# *Public Health Extreme Events Research: Leveraging location-based data to identify health impacts of hurricanes and other extreme events*

Michael A. Stoto, PhD

National Hurricane Conference
New Orleans, April 16, 2025

**Public health emergency preparedness and response (PHEPR) practice lacks a sufficient evidence base**

"Despite the investments that have been made in PHEPR research over the past two decades, **the science underlying the nation's system of response to public health emergencies is seriously deficient**, *hampering the nation's ability to respond to emergencies most effectively to save lives and preserve well-being*."

National Academy of Sciences, Engineering, and Medicine, 2020

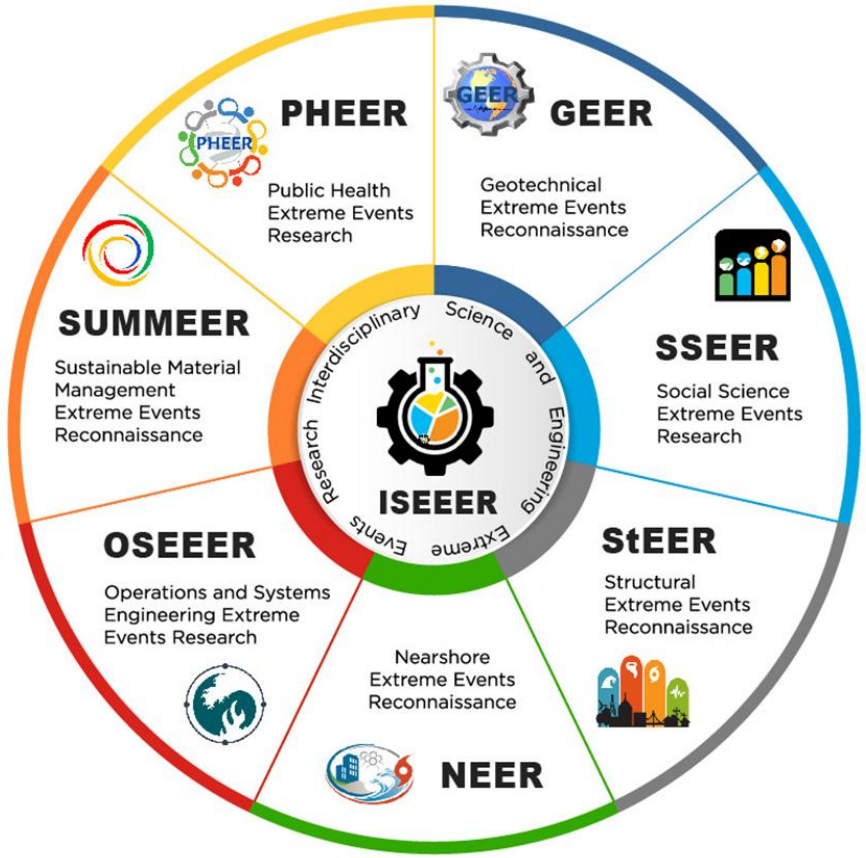

**Figure 1**: National PHEPR Science Framework

# The Public Health Extreme Events Research (PHEER) Network

- A unique researcher-led network that can
  - mobilize rapidly
  - inform evolving disaster research agendas and funding decisions
  - advance the field of public health disaster science
- Purpose
  - coordinate the public health research response to extreme events & advance the field of public health disaster science
  - by supporting and coordinating a community of practice that can mobilize rapidly to conduct time-sensitive disaster investigations
- Coordinated by NYU, UCLA, University of Washington, and University of Delaware

# The Public Health Extreme Events Research (PHEER) Network

- Seed funding provided in August 2022 by CDC Center for Preparedness and Response through the National Science Foundation
- Integrated with NSF Interdisciplinary Disaster Science Community
- CONVERGE – National Hazards Center at University of Colorado Boulder




CONVERGE
NHERI

# PHEER Hurricane Beryl Task Forces

1. The Public Health Systems Impact Task Force: identify opportunities to learn about public health systems capacity and decision-making in concurrent or anticipated disasters
2. The Health Impacts Task Force: identify research and data opportunities to estimate the indirect effects of Hurricane Beryl on the health and well-being of the exposed population
    - mount a research response to identify unique and innovative uses of Location-Based Data (LBD) for estimating early signals of health vulnerability
    - e.g. mobile phone, social media, or satellite data
    - could include measures of system and supply-chain disruptions, population movement and displacement, or resource losses, among the many indirect pathways that link hurricane exposure with poor health outcomes

# Premise of Rapid Research Awards

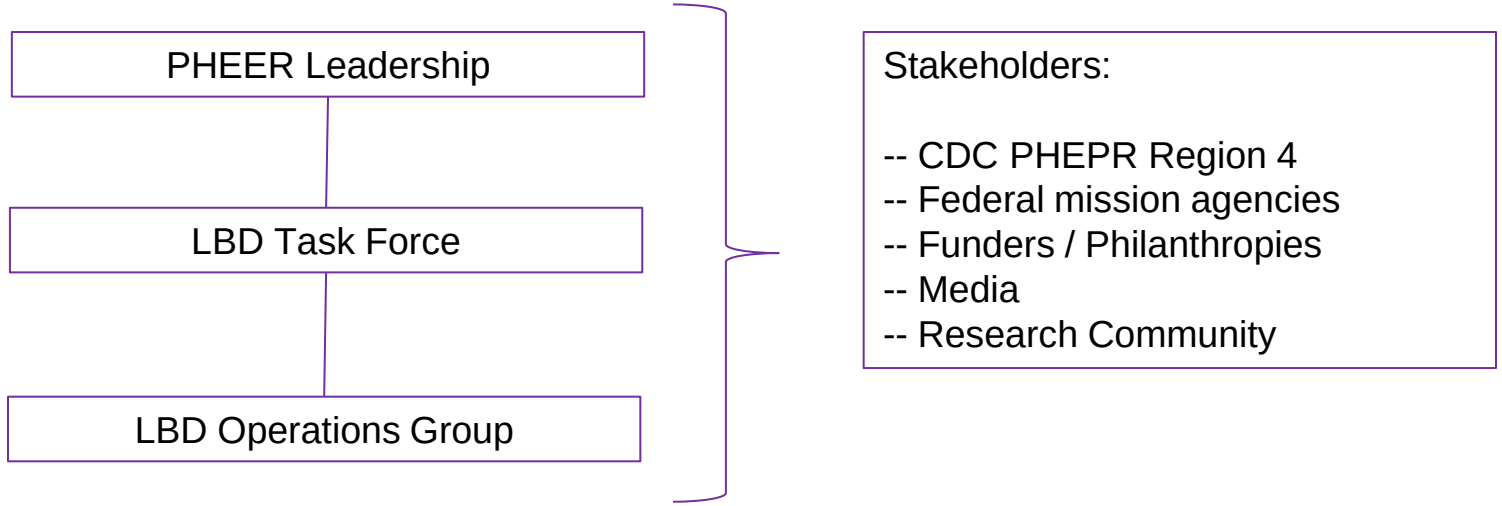
1. Given the ubiquity of location-based technology such as cell phones and social media channels, LBD
   - may serve as an early signal of health system disruptions, population vulnerabilities, supply chain fractures, population movement, mitigation and adaptation strategies, and predict future health effects
   - are often standardizable and representative of populations of interest may be readily available in the hours leading up to and following an extreme event
   - may function as a remote sensing tool valuable to the public health practice community as well as the public health disaster research field
2. PHEER using Rapid Research Award mechanism to deploy in response to Hurricane Beryl
   - applicants may use a common data source, e.g. Meta's Data for Good or LBD of their own choosing (e.g., proprietary mobile phone data, Copernicus Satellite Imagery, or Google Location History data)

# Research themes

1. How can LBD be used to illustrate indirect health effects such as system and supply-chain disruptions, population or workforce movement, and resource losses or constraints?
2. Can LBD serve as an early warning signal of later health effects and be incorporated into complex analyses of indirect effects of extreme event exposure and later health outcomes?
3. What are productive and innovative ways of identifying, assembling, manipulating, analyzing, and presenting LBD and their implications for population health and well-being?

# Hurricanes Helene & Milton

- Activated PHEER network within 2 days of US landfall
- Testing a model of a centralized virtual mobilization
- Crowd-sourcing location-based data analyses via collective research tracker
- Funding provided by National Center for Disaster Medicine and Public Health Preparedness



# LBD research questions

1. Were specific socially or physically vulnerable populations particularly susceptible to the immediate effects of the storm(s)?
2. **Were there patterns of disruptions to the health system associated with specific community characteristics of vulnerability or deprivation?**
3. How long are different disruptions lasting, and is the length of disruption associated with extent of hurricane exposure, to social vulnerability, or both?
4. Are there high-need areas associated with ongoing social and systemic disruptions?
5. **Are there specific health services that have been disrupted, and are these service areas related to particular social vulnerabilities?**
6. **Are the system and social disruptions associated with specific health outcomes, such as excess mortality, excess hospitalizations, MH effects, specific conditions (such as respiratory, cardiovascular, etc.)?**
7. Are there historical policy effects such as redlining, urban renewal, or other policies associated with damage, vulnerability, or health outcomes

# Presenters

- Diana Ramirez-Rios, PhD
  - Department of Industrial and Systems Engineering
  - School of Engineering and Applied Sciences, University at Buffalo
  - Disaster-Induced Transportation Barriers and their Impact on Access to Health Facilities for Socially Vulnerable Communities
- Marissa Sogluizzo, MPH
  - Program in Public Health, Stony Brook University
  - Using Facebook data to understand the impacts of hurricane-induced health system disruptions and social vulnerabilities
- Sangung Park, PhD
  - University of Florida Transportation Institute
  - Developing a Dynamic Social Vulnerability Index (DSVI) for public health using location-based data

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- Join https://nyu.qualtrics.com/jfe/form/SV_3dtHl9YPmqSu1RI

# Hurricanes Helene and Milton Disaster-Induced Transportation Barriers and their Impact on Access to Health Facilities for Socially Vulnerable Communities

Diana Ramirez-Rios, PhD

Assistant Professor, University at Buffalo

# PHEER Research Task 1005.1 Team

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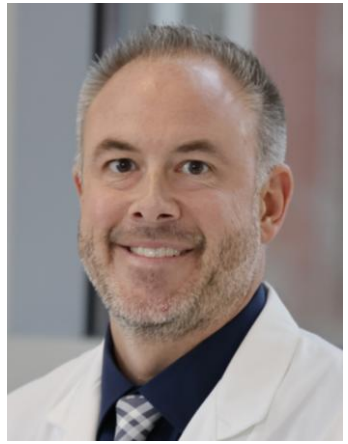


Nicholas Kman, MD
Clinical Professor of Emergency Medicine

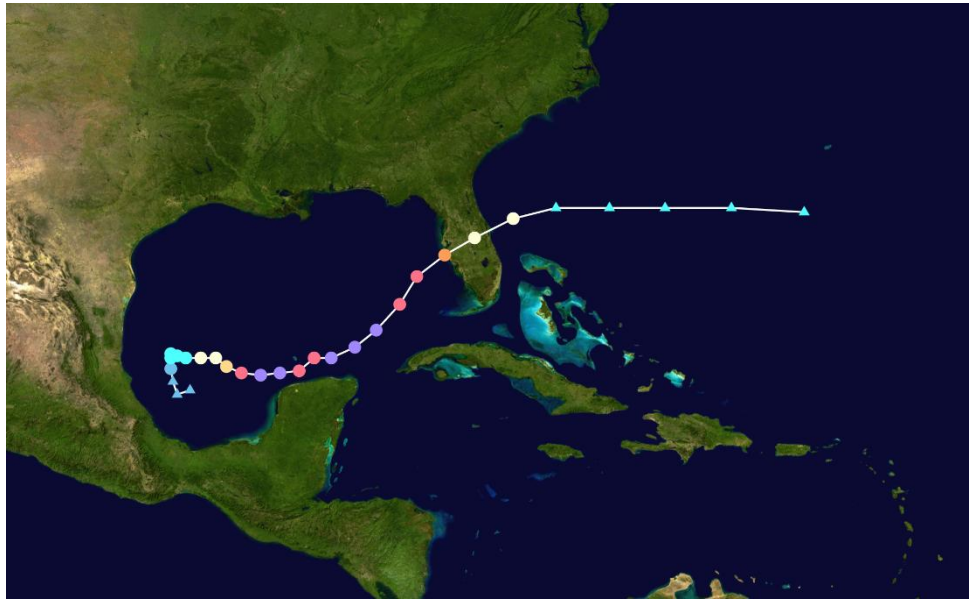
# 2024 Hurricane Helene in Southeastern US

- Category 4 Hurricane Helene made landfall on Sept. 26 over Florida's Big Bend region.
- As it moved inland, it weakened, degenerating into a post-tropical storm over Tennessee on Sept 27.
- Caused catastrophic flooding over the SE, particularly in western NC, East TN, and southwestern VA.
- Caused 250 deaths and an estimated total of $78.7 billion in damage

Images from the National Hurricane Center

# 2024 Hurricane Milton in Florida

- Hurricane Milton made landfall near Siesta Key late on October 9.
- Milton rapidly weakened as it moved across the state into the Atlantic Ocean.
- It became extratropical on October 10.
- Killed at least 42 in the US
- Estimated damage of US$34.3 billion



Images from the National Hurricane Center

# Research Questions

- Were there disaster-induced transportation barriers impeding the affected population from accessing medical facilities after Hurricanes Helene and Milton in **Florida**?
- Did these transportation barriers disproportionately impact socially vulnerable populations, including disadvantaged populations, living in locations of poor property and transportation infrastructure and healthcare access?

## Locations

Florida

## Timeframe

September 27- October 19, 2024

# Research Questions

- Were any disaster-induced transportation barriers impeding the affected population from accessing medical facilities after Hurricane Helene in Georgia, **North Carolina**, and South Carolina?
- Did these transportation barriers disproportionately impact socially vulnerable populations, including disadvantaged populations, living in locations of poor property and transportation infrastructure and healthcare access?

## Locations

Florida, Georgia, North Carolina, South Carolina

## Timeline

November 27- October 4, 2024

# Methodology

Constructed a database with county-level data related to population, household and location characteristics, transportation, and health capacities.

Performed PCA on historical data to capture significant grouping of variables that influence social vulnerability

Used location-based data to analyze transportation delays and road access to hospitals at a county level and its correlations with socially vulnerable populations

# Data Collected

| Data Source | Variables |
|---|---|
| US Census Bureau (2018-2022) | • Sociodemographic<br>• Economic (poverty index)<br>• County's area |
| National Bridge Inventory (2022) | • # of bridges<br>• Total length<br>• Total deck area<br>• Average age<br>• Average condition |
| U.S. Transportation Network – ArcGIS | • Interstate lengths<br>• Highway lengths |
| FEMA | • Flood risk maps |
| American Hospital Directory (2022) | • Number of hospitals<br>• Distances to hospitals<br>• Number of staffed beds<br>• Number of discharges |

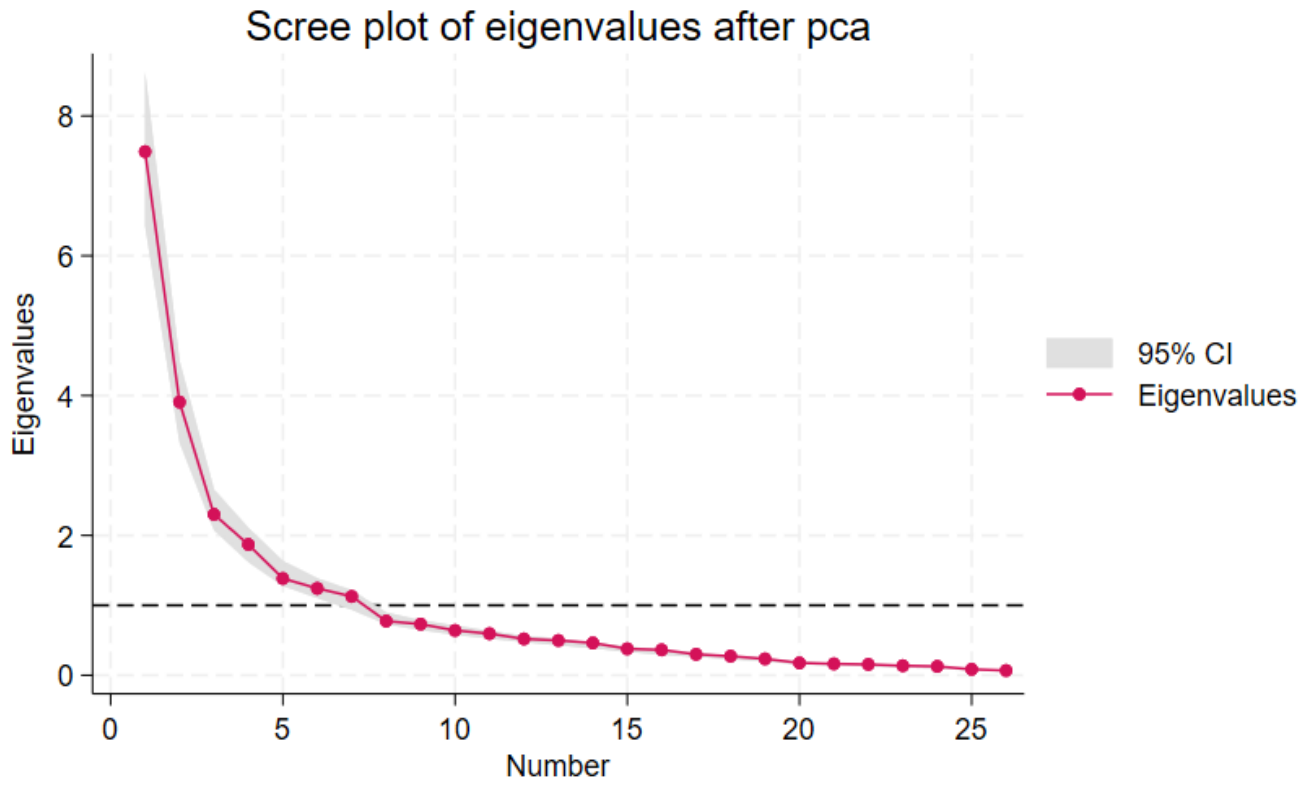
**Post-Hurricane Data**
**September 27- October 19, 2024**

| Data Source | Variables |
|---|---|
| Point of interest data in Dewey* | • Opened gas stations<br>• Opened hospitals |
| RITIS | • Transportation network incidents |
| TIMS – North Carolina | • Transportation network incidents |

*Acknowledge Dr. Qingchun Li for sharing this data with us.

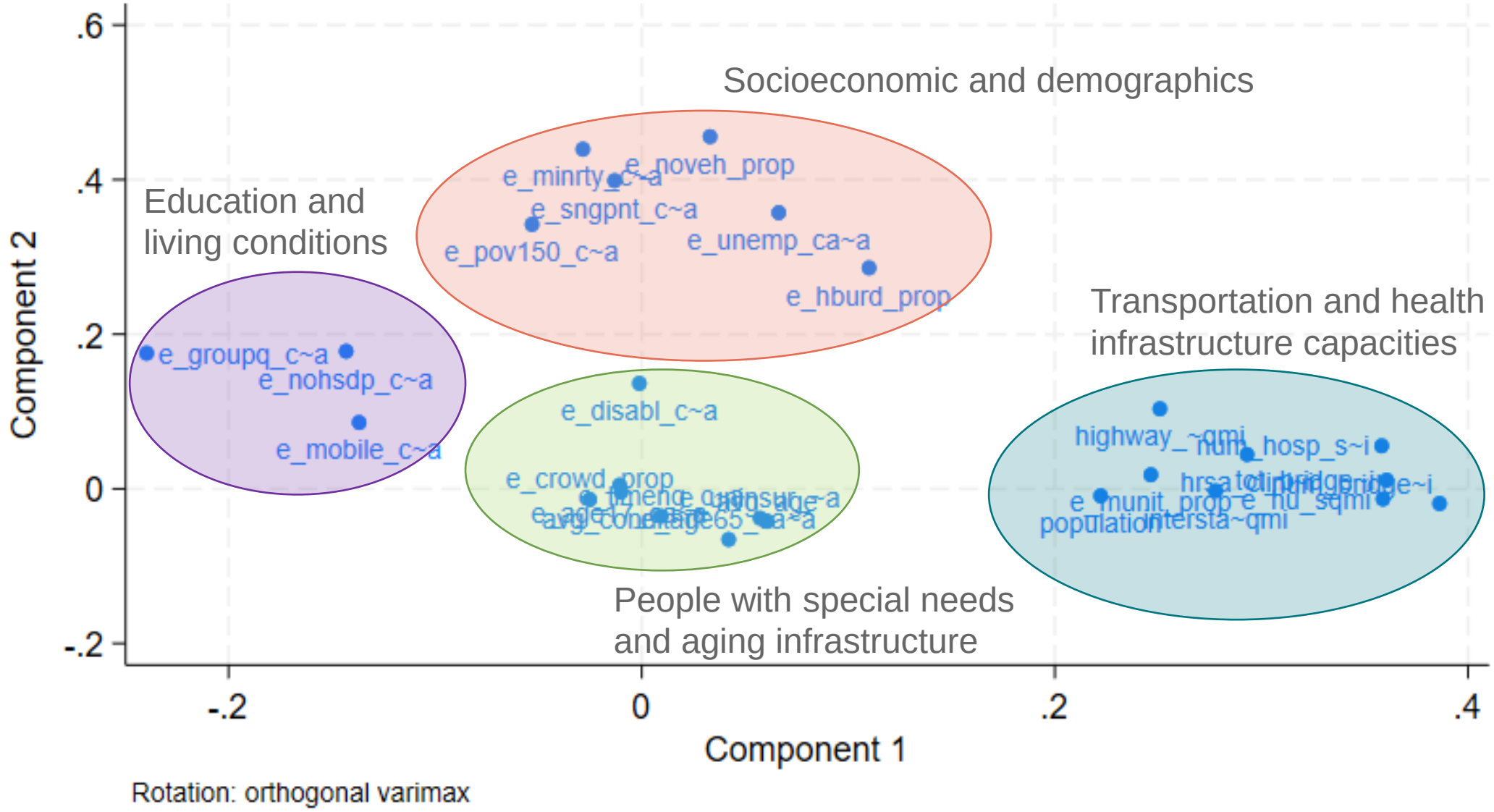
# Principal Component Analysis: Socially Vulnerable

