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Identifying Geographic Disparities in Suicide Determinants Across United States Counties with Spatial Modeling

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Abstract: The United States is experiencing an unprecedented rise in suicide rates amid a growing mental health crisis. While many public health studies examine contextual factors associated with suicide using individual or group-level data, these approaches often overlook spatial dynamics that could reveal geographic and scale-dependent variations. County-level research on suicide determinants in the U.S. remains limited, leaving significant gaps in understanding geographic disparities. Therefore, this study leverages spatial analysis and modeling to identify clusters of high and low suicide rates across the U.S., and explores the geographic variations in the associations between social determinants and suicide to better understand these patterns. Using Local Moran's I for cluster and outlier analysis, alongside comparisons between Ordinary Least Squares (OLS) and Multiscale Geographically Weighted Regression (MGWR) models, the analysis evaluates the relationships between age-adjusted suicide rates and 17 independent variables across 2,410 U.S. counties. Results uncover geographic heterogeneity, with higher suicide rates concentrated in the Western U.S. and several determinants demonstrating spatially varying effects. For instance, the percent of veteran population is a statistically significant predictor across all counties, with the strongest effects in the Northeast. Other variables show more localized patterns: living alone is significant in 14% of counties, mainly in the Southwest, and American Indian population is significant in 17% of counties, primarily in the West. Our findings highlight the non-stationarity of suicide determinants across geographic space and scales, providing a data-driven framework to identify geospatial disparities and inform the development of targeted intervention strategies to reduce suicides in specific locations.

Keywords: Multiscale Geographically Weighted Regression, suicide, mental health, spatial heterogeneity, spatial analysis

1. Introduction

The United States is facing a growing mental health crisis where suicide has emerged as a critical public health issue and ranks among the top 10 leading causes of death in the country (Ivey-Stephenson, 2017). Between 2000 and 2018, suicide rates increased by 37%, followed by a 5% decrease from 2018 to 2020. However, an unprecedented peak in suicides began in 2021, and reached an all-time high in 2022 (Weiss, 2023). Certain demographic groups are particularly vulnerable, with American Indian or Alaskan Native individuals experiencing age-adjusted rates per 100,000 of 28.1, White individuals at 17.4, and males at 22.8—four times higher than females (CDC, 2023). These alarming statistics highlight the disparities within the population and the pressing need to address the underlying causes of poor mental health and suicide.

Geographically, suicide rates vary widely across states, ranging from 6.21 per 100,000 in Washington, D.C., to 32.34 in Wyoming, with a median rate of 15.3 per 100,000 in 2021. From 2011 to 2021, 12 states witnessed a surge in suicide rates of 25% or more, with Alaska experiencing the largest increase at 54%, followed by South Dakota (48%), Nebraska (43%), and Montana (42%) (Saunders and Panchal, 2023). Although disparities in age-adjusted suicide rates between states are well-documented, a more comprehensive understanding of geographic variation can be achieved through county level analysis. For example, Rossen et al. (2018) found that between 2005 and 2015, suicide rates increased by at least 10% in 99% of U.S. counties, with 87% of these counties experiencing increases of 20% or more, and the highest rates were consistently observed in the western U.S., excluding southern California and parts of Washington. Yet, there remains a limited understanding of the associations between contextual factors and suicide rates at the county level across the entire country (Steelesmith et al., 2019).

Given the geographic distribution in suicides, as observed in Figure 1, it is essential to consider spatial non-stationarity when examining determinants at the county-level. Spatial non-stationarity refers to the statistical variation in relationships between certain variables over geographic space (Fotheringham et al., 1996). To address this, spatial regression approaches such as geographically weighted regression (GWR) (Brunsdon et al., 1998) have been used to investigate the spatially varying relationships between risk factors and suicide across U.S. counties. Trgovac et al. (2015) revealed that social isolation factors, including divorce rates, migration, and unemployment, had varying influences on male suicide rates, with strong positive associations observed in the Southwest, Upper Northeast, and parts of the Midwest. Tran and Morrison (2020) observed that income inequality was negatively associated with suicide rates in some central U.S. counties but positively associated in others. Ha and Tu (2018) identified a significant positive association between altitude and suicide rates, particularly in northern regions, northern plains, and the Southeastern U.S.

Despite the valuable insights offered by GWR in better understanding spatial non-stationarity between county-level suicide rates and different risk factors, these studies overlook the possibility that determinants of suicide rates may emerge at different spatial scales. For instance, on a more local scale, counties or cities may have varying degrees of access to mental health resources, such as counseling services or support groups. On a larger regional scale, states may implement different policies related to mental health care funding, suicide prevention programs, and access to crisis intervention services. Multiscale geographically weighted regression (MGWR) extends GWR to investigate how determinants of suicide vary across geographic space and at different spatial scales (Fotheringham et al., 2017). To our knowledge, MGWR has yet to be applied to investigate non-stationarity in suicide rates across space and scale.

