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An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
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Abstract

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Opioid-related mortality has emerged as one of the most pressing public health challenges in the United States, underscoring the need for improved surveillance and a deeper understanding of its social and structural determinants of health (SSDH). We estimated county-level opioid mortality rates in Georgia from 2020 to 2022 and examined their associations with key SSDH indicators. Using mortality data and covariates related to these determinants, including the Centers for Disease Control and Prevention's (CDC) Social Vulnerability Index (SVI), poverty, unemployment, and distances to the nearest interstate highway and treatment center, we employed Poisson regression models with county-specific random effects and Bayesian conditional autoregressive (CAR) models to generate smoothed estimates. Most covariates were inversely associated with opioid mortality across all years, although few remained statistically significant after accounting for spatial correlation. The SVI component representing racial and ethnic minority status showed a consistently significant negative association. When spatial correlation was incorporated into the CAR models, many covariate effects became less pronounced, with estimates shifting toward the null and credible intervals becoming wider. This pattern may reflect overdispersion, weak spatial dependence, or multicollinearity among covariates. These findings highlight spatial disparities in opioid-related mortality in Georgia and provide insight to inform local prevention strategies and resource allocation. They also point to the need to further investigate the drivers of spatial heterogeneity and to incorporate spatial structure in efforts to better understand and address opioid-related health disparities.

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1 Introduction

The opioid epidemic remains a major public health crisis in the United States, significantly impacting communities across the country. Over the past decade, opioid-involved deaths have increased consistently. This rise has contributed to the growing number of drug overdose fatalities, which are among the leading causes of injury deaths (Spencer et al., 2024). In 2022 alone, 81,806 opioid-involved overdose deaths were reported nationwide, a 64% increase compared to 2019 (National Institute on Drug Abuse, 2024). In Georgia specifically, opioid-involved deaths totaled 1,976 in 2022, marking a more than 131% increase from 2019 (Georgia Department of Public Health, n.d.-b).

In order to effectively address this crisis, it is critical to accurately identify areas at highest risk, ensuring that resources, interventions, and support are distributed efficiently and equitably (Blanco et al., 2020; Jalali et al., 2020). However, estimating opioid-related mortality rates at the county level is often challenging, especially in counties with smaller populations. Furthermore, spatial autocorrelation between neighboring counties, which remains even after adjusting for covariate effects, can further complicate reliable mortality estimations (Waller & Gotway, 2004).

Bayesian hierarchical models, including the conditional autoregressive (CAR) model, are widely used in disease mapping to account for spatial autocorrelation. The CAR model was first proposed by (Besag, 1974) and was later extended in a Bayesian framework by (Besag et al., 1991; Leroux et al., 2000; Stern & Cressie, 2000). These models stabilize estimates by modeling spatial random effects, which smooth the estimates by borrowing strength from neighboring areas (Waller & Carlin, 2010).

In addition to addressing challenges in small-area estimation through spatial modeling, understanding the role of social and structural determinants of health is also critical. The opioid epidemic disproportionately impacts vulnerable communities, highlighting the need for targeted public health strategies and policy interventions to address these disparities (Lin et al., 2020; Ruhm, 2018; Scutchfield & Keck, 2017). Recent studies suggest a significant correlation between drug use disorders, overdose deaths, and social vulnerability (Altekruse et al., 2020; Sistani et al., 2023), which has promoted increased utilization of social vulnerability measures to examine substance use disorders (Gibbons et al., 2024; Tatar et al., 2023).

One such measure is the Social Vulnerability Index (SVI), developed by the Centers for Disease Control and Prevention (CDC). It was initially designed to assist public health officials and emergency planners in preparing communities for hazardous events (Flanagan et al., 2011). Although originally developed for disaster management, the SVI has since been applied in various public health contexts and may provide valuable insights into identifying communities susceptible to high opioid-related mortality (El Ibrahimi et al., 2023; Joudrey et al., 2022; Sistani et al., 2023; Tatar et al., 2023).

This study aims to (1) examine the association between social and structural determinants of health, including SVI, as well as related socioeconomic, demographic, and geographic access factors, and opioid-related mortality at the county level in Georgia; and (2) generate stabilized county-level mortality estimates using spatial models to identify high-risk counties.

2 Methods

2.1 Data

County-level data on opioid-involved overdose deaths from 2020 to 2022 were obtained from the Georgia Department of Public Health (2021, 2022, 2024). According to the Georgia County Opioid Overdose Report, these data were derived from DPH Vital Records death certificates and include deaths that occurred both within and outside the state among Georgia residents.

Opioid-involved overdose deaths include those caused by prescription pain relievers (e.g., oxycodone, hydrocodone, and morphine), medications used for opioid use disorder (e.g., methadone), illicit opioids (e.g., heroin and opium), and synthetic opioids (including fentanyl and tramadol, whether prescription or illicitly manufactured). These deaths are identified using ICD-10 codes, with underlying causes of death classified under X40-X44 (accidental poisoning), X60-X64 (intentional self-poisoning), X85 (assault by drug poisoning), and Y10-Y14 (poisoning of undetermined intent). Additionally, opioid-specific codes include T40.0 (opium), T40.1 (heroin), T40.2 (natural and semisynthetic opioids), T40.3 (methadone), T40.4 (synthetic opioids other than methadone), and T40.6 (other and unspecified narcotics) (Georgia Department of Public Health, n.d.-a).

In addition to ICD-10 coding, deaths were also identified based on the presence of opioid-related terms (e.g., heroin, fentanyl, methadone) in the cause of death text fields. For cases without underlying X or Y code, cases were included if the term "TOXIC" appeared alongside at least one of the specified opioid-related terms.

Crude mortality rates for each county were calculated by dividing the number of deaths by the respective county population and multiplying by 100,000 to express the rate per 100,000 population. Figure 1 displays the distribution of these county-level crude mortality rates for each year from 2020 to 2022.

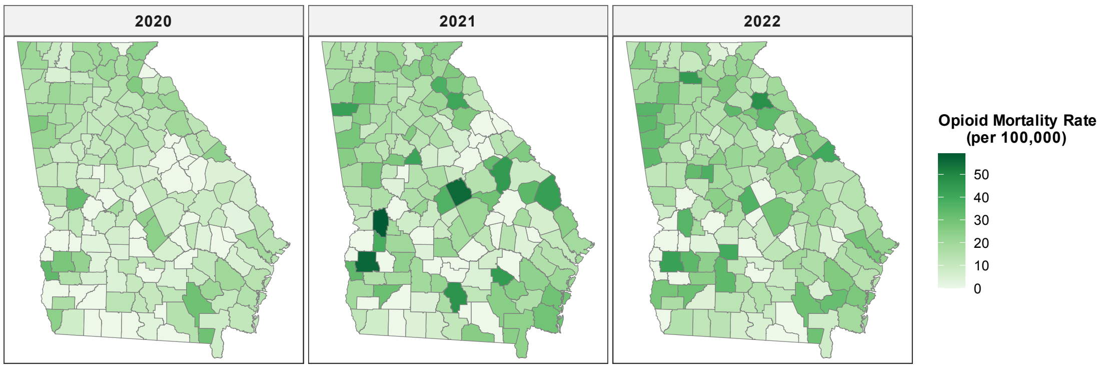

Figure 1. Distribution of County-level Crude Mortality Rates in Georgia (2020-2022)

County population estimates were provided by the Georgia Governor's Office of Planning and Budget (n.d.). The U.S. Census Bureau (USCB) also provided county-level demographic and socioeconomic data, as well as road network shapefiles (U.S. Census Bureau, n.d., 2020), which were used to calculate the distance to the nearest interstate and treatment center. County seat data were sourced from the Georgia Department of Community Affairs (2018). The Substance Abuse and Mental Health Services Administration (SAMHSA) provided information on treatment center locations in Georgia (Substance Abuse and Mental Health Services Administration, n.d.). Social Vulnerability Index (SVI) data were obtained from the Centers for Disease Control and Prevention (2024). The SVI consists of four themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation, within which 16 social attributes are grouped. For each theme, the percentile ranks of the component attributes were summed to create a theme-specific percentile ranking at the U.S. census tract level. These rankings range from 0 to 1, with higher values indicating greater vulnerability.

The covariates of interest included vacancy rate, unemployment rate, poverty rate, the percentage of the population that self-identifies as Black in U.S. Census responses, distance to the nearest interstate, distance to the nearest treatment center, and components of the SVI, including socioeconomic status, household characteristics, racial and ethnic minority status, housing type and transportation, and the overall SVI score. All covariates were standardized prior to analysis, and detailed information on these variables is provided in Appendix A.

2.2 Poisson Regression with Random Intercepts

We initially fitted Poisson regression models with county-specific random intercepts, including an offset to adjust for differences in population size across counties. For each county i, the observed mortality count, y_i, was modeled as a function of the expected mortality count, μ_i, as follows:

$$y_i|\mu_i \sim \text{Poisson}(\mu_i), \quad i = 1, \ldots, 159 \tag{2.1}$$

$$\log(\mu_i) = \log(p_i) + \beta_0 + X_i\beta + \theta_i \tag{2.2}$$

$$\theta_i \sim N(0, \tau^2) \tag{2.3}$$

where the model includes:

- y_i: observed mortality count for county i
- μ_i: expected mortality count for county i
- $\log(p_i)$: offset term, representing the log of the population for county i
- X_i: covariates of interest for county i (e.g., social vulnerability indices)

and parameters to be estimated:

- β_0: overall intercept, representing the baseline log expected mortality rate
- β: vector of regression coefficients corresponding to X_i
- θ_i: random intercept for county i, representing county-specific deviation from the baseline log expected mortality rate
- τ^2: variance of the random intercepts

2.3 Conditional Autoregressive (CAR) Model

To account for spatial correlation between counties, we modeled the random effects using the class of conditional autoregressive (CAR) prior distributions proposed by (Leroux et al., 2000). Spatial dependence was defined through a binary $n \times n$ neighborhood matrix $\mathbf{W}$, where the (i, j)th element, w_{ij}, is equal to one if counties i and j are adjacent, and zero otherwise. We employed the conditional specification of the Leroux CAR model, in which the spatial random effect ϕ_i follows a normal distribution conditional on its neighbors:

$$y_i|\mu_i \sim \text{Poisson}(\mu_i), \quad i = 1, \dots, 159 \tag{2.4}$$

$$\log(\mu_i) = \log(p_i) + \beta_0 + X_i\beta + \phi_i \tag{2.5}$$

$$\phi_i|\boldsymbol{\phi_{-i}}, \mathbf{W}, \tau^2, \rho \sim \mathcal{N}\left(\frac{\rho\sum_{j=1}^{N} w_{ij}\phi_j}{\rho\left(\sum_{j=1}^{N} w_{ij}\right) + 1 - \rho}, \frac{\tau^2}{\rho\left(\sum_{j=1}^{N} w_{ij}\right) + 1 - \rho}\right) \tag{2.6}$$

$$\tau^2 \sim \text{Inverse-Gamma}(1, 0.01) \tag{2.7}$$

$$\rho \sim \text{Uniform}(0, 1) \tag{2.8}$$

where the model includes:

- y_i: observed mortality count for county i
- μ_i: expected mortality count for county i
- $\log(p_i)$: offset term, representing the log of the population for county i
- X_i: covariates of interest for county i (e.g., social vulnerability indices)
- w_{ij}: element of the neighborhood matrix $\mathbf{W}$, indicating adjacency between counties i and j

and parameters to be estimated:

- β_0: overall intercept, representing the baseline log expected mortality rate
- β: regression coefficients corresponding to X_i
- ϕ_i: spatially structured random effect for county i
- τ^2: variance of the spatial random effects
- ρ: spatial dependence parameter

Although the Leroux model generally allows the spatial dependence parameter ρ to vary between 0 and 1, we fixed $\rho = 1$ in this study to ensure strong global spatial smoothing. This specification corresponds to the intrinsic CAR (ICAR) model, which assumes perfect spatial correlation among neighboring counties. While this simplifies estimation, it also imposes a strong structural assumption about spatial dependence.

All analyses and visualizations were performed in R (version 4.4.1; R Core Team, 2024), using the lme4 (2024), CARBayes (2024), dplyr (2023), ggplot2 (2024), tmap (2025), sf (2024), and spdep (2024) packages.