- Purpose: Identify the most influential group of variables that comprises socially vulnerable populations.




| Component | Theme | Variables | Explained Var |
|---|---|---|---|
| 1 | Property and Surrounding Infrastructure | e_hu_sqmi | 0.3588 |
| | | num_hosp_sqmi | 0.3582 |
| | | tot_bridge_len_ft_sqmi | 0.3606 |
| | | num_bridges_sqmi | 0.3862 |
| 2 | Socioeconomic and household travel capacity | e_pov150_capita | 0.342 |
| | | e_unemp_capita | 0.3573 |
| | | e_sngpnt_capita | 0.3986 |
| | | e_minrty_capita | 0.4393 |
| | | e_noveh_prop | 0.4556 |
| 3 | Age | e_age65_capita | 0.4853 |
| | | e_age17_capita | -0.5824 |
| 4 | Education, Health, and Transportation | e_nohsdp_capita | 0.3062 |
| | | e_uninsur_capita | 0.5447 |
| | | avg_age_bridges | 0.3843 |
| 5 | Population characteristics | population | 0.3257 |
| | | e_limeng_capita | 0.576 |
| | | e_crowd_prop | 0.3338 |
| | | e_groupq_capita | 0.3201 |

# Component loadings

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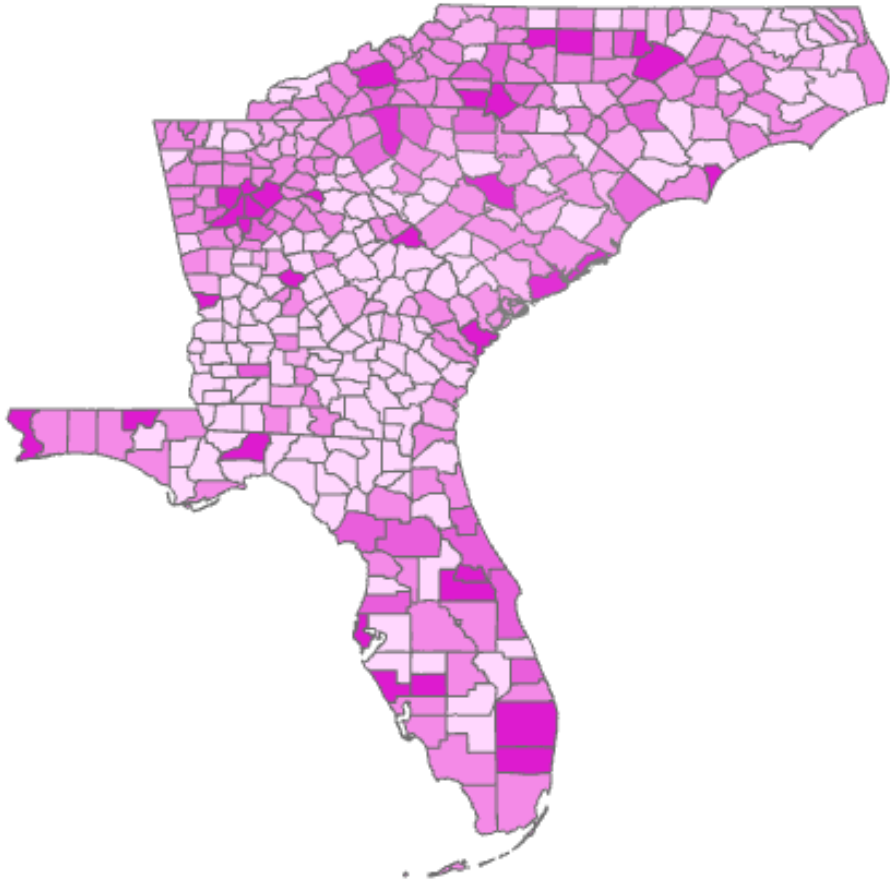
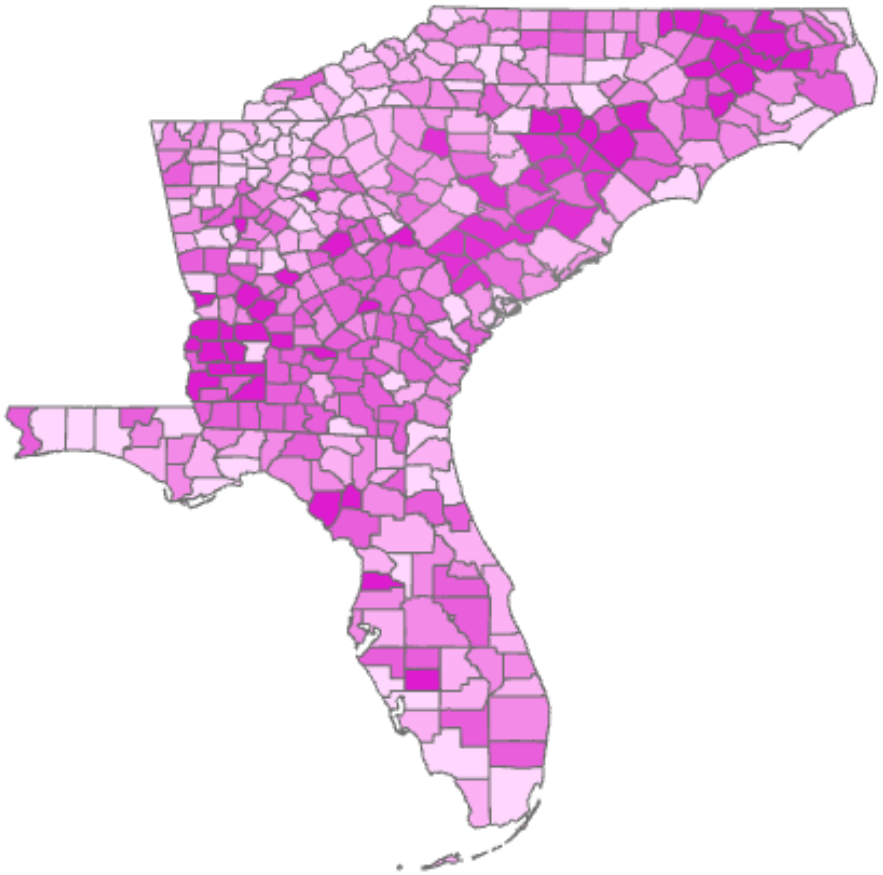
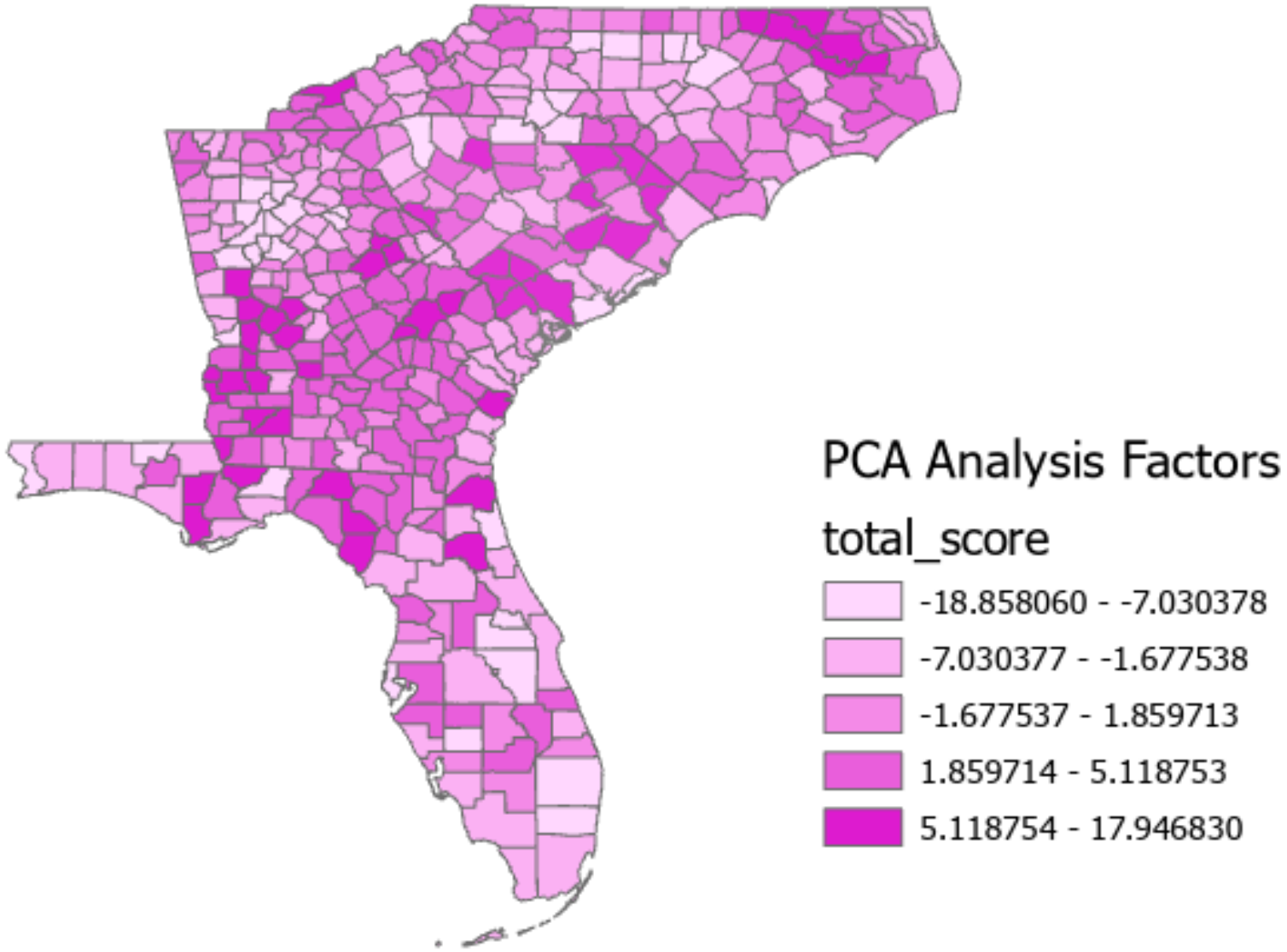
# Analyzing components PC 1 and PC 2 separately

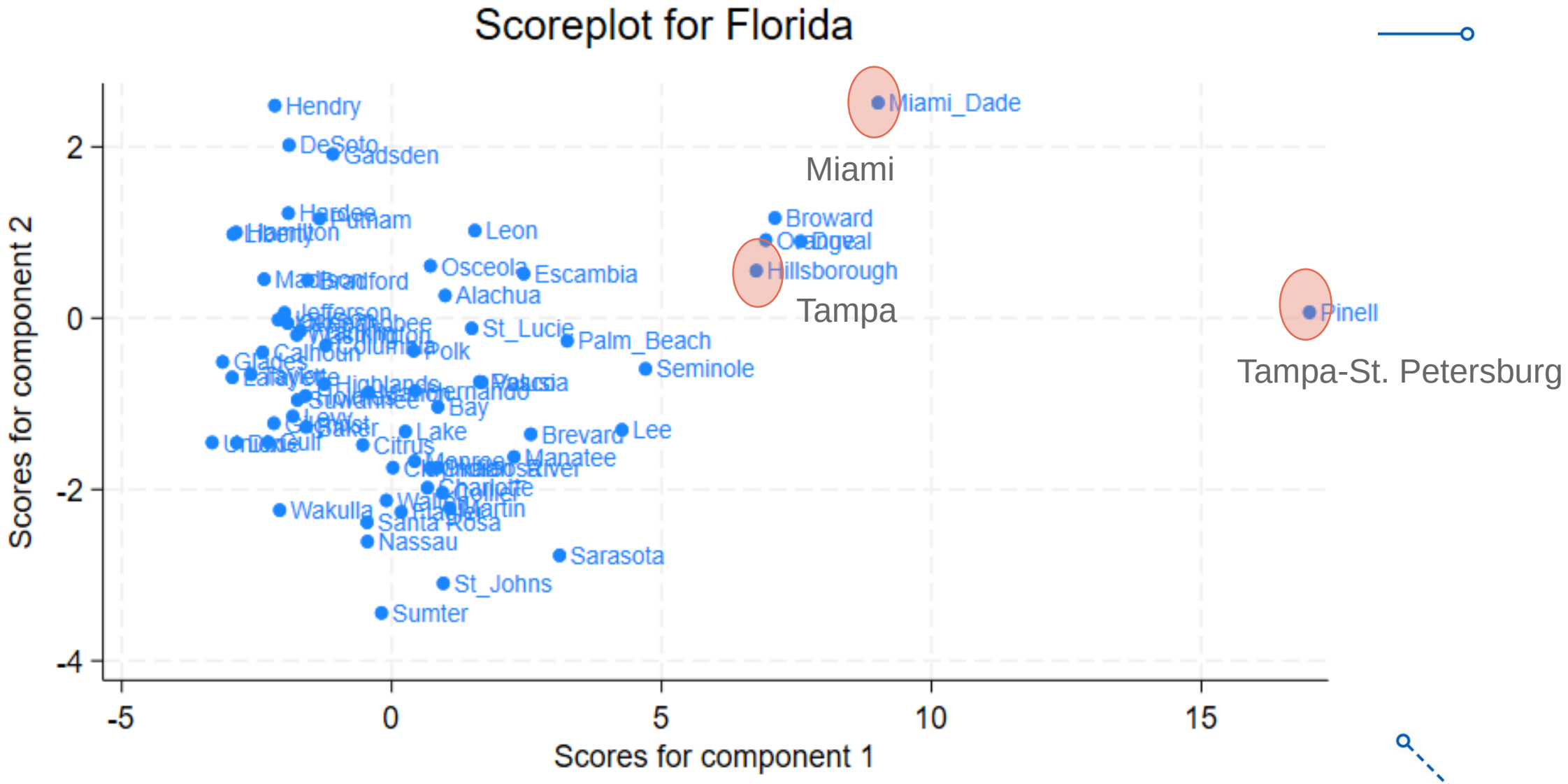


Population density and infrastructure capacities



Socioeconomic and other household characteristics


PCA Analysis Factors
total_score
-18.858060 - -7.030378
-7.030377 - -1.677538
-1.677537 - 1.859713
1.859714 - 5.118753
5.118754 - 17.946830

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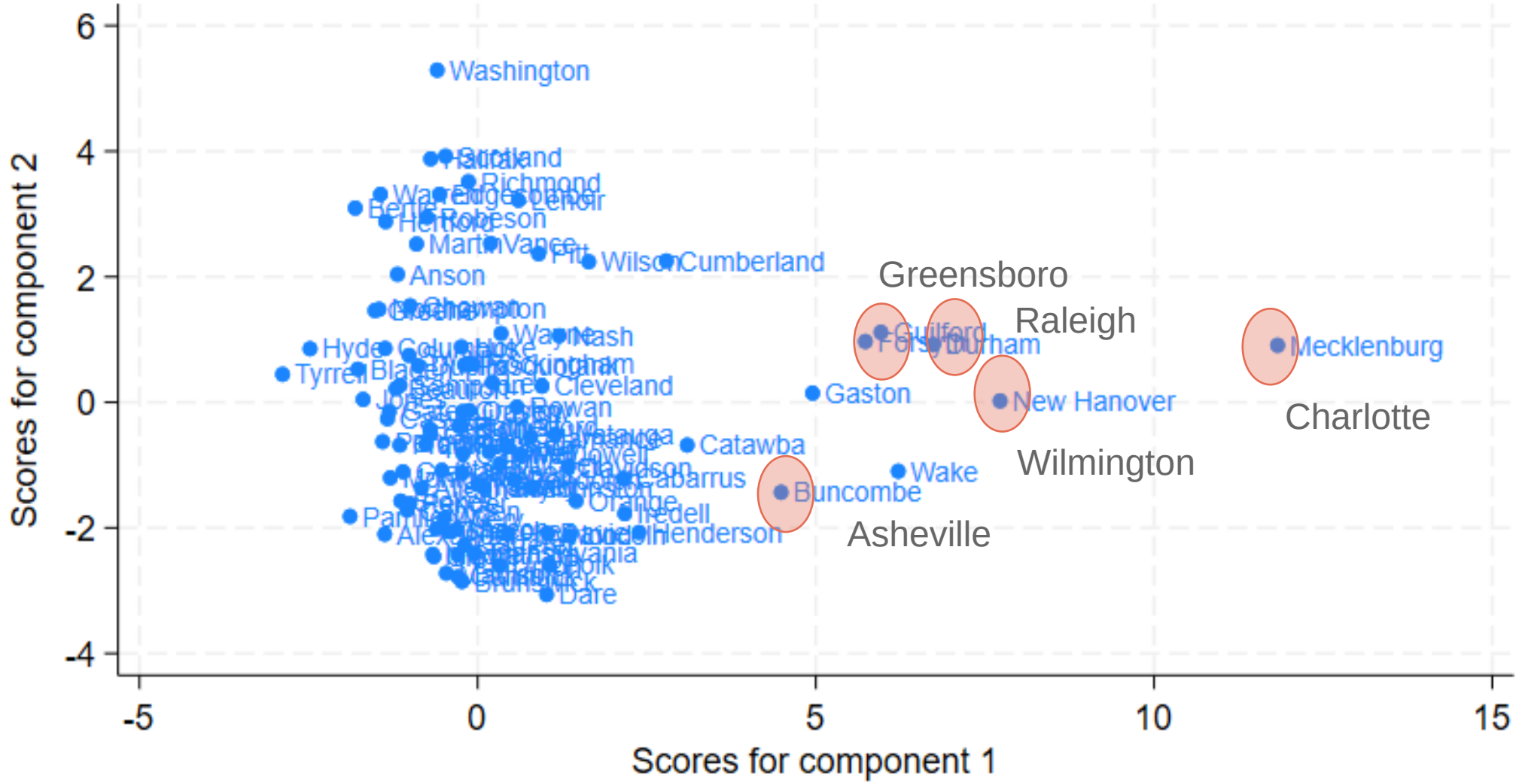
# Scoreplot for North Carolina

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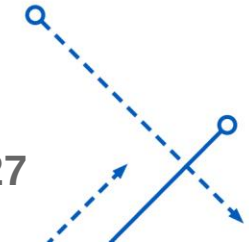
# Regression Modeling

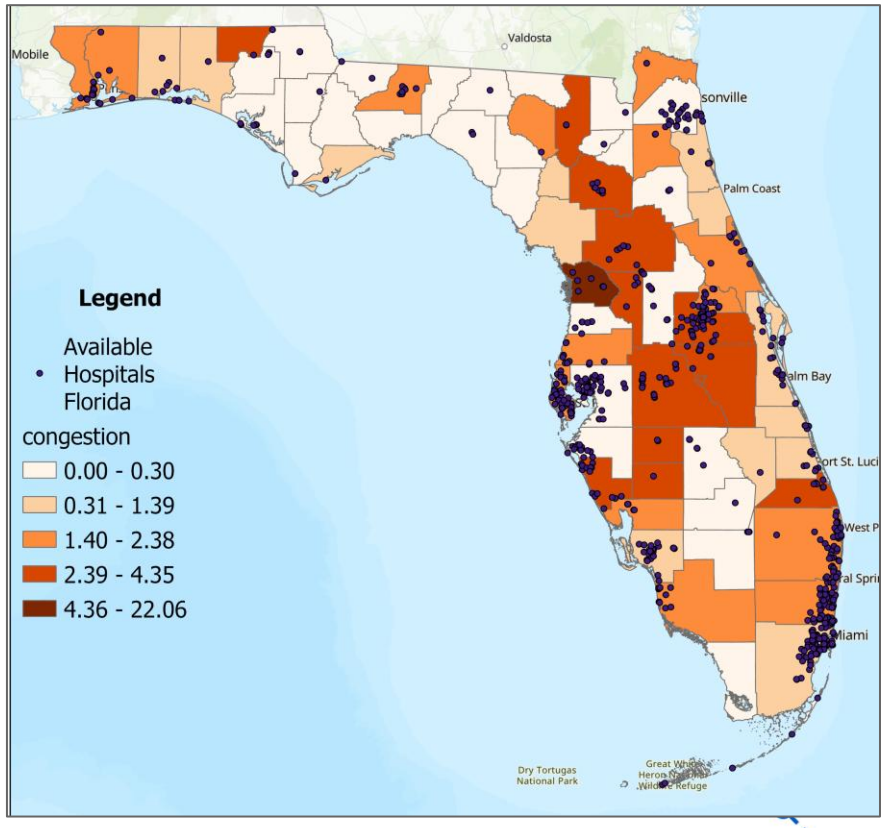
- Objective: determine the correlation between the transportation delays (specifically to hospitals) caused by the post disaster disruptions and socially vulnerable locations
- Used Ordinary Least Squares Regression and multiple non-linear transformations
- Considered models with the following dependent variables:
  - Hurricane-related road network delays
  - Congestion-related road network delays
  - Times to the nearest hospital after road network disruptions



# Average Congestion delays in Florida

⇩ Opened gas stations per capita
⇩ Opened hospitals per capita
⇩ Proportion of the population without a high school diploma

⇧ # of mobile homes per capita
⇧ Proportion of people living in residential facilities
⇧ Proportion of cost-burdened housing units
⇧ Proportion of housing in structures with 10 or more units
⇧ Proportion of persons aged 65 or higher
⇧ Proportion of persons aged 17 or lower