This knowledge gap presents an opportunity to leverage spatial regression techniques to examine contextual factors contributing to spatial disparities in suicide rates and the potential non-stationarity of these relationships across geographical areas and scales. This geospatial cross-sectional study applies MGWR alongside a traditional regression model to analyze the non-stationarity in the relationship between county suicide rates (2016-2020) and various social determinants. These include factors related to community and social context, economic stability, education, food security, healthcare systems, physical environments, and sociodemographics across U.S. counties. By spatially assessing these associations and exploring their variations across space and scale, this study has significant implications for identifying locations where targeted suicide intervention programs and resources can have the greatest impact.

2. Methods

2.1 Data and Variable Selection

This study relies on two data repositories including County Health Rankings & Roadmaps (CHR) and United States Census Bureau's American Community Survey (ACS). The CHR data repository contains variables for many measures of health factors and outcomes collected from a variety of sources (The University of Wisconsin Population Health Institute, 2023). The ACS provides annual data on social, economic, housing, and demographic characteristics data through ongoing surveys of the U.S. population (US Census Bureau, 2024). It's important to recognize that data collection, whether through a census or survey, involves lag times. As a result, this study uses the most recent reliable data available, with the ACS providing 2017-2021 5-year estimates, and CHR data ranging from 2020 to 2022, depending on the specific variable and its source.

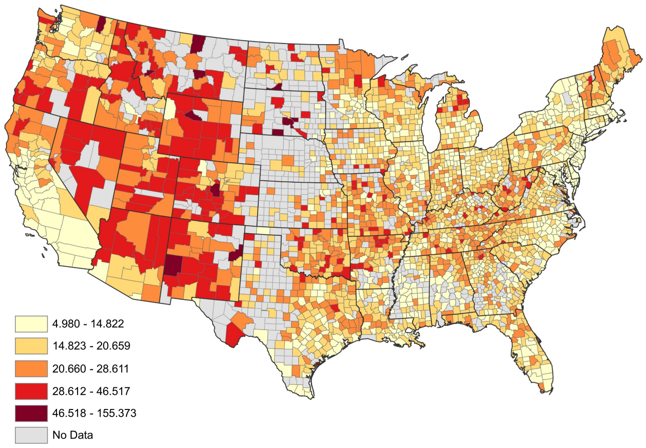

Figure 1. Spatial patterns of suicide rates across contiguous U.S. counties. Suicide rates are defined as the number of deaths due to suicide per 100,000 population (age-adjusted) from 2016-2020.

The outcome, county-level suicide rates, is expressed as the number of suicide-related deaths (age-adjusted) per 100,000 in the county between 2016 and 2020. This data was obtained from CHR, who transformed data from National Center for Health Statistics - Mortality Files; Census Population Estimates Program into county level estimates. This analysis focuses on the continuous U.S., thus excluding counties that belong to Alaska or Hawaii. U.S. counties with missing values for suicide mortality rates (N=693) were also excluded from the analysis, resulting in a total of 2,410 counties.

Independent variables were selected based on known social determinants of health (SDoH), including economic stability, neighborhood and physical environment, education, food, community and social context, and healthcare system (RTI Health Advance, 2023). Based on the availability of data at the county level, we included at least one variable from each SDoH category. Sociodemographic variables such as race, gender, age, and marital status, although not considered a SDoH, were also included considering their strong associations with suicide risk (CDC, 2023).

Initially, we compiled 34 county-level variables, of which 17 were selected for analysis (see Table 1) based on expert knowledge and collinearity and significance measures. Missing values in the independent variables were addressed using the Fill Missing Values tool in ArcGIS Pro, following the standard practice of not exceeding 5% of the dataset. Spatial autocorrelation testing revealed clustering in the 3 variables with missing values, which led to the application of K-nearest neighbors and averaging of neighboring values for imputation (Heymans and Twisk, 2022). To allow for comparison, the final 17 selected variables were normalized using Box-Cox transformation and standardized to have a mean of 0 and a standard deviation of 1.

Table 1. County-aggregated independent variables (determinants), grouped by SDoH categories, analyzed in this study.

Variable	Description
Community and Social Context	
Living Alone	Percent of population living alone
Smart Phone Access	Percent of households without access to a smart phone
Veteran	Percent of veteran civilian population aged 18+
Economic Stability	
Unemployed	Percent of population unemployed
Education	
Bachelor's Degree	Percent of population aged 25+ who completed at least a bachelor's degree
Food	
Food Insecurity	Percent of population who did not have access to a reliable source of food
Healthcare System	
Mental Care Providers	Number of mental health providers per 100,000 population
No Health Insurance	Percent of population with no health insurance
Poor Mental Health Days	Average number of mentally unhealthy days reported in past 30 days (age-adjusted)
Primary Care Physicians	Number of primary care physicians per 100,000 population
Physical Environment	
Rural	Percent of land considered rural area
Socioeconomic	
American Indian/Alaskan Native	Percent of American Indian and Alaskan Native alone population
Black	Percent of Black population alone
Dependent	Percent of population within dependent age groups: individuals under 18 or over 65
Divorced	Percent of divorced population
Female	Percent of Female population
White	Percent of White population alone

