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MAJOR ARTICLE

Use of Activity Space in a Tuberculosis Outbreak: Bringing Homeless Persons Into Spatial Analyses

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Background. Tuberculosis (TB) causes significant morbidity and mortality in US cities, particularly in poor, transient populations. During a TB outbreak in Fulton County, Atlanta, GA, we aimed to determine whether local maps created from multiple locations of personal activity per case would differ significantly from traditional maps created from single residential address.

Methods. Data were abstracted for patients with TB disease diagnosed in 2008–2014 and receiving care at the Fulton County Health Department. Clinical and activity location data were abstracted from charts. Kernel density methods, activity space analysis, and overlay with homeless shelter locations were used to characterize case spatial distribution when using single versus multiple addresses.

Results. Data were collected for 198 TB cases, with over 30% homeless US-born cases included. Greater spatial dispersion of cases was found when utilizing multiple versus single addresses per case. Activity spaces of homeless and isoniazid (INH)-resistant cases were more spatially congruent with one another than non-homeless and INH-susceptible cases ($P < .0001$ and $P < .0001$, respectively).

Conclusions. Innovative spatial methods allowed us to more comprehensively capture the geography of TB-infected homeless persons, who made up a large portion of the Fulton County outbreak. We demonstrate how activity space analysis, prominent in exposure science and chronic disease, supports that routine capture of multiple location TB data may facilitate spatially different public health interventions than traditional surveillance maps.

Keywords. geospatial; mycobacterial; polygamy.

Although great strides have been made in reducing the rate of tuberculosis (TB) in the United States, TB outbreaks continue and cause strain on public health resources [1–3]. Homeless and incarcerated persons have been identified as the source cases for major outbreaks in the United States from 2002 to 2011 [2]. Addressing TB among the homeless is challenging with financial, logistical, and clinical barriers, but it is critically important for public health.

Spatial context of disease is important for all infectious disease investigation. Various analytical methods have been applied to geolocated TB case data to understand spatial patterns and clusters, space-time clustering, autocorrelation, and spatial risk factors [4–16]. In a study combining location data, network analysis, and molecular strain-typing, TB location data were shown to be as useful, if not more so, as contact tracing alone in identifying etiologies of specific outbreaks [17]. An understanding of spatial factors helps public health practitioners understand disease transmission, create effective surveillance systems, focus disease-screening and prevention activities, and target interventions [18].

Spatial methodologies facilitate increased understanding of the local context of TB disease, but these methods generally utilize one address per case, that of primary residence. Using a single address to define disease transmission areas for a person is limited because it assumes that humans are stationary. However, people are mobile, moving to work, socialize, or run errands. The concept of spatial polygamy, "the simultaneous belonging or exposure to multiple nested and non-nested, social and geographic, real, virtual and fictional, and past and present contexts," has previously been described as a way to understand the neighborhood context, which cannot simply be distilled down to a zip code or census tract [16]. Spatial polygamy is particularly important, yet challenging, for investigating transient populations. Many spatial analyses exclude homeless cases due to their transient status or ignore homelessness as an important issue when collecting spatial data [6, 7, 11]. Prior studies incorporating location data for TB case analysis have captured only 1%–2% of homeless persons in their study cohorts, which is important because homeless persons with TB are often more likely to be infectious at the time of diagnosis than non-homeless persons [19, 20]. Other studies have included homeless cases in spatial analyses, but they have only included a single address for analysis [4]. However, many homeless individuals circulate among a variety of locations.

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Use of activity space, a multidimensional space that represents spatial movement of people in their day-to-day lives [16, 21], could provide a simple and useful framework for analysis. A recent study in Tokyo used activity spaces to pinpoint potential transmission points for TB [22]. We analyzed data from TB cases diagnosed in Fulton County (a core urban county in metropolitan Atlanta) during a large TB outbreak involving a large proportion of unstably housed persons. Our aim was to determine whether local maps created from multiple activity locations per case would significantly differ from traditional health department maps based on single residential address.

METHODS

Study Population

We performed a cross-sectional study involving demographic and spatial data from a sample of persons diagnosed with TB disease in Fulton County, Georgia. The study population included persons 18 years and older diagnosed with active TB disease receiving care at the Fulton County Department of Health between January 1, 2008 and October 31, 2014.

