

The dynamic roles of chronic disease, socioeconomic factors, and mobility on population vulnerability during the COVID-19 pandemic

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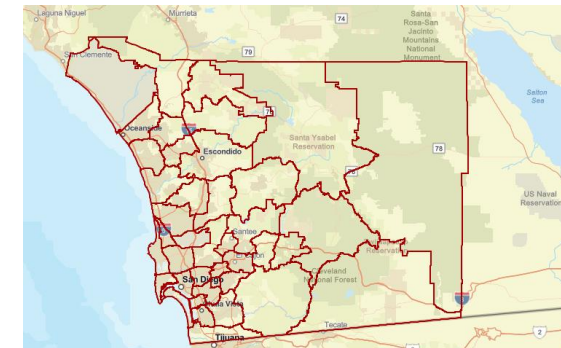
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Agenda

1. Study Area and Time Frame
2. COVID-19, Chronic Disease, and the Social Determinants of Health (SDOH)
3. Spatial Analysis & Modeling
4. Conclusions

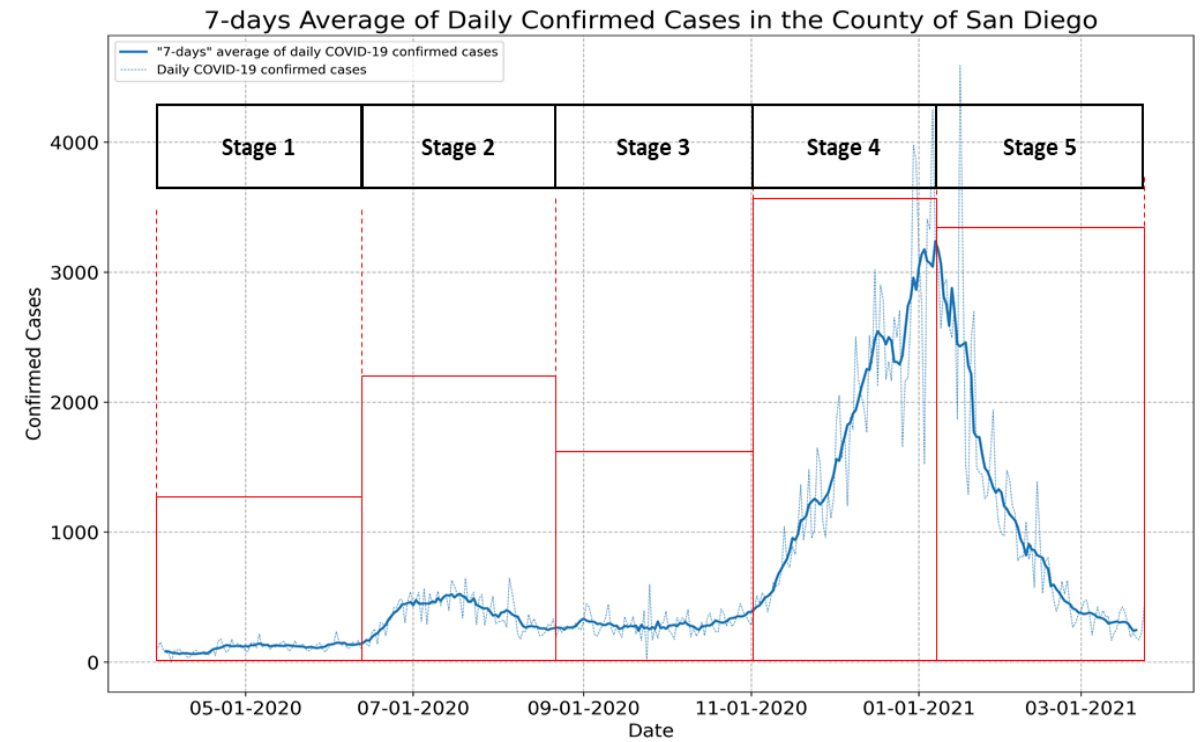
COVID-19 in San Diego County, California