3 Results

In this section, we present the results of the models described above for the years 2020, 2021, and 2022 separately, as well as for the combined three-year dataset. Following a consistent structure, we begin with the univariate Poisson and Conditional Autoregressive (CAR) models and subsequently report the multivariate Poisson and CAR models for each year. Tables display the model estimates along with 95% confidence intervals and Akaike Information Criterion (AIC) and Deviance Information Criterion (DIC) values, which are measures of model fit. Results are interpreted based on both statistical significance and overall model performance. The primary objective of this analysis is to identify the best subset model for each year while adjusting for residual spatial correlation.

3.1 2020 Results

3.1.1 Univariate Poisson Regression

Table 1.1 and Table 1.2 summarize the results of the univariate Poisson regression models. In 2020, the percentage of the population identifying as Black (Incidence Rate Ratio (IRR) = 0.855, 95% CI: 0.783-0.934), poverty rate (IRR = 0.849, 95% CI: 0.765-0.943), and unemployment rate (IRR = 0.860, 95% CI: 0.763-0.968) were significantly associated with lower opioid mortality rates.

Table 1.1. Univariate Poisson Regression Results (2020)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	p-value	AIC
% Black Pop.	-0.156	**0.855**	0.783, 0.934	<0.001	**658.89**
Poverty Rate	-0.164	**0.849**	0.765, 0.943	0.002	661.35
Unemployment Rate	-0.151	**0.860**	0.763, 0.968	0.013	664.71
Vacancy Rate	-0.041	0.959	0.858, 1.073	0.468	670.56
Distance to Interstate	-0.071	0.932	0.828, 1.048	0.238	669.68
Distance to Treatment	0.002	1.002	0.890, 1.129	0.969	671.10

% Black Pop.: Percentage of Population identifying as Black
[1] IRR = Incidence Rate Ratio, CI = Confidence Interval

Among the SVI indicators, socioeconomic status (IRR = 0.851, 95% CI: 0.771-0.940), racial and ethnic minority status (IRR = 0.859, 95% CI: 0.788-0.936), housing type and transportation (IRR = 0.862, 95% CI: 0.785-0.947), and overall SVI (IRR = 0.844, 95% CI: 0.768-0.928) also showed significant negative associations with mortality. Taken together, these results indicate that counties with higher social vulnerability tended to experience lower opioid mortality, which is an unexpected pattern given the established associations between disadvantage and poor health outcomes.

Table 1.2. Univariate Poisson Regression Results for SVI (2020)

Covariate	β (Coefficient)	IRR	95% CI	p-value	AIC
Socioeconomic Status	-0.161	**0.851**	0.771, 0.940	0.001	660.59
Minority Status	-0.152	**0.859**	0.788, 0.936	<0.001	**658.97**
Housing/Transport	-0.149	**0.862**	0.785, 0.947	0.002	661.32
Overall SVI	-0.170	**0.844**	0.768, 0.928	<0.001	658.55
Household	-0.087	0.917	0.832, 1.010	0.078	667.99

Minority Status: Racial & Ethnic Minority Status
Housing/Transport: Housing Type & Transportation
Household: Household Characteristics

Although social vulnerability indicators, such as poverty, unemployment, and other SVI components, are often seen as risk factors for opioid-related mortality, the negative associations observed in our results may be partially explained by strong collinearity among these indicators or by other local factors not captured in our data. For example, counties with lower poverty rates may also have other characteristics, such as high housing vacancy or greater distance to treatment centers, which could contribute to higher mortality. These relationships, identified in univariate models, should therefore be interpreted with caution, as they may not represent direct or independent effects.

3.1.2 Univariate CAR Model

Table 2.1 and Table 2.2 display the results of univariate CAR models. Incorporating spatial correlation introduced some noise into the estimated IRRs, slightly increasing the point estimates and widening the confidence intervals. Among the covariates, only racial and ethnic minority status was found to be significantly associated with lower mortality (IRR = 0.914, 95% CI: 0.838-0.997), while the others did not show statistically significant associations. Although the differences in DIC values across models were relatively small, the model including racial and ethnic minority status resulted in the lowest DIC (624.26).

Table 2.1. Univariate CAR Model Results (2020)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	DIC
% Black Pop.	-0.070	0.932	0.843, 1.028	**625.39**
Poverty Rate	-0.009	0.992	0.885, 1.115	626.87
Unemployment Rate	-0.042	0.959	0.847, 1.082	626.36
Vacancy Rate	0.044	1.045	0.924, 1.180	626.81
Distance to Interstate	0.018	1.018	0.892, 1.160	626.92
Distance to Treatment	0.012	1.012	0.896, 1.137	627.20

[1] IRR = Incidence Rate Ratio, CI = Credible Interval

Table 2.2. Univariate CAR Model Results for SVI (2020)

Covariate	β (Coefficient)	IRR	95% CI	DIC
Minority Status	-0.089	**0.914**	0.838, 0.997	**624.26**
Socioeconomic Status	-0.049	0.952	0.862, 1.053	626.53
Household	-0.011	0.989	0.904, 1.082	627.04
Housing/Transport	-0.059	0.943	0.866, 1.027	625.68
Overall SVI	-0.062	0.940	0.856, 1.031	626.36

3.1.3 Multivariate Poisson Regression

Before fitting the multivariate Poisson regression models, we examined the correlations among covariates that were found to be significant in the univariate analyses. As social vulnerability indicators represent distinct yet interrelated aspects of community conditions, the variables were moderately to strongly correlated, as shown in Appendix A.9.

In particular, the percentage of Black population was highly correlated with racial and ethnic minority status, as both capture similar demographic characteristics. Overall SVI, being a composite measure, also showed high correlation with each of its component themes. While some correlations existed among the individual SVI themes, these were generally weaker than those with the overall index. To address multicollinearity, we fitted two separate sets of multivariate models, each including only one variable from each correlated pair.

Table 3.1 summarizes the covariate combinations used in the multivariate Poisson models. Models A1–A5 include the percentage of Black population along with different combinations of covariates, while Models B1–B7 include racial and ethnic minority status. This structure allows us to evaluate the influence of these related variables separately and assess model performance across varying specifications.

Table 3.1. Summary of Multivariate Poisson Model Specifications (2020)

Model	Covariates			
A1	% Black Pop.	Poverty	-	-
A2	% Black Pop.	-	Unemployment	-
A3	% Black Pop.	Poverty	Unemployment	-
A4	% Black Pop.	-	-	Housing/Transport
A5	% Black Pop.	-	-	Overall SVI
B1	Minority Status	Poverty	-	-
B2	Minority Status	-	Unemployment	-
B3	Minority Status	-	-	Housing/Transport
B4	Minority Status	Poverty	Unemployment	-
B5	Minority Status	Poverty	-	Housing/Transport
B6	Minority Status	-	Unemployment	Housing/Transport
B7	Minority Status	Poverty	Unemployment	Housing/Transport

Table 3.2 presents the results of the multivariate Poisson regression models that included the percentage of Black population. In Models A1-A4, this variable was significantly associated with lower opioid mortality rates, with IRRs of 0.889 (95% CI: 0.807–0.979), 0.874 (95% CI: 0.788–0.970), 0.895 (95% CI: 0.804–0.995), and 0.890 (95% CI: 0.807–0.981), respectively. In contrast, the poverty rate, unemployment rate, housing type and transportation, and overall SVI did not exhibit statistically significant associations in any of the A-series models.

Table 3.2. Multivariate Poisson Regression Results (2020)
- Models with Percentage of Population identifying as Black

Model	IRR (95% CI)			AIC
	% Black Pop.	Poverty	Unemployment	
A1	**0.889** (0.807, 0.979)	0.903 (0.807, 1.010)	-	657.64
A2	**0.874** (0.788, 0.970)	-	0.947 (0.826, 1.085)	660.27
A3	**0.895** (0.804, 0.995)	0.907 (0.807, 1.019)	0.978 (0.848, 1.128)	659.54
	% Black Pop.	Housing/Transport	Overall SVI	
A4	**0.890** (0.807, 0.981)	0.913 (0.824, 1.012)	-	657.86
A5	0.908 (0.816, 1.011)	-	0.898 (0.800, 1.007)	**657.48**

Table 3.3 displays the results of the multivariate Poisson regression models that included racial and ethnic minority status. In all models (B1–B7), this variable was significantly associated with lower opioid mortality, with IRRs ranging from 0.879 to 0.902 and 95% confidence intervals that did not include 1. In Model B1, which included both racial and ethnic minority status and the poverty rate, the poverty rate was also significantly associated with reduced mortality (IRR = 0.893, 95% CI: 0.803–0.994). In contrast, the unemployment rate and housing type and transportation indicator were not significantly associated with mortality in any of the B-series models.

Table 3.3. Multivariate Poisson Regression Results (2020) - Models with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)				
Model	Minority	Poverty	Unemployment	Housing/Transport	AIC
B1	**0.887** (0.812, 0.970)	**0.893** (0.803, 0.994)	-	-	**656.60**
B2	**0.879** (0.799, 0.967)	-	0.931 (0.819, 1.059)	-	659.76
B3	**0.893** (0.812, 0.982)	-	-	0.914 (0.825, 1.012)	657.96
B4	**0.893** (0.812, 0.983)	0.900 (0.804, 1.009)	0.972 (0.848, 1.115)	-	658.44
B5	**0.894** (0.813, 0.982)	0.913 (0.792, 1.053)	-	0.969 (0.845, 1.110)	658.39
B6	**0.902** (0.816, 0.997)	-	0.958 (0.838, 1.096)	0.923 (0.829, 1.027)	659.57
B7	**0.899** (0.814, 0.993)	0.919 (0.794, 1.063)	0.975 (0.849, 1.119)	0.970 (0.846, 1.113)	660.26

3.1.4 Multivariate CAR Model

Although only the racial and ethnic minority status was significantly associated with decreased mortality in the univariate CAR model, we selected the covariates based on the multivariate Poisson regression results. We then compared the DIC, a Bayesian model selection metric where lower values indicate better model fit, to assess whether adding these covariates improved model performance. Similar to the multivariate Poisson model, we fitted the same separate sets of models to address multicollinearity.

Table 4.1 summarizes the covariate combinations used in the multivariate CAR models. Models A6–A10 include the percentage of Black population along with various combinations of covariates, while Models B8–B13 include racial and ethnic minority status in place of that variable.

Table 4.1. Summary of Multivariate CAR Model Specifications (2020)

Model	Covariates			
A6	% Black Pop.	Poverty	-	-
A7	% Black Pop.	-	Unemployment	-
A8	% Black Pop.	Poverty	Unemployment	-
A9	% Black Pop.	-	-	Housing/Transport
A10	% Black Pop.	-	-	Overall SVI
B8	Minority Status	Poverty	-	-
B9	Minority Status	-	-	Housing/Transport
B10	Minority Status	Poverty	Unemployment	-
B11	Minority Status	Poverty	-	Housing/Transport
B12	Minority Status	-	Unemployment	Housing/Transport
B13	Minority Status	Poverty	Unemployment	Housing/Transport

Tables 4.2 and Table 4.3 present the results of the multivariate CAR models including the percentage of Black population and racial and ethnic minority status, respectively. None of the covariates were significantly associated with opioid mortality in the A-series models. In contrast, racial and ethnic minority status was significantly associated with lower mortality in Model B8 (IRR = 0.905, 95% CI: 0.822–0.995). Including additional covariates did not substantially improve model fit, as DIC values across the multivariate CAR models were similar to those of the univariate CAR models. Although Model B11 had the lowest DIC (625.09), the difference from B8 (DIC = 625.15) was minimal, and the inclusion of the housing type and transportation indicator did not appear to meaningfully enhance model fit.

