TERRORISM AND TARGETED VIOLENCE IN THE UNITED STATES

Alternative Scales of Extremism:

The Relationship Between Scale and Predictive Measures of Extremism in the United States

Report to the Department of Homeland Security

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NATIONAL CONSORTIUM FOR THE STUDY OF TERRORISM AND RESPONSES TO TERRORISM
University of Maryland, College Park, MD
301.405.6600 • www.start.umd.edu

ABOUT THIS REPORT

The authors of this report are Marcus A. Boyd, Senior Researcher at START, and Samuel Henkin, Senior Researcher at START. Questions about this report should be directed to Marcus A. Boyd at boydma@umd.edu.

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ABOUT START

The National Consortium for the Study of Terrorism and Responses to Terrorism (START) is a university-based research, education and training center comprised of an international network of scholars committed to the scientific study of terrorism, responses to terrorism and related phenomena. Led by the University of Maryland, START is a Department of Homeland Security Emeritus Center of Excellence that is supported by multiple federal agencies and departments. START uses state-of-the-art theories, methods and data from the social and behavioral sciences to improve understanding of the origins, dynamics and effects of terrorism; the effectiveness and impacts of counterterrorism and CVE; and other matters of global and national security. For more information, visit www.start.umd.edu or contact START at infostart@umd.edu.

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Introduction

This report investigates spatial patterns of terrorism and targeted violence in the United States. Such investigations are rare because terrorist attacks are rare in the United States compared to other nations and the terrorist attacks that do occur are dispersed in similar patterns as population centers. In sum, the relative rarity of attacks, the geographic size of the United States, and the distribution of population density create inherent challenges historically. However, the recent outbreak of political violence throughout the United States coupled with advances in spatial statistics creates an opportunity to investigate emerging patterns at subnational scales.

This investigation blends spatial statistics, clustering methods, and binary logistic regression to attempt to understand potential underlying issues that may cause or exacerbate terrorism and targeted violence in the United States. To construct this analysis, we use secondary data analysis and existing methods. Clustering and spatial statistics, specifically, local indicators of spatial autocorrelation, are used to identify spaces of interest that warrant further investigation. The binary logistic regressions are used to attempt to understand what variables may be useful, that is predictive, of precursors of terrorism and targeted violence.

In sum, we identify mixed results. Traditional clustering methods like kernel density estimation (KDE) at the national scale are not sensitive enough to provide support to policymakers. However, more advanced methods like convex hulls and local indicators of spatial autocorrelation (LISA) analysis do suggest locations of concern and/or further investigation. Localized variables at the county level or smaller continue to provide the most useful analyses. Overall, we find support for "pockets" of extremism and that, more specifically, some social determinants of health correlate with the presence of violent extremism.

Data and Methodology

Data

The data for this analysis comes from publicly available government, civil society, and academic sources. All geospatial boundary data are derived from the Database of Global Administrative Areas (GADM) and the U.S. Census Bureau. Demographic data are from the U.S. Census Bureau and the U.S Department of Agriculture's Economic Research Service. Terrorism and targeted violence data come from ACLED's U.S. dataset. The locations of hate groups are based on Southern Poverty Law Center data. QAnon crimes data was created by START's Radicalization and Deradicalization (RaD) team. County-level location of January 6th insurrectionists is based on data from The George Washington University's Program on Extremism. Social determinants of health data, along with all other data used in the regressions are listed below.

The dependent variables used in this report are derived from multiple sources and are utilized at different scales appropriate to the analysis of those variables. There are only a handful of existing datasets related directly or indirectly to terrorism and targeted violence within the United States. ACLED data for the United States consists of all events occurring between the start of the U.S. dataset in 2020 through July 15, 2021. Event types include attacks, mob violence, violent demonstrations, armed clashes, sexual violence, remote explosive/landmine/IED, suicide bombs, and grenades. The ACLED data are used as points to develop the convex hulls and, subsequently, at the county level to investigate potential relationships to independent variables. We also use SPLC-geocoded locations of hate groups within the United States. We aggregate these locations up to the county and use them in binary logistic regression. We also visualize the locations of the hate groups at the national level. Additionally, we examine the QAnon crimes dataset developed by START's RaD team. These data are aggregated to the county level and are used in theory logistic regression. Lastly, we developed a flag variable based on the Program on Extremism's collection of records relating to the January 6 defendants. These data are again used at the county level.

Robert Pape (2021) found a connection between the county of origin of those charged in connection with storming the Capitol on January 6th and the five-year change in White population while controlling for county unemployment, whether the county is designated as urban or rural, population, and distance from D.C. As a result of his finding, we included a variable based on the 10-year change between the 2010 and 2020 decennial census in the population of those identifying only as White. We include a similar urban/rural variable, but instead of using a binary urban or rural, we use a variable that identifies the percentage of the county classified as rural. To investigate what may help understand whether or not the decline in whiteness alone could be an underlying cause, we include the percent of the population who identifies as Hispanic and the estimated percentage of the population who primarily speak a language other than English. The inclusion of these two variables stems from recurring negative stereotypes of minority populations, but specifically the Hispanic population and those who cannot speak English. In other words, does exposure to Hispanic populations or non-English speaking populations affect terrorist and targeted violence events? It is also important to note that Pape's analysis does not appear to state whether or not the change in White population variable was inclusive of White Non-Hispanic populations *and* White Hispanic populations. We did not separate out Hispanicity from the White population change. As such, the percent Hispanic variable may help identify an interaction between the White race category and Hispanicity.

