

Accounting for Spatial Dependence in Neighborhood Perceived Social Isolation: An Analysis of Florida Census Tracts

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Research Article

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Abstract

Social isolation is a major public health concern, yet census-tract-level indicators often exhibit spatial autocorrelation that violates standard regression assumptions. We evaluated geographic patterns and urban-suburban-rural gradients of perceived social isolation across 5,122 Florida census tracts using 2024 CDC PLACES crude prevalence estimates, controlling for spatial dependence. Spatial structure was assessed via global Moran's I and Anselin's Local Indicators of Spatial Association (LISA). Tracts were classified as urban, suburban, or rural by population density. Population-weighted linear regression was used to compare ordinary least squares (OLS) with Conley spatial heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. Perceived social isolation showed substantial positive spatial clustering across Florida (Moran's I = 0.67, $p < 0.001$). LISA mapping revealed high-high hotspots in urban metropolitan belts and rural interior areas, whereas low-low cold spots clustered along coastal regions. Conventional population-weighted OLS models suggested small, statistically significant reductions in isolation for suburban areas (-1.37 percentage points; 95% CI: -1.61, -1.13) and rural tracts (-1.28 percentage points; 95% CI: -1.54, -1.02) relative to urban areas. However, accounting for spatial autocorrelation with Conley spatial HAC standard errors expanded the standard errors sixfold, making the urban-suburban and urban-rural differences statistically nonsignificant. Compared with regional spatial clustering, broad urbanicity categories explain little geographic variation in social isolation in Florida. Public health strategies and resource allocation should focus on localized spatial hotspots rather than broad administrative classifications.

49 Keywords: social isolation, urbanicity, spatial autocorrelation, census tracts, public
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Introduction

Defined as an absence of social contact, relationships, and meaningful interactions, social isolation poses a critical public health challenge that significantly increases the risks of all-cause mortality, stroke, cardiovascular disease, and cognitive decline (Henning-Smith et al., 2019; Holt-Lunstad et al., 2015; Leigh-Hunt et al., 2017; Menec et al., 2019; Sherman et al., 2024; Umberson & Donnelly, 2023). Epidemiological research has demonstrated that the health risks associated with social isolation are comparable to those associated with major lifestyle risk factors, including obesity and smoking (Earnest et al., 2026; Meehan et al., 2023; Umberson & Donnelly, 2023). Geographic and environmental contexts often shape isolation-related outcomes by affecting accessibility, mobility, neighborhood cohesion, and exposure to social opportunities (Card & Delgado-Ron, 2025; Meehan et al., 2023; Menec et al., 2019; Van Den Berg et al., 2026). As such, emerging studies continue to investigate how environmental and geographic factors influence isolation-related outcomes (Earnest et al., 2026; Finlay et al., 2025; Meehan et al., 2023; Wu et al., 2026). Consequently, mapping and evaluating the localized spatial distribution of social isolation is imperative for effective public health surveillance, the equitable distribution of healthcare resources, and the design of targeted community-level interventions.

Small-area indicators of social isolation, estimated with disease mapping, multilevel regression, and poststratification, can support public health planning by revealing local geographic disparities and priority areas for targeted intervention; identifying environmental inequities usually requires linking those indicators to contextual

measures of the built environment (Earnest et al., 2026; Lu & Kang, 2026; Saville, 2019; X. Zhang et al., 2015). However, tract-level measures often exhibit substantial spatial dependence: neighboring census tracts often share similar demographics, socioeconomic conditions, and built-environment characteristics. This spatial clustering violates the independent-and-identically distributed error assumption underlying conventional ordinary least squares (OLS) regression.

In small-area research, ignoring spatial autocorrelation can distort standard error calculations and inflate Type I error rates (F. Dormann et al., 2007). Additionally, census tracts vary in population size (U.S. Census Bureau, 2022). Therefore, giving each tract equal weight gives residents of less-populated tracts greater implicit weight than residents of more-populated tracts, potentially misrepresenting population-level experiences. To address these challenges, this study introduces a reproducible population-adjusted geospatial analysis framework to examine the geographic distribution and urbanicity gradients in perceived social isolation while accounting for spatial autocorrelation. This approach includes combining population-weighted linear regression with nonparametric Conley spatial heteroscedasticity- and autocorrelation-consistent (HAC) standard errors and uses Florida census tract data (Conley, 1999).

