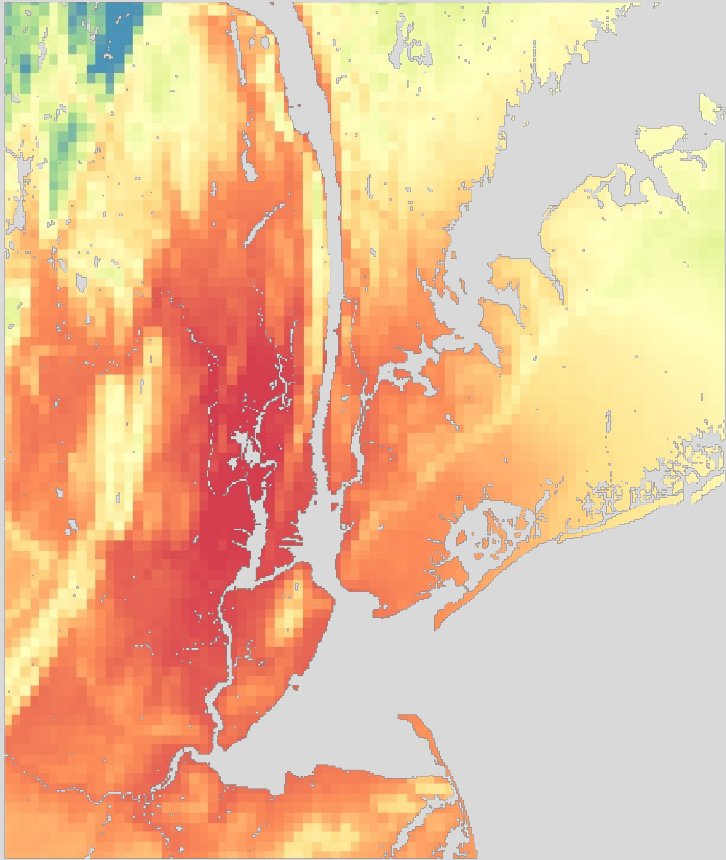
<https://doi.org/10.1016/j.envres.2024.120731>

Just et al. *Env Research* 2025 (PM_{2.5} model)

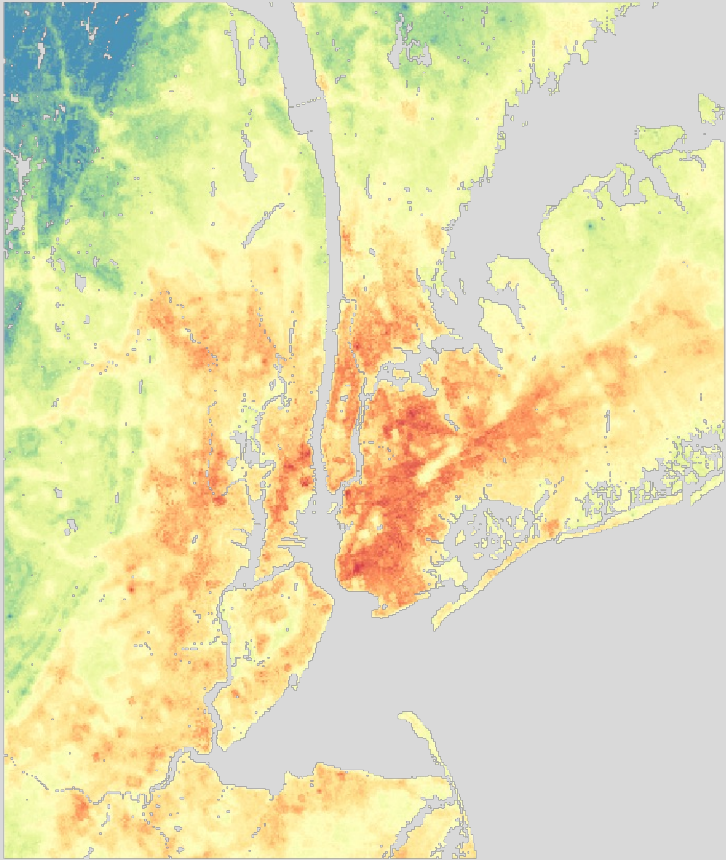
<https://doi.org/10.1016/j.envres.2025.120948>

