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ORIGINAL RESEARCH CONTRIBUTION

Identifying High-risk Geographic Areas for Cardiac Arrest Using Three Methods for Cluster Analysis

Comilla Sasson, MD, MS, Michael T. Cudnik, MD, MPH, Ariann Nassel, MS, Hugh Semple, PhD, David J. Magid, MD, MS, Michael Sayre, MD, David Keseg, MD, Jason S. Haukoos, MD, MSc, and Craig R. Warden, MD, MPH, MS (The Columbus Study Group)

Abstract

Objectives: The objective was to identify high-risk census tracts, defined as those areas that have both a high incidence of out-of-hospital cardiac arrest (OHCA) and a low prevalence of bystander cardiopulmonary resuscitation (CPR), by using three spatial statistical methods.

Methods: This was a secondary analysis of two prospectively collected registries in the city of Columbus, Ohio. Consecutive adult (≥18 years) OHCA patients, restricted to those of cardiac etiology and treated by emergency medical services (EMS) from April 1, 2004, to April 30, 2009, were studied. Three different spatial analysis methods (Global Empirical Bayes, Local Moran's I, and SaTScan's spatial scan statistic) were used to identify high-risk census tracts.

Results: A total of 4,553 arrests in 200 census tracts occurred during the study period, with 1,632 arrests included in the final sample after exclusions for no resuscitation attempt, noncardiac etiology, etc. The overall incidence for OHCA was 0.70 per 1,000 people for the 6-year study period (SD = ±0.52). Bystander CPR occurred in 20.2% (n = 329), with 10.0% (n = 167) surviving to hospital discharge. Five high-risk census tracts were identified by all three analytic methods.

Conclusions: The five high-risk census tracts identified may be possible sites for high-yield targeted community-based interventions to improve CPR training and cardiovascular disease education efforts and ultimately improve survival from OHCA.

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From the Department of Emergency Medicine, University of Colorado School of Medicine (CS, AN, JSH), Aurora, CO; the Department of Emergency Medicine, The Ohio State University (MTC, MS, DK), Columbus, OH; the Department of Geography, Eastern Michigan University (HS), Ypsilanti, MI; the Institute for Healthcare Research, Kaiser Permanente (DJM), Denver, CO; the Department of Emergency Medicine, Denver Health Medical Center (JSH), Denver, CO; and the Department of Emergency Medicine, Oregon Health and Sciences University (CRW), Portland, OR.

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Supervising Editor: Clifton W. Callaway, MD, PhD.

Address for correspondence and reprints: Comilla Sasson, MD, MS; e-mail: comilla.sasson@ucdenver.edu.

Survival from out-of-hospital cardiac arrest (OHCA) varies greatly between cities throughout the United States.[1] However, little is known about how this variation in survival differs within specific communities in different cities. Our previous research in Fulton County, Georgia, has shown that, at the community level, there is stability in the incidence of cardiac arrest by census tracts across time.[2] This suggests that certain clusters for cardiac arrest incidence persist across time. Our previous work, using Global Empirical Bayes population-adjusted rates has also shown that ''high-risk'' census tracts can be identified that have both a high incidence of OHCA and a low prevalence of bystander-performed cardiopulmonary resuscitation (CPR).[2] These census tracts could be targets for public health interventions to increase cardiovascular disease education and CPR knowledge. Our previous, less sophisticated approach did manage to highlight the small areas (census tracts) that have

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persistently high or low rates of cardiac arrests over a period of time. Still, there is a need for more robust techniques that use more advanced and perhaps more sophisticated statistical methods to detect cardiac arrest hot spots.

Hot spot analysis is a major field of study within geographic information systems (GIS), and robust analytical techniques exist for cluster detection. These statistical methods employ different types of algorithms to determine which areas are outliers in comparison to their neighbors and can take into account the underlying distribution of the population. However, only a small amount of research has been done to use these techniques to identify OHCA hot spots. Lerner et al.[3] used kernel density mapping to identify clusters of OHCA in Rochester, New York. This approach simply creates a smoothed map of the density of cardiac arrest without taking into account the underlying variation in population density within an area. It also does not calculate the statistical significance of the clusters. As the field of GIS becomes more advanced, new software and more robust techniques for cluster analysis have emerged. Such applications are being widely used in the GIS, criminal justice, and infectious disease literature. However, little is known about how well these methods can be applied to a public health registry for cardiac arrest.