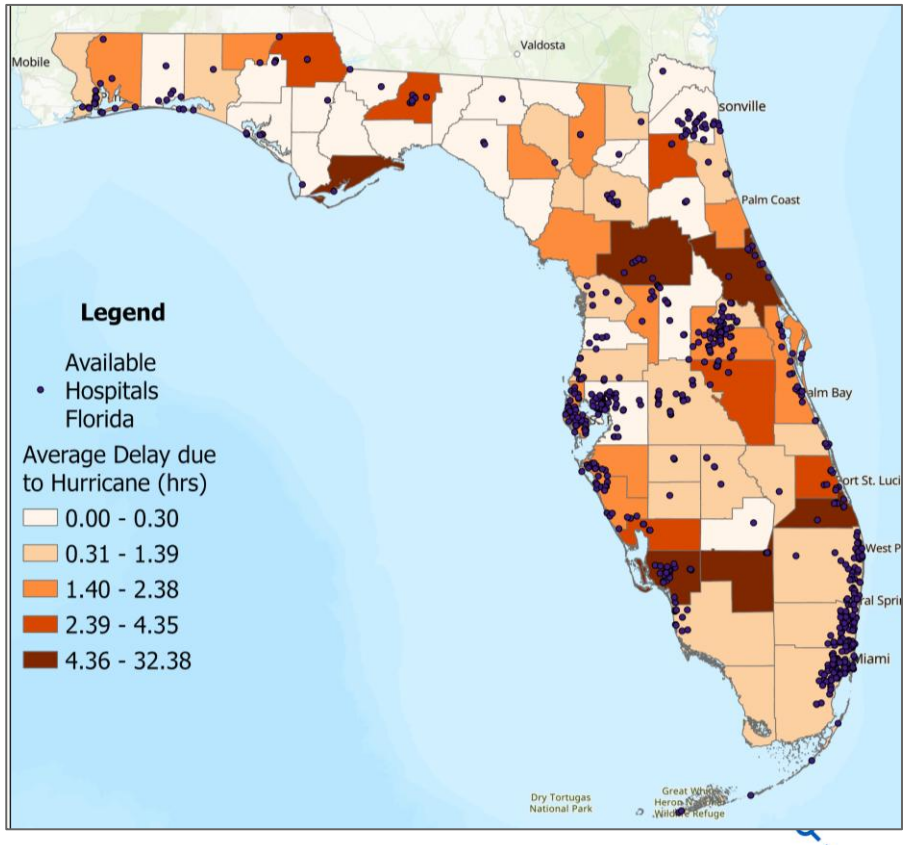

*Note. All p values < .05.*

# Average Hurricane-Related Delays in Florida

⇩ Opened gas stations per capita
⇩ Opened hospitals per capita

⇧ Average distances to hospitals in the county
⇧ Proportion of persons aged 65 or higher
⇧ Persons below 150% poverty estimate

*Note. All p values < .05.*



# Aftermath: Orlando, FL

Courtesy of Drs. Bachmann and Kman, The Ohio State University

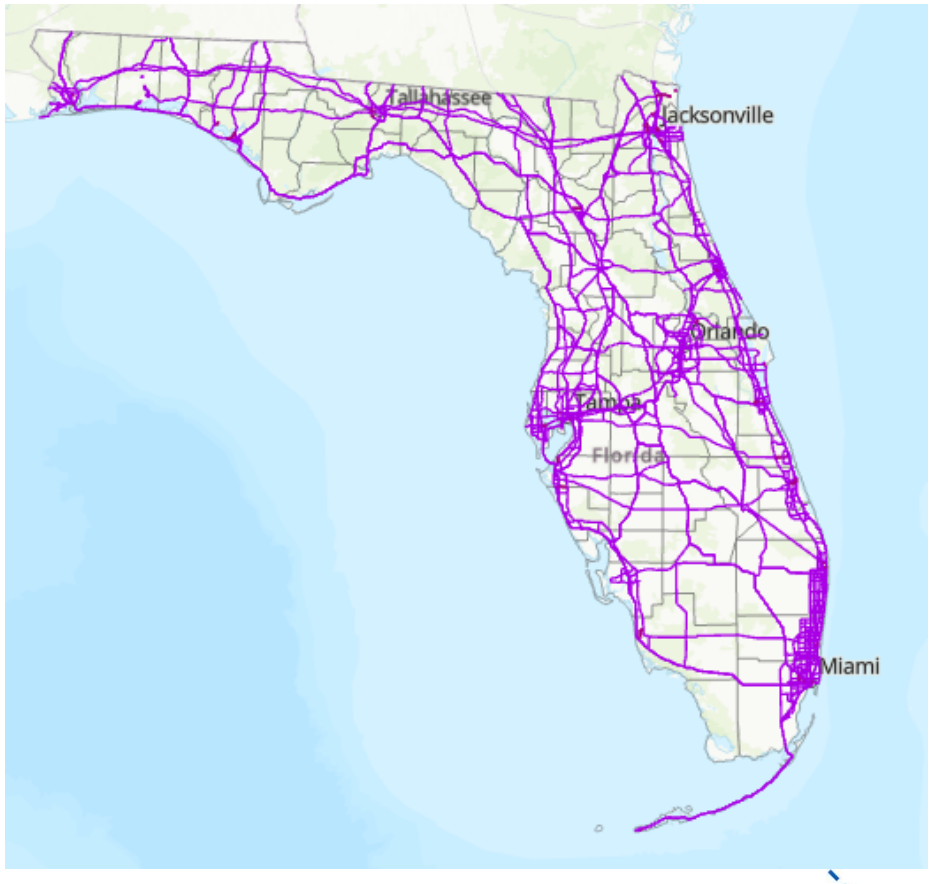
# Access to Hospitals in Florida

Dependent variable:
Distance to closest hospital with disruptions

⇩ Opened hospitals per capita
⇩ Number of bridges per sqmi

⇧ Proportion of the population without a high school diploma

*Note. All p values < .05.*



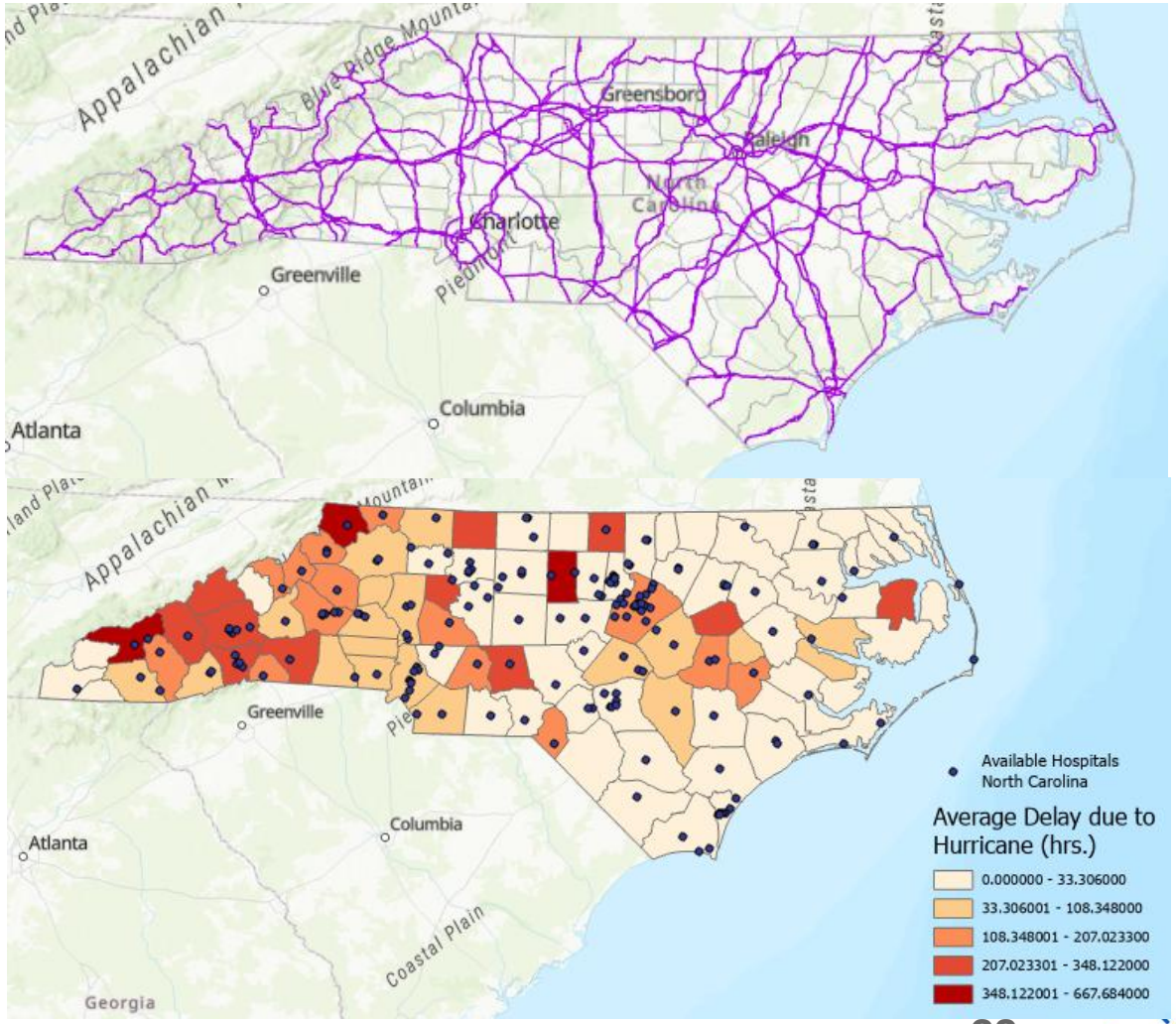
# Access to Hospitals in North Carolina

Dependent variable:
Distance to closest hospital with disruptions

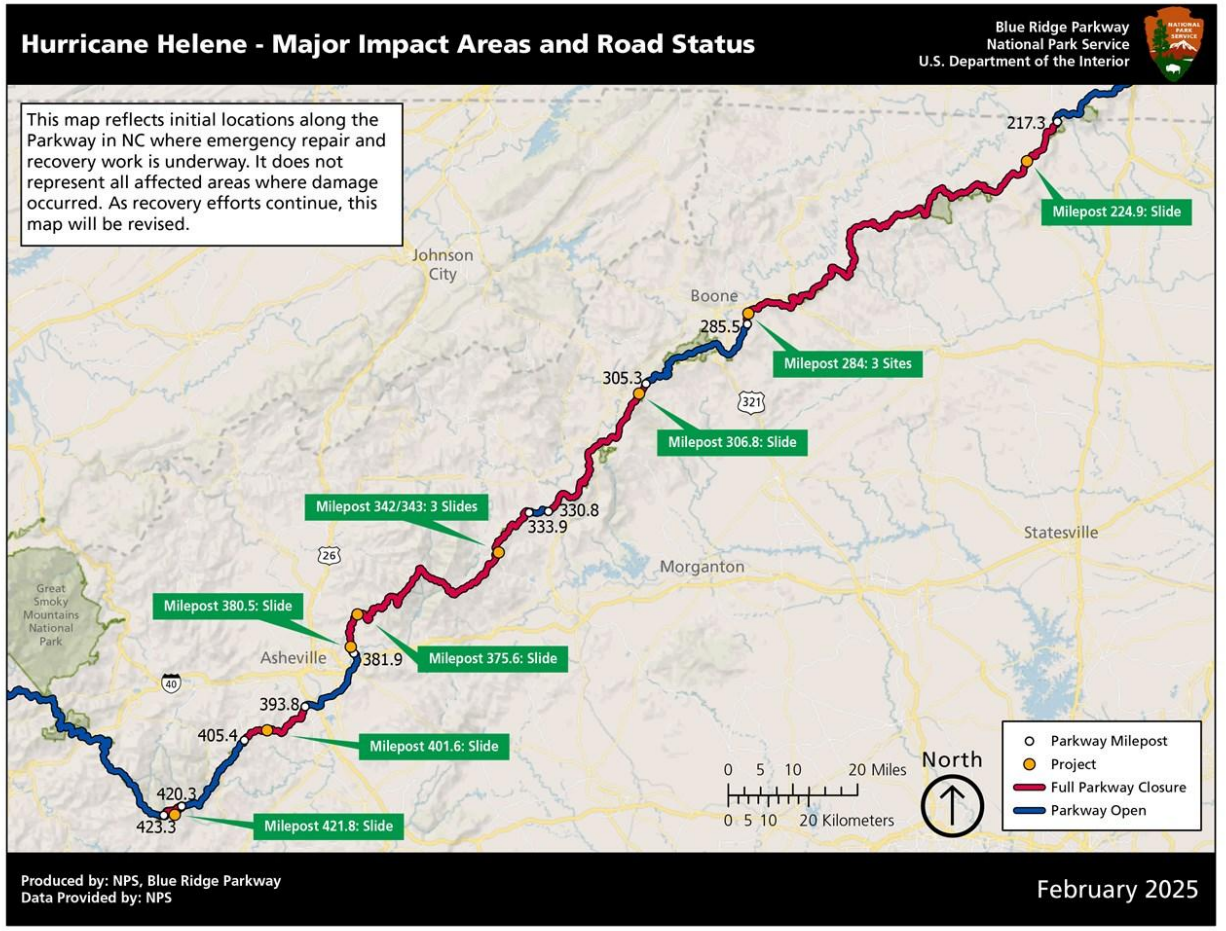
⇩ Opened hospitals per capita
⇩ Number of bridges per sqmi
⇩ Proportion of housing in structures with 10 or more units

⇧ Proportion of unemployed
⇧ Proportion of persons aged 65 or higher
⇧ Proportion of uninsured people

*Note. All p values < .05.*



# Hurricane Helene: Impacts Blue Ridge Parkway


National Park Service, available @www.nps.gov/blri/planyourvisit/helene-impacts-and-recovery.htm

# Aftermath: Transportation Disruptions in Boone, NC

Courtesy of Drs. Bachmann and Kman, The Ohio State University

# Aftermath: Property Damages and Debris in Cherokee, NC

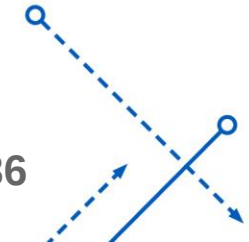
Courtesy of Drs. Bachmann and Kman, The Ohio State University

# Preliminary Findings

1. Social vulnerability is influenced by access to healthcare facilities and network capacities, in addition to the region's socioeconomic and household characteristics.

2. Disaster-induced transportation barriers do impact healthcare access and disproportionately affect the elderly, the poor population, and the communities that have low infrastructure capacities.

3. Modeling post-hurricane delays and travel times to hospitals from road incidents provide opportunities to improve medical emergency response.



# DISCUSSION

Thank you! Any questions?

# UNDERSTANDING THE IMPACTS OF HURRICANE-INDUCED HEALTH SYSTEM DISRUPTIONS THROUGH FACEBOOK UTILIZATION DATA

Public Health Extreme Events Research (PHEER) Network

National Hurricane Conference

April 15, 2025

Marissa Sogluizzo, MPH, PhD Student

Stony Brook University

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# RESEARCH QUESTION & HYPOTHESIS

*Is there an association between a county's Social Vulnerability Index (SVI) score and health system disruptions (approximated through Facebook Utilization rates) during and after Hurricane Helene made landfall among affected counties in Florida, Georgia, and North Carolina?*

*Among vulnerable counties, there will be longer periods of disruption during and after Hurricane Helene made landfall, indicating higher levels of disruption to health systems within that county compared to less vulnerable counties.*

# SUMMARY OF FINDINGS

- More vulnerable counties (higher SVI scores) had less healthcare facilities per area square mile and longer periods of disruption
- Higher levels of disruption were marked by an increased number of days after Hurricane Helene made landfall for population activity to return to baseline activity.
- Storm impact moderated this relationship
  - Counties that experienced higher levels of impact by Hurricane Helene had higher levels of disruption regardless of vulnerability score.

# BACKGROUND

Social Vulnerability → socioeconomic and demographic factors that increase a community's risk for adverse consequences during and following a disaster

- Socioeconomic status, poverty, lack of access to transportation, physical and mental disabilities, racial/ethnic minority status, poor health status, etc.,

Health System Disruptions → like communities, health systems can also be vulnerable to disasters

- Infrastructure damage, power outages, reduced staff, loss of critical supplies
- Evacuations affect both the evacuating and receiving hospital
- Facility closures lead to increased number of patients at other facilities
- Influx of non-medical patients

(Centers for Disease Control and Prevention [CDC], 2024)

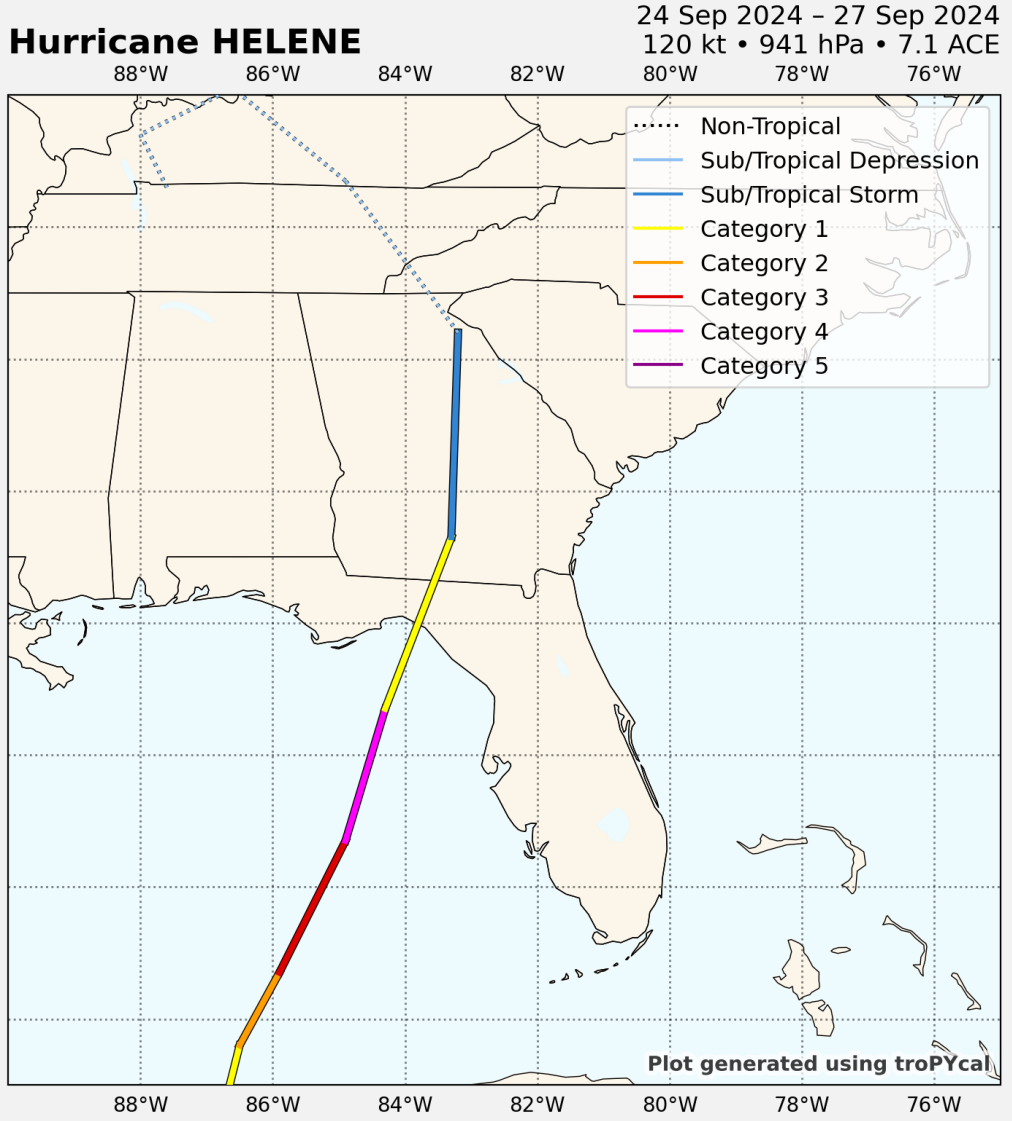
# HURRICANE HELENE

Summary:

- Formed in Atlantic Ocean and intensified rapidly due to favorable conditions (warm sea surface temperatures, low wind shear)
- Made landfall on the evening of Thursday, September 26th, 2024, as a Category 4 storm in Florida's Big Bend region
- Maximum wind speed at landfall: 140 mph

Impact:

- Fatalities: > 200 deaths across multiple states with North Carolina (NC) bearing the burden
- Economic Damage: estimated at $78.7 Billion
- Flooding: Unprecedented rainfall led to catastrophic flooding (29 inches in NC)
- Storm Surge: FL's Gulf Coast experienced storm surges up to 15 feet high
- Power Outages: more than 4.5 million across Southeastern US lost power, which took weeks to restore




(Internet Geography, 2024)

# METHODS

# LOCATION-BASED DATA AND DATA SOURCES

Multiple datasets and shapefiles were combined for geospatial analysis using Python Programming Language and statistical analysis using RStudio.

1. Caliper Maptitude: *Healthcare Facility Data for 2024 was downloaded and exported as shape files*
2. Meta Data for Good: *Facebook Population During Crisis datasets were obtained and cleaned to determine population activity before, during, and after Hurricane Helene (Sep 24th to Oct 21st, 2024)*
3. Center for Disease Control and Prevention (CDC): *Social Vulnerability Index county-level scores, 2022*
4. Federal Emergency Management Agency (FEMA): *Disaster declarations and designated area maps were utilized to determine level of storm impact*

# META: *FACEBOOK POPULATION DURING CRISIS*

Why use Facebook Utilization Rates?