Daily minimum temperature over NYC in a 2021 heatwave

Daymet



XIS



24.6

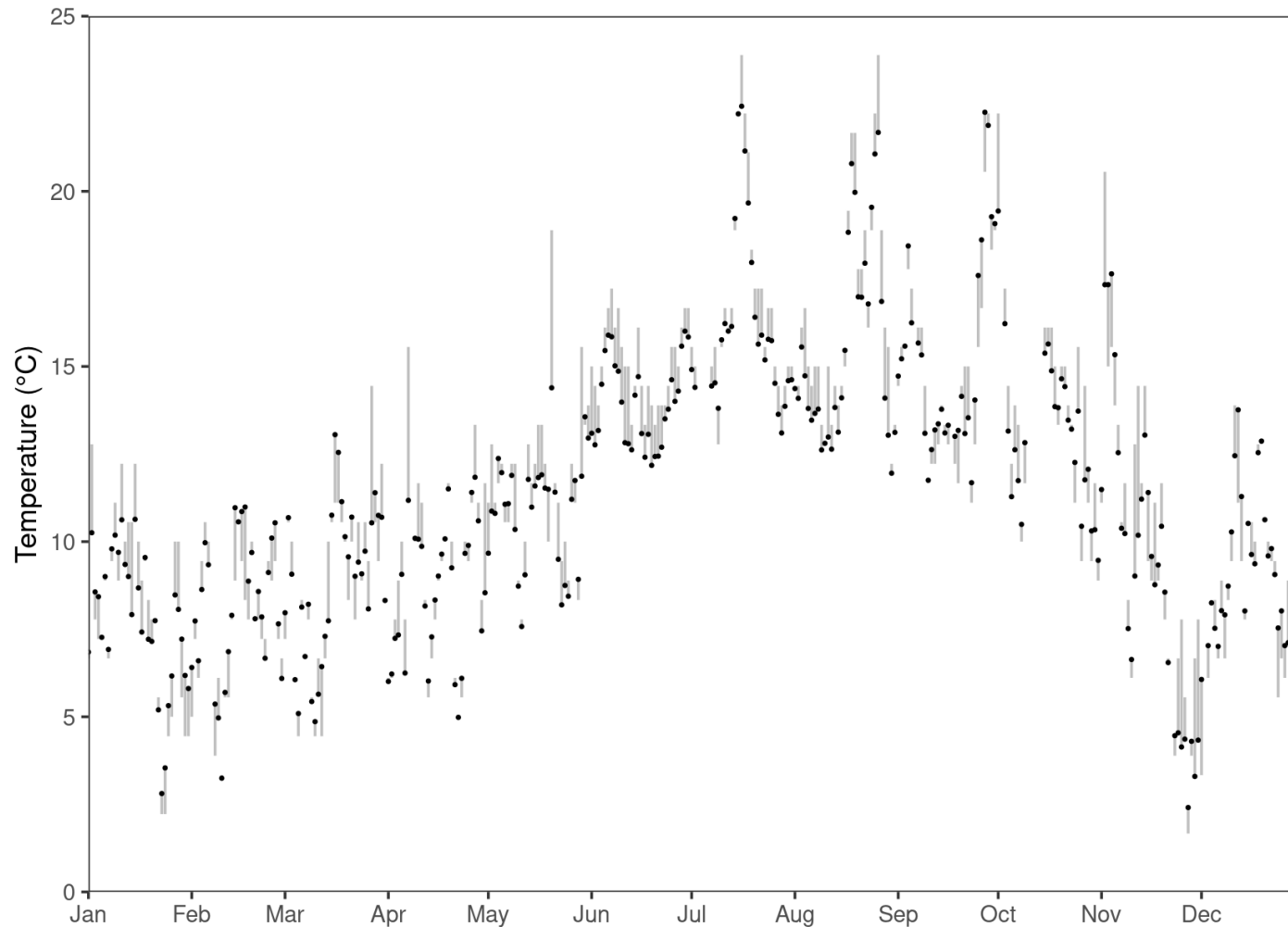