GeoDa (http://geodacenter.asu.edu/)[4] and SaTScan (http://www.satscan.org/)[5] are two freely available spatial statistics software packages for hot spot analysis. GeoDa uses Local Moran's I method to identify outliers by considering the deviation of an area and its neighbors from the overall mean. However, Local Moran's I is difficult to interpret at the edges of a geographic boundary, as those regions with few neighbors have a less robust statistic to identify outliers. SaTScan employs a spatial scan statistic to draw circles of varying magnitude, which are set by the user, around an area, comparing the observed versus the expected outcomes in that area. A drawback to this type of analysis is that large clusters can sometimes be identified, which do not allow for the discrete identification of smaller areas. SaTScan also does not take into account geographic boundaries such as rivers and freeways that may divide neighborhoods. The Global Empirical Bayes approach, which has been used in prior research,[2] also has its own limitations, as it adjusts for small sample size and may reduce variability of estimates so much that real outliers cannot be identified. Because each approach has its advantages and limitations, no single method is considered the "criterion standard" for hot spot analysis.

The primary goal of this study was to identify census tracts considered to be high risk (high OHCA incidence, low prevalence of bystander CPR) using three different statistical methods for hot spot analysis: Global Empirical Bayes, Local Moran's I, and spatial scan statistic. The secondary goal was to identify which census tracts were identified by at least two out of the three methods, as these may represent the "true" high-risk areas for disease within an area and could serve as potential sites for community-based interventions.

METHODS

Study Design

This was a retrospective analysis of two distinct OHCA surveillance registries that prospectively collected data on all cardiac arrests events in the city of Columbus, in Franklin County, Ohio. The first data set was collected by the city emergency medical services (EMS) agency from April 1, 2004, through December 31, 2007, and included all cardiac arrest events in the area. The methodology of this registry has been previously described.[6] The second data set included data from the CARES (Cardiac Arrest Registry to Enhance Survival) registry from January 1, 2008, to April 20, 2009. Detailed information about the CARES registry has been published previously.[7,8] Since both registries contain only deidentified data, our study was considered exempt research by The Ohio State and University of Michigan Institutional Review Boards.

Study Setting and Population

The city of Columbus has a population of 729,369 people and covers approximately 212 square miles, with 65.4% of citizens classified as white, 26.4% as African American, and 4.5% as Hispanic ethnicity by the U.S. Census Bureau.[9] Approximately 95% of all ambulance runs within the city are serviced by the single-city fire-based EMS system, which provides all advanced life support EMS units, with at least one paramedic on each fire engine and two paramedics on each ambulance. The EMS system responded to over 107,000 runs in 2008 (the last full year of the study sample; D.P. Keseg, personal communication, 2010).

The two registries captured all 9-1-1–activated cardiac arrest events that took place within the city limits of Columbus. They contained similar data elements and were therefore able to be combined. EMS administrators and CARES analysts confirmed the capture of all cardiac arrests in the county by each city's 9-1-1 center during the data review process. Columbus Fire and EMS prospectively submitted data to the registries, which collected and linked a limited standard set of data elements from three sources: 9-1-1 call centers, EMS providers, and receiving hospitals. A data analyst independently reviewed all submitted reports. After quality checks, a deidentified case was permanently entered into the registry database.

All cases submitted to the registries during the study interval (N = 4,553) were eligible for study if they met inclusion criteria. A case was excluded if: 1) prehospital resuscitation was not attempted based on local EMS protocols (e.g., obvious signs of death such as rigor mortis, decomposition, lividity; n = 1,998); 2) EMS personnel determined that the arrest was due to a noncardiac etiology (e.g., trauma, electrocution, drowning, or respiratory; n = 329); 3) the patient was not eligible for bystander CPR by a non–health care professional because of the ready availability of health care professionals (e.g., patient's arrest occurred in a medical facility such as a nursing home or medical clinic; n = 403); 4) data documenting the patient's clinical outcome were missing (n = 34); 5) the patient's cardiac arrest location address could not be mapped (n = 5); 6) the patient was younger than 18 years of age (n = 97); and 7) the event occurred outside of the city limits of Columbus (n = 55). Finally, for the calculation of the CPR rates, those events that were witnessed by EMS (n = 182) were excluded, as these patients would not have been eligible for bystander CPR.