2.2 Spatial Statistical Analyses

ArcGIS Pro (version 3.2.0) was used for the following spatial modeling tasks: Local Moran's I, Ordinary Least Squares (OLS) regression, and MGWR. A cluster and outlier analysis using the Local Moran's I method (Anselin, 1995) reveals the spatial patterns and heterogeneity in suicide rates across U.S. counties. An OLS regression model was then applied to the county-level data, where the selected 17 independent variables were regressed against age-adjusted suicide rates to assess the direction, strength and significance of the relationships. The OLS regression model provides a single set of coefficients describing the global association between each of the independent variables and county suicide rates for the 2,410 U.S. counties analyzed in this study. Finally, MGWR (Fotheringham et al., 2017) was used to explore potential geographic variations in the relationships between the independent variables and suicide.

The MGWR model is expressed below (Fotheringham et al., 2017):

$$y_i = \sum_{j=1}^{M} \beta_{bw_j} X_{ij} + \varepsilon_i. \tag{1}$$

For the 17 independent variable assessed in this study (M), MGWR computes a local regression model for each U.S. county (i), where X_{ij} represents the jth independent variable for county i. This model incorporates a bandwidth size specific to each independent variable, indicating the number of neighboring counties from which data is borrowed in the computation. The bandwidth for each variable is determined using the Golden Section Search algorithm—an iterative optimization process that explores various bandwidth values within a specified range to minimize the corrected Akaike Information Criterion (AICc). The coefficient estimation (β_{bw_j}) for each independent variable j and county i is calculated using this optimal bandwidth size ($_{bw}$). The bw_j in β_{bw_j} reflects the spatial scale of the relationship between the independent variable and suicide rates, with smaller bandwidths indicating more local variation and larger bandwidths suggesting broader, regional influences. ε_i is the error term for county i, capturing the variability in suicide rates not explained by the independent variables. Results from the MGWR model are compared to those from the global OLS model to identify variables exhibiting spatial non-stationarity and to highlight geographic variability in these relationships.

3. Results

3.1 Cluster and Outlier Analysis

The Local Moran's I statistic identified spatial clusters and outliers among counties based on their age-adjusted suicide rates (Figure 2). The counties with high suicide rates that are near other counties with high suicide rates (i.e., high-high; HH cluster) are concentrated in the western part of the United States, including states like Wyoming, Utah, and Colorado. Another grouping of HH clustering counties stretches from Oklahoma through Arkansas and Missouri, with an additional belt extending from West Virginia into Eastern Tennessee. Counties with low suicide rates that are near other counties with low suicide rates (i.e., low-low; LL cluster) are predominantly found along the eastern coast of the United States, with a significant concentration in states such as New York and New Jersey. This pattern also extends to the northern Midwest, covering states like Ohio, Indiana, and Michigan. However, in comparison to the high suicide rates in the western half of the country, the western border of California exhibits low suicide rates. Counties that have statistically high or low suicide rates relative to their spatial neighbors, (i.e., low-high; LH outlier, high-low; HL outlier) are scattered throughout the country. For example, three counties in California are HL outliers (dark red in Figure 2), indicating higher suicide rates compared to neighboring counties classified as LL clusters. Conversely, a few counties in West Virginia are LH outliers (dark blue in Figure 2), with lower suicide rates relative to nearby counties considered as HH clusters.

3.2 OLS and MGWR Models

Table 2 presents the results from both the OLS regression and MGWR models. The second column shows the coefficient from the OLS regression model, which explains the global relationship between each independent variable and suicide rates across the 2,410 counties analyzed in this study. An asterisk (*) represents a statistically significant association at a 95% confidence level. Since the MGWR model calculates a coefficient for each county, columns 3