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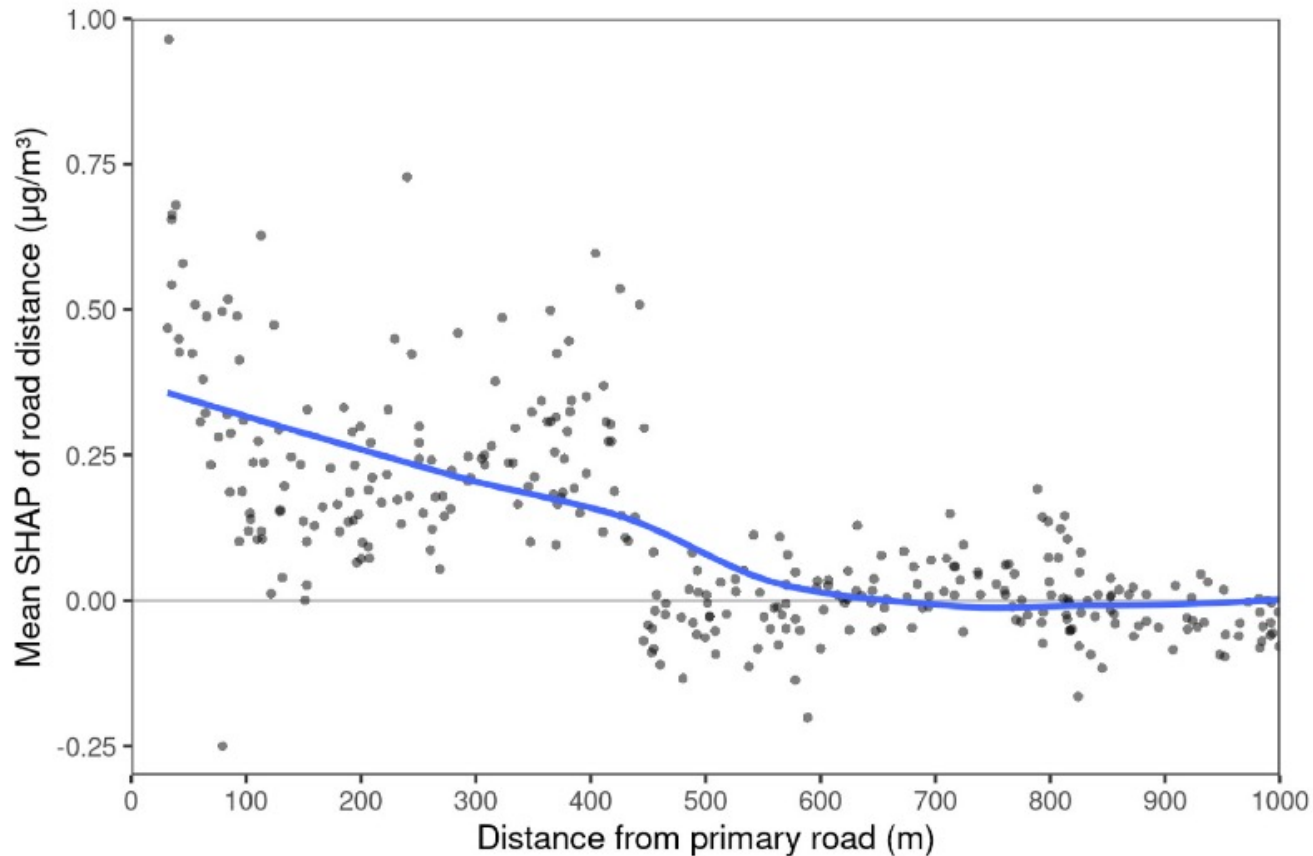
28