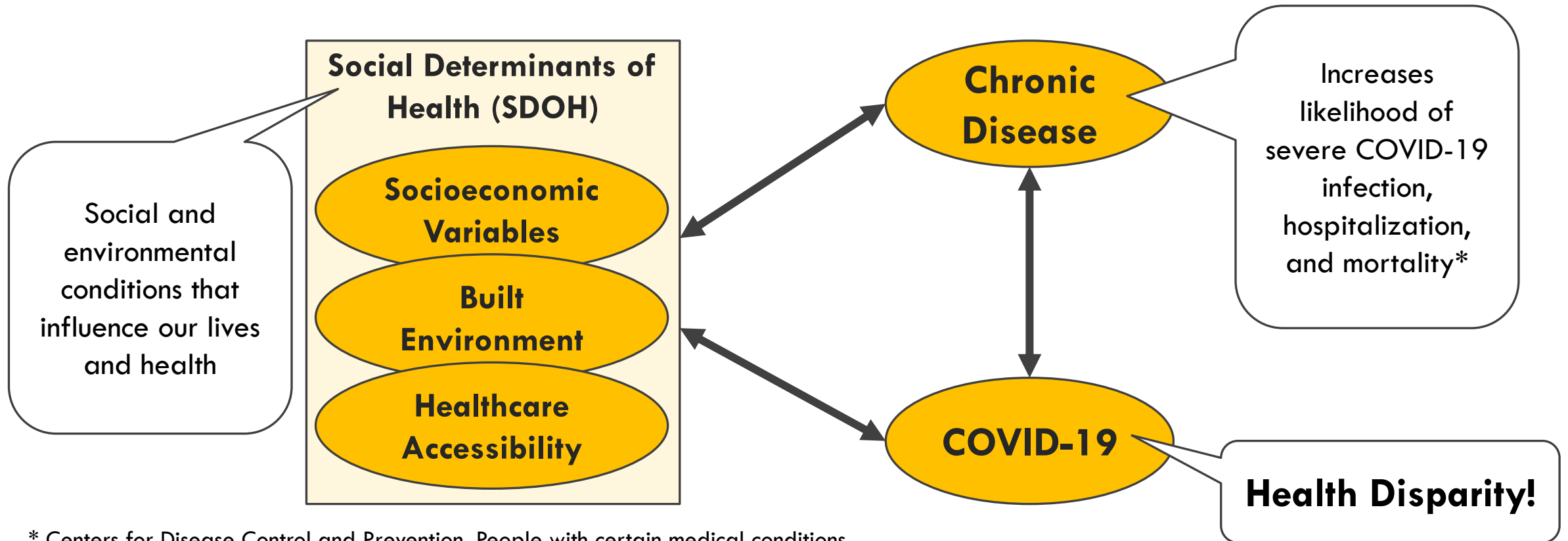
41 Sub-Regional Areas (SRAs)

~12-Month period from 3/31/2020 – 4/3/2021

- Stage 1 (3/31- 6/24): Introduction
- Stage 2 (6/25 – 8/18): “First wave”
- Stage 3 (8/19 – 10/31): Stability
- Stage 4 (11/1 – 1/23): “Second wave”
- Stage 5 (1/24 – 4/3): Vaccinations

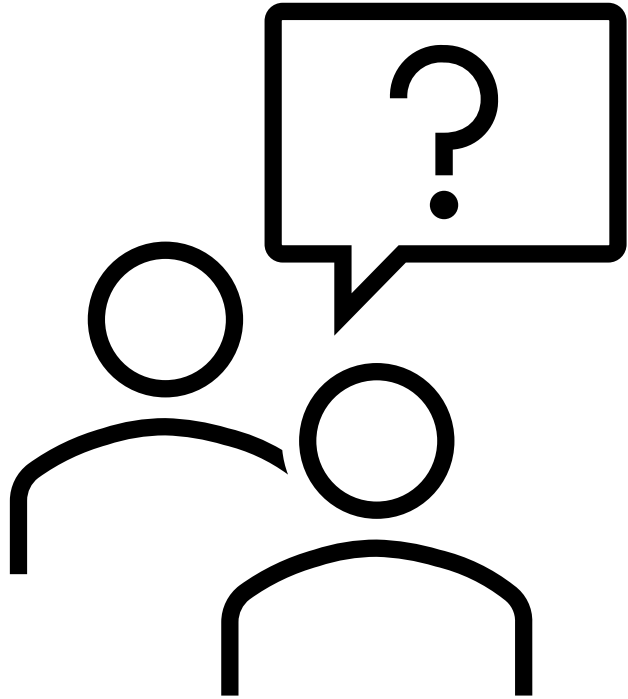


The links between COVID-19, Chronic Disease, and the Social Determinants of Health (SDOH)