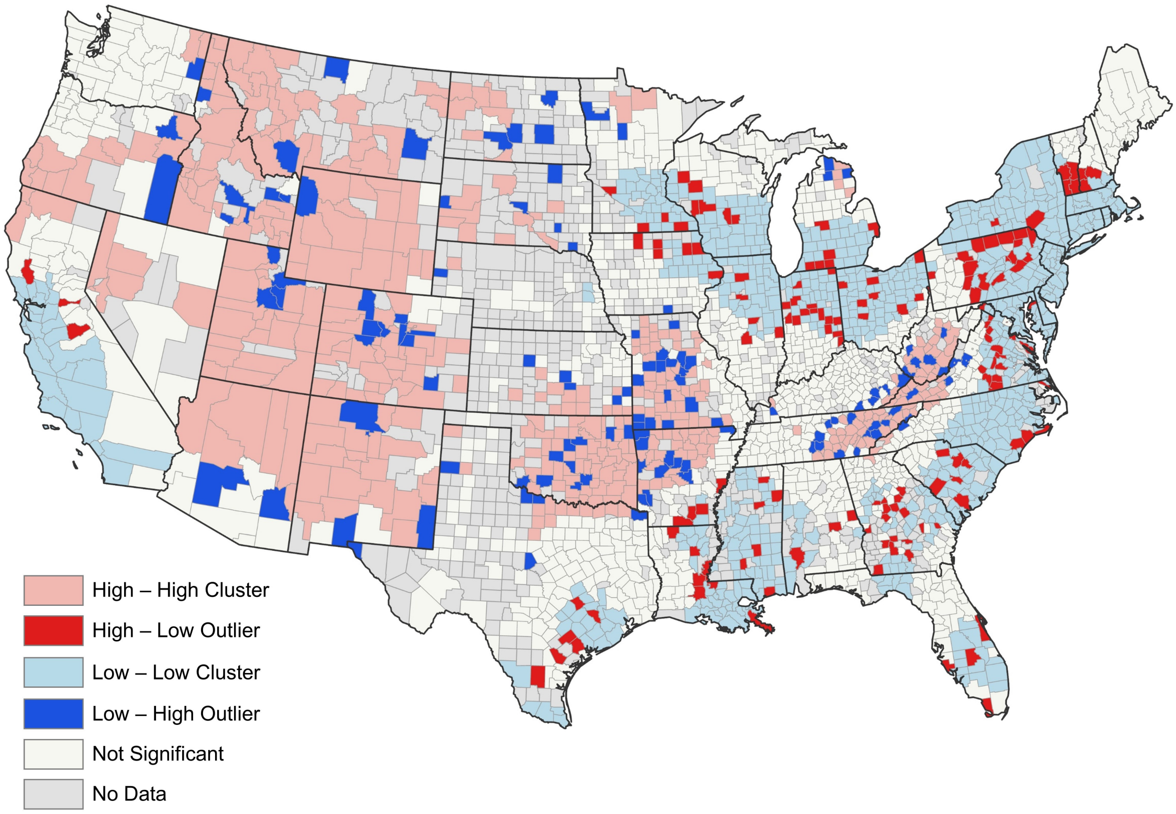

Figure 2. Cluster or outlier types based on age-adjusted suicide rate defined by Local Moran's I statistic. Patterns include clusters of high (light red) or low (light blue) suicide rates, indicating the county is surrounded by neighboring counties with similar rates. Additionally, outliers involve cases where a county with high suicide is predominantly surrounded by low suicide (dark red) and vice versa (dark blue). Statistical significance is determined at the 95% confidence level. An interactive map of the results can be accessed at: https://arcg.is/0i018f1.

through 9 in Table 2 provide summary statistics for these coefficients, along with the count of counties where the independent variable was a significant predictor of suicide at a 95% confidence level. The OLS model produced a multiple R-squared value of 0.4660 (adjusted R-squared: 0.4622), indicating that 46.60% of the variance in suicide rates is collectively explained by the independent variables. However, by relaxing the assumption of stationarity both across space and at different scales, the MGWR model performed better, with a higher multiple R-squared value of 0.6977, or adjusted R-squared of 0.6654. Additionally, all independent variables had a Variance Inflation Factor (VIF) below 4, suggesting that multicollinearity is not a concern and that the predictor variables are not strongly correlated in the regression models.

The OLS and the MGWR models show consistent directional associations between the independent variables and suicide rates. In general, both models identified positive significant coefficients for living alone, veteran population, lack of health insurance, poor mental health days, rural living, American Indian or Alaskan Native population, dependent population, and divorce rate. These coefficient values indicate that for each one-unit increase in the independent variable (recall standardization), the suicide rate changes by the corresponding coefficient value in that specific county. For example, the OLS model shows that a one standard deviation increase in the percentage of the population living alone is associated with a 0.129 standard deviation increase in suicide rates. However, the MGWR model demonstrates that the magnitude of this relationship differs for each county. In contrast, both models identified significant negative coefficients for smartphone access, Black population, and female population, suggesting that increases in these variables are associated with decreases in county suicide rates.

While OLS computes a single global coefficient for each variable, MGWR computes a local coefficient for each county so that the non-stationarity in the relationship between the independent variables and county suicide rates across space and scales can be examined (see Figure 3). In Figure 3, counties with statistically significant coefficients ($p < 0.05$) are outlined in red. Counties without a red outline do not exhibit a statistically significant relationship between the given independent variable and suicide rates. For example, significant coefficients for the association between poor mental health days and suicide rates (Figure 3A) are stronger in western U.S. counties, with a cluster of coefficients between 0.20 and 0.25 observed in the Midwest (e.g., Iowa, Northern Missouri). In contrast, the highest significant coefficients for living alone (Figure 3B) are found in parts of the Southwest, including New Mexico, Arizona, and Colorado, as well as in southwestern Virginia counties extending into North Carolina.

