

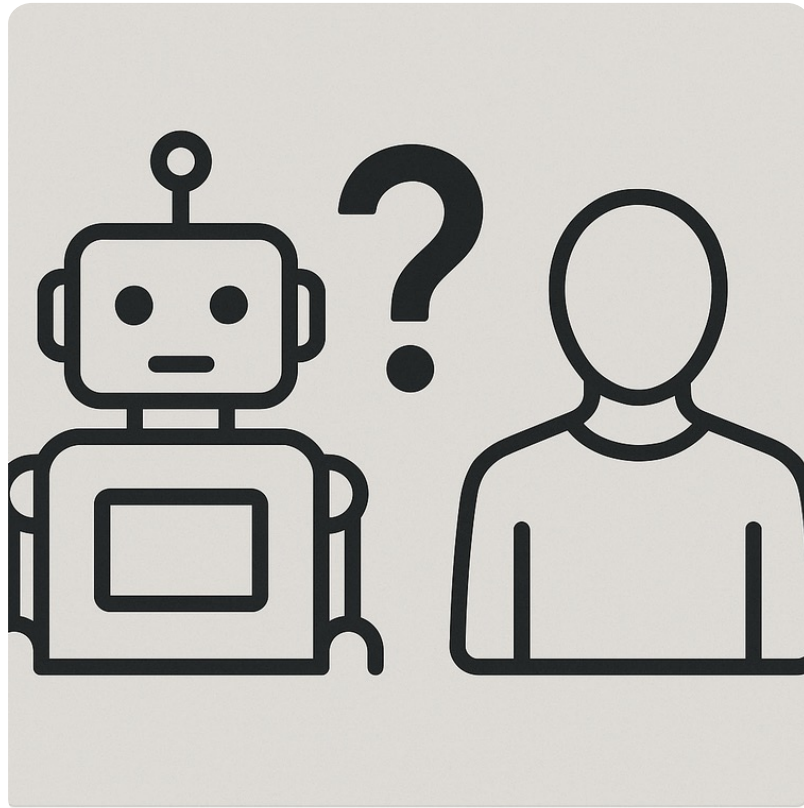


HDSI | Harvard Data
Science Initiative

AI: Solution or Obstacle for Climate Action?

- Francesca Dominici, PhD
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- Harvard T.H. Chan School of Public Health
- Director of the Harvard Data Science Initiative

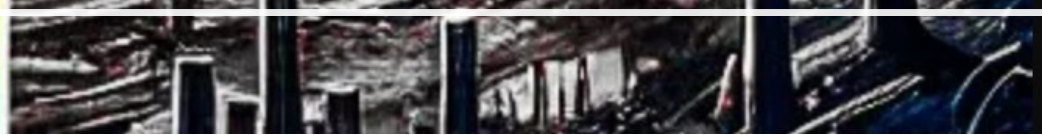
Outline



- The trillion-dollar, highly political scientific questions
- **AI as a promising solution**
- My journey
- Geo-AI for Air Pollution Exposure Estimation
- The first foundation model for climate adaptation
- **Responsible AI**
- The Environmental Impact of AI
- Conclusions



AI as Eutopia or Dystopia?



The trillion-dollar, highly political scientific questions

- Does exposure to fine particulate matter, even at low levels, cause an increase in hospitalizations?
- Is air pollution from coal-fired power plants more toxic than air pollution from other sources?



DATA

Data integration of over
20 government data
repositories

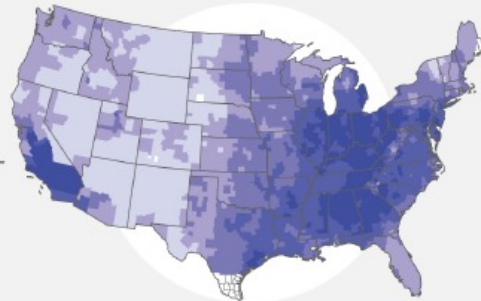
- All Medicare participants (n=67,682,479) in the continental United States from 2000 to 2021
- Outcomes: all-cause mortality and cause specific hospitalization
- Individual level information: date of death, age of entry, year of entry, sex, race, whether eligible for Medicaid (proxy for SES)
- Zip code of residence and other covariates

Causal Reasoning AI for Policy Decisions (9 TB of data)



EXPOSURES AND INTERVENTIONS (E OR I)

PM_{2.5} exposure levels by county (average 2000-2012)



DATA SOURCES

Criteria air pollutants

EPA AQS daily average of PM_{2.5}, ozone, NO₂, 1995-2015;