- Allow us to measure population activity

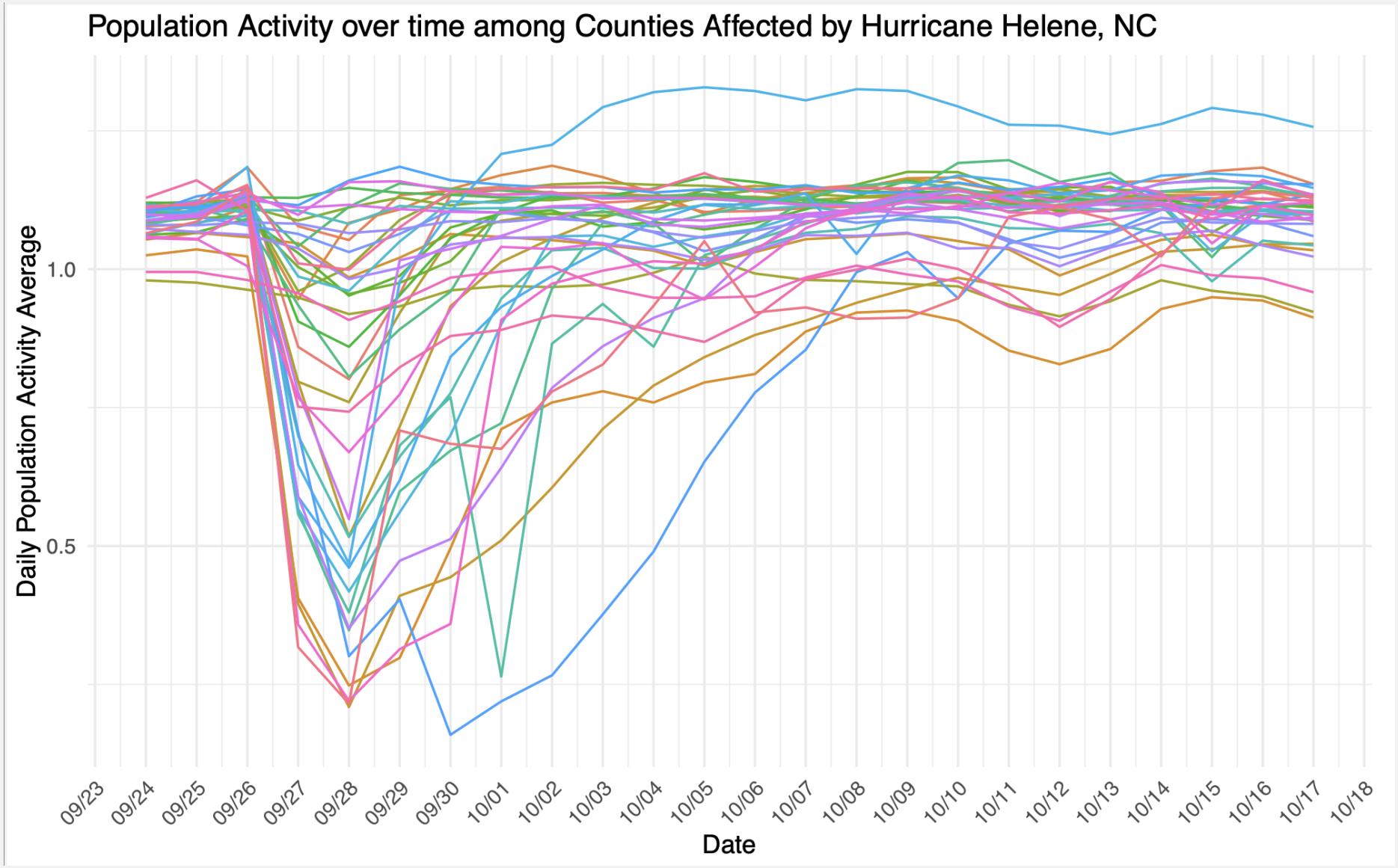
  *Geographic Aggregation* → *Bing Tile Level 14 (2.4 km)*

  *Variables:* Baseline Population Activity & Crisis Population Activity

  Drops in population activity can indicate disruptions due to the crisis

- Paired with other data, we can make assumptions and conclusions about what these drops in population activity likely mean for other sectors, including health systems


(Meta, 2024)




$$\text{POPULATION ACTIVITY} = \frac{\textit{Average Daily Population Activity During Crisis}}{\textit{Average Daily Population Activity at Baseline}}$$

# OUTCOME VARIABLES

## Level of Disruption (LOD)

- *The number of days after Hurricane Helene made landfall for population activity to return to baseline activity, defined as the population activity one day prior to landfall.*
  - *Florida: baseline date = September 24th*
  - *Georgia: baseline date = September 26th*
  - *North Carolina: baseline date = September 26th*
- Facebook Population During Crisis were geospatially processed and aggregated from the Bing Tile level to the County level
- Population Activity was aggregated across 3 daily timepoints for a daily average
- LOD was categorized for logistic regression:
  - High = 4.7 days or more to return to baseline activity
  - Low = less than 4.7 days to return to baseline activity

# PREDICTOR VARIABLES

## Social Vulnerability Index (SVI) Scores

- Scores were obtained from CDC at the county-level
- Scores range from 0 – 1 (low vulnerability to high vulnerability)
- Categorized into:
  - High = SVI >/= 0.48
  - Low = SVI < 0.48

## SVI Thematic Scores

- Scores are calculated from a range of variables, thematically organized into four themes:
  - Socioeconomic
  - Housing Characteristics
  - Racial/Ethnic Minority Status
  - Housing and Transportation

(CDC, 2024)

# COVARIATES

## Population Density

= *(Population Estimate)/area square miles*

## Healthcare Facility Density

= *(Number of healthcare facilities)/area square miles*

## Storm Impact

- Mild = Counties receiving Public-B assistance only from FEMA and a low percentage reduction in population activity on day of impact
- Moderate = Counties receiving Public (all types) and/or Individual assistance from FEMA and a moderate percentage reduction in population activity on day of impact
- Severe = Counties receiving all types of assistance from FEMA and a high percentage reduction in population activity on day of impact

(FEMA, 2024)

# GEOSPATIAL AND STATISTICAL ANALYSIS

## Geospatial Analysis

- Conducted with Python Programming Language
- Assessed population activity from September 24th to October 21st, 2024
- Assessed county-level SVI scores among impacted counties

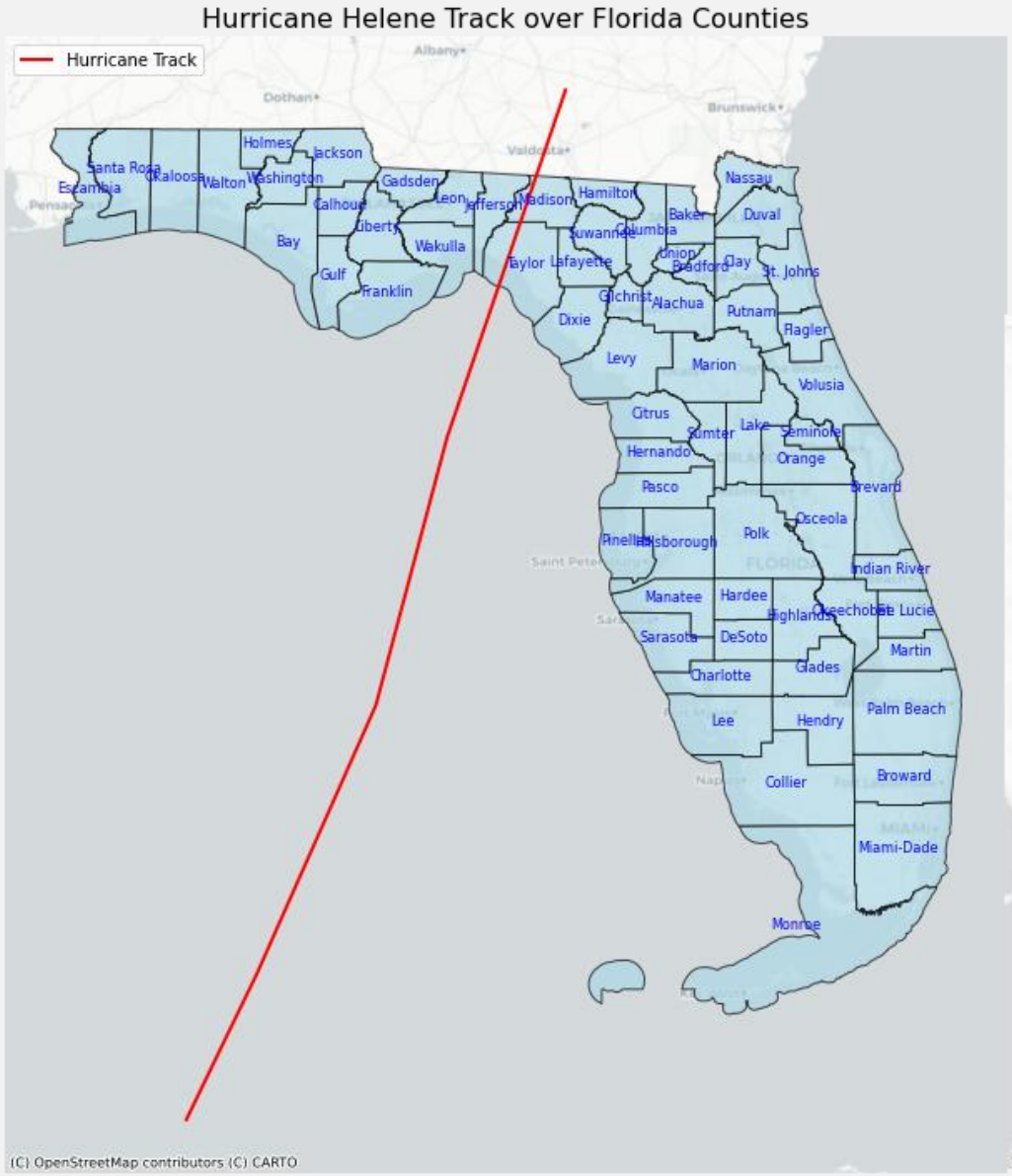
## Statistical Analysis

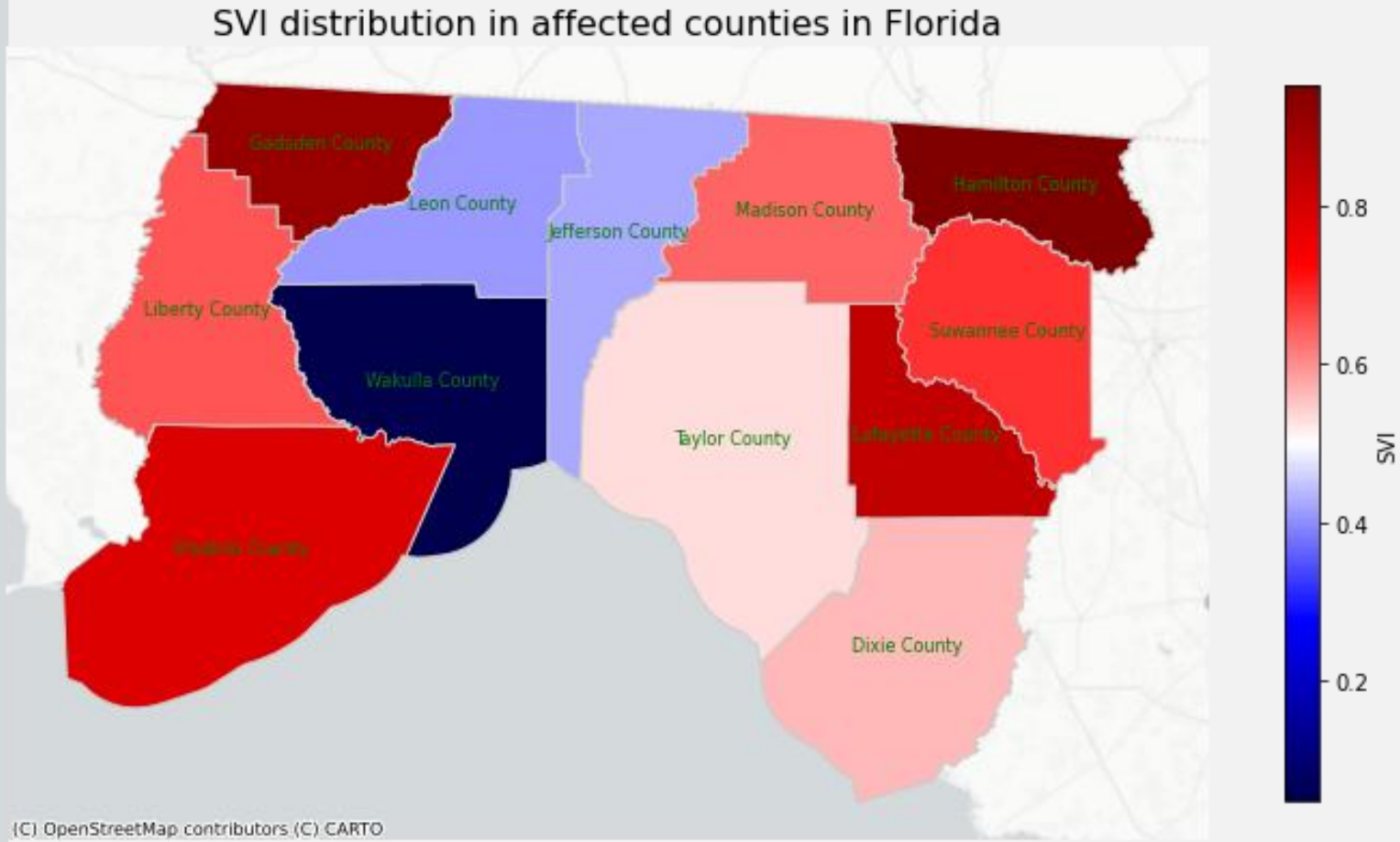
- Conducted in RStudio
- Combined county-level datasets for Florida, Georgia, and North Carolina to increase sample size
- Due to skewness in outcome of level of disruption, logistic regression was employed to estimate relationships between SVI, population density, healthcare facility density, storm impact and level of disruption

# RESULTS

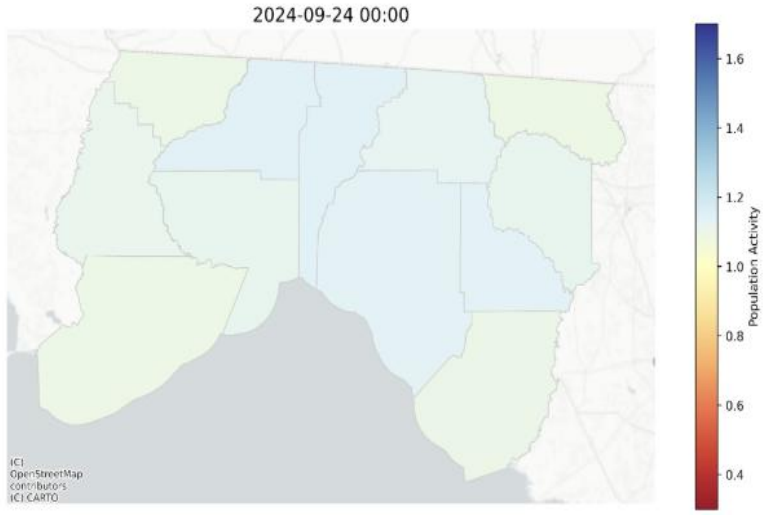
| Table 1: Summary statistics | Florida | Georgia | North Carolina | Overall |
|---|---|---|---|---|
| **Number of Affected Counties** (N, %) | 56 (83.6%) | 94 (59.1%) | 39 (39%) | 189 (58%) |
| **SVI Score** | | | | |
| Mean (SD) | 0.49 (0.28) | 0.52 (0.28) | 0.40 (0.23) | 0.48 (0.27) |
| Range | (0.02 to 1) | (0.01 to 0.99) | (0.02 to 0.82) | (0.01 to 1) |
| **Level of Disruption** | | | | |
| Mean Number of Days (SD) | 1.96 (3.11) | 5.36 (4.64) | 5.84 (5.64) | 4.79 (5.59) |
| Range | (1 to 18) | (1 to 23) | (1 to 24)* | (1 to 24) |
| **Storm Impact** | | | | |
| Mild (n, %) | 13 (23.2%) | 24 (25.5%) | 10 (25.6%) | 13 (6.9%)* |
| Moderate (n, %) | 8 (14.3%) | 35 (37.2%) | 11 (28.2%) | 54 (28.6%)* |
| Severe (n, %) | 35 (62.5%) | 35 (37.2%) | 18 (46.2%) | 122 (64.6%)* |
| **Percent Change in Population Activity on Day of Impact** | | | | |
| Mean (SD) | 3.7 (13.5) | -8.82 (28.53) | -21.1 (33.72) | -7.64 (27.6) |
| Range | (-39.8 to 17.23) | (-81.1 to 32.6) | (-78.6 to 16.9) | (-81.1 to 32.6) |
| **Healthcare Facility Density** | | | | |
| Mean(SD) | 2.30 (4.42) | 0.52 (1.57) | 1.52 (2.55) | 1.25 (2.98) |
| Range | (0.03 to 25.5) | (0.01 to 14.2) | (0.14 to 15.2) | (0 to 25.5) |

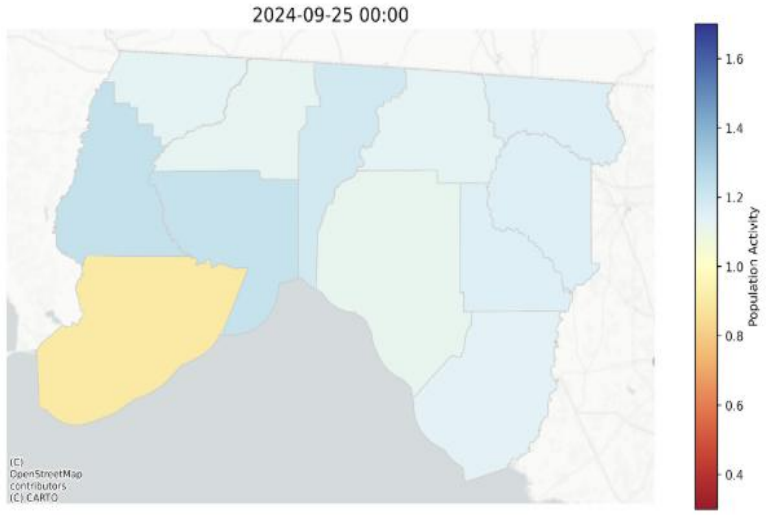
# SVI DISTRIBUTION AMONG AFFECTED COUNTIES IN FLORIDA