Table 2 also presents the proportion of neighboring counties included in the MGWR coefficient calculations for each independent variable (i.e., bandwidth), indicating the

Table 2. Comparison of OLS and MGWR model results for each standardized independent variable. The second column displays the coefficients from the OLS model, with an asterisk (*) denoting statistically significant associations at a 95% confidence level. Columns 3–9 present the MGWR model results, including the mean coefficient, standard deviation, minimum coefficient, median coefficient, maximum coefficient, the number and percentage of neighbors used in the computation, and the number and percentage of significant counties for each variable.

	OLS Model	**MGWR Model**						
Standardized Variable	**Coefficient**	**Mean**	**Standard Deviation**	**Minimum**	**Median**	**Maximum**	**Neighbors (% of Counties)**	**Significance (% of Counties)**
Community and Social Context								
Living Alone	0.129*	0.083	0.0664	-0.0503	0.0792	0.2517	377 (15.64)	328 (13.61)
Smart Phone Access	-0.092*	-0.0508	0.0563	-0.1666	-0.0478	0.0329	1072 (44.48)	317 (13.15)
Veteran	0.213*	0.1475	0.0427	0.0839	0.1316	0.2325	1583 (65.68)	2410 (100.00)
Economic Stability								
Unemployed	-0.007	0.0106	0.0638	-0.2464	0.0127	0.1493	346 (14.36)	0 (0.00)
Education								
Bachelor's Degree	-0.052	-0.1248	0.0439	-0.18197	-0.1334	-0.0292	1072 (44.48)	1110 (46.06)
Food								
Food Insecurity	0.054	0.0929	0.0547	0.0101	0.0866	0.2036	1021 (42.37)	566 (23.49)
Healthcare System								
Mental Care Providers	0.016	0.0005	0.0018	-0.0048	0.0006	0.0049	2410 (100.00)	0 (0.00)
No Health Insurance	0.153*	0.0095	0.0568	-0.107	0.0067	0.105	806 (33.44)	18 (0.75)
Poor Mental Health Days	0.090*	0.0992	0.0352	0.0492	0.096	0.1601	1021 (42.37)	1118 (46.39)
Primary Care Physicians	0.008	-0.0064	0.0035	-0.0112	-0.0075	0.0023	2410 (100.00)	0 (0.00)
Physical Environment								
Rural	0.160*	0.1027	0.0876	-0.0996	0.1179	0.3183	327 (13.57)	235 (9.75)
Socioeconomic								
American Indian/Alaskan Native	0.107*	0.0482	0.1001	-0.1658	0.0379	0.2533	327 (13.57)	412 (17.10)
Black	-0.305*	-0.0681	0.0356	-0.1512	-0.0664	-0.0054	1154 (47.88)	191 (7.93)
Dependent	0.094*	0.0974	0.0383	0.0353	0.0935	0.163	1501 (62.28)	1335 (55.39)
Divorced	0.106*	0.0282	0.0935	-0.1682	0.033	0.2872	346 (14.36)	238 (9.88)
Female	-0.070*	-0.0301	0.0414	-0.1389	-0.0164	0.04	939 (38.96)	210 (8.71)
White	0.021	0.2168	0.2515	-0.5175	0.2079	0.8281	69 (2.86)	384 (15.93)

spatial scale at which these variables are associated with suicide rates. For instance, the veteran population variable uses 65.68% of counties as neighbors, indicating a closer alignment with global models (Figure 3C), whereas the American Indian or Alaskan Native population variable uses 13.57% of counties as neighbors, reflecting more localized models and greater spatial variability (Figure 3D). While the global OLS model finds that the relationships between these variables and suicide rates are significant, MGWR finds that they are significant only for some locations (see Table 2, Significance (% of Counties)). For example, a statistically significant relationship between food insecurity and suicide rates is found in 23.49% of counties (566 counties; Figure 3E), while the dependent population shows significance in 55.39% of counties (1,335 counties; Figure 3F). There is one exception to this, where the MGWR model revealed that veteran population is a significant predictor of county suicide rate for 100% of counties. This is evident in Figure 3C, where all 2,410 counties are outlined in red, indicating statistical significance.

Both the OLS and MGWR models agree that unemployment, the ratio of primary care physicians, and mental health care providers are not statistically significant predictors of county suicide rates. However, where the OLS model finds that attainment of a Bachelor's degree, food insecurity, and White population were not significant, the MGWR shows that they are significant in 46%, 24%, and 16% of counties, respectively (see Table 2, Significance (% of Counties)). For an interactive visualization of the MGWR results for all independent variables, refer to the ArcGIS Online StoryMap: https://arcg.is/0i018f1.