Table 4.2. Multivariate CAR Model Results (2020)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)			
Model	% Black Pop.	Poverty	Unemployment	DIC
A6	0.918 (0.819, 1.026)	1.037 (0.903, 1.191)	-	**625.77**
A7	0.933 (0.832, 1.047)	-	1.002 (0.868, 1.146)	626.69
A8	0.923 (0.818, 1.046)	1.029 (0.899, 1.175)	0.997 (0.861, 1.147)	627.51
	% Black Pop.	Housing/Transport	Overall SVI	
A9	0.953 (0.846, 1.080)	0.962 (0.868, 1.062)	-	626.16
A10	0.957 (0.839, 1.088)	-	0.962 (0.855, 1.082)	626.61

Table 4.3. Multivariate CAR Model Results (2020)
- Models with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)				
Model	Minority	Poverty	Unemployment	Housing/Transport	DIC
B8	**0.905** (0.822 0.995)	1.035 (0.912, 1.174)	-	-	625.15
B9	0.926 (0.833, 1.027)	-	-	0.981 (0.887, 1.084)	625.16
B10	0.907 (0.817 1.003)	1.036 (0.906, 1.194)	0.995 (0.868, 1.137)	-	626.60
B11	0.927 (0.834, 1.031)	1.084 (0.928, 1.262)	-	0.942 (0.829, 1.062)	**625.09**
B12	0.923 (0.829, 1.027)	-	1.015 (0.880, 1.159)	0.978 (0.880, 1.082)	626.83
B13	0.928 (0.836, 1.031)	1.078 (0.924, 1.271)	1.001 (0.873, 1.144)	0.942 (0.832, 1.064)	626.59

Notably, the univariate models including the percentage of Black population and racial and ethnic minority status exhibited slightly lower DIC values compared to the corresponding multivariate models, suggesting that these covariates may independently account for substantial spatial variation. For the other covariates, DIC values varied across model specifications, with some showing slight decreases in multivariate models and others showing minor increases. This pattern suggests that the explanatory power of these covariates is relatively limited and may depend on their specific combination with other variables. Based on these results, we selected Model B8 as the final model for 2020. Its DIC value was close to the lowest observed, and it included a statistically significant covariate, racial and ethnic minority status.

Figure 2 shows a comparison of county-level crude and smoothed opioid-related mortality rates (per 100,000) in Georgia for 2020, along with the posterior standard deviation of the mortality estimates. The highest crude mortality rates were observed in counties such as Clay (33.76), Talbot (32.01), and Ware (30.67). After applying spatial smoothing, the high mortality estimates appeared in counties such as Haralson (22.03), Dade (20.17), and Rabun (18.79).

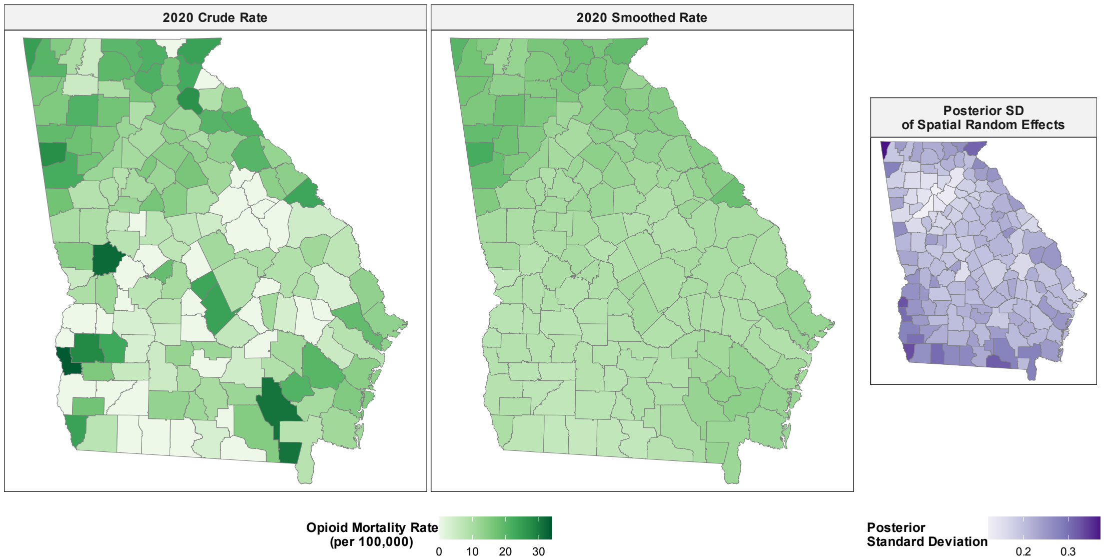

Figure 2. County-Level Crude and Smoothed Opioid Mortality Rates and Posterior SD of Spatial Random Effects in Georgia (2020)

Note. Year-specific color scales are used in the Results section to compare crude and smoothed rates. In contrast, maps in the Data section use a unified scale to enable comparison across years. This applies to all maps shown in the Results section.

3.2 2021 Results

3.2.1 Univariate Poisson Regression

The results of the univariate Poisson regression models for 2021 are presented in Table 5.1 and Table 5.2. In contrast to 2020, only the percentage of Black population was significantly associated with lower opioid mortality (IRR = 0.917, 95% CI: 0.841–0.999), although the confidence interval was close to 1. Among the SVI components, racial and ethnic minority status (IRR = 0.893, 95% CI: 0.822–0.969), housing type and transportation (IRR = 0.898, 95% CI: 0.819–0.985), and overall SVI (IRR = 0.904, 95% CI: 0.824–0.993) were also significantly associated with reduced mortality.

Table 5.1. Univariate Poisson Regression Results (2021)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	p-value	AIC
% Black Pop.	-0.087	**0.917**	0.841, 0.999	0.048	**779.13**
Poverty Rate	-0.065	0.937	0.846, 1.038	0.211	781.41
Unemployment Rate	-0.043	0.958	0.860, 1.068	0.437	782.43
Vacancy Rate	-0.003	0.997	0.899, 1.106	0.962	783.04
Distance to Interstate	-0.036	0.965	0.867, 1.074	0.511	782.60
Distance to Treatment	0.015	1.016	0.911, 1.132	0.781	782.96

[1] IRR = Incidence Rate Ratio, CI = Confidence Interval

Table 5.2. Univariate Poisson Regression Results for SVI (2021)

Covariate	β (Coefficient)	IRR	95% CI	p-value	AIC
Minority Status	-0.114	**0.893**	0.822, 0.969	0.007	**776.00**
Housing/Transport	-0.107	**0.898**	0.819, 0.985	0.023	777.71
Overall SVI	-0.101	**0.904**	0.824, 0.993	0.035	778.43
Socioeconomic Status	-0.078	0.925	0.840, 1.019	0.114	780.45
Household	-0.029	0.972	0.886, 1.066	0.543	782.67

3.2.2 Univariate CAR Model

Table 6.1 and Table 6.2 display the univariate CAR model results for 2021. None of the covariates—including the percentage of Black population, racial and ethnic minority status, housing type and transportation, or overall SVI—were significantly associated with opioid mortality, in contrast to the results from the Poisson models. A notable distinction between the univariate CAR and Poisson regression results is that incorporating spatial correlation in the CAR models led to shifts in the estimated coefficients toward the null. Although the estimates remained statistically non-significant, this pattern suggests that spatial structure may influence the relationship between these covariates and the outcome.

Table 6.1. Univariate CAR Model Results (2021)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	DIC
% Black Pop.	-0.022	0.978	0.873, 1.093	**747.85**
Poverty Rate	0.054	1.055	0.938, 1.187	749.94
Unemployment Rate	0.011	1.011	0.899, 1.135	749.36
Vacancy Rate	0.047	1.048	0.923, 1.182	749.23
Distance to Interstate	0.035	1.035	0.905, 1.188	748.60
Distance to Treatment	0.028	1.029	0.919, 1.149	749.03

[1] IRR = Incidence Rate Ratio, CI = Credible Interval

Table 6.2. Univariate CAR Model Results for SVI (2021)

Covariate	β (Coefficient)	IRR	95% CI	DIC
Minority Status	-0.076	0.926	0.843, 1.019	747.51
Socioeconomic Status	0.001	1.001	0.905, 1.103	748.27
Household	0.024	1.024	0.936, 1.121	748.37
Housing/Transport	-0.048	0.953	0.868, 1.040	**746.42**
Overall SVI	-0.026	0.974	0.884, 1.068	747.81

3.2.3 Multivariate Poisson Regression

Similar to 2020, we explored two separate sets of multivariate Poisson models due to the high correlation between certain covariates. Table 7.1 presents the covariate combinations included in the 2021 models. Models C1 and C2 incorporate the percentage of Black population, while Model D1 includes racial and ethnic minority status.

Table 7.1. Summary of Multivariate Poisson Model Specifications (2021)

Model	Covariates		
C1	% Black Pop.	Housing/Transport	-
C2	% Black Pop.	-	Overall SVI
D1	Minority Status	Housing/Transport	-

Tables 7.2 and 7.3 present the results of the multivariate Poisson models. In Models C1 and C2, there was no evidence of a significant association between any of the covariates and mortality. Similarly, in Model D1, neither racial and ethnic minority status nor housing type and transportation was significantly related to mortality.

Table 7.2. Multivariate Poisson Regression Results (2021)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)			
Model	% Black Pop.	Housing/Transport	Overall SVI	AIC
C1	0.950 (0.862, 1.048)	0.922 (0.831, 1.023)	-	**778.69**
C2	0.953 (0.856, 1.062)	-	0.933 (0.831, 1.047)	779.69

Table 7.3. Multivariate Poisson Regression Results (2021)
- Model with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)		
Model	Minority Status	Housing/Transport	AIC
D1	0.917 (0.834, 1.008)	0.942 (0.850, 1.044)	**776.653**

3.2.4 Multivariate CAR Model

Although no covariates showed a significant relationship with the mortality rate in the univariate CAR models, we retained the percentage of Black population, racial and ethnic minority status, housing type and transportation, and overall SVI as covariates based on the multivariate Poisson regression results.

Table 8.1 outlines the covariate combinations used in the multivariate CAR models for 2021. Models C3 and C4 include the percentage of Black population, along with different combinations of SVI components, while D2 includes racial and ethnic minority status instead.

Table 8.1. Summary of Multivariate CAR Model Specifications (2021)

Model	Covariates		
C3	% Black Pop.	Housing/Transport	-
C4	% Black Pop.	-	Overall SVI
D2	Minority Status	Housing/Transport	-

Table 8.2 and Table 8.3 summarize the multivariate CAR model results. None of the covariates reached statistical significance in any of the models (C3–C5 and D2). Notably, Model C3 showed a slight improvement in model fit compared to the univariate CAR models, as indicated by a lower DIC value. Specifically, in the univariate CAR models, DIC values for the percentage of Black population and housing type and transportation were 747.85 and 746.42, respectively. In contrast, the multivariate CAR model including both of these covariates returned a lower DIC of 745.99. These findings suggest that including additional covariates can improve overall model performance, even when individual predictors are not statistically significant. Model C3, which had the lowest DIC, was therefore selected as the final model for 2021.

Table 8.2. Multivariate CAR Model Results (2021)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)			
Model	% Black Pop.	Housing/Transport	Overall SVI	DIC
C3	1.021 (0.889, 1.178)	0.942 (0.842, 1.049)	-	**745.99**
C4	0.999 (0.867, 1.150)	-	0.974 (0.861, 1.101)	747.97

Table 8.3. Multivariate CAR Model Results (2021)
- Model with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)		
Model	Minority Status	Housing/Transport	DIC
D2	0.930 (0.833, 1.043)	0.990 (0.888, 1.101)	747.81

Figure 3 presents the 2021 county-level crude and smoothed opioid-related mortality rates (per 100,000) in Georgia, along with the posterior standard deviation of the mortality estimates. While the highest crude rates were observed in Marion (59.17), Randolph (56.54), and Wilkinson (55.81), smoothing shifted the highest estimates to Polk (33.04), Camden (27.60), and Glynn (27.31).

