Detection of Suicide Clusters using Small-Area Geographic Data from the Virginia Violent Death Reporting System, 2010 – 2015

Kurtis M. Anthony[1], Allison Ertl[1], Rachel A. Leavitt[1], Alexander E. Crosby[1], Ryan M. Diduk-Smith[2], Kevin A. Matthews[3]

[1]Division of Violence Prevention, National Center for Injury Prevention and Control, Centers for Disease Control

[2]Office of the Chief Medical Examiner, Virginia Department of Health

[3]Division of Population Health, National Center for Chronic Disease Prevention and Health Promotion, Centers for Disease Control

Corresponding author:
Allison Ertl, PhD, MS
Centers for Disease Control and Prevention
moq4@cdc.gov

Abstract

Introduction: From 1999 to 2020, the suicide rate in Virginia increased from 13.1 to 15.9 per 100,000 persons aged 10 years and older. Few studies have examined spatial patterns of suicide geographies smaller than the county level.

Methods: We analyzed data from suicide decedents aged ≥10 years from 2010 through 2015 in the Virginia Violent Death Reporting System. We identified spatial clusters of high suicide rates using spatially adaptive filtering with standardized mortality ratio (SMR) significantly higher than the state SMR ($p < 0.001$). We compared demographic characteristics, method of injury, and suicide circumstances of decedents within each cluster to decedents outside any cluster.

Results: We identified 13 high-risk suicide clusters (SMR between 1.7 and 2.0). Suicide decedents in the clusters were more likely to be older (40+ years), non-Hispanic white, widowed/divorced/separated, and less likely to have certain precipitating suicide circumstances than decedents outside the clusters. Suicide by firearm was more common in four clusters, and suicide by poisoning was more common in two clusters compared to the rest of the state.

Conclusions: There are important differences between geographic clusters of suicide in Virginia. These results suggest that place-specific risk factors for suicide may be relevant for targeted suicide prevention.

Introduction

Suicide is a complex issue with risks occurring at the individual, relationship, community, and societal levels (U.S. Department of Health and Human Services, 2012; Stone *et al.*, 2018; Virginia Department of Health, 2016). Suicide risk varies according to age, sex, race, and other demographic factors. Some common circumstances preceding a suicide death include mental health problems, relationship problems, a recent crisis, alcohol or substance misuse, physical health problems, and financial problems. While understanding individual-level risk factors is essential for suicide prevention efforts, exploring spatial patterns and identifying high-risk areas of suicide can inform more targeted and comprehensive prevention efforts and improve resource allocation. Culturally appropriate suicide prevention interventions that address specific risk factors in different populations and places are most effective (Barnhorst et al., 2021).

There are some important limitations to methods that have been previously used to identify geographic clusters of suicide. Several studies have used spatial scan statistics to identify geographic clusters of suicide and characteristics associated with the clusters (Fontanella et al., 2018; Kulldorff & Nagarwalla, 1995; Saman et al., 2012); however, this method will identify the most likely clusters, even if they are not significantly different from the rest of the study area. Bayesian spatial regression is another method for identifying geographic clusters of suicide. One such study identified 52 counties in Virginia with greater than expected suicide risk and found that suicide risk was positively associated with the percentage of the White population and higher median age (Orndahl & Wheeler, 2018). However, using county boundaries severely limits the ability to detect geographic clusters since the risk of suicide can be highly concentrated in only one part of a county and can cross county boundaries. Therefore, new methods for identifying small-area geographic suicide clusters and community-level risk factors should be explored.

An important aspect of our method for detecting geographic clustering of suicide risk is our use of the National Violent Death Reporting System (NVDRS). The NVDRS is a state-based surveillance system containing individual-level data about each suicide, including demographic characteristics and the residential tract of each decedent. Importantly, this surveillance system contains unique information about individual circumstances that precipitated a suicide. Our method for detecting geographic clusters of high suicide risk differs from other studies because all geographic units in the state have a uniform and minimum level of statistical reliability instead of a minimum level of geographic precision. We accomplished this using a series of overlapping moving windows called spatially adaptive filters (Cai et al., 2011; Talbot et al., 2000; Tiwari & Rushton, 2005). Spatially adaptive filters are aggregations of smaller neighboring geographic units (in this case, Census tracts) that, by themselves, do not have sufficiently large populations to calculate statistically reliable disease rates (Matthews, 2018). The size of the spatial filters varies according to population density; filters are smaller in urban areas and larger in rural areas. Others have used spatially adaptive filters to create an interpolated map of disease rates with a uniform statistical reliability for other diseases. However, identifying geographic clusters, areas where disease rates are statistically significantly elevated compared to the state overall, is a novel application of spatially adaptive filters. Using Virginia as an example, we identified clusters with elevated suicide rates and then compared the suicide circumstances of the decedents residing within the clusters to all other parts of the state outside the clusters.

