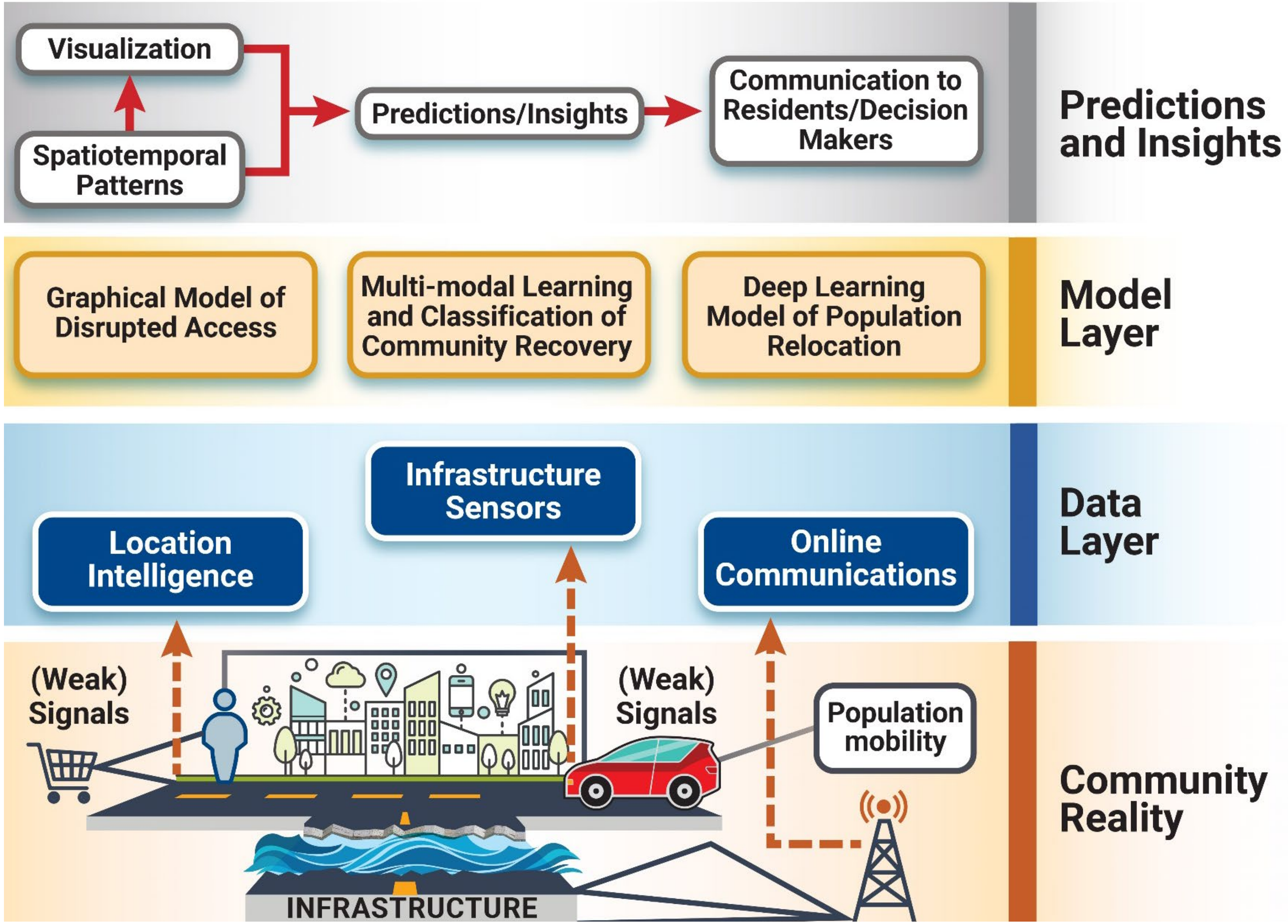
# AI for Augmenting Urban Resilience to Health Emergencies

**Ali Mostafavi**
Zachry Endowed Associate Professor
Director, UrbanResilience.AI Lab
Department of Civil and Environmental Engineering
Texas A&M University

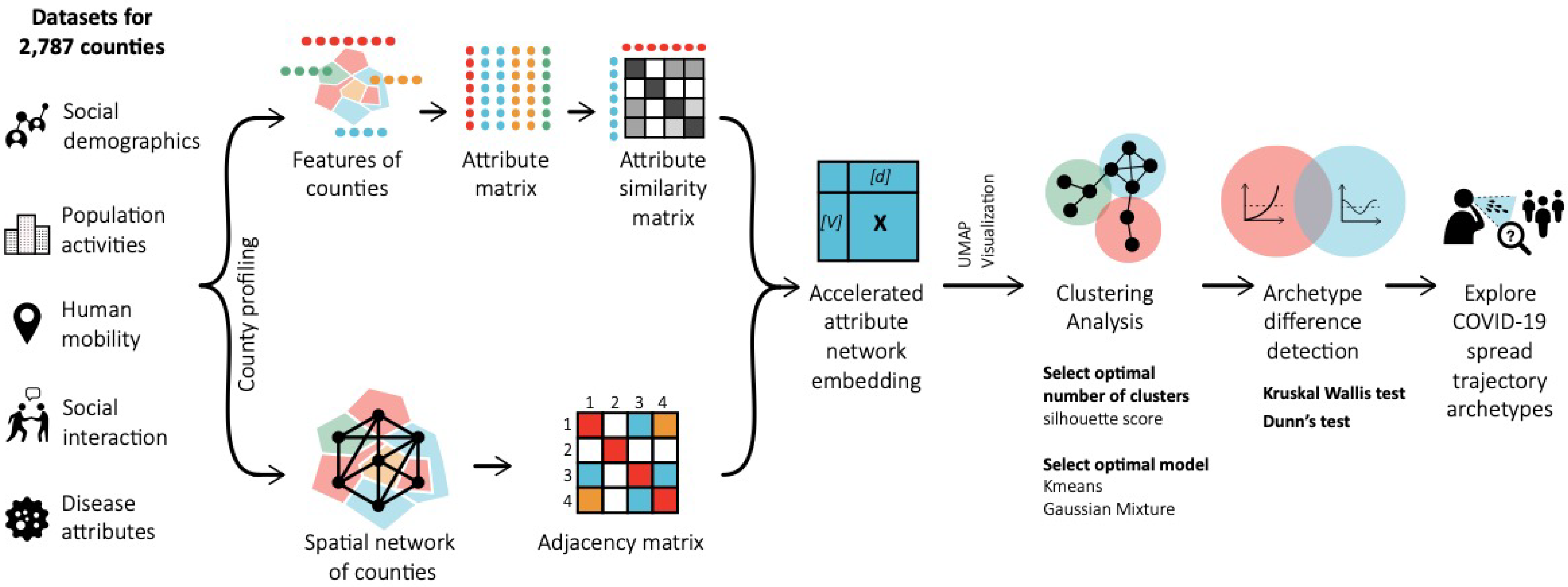
# Data to Decision Pipeline to Augment Resilience to Emergencies



# DeepCOVIDNet: An Interpretable Deep Learning Model for Predictive Surveillance of COVID-19 Using Heterogeneous Features and Their Interactions

# DeepCovidNet Model: Workflow

- **Region:** 2,787 counties in the continental U.S.
- **Period:** March 3 to June 29, 2020 (the first wave and initial outbreak of the pandemic)