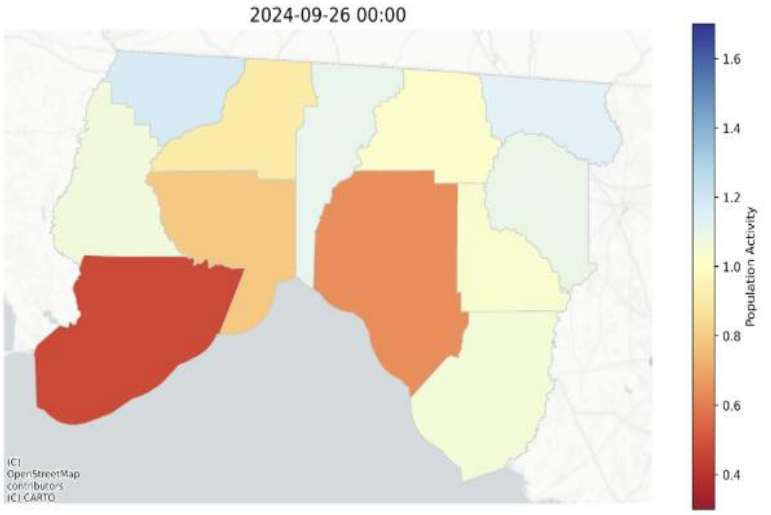


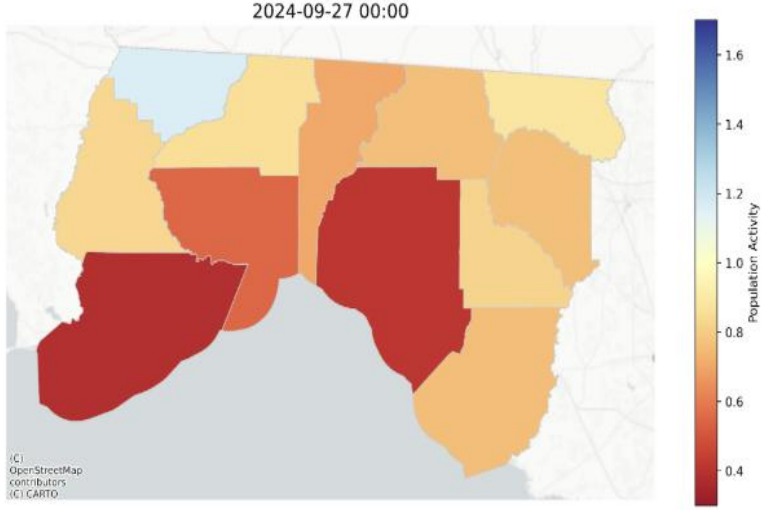



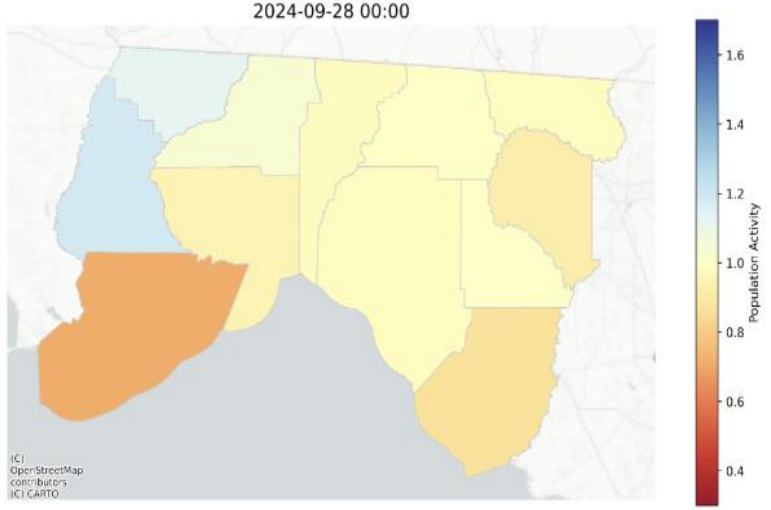
# POPULATION ACTIVITY, FLORIDA

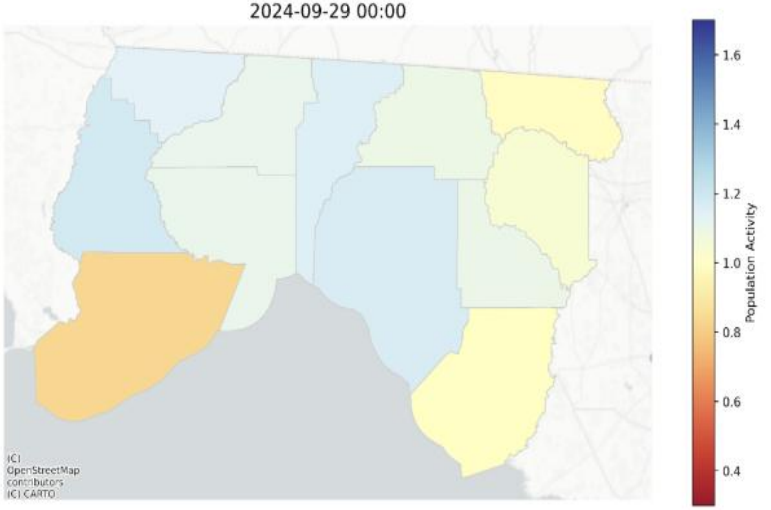


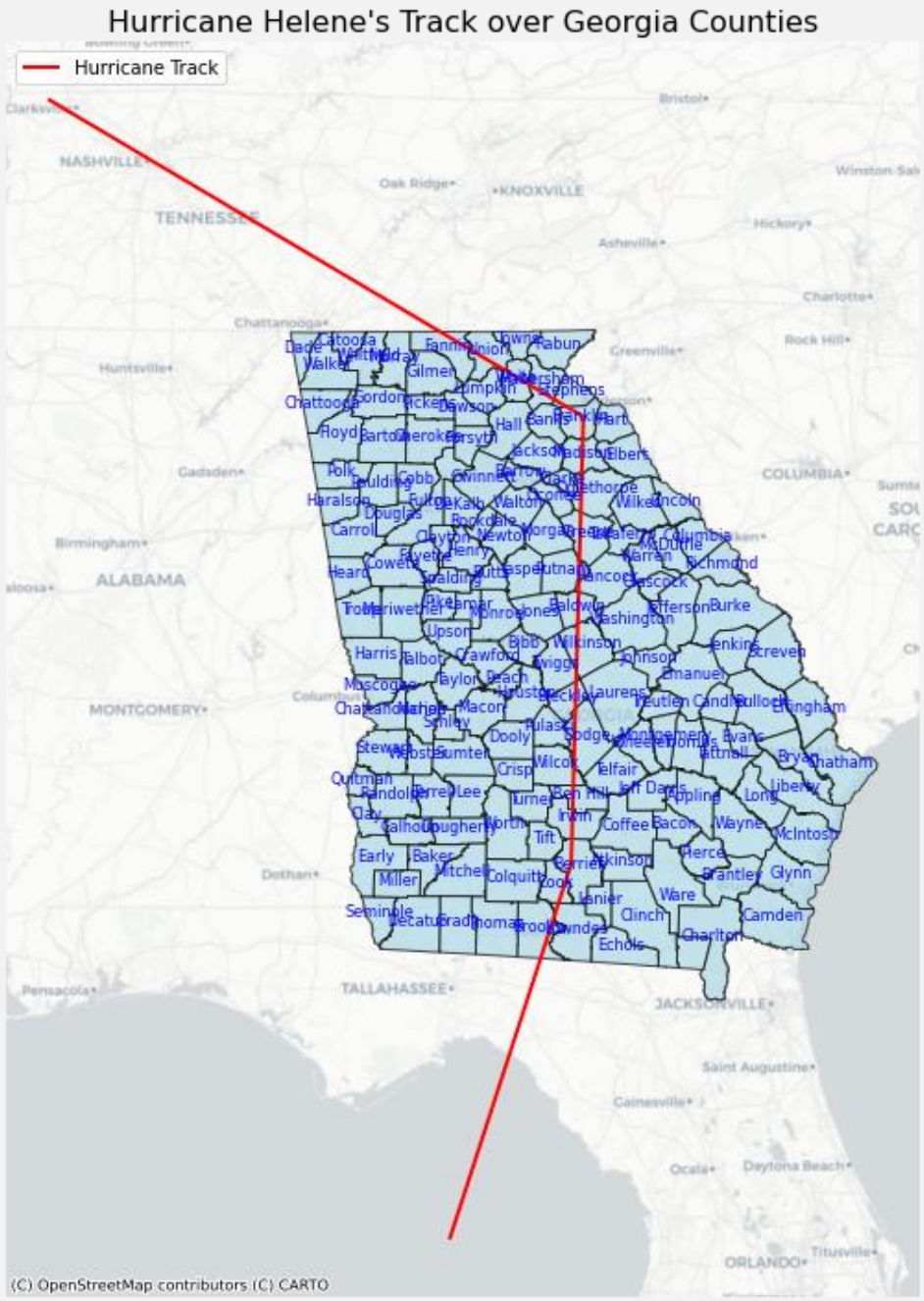



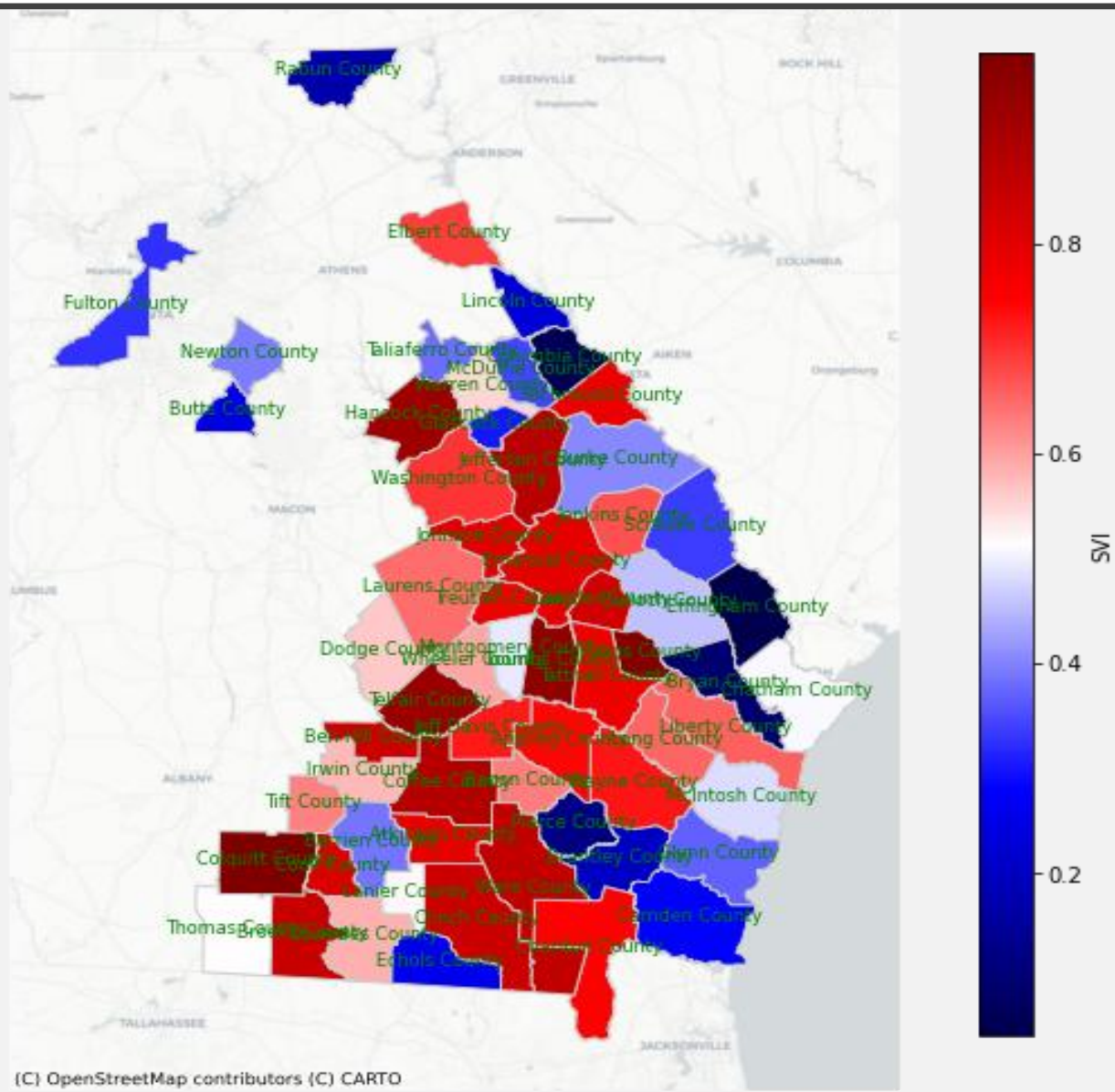



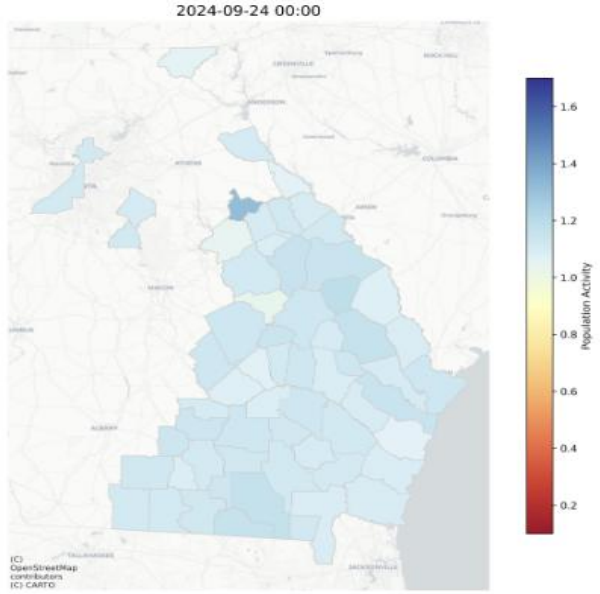



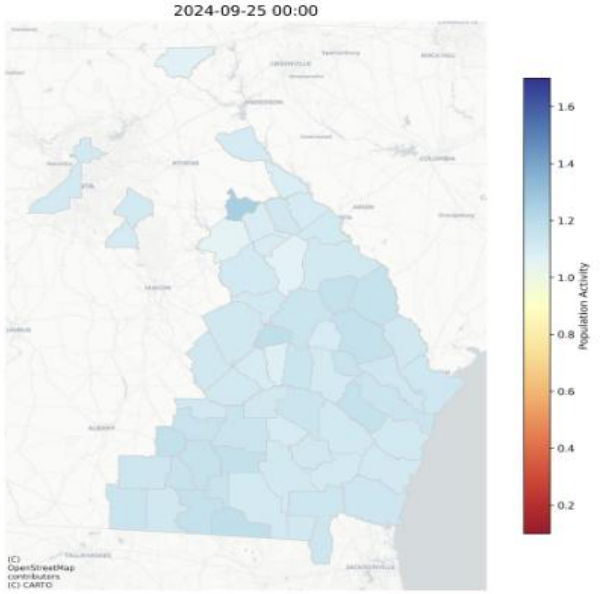
# SVI DISTRIBUTION AMONG AFFECTED COUNTIES IN GEORGIA

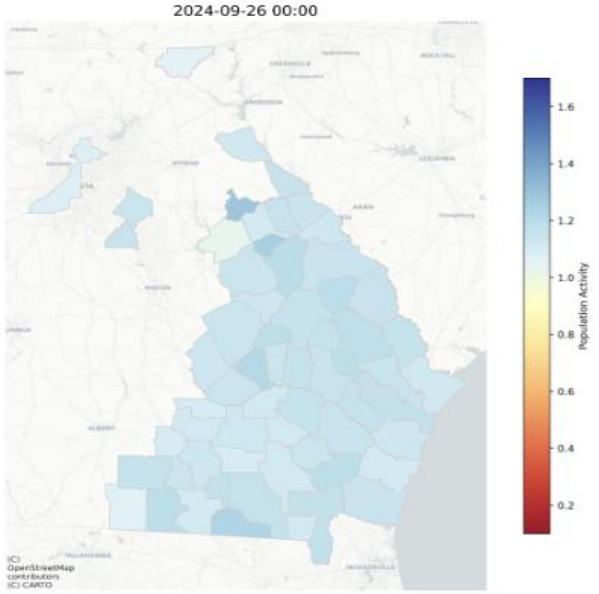


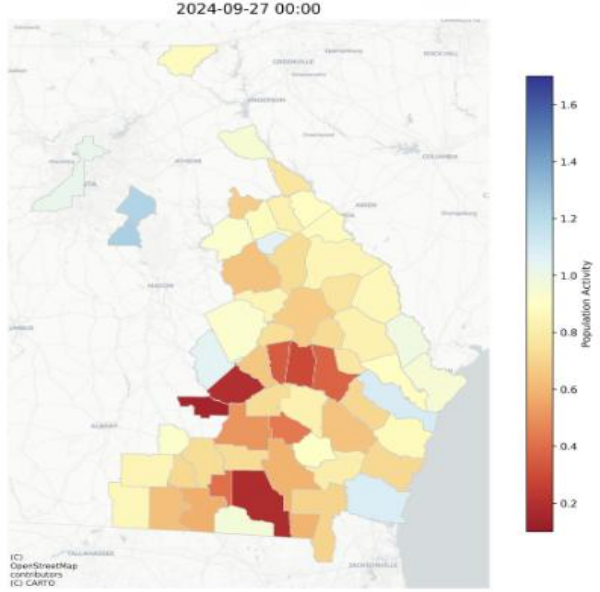



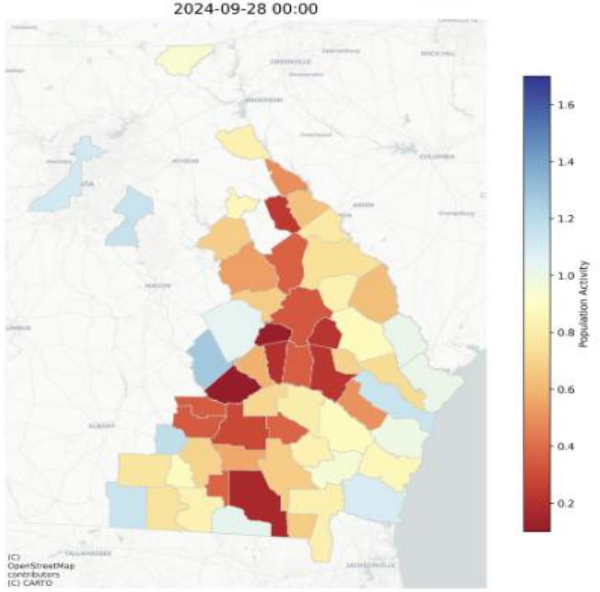
# POPULATION ACTIVITY, GEORGIA

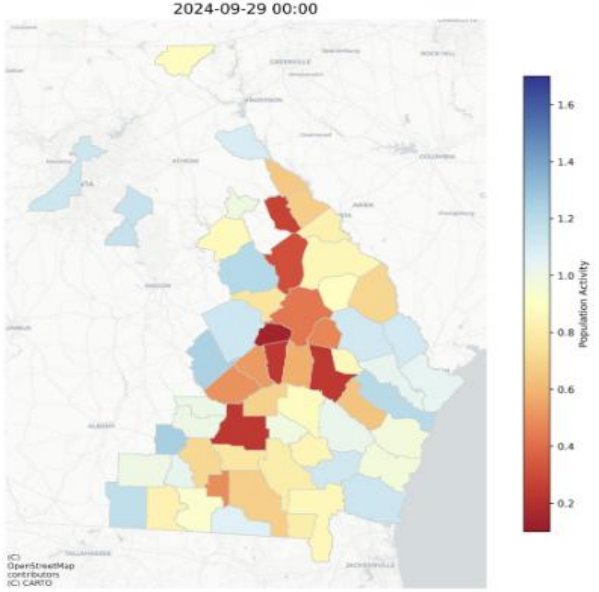


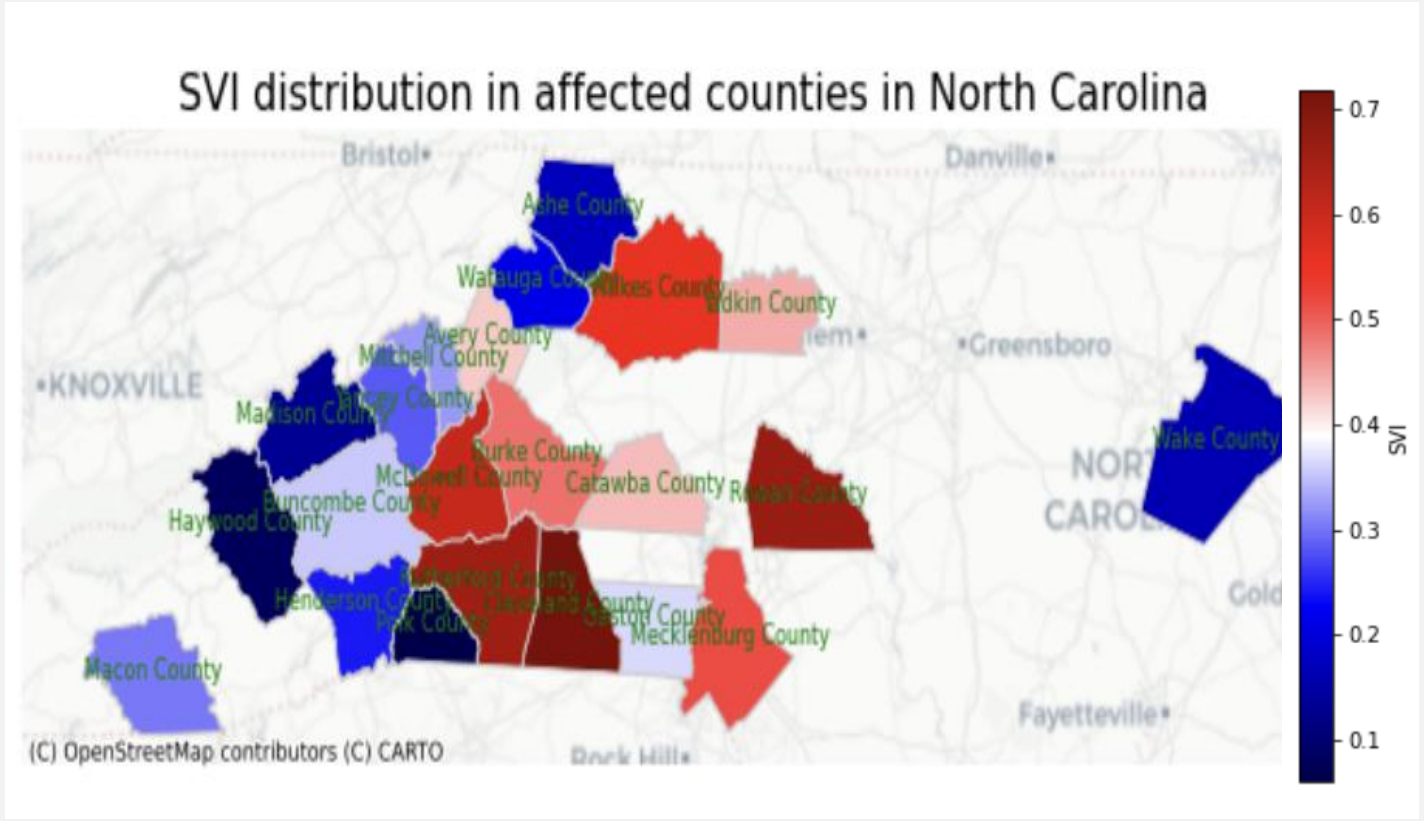



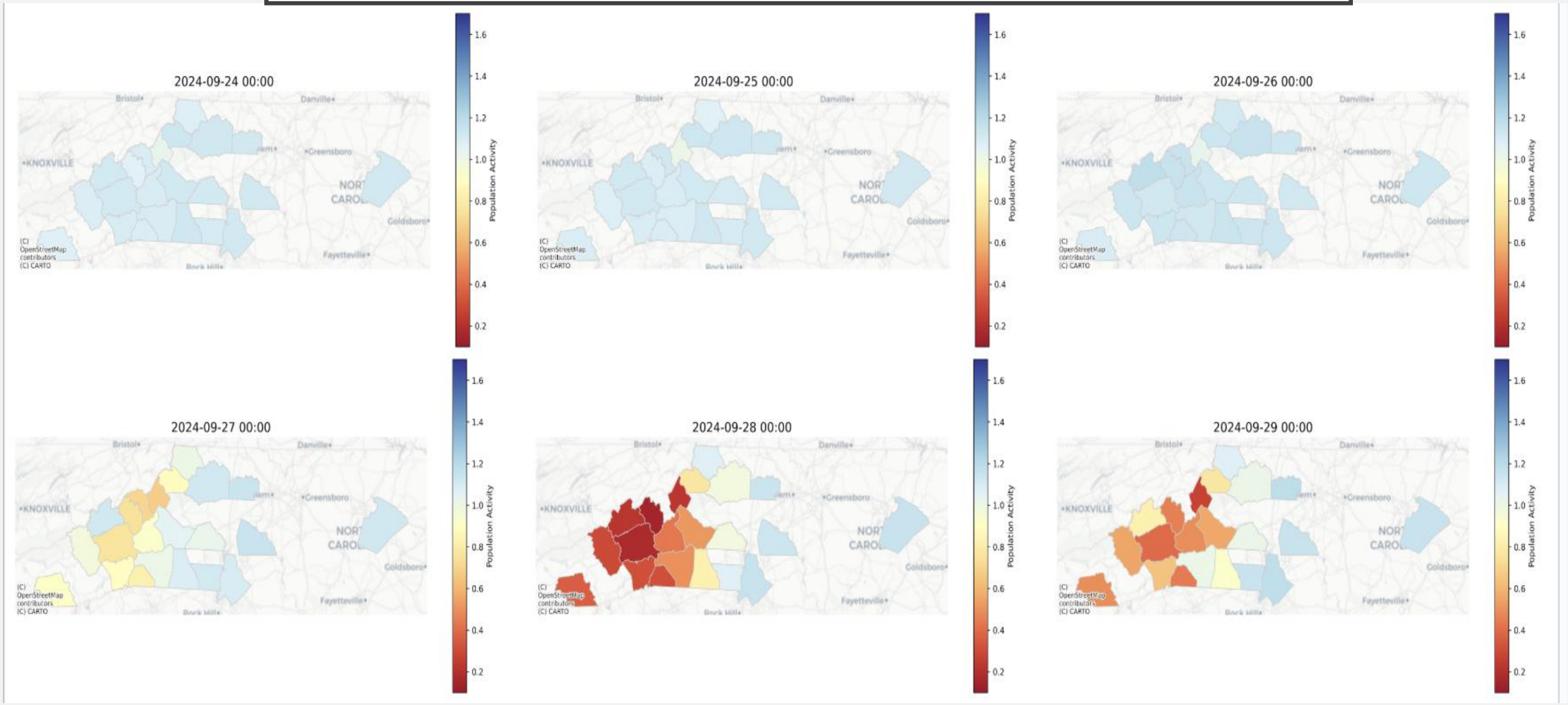



# SVI DISTRIBUTION AMONG AFFECTED COUNTIES IN NORTH CAROLINA

# POPULATION ACTIVITY, NORTH CAROLINA



# TABLE 2: LOGISTIC REGRESSION MODELS

| | Estimated Odds Ratio | p-value |
|---|---|---|
| Model 1: SVI score (categorized as low vulnerability and high vulnerability) as a predictor of Level of Disruption (high disruption and low disruption) | | |
| Intercept | 0.44 | <0.001 |
| SVI Score | 1.7 | 0.08 |
| Model 2: Full model | | |
| Intercept | 0.15 | 0.09 |
| SVI Score | 1.11 | 0.78 |
| Healthcare Facility Density | 1.17 | 0.71 |
| Population Density | 0.46 | 0.07 |
| Storm Impact (moderate) | 1.17 | 0.89 |
| Storm Impact (severe) | 11.43 | <0.05 |

# DISCUSSION & CONCLUSIONS

# CONCLUSIONS

- Disruptions related to natural disasters can be estimated through location-based data.
- Vulnerable counties in FL, GA, and NC had fewer healthcare facilities per area square mile than less vulnerable counties.
- Vulnerable counties in FL, GA, and NC had higher levels of disruption than less vulnerable counties, with inland regions experiencing longer disruptions (i.e., NC had the longest level of disruption).
- Based on the high percentage changes in population activity during and after Helene compared to before and the length of disruption in vulnerable areas, healthcare facilities in these areas likely faced similar disruptions.
- There may be specific vulnerabilities associated with widespread disruption.

