Workshop on Innovative Applications of Geospatial Data Science in Drug Use Research

Tuesday, December 3, 2024
12:00 p.m. - 4:00 p.m. EST

NIDA DESPR Planning Members:
Janet Kuramoto-Crawford, Ph.D., M.H.S.
Tamara Haegerich, Ph.D.
Courte Van Voorhees, Ph.D.

National Institute on Drug Abuse

Housekeeping

- The meeting will be recorded.
- The chat for the meeting will be closed.
- To ask a question, please use the Q&A box on the menu bar. If your question is for a particular speaker, please include their name in your question.
- If you need closed captioning, select the CC icon at the bottom of the Zoom screen.

Welcoming Remarks

Nora D. Volkow, M.D.

Director of the National Institute on Drug Abuse (NIDA) at the National Institutes of Health

Carlos Blanco, M.D., Ph.D., M.S.

Director of the Division of Epidemiology, Services and Prevention Research (DESPR), NIDA

NIH Guest Speaker

Samson Gebreab, Ph.D.

Program Lead, NIH's Artificial Intelligence/Machine Learning Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD)

The Office of Data Science Strategy (ODSS)

AIM-AHEAD

NIH Landscape in Application of Geospatial Data Science and Priorities/Opportunities/Challenges.

Dr. Samson Gebreab

AIM-AHEAD Program Lead

Office of Data Science Strategy (ODSS)

Dec 3, 2024

Advance of Health Research through Geospatial Data

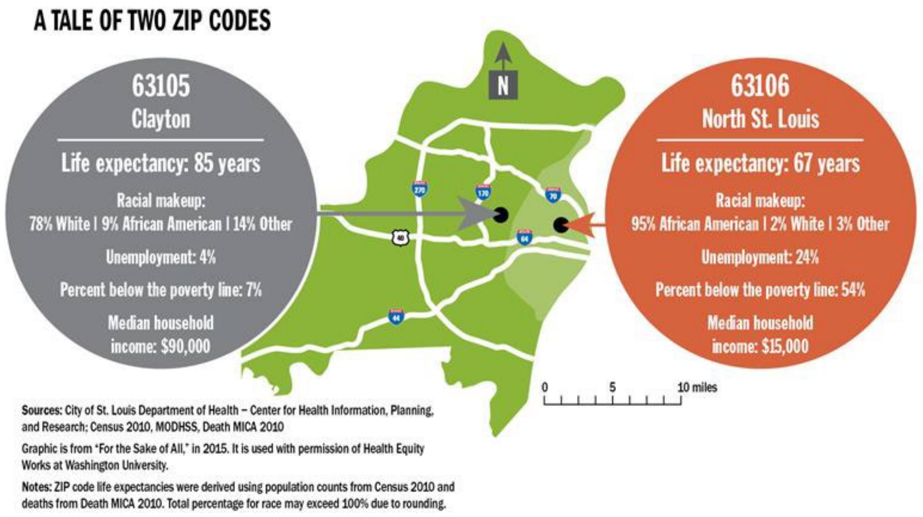
Geospatial data, also known as spatial data, refers to information linked to specific geographic locations on earth (e.g., Lat & Log, zip codes)

- Geospatial data is increasingly being collected from a variety of sources
  - GPS, Satellites, Drones, Sensors, Smartphones, Social media…
- Open new avenues for numerous areas of biomedical, behavioral, and public health research

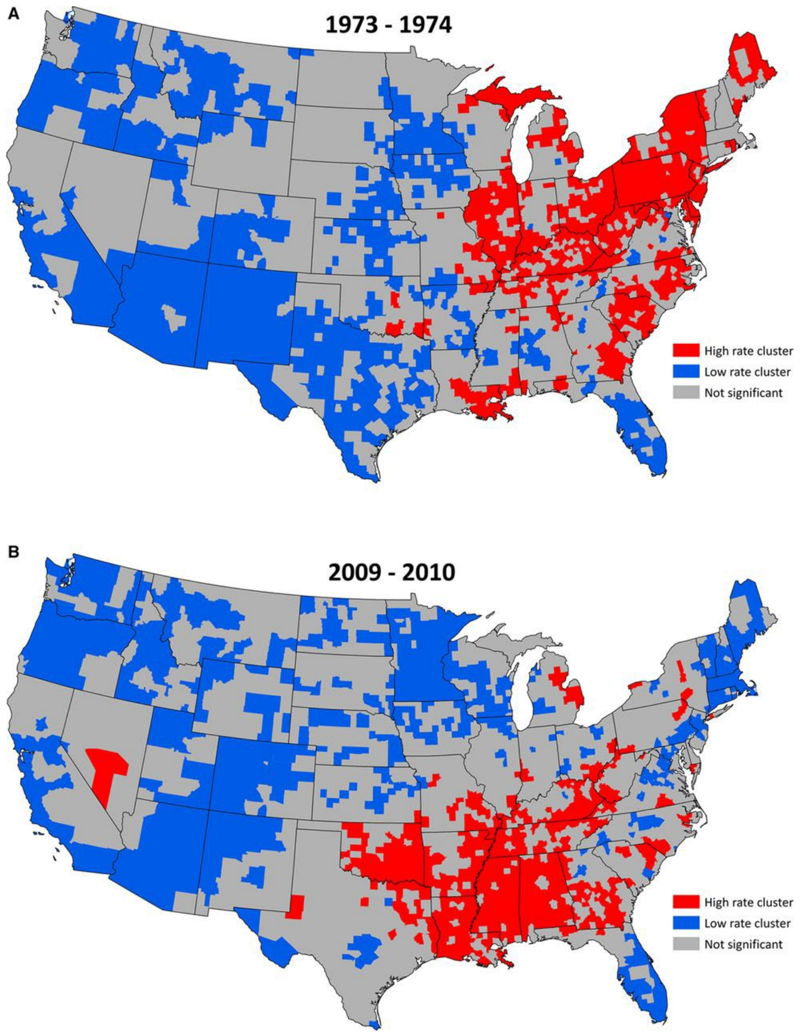
Why Geospatial Data Matters?

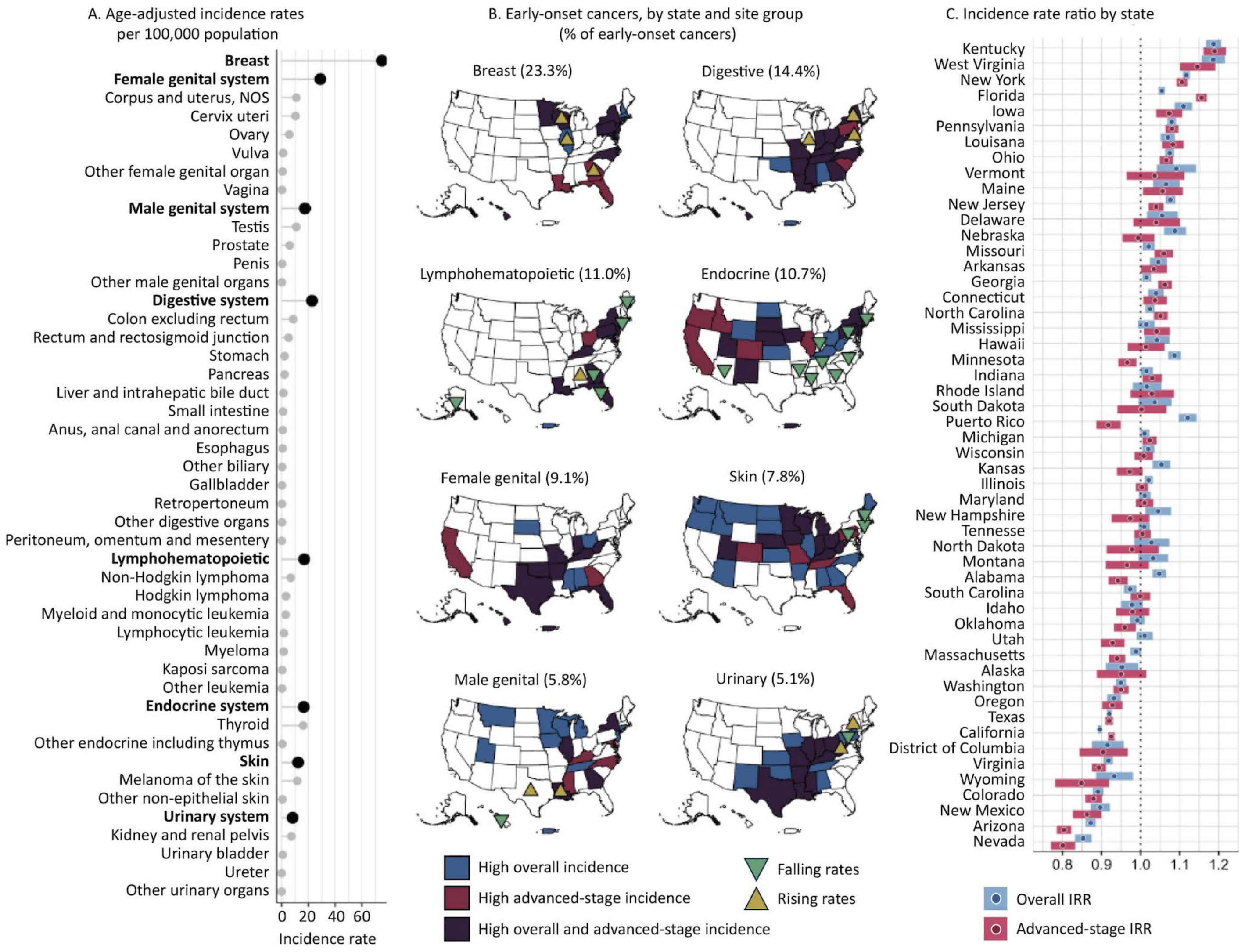
“Your ZIP code is more important than your genetic code” – highlights that where a person lives (geographic location) has a more significant impact on health outcomes than genetic factors.

- Primarily due to Social Determinants of Health (SDOH), like access to healthcare, food environment, economic opportunities, and environmental conditions, which vary widely by neighborhood
- Determine life expectancy, disease rates, and overall quality of life....
- Underscores the importance of geospatial data in addressing systemic inequalities to improve public health.



Applications: Geographic Patterns of Chronic Diseases





Casper et al. Circulation 133:12
https://doi.org/10.1161/CIRCULATIONAHA.115.01866

DuBois et al. Prev Chronic Dis 2024;21:230335
DOI: http://dx.doi.org/10.5888/pcd21.230335.

What are the Federal Efforts in Geospatial Data

2.13 Geospatial Data Act (2018)

Information Technology Laws

- Executive Summary
- CIO Role at a Glance
- 1. CIO Responsibilities
- **2. IT Laws**
- 3. Other Authorities
- 4. Key Stakeholders
- 5. Key Organizations
- 6. Policies & Initiatives
- 7. Reporting

2.13 Geospatial Data Act (2018)

Codifies the Federal Geographic Data Committee and supports the National Spatial Data Infrastructure

The Geospatial Data Act of 2018 (GDA) became law on October 5, 2018. The GDA was included as a component of the FAA Reauthorization Act (P.L. 115-254, Subtitle F). The GDA codifies the committees, processes, and tools used to develop, drive, and manage the National Spatial Data Infrastructure (NSDI) and recognizes responsibilities beyond the Federal government for its development. The GDA reflects growing recognition of the essential role of geospatial data and technology in understanding and managing our world and highlights the need to support their continuing development as critical investments for the Nation. (Federal Geographic Data Committee. Geospatial Data Act of 2018.)

The GDA reduces duplicative efforts and facilitates the efficient procurement of geospatial expertise, technology, services, and data from the rapidly growing geographic community in the United States. The GDA:

Building the Geospatial Future Together—The NSDI Strategic Plan 2025–2035

https://www.fgdc.gov/nsdi-plan

Geospatial Data Strategy

Department of Health and Human Services

2023-2026

https://www.hhs.gov/sites/default/files/hhs-geospatial-data-strategy-2023-2026.pdf

Office of Data Science Strategy | OD/DPCPSI

Provides NIH-wide leadership and coordination for a modernized NIH data resource ecosystem

AIM-AHEAD
- Enhance participation and representation in AI/ML research and data

Clinical Informatics & Standards
- Clinical data standards
- Clinical and SDoH data using CDEs
- Providing clinical informatics trainings

FAIR Data and Repositories
- Data storage, management, and integration
- Adoption of FAIR data principles

Integrated Infrastructure and Emerging Technologies
- AI, Cloud Services, & Quantum Information Science

Training, Workforce, and Community Engagement
- Promoting interdisciplinary collaborations
- Capacity Building
- Engaging broader community

What we do

Provides **leadership and coordination** on the strategic plan for data science

Develops NIH's vision for a **modernized** and **integrated** biomedical data ecosystem

Enhances a **diverse and talented** data science workforce

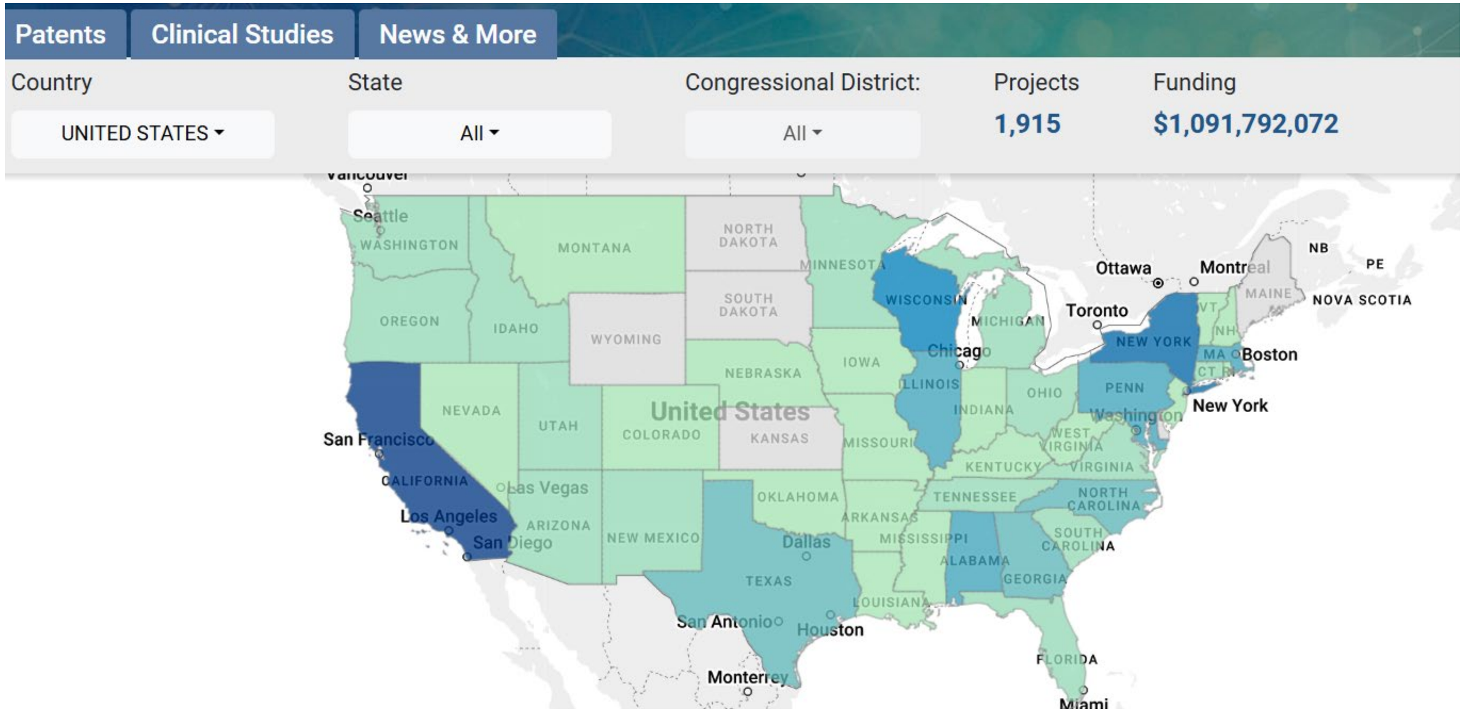
Builds strategic partnerships to advanced technologies and methods

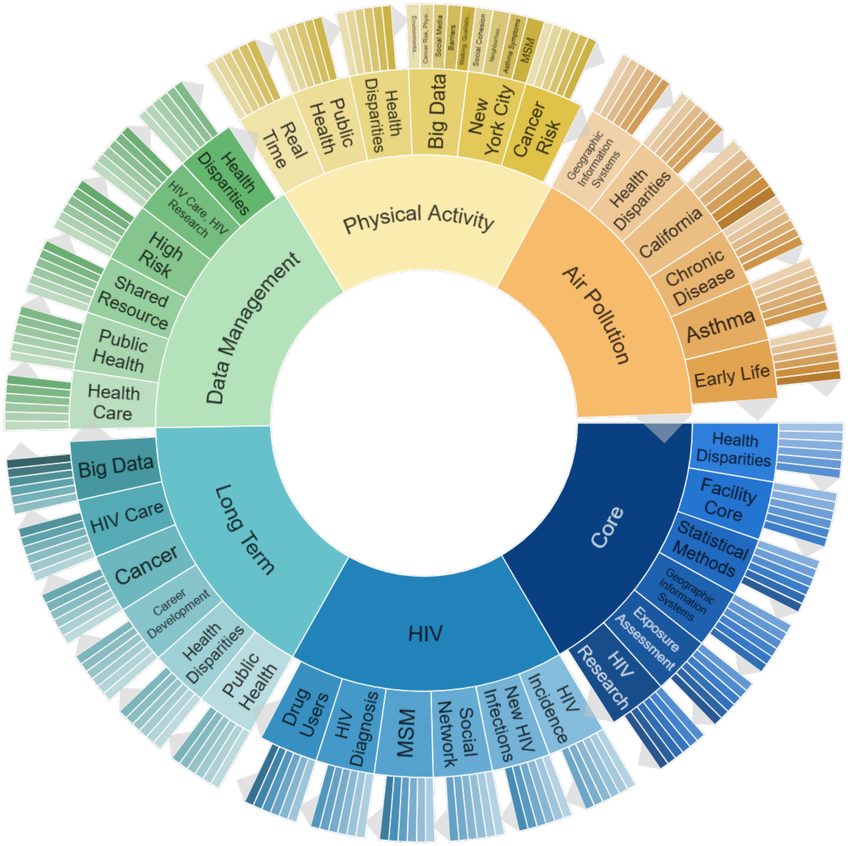
NIH Data Science Strategy in the next 5 years

- Improve Capabilities to Sustain the NIH Policy for Data Management and Sharing
- Develop Programs to Enhance Human Derived Data for Research
- Provide New Opportunities in Software, Computational Methods, and Artificial Intelligence
- Support for a Federated Biomedical Research Data Infrastructure
- Strengthen a Broad Community in Data Science

We are finalizing the next strategic plan!
[NIH-STRATEGIC-PLAN-FOR-DATA-SCIENCE-2023-2028-final-draft.pdf]

NIH Landscape in Geospatial Data Applications

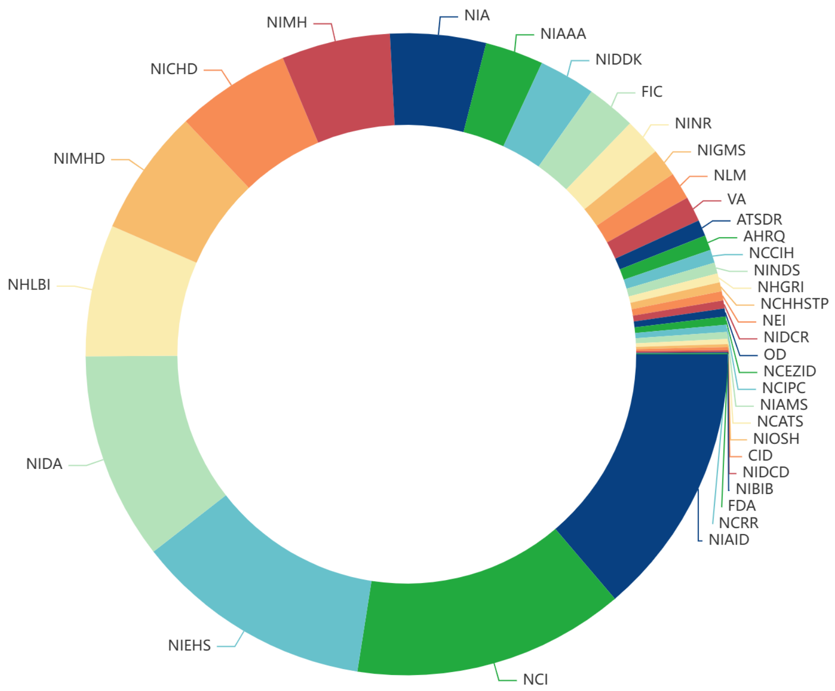




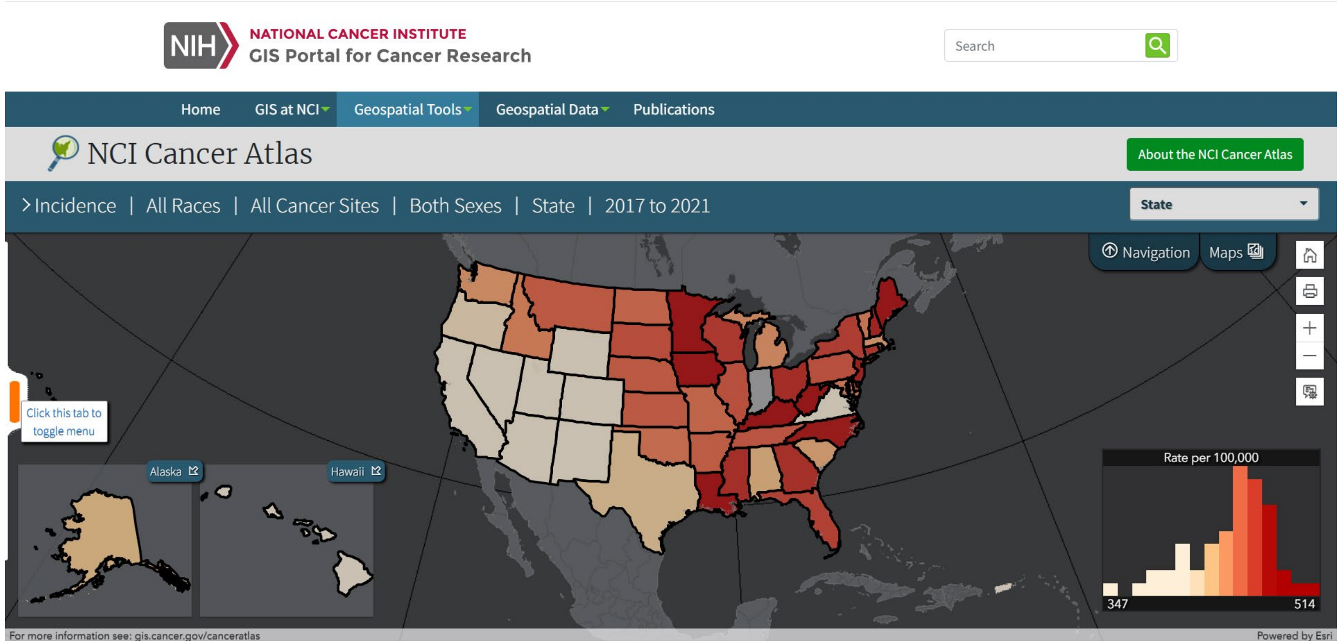
NIH Institutes and Centers increasingly recognize the importance of geographic context in advancing biomedical and public health research

https://reporter.nih.gov/

NIH ICs Activities in Geospatial Data Research

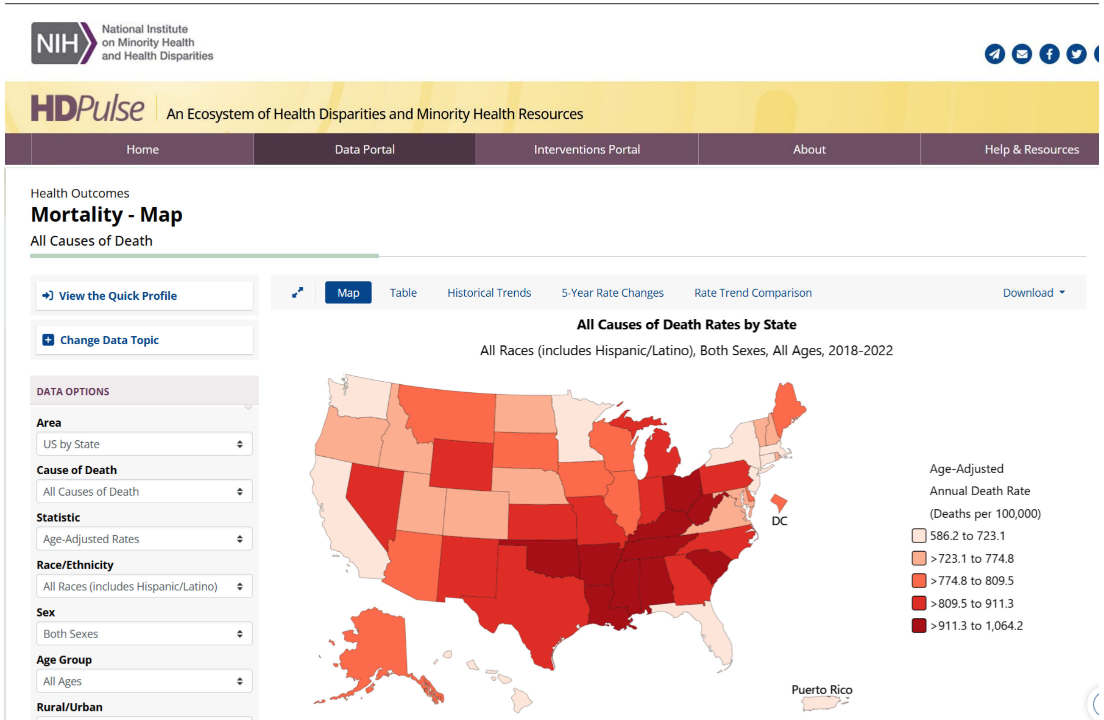


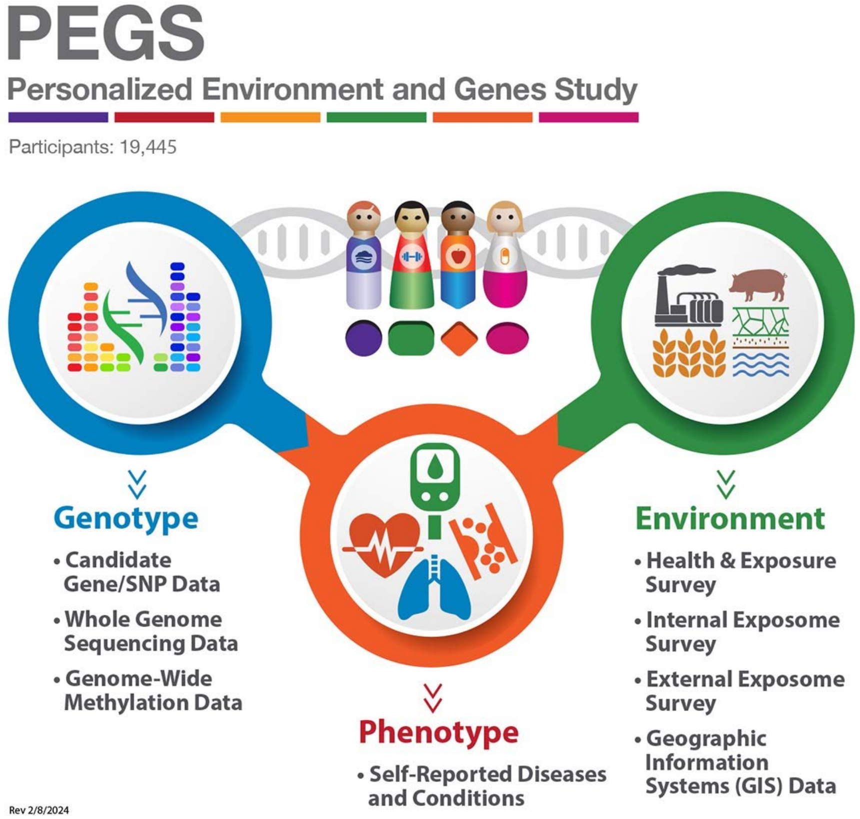
Several NIH ICs (NCI, NIDA, NIMHD, NIADA, NIEHS..) leverage geospatial data in biomedical and public health research.



The NCI Cancer Atlas is an interactive digital atlas that enables users to generate geographic maps of cancer rates, risk factors for cancer, screening statistics, and other geographical data related to cancer.

NIH ICs Activities in Geospatial Data Research





NIMHD research uses geospatial data to study how neighborhood characteristics impact mental health, chronic stress, and cardiovascular health.

Studies of gene-environment-health interactions (NIEHS)

Combining Geospatial Data and Social Determinants of Health

- Geospatial and SDOH intersect
  - SDOH is an increasingly high-priority research area for the NIH at the forefront of improving health and advancing health equity.
  - FYI 2022, NIH invested about $4.1 billion, funding more than 8,300 SDOH research and training programs.
  - NIH's 2021-2025 strategic plan calls for research on SDOH, and most NIH ICOs explicitly mention SDOH in their strategic plans.
- Interdisciplinary leverage of GIS and geospatial data with SDOH provides a powerful lens to understand and address health disparities.

Health outcomes and SDOH are not evenly distributed across locations!

https://blog.nimhd.nih.gov/nimhd-insights-current-blog-posts-2023/news_feed/cross-cutting-collaboration

Example NOSI: Leveraging Geospatial Data

Notice of Special Interest (NOSI): Data Informed, Place-Based Community-Engaged Research to Advance Health Equity

Notice Number:

NOT-HL-23-110

Key Dates

Release Date:	November 28, 2023
First Available Due Date:	February 05, 2024
Expiration Date:	January 08, 2027

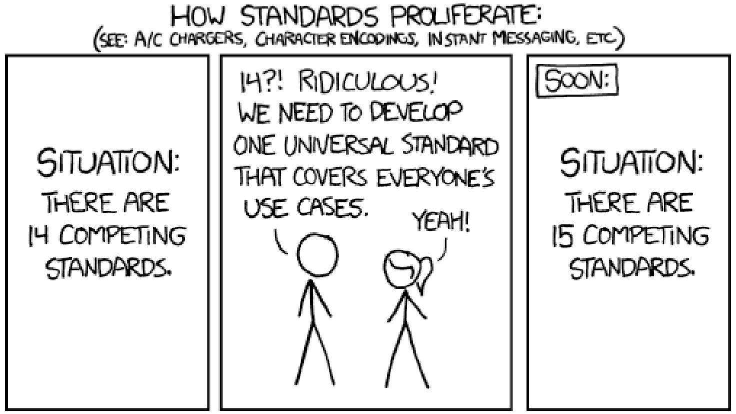
Related Announcements

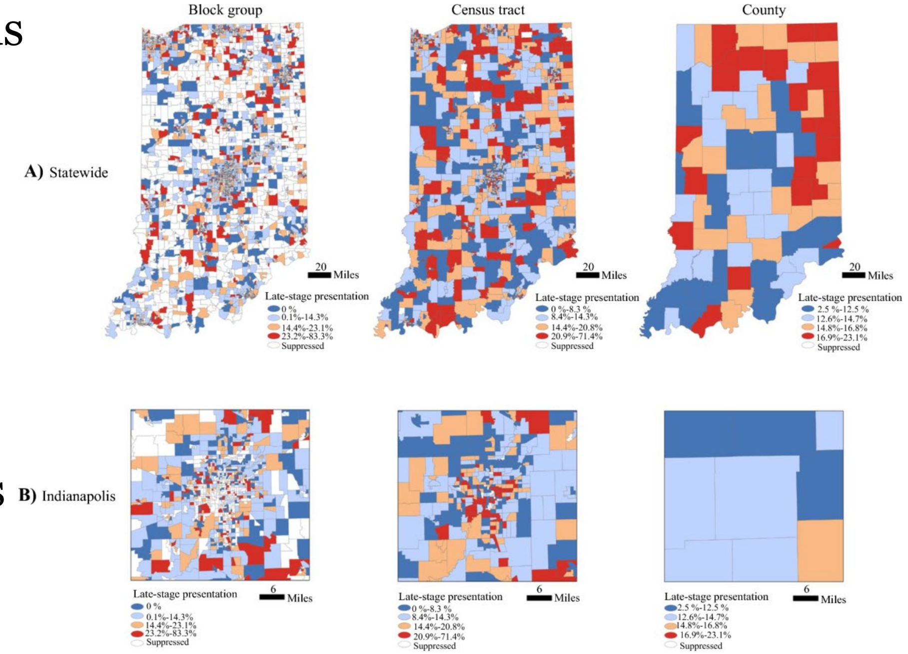
- **March 27, 2024** - Notice of NICHD Participation in NOT-HL-23-110 "Notice of Special Interest (NOSI): Data Informed, Place-Based Community-Engaged Research to Advance Equity". See Notice NOT-HD-24-014
- **July 20, 2023** - Social Disconnection and Suicide Risk in Late Life (R01 Clinical Trial Optional). See NOFO PAR-23-238.
- **July 20, 2023** - Social disconnection and Suicide Risk in Late Life (R21 Clinical Trial Optional). See NOFO PAR-23-239.

https://grants.nih.gov/grants/guide/notice-files/NOT-HL-23-110.html

Challenges of Geospatial Data in Health Research

- **Data Availability and Quality**
  - Geocoding errors, missing/incomplete or outdated administrative boundaries, limited data in rural or underserved areas…
- **Data Integration and Standardization**
  - Inconsistencies in data formats and definitions across different sources.
  - Temporal discrepancies, spatial and attribute data misalignments
  - Data integration difficulties due to differing formats and standards
- **Granularity and Scale**
  - State level may mask high-risk areas like rural communities
  - Modifiable Area Problem
- **Ethical and Privacy Concerns**
  - Privacy concerns include the potential for discrimination and stigma, lack of transparency, regulatory compliance
- **Managing big geospatial data and technical challenges**
  - Lack of infrastructure to store, process, and analyze large datasets
  - Lack of specialized skills
  - Challenges for interdisciplinary collaborations





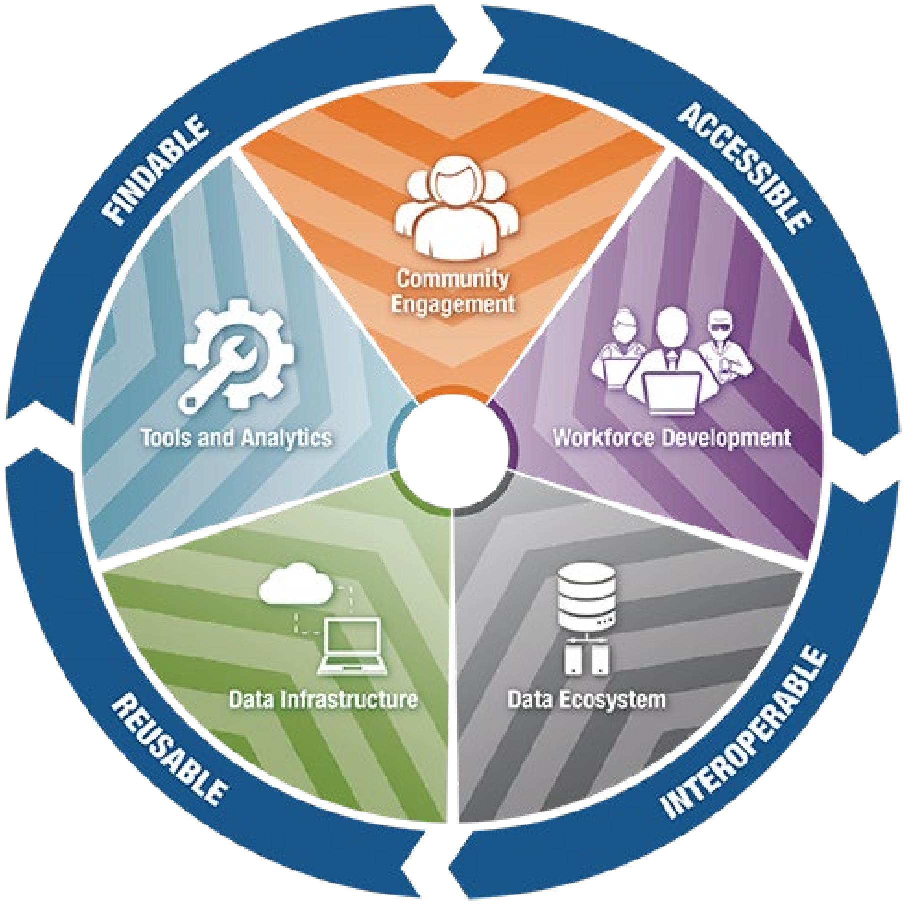
Onega et al 2023 *Ann Surg Oncol* 30, 6987–6989 (2023). https://doi.org/10.1245/s10434

Opportunities: Develop FAIR Geospatial Data

Develop FAIR geospatial data, and ensure it is Findable, Accessible, Interoperable, and Reusable

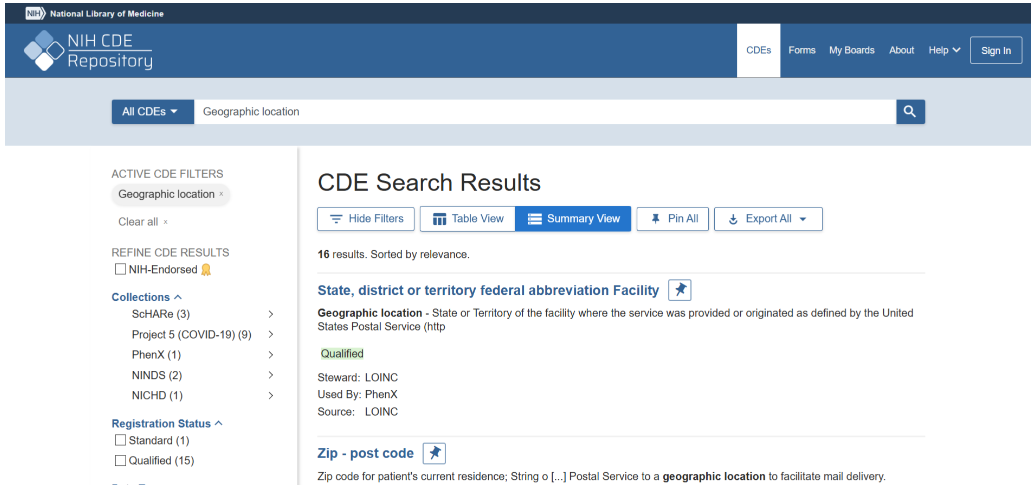
Implement comprehensive, detailed metadata, standardized data formats, clear access protocols, and proper documentation

Enable scientists to quickly find existing geospatial data and apply it, potentially accelerating research and its impact on public health.

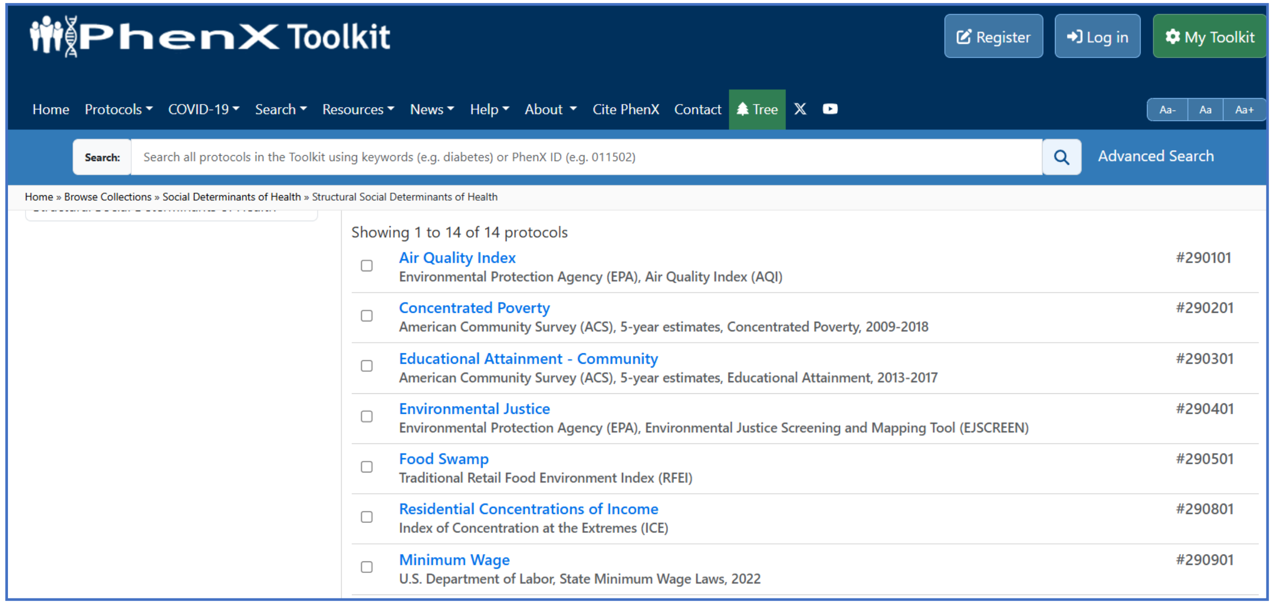


Opportunities: NIH Common Data Elements (CDEs)

- NIH "geospatial data CDE" refers to a standardized set of data elements specifically designed to capture location-based information
    - Encourages researchers to use CDEs to standardize geospatial data collection, sharing, and interoperability in health and disease research
- The HEAL geospatial data CDE collects standardized geographic information, like location coordinates, that are collected alongside other clinical data within the HEAL Initiative research studies
    - Allow researchers to analyze health outcomes in relation to specific geographic areas, enabling a better understanding of spatial patterns related to pain and other health conditions studied by HEAL.



NIMHD: ScHARe/PhenX Core Common Data Elements



https://www.nimhd.nih.gov/resources/schare/platform-components.html#core-common-data-elements

Opportunities: Develop a Culture of Reuse Geospatial data

- **Build once and use many times**.
  - Ensure geospatial data are created efficiently and cost-effectively,
  - Focus on reusability across multiple disciplines and applications,
  - Maximize the value and impact of existing geospatial data rather than collecting new data for every need.
  - Accelerate the pace of future research directions
  - Foster multidisciplinary collaborations

Opportunities: Integrate Geospatial Data with SDoH, wearables, and clinical data

SDoH, EDoH, Wearable Sensors: Encourage geospatial links with SDoH, EDoH, and wearable sensors to explore how geographic factors might influence health outcomes.

Electronic Health Records (EHRs): Addition of location variables or geocoded patient data to EHRs

Remote sensing data: Satellite imagery can provide information on land use, vegetation cover, and environmental factors.

Social media data: Aggregated social media data can be used to understand population movement and potential disease spread

Opportunities: Geospatial Ethical and Privacy Consideration

- Geospatial data can often be linked directly to individuals, raising significant ethical and privacy concerns, like identifying specific homes or movements of people through location tracking.

- Prioritize ethical and privacy concerns through
    - Practices informed consent,
    - Data anonymization
    - Robust security measures
    - Transparency in algorithms
    - Data gaps and underrepresentation, especially for marginalized communities
    - Data sovereignty
    - Federated or distributed data approach

Opportunities: Geospatial Artificial Intelligence (GeoAI)

- GeoAI is an emerging area that combines artificial intelligence/machine learning, data mining, and high-performance computing to extract knowledge from big geospatial data

- Leverage GeoAI /Digital Twins
  - Predict outbreaks, identify health risks, and understand disparities, as well as future health trends, from large amounts of geospatial data in various formats (e.g., image, text, voice, social media).
  - Computational efficiency
  - Flexibility in algorithms and workflows to accommodate relevant data
  - Scalability of the model for other geographic areas or health/behavioral outcomes

The NIH STRIDES Initiative

STRIDES: Science & Technology Research Infrastructure for Discovery, Experimentation, & Sustainability

Overview

Serving **both the NIH intramural and extramural research communities**, the STRIDES Initiative accelerates biomedical research in the cloud by:

- Simplifying access
- Reducing costs
- Lowering technological barriers
- Standardizing administrative & financial processes

Core Motivations

1. **Democratization of computational research & data science**
   Leveling the playing field for those traditionally underrepresented in biomedical research

2. **Cost savings & efficiencies for the research community**
   More usage begets more savings and greater overall discounts for all

3. **Strong partnerships with cloud providers**
   Resulting in collaborative R&D engagements and more direct focus and support on research

Partnerships with: aws Google Cloud Microsoft Azure

NIH Cloud Lab: Experiment in the Cloud

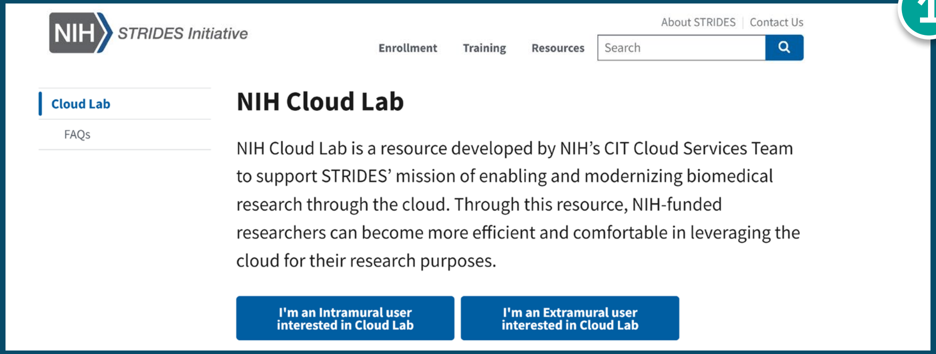
NIH Cloud Lab is a no-cost, 90-day program for NIH intra- and extramural researchers to try commercial cloud services in an NIH-approved environment. Cloud Lab provides training and guardrails to protect against financial and security risks.

How It Works

1. **Fill out** interest form, or apply in NAIRR Classroom
2. **Get** account and $500 of credits
3. **Access** tailored cloud trainings
4. **Practice and learn** for 90 days

NIH Cloud Lab Sign Up Page

1



NIH Cloud Lab AWS Tutorial Repository

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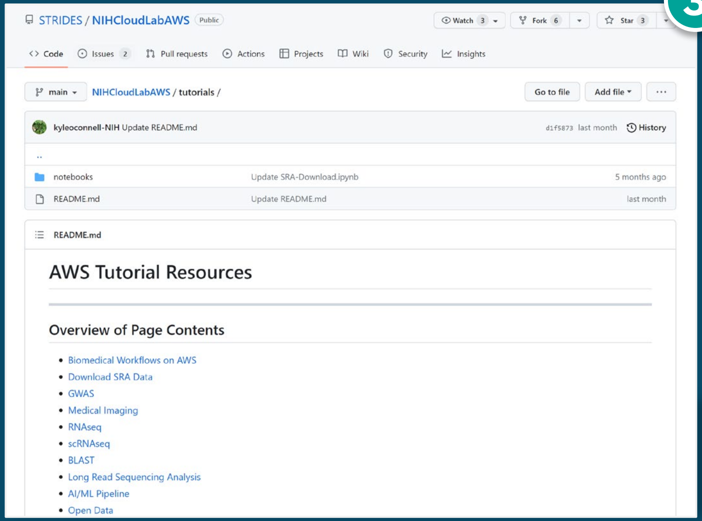

Example of NIH Cloud Lab Use Case

4

NIH Use Cases

Evaluate Utility & Cost

Provides an easy route to evaluate the cloud's utility/cost for a project without major time or financial commitments

Develop New Tools

Allows experienced teams to prototype new architectures and evaluate software and hardware combinations

Share Ideas

Connects NIH'ers from across ICs to share ideas on how to conduct biomedical research in the cloud

Learn New Skills

Simplifies access to tools and cloud environments that participants can use for training purposes

The Artificial Intelligence/Machine Learning Consortium to Advance Health Equity and Researcher Diversity (AIM-AHEAD)

AIM
AHEAD

Goals

Enhance the **participation** and **representation** of researchers and communities currently underrepresented in the development of AI

Address health disparities and inequities using AI/ML

Improve the capabilities of this emerging technology

https://aim-ahead.net/

Closing thoughts…

•Increased recognition of geospatial data by NIH ICs to address complex challenges in biomedical and behavioral research

•Exciting times for geospatial data and public health research

- •The fusion of geospatial data with AI/ML, cloud computing, and digital twins, the implementation of **FAIR** principles and **ethical** practices

•All these will transform the way we leverage geospatial data to understand numerous health and behavioral issues while ensuring equitable benefits for all communities…..

Thank you!

Contact Info:

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https://www.aim-ahead.net/

Prevention Research

Lance Waller, Ph.D.

Professor, Emory University

Small Area Estimation Opioid Abuse Prevention and Response

Tom Stopka, Ph.D., MHS

Professor, Tufts University School of Medicine

Spatial Epidemiology and Geospatial Data Science in Opioid-Related Research

Courte Van Voorhees, Ph.D.

Moderator

Program Official, Prevention Research Branch, DESPR, NIDA

Small Area Estimation Opioid Abuse Prevention and Response

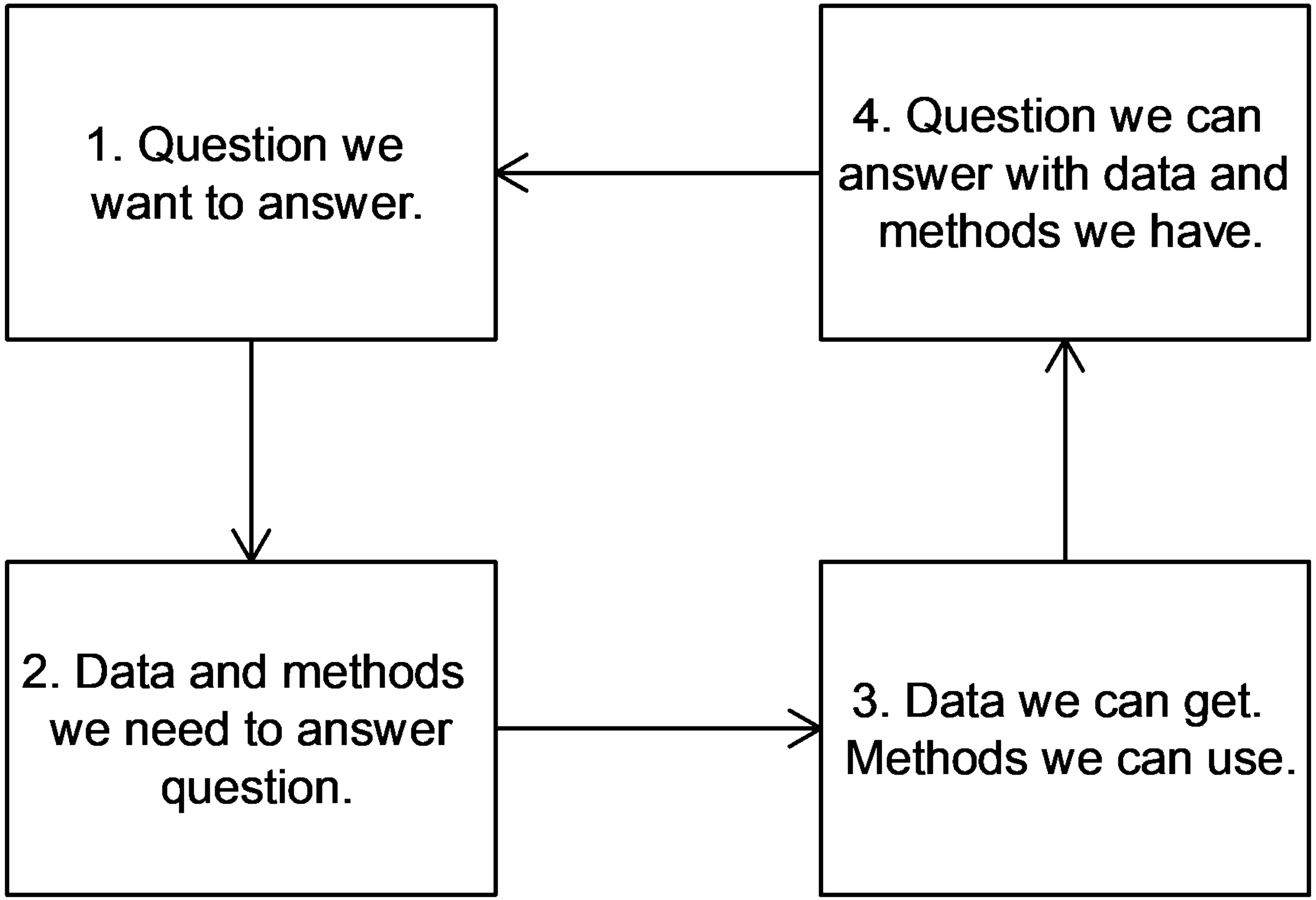
Lance A. Waller
Department of Biostatistics and Bioinformatics
Rollins School of Public Health, Emory University

Joint work with Zev Ross, Rob Lyerla, Donna Stroup, Hannah Cooper, and Janet Cummings

Outline

- Questions we want to answer with maps
- What data do we need?
- What data do we want? What data do we see?
- What questions can we answer?
- What patterns do we see? Why?
- Summary and next steps

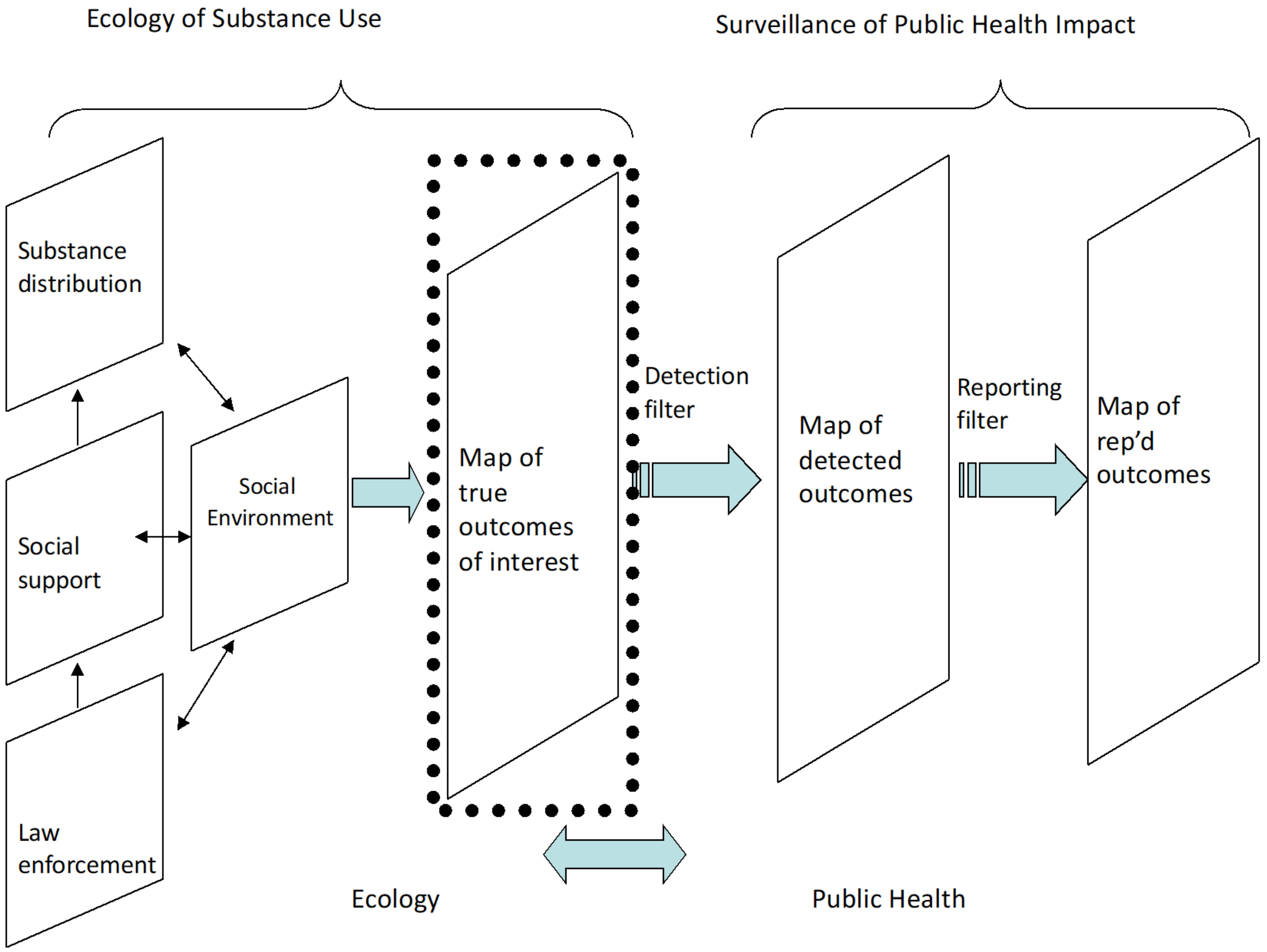
The whirling vortex of data analysis



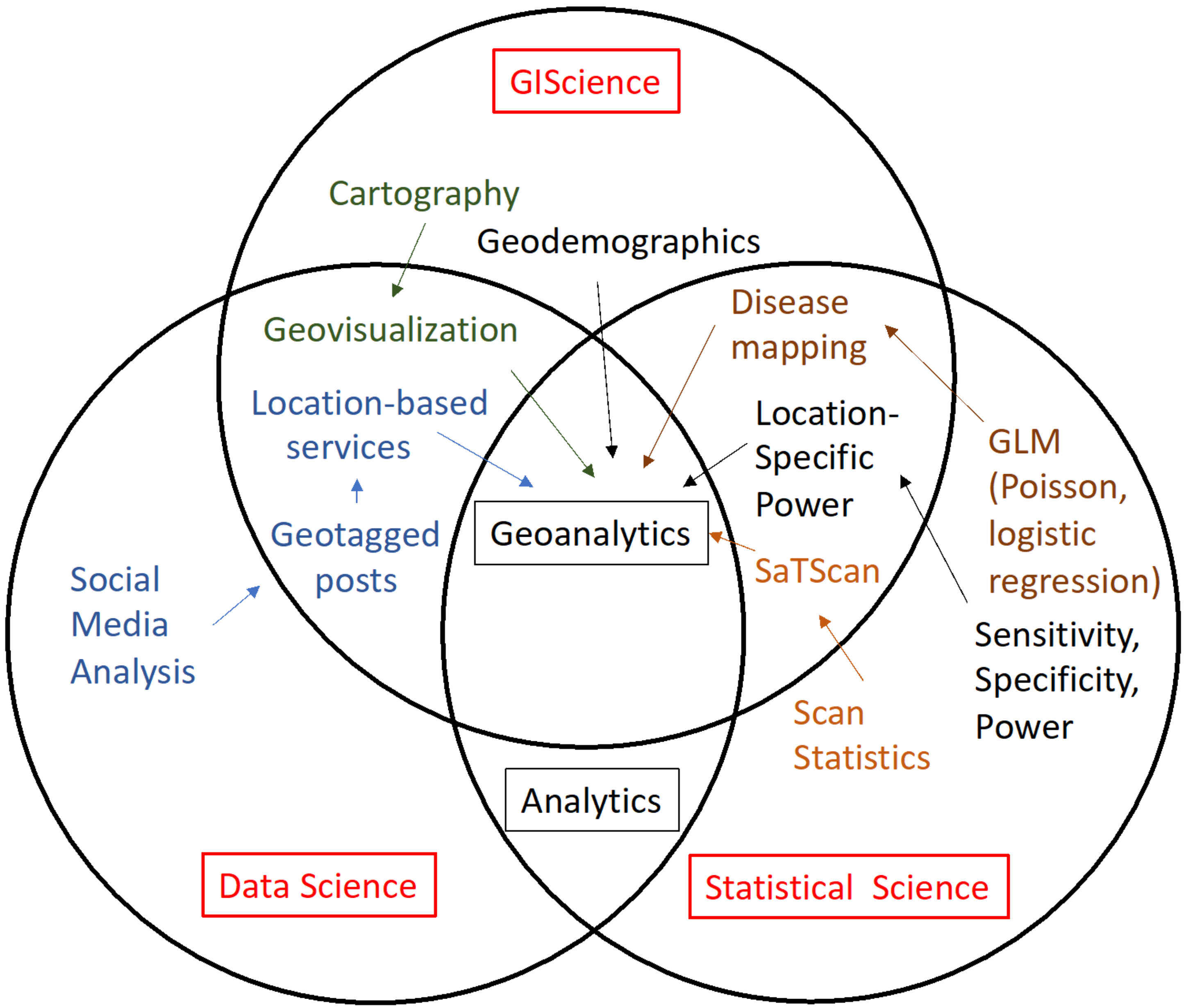
Questions: What do we want to answer?

- Outcomes
    - Mortality? Morbidity? Use? Sales? Arrests? Treatment?
- Risk factors
- Resiliency factors
- At what scale (individual, community, both)?
- How do they relate/interact?
- Social determinants of “disease”...

What do we get to see? A disease ecology perspective



Geoanalytics



What data do we see? Public health surveillance perspective

- Building public health surveillance from existing data sources:
  - **Mortality**
  - Emergency response
  - Medical records
  - Law enforcement
  - Treatment
  - **Community measures (vulnerability indices)**

What questions can we begin to answer?