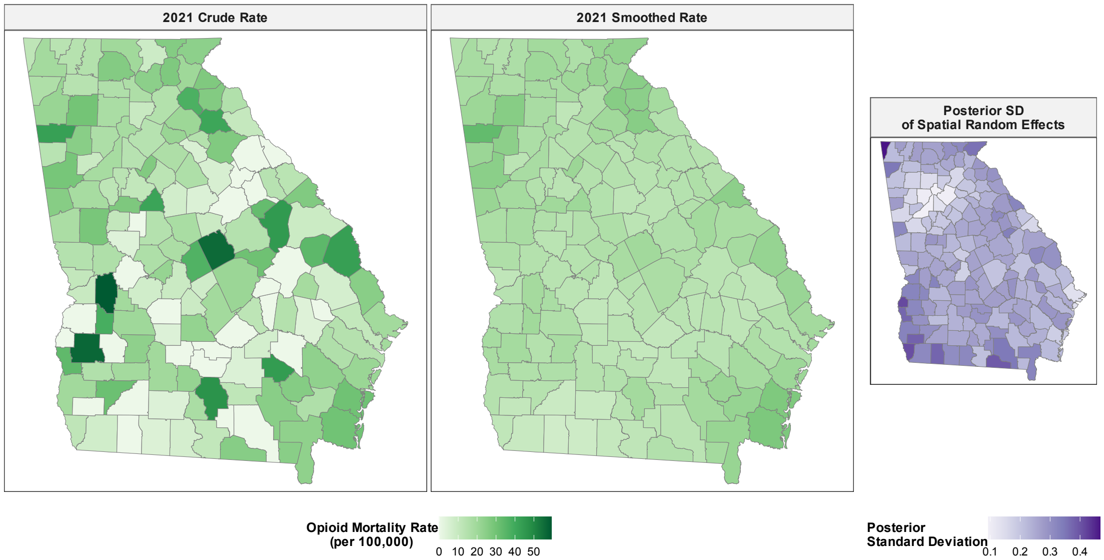

Figure 3. County-Level Crude and Smoothed Opioid Mortality Rates and Posterior SD of Spatial Random Effects in Georgia (2021)

3.3 2022 Results

3.3.1 Univariate Poisson Regression

The results of the univariate Poisson regression models for 2022 are presented in Table 9.1 and Table 9.2. Similar to 2021, the percentage of Black population was significantly associated with a lower mortality rate (IRR = 0.902, 95% CI: 0.832–0.979). Among the SVI components, racial and ethnic minority status (IRR = 0.890, 95% CI: 0.821–0.963), housing type and transportation (IRR = 0.897, 95% CI: 0.822–0.979), and overall SVI (IRR = 0.904, 95% CI: 0.829–0.986) also showed significant negative associations with mortality. In contrast, other covariates, including poverty rate, unemployment rate, vacancy rate, distance to interstate, and distance to treatment, were not significantly associated with the outcome.

Table 9.1. Univariate Poisson Regression Results (2022)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	p-value	AIC
% Black Pop.	-0.103	**0.902**	0.832, 0.979	0.013	**762.86**
Poverty Rate	-0.076	0.927	0.843, 1.019	0.117	766.34
Unemployment Rate	-0.037	0.964	0.870, 1.068	0.485	768.38
Vacancy Rate	-0.092	0.913	0.821, 1.014	0.089	765.84
Distance to Interstate	-0.062	0.940	0.847, 1.043	0.241	767.47
Distance to Treatment	-0.020	0.980	0.882, 1.090	0.715	768.74

[1] IRR = Incidence Rate Ratio, CI = Confidence Interval

Table 9.2. Univariate Poisson Regression Results for SVI (2022)

Covariate	β (Coefficient)	IRR	95% CI	p-value	AIC
Minority Status	-0.117	**0.890**	0.821, 0.963	0.004	**760.78**
Housing/Transport	-0.109	**0.897**	0.822, 0.979	0.014	762.76
Overall SVI	-0.101	**0.904**	0.829, 0.986	0.023	763.60
Socioeconomic Status	-0.081	0.922	0.843, 1.009	0.076	765.67
Household	-0.023	0.977	0.896, 1.066	0.605	768.61

3.3.2 Univariate CAR Model

Table 10.1 and Table 10.2 summarize the univariate CAR model results for 2022. In the spatial models, no covariates were found to be significantly associated with the mortality rate. Incorporating spatial correlation appeared to slightly reduce the precision of the estimates, as reflected in wider credible intervals compared to the non-spatial models. The DIC values were fairly similar across models, with the model including racial and ethnic minority status yielding the lowest DIC (724.52).

Table 10.1. Univariate CAR Model Results (2022)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	DIC
% Black Pop.	-0.072	0.931	0.841, 1.027	**725.90**
Poverty Rate	0.033	1.034	0.921, 1.156	728.21
Unemployment Rate	0.020	1.020	0.915, 1.133	727.68
Vacancy Rate	-0.051	0.950	0.837, 1.070	726.25
Distance to Interstate	-0.032	0.968	0.853, 1.097	727.49
Distance to Treatment	-0.036	0.964	0.863, 1.073	727.47

[1] IRR = Incidence Rate Ratio, CI = Credible Interval

Table 10.2. Univariate CAR Model Results for SVI (2022)

Covariate	β (Coefficient)	IRR	95% CI	DIC
Minority Status	-0.088	0.916	0.837, 1.000	**724.52**
Socioeconomic Status	-0.004	0.996	0.906, 1.096	727.40
Household	0.019	1.019	0.938, 1.109	727.17
Housing/Transport	-0.042	0.959	0.882, 1.039	725.65
Overall SVI	-0.029	0.972	0.889, 1.061	726.91

3.3.3 Multivariate Poisson Regression

Similar to previous years, two sets of multivariate Poisson regression models were fitted to address high correlation among covariates. Table 11.1 outlines the covariate combinations included in the multivariate Poisson models for 2022.

Table 11.1. Summary of Multivariate Poisson Model Specifications (2022)

Model	Covariates		
E1	% Black Pop.	Housing/Transport	-
E2	% Black Pop.	-	Overall SVI
F1	Minority Status	Housing/Transport	-

Table 11.2 presents the models including the percentage of Black popluation, while Table 11.3 summarizes the model incorporating racial and ethnic minority status. None of the covariates were significantly associated with the mortality rate in these models. Among them, Model F1, which included racial and ethnic minority status and housing type and transportation, had the lowest AIC (761.24). However, the differences in AIC values across models were minimal, suggesting no substantial improvement in model performance.

Table 11.2. Multivariate Poisson Regression Results (2022)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)			
Model	% Black Pop.	Housing/Transport	Overall SVI	AIC
E1	0.933 (0.850, 1.023)	0.929 (0.843, 1.025)	-	**762.65**
E2	0.932 (0.841, 1.032)	-	0.946 (0.850, 1.052)	763.79

Table 11.3. Multivariate Poisson Regression Results (2022)
- Model with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)		
Model	Minority Status	Housing/Transport	AIC
F1	0.915 (0.835, 1.002)	0.941 (0.854, 1.037)	**761.24**

3.3.4 Multivariate CAR Model

Table 12.1 shows the covariate sets used in the corresponding CAR models. Models E3 and E4 include the percentage of Black population, along with different SVI components, while F2 incorporates racial and ethnic minority status instead.

Table 12.1. Summary of Multivariate CAR Model Specifications (2022)

Model	Covariates		
E3	% Black Pop.	Housing/Transport	-
E4	% Black Pop.	-	Overall SVI
F2	Minority Status	Housing/Transport	-

The multivariate CAR model results for 2022 are displayed in Table 12.2 and Table 12.3. None of the covariates, including the percentage of Black population, racial and ethnic minority status, housing type and transportation, or overall SVI, showed a significant association with opioid mortality in any of the models. While the differences in DIC values were modest, Model F2, which included racial and ethnic minority status and housing type and transportation, achieved the lowest DIC (725.24). Accordingly, we identified Model F2 as the final model for 2022.

Table 12.2. Multivariate CAR Model Results (2022)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)			
Model	% Black Pop.	Housing/Transport	Overall SVI	DIC
E3	0.941 (0.826, 1.068)	0.986 (0.894, 1.089)	-	**725.97**
E4	0.913 (0.796, 1.042)	-	1.024 (0.908, 1.148)	726.13

Table 12.3. Multivariate CAR Model Results (2022)
- Model with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)		
Model	Minority Status	Housing/Transport	DIC
F2	0.911 (0.814, 1.019)	1.009 (0.911, 1.118)	**725.24**

Figure 4 illustrates county-level crude and smoothed opioid-related mortality rates (per 100,000) in Georgia for 2022. In the crude map, the highest mortality rates were observed in Madison (47.78), Pickens (44.32), and Randolph (42.40). With spatial smoothing, however, the high rates shifted to Richmond (35.41), Haralson (32.33), and Polk (30.73).

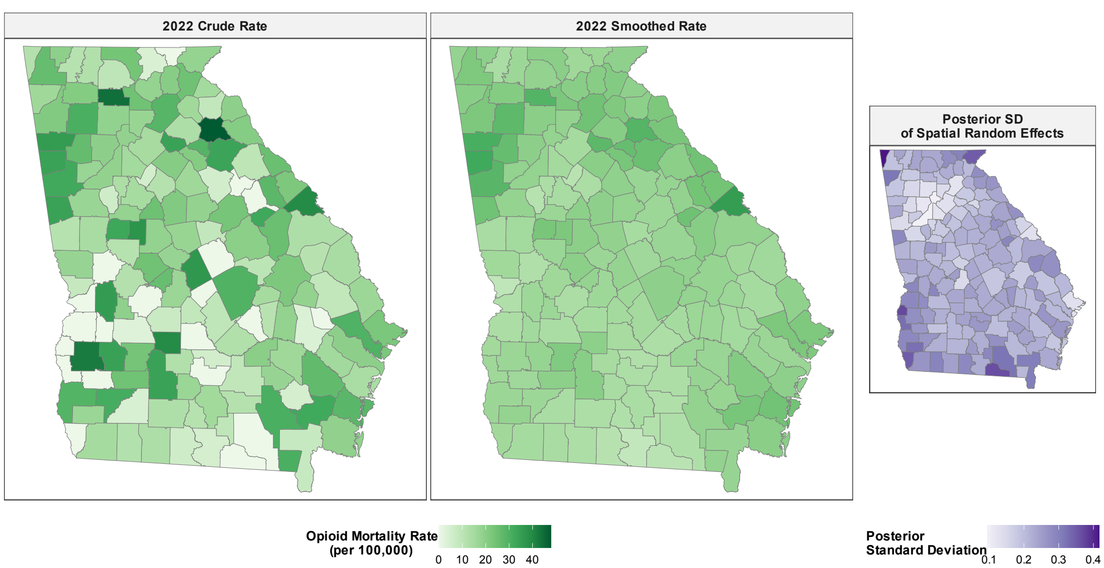

Figure 4. County-Level Crude and Smoothed Opioid Mortality Rates and Posterior SD of Spatial Random Effects in Georgia (2022)

3.4 2020–2022 Combined Results

To improve estimation precision and assess consistent spatial patterns across years, we additionally fitted models using combined mortality data from 2020 to 2022. Given that several covariates showed borderline or inconsistent associations in year-specific models, pooling the data was expected to increase statistical power and enhance model stability. The same modeling strategy was applied, including both univariate and multivariate Poisson and CAR models, to ensure comparability with prior analyses.

3.4.1 Univariate Poisson Regression

The univariate Poisson regression results are reported in Table 13.1 and Table 13.2. Several covariates—including the percentage of Black population, poverty rate, racial and ethnic minority status, housing type and transportation, overall SVI, and socioeconomic status—were significantly linked to reduced opioid mortality, as indicated by IRRs less than 1 and confidence intervals excluding 1.

Table 13.1. Univariate Poisson Regression Results (2020-2022)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	p-value	AIC
% Black Pop.	-0.126	**0.882**	0.824, 0.944	<0.001	**999.80**
Poverty Rate	-0.119	**0.888**	0.822, 0.959	0.003	1003.10
Unemployment Rate	-0.075	0.928	0.854, 1.008	0.075	1009.32
Vacancy Rate	-0.061	0.941	0.868, 1.020	0.142	1010.29
Distance to Interstate	-0.058	0.944	0.871, 1.023	0.161	1010.51
Distance to Treatment	-0.004	0.996	0.918, 1.081	0.924	1012.48

[1] IRR = Incidence Rate Ratio, CI = Confidence Interval

Table 13.2. Univariate Poisson Regression Results for SVI (2020-2022)

Covariate	β (Coefficient)	IRR	95% CI	p-value	AIC
Minority Status	-0.140	**0.869**	0.814, 0.929	<0.001	**995.95**
Housing/Transport	-0.139	**0.871**	0.811, 0.935	<0.001	997.88
Overall SVI	-0.137	**0.872**	0.812, 0.936	<0.001	998.16
Socioeconomic Status	-0.122	**0.885**	0.822, 0.953	0.001	1001.89
Household	-0.045	0.956	0.889, 1.028	0.226	1011.03

3.4.2 Univariate CAR Model

Consistent with the findings from 2020, racial and ethnic minority status was the only covariate that demonstrated a statistically significant association with reduced mortality (IRR = 0.911, 95% CI: 0.844–0.984), whereas the remaining covariates did not exhibit significant relationships, as shown in Table 14.1 and Table 14.2.