Materials and Methods

This study used publicly available data from the 2024 Centers for Disease Control and Prevention (CDC) PLACES, which is based on the 2022 Behavioral Risk Factor Surveillance System (BRFSS) data (Centers for Disease Control and Prevention, 2024). The data provide various health-related metrics for adults (at least 18 years of age). The

Florida Atlantic University Institutional Review Board (IRB) classified the cross-sectional ecological analysis as not involving human subjects (IRB2609340). Census tract perceived social isolation was measured using the 2024 CDC PLACES model-based crude prevalence estimate, derived from 2022 BRFSS data (Greenlund et al., 2022). The indicator represents the estimated percentage of adults who reported feeling socially isolated from others “always,” “usually,” or “sometimes.” Census-tract estimates were generated using multilevel regression and poststratification. Small-area estimates of perceived adult social isolation prevalence were assessed at the census tract level (expressed in percentage points) across 5,122 census tracts in Florida nested within counties. For tracts with missing values, the value was set to the mean. Tract- and county-level administrative boundaries were obtained as vector polygons, and geometric centroids were calculated to assign spatial coordinates (longitude and latitude). Adapted from the Centers for Medicare and Medicaid Services urbanicity classification for zip codes, the primary exposure was a study-defined three-category classification of urbanicity, using urban areas as the reference baseline alongside suburban and rural categories (Centers for Medicare & Medicaid Services, 2015). Census tracts were classified by population density thresholds: urban ($\geq 3,000$ persons/mi²), suburban ($\geq 1,000$ to $<3,000$ persons/mi²), and rural ($< 1,000$ persons/mi²).

Spatial Analysis

All analyses were performed using R (version 4.5.2). To visualize the unadjusted geographic distribution of perceived social isolation, tract-level prevalence estimates

were mapped. Because conventional choropleth maps overemphasize expansive rural tracts at the expense of densely populated urban centers, the adult population and isolation counts were aggregated at the county level to construct a density-equalizing cartogram using the Gastner–Newman diffusion algorithm (Gastner & Newman, 2004). This transformed county geometries proportionally to the adult population size while preserving regional topology.

Spatial dependence in tract-level isolation was assessed using global and local spatial autocorrelation statistics:

1. Global Moran's I: Evaluated under a row-standardized spatial weights matrix (**S**) constructed using a hybrid spatial weights framework. First, spatial proximity was established using a first-order queen contiguity matrix. For isolated polygons, k-nearest neighbors were used with Euclidean distance ($k = 6$). Significance was determined with a 0.05 threshold.
2. Anselin's Local Indicators of Spatial Association (LISA): Decomposed global autocorrelation into local spatial clusters (high-high hotspots and low-low coldspots) and spatial outliers (high-low and low-high), categorized at a pseudo $p < 0.05$ threshold with Benjamini–Hochberg false discovery rate correction applied to adjust for multiple testing.

To assess how spatial dependence affects inferential validity, two modelling specifications were evaluated. The first was a standard adult population-weighted OLS, which assumed independent and identically distributed errors:

$$\text{ISOLATION}_i = \beta_0 + \beta_1 \mathbb{I}(\text{Suburban}_i) + \beta_2 \mathbb{I}(\text{Rural}_i) + e_i \text{ (Eq. 1)}$$

weighted by the adult population w_i for each tract, using classical model-based standard errors. The identical population-weighted specification was subsequently re-estimated to accommodate spatial dependence using a nonparametric Conley spatial HAC variance–covariance estimator:

$$\hat{V}_{\text{Conley}} = (X'WX)^{-1} \left(\sum_{i=1}^N \sum_{j=1}^N w_i w_j e_i e_j x_i x_j' K(d_{ij}) \right) (X'WX)^{-1} \quad (\text{Eq. 2})$$

where N denotes the total census tract count across Florida, $W = \text{diag}(w_1, w_2, \dots, w_N)$; x_i and x_j represent row vectors containing the urbanicity indicators for census tracts i and j ; e_i and e_j correspond to the estimated OLS residuals for tracts i and j , respectively; d_{ij} indicates the geographic distance separating the centroids of tracts i and j ; and $K(d_{ij})$ signifies the kernel weight (Bartlett kernel) assigned to d_{ij} according to spatial distance up to a 50-mile cut-off threshold (sensitivity analyses were conducted using alternative distance cut-offs of 40, 60, and 70 miles). Statistical significance was set at an alpha level of 0.05 using a two-sided test.