- Patterns of mortality, patterns of reporting.
- Patterns of risk factors
  - Comparing:
    - a data science perspective
    - a traditional variable selection perspective
- Resiliency: Just another (negative) risk factor?
- Thoughts on interactions, confounding, effect modification, and causation...what do we care about here?

Trends in mortality, trends in reporting

- 2000-2017 Multiple Cause of Death data from US National Center for Health Statistics (NCHS).

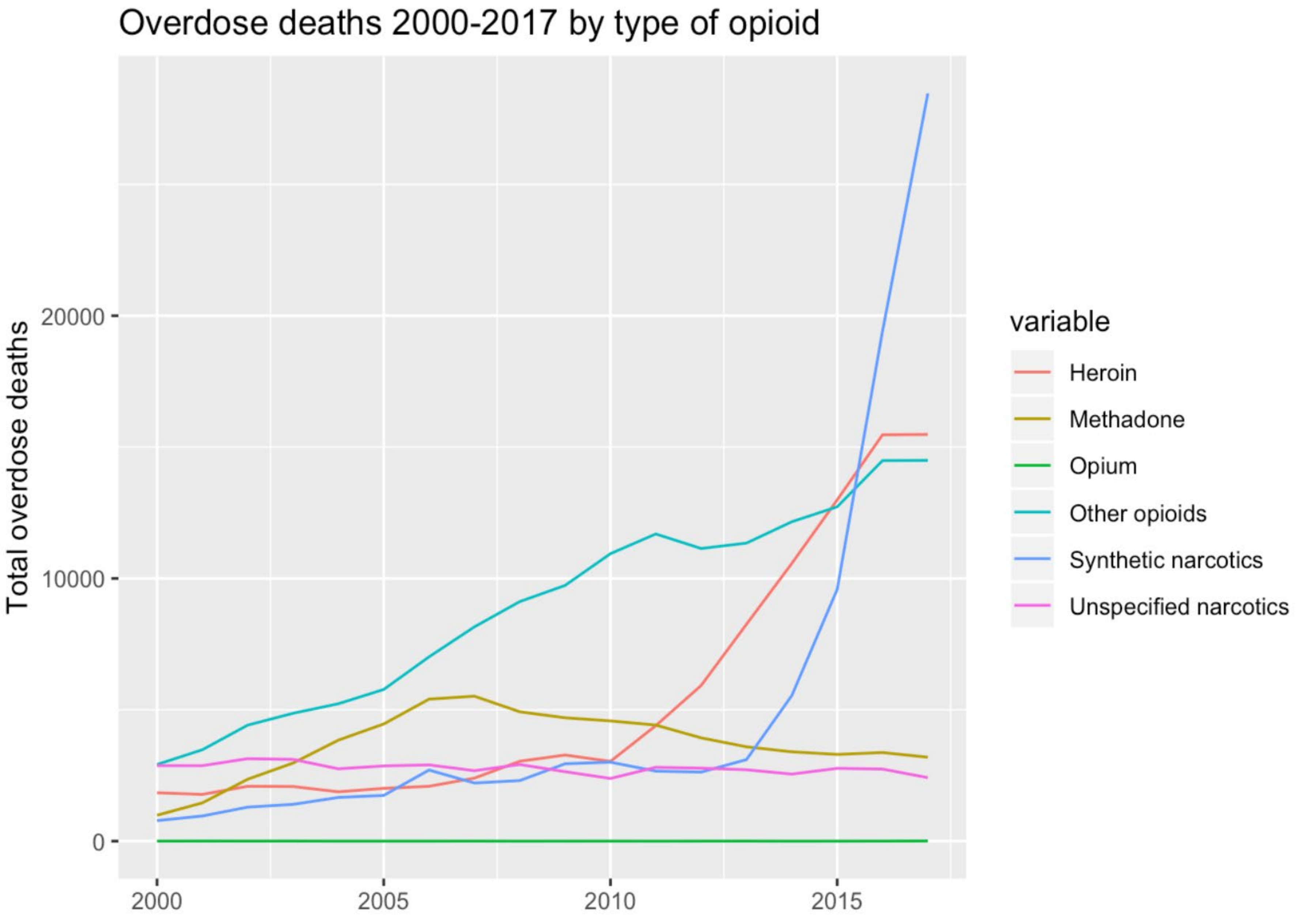
Data use agreement for individual level data on:

  - Underlying (primary) cause of death (ICD-10)
  - Up to 20 contributory causes
  - State and county of residence

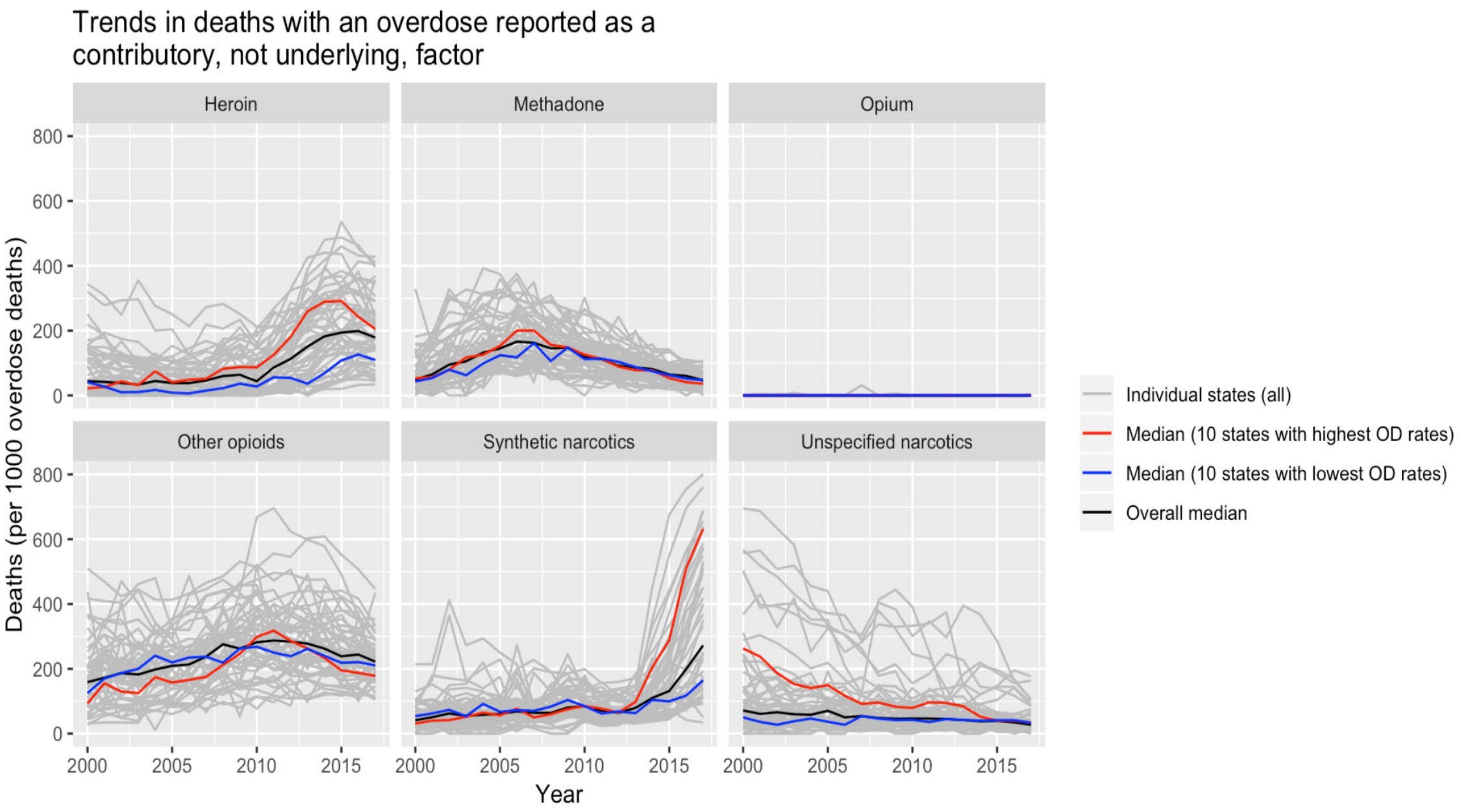
Defining opioid mortality

- CDC Guidance (2018): Underlying overdose deaths include:
  - Unintentional (ICD-10 codes X40-X44) and intentional poisonings (X60-X64)
  - Those of undetermined intent (Y10-Y14) and
  - Homicides by drugs (X85)
- Also, deaths classified via contributory causes:
  - Opium (T40.0),
  - Heroin (T40.1)
  - “Other” opioids including codeine and morphine (T40.2), methadone (T40.3), other synthetic narcotics (T40.4) and “other and unspecified narcotics” (T40.6).
  - “Any opioids” includes all six of these T-codes

Opioid Mortality Trends: National (2000-2017)



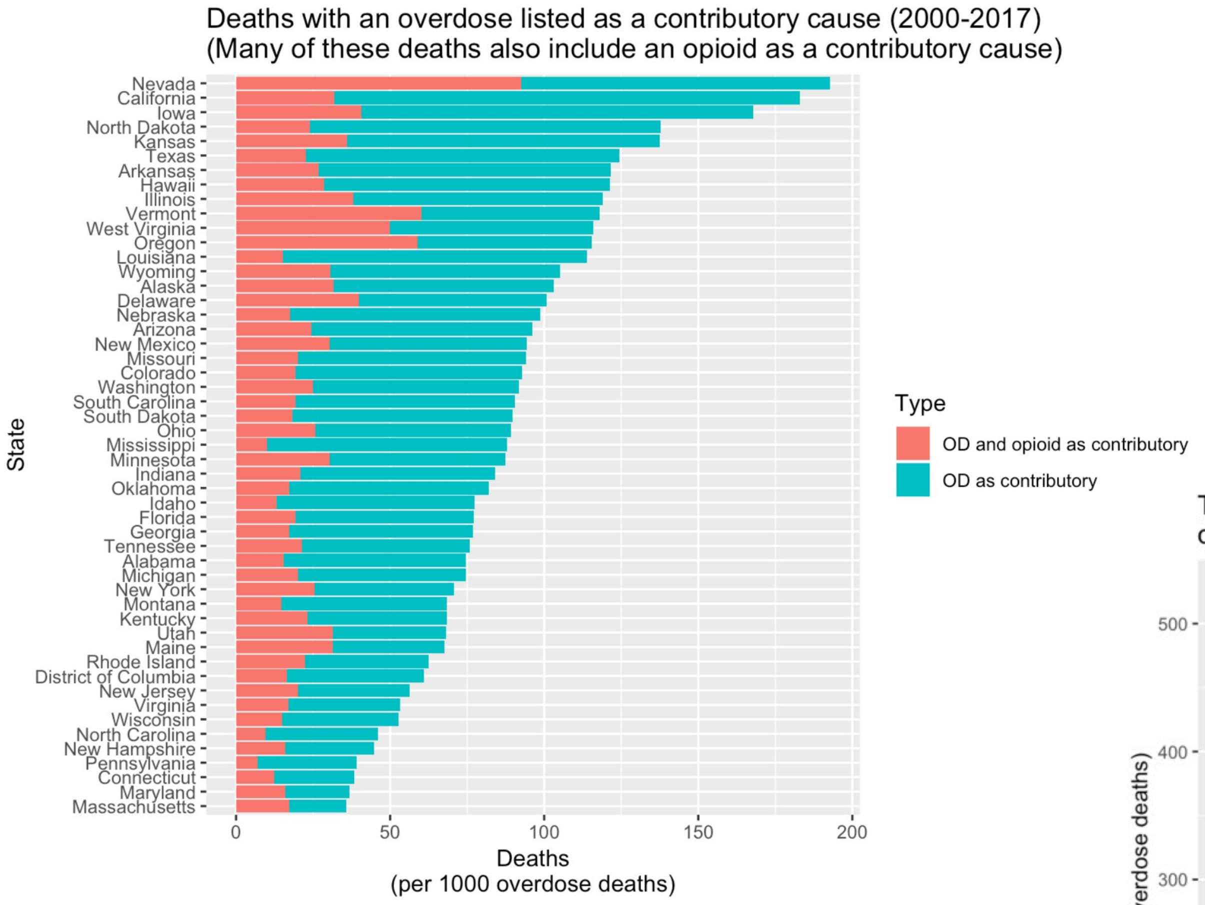
Opioid Mortality Trends by State and Type

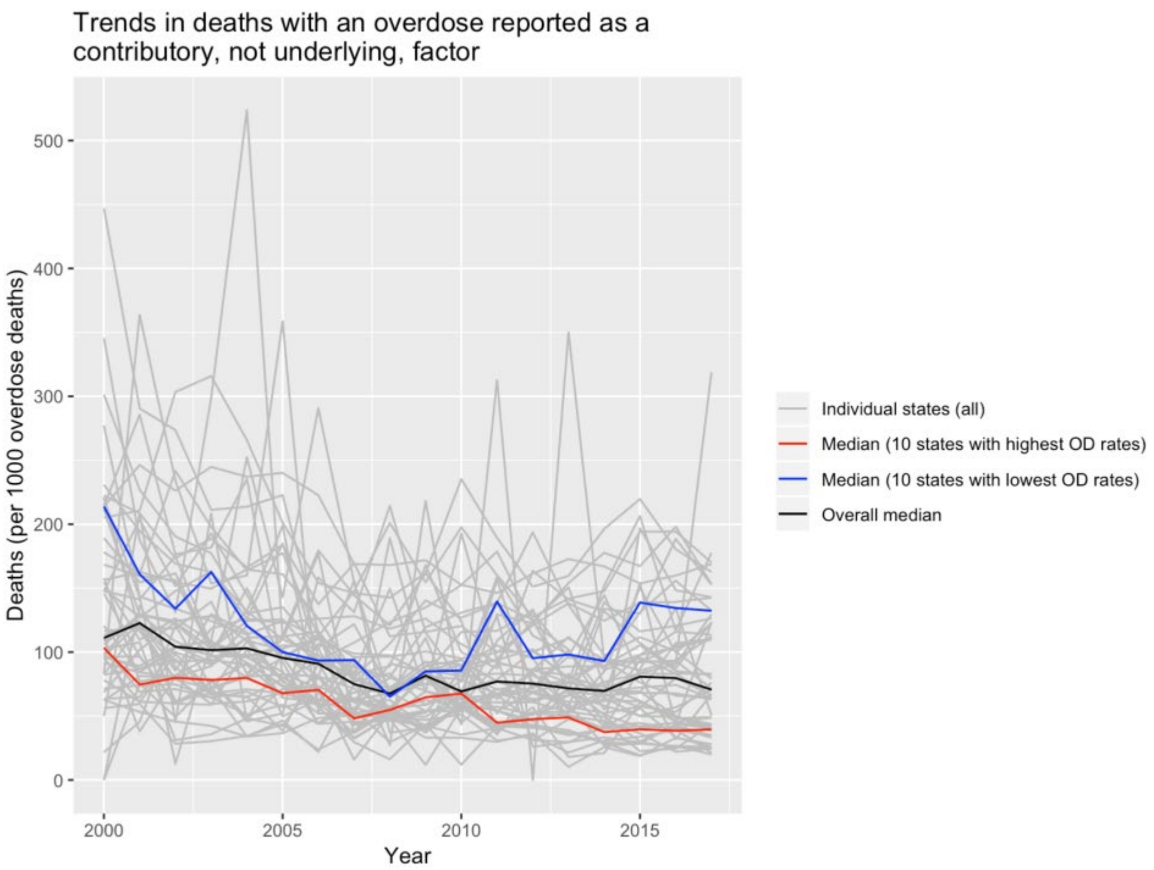


Potential “hidden” deaths

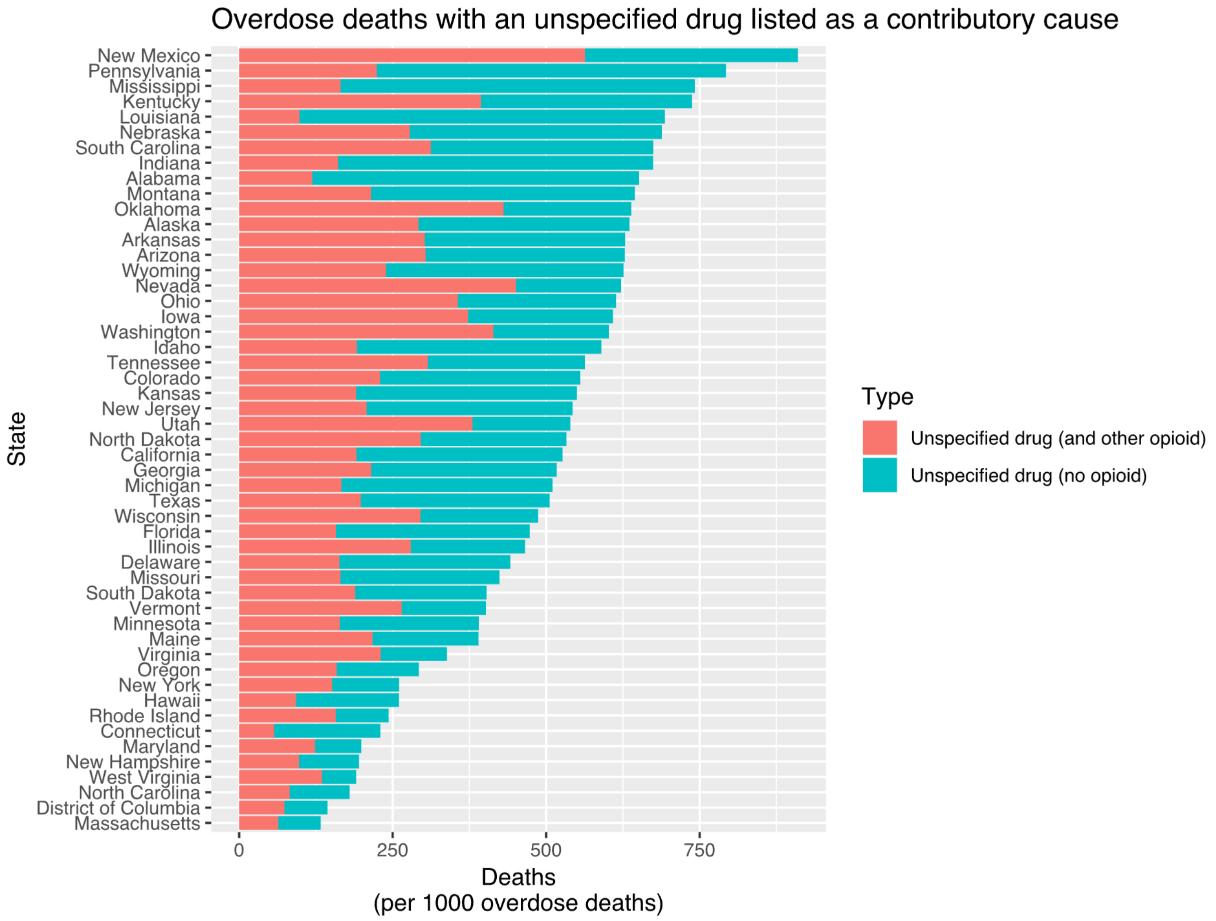
- Overdoses recorded as a contributory cause but the underlying cause is not an overdose
  - Underlying cause does not include any of the X or Y overdose codes but contributory cause does
- Overdoses recorded as a primary cause but the contributory code only lists “unspecified drug”
  - Some overdoses may be coded as “other and unspecified drugs, medicaments and biological substances” (T50.9).
- Not all are opioid deaths, but some may be (Ruhm 2016, 2017).
- What patterns do we see across states?

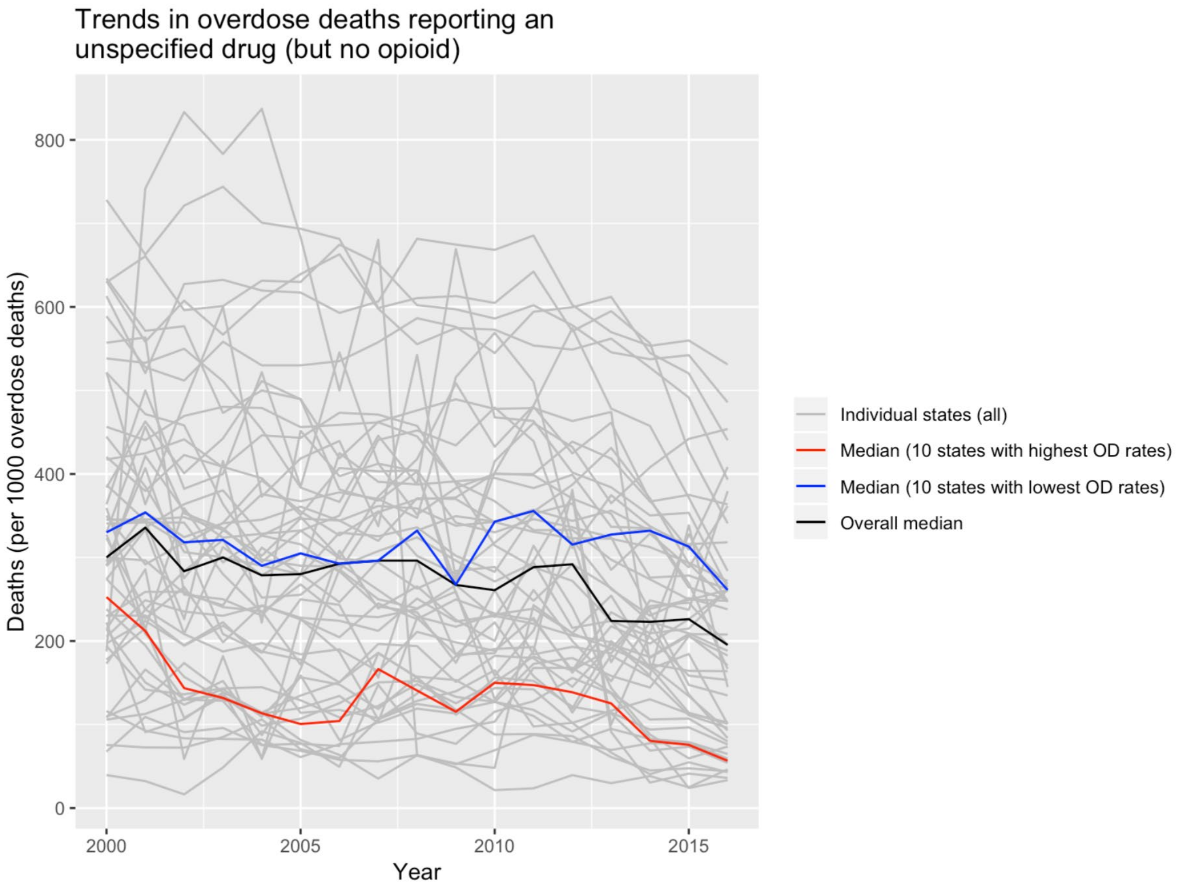
Opioids contributory but not underlying cause





Unspecified drug cases as contributing cause





What are we seeing?

- Combination of mortality and reporting patterns.
- States with lower overdose mortality rates have higher numbers of deaths in these potentially “hidden” categories.
- Faster decline in “hidden” categories in states with higher overdose mortality rates.
- Negative correlation between contributing synthetic opioids and contributing-only overdose (-0.65).
- Negative correlation between contributing synthetic opioids and contributing unspecified drugs (-0.67).

Epidemiology and vulnerability indices

- Traditional: Measuring association between outcome and risk factors.
- Vulnerability indices: Examine associations observed in one location in predicting outcomes elsewhere.
    - Goal: Ranking of regions by vulnerability to future event.
    - Literature on natural disaster vulnerability indices.
    - Opioids: CDC vulnerability index from Scott County, IN.
    - Tennessee vulnerability index (Rickles et al. 2017).
- Combination of dimension reduction (PCA, factor analysis) and variable selection.
- Goals are different from typical epidemiology goals...

Different goals?

- Risk factor selection (individual and community level)
- Resiliency factors
  - Just a negative risk factor?
  - Interaction with a risk factor?
  - Effect modification?
  - Same scale? Cross scales?
  - Adjusting vulnerability?

Example: Social Vulnerability Index

- From the US CDC
- Fact sheet: https://www.atsdr.cdc.gov/placeandhealth/svi/fact_sheet/fact_sheet.html
- 16 social factors including
  - Poverty
  - Lack of vehicle access
  - Crowded housing
  - ...
- Grouped into four related themes
  - Socioeconomic Status, Household characteristics, Racial and Ethnic Minority Status, Housing type and transportation

- Grouped into four related t
  - Socioeconomic Status
  - Household characteristics
  - Racial and ethnic minority s
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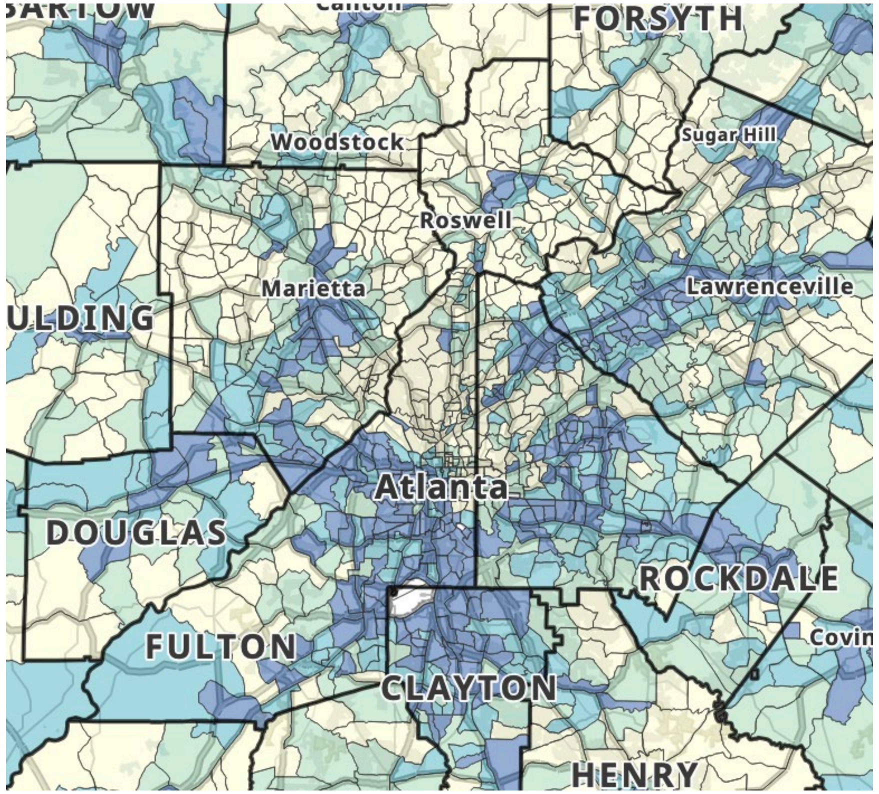
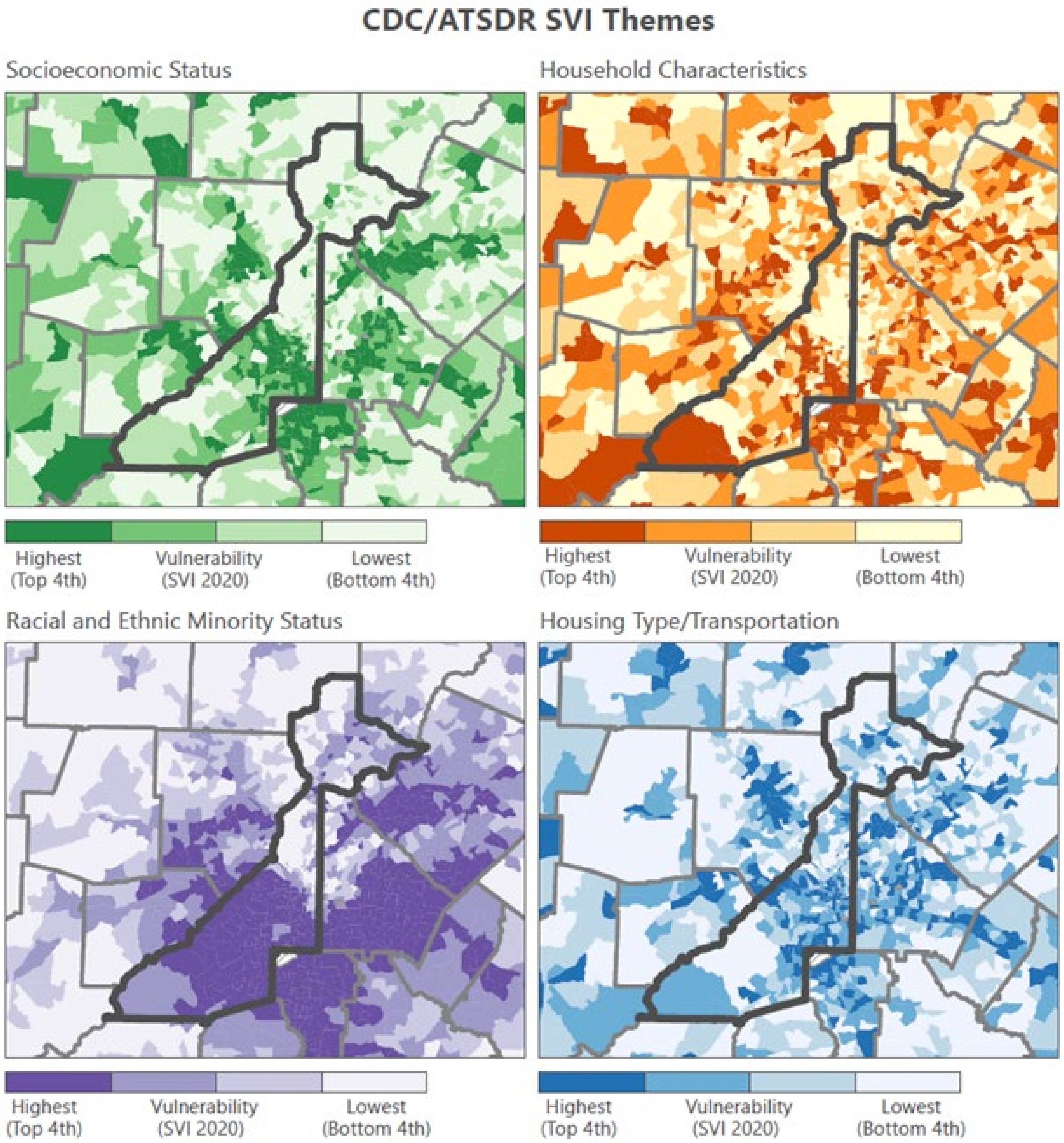
Overall SVI



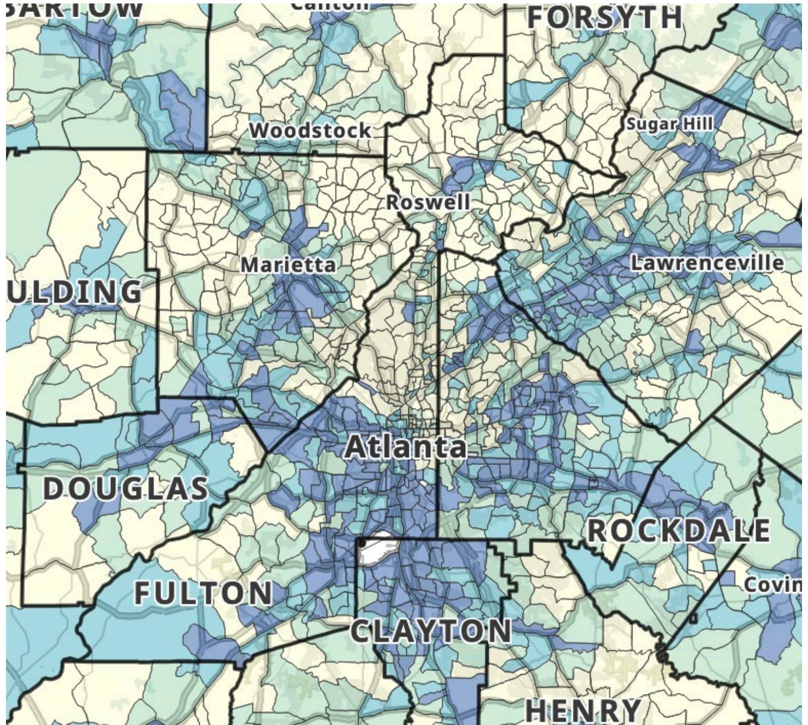
https://www.atsdr.cdc.gov/placeandhealth/svi/fact_sheet/img/SVI-2020-Fulton-County-4-Theme-Map.png?_=01213?noicon



Mapping SVI

- Interactive map!
  - https://www.atsdr.cdc.gov/place-health/php/svi/svi-interactive-map.html
- Data download
  - https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html
  - County or Census Tract
  - 2000, 2010, 2014, 2016, 2018, 2020, 2022

Overall SVI



Social Vulnerability *Indices*?

- Is CDC’s SVI *the* social vulnerability index?
- Or is it more important to think of how to develop the most appropriate index for a particular application?
- Tennessee developed an in-state vulnerability assessment for a specific application.

- Rickles et al. (2018) Tennessee’s in-state vulnerability assessment for ‘a rapid dissemination of human immunodeficiency virus or Hepatitis C virus infection event’ utilizing data about the opioid epidemic. *Clinical Infectious Diseases*.
  - https://academic.oup.com/cid/article/66/11/1722/4706246

Why develop your own?

- Earlier indices:
  - Few variables, use same weights for multiple applications.
- Now:
  - Access to many variables, want *reproducible* definitions and calculations.

Summary

- Questions we want to answer
- Data we need to answer those questions
- Data we can get
- Questions we can answer from the data we can get.
- How close are the questions we can answer to the questions want to answer?
- Patterns we observe are echoes of the true process, the observation process, and the reporting process.
- Can we learn to see these echoes? Measure them?
- Can we learn to see the factors that influence the echoes?
- Epidemiology of reporting?

References

- CDC (2018) Annual Surveillance Report of Drug-Related Risks and Outcomes — United States. Surveillance Special Report. Centers for Disease Control and Prevention, U.S. Department of Health and Human Services. August 31, 2018.
- Rickles M et al. (2017) Tennessee's in-state vulnerability assessment for a 'rapid dissemination of HIV or HCV' event utilizing data bout the opioid epidemic. Clinical Infectious Disease.
- Ruhm CJ (2016) Drug poisoning deaths in the United States,1999-2012: a statistical adjustment analysis. Population Health Metrics 14, 2.
- Ruhm CJ (2017) Geographic variation in opioid heroin involved drug poisoning mortality rates. American Journal of Preventive Medicine 53, 745-753.
- Waller LA (2022). Building the analytic toolbox: From spatial analytics to spatial statistical inference with geospatial data. In *Geospatial Technology for Human Well-Being and Health* (pp. 29-35). Cham: Springer International Publishing.

Spatial Epidemiology and Geospatial Data Science in Opioid-Related Research

Thomas J. Stopka, PhD, MHS
Professor

Department of Public Health and Community Medicine
Tufts University School of Medicine

Workshop on Innovative Applications of Geospatial Data Science in Drug Use Research, National Institute on Drug Abuse (NIDA)

December 3, 2024

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Overview

- Spatial epidemiology, geospatial data, and disease prevention
- Applications of spatial epidemiology in prevention
  - Identifying and characterizing the risk landscape and hotspots
  - Assessing access to services and resource allocation
  - Assessing social determinants of health
  - Monitoring interventions and change
  - Conducting predictive analytics and simulation modeling
- Focus on 3 NIDA-funded studies

NIDA Funding

- **Rural Opioid Initiative New England (DISCERNNE)**. UG3DA044830, UH3DA044830. MPIs: Friedmann, Stopka
- **Predict to Prevent (P2P): Dynamic Spatiotemporal Analyses of Opioid Overdose to Guide Pre-Emptive Public Health Responses.** R01DA054267. MPIs: Stopka, Bauer
- **Assessing Optimal XR-Buprenorphine Initiation Points in Jail.** R01DA056446. MPIs: Farabee, Friedmann, Stopka
- **Examining Xylazine Exposure & Risk of Skin and Soft Tissue Infections** in People Who Inject Drugs. R21DA061423. MPIs: Stopka, Shrestha
- **HEALing Communities Study (MA).** UM1DA04912. PI: Samet
- **MA Justice Community Opioid Innovation Network (JCOIN).** UG3DA050067. MPIs: Friedmann, Evans

Sensitivity Notice

Representing Lives Lost

The symbols on these maps represent much more than data. They represent loved children, parents, friends, coworkers, and peers who were lost to an opioid overdose. With respect to confidentiality for family and neighbors of those who have passed on, these maps mask the exact locations of decedent residences.

Spatial Epidemiology & Public Health Impact

Can spatial analyses and spatial data inform disease prevention?

The facts are coming! The facts are coming!

Spatial Epidemiology

- Facilitates description and examination of disease and its geographic variations…
- Place matters
  - Source: Carpenter (2011). *Spatial & Spatiotemporal Epidemiology.* PMID: 22748171

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GIS/Spatial Analytical Approaches in Prevention

1. **Descriptive mapping/risk maps**
   - Study sites
   - Spatial distribution of risk (e.g., nonfatal and fatal overdose)
   - Locations of services (e.g., treatment providers)
   - Geolocation of prevention tools (e.g., harm reduction agencies)
2. **Calculation of variables**
   - Distance from homes to MOUD treatment
   - Small area measures of OD risk and health disparities
   - Areal interpolation/Spatial Krieging
3. **Geostatistical analysis/spatial epidemiology**
   - Incremental spatial autocorrelation; cluster analyses
   - Spatial regression; geographically weighted regression
   - Spatiotemporal cluster analysis
   - Health services access: location-allocation and 2-stage floating catchment area analysis

Exploratory Spatial Data Analysis (ESDA)

Applications: Spatial epidemiology in prevention

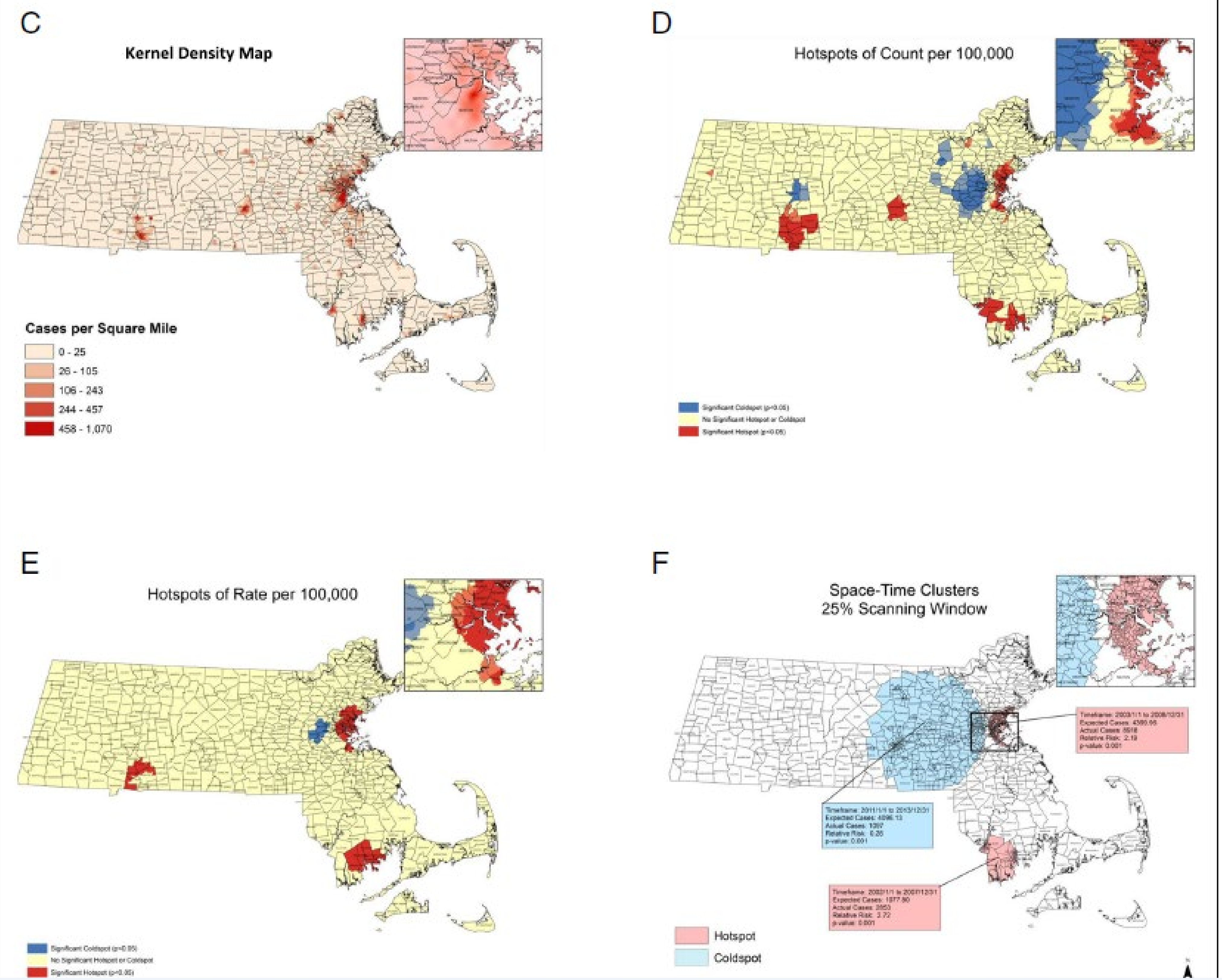
- Identifying and characterizing the risk landscape and hotspots
- Assessing access to services and resource allocation
- Assessing social determinants of health
- Monitoring interventions and change
- Conducting predictive analytics and simulation modeling

RESEARCH ARTICLE Open Access

Identifying and characterizing hepatitis C virus hotspots in Massachusetts: a spatial epidemiological approach

Thomas J. Stopka[1*], Michael A. Goulart[1], David J. Meyers[1,2], Marga Hutcheson[1], Kerri Barton[3], Shauna Onofrey[3], Daniel Church[3], Ashley Donahue[1] and Kenneth K. H. Chui[1]

Stopka et al. *BMC Infectious Disease.* 2024. PMID: 38245914



Stopka et al. *BMC Infectious Dis.* 2024. PMID: 38245914

Identifying and characterizing HCV hotspots in Massachusetts: A spatial epidemiological approach

- Identified 9 HCV mortality clusters across MA ($p < 0.05$)
- Hotspots were positively associated with % of pop. Hispanic (AOR: 1.07; 95% CI: 1.04, 1.09) and % households receiving food stamps (AOR: 1.83; 95% CI: 1.22, 2.74).
- HCV hotspots were negatively associated with:
  - % of the population that were HS graduates or higher (AOR: 0.91; 95% CI: 0.89, 0.93)
  - “Other” race/ethnicity category (AOR: 0.88; 95% CI: 0.85, 0.91)

Stopka et al. *BMC Infectious Disease.* 2024. PMID: 38245914

Contents lists available at ScienceDirect

International Journal of Drug Policy

journal homepage: www.elsevier.com/locate/drugpo

Research Paper

Characterizing opioid overdose hotspots for place-based overdose prevention and treatment interventions: A geo-spatial analysis of Rhode Island, USA

SCHOOL OF MEDICINE
Public Health

Samuels et al. IJDP. 2024. PMID: 38245914

Characterizing opioid OD hotspots for place-based OD prevention and treatment interventions: A geo-spatial analysis of Rhode Island

- Identified 7 non-fatal & 3 fatal overdose hotspots in RI
- Hotspot neighborhoods had higher proportions of Black and LatinX residents, renter-occupied housing, vacant housing, unemployment, and cost-burdened households
- Increased relative risk of non-fatal and fatal ODs in neighborhoods with crowded housing (RR 1.19 [95 % CI 1.05, 1.34]; RR 1.21 [95 % CI 1.18, 1.38], respectively)
- Higher proportion of hotspot neighborhoods had a religious organization, a health center, or a police station

Samuels et al. IJDP. 2024. PMID: 38245914

Applications: Spatial epidemiology in prevention

- Identifying and characterizing the risk landscape and hotspots
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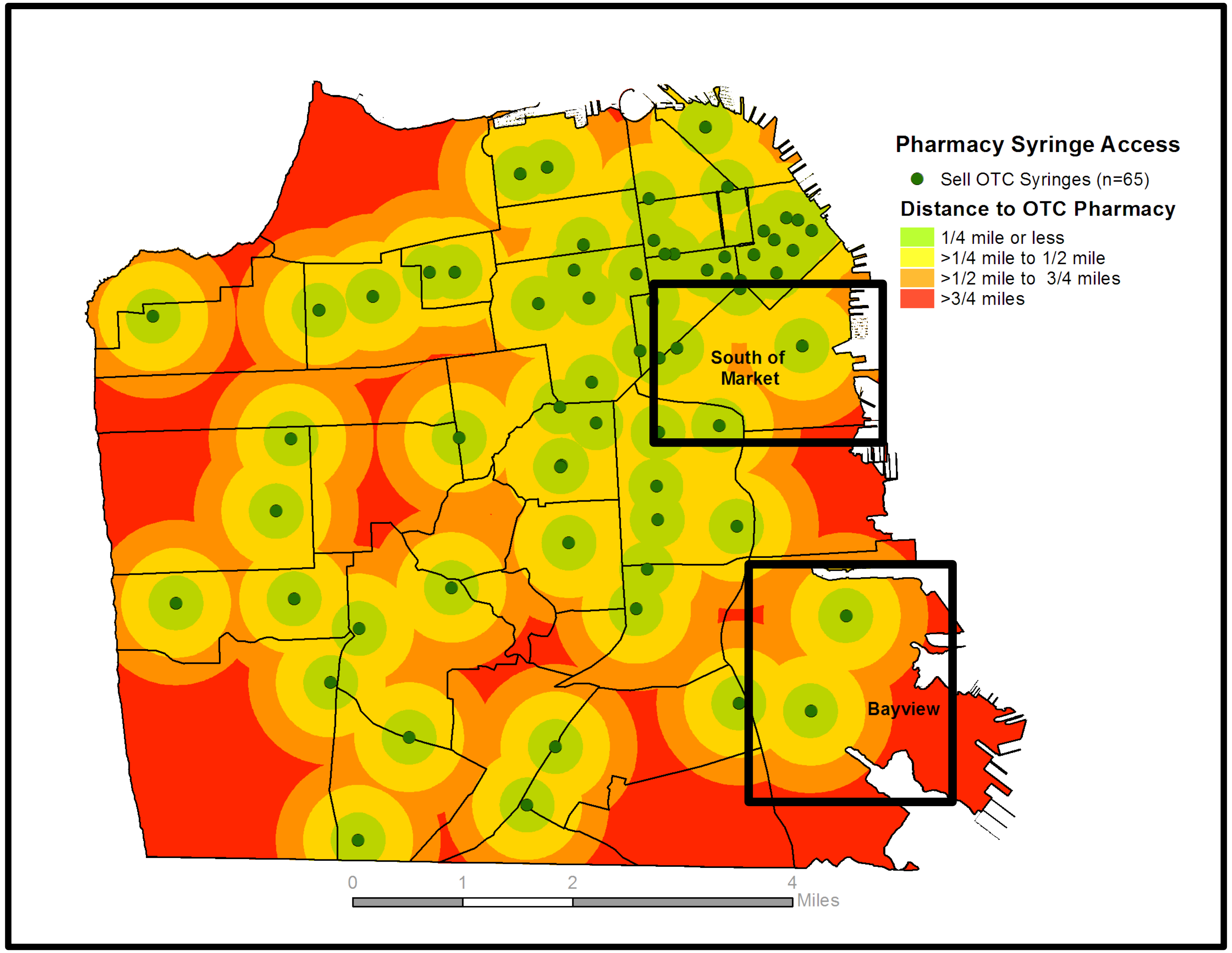
Measuring Accessibility to Services

- Measures of accessibility
  - Euclidean distances
  - Buffer zones
  - Drive- and walk-times
  - Enhanced 2-3 Step Floating Catchment Areas
  - Location-Allocation

Access to pharmacies and sterile syringes



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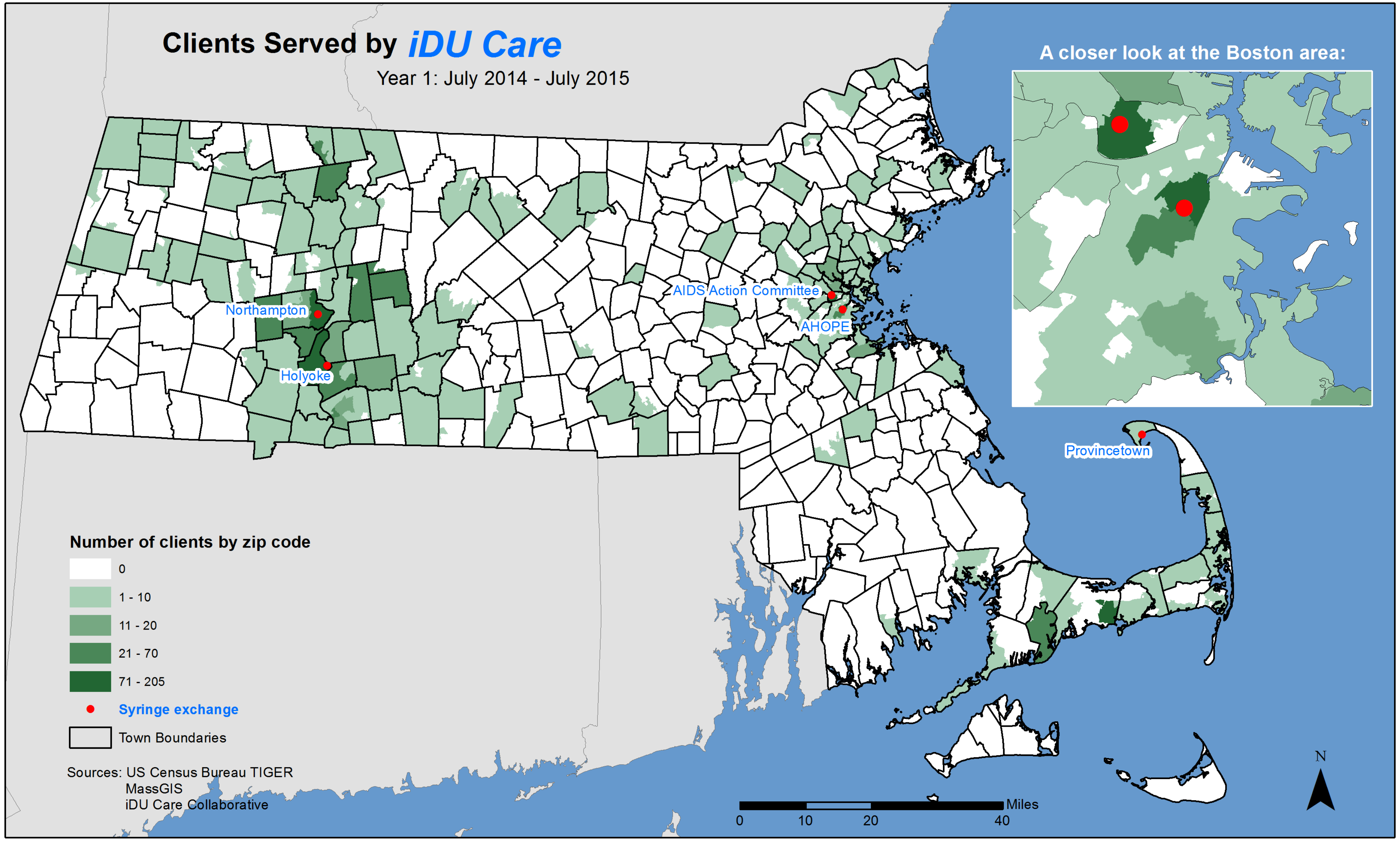
Stopka (2012). Am J Epidemiology PMID: 22562660

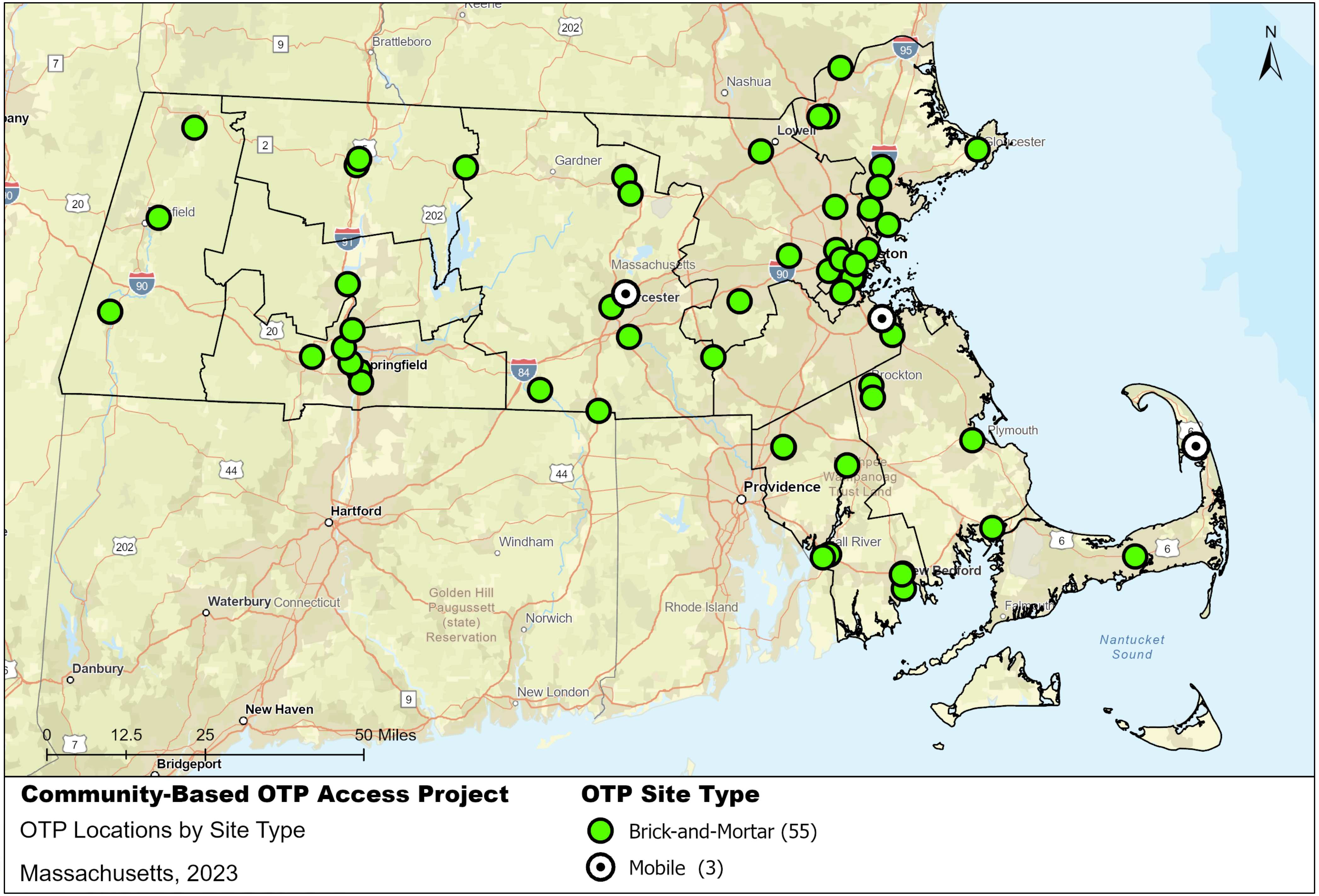
Client Catchment Areas: Distances Traveled by Harm Reduction Clients



Tufts UNIVERSITY | SCHOOL OF MEDICINE Public Health

Stopka et al. (2016). APHA

Opioid Treatment Program (OTP) Locations by Site Type as of 2023

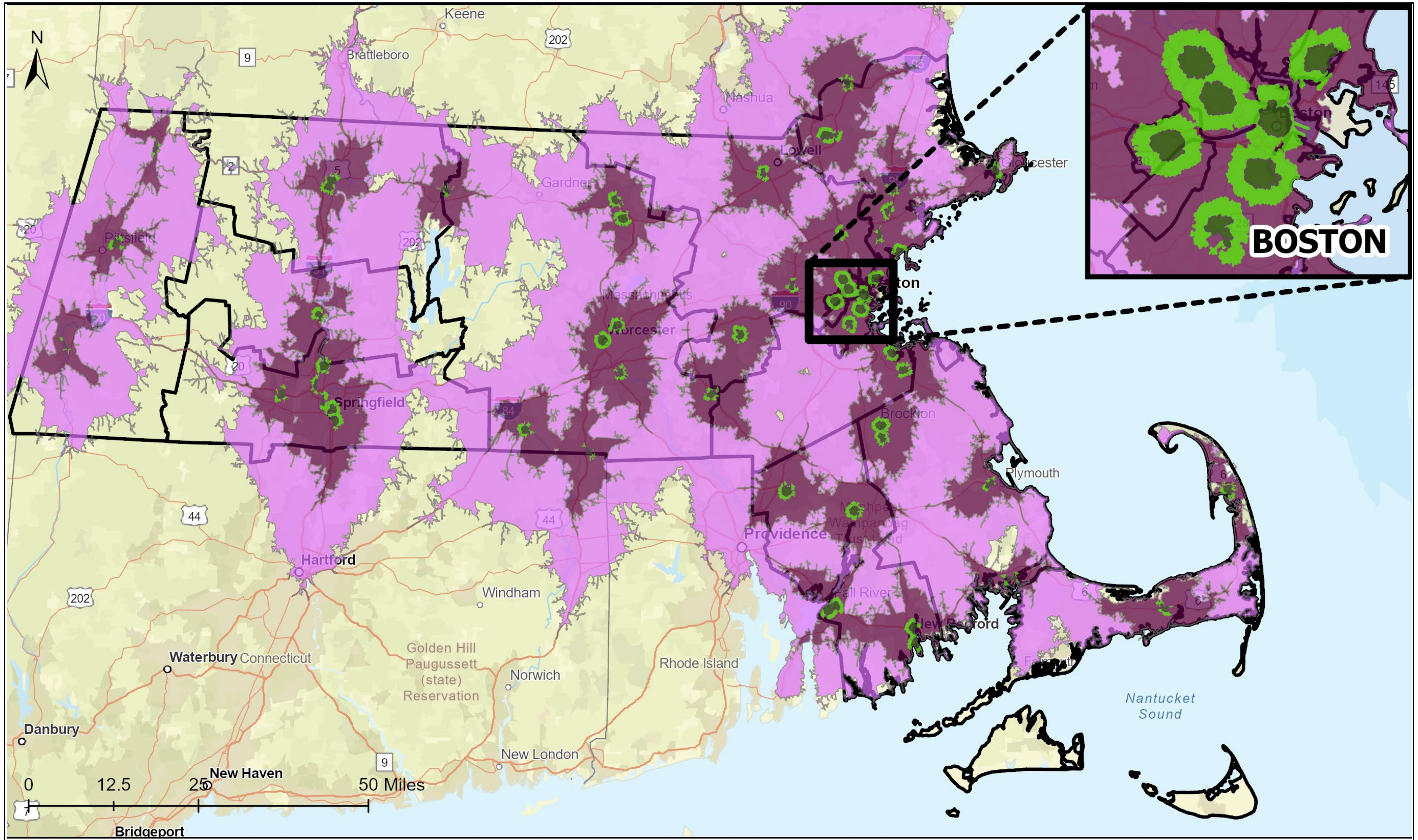


Stopka et al. 2024
BSAS Report for Gov's. Office

Tufts UNIVERSITY

Only 13% of Massachusetts residents lived within a 15-minute walk of an OTP

Stopka et al. 2024
BSAS Report for Gov's. Office



Community-Based OTP Access Project

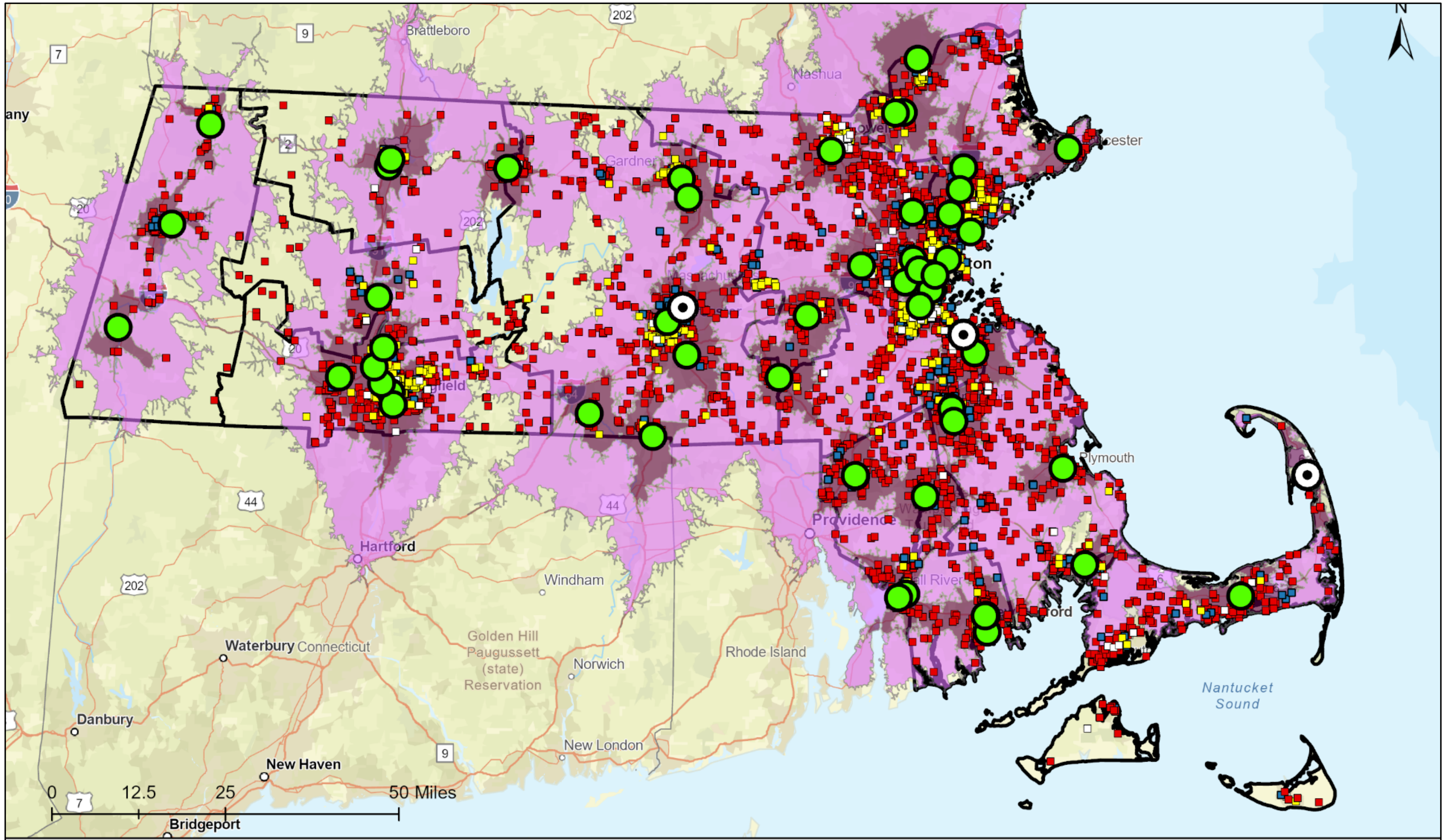
Access to OTPs

Massachusetts, 2023

Walking Time to OTP	Driving Time to OTP
15 minutes or less	15 minutes or less
16-30 minutes	16-30 minutes

Only 9% of decedents lived within 15 minutes walking to an OTP

Stopka et al. 2024
BSAS Report for Gov's. Office



Community-Based OTP Access Project
OTP Access as of 2023
With Decedent Residence by Race/Ethnicity, 2020-2022

Updated: 3/20/24
Cartographer/Analyst: O. Lewis, S. Shrestha
Tufts University School of Medicine
Principal Investigator: T. Stopka
Data Source: RVRS, BSAS
Driving time calculated for 8AM on a Thursday.