Daily 1km x 1km predictions of PM_{2.5}, ozone, NO₂, 2000-2014

Methane

1km x 1km predictions at 3-day intervals, 2009-present

Weather

NOAA daily estimates (temperature, precipitation, humidity, ...) on a 0.3° grid

Power plants

EPA AMPD daily emissions, 1995-2015

Coal mines

MSHA location and producing pits, 1970-2015

Fracking wells and disposal wells

Drillinginfo database with well location and depth, daily production

Traffic

Annual traffic counts and density from the Department of Transportation

Residential community green space

NASA vegetation index on a 250m² grid

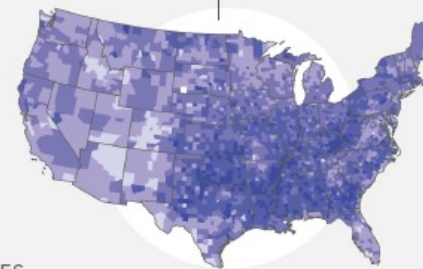
Factories and industrial sites

Geocoded locations of businesses



HEALTH OUTCOMES (Y)

Medicare mortality rate by county (average 2000-2012)



DATA SOURCES

Medicare

28 million per year, 1999-2015

Medicaid

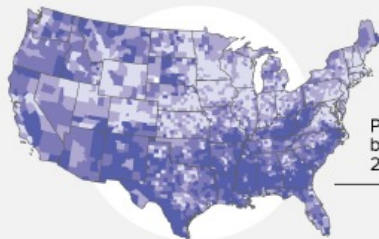
28 million per year, low income, 2010-2011

Aetna

40 million, all ages, above-average income, 2008-2016



CONFOUNDERS (X)



Poverty prevalence by county (average 2000 and 2010)

DATA SOURCES

Individual demographics

Age, sex, race, ZIP code of residence

Individual medical history

Previous diagnoses, medications prescribed

ZIP code level variables

Income, education, demographics, employment, household size

County-level variables

Crime, smoking, BMI

Seing

Doing

Imagining



The NEW ENGLAND JOURNAL of MEDICINE

Air Pollution and Mortality at the Intersection of Race and Social Class

Kevin P. Josey, Ph.D., Scott W. Delaney, Sc.D., J.D., Xiao Wu, Ph.D., Rachel C. Nethery, Ph.D., Priyanka DeSouza, Ph.D., Danielle Braun, Ph.D., and Francesca Dominici, Ph.D.

AIR POLLUTION, MORTALITY, RACE, AND SOCIAL CLASS

Table 1. Characteristics of the Medicare Cohort, 2000 through 2016.*					
Characteristic	Full Cohort†	Black Persons		White Persons	
		Higher Income‡	Low Income§	Higher Income‡	Low Income§
Persons — no. (% of full cohort)	73,129,782 (100)	4,872,714 (6.7)	1,671,776 (2.3)	56,422,414 (77.2)	4,989,457 (6.8)
Person-yr — no. (% of total person-yr)	623,042,512 (100)	37,862,780 (6.1)	14,886,928 (2.4)	483,479,863 (77.6)	48,247,908 (7.7)
Deaths — no. (% of total deaths)	29,467,648 (100)	1,488,555 (5.1)	1,154,227 (3.9)	20,773,208 (70.5)	4,769,240 (16.2)
Median follow-up time — yr	8.0	7.0	8.0	8.0	8.0
Age at entry — %					
65–74 yr	80.6	86.2	77.4	80.4	72.7
75–84 yr	14.8	10.7	15.6	15.3	17.2
85–94 yr	4.2	2.5	6.2	4.0	9.0
≥95 yr	0.4	0.6	0.8	0.3	1.1
Female sex — %	55.4	54.9	68.1	54.3	68.0
Medicaid eligible — %	11.6	0	100	0	100

Lowering exposure from 12 to 9 unit → 5 % mortality reduction among Black Americans; 2.5% mortality reduction among White Americans

NEW RESEARCH

Cleaner Air Helps Everyone. It Helps Black Communities a Lot.

A new study quantified the benefits of pollution reduction in terms of race and class.

Share full article



St. James, La., one of several Mississippi River towns dotted by chemical plants and oil refineries. William Widmer for The New York Times