To verify residual spatial dependence after model estimation, weighted regression residuals ($e_i^* = \sqrt{w_i} \cdot e_i$) were derived from the population-weighted OLS model to calculate a residual Moran's I statistic relative to $\mathbf{S}$. A statistically significant residual autocorrelation index served as empirical justification for unobserved spatial clustering in perceived social isolation prevalence after accounting for urbanicity.

Results

Across the 5,122 Florida tracts, the estimated adult-population-weighted mean isolation prevalence was 31.1% (SE = 0.49, 95% CI: 30.15, 32.05). Forty-five census tracts had

missing perceived social isolation values. Across the Florida tracts, 2273 (44.38%) were classified as urban, 1532 (29.91%) as suburban, and 1317 (25.71%) as rural.

The existence of global spatial autocorrelation in tract-level perceived social isolation prevalence was verified through Moran's I analysis (Moran's I = 0.67, expected I = -0.0002, variance = 6.61×10^{-5}). The resulting statistic showed pronounced positive spatial dependence ($z = 82.29$, $p < 0.001$), indicating that perceived social isolation rates across Florida census tracts are geographically nonrandom and exhibit strong regional clustering among tracts with comparable prevalence levels.

The estimated prevalence of perceived social isolation across Florida census tracts is shown in Figure 1. The estimated prevalence ranges from 19.5% to 48.4%. Visually, higher prevalence clusters appear in parts of northern Florida, pockets of the Panhandle, sections of inland central Florida, and select tracts in southern Florida. Additionally, census tracts with lower prevalence rates are scattered across select coastal and central corridors.

To account for uneven population distribution across the state, the prevalence of county-level perceived social isolation was visualized using a Gastner–Newman diffusion cartogram (Figure 2). By distorting geographic boundaries in proportion to the county population, this cartogram emphasizes densely populated counties while compressing sparsely populated counties. At the county level, the population-weighted perceived prevalence of social isolation ranged from 24.38% to 36.39%. Notably elevated rates clustered in major urban counties in northeastern and central Florida (Duval and Orange) and in rural counties statewide. Conversely, the lowest prevalence

rates clustered along parts of the southwestern Gulf Coast and in select central and northern counties (Sumter, Charlotte, Nassau, and Sarasota).

Anselin's LISA was calculated to examine local spatial patterns of tract-level perceived social isolation prevalence across Florida, with county boundaries overlaid for geographic context (Figure 3). For high-high spatial clusters (hotspots), the population-weighted average perceived social isolation prevalence was 37.1%, and low-low spatial clusters (coldspots) demonstrated a population-weighted average prevalence of 25.3%. Statistically significant high-high spatial clusters, indicating contiguous census tracts with elevated isolation prevalence, were identified within urbanized metropolitan corridors, most notably around Jacksonville in northeastern Florida, the greater Orlando area in central Florida, parts of south-central Florida, and localized clusters throughout the Panhandle. In contrast, low-low spatial clusters comprise low-prevalence tracts surrounded by adjacent low-prevalence areas and cluster along the southwestern Gulf Coast, west-central coastal areas north of Tampa Bay, and specific coastal stretches along the southeastern Atlantic seaboard.