OTPs
- Brick-and-Mortar (55)
- Mobile (3)

Driving Time to OTP
- 15 minutes or less
- 16-30 minutes

Decedent Race/Ethnicity (N=6,197)
- White, non-Hispanic (4,474)
- Black, non-Hispanic (682)
- Hispanic (939)
- Other race/ethnicity (102)

Data-to-Action: Presentation to OTP Providers

98% of decedents lived within a 30-minute drive time of an OTP.

80% of decedents lived within a 15-minute drive of an OTP.

32% of decedents lived within a 30-minute walk of an OTP.

Only 9% of decedents lived within a 15-minute walk of an OTP.

2-Stage Floating Catchment Area (2SFCA) Analysis

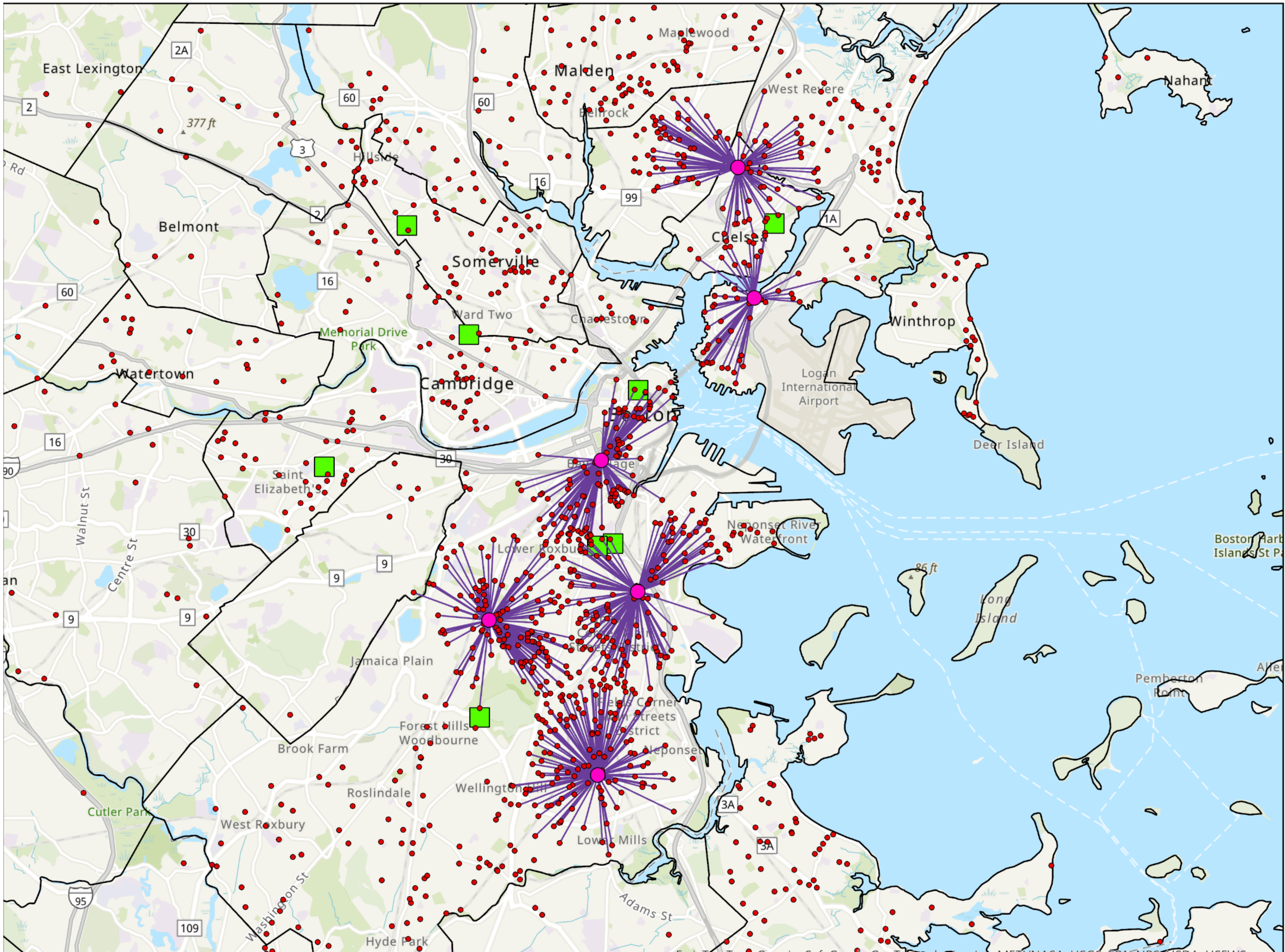
- Accessibility calculated in two steps
  - Assess the proportion of services (e.g., treatment providers) to the population in need within a designated search area
  - Calculate "service availability" within a 30-minute drive from each population center developing an accessibility index

Location allocation analyses

Suffolk County
(Boston, Chelsea, Revere, Winthrop)

30-minute walk time

- Existing OTP
- Allocated OTP
- Decedent



Applications: Spatial epidemiology in prevention

- Identifying and characterizing the risk landscape and hotspots
- Assessing access to services and resource allocation
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- Monitoring interventions and change
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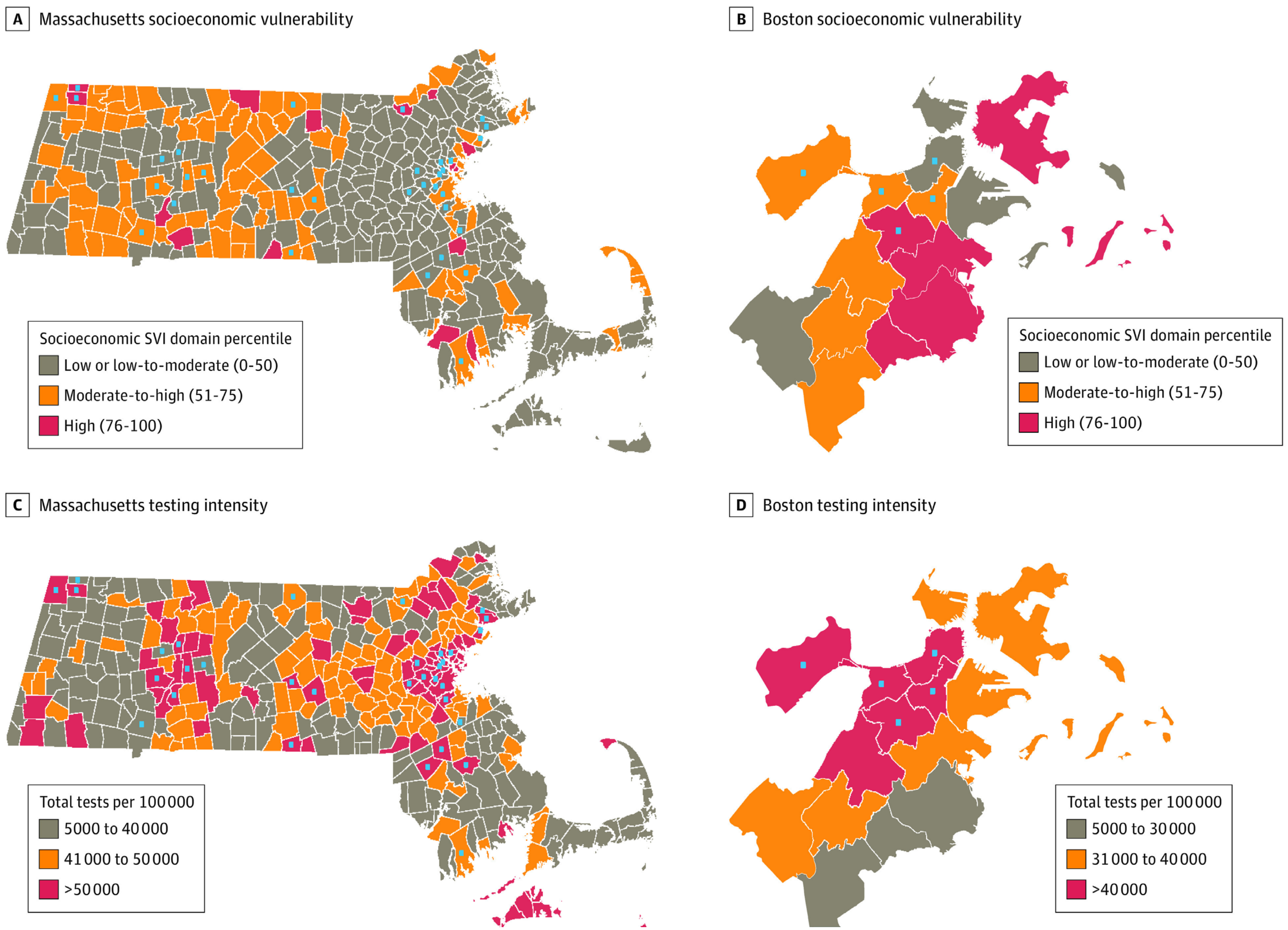
Social Determinants and Disease Testing Gaps



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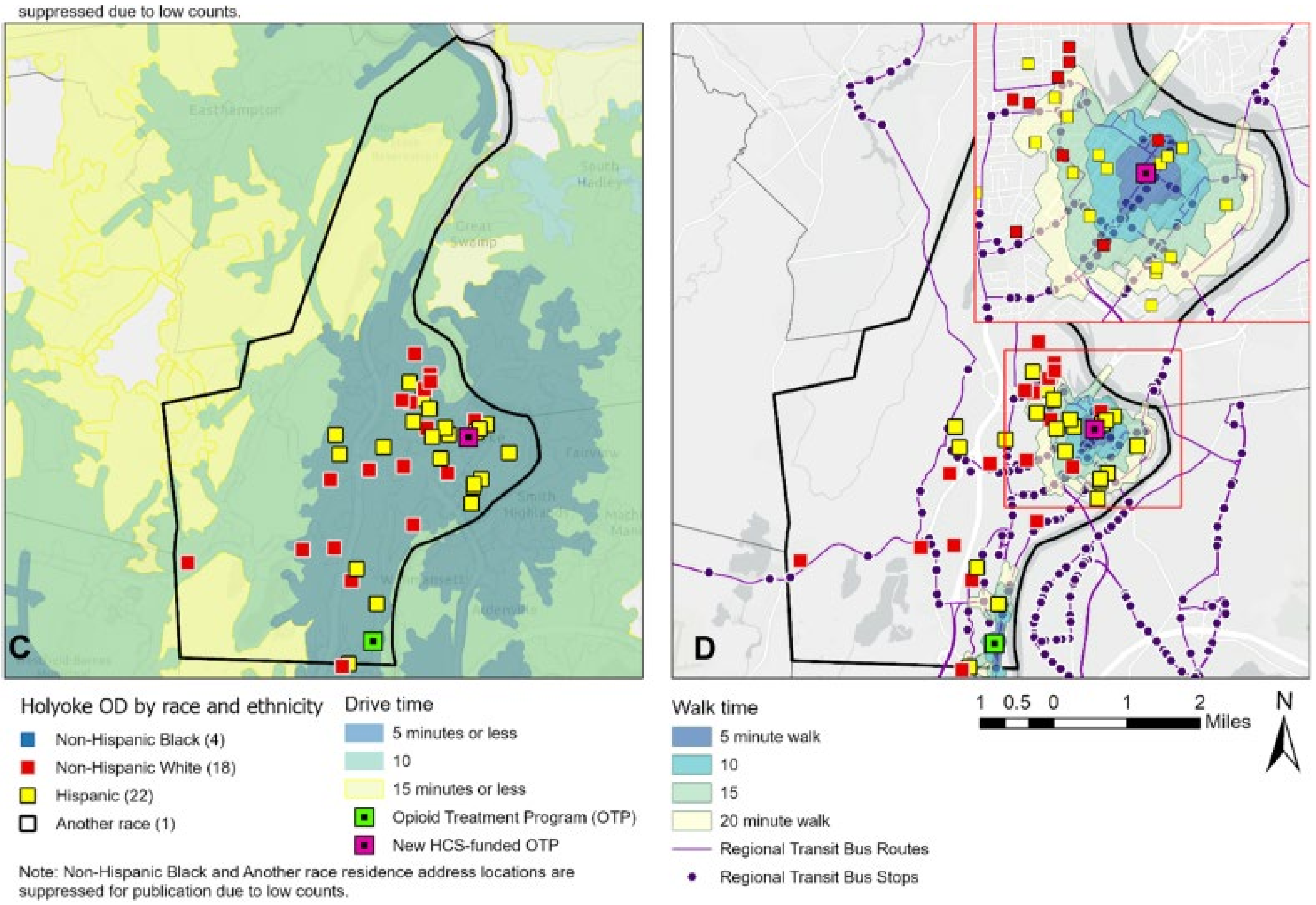
Dryden-Peterson et al. (2021). *JAMA Netw Open.* PMID: 33560423

Applications: Spatial epidemiology in prevention

- Identifying and characterizing the risk landscape and hotspots
- Assessing access to services and resource allocation
- Assessing social determinants of health
- Monitoring interventions and change
- Conducting predictive analytics and simulation modeling

Methadone Access: Holyoke, MA



Tufts University | School of Medicine Public Health

Pustz et al (2023). *Drug & Alcohol Dep*. PMID: 37666091

Applications: Spatial epidemiology in prevention

- Identifying and characterizing the risk landscape and hotspots
- Assessing access to services and resource allocation
- Assessing social determinants of health
- Monitoring interventions and change
- Conducting predictive analytics and simulation modeling

Applications in NIDA-funded Studies…

Mobile telemedicine-based treatment of chronic HCV among PWID in rural northern New England: A randomized clinical trial

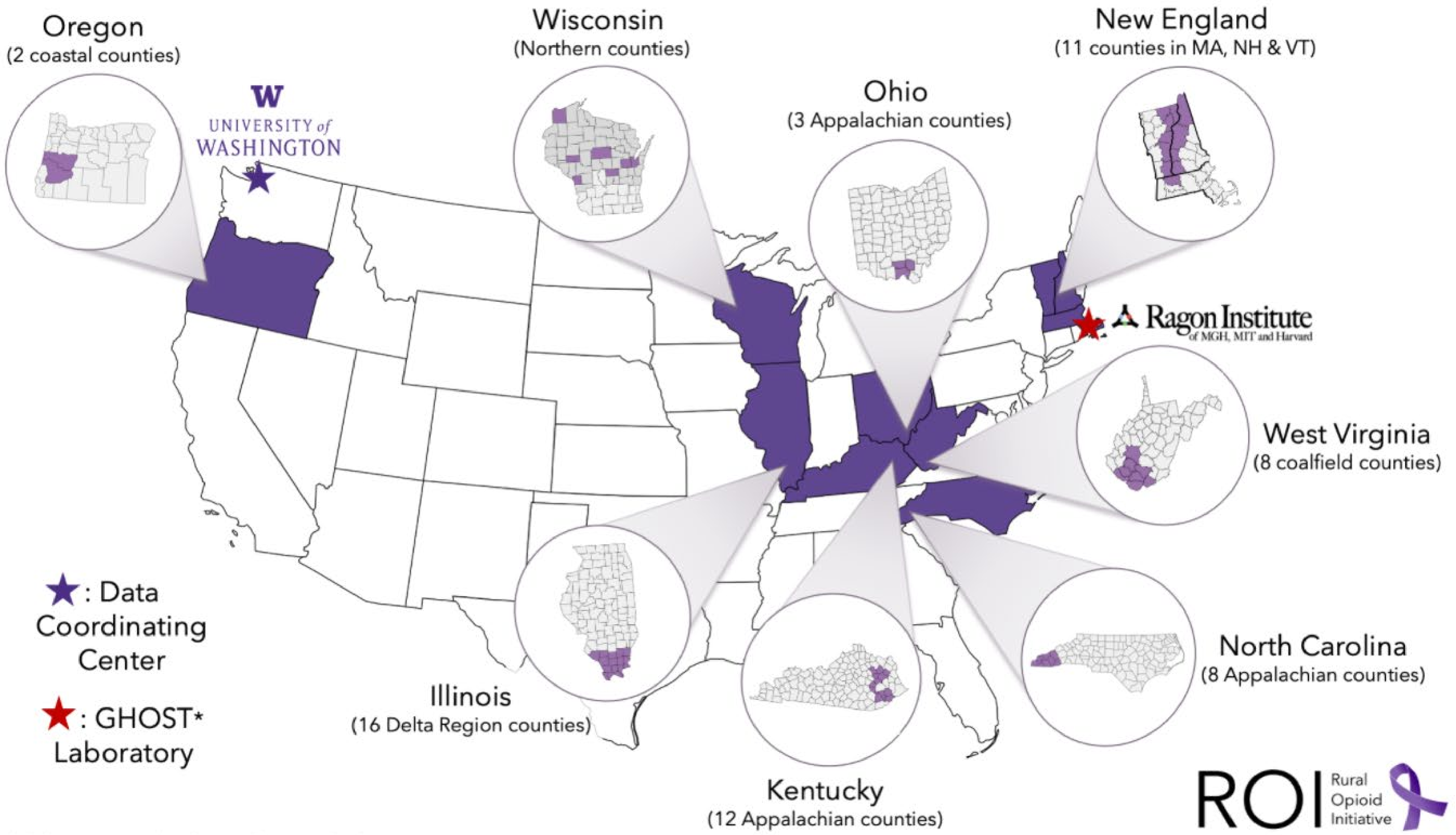
The DISCERNNE Study

Drug Injection Surveillance and Care Enhancement in Rural Northern New England

Thomas J. Stopka, Donna Wilson, David de Gijsel, Kerry Nolte, Jean Dejace, Randall Hoskinson Jr., Lizbeth Del Toro-Mejias, Elyse Bianchet, Patrick Dowd, and Peter D. Friedmann

Baystate Health | UMass Chan Medical School | Tufts University School of Medicine | Tufts University School of Public Health | University of New Hampshire | The University of Vermont Larner College of Medicine | Vermont Department of Health | New Hampshire DHHS Department of Health & Human Services | Dartmouth Health | The Dartmouth Institute for Health Policy & Clinical Practice | Better Life Partners

Rural Opioid Initiative Sites



*Global Hepatitis Outbreak Surveillance Technology

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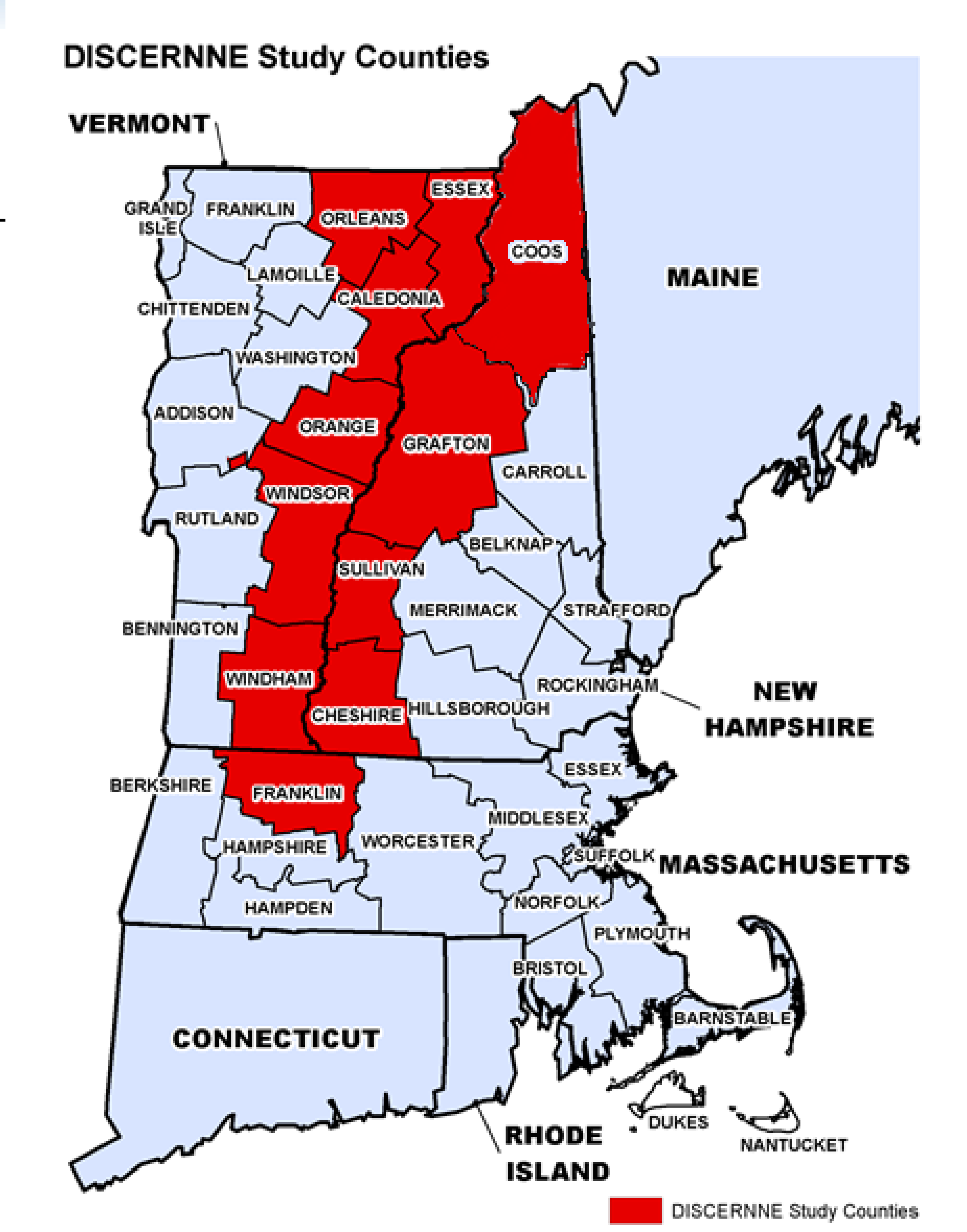
http://ruralopioidinitiative.org/studies.html



NIH-Funded Study
MPIs: Friedmann, Stopka

Massachusetts: Franklin County

New Hampshire: Cheshire, Sullivan, Grafton, Essex, and Coos Counties

Vermont: Caledonia, Orleans, Orange, Windham and Windsor Counties

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Stopka et al. (2019). *Preventive Med*. PMID: 31158400

Epidemiologic, Policy and Legal Environment

Preventive Medicine 128 (2019) 105740

Contents lists available at ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

The opioid epidemic in rural northern New England: An approach to epidemiologic, policy, and legal surveillance

Thomas J. Stopka[a,*], Erin Jacque[b], Patsy Kelso[c], Haley Guhn-Knight[d], Kerry Nolte[e], Randall Hoskinson Jr[d], Amanda Jones[c], Joseph Harding[f], Aurora Drew[g], Anne VanDonsel[c], Peter D. Friedmann[d]

[a] Department of Public Health and Community Medicine, Clinical and Translational Science Institute, Tufts University School of Medicine, Boston, MA, United States of America
[b] Department of Public Health and Community Medicine, Tufts University School of Medicine, Boston, MA, United States of America
[c] Vermont Department of Health, Burlington, VT, United States of America
[d] University of Massachusetts Medical School – Baystate, Springfield, MA, United States of America
[e] University of New Hampshire, Durham, NH, United States of America
[f] Substance-Misuse Systems Planning and Evaluation Quality Assurance & Improvement, New Hampshire Department of Health & Human Services, Concord, NH, United States of America
[g] Geisel School of Medicine at Dartmouth, Hanover, NH, United States of America

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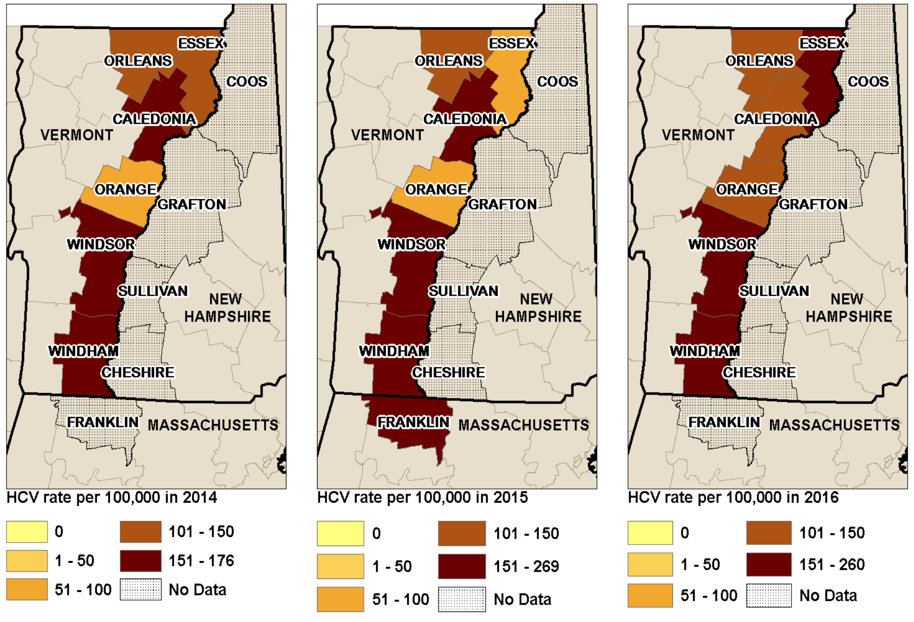
Stopka et al., *Prev Med* (2019). PMID: 31158400

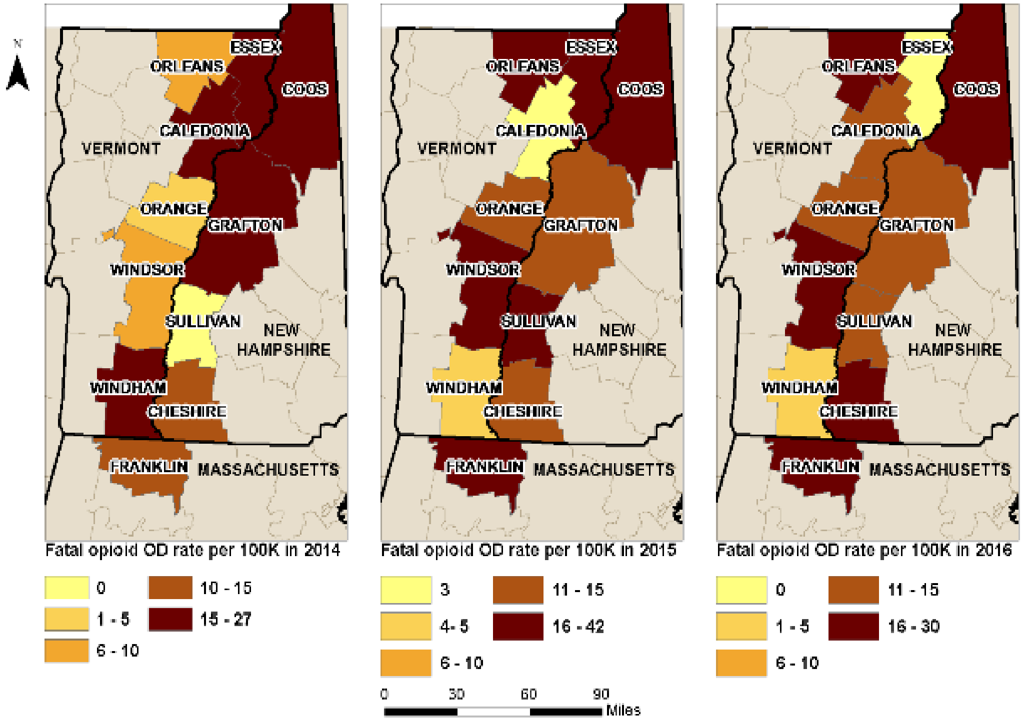
Disease Outcomes of concern, 2014-16

HCV Prevalence



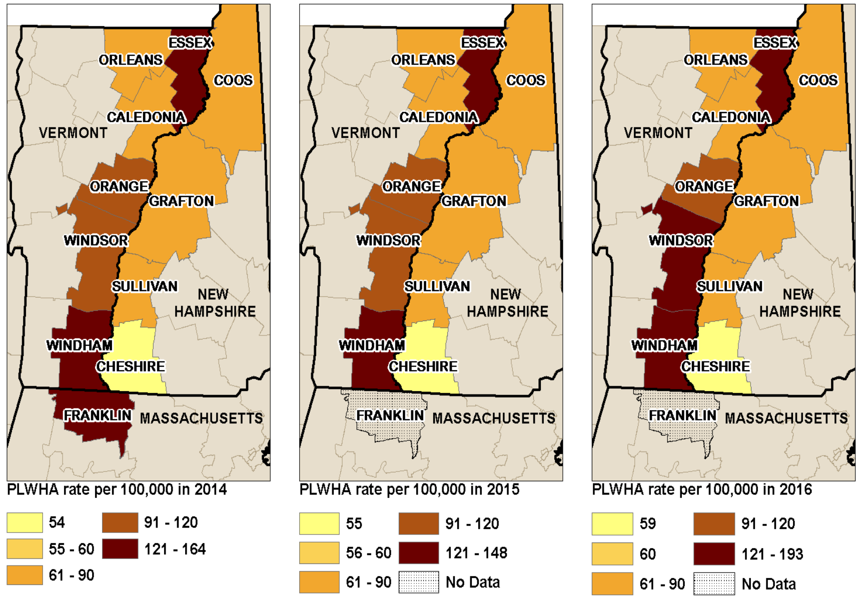
National 2015 Rate: 1,295.4 per 100,000

Fatal Overdose Rate



National 2015 Rate: 10.4 per 100,000

Prevalence of people living with HIV/AIDS



National 2015 Rate: 303.5 per 100,000

Stopka et al. (2019). *Preventive Med*. PMID: 31158400

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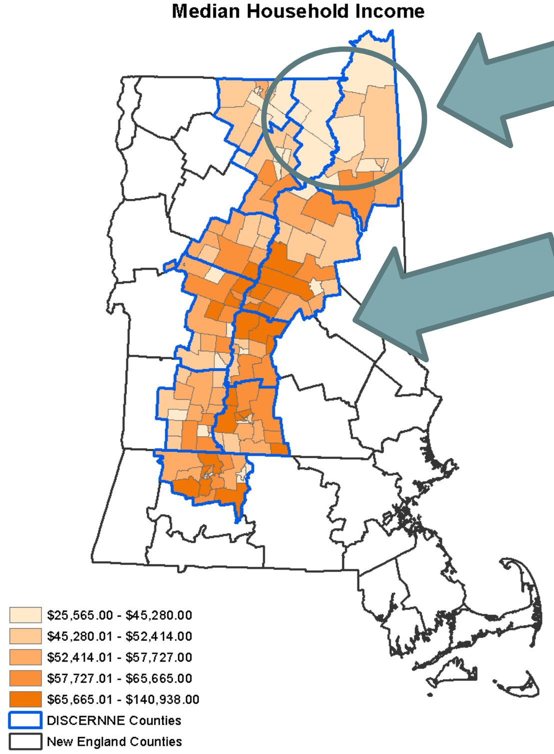
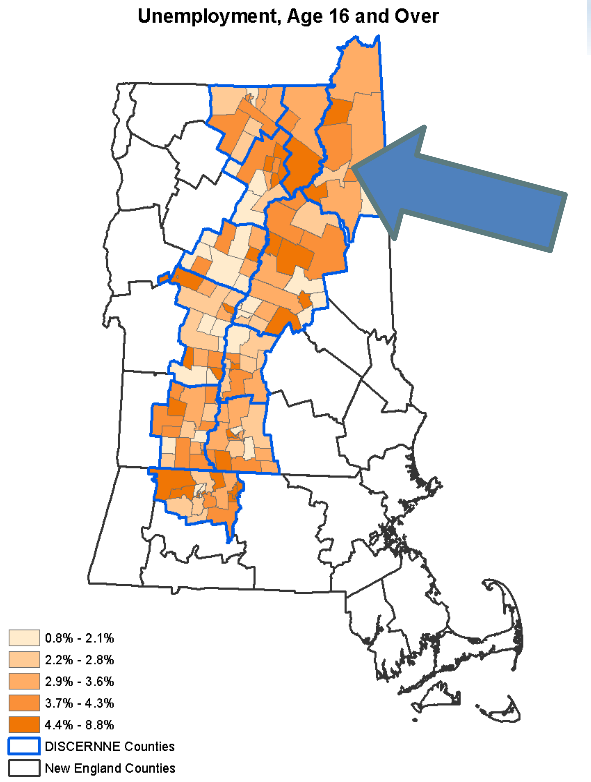
Socioeconomic Context, 2016

Economic disparities



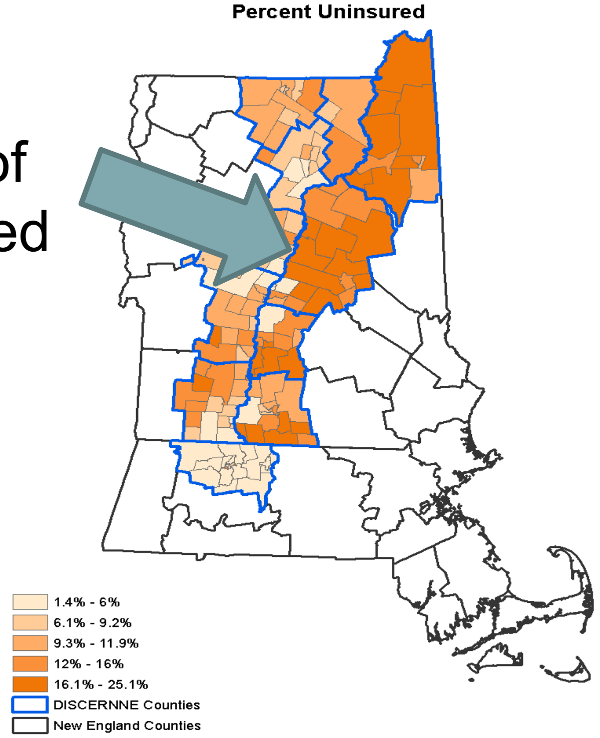
Low Income

High Income



High Unemployment

High Rates of Uninsured



Stopka et al. (2019). *Preventive Med*. PMID: 31158400

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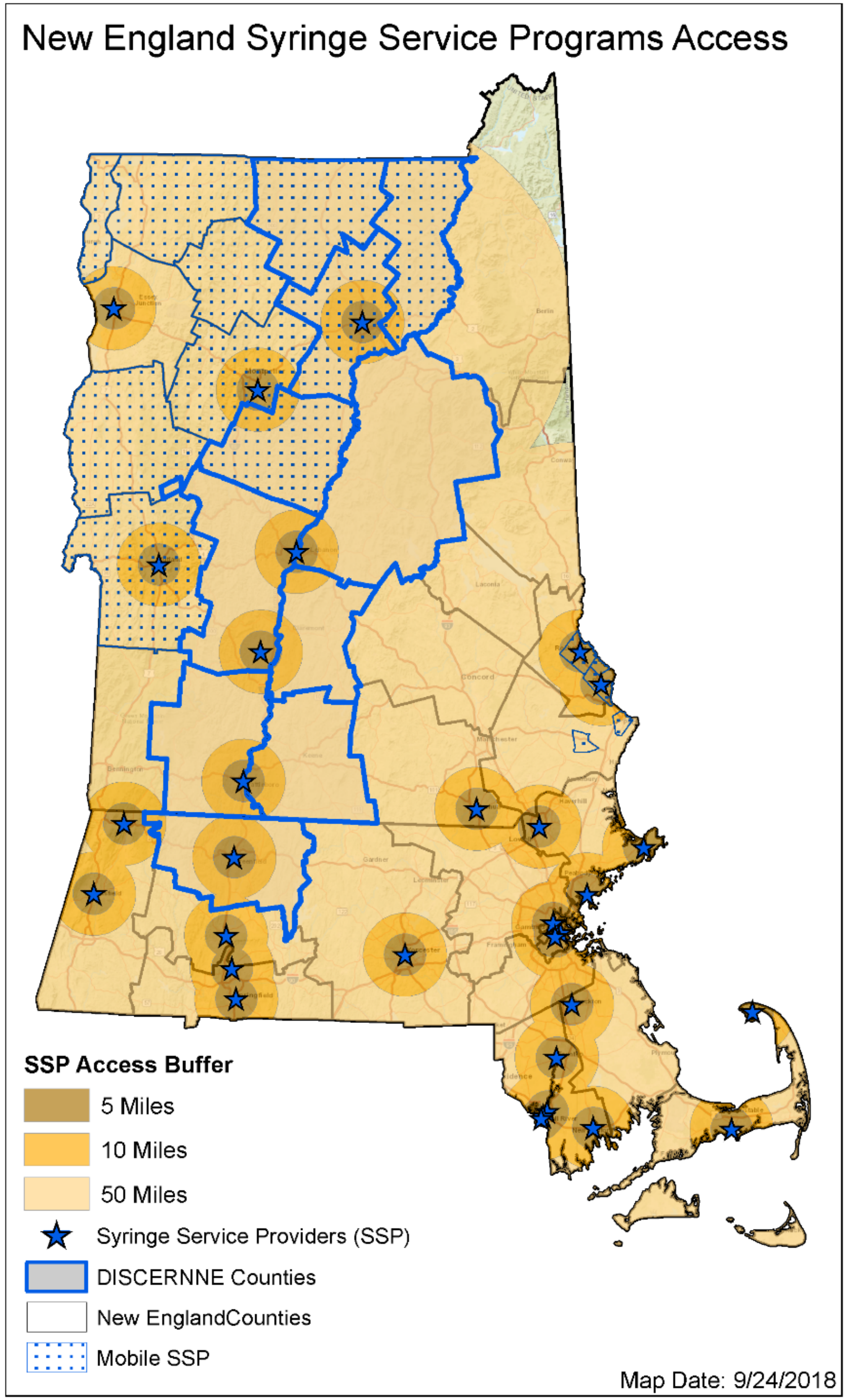
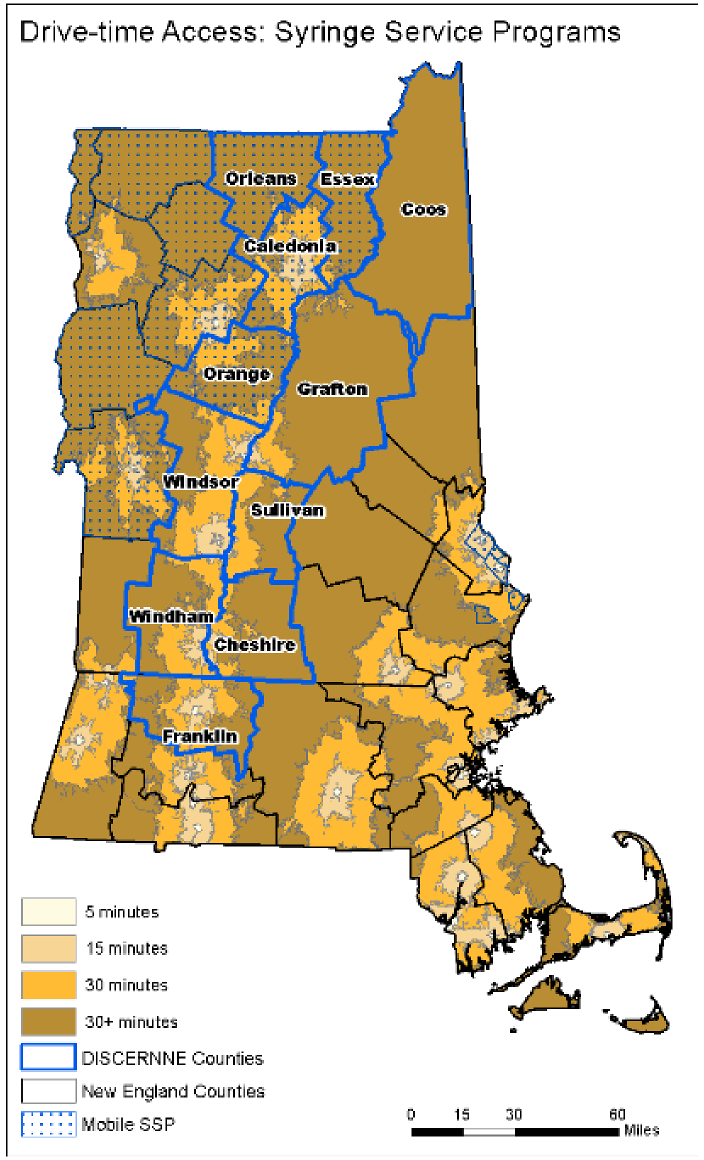
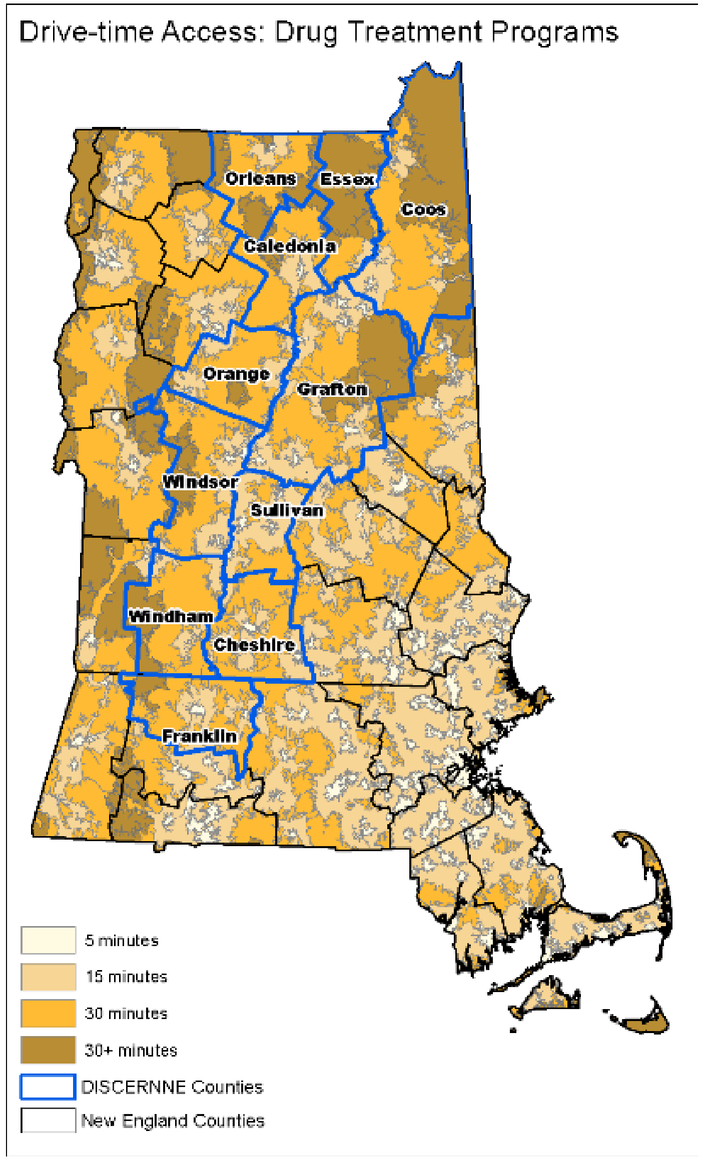
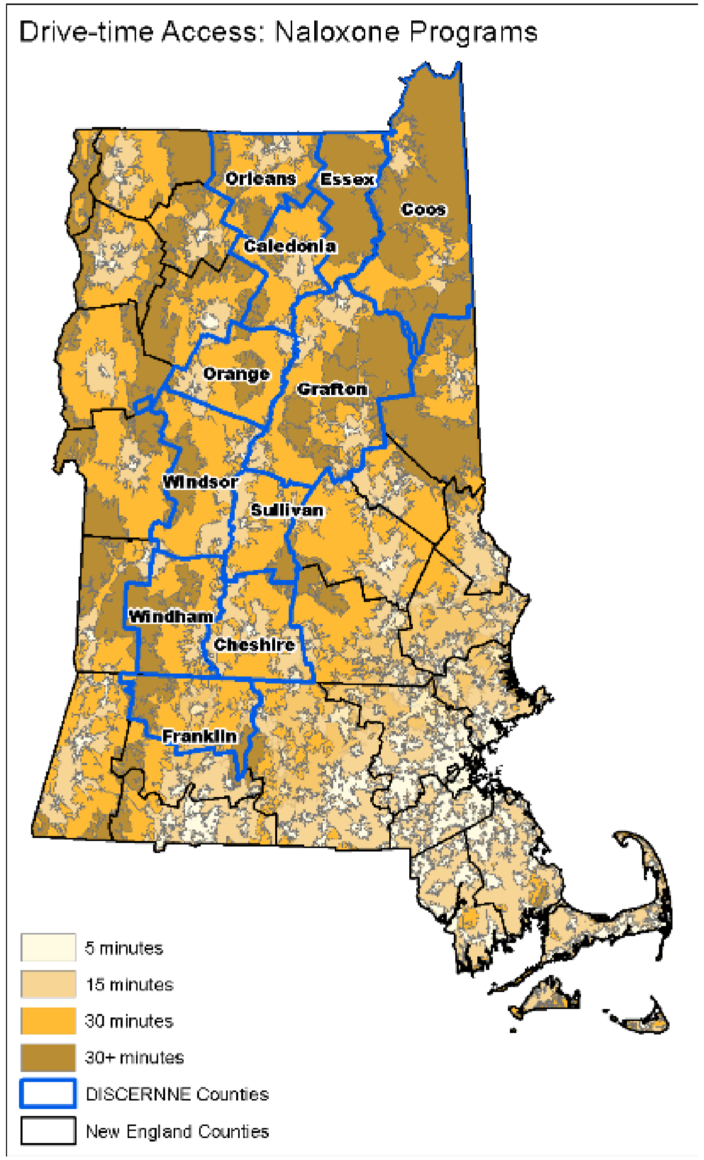

New England Syringe Service Programs Access
SSP Access Buffer
5 Miles
10 Miles
50 Miles
Syringe Service Providers (SSP)
DISCERNNE Counties
New EnglandCounties
Mobile SSP
Map Date: 9/24/2018

Service Environment







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Stopka et al. (2019). *Preventive Med*. PMID: 31158400

HCV & Risk Landscape Results: 2017-2019

	All	VT	NH	MA
HCV seropositivity	59%	54%	66%	58%
Shared injection equipment	53%	46%	65%	51%

- Limited access to injection gear and HCV testing and treatment
- High Risk of HIV outbreak considering lack of harm reduction services and high HCV rates

Comparative Study > Prev Med. 2019 Nov:128:105740. doi: 10.1016/j.ypmed.2019.05.028. Epub 2019 May 31.

The opioid epidemic in rural northern New England: An approach to epidemiologic, policy, and legal surveillance

Thomas J Stopka [1], Erin Jacque [2], Patsy Kelso [3], Haley Guhn-Knight [4], Kerry Nolte [5], Randall Hoskinson Jr [4], Amanda Jones [3], Joseph Harding [6], Aurora Drew [7], Anne VanDonsel [3], Peter D Friedmann [4]

> Viruses. 2024 Aug 27;16(9):1364. doi: 10.3390/v16091364.

Syringe Access, Syringe Sharing, and Perceptions of HCV: A Qualitative Study Exploring the HCV Risk Environment in Rural Northern New England, United States

Eric Romo [1], Elyse Bianchet [2], Patrick Dowd [2], Kathleen M Mazor [1], Thomas J Stopka [3], Peter D Friedmann [2]

Data to Action: HCV Treatment RCT

A randomized controlled trial to evaluate:

Mobile telemedicine care (MTC) with integrated syringe services

vs

Enhanced usual care (EUC) referral with care navigation to a local or regional provider

Results: Primary outcomes

Odds Ratios (95% CI), MTC vs EUC		
Outcome	**Comparison**	**Unadjusted Odds Ratio** (95% CI)
Initiated DAA	MTC vs EUC	**6.95 (3.07-15.73)**
Cleared on SVR-12	MTC vs EUC	**4.03 (1.76-9.24)**
Shared syringes in FU	MTC vs EUC	0.60 (0.26-1.39)

Stopka et al., *APHA* 2024

NIH HEAL INITIATIVE

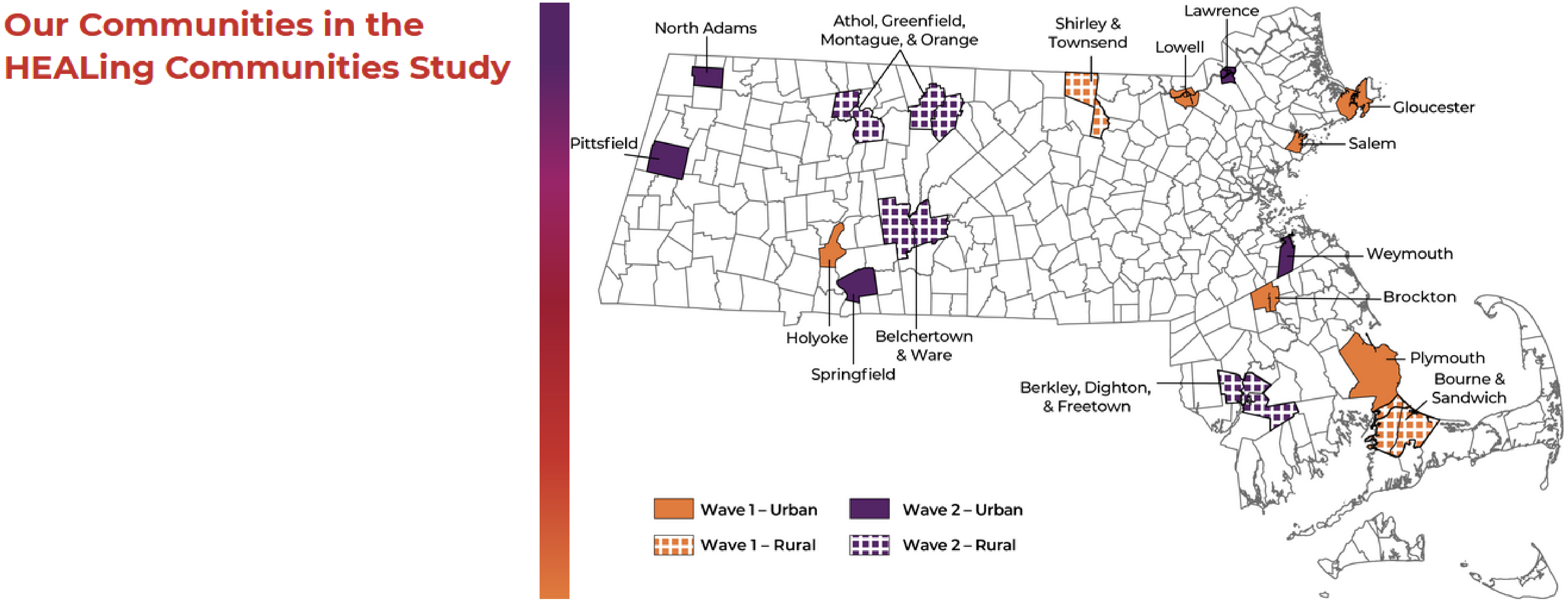
HEALing Communities Study Massachusetts

HEALing Communities Study: Spatial Epidemiology and Overdose Prevention

Massachusetts PI: Jeffrey Samet; Co-I/Spatial Epi Lead: Tom Stopka

University of Kentucky · Boston Medical Center · Columbia University in the City of New York · The Ohio State University · RTI International · SAMHSA Substance Abuse and Mental Health Services Administration · NIH National Institute on Drug Abuse

HEALing Communities Study (HCS) in MA



Wave One

Bourne & Sandwich	Brockton	Gloucester	Holyoke
Lowell	Plymouth	Salem	Shirley & Townsend

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https://healingcommunitiesstudy.org/sites/massachusetts.html

HCS and Spatial Epidemiology

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Spatial and Spatio-temporal Epidemiology

ELSEV

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Thomas

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Drug and Alcohol Dependence

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Alexander Y. \
Thomas J. Sto

Contents lists available at ScienceDirect

Journal of Substance Use and Addiction Treatment

ELSEV

Spatia
comm
Massa

Shikhar
Jennifer

Contents lists available at ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

ELSEVIER

Short Communication

The optimization of harm reduction services in Massachusetts through the use of GIS: Location-allocation analyses, 2019–2021

Check for updates

Joshua R. Parbs [a,*], Sumeeta Srinivasan [a], Jennifer Pustz [a], Ric Bayly [a], Shikhar Shrestha [a], Olivia Lewis [a], Simeon Kimmel [b,d], Thera Meehan [c], Hermik Babakhanlou-Chase [d], Thomas J. Stopka [a]

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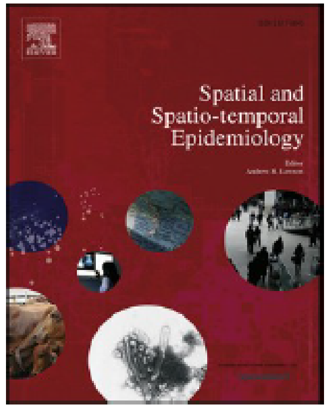
Spatial and Spatio-temporal Epidemiology

journal homepage: www.elsevier.com/locate/sste



Relationships between places of residence, injury, and death: Spatial and statistical analysis of fatal opioid overdoses across Massachusetts

Jennifer Pustz [a], Sumeeta Srinivasan [b], Marc R. Larochelle [c], Alexander Y. Walley [c], Thomas J. Stopka [a,b,d,e,*]

[a] Department of Public Health and Community Medicine, Tufts University School of Medicine, 136 Harrison Avenue, Boston, MA 02111, United States
[b] Department of Urban and Environmental Policy and Planning, Tufts University, 97 Talbot Avenue, Medford, MA 02155, United States
[c] Grayken Center for Addiction, Clinical Addiction Research and Education Unit, Section of General Internal Medicine, Department of Medicine, Boston University School of Medicine and Boston Medical Center, One Boston Medical Center Place, Boston, MA 02118, United States
[d] Department of Community Health, Tufts University, 574 Boston Avenue, Suite 208, Medford, MA 02155, United States
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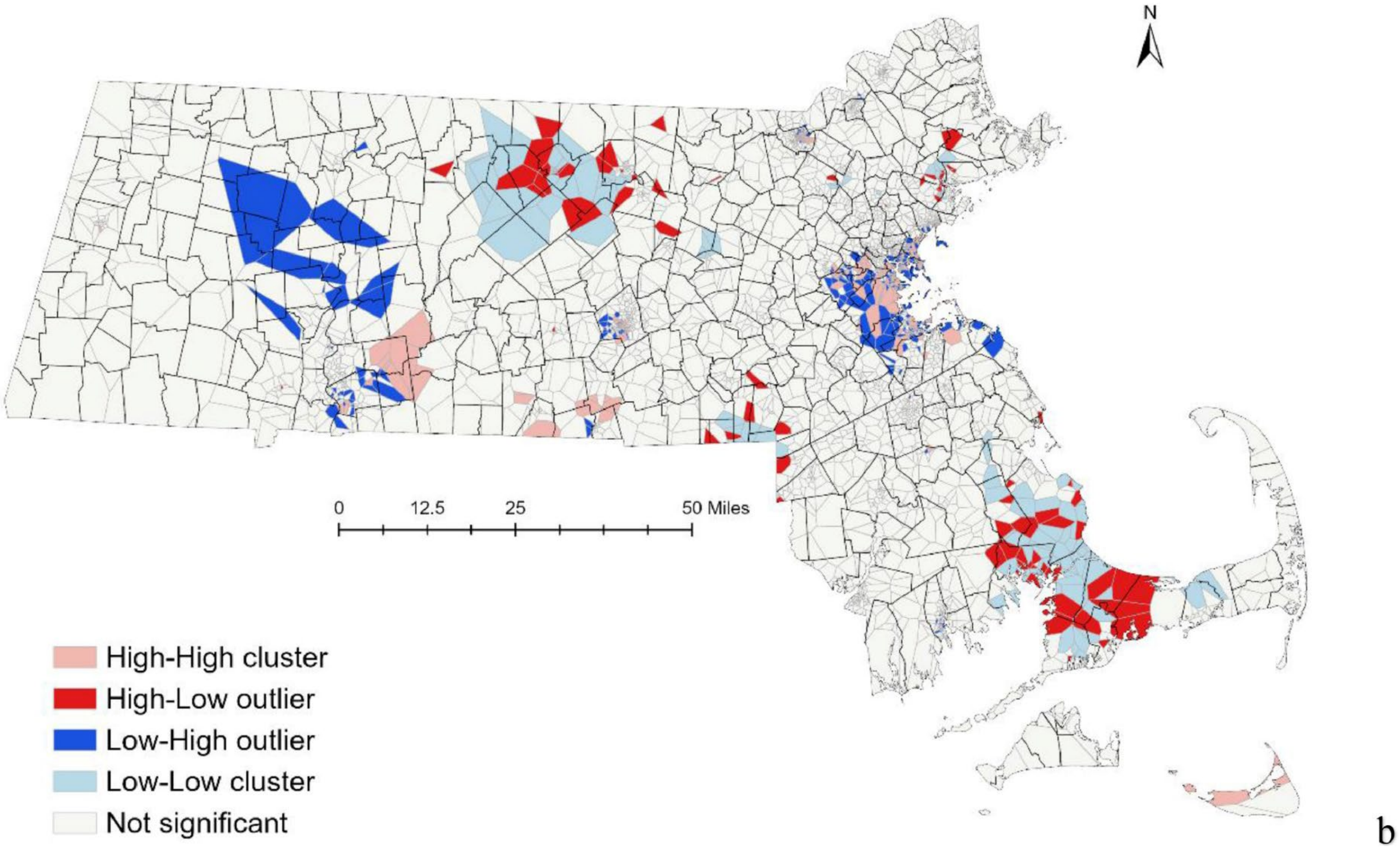
Pustz et al (2022). *Spatial & Spatiotemporal Epi*. PMID: 36460457

Overdose Clustering:
Local Indicators of Spatial Association (LISA)