Study Protocol

Patient-level characteristics were obtained from the registries. They included age, sex, race/ethnicity (as coded by the EMS provider), location of arrest (public location vs. private residence), witnessed arrest (arrest witnessed by someone other than the first responder/EMS provider), who initiated CPR (bystander vs. first responder/EMS provider), receiving emergency department (ED), and neurologic outcome at the time of hospital discharge. Any bystander who was not part of the medical or EMS team was considered eligible to initiate bystander CPR. We used EMS provider-identified race/ethnicity in our analysis, as CPR provision is more plausibly influenced by how others perceive the unconscious victim rather than how a victim self-identifies himself or herself. Individual-level race/ethnicity was coded as unknown in 6.3% of our sample. To control for nonresponse, we categorized these patients as a separate "missing" or "unknown" race/ethnicity category, rather than dropping them from the sample or attempting to impute the racial/ethnic distribution of these cases based on the census tract in which the incident occurred.

We used census tracts as proxies for neighborhoods because they tend to represent social and economically homogenous groups of approximately 4,000 to 7,000 persons.[10] Census tract shapefiles were obtained from the U.S. Census Bureau along with critical socioeconomic data for the county, including population per census tract. Census tract factors were then added to the existing data set based on the geocoded location of the event: median household income; percentage of whites, African Americans, and nonwhite Hispanics; 18 years and older population that fell within the city of Columbus; percentage of high school graduates; and percentage of individuals living below the poverty line.

Data Analysis

The data set was geocoded based on the address of the cardiac arrest event using ArcGIS 9.3 Software (Environmental Systems Research Institute [ESRI] Inc., Redlands, CA). Street centerline shapefiles were downloaded from ESRI's website (http://www.esri.com). Socioeconomic and demographic variables at the census tract level were linked to each geocoded address using the 2000 U.S. Census Bureau summary files.[9] Global Empirical Bayes analysis was conducted using Stata version 10.1 (College Station, TX), Local Moran's I analysis was conducted using ArcGIS 9.3 and GeoDa, and ArcGIS 9.3 and SaTScan were used for the SatScan analysis. No a priori sample size was calculated for these analyses. Pycnophylactic interpolation[11] was used to estimate population counts for the portions of census tracts lying within the Columbus city boundaries. The interpolation method generated a smooth population density surface covering the study area. The method works by letting census tracts with locally high or low population densities influence the surface by shifting local population densities in neighboring census tracts toward or away, respectively. This is done while the value of the population density surface for each tract (total tract population) is kept equal to the tract populations. Integration of the density surface lying above the partial census tracts was then used to provide a geographically adjusted population estimate for these areas. Rates of OHCA incidence and bystander CPR are reported in all three analyses as the proportion of events per census tract per the aggregate 6-year study period.

Statistical Methods Used for Identification of High-risk Census Tracts

Global Empirical Bayes Smoothed Rates. We first calculated the Global Empirical Bayes smoothed rates, over the 6-year period, for OHCA and bystander CPR using Stata. The Empirical Bayes smoother works by adjusting rates toward the global mean of the observed data with the amount of shrinkage inversely proportional to the size of the population at risk. Census tracts with large populations experience very little adjustment. Tracts with small populations, and therefore unstable rates, are stabilized by a greater adjustment.[12,13] The reliability-adjusted rates for OHCA incidence rates and prevalence of CPR by census tract per 6-year study period were graphed to determine which census tracts fell in the highest quartile for OHCA incidence and lowest quartile for CPR rates. These census tracts were then identified as the high-risk areas. Additional details of this methodology have been described elsewhere.[2]

Local Moran's I Analysis. Local Moran's I measures the degree to which similar observations tend to occur next to each other so that local areas of similar value may be defined as a cluster.[14] We used Geoda to calculate a Local Moran's I statistic for the study area, using the adjusted Spatial Empirical Bayes rates. Spatial Empirical Bayesian rates differ from Global Empirical Bayesian rates in that the calculated rates are adjusted toward the average rate of the surrounding census tracts rather than the overall mean of the study area.[15]