Background

Suicide was the 12th leading cause of death in the United States in 2020, with approximately 46,000 deaths from suicide or 15.9 deaths per 100,000 persons aged 10 years and older (National Center for Injury Prevention and Control, 2020). Furthermore, suicide rates have increased in 49 of the 50 U.S. states and by 25% nationwide from 1999 through 2016 (Stone et al., 2018). Virginia's suicide rate was 15.9 per 100,000 persons aged 10 years and older in 2020 and increased by 17.4% between 1999 to 2016 (Stone et al., 2018; National Center for Injury Prevention and Control, 2020). Consistent with the rest of the United States, people in Virginia who are over 65 years of age, White, and male are at higher risk of suicide than other groups (Hassamal et al., 2015; Mościcki, 2001; Virginia Department of Health, 2016). However, the suicide rate varies widely within the state; county-level suicide rates in the state ranged from 7.0 per 100,000 (Arlington County) to 62.5 per 100,000 (Patrick County) in 2020 (Centers for Disease Control and Prevention, 2020). In Virginia, firearms are the most common method of suicide, followed by hanging and poisoning (Hassamal et al., 2015; Viriginia Department of Health, 2016).

Methods

Data and Study Sample

The National Violent Death Reporting System (NVDRS) is an active state-based surveillance system that collects and compiles information on violent death, including suicide, from three required data sources: death certificates, coroner/medical examiner reports, and law enforcement reports. NVDRS collects information related to the manner of death (e.g., suicide), mechanism of injury (e.g., firearm), demographics, toxicology, and circumstances preceding the decedent's death. Data used in this analysis were collected by the Virginia Violent Death Reporting System (VVDRS), which has been participating in NVDRS since 2003 (Virginia Department of Health, 2020). The VVDRS follows standardized methodology, coding, and web-based data collection. The NVDRS does not collect personally identifying information. NVDRS defines suicide as a death resulting from the use of force against oneself when most evidence indicates that the use of force was intentional (Jack et al., 2018). In addition, NVDRS collects geographic information related to the incident, including the Census tract of the decedent’s residence. Census tracts are small geographic units containing between 1,200 and 8,000 people (US Census, 2020).

We obtained data for suicides occurring in Virginia among people aged ≥ 10 years from NVDRS. From these, we selected decedents who were residents of Virginia and who died between 2010 and 2015 (n= 6,290). For decedents who were missing Census tract information but had a known residential ZIP code (n=428), we assigned a Census tract using the population-weighted centroid of the ZIP code. We excluded decedents who were missing both Census tract and ZIP code information (n=69). In addition, we excluded three suicide decedents in Census tracts with zero population. As a result, we had a final study population of 6,218 decedents from NVDRS.

Spatial and Statistical Analyses

We constructed spatial filters to generate statistically reliable estimates for suicide risk across areas of varying population density throughout the state. Spatial filters are moving windows constructed by combining the data from a given geographic unit with data from neighboring geographic units. We combined units by measuring the Euclidean distance from the population-weighted Census tract centroids of the target unit to the population-weighted Census tracts of the neighboring units (Hallisey et al., 2017). Each spatial filter contains a threshold number of at least 20 expected suicides to ensure reliable estimates. If the expected number of suicides in a Census tract were less than 20, it would expand to include expected suicides from the nearest neighboring Census tracts until it reaches the threshold. To avoid the possibility that a suicide rate for a rural tract is obscured by the rate in a neighboring urban tract, filters for Census tracts that are classified as rural by the Rural-Urban Continuum Codes (RUCC) only used rural Census tracts, even if an urban tract was nearer (WWAMI Rural Health Research Center, 2020).