Table 14.1. Univariate CAR Model Results (2020-2022)

Covariate	β (Coefficient)	IRR[1]	95% CI[1]	DIC
% of Black Pop.	-0.068	0.934	0.850, 1.020	**927.28**
Poverty Rate	0.009	1.009	0.915, 1.113	930.95
Unemployment Rate	-0.014	0.986	0.904, 1.077	929.85
Vacancy Rate	-0.003	0.997	0.899, 1.105	929.91
Distance to Interstate	0.005	1.005	0.905, 1.115	929.64
Distance to Treatment	0.000	1.001	0.922, 1.083	930.33

[1] IRR = Incidence Rate Ratio, CI = Credible Interval

Table 14.2. Univariate CAR Model Results for SVI (2020-2022)

Covariate	β (Coefficient)	IRR	95% CI	DIC
Minority Status	-0.094	**0.911**	0.844, 0.984	**924.94**
Socioeconomic Status	-0.024	0.976	0.902, 1.057	928.60
Household	0.019	1.020	0.950, 1.097	928.08
Housing/Transport	-0.067	0.935	0.871, 1.001	926.48
Overall SVI	-0.044	0.957	0.886, 1.031	926.09

3.4.3 Multivariate Poisson Regression

Table 15.1 lists the covariate combinations used in the multivariate Poisson models fitted to the combined 2020–2022 dataset. As in previous years, two parallel sets of models were specified to account for the high correlation between the percentage of Black population and racial and ethnic minority status. Models G1–G3 incorporate the percentage of Black population along with different subsets of SVI variables, whereas Models H1–H3 include racial and ethnic minority status.

Table 15.1. Summary of Multivariate Poisson Model Specifications (2020-2022)

Model	Covariates			
G1	% Black Pop.	Poverty	-	-
G2	% Black Pop.	-	Housing/Transport	-
G3	% Black Pop.	-	-	Overall SVI
H1	Minority Status	Poverty	-	-
H2	Minority Status	-	Housing/Transport	-
H3	Minority Status	Poverty	Housing/Transport	-

Multivariate Poisson regression results are outlined in Table 15.2 and Table 15.3. Among the models including the percentage of Black population, this variable showed a significant negative association with mortality in Models G1 (IRR = 0.908, 95% CI: 0.840–0.981) and G2 (IRR = 0.923, 95% CI: 0.855–0.997). In addition, housing type and transportation in Model G2 (IRR = 0.906, 95% CI: 0.837–0.981) and overall SVI in G3 (IRR = 0.912, 95% CI: 0.836–0.995) were also significantly related to lower mortality. In the H-series models, which include racial and ethnic minority status, this variable consistently demonstrated a negative association with mortality across all models. Housing type and transportation also showed a significant inverse effect in Model H2 (IRR = 0.918, 95% CI: 0.848–0.993).

Table 15.2. Multivariate Poisson Regression Results (2020-2022)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)				
Model	% Black Pop.	Poverty	Housing/Transport	Overall SVI	AIC
G1	**0.908** (0.840, 0.981)	0.935 (0.859, 1.019)	-	-	999.38
G2	**0.923** (0.855, 0.997)	-	**0.906** (0.837, 0.981)	-	**995.80**
G3	0.931 (0.855, 1.013)	-	-	**0.912** (0.836, 0.995)	997.47

Table 15.3. Multivariate Poisson Regression Results (2020-2022)
- Model with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)			
Model	Minority Status	Poverty	Housing/Transport	AIC
H1	**0.889** (0.827, 0.956)	0.940 (0.867, 1.019)	-	995.63
H2	**0.905** (0.840, 0.976)	-	**0.918** (0.848, 0.993)	**993.35**
H3	**0.906** (0.840, 0.977)	0.998 (0.980, 1.016)	0.925 (0.837, 1.022)	995.29

3.4.4 Multivariate CAR Model

Table 16.1 presents the covariate combinations used in the multivariate CAR models, which follow the same structure as the corresponding multivariate Poisson models.

Table 16.1. Summary of Multivariate CAR Model Specifications (2020-2022)

Model	Covariates			
G4	% Black Pop.	Poverty	-	-
G5	% Black Pop.	-	Housing/Transport	-
G6	% Black Pop.	-	-	Overall SVI
H4	Minority Status	Poverty	-	-
H5	Minority Status	-	Housing/Transport	-
H6	Minority Status	Poverty	Housing/Transport	-

The combined-year results are shown in Table 16.2 and Table 16.3. In Model H4, racial and ethnic minority status was significantly associated with reduced mortality (IRR = 0.888, 95% CI: 0.816–0.967). Including housing type and transportation appeared to improve model fit, as reflected in lower DIC values in Model G5 (923.73) and H5 (922.33) relative to the univariate CAR models. Model H4 was selected as the final model for its statistically significant covariate, despite H5 having a slightly lower DIC.

Table 16.2. Multivariate CAR Model Results (2020-2022)
- Models with Percentage of Population identifying as Black

	IRR (95% CI)				
Model	% Black Pop.	Poverty	Housing/Transport	Overall SVI	DIC
G4	0.910 (0.926, 1.008)	1.056 (0.940, 1.180)	-	-	927.99
G5	0.974 (0.867, 1.087)	-	0.949 (0.873, 1.034)	-	**923.73**
G6	0.939 (0.833, 1.058)	-	-	0.990 (0.898, 1.092)	925.07

Table 16.3. Multivariate CAR Model Results (2020-2022)
- Models with Racial & Ethnic Minority Status (SVI)

	IRR (95% CI)			
Model	Minority Status	Poverty	Housing/Transport	DIC
H4	**0.888** (0.816, 0.967)	1.071 (0.967, 1.180)	-	924.72
H5	0.923 (0.838, 1.017)	-	0.978 (0.898, 1.064)	**922.33**
H6	0.918 (0.836, 1.005)	1.123 (1.000, 1.257)	0.929 (0.848, 1.021)	925.18

Figure 5 compares the crude and smoothed opioid-related mortality rates (per 100,000) across Georgia counties for the combined 2020-2022 period, along with the posterior standard deviation of the mortality estimates. Crude mortality rates were highest in counties such as Randolph, Madison, and Marion, while the smoothed estimates highlighted Polk, Richmond, and Madison as having the highest rates.

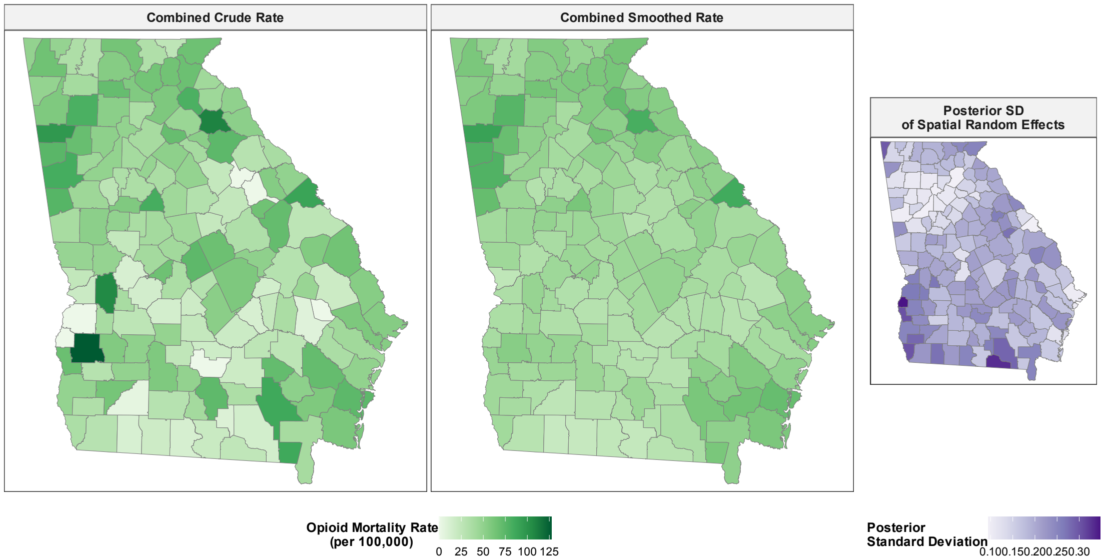

Figure 5. County-Level Crude and Smoothed Opioid Mortality Rates and Posterior SD of Spatial Random Effects in Georgia (2020-2022)

Figures 6 through 8 visually summarize the estimated incidence rate ratios (IRRs) and associated 95% confidence and credible intervals across all univariate and multivariate Poisson and CAR models. Several general patterns emerge from these figures. First, across all years and covariates, the incorporation of spatial correlation in the CAR models tends to shift point estimates toward the null value. Second, credible intervals are generally wider in the CAR models than in their Poisson counterparts.

In particular, the estimated effect of poverty rate illustrates an interesting shift: in Poisson models, it appears marginally protective, whereas, in CAR models, it crosses the null or even reverses direction when spatial structure is introduced. Such variability may reflect underlying spatial heterogeneity or sensitivity to covariate structure, especially given that most intervals contain the null value. These findings suggest that adjusting for spatial correlation may lead to more accurate and robust estimates, highlighting the importance of incorporating spatial structure in models of opioid-related mortality.

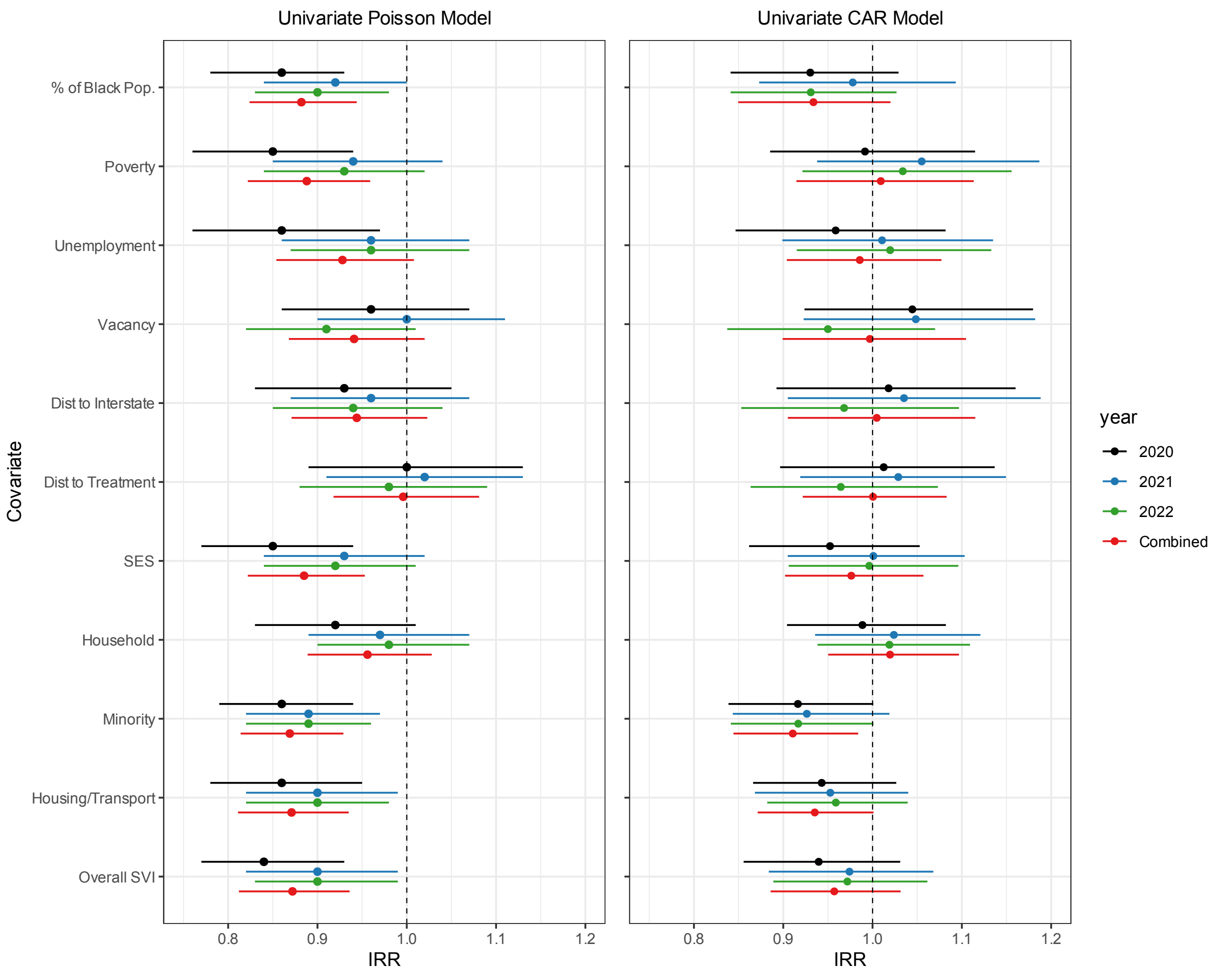

Figure 6. Comparison of Estimated IRRs with 95% Confidence and Credible Intervals from Univariate Poisson and CAR Models (2020–2022)