# Features Influencing the Spread of COVID-19

URBAN RESILIENCE.AI LAB

| Datasets | Features | Characteristics | Sources |
|---|---|---|---|
| Social Demographic | Population Density (PD) | Constant feature | U.S. Centers for Disease Control and Prevention |
| | Gross Domestic Product (GDP) | Constant feature | U.S. Department of Commerce |
| | Overall COVID-19 Community Vulnerability Index (CCVI)<br>• Socioeconomic status<br>• Household composition and disability<br>• Minority status and language<br>• Housing type and transportation<br>• Epidemiologic factors<br>• Healthcare system factors | Constant feature | Surgo Foundation |
| Population Activities | Point-of-interest visits (POI Visits) | Time-dependent feature | SafeGraph |
| | Urban Activity Index (UAI)<br>• Work<br>• Social<br>• Home<br>• Traffic | Time-dependent feature | Mapbox |
| | Social Distancing Index (SDI) | Time-dependent feature | SafeGraph |
| | Venables Distance (VD) | Time-dependent feature | Mapbox |
| Human Mobility | Shelter-in-place Index (SIP) | Time-dependent feature | Spectus |
| | County Mobility Index (CMI) | Time-dependent feature | Spectus |
| | Colocation degree centrality (CDC) | Time-dependent feature | Meta |
| Social Interaction | Social Connectedness Index (SCI) | Constant feature | Meta |
| Disease Attribute | Reproduction Number (R0) | Time-dependent feature | U.S. Centers for Disease Control and Prevention |

CDC CENTERS FOR DISEASE CONTROL AND PREVENTION

DEPARTMENT OF COMMERCE UNITED STATES OF AMERICA

Surgo Foundation

SAFEGRAPH

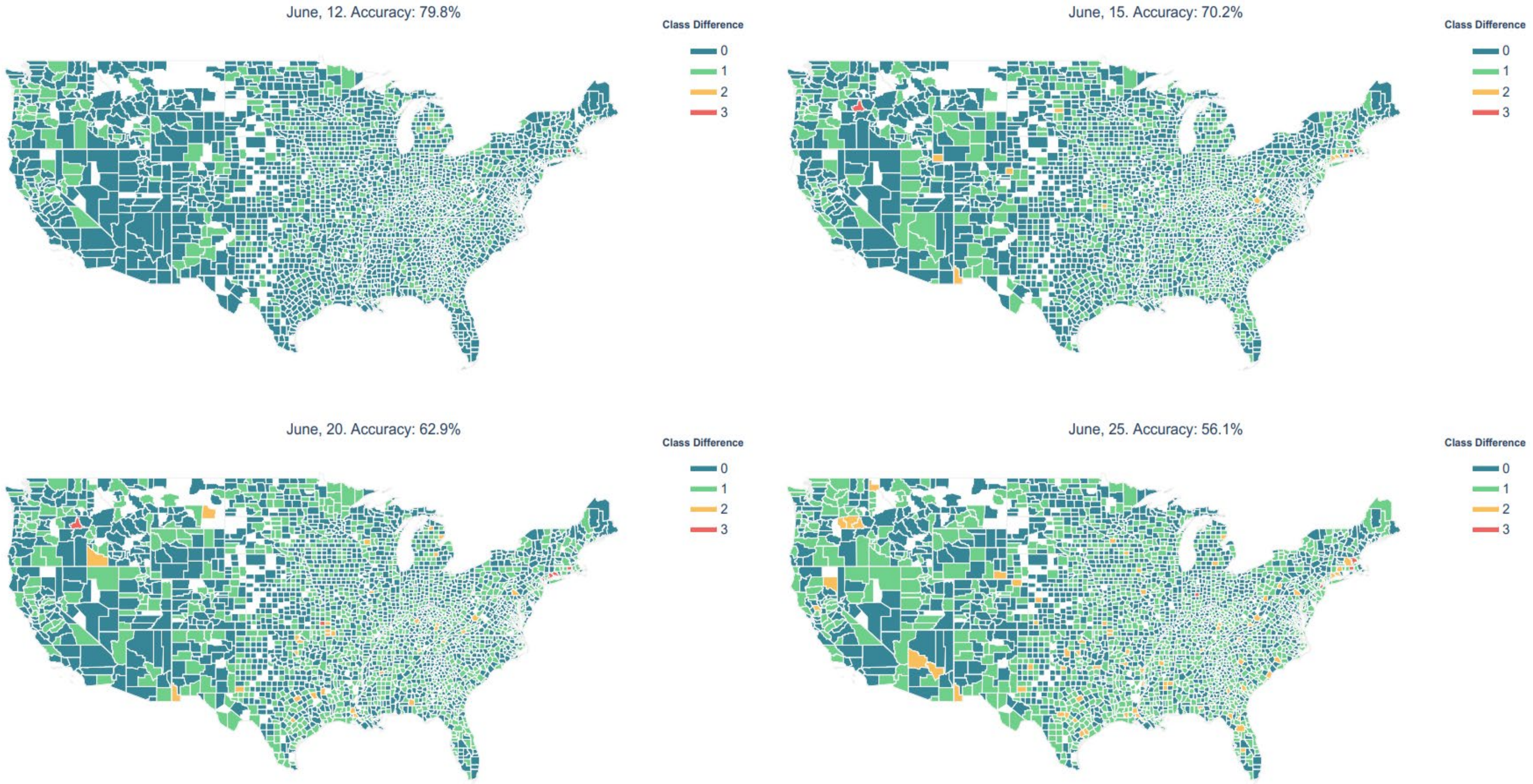
mapbox

spectus

Meta

# Prediction Results

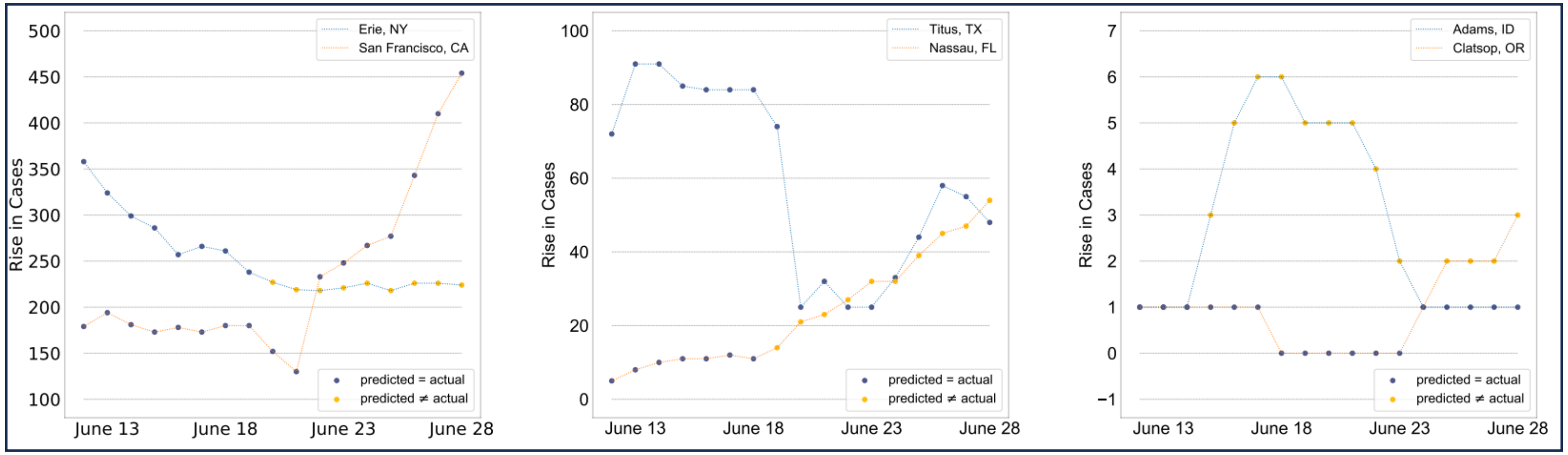





Absolute difference in predicted class and the actual class for all counties:

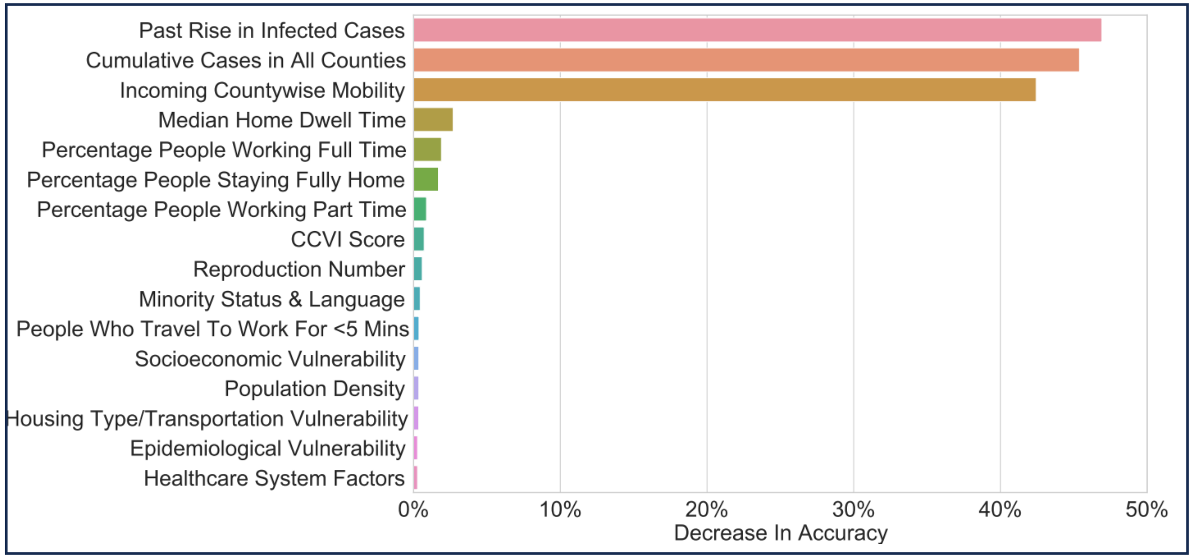
- **0** means the model's prediction was correct
- **1** means it was one class away from ground truth, and **so on**

# Prediction Results



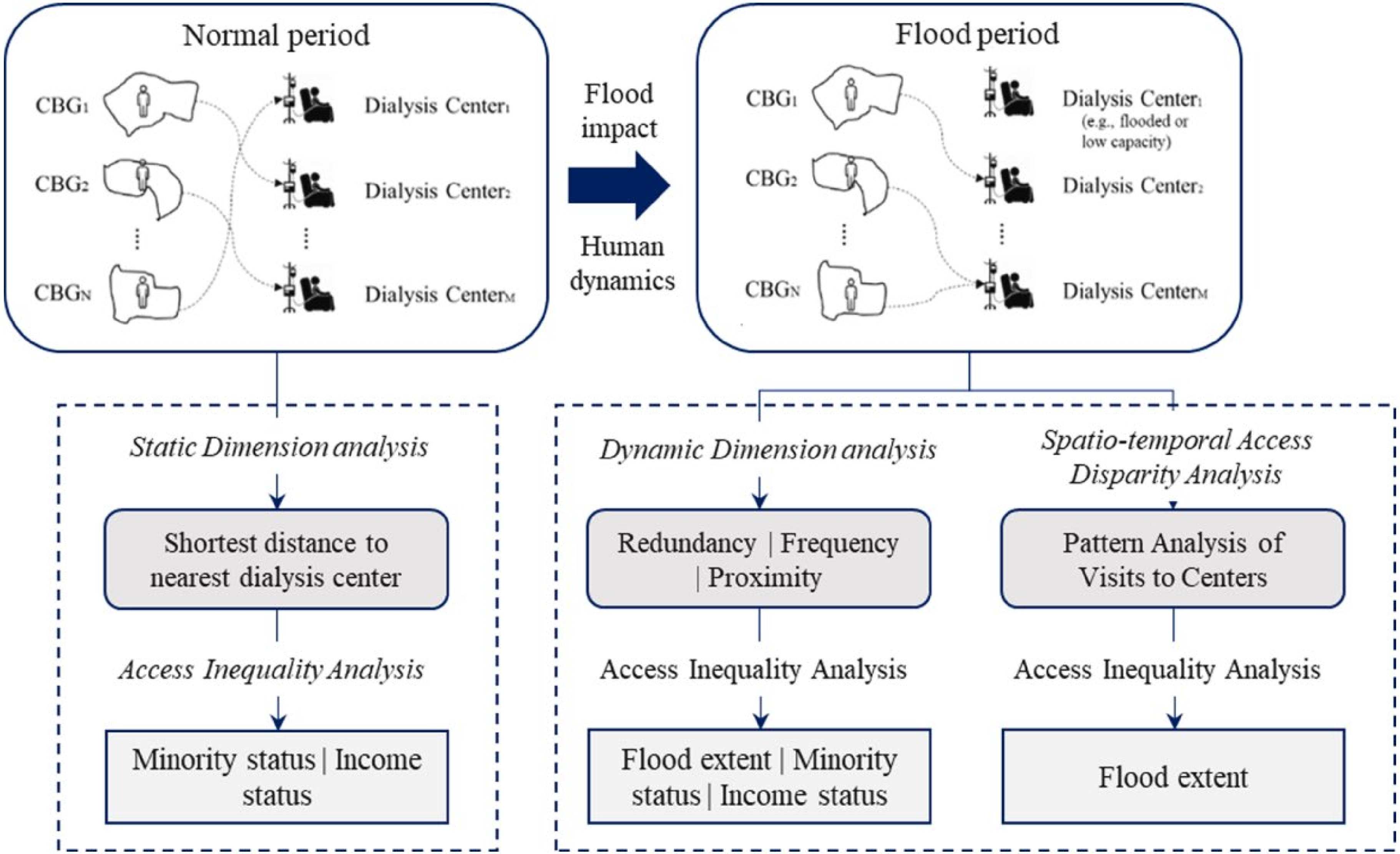

Predictions over time for three types of counties: counties with high growth, counties with medium growth, and counties with low growth of cases.