A time series of typical predictions



A plot of predicted min temperature in 2010 (points), and the distance from the observed value (line segments), for a station in the Chatsworth neighborhood of Los Angeles. This station was selected to have the yearly per-station unweighted RMSE closest to the median among all stations that had an observation for at least 347 days of 2010. Its RMSE is 1.27 K.

Learning about near-roadway gradients for PM_{2.5}



SHAP of road distance as a function of road distance in 2010, showing only cases within 1 km of a primary road. A trendline is fit with locally estimated scatterplot smoothing (LOESS)

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., 305 sites with 76,596 days in 2021)

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

we have 14% lower Mean Absolute Error

Making predictions to exact monitor locations:

we have 17% lower Mean Absolute Error

XGBoost-IDW-Synthesis (XIS) temperature models

Daily minimum, mean, and maximum models (three separate variables for each point-day)

- Point-based (can use exact home address long/lat)
- Daily model 2003-01-01 through 2024-12-31 so far

Comparison at 10,000 random private weather stations (not used in

| Year | Observations | SD | PRISM (4km) | gridMET (4km) | Daymet (1km) | XIS |
|------|--------------|-------|-------------|---------------|--------------|------|
| 2015 | 3,613,296 | 10.67 | 2.56 | 2.55 | 2.36 | 1.68 |
| 2016 | 3,612,812 | 10.39 | 2.62 | 2.61 | 2.36 | 1.81 |
| 2017 | 3,602,753 | 10.56 | 2.64 | 2.68 | 2.40 | 1.82 |
| 2018 | 3,593,725 | 11.25 | 2.67 | 2.68 | 2.45 | 1.89 |
| 2019 | 3,600,723 | 11.22 | 2.60 | 2.59 | 2.36 | 1.72 |
| 2020 | 3,609,000 | 10.54 | 2.62 | 2.61 | 2.39 | 1.79 |
| 2021 | 3,508,692 | 10.77 | 2.57 | 2.59 | 2.32 | 1.79 |

For min temperature, with averaging across years, our model has 47% of the MSE of PRISM, 47% of gridMET, and 56% of Daymet

XIS-Humidity

A daily spatiotemporal machine-learning model for dew point in the contiguous United States

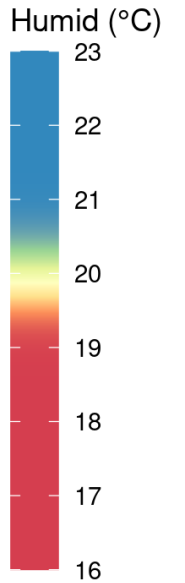
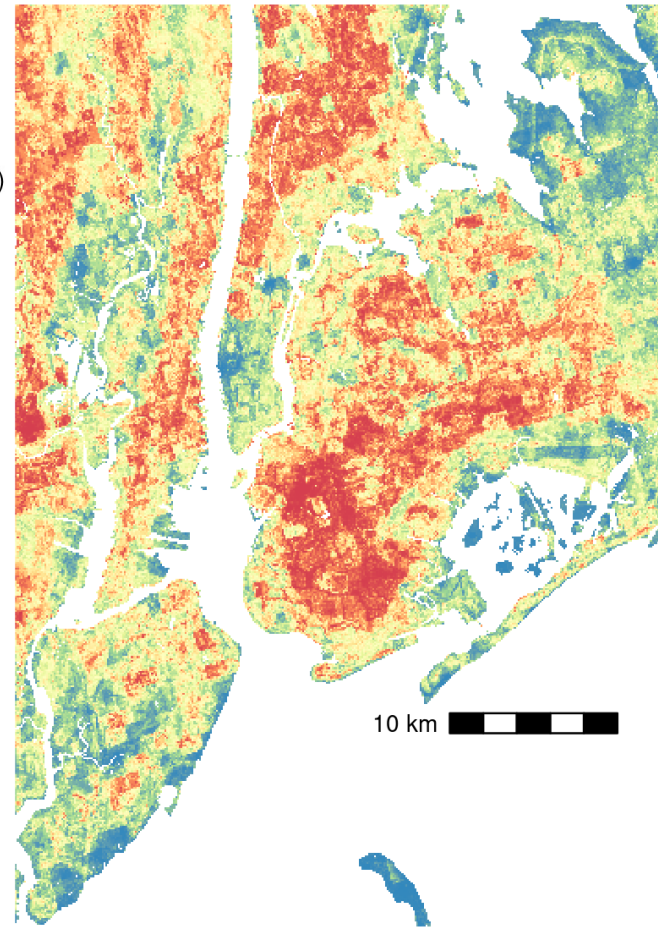
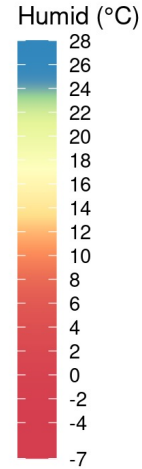
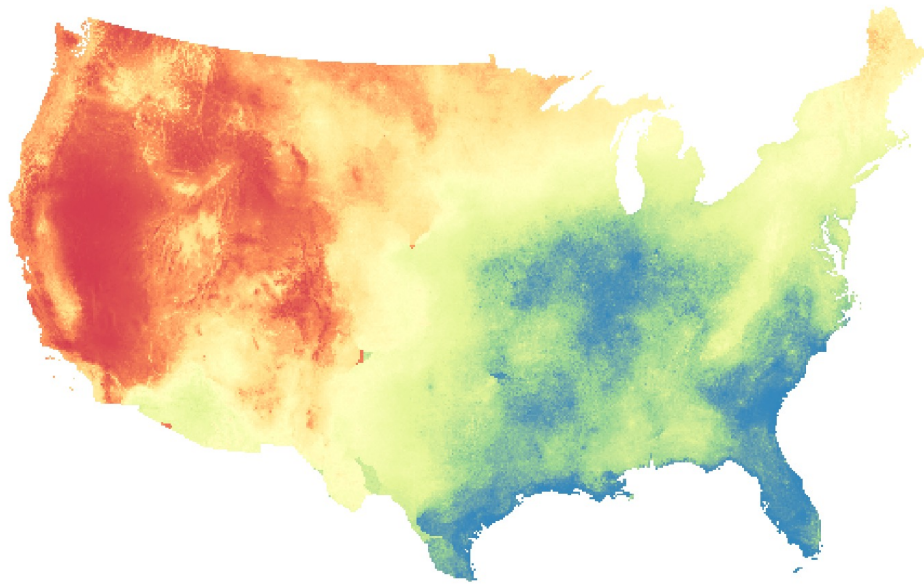
“The dew point is the temperature the air needs to be cooled to (at constant pressure) in order to achieve a relative humidity (RH) of 100%” -- weather.gov