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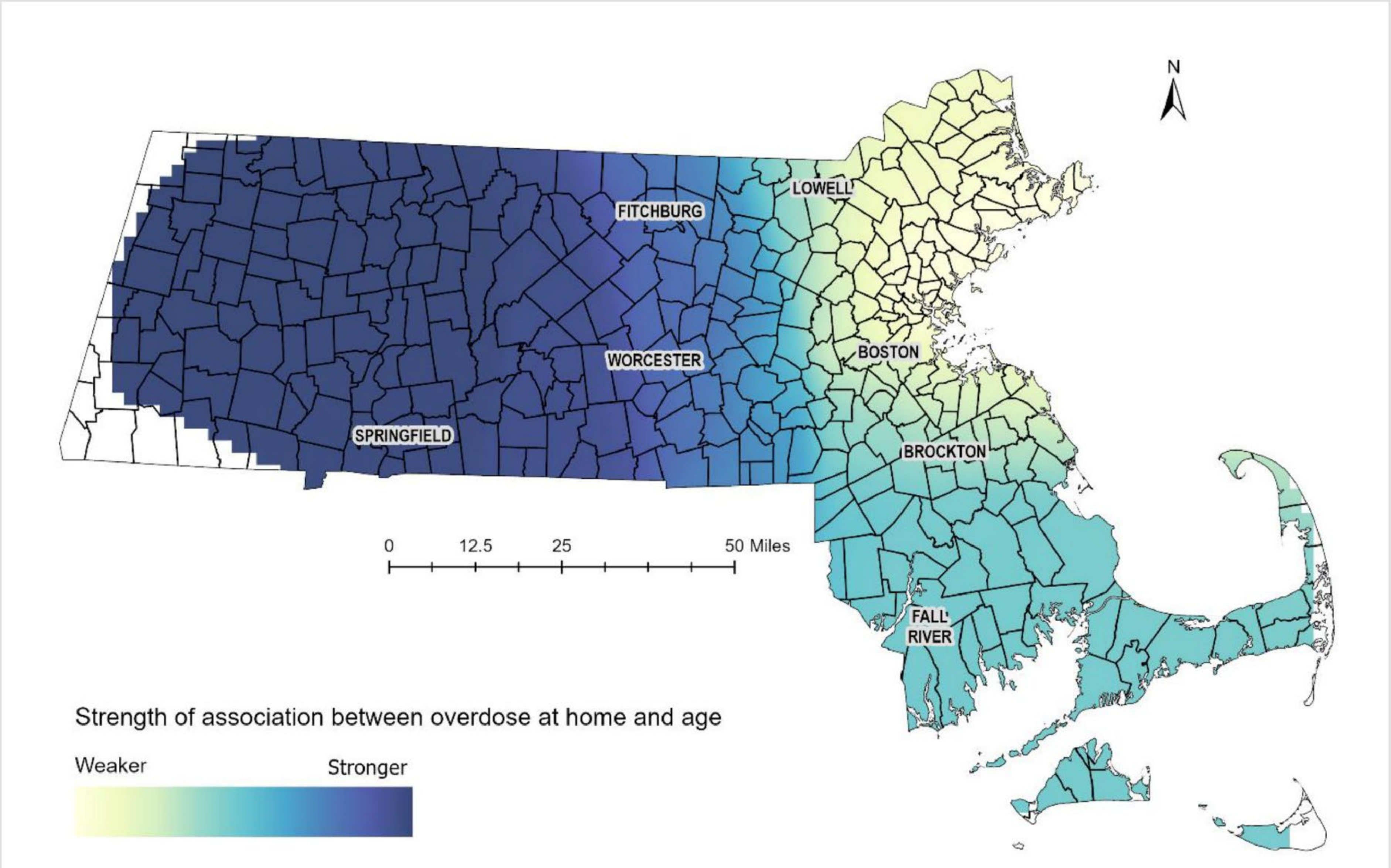
Pustz et al (2022). *Spatial & Spatiotemporal Epi*. PMID: 36460457

Geographically Weighted Regression: Opioid-related overdose, home, age

Older individuals were more likely to overdose in their own home in western and central MA than in eastern MA



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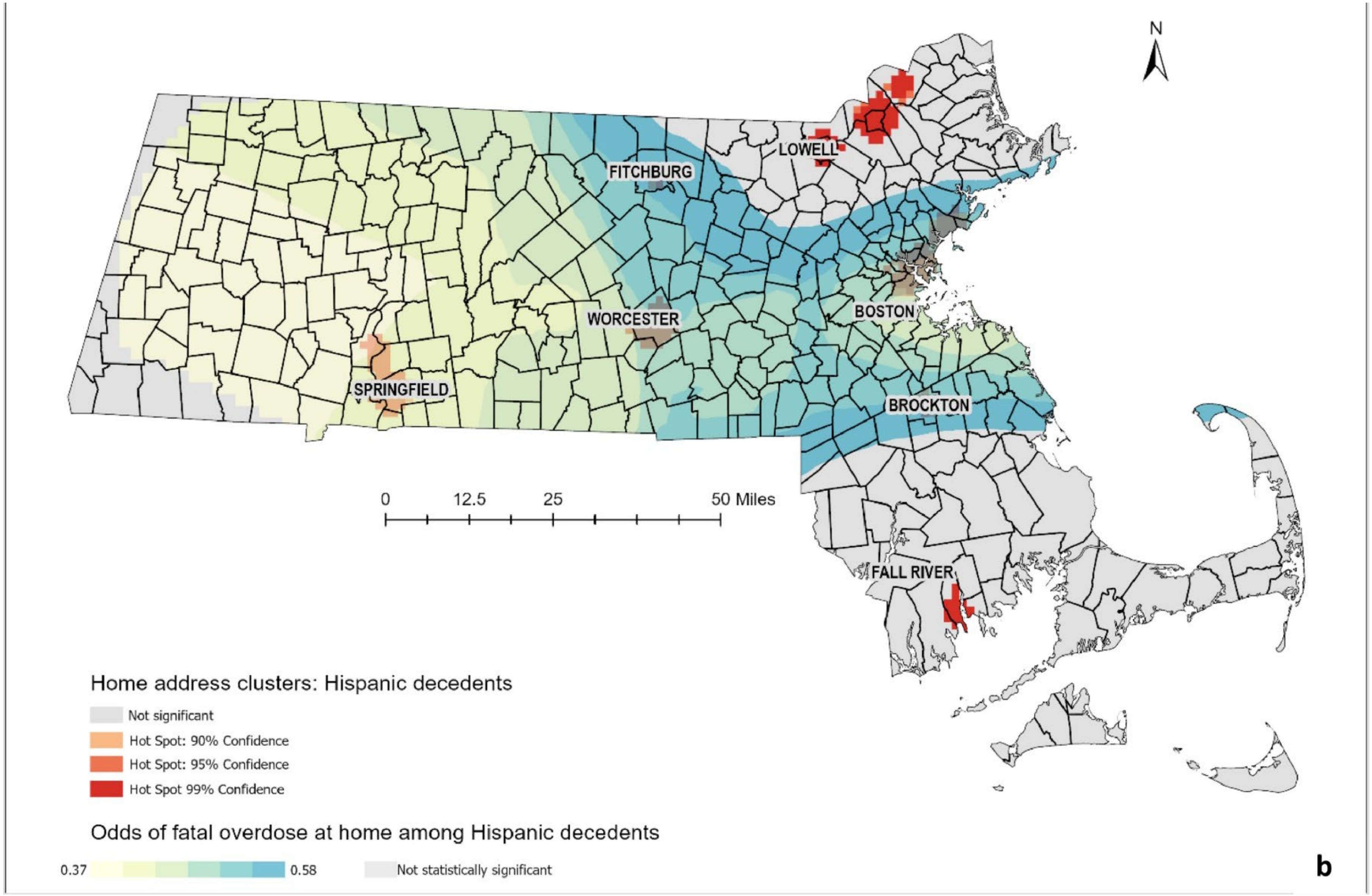
Pustz et al (2022). *Spatial & Spatiotemporal Epi*. PMID: 36460457

Hispanic decedents in Springfield were less likely to overdose at their home, compared to those who lived in Worcester and Boston



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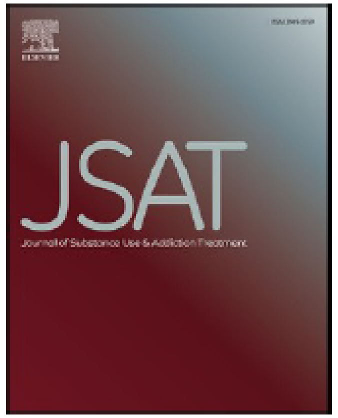
Pustz et al (2022). *Spatial & Spatiotemporal Epi*. PMID: 36460457

Buprenorphine Accessibility Index

Contents lists available at ScienceDirect

Journal of Substance Use and Addiction Treatment

journal homepage: www.journals.elsevier.com/journal-of-substance-use-and-addiction-treatment



Check for updates

Spatial access to buprenorphine-waivered prescribers in the HEALing communities study: Enhanced 2-step floating catchment area analyses in Massachusetts, Ohio, and Kentucky

Shikhar Shrestha [a], Megan R. Lindstrom [b], Daniel Harris [c,d], Peter Rock [e], Sumeeta Srinivasan [f], Jennifer C. Pustz [a], Ric Bayly [a], Thomas J. Stopka [a,g,h,i,*]

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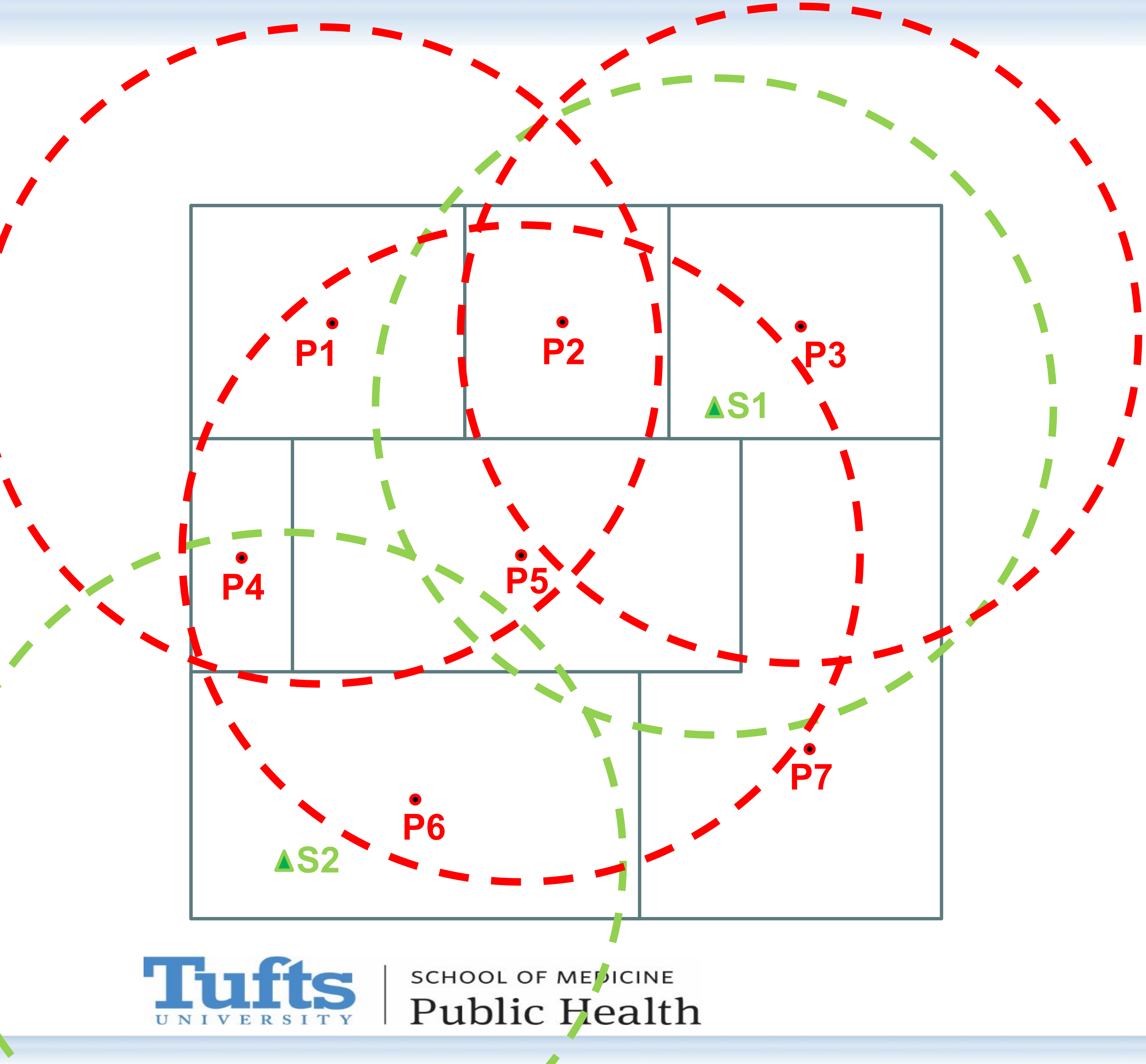

Administrative boundary
Population centroid (P_i)
Service provider(S_j)
Service catchment area
Population catchment area

$$Step\ 1{:}\ R_j = \frac{S_j}{\sum_{j \in d_{jk}} P_k}$$

$$Step\ 2{:}\ A_i = \sum_{j \in d_{ij}} R_j$$

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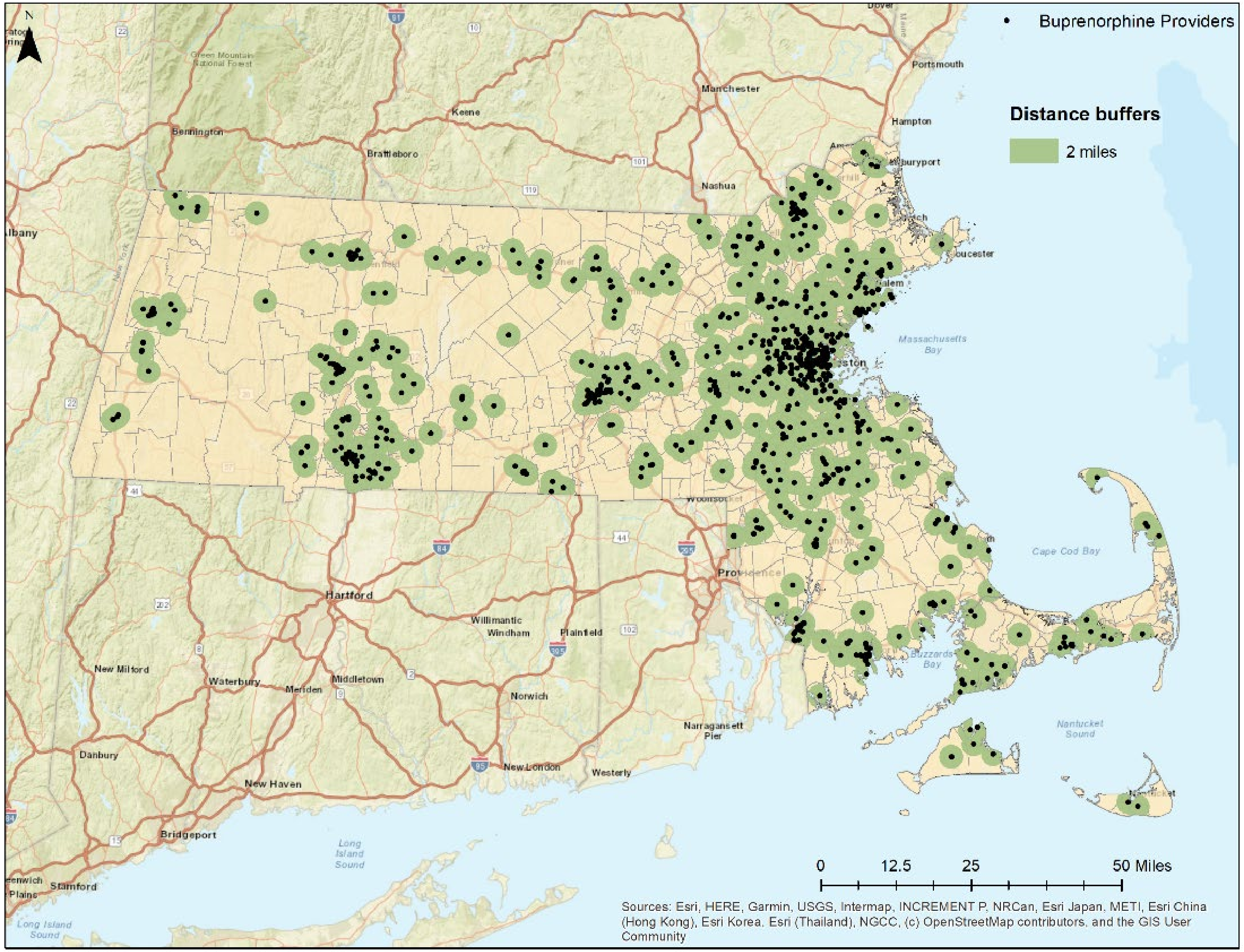
Shrestha et al., APHA. 2020.

Results: Access to Buprenorphine Providers



- Number of Buprenorphine providers ~ 2094
- Most providers located in Eastern Massachusetts
- A large rural areas underserved (Euclidean distance >5 miles)
- Floating catchment area analysis:
    - Relative accessibility lower in rural regions

Shrestha et al., APHA. 2020.

Predict to Prevent (P2P): Dynamic Spatiotemporal Analyses of Opioid Overdose to Guide Pre-Emptive Public Health Responses

MDPH BSAS Presentation
November 20, 2023

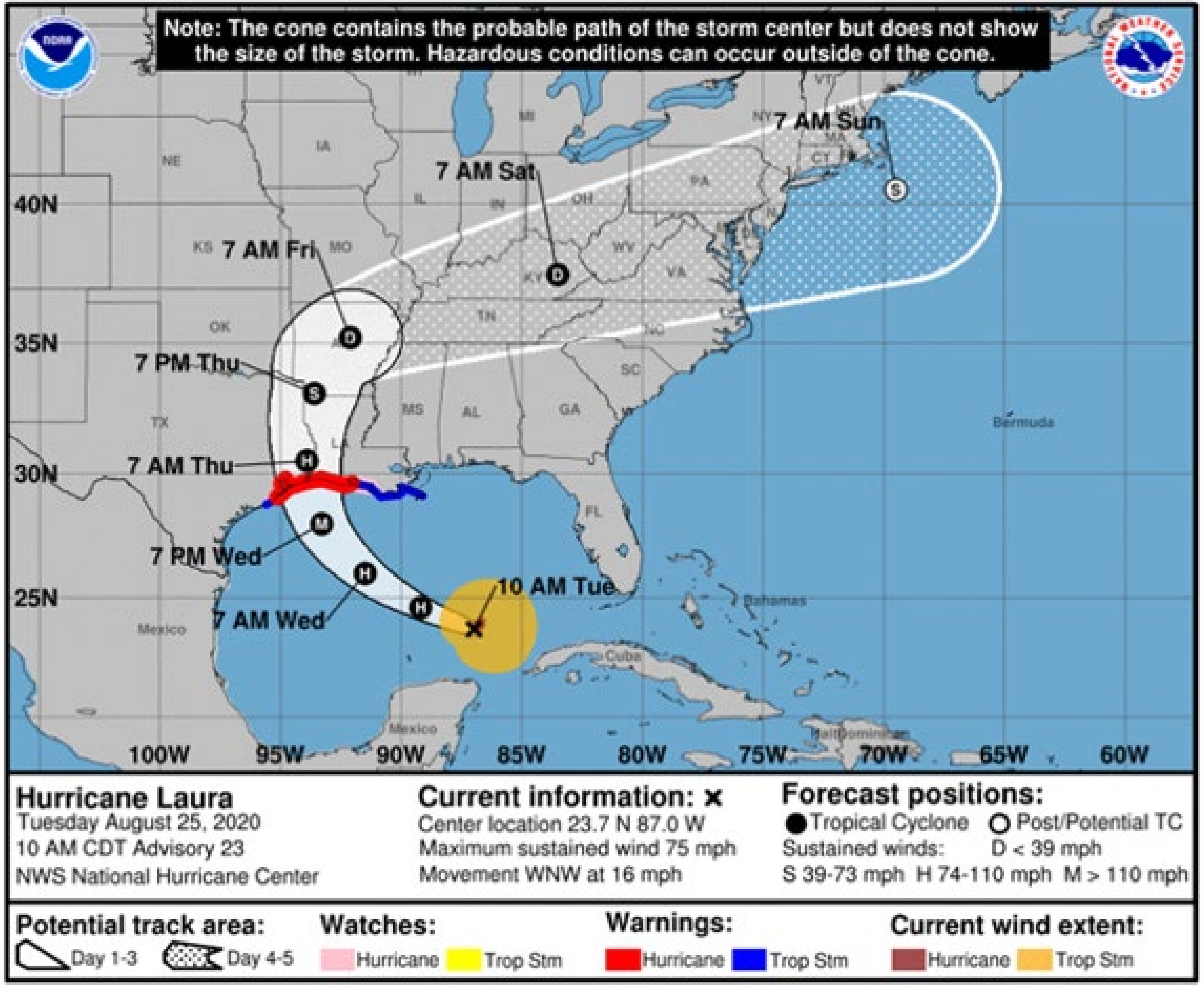
Thomas J. Stopka, PhD, MHS
Professor, P2P MPI
Dept. of Public Health and Community Medicine,
Tufts University School of Medicine

Cici Bauer, PhD
Associate Professor, P2P MPI
Univ. of Texas Health Science Center at Houston

Matilde Castiel, MD
P2P CAB Chair
Worcester Dept. of Health and Human Services

P2P Study: NIDA; R01-DA054267

Predicting the Future
(e.g., Hurricanes)



https://www.nhc.noaa.gov/aboutcone.shtml

P2P Multi-Principal Investigators

Thomas Stopka, PhD, MHS
Tufts University School of Medicine

Cici Bauer, PhD
The University of Texas
Health Science Center at Houston

Tufts University | SCHOOL OF MEDICINE Public Health

UTHealth
The University of Texas
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Dana Bernson
MPH
MDPH

Wenjun Li
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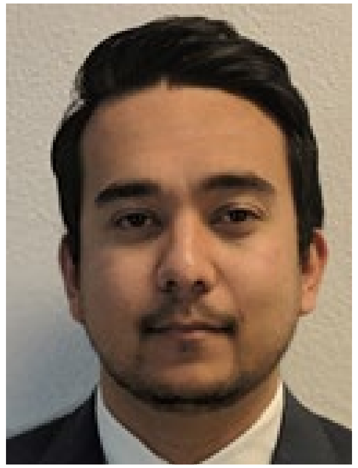
Leland Ackerson
PhD
UMass Lowell



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Ghada Hassan PhD
UTHealth

Ric Bayly MS MPH
Tufts Med. ***(Researcher)***

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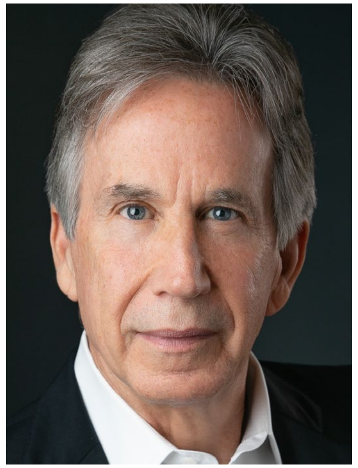
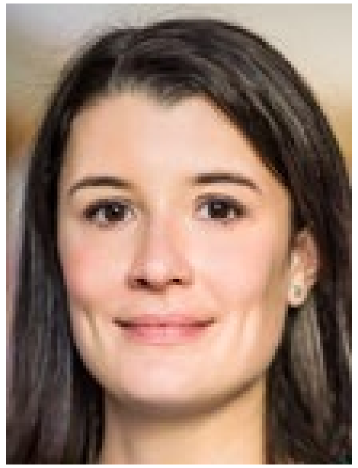
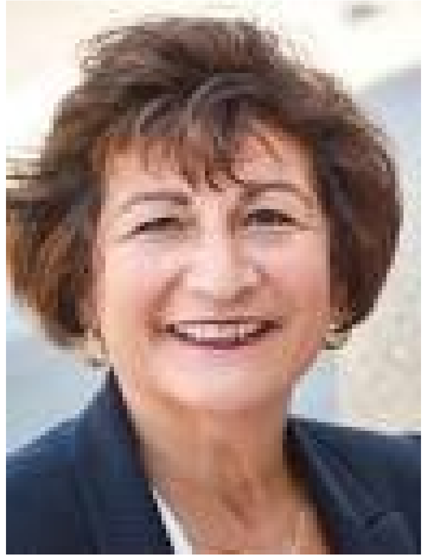
P2P Community Advisory Board


Sai Cherala
MDPH


Dr. James Baker
Consultant


Dana Bernson
MDPH

Chair


Dr. Matilde Castiel
Worcester Health and Human Services


Stephanie Sloan
New Bedford Public Health


Liz Whynott
Tapestry


Claire Hoffman
MAPC


Debra McLaughlin
Opioid Task Force


Jennifer Tracey
Boston Office of Recovery Services


Michelle Smith
AIDS Project Worcester


Maricia Verma
Lowell Community Opioid Outreach


Dr. Cedric Woods
Institute for N.E. Native American Studies

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P2P Study: NIDA; R01-DA054267

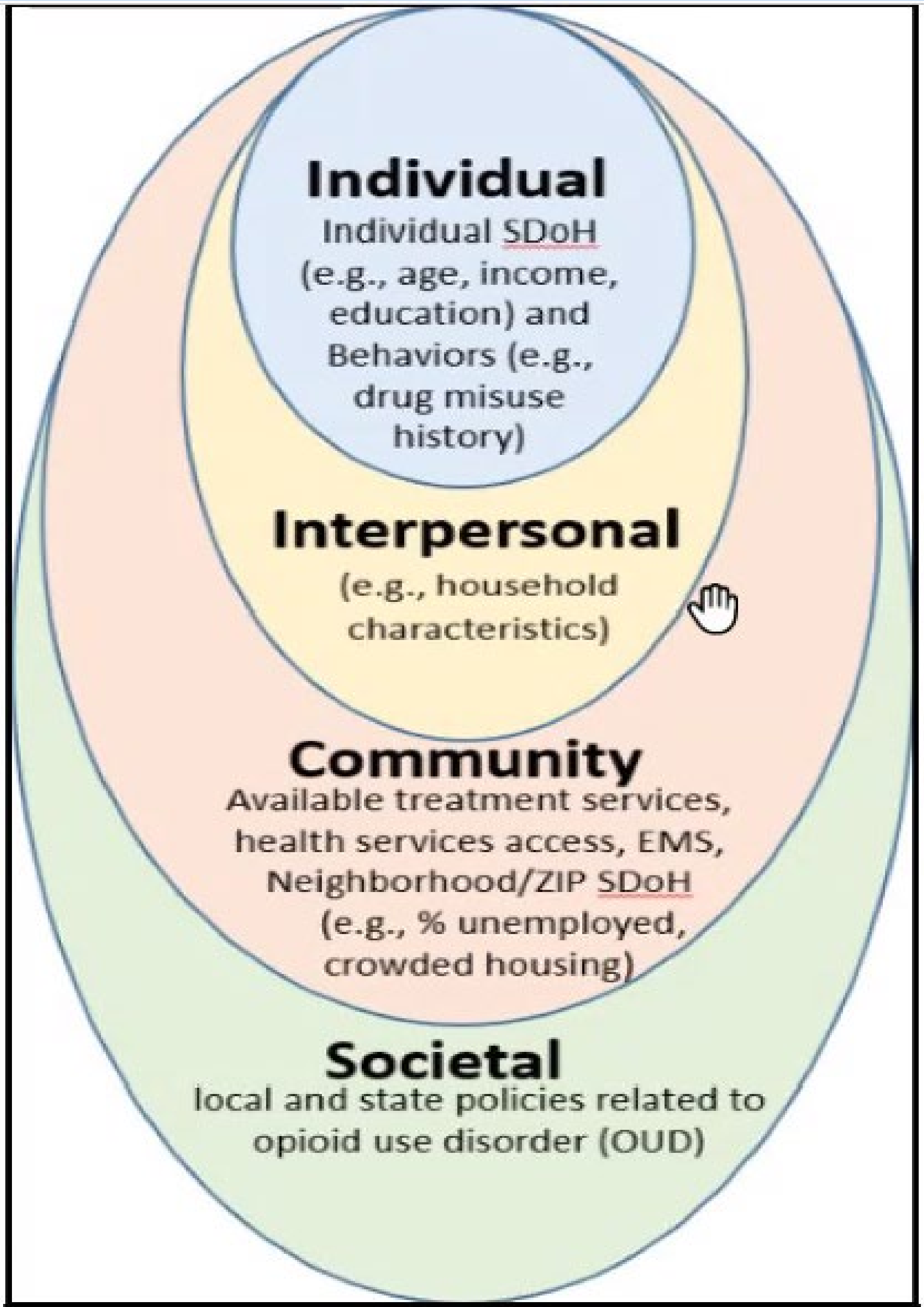
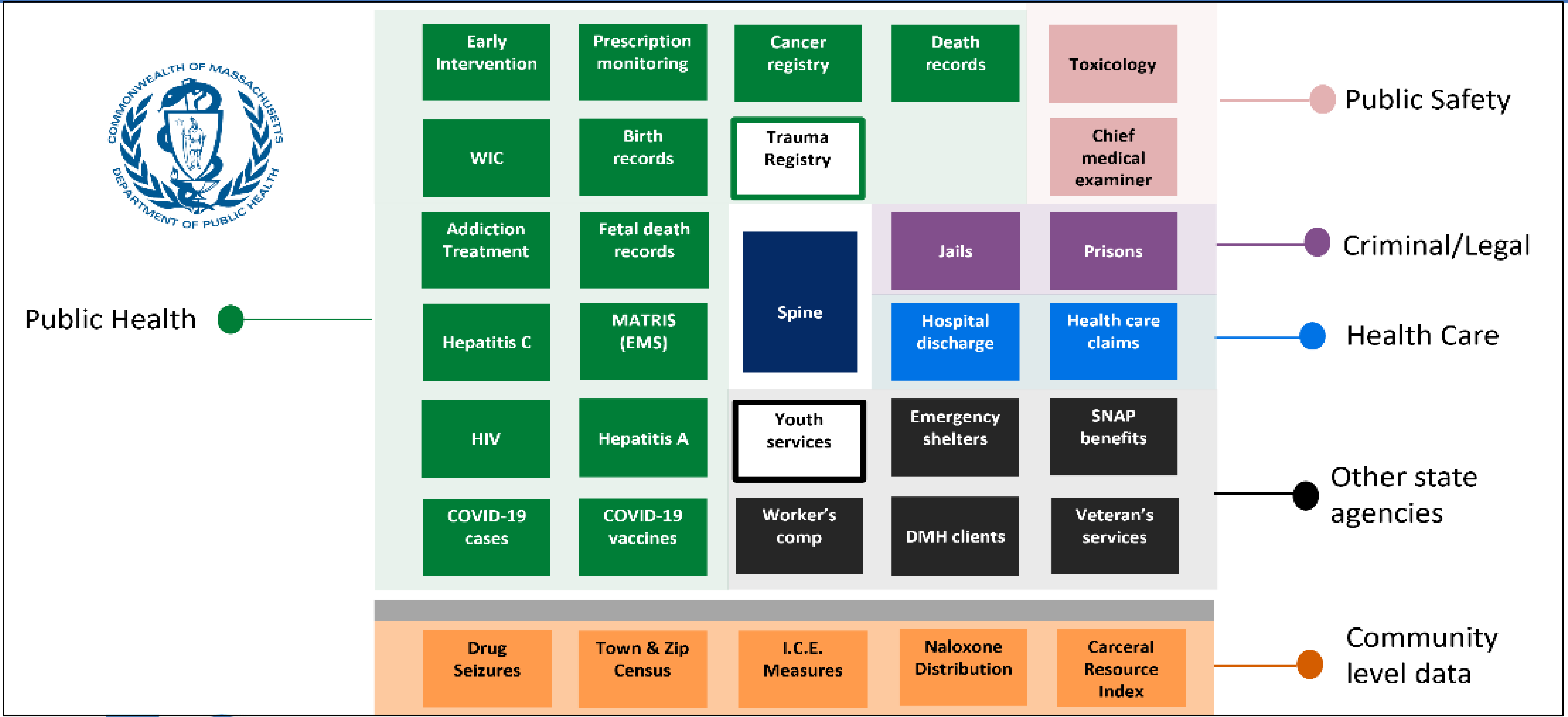


Figure 3: Social Ecological Model (SEM) with illustrative measures from the PHD.

Public Health Data Warehouse (PHD) 2.0



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Bayesian Spatiotemporal Modeling

- Combining prior distribution & likelihood function to calculate posterior distribution
- Including time and geographic areas to provide additional information/effect of surrounding areas and contiguous times
- Bayesian Spatiotemporal models incorporate
  - Spatial random effects to **model spatial autocorrelation**
  - **Time effects** to model dependent structure of the data
  - **Time varying covariates** to model uncertainty tied to unmeasured confounders
  - And **space-time interaction effects** to model residual spatiotemporal variation

Predict to Prevent Opioid Overdose

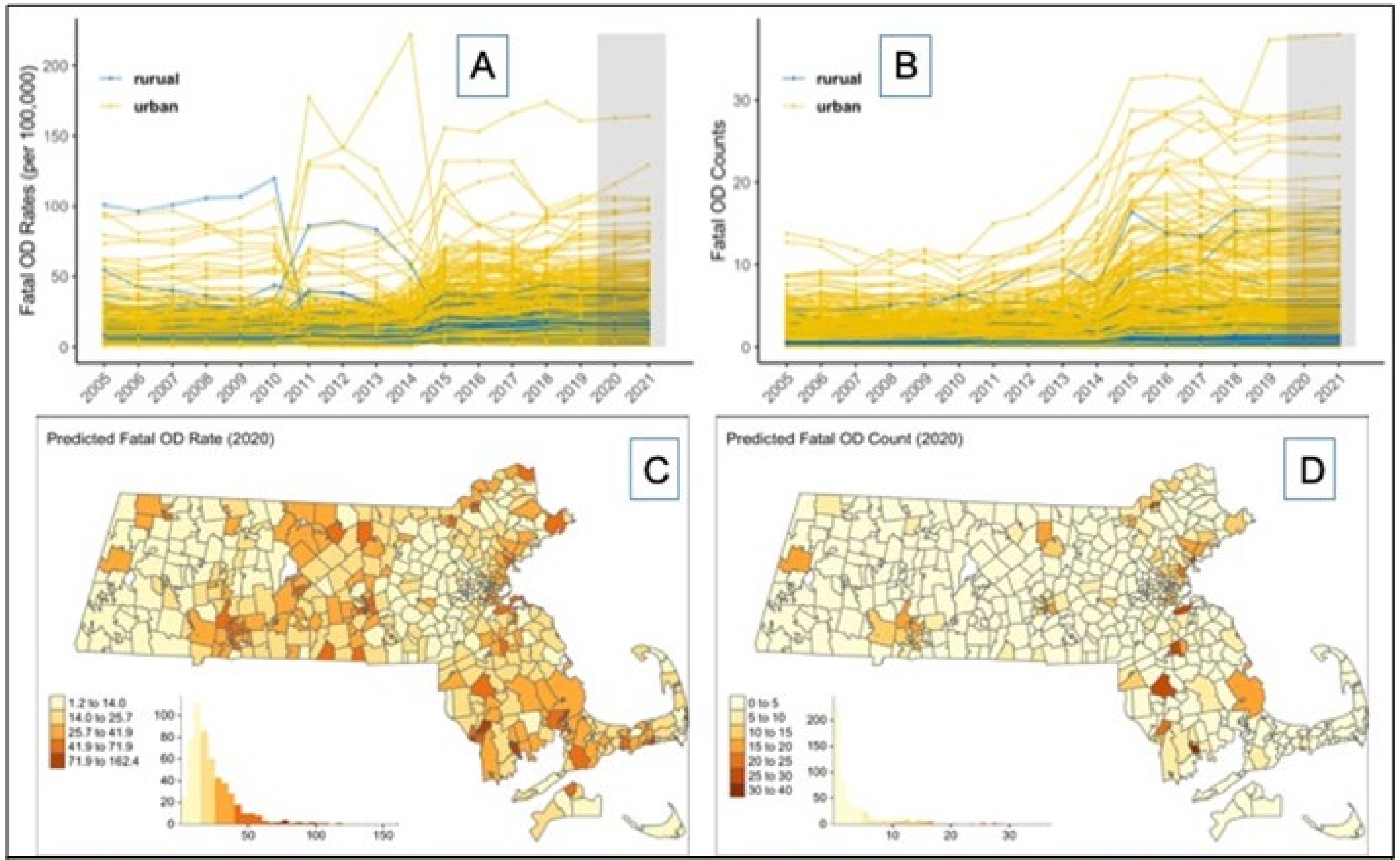

Figure 2: Temporal trends and maps of predicted fatal OD rates (per 100,000 population) and counts for 2020 and 2021 (in grey shade). Each line represents one ZCTA in panels (A) and (B), color coded by their rural/urban status. Data were obtained from the MA Registry for Vital Records and Statistics for 2005 to 2019 and used to predict ODs for 2020 and 2021 with Bayesian spatiotemporal models.

Bauer et al., *JMIR Surveillance & Public Health*. 2022. PMID: 36763450

Drug and Alcohol Dependence 246 (2023) 109836

Contents lists available at ScienceDirect

Drug and Alcohol Dependence

journal homepage: www.elsevier.com/locate/drugalcdep

Opioid-related mortality: Dynamic temporal and spatial trends by drug type and demographic subpopulations, Massachusetts, 2005–2021

Thomas J. Stopka [a,*], Marc R. Larochelle [b], Xiaona Li [c], Dana Bernson [d], Wenjun Li [e], Leland K. Ackerson [e], Ric Bayly [a], Olaf Dammann [a,f], Cici Bauer [c]

[a] Department of Public Health and Community Medicine, Tufts University School of Medicine, Boston, MA, United States
[b] Clinical Addiction Research and Education Unit, Section of General Internal Medicine, Department of Medicine, Boston University School of Medicine and Boston Medical Center, United States
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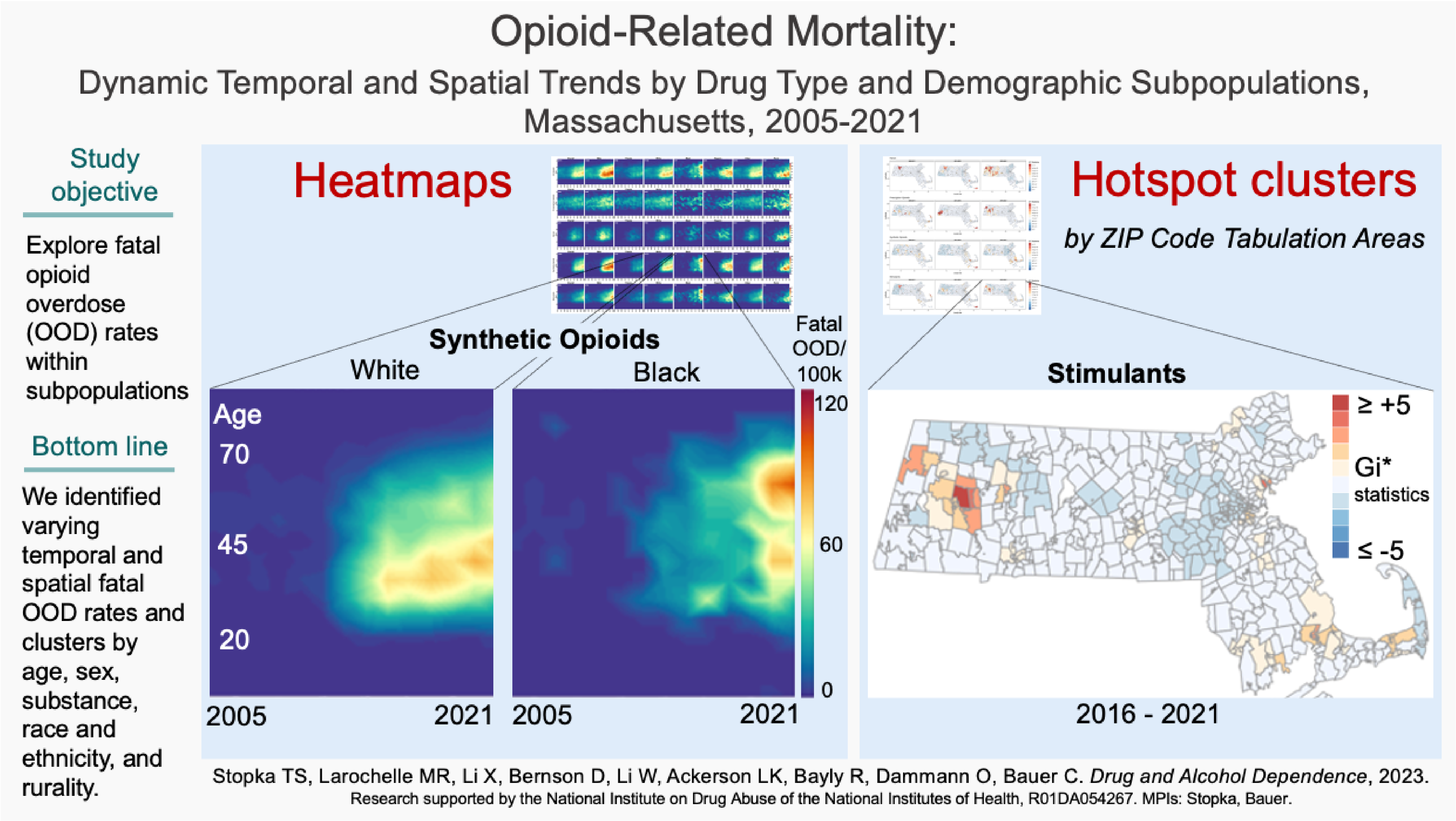
[d] Office of Population Health, Department of Public Health, Commonwealth of Massachusetts, Boston, MA, United States
[e] Center for Health Statistics and Department of Public Health, University of Massachusetts Lowell, Lowell, MA, United States
[f] Department of Gynecology and Obstetrics, Hannover Medical School, Hannover, Germany

Uncovering new time varying and spatiotemporal patterns in fatal overdose rates not previously reported…



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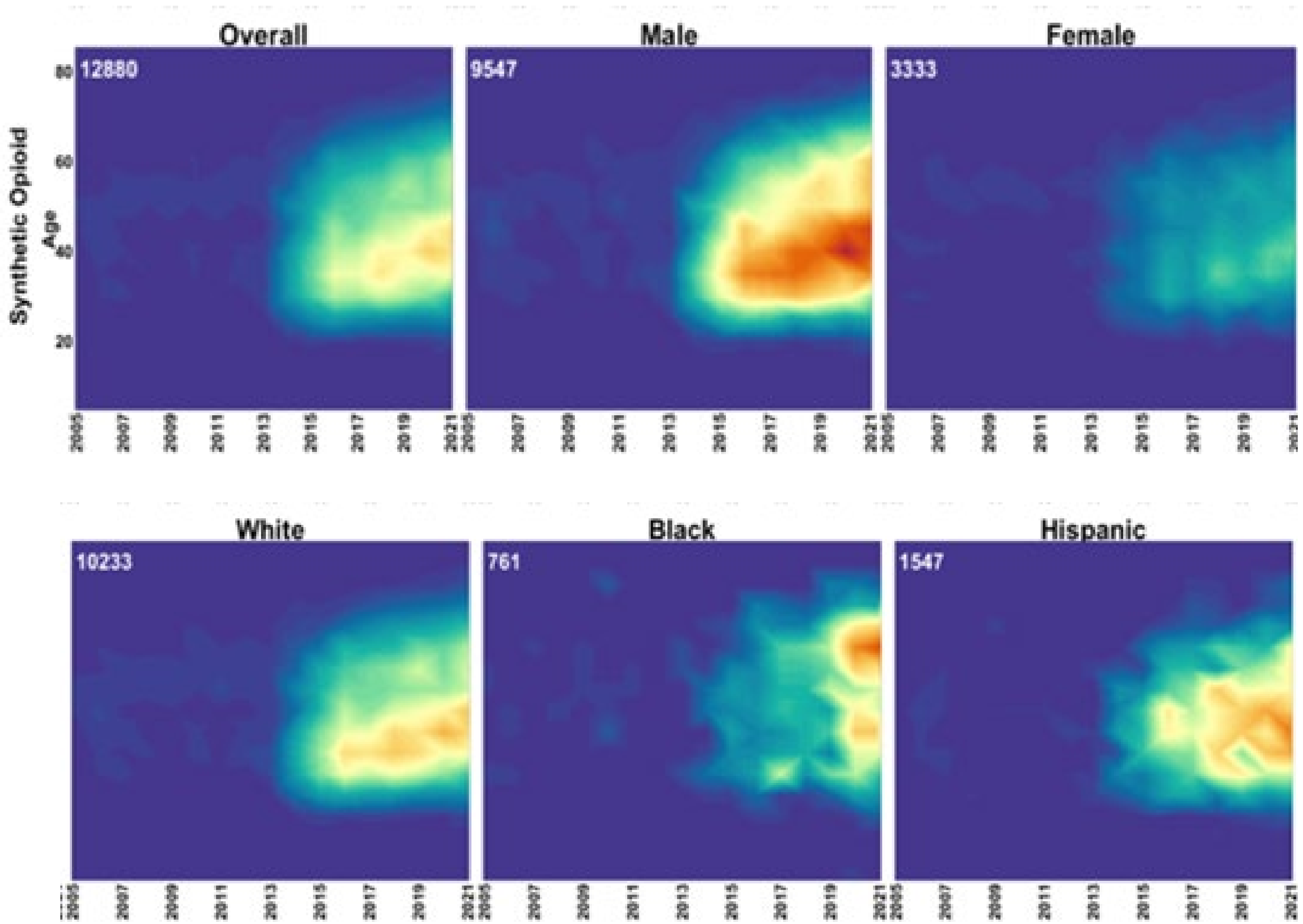
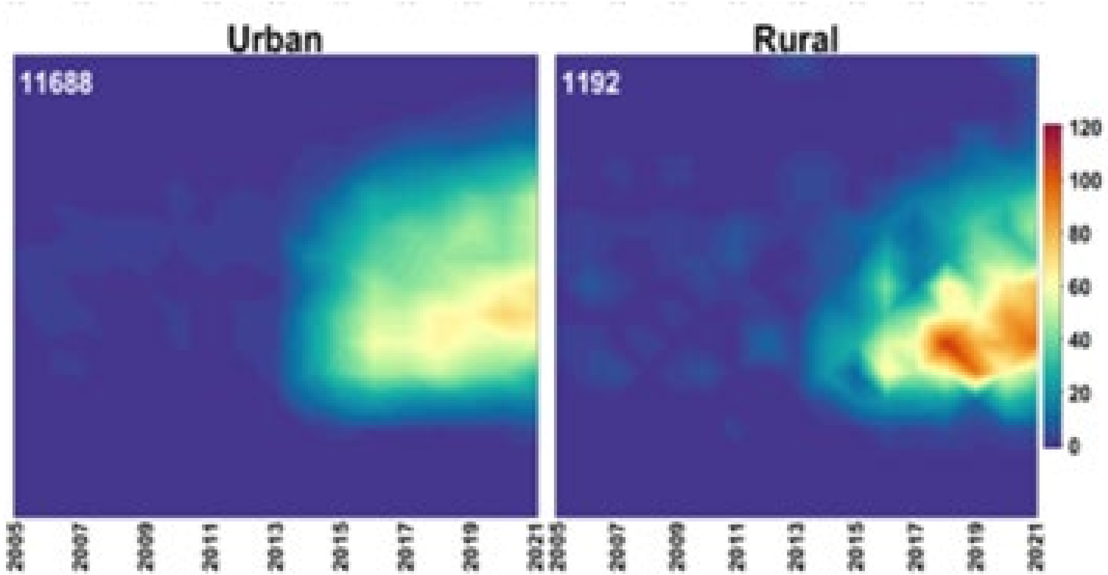
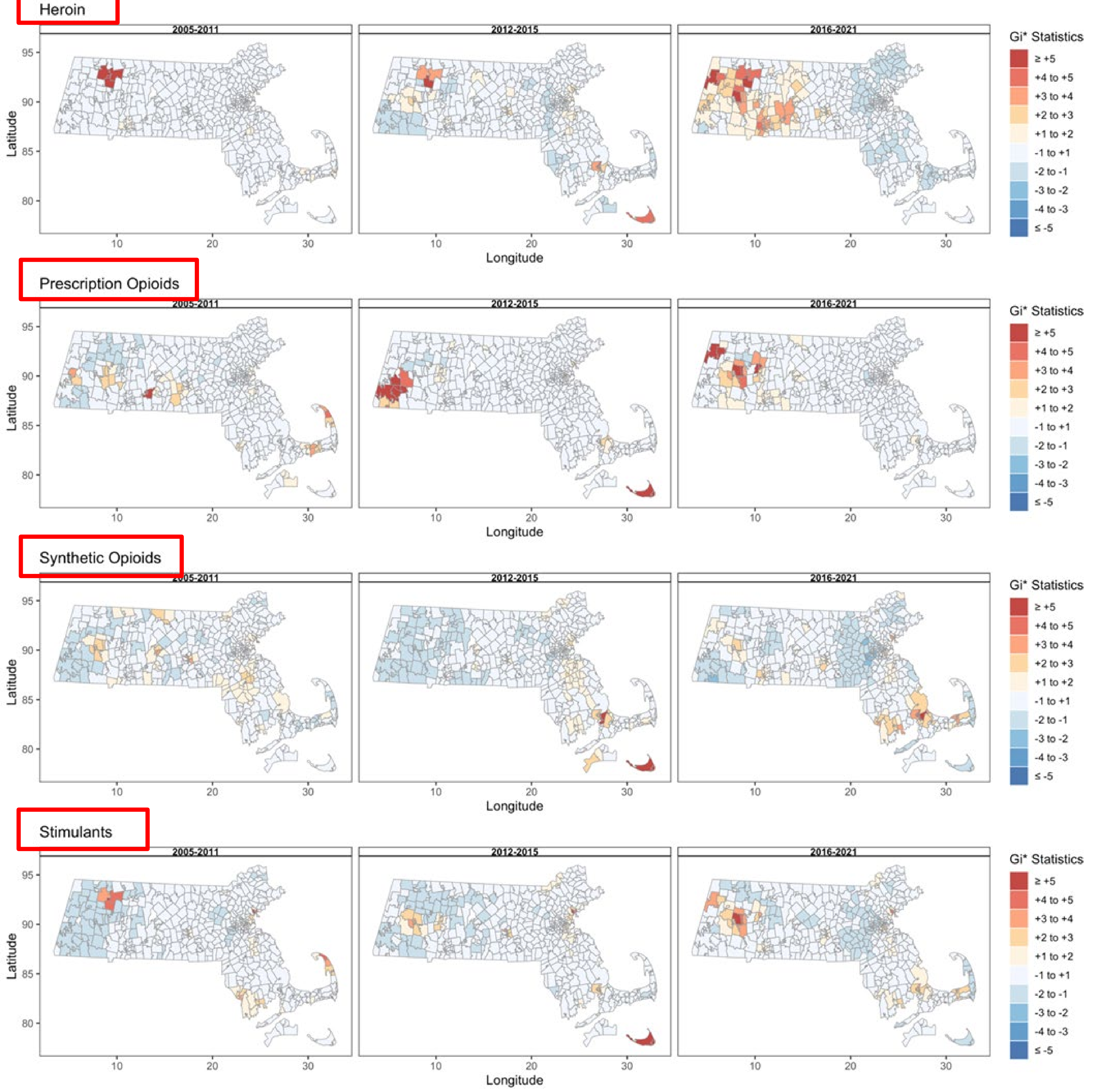
Stopka et al., *Drug Alcohol Dependence*. 2023. PMID: 36931131

Opioid-related fatal overdoses: Fentanyl





Stopka et al. 2023. *DAD*. PMID: 36931131

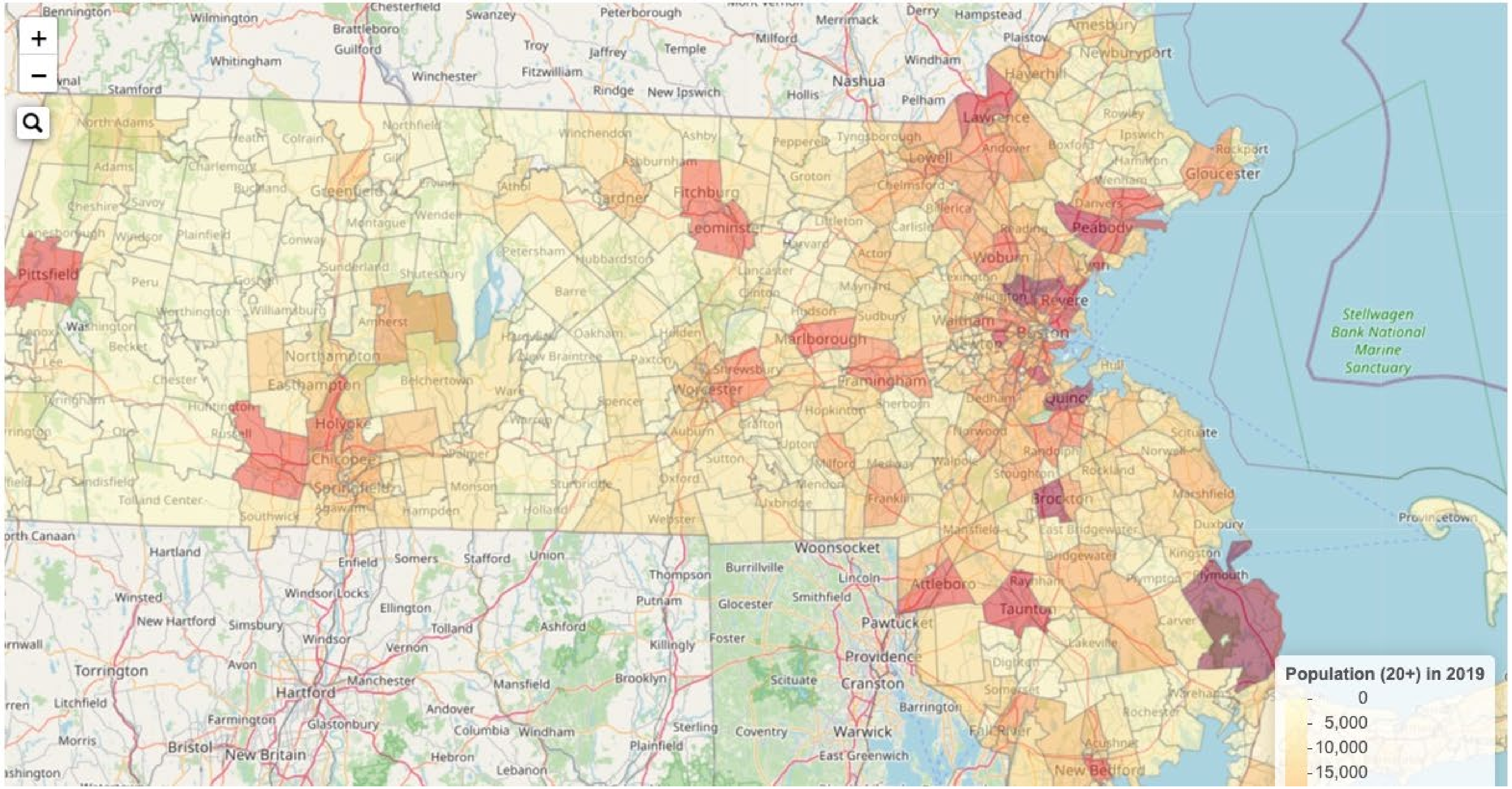


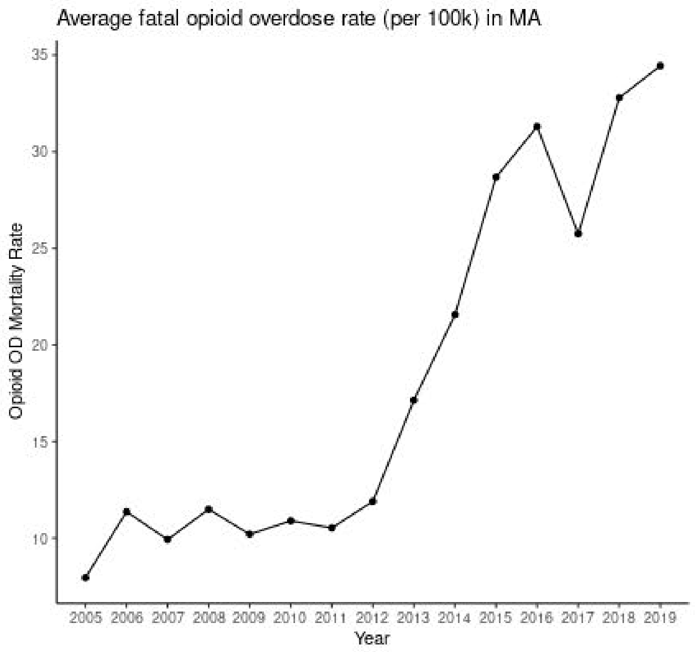
Stopka et al. 2023. *DAD*.
PMID: 36931131

Data-to-Action-to-Prevention

Interactive map with search bar

The interactive map has a search bar on the top left. The map can zoom in to a ZCTA by entering a 5-digit zip code number, and the popup information includes total population, population aged 20 and greater, and death rate (in quintiles Q1- Q5, with Q5 the highest) in year 2010, 2015 and 2019. The plot on the right side compares the state average death rate and the selected zip code death rate by year.





ZCTA level fatal opioid overdose rate in Massachusetts

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Recap

- Spatial epidemiology, geospatial data, and disease prevention
- Applications of spatial epidemiology in prevention
  - Identifying and characterizing the risk landscape and hotspots
  - Assessing access to services and resource allocation
  - Assessing social determinants of health
  - Monitoring interventions and change
  - Conducting predictive analytics and simulation modeling
- Focus on 3 NIDA-funded studies

Spatial Epidemiology & Public Health Impact

Can spatially oriented data inform disease prevention?

The facts are coming! The facts are coming!

Prevention Impact

- Spatial epidemiology and spatial data to inform prevention?
- Can inform and monitoring prevention interventions by…
  - Guiding public health, community, academic partnerships
  - Targeting locations for new health services
  - Informing local communities & policymakers
  - Using spatial analysis tools for surveillance
    - Health service access (disease prev./care, treatment centers)
    - Assess risky behavior, disease spread across populations
    - Assess spatial relationships for health outcomes
    - Model risk for future outbreaks

Thank you!

Questions?

Thomas J. Stopka, PhD, MHS

thomas.stopka@tufts.edu

Prevention Research

Lance Waller, Ph.D.

Professor, Emory University

Small Area Estimation Opioid Abuse Prevention and Response

Tom Stopka, Ph.D., MHS

Professor, Tufts University School of Medicine

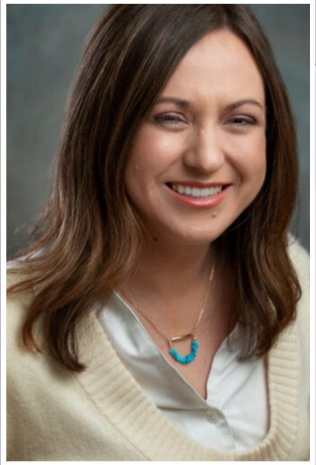
Spatial Epidemiology and Geospatial Data Science in Opioid-Related Research

Courte Van Voorhees, Ph.D.

Moderator

Program Official, Prevention Research Branch, DESPR, NIDA

Treatment and Services Research



Marynia Kolak, MS, MFA, Ph.D.

Assistant Professor, University of Illinois Urbana-Champaign

Measuring the Spatial Availability of Medications for Opioid Use Disorder

Devin Banks, Ph.D.

Assistant Professor, Washington University in St. Louis

Integrating Community Engagement and Geospatial Methods to Address Racial Inequities: Benefits and Barriers

Tamara Haegerich, Ph.D.

Moderator

Program Official, Services Research Branch, DESPR NIDA

Measuring the Spatial Availability of Medications for Opioid Use Disorder

M. Kolak, PhD, University of Illinois at Urbana-Champaign
NIH Workshop on Innovative Applications of Geospatial Data Science in Drug Use Research

Study Co-Authors:
Wataru Morioka, PhD & Qinyun Lin, PhD

Healthy Regions + Policies Lab

What medications are available for OUD?

Methadone

Full agonist.

Buprenorphine

Partial agonist.

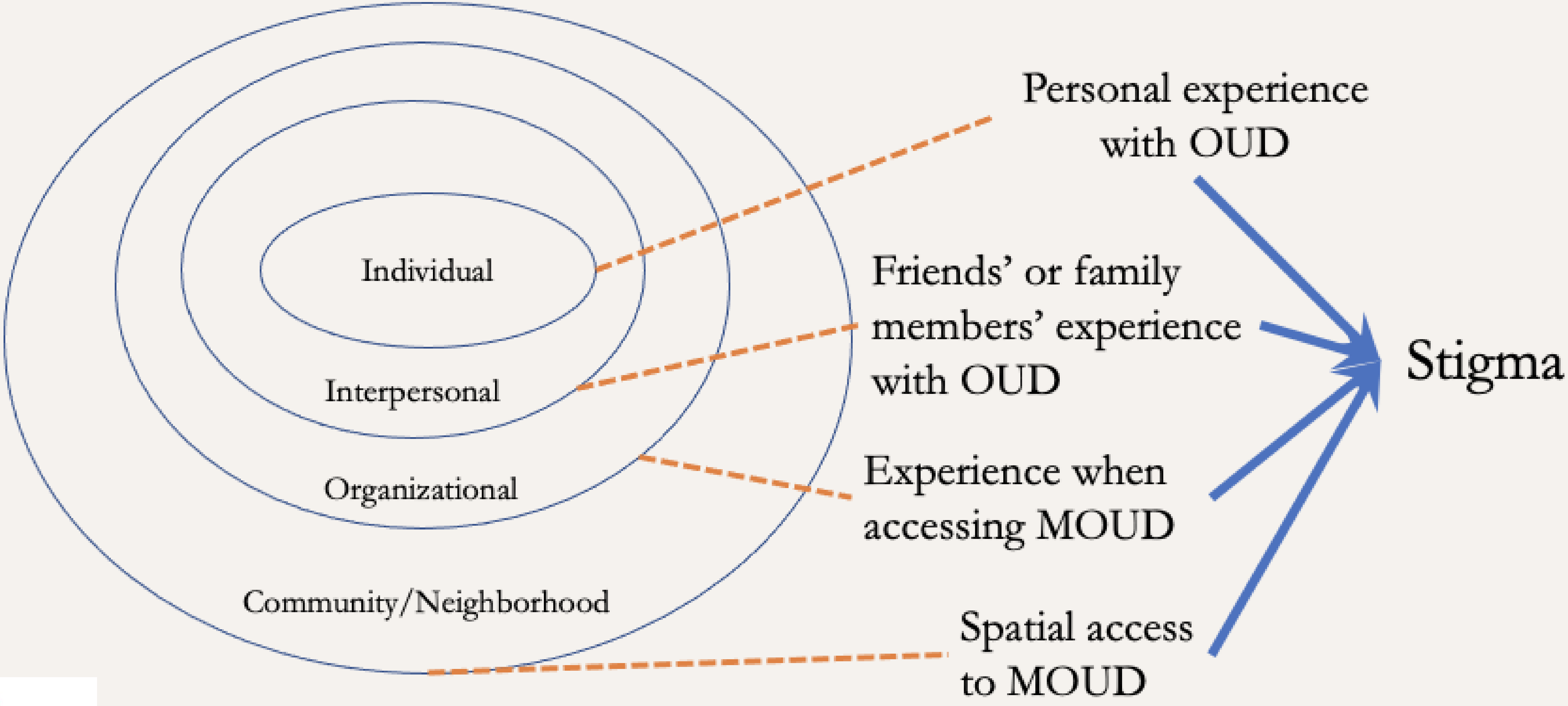
Naltrexone

Antagonist.