After adjusted OHCA incidence rates per year and bystander CPR prevalence were calculated, a Local Moran's I statistic was calculated for each census tract using the first order neighbors of each tract to define local neighborhoods. Areas of elevated OHCA were determined to be significant if the p-value resulting from nonparametric Monte Carlo simulations was less than 0.05. Those areas that had a significant p-value for OHCA incidence or bystander CPR prevalence were considered clusters. Clusters of high OHCA rates were then identified for the period of 2004 to 2009. The data were analyzed in aggregate, so that all arrests occurring during the study time period were included for possible analysis. Both incidence and bystander CPR are reported as per the 6-year time period, not as annual incidence rates. Once clusters of high incidence of OHCA and low prevalence of bystander CPR were identified, these two sets of clusters were overlaid on each other to find those high-risk census tracts that had both statistically significant high rates of OHCA and low prevalence of bystander CPR.

Spatial Scan Statistic. SaTScan employs a spatial scan statistic to draw circles of varying magnitude, which are set by the user, around an area, comparing the observed versus the expected outcomes in that area. Incidence rates of OHCA and bystander CPR for the aggregate time period (2004–2009) were first calculated using the "point-in-polygon" method of overlaying the respective event locations and census tract polygon and its population at risk. For the SaTScan Poisson analysis, centroids of the census tracts were used to define the location of the population at-risk and cardiac arrest cases that occurred within the census tract.

The likelihood ratio was tested for significance using the Monte Carlo method and 999 simulations, with a significance level of 0.05. A circular window was centered on each census tract centroid and the maximum circle size was allowed to contain between 10 and 50% (in 10% increments) of the total cases being analyzed to find the best cluster(s) size. The likelihood function was maximized over all window locations and sizes, and the one with the maximum likelihood constituted the most likely cluster. Secondary nonoverlapping clusters were then found by subtracting the most likely cluster cases from the pool and repeating the above procedure.

Cardiopulmonary resuscitation rates were then calculated for each census tract. A "low" bystander CPR rate was considered to be less than the 25th percentile of the overall bystander CPR rate. Those tracts that were within the identified SaTScan-derived clusters and had a low CPR rate were then identified as high-risk census tracts (e.g., having both a significantly elevated risk of OHCA and a low bystander CPR rate). These were identified by overlaying the two sets of maps in ArcGIS.

RESULTS

There were a total of 1,632 cardiac arrest events that were included in the final sample, with 1,450 events eligible for bystander CPR (e.g., not witnessed by EMS). Table 1 shows the patient and cardiac arrest event characteristics of the full sample (n = 1,632). Out-of-hospital cardiac arrest patient characteristics were more likely to be white (n = 957, 58.6%) and have a presenting rhythm of asystole (n = 783, 48.0%), with the majority of these events occurring at home (n = 1,378, 84.5%). The mean crude bystander CPR percentage for the study period, defined here as total numbers of patients who received bystander CPR divided by the total number of CPR eligible arrests, was 20.2%, with an overall survival to hospital discharge of 10.0% (n = 164).

The city of Columbus includes 200 census tracts. The mean crude OHCA incidence per census tract for the 6-year study period was 0.70 per 1,000 people (interquartile range [IQR] = 0.31 to 0.98 per 1,000 people). The mean crude bystander CPR percentage per census tract was 23.8% (IQR = 0 to 33.3). The crude mean of total arrests per census tract for the study period was 9.8 (IQR = 4.0 to 13.3).