4. Discussion

This study uses spatial modeling, specifically MGWR, to explore the non-stationarity of county-level associations between social determinants and suicide rates across space and scale in the U.S., with the goal of gaining insights into suicide clusters and outliers identified through Moran's I analysis. To our knowledge, this is the first study to comprehensively leverage these methods to assess the relationship between multiple determinants and suicide rates from a geographic perspective across the country at the county level. While results align with established public health research — showing that higher prevalence of sociodemographic factors such as dependent individuals (under 18 or over 65) and American Indian or Alaskan Natives (CDC, 2023), as well as social factors like veteran status, isolation (i.e., living alone), food insecurity, and mental health issues (RTI Health Advance, 2023) are correlated with increased suicide rates — the novelty of this work lies in uncovering how these relationships vary across U.S. counties and at different scales.

Both the OLS and MGWR models resulted in similar outcomes, but MGWR offered a deeper understanding of how these associations differ geographically. For instance, MGWR revealed a significant positive association between veteran population and suicide rates across all U.S. counties, with the strongest relationship observed in the Northeast (Figure 3C). In contrast, MGWR revealed that the association between American Indian and Alaskan Native population and suicide rates is significant and positive primarily in the western U.S., with the highest coefficients around New Mexico and Colorado (Figure 3D). While previous studies have explored spatial non-stationarity in county-level suicide risk factors, they did not examine relationships across multiple spatial scales. This study addresses this gap by modeling spatial relationships at various scales, showing, for instance, that the association between dependent populations and suicide rates shows less geographic variability (MGWR used 62% of counties), while the relationship between the White population and