# LIMITATIONS

1. Decreased population activity can be attributed to power outages
    a. *Obtaining power outage data was expensive for this timeframe but reports showed power being back on before baseline population activity was reached again.*
2. Health system disruptions can be better estimated using healthcare data
    a. *Healthcare facility data was not available at the time of this study for this timeframe.*
    b. *The idea was to measure not only disruptions to hospitals but other types of facilities (pharmacies, rehab centers, outpatient services), which is why we chose to use geospatial data rather than measuring hospitalization and ED visit rates.*
3. Sample limited to Facebook Users, and further limited to those who enabled location services
    a. *Population density was a covariate controlled for to attempt to overcome this.*

# NEXT STEPS & RECOMMENDATIONS

- Obtain healthcare facility data to better estimate health system disruptions
  - Closures, damage, and power outages may never be publicly available
  - Estimate disruptions using hospitalization rates and ED visit rates before, during, and after Hurricane Helene
- Expand sample to all states that were impacted by Hurricane Helene, and expand the timeframe to include the 30 days post Hurricane Milton
  - Increase power and reliability of results
  - Measure effects of exposure to multiple back-to-back hurricanes
  - Determine if specific vulnerabilities, such as the SVI themes, are associated with widespread health system disruptions

# THANK YOU!

# REFERENCES


Centers for Disease Control and Prevention. (2024). *Social vulnerability index (SVI)*. Retrieved from https://www.atsdr.cdc.gov/placeandhealth/svi/index.html

Caliper Corporation (2024). 2024 Health Data Layers [Data set]. Caliper. https://www2.caliper.com/store/product/health-care-mapping-data/

FEMA. (2024). *Florida Disaster Declaration (FEMA-4828-DR) designated areas map* [Map]. U.S. Department of Homeland Security. https://www.fema.gov/disaster/4828/designated-areas

FEMA. (2024). *Georgia Disaster Declaration (FEMA-4830-DR) designated areas map* [Map]. U.S. Department of Homeland Security. https://www.fema.gov/disaster/4830/designated-areas

FEMA. (2024). *North Carolina Disaster Declaration (FEMA-4827-DR) designated areas map* [Map]. U.S. Department of Homeland Security. https://www.fema.gov/disaster/4827/designated-areas

Internet Geography. (2024). *Hurricane Helene 2024:A catastrophic Category 4 storm*. Retrieved from https://www.internetgeography.net/hurricane-helene-2024-a-catastrophic-category-4-storm

Meta. (2024). *Facebook Population during Crisis* [Data set]. Data for Good at Meta.

# Developing a Dynamic Social Vulnerability Index (DSVI) to Support Emergency Response

**Sangung Park**, Yuran Sun, Shangkun Jiang, and Xilei Zhao

16th April 2025

@ New Orleans

National Hurricane Conference 2025

UF UNIVERSITY of FLORIDA

SERMOS LAB
Smart, Equitable, Resilient Mobility Systems

# Social vulnerability index (SVI)

- SVI wants to capture the communities that will most likely need support **before, during, and after disasters.**
  – CDC/ATSDER SVI 2022 Documentation.
- SVI is static at the perspective of disaster stakeholders because SVI is usually updated every 2 years.

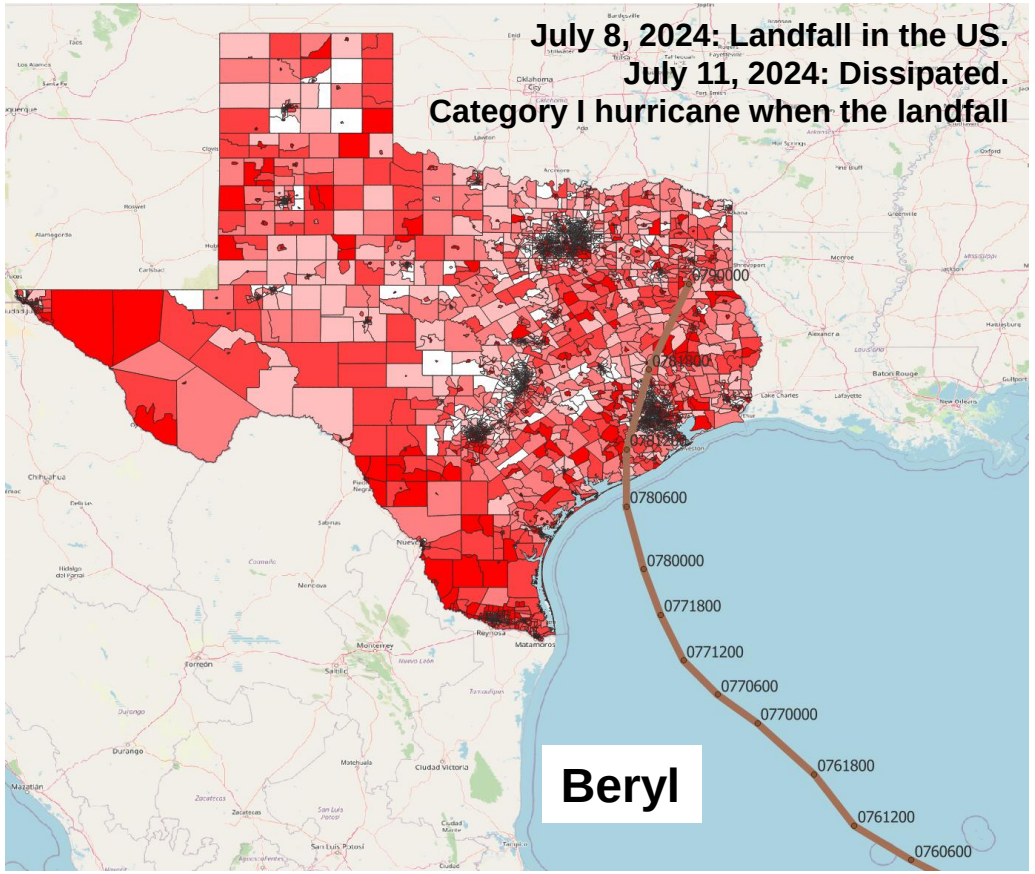



**Figure**. Census tracts colored by SVI in Hurricane Beryl, 2024.

Elements of SVI

- Socioeconomic attributes
- Housing composition and disability
- Minority Status and Language
- Housing and Transportation

# Social vulnerability index (SVI)

- SVI wants to capture the communities that will most likely need support **before, during, and after disasters.**
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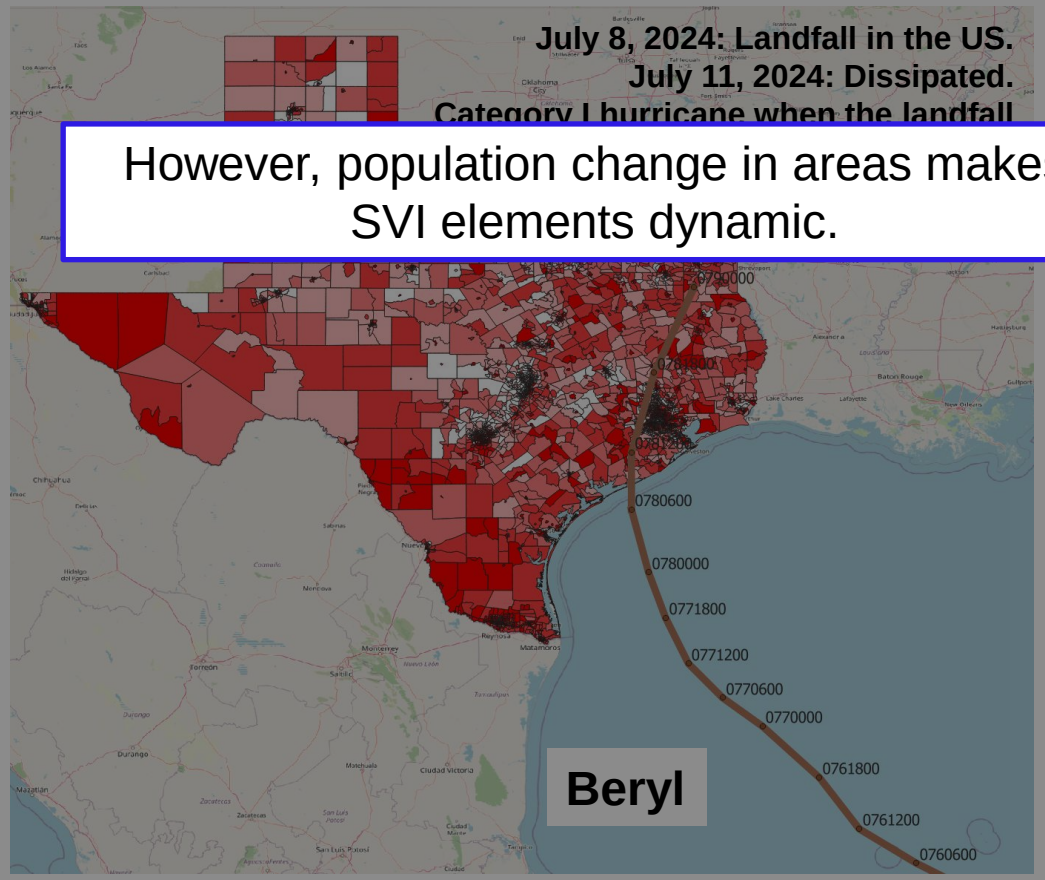



However, population change in areas makes SVI elements dynamic.

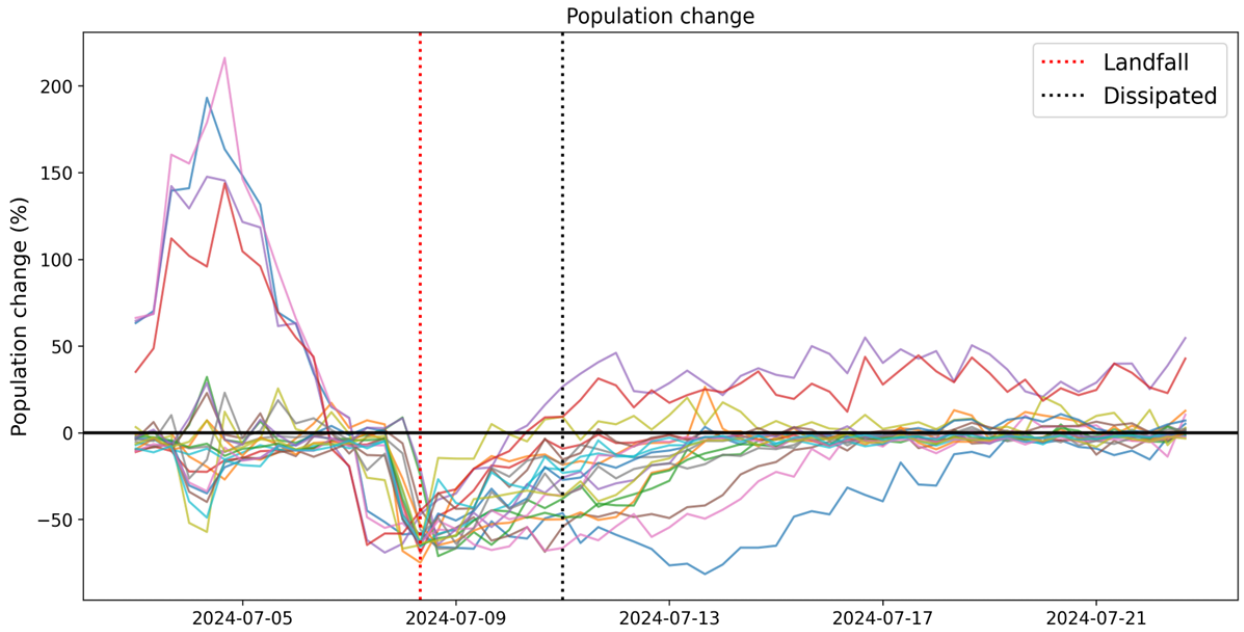
Elements of SVI

- Socioeconomic attributes
- Housing composition and disability
- Minority Status and Language
- Housing and Transportation

**Figure**. Census tracts colored by SVI in Hurricane Beryl, 2024.

# Meta movement can make SVI dynamic

- Meta movement approximately captures people's movement over time, so we can estimate the socioeconomic attribute changes.
  - Two unusual patterns are observed before and during disasters
    - Many evacuation trips to inland, and
    - Long evacuation trips are observed.



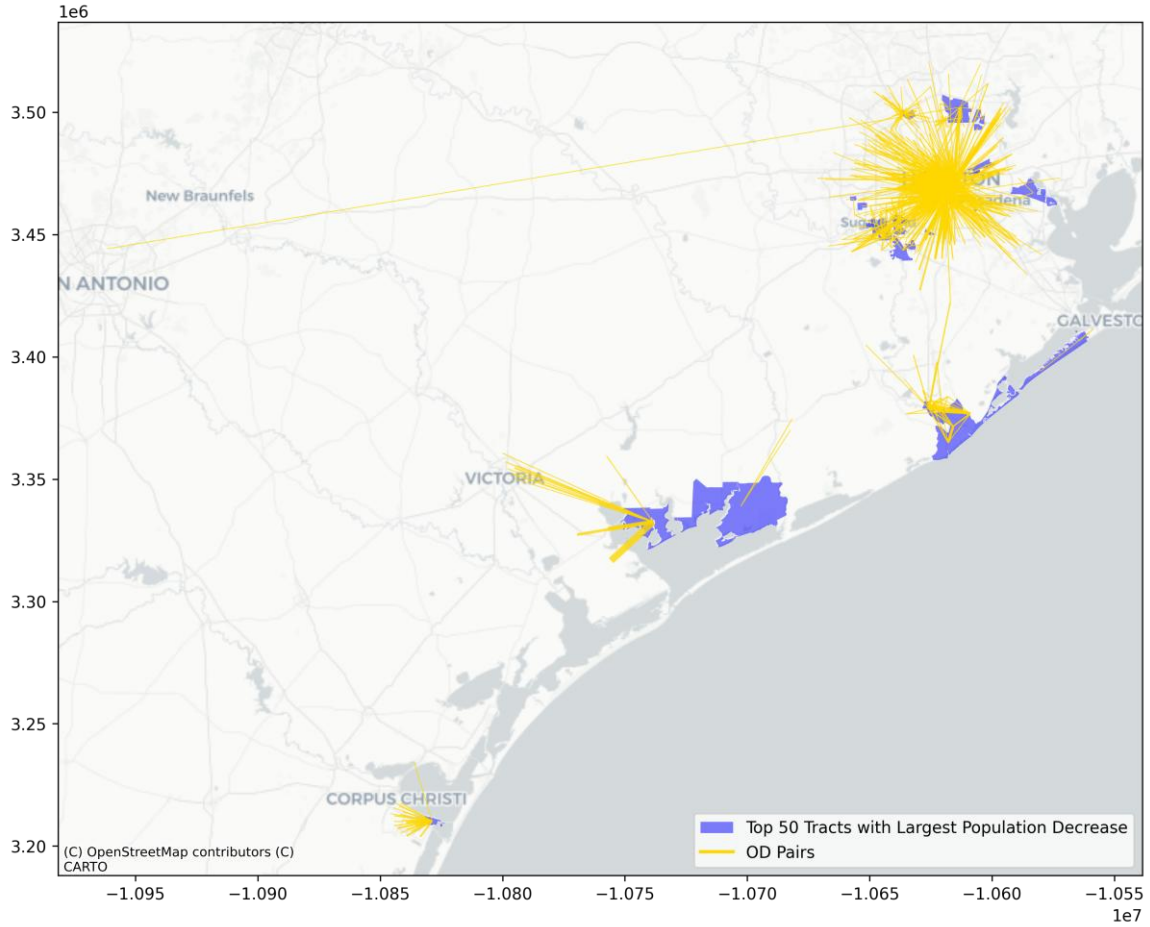




**Figure**. Movement patterns in Hurricane Beryl.

# Hospitals can be affected by population movement

- Population surges strain healthcare resources in an emergency, like hurricanes.

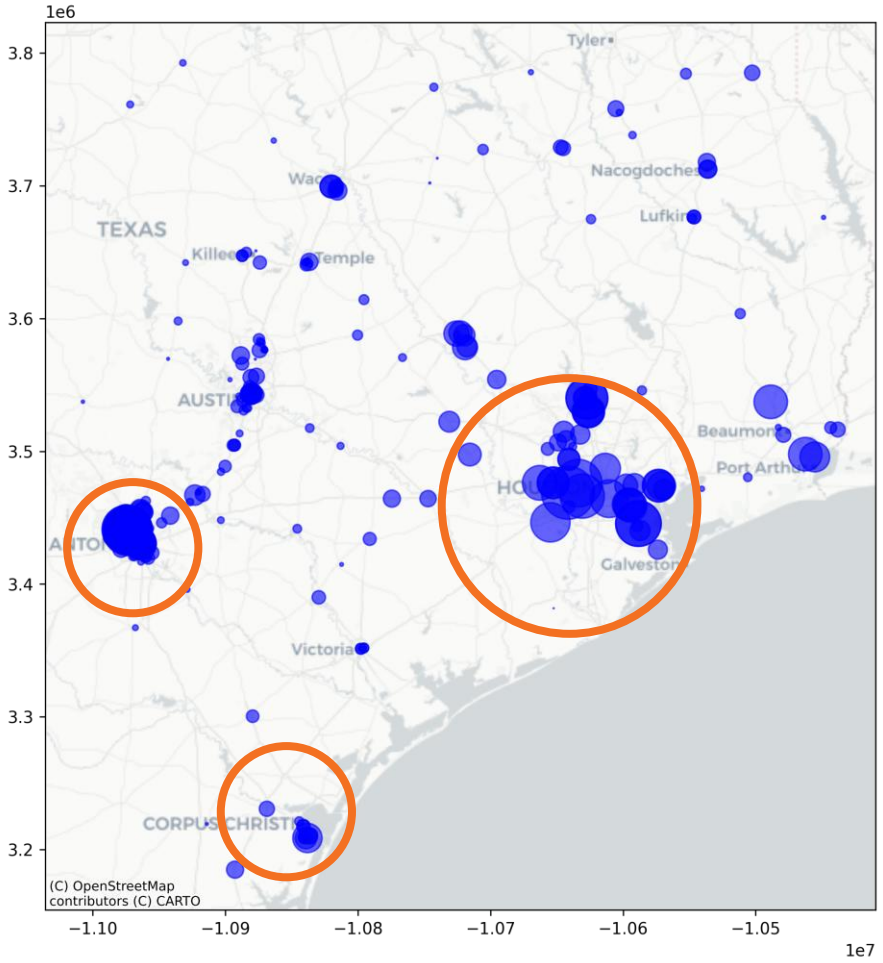



**Figure**. Hospital population surge counts.

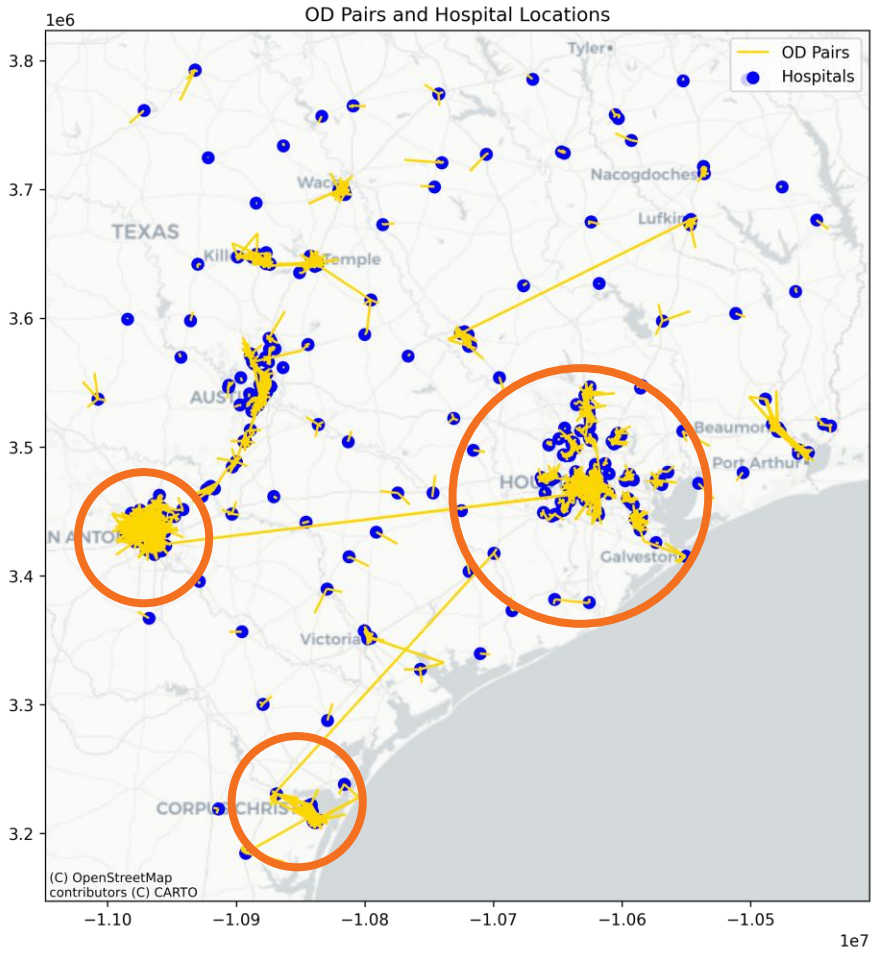



**Figure**. Hospital destinations by origin tracts.

# Summary

- Research Questions
  - (1) How do sociodemographic changes and hospital accessibility during the disaster response phase influence the evolution of SVI for public health?
  - (2) Can population density and movement datasets effectively represent these changes?, and
  - (3) How can DSVI be utilized to gain insights into the social inequity considering the hospital accessibility?
- Research Objectives
  - Develop a **Dynamic Social Vulnerability Index (DSVI)** that integrates the traditional SVI with daily data on population density and movement provided by Meta and publicly available hospital location datasets.