* Centers for Disease Control and Prevention. People with certain medical conditions.

<https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-with-medical-conditions.html>



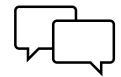
Question #1

WHICH SOCIOECONOMIC VARIABLES
ARE POTENTIAL SOCIAL
DETERMINANTS OF HEALTH?

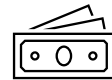
What socioeconomic variables are correlated with COVID-19 case rates?

- Pearson's correlation analysis with COVID-19 case rates and socioeconomic variables (26 highly correlated, p -values ≤ 0.05 for the 5 pandemic stages)

- 5 “Potential SDOH” Categories:



(1) Language spoken at home



(4) Income



(2) Employment industry



(5) “Crowded” home living situation



(3) Educational attainment

- Relationship strengths decrease over time
- Multicollinearity concerns

Can the SDOH variable subset characterize chronic disease rates?

- Ridge regression modeling addresses multicollinearity

- 2017 hospitalization and mortality rates:

 (1) Coronary Heart Disease

 (4) Mental Illness

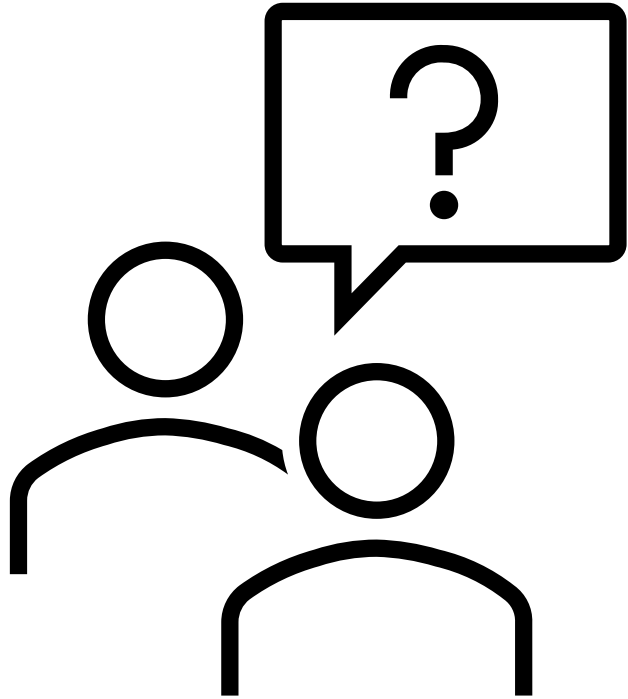
 (2) Diabetes

 (5) Pulmonary Disease

 (3) Hypertensive Diseases (HTN)

- Hypertensive Disease Hospitalization Rate ($R^2 = 0.952$): Relationship strengths decrease

- Diabetes Death Rate ($R^2 = 0.903$): Linear relationship stable, but data suppression