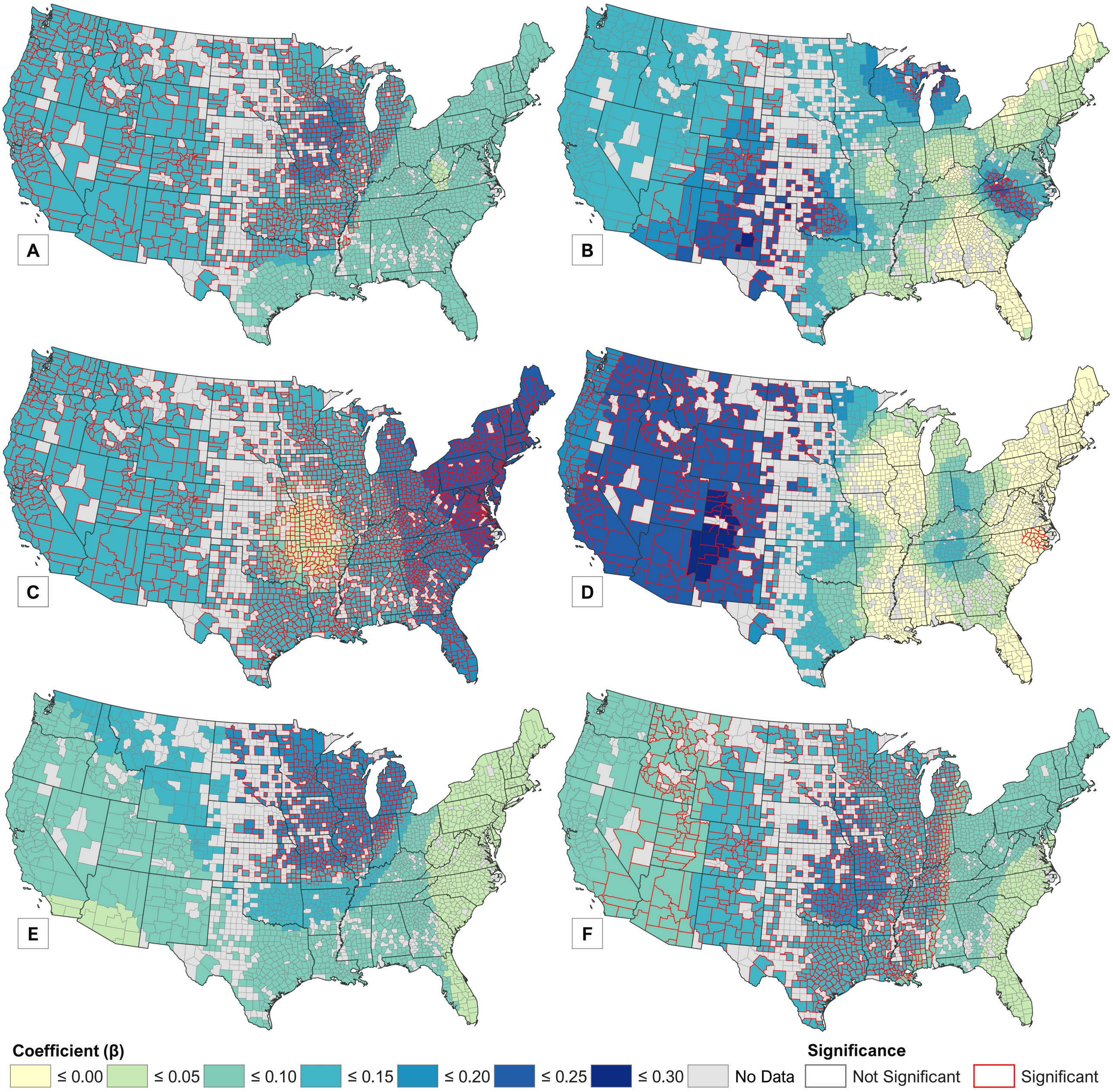

Figure 3. MGWR results showing the spatial variability of coefficients for selected independent variables and their statistical significance in explaining suicide rates across U.S. counties, featuring (A) poor mental health days, (B) living alone, (C) veteran, (D) American Indian or Alaskan Native, (E) food insecurity, and (F) dependent population. The colors within each county represent the coefficient values, while county boundaries indicate statistical significance. Counties outlined in red are statistically significant at the 95% confidence level, while those outlined in gray are not statistically significant. Counties with no available suicide data (not included in the study analyses) are fully shaded in gray. Additional map visualizations of MGWR results for all independent variables are available at https://arcg.is/0i018f1.

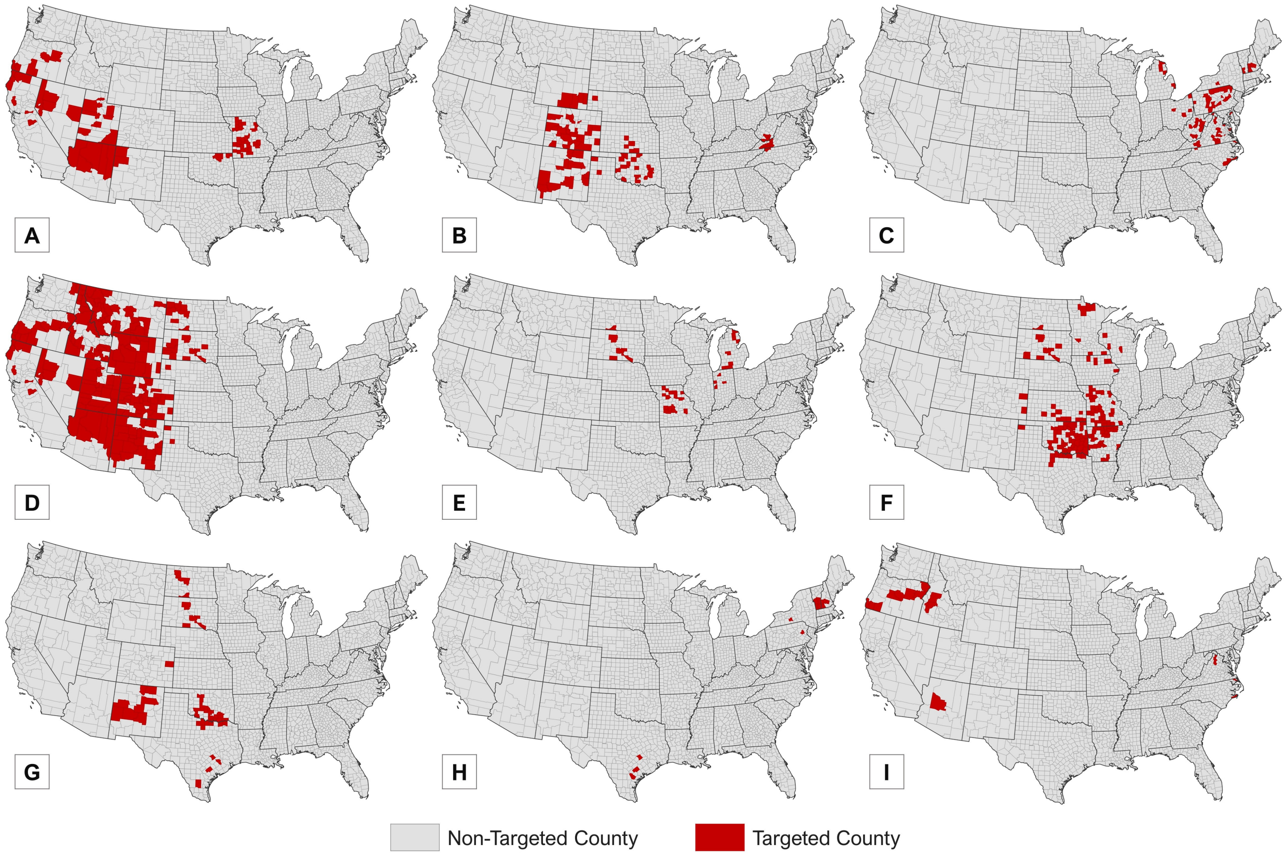

Figure 4. Counties identified for targeted suicide prevention interventions based on: (A) poor mental health days, (B) living alone, (C) veteran population, (D) American Indian or Alaskan Native population, (E) food insecurity, (F) dependent population, (G) rural area, (H) divorced population, and (I) White population. Counties highlighted in red meet the all of the following analysis criteria: high values for the given variable, high clusters or outliers of suicides, and high statistically significant MGWR coefficients. Each of these maps can be viewed interactively through: https://arcg.is/0i018f1.

suicide rates exhibits greater variability (MGWR used only 3% of counties).