# Flowchart

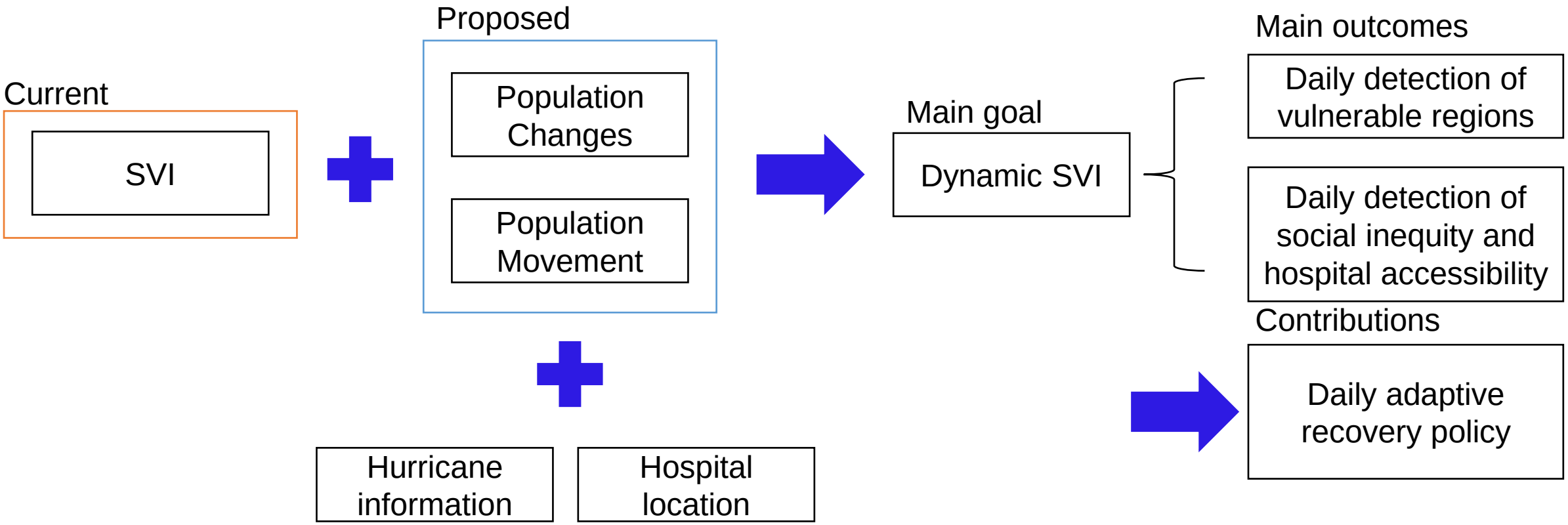
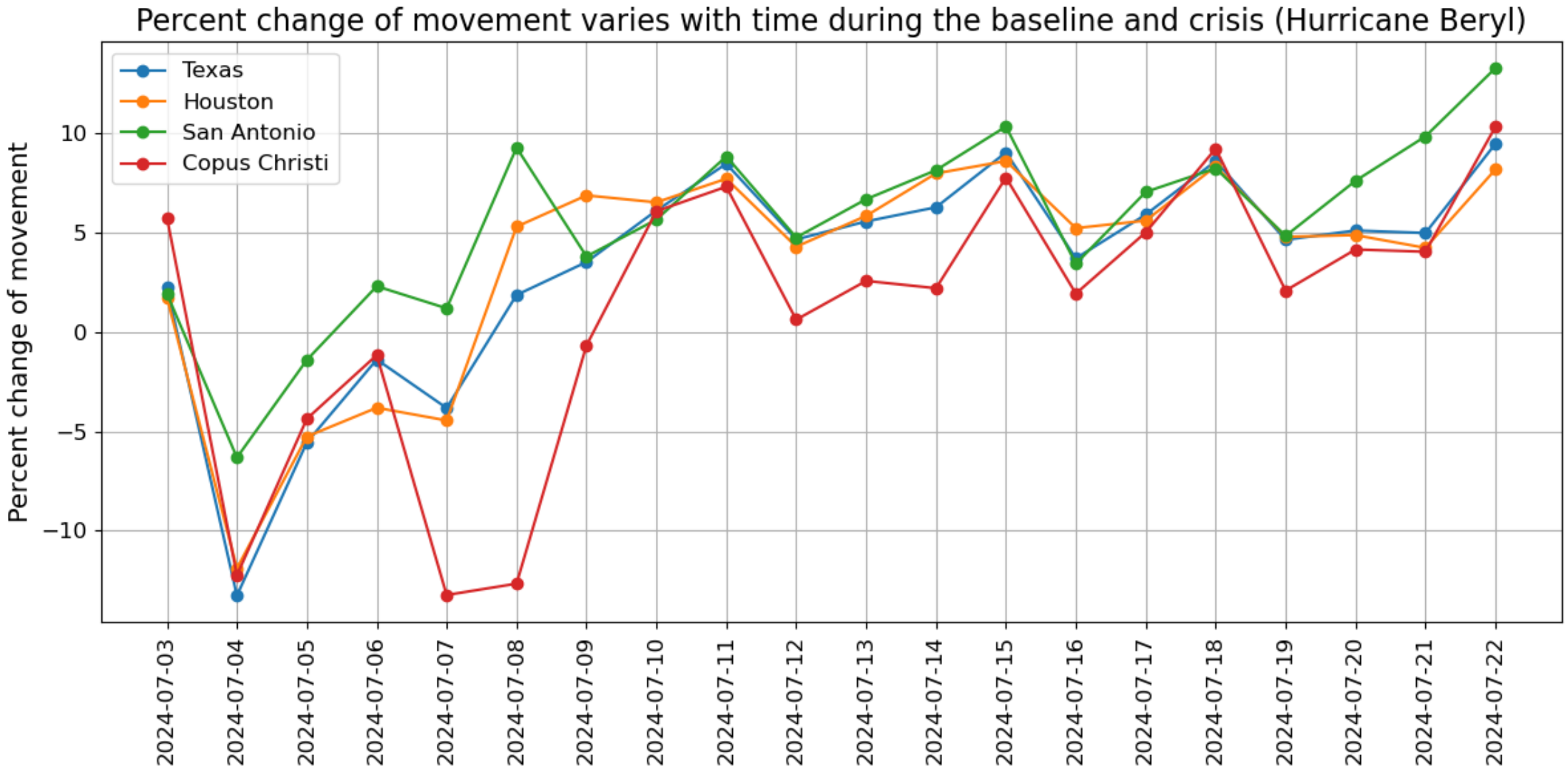



**Figure**. Flowchart of this study.

# Movement data can represent the population movement



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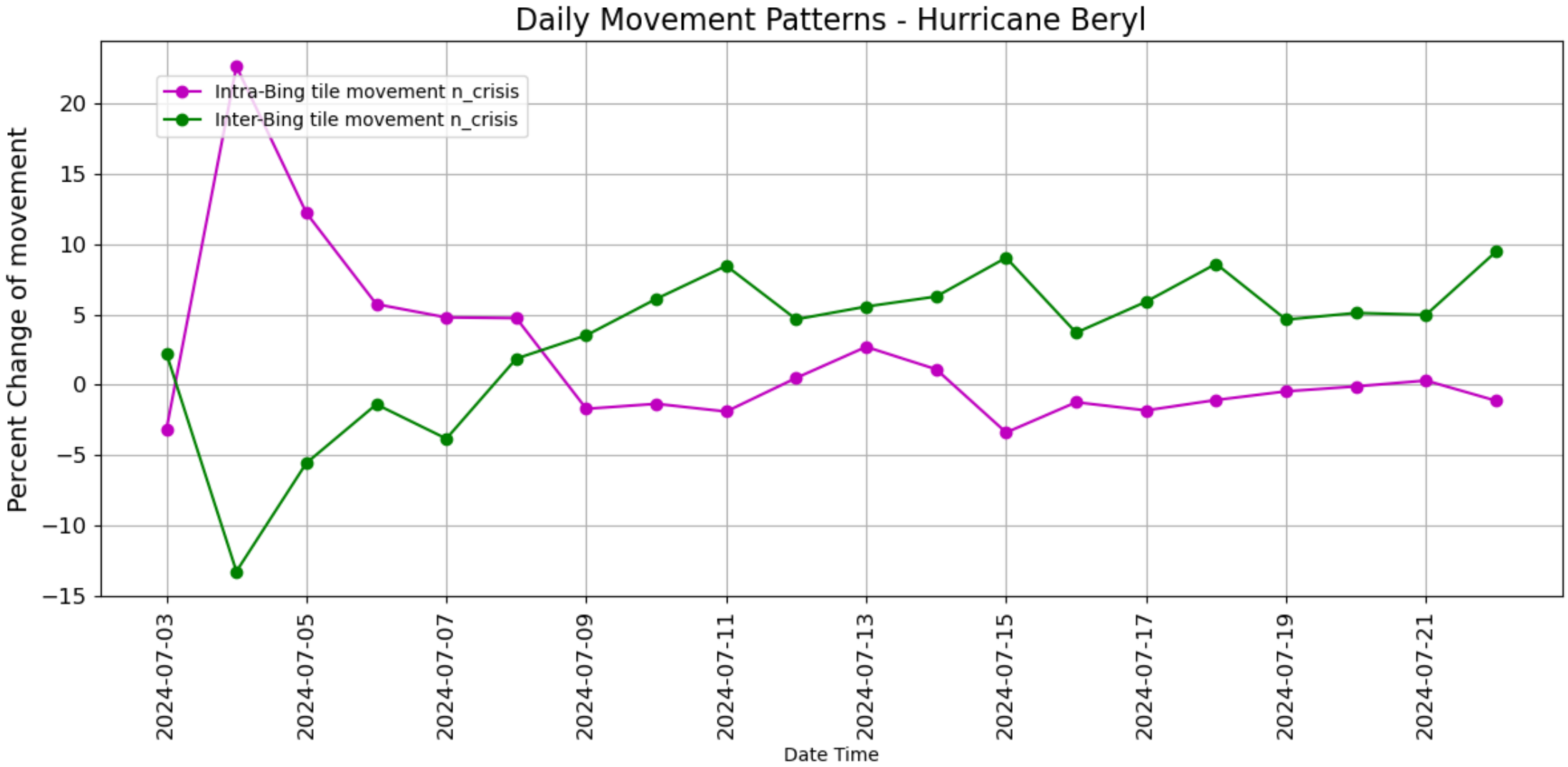

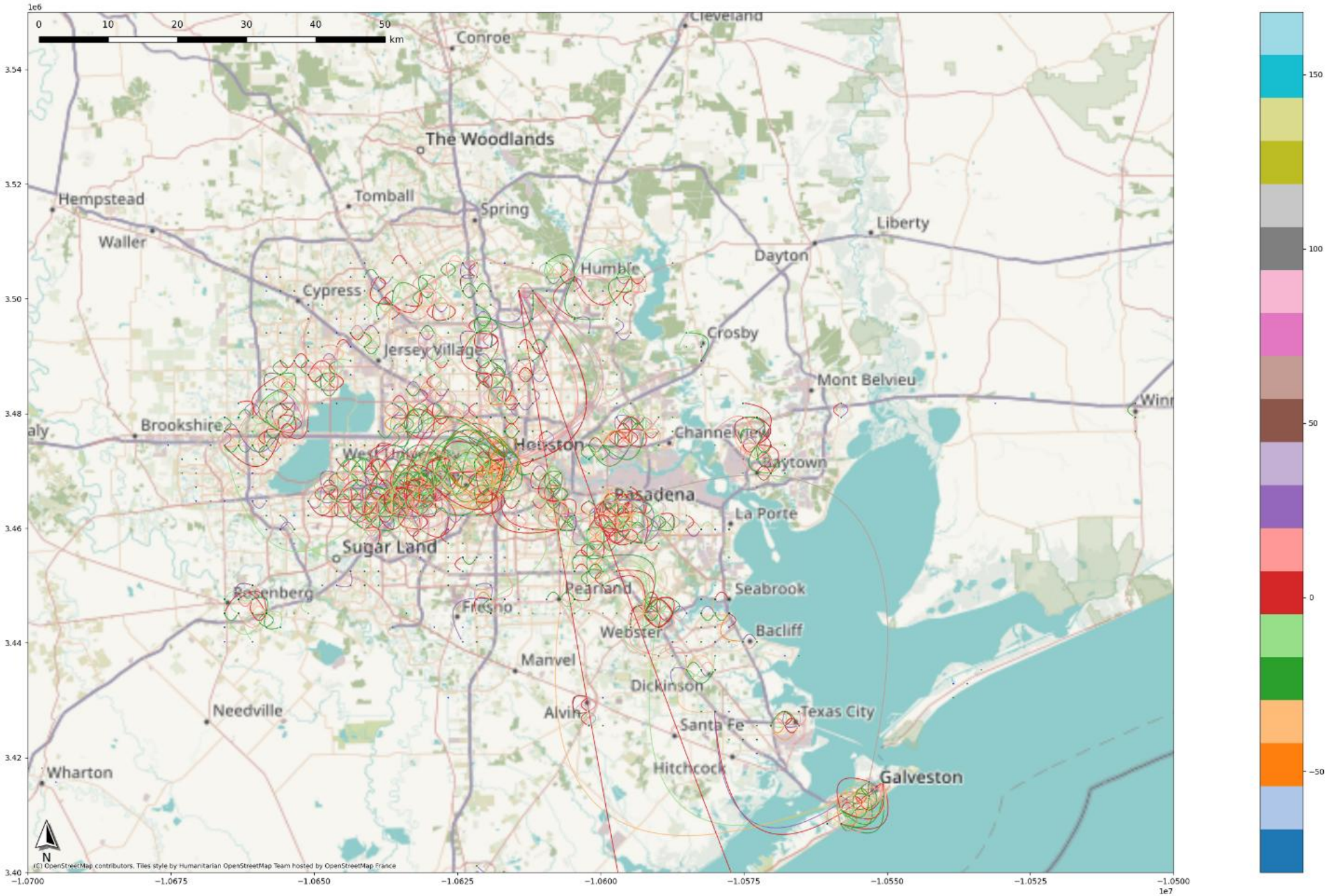
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Houston
Baytown
Pasadena
La Porte
Sugar Land
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# Basic idea of DSVI

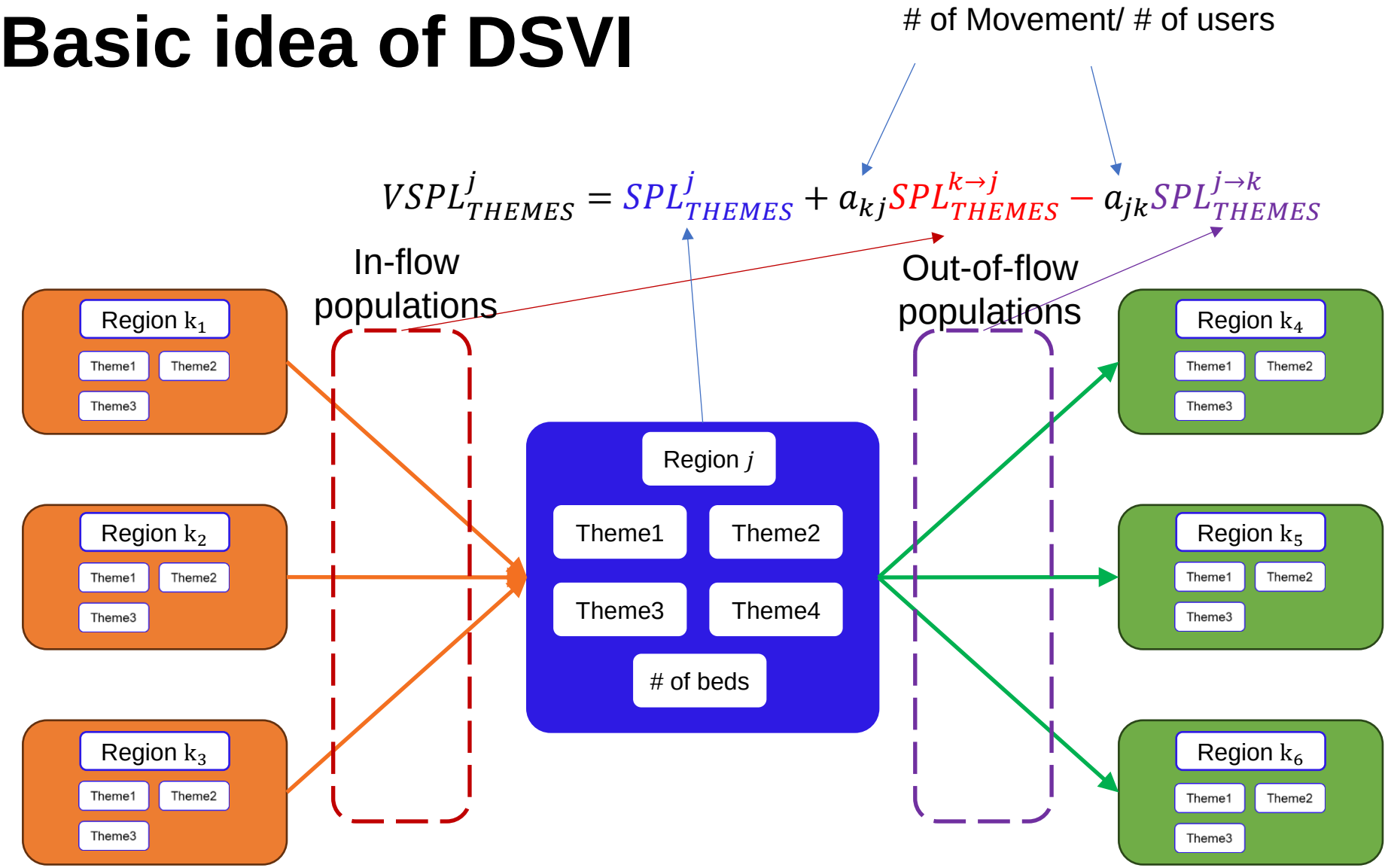


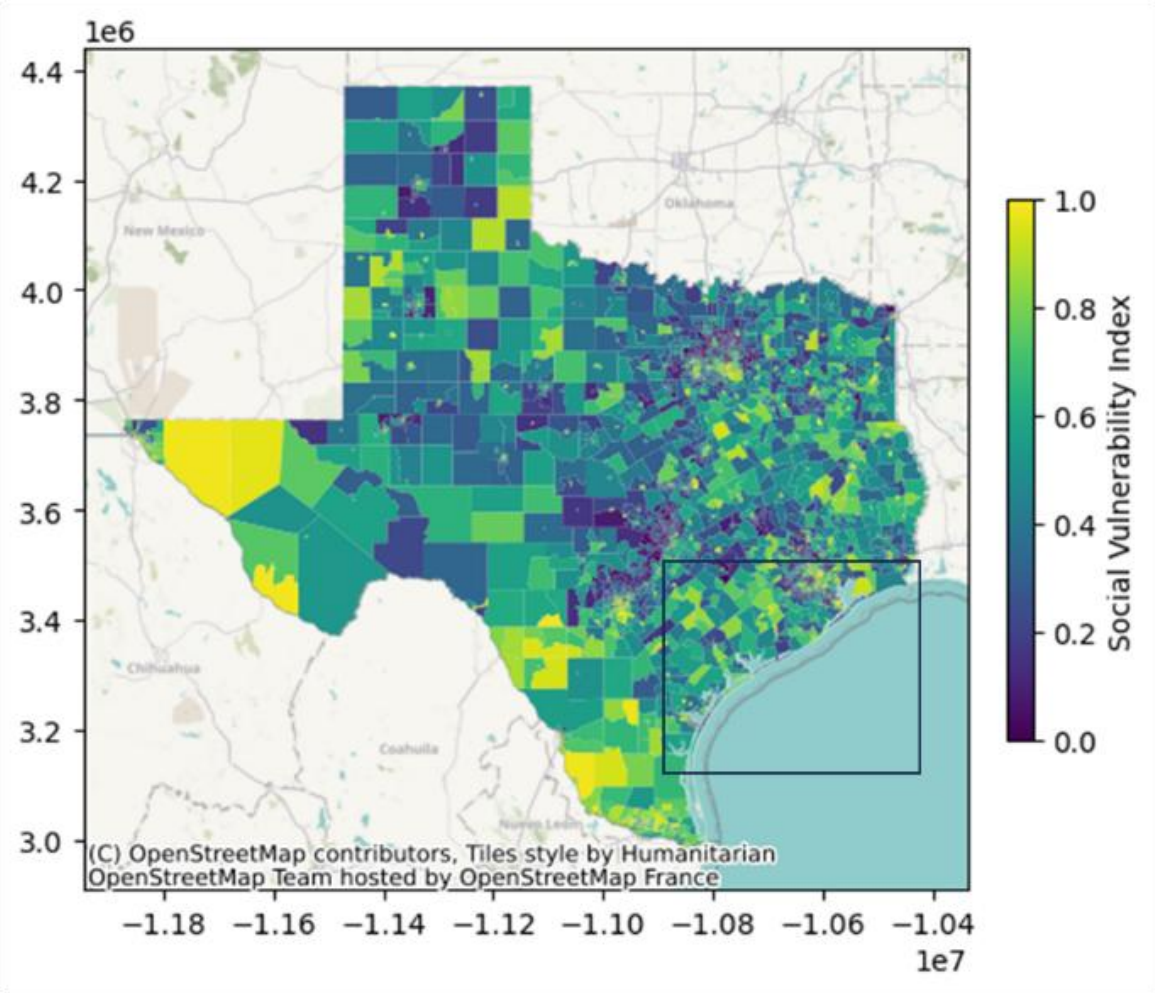

**Figure**. Basic idea of DSVI

# Comparison between SVI and DSVI-PH

- We can capture DSVI-PH only at some areas containing Facebook movement data.