We calculated standardized mortality ratios (SMR) and indirectly adjusted age-sex standardized suicide rates (IAR) for each of Virginia's spatially adaptive filter areas (Breslow & Day, 1987). We calculated the expected number of suicides for a given Census tract by multiplying the age- and sex-specific state-level suicide rates for people aged ≥ 10 years by the stratum-specific Census tract population. We then calculated the SMR for a spatial filter as the observed number of suicides within a spatial filter divided by the number of expected suicides. Next, we calculated the IAR by multiplying the Census tract-level SMR by the statewide crude rate of suicide. We represented the suicide rates continuously across space using inverse distance weighting interpolation and applied a diverging classification scheme to symbolize areas where the IAR was higher (red) or lower (blue) than the state suicide rate.

We identified geographic clusters of suicide using the filter SMRs and compared the characteristics and precipitating circumstances of decedents in those clusters. We identified any spatial filter with an SMR greater than 1.69 as part of a geographic cluster because the suicide rate for these filters was significantly greater than the statewide rate at the P <0.001 level for 20 expected suicides (Cai et al., 2011). We assigned a unique cluster identifier to each geographically distinct cluster that did not share a border with other qualifying Census tracts and then assigned each decedent to the cluster that contained the decedent's residential Census tract. We compared the demographic characteristics, suicide method, and precipitating suicide circumstances between decedents in clusters with decedents outside all clusters using Chi-square tests sequentially for individual clusters and all clusters combined (P < 0.05). We performed spatial analysis for this paper in STATA/SE 14.0 (StataCorp LP, College Station, TX), created maps in ArcGIS 10.5 (ESRI, Redlands, CA), and conducted statistical analysis in SAS v 9.4 (SAS, Cary, NC).

Results

We analyzed data for 6,218 suicide deaths reported to Virginia VDRS from 2010 through 2015. We identified 13 high-risk suicide clusters, which captured 1,005 (16.1%) suicides in the state over the six years. These high-risk clusters accounted for 8.7 % (n = 166) of the Census tracts in Virginia and represented 9.0% (n = 626,864) of the population at-risk. The clusters were dispersed throughout the state and the geographic variation in the IAR is high (**Figure 1**). The clusters had a population ranging between 22,915 and 124,232 and an SMR for suicide ranging between 1.7 and 2.0 (**Table 1**). Six of the clusters contained rural Census tracts as defined by RUCC.

Figure 1. Suicide Clusters and Risk Surface in Virginia, Virginia Violent Death Reporting System, 2010-2015