Feature Importance Analysis



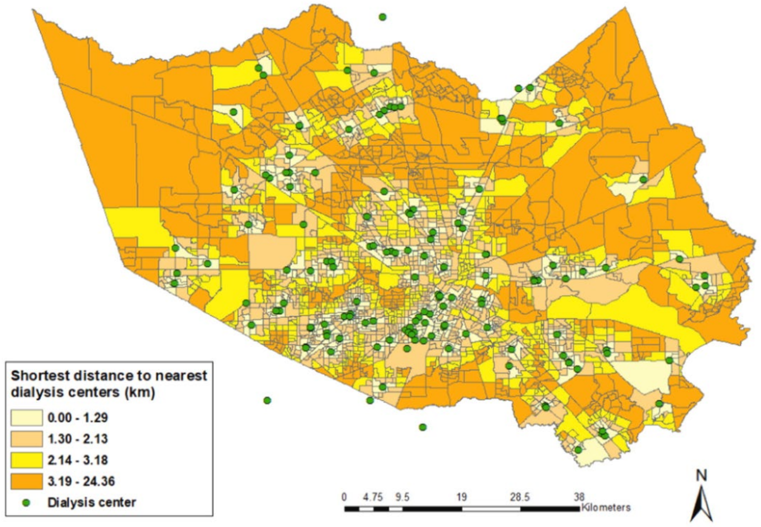
# Unveiling dialysis centers’ vulnerability and access inequality during urban flooding

# Study Overview

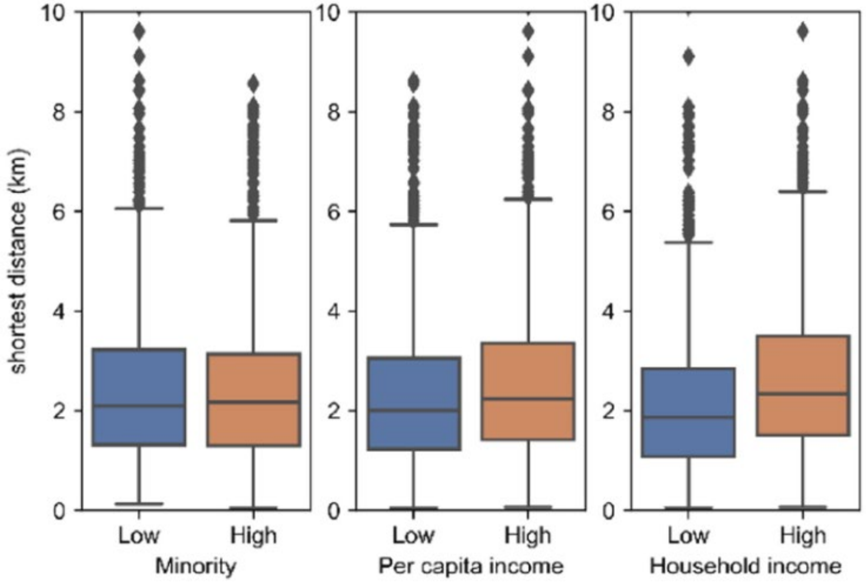


# Access disparities based on the shortest distance from CBGs to their nearby dialysis centers.

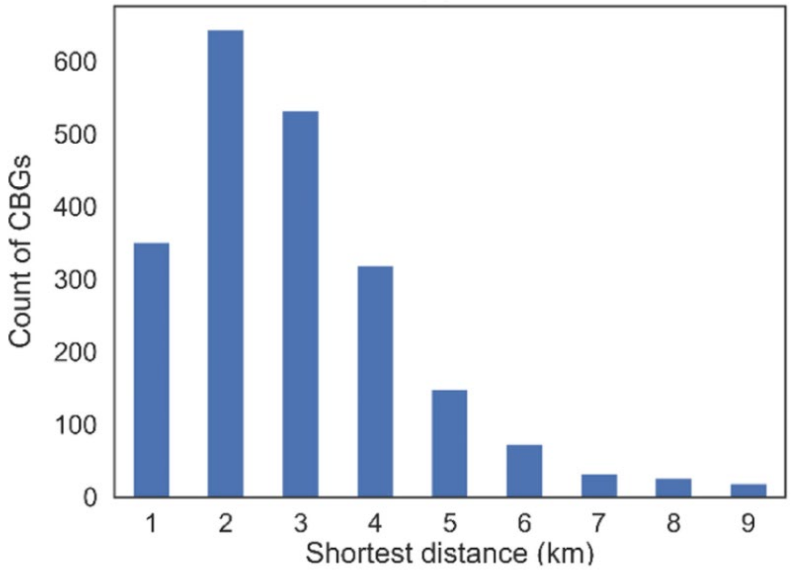
Spatial distribution of dialysis centers and CBGs with their shortest distances in kilometers (km)



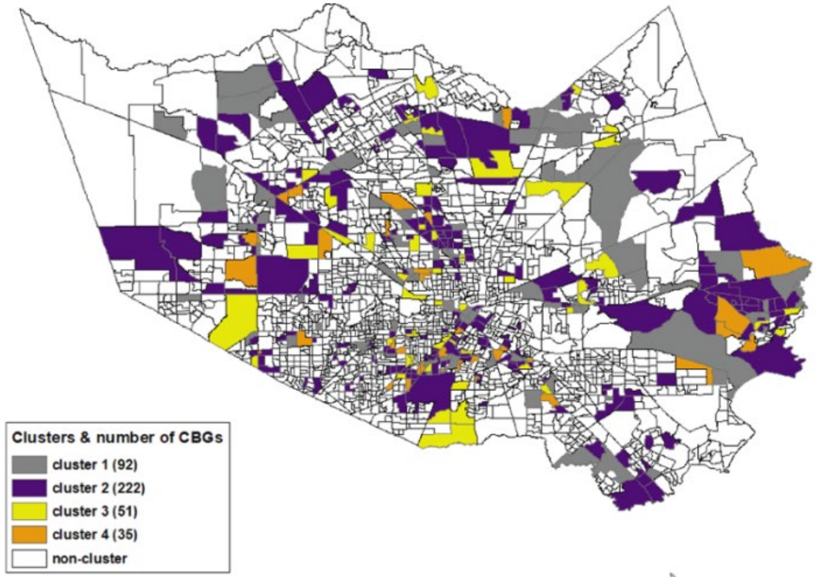

Sociodemographic characteristics of CBGs versus their shortest distances



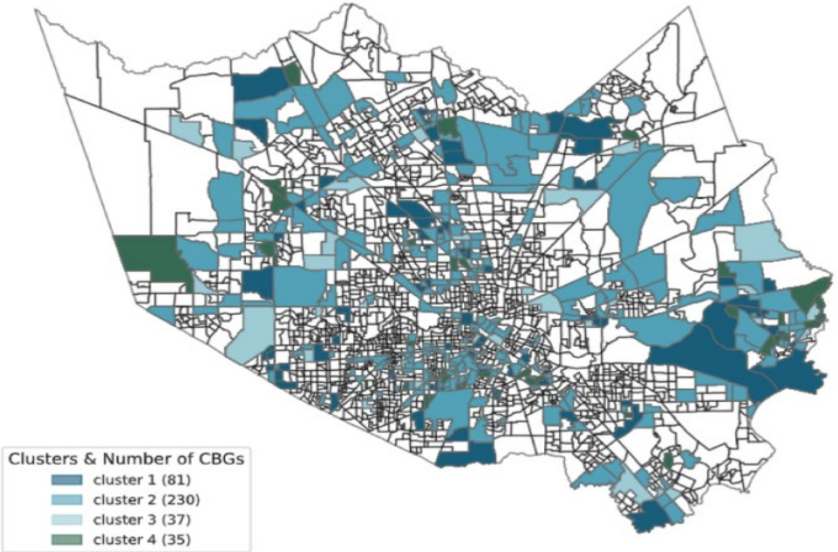

Count of CBGs in terms of the range of their shortest distances to dialysis centers