Table 1
Patient Demographics and Cardiac Arrest Characteristics

Characteristics	n (%)
Age (yr), mean (SD) (n = 1,632)	61.3 (15.5)
Sex, female (n = 1,617)	658 (40.7)
Race (n = 1,632)	
White	957 (58.6)
Black or African American	542 (33.2)
Other	31 (1.9)
Unknown	102 (6.3)
Bystander-witnessed arrest (n = 1,629)	329 (20.2)
EMS-witnessed arrest (n = 1,632)	182 (11.2)
Location of arrest (n = 1,631)	
Home	1378 (84.5)
Public building/mass gathering	157 (9.6)
Street	49 (3.0)
Recreation/sports facility	10 (0.6)
Medic unit/fire station	7 (0.4)
Jail	5 (0.3)
Other	25 (1.6)
Presenting rhythm (n = 1,624)	
VF/VT/unknown shockable	451 (27.8)
Unknown unshockable	4 (0.3)
Asystole	783 (48.0)
Pulseless electrical activity	329 (20.2)
Other	57 (3.5)
Public access defibrillator applied (n = 1,629)	21 (1.4)
Bystander CPR (n = 1,630)	329 (20.2)
Outcome (n = 1,632)	
Died in the field	324 (19.9)
Died in the ED	802 (49.1)
Died in the hospital	342 (21.0)
Survived to hospital discharge	164 (10.0)

n = 1,632.
CPR = cardiopulmonary resuscitation; VF = ventricular fibrillation; VT = ventricular tachycardia.

Three Methods of Cluster Analyses

The OHCA incidence rates, adjusted with the Empirical Bayes smoother, showed a mean rate per census tract for the study period of 0.57 per 1,000 people (IQR = 0.32 to 0.72 per 1,000 people). Figure 1 shows the census tracts that were identified using the Global Empirical Bayes rates. OHCA incidence and CPR prevalence had a modest inverse correlation with a correlation coefficient of –0.23. Ten census tracts were identified within the highest quartile for OHCA incidence and lowest quartile for CPR prevalence.

The Local Moran's I analysis identified 27 high-risk census tracts (Figure 2). These census tracts were clustered in three areas throughout the city, predominantly in the lower socioeconomic status neighborhoods.

Finally, SaTScan identified one large primary cluster and four secondary clusters of significantly higher than the mean OHCA incidence in Columbus using the 10% of cases threshold (Figure 3). It was decided to restrict the window size to include only 10% of the cases because increases in the window size resulted in the identification of a single cluster centered on downtown Columbus. There were a total of 74 census tracts included in the five clusters identified as having higher risk. Thirty-one census tracts were identified that fell within the five SaTScan Poisson clusters and were below the 25th percentile for CPR rates. Table 2

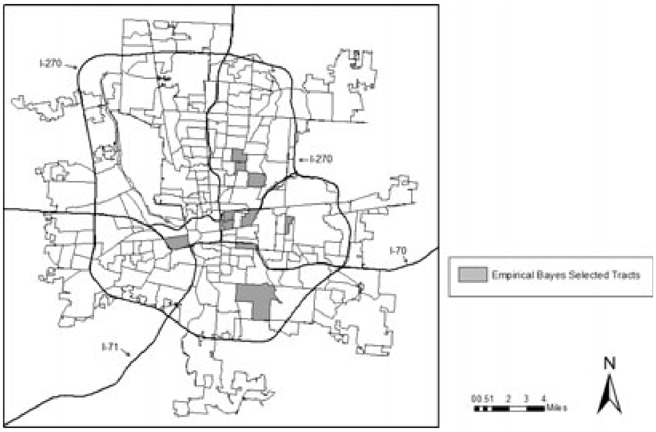

Figure 1. High-risk census tracts detected using Global Empirical Bayes analysis in Columbus, Ohio. High-risk census tracts were defined by having higher than the 75th percentile of adjusted OHCA incidence and lower than the 25th percentile of adjusted bystander CPR rates. CPR = cardiopulmonary resuscitation; OHCA = out-of-hospital cardiac arrest.