Barriers to MOUD

- **Regulatory:** policy, how medication is prescribed & dispensed
- **Logistical:** access to reliable transit at all stages of seeking MOUD
- **Geographic:** spatial availability of medication of choice/preference
- **Financial:** cost of medication, insurance, economic opportunity
- **Attitudinal:** individual, interpersonal, & organizational-level stigma

OUD Stigma is Associated with MOUD Access



NIH HEAL INITIATIVE
JUSTICE COMMUNITY OPIOID INNOVATION NETWORK (JCOIN)

While multiple barriers to accessing MOUD are well documented, ***measurement*** of spatial access are not well understood.

What are best practices in
measuring access to MOUD?

Factors Influencing Spatial Access

Spatial Resolution
Tract, ZCTA, County

Temporal Resolution
year, historical

Distance Measure
Euclidean, Network (walk, bike, transit, drive)

Access Measure
Count, Nearest, Density, Gravity

Boundary Conditions
Across borders, Within borders

Degree of Urbanicity
Urban, Suburban, Rural

Study Objective

Calculate and compare neighborhood-level associations of spatial availability metrics, and contextualize within additional dimensions of access at a community scale:

- Across **various access metrics:** distance-based metrics using various **transit modes,** as well as gravity supply and demand models that account for population & congestion
- Across rurality, type of neighborhood characterized by **SDOH characteristics**, and racial/ethnic characteristics to identify gaps and trends in spatial access
- In order to identify a meaningful & consistent measure with **sufficient variability** for further analyses

When aggregating up to the county level to link drug-poisoning mortality metrics, where are locations that have the greatest mismatch in need and resource availability?

Methods

Defining Resources & Need, + Plan for Analyses

Study Population and Spatial Scale

This research included all the **populated areas** counted in the census across the continental United States, covering about 322 million people according to the 2019 census (ACS 2019).

The US Census Bureau refers to these areas as small, consistent sections with fixed borders. We focused only on the continental states to keep the neighboring areas connected, ignoring state borders.

MOUD Resources

Methadone

SAMSHA directory.

= Methadone Maintenance (disclude 'short-term)

May not be accepting more patients

May have varying cost associated, Tend to take cash.

Buprenorphine

SAMSHA directory.

DATA 2000 Waivered Physician Directory.

Many in directory don't prescribe; address may be incorrect.

Naltrexone

SAMSHA + Vivitrol web scraping

Still may underestimate total prescribers.

Billing Claims, EHR data may be more precise.

What are ways to access MOUDs?

Driving

Travel Time Matrix
developed using
Open Street Map
road network,
street limits, and
impedance factor for
Urban locations (x2)

Approximated with %
households with
no vehicle

Biking

Travel Time Matrix
developed using
Open Street Map
bike network

Public Transit

Approximated with %
commuters using
public transit

Walking

Travel Time Matrix
developed using
Open Street Map
pedestrian network

Approximated with %
commuters using
public transit

Access Metrics Calculated

Supply-Only Models

- **Minimum Distance** from tract centroid to nearest resource, in miles
  - Euclidean Distance
- **Travel Time** from tract centroid origin, to tract centroid destination (nearest resource), in minutes
  - Walking
  - Biking
  - Driving
- **Count of Resources** within 30-minutes driving time

Access Metrics Calculated

Supply & Demand Models

- **Floating Catchment Area** measures the ratio of providers to clients within a travel time
- **Two-Step Floating Catchment Areas (2SFCA)** extends FCA by calculating catchment areas for both the medication providers and the population
- **Enhanced 2SFCA (E2SFCA)** extends E2SFCA by assigning weights to various travel time zones, thereby accounting for the distance decay function
- **Rational Agent Access Model (RAAM)** aims to equalize congestion and minimize costs, where an individual's expense for accessing services depends on both congestion levels and travel time

Computational Framework

- Pre-computed travel time matrices enabled quick calculations of supply-only models across the country for all tracts, quickly, using R or Python.

- Spatial accessibility was calculated using the "pysal" library in Python. Due to the large volume of data, a **high-performance computing** environment was necessary.
  - Supply-demand models for spatial accessibility were executed on the Keeling computer cluster at the University of Illinois.
  - The Keeling node features 24 compute threads and 192 GB of memory, runs on Scientific Linux 6.3, and provides Python access.
  - Running the Rational Agent Access Model with a 90-minute threshold took approximately **5 hours** in this high-performance environment.

Defining Need: Rurality

Places with differing **rurality type** will have differing travel behaviors, characteristics, and expectations. Rural-Urban Continuum Area (RUCA) codes capture commuting behaviors and segment areas accordingly.

- **Urban Areas**
- **Suburban Areas**
- **Rural Areas**

RUCA Code	Description	Category	Count	Pop. Median	Pop. Density	Pop. Density 1Q	Pop. Density Median	Pop. Density 3Q	Pop. Density Avg.
1	Metro	Urban	50,727	4,086	1,140	1,637	3,610	6,901	7,196
1.1	Metro: Secondary flow to larger UA	Urban	896	4,461	833	795	2,219	4,025	2,819
2	Metro High Commuting	Suburban	6,669	4,133	51	46	96	202	373
2.1	Secondary flow to larger UA	Suburban	110	3,893	87	69	120	206	198
3	Metro Low Commuting	Rural	653	3,838	39	30	54	107	145
4	Micro	Suburban	3,877	4,095	137	269	748	1,876	1,389
4.1	Secondary flow to a UA	Suburban	291	4,756	208	277	591	1,645	1,144
5	Micro High Commuting	Rural	1,907	3,749	23	21	43	78	81
5.1	Secondary flow to a UA	Rural	46	4,197	53	35	55	94	69
6	Micro Low Commuting	Rural	408	3,810	30	25	43	72	63
7	Small town core	Rural	1,926	4,088	48	77	203	534	440
7.1	Secondary flow to a UA	Rural	156	4,288	56	79	201	405	387
7.2	Secondary flow to a large UC	Rural	55	3,483	26	51	157	376	351
8	Small town high commuting	Rural	792	3,138	12	12	24	45	37
8.1	Secondary flow to a UA	Rural	18	3,096	14	7	33	41	48
8.2	Secondary flow to a large UC	Rural	10	3,024	20	34	269	1,059	834
9	Small town low commuting	Rural	343	3,442	24	19	34	53	43
10	Rural	Rural	3,022	2,772	9	6	19	48	67
10.1	Secondary flow to a UA	Rural	105	3,213	8	5	24	65	61
10.2	Secondary flow to a large UC	Rural	110	2,788	5	4	14	40	39
10.3	Secondary flow to a small UC	Rural	90	2,706	6	4	12	41	37

Figure 1. RUCA Code distribution of Census tracts by Urban, Suburban, Rural classifications

Rural, Suburban, Urban Classification for Small Area Analysis. September 2021. DOI:10.13140/RG.2.2.25148.16009

Defining Need: SDOH Area Clusters

Social Determinants of Health (SDOH) drive health outcomes, and exist as intersecting community context at various scales.

Using a Spatial & Social Science Data-Driven Approach, we identified distinct indices & 7 clusters characterizing SDOH, moving beyond SES measures alone.

(b) US Typology (↑, ↓: magnitude < 1, ⇑, ⇓: magnitude > 1)

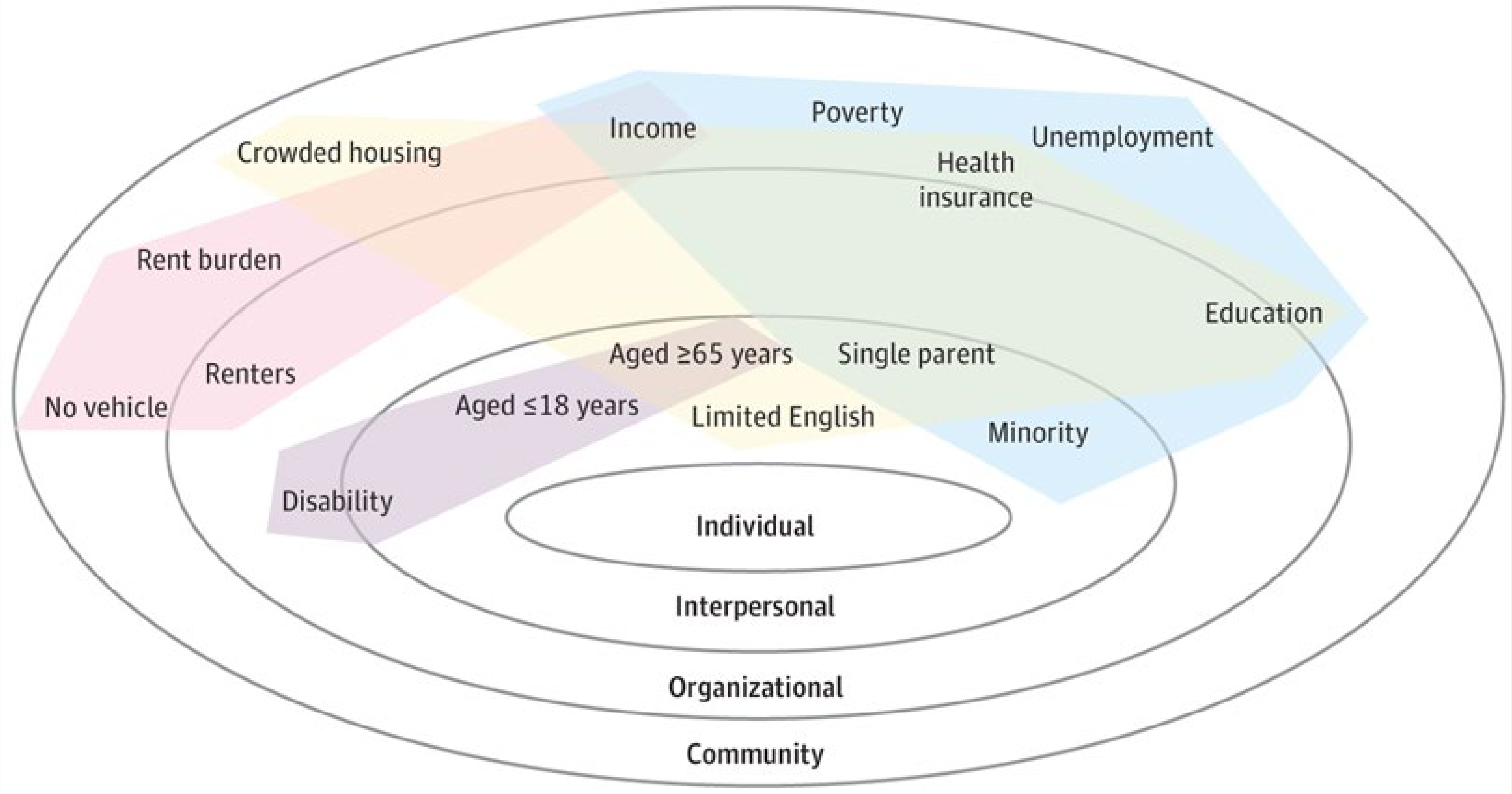
	Rural Affordable	Vibrant Urban Core	Suburban Affordable	Extreme Poverty	Multilingual Working	Suburban Affluent	Sparse Area
PC1 **Socioeconomic Advantage**	↑	↓	↑	⇓	⇓	⇑	⇑
PC2 **Mobility-Related Isolation**	↓	↓	⇑	⇓	⇑	↑	⇓
PC3 **Urban Opportunity**	↓	⇑	↓	↓	↑	↑	↑
PC4 **Mixed Cohesion & Accessibility**	↓	↑	↑	⇑	⇓	↑	⇓

Kolak M, Bhatt J, Park YH, Padrón NA, Molefe A. Quantification of Neighborhood-Level Social Determinants of Health in the Continental United States. JAMA Netw Open. 2020;3(1):e1919928. doi:10.1001/jamanetworkopen.2019.19928

Defining Need: SDOH Area Clusters

SDOH were mapped onto different spheres of the socioecological model of health adapted from Bronfenbrenner. Indices persisted across different intersections & layers.

<u>Blue</u> = socioeconomic advantage
<u>Purple</u> = limited mobility,
<u>Red</u> = urban core opportunity
<u>Yellow</u> = mixed immigrant cohesion and accessibility.



Kolak M, Bhatt J, Park YH, Padrón NA, Molefe A. Quantification of Neighborhood-Level Social Determinants of Health in the Continental United States. JAMA Netw Open. 2020;3(1):e1919928. doi:10.1001/jamanetworkopen.2019.19928

Correlation Analyses & Summary Statistics

- We created correlation matrices using **Spearman rank correlation** to examine the relationship between overall spatial accessibility measurements to each treatment type, for all census tracts and within each urban-rural category.
- To further understand the spatial accessibility within a specific type and rurality, we additionally created **box plots** and **mapped** spatial access.
- **Summary statistics** of covariate data and access metrics included:
  - Breakdown by mode of transit
  - Stratified by urbanicity measures
  - Stratified by SDOH Cluster measures
  - Across multiple access metric calculations
  - Across SDOH indices, socioeconomic, and racial/ethnic measures

Internal Consistency Analyses

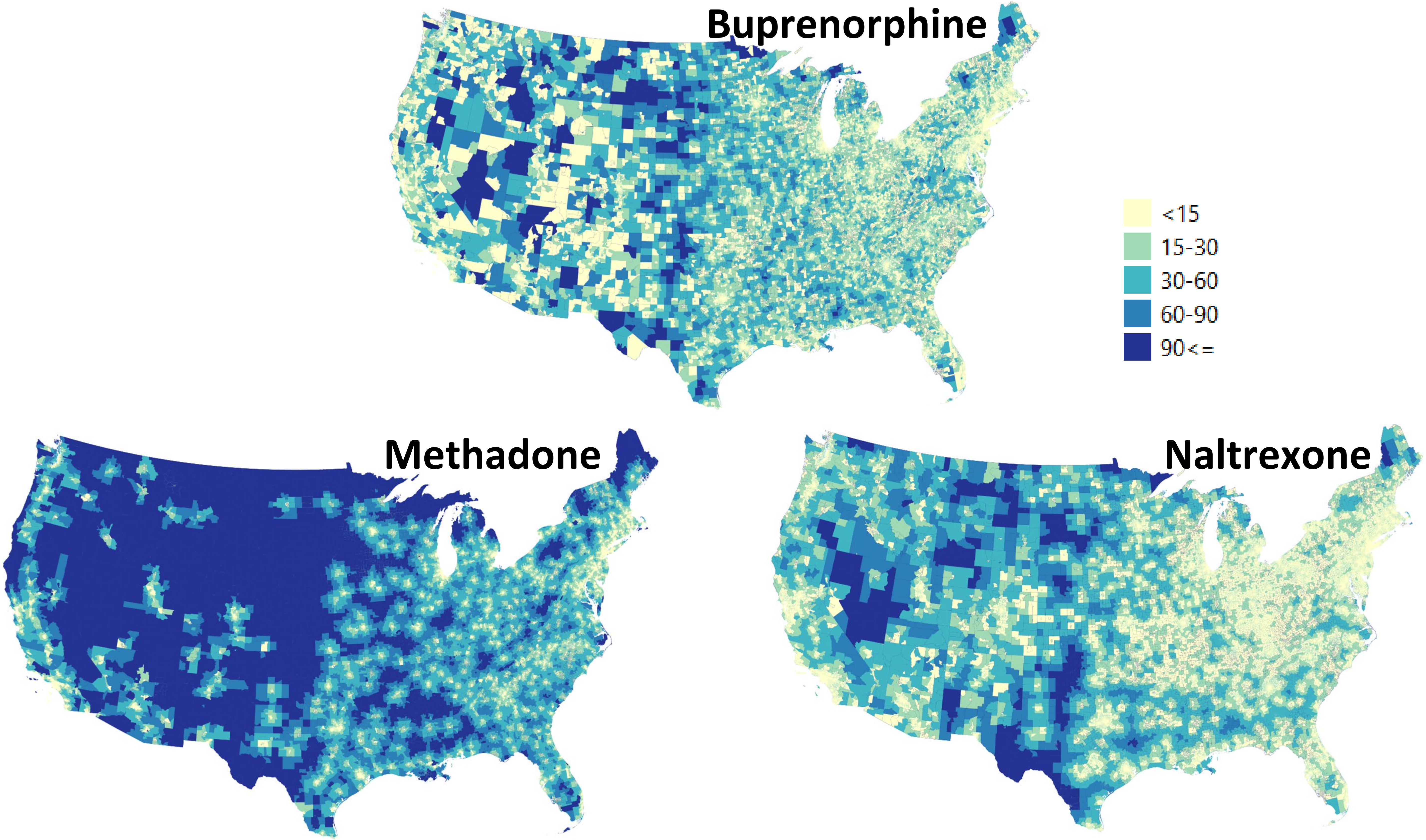
For measuring the **internal consistency among measurements**, we computed standard deviations among various spatial access on each treatment type:

1) First, we computed the standard deviations within each accessibility measurement to standardize values among different measurements.
2) Then, we computed values of standard deviations within the same census tracts among different measurements.

From the analysis, census tracts having high internal consistency show low variance; on the other hand, ones of low consistency show high variance.

Results

Figures, Tables & Maps

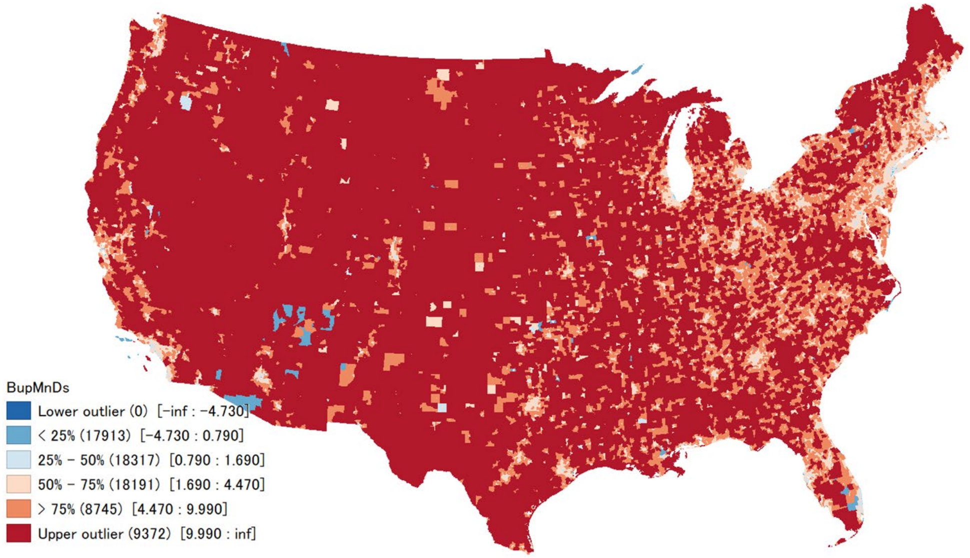


Buprenorphine
<15
15-30
30-60
60-90
90<=
Methadone
Naltrexone

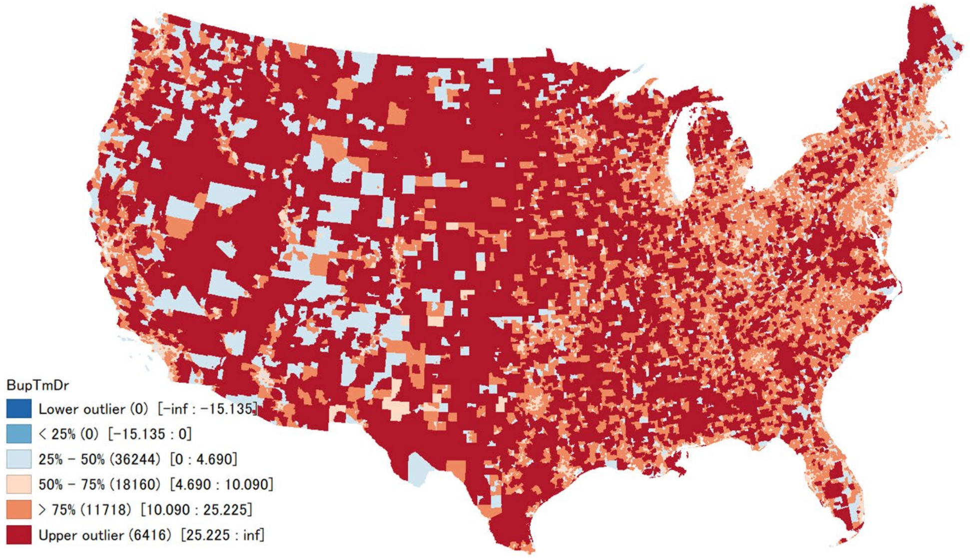
Metrics of Buprenorphine Spatial Availability

Kolak, Morioka & Lin, in prep.

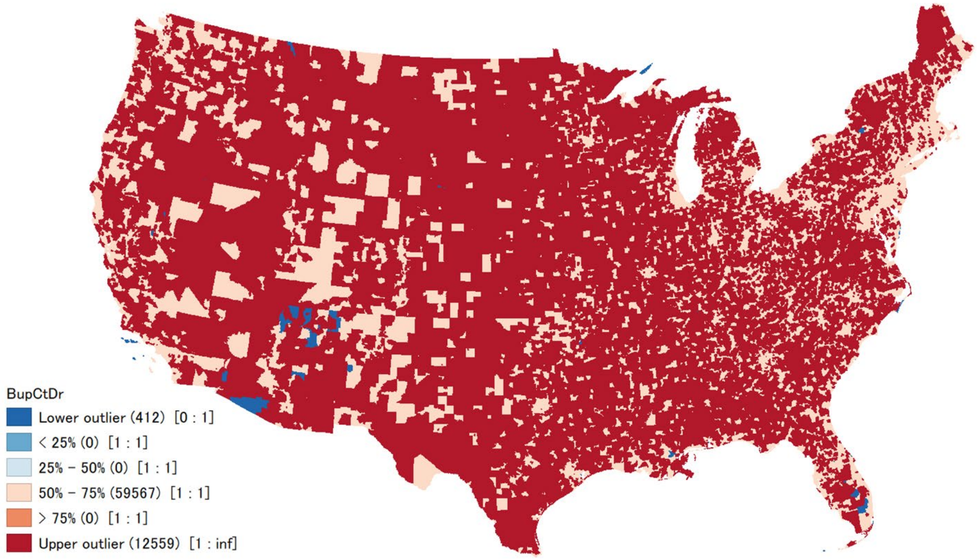
Euclidean distance



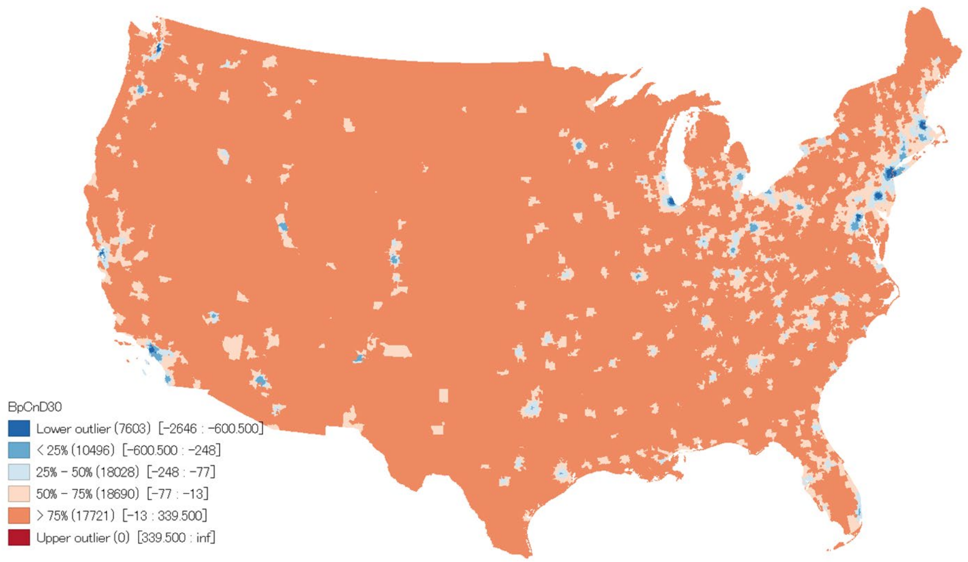
Driving time



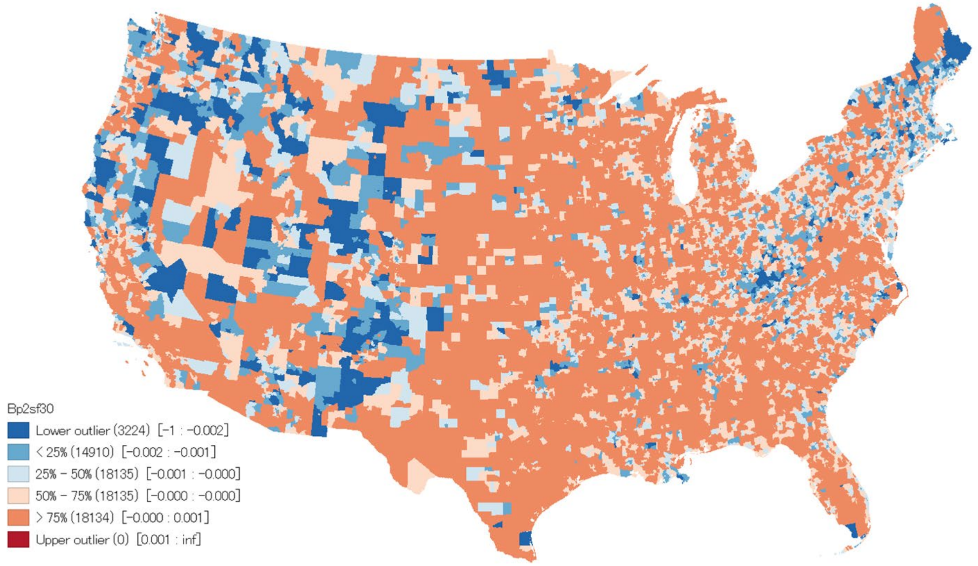
Categorical dr tm



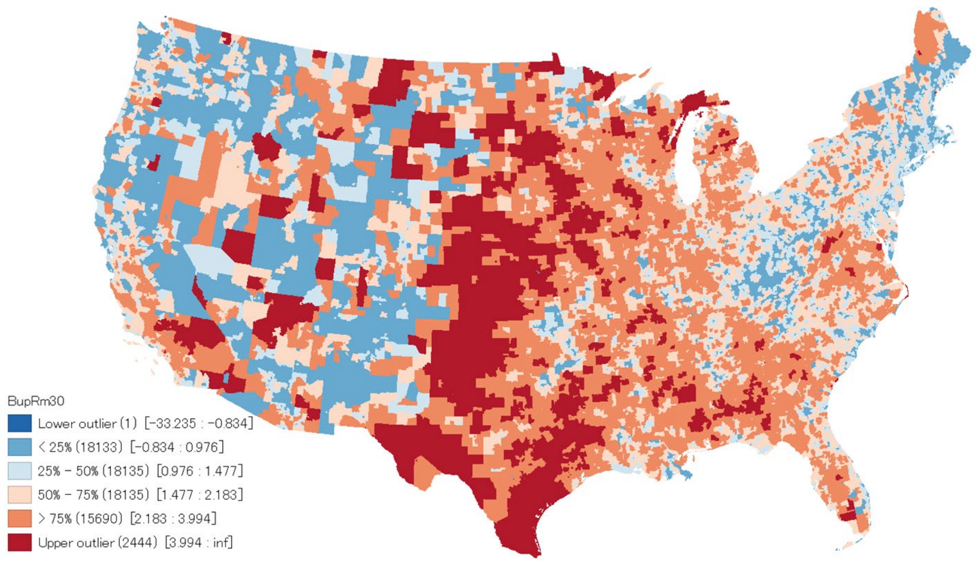
Total count within 30mins



2SFCA 30mins

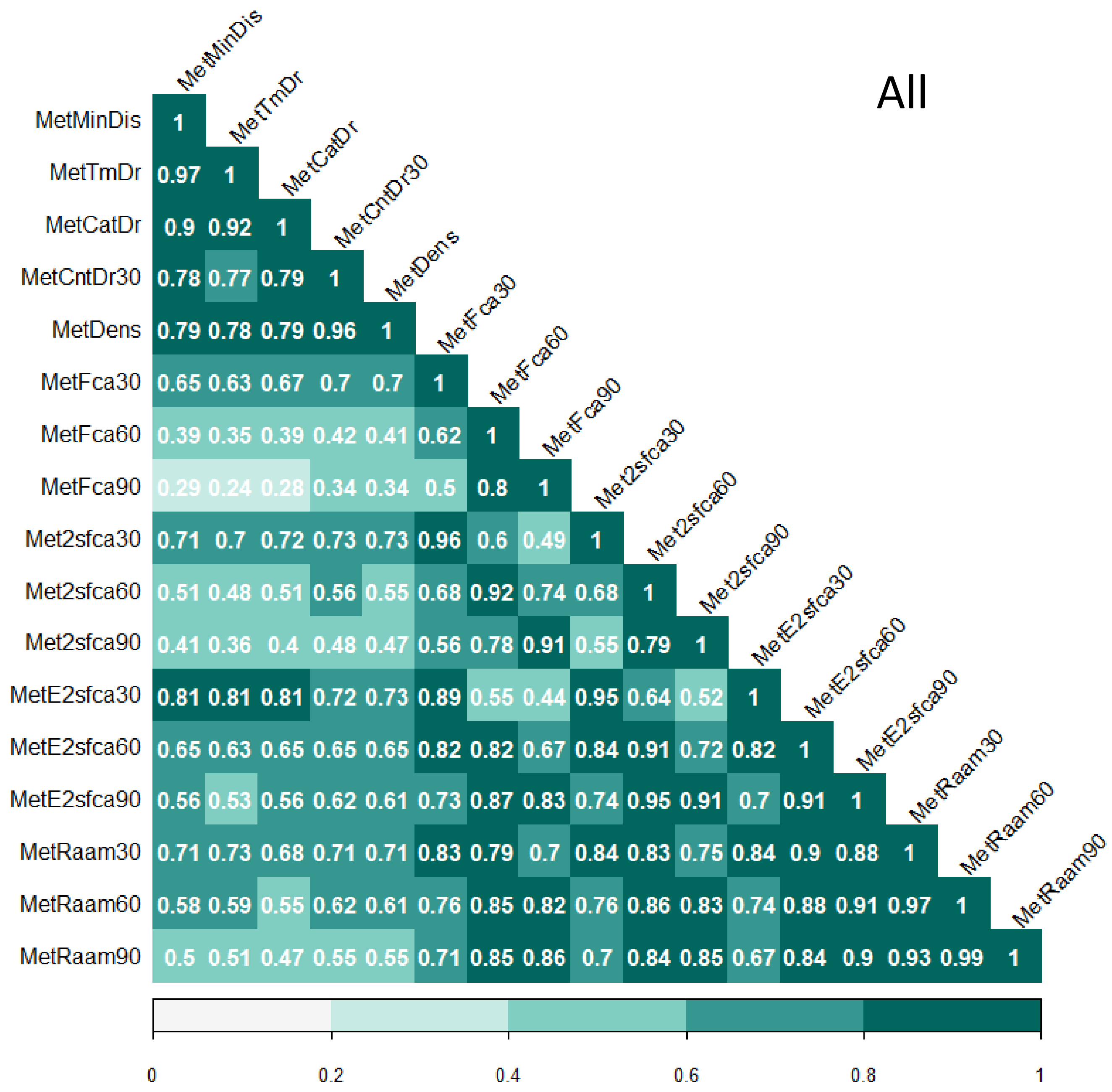


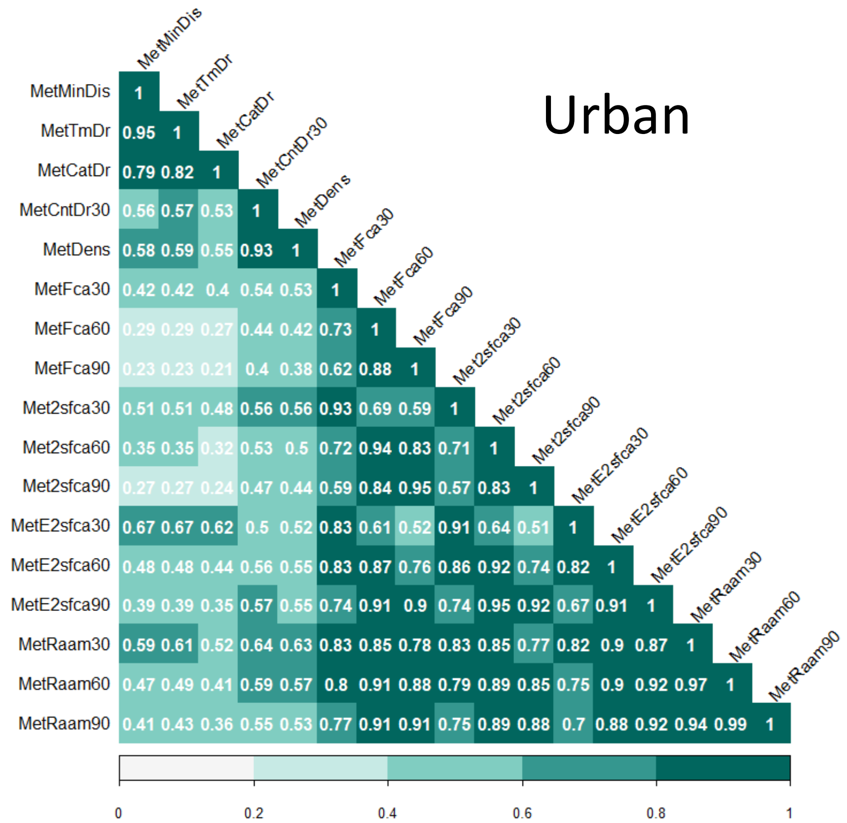
RAAM 30mins

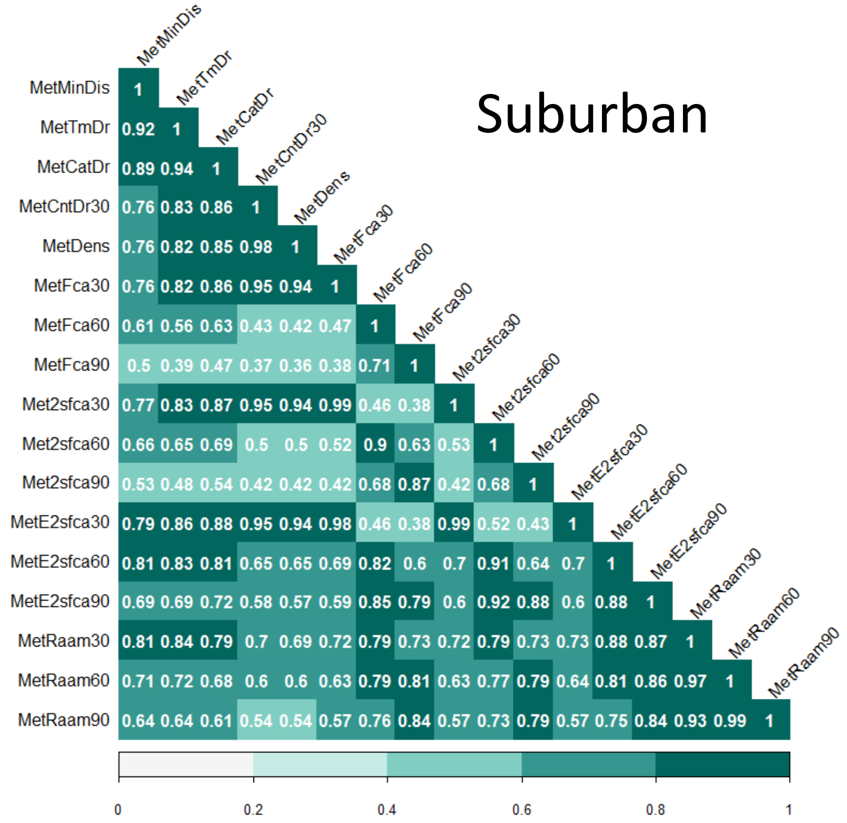


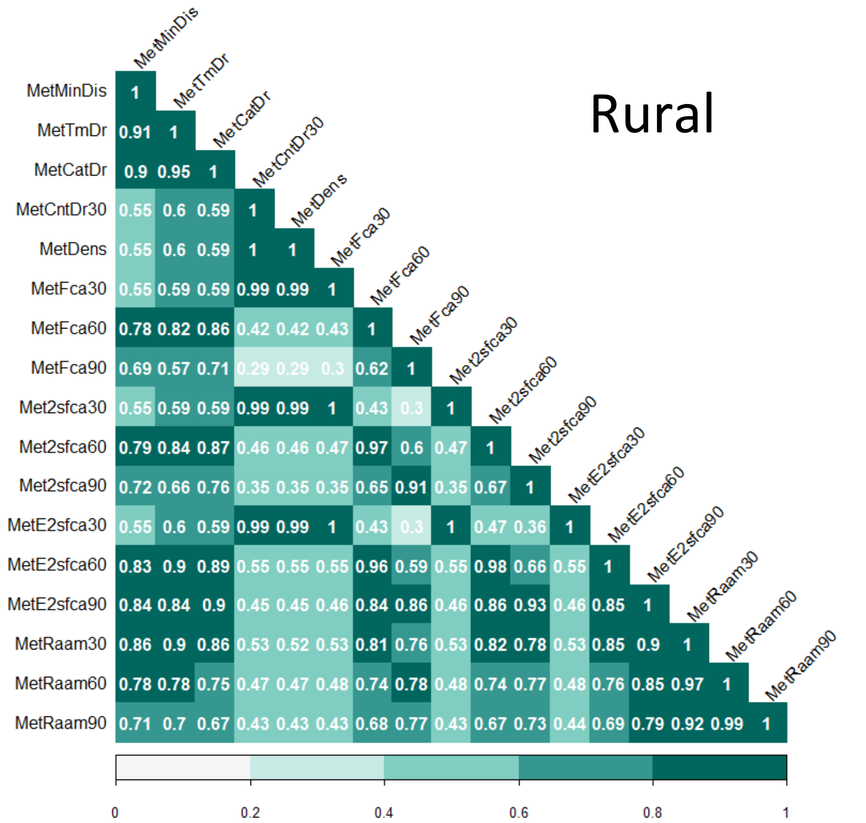
Buprenorphine

Methadone

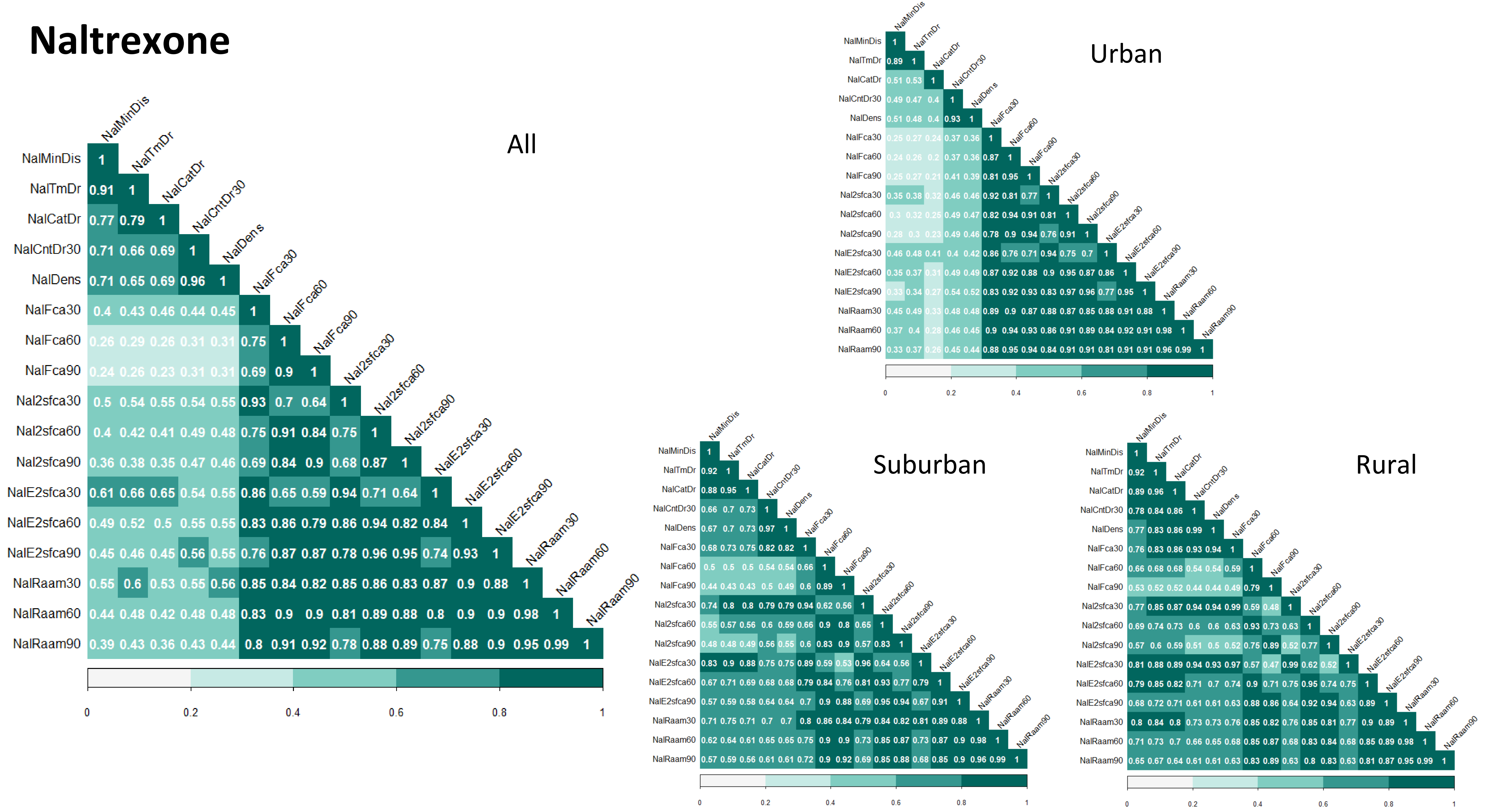

All
MetMinDis
MetTmDr
MetCatDr
MetCntDr30
MetDens
MetFca30
MetFca60
MetFca90
Met2sfca30
Met2sfca60
Met2sfca90
MetE2sfca30
MetE2sfca60
MetE2sfca90
MetRaam30
MetRaam60
MetRaam90
0
0.2
0.4
0.6
0.8
1


Urban

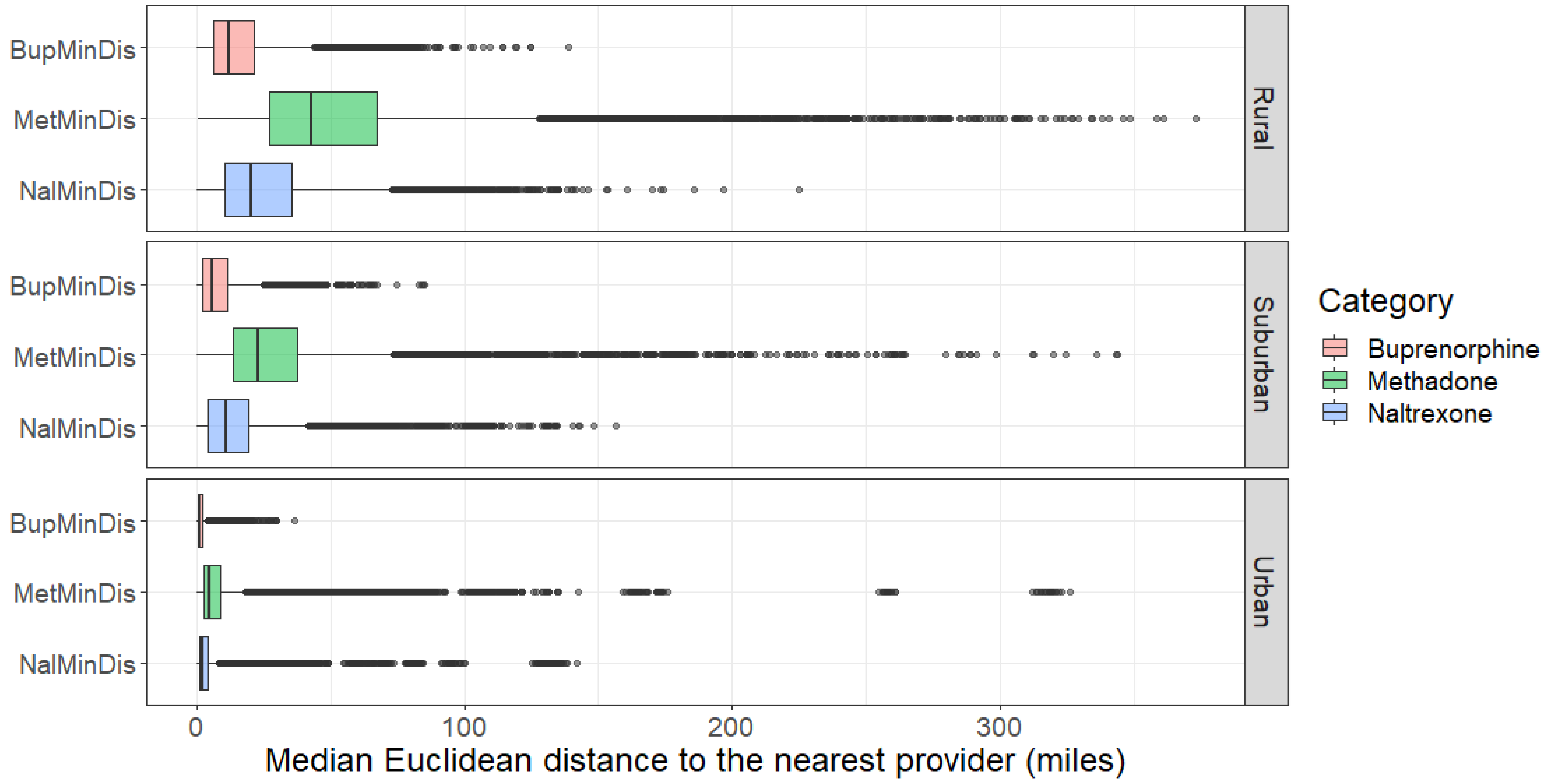

Suburban


Rural

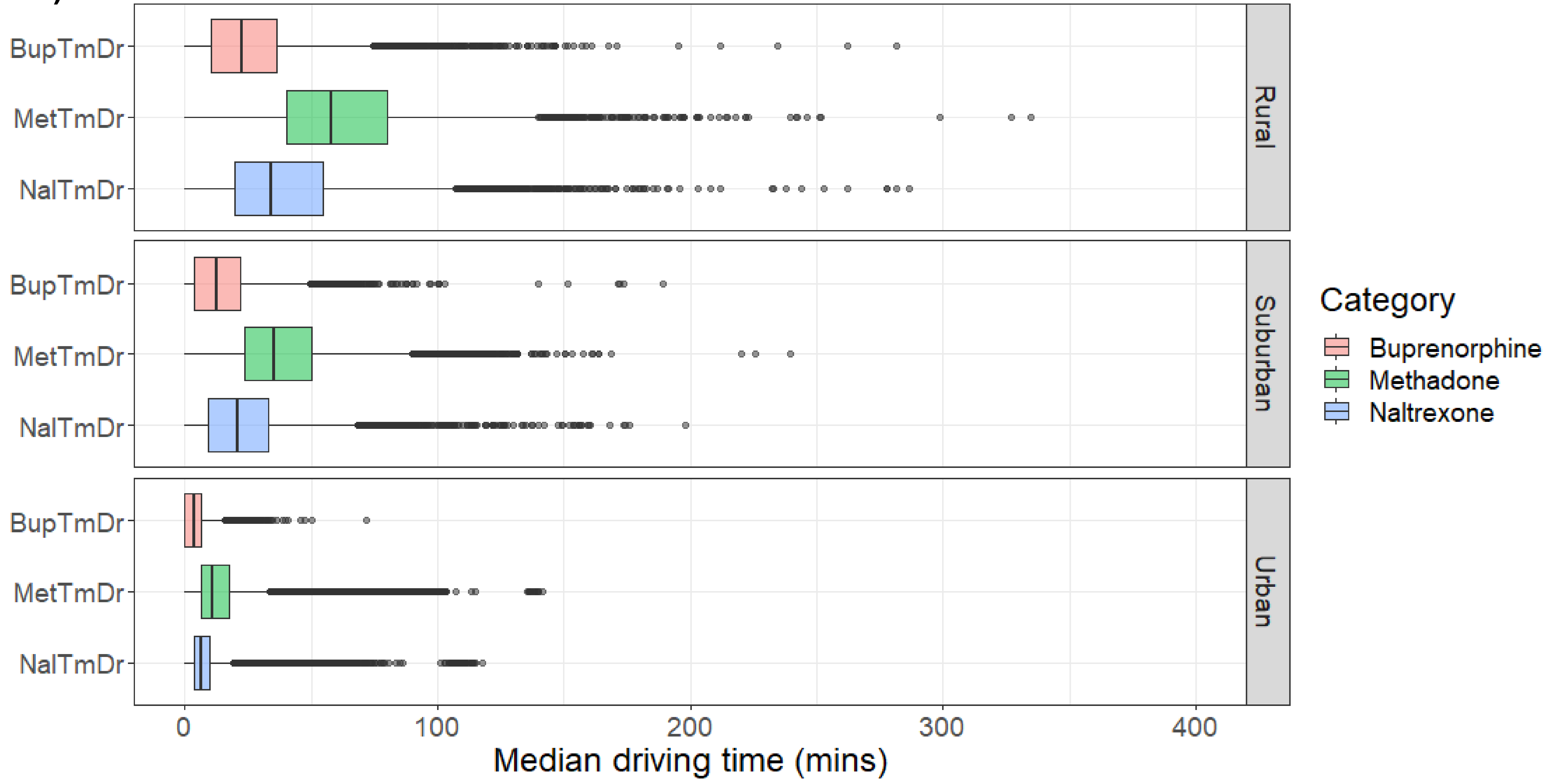
Naltrexone


All
Urban
Suburban
Rural
NalMinDis
NalTmDr
NalCatDr
NalCntDr30
NalDens
NalFca30
NalFca60
NalFca90
Nal2sfca30
Nal2sfca60
Nal2sfca90
NalE2sfca30
NalE2sfca60
NalE2sfca90
NalRaam30
NalRaam60
NalRaam90
0
0.2
0.4
0.6
0.8
1

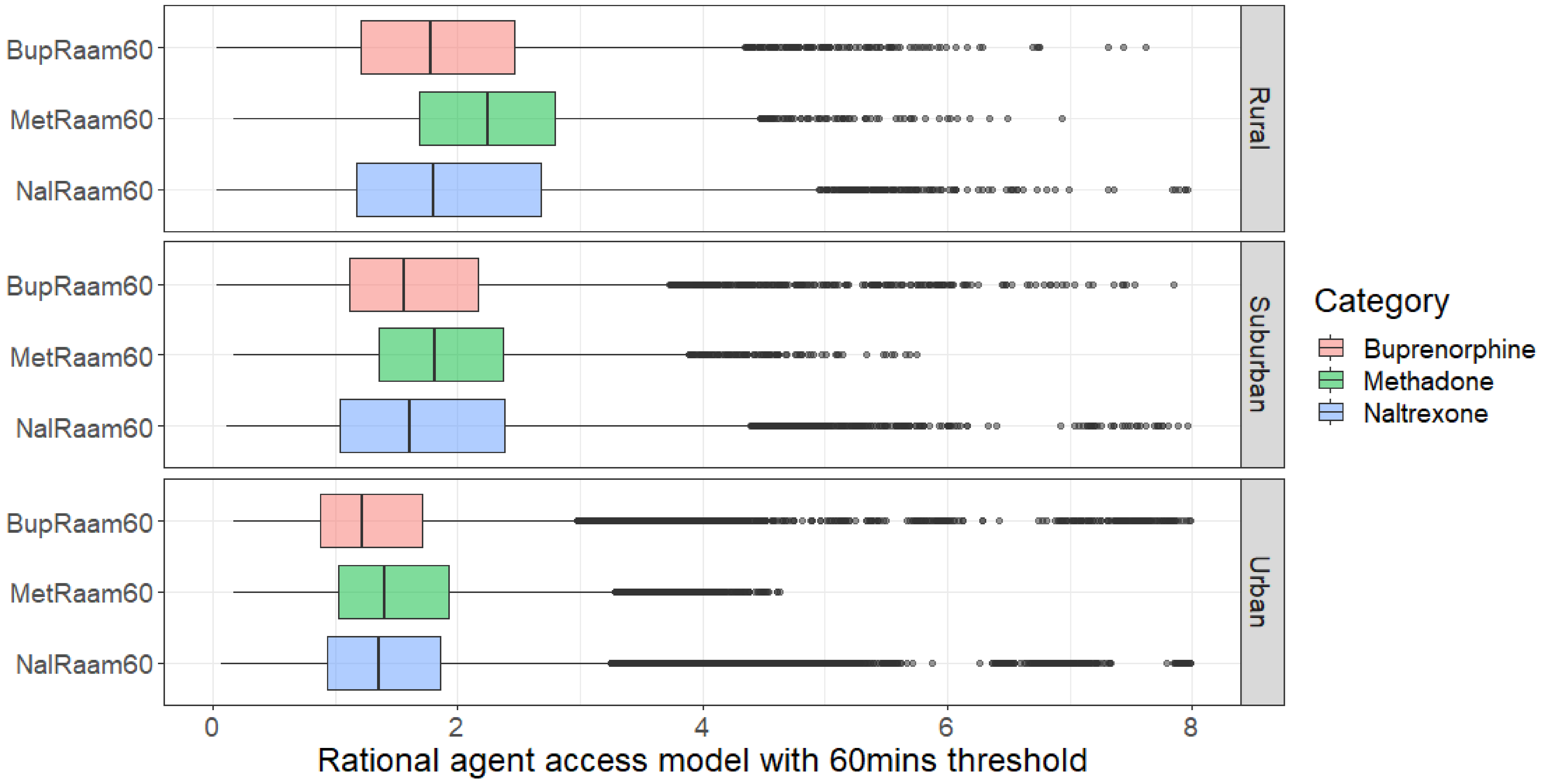
Nearest resource - Euclidean distance (miles)



Nearest resource - Network distance, driving (minutes)



RAAM 60mins



BupRaam60
MetRaam60
NalRaam60
Rural
Suburban
Urban
0
2
4
6
8
Rational agent access model with 60mins threshold
Category
Buprenorphine
Methadone
Naltrexone

SDOH Metrics Table, By Rurality

Variable	Overall N = 69,602[1]	Rural N = 8,197[1]	Suburban N = 10,284[1]	Urban N = 51,121[1]	p-value[2]
ComWlkP	1.2 (0.3, 3.1)	1.7 (0.6, 3.4)	1.1 (0.3, 2.6)	1.2 (0.3, 3.2)	<0.001
ComPubP	1 (0, 5)	0 (0, 0)	0 (0, 1)	2 (0, 7)	<0.001
NoVHHP	5 (2, 11)	5 (3, 8)	4 (2, 8)	6 (2, 13)	<0.001
SocEcAdvIn	0.58 (-1.30, 1.78)	0.81 (-0.12, 1.55)	0.92 (-0.24, 1.80)	0.39 (-1.89, 1.83)	<0.001
LimMobInd	0.07 (-0.82, 0.92)	-0.76 (-1.43, -0.14)	-0.29 (-1.02, 0.40)	0.32 (-0.58, 1.14)	<0.001
UrbCoreInd	-0.21 (-0.80, 0.56)	-0.80 (-1.15, -0.42)	-0.67 (-1.04, -0.25)	0.06 (-0.58, 0.84)	<0.001
MicaInd	0.04 (-0.54, 0.62)	-0.45 (-0.89, -0.07)	-0.15 (-0.60, 0.28)	0.20 (-0.41, 0.77)	<0.001
BlackP	5 (1, 16)	1 (0, 5)	2 (0, 8)	6 (2, 19)	<0.001
HispP.y	8 (3, 21)	2 (1, 6)	4 (1, 10)	10 (4, 26)	<0.001
WhiteP.y	81 (60, 92)	94 (84, 97)	91 (80, 96)	75 (53, 88)	<0.001

[1] Median (Q1, Q3)

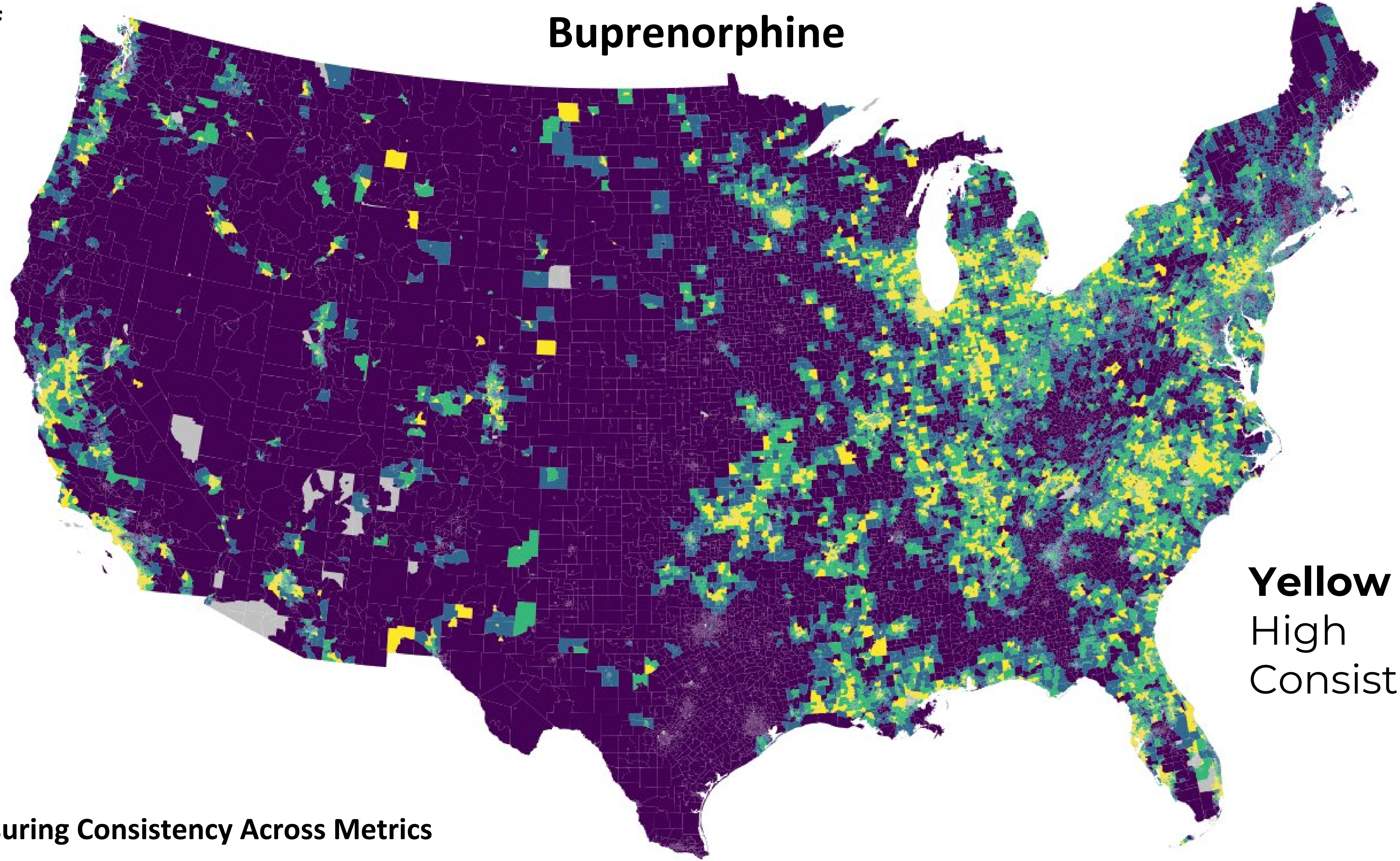
[2] Kruskal-Wallis rank sum test

SDOH Metrics Table, By SDOH Cluster

Characteristic	Overall N = 71,828[1]	1 N = 19,508[1]	2 N = 17,778[1]	3 N = 14,012[1]	4 N = 6,897[1]	5 N = 6,335[1]	6 N = 4,618[1]	7 N = 2,680[1]	p-value[2]
ComWlkP	1.2 (0.3, 3.1)	1.1 (0.2, 2.6)	1.2 (0.4, 2.6)	0.6 (0.0, 1.6)	2.5 (0.7, 5.5)	1.5 (0.5, 3.3)	7.2 (3.4, 14.8)	1.2 (0.0, 3.4)	<0.001
ComPubP	1 (0, 5)	0 (0, 1)	2 (0, 6)	1 (0, 2)	5 (1, 14)	3 (1, 8)	24 (6, 50)	0 (0, 2)	<0.001
NoVHHP	5 (2, 11)	5 (3, 9)	4 (2, 7)	3 (1, 5)	20 (13, 30)	8 (4, 14)	26 (13, 47)	6 (3, 12)	<0.001
SocEcAdvIn	0.60 (-1.28, 1.78)	0.51 (-0.39, 1.26)	2.06 (1.27, 2.63)	0.86 (-0.31, 1.77)	-3.12 (-4.34, -2.06)	-3.99 (-5.50, -2.68)	-0.76 (-2.34, 0.77)	1.70 (0.54, 2.80)	<0.001
LimMobInd	0.06 (-0.82, 0.92)	-0.73 (-1.26, -0.28)	0.36 (-0.11, 0.84)	1.13 (0.65, 1.67)	-1.21 (-2.04, -0.46)	1.63 (0.95, 2.32)	-0.22 (-0.95, 0.45)	-2.52 (-3.44, -1.86)	<0.001
UrbCoreInd	-0.23 (-0.80, 0.54)	-0.74 (-1.09, -0.37)	0.42 (-0.01, 0.91)	-0.64 (-1.00, -0.26)	-0.41 (-1.03, 0.30)	0.09 (-0.58, 0.83)	2.60 (1.98, 3.52)	0.61 (-0.11, 1.34)	<0.001
MicaInd	0.03 (-0.55, 0.60)	-0.37 (-0.73, -0.02)	0.06 (-0.28, 0.41)	0.55 (0.19, 0.91)	1.35 (0.86, 2.04)	-1.49 (-2.25, -0.88)	0.73 (0.08, 1.34)	-1.61 (-2.20, -1.16)	<0.001
BlackP	4 (1, 16)	3 (1, 12)	2 (1, 7)	5 (1, 15)	54 (21, 83)	4 (1, 13)	9 (3, 24)	2 (0, 7)	<0.001
HispP.y	7 (3, 21)	4 (1, 11)	5 (3, 12)	11 (4, 23)	7 (2, 19)	66 (47, 83)	13 (7, 27)	5 (2, 12)	<0.001
WhiteP.y	81 (60, 92)	89 (76, 96)	87 (76, 93)	79 (63, 90)	31 (10, 60)	59 (41, 77)	64 (42, 78)	92 (82, 96)	<0.001

SDs of SDs

Buprenorphine



Yellow = High Consistency

Measuring Consistency Across Metrics

Discussion

Main Findings

Which Metric Was Best?