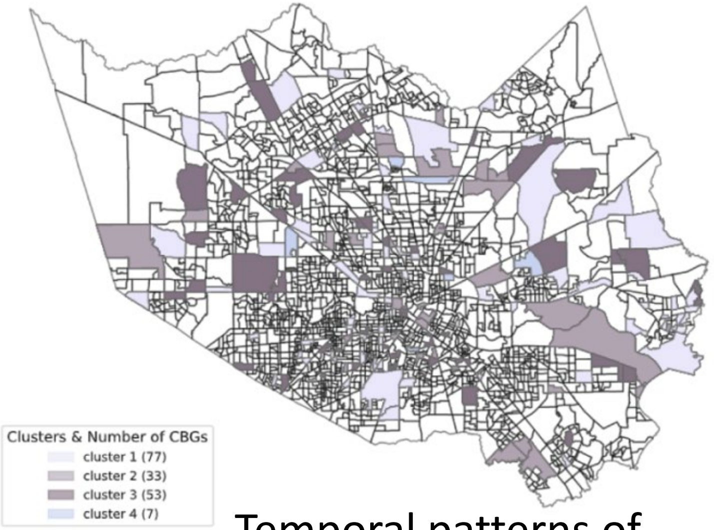
# Spatiotemporal patterns of dynamic access to dialysis centers during Hurricane Harvey