Our other variables are chosen from recognized social determinants of health and corollaries. While traffic volume and percent rural are moderately correlated (Pearson's $r = -0.56$), Harding et al. (1998) suggest that traffic volume and "road rage" incidents are positively correlated. We include the rate of juvenile incarceration as a proxy for a symbolic threat to societal order. Mears (2006, 478) found a "strong, positive, and statistically significant" relationship between symbolic threat effect and an increase in the number of juvenile offenders incarcerated per 100,000. This suggests that counties experiencing a symbolic threat to societal order will likely have higher rates of juvenile incarceration. In turn, this feeling of symbolic threat may result in identifiable extremist violence and/or events. Next, we include the percentage of the population, under age 65, without health insurance. Since many low, and some, middle-income workers do not have health insurance, we include this variable as a measure of precarity.

Lastly, we investigate three health and wellbeing variables. The first is the percentage of the population who reported insufficient sleep. Maric et al. (2017) found that chronic insufficient sleep increased risk-seeking behavior. We also include the percent of the population self-reporting frequent mental distress. Strine et al. (2004) identified positive relationships between frequent mental distress and a variety of risk behaviors (smoking, drinking heavily, physical inactivity, and obesity) and experience of chronic disease. There does appear to be a positive relationship between lack of sleep and frequent mental distress such that the less sleep one gets, the more likely they are to report frequent mental distress (Blackwelder, Hoskins, and Huber 2021). The final variable is those reporting frequent physical distress to examine potential interactions between frequent mental and physical distress.

Table 1: Independent Variable Data Sources

Type	Measure	Description	Source	Date
Social Determinants of Health	Insufficient Sleep	Percentage of Adults who reported fewer than 7 hours of sleep	Behavioral Risk Factor Surveillance System	2018
	Frequent Mental Distress	Percentage of adults reporting 14 or more days of poor mental health per month	Behavioral Risk Factor Surveillance System	2018
	Physical Distress	Percentage of adults reporting 14 or more days of poor physical health per month	Behavioral Risk Factor Surveillance System	2018
	Percent Uninsured	Percentage of adults under age 65 without health insurance	Small Area Health Insurance Estimates	2018
Societal Crisis Correlates	Traffic Volume	Average Traffic Per Meter of Major Rodway in the County	EJSCREEN: Environmental Justice Screening and Mapping Tool	2019
	Juvenile Arrests	Rate of delinquency cases per 1,000 juveniles	Easy Access to State and County Juvenile Court Case Counts	2018
Demographic Variables	Change in White Population	Change in White population 2010-2020	U.S. Census Bureau	2010, 2020
	Percent Hispanic	Percent of the population identifying as Hispanic	U.S. Census Bureau	2020
	Percent Foreign Language	Percent of the population who primarily speaks a language other than English	U.S. Census Bureau	2020

Methods

Identifying Point Pattern Clusters

Methods of identifying spatial patterns of terrorism and targeted violence are borrowed from ecology literature (Cornwell et al. 2006; Downs and Horner 2008; Downs and Horner 2009) and basic research into characterizing patterns (Duckman et al. 2008). Three methods are used to identify patterns based on the point patterns of terrorism and targeted violence events from the ACLED data.

Kernel density estimation (KDE) is the first. KDE is a well-established method for identifying neighborhoods (Downs and Horner 2009; Leslie 2010). Bandwidth selection has a great effect on the outcome of the analysis (Gitzen et al. 2006; Horne and Garton 2006; Fieberg 2007). Leslie (2010) notes that, when bandwidth selection is done poorly, groupings of small values become significant while groupings of large values can eliminate granular changes in density by simply overpowering the data set. Others show that KDE is sensitive to sample size (Seaman et al. 1996; Blundell et al. 2001) and that KDE does not accurately estimate a robust pattern of point data (Downs and Horner 2008; Mitchell and Powell 2008). Despite these concerns, KDE remains a common and popular technique of analysis in social science research. For example, Gerber (2014) uses KDE to forecast crime in Chicago, Hart and Zandbergen (2014) use KDE hot spot analysis and other interpolation methods for crime mapping, Xie and Yan (2013) examine traffic accidents using network KDE, and numerous researchers have used KDE to analyze and identify central business districts (Leslie 2010; Yu et al. 2015; Zhu et al. 2017).

Minimum Convex Hulls

The second method is the minimum convex polygon (MCP) – also referred to as convex hulls in the literature (c.f. Duckman et al. 2008 and Downs and Horner 2009). MCP is especially sensitive to sample size and the shape of the point pattern (Worton 1987; Downs and Horner 2008). In short, convex hulls are minimum bounding polygons around the point data. This method is straightforward, but due to the above-mentioned sensitivity, the results can result in "mundane geographic explanation[s]" (Diamond et al. 2015). This is especially applicable when using traditional convex hulls to identify operating areas of terrorist organizations. For example, if a group commits attacks in Portland, Maine, Portland, Oregon, San Diego, California, and Orlando, Florida, the resulting convex hull will cover the majority of the continental United States. However, this approach can work quite well when attempting to analyze discrete patterns over small geographic spaces (c.f. Dellicour et al. 2016 work on emerging epidemic patterns).

Duckham et al. (2008) overview numerous improvements on the traditional MCP and further refine these by developing their own. They note that the goal of these analyses is to measure with some accuracy the boundaries of these points. Their algorithm for characteristic hulls is based on Delaunay tessellations and is the third method used to show spatial patterns in the group data. The method suggested by Duckham et al. (2008, 6) is as follows:

1) Generate the Delaunay triangulation of the set of points
2) Remove the longest exterior edge from the triangulation such that:
    a. The edge to be removed is longer than the length of parameter *l*; and
    b. The exterior edges of the resulting triangulation form the boundary of a simple polygon (at least three sides)
3) Repeat step 2 as long as there are more edges to be removed
4) Return the polygon formed by the exterior edges of the triangulation

The results of this method return non-convex edges and, taken a step further, can show how a pattern could be geographically segregated such that there are discrete pockets of activity in divergent geographic spaces (Downs and Horner 2009). We use MCP to determine the bounding location of the point-level ACLED data. The findings will help identify geographies that may require further investigation and may help inform our understanding of terrorism and targeted violence within the United States. If the location of the ACLED event is sufficiently distributed throughout the United States, the results will return no useful geographic area (e.g., the result could be a convex hull encompassing the bulk of the United States). We suspect that the data are clustered and will result in meaningful regions. We then use the resulting convex hulls to define counties for a subsequent set of binary logistic regressions described in full below.