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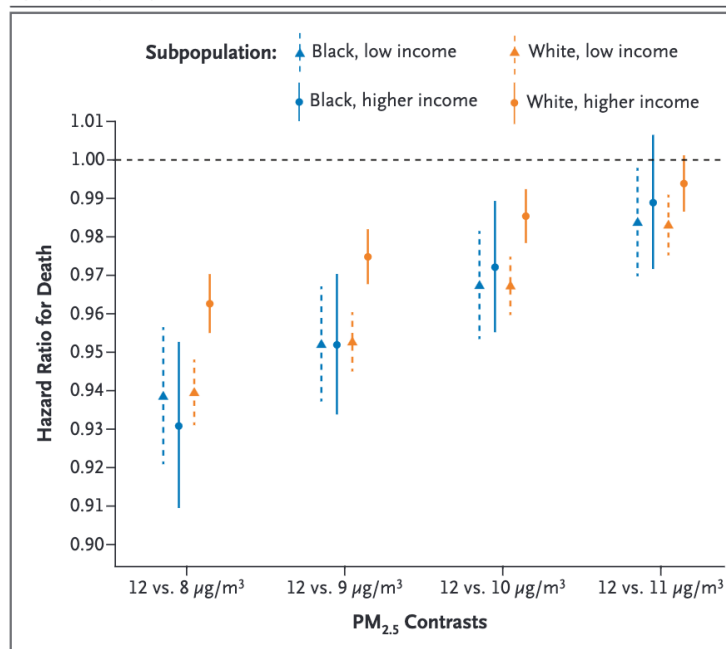


Figure 4. Differences in Mortality with Decreasing PM_{2.5} Exposure among Marginalized Subpopulations.

Shown are point estimates and 95% confidence intervals of the hazard ratio for death comparing different levels of annual average PM_{2.5} exposure (12 µg per cubic meter vs. 11, 10, 9, or 8 µg per cubic meter) on average for subpopulations defined in selected ways. Low income was defined as dual eligibility for both Medicare and Medicaid. Confidence intervals were not adjusted for multiplicity; therefore, they should not be used in place of hypothesis testing.

Doing

How my lab has impacted this decision

Data Science

April 2023



The NEW ENGLAND
JOURNAL of MEDICINE

SPECIAL ARTICLE | VOL. 388 NO. 13, APR 13, 2023

Air Pollution and Mortality at the Intersection of Race and Social Class

K.P. Jossey and Others | N Engl J Med 2023; 388:1396-1404

In this large study, the mortality benefits of reducing levels of fine particulate matter air pollution were greater for low-income and higher-income Black persons and for low-income White persons than for higher-income White persons.

Nov 2023

Science

RESEARCH ARTICLE

POLLUTION

Mortality risk from United States coal
electricity generation



Policy

Dec 2023, COP28 Opening day, Kerry talk about my
study: Climate Crisis is a Health Crisis.



Impact

February 2024

***Biden Administration Moves to
Tighten Limits on Deadly Air Pollution***

A new rule would, for the first time in a decade, reduce emissions
of soot that disproportionately harm communities of color.

Give this article



A lot of seeing
and doing

- ✓ Cleaner Air
- ✓ Lives Saved
- ✓ Less GHG

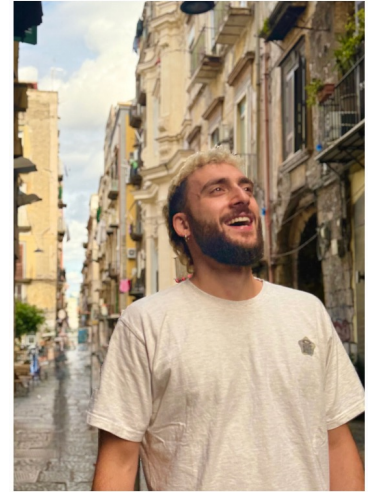
The potential of AI for Climate Adaptation

- Climate change brings more extreme weather, wildfires, and shifting disease patterns
 - Understanding and mitigating health impacts is *complicated* – e.g. heatwaves affecting vulnerable people, wildfire smoke causing respiratory illnesses
- **AI's Promise:** AI can analyze *unprecedentedly massive multimodal* data to find *generalizable* patterns and make predictions *more accurately* than traditional methods
 - This can inform early warnings and adaptive responses (e.g. alerting hospitals of an incoming heat-related patient surge)