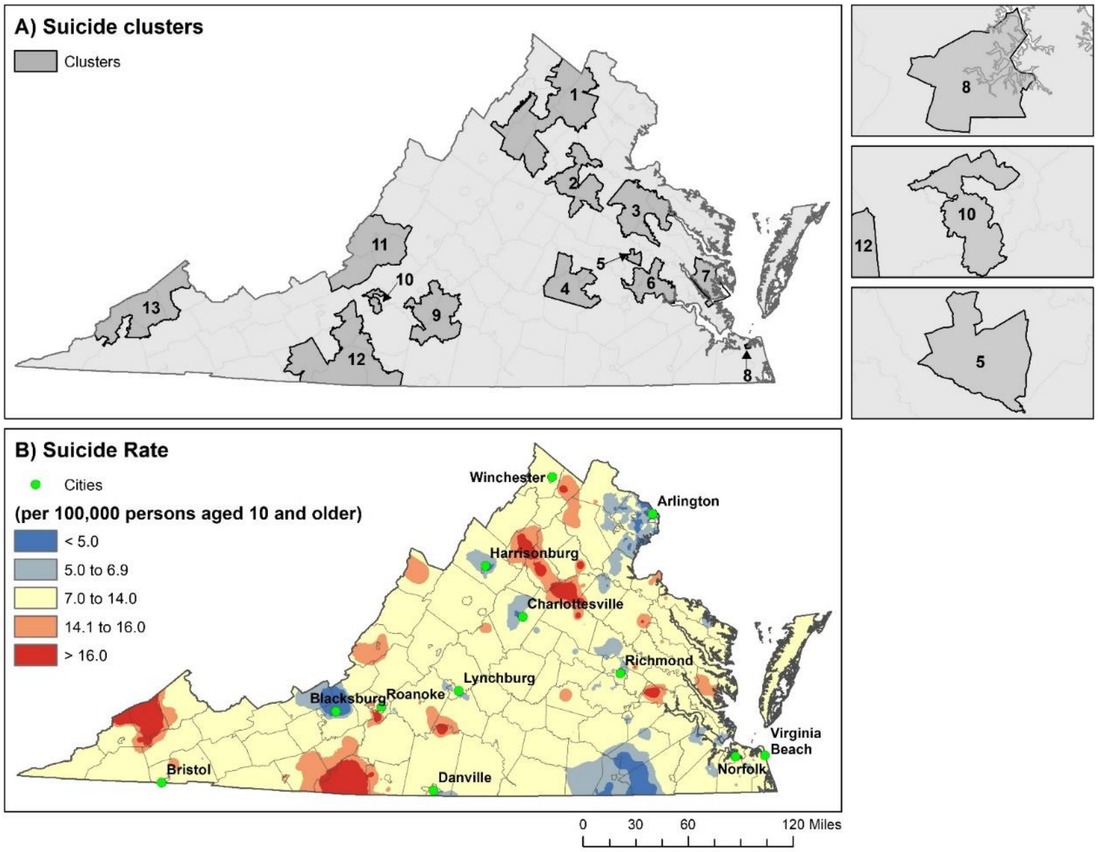

Figure 1 A) Suicide clusters in Virginia identified using spatially adaptive filters with an expected count of 20 and significance of p < 0.001 B) Indirectly age-sex standardized suicide rates per 100,000 persons ages ≥ 10 years (smoothed)

Table 1. Observed and Expected Counts and Indirectly Age- and Sex-Adjusted Suicide Rate in Virginia by Spatial Cluster, Virginia Violent Death Reporting System, 2010 – 2015

Cluster	Observed Suicide Count	Population (aged ≥10 yrs)	Expected Suicide Count*	Standardized Mortality Ratio	Indirectly Adjusted Rate†	Rural Pop. (%)
1	191	124232	112	1.7	25.2	8
2	52	32885	30	1.7	25.8	59
3	39	23360	21	1.8	27.0	0
4	38	24110	22	1.8	26.1	0
5	42	25197	22	1.9	28.5	0
6	52	29161	26	2.0	29.2	0
7	55	35300	32	1.7	25.5	0
8	36	22915	21	1.8	26.1	0
9	72	44772	41	1.8	26.1	17
10	154	97369	87	1.8	26.2	0

11	43	27563	26	1.7	24.9	6
12	147	89678	83	1.8	26.3	77
13	84	50322	47	1.8	26.6	100
n/a‡	5213	6352686	5648	0.9	13.7	7
Total	6218	6979550	6218	1.0	14.8	9

*****Expected number of suicides for each area were calculated by multiplying the age- and sex-specific state-level suicide rates among persons aged ≥ 10 years by the stratum-specific population. †Rates were calculated as suicides per 100,000 population. ‡Represents locations in Virginia that were not part of any suicide cluster.

The clusters differed from the rest of the state for certain suicide decedent characteristics (**Table 2**). Suicide decedents in the clusters were more likely to be older (40+ years), White, and widowed/divorced/separated than decedents in the rest of the state (i.e., decedents outside the clusters). Firearm was the most common suicide method in clusters and the rest of the state, accounting for 62% of suicides in clusters compared to 55% of suicides in the rest of the state. The proportion of suicide by firearm was significantly higher in cluster 9 (78%, $P < .01$), cluster 11 (79%, $P < .01$), cluster 12 (72%, $P < .01$), and cluster 13 (75%, $P < .01$) compared to the rest of the state. The proportion of suicide by poisoning was significantly greater in clusters 1 (25%, $P < .01$) and 2 (29%, $P < .01$) compared to the rest of the state; however, the proportion of suicide by poisoning was not significantly different from the rest of the state for all clusters combined.