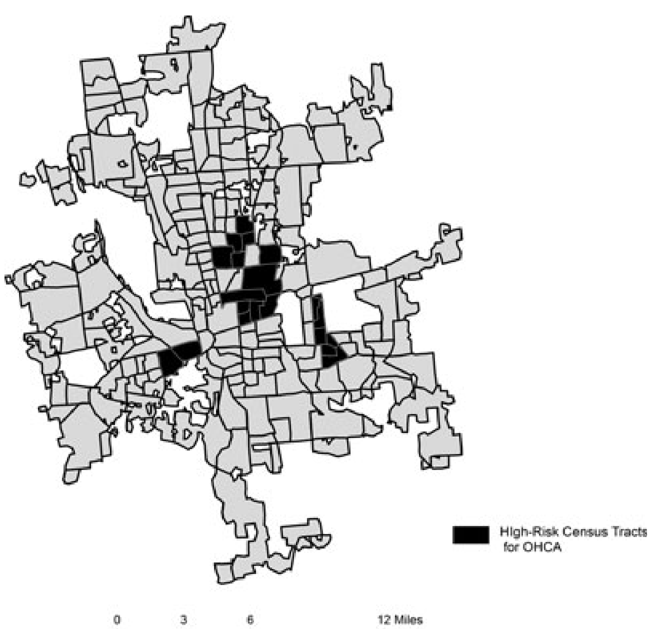

Figure 2. High-risk census tracts detected using Local Moran's I analysis in Columbus, Ohio. Once clusters of high incidence of OHCA and low prevalence of bystander CPR were identified, these two sets of clusters were overlaid on each other to find those high-risk census tracts that had both statistically significant high rates of OHCA and low prevalence of bystander CPR. CPR = cardiopulmonary resuscitation; OHCA = out-of-hospital cardiac arrest.

displays the identified tracts, as well as the socioeconomic and demographic characteristics associated with these areas.

Comparison of Cluster Analyses Results

Figure 4 displays the census tracts that were detected using each method, as well as those tracts that were

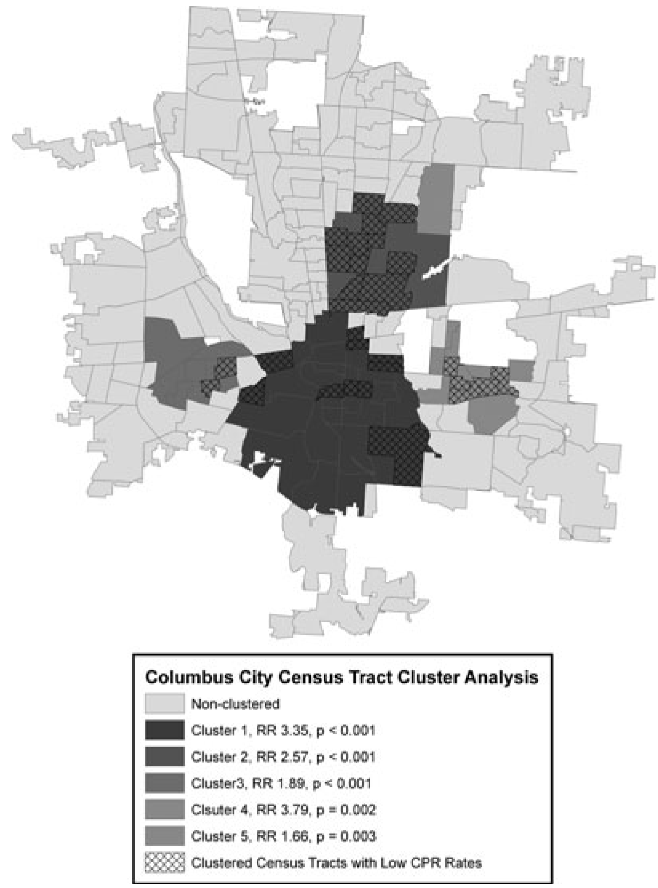

Figure 3. High-risk census tracts detected using SaTScan Poisson analysis in Columbus, Ohio. Those tracts that were within any identified SaTScan-derived clusters and had a low CPR rate were then identified as high-risk census tracts, i.e., having both a significantly elevated risk of OHCA and having a low bystander CPR rate. CPR = cardiopulmonary resuscitation; OHCA = out-of-hospital cardiac arrest; RR = relative risk.

identified in two or three of the three methods. Five census tracts appeared in all three analyses. Characteristics of these census tracts are displayed in Table 2. The five census tracts are composed of more African American residents (36.6% to 91.2%; Franklin County mean = 17.9%), lower median household incomes ($14,365 to $33,154; Franklin County median income = $42,734), and fewer high school graduates (62.3% to 72.0%; Franklin County mean = 85.7%) than is typical of Franklin County.