ClimaCare: A Foundation Model for Healthy Climate Adaptation

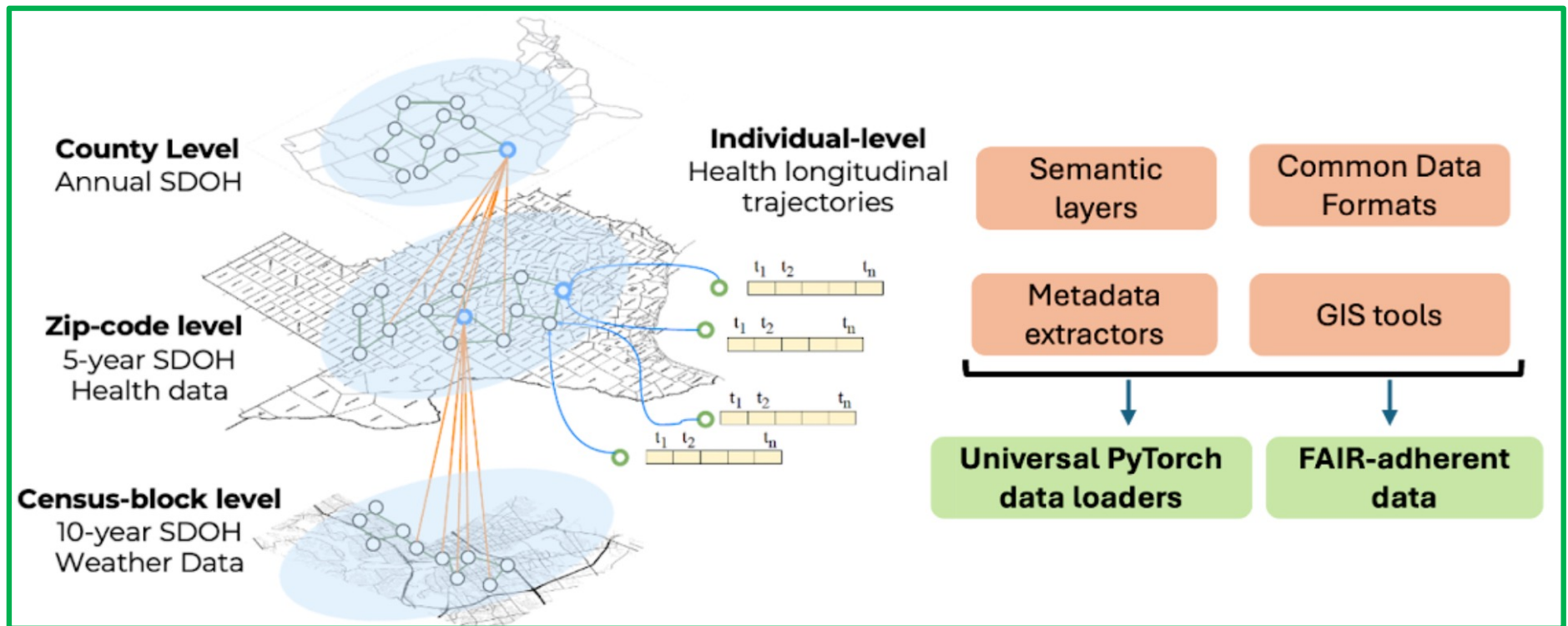
Claudio Battiloro^{*,†}, James Kitch^{*,†}, Bret Nestor^{*,†},
Mauricio Tec[†], Michelle Audirac, Danielle Braun,
Francesca Dominici



Claudio Battiloro

1. Pre-trained on the entire US health care system x environmental data x societal data
2. It produces unified embeddings that capture the complex spatiotemporal relationships between climate stressors, socioeconomic variables, and health outcomes.
3. We evaluate the model on benchmark downstream tasks, i.e., health outcomes interpolation, extrapolation, downscaling, and forecasting
4. We implement “**what-if**” scenario forecasting for climate adaptation using synthetic ground-truth data to validate counterfactual predictions when any input exposure is altered.

Towards a One-of-a-Kind geo-AI for Healthy Climate Adaptation

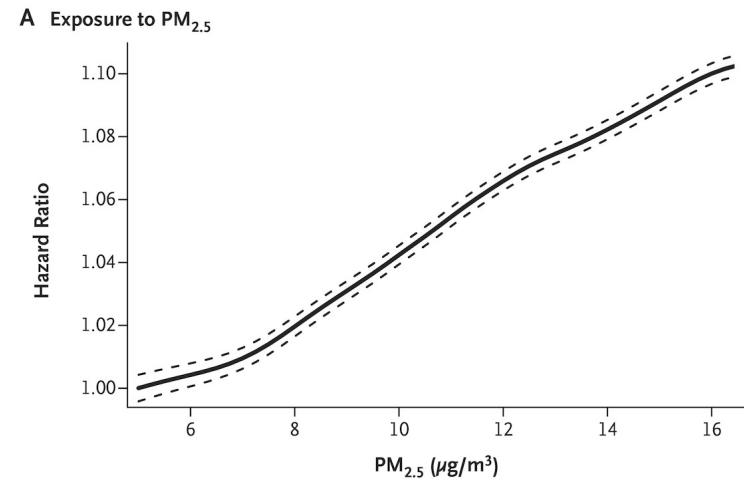


ClimaCare: Downstream Tasks

- **Spatiotemporal Downstream Tasks:**
 - Spatial Interpolation
 - Spatial Extrapolation
 - Forecasting