Question #2

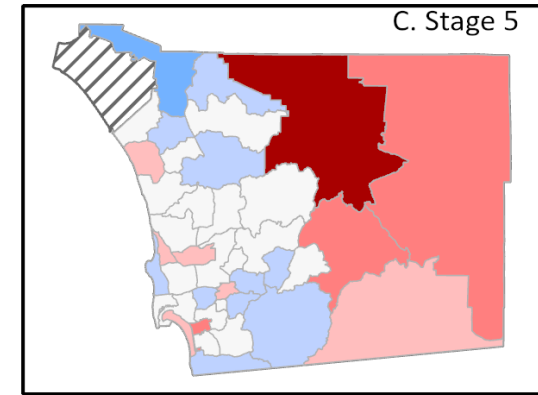
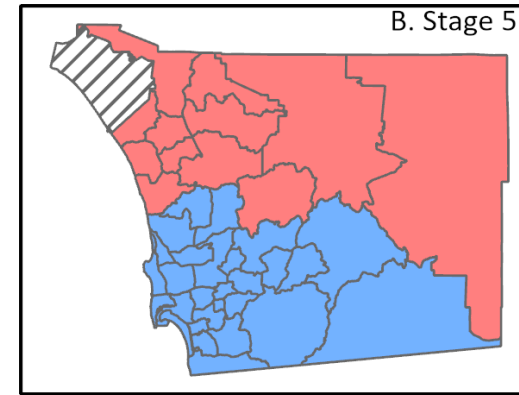
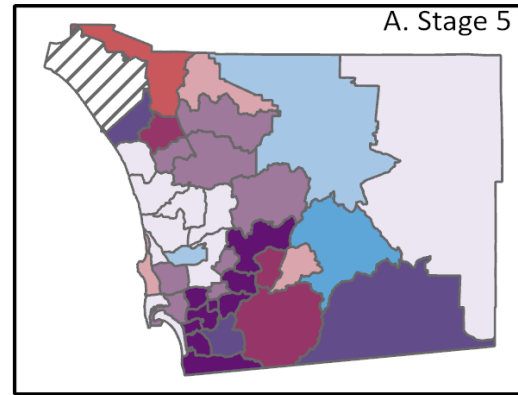
CAN SPATIAL MODELING WITH
CHRONIC DISEASE RATES IDENTIFY
THE COMMUNITIES THAT ARE MOST
VULNERABLE TO COVID-19?

Spatial Analysis

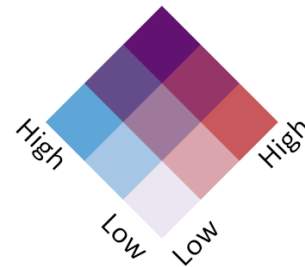
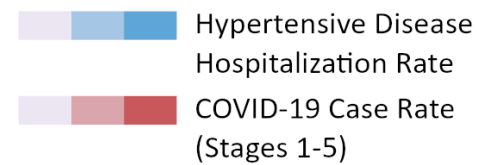
A. QUANTILE CLASSIFICATION:
General H-H, L-L pattern