2003-01-01 to 2024-12-31

Three models predicting:

- Dew point at the time of the daily min temperature
- Mean dew point
- Dew point at the time of the daily max temperature

Example: Dew point on 2010-07-28



(different color scale)

Manuscript still under review

What are we (still) missing?

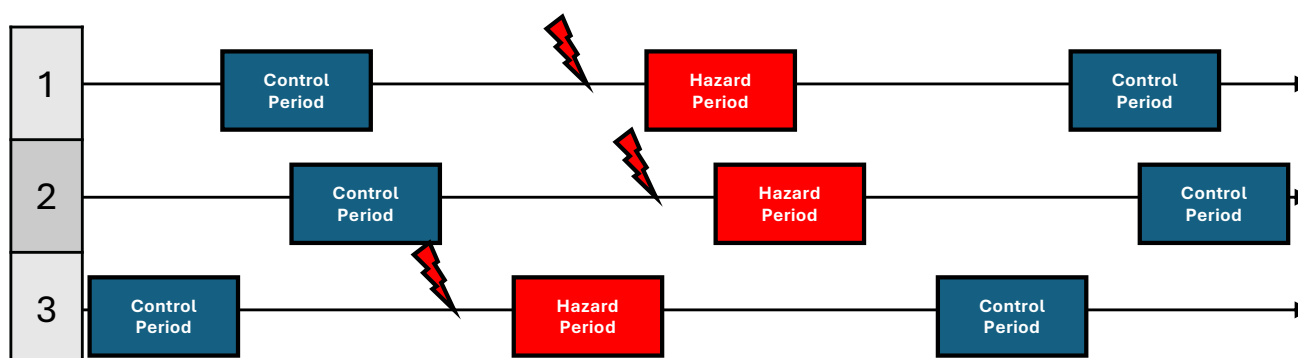
- No one breathes “averaged” air

While long-term average exposures will shift, health risks may be greatest with episodic **extremes** (heat waves, smoke events, etc)