Local Indicators of Spatial Autocorrelation (LISA) Analysis

Next, we attempt to refine our regions of investigation by using LISA analysis on the ACLED dataset, the QAnon Crimes data, and the Program on Extremism's counts of January 6th Insurrection defendants by county. LISA analysis is used to identify whether or not a variable (or series of variables) moves in the same direction between an area and its neighboring geographies. The results of a LISA analysis are in the form of determinations of a specific geographic area. The determinations are as follows: High-High, High-Low, Low-High, Low-Low, and Insignificant. Areas that result in a High-High or Low-Low are suggestive of statistically significant hot or cold spots accordingly. That is, a Low-Low area and its neighbors possess statistically significantly similarly low values. Conversely, areas determined to be High-High will have significant high values. High-Low and Low-High areas are most interesting because they are outliers. These are areas where the variable (or variables) is statistically significantly trending in opposite directions from one another. Thus, when we observe an area that is oppositive of its surroundings, we want to understand what is happening there.

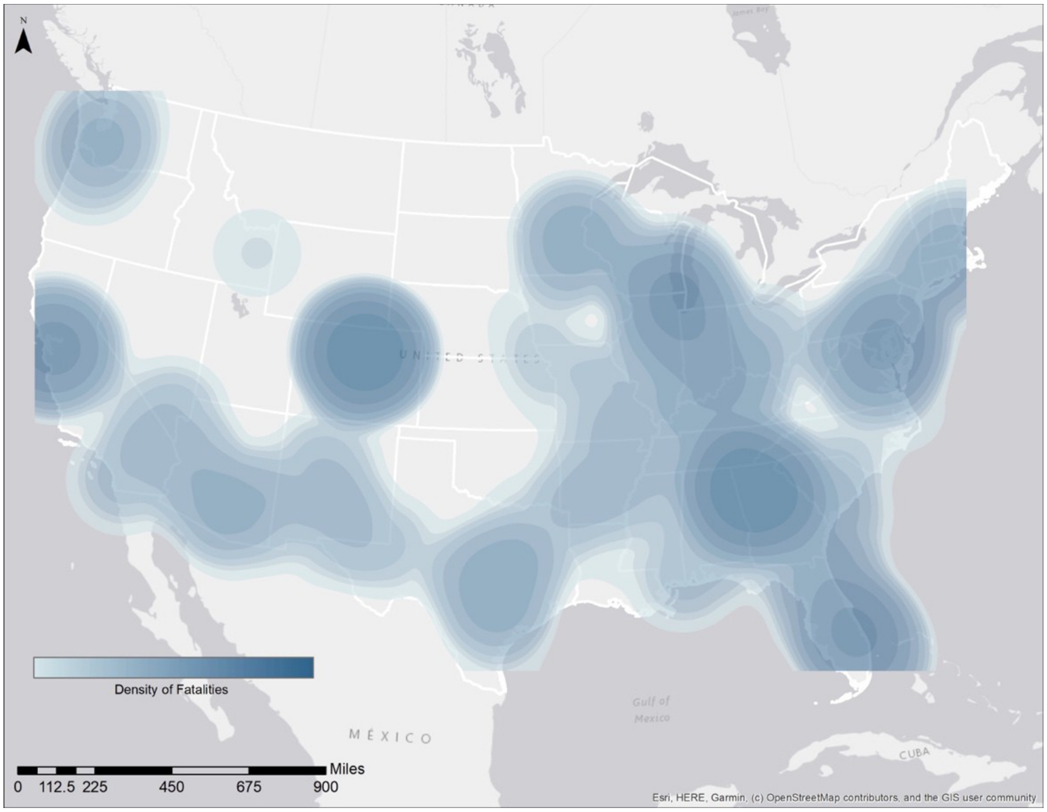
After completing the regional analyses, we want to begin to examine county-level characteristics and identify potentially explanatory variables. To achieve this, we conduct a series of binary logistic regressions. We use a set of demographic data and social determinants of health to identify potential trends in counties contained within a convex hull, where there are terrorism and targeted violence events (ACLED), the location of QAnon crimes, and counties that produced January 6th insurrection defendants (J6 defendants).

Results

Identifying Point Pattern Clusters

The results of the KDE analysis (fig. 1) are uninformative and largely adhere to patterns of population density. We used the number of fatalities in an attempt to refine the ACLED results, but this was largely unsuccessful. What we can see is that there appear to be "pockets" of events centered in major cities throughout the United States.