The other 16 census tracts that were identified in at least two of the three methods are also shown in Table 2. These census tracts displayed similar characteristics of the previous five census tracts (e.g., lower median household income, higher proportion of African American residents, and fewer high school graduates).

DISCUSSION

Out-of-hospital cardiac arrest research has recently focused on the variations in care and survival between small geographic areas, rather than within large

Table 2
Characteristics of High-risk Census Tracts

Tract ID	Incidence	Adjusted Incidence	CPR Rate	Adjusted CPR Rate	% White Race	% African American Race	Median* Age, yr	Median* Household Income	% of High School Grads
Primary identified clusters									
820	0.70	0.93	0.00	0.14	56.7	36.6	33	$31,756	69.6
920	1.17	0.96	0.00	0.14	26.3	67.4	29	$22,333	64.4
3600	1.28	0.96	0.08	0.15	9.4	83.4	40	$14,365	63.0
5000	1.05	0.96	0.06	0.15	85.5	9.2	31	$20,954	44.4
7512	0.78	0.94	0.00	0.14	6.7	90.2	36	$33,154	72.0
Franklin County	*0.44*	*0.84*	*0.21*	*0.19*	*75.5*	*17.9*	*32*	*$42,734*	*85.7*
Secondary identified clusters									
710	1.41	0.97	0.10	0.15	70.8	21.8	35	$28,231	66.6
720	1.15	0.96	0.13	0.16	21.9	70.8	33	$24,821	66.6
730	0.57	0.92	0.00	0.14	3.4	91.7	30	$23,810	63.1
910	0.59	0.92	0.20	0.17	27.4	66.6	30	$28,375	70.8
2300	0.81	0.94	0.17	0.17	8.0	86.4	31	$22,140	61.7
2510	0.75	0.94	0.08	0.15	14.1	81.1	40	$31,265	73.1
2520	0.86	0.95	0.07	0.15	12.1	82.5	39	$26,708	79.0
2730	0.91	0.95	0.00	0.14	38.0	50.3	29	$28,429	85.0
2770	0.53	0.92	0.00	0.14	43.7	48.2	36	$28,169	76.1
2900	0.95	0.95	0.00	0.14	3.9	88.9	24	$9,769	58.6
4700	0.51	0.91	0.00	0.14	56.4	32.9	30	$28,854	65.8
4900	0.70	0.94	0.15	0.16	71.0	19.8	34	$29,831	62.5
5420	1.12	0.96	0.00	0.14	3.8	91.2	32	$22,226	67.2
8812	0.64	0.93	0.00	0.14	27.0	67.0	40	$38,611	73.4
9333	0.43	0.90	0.00	0.14	25.2	62.6	39	$32,054	81.6
9334	0.48	0.91	0.00	0.14	20.4	72.1	38	$39,911	82.8
Franklin County	*0.44*	*0.84*	*0.21*	*0.19*	*75.5*	*17.9*	*32*	*$42,734*	*85.7*

CPR = cardiopulmonary resuscitation.
*U.S. Census Bureau data; no ranges provided.

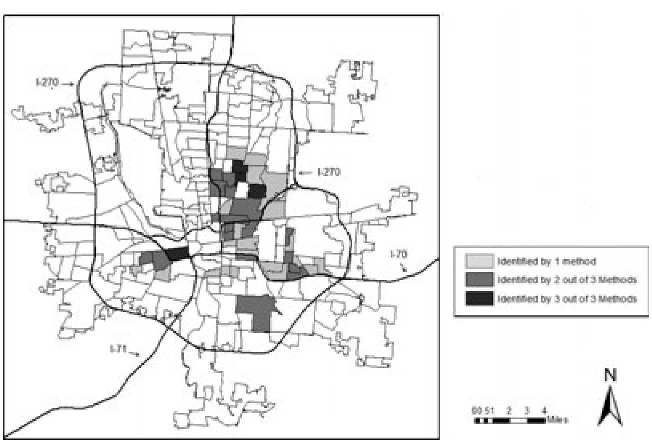

Figure 4. High-risk census tracts detected by the three spatial analysis methods for the city of Columbus, Ohio. Census tracts are shown that were identified in 1, 2, or 3 of the spatial analysis methods (Global Empirical Bayes, Local Moran's I, and SatScan).