Temporal patterns of variations of redundancy



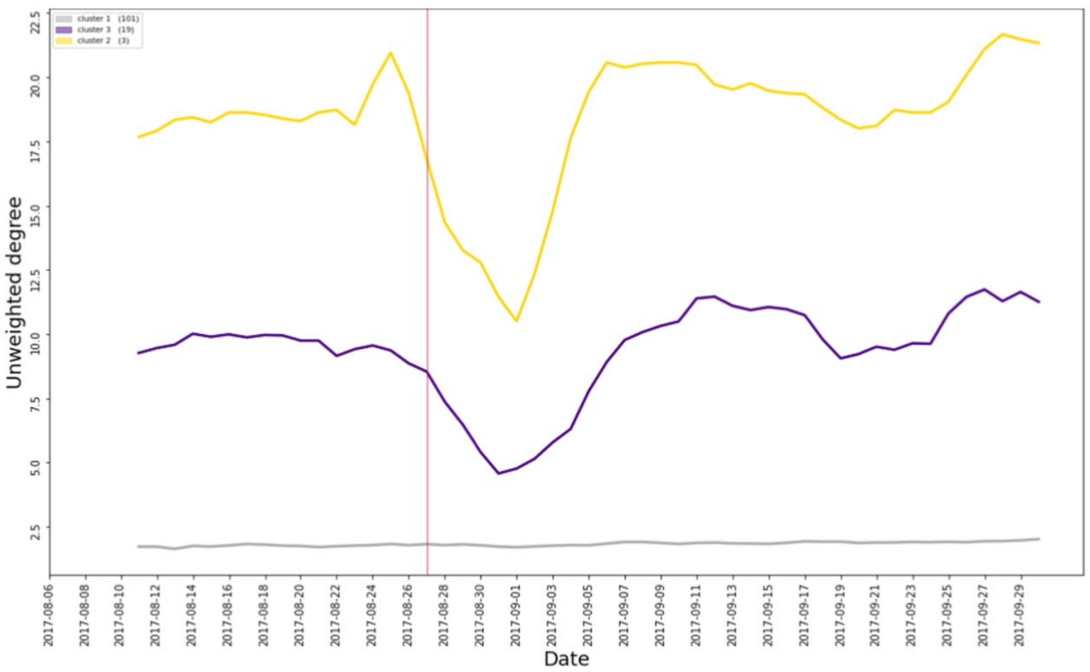

Temporal patterns of variations of proximity



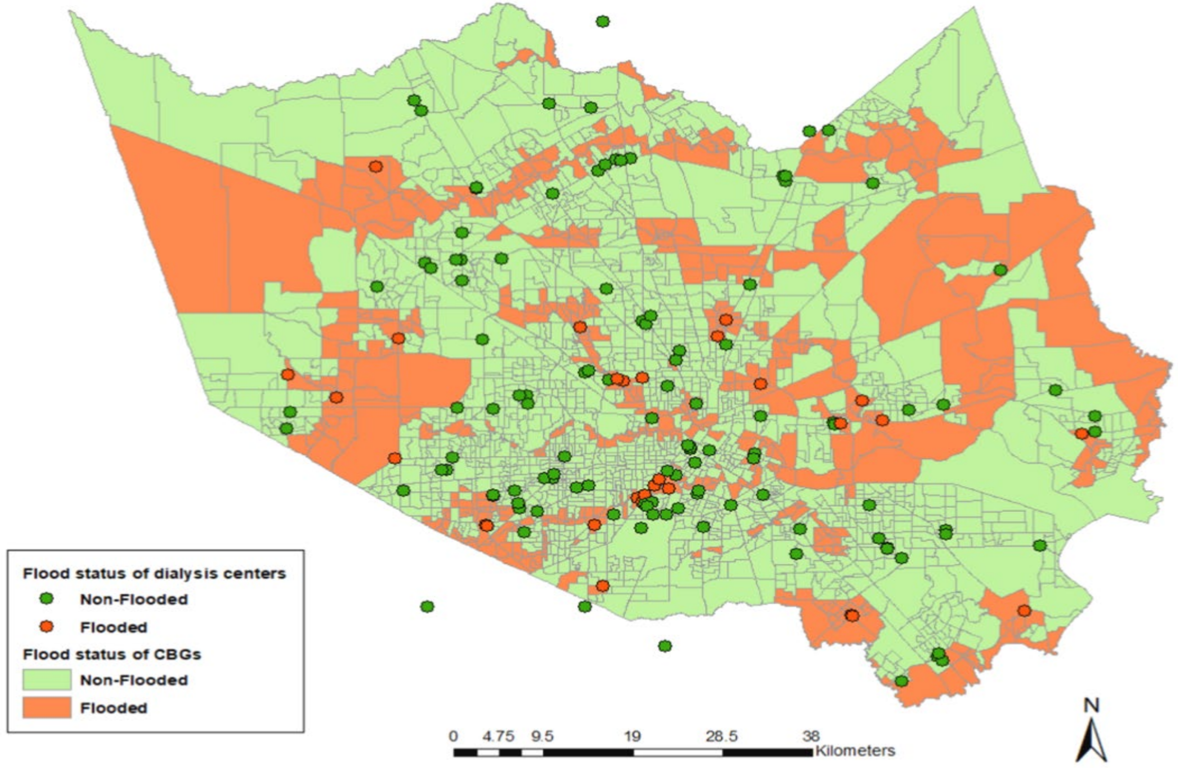

Temporal patterns of variations of frequency

# Clusters of dialysis centers based on service levels

URBAN RESILIENCE.AI LAB



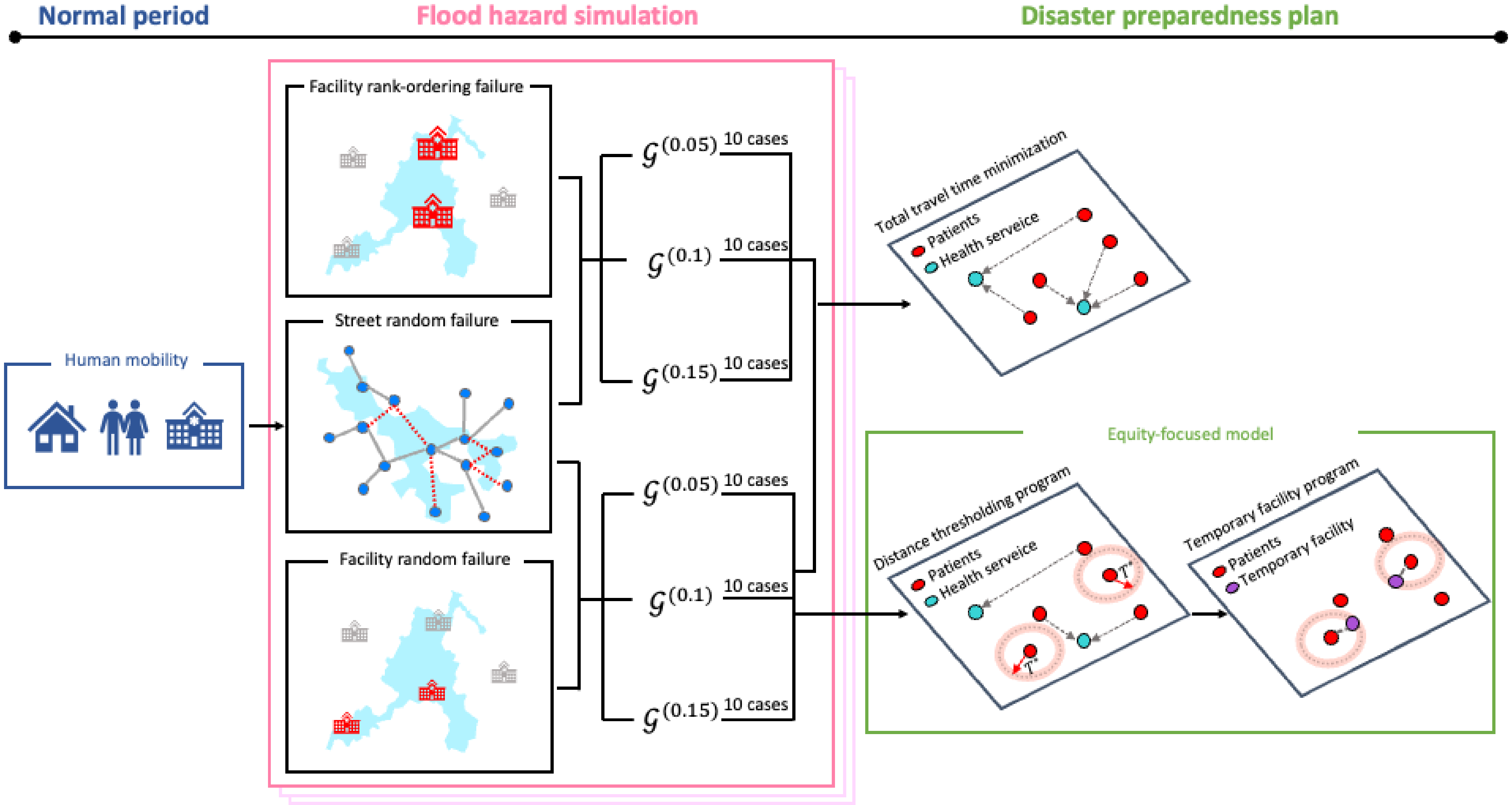

Spatiotemporal pattern of provided services levels of dialysis centers




Geographic distribution of the identified clusters and flooded status of CBGs in Harris County

# An Equitable Patient Reallocation Optimization and Temporary Facility Placement Model for Maximizing Critical Care System Resilience

# Modeling Framework

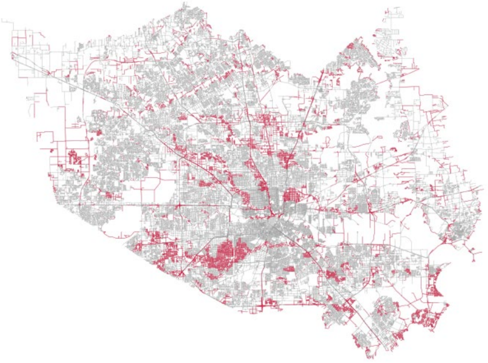


# Methodology

## Flood simulation

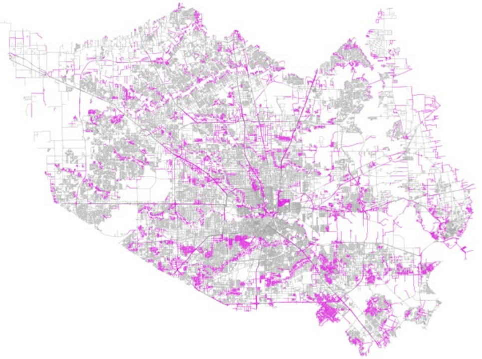
Road network

Dialysis center



15.3% on the 100-year FP

17.6% on the 100-year FP



17.8% on the 500-year FP

19.0% on the 500-year FP

**Random failure**

**Capacity rank-ordering failure**

## Healthcare optimization

**Total travel time minimization model**

$$\min \ T = \sum_{i=1}^{m} \sum_{j=1}^{n+1} T_{ij}^{f} \cdot x_{ij} \quad (1)$$

$$\sum_{j=1}^{n+1} x_{ij} = p_i \quad \forall i \in S_c \quad (2)$$

$$\sum_{i=1}^{n} x_{ij} \le c_j \quad \forall \in S_f \quad (3)$$

$$x_{ij} \in \mathbb{Z}^{+} \quad \forall i \in S_c, \forall j \in S_f \quad (4)$$

**Equity-focused model**

1. Distance thresholding program

$$\min \ T = \sum_{i=1}^{m} \sum_{j=1}^{n+1} T_{ij}^{f} \cdot x_{ij} \quad (1)$$

$$\sum_{j=1}^{n+1} x_{ij} = p_i \quad \forall i \in S_c \quad (2)$$

$$\sum_{i=1}^{n} x_{ij} \le c_j \quad \forall j \in S_f \quad (3)$$

$$x_{ij} \in \mathbb{Z}^{+} \quad \forall i \in S_c, \forall j \in S_f \quad (4)$$

$$x_{ij} = 0 \quad \forall T_{ij}^{f} > T^{*}, \forall i \in S'_c, \forall j \in S_f \backslash \{n+1\} \quad (5)$$

2. Temporary facility program

$$max \sum_{i \neq i'} x_{ii'} \quad (6)$$

$$\min \ T = \sum_{\substack{i=1 \\ i \neq i'}}^{m} \sum_{\substack{i'=1 \\ i \neq i'}}^{m} T_{ii'}^{c} \cdot x_{ii'} \quad (7)$$