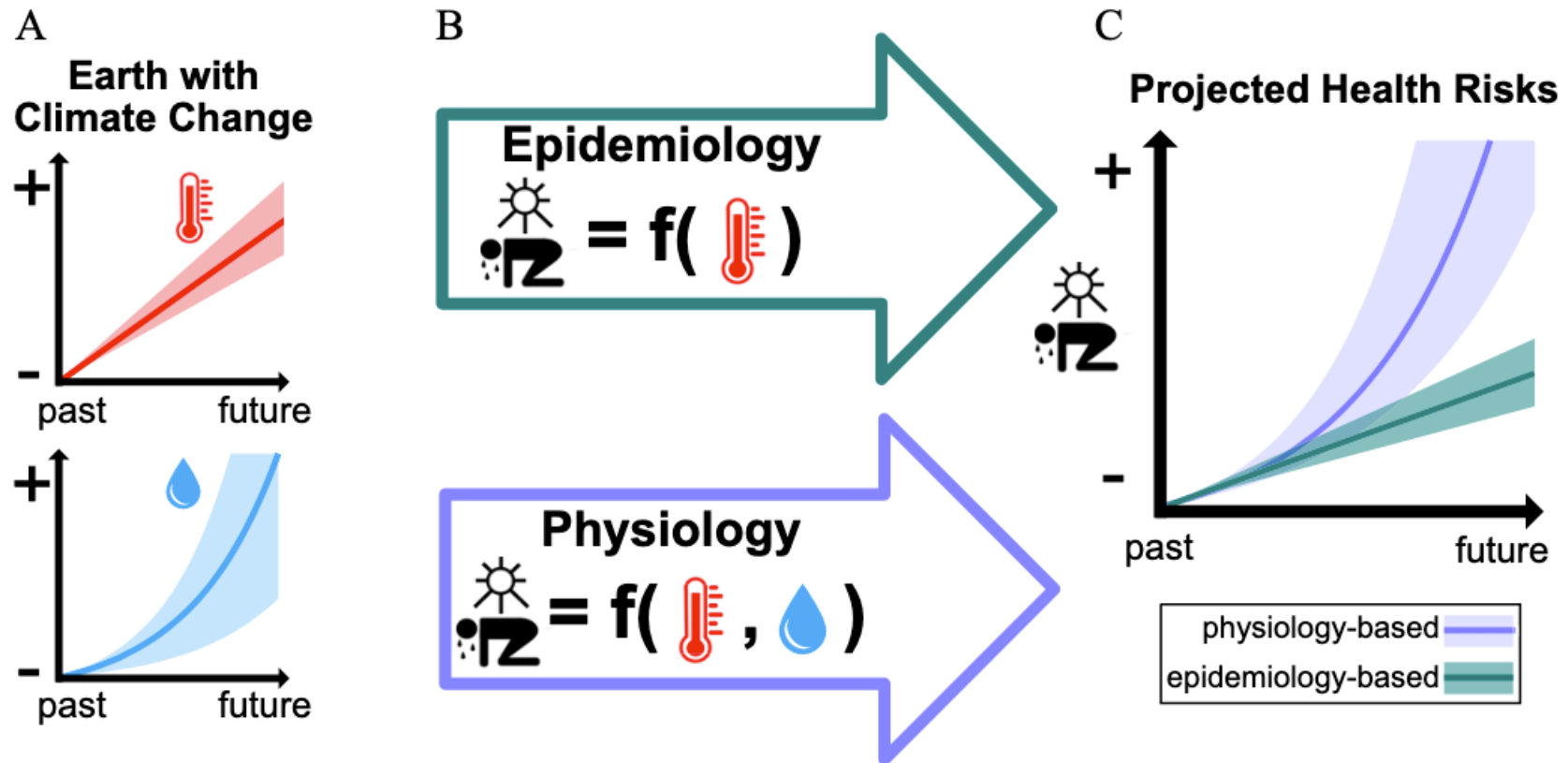
Analyzing short-term exposures: *Because no one breathes 24-hour averaged air*

- *Goal:* Analysis of short-term pollutant concentrations and acute health events
- *Exposure:* sub-daily pollutant estimates from hybrid satellite / LUR models over sub-county regions
- *Outcomes:* Asthma-related emergency dept visits, other acute health outcomes
- *Method:* matched lagged case crossover analysis