Differences in the prevalence of perceived social isolation across urbanization designations were assessed by comparing a population-weighted OLS regression model (Model A) with a Conley spatial HAC model (Model B) that accounts for spatial dependence (Table 1). In Model A, the baseline perceived social isolation in urban census tracts was estimated at 31.84% (95% CI: 31.68, 31.99%), with the scores of the suburban and rural areas demonstrating statistically significant decreases of 1.37 percentage points (95% CI: -1.61, -1.13) and 1.28 percentage points (95% CI: -1.54, -1.02), respectively. However, correcting for spatial autocorrelation under Model B

increased standard errors by approximately sixfold, yielding wider confidence intervals that included zero for both suburban (estimate: -1.37, 95% CI: -2.8, 0.06) and rural (estimate: -1.28, 95% CI: -2.92, 0.36) tracts. Consequently, while point estimates suggest slightly lower isolation outside urban cores, these geographic differences are not statistically distinguishable after accounting for spatial clustering. Sensitivity checks using spatial bandwidth cut-offs of 40, 60, and 70 miles yielded consistent results across specifications. A minor divergence emerged at the 70-mile spatial threshold, where the suburban reduction of 1.37 percentage points became statistically significant. Consequently, these outcomes highlight modest sensitivity to spatial-range parameters within the variance estimation framework.

To confirm residual spatial dependence after model estimation, weighted regression residuals were evaluated using Moran's I test under a randomization assumption (Moran's I = 0.66, expected I = -0.0002, variance = 6.60×10^{-5}). The resulting statistic showed marked positive spatial autocorrelation ($z = 80.92$, $p < 0.001$), providing empirical justification that urbanicity designations do not fully capture unobserved spatial clustering in the prevalence of perceived social isolation at the census tract level in Florida.

Discussion

By evaluating the geographic distribution and urbanicity gradients in the prevalence of perceived social isolation among adults across 5,122 Florida census tracts while adjusting for spatial dependence, this study yielded three core insights. First, tract-level prevalence exhibited marked, nonrandom spatial clustering across the state (Moran's I

= 0.67), featuring pronounced high-high hotspots in the Jacksonville and greater Orlando metropolitan corridors, sections of south-central Florida, and regions of the Panhandle, alongside low-low coldspots along the southwestern Gulf Coast and select west-central and southeastern coastal areas. Second, standard population-weighted OLS estimates indicated that compared with urban baselines, suburban and rural tracts experienced small but statistically significant reductions in isolation prevalence (ranging from 1.3 to 1.4 percentage points). Third, accounting for spatially autocorrelated error structures with Conley spatial HAC standard errors attenuated these geographic contrasts, making them statistically indistinguishable from zero, while residual spatial autocorrelation remained largely unchanged from the baseline (0.66 versus 0.67). Collectively, these findings show that observed urban–suburban and urban–rural differences are subtle relative to broader regional spatial dependence, indicating that simple three-tier urbanicity categories capture little geographic variance in perceived social isolation.

Crucially, the main methodological takeaway is the approximately sixfold expansion of standard errors when the Conley spatial HAC covariance matrix is applied. Because point estimates remained invariant between Model A and Model B, this shift in statistical inference stems entirely from variance-estimation adjustments rather than changes in effect magnitude (Conley, 1999). Heuristically, a sixfold increase in standard error reflects a variance ratio near 36 to 40, indicating that the effective sample size across all 5,122 census tracts provides information comparable to approximately 130 to 145 independent spatial observations regarding urbanicity gradients. Consequently, contiguous census tracts contain substantial redundant information, showing that

conventional independent-error assumptions produce artificially narrow confidence intervals.

These observations align with findings in the spatial econometric literature: regression analyses on highly autocorrelated datasets often produce inflated t-statistics, and elevated residual Moran's I suggests that nominal statistical significance can be deceptive (Kelly, 2019). The current empirical investigation reveals the same methodological vulnerability in public health surveillance: an analytical specification that shows pronounced urban–suburban–rural disparities under conventional testing ($p < 0.001$) loses statistical significance after adjusting for spatial dependence.

Consequently, for small-area epidemiological investigations that often compare tract-level health metrics with administrative geographic categories, these results highlight the need to consistently assess residual spatial autocorrelation and use spatially adjusted variance estimators as standard practice.

Two primary analytical constraints contextualize these overarching inferences. First, although sensitivity evaluations across spatial bandwidths were generally consistent, the suburban disparity was statistically significant only at the expanded 70-mile threshold. Because Conley spatial HAC standard errors do not invariably scale monotonically alongside spatial cut-offs, this localized divergence highlights that the suburban coefficient resides on the margin of standard statistically significant thresholds; presenting the comprehensive standard error profile across alternative distance thresholds offers greater empirical utility than relying on an isolated cut-off does. Second, nonparametric Conley adjustments may remain somewhat anti-conservative in scenarios with pronounced spatial clustering or extended geographic

ranges (Kelly, 2019), and spatial HAC estimation frameworks may not sufficiently guard against spurious regressions when spatial autocorrelation approaches nonstationary behavior (Müller & Watson, 2024).

