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Geospatial mapping can be used to identify geographic areas and social factors associated with intentional injury as targets for prevention efforts distinct to a given community

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Abstract

BACKGROUND—Geographic information systems (GIS) have proven effective in studying intentional injury in various communities; however, GIS is not implemented widely for use by Level I trauma centers in understanding patient populations. Our study of intentional injury combines the capabilities of GIS with a Level I trauma center registry to determine the spatial distribution of victims and correlated socioeconomic factors.

METHODS—One thousand ninety-nine of 3,109 total incidents of intentional trauma in the trauma registry from 2005 to 2015 had sufficient street address information to be mapped in GIS. Comparison of these data, coupled with demographic data at the block group level, determined if any clustering or spatial patterns existed. Geographic information systems delivered these comparisons using several spatial statistics including kernel density, ordinary least squares test, and Moran's index.

RESULTS—Kernel density analysis identified four major areas with significant clustering of incidents. The Moran's I value was 0.0318. Clustering exhibited a positive z -score and significant p value ($p < 0.01$). Examination of socioeconomic factors by spatial correlation with the distribution of intentional injury incidents identified three significant factors: unemployment, single-parent households, and lack of a high school degree. Tested factors did not exhibit substantial redundancy (variance inflation factor < 7.5). Nonsignificant tested factors included race, proximity to liquor stores and bars, median household income, per capita income, rate with public assistance, and population density.

CONCLUSION—Spatial representation of trauma registry data using GIS effectively identifies high-risk areas for intentional injury. Analysis of local socioeconomic data identifies factors unique to those high-risk areas in the observed community. Implications of this study may include

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DISCLOSURE

No conflicts of interest are declared for this study.

the routine use of GIS by Level I trauma centers in assessing intentional injury in a given community, the use of that data to guide the development of trauma prevention, and the assessment of other mechanisms of trauma using GIS.

LEVEL OF EVIDENCE—Epidemiological, level IV.

Keywords

GIS; intentional injury; trauma; prevention; mapping

Traumatic injury is the leading cause of death for those under the age of 44 years.¹ Intentional trauma disproportionately affects youth and is the third leading cause of death for those between the ages of 15 years and 24 years.² Thus, intentional injury greatly contributes to overall years of life lost. Trauma centers can only have a limited impact by approaching this problem through the advancement of trauma clinical care.³ Conversely, the idea of preventing the occurrence of violence has a larger potential. Trauma centers can have a strategic involvement in the development of violence prevention programs through the analysis of trauma registry data.

The Centers for Disease Control and Prevention (CDC)'s public health approach to injury prevention is composed of four steps. The first is to define the problem by the magnitude, population affected, and location involved while monitoring changes over time. The second is to identify risk and protective factors associated with the injury in the population studied. The third is to develop prevention strategies based on the data gathered. The final step is to implement those prevention strategies and evaluate their efficacy over time. This study analyzes trauma registry data using geographic information systems (GIS) to satisfy the first step of the CDC's public health approach to injury prevention. In addition, GIS analysis may be used as a supplemental tool to satisfy the second step of the CDC's approach.

After reviewing past literature on the study of intentional injury in local communities, we determined GIS to be a useful tool to geographically analyze our trauma registry.⁴⁻¹² GIS is a broad term used to describe programs that analyze, manipulate, and display geographic data in various ways. The capabilities of GIS are expansive, and its mastery is critical in the discipline of geoinformatics. There are multiple brands of GIS, each with unique capabilities. For this study, GIS generated detailed maps of intentional injury incidents using street address information. With those maps, GIS determined spatial correlations between the distribution of incidents and socioeconomic factors.

This study used the University of South Alabama Medical Center (USAMC) trauma registry to generate data relevant to the USAMC patient population. University of South Alabama Medical Center is the only Level I trauma center for Southwest Alabama and Southern Mississippi. The institution admits approximately 1,600 patients per year to the trauma service. In this study, the data were restricted to members of Mobile County.

METHODS

Mapping Areas of Significant Risk

First, we used GIS to create a map of the locations of intentional injury incidents in Mobile County. This study defines intentional injury as all forms of assault and self-harm. Intentional injury street address data was obtained from the USAMC trauma registry over a 10-year period (2005–2015). Arcmap 10.4.1 was the specific GIS program used. Sufficient street address information allowed for the inclusion of 1,009 of 3,109 total incidents. This project used point level data where the injury occurred rather than the victim's place of residence.¹³ Then, we created another map showing a kernel density analysis of the incidents, which only shows statistically significant spatial clustering. This method of analysis ensures exclusion of points determined to be random.