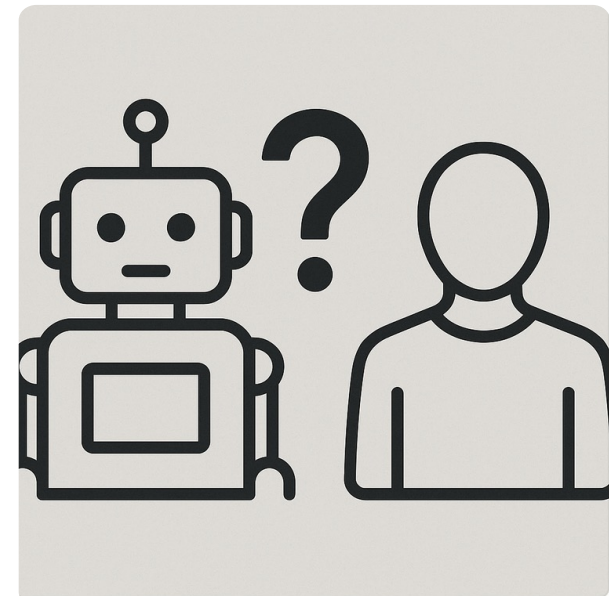
What-If Downstream Tasks:

ERC Estimation
Enhanced Causal Inference



2050: Let's imagine a world where we have solved causal reasoning

- AI agents are everywhere
- Is this a better future?





At Amazon's Biggest Data Center, Everything Is Supersized for A.I.

On 1,200 acres of cornfield in Indiana, Amazon is building one of the largest computers ever for work with Anthropic, an artificial intelligence start-up.

