COVID Risk Is Not Random: A Spatial Network Analysis

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Problem Statement

Research Question: How do socioeconomic characteristics and mobility patterns influence COVID-19 transmission across U.S. counties?

Goal: Attribute socioeconomic and mobility factors to COVID-19 transmission by quantifying their influence on disease spread.

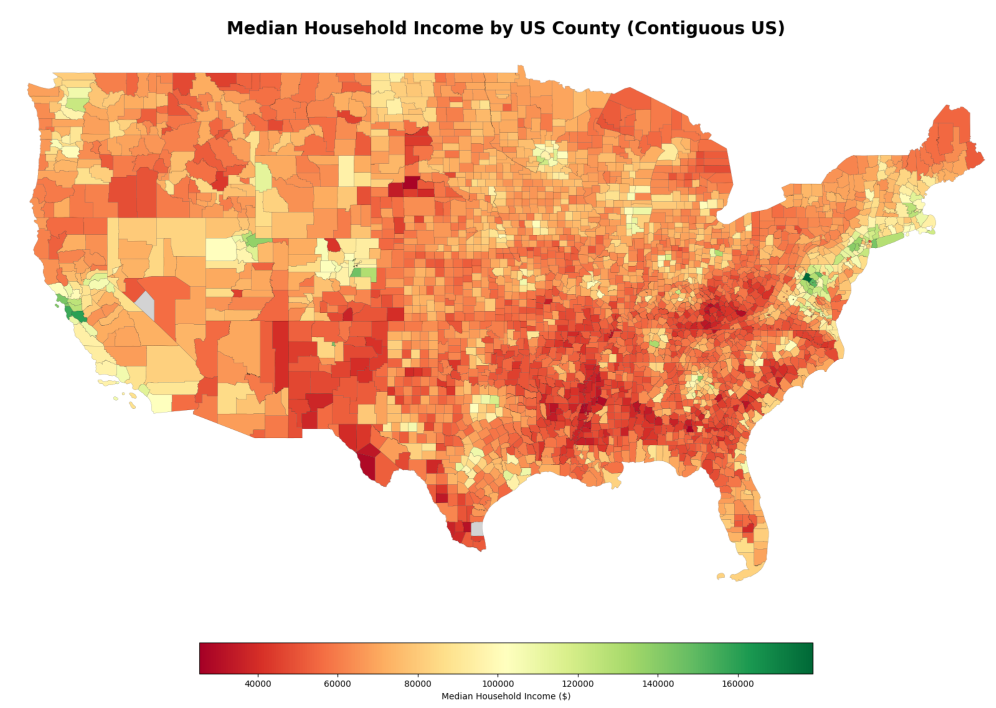


Figure 1. Median Household Income by US County

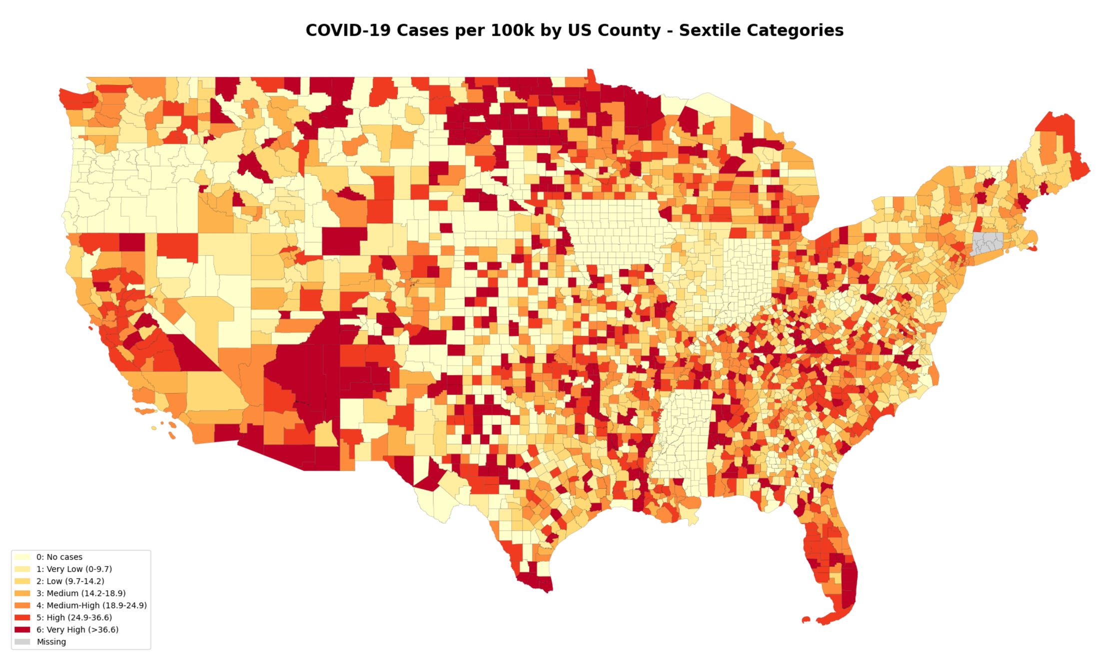


Figure 2. COVID-19 Cases per 100k by US County

Observation: Spatial overlap between low-income regions and high COVID-19 burden.