Geographic patterns of perceived social isolation across Florida depart substantially from a simplistic urban-to-rural continuum. High-high spatial clusters emerged within major metropolitan centers (such as Duval and Orange counties) alongside sparsely populated rural regions, whereas low-low coldspots were concentrated primarily throughout coastal jurisdictions. These complex spatial dynamics mirror broader empirical literature, which yields inconsistent conclusions regarding urban–rural differences. For instance, national evaluations of older populations have shown that compared with urban cohorts, rural inhabitants maintain broader interpersonal networks and lower objective isolation, despite reporting higher feelings of exclusion (Henning-Smith et al., 2019), whereas complementary analyses often find no statistically significant urban–rural differences in some social isolation measures (Abshire et al., 2022; Card & Delgado-Ron, 2025; Lynch et al., 2021; Naito et al., 2021). Similarly, expert consensus syntheses note that empirical evidence surrounding rurality and perceived social isolation remains inconclusive (Committee on the Health and Medical Dimensions of Social Isolation and Loneliness in Older Adults et al., 2020). This investigation builds on prior work within a statewide, small-area framework and shows that urbanicity categories are limited indicators for identifying geographic concentrations of perceived social isolation in Florida for the year 2022. Future research should also examine social determinants of health (SDOH), policy contexts, and environmental

315 conditions in high-high and low-low clusters to better understand perceived social
316 isolation and inform targeted interventions.

317 Implications for Public Health Practice

318 Within public health surveillance and policy frameworks, targeted intervention strategies
319 often rely heavily on inferential modelling outcomes. However, when standard
320 specifications omit adjustments for spatial dependence, they can produce artificially
321 narrow confidence intervals that project nominal disparities that may attenuate once
322 spatial autocorrelation is properly accounted for. Relying on uncorrected model
323 specifications risks misdirecting critical public health investments and undermining
324 population impact by diverting localized resources from communities facing genuine,
325 spatially concentrated health-related burdens.

326 Methodologically, this analytical paradigm integrates population weights, spatial
327 autocorrelation metrics, nonparametric Conley HAC variance estimators, distance-cut-
328 off sensitivity checks, and residual dependence evaluations, offering a replicable
329 framework for broader public health surveillance using free, open-access data and
330 software. Because the CDC PLACES repository tracks small-area indicators across
331 multiple SDOH, future empirical work can use this methodology to assess whether
332 regional disparities in food access, transit limitations, or housing instability also
333 attenuate after adjusting for underlying spatial dependence.

334 These empirical outcomes provide actionable guidance for public health surveillance
335 and resource deployment. Because social disconnection is associated with mortality
336 risks comparable to those associated with conventional clinical risk factors (Holt-

Lunstad et al., 2015), national directives emphasize strengthening local social infrastructure and engaging health systems to reduce isolation (Office of the Surgeon General (OSG), 2023). Allocating interventions based solely on broad administrative urbanicity classifications misaligns intervention targets with spatial risk profiles. Conversely, LISA hotspot analyses delineate localized geographical clusters, such as concentrated high-prevalence census tracts within the Jacksonville and Orlando metropolitan regions, offering precise spatial targets where community-based initiatives, clinical social prescribing, and specialized nursing outreach can maximize population impact. Furthermore, density-equalizing cartograms show that populous urban centers carry a substantial share of the total social isolation burden, a geographic reality that traditional choropleth maps obscure by overemphasizing expansive, low-density rural tracts.

Strengths and Limitations

The key methodological strengths of this investigation include comprehensive statewide coverage across more than 5,000 Florida census tracts, the integration of analytical population weights to mirror true demographic distributions, the implementation of rigorous global and local spatial autocorrelation diagnostics featuring false discovery rate adjustments, and a robust empirical comparison between weighted OLS and spatially corrected inferential models supplemented by multithreshold bandwidth sensitivity evaluations.