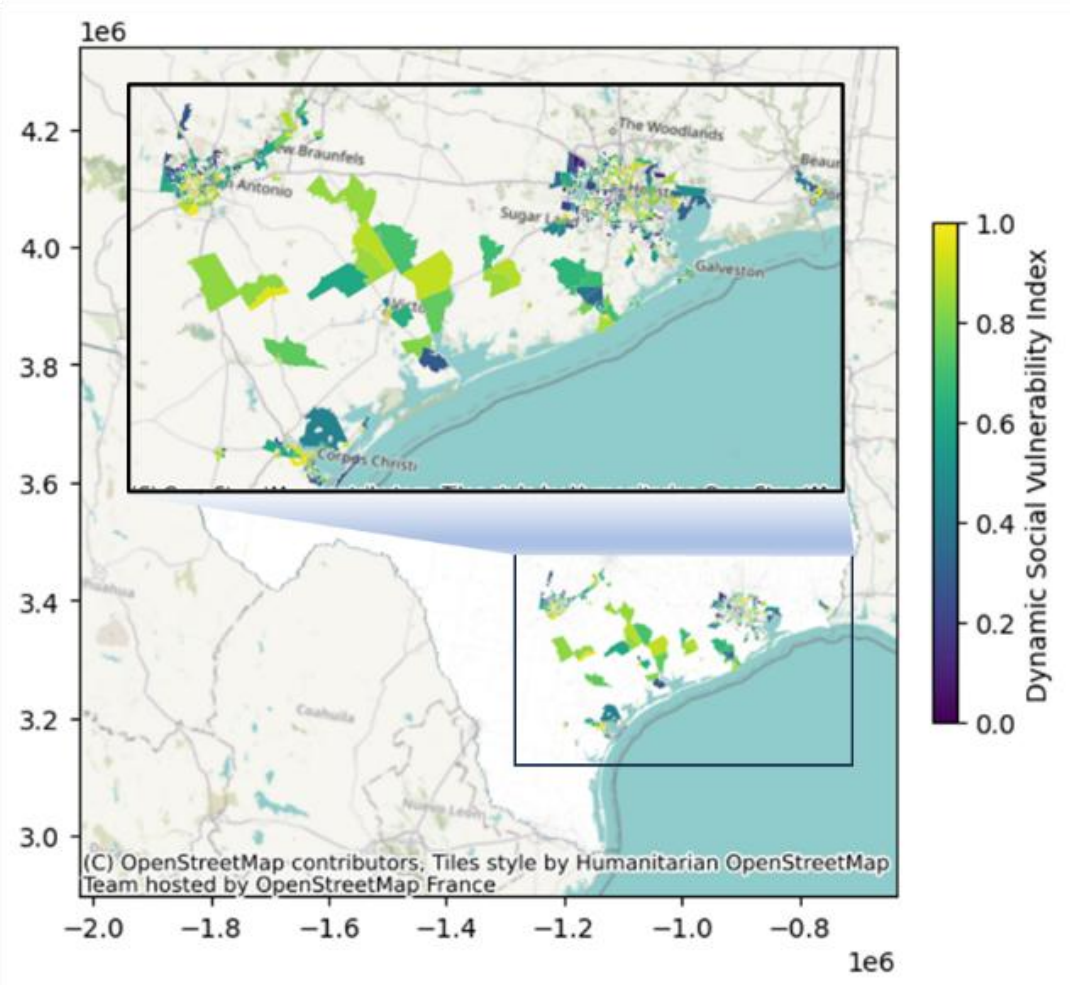
(a)

Social Vulnerability Index, 2022




(b)

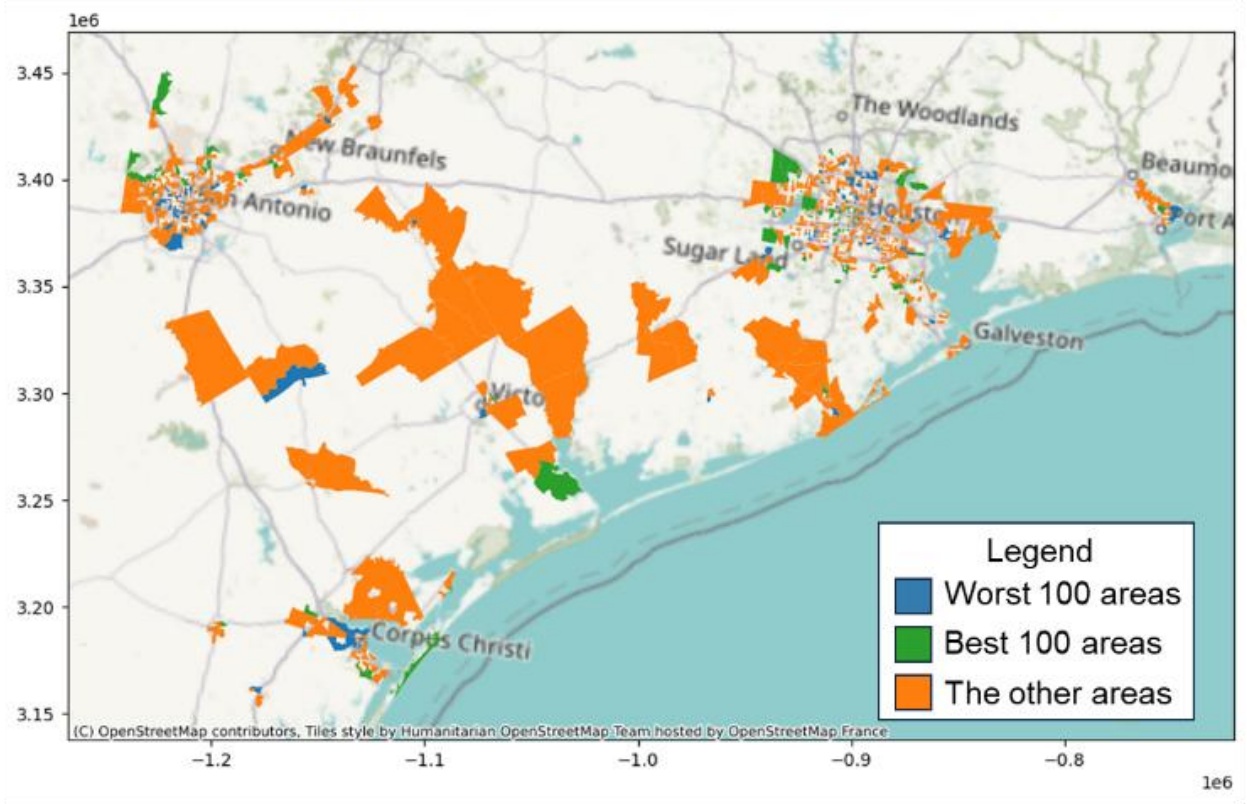
Dynamic Social Vulnerability Index, 2022



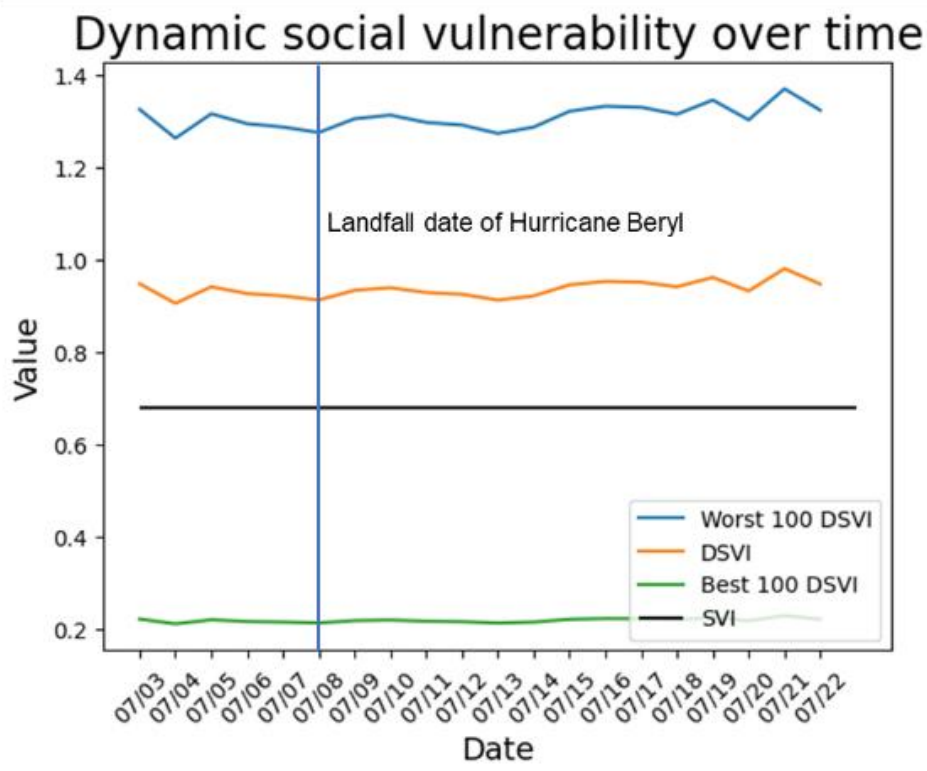
# Hot & cold spots of DSVI-PH for vulnerable areas

- Highly vulnerable areas and highly secure areas are mixed at the census tract level.

(a)

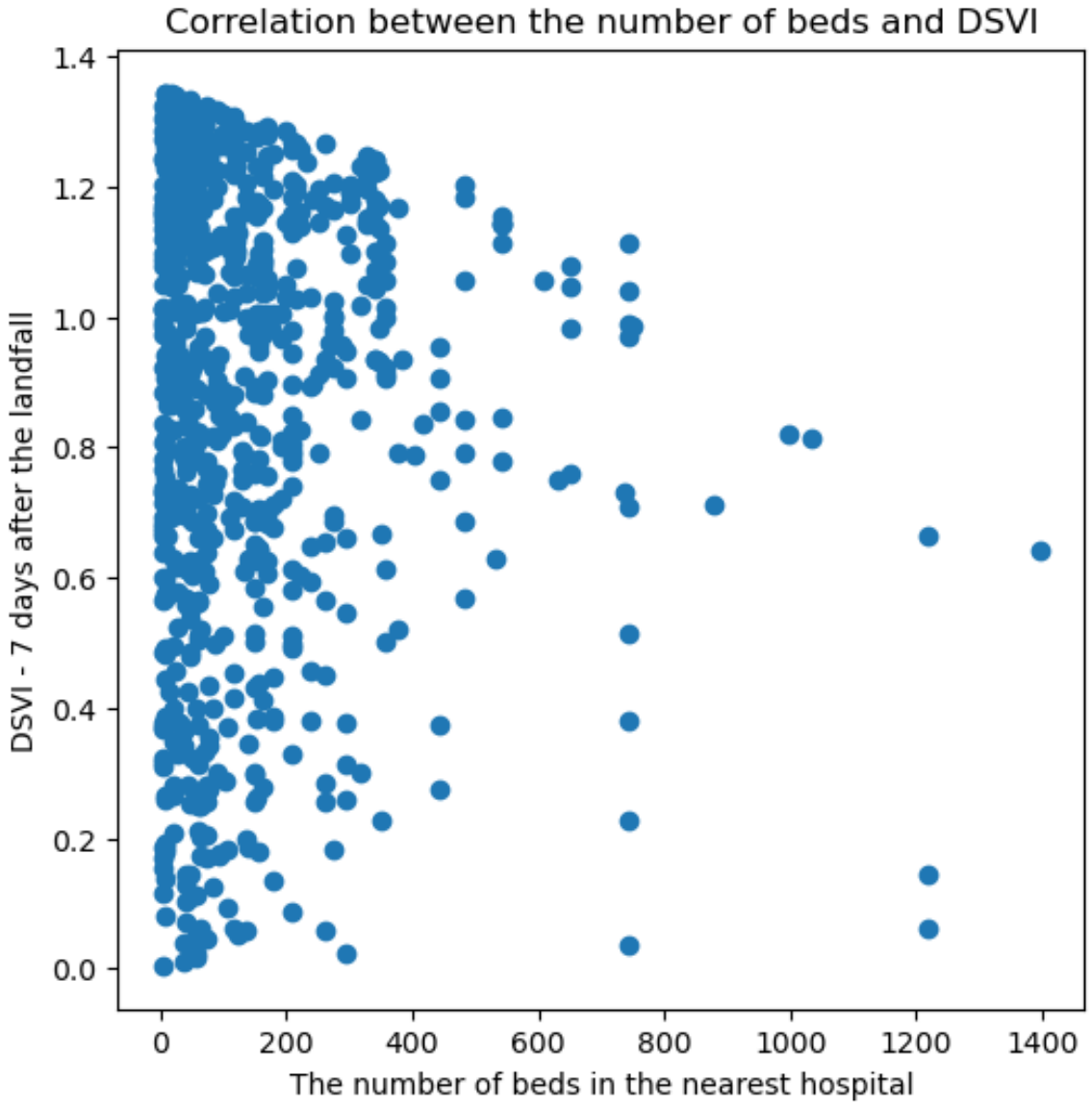



(b)



# Correlation between the number of beds in the nearest hospital and DSVI-PH

- Negative correlation between the number of beds and DSVI-PH.



# Conclusions

- DSVI can identify the daily changes of social vulnerability.
- Highly vulnerable and highly secure areas are captured through hot & cold spot analysis by DSVI.
  - Currently two area types are mixed in three large cities.
- Policymakers can set up a daily adaptive recovery policy based on diagnosing the socially vulnerable areas daily.
- Next steps
  - Link the results with real-time hospital accessibility information.
  - Validate DSVI compared with the real disaster damage estimated (FEMA individual assistance data).
  - Solve the data quality issues of DSVI.

Thank you

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  - www.pheernetwork.org


- Join https://nyu.qualtrics.com/jfe/form/SV_3dtHl9YPmqSu1RI

# Cross-study overview

- LBD revealed gaps in healthcare access in vulnerable areas
  - Counties with higher social vulnerability scores had fewer healthcare facilities and experienced longer service disruptions following hurricanes
  - Socially vulnerable groups—such as older adults and those in poverty—faced longer delays in accessing care
- Population movement data tracked disruption and recovery timelines
  - Researchers identified causal relationships between population movement patterns and power outage data, highlighting LBD's value in detecting and timing systematic stress and recovery across affected areas

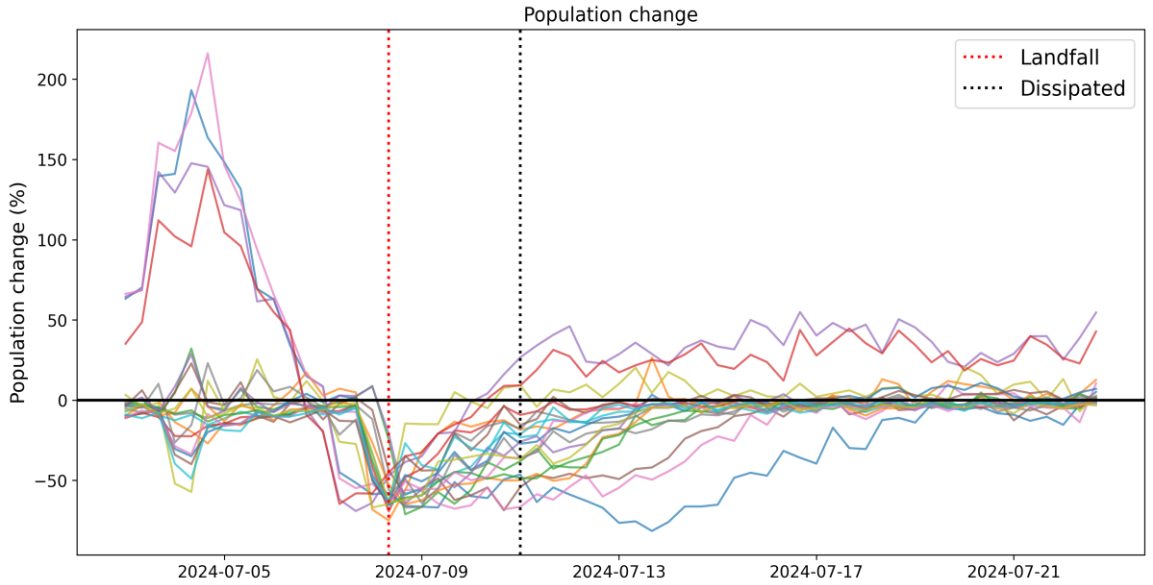
# Cross-study overview

- Image-based LBD supported community risk messaging
  - Social media image analysis was used to document visible disruptions and community impacts, helping researchers generate narrative-based insights and issue calls for improved risk reduction strategies, suggesting LBD's utility for public communication as well as research

# Appendix. - Sangung

# Population change over time

- Data scope: July 3, 2024, to July 22, 2024, and updates every 8 hours.
- 20 US census tracts with the highest overall population percentage changes.
- Hurricane Beryl made landfall on July 8 at 4 a.m. The population reached its lowest point at this time, followed by a gradual increase.
- The hurricane dissipated on July 11, and the population returned to normal levels around July 14.



# Heatmap of population changes

**The first voluntary notice** was issued, but no significant population changes were observed in coastal areas.

**The day before all mandatory orders were issued**, voluntary notices were issued in two counties. Still no significant population changes.

**On the day all mandatory orders were issued**, significant population changes were observed, suggesting that evacuation orders likely influenced these changes. Major evacuations likely began on July 7th.

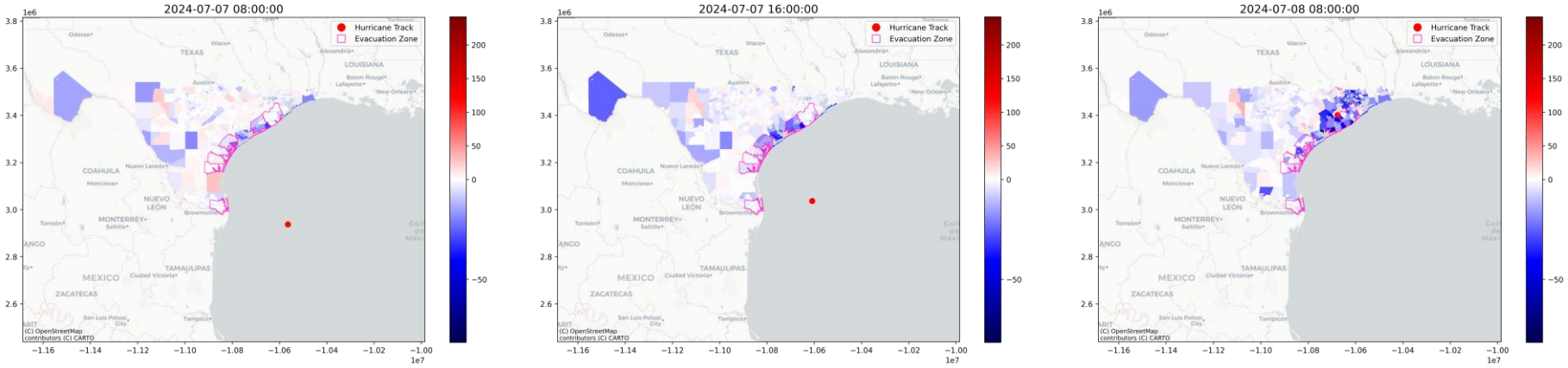



**Figure**. Heatmaps of population changes before and during the landfall of Hurricane Beryl.

# Heatmap of population changes

- Population change percentages gradually decreased leading up to the hurricane's landfall.
  - People evacuated increasingly right before and during the landfall of Hurricane Beryl.

On the day the hurricane made landfall, the percentage of population change reached its peak.

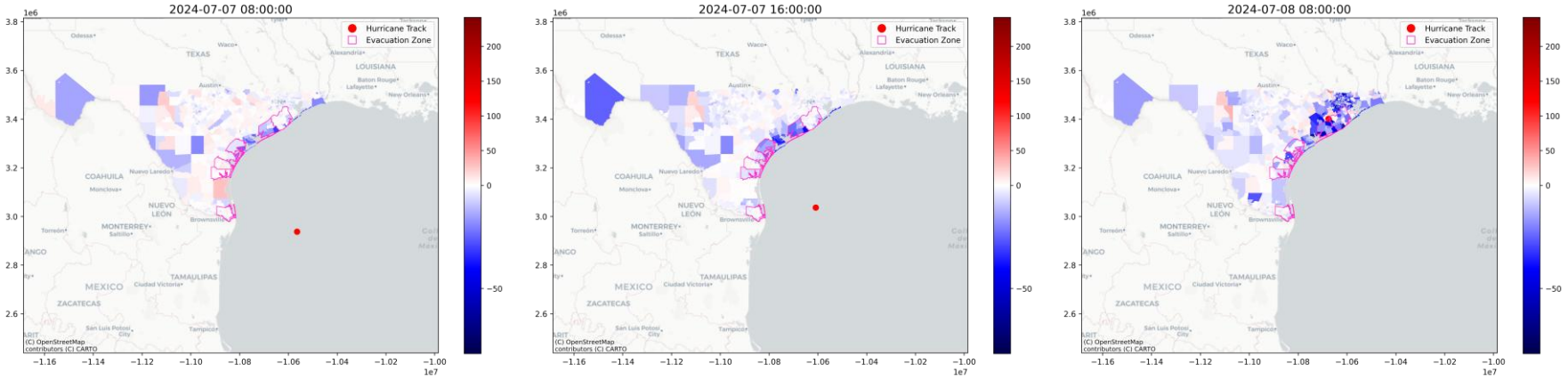



**Figure**. Heatmaps of population changes before and during the landfall of Hurricane Beryl.