a case-only design used to identify triggers of acute health events



Humidity's Role in Heat-Related Health Outcomes: A Heated Debate

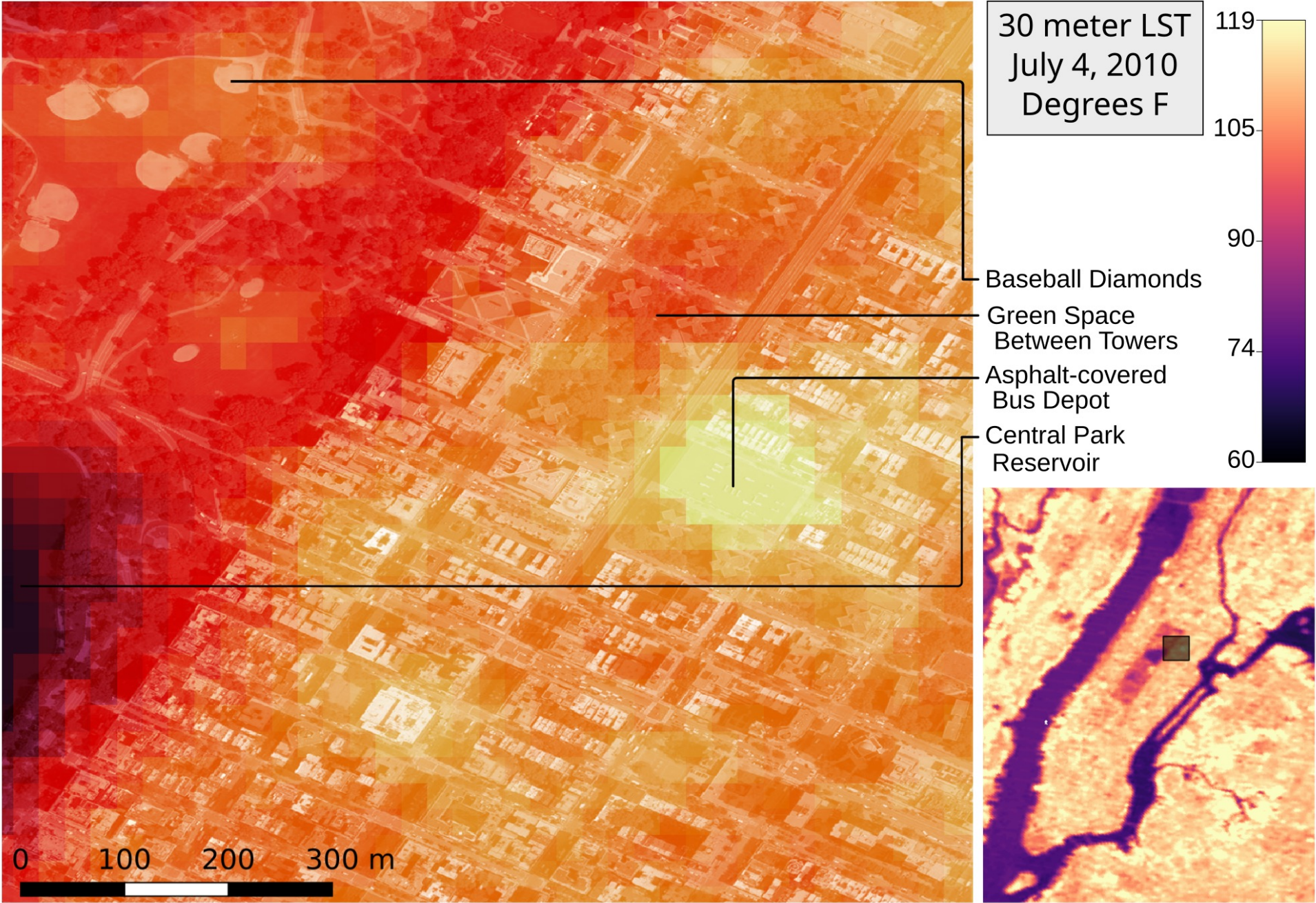


Humidity's Role in Heat-Related Health Outcomes: A Heated Debate

Let's stop using Relative Humidity:

“Changes inversely with T_a , as the denominator varies with T_a . RH varies diurnally and seasonally; is not useful in epidemiological and environmental health studies. Avoid use.”

Working towards higher resolution predictions: Satellite-derived Land Surface Temperature Product During a Heatwave



Background imagery: Bing Maps (c) Microsoft Corporation and its data suppliers. Landsat Level 2 Surface Temperature Science Products courtesy of USGS.