Several analytical limitations contextualize these empirical findings. First, tract-level prevalence metrics represent model-based small-area estimates rather than direct

empirical observations; consequently, observed spatial structures partly inherit the operational framework of the underlying multilevel regression and poststratification process. Second, given the cross-sectional ecological design, observed tract-level patterns cannot support individual-level inferences or causal claims about urbanicity. Third, parameter estimates remain sensitive to bandwidth cut-offs, and the modifiable areal unit problem and geometric centroid assignments may imperfectly capture population distribution within geographically expansive rural tracts. Finally, statewide findings from a single cross-sectional cycle may not be extrapolated to other geographic regions or time periods, especially given evolving post-pandemic social connection patterns.

Conclusions

In summary, tract-level adult perceived social isolation metrics across Florida exhibit marked, nonrandom spatial clustering, with localized high-high hotspots emerging within both major metropolitan corridors and rural interior regions. While standard population-weighted OLS estimates indicated minor reductions in perceived social isolation prevalence in suburban and rural tracts relative to urban baselines, these contrasts attenuated and became statistically indistinguishable from zero after adjusting for spatial dependence using Conley spatial HAC standard errors. Significant residual spatial autocorrelation persisted after estimation, indicating that simple urbanicity categories capture little geographic variance in perceived social isolation. Methodologically, these outcomes highlight the need for small-area epidemiological investigations to consistently assess residual spatial autocorrelation and use spatially robust variance

estimators because failing to account for spatial structure yields artificially narrow confidence intervals and misleading statistical inference. From a public health surveillance perspective, resource allocation and targeted community interventions should be informed by local spatial cluster identification and population-weighted disease burden rather than broad administrative urban-suburban-rural classifications.

Abbreviations

BFRSS, Behavioral Risk Factor Surveillance System; CI, Confidence Interval; HAC, Heteroscedasticity- and Autocorrelation-Consistent; IRB, Institutional Review Board; LISA, Local Indicators of Spatial Association; OLS, Ordinary Least Squares; OSG, Office of the Surgeon General; SDOH, Social Determinants of Health; SE, Standard Errors

Declarations

Ethical Approval

The Florida Atlantic University Institutional Review Board (IRB) classified the cross-sectional ecological analysis as not involving human subjects (IRB2609340).

Availability of Data and Material

Data are openly available at <https://www.cdc.gov/places/>

398 **Competing Interests**

399 The author is an employee of Florida Atlantic University and reports no financial
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404 **Author Contributions**

405 The author contributed to the study's conception or design and to the acquisition,
406 analysis, or interpretation of the data. The author drafted or critically revised the
407 manuscript and gave final approval of the version submitted for publication. The author
408 agrees to be accountable for all aspects of the work, ensuring integrity and accuracy.

409 **Declaration of Generative Artificial Intelligence and Artificial** 410 **Intelligence-Assisted Technologies in the Writing Process**

411 During the development of this manuscript, the author utilized Google Gemini (gemini-4
412 Argon) and Perplexity AI to refine linguistic clarity and enhance overall readability. The
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Table 1. Regression Estimates: Perceived Social Isolation (Outcome)

Term	Estimate	Model A: Population-		Model B: Conley Spatial	
		Weighted OLS		HAC OLS	
		Std. Error	95% CI	Std. Error	95% CI
Intercept	31.84	0.08	(31.68, 31.99)	0.86	(30.16, 33.51)
Suburban vs Urban	-1.37	0.12	(-1.61, -1.13)	0.73	(-2.8, 0.06)
Rural vs Urban	-1.28	0.13	(-1.54, -1.02)	0.84	(-2.92, 0.36)

Notes: The dependent variable is Social Isolation. Model A reports standard errors and 95% confidence intervals from a population-weighted OLS regression.

Model B estimates standard errors using the nonparametric Conley spatial HAC variance–covariance estimator to correct for spatial dependence.