Which access metric proved to be the most distinct, and variable across places?

- The **RAAM** Model (that takes into account congestion)

However, for resources that were scarce such as Methadone,
the RAAM metric was highly correlated with minimum distance in rural settings.

- Minimum distance may be a reasonable approximation for Methadone, depending on the region of study.

- RAAM should be used in other settings to best account for population & congestion factors

Discussion

- Large portions of the country were outside of 90 minutes to nearest Methadone provider. Distance decay are important factors to consider...
- Consistency between measurements was **spatially heterogeneous**
  - Resources generally had **less consistency in suburban and rural areas** overall.
  - How **population** is accounted for, or not, can generate great inconsistency across all types of resource measurement.

Discussion

- Availability for some medications in tracts of **extreme poverty** were similar to tracts of **suburban affluence**, despite greater need, less access to a variety of reliant transit modes, and higher population & density of residents.

- Measures of greater MOUD access in city tracts from prior research may **overestimate actual access** due to higher population numbers within cities, as well as greater transit times spent walking or using public transportation

- **Vulnerable** census tracts by SDOH Cluster with fewer resources also included:

    - Sparse areas (mainly rural settings)
    - Rural affordable areas

Discussion

- Translating RAAM metric scores to plain language remains a challenge
    - Recommend including multiple metrics (e.g. travel time, minimum distance) to facilitate greater clarity

- Accessing RAAM algorithms & computing environments is challenging.
    - Developing computational notebook to calculate RAAM with python in the cloud using *Google Colab*, which may be scaled at 30-min resolution.
    - For greater computational needs, generating detailed instructions for computing frameworks needed for calculation

Thanks

Questions? Email
mkolak@illinois.edu
@maryniakolak

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Integrating Community Engagement & Geospatial Methods to Address Racial Inequities

Benefits & Barriers

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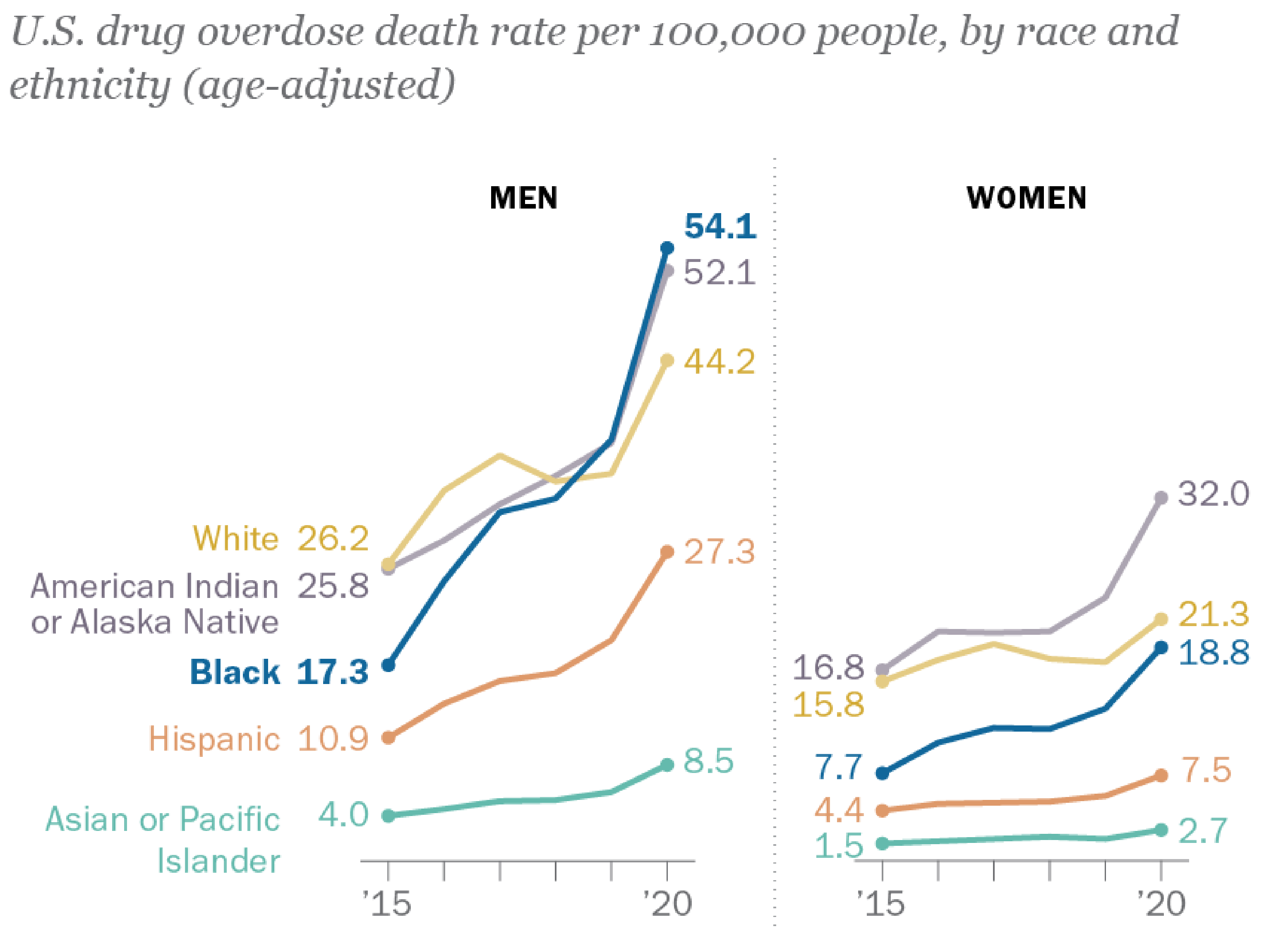
Assistant Professor
Division of Addiction Science, Treatment, & Prevention
Department of Psychiatry

WashU Medicine

Racial Inequities in Overdose

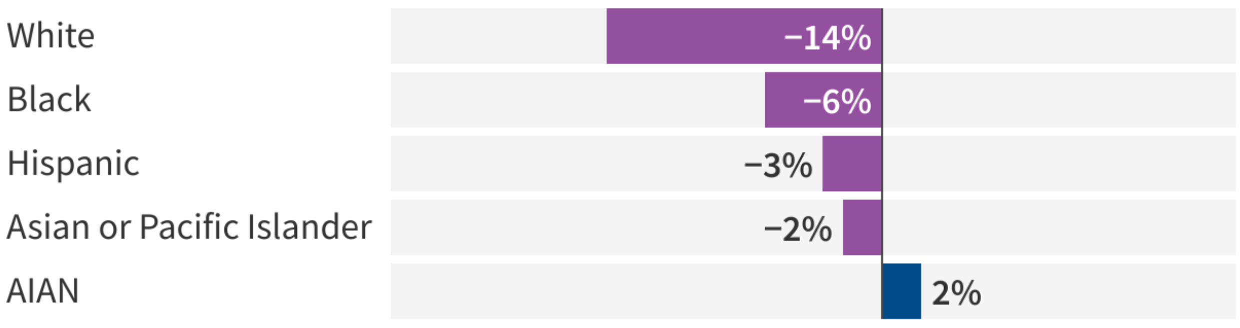
- Fatal drug overdoses increased drastically for **Black, American Indian** & **Hispanic** people in U.S. since mid- 2010s
- Increasing disparities concurrent with proliferation of illicitly-manufactured fentanyl
- Prevention & treatment efforts are not equally benefitting minoritized racial/ethnic groups



Pew Research Center, 2022 *(based on CDC WONDER data)*

Opioid Overdose Deaths Fell Across Most Demographics in the Second Half of 2023, but the Magnitude of that Change Was Uneven Across Demographic Groups

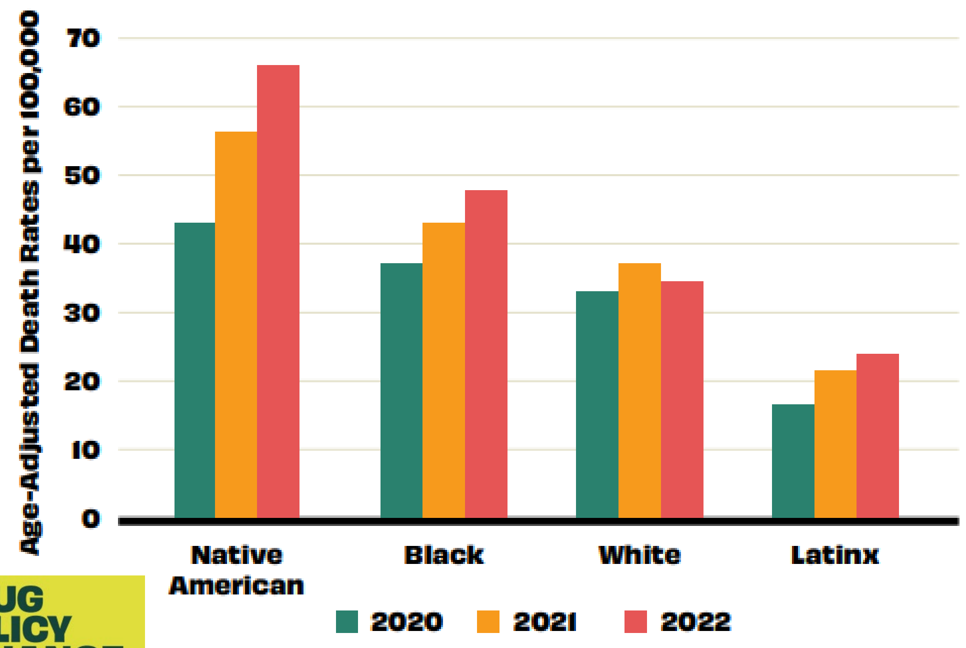
Percent change in the number of opioid overdose deaths in Jul-Dec 2023 vs. Jul to Dec 2022



Source: KFF analysis of CDC WONDER Multiple Cause of Death Cause of Death File, Final 2022 and Provisional 2023

KFF

NATIONAL DRUG OVERDOSE DEATH RATES SINCE 2020, BY RACE



Source: CDC WONDER, 2024

DRUG POLICY ALLIANCE.
JUNE 2024

Racial Inequities in Overdose

Racial Inequities in Overdose

CDC Vital Signs

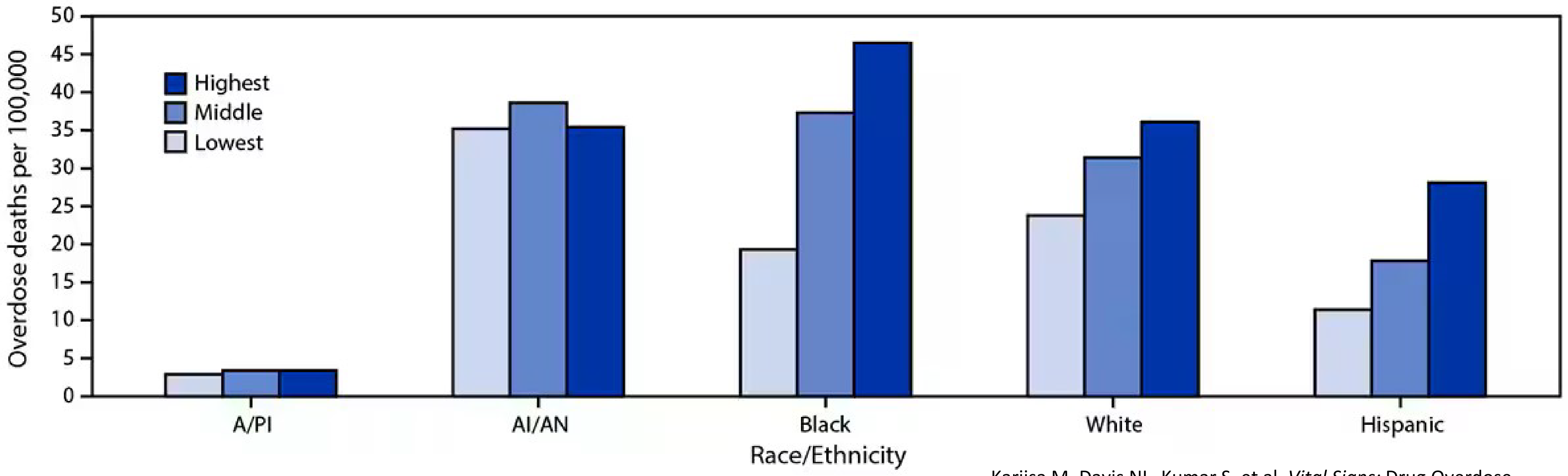
Drug Overdose Deaths Rise, Disparities Widen

Differences Grew by Race, Ethnicity, and Other Factors

Updated July 19, 2022 | Print

2 X In counties with more income inequality, overdose death rates for Black people were more than two times as high as in counties with less income inequality in 2020.

Age-adjusted rates of drug overdose deaths by race/ethnicity and income inequality ratio



Kariisa M, Davis NL, Kumar S, et al. *Vital Signs:* Drug Overdose Deaths, by Selected Sociodemographic and Social Determinants of Health Characteristics — 25 States and the District of Columbia, 2019–2020. MMWR Morb Mortal Wkly Rep 2022;71:940–947

Racial Inequities in Overdose

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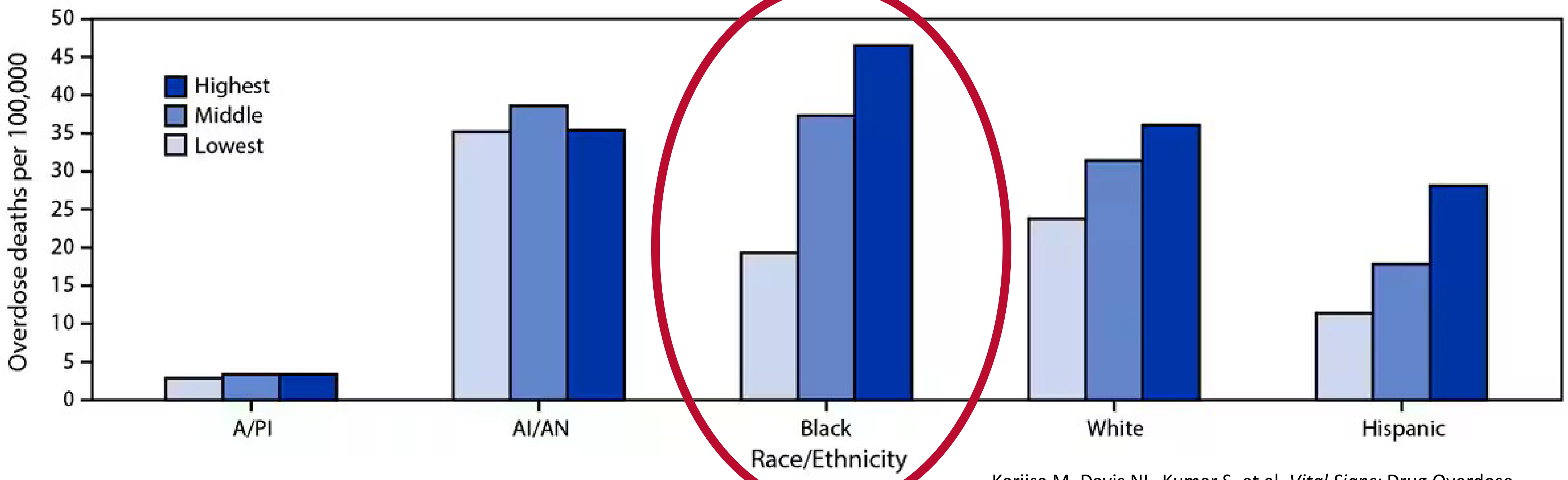
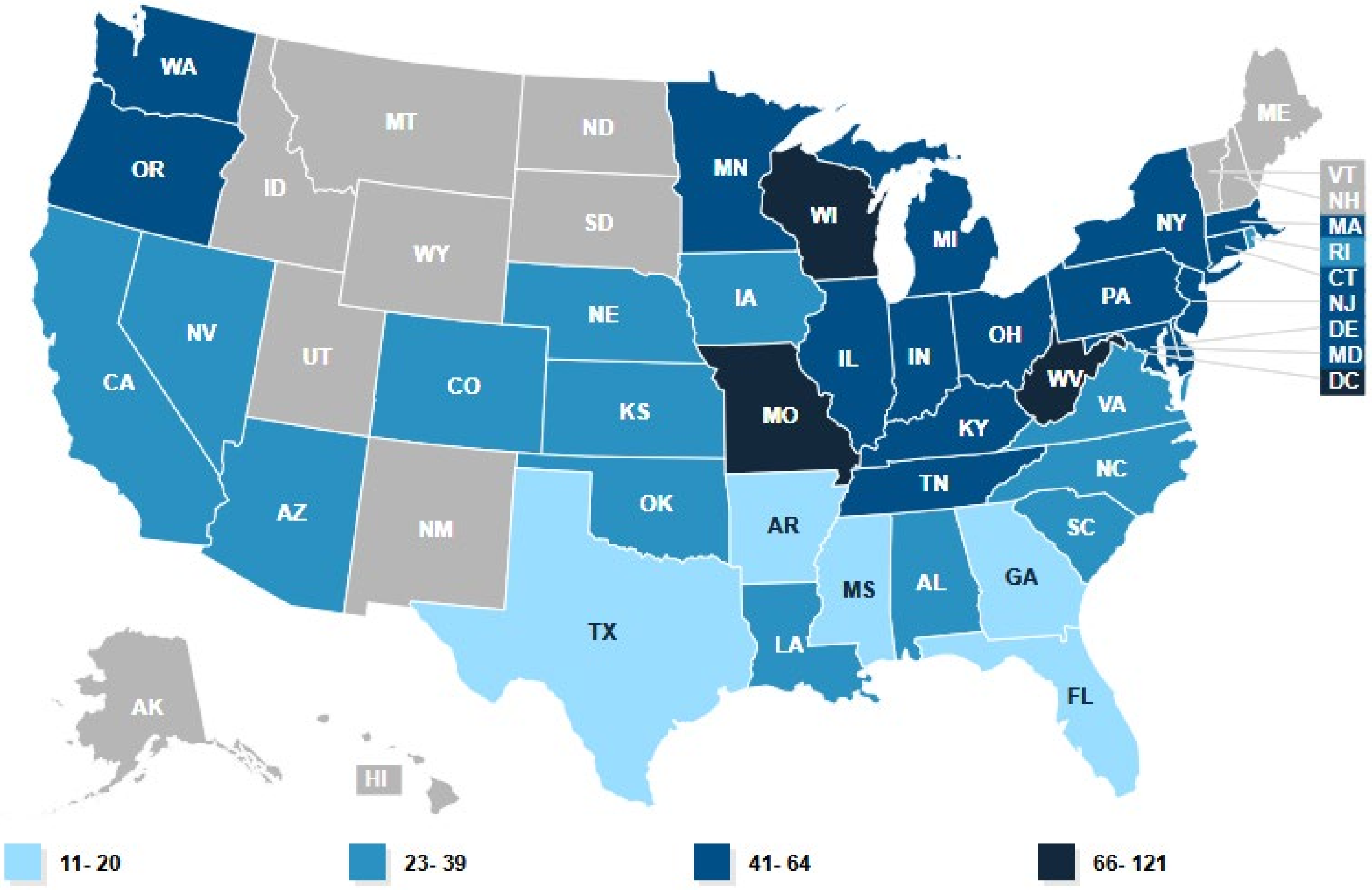


Kariisa M, Davis NL, Kumar S, et al. *Vital Signs:* Drug Overdose Deaths, by Selected Sociodemographic and Social Determinants of Health Characteristics — 25 States and the District of Columbia, 2019–2020. MMWR Morb Mortal Wkly Rep 2022;71:940–947

Racial Inequities in Overdose

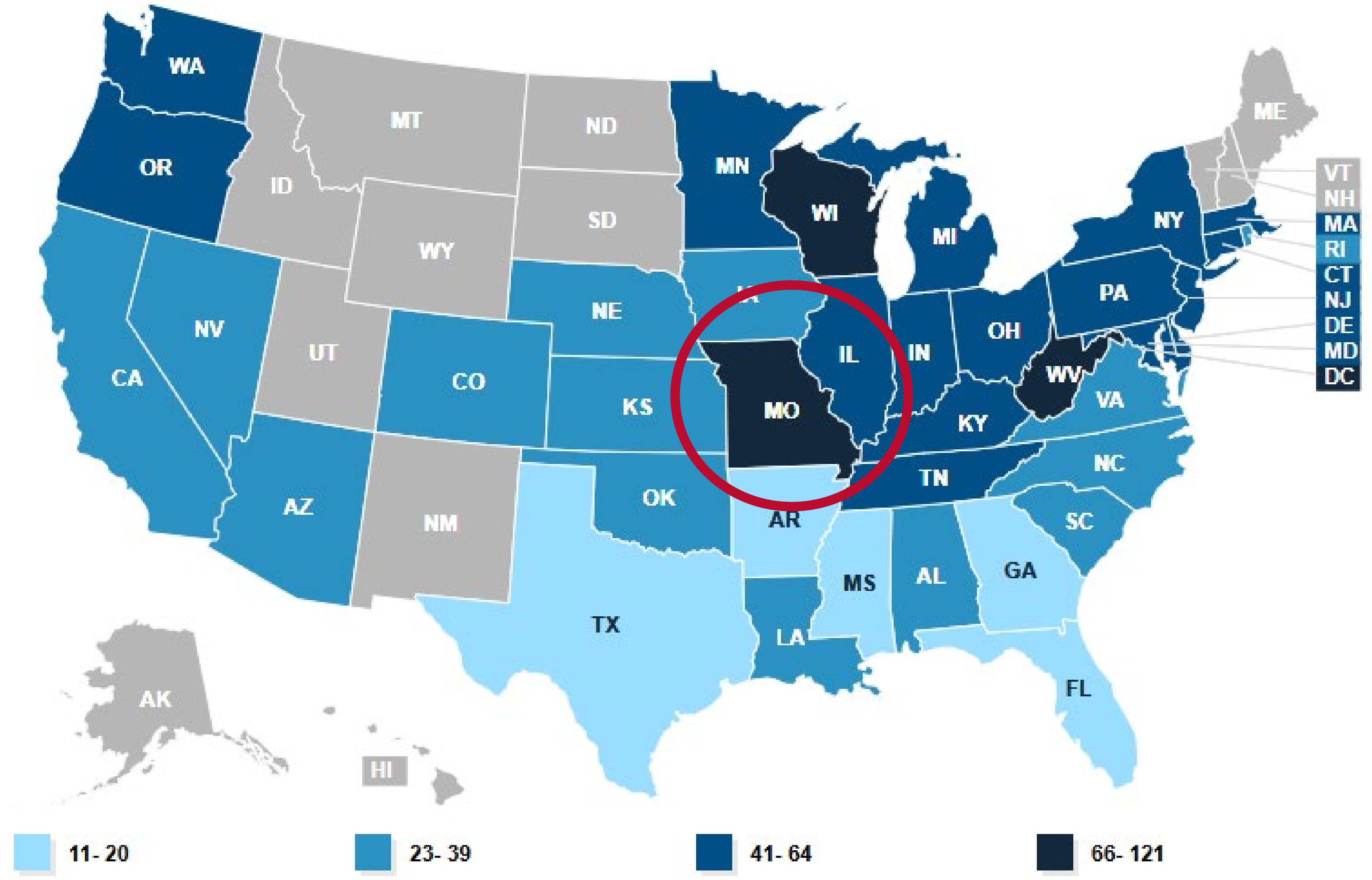
Age-adjusted rate of overdose among Black individuals in the US, 2022



Source: KFF State Health Facts

Racial Inequities in Overdose

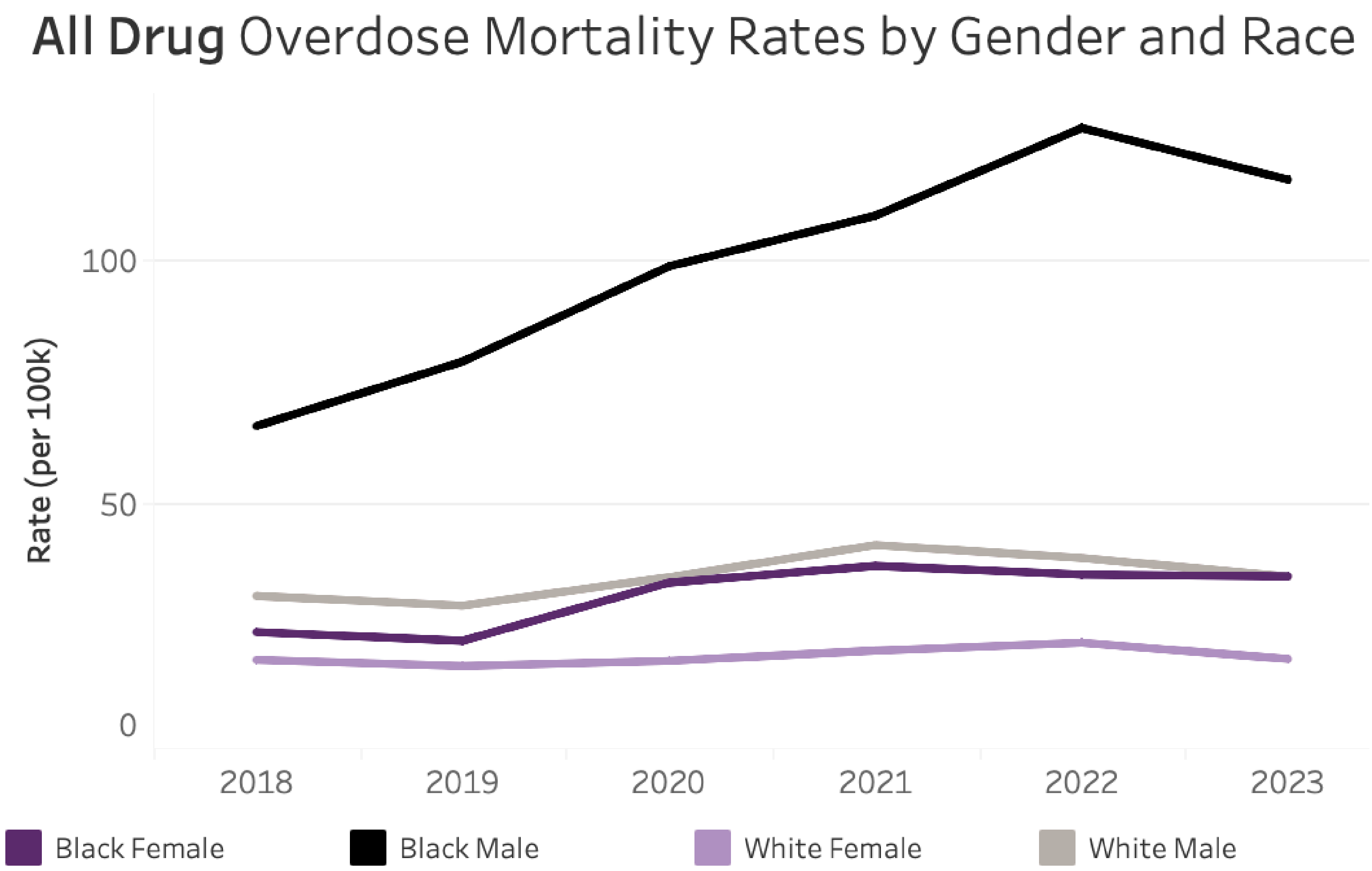
Age-adjusted rate of overdose among Black individuals in the US, 2022



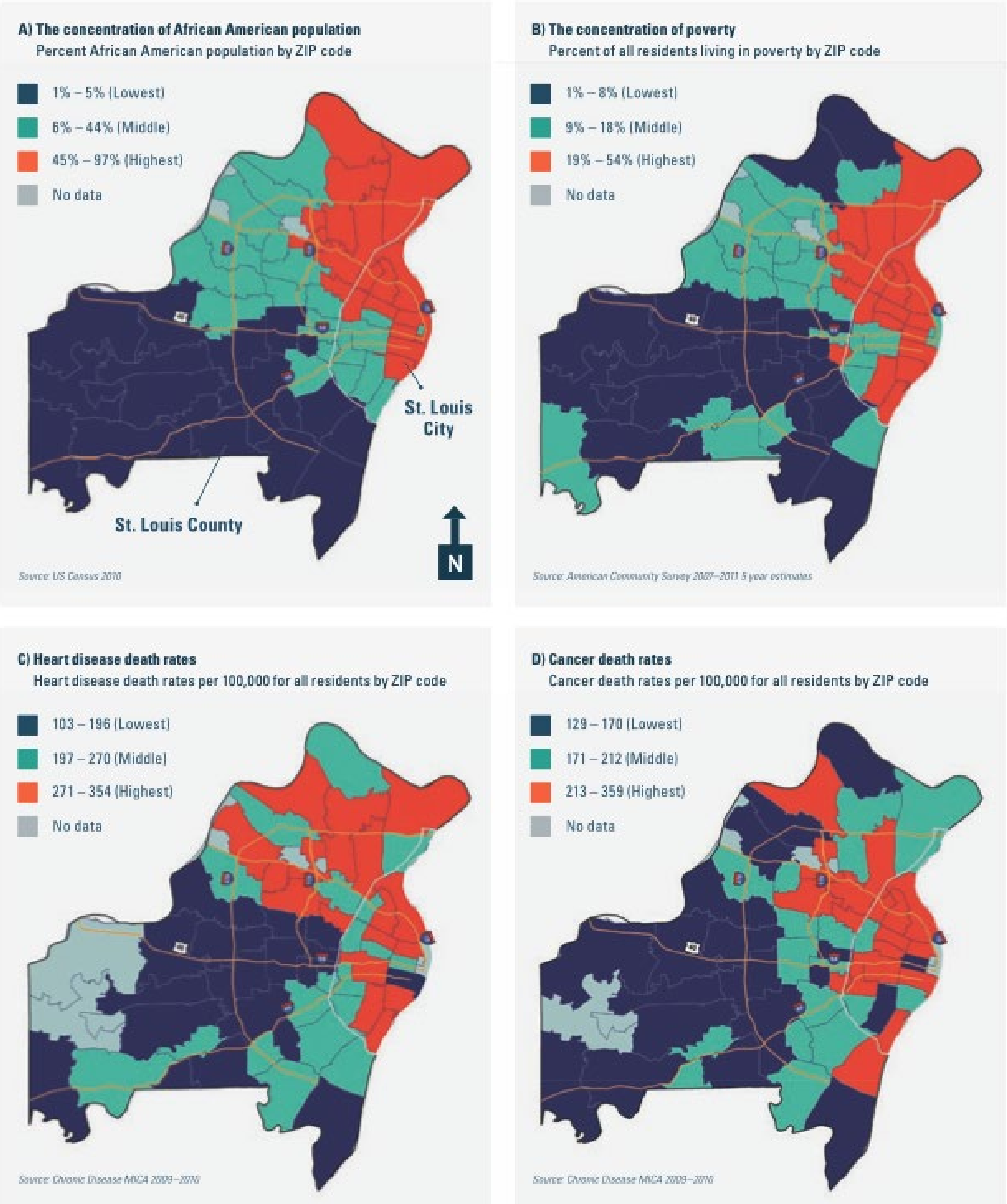
Source: KFF State Health Facts

Racial Inequities in Overdose

- Missouri's high Black fatal overdose driven by deaths among Black men in St. Louis metro
- Opioid-involved deaths increased **388% from 2015-2021** among St. Louis Black residents; 48% among Whites
- In 2023 St. Louis metro accounted for 45% of total MO overdoses but 75% of Black MO overdoses.



Source: Missouri Department of Health & Senior Services
health.mo.gov/data/opioids



Social Determinants of ~~Health~~ Overdose

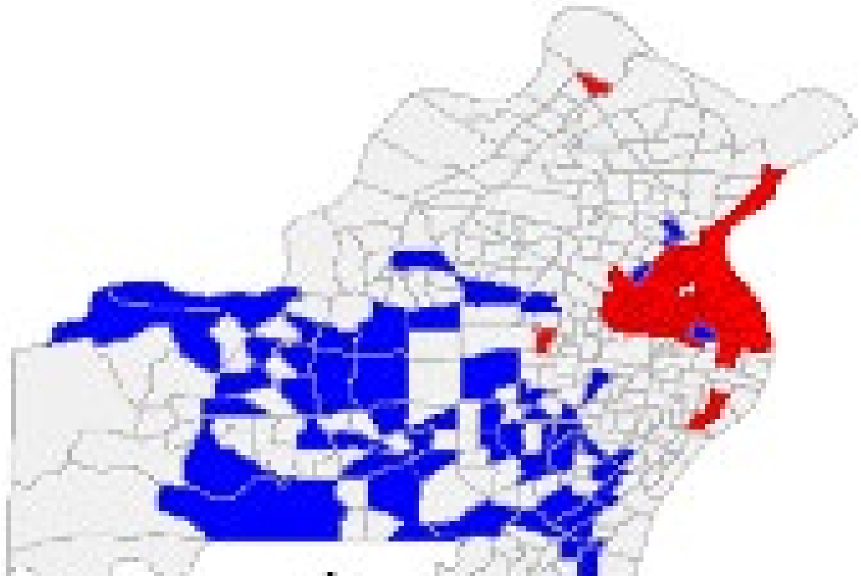
Environmental exposures drive racial inequities.

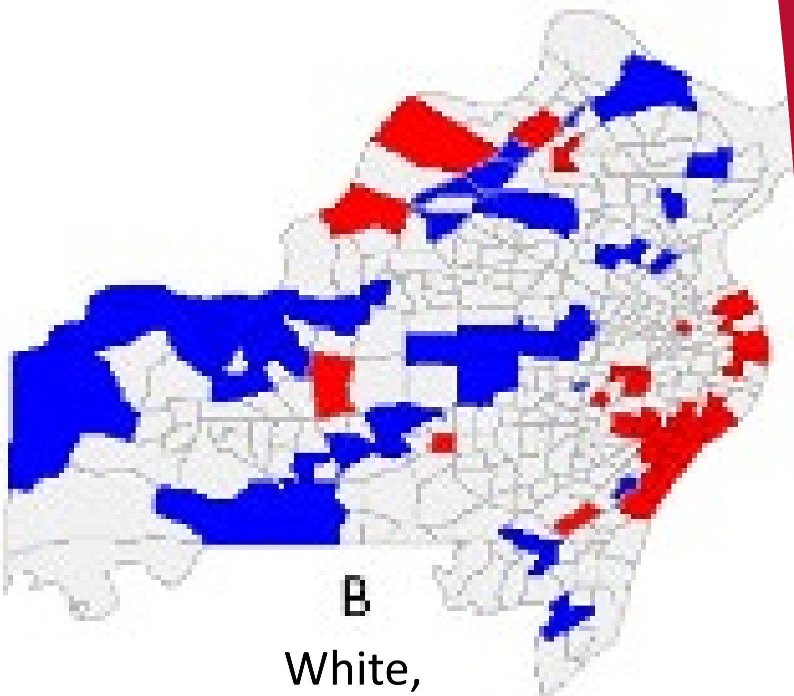
Goodman & Gilbert, 2013, *For the Sake of All*

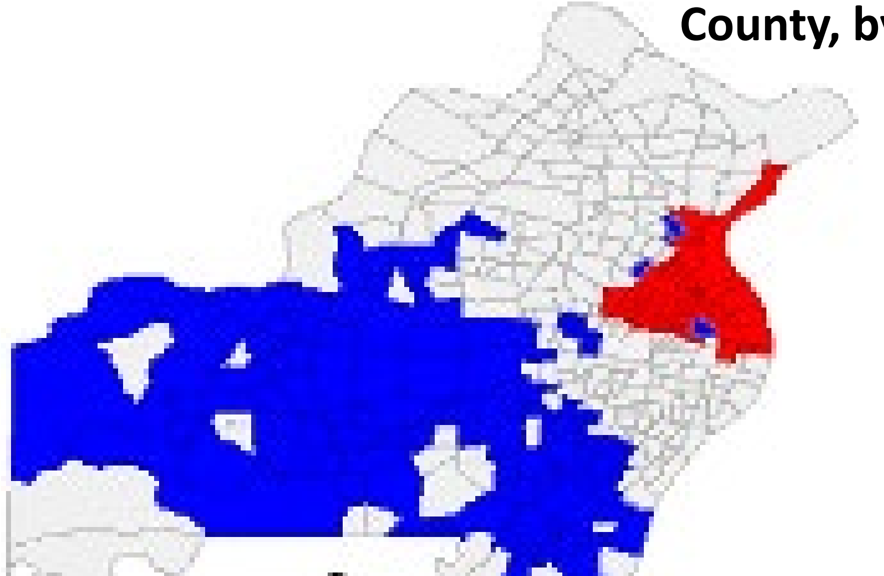
Social Determinants of ~~Health~~ Overdose

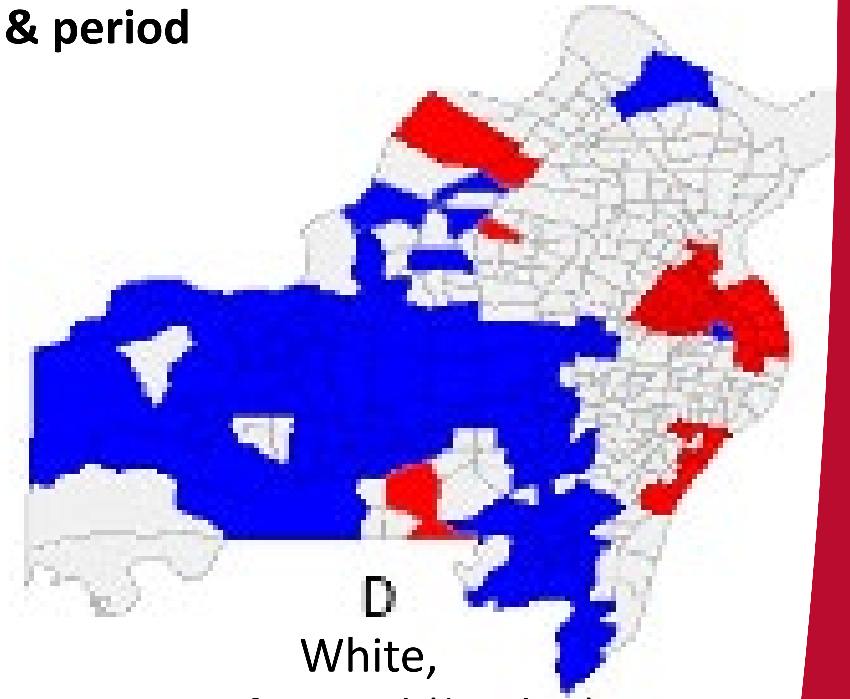
In fentanyl era of OD crisis, environmental exposures more prominent.

Fatal Overdose, St. Louis City & County, by race & period


A
Black,
Pre-fentanyl (‘11-’15)


B
White,
Pre-fentanyl (‘11-’15)

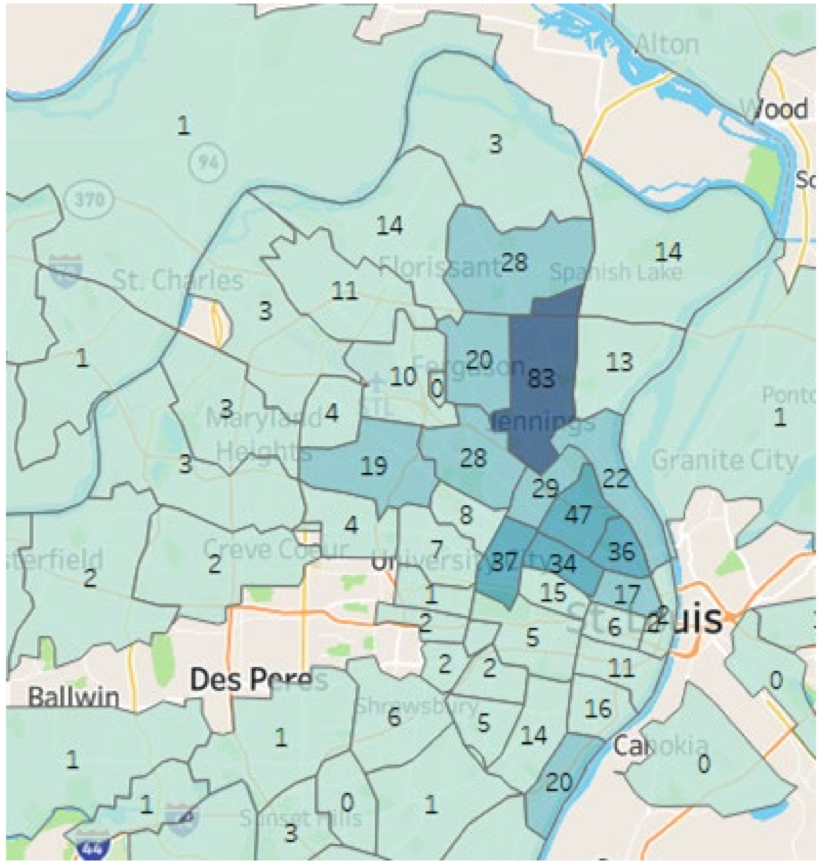

C
Black,
Post-fentanyl (‘16-’21)


D
White,
Post-fentanyl (‘16-’21)

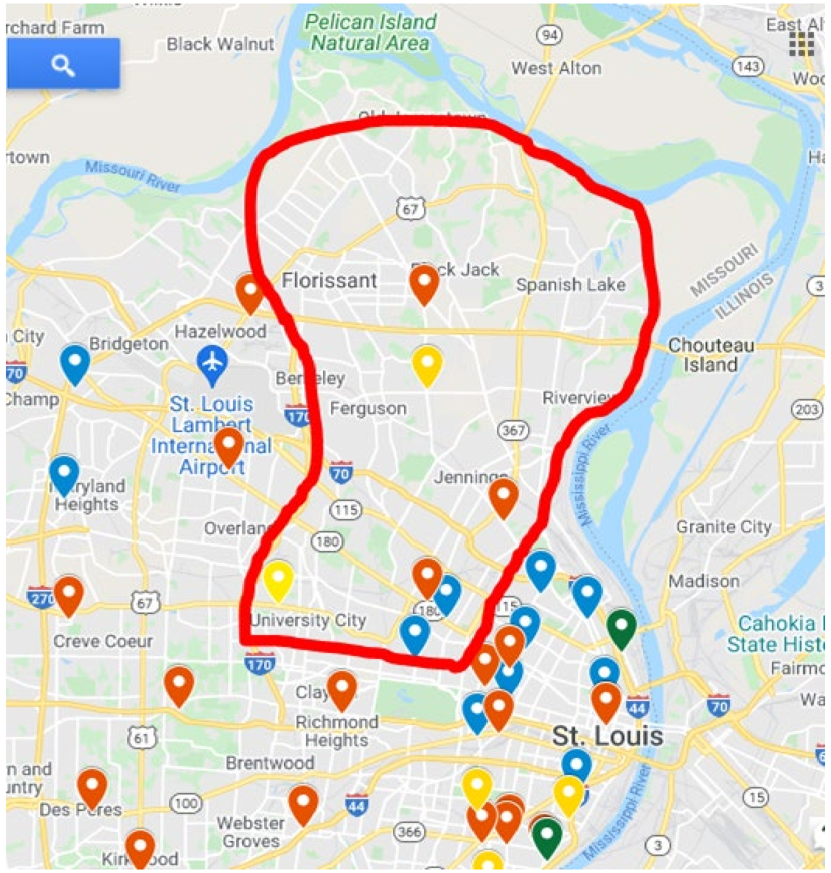
Banks et al., 2023, *Journal of Urban Health*

Social Determinants of ~~Health~~ Overdose

Overdose Deaths among Black Individuals 2019-2020



Treatment Resource Desert



Source: Addiction Science Team, Missouri Institute of Mental Health, University of Missouri St. Louis

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SOCIAL SCIENCE & MEDICINE

Check for updates

Geographic information science and the United States opioid overdose crisis: A scoping review of methods, scales, and application areas

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A R T I C L E I N F O

Keywords:
Opioid crisis
United State
Scoping review
Geographic information science (GIScience)
Geographic information systems (GIS)
Spatial analysis
Bibliometrics

A B S T R A C T

Background: The Opioid Overdose Crisis (OOC) continues to generate morbidity and mortality in the United States, outpacing other prominent accident-related reasons. Multiple disciplines have applied geographic information science (GIScience) to understand geographical patterns in opioid-related health measures. However, there are limited reviews that assess how GIScience has been used.

Objectives: This scoping review investigates how GIScience has been used to conduct research on the OOC. Specific sub-objectives involve identifying bibliometric trends, the location and scale of studies, the frequency of use of various GIScience methodologies, and what direction future research can take to address existing gaps.

Methods: The review was pre-registered with the Open Science Framework ((https://osf.io/h3mfx/) and followed the PRISMA-ScR guidelines. Scholarly research was gathered from the Web of Science Core Collection, PubMed, IEEE Xplore, ACM Digital Library. Inclusion criteria was defined as having a publication date between January 1999 and August 2021, using GIScience as a central part of the research, and investigating an opioid-related health measure.

Results: 231 studies met the inclusion criteria. Most studies were published from 2017 onward. While many (41.6%) of studies were conducted using nationwide data, the majority (58.4%) occurred at the sub-national level. California, New York, Ohio, and Appalachia were most frequently studied, while the Midwest, north Rocky Mountains, Alaska, and Hawaii lacked studies. The most common GIScience methodology used was descriptive mapping, and county-level data was the most common unit of analysis across methodologies.

Conclusions: Future research of GIScience on the OOC can address gaps by developing use cases for machine learning, conducting analyses at the sub-county level, and applying GIScience to questions involving illicit fentanyl. Research using GIScience is expected to continue to increase, and multidisciplinary research efforts amongst GIScientists, epidemiologists, and other medical professionals can improve the rigor of research.

Community-based Intervention to Mitigate Social Determinants of Overdose

- Grassroots/community orgs dispatch **lay health workers** to underserved communities to address social determinants
- **Outreach** improves trust & access to treatment, resources & OD prevention services
- Limited by reliance on convenience or arbitrary methods (e.g., word of mouth, funding, agency policy, stigma)
- **Can data-driven outreach using GIS improve service impact & inform intervention?**

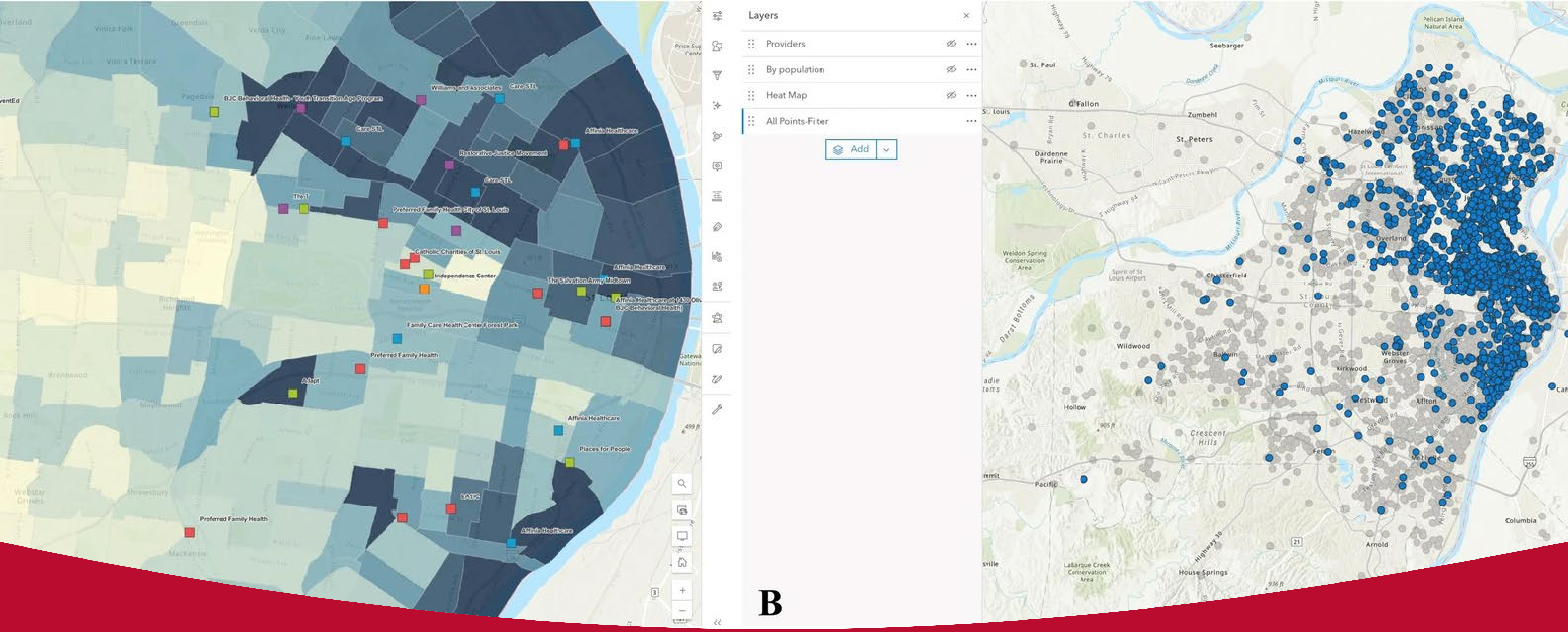
Benefits & Challenges of GIS to Guide Black Overdose Prevention

- **Stakeholder focus group** (n=8) leveraged **community partnerships** with orgs conducting outreach in Black neighborhoods in North St. Louis

- Represented orgs ranged from **grassroots nonprofits** to large **service/treatment agencies**

- All participants had **operational or supervisory rol**e in substance use or harm reduction programming

Banks DE, Paschke M, Ghonasgi R, Thompson VL. Benefits and challenges of geographic information systems (GIS) for data-driven outreach in black communities experiencing overdose disparities: results of a stakeholder focus group. BMC Public Health. 2024 Aug 5;24(1):2103



Benefits & Challenges of GIS to Guide Black Overdose Prevention

Banks et al., 2024, *BMC Public Health*

Benefits & Challenges of GIS to Guide Black Overdose Prevention

Importance of Considering Broader Community Context
Data Manipulation & Validity Concerns
Potential for Awareness, Engagement & Community Collaboration
Ensuring Data Relevance to the Affected Community

Banks et al., 2024, *BMC Public Health*

Benefits & Challenges of GIS to Guide Black Overdose Prevention

Importance of Considering Broader Community Context

Data Manipulation & Validity Concerns

Potential for Awareness, Engagement & Community Collaboration

Ensuring Data Relevance to the Affected Community

In our community, it's not just drugs, it's not just bullets. From the day you're born, you are faced with racism and that manifests in so many things. It's a struggle, honestly is a struggle to be Black in America.

When we talk about resources, what kind of resources?...Well it was just explained that this a deeper problem than substance use. This is a neighborhood problem where we just have a lack of employment. Education is poor. It's 40 kids to one teacher.

Banks et al., 2024, *BMC Public Health*

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I lived for 30 years in the central corridor in the 17th ward…once [a local university] wanted our neighborhood, it was over with. We had really high rates of everything you can think of. And the population was 70:30, 70 African American, 30 White. Now it's flipped. And what happened was [the university] wrote a bunch of grants showing that the demographics needed this money[, then] used that money to wipe that demographic out.

So, how we capture data is… I've seen how it comes really from a certain stream. It's really cleansed and it's not the real data that we see on the streets.

Banks et al., 2024, *BMC Public Health*

Benefits & Challenges of GIS to Guide Black Overdose Prevention

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"It's helpful in the sense that I can go now, myself, and see if [the data are] true. So, I don't just take it at its face value, I go now to experience it for myself…The numbers showed us that these were the places that we needed to be for a lot of reasons. But I don't just take a map at face value like, "Okay, that's the way it is, let's go see parts of it," but let me check that, check that skepticism, take that and go learn from there."

Banks et al., 2024, *BMC Public Health*

Benefits & Challenges of GIS to Guide Black Overdose Prevention

Importance of Considering Broader Community Context
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There's situations where we pull up in a place and they're like, "we don't want you here." Well okay, but let me show you why I'm here. I can use that map to show there's a reason why. "I came because look at these numbers right here"… Now I can get the whole community involved, in a way that I couldn't before … because the communities we go to right now don't acknowledge that there's an [overdose] issue in their community.

With the mapping… [local government could] utilize the community organizations within those zip codes to be at the table to resolve problems in that zip code versus making their own plan… bring those people to the table, because those are the people that see and know that community.

Banks et al., 2024, *BMC Public Health*

Benefits & Challenges of GIS to Guide Black Overdose Prevention

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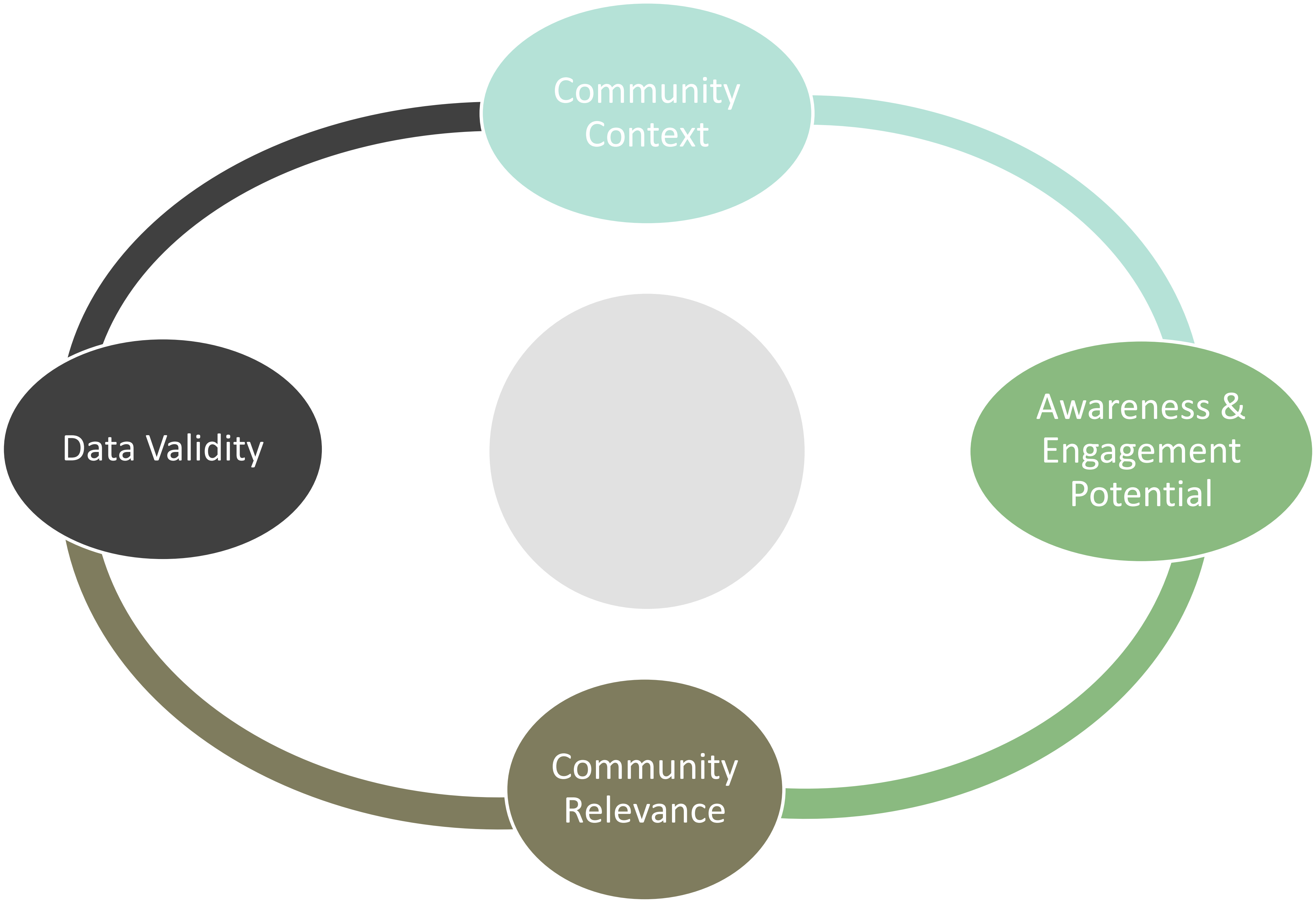
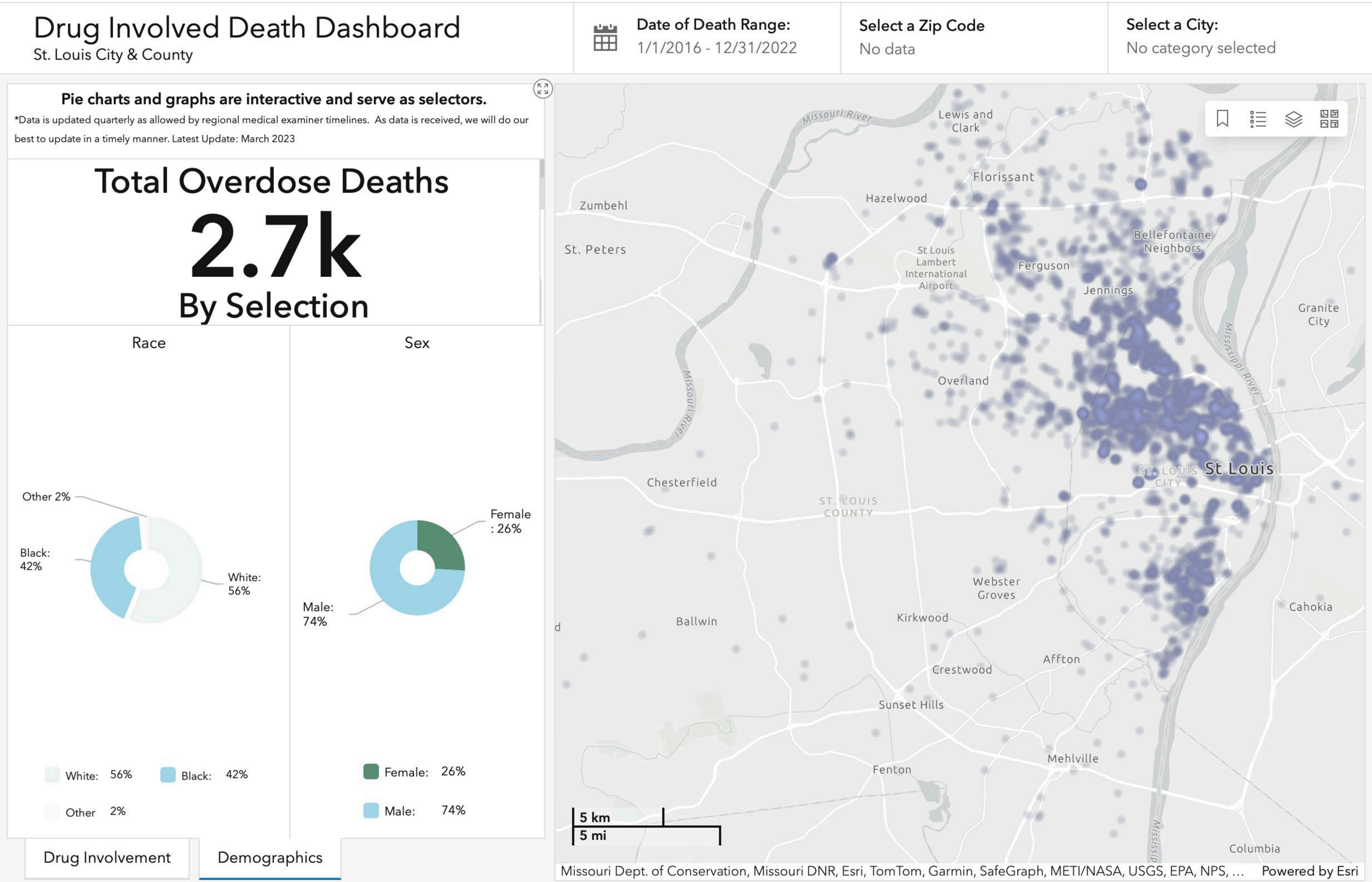
The last big map I saw was the high rates of STDs and it had every zip code, and it broke down all this stuff. Yet, you didn't put a STD clinic in the highest area that had these numbers. But then big people got grants to give instant HIV tests and all this stuff. But…for my people in the community, they don't go to that place. So…the maps can do whatever you want them to do, but they usually do things specific for people to get resources other than in the community.