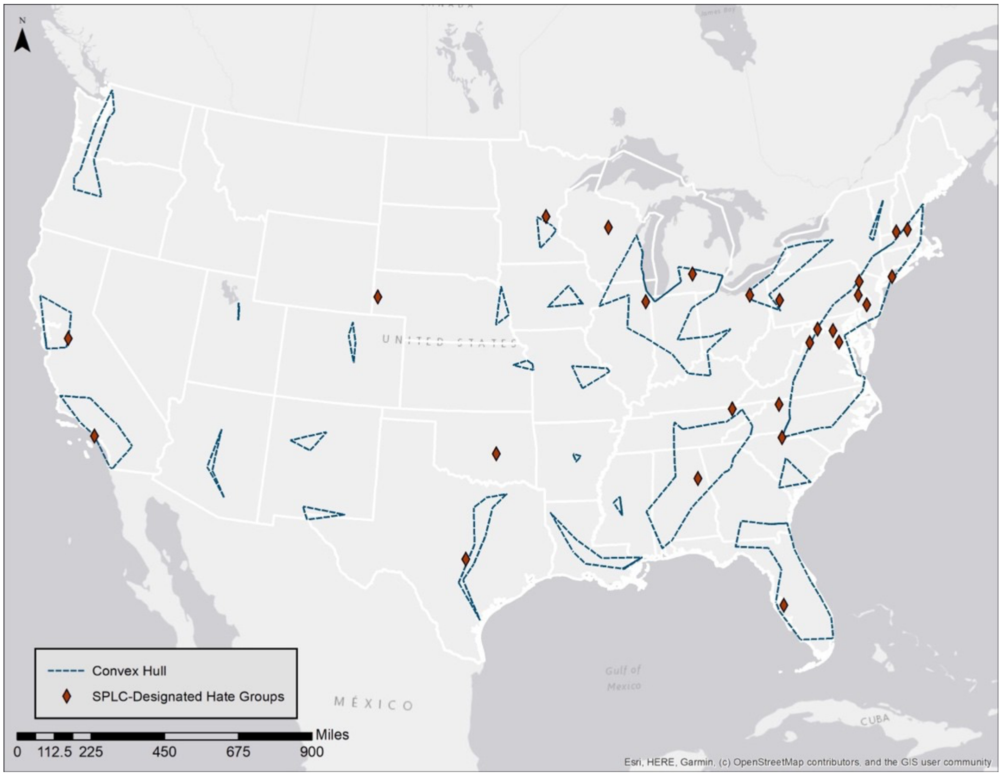
Fig 1. Kernel Density Estimation of Fatalities in ACLED



Minimum Convex Hull

The results of the MCP (Fig. 2) show clearly delineated regions in the United States. These are the regions defined by the Duckham et al. (2008) algorithm. The edges used for initial construction are from the ACLED data. Fig. 2 also shows the location, at the city level, of SPLC-designated hate groups. You can see that many, but not all, SPLC-designated hate groups are located within the MCP. This is suggestive of a correlation between the two as they are largely collocated, but it is also important to note that the convex hulls do cover many large population centers. Understanding whether or not the convex hull results are meaningful will require further investigation presented below.

Fig 2. Final Convex Hull of ACLED Events



Local Indicators of Spatial Autocorrelation (LISA) Analysis

ACLED Data

Moran's *I* results for the ACLED data show that, globally, the data are only mildly clustered (fig. 3). However, when examined at the local scale (fig. 4), we observe that clusters do exist in various pockets around the United States. High-high results, which suggests clusters or hotspots, exist in many urban counties. These are most prominent in Southern California, San Francisco and Silicon Valley, the Interstate 5 corridor between Oregon and Washington State, Interstate 94 between Chicago and Milwaukee, and South Florida between Miami and Naples. Low-high and High-low counties are most interesting because they represent statistically significant outliers. Low-high counties, that is counties that have statistically significant low counts of ACLED events but neighbor counties with high counts, are largely adjacent to High-High counties. Given the proximity, future research could examine whether or not there are protective factors in the form of diverging relationships between adjoining High-High and Low-High counties. Conversely, the High-Low counties are statistically significantly high in ACLED event counts, but are surrounded by counties with low numbers of events. More research is necessary to understand the factors that could be causing this given that High-Low counties are distributed throughout the United States. Some of the High-Low counties may be explained by population centers, but there are numerous high population counties that have statistically insignificant results so population can only explain part of the issue.

Fig 3. Moran's I Scatter Plot of ACLED Data

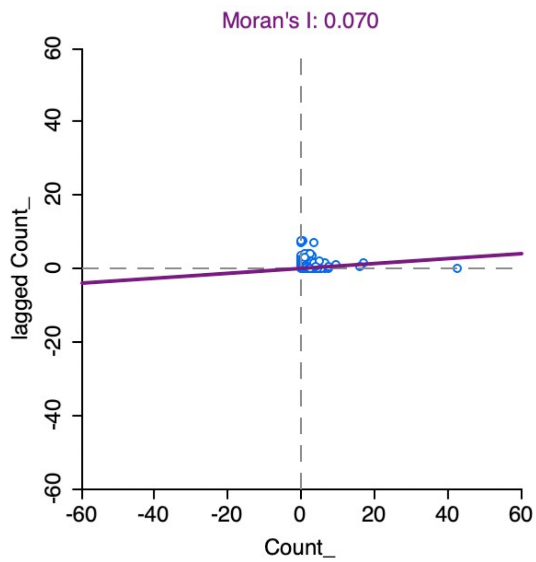
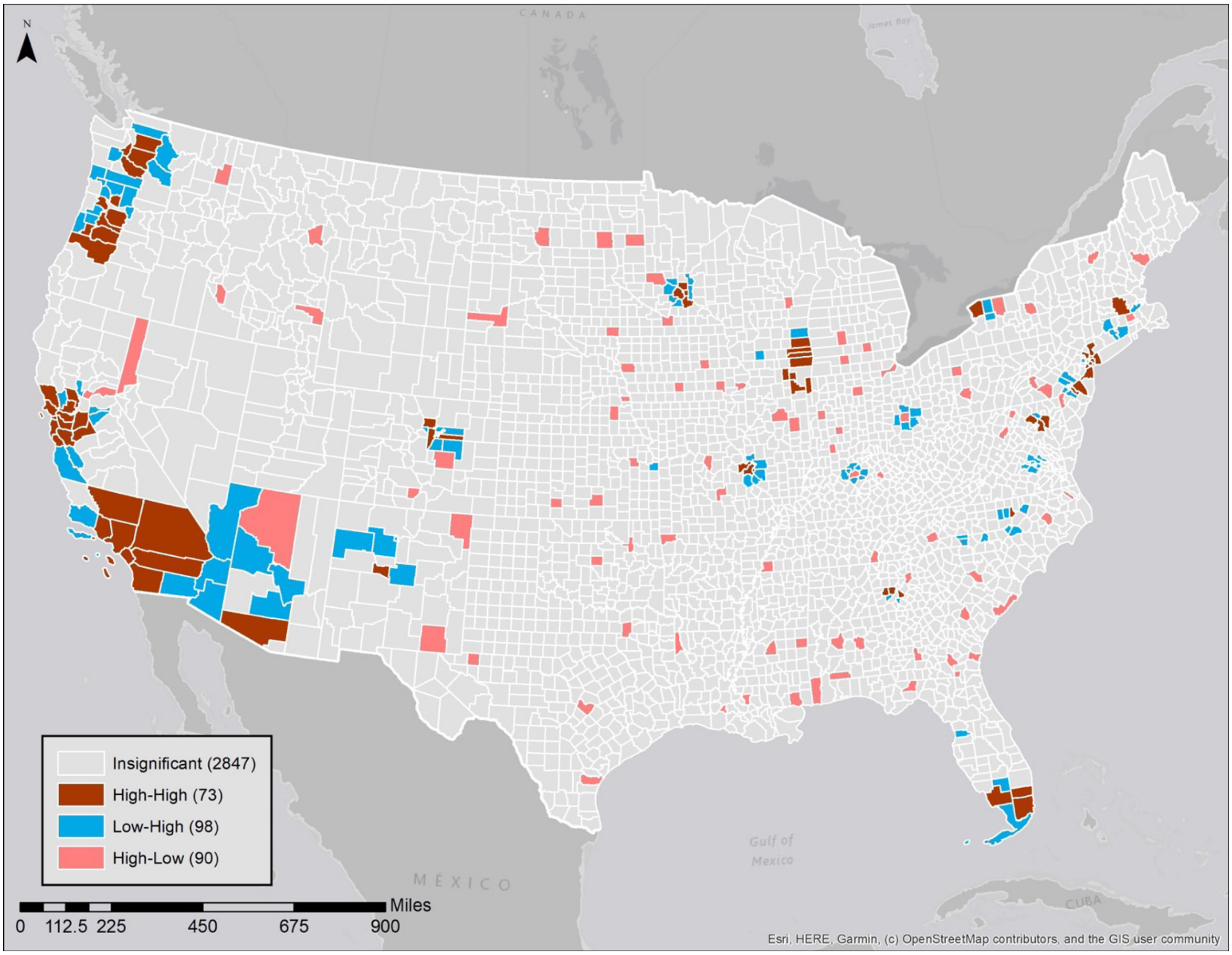