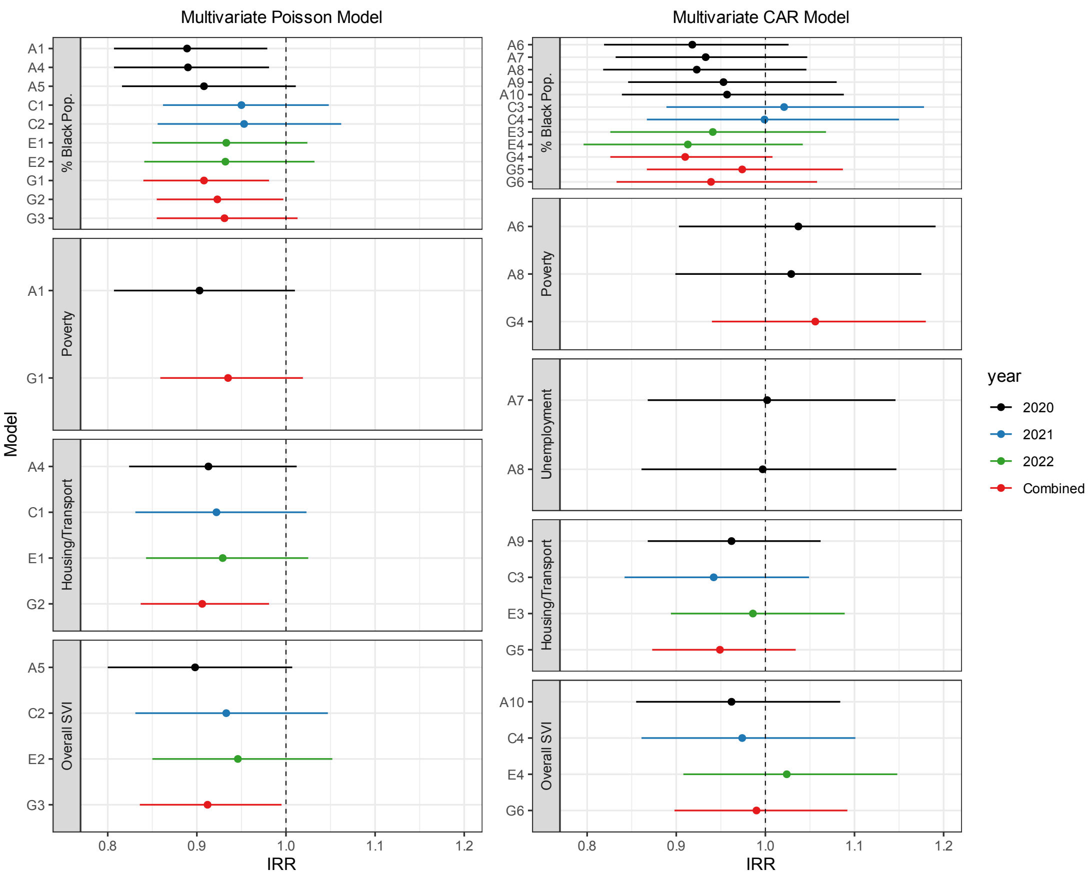

Figure 7. Comparison of Estimated IRRs with 95% Confidence and Credible Intervals from Multivariate Poisson and CAR Models (2020–2022) - % Black Pop.

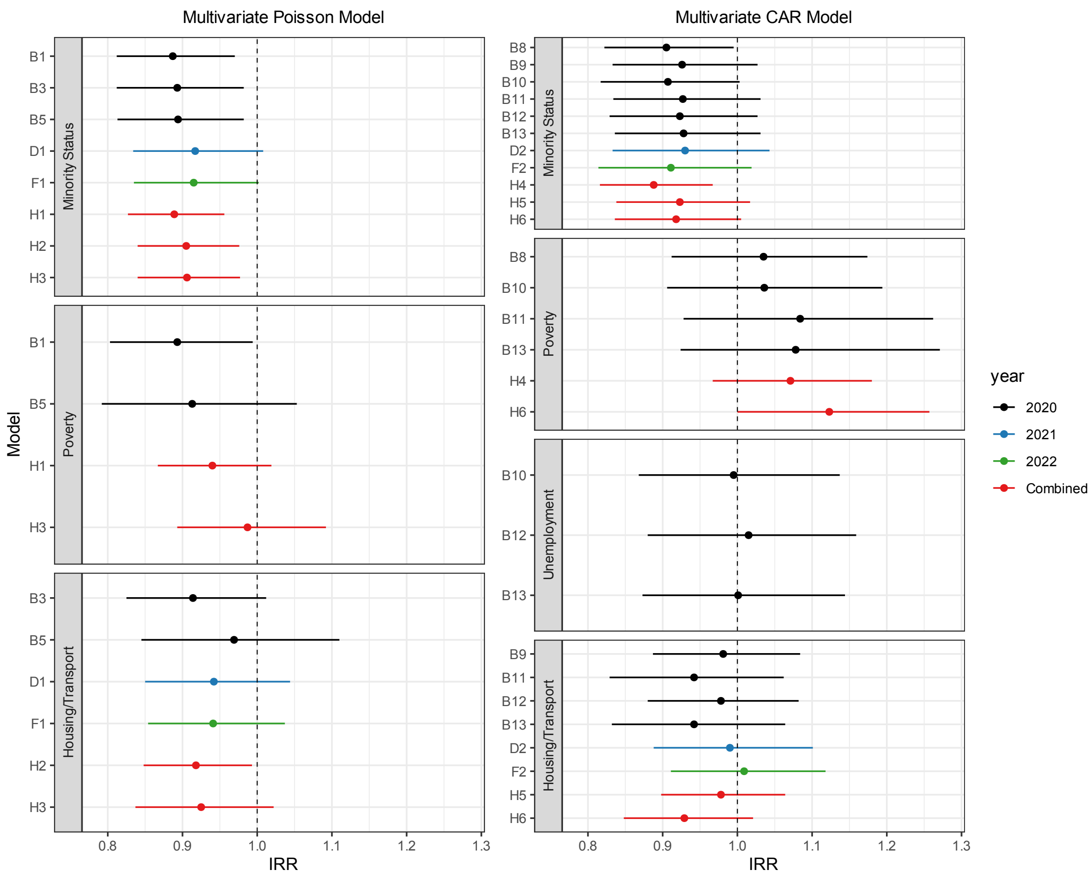

Figure 8. Comparison of Estimated IRRs with 95% Confidence and Credible Intervals from Multivariate Poisson and CAR Models (2020–2022) - Minority Status

4 Discussion

We investigated how county-level social vulnerability, socioeconomic, and demographic factors were associated with opioid-related mortality in Georgia from 2020 to 2022. Overall, the findings were consistent across the three years of analysis. Most covariates were associated with reduced mortality, with estimated IRRs generally below 1 across models. Even when associations were not statistically significant, these inverse trends were consistently observed, particularly for variables such as the percentage of the population identifying as Black and racial and ethnic minority status. As visualized in the forest plots (Figures 6, 7, and 8), these patterns remained stable across different modeling approaches and years.

Some of the observed patterns, such as the shift toward the null and widening of credible intervals in spatial models, may reflect the presence of overdispersion or weak spatial correlation among neighboring counties. These factors may have contributed to weaker associations in spatial models. Future research could investigate the underlying drivers of overdispersion or weak spatial correlation in this context. It could also further explore the role of poverty and other structural determinants in shaping spatial patterns of opioid mortality.

Underreporting of opioid-related mortality or misclassification of social vulnerability measures may have influenced the observed associations. If reporting practices differ by geographic region, racial composition, or levels of social vulnerability, such bias could lead to inaccurate mortality estimates and obscure meaningful disparities. The relatively short study period (2020–2022) may also limit our ability to detect longer-term trends. As a result, the observed associations may differ in other geographic regions or when examined over longer time periods. Future work could address potential underreporting and incorporate spatio-temporal autocorrelation structures to better understand how opioid-related mortality evolves across counties over time.

A Appendix

A.1 Covariate Information

A.1.1 Poverty Rate

Definition. Percentage of people whose income in the past 12 months is below the poverty level in each county.

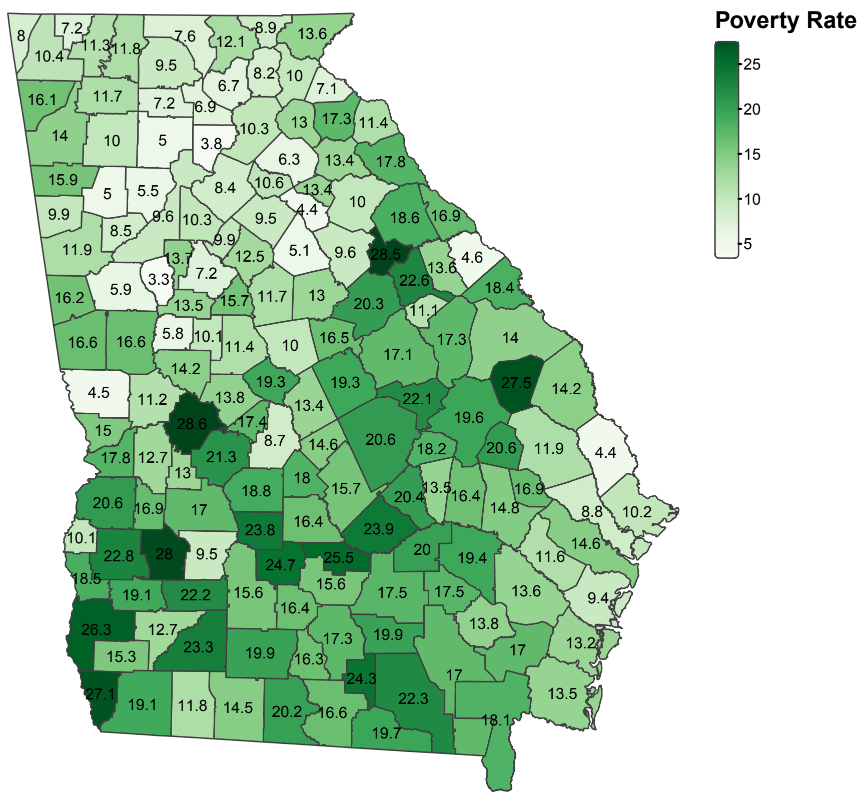

Figure A.1. County-Level Poverty Rates in Georgia (2020)

Taylor County had the highest poverty rate in Georgia at 28.6%, followed by Taliaferro (28.5%), Terrell (28.0%), Jenkins (27.5%), and Seminole (27.1%). A clear geographic pattern was observed, with southern and central Georgia experiencing relatively higher poverty rates than the northern regions.

A.1.2 Unemployment Rate

Definition. Unemployment rate after adjusting for outliers in each county.