Data Collection

Data were abstracted from health department charts; charts were sorted alphabetically and analyzed sequentially, with full capture of charts limited by time, capacity, and funding. Demographic characteristics included sex, ethnicity, country of origin, human immunodeficiency virus (HIV) status, homelessness, history of incarceration, excessive alcohol use, and employment status (employed, not employed, student, unknown). Diagnosis year was based on date of first positive TB culture or date of hospital admission/clinic visit (for clinical cases). Isoniazid (INH) resistance status was collected from laboratory reports. SAS 9.4 (SAS Institute, Cary, NC) was used for analysis.

Spatial Analyses

Fulton County Department of Health charts include multiple addresses used for follow-up contact and contact tracing such as home, work, school, activity (eg, church, volunteer work), and hangout spots. A list of addresses was collected for each patient; primary address was designated as the address sent to the Georgia State Electronic Notifiable Disease Surveillance System (SendSS).

Geocoding the latitude and longitude of case addresses and homeless shelter locations extracted from the Homeless Shelter Directory (http://www.homelessshelterdirectory.org/cgi-bin/id/city.cgi?city=Atlanta&state=GA) was performed using ArcGIS 10.2.2 (ESRI, Redlands, CA) using reference data from Topologically Integrated Geographic Encoding and Referencing (TIGER)/Line shapefiles (www.census.gov). Locations without street addresses were identified using Google Earth, and latitude and longitude were recorded and mapped in ArcGIS. Shapefiles were projected into the UTM 17N projection for analyses.

A choropleth map showing the prevalence of TB in Fulton County was created with geolocated primary address and 2010 census data from the census block data from the TIGER database. In addition, kernel density methods were used to describe variation between the densities of TB case locations when using primary addresses versus the comprehensive list of all of the patients' addresses. All addresses were weighted equally for the analysis. The Akaike's information criterion (AIC)-optimized bandwidth for the primary addresses, 242 meters, was used for generating the density maps for both the primary maps and all area maps.

For the activity space analysis, we included only TB cases with 3 or more addresses. First, in ArcGIS and Quantum GIS 2.8, convex hull polygons were created for each case using the 3 (or more) address points as vertices. These polygons approximate the space in which each case has routine movement and activity. Three addresses were outliers, because they were far outside the greater Atlanta area, and therefore these were excluded from further analyses. Risk factor attributes were then joined to the activity space polygon shapefiles. For this analysis, INH resistance classification excluded cases in which INH drug resistance was not tested.

Activity space analysis included area and overlay analyses. For area analysis, area (km^2) of each polygon encompassed by the reported addresses was calculated using ArcGIS; this area approximates the size or scale of the space in which people live and move. People who live, work, and hangout in close proximity have a smaller area, whereas those who live, work, and hangout farther away have a larger area. Data were log-transformed to produce a normal distribution. Two-sample t tests with a threshold P value of .05 were used to evaluate the difference between the mean areas of polygons stratified on homeless status and INH resistance.

Second, degree of overlap between polygons was assessed. Overlap of polygons represent potentially shared space between 2 or more cases. A ternary classification was used to classify polygon overlap: no overlap, intersection at a point (but polygon does not overlap), and overlap at more than a point. A matrix of overlap and intersection indicators among all pairs of cases was created. Percentage overlap was calculated for each polygon. Two-sample t tests with a threshold P value of .05 were used to evaluate whether differences in percentage overlap were associated with features of the patient, including homeless status and INH drug susceptibility.

Ethics Statement

Patient consent was not obtained because retrospective analysis was performed on data collected as part of routine public health activities. The Emory University Institutional Review Board and Fulton County Department of Health approved the study protocol (IRB00078048).

RESULTS

During our 7-year study period, 431 cases of active TB were reported in Fulton County. A subset of 198 active TB cases, 46% of the total reported in the time period, was used for this study. Thirty-two percent of the cases were identified as homeless, 66% were not identified as homeless, and 2% had unknown homeless status (Table 2). Homeless TB cases were predominantly non-Hispanic black males, and homeless TB cases showed higher prevalence of other risk factor characteristics including excessive alcohol use and HIV positivity compared with the non-homeless group. The homeless group showed a higher percentage of US-born cases (90%) compared with the non-homeless group (60%). Nineteen percent of TB cases in the study were resistant to the drug INH; 41% of homeless patients' TB were resistant to INH, whereas 10% of the non-homeless patients' TB were resistant to INH (Tables 1 and 2).