Fig 4. LISA Analysis of ACLED Data by County Count



QAnon Crimes

The global spatial autocorrelation results for QAnon crimes shows minor, statistically significant clustering (fig 5). Figure 6 shows the results of the LISA. These results are quite different than the accompanying results for the ACLED data and the J6 defendant data (below). The major noticeable difference relates to the bullseye pattern around some population centers. This phenomenon is most evident in the Dallas and Austin, Texas regions where Travis County and Dallas County are High-Low outliers while the surrounding counties are Low-High outliers. We see this occur around mid-sized population centers around the United States. High-High counties, meaning hotspots, are rare in these data and only appear in certain population centers in California (Santa Barbara, Los Angeles, Orange, Riverside, and San Diego), Arizona (Maricopa and Pima), New Hampshire (Merrimack), New Jersey (Essex), and New York (New York County). Given the low number of hotspots and that they do not necessarily correlate with population or the LISA results for the other analyses, more research may be necessary.

Fig 5. Moran's I Scatter Plot of QAnon Arrest Data

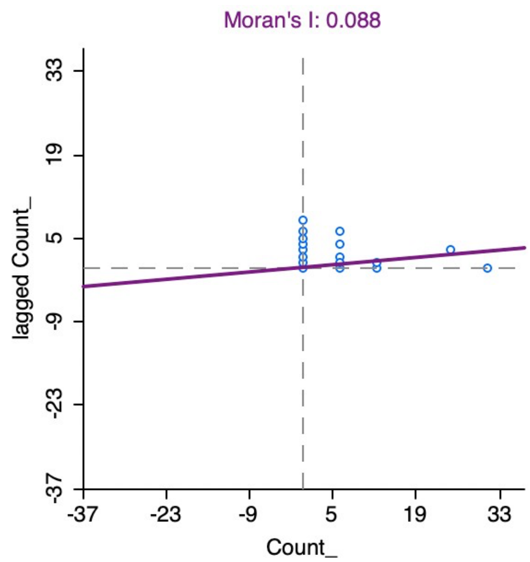
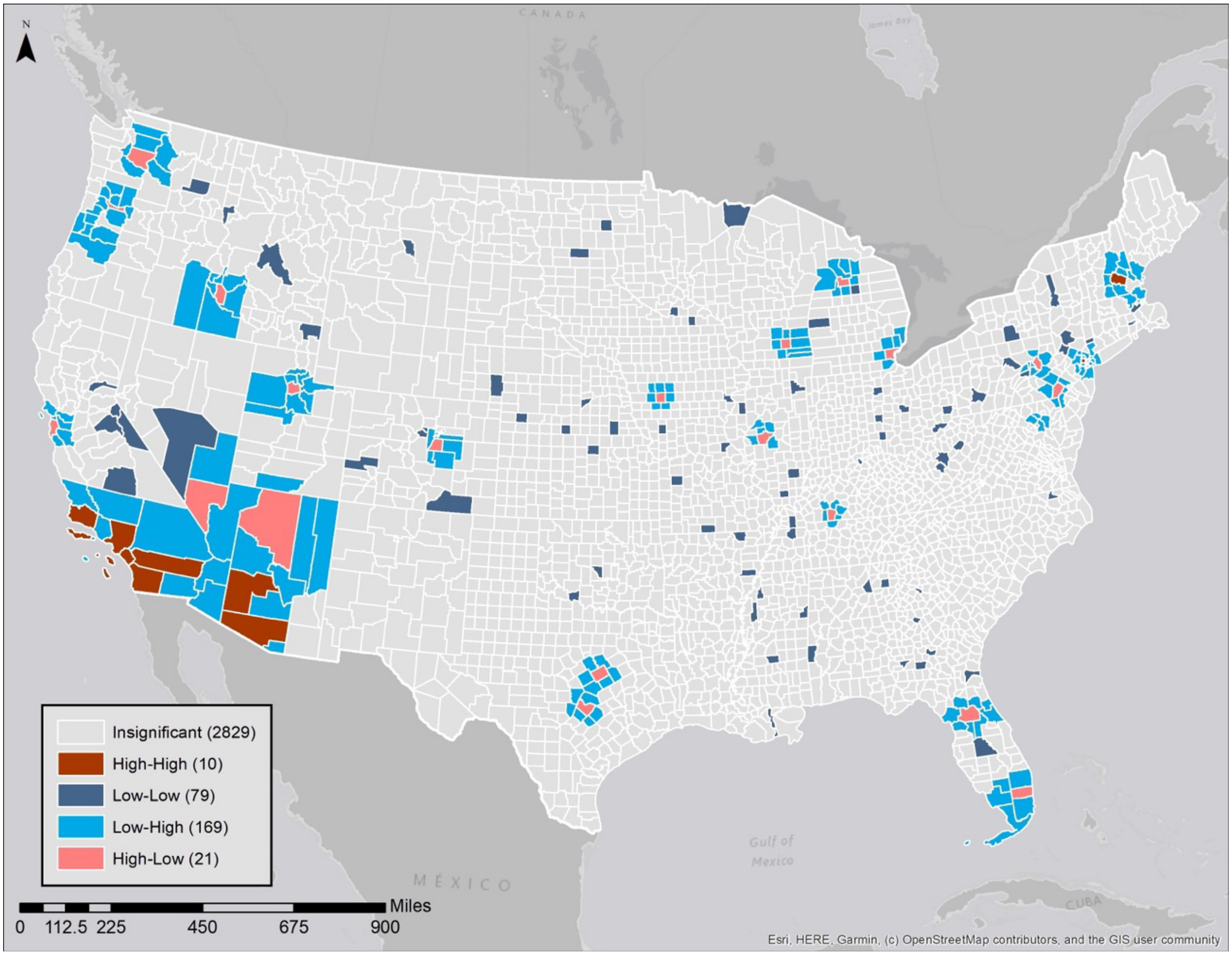


Fig 6. Moran's I Scatter Plot of QAnon Arrest Data



January 6 Defendant Data

The LISA analysis (Fig. 4) of the number of J6 defendants by county show clusters of High-High values. Interestingly, there were no statistically significant Low-Low values. In figure 3 we see the global Moran's I scatter plot of the results, which shows that the results do significantly cluster. We also observe several outlier (Low-High or High-Low) counties. There are numerous clusters. One stretches between the Maryland suburbs to Philadelphia and its surrounding counties. Another runs along Interstate 4 in Florida. There are small clusters around Milwaukee and various cities in Texas. The last cluster goes from Southern California to Clark County, Nevada along the Interstate 15 corridor. Outlier hot and cold spots appear to be randomly distributed throughout the country and do not follow, for example, population density patterns.

Fig 7. Moran's I Scatter Plot of Counties by Count of January 6 Defendants

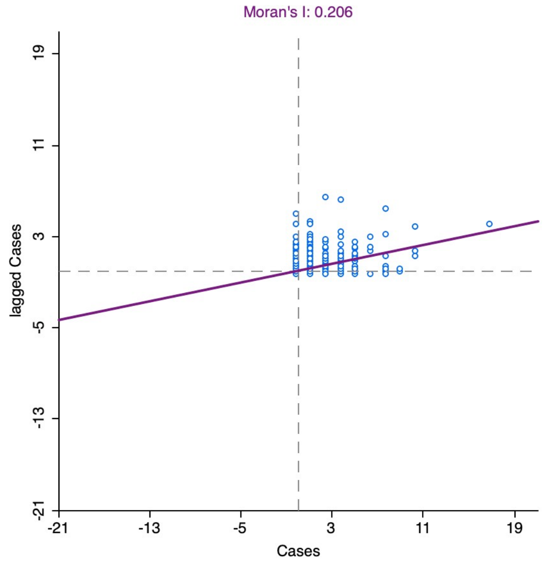
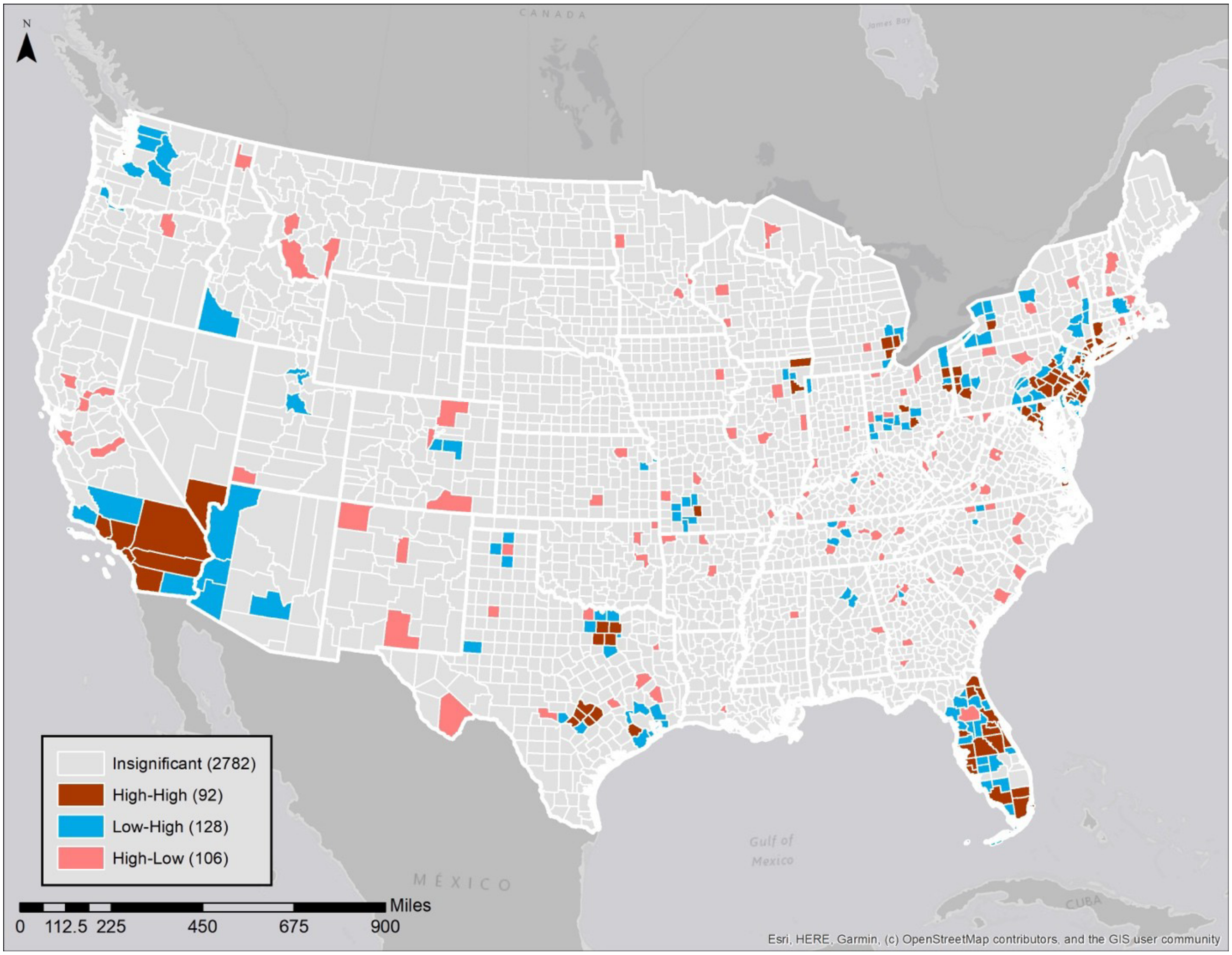