403 Hyperscale
data centers and
3318 energy
supplier power
plants in the US
(May 2024 to April
2025)

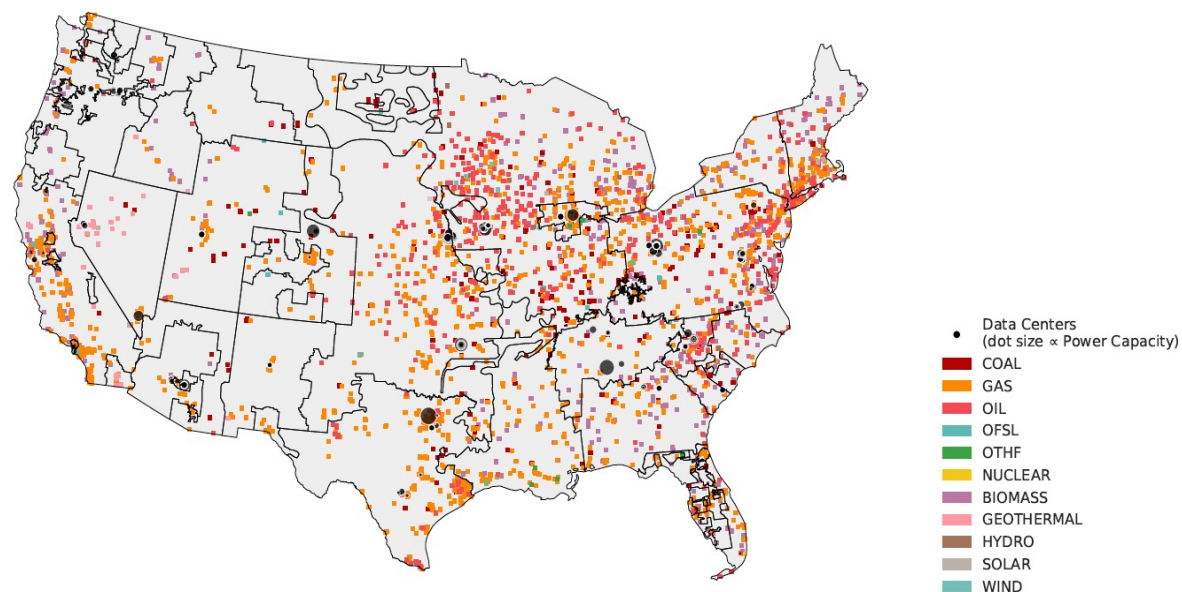


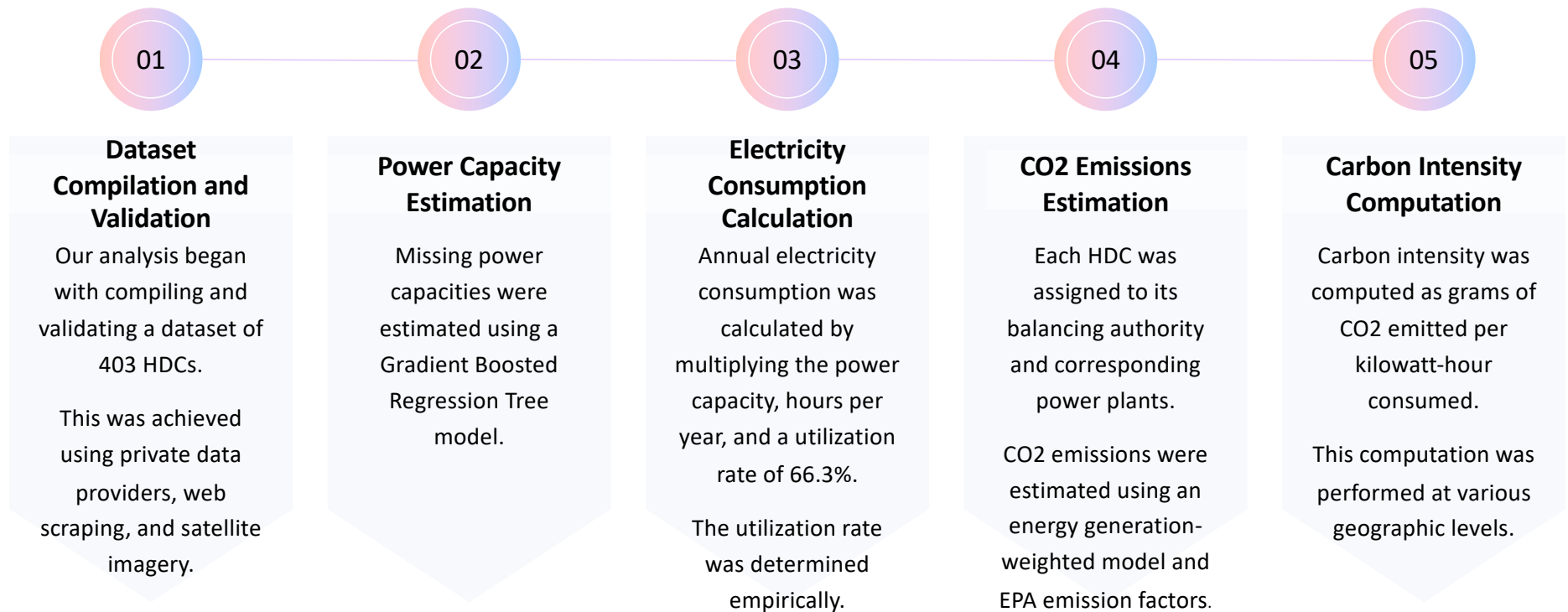
Fig. 1. Geographic distribution of hyperscale data centers and power plants in the contiguous US, overlaid with balancing authority regions. This figure shows the 403 hyperscale data centers and 3,318 operational power plants included in our analysis for the study period from May 2024 to April 2025. The map is displayed at the balancing authority (BA) level, representing regions where electricity supply and demand are managed in real time. The size of each hyperscale data center marker is proportional to its power capacity, while power plants are colored by their primary fuel type.

Scientific questions

1. What are the electricity consumption, sources, and attributable CO2 emissions of those 403 data centers?
2. What is the fuel mix of the power plants supplying electricity to data centers?
3. Which states have the highest CO2 emissions attributable to data centers?

Hint: With a data pipeline that can answer those questions, we make informed decisions, such as: Where should I place a data center? Where should I intervene on the power grid? How can we decarbonize this sector?