B. LOCAL BIVARIATE:
Transition from linear to concave
in the south

C. GEOGRAPHICALLY
WEIGHTED REGRESSION:
Underpredictions reveal
vulnerable communities

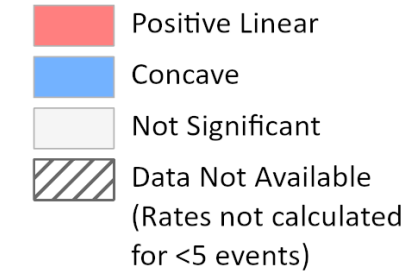


A. Quantile Classification Method

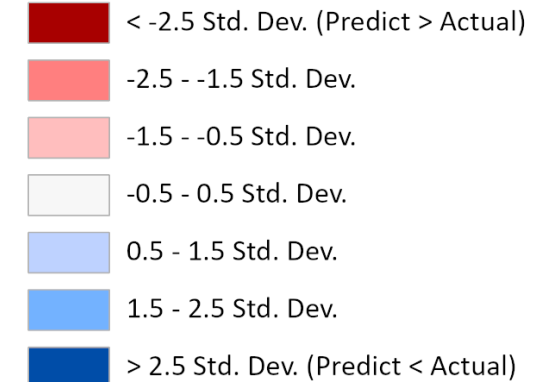


B. Local Bivariate Relationship:
Hypertensive Disease Hosp.
Rate and COVID-19 Case Rate
(Stages 1-5) (95% Confidence)

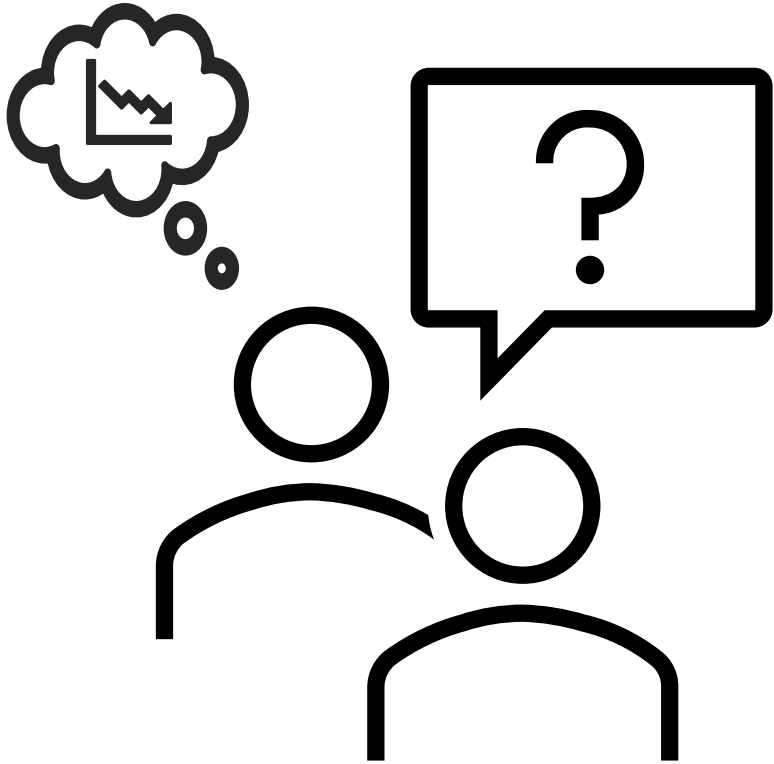
Type of Relationship



C. GWR: Hypertensive Disease Hosp. Rate
and COVID-19 Case Rate (Stages 1-5) (Dep.)
GWR Standardized Residuals



Hypertensive disease hospitalization (hosp.) rate (2017) considers the annual, age-adjusted rate per 100,000 residents. COVID-19 case rates consider the average daily stage rates per 100,000 residents.








Question #3

HOW DOES MOBILITY DATA
AUGMENT THE SPATIAL MODELS?