Maps without a story is meaningless to the community. Are we taking the maps back to the community? Get them in touch with what's happening in their community? Telling them that we need their buy-in to come to their community?

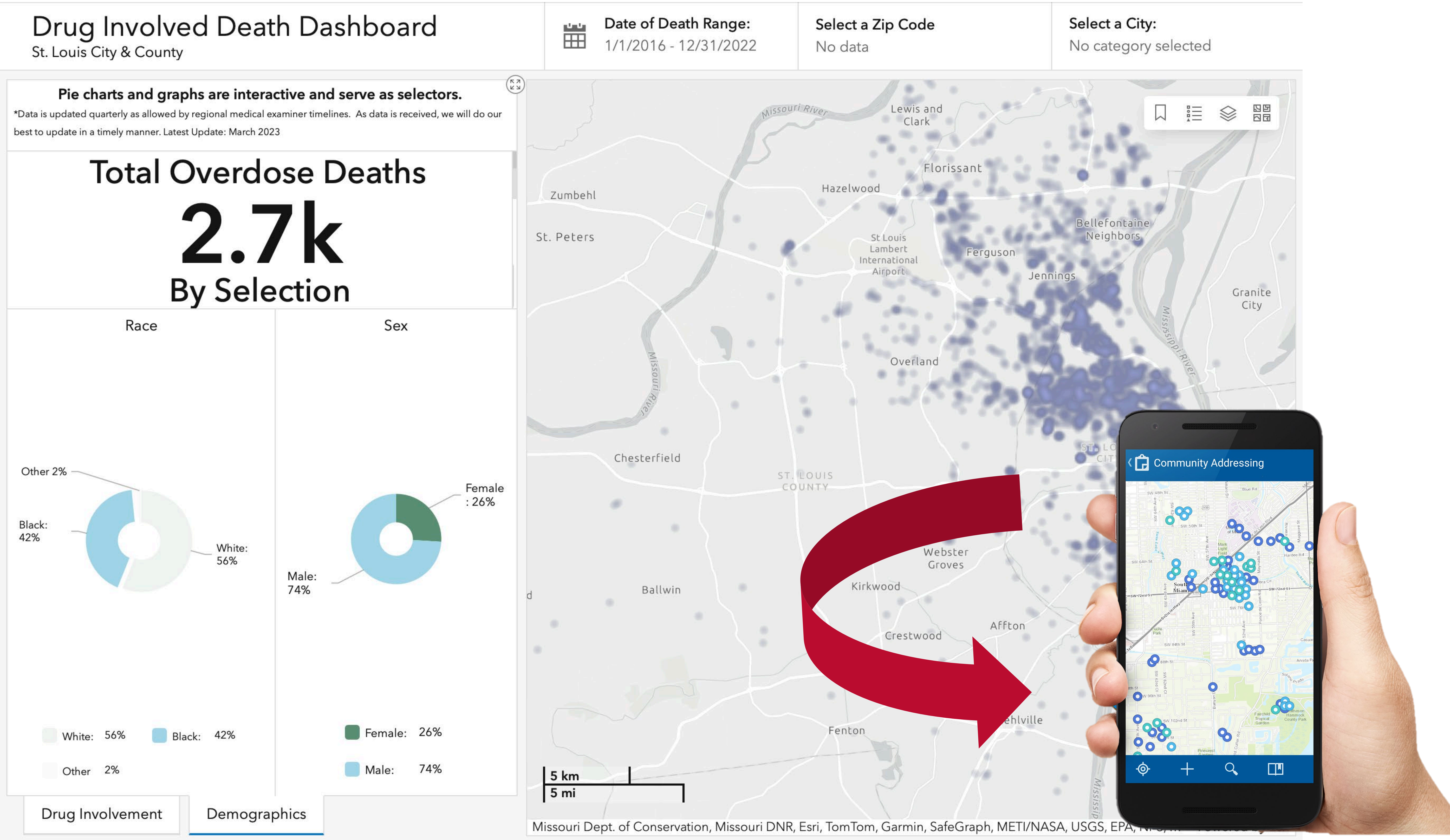
Banks et al., 2024, *BMC Public Health*

We've got to recognize that [bad actors are] an inherent risk and roll with it, but there's also so many benefits. We've all talked about all the different ways we can use this [mapping tool] and we've got to think about those more than we think about the harmful.


Community Context
Awareness & Engagement Potential
Community Relevance
Data Validity



Drug Involved Death Dashboard
St. Louis City & County
Date of Death Range:
1/1/2016 - 12/31/2022
Select a Zip Code
No data
Select a City:
No category selected
Pie charts and graphs are interactive and serve as selectors.
*Data is updated quarterly as allowed by regional medical examiner timelines. As data is received, we will do our best to update in a timely manner. Latest Update: March 2023
Total Overdose Deaths
2.7k
By Selection
Race
Other 2%
Black: 42%
White: 56%
White: 56%
Black: 42%
Other 2%
Sex
Female : 26%
Male: 74%
Female: 26%
Male: 74%
Drug Involvement
Demographics
Missouri River
Lewis and Clark
Florissant
Hazelwood
Zumbehl
St. Peters
St Louis Lambert International Airport
Ferguson
Bellefontaine Neighbors
Jennings
Granite City
Mississippi River
Overland
St Louis
ST. LOUIS CITY
Chesterfield
ST. LOUIS COUNTY
Webster Groves
Ballwin
Kirkwood
Cahokia
Affton
Crestwood
Sunset Hills
Fenton
Mehlville
Columbia
5 km
5 mi
Missouri Dept. of Conservation, Missouri DNR, Esri, TomTom, Garmin, SafeGraph, METI/NASA, USGS, EPA, NPS, ...
Powered by Esri



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Drug Involvement
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Lewis and Clark
Florissant
Hazelwood
Zumbehl
St. Peters
St Louis Lambert International Airport
Ferguson
Bellefontaine Neighbors
Jennings
Granite City
Overland
Chesterfield
ST. LOUIS COUNTY
Webster Groves
Kirkwood
Ballwin
Crestwood
Affton
Fenton
Missouri River
Mississippi River
5 km
5 mi
Missouri Dept. of Conservation, Missouri DNR, Esri, TomTom, Garmin, SafeGraph, METI/NASA, USGS, EPA
Community Addressing

K08 DA058080; PI: Banks

Project MOST

Community consultants (n=7) brainstorm, then rank social determinants of health variables contributing to Black overdose in **analytic hierarchy process** toward a **community-derived geospatial index**

STAGES OF PARTICIPATORY GIS

Convening → Deliberation → Outcomes

Haklay & Francis, 2018; Cromley & McLafferty, 2012

Project MOST

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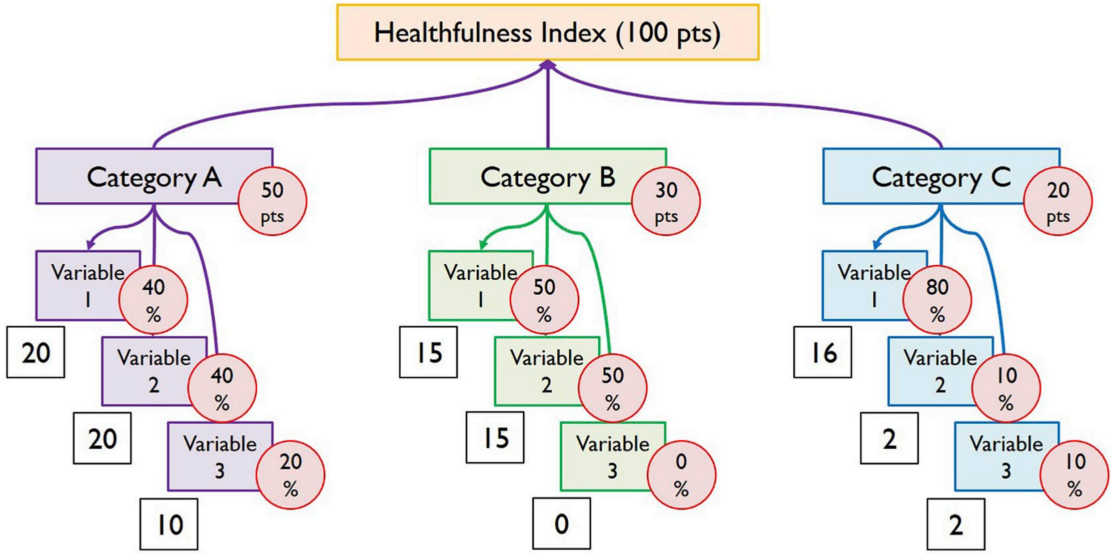

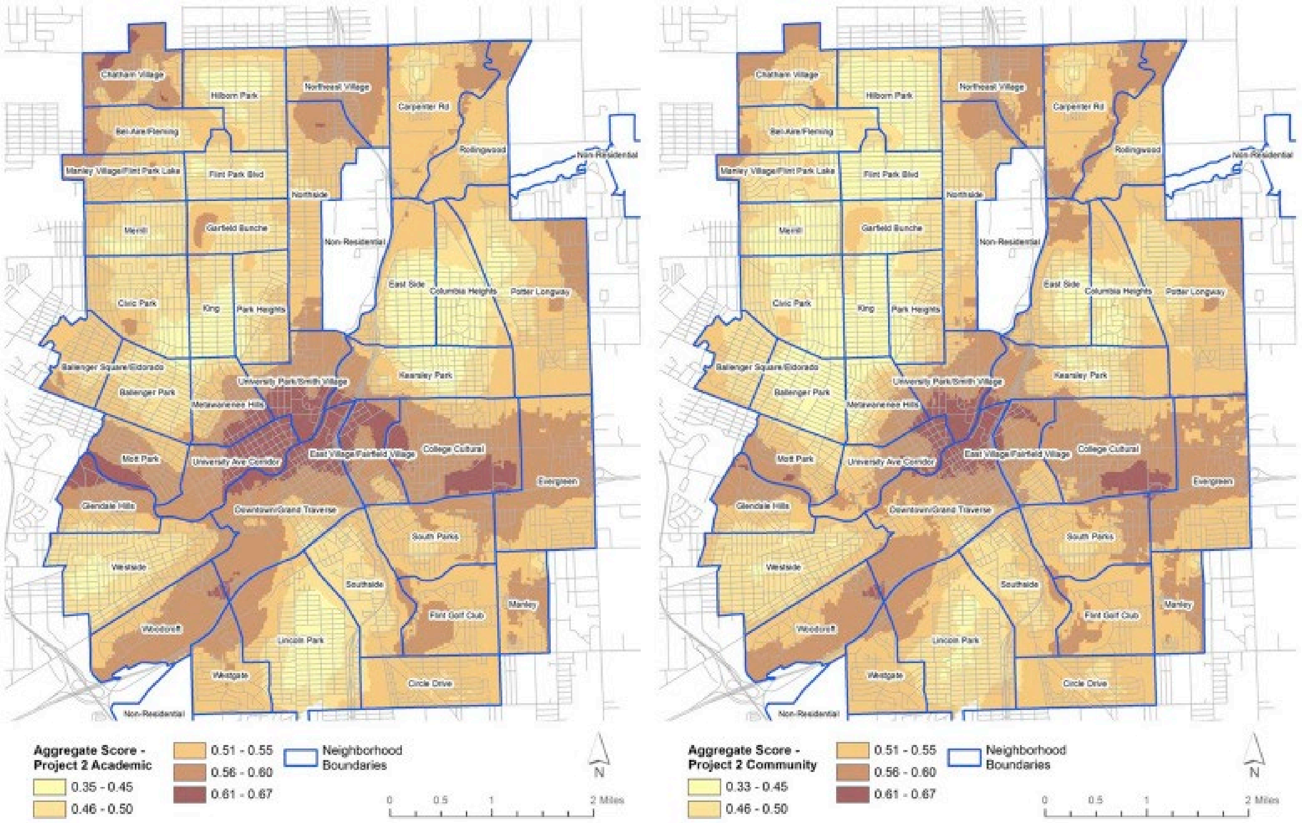

Flint Geospatial Healthfulness Index
Sadler et al., 2019, *Social Science & Medicine*

Category	Social Determinant of Health	Literature Review	Consultants
Neighborhood Deprivation	Income	X	X**
	Education	X	X**
	Employment	X	X**
	Housing quality & stability	X	X**
	Internet & technology access	X	X**
	Vehicle ownership	X	X**
	Physical neighborhood deprivation	X	X
	Redistricting & district funding		X
Community Health & Healthcare Access	Substance use treatment	X	X**
	Harm reduction & naloxone access	X	X**
	Healthcare access	X	X**
	Mental/behavioral health	X	X**
	Availability of opioids, tobacco, alcohol	X	X
	Health insurance	X	X**
	Physical health & disability	X	
Built Environment	Parks, libraries & public land	X	X**
	Vacant and foreclosed buildings/land	X	X
	Places of worship	X	X
	Grocery stores & restaurants	X	X**
	Hotels & single room occupancies	X	X
	Convenience / “mom & pop” stores		X
	Bus stops	X	
	Police stations	X	
	Auto shops	X	
Criminal-Legal Activity & Involvement	Crime & safety	X	X**
	Arrests & police activity	X	X**
	Drug-related raids/busts	X	X
	Incarceration & prison release	X	X
	“Law & order” policies		X
	Police conduct		X
Community Demographic & Family Makeup	Age of population	X	X
	Racial segregation & racial makeup	X	
	Urbanicity	X	
	Divorce, widowed, single-parent families	X	
	Foster care & family separation		X

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Besides traditional indicators of **housing quality & stability**, consultants identified racism-related indicators like **gentrification/ displacement, predatory lending, & exclusionary zoning practices**

Consultants highlighted the impact of not only **insurance status & type**, but also **insurance utilization** (e.g., self-efficacy to use insurance)

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Over 2/3 of determinants identified by consultants were **new**

Community-informed vs. Traditional GIS Index

Box. Census Variables in the Area Deprivation Index

Domain	Variable
Education	% Population aged 25 years or older with less than 9 years of education
	% Population aged 25 years or older with at least a high school diploma
	% Employed population aged 16 years or older in white-collar occupations
Income/employment	Median family income in US dollars
	Income disparity
	% Families below federal poverty level
	% Population below 150% of federal poverty level
	% Civilian labor force population aged 16 years and older who are unemployed
Housing	Median home value in US dollars
	Median gross rent in US dollars
	Median monthly mortgage in US dollars
	% Owner-occupied housing units
	% Occupied housing units without complete plumbing
Household characteristics	% Single-parent households with children younger than 18
	% Households without a motor vehicle
	% Households without a telephone
	% Households with more than 1 person per room

Maroko AR, Doan TM, Arno PS, Hubel M, Yi S, Viola D. Integrating social determinants of health with treatment and prevention. A new tool to assess local area deprivation. Prev Chronic Dis 2016;13:160221

Community-informed vs. Traditional GIS Index

Project MOST Index Domains
Trauma & Mental Health
Income & Housing
Drug & Alcohol Access
Education & Youth Support
Treatment & Healthcare Access
Food Insecurity & Access
Inequitable Policies

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Summary

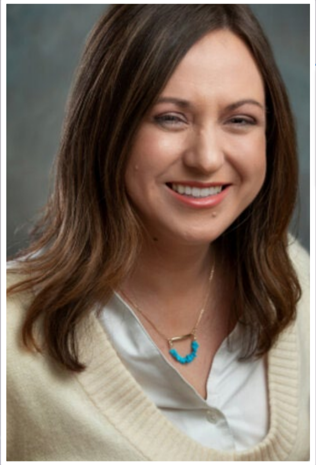
- GIS has several potential benefits for improving services in Black communities overburdened by overdose crisis but under-resourced
  - Informing location-based service targets
  - Improving awareness and reducing stigma
  - Facilitating collaboration, advocacy & resource allocation
- Despite benefits, challenges and skepticism remain due to inequities in data validity and use
- Community-engaged geospatial science may enhance potential benefits, mitigate challenges, and illuminate new social determinants of overdose to advance the science of health equity

PROJECT MOST

MAPPING OVERDOSE FOR
SAINT LOUIS TRANSFORMATION

Devin Banks
Washington University in St. Louis
banks.devin@wustl.edu

Treatment and Services Research



Marynia Kolak, MS, MFA, Ph.D.

Assistant Professor, University of Illinois Urbana-Champaign

Measuring the Spatial Availability of Medications for Opioid Use Disorder

Devin Banks, Ph.D.

Assistant Professor, Washington University in St. Louis

Integrating Community Engagement and Geospatial Methods to Address Racial Inequities: Benefits and Barriers

Tamara Haegerich, Ph.D.

Moderator

Program Official, Services Research Branch, DESPR NIDA

Epidemiology Research

Johannes Eichstaedt, Ph.D.

Assistant Professor, Stanford University

Using Geolocated Social Media for Monitoring the Opioid Epidemic

Chelsea Shover, Ph.D.

Assistant Professor, University of California, Los Angeles

Mapping Harm Reduction Service Deserts: Methodological and Applied Considerations from Los Angeles

Janet Kuramoto-Crawford, Ph.D, M.H.S.

Moderator

Program Official, Epidemiology Research Branch, DESPR NIDA

Using Geo-located Social Media to Track the Opioid Epidemic

Johannes Eichstaedt & Russ Altman
(on behalf of Stanford Research team)

Outline

- Data sources overview
- Language estimation
- Twitter results
    - Kentucky RADOR-KY collaboration
- Reddit results

Social media data sources

Platform Name	Platform focus	Text data available	Platform URL	Drug discussion not restricted?	Has API?	Has research portal?	Previously researched for opioid pharmacovigilance?	Geolocation available?	Example of geolocation inference strategy
Facebook	Personal profiles and friend activity	Posts, comments, captions	facebook.com	✗	✓	✗	✓✓	✓	Consensus of friend locations
Instagram	Sharing photos and videos	Captions, comments	instagram.com	✗	✓	✗	✓✓	✓	Consensus of friend locations
LinkedIn	Professional networking	Posts, comments	linkedin.com	✗	✓	✗	✗	✓	Location-specific company
TikTok	Sharing short videos	Captions, comments, transcripts	tiktok.com	✗	✓	✗	✗	✓	Location-specific hashtags
X (Twitter)	Broadcasting short posts	Posts, comments	twitter.com	✗	✓	✗	✓✓✓✓	✓	Self-described location of user
Reddit	Community networks and discussion	Posts, comments, captions	reddit.com	✓	✓	✗	✓✓✓✓	✗	Location-specific subreddits

Carpenter et al., 2024, Preprint

Outline

- Data sources overview
- Language estimation methods
- Twitter results
  - Kentucky RADOR-KY collaboration
- Reddit results

How to measure opioid use from language use?

- Keywords
  - Extended through LLMs and embeddings
  - Seems to work on Reddit, not on Twitter

- General markers of psychological distress (whole vocabulary)
  - Works well on Twitter, TBD on Reddit

Outline

- Data sources overview
- Language estimation
- Twitter results
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Social media data sources

- Twitter/X
  - Geolocation through Twitter profile location or GPS tags, total 8-10% of the sample
  - API access ended March 2023
- Reddit
  - Geolocation through users posting in a location subreddit (e.g., R/LosAngeles)
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  - We are exploring, but unclear.

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Twitter data geospatial **data processing**

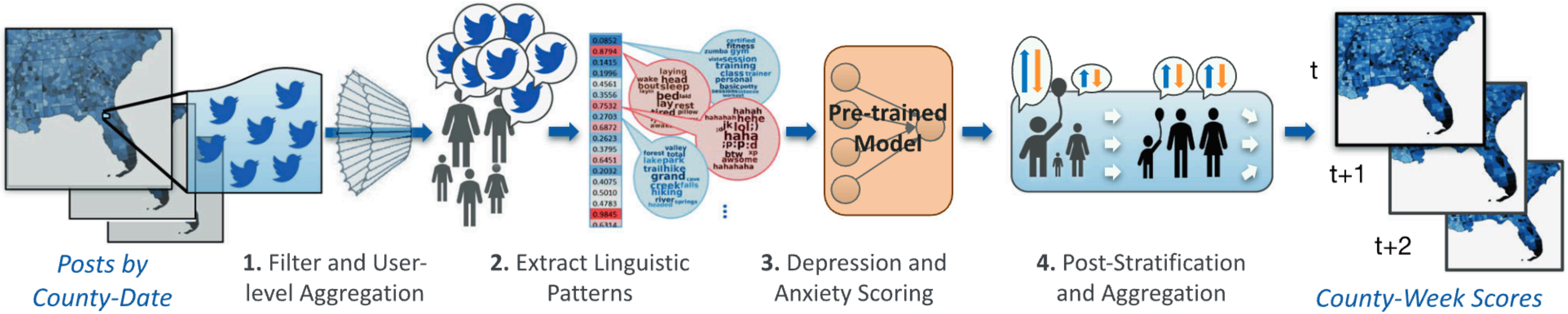


Fig. 1 | The Language Based Mental Health Assessment pipeline. Visual overview of the *language-based mental health assessments* pipeline. County-mapped messages are filtered to self-written posts, from which language features are extracted and passed through pretrained language-based mental health assessments to generate user scores. These scores are then reweighted to better represent county demographics and are then aggregated to communities in time.

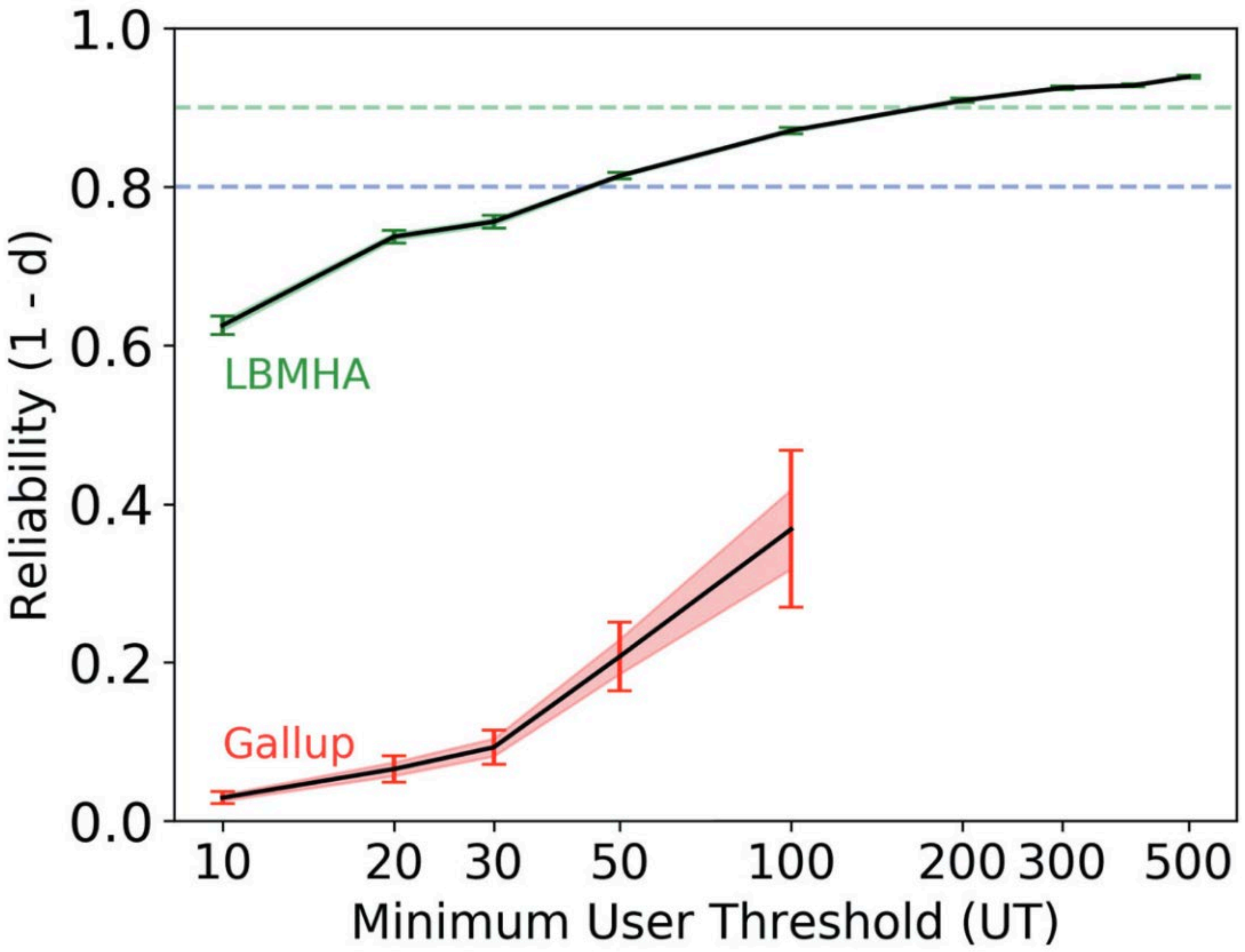
- Geolocation through profiles and GPS tags
- Language estimation through full-vocabulary language models trained with supervised machine learning

Mangalik et al., 2024, *npj digital medicine*

Twitter data geospatial **density**

Reliability per Spatiotemporal Unit

	MSA (1)	County (23)	Township (155)
Year (2)	0.993	0.933	0.802
Quarter (3)	0.996	0.948	0.816
Month (8)	0.987	0.938	0.753
Week (36)	0.986	**0.921**	0.765
Day (252)	0.977	0.888	0.684

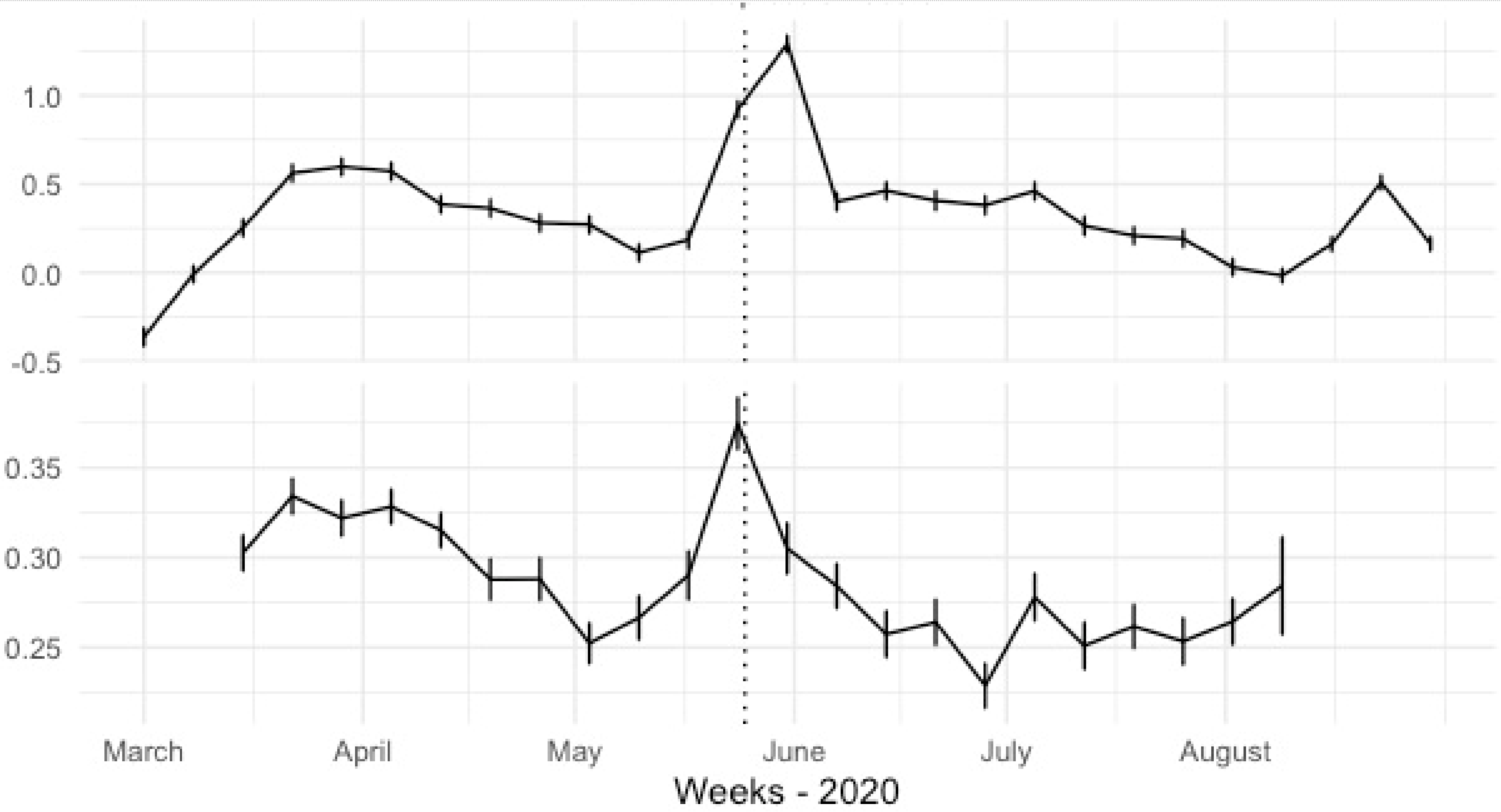


Mangalik et al., 2024, *npj digital medicine*

Longitudinal evaluation (US counties)

Twitter Depression

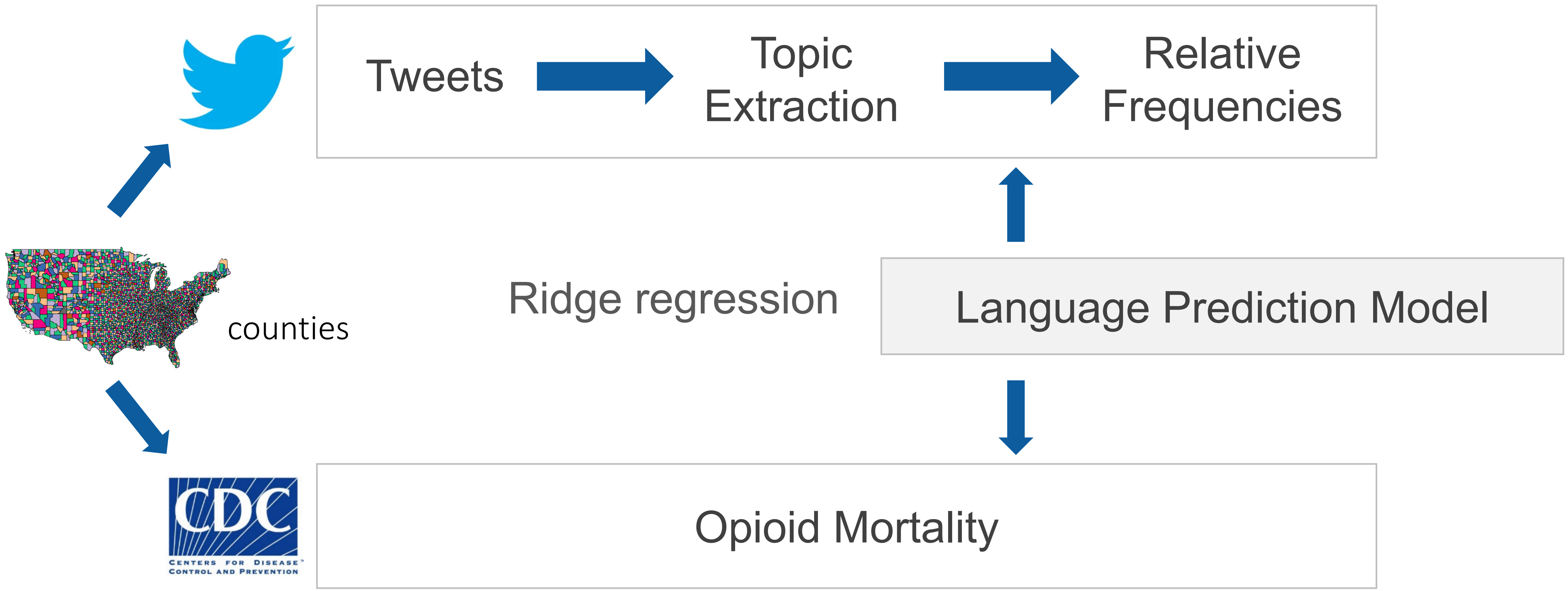
Sadness



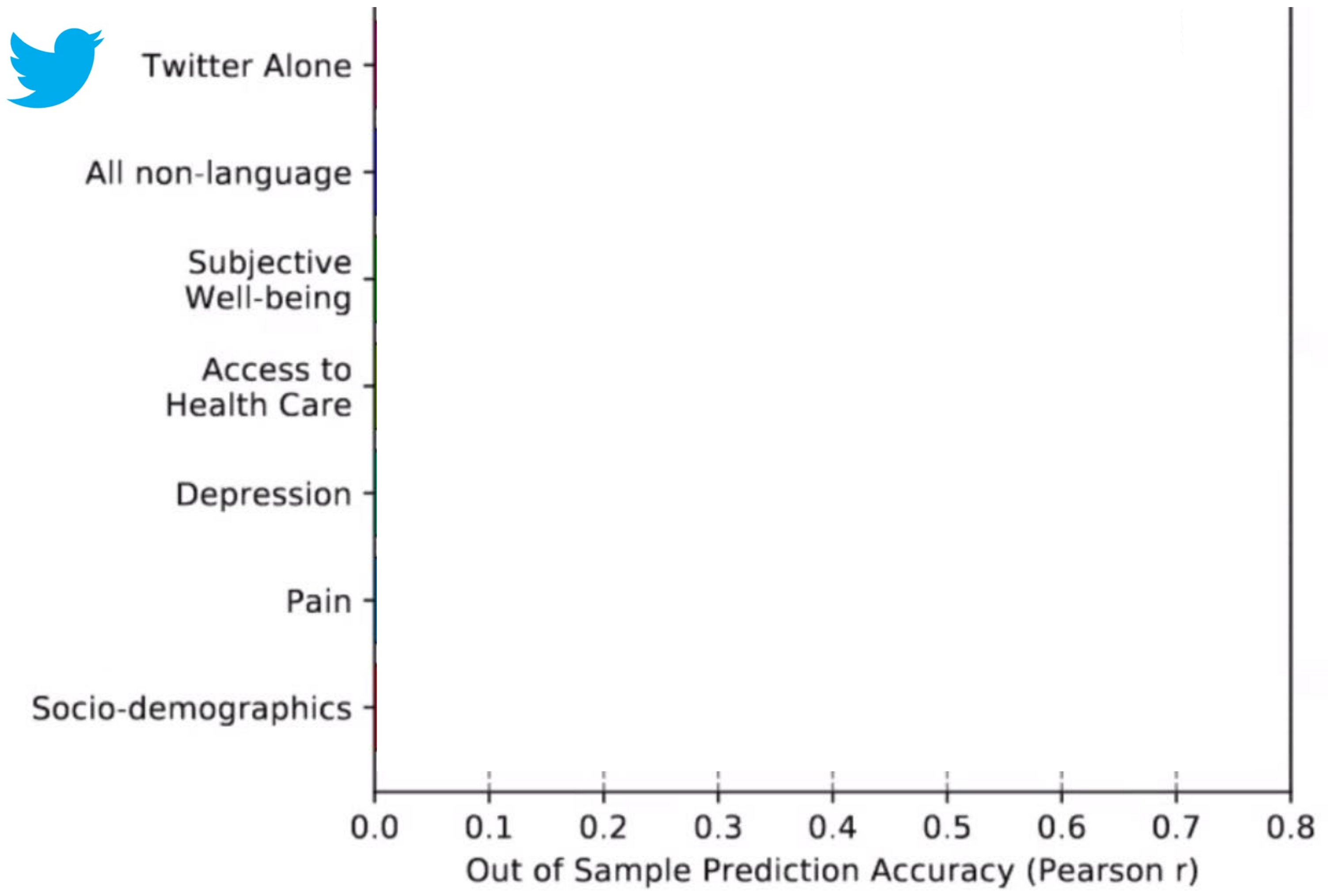
National Institute of Mental Health

R01 MH125702

Prediction of Opioid Mortality with Twitter



Predicting **opioid mortality**



662 counties;
Cross-sectional
10-fold cross-validation

Giorgi et al., 2023, *Scientific Reports*

Collaboration with Kentucky RADOR-KY

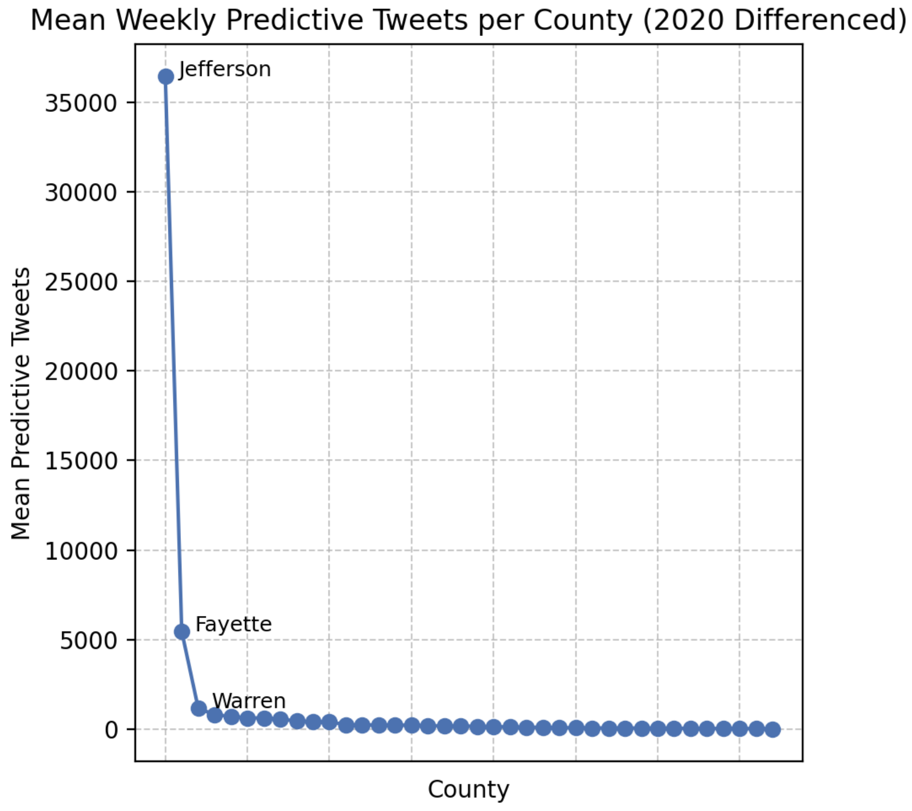
- Kentucky opioid mortality tracking system based on many data feeds
  - EMS, hospitals…
- Adding social media to test incremental predictive value

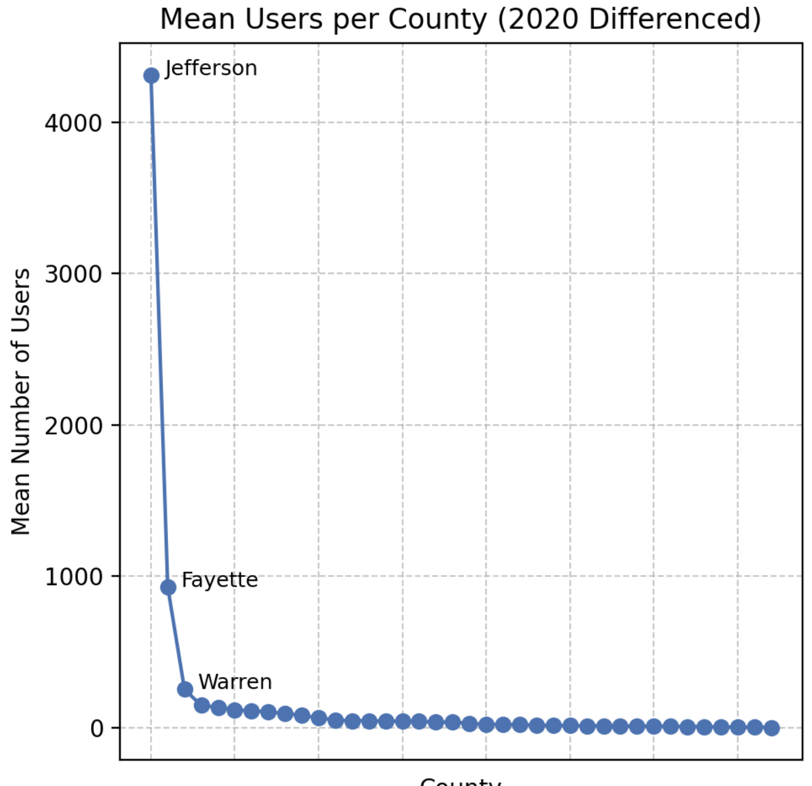
2020 Twitter data for Kentucky RADOR-KY

Top 10 counties by n_users

county_name	n_users	avg_users	avg_n_lexwords	avg_dep_score	avg_anx_score
Jefferson	447998	4307.67	364594.29	2.62	2.58
Fayette	96756	930.35	54504.52	2.59	2.53
Warren	26316	253.04	11749.9	2.57	2.52
Madison	15282	146.94	7098.83	2.64	2.57
Kenton	14048	135.08	7768.04	2.63	2.56
Daviess	12068	116.04	5576.46	2.6	2.53
Boone	11802	113.48	6113.44	2.62	2.54
Hardin	10732	103.19	6066.46	2.61	2.56
Campbell	9850	94.71	4316.6	2.66	2.58

See all counties: [Descriptives for KY on LBMHA]





Kentucky tweets from 2021

Tweets in 2021

Tweets	7,127,150
Counties	117
Users	20,521

After English filtered

Tweets	5,758,726
Counties	117
Users	20,245

After removing duplicates (county-level) and retweets

Tweets	3,303,236
Counties	117
Users	18,649

Users

min	1
mean	177
sd	317
median	40
max	2583

Counties / Tweets

min	8
mean	28,233
sd	168,079
median	3,134
max	1,753,560

Counties / Users

min	1
mean	159
sd	845
median	20
max	8723

Kentucky tweets from 2022

Tweets in 2022

Tweets	4,636,877
Counties	117
Users	14,046

After English filtered

Tweets	3,697,559
Counties	117
Users	13,791

After removing duplicates (county-level) and retweets

Tweets	2,069,332
Counties	117
Users	12,535

Outline

- Data sources overview
- Language estimation
- Twitter results
  - Kentucky RADOR-KY collaboration
- Reddit results

Monitoring the opioid epidemic via social media discussions

Delaney A. Smith[1†] Adam Lavertu[2†], Aadesh Salecha[3], Tymor Hamamsy[4], Keith Humphreys[5,8], Mathew V. Kiang[7], Russ B. Altman[2,6] & Johannes C. Eichstaedt[3*]

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† These authors contributed equally to the work.

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Abstract

Opioid-involved overdose deaths have risen significantly since 1999 with over 80,000 deaths annually since 2021, primarily driven by synthetic opioids, like fentanyl. Responding to the rapidly changing opioid crisis requires reliable and timely information. One possible source of such data is the social media platforms with billions of user-generated posts, a fraction of which are about drug use. We therefore assessed the utility of Reddit data for surveillance of the opioid epidemic, covering prescription, heroin, and synthetic drugs (as of September 2024, up-to-date Reddit data was still accessible on the open web). Specifically, we built a natural language processing pipeline to identify opioid-related comments and created a cohort of 1,689,039 geo-located Reddit users, each assigned to a state. We followed these users from 2010 through 2022, measured their opioid-related posting activity over time, and compared this posting activity against CDC overdose and National Forensic Laboratory Information System (NFLIS) drug report rates. To simulate the real-world prediction of synthetic drug overdose rates, we added near real-time Reddit data to a model relying on CDC mortality data with a typical 6-month reporting lag and found that Reddit data significantly improved prediction accuracy. We observed drastic, largely unpredictable changes in both Reddit and overdose patterns during the COVID-19 pandemic. Reddit discussions covered a wide variety of drug types that are currently missed by official reporting. This work suggests that social media can help identify and monitor known and emerging drug epidemics and that this data is a public health "common good" to which researchers should continue to have access.

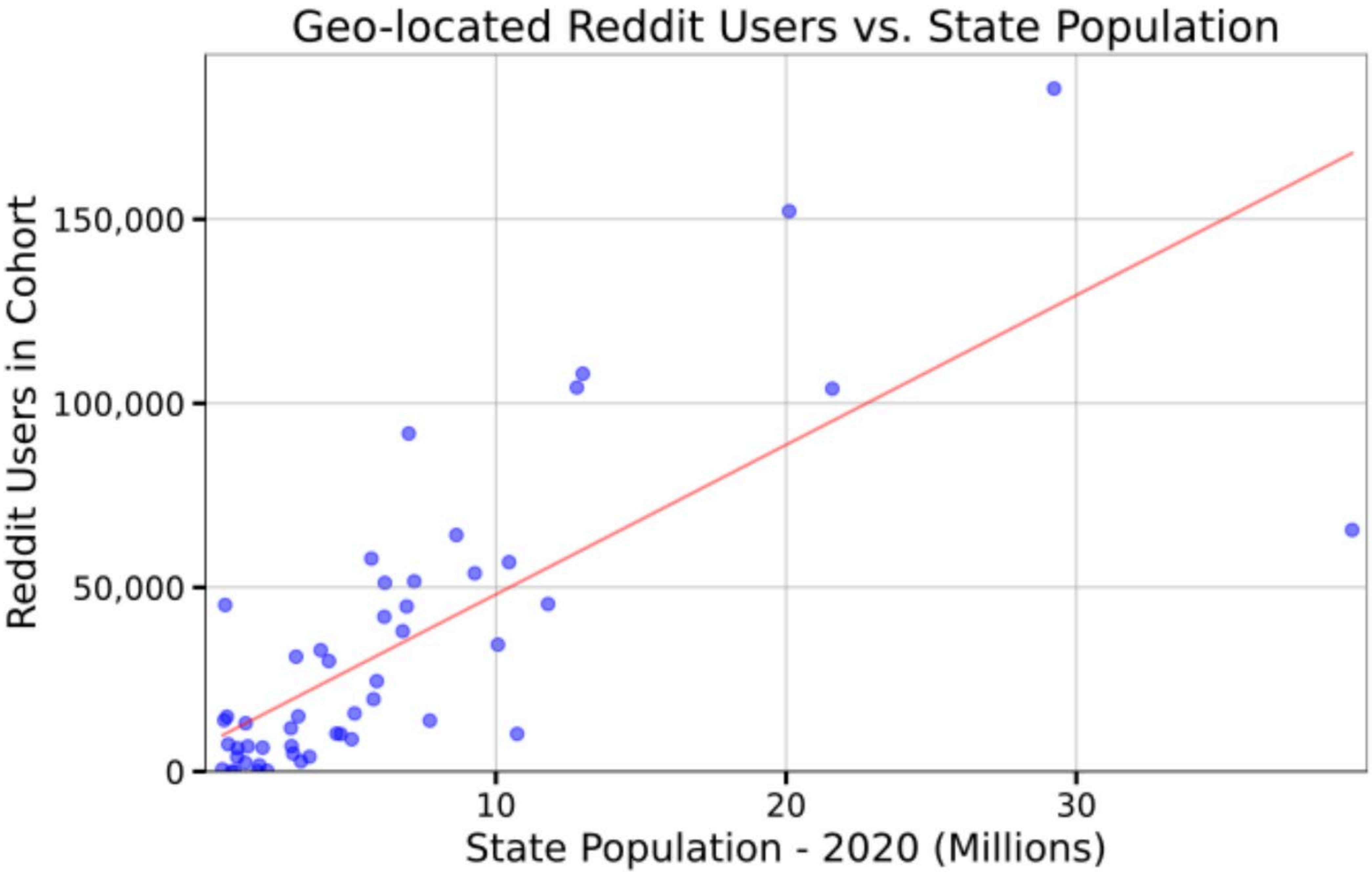
Keywords applied to Reddit

Location through users posting in location subreddits (e.g., R/losAngeles)

link

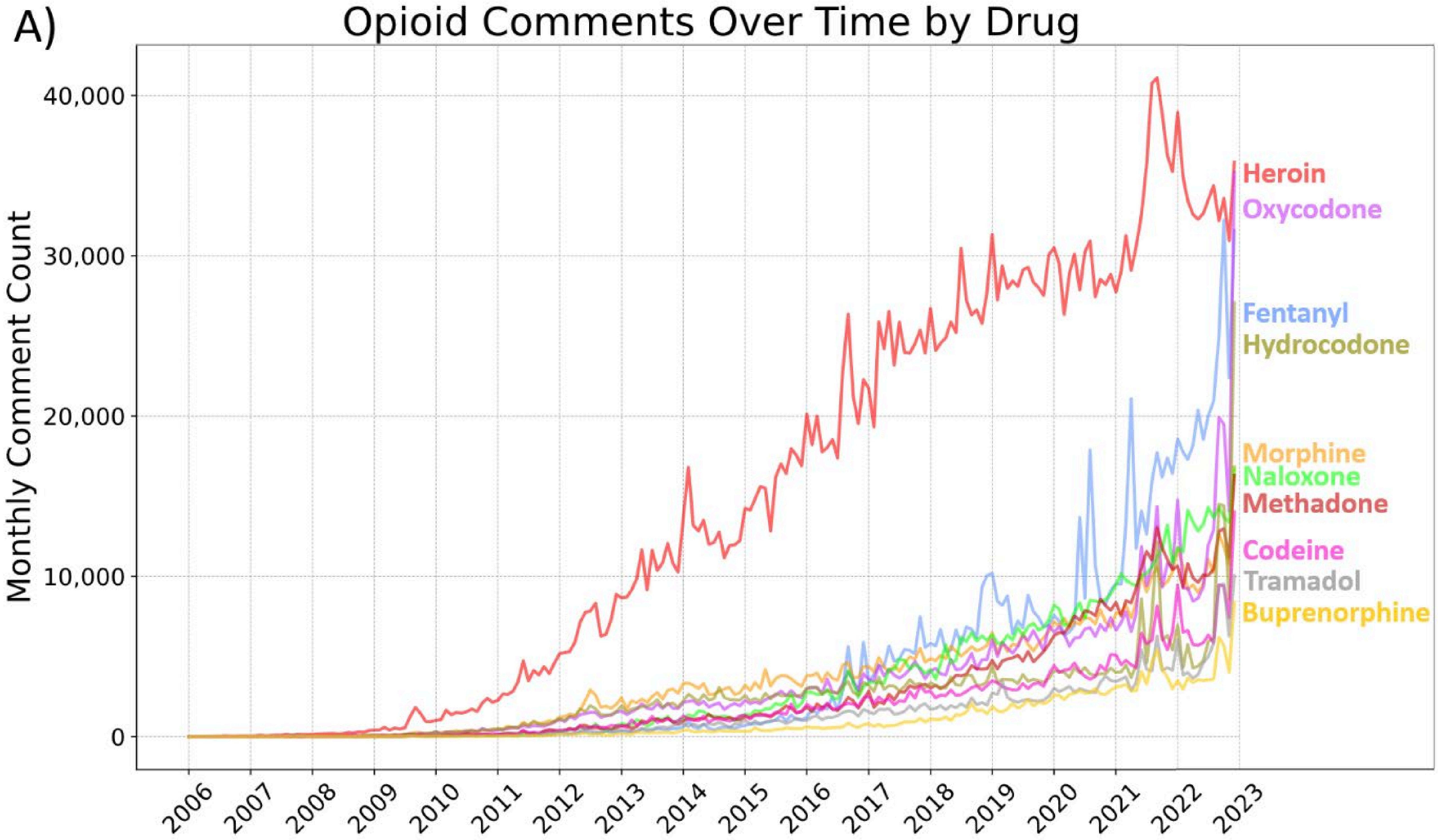
Smith et al., 2024, *MedArXiv preprint*

Using Reddit to monitor the opioid epidemic



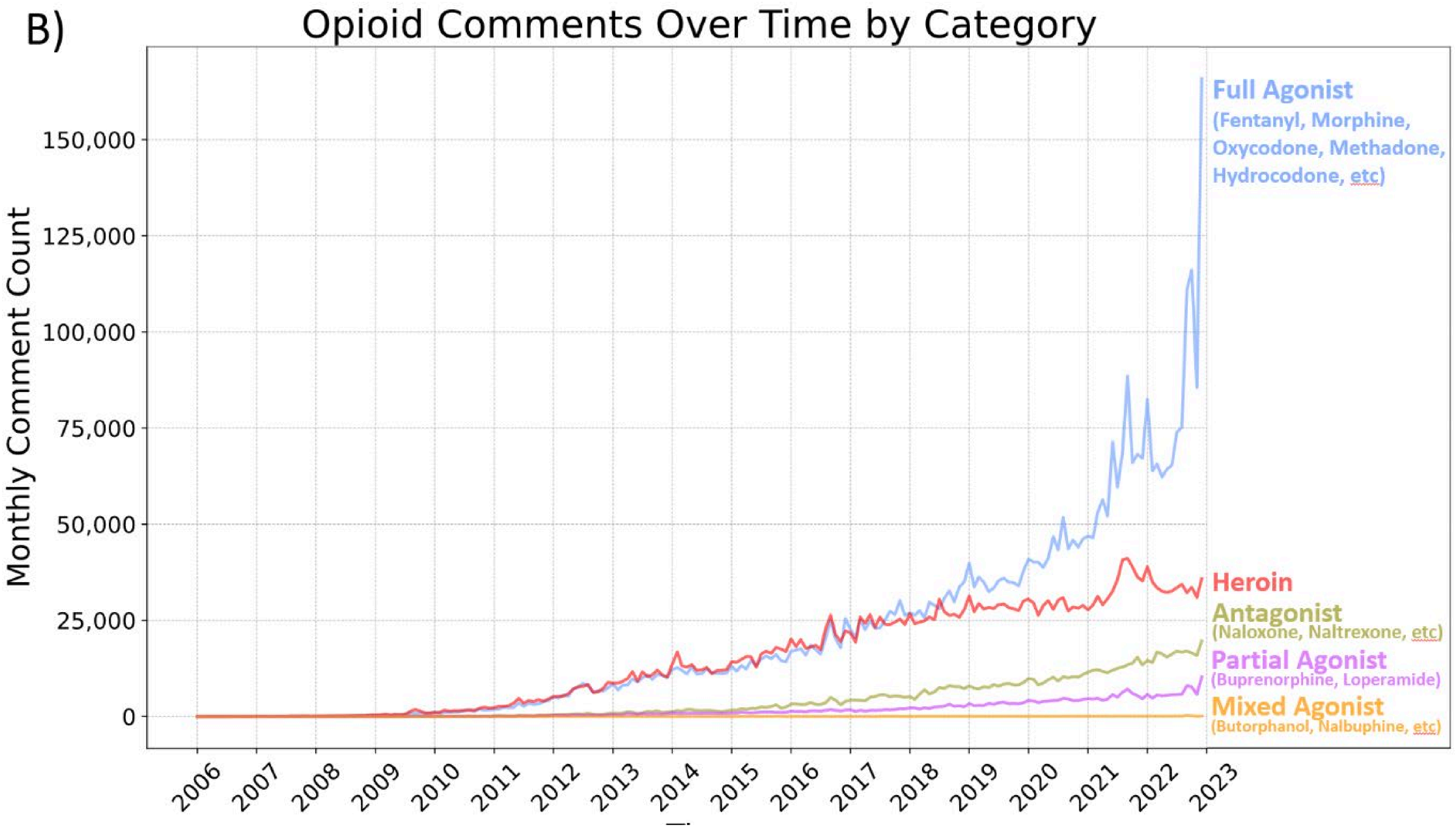
Smith et al., 2024, *MedArXiv preprint*

A)



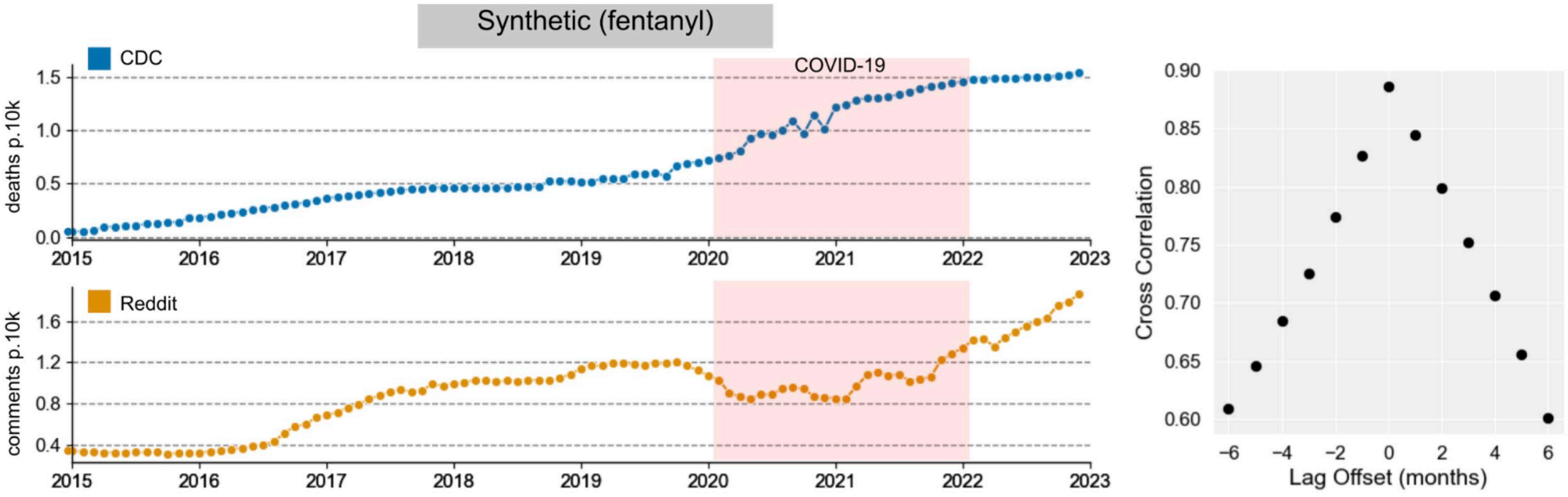
Smith et al., 2024, *MedArXiv preprint*

B)



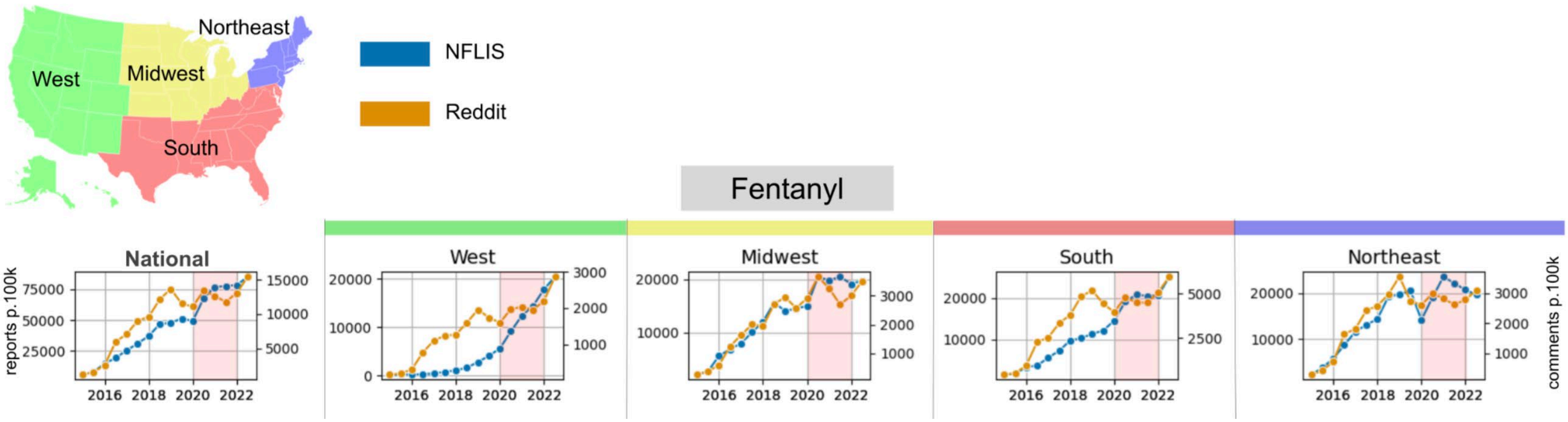
Smith et al., 2024, *MedArXiv preprint*

Reddit rates vs. CDC mortality rates



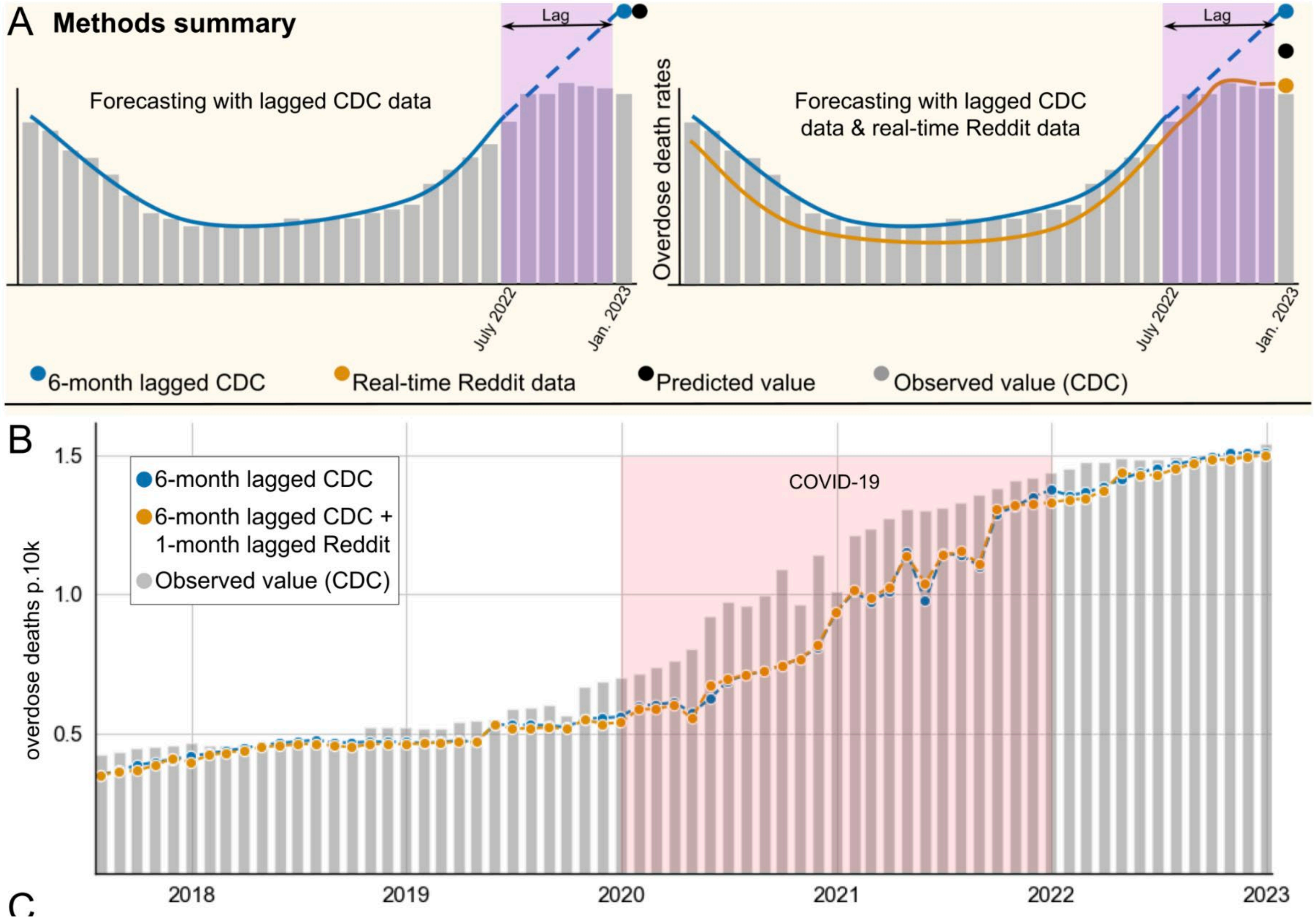
Smith et al., 2024, *MedArXiv preprint*

Reddit vs.
National Forensic Laboratory Information System (NFLIS) drug report rates



Smith et al., 2024, *MedArXiv preprint*

Testing the incremental predictive validity



Adding near real-time Reddit data as an exogenous variable significantly improved the model's prediction accuracy at the national level for synthetic opioids, using 6 months lagged opioid data (Wilcox signed rank test of absolute errors, **p = 0.019**)

Smith et al., 2024, *MedArXiv preprint*

Thank you!