Table 2. Associations between Spatial Clusters and Demographic Characteristics/Precipitating Circumstances for Suicide Decedents in Virginia, Virginia Violent Death Reporting System, 2010-2015

	Cluster Number													Number (percent)†	
	1	2	3	4	5	6	7	8	9	10	11	12	13	Within Clusters	Outside Clusters
Sex															
Male	↓	↓	↑	↑	↑	↓	↑	↓	↑	↑	↑	↓	↑	785 (78.1)	4034 (77.4)
Female	↑	↑	↓	↓	↓	↑	↓	↑	↓	↓	↓	↑	↓	220 (21.9)	1179 (22.6)
Age group (years)															
10-17	↑	↓	↑	↓	↓	↓	↑	↓	↓	↓	↑	↓	↓	22 (2.2)	162 (3.1)
18-39	**↓**	↓	**↓**	↓	↓	↑	↑	**↑**	↓	**↓**	↓	↓	↓	**281 (28.0)**	1755 (33.7)
40-64	↑	**↑**	↑	↓	↑	↓	↓	↓	↑	↑	↑	↑	↑	**500 (49.8)**	2404 (46.1)
65+	↑	↓	↑	↑	↓	↓	↑	↓	↑	**↑**	↓	**↑**	↑	**202 (20.1)**	892 (17.1)
Race/Ethnicity															
White, nH	**↑**	↑	↓	↑	↑	↓	**↑**	↑	**↑**	**↑**	**↑**	**↑**	**↑**	**934 (92.9)**	4383 (84.1)
Black, nH	**↓**	–	↑	↓	↓	↑	**↓**	↓	↓	↓	↓	**↓**	**↓**	**48 (4.8)**	502 (9.6)

Hispanic	↓	↓	↓	↓	↓	↓	↓	↑	↓	↓	↓	↓	↓	**11 (1.1)**	137 (2.6)
Marital Status															
Married	↑	↑	↑	↓	↑	↑	↑	↑	↑	↓	↑	↑	↑	329 (32.8)	1574 (30.3)
Widowed, Divorced, or Separated	↑	↑	↑	↑	↑	↑	↑	↓	↓	↑	**↓**	↑	**↑**	**408 (40.6)**	1845 (35.5)
Single	**↓**	↓	↓	↓	**↓**	↓	↓	↓	↓	↓	↑	↓	**↓**	**267 (26.6)**	1774 (34.2)
Suicide Weapon															
Firearm	↓	↓	↑	↑	↑	↑	↑	↑	**↑**	↓	**↑**	**↑**	**↑**	**623 (62.0)**	2884 (55.3)
Hanging, Strangulation, or Suffocation	**↓**	↓	↓	↓	↓	↑	↑	↓	**↓**	↓	↓	**↓**	↓	**182 (18.1)**	1217 (23.4)
Poisoning	**↑**	**↑**	↓	↑	↓	↓	↓	↑	↓	↑	↓	↓	**↓**	157 (15.6)	752 (14.4)
Suicide Location															
Home	↑	↑	↓	↑	↑	↓	↓	–	–	↓	↑	↑	↑	778 (77.4)	3911 (75.0)
Road/vehicle	↑	↓	↑	↓	↑	↑	↑	↑	**↑**	↑	↓	↓	↓	92 (9.2)	442 (8.5)
Veteran status															
Military	↓	–	↓	↑	–	↓	↑	↑	↓	↑	↓	↓	**↓**	202 (20.7)	1119 (22.0)
Home injury															
Injured at home	↑	↑	↓	↑	↑	↑	↓	↑	↑	↑	↑	↑	↑	**780 (77.7)**	3845 (73.8)
Suicide Circumstances															
Current mental health problem	**↑**	↑	↓	**↓**	↓	↓	**↓**	↑	↓	↑	**↓**	↑	↓	574 (58.2)	2978 (58.6)
Current mental illness treatment	↑	↓	↓	↓	↑	**↓**	↓	↑	↓	↑	↓	↓	–	387 (39.3)	2146 (42.2)
History of mental illness treatment	**↑**	↓	↓	↓	↓	↓	**↓**	↑	↓	↓	↓	↓	↑	487 (49.3)	2616 (51.5)
Alcohol problem	**↑**	**↑**	↓	↓	**↑**	↓	↑	↓	↓	↓	↓	↓	↓	211 (21.4)	1073 (21.1)
Intimate partner problem	↑	↓	↓	↓	↓	↑	↑	↓	↓	↓	↑	↓	↑	322 (32.7)	1681 (33.1)
Suicide attempt history	↑	↑	↓	↓	↓	↓	↑	↑	↓	↑	↓	**↓**	**↓**	207 (21.0)	1137 (22.4)
Recent criminal legal problem	↑	↓	↑	↓	↑	↑	↑	↓	↓	↓	↓	↓	↓	101 (10.2)	531 (10.5)
Physical health problem	↑	↑	↑	**↑**	↓	↑	↓	↑	↓	↓	↓	↓	↓	199 (20.2)	968 (19.0)
Job problems	**↑**	↑	↓	↓	↑	↓	↓	↑	**↓**	**↓**	**↓**	**↓**	**↓**	**109 (11.1)**	740 (14.6)
Financial problems	**↑**	↑	↓	↓	↓	↓	–	↑	↓	↓	↓	**↓**	**↓**	**117 (11.9)**	751 (14.8)
Eviction or Loss of Home	↑	↑	↓	↑	↓	↓	↓	↓	↓	↓	↓	**↓**	**↓**	**34 (3.5)**	253 (5.0)