Analyzing Socioeconomic Factors Associated With High-Risk Areas

Second, incidents were associated with census block groups using GIS. Those census block groups were then compared with socioeconomic data. We analyzed individual factors to determine possible spatial correlation with the high-risk areas, also called hot spots. In other words, we determined the factors unique to high-risk areas that are not significant in low-risk areas. Ordinary least squares analysis compared each tested factor with the number of incidents for each block group. The type and strength of association between each factor and the number of incidents in a block group was determined. The variance inflation factor was also determined which indicates the existence of redundancy among tested socioeconomic factors. Our analysis included race, proximity to liquor stores and bars, median household income, per capita income, rate with public assistance, population density, unemployment, rate with a high school degree, and single-parent homes.

RESULTS

The results of this study are based on the USAMC patient population from 2005 to 2015. One thousand nine patients treated at the USAMC for injuries related to intentional violence were included in this study. Table 1 delineates the characteristics of the included and excluded patient populations. Of those included, victims were overwhelmingly men (86.5%) with the most victims in the 20-year to 29-year age group. Most victims were black (71%), followed by white (27.2%), with other races making up 2% of the victims seen at this center.

Mapping Areas of Significant Risk

Spatial statistical analysis determined significant clustering of incidents using Moran's Index. These clusters (hot spots) were mapped using kernel density (Fig. 1). Further analysis determined four primary areas with clustering of incidents ($Z = 4.1287$, $p < 0.01$). The Moran's I value was 0.0318. Figure 2 displays intentional injury organized by census block groups.

Analyzing Socioeconomic Factors Associated With High-Risk Areas

Ordinary least-squares analysis determined that the spatial distributions of three factors correlated with the distribution of intentional injury in the community: unemployment,

single-parent households, and lack of a high school degree. Each factor was determined to be significant and have no substantial redundancy with other tested factors (variance inflation factor < 7.5). Table 2 shows the strength of the relationship between the distribution of each factor and the distribution of violent incidents.

DISCUSSION

The public health approach to injury prevention as defined by the CDC is a four-step process: define the problem, identify risk and protective factors, develop prevention strategies, and study the efficacy of those strategies upon implementation. The goal of this study was to demonstrate the utility of GIS in defining intentional injury for a select population and in detecting risk factors. The trauma registry identifies individuals affected by intentional injury. Geographic information system then determines significant clustering representing the areas where intentional injury occurs most often. This method can define the magnitude, population, and location of intentional injury in the population served by a trauma center. If repeated at intervals, changes and trends in the data may be monitored. Geographic information system can then incorporate socioeconomic data to identify factors correlating with the spatial distribution of intentional injury. The study of risk and protective factors associated with intentional injury is complex, and involves the individual, family, and community.¹⁴ Spatial correlation between socioeconomic factors and violence provides only a piece of the picture concerning the forces that shape intentional injury. Therefore, GIS is just one tool to be used along with others when attempting to identify risk and protective factors.

The social determinants of health include conditions affecting an individual that alter their overall health, including risk for intentional injury.¹⁵ These may include employment, availability of resources, education, access to health care, social support, culture, and more.¹⁵ Strong associations between these factors and health suggest that they play a large role.¹⁶ However, the many barriers present when investigating social factors by randomized controlled trials limit causal evidence.^{16,17} In the primary care setting, screening for these factors results in a higher utilization of community resources.^{18,19} For the study of intentional injury, analysis of trauma data with tools, such as GIS, can correlate the geographic distribution of violence and social determinants. This allows for identification of which social determinants geographically overlap most heavily with high-risk areas.

Nonsignificant Factors

In our analysis, we tested many factors for spatial correlation with intentional injury. Although 71% of incidents involved black victims and 27% involved white victims, race was not spatially correlated with high-risk areas. There are high and low-risk areas for both predominately black and white communities. Therefore, the geographical predominance of either race does not represent a linear relationship with the distribution of incidents in Mobile County. There are clear disparities involving race and intentional injury. However, this analysis suggests that the geographic distribution of a particular race alone does not correlate with the distribution of intentional injury hot spots in Mobile County. Another way to consider this is that if you pick any black resident of Mobile County, the chance that they

live in a high-risk area is not significant. On the other hand, if you pick any unemployed resident of Mobile County, the chance that they live in a high-risk area is significant.

Population density, proximity to liquor stores, and proximity to bars did not significantly correlate with high-risk areas. Past research of intentional injury using GIS has identified significant associations with these factors and violence.⁴⁻⁶ Urban communities seem to have a greater association between alcohol serving establishments and violence.⁶ Mobile County is more disperse than areas usually studied in this kind of research. For example, Mobile County is estimated to have 87.4 people per square mile, whereas Dallas County, Texas is estimated to have 3,517.6.²⁰ The fact that population density and proximity to alcohol serving establishments are not significant in Mobile County illustrates that every community is unique. Income and rate with public assistance were also elevated in both high- and low-risk areas. Therefore, they are not defining features shaping high-risk areas for intentional injury.