geographic regions. To our knowledge, this is the first study to use three different spatial statistical methods to identify areas within a city that are potentially different in regard to their residents' risk of experiencing an OHCA and not receiving bystander CPR. For example, the same person who arrests in two different census tracts within Columbus will have markedly different chances of receiving CPR, a simple, life-saving intervention, and thus a different chance for survival, strictly due to where the event occurred. Identifying high-risk areas that are in the greatest need for CPR training, coupled with the new focus on chest compression-only CPR for bystanders[16] (an American Heart Association initiative aimed at increasing rates of bystander CPR), could have the greatest effect and potentially decrease health disparities within a city.

The three methods for identifying hot spots for OHCA each have their own advantages and disadvantages. Because there is no one acceptable method, we have identified those census tracts that appeared in all three analyses. By finding the overlap between these three methods, we believe that we are able to identify the "true" high-risk areas. This approach can now be applied within other communities to identify potential targets for disease interventions. For example, these methods could be used on the CARES data set, which includes information from over 40 U.S. cities, which would vastly increase the generalizability and validity of these findings. Additionally, these findings have potential health policy implications. Currently, CPR training is often employer-initiated, work-based, or nontargeted. Hot spot analysis could be used to focus scarce public health resources, like CPR training, in those neighborhoods that need it the most, using targeted, community-based interventions. This suggested approach may be a more feasible method for increasing CPR rates and ultimately survival from OHCA in U.S. cities.

In addition to the potential policy implications, we have also identified clusters of census tracts that appear to be different than the average census tract in Columbus. Consistent with prior research, the census tracts that were identified as higher risk in our study are more likely to be composed of African American, poor, and less educated individuals. There was one census tract (5000) that was predominantly comprised of white, poor, and less educated individuals. Future research will need to be conducted to better understand how race, socioeconomic status, and educational attainment affect the likelihood of being a high-risk census tract. However, not all census tracts with these same sociodemographics were considered to be high-risk areas. There are likely other characteristics of these census tracts and communities that contribute to these differences. For example, these ''cool spots'' (e.g., lower risk of OHCA, higher prevalence of bystander CPR) may already have community-based programming that has effected change in their neighborhoods. Identifying both high- and low-risk areas may provide insight into those programs and features of a community that have already been successful.

With the ability to identify high-risk areas within a community, the next step will be to work with community members from these high-risk areas to better understand what could be driving disparities in OHCA incidence and provision of bystander CPR and to then develop, using principles of community-based participatory research, CPR interventions that can be deployed in these areas.

LIMITATIONS

We chose to use three methods for the analysis of clusters of OHCA. There are other methods within GIS that can be used for cluster analysis. However, we chose three commonly employed methods that use different principles for identifying high-risk areas. It is also possible that there were some cases that were responded to by an alternate EMS provider and were not captured in our data set; however, more than 95% of cases that occur within the city of Columbus are serviced by Columbus EMS and would be included in this data set. We also did not separate OHCA events by public versus private location, although greater than 80% of all events did occur at home (private location). It is possible that certain areas may have a higher proportion of people during the daytime hours (e.g., downtown business area) and therefore a higher absolute number of arrests. However, our analysis did not find this relationship and instead identified five high-risk neighborhoods that were residential rather than commercial areas. Finally, we chose to use census tract as a proxy for neighborhood. Although this approach does not consider the true neighborhoods, which rarely follow census tract boundaries within a city or county, they do allow for us to better understand the demographics underlying the people who reside in those communities. Further research, which can create neighborhoods based on community land use surveys and surveys of the people themselves, may be used to identify more representative neighborhoods.

CONCLUSIONS

In this project, we have observed that there are marked differences in the incidence of out-of-hospital cardiac arrest and prevalence of bystander cardiopulmonary resuscitation between census tracts within a large, metropolitan city. Even with the application of three different methods for cluster analysis, 21 census tracts appear to be markedly different than their neighbors. Identification of these high-risk communities is the first step in a process to engage these communities to work together to decrease health disparities and improve survival from out-of-hospital cardiac arrest.

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