HAC = heteroskedasticity- and autocorrelation consistent

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Figure 1. Spatial Distribution of Perceived Social Isolation Prevalence across Florida
Census Tracts

Perceived social isolation prevalence, Florida census tracts

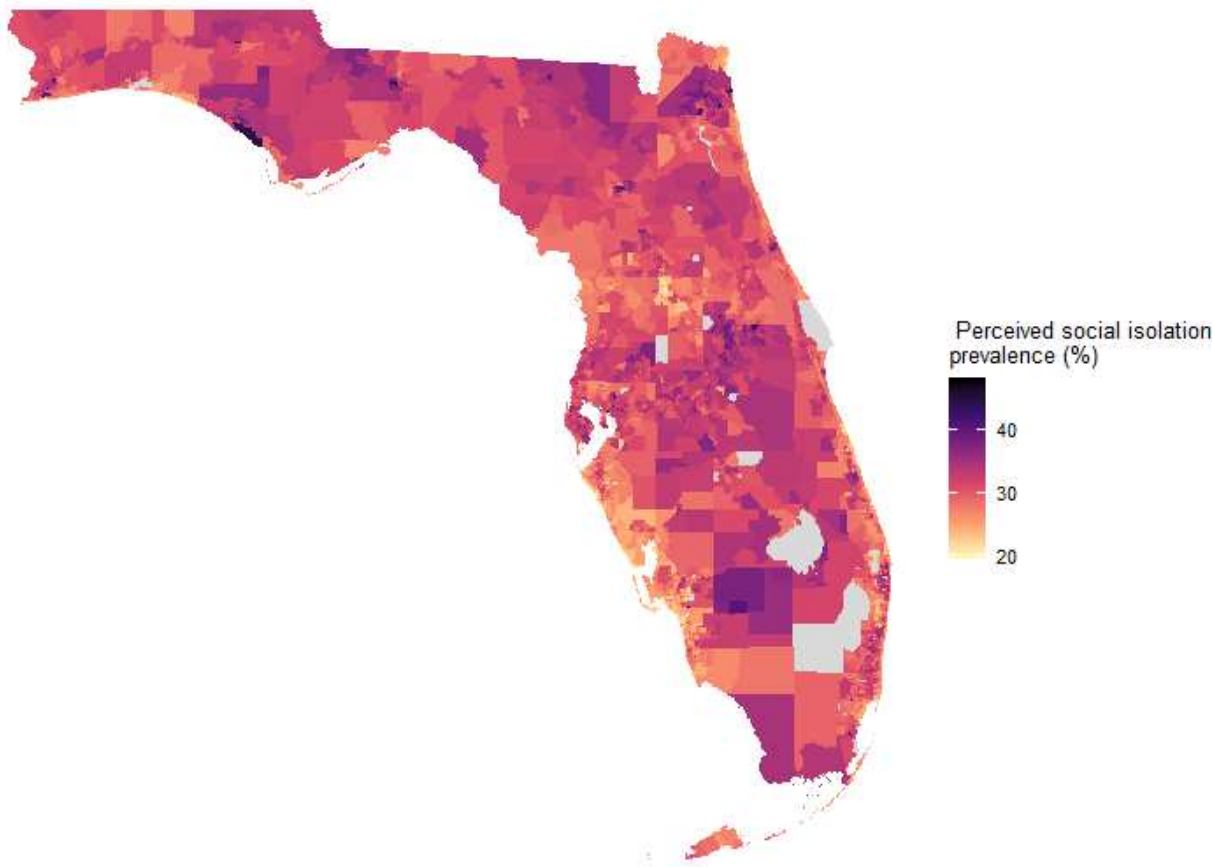


Figure 1. Geographic variation in model-based prevalence estimates of adult perceived social isolation across 5,122 Florida census tracts based on 2022 BRFSS data. The percentages range from 19.5% to 48.4%, with elevated prevalence clustered across northern Florida, parts of the Panhandle, inland central regions, and localized southern census tracts, while lower prevalence rates are scattered along select coastal corridors.

Figure 2. Population-Weighted County-Level Perceived Social Isolation Prevalence in Florida via a Gastner–Newman Diffusion Cartogram

Perceived social isolation prevalence by county, (Gastner-Newman diffusion algorithm)



Figure 2. The prevalence of county-level adult perceived social isolation across Florida was visualized through a Gastner–Newman diffusion cartogram, with geographic boundaries distorted proportionally to adult population size. Prevalence rates range from 24.4% to 36.4%, highlighting elevated clustering in major metropolitan counties (Duval and Orange) and rural jurisdictions, alongside a lower prevalence along the southwestern Gulf Coast and select central-northern counties.