There are several limitations to this study. Only 1,009 of 3,109 total incidents were included because many lacked sufficient street address information. This may be due to a lack of documentation by health care professionals, incomplete documentation of address information, or an inability to identify the location of injury if the patient arrives to the hospital by personal vehicle. Table 1 contains information to compare the included and excluded groups by demographics. Comparison of the included and excluded groups by two-sample *t*-test found no significant difference in their composition by age ($p = 0.19$), race ($p = 0.75$), or sex ($p = 0.62$). Another limitation is the grouping of incidents into census block groups. Ideally, the predictive factors would be analyzed along boundaries more specific to the hot spot areas. However, the smallest areas available for use that include socioeconomic data are the census block groups. The factors selected for study were those that were both relevant to intentional injury and had data within GIS that could be analyzed. There are additional factors that we did not or could not assess using GIS that may also be predictive for intentional injury. There is the possibility of institutions such as jails or prisons located within a given census block that may skew results. In our study, for example, there is a small hot spot area clustered around the city jail. If injuries occurring in the jail were removed from this block group then no hot spot is evident. It is important to recognize the increased rate of intentional violence in jails as it may be important to identify needs for reform. However, the jail hot spot is not associated with the census block data because the occupants of the jail do not contribute to the local socioeconomic data. There is also a possibility of unidentified hot spot areas. If an area sends victims of intentional injury to two trauma centers for example, each center could complete this study without identifying that area as a hot spot. The results of this study are meant to predict current risk in the patient population, but are based on past data. In this study we used data from 2005 to 2015. We recommend new analysis to replace existing data approximately every 5 years to 10 years to maintain current information.

CONCLUSION

This study demonstrates the combined use of GIS with trauma registry data to study intentional injury in local patient populations. Using the USAMC trauma registry, we

identified four major high-risk areas and three socioeconomic factors spatially correlated with those areas. We identified the past victims of violence presenting to our hospital and the geographic clusters where their injuries occurred. Our spatially significant factors included unemployment, lack of a high school degree, and single parent households. With the results of this study, we know that these factors are important for distinguishing high-risk from low-risk areas in the USAMC community, and we can quantify the strength of each factor's influence.

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Figure 1. Kernel density analysis of intentional injury incident locations in Mobile County for victims treated at USAMC from 2005 to 2015 ($n = 1,009$) ($p < 0.01$) (Moran's $I = 0.0318$).

Figure 2.
Intentional injury incident locations in Mobile County for victims treated at USAMC organized into census block groups (n = 1,009).

TABLE 1

Demographics of Patient Population

		Total (3,109)	Included (1,009)	Excluded (2,100)
Sex	Male	2,635 (84.8%)	873 (86.5%)	1,762 (84.0%)
	Female	474 (15.2%)	136 (13.5%)	338 (16.1%)
Race	White	1,124 (36.2%)	274 (27.2%)	850 (40.5%)
	Black	1,893 (60.9%)	716 (71.0%)	1,177 (56%)
	Native American	4 (0.13%)	1 (0.10%)	3 (0.14%)
	Asian	11 (0.35%)	2 (0.20%)	9 (0.43%)
	Other/unknown	77 (2.5%)	16 (1.6%)	61 (3.0%)
Age, y	0–9	7 (0.23%)	1 (0.10%)	6 (0.29%)
	10–19	315 (10.1%)	134 (13.3%)	181 (8.6%)
	20–29	1,007 (35.6%)	351 (34.8%)	656 (31.2%)
	30–39	690 (22.2%)	222 (22.0%)	468 (22.3%)
	40–49	594 (19.1%)	177 (17.5%)	417 (19.9%)
	50–59	362 (11.6%)	103 (10.2%)	259 (12.3%)
	60–69	92 (3.0%)	15 (1.5%)	77 (3.7%)
	70–79	30 (1.0%)	2 (0.20%)	28 (1.3%)
	80–	12 (0.40%)	3 (0.30%)	9 (0.43%)

TABLE 2

Analysis of Significant Factors

Socioeconomic Factors	Coefficient [a]	Standard Error	<i>t</i>-statistic	Probability [b]
Single parent household	4.847	1.541	3.145	0.00186
No high school degree	8.316	2.984	2.787	0.00571
Unemployment	13.239	3.252	4.071	0.000068