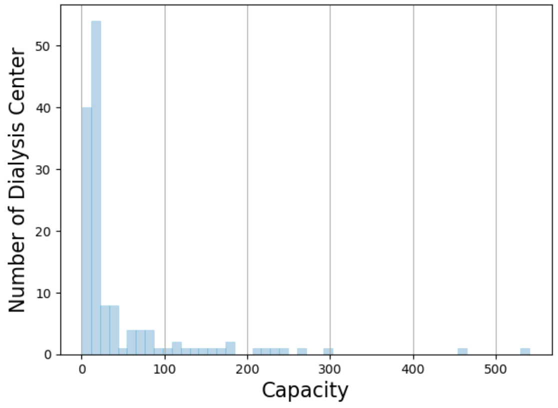
$$\sum_{j=1}^{m} x_{ii'} \le p_i^{dt} \quad \forall i \in S_c \quad (8)$$

$$x_{ii'} \in \mathbb{Z}^{+} \quad \forall i, i' \in S_c \quad (9)$$

# Results



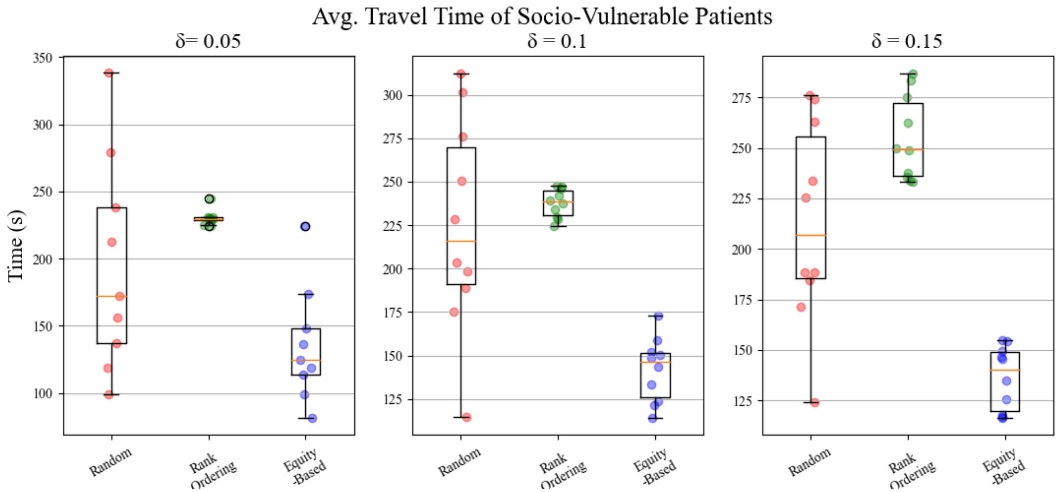
## Demand estimation



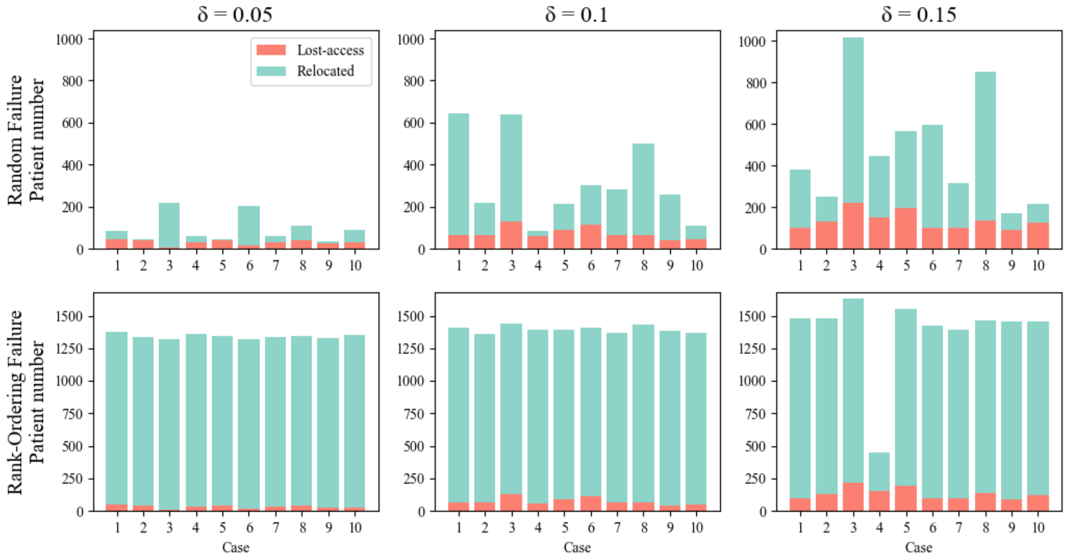

87.32% of medical care has a capacity of less than 100.

Therefore, the healthcare network relies heavily on a few medical centers with large capacity.