Fig 8. LISA Analysis of Counties by Count of January 6 Defendants



Binary Logistic Regressions

The results of the binary logistic regression analysis show mixed results. When we examine the counties inside the convex hull versus those outside, our model is significant, but we observe very few interesting interactions. Note that traffic volume, lack of sleep, the rate of juvenile incarceration, change in White population, and percent speaking a foreign language are all significant. However, with the exception of lack of sleep, the significant variables' expected β values hover close to zero. It is worth noting that the people living in counties inside the convex hulls were almost 1.3 times as likely to have insufficient sleep than those living in counties outside of the convex hulls. When we review the results of the ACLED data we observe much the same as the previous model. We have an impressive pseudo-R^2, but again the variables are weak predictors of the location of terrorism and targeted violence within the ACLED data.

The chi-square for the model examining QAnon crimes is significant which suggests a poor model fit. However, we do notice that the variables begin to show direction, despite largely being insignificant. For example, the populations in counties where QAnon crimes occurred are less likely to report lack of sleep or frequent physical distress. They are, however, more likely to report frequent mental distress. The last model, of J6 defendants, is the most interesting. We have a strong pseudo-R^2 and an insignificant chi-square. All the variables, with the exceptions of percent of population uninsured, juvenile detention rate, and percent of population speaking a language other than English, are significant. Percent rural and traffic volume appear to have very little impact on the presence (or not) of J6 defendants in a county. However, frequent mental and physical distress are both significant and move in different directions. The populations living in counties where J6 defendants reside are about 40 percent less likely than those in all other counties to complain of frequent physical distress. Conversely, the same population is over twice as likely as those in counties without J6 defendants to report frequent mental distress. Notice that the percent of the population identifying as Hispanic and the change in White population are significant but have a positive impact on the model. This suggests that increases in White and Hispanic populations will slightly increase the likelihood of the county having a J6 defendant present.

Fig 9. Binary Logistic Regression Results

	Convex Hull		ACLED		Qanon Crimes		J6 Counties	
	Logit (SE)	Exp ( )	Logit (SE)	Exp ( )	Logit (SE)	Exp ( )	Logit (SE)	Exp ( )
Percent Rural	-0.00 (0.00)	0.99	-0.06 (0.01)**	0.95	-0.05 (0.02)*	0.95	-0.03 (0.01)**	0.97
Traffic Volume	0.00 (0.00)**	1.00	0.00 (0.00)**	1.00	0.00 (0.00)*	1.00	0.00 (0.0)*	1.0
Lack of Sleep	0.24 (0.03)**	1.27	-0.01 (0.04)	1.00	-0.18 (0.10)	0.84	0.14 (0.03)**	1.15
Frequent Mental Distress	-0.07 (0.11)	0.93	0.03 (0.17)	1.03	0.50 (0.470)	1.64	0.80 (0.15)**	2.23
Frequent Physical Distress	-0.16 (0.10)	0.85	0.07 (0.15)	1.08	-0.18 (0.42)	0.84	-0.96 (0.15)**	0.38
Percent Uninsured	-0.04 (0.02)	0.97	-0.01 (0.2)	0.99	-0.04 (0.07)	0.96	0.01 (0.02)	1.01
Juvenile Rate	-0.01 (0.00)*	0.99	-0.02 (0.01)	0.98	-0.03 (0.02)	0.97	-0.00 (0.00)	0.99
Change in White Population	0.05 (0.01)**	1.06	0.03 (0.01)*	1.03	0.04 (0.03)	1.04	0.04 (0.00)**	1.04
Percent Hispanic	0.01 (0.01)	1.00	0.01 (0.01)	1.02	0.04 (0.3)	1.04	0.03 (0.01)*	1.03
Percent Foreign Language	0.10 (0.04)*	1.11	-0.03 (0.06)	0.97	-0.04 (0.14)	0.97	0.04 (0.06)	1.04
Constant	-6.04 (0.69)**	0.00	-1.27 (1.06)	0.28	-1.14 (2.52)	0.32	-5.54 (0.91)**	0.00
Chi-square	21.06		9.30		33,20**		14.87	
Pseudo R^2	0.360		0.455		0.287		0.369	