Key Findings

Model Performance:

- Baseline SIR: $R^2 = -0.028$ (fails to capture heterogeneity)
- Extended SIR: $R^2 = -4.609$ (linear parameterization fails)
- **GNN:** $R^2 = 0.441$ (only model with positive explanatory power)

Key Findings

Attribution Results:

- **Top predictors:** Median household income, residential mobility
- Structural factors (income, education, housing) and behavioral mobility jointly drive transmission
- **Main insight:** Effects are highly non-linear—requiring flexible models (GNN) to capture

Methods

Dual-Model Framework:

1. Mechanistic SIR Models:

- Baseline: Constant β, spatial diffusion
- Extended: $\beta_i = \exp(\alpha_0 + \sum_{j=1}^{18} \alpha_j \cdot X_{ij})$ from 18 SE features
- **Attribution:** Causal pathway (SE/mobility → transmission rate → disease burden)

2. Graph Neural Network (GNN):

- Counties as nodes, adjacency as edges, 23 features (18 SE + 5 mobility)
- Non-linear learning with spatial message passing
- **Attribution:** Identifies which factors matter most (predictive)

Why Both? SIR reveals *how* factors influence transmission; GNN identifies *which* factors matter most.

Data and Experimental Design

Dataset: 3,222 U.S. counties

- COVID-19 outcomes: CDC Community Levels
- 18 socioeconomic indicators: Census Bureau
- 6 mobility metrics: Google Mobility Reports
- Spatial structure: County adjacency network

Spatial SIR Framework:

$$\frac{dI_i}{dt} = \beta_i S_i \sum_{j \in \mathcal{N}(i)} w_{ij} \frac{I_j}{N_j} - \gamma I_i + m \sum_{j \in \mathcal{N}(i)} w_{ij} \left(\frac{I_j}{N_j} - \frac{I_i}{N_i} \right)$$

Baseline: $\beta_i = \beta$ (constant)

Data and Experimental Design

Extended: $\beta_i = \exp(\alpha_0 + \sum_{j=1}^{18} \alpha_j \cdot X_{ij})$

GNN: Counties as graph nodes, message passing for spatial learning, non-linear feature interactions.

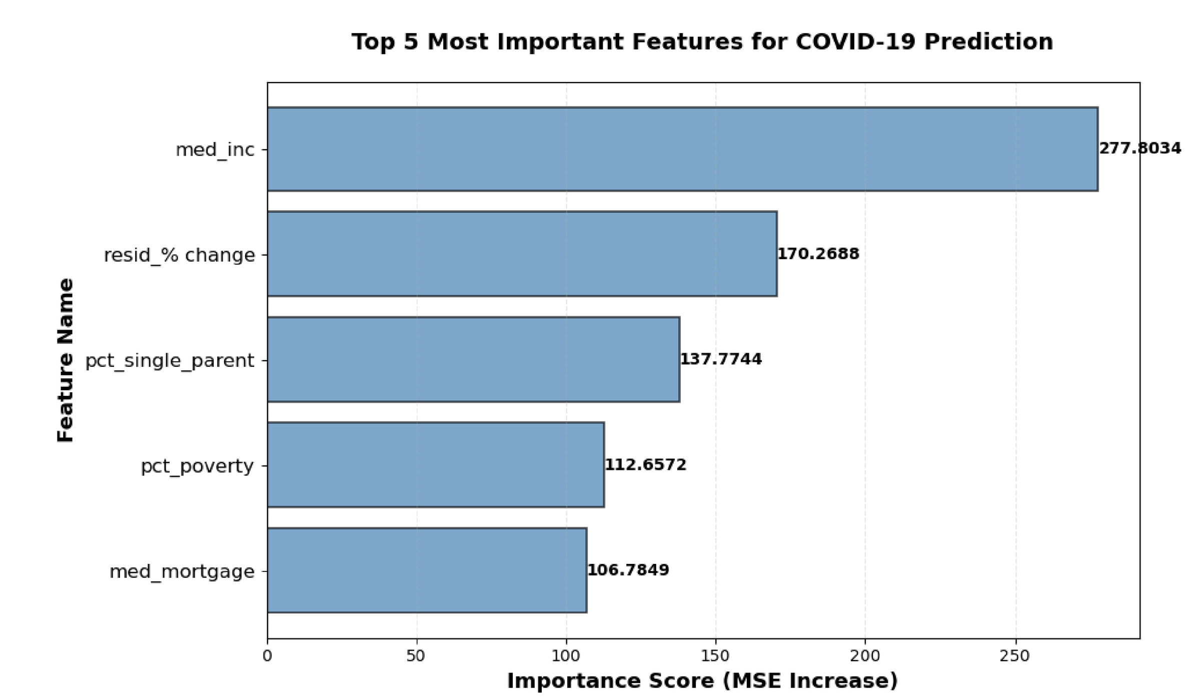
Results and Attribution

Model	MAE	RMSE	R^2
Baseline SIR	1.26	7.65	-0.028
SE-Mobility SIR	13.53	17.88	-4.609
GNN	27.48	39.59	0.441

Table 1. Predictive performance (cases per 100k). GNN explains 44.1% of variance.

Key Findings:

- **SIR models fail:** Linear parameterization cannot capture complex non-linear interactions
- **GNN succeeds:** Only model with positive R^2; learns spatial patterns and feature interactions



Conclusion: Structural socioeconomic factors (income, education, housing) and behavioral mobility patterns jointly drive COVID-19 transmission. Effects are highly non-linear, requiring flexible models for accurate attribution.

References

Khanijahani, A., Iezadi, S., Gholipour, K., Azami-Aghdash, S., and Naghibi, D. (2021). A systematic review of racial/ethnic and socioeconomic disparities in covid-19. *International Journal for Equity in Health*, 20(1):248.