Boldface text indicates statistical significance; ↑/**↑**: Proportion higher/significantly higher than the rest of the state; ↓/**↓** : Proportion lower/significantly lower than the rest of the state; – : Proportion same as the rest of the state. †: A total of 6218 suicides occurred during the study period. Counts may not sum to total due to missing data.

We found differences in decedents' suicide circumstances between clusters (**Table 2**); however, no precipitating suicide circumstance was more prevalent for all clusters combined compared to the rest of the state. "Current mental health problem" was the most common circumstance in all clusters (58%), followed by "history of mental illness treatment" (49%) and "current mental illness treatment" (39%). Some individual clusters differed from the rest of the state for specific suicide circumstances. Clusters 4, 7, and 11 had significantly lower proportions of suicides with reported mental health problems than the rest of the state (Cluster 4: 38%, $P = .01$; cluster 7: 39%, $P < .01$; cluster 11: 40%, $P = .02$). Similarly, the proportion of suicides with current mental illness treatment was lower in cluster 6 (28%, $P = .04$) and the proportion of suicides with a history of mental illness was lower in cluster 7 (37%, $P = .03$) compared to the rest of the state. The proportion of suicides with "job problems" as a precipitating circumstance was significantly lower in clusters 9 through 13 (range: 2-8%; $P \leq .02$) compared to the rest of the state. The proportion of suicides with “financial problems” was significantly lower in cluster 12 (5%, $P < .01$) and cluster 13 (4%, $P < .01$) compared to the rest of the state; similarly, the proportion of suicides with “eviction or loss of home” was significantly lower in cluster 12 (1%, $P < .01$) and cluster 13 (0%, $P = .03$). Among all clusters combined, the proportion of suicides with job problems (11%, $P < .01$), financial problems (12%, $P = .02$), and eviction or loss of home (3%, $P = .04$) was significantly lower than the rest of the state.

Discussion

This analysis demonstrates the potential utility of enhancing surveillance systems such as NVDRS with small-area level geographic data. The pairing of geographic information with surveillance data can assist in the identification of both areas with higher than state average suicide rates and place-specific suicide risk factors. In this descriptive analysis, we described the location of high-risk areas in the state to encourage future investigations into causes and protective factors of suicide in Virginia and to develop data-driven, targeted suicide prevention activities.

We used a novel approach to identify clusters with spatially adaptive filters, which diverges from the contemporary literature on suicide cluster identification. The most commonly used method for detecting suicide clusters, the spatial scan statistic method, identifies a most likely cluster even when the statistical significance of the test statistic is low. However, our analysis used spatially adaptive filters as the basis for our clustering method to address the impact that different population sizes have on the statistical reliability of the disease rates (Choynowski, 1959; Waller et al., 2006). While other studies have used spatially adaptive filters to represent geographic patterns of disease rates as a continuous surface (**Figure 1B**), we extended the use of spatial filters as a new way to identify geographic clusters. In doing so, we detected several highly geographically detailed clusters where suicide rates were significantly higher than in Virginia (**Figure 1A**). Moreover, the identified clusters in this analysis tended not to follow county administrative boundaries; they either occurred within counties or contained regions from neighboring counties. These results could inform future work examining sub-county clustering of suicide and changes in suicide clusters over time.