Materials and Methods



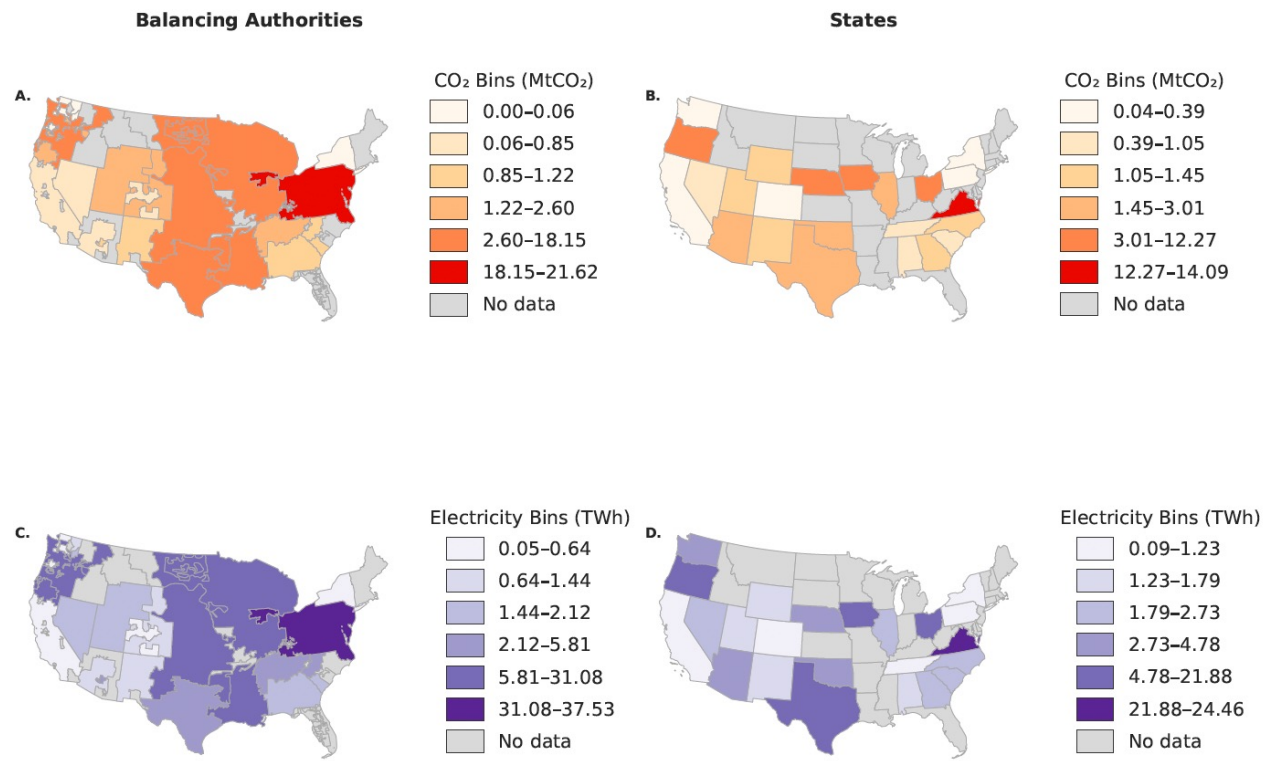


Fig. 2. Hyperscale Data Center electricity consumption and CO₂ emissions. (Left column, A and C) The balancing authority (BA) region in which a hyperscale data center is located determines the mix of power plants that supply its electricity and thus its attributable emissions. See fig.S.4.1 for BA regions and corresponding names. (Right column, B and D) Maps at the state level show electricity consumption and emissions for which the hyperscale data centers within the state are responsible for. Color bins represent percentile-based ranges: 0–20%, 20–40%, 40–60%, 60–80%, 80–99%, and 99–100%.