Generally, MGWR results provide valuable insights for designing suicide prevention strategies. For instance, the low variability in the coefficients measuring the relationship between veteran populations and suicide rates across the U.S., combined with a large neighborhood size (MGWR used 66% of neighbors) and 100% statistical significance, suggests that nationwide interventions may be effective. However, other factors, such as demographic disparities, may require different approaches. For example, MGWR revealed high variability in coefficients related to demographics, such as the White and American Indian and Alaskan Native populations, with smaller neighborhood sizes and fewer statistically significant counties. These findings indicate that geographically targeted interventions would be more effective for addressing disparities among these populations.

To better synthesize the spatial heterogeneity revealed by MGWR and pinpoint areas for geographically tailored interventions, an overlay analysis was conducted (Figure 4). This analysis identifies counties where a high population of a certain variable (greater than the mean), a cluster or outlier of high suicide rates (determined through Moran's I analysis, see Figure 2), and high MGWR coefficients that are statistically significant (mean +1 standard deviation and p-value < 0.05) intersect. This approach connects MGWR findings with suicide clusters and outliers, providing insights into the determinants driving higher suicide rates. For instance, analysis of veteran population data revealed counties in the northeastern U.S. where veteran prevalence coincides with high suicide outliers and significant MGWR coefficients above 0.19 (Figure 4C). This suggests that the veteran population plays a role in observed outliers of high suicide, highlighting the need for more strategically allocated programs tailored to veterans in these areas despite the overall need for nationwide strategies.

Other determinants also exhibit geospatial disparities. Poor mental health days correlate strongly with clusters of high suicide rates in Missouri and Southwestern states like Arizona (Figure 4A), while living alone also significantly impacts southwestern counties and some parts of West Virginia (Figure 4B). The American Indian and Alaskan Native population is a major determinant in many western U.S. counties (Figure 4D). Food insecurity (Figure 4E), although less consistently associated with high suicide rates, has localized significance in states like Missouri, Michigan, and South Dakota. Factors like dependent population (4F) and rural area (4G) have a stronger influence in central regions of the U.S. Disparities for some determinants, such as the divorced population (4H), are more spread out and less prominent, though they do help explain some suicide outliers in the Northeast. Similarly, the White population (4I) aligns with higher suicide rates in a few counties in Oregon and Virginia. However, some regions, such as the high-suicide belt in West Virginia, remain inadequately explained by the analyzed variables, suggesting the need for further investigation into additional factors.

Overall, these findings highlight the importance of geographically targeted interventions based on specific determinants, such as addressing mental health in Missouri and Arizona, focusing on individuals living alone in New Mexico and Colorado, and refining veteran programs for select northeastern counties. However, it is important to recognize that suicide is a complex and multifaceted issue, shaped by a variety of factors. The findings of this study do not suggest direct causality between the analyzed variables and suicide rates. While the variables were analyzed independently, there is evidence suggesting that they may interact and have multiplicative effects. This is evident in the overlap of some results in Figure 4, where factors like living alone, the dependent population, and rural areas contribute to suicide clusters in Oklahoma.

The methods presented in this study provide a data-driven framework that other researchers can adopt to address limitations and pursue future spatial research on suicides or other public health issues. One challenge is the differing time periods of the independent variables and suicide data from 2016–2020, which may not fully capture the increase in suicides since 2021 due to the unavailability of updated datasets. This research establishes a strong foundation for region-specific analyses, such as those focused on areas like the West Virginia-to-Tennessee region or demographic groups like males and individuals aged 65+, particularly at finer spatial scales, such as census tracts, where data is available. These methods can also be applied to better understand spatial non-stationarity in other health challenges, such as substance abuse or crime. While this study focuses primarily on spatial modeling and analysis, building upon its findings can enhance its strategic value for public health officials, making the results more relevant for decision-making and supporting the development of more informed, geographically targeted suicide prevention strategies.

5. Conclusion

This geospatial cross-sectional study advances the understanding of spatial variation and scale in suicide determinants across 2,410 U.S. counties, offering insights into identified clusters and outliers of suicide rates and introducing a novel spatial perspective on suicides within the public health domain. Results show that factors such as sociodemographics, mental distress, and loneliness are significantly associated with suicide rates, aligning with existing literature. However, through spatial modeling and analysis techniques, our study extends this knowledge by exploring the influence of spatial variation and scale in these relationships and identifying geographic disparities where targeted interventions would be most beneficial. Overall, these findings make a significant contribution by offering insights into the spatial dynamics of suicide rates and their social determinants across the U.S., thus highlighting the importance of considering local context and spatial variations when developing suicide prevention strategies. These insights provide a valuable foundation for creating more effective geographically targeted suicide prevention initiatives aimed at reducing suicide rates and improving mental health outcomes nationwide.

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