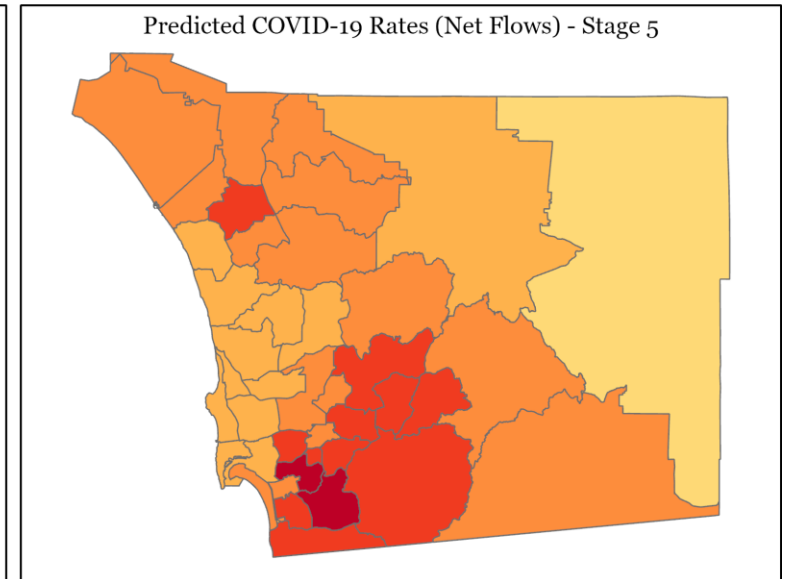
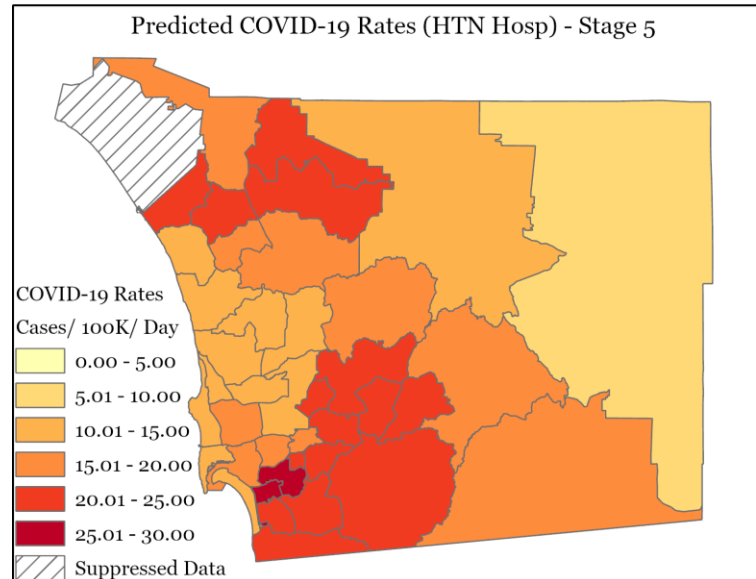
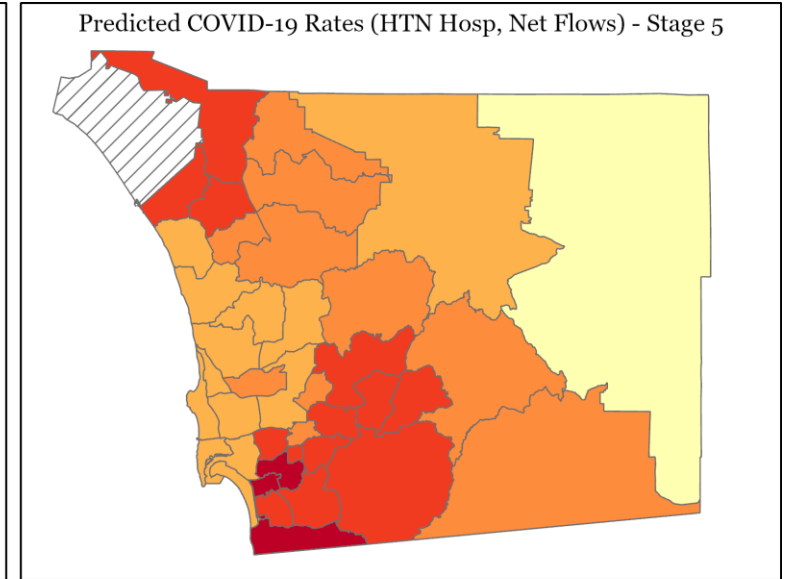
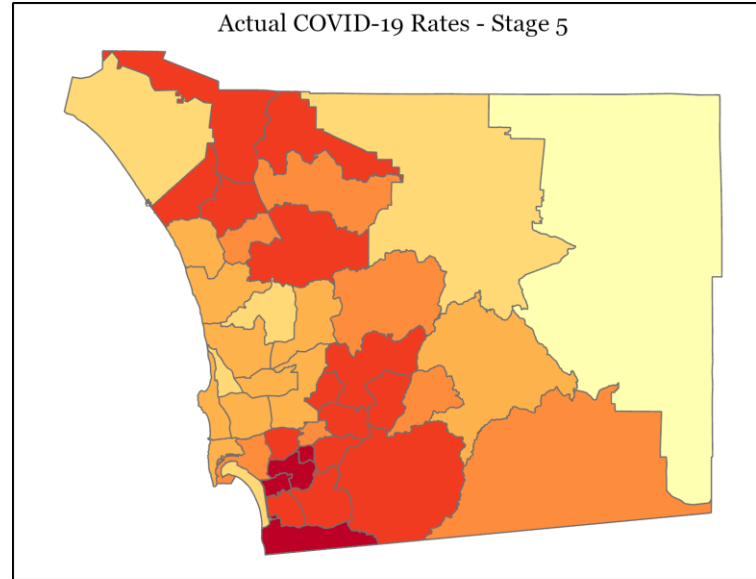