This analysis revealed important differences in suicide methods between high suicide risk clusters. Compared to the rest of the state, four clusters in western Virginia had a significantly higher proportion of suicides from firearm-related injuries, and two clusters in northern Virginia had a significantly higher proportion of suicides from poisoning. These clusters contain a higher proportion of rural Census tracts than any other cluster in the study. An important driver of urban-rural differences in suicide is the increased rate of suicide by firearm in rural areas (Ivey-Stephenson et al., 2017; Nestadt et al., 2017). Two firearm suicide clusters were previously identified in Ohio, in the Appalachian region of the state (Fontanella et al., 2018); the clusters with a higher proportion of firearm suicides in this paper, which also occurred in or near the Appalachian region of Virginia, may indicate larger regional trend. Poisoning has a relatively low case fatality rate, which may suggest high levels of non-fatal substance misuse in the clusters with a higher proportion of poisoning suicides (Miller et al., 2004).

The pattern of mental health circumstances in all suicide clusters combined was not different from that of the rest of the state, although the proportion of decedents reporting mental health circumstances did differ for some individual clusters. Overall, mental health circumstances were common among decedents inside and outside clusters, which underscored the importance of preventing and treating mental health conditions for suicide prevention. However, some individual clusters reported a significantly lower proportion of mental health conditions (clusters 4, 7, & 11) and mental health treatment (cluster 6) compared to the rest of the state. Treatment for mental health conditions could be affected by various individual (e.g., health insurance status, mental health condition) and environmental (e.g., health and mental health provider density) factors. Furthermore, these results do not account for regional variations in mental health care, such as differences in quality of care between urban and rural areas (Gamm et al., 2010; Ziller et al., 2010).

Job problems, financial problems, and eviction or loss of home were less likely to be reported as precipitating suicide circumstances in all clusters combined compared to the rest of the state, although these circumstances varied regionally. Decedents in three high-risk clusters (9-11) in western Virginia were less likely to have known job problems, and decedents in two high-risk suicide clusters (12 & 13) in rural Appalachian Virginia were less likely to have known job problems, financial problems, and eviction or loss of home compared to the rest of the state. Some research has found an association between individual socioeconomic disadvantage and suicide, but the association is inconsistent (Burrows et al., 2011). The results from this analysis may indicate the relative importance of precipitating factors other than job problems, financial problems, and eviction for suicide in clusters 9-13.

Limitations

This analysis has some important limitations. First, information about precipitating circumstances, medical/mental health status, and/or intent of the deceased may be misclassified or incomplete depending on the circumstances of the death investigation. In particular, the probability of a death being classified as undetermined instead of suicide is substantially greater for poisoning deaths than gunshot/hanging deaths when documentation of a suicide note is missing (Rockett et al., 2018). Virginia’s statewide medical examiner system likely mitigates some of these data quality issues (Institute of Medicine, 2003). Second, the bivariate descriptive analyses in these surveillance data do not account for confounding, which could be addressed in future studies through multivariate analysis. However, we standardized suicide mortality ratios in the analysis by age and sex to control for demographic differences across the state.

Third, the associations from the bivariate analyses may be inaccurate due to multiple comparisons testing and the variation in cluster size, which may lead to false positive results and/or limit statistical power. Finally, we did not examine the effects of contextual factors such as neighborhood poverty in this analysis. Future studies could examine the interaction between individual-level risk factors from NVDRS and contextual factors.

Conclusions

Information about spatial variation in suicide rates could help direct suicide prevention resources to areas with the greatest need in Virginia and elsewhere. These data could encourage the development of more targeted, effective prevention programs, such as strategies described in the CDC's suicide prevention technical package (Stone et al., 2017). The integration of small-area geographic data to NVDRS provides valuable information about spatial variation in suicide risk factors that can facilitate place-based suicide prevention strategies and be used in small-area geographic analyses with other topics (e.g., homicide). This analytic strategy is useful for guiding targeted suicide prevention efforts and informing additional research to understand the increasing rates of suicide.

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