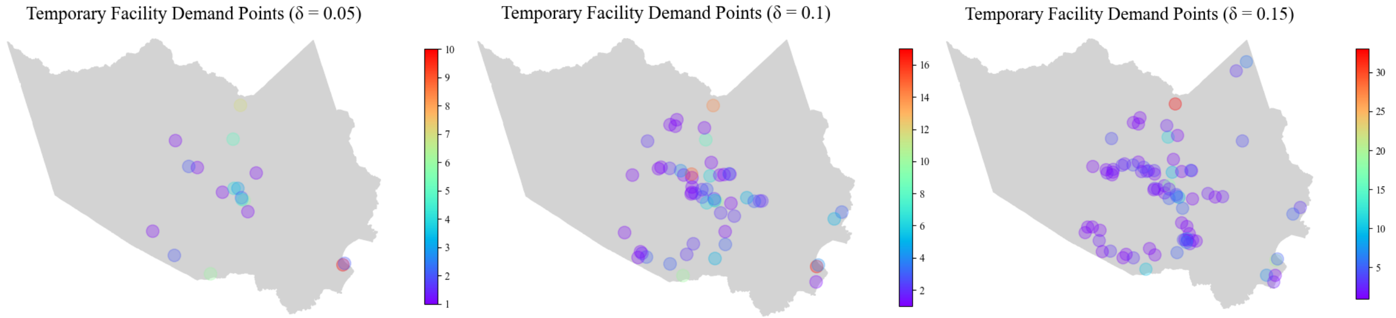
## Equity-focused model




## Total travel time minimization model

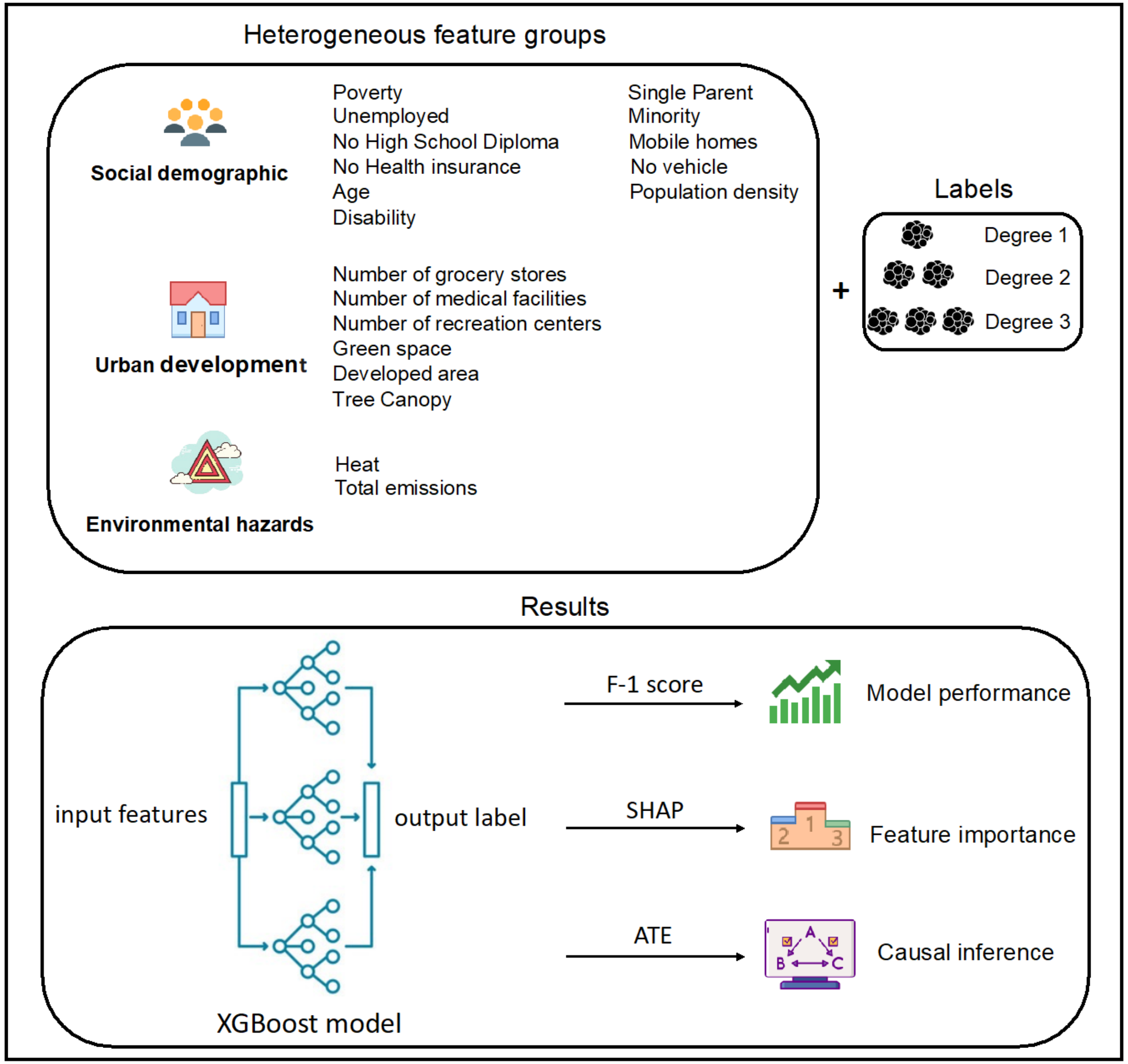



## Temporary facility demand points



# Decoding Urban-health Nexus: Interpretable Machine Learning Illuminates Cancer Prevalence based on Intertwined City Features

# Model Framework



# Features Shaping Cancer Prevalence

URBAN RESILIENCE.AI LAB

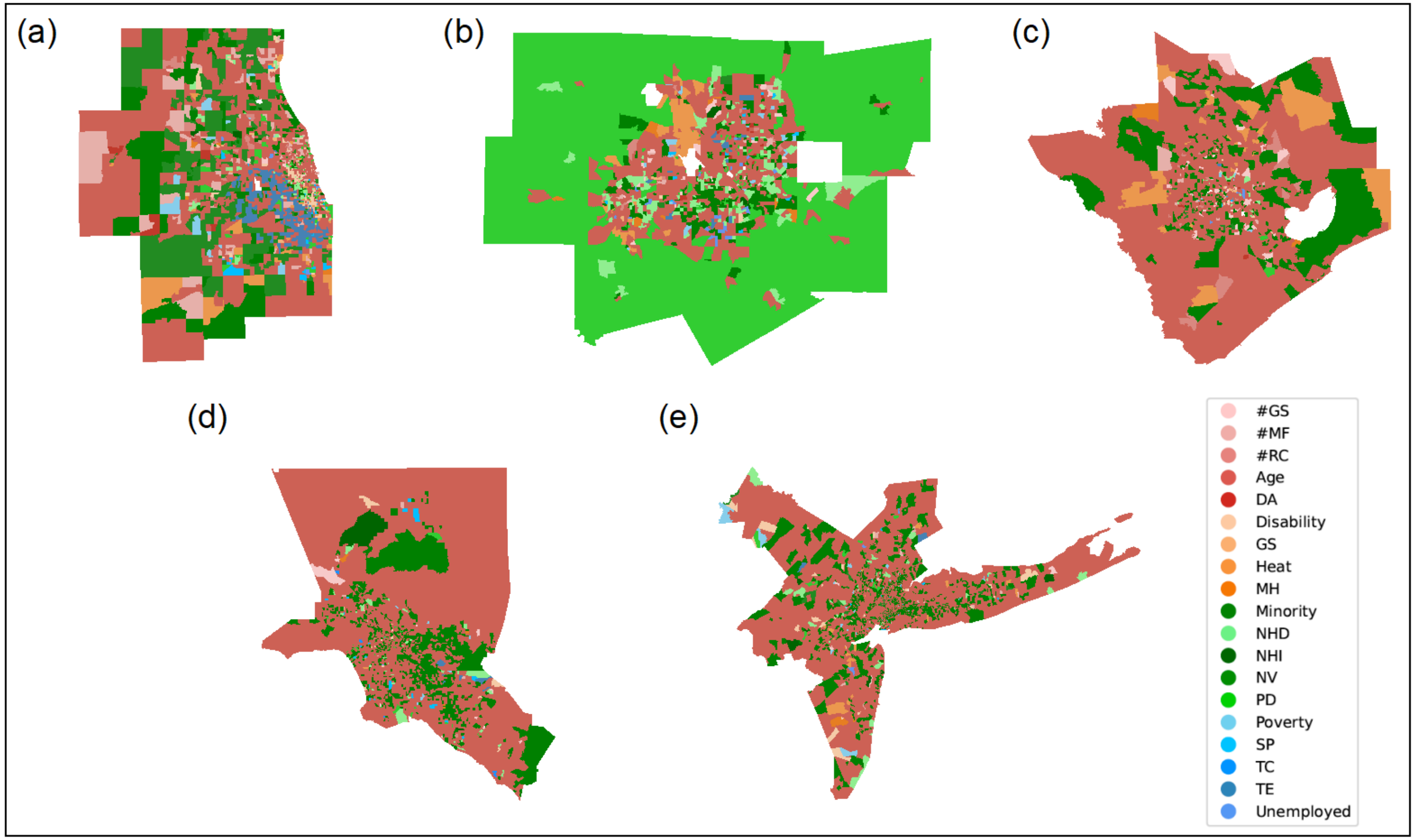



***Fig 3. Geographical Distribution of the Most Important Feature Across Five Key Metropolitan Statistical Areas. The figure illustrates the spatial distribution of the feature with the highest importance across the following MSAs:*** (a) Chicago-Naperville-Elgin, (b) Dallas-Fort Worth-Arlington, (c) Houston-The Woodlands-Sugar Land, (d) Los Angeles-Long Beach-Anaheim, and (e) New York-Newark-Jersey City.

# Features Shaping Cancer Prevalence