Figure 3. Anselin's Local Indicators of Spatial Association (LISA) Cluster Map of Perceived Social Isolation Prevalence in Florida Census Tracts

LISA clusters for perceived social isolation prevalence with county boundaries

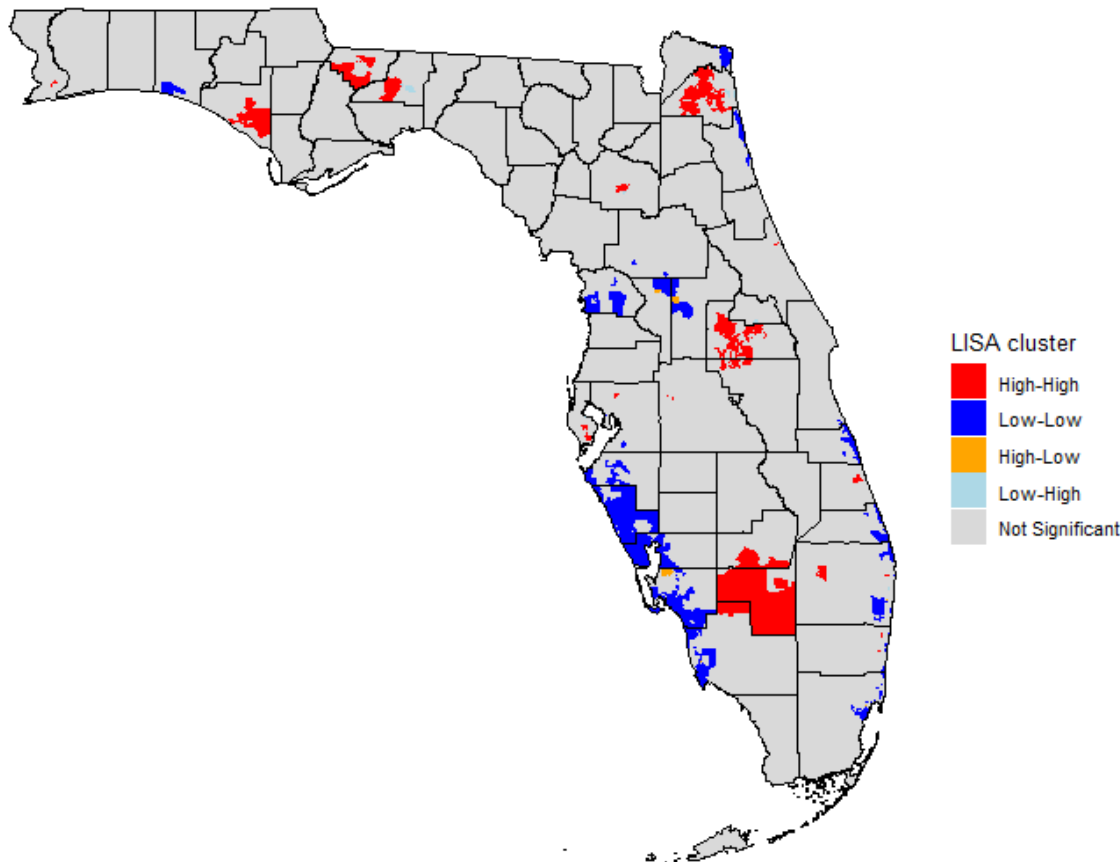


Figure 3. Local spatial clustering of adult perceived social isolation prevalence across Florida census tracts with county boundaries overlaid for geographic context. Statistically significant high-high spatial clusters (hotspots, shown in red) are concentrated in metropolitan corridors, including Jacksonville, Orlando, south-central Florida, and parts of the Panhandle. Low-low spatial clusters (coldspots, shown in blue) are located primarily along the southwestern Gulf Coast and west-central coastal areas north of Tampa Bay, and stretches are selected along the southeastern Atlantic seaboard.