SAFE GRAPH Mobility Data

- Big data from location-aware devices (e.g., mobile phones)
- Origin-Destination (O-D) mobility flows aggregated to match the extents of the project (SRAs, 5 pandemic stages)
 -  (1) Within SRA flows
 -  (2) Inflows
 -  (3) Outflows
 -  (4) Net flows (Inflow – Outflow)
 -  (5) Total flows (Within + In + Out)
- Spatial autocorrelation (Clustering) & Linear relationships with COVID-19 case rates
- Mobility Connection: Community entry/exit increases COVID-19 exposure

Spatial Analysis

- Net flows added to GWR
- Coefficients
 - Net flow < HTN (x100)
- Net flows improve models during Stages 2, 3, and 5
- HTN-only models better during Stages 1 and 4





Project Challenges

- Data challenges:



(1) Privacy & Suppression



(3) SRA (few units, high variability)



(2) Healthcare Access



(4) Community level results

- Effects of movement and travel:

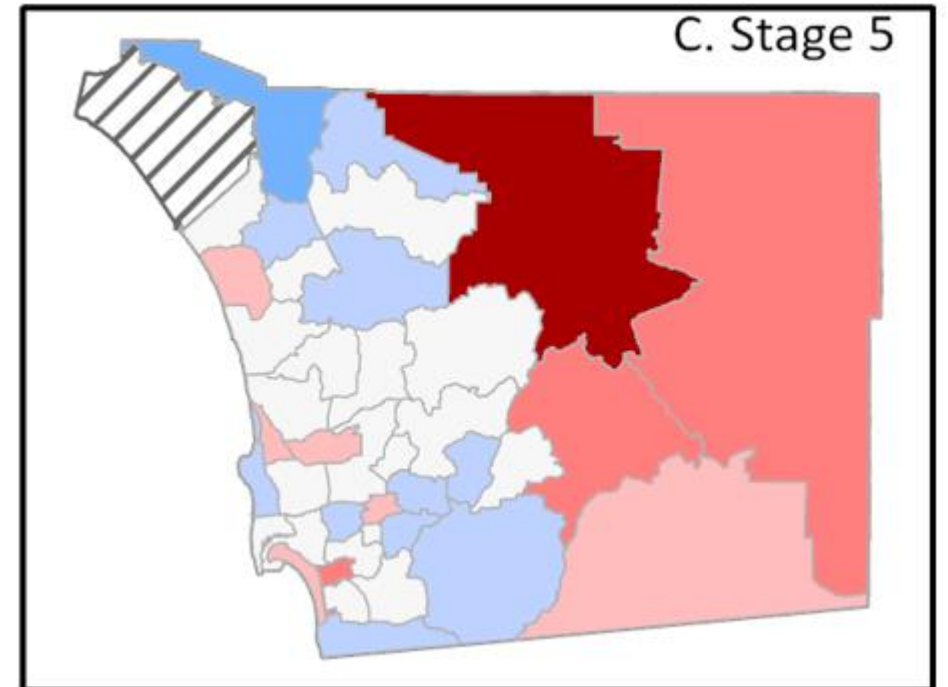


Need to model at finer spatial and temporal resolutions



Project Findings

- Clear connection between COVID-19, chronic disease, and the potential SDOH
- Insights from GWR (supplemented with local area knowledge)
 - (1) Resilience
 - (2) Vulnerability
 - (3) Rural communities
 - (4) Military areas
- Supports call for spatially differentiated public health policies to meet the needs of diverse communities





Acknowledgement

We thank the staff and epidemiologists in the County of San Diego, Health and Human Services Agency, Public Health Services, Epidemiology and Immunization Services Branch and Community Health Statistics Unit for their great efforts to create the public COVID-19 data sharing website and chronic disease datasets in the San Diego County Data Portal.

Data Sources: County of San Diego Health and Human Services Agency, San Diego Association of Governments, US Census Bureau American Community Survey, SafeGraph



Thank You!

Coming Soon to the CDC's Preventing Chronic Disease journal:

A spatio-demographic perspective on the role of social determinants of health and chronic disease in determining COVID-19 population vulnerability

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<https://www.cdc.gov/pcd/>

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