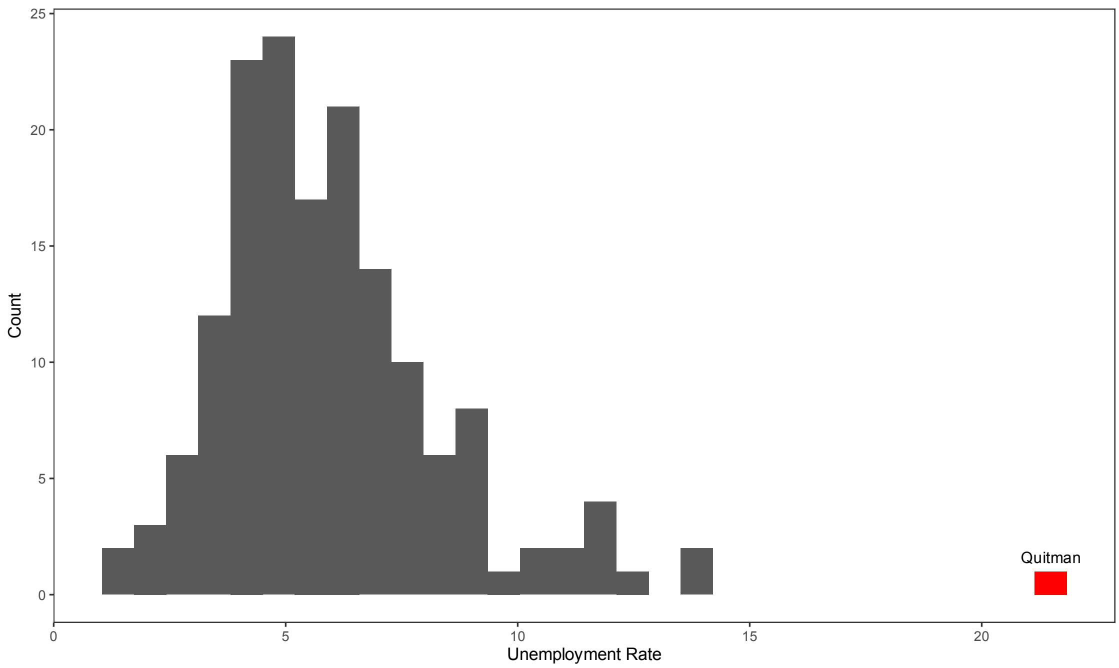

Figure A.2. Distribution of County-Level Unemployment Rates in Georgia (2020)

Quitman County reported a notably high unemployment rate of 21.4%, marking it as a clear outlier among Georgia counties. To address this extreme value, we replaced unemployment rates exceeding the 99th percentile with the 99th percentile value, ensuring a more balanced representation across counties.

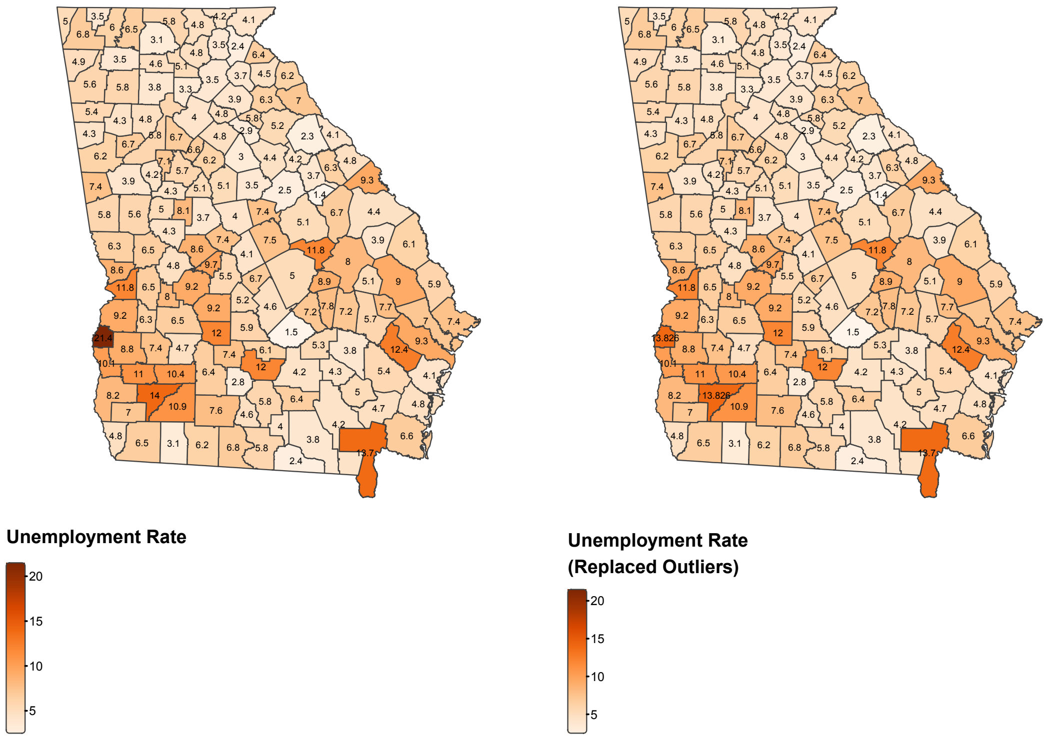

Figure A.3. County-Level Unemployment Rates in Georgia (2020), Before and After Outlier Adjustment

After outlier adjustment, Quitman and Baker counties have the highest unemployment rate at 13.83%, followed by Charlton (13.7%), Long (12.4%), and both Crisp and Irwin (12%). The geographic distribution of unemployment indicates a concentration of higher rates in rural and southern Georgia, whereas northern counties generally reported lower rates.

A.1.3 Vacancy Rate

Definition. Percentage of housing vacancy in each county.

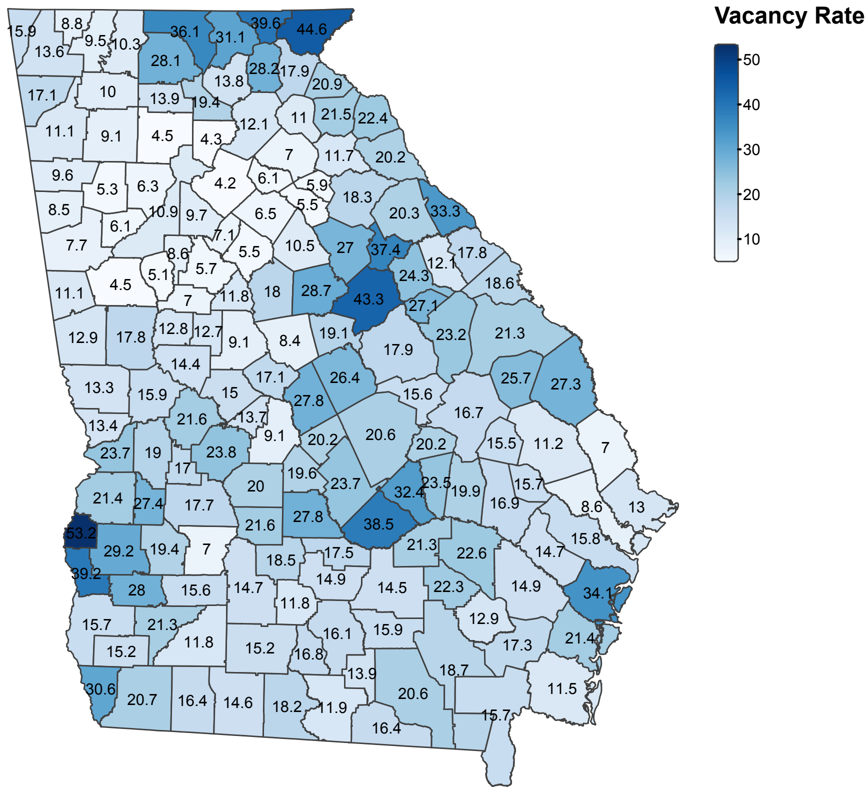

Figure A.4. County-Level Housing Vacancy Rates in Georgia (2020)

Quitman County had the highest housing vacancy rate in Georiga at 53.2% followed by Rabun (44.6%), Hancock (43.3%), Towns (39.6%), and Clay (39.2%) counties. Vacancy rates varied widely across the state, with higher concentrations in northern, central-eastern, and southwestern Georgia. In contrast, urban areas tended to have lower vacancy rates, likely reflecting greater population density and higher demand for housing.

A.1.4 Percentage of Population identifying as Black

Definition. Percentage of residents responding Black to the U.S. Census race question in each county.

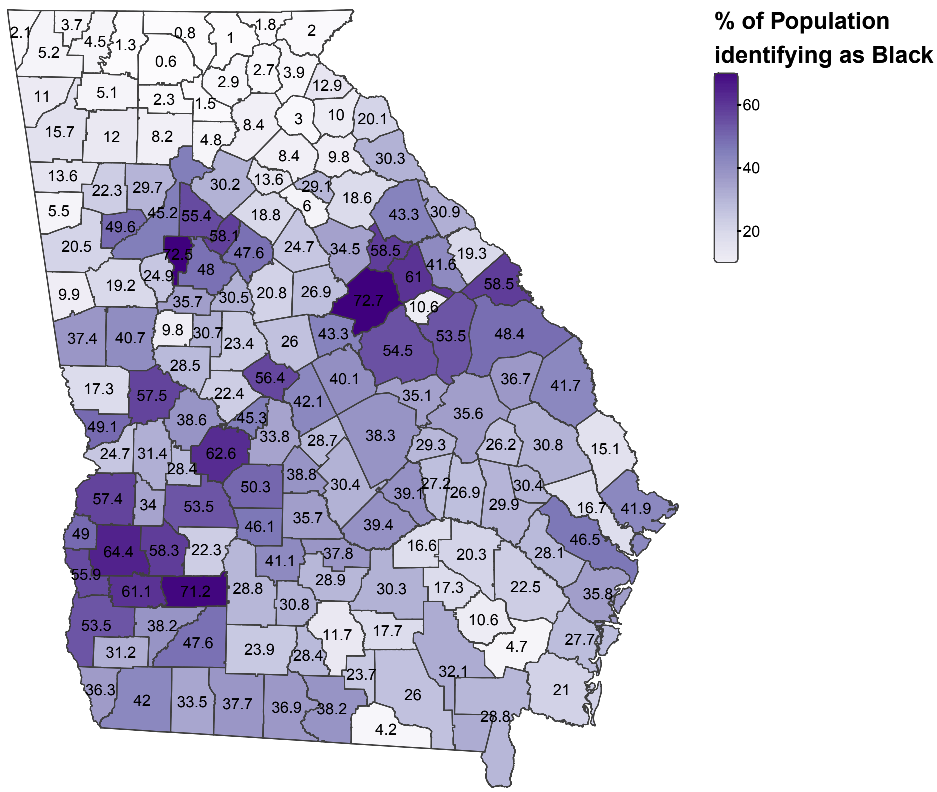

Figure A.5. County-Level Percentage of Black Population in Georgia (2020)

Hancock County had the highest percentage of Black population in Georgia at 72.7%, followed by Clayton (72.5%), Dougherty (71.2%), Randolph (64.4%), and Macon (62.6%) counties. Counties with higher percentages of Black population are predominantly concentrated in central and southwestern Georgia, as shown in the map.

A.1.5 Distance to Interstate

Definition. Distance from the county seat (administrative center) to the nearest interstate highway in each county.