Conclusions

The ability to conduct spatial analysis on terrorism and targeted violence within the United States is improving. One unfortunate reason for this is that incidents of terrorism and targeted violence are increasing. But there are other reasons as well, which are demonstrated in this report. The inclusion of social determinants of health, for example, potentially elucidate emerging trends in the data and will help foster additional debate focused on the importance of a public-health-based approach to understanding violent extremism.

As a systematic and strategy-led approach to addressing violent extremism, public-health-based approaches create opportunities for violence prevention grounded in multi-purpose prevention and intervention programming (Weine et al 2016). The findings presented in this report offer evidence to consider the value of spatial analytical approaches to public health data in potentially identifying risk factors that can lead to radicalization into (violent) extremism (e.g., frequent mental distress). Understanding that some social determinants of health correlate with the presence of violent extremism indicates the need for fostering protective factors which address underlying vulnerabilities and promote resilience. Given that many people have known risk factors for radicalization into extremism, yet it remains a low base-rate phenomenon, the interactions between risk and resilience bear greater examination. Understanding how protective factors influence risk or resilience requires examining new ways and data points through which these characteristics interact. The spatial methodologies employed in this report offer a starting point to do just that.

References

Blackwelder, A., Hoskins, M., & Huber, L. (2021). Peer Reviewed: Effect of Inadequate Sleep on Frequent Mental Distress. *Preventing chronic disease*, *18*.

Blundell, G. M., Maier, J. A., & Debevec, E. M. (2001). Linear home ranges: effects of smoothing, sample size, and autocorrelation on kernel estimates. *Ecological monographs*, *71*(3), 469-489.

Dellicour, S., Rose, R., & Pybus, O. G. (2016). Explaining the geographic spread of emerging epidemics: a framework for comparing viral phylogenies and environmental landscape data. *BMC bioinformatics*, *17*(1), 1-12.

Downs, J. A., & Horner, M. W. (2008). Effects of point pattern shape on home-range estimates. *The Journal of Wildlife Management*, *72*(8), 1813-1818.

Downs, J. A., & Horner, M. W. (2009). A characteristic-hull based method for home range estimation. *Transactions in GIS*, *13*(5-6), 527-537.

Duckham, M., Kulik, L., Worboys, M., & Galton, A. (2008). Efficient generation of simple polygons for characterizing the shape of a set of points in the plane. *Pattern recognition*, *41*(10), 3224-3236.

Faulks, I. J. STAYSAFE 58.

Fieberg, J. (2007). Kernel density estimators of home range: smoothing and the autocorrelation red herring. *Ecology*, *88*(4), 1059-1066.

Gerber, M. S. (2014). Predicting crime using Twitter and kernel density estimation. *Decision Support Systems*, *61*, 115-125.

Gitzen, R. A., Millspaugh, J. J., & Kernohan, B. J. (2006). Bandwidth selection for fixed-kernel analysis of animal utilization distributions. *The Journal of Wildlife Management*, *70*(5), 1334-1344.

Hart, T., & Zandbergen, P. (2014). Kernel density estimation and hotspot mapping: Examining the influence of interpolation method, grid cell size, and bandwidth on crime forecasting. *Policing: An International Journal of Police Strategies & Management*.

Horne, J. S., & Garton, E. O. (2006). Selecting the best home range model: an information-theoretic approach. *Ecology*, *87*(5), 1146-1152.

Leslie, T. F. (2010). Identification and differentiation of urban centers in Phoenix through a multi-criteria kernel-density approach. *International Regional Science Review*, *33*(2), 205-235.

Maric, A., Montvai, E., Werth, E., Storz, M., Leemann, J., Weissengruber, S., ... & Baumann, C. R. (2017). Insufficient sleep: Enhanced risk-seeking relates to low local sleep intensity. *Annals of neurology*, *82*(3), 409-418.

Mears, D. P. (2006). Exploring state-level variation in juvenile incarceration rates: Symbolic threats and competing explanations. *The Prison Journal*, *86*(4), 470-490.

Seaman, D. E., & Powell, R. A. (1996). An evaluation of the accuracy of kernel density estimators for home range analysis. *Ecology*, *77*(7), 2075-2085.

Strine, T. W., Balluz, L., Chapman, D. P., Moriarty, D. G., Owens, M., & Mokdad, A. H. (2004). Risk behaviors and healthcare coverage among adults by frequent mental distress status, 2001. *American journal of preventive medicine*, *26*(3), 213-216.

Yu, W., Ai, T., & Shao, S. (2015). The analysis and delimitation of Central Business District using network kernel density estimation. *Journal of Transport Geography*, *45*, 32-47.

Weine, S., Eisman, D. P., Kinsler, J., Glik, D. C., & Polutnik, C. (2016). Addressing violent extremism as public health and practice. *Behavioral Sciences of Terrorism and Political Aggression*, *9*(3), 208-221.

Worton, B. J. (1987). A review of models of home range for animal movement. *Ecological modelling*, *38*(3-4), 277-298.

Zhu, D., Wang, N., Wu, L., & Liu, Y. (2017). Street as a big geo-data assembly and analysis unit in urban studies: A case study using Beijing taxi data. *Applied Geography*, *86*, 152-164.