Johannes Eichstaedt Eichstaedt@Stanford.edu
Russ B Altman russ.altman@stanford.edu

Carpenter, K. A., Nguyen, A. T., Smith, D. A., Samori, I. A., Humphreys, K., Lembke, A., Kiang, M. V., Eichstaedt, J. C. & Altman, R. B. (2024). Which Social Media Platforms Provide the Most Informative Data for Monitoring the Opioid Crisis? *medRxiv*, 2024-07.

Carpenter, K. A., & Altman, R. B. (2023). Using GPT-3 to build a lexicon of drugs of abuse synonyms for social media pharmacovigilance. *Biomolecules*, *13*(2), 387.

Giorgi, S., Yaden, D. B., Eichstaedt, J. C., Ungar, L. H., Schwartz, H. A., Kwarteng, A., & Curtis, B. (2023). Predicting US county opioid poisoning mortality from multi-modal social media and psychological self-report data. Scientific Reports, 13(1), 9027.

Mangalik, S., Eichstaedt, J. C., Giorgi, S., Mun, J., Ahmed, F., Gill, G., ... & Schwartz, H. A. (2024). Robust language-based mental health assessments in time and space through social media. *njp Digital Medicine.* 7, 109 (2024)

Smith, D.L, Lavertu, A., Salecha, A., Hamamsy, T., Humphreys K, Kiang, M.V, Altman, R.B., Eichstaedt, J.C. Monitoring the opioid epidemic via social media discussions. *MedRxiv*, 2021-04.

Mapping Harm Reduction Service Deserts: Methodological and Applied Considerations from Los Angeles

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December 3, 2024
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Funding and Project Team

R01DA057630: Predicting fatal and non-fatal overdose in Los Angeles County with Rapid Overdose Surveillance Dashboard to target street-based addiction treatment and harm reduction services

David Goodman-Meza, MD, PhD

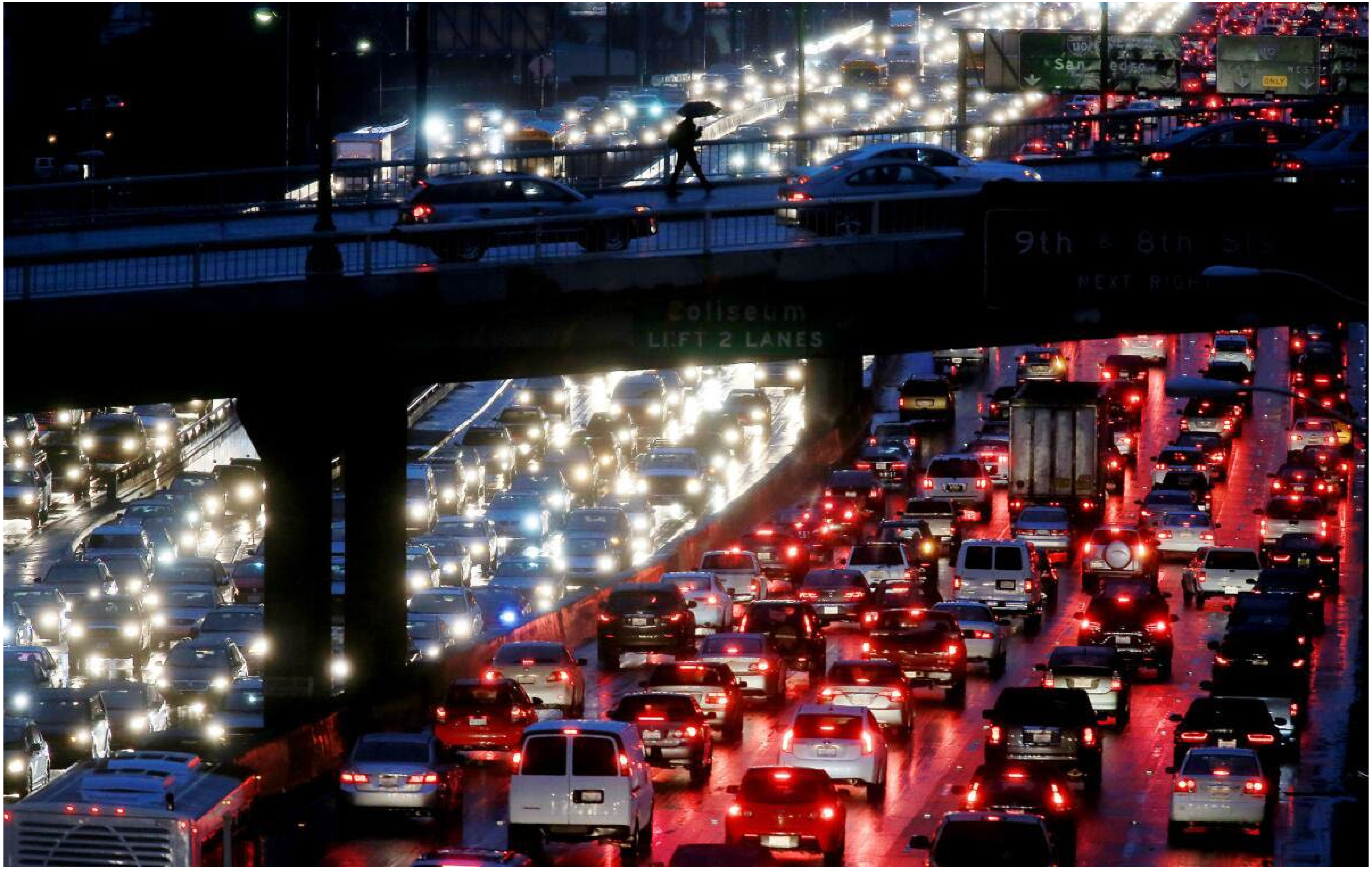
Michael Shin, PhD

Tucker Avra, DVM

Ruby Romero, BA

AND MANY MORE!

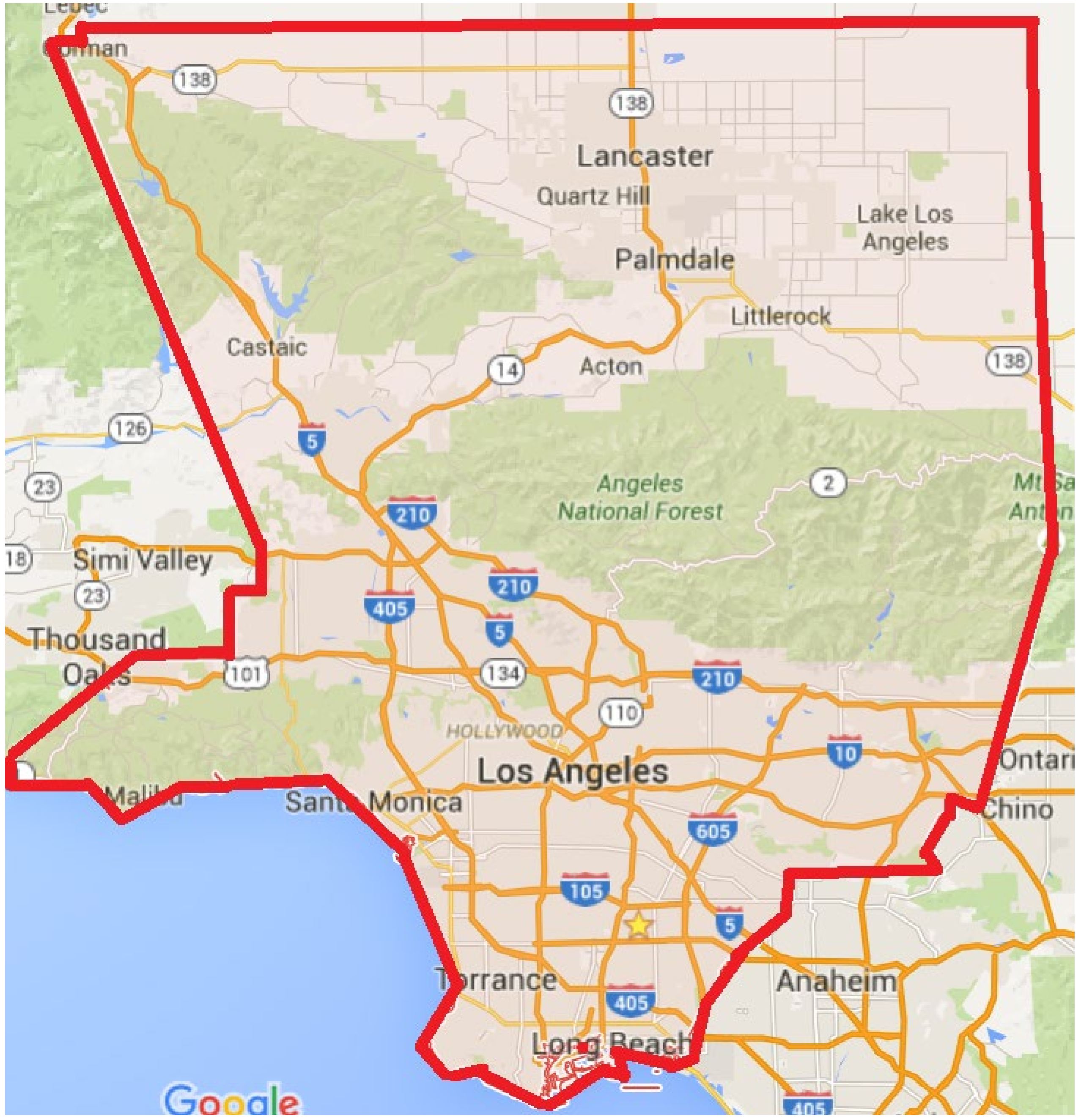
Los Angeles



- Photo: Luis Sinco, *Los Angeles Times*

Los Angeles County Stats

- Population: 9.7 million (2023)
  - More than 40 individual U.S. states
- 4,083 sq miles
- 88 cities + unincorporated areas
- In recent years, U.S. county with largest number of fatal overdoses (population-adjusted rate slightly lower than national average)

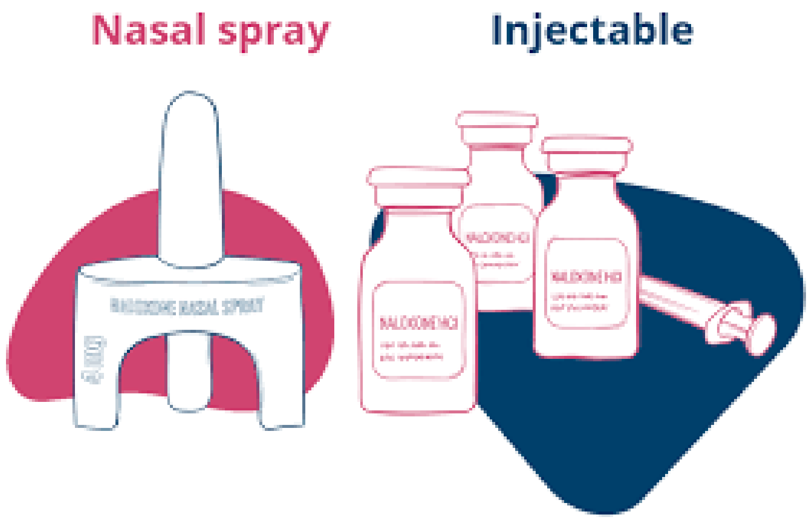


Motivating question: Where are harm reduction service deserts in Los Angeles County?

Big question #1: Where are harm reduction services?

Survey of services (Spring-Summer 2023)

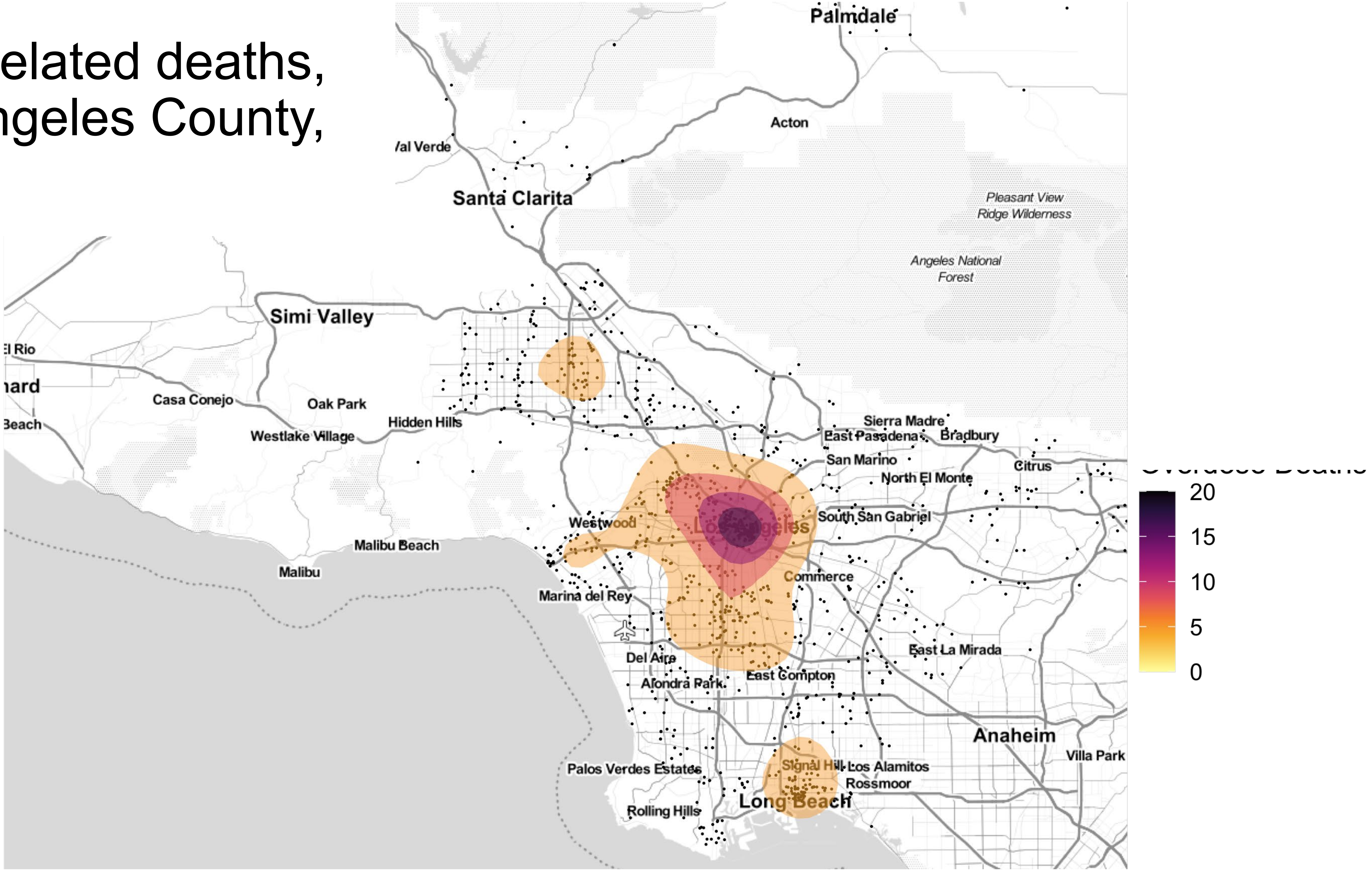
- What do you offer?
- Where?
- When?



Big question #1: How do we define harm reduction service “desert?”

Big question #2: What do the maps tell us?

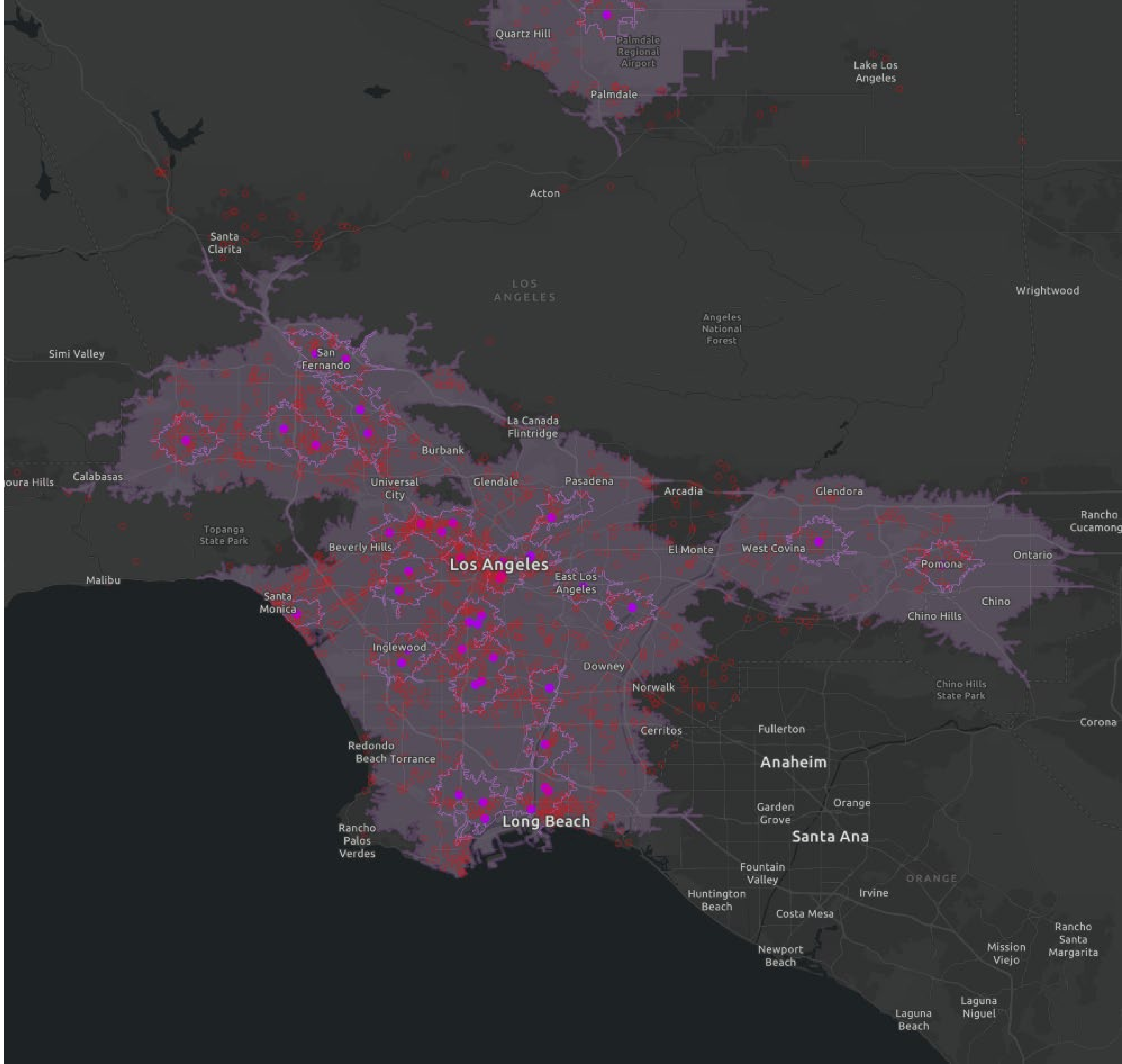
Drug-related deaths, Los Angeles County, 2021

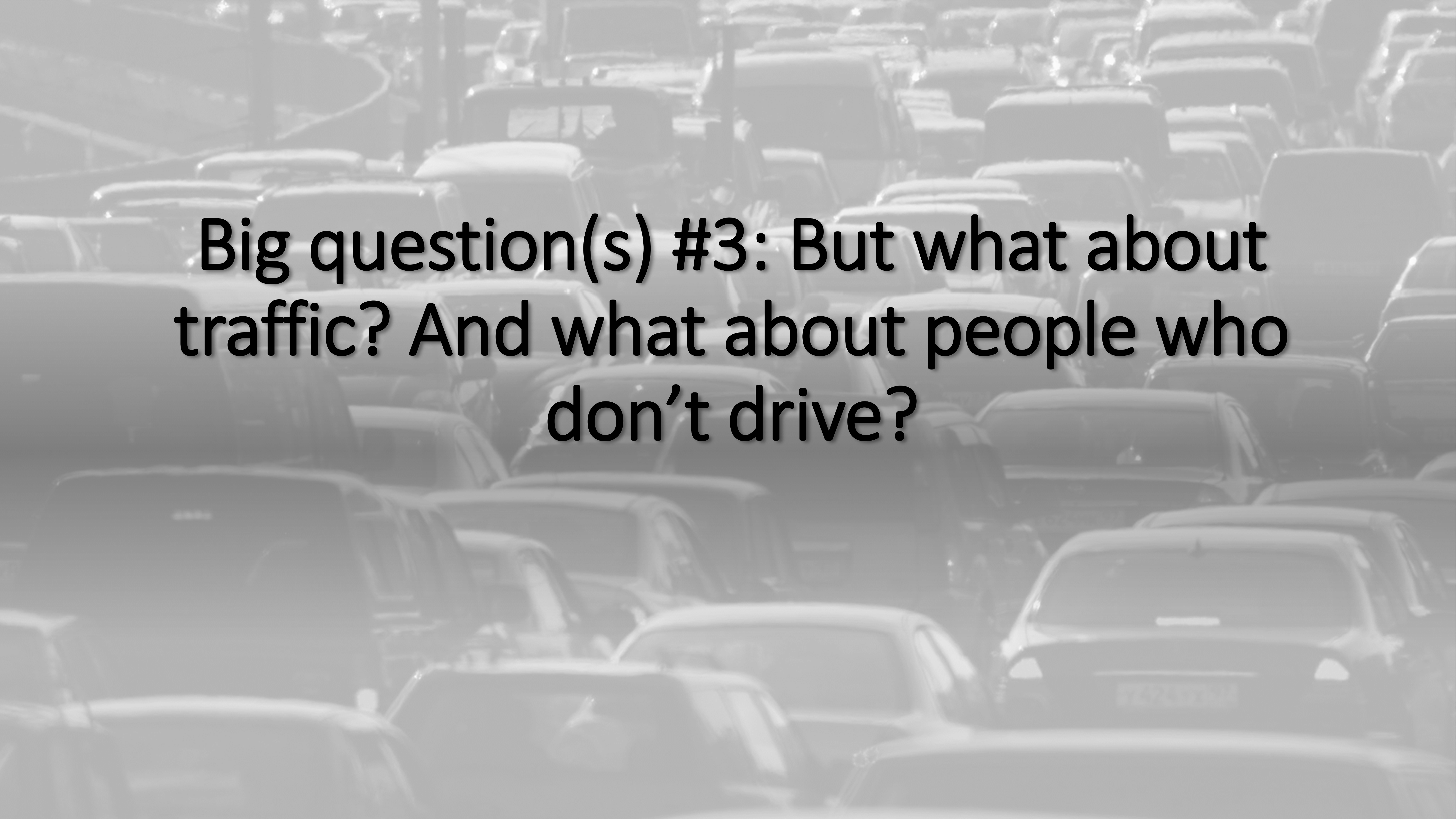


5- and 15-minute drivetime to SSPs

Los Angeles

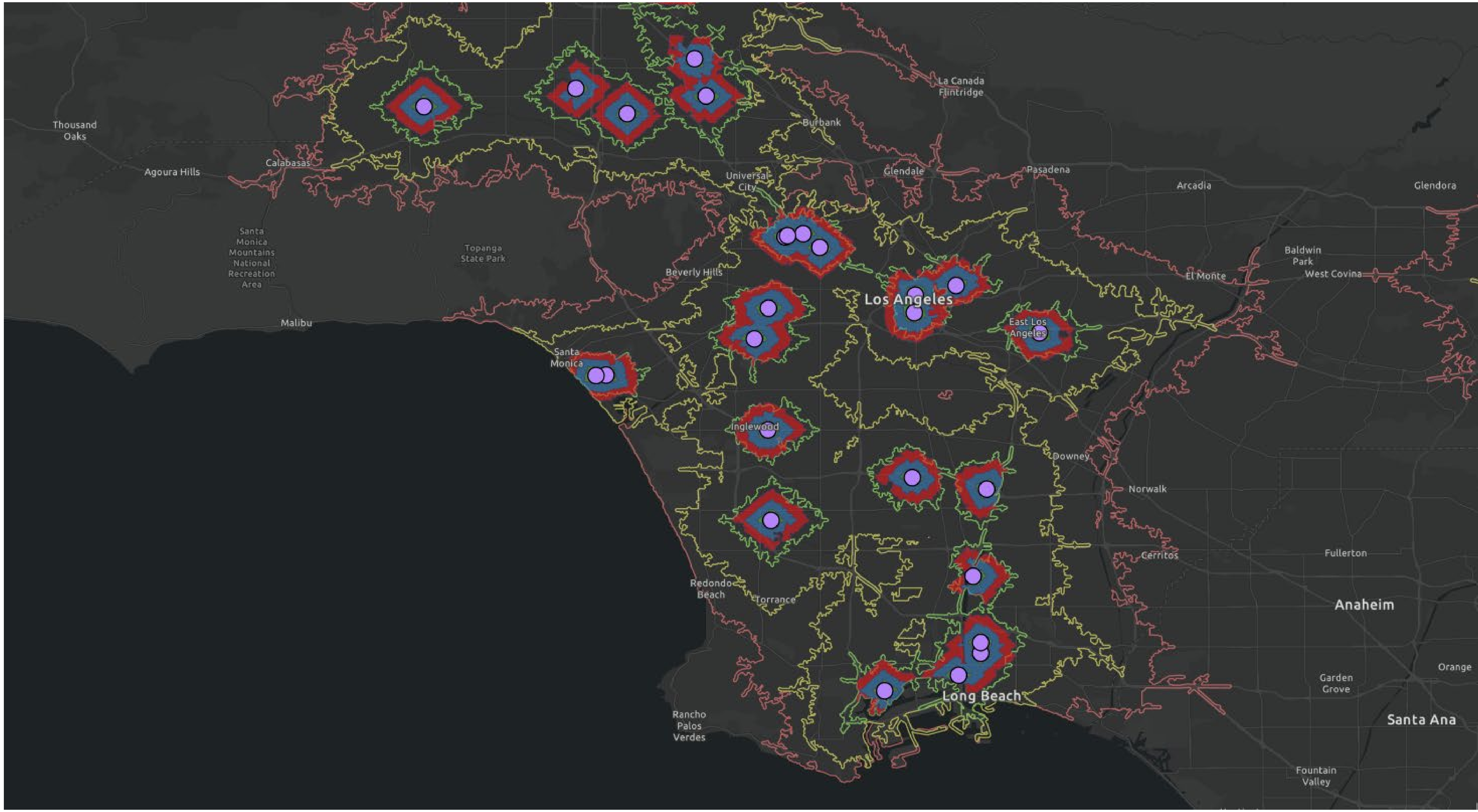
Red dots: 2021 overdose deaths





Big question(s) #3: But what about traffic? And what about people who don’t drive?

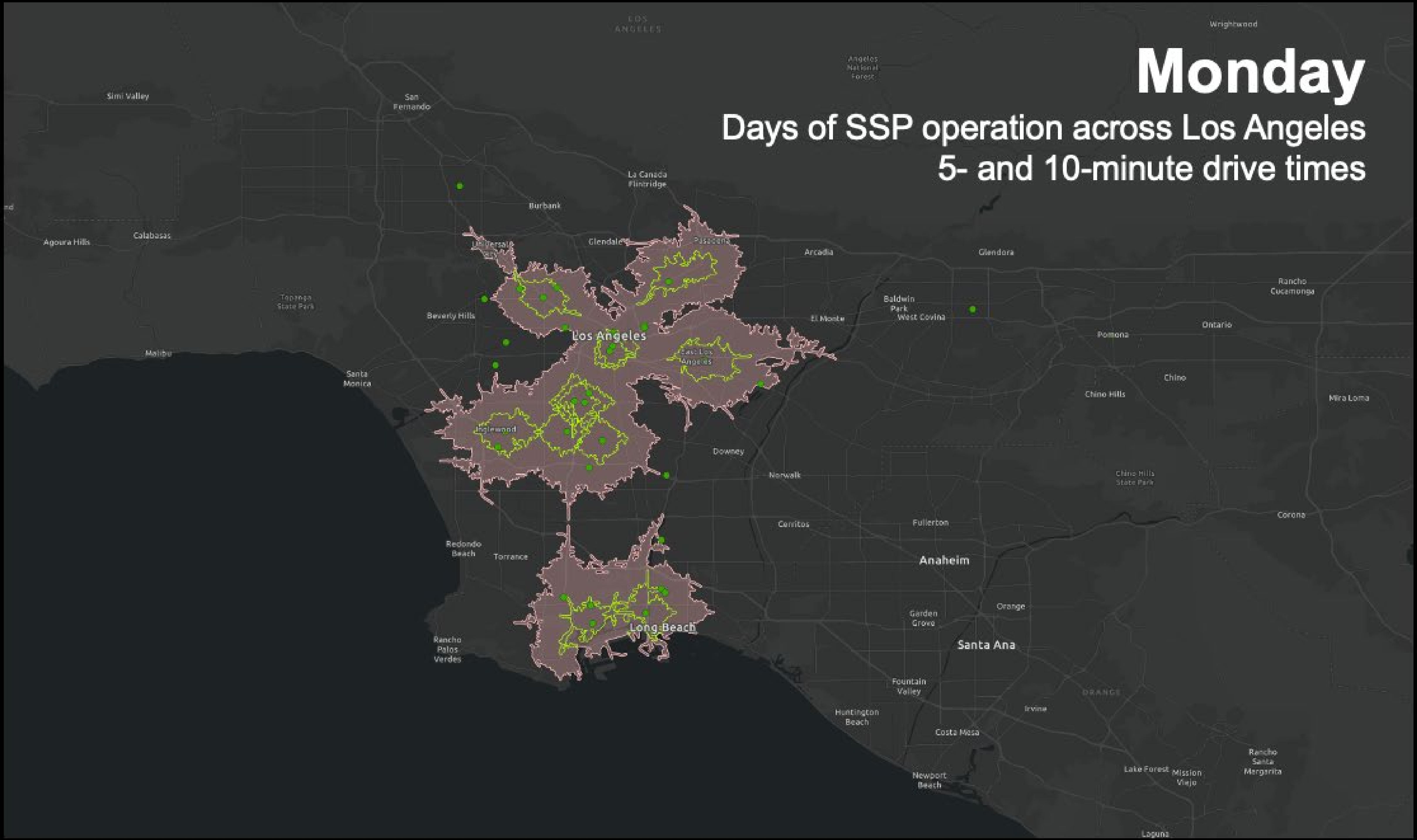
Walking vs. driving



Big question #4: So, are there almost no service deserts?

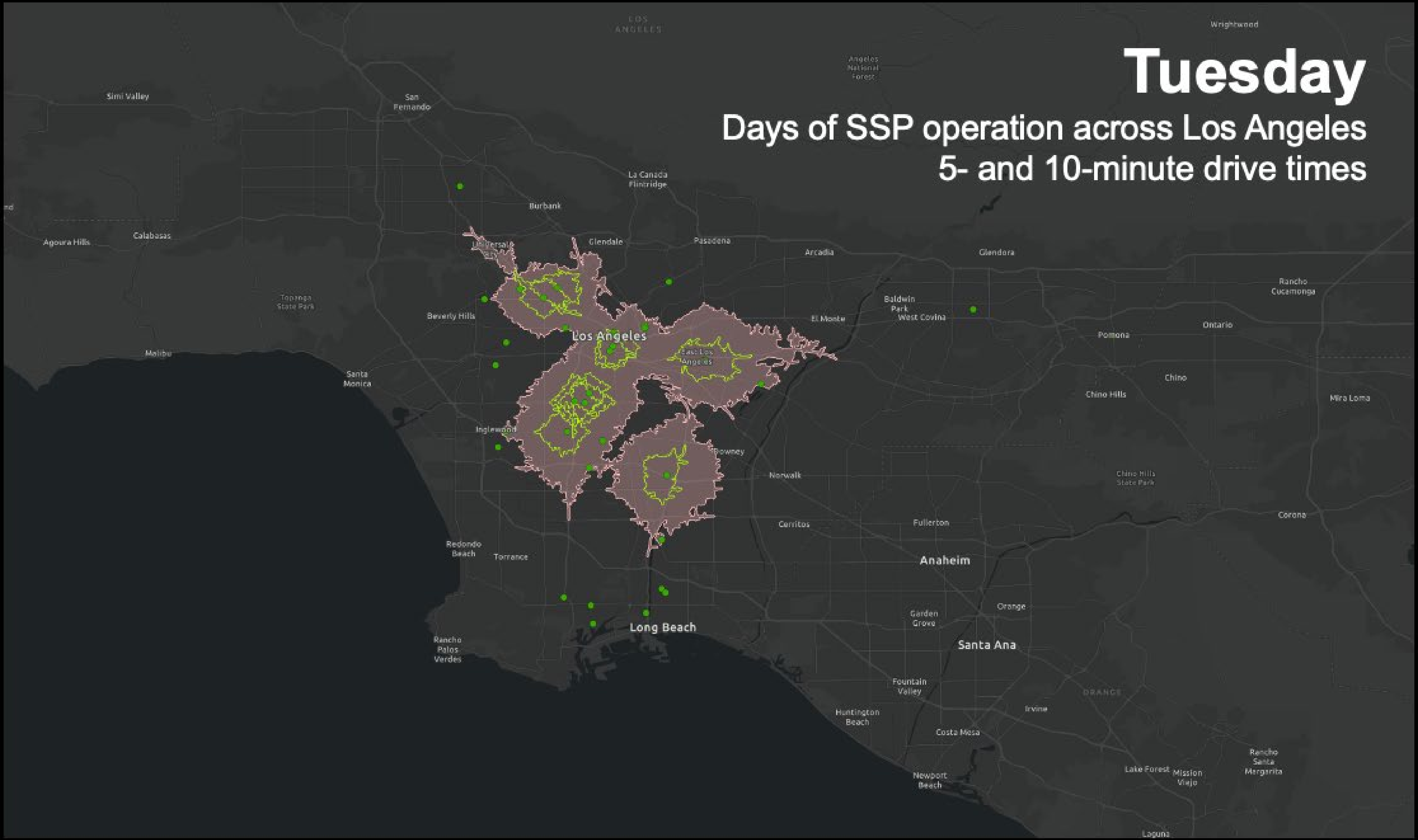
Monday

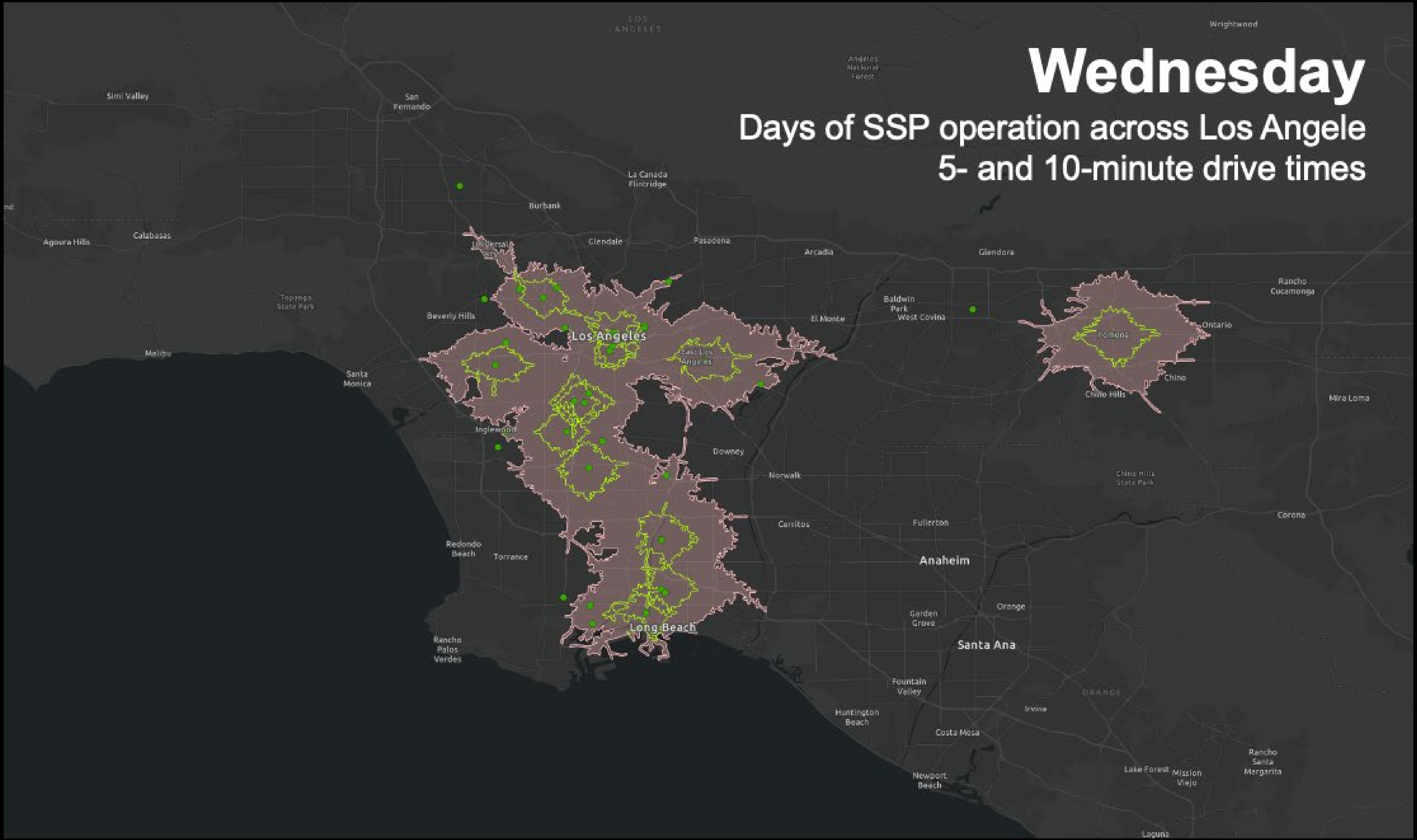
Days of SSP operation across Los Angeles
5- and 10-minute drive times

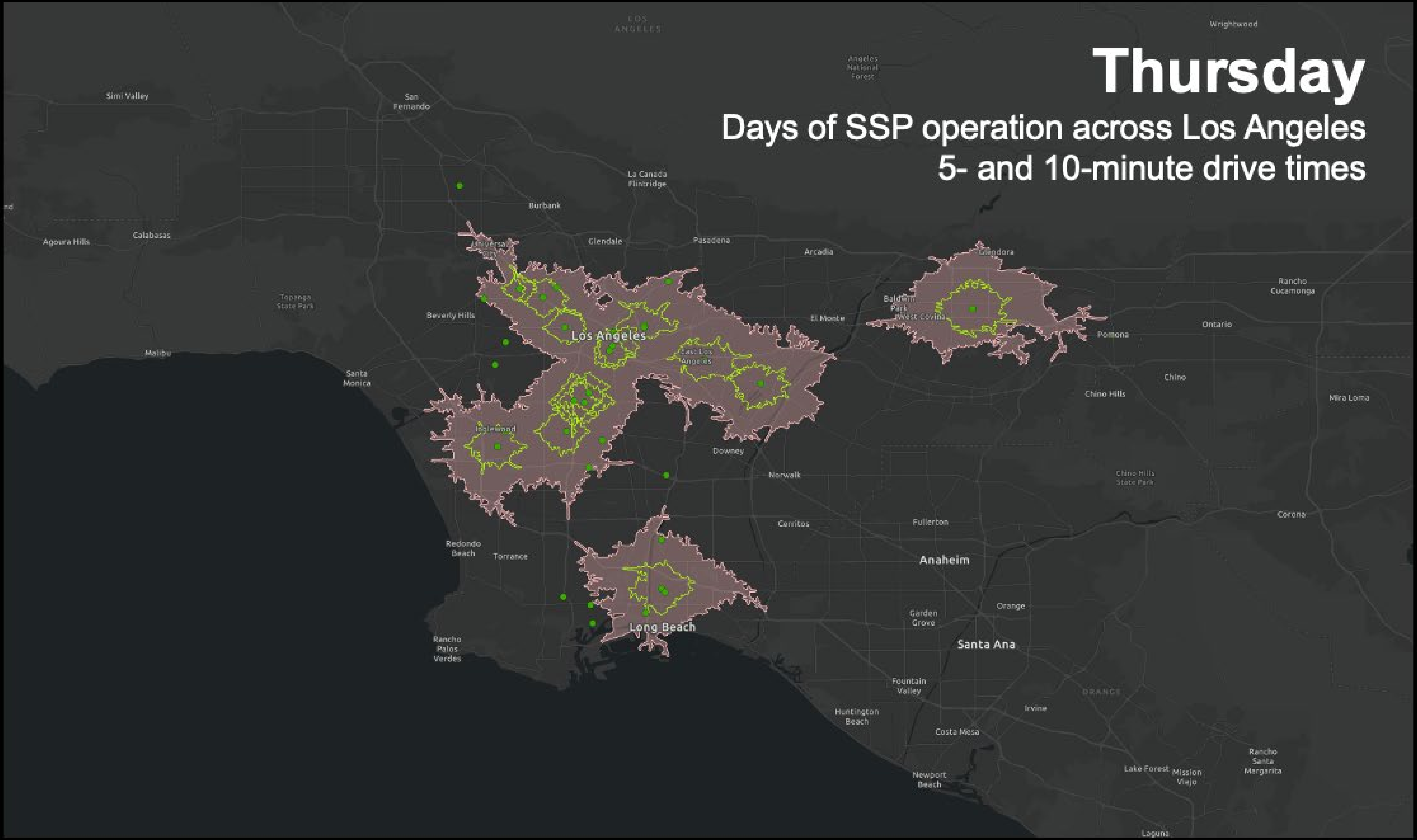


Tuesday

Days of SSP operation across Los Angeles
5- and 10-minute drive times

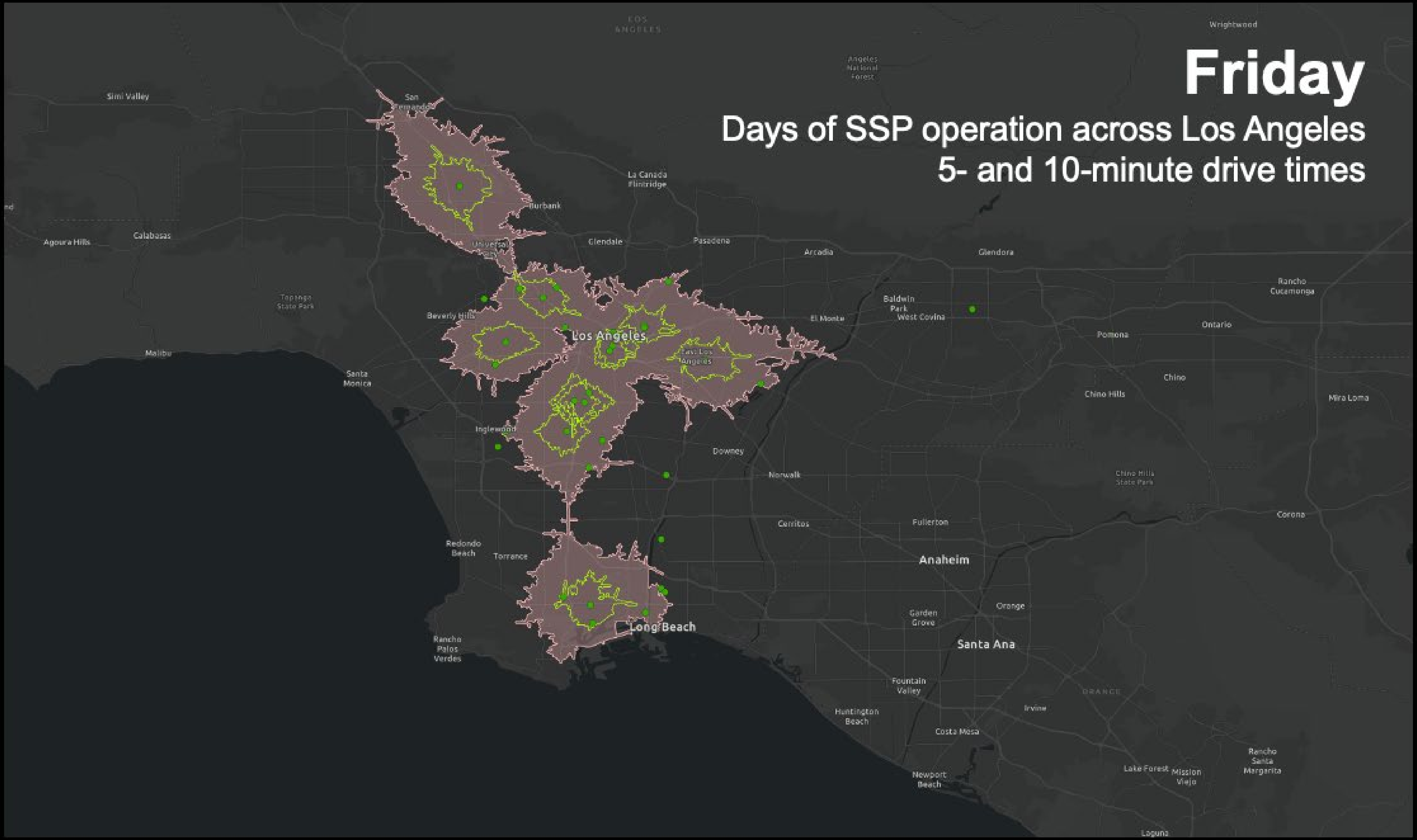



Wednesday
Days of SSP operation across Los Angele
5- and 10-minute drive times
Simi Valley
San Fernando
Burbank
La Canada Flintridge
Agoura Hills
Calabasas
Glendale
Pasadena
Arcadia
Glendora
Beverly Hills
Los Angeles
East Los Angeles
El Monte
Baldwin Park
West Covina
Pomona
Ontario
Rancho Cucamonga
Chino
Chino Hills
Mira Loma
Malibu
Santa Monica
Inglewood
Downey
Norwalk
Cerritos
Fullerton
Anaheim
Redondo Beach
Torrance
Long Beach
Rancho Palos Verdes
Garden Grove
Orange
Santa Ana
Fountain Valley
Huntington Beach
Costa Mesa
Newport Beach
Irvine
Lake Forest
Mission Viejo
Rancho Santa Margarita
Corona
Wrightwood
Laguna


Thursday
Days of SSP operation across Los Angeles
5- and 10-minute drive times
Simi Valley
San Fernando
La Canada Flintridge
Burbank
Agoura Hills
Calabasas
Glendale
Pasadena
Arcadia
Glendora
Rancho Cucamonga
Beverly Hills
Los Angeles
El Monte
Pomona
Ontario
Malibu
Santa Monica
East Los Angeles
Chino
Chino Hills
Mira Loma
Inglewood
Downey
Norwalk
Corona
Redondo Beach
Torrance
Cerritos
Fullerton
Anaheim
Orange
Garden Grove
Long Beach
Santa Ana
Rancho Palos Verdes
Fountain Valley
Huntington Beach
Irvine
Costa Mesa
Lake Forest
Mission Viejo
Rancho Santa Margarita
Newport Beach
Laguna

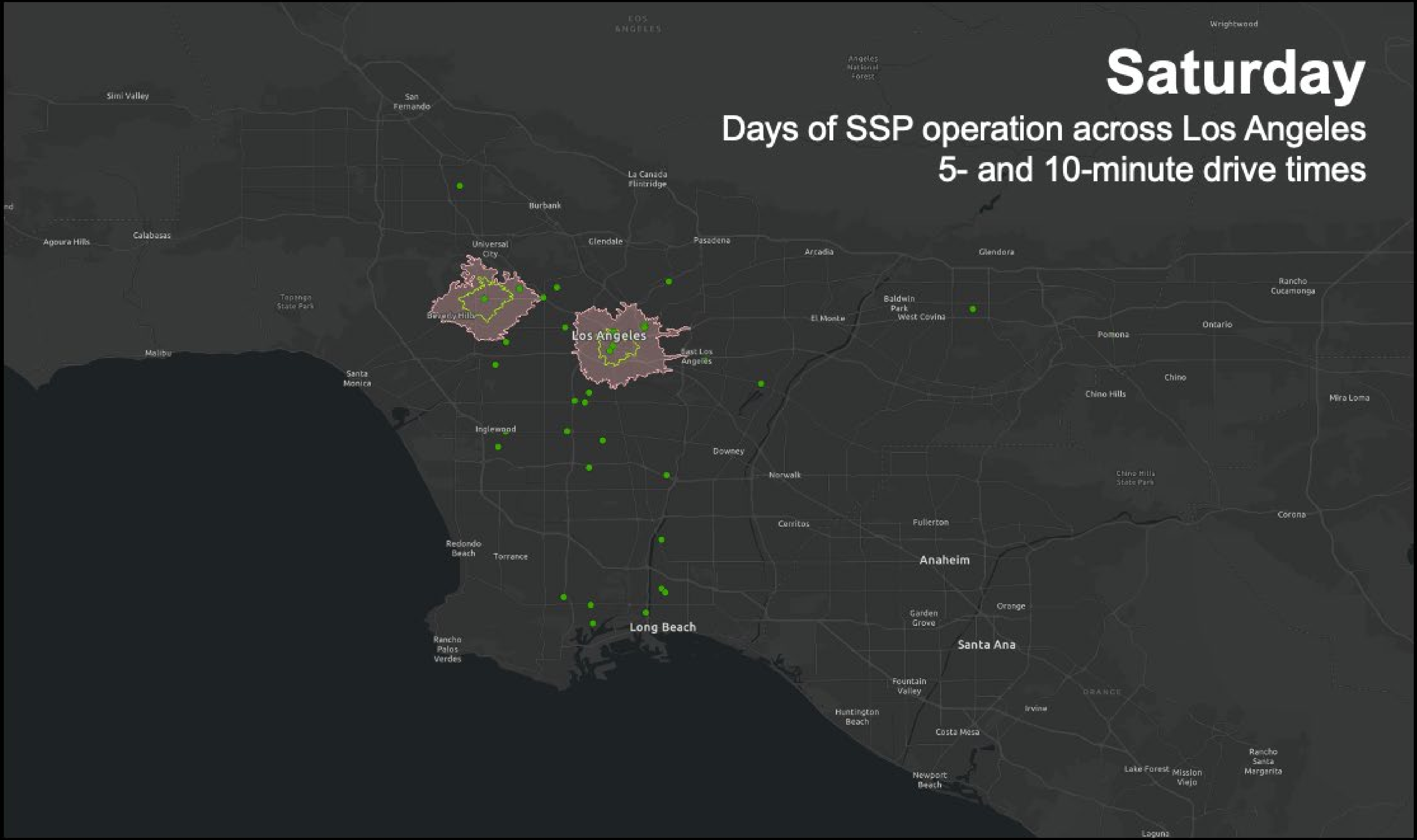
Friday

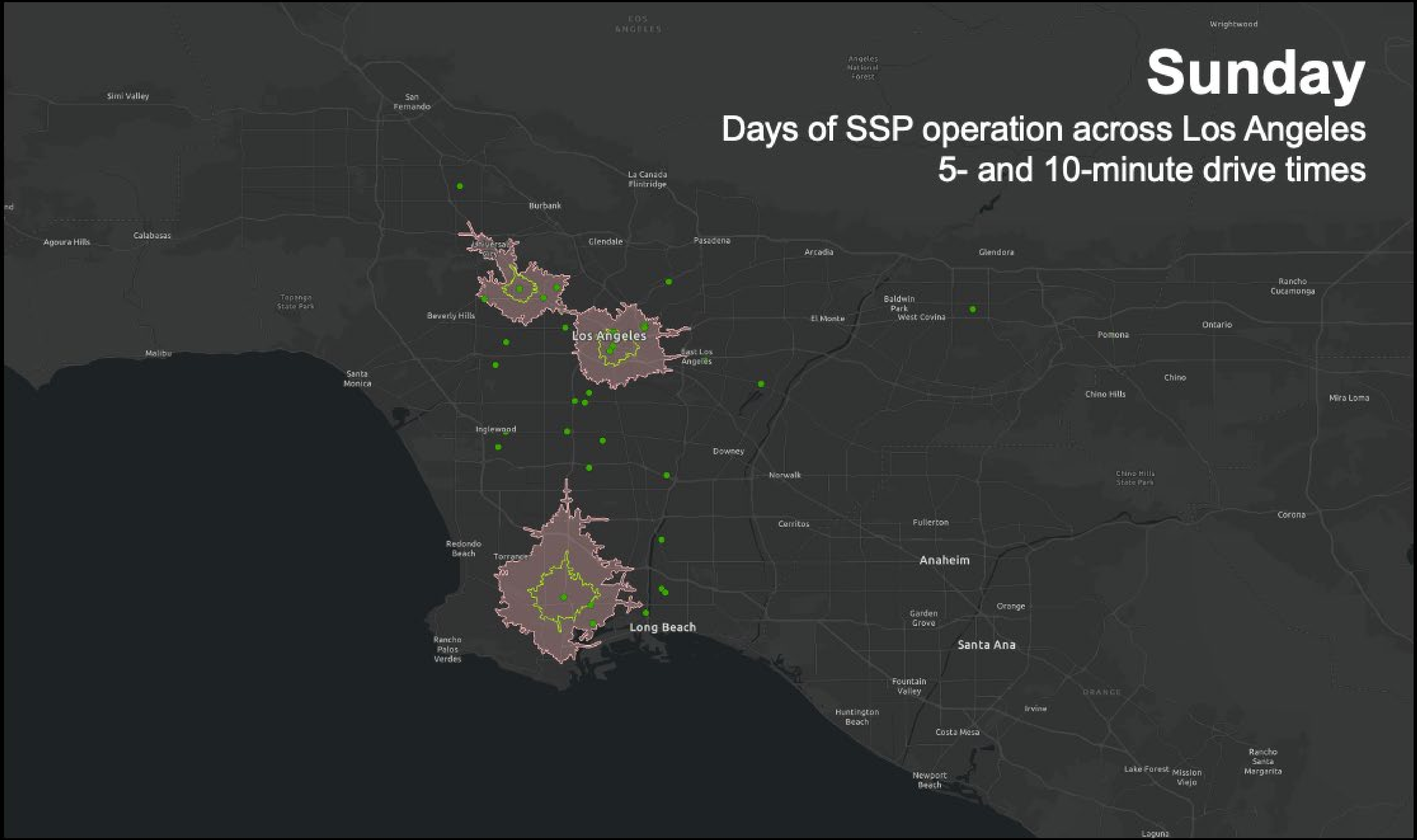
Days of SSP operation across Los Angeles
5- and 10-minute drive times



Saturday

Days of SSP operation across Los Angeles
5- and 10-minute drive times




Sunday
Days of SSP operation across Los Angeles
5- and 10-minute drive times
Los Angeles
Long Beach
Anaheim
Santa Ana
Simi Valley
San Fernando
Burbank
Glendale
Pasadena
Arcadia
Glendora
Agoura Hills
Calabasas
Beverly Hills
Malibu
Santa Monica
Inglewood
Downey
Norwalk
Cerritos
Fullerton
Redondo Beach
Rancho Palos Verdes
El Monte
West Covina
Pomona
Ontario
Chino
Chino Hills
Corona
Orange
Garden Grove
Fountain Valley
Huntington Beach
Costa Mesa
Irvine
Newport Beach
Lake Forest
Mission Viejo
Rancho Santa Margarita
Rancho Cucamonga
Mira Loma
Wrightwood

Big question #5: Where do we go from here?

Thank you to the team!

MPI: David Goodman-Meza, MD, PhD
Geospatial analysis: Michael Shin, PhD
Concept: Tucker Avra, DVM
Surveys: Ruby Romero, BA

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Using Geolocated Social Media for Monitoring the Opioid Epidemic

Chelsea Shover, Ph.D.

Assistant Professor, University of California, Los Angeles

Mapping Harm Reduction Service Deserts: Methodological and Applied Considerations from Los Angeles

Janet Kuramoto-Crawford, Ph.D, M.H.S.

Moderator

Program Official, Epidemiology Research Branch, DESPR NIDA

Closing Remarks

We appreciate hearing from you! Survey ⟶

"Research agendas that systematically incorporate spatial data and analysis into global health research hold extraordinary potential for creating new discovery pathways in science."

- Richardson DB, Volkow ND et al. Spatial turn in health research. Science. 2013 doi: 10.1126/science.1232257

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NIH National Institute on Drug Abuse