Indoor temperatures

- More stable than outdoor temperature
- The peak lags behind outdoors; can exceed outdoors
- Risk characterization / forecasting will need to consider housing characteristics

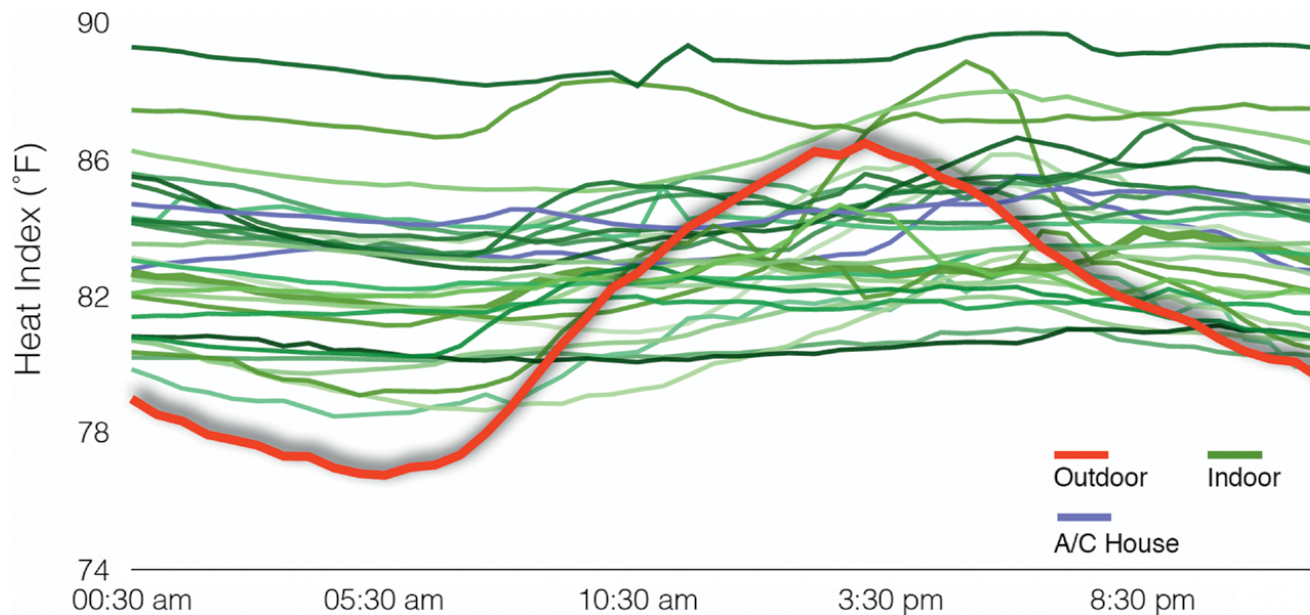


FIG. 4. Average diurnal variation of heat index, indoor vs outdoor for multiple residences. Green lines indicate homes with no AC or window units in a room separate from the sensor. Blue lines indicate residences with AC in the same room as the sensor.

THE HARLEM HEAT PROJECT

A Unique Media–Community Collaboration
to Study Indoor Heat Waves

Why study heat & air pollution together?

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

Avenues to solutions

Center for Heat, Health, and Aging Innovation and Research Solutions for Communities (CHAIRS-C)

Brown University P20 award from NIA (MPIs Just and Shireman)

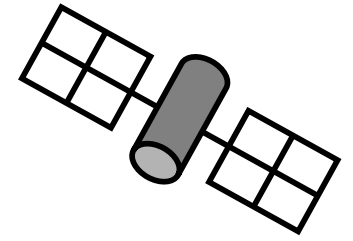
Coordination, Community Engagement, & Capacity Building

Big Data Heat Epidemiology Project

- 1. Link daily national temperature, humidity, and particulate air pollution reconstructions with >20 million heat-relevant hospitalizations in the Medicare cohort 2016-2023**
- 2. Quantify sensitivity within susceptible subpopulations with a focus on social determinants of health**
- 3. Comparative effect modification to assess heat-risks between pairs of common medications for hypertension and diabetes to assess evidence-basis for substitutions**



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email: allan_just@brown.edu

Main XIS publications:

Just AC, Arfer KB, Rush J, Lyapustin A, Kloog I. XIS-PM2.5: A daily spatiotemporal machine-learning model for PM2.5 in the contiguous United States. *Environmental Research*. 2025;271:120948.

<https://doi.org/10.1016/j.envres.2025.120948>.

Just AC, Arfer KB, Rush J, Kloog I. XIS-temperature: A daily spatiotemporal machine-learning model for air temperature in the contiguous United States. *Environmental Research*. 2025;270:120731.

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Allan Just PhD
allan_just@brown.edu



NOAA's GOES-T
2022-03-01 launch

<https://www.flickr.com/photos/nasakennedy/51944138873/>