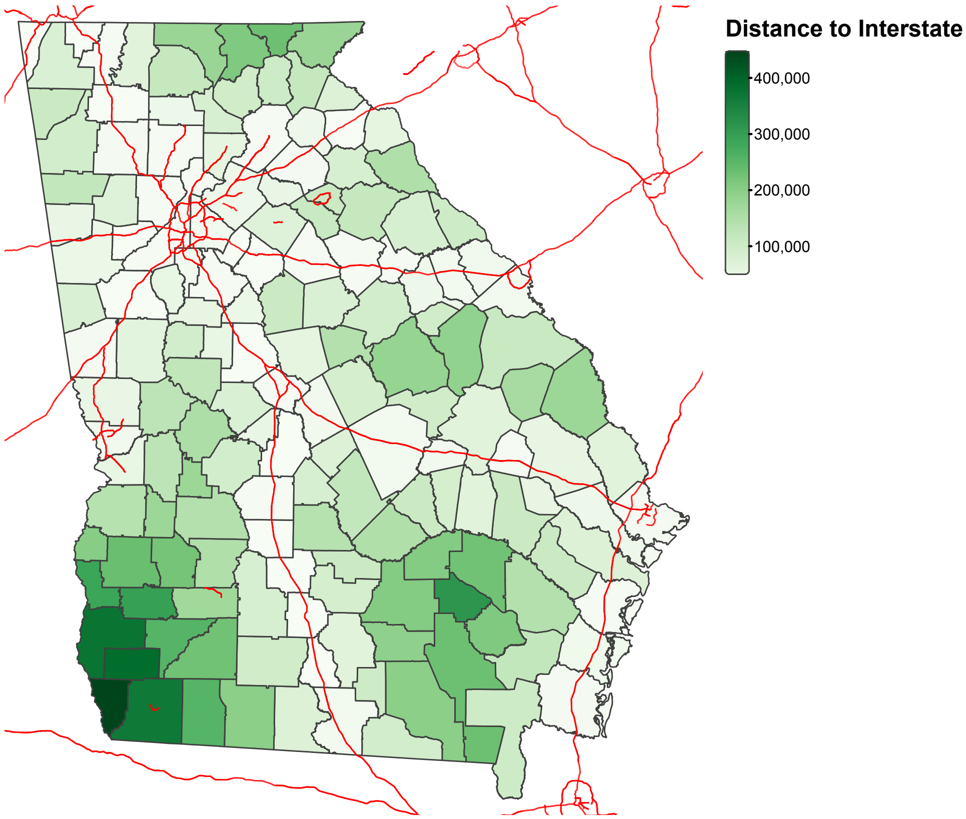

Figure A.6. County-Level Distance to Interstate in Georgia (2020)

Seminole County has the longest distance from its county seat to the nearest interstate, measuring 446,751.0 feet, followed by Miller (388,134.3 feet), Early (371,696.9 feet), Decatur (364,475.0 feet), and Bacon (313,543.6 feet) counties. Longer distances to interstates are generally observed in southwestern and southeastern rural counties in Georgia.

A.1.6 Distance to Treatment Center

Definition. Distance from the county seat (administrative center) to the nearest treatment center in each county.

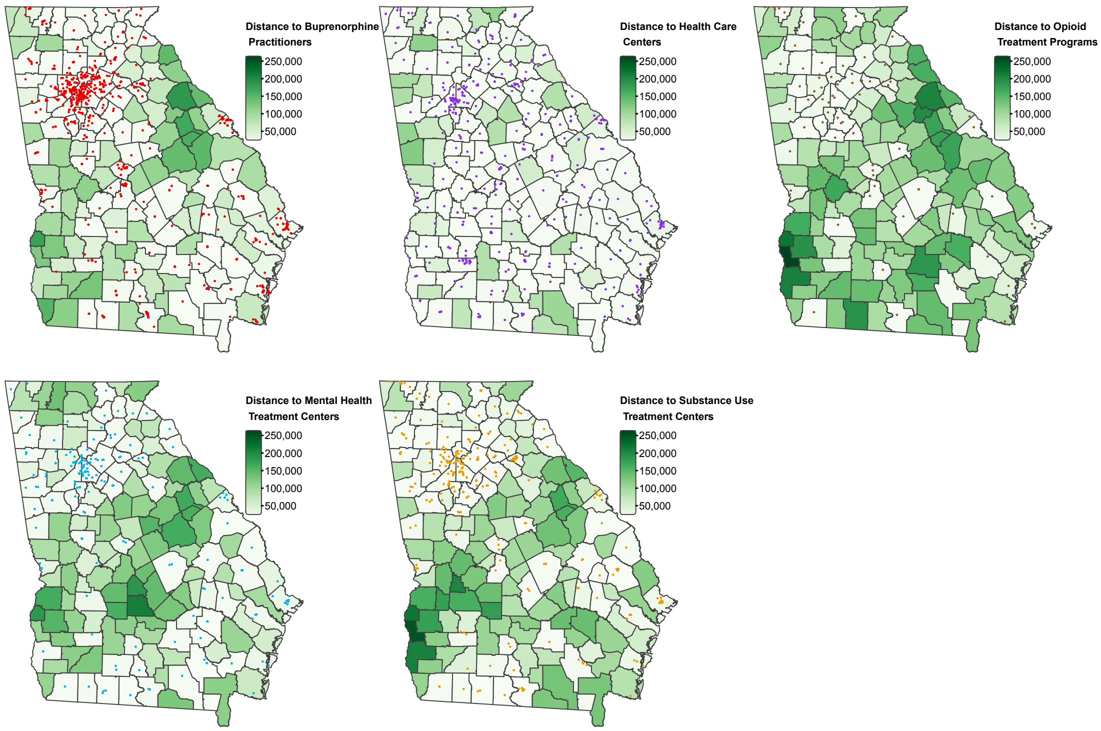

Figure A.7. County-Level Distance to Treatment Center and Facility Locations in Georgia

Note. Treatment center locations were obtained from the most recent available data at the time of analysis and may not reflect the exact 2020 distribution.

Wilkes County had the longest distance to the nearest treatment center at 82,403.2 feet, followed by Lanier (82,078.4), Morgan (81,930.1), Worth (75,062.8), and Echols (74,559.3) counties. Overall, counties in central and southeastern Georgia tend to have greater distances to treatment centers, indicating potential barriers to access in these regions.

A.1.7 Social Vulnerability Index (SVI)

Definition. For definitions and descriptions of the SVI domains, refer to the main text (Section 2).

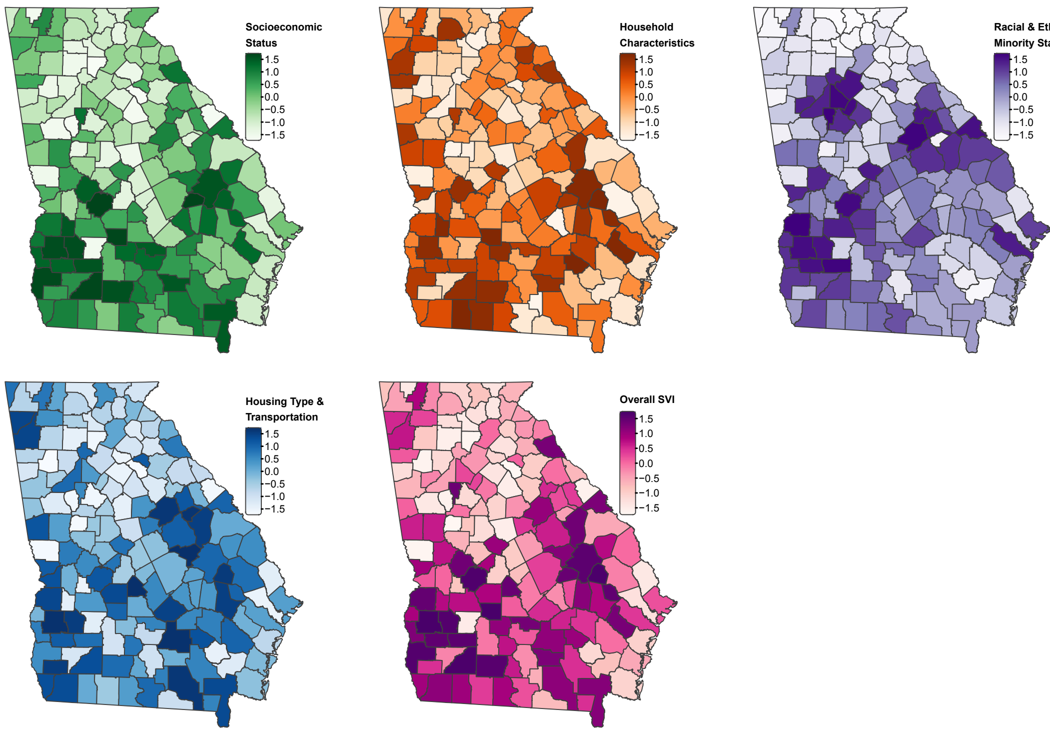

Figure A.8. County-Level Social Vulnerability Indices in Georgia (2020)

Overall, higher socioeconomic and household characteristic values are concentrated in the southern and southwestern parts of Georgia. Racial and ethnic minority populations are usually located in the southwestern, central, and some eastern counties. Additionally, higher values related to housing type and transportation are found in central, southeastern, and southwestern areas. The overall SVI is similarly elevated in these regions, especially in the southwestern and southeastern parts of the state.

A.1.8 Correlation Between Covariates

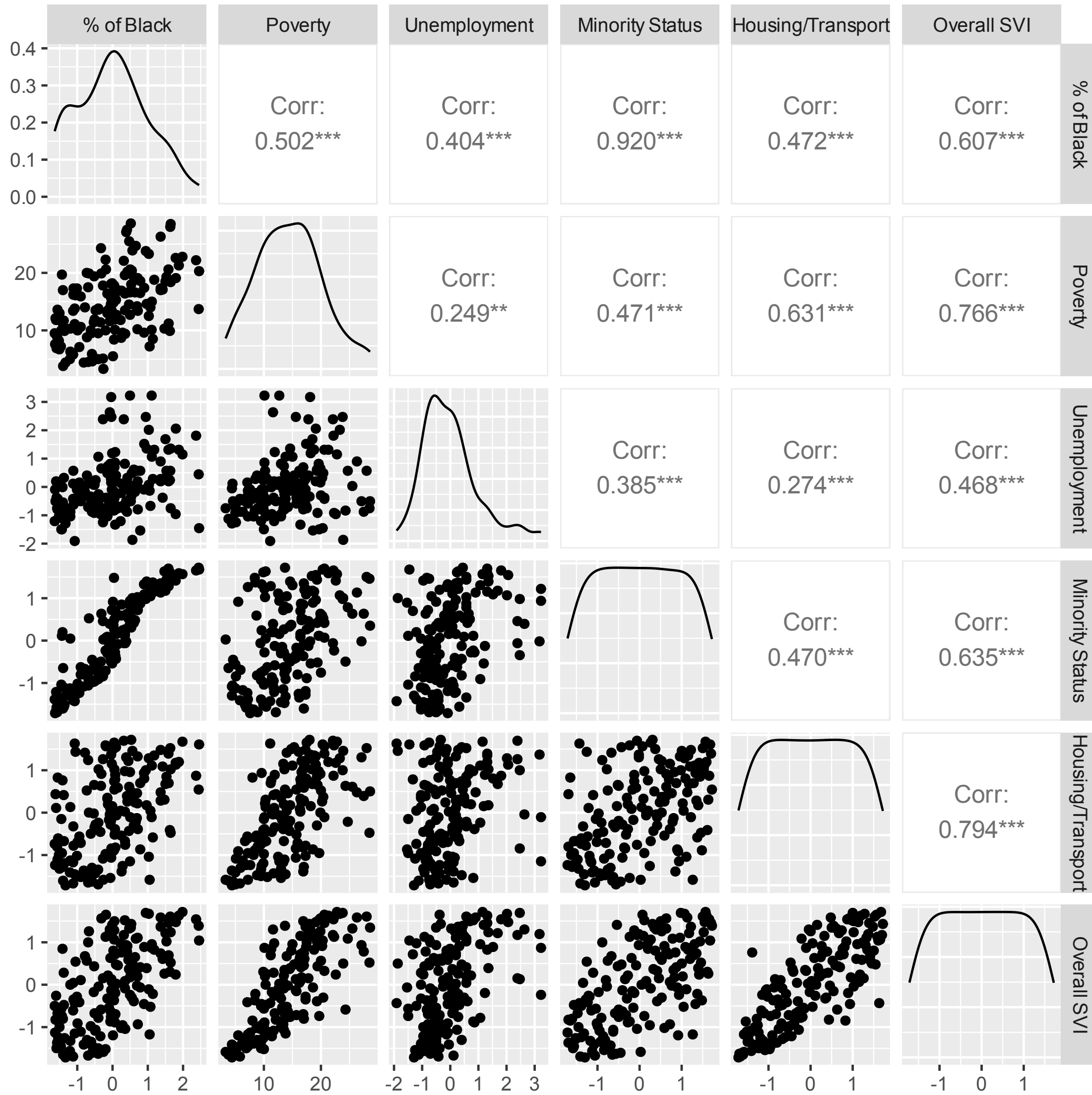

Figure A.9. Scatterplot Matrix of Selected Covariates

Note. Includes covariates that were selected based on statistical significance in univariate analyses.

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