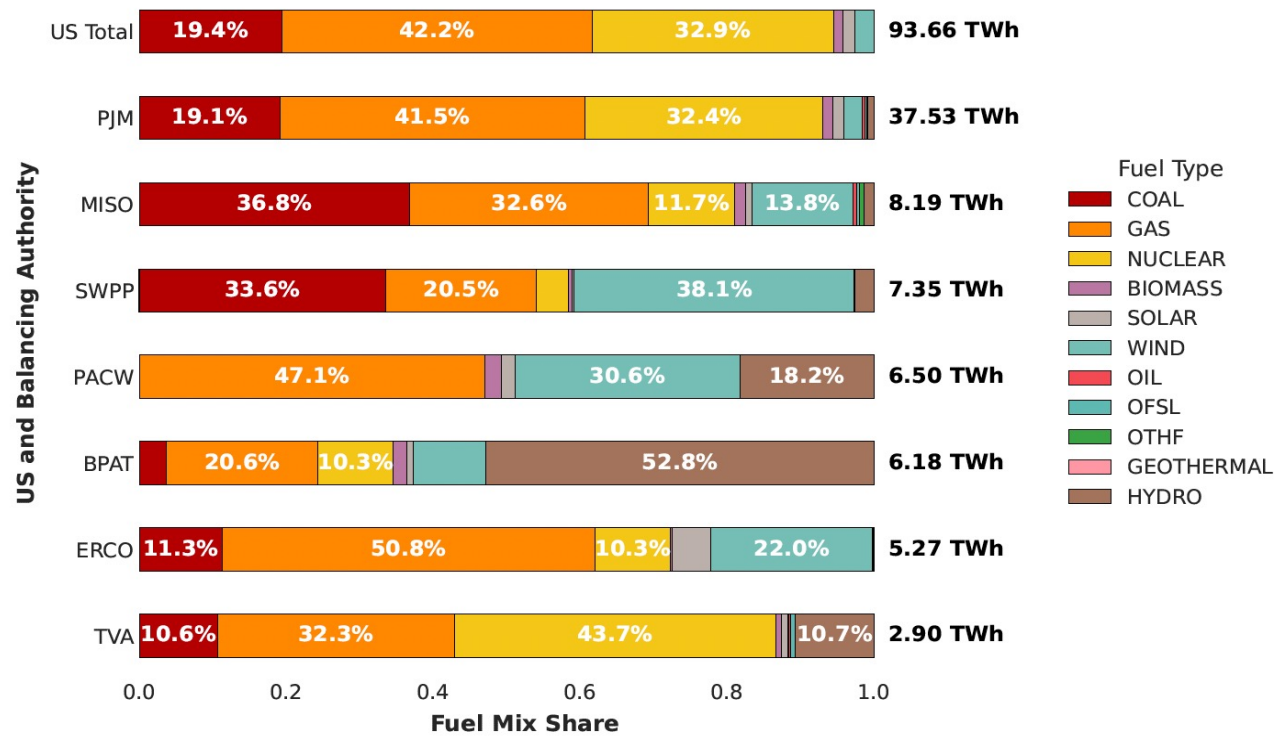


Fig. 4. Fuel mix of power plants supplying electricity for hyperscale US data centers. The top bar represents the distribution of fuel types used by the power plants supplying electricity for hyperscale US data centers in our study. The bottom bars show the largest balancing authorities ranked by aggregated power capacity of hyperscale data centers (shown on the vertical axis), and the amount of electricity produced per fuel type. See fig.S.4.1 for BA regions and corresponding names.

Carbon Emissions Attributable to Hyperscale Data Centers

Total CO2 Emissions
from HDCs

52.69M

The total CO2 emissions attributable to the 403 hyperscale data centers (HDCs) amounted to 52.69 million metric tons.

Proportion of US
Carbon Emissions

1.10%

This represents approximately 1.10% of the total US carbon emissions from electricity consumption in 2023.

Increase Since 2018

5x

This is more than five times the total emissions reported for HDCs in 2018.

Highest Emissions by
State

24.46M

Virginia had the highest CO2 emissions attributable to HDCs, amounting to 24.46 million metric tons.

Significant State
Contributions

5.82M

Ohio followed with 5.82 million metric tons of CO2 emissions attributable to HDCs.

- 52.69 M represents the annual CO₂ emissions of a major U.S. city or a sizable portion of the U.S. aviation industry.

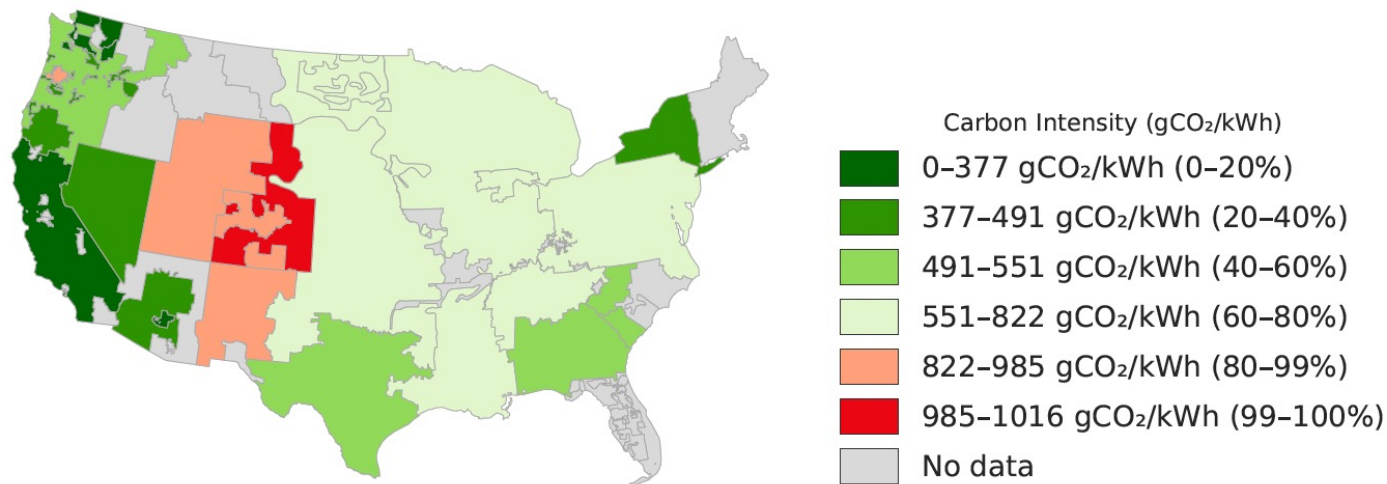


Fig. 3. Carbon intensities of electricity consumption for hyperscale US data centers by balancing authority. Carbon intensity is defined as the amount of carbon dioxide emissions produced per unit of electricity generated, or consumed, and is expressed in units such as grams of CO₂ per kilowatt-hour (gCO₂/kWh) for electricity generation. The figure shows HDCs' carbon intensity for electricity consumption at the balancing authority level, in grams of CO₂ per kWh. Color bins represent percentile-based ranges: 0–20%, 20–40%, 40–60%, 60–80%, 80–99%, and 99–100%.

AI as Eutopia or Dystopia?



The EPA's 2024 regulatory analysis projects that new standards for coal (and some new gas) power plants will cut about 55 million metric tons per year



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