Table 1. Characteristics of Study TB Cases and Total TB Cases, Fulton County, GA, 2008–2014

Demographics	Study TB Cases (N = 198) N (%)	All Fulton County TB Cases (N = 430) N (%)	*P* Value
Median age (years)	47	48	.50
Male sex	133 (67%)	310 (72%)	.26
Black	134 (68%)	307 (71%)	<.01
White	36 (18%)	31 (7%)	
Asian	28 (14%)	50 (12%)	
Hispanic ethnicity	22 (12%)	42 (10%)	
Homeless	63 (32%)	143 (33%)	.88
US born	139 (70%)	314 (73%)	.59
Employed[b]	61 (31%)	171 (40%)	.27
Excessive alcohol	36 (18%)	87 (20%)	.78
HIV positive	52 (26%)	103 (25%)[c]	.43
Isoniazid resistant	38 (19%)	75 (23%)	.95
Year of Diagnosis			.17
2008	37 (19%)	71 (17%)	
2009	40 (20%)	82 (319%)	
2010	33 (17%)	51 (12%)	
2011	23 (12%)	46 (11%)	
2012	20 (10%)	54 (13%)	
2013	25 (13%)	49 (11%)	
2014	20 (10%)	77 (18%)	
Culture positive	170 (86%)	329 (77%)	.01
Genotype			.64
PCR00231[c]	27 (18%)	58 (18%)	
PCR00015[c]	13 (9%)	24 (8%)	
PCR00016[c]	10 (7%)	33 (10%)	
Other	97 (66%)	203 (64%)	

Abbreviations: GA, Georgia; HIV, human immunodeficiency virus; TB, tuberculosis; US, United States.

[a]

[b]Employed includes full-time students and retired.

[c]Percent represents total of number tested.

Mapping

Tuberculosis cases in our sample were found throughout Fulton County, but they appeared to concentrate in the downtown Atlanta area (Figure 1A), consistent with surveillance maps of all TB cases in metropolitan Atlanta reported to the Georgia Department of Public Health in 2008–2014. This TB case map was distinct from a general population Fulton County map. In downtown Atlanta, we identified 13 locations that provide services for homeless persons. Nine of the 13 locations (69%) reside within census tracts with TB rates of greater than 65 cases per 100 000 people.

The kernel density map of the primary address of TB cases shows a high density of cases in the central region of the county, specifically in the city of Atlanta. When all locations for the TB cases, not just the primary addresses, were smoothed using kernel density, point density appears more dispersed compared with that of the primary addresses alone (Figure 1B). With all addresses, areas of high density in the central region appear wider, and additional high-density areas in the northern region of the county were visible.

Homeless shelters reside in areas of high density of TB cases in Atlanta. When using single address for the kernel density, 6 of the 13 (46%) shelters reside in the area of highest density (Figure 1C); when using all addresses for the kernel density, 11

Table 2. Demographics and Clinical Characteristics of Study Population, Active Tuberculosis Cases in Fulton County, GA, 2008–2014 (n = 197)

Demographics[a]	Homeless (N = 63) N (%) or Mean (SD)	Not Homeless (N = 130) N (%) or Mean (SD)	*P* Value
Median age (years)	50 (9)	45 (18)	.02
Male sex	53 (84%)	75 (58%)	<.01
Race			<.01
Black	51 (81%)	80 (61%)	
White	11 (17%)	24 (18%)	
Asian	1 (2%)	26 (20%)	
Hispanic ethnicity	5 (8%)	17 (13%)	.29
US born	57 (90%)	78 (60%)	<.01
Employed	6 (10%)	61 (31%)	<.01
Excessive alcohol	20 (32%)	15 (12%)	<.01
HIV positive	23 (37%)	29 (22%)	.04
Isoniazid resistant	25 (41%)	13 (10%)	<.01
Year of Diagnosis			<.01
2008	14 (22%)	23 (18%)	
2009	15 (24%)	23 (18%)	
2010	7 (11%)	26 (20%)	
2011	3 (5%)	19 (15%)	
2012	3 (5%)	17 (13%)	
2013	8 (13%)	15 (12%)	
2014	13 (21%)	7 (5%)	
Culture positive	52 (80%)	114 (88%)	.22

Abbreviations: GA, Georgia; HIV, human immunodeficiency virus; SD, standard deviation; US, United States.

[a]Two-sample *t* test was used for continuous variable. The χ^2 test was used for categorical variables; Mantel-Haenszel χ^2 was used for categorical variables with low cell counts. All categories had <5 missing values. There were 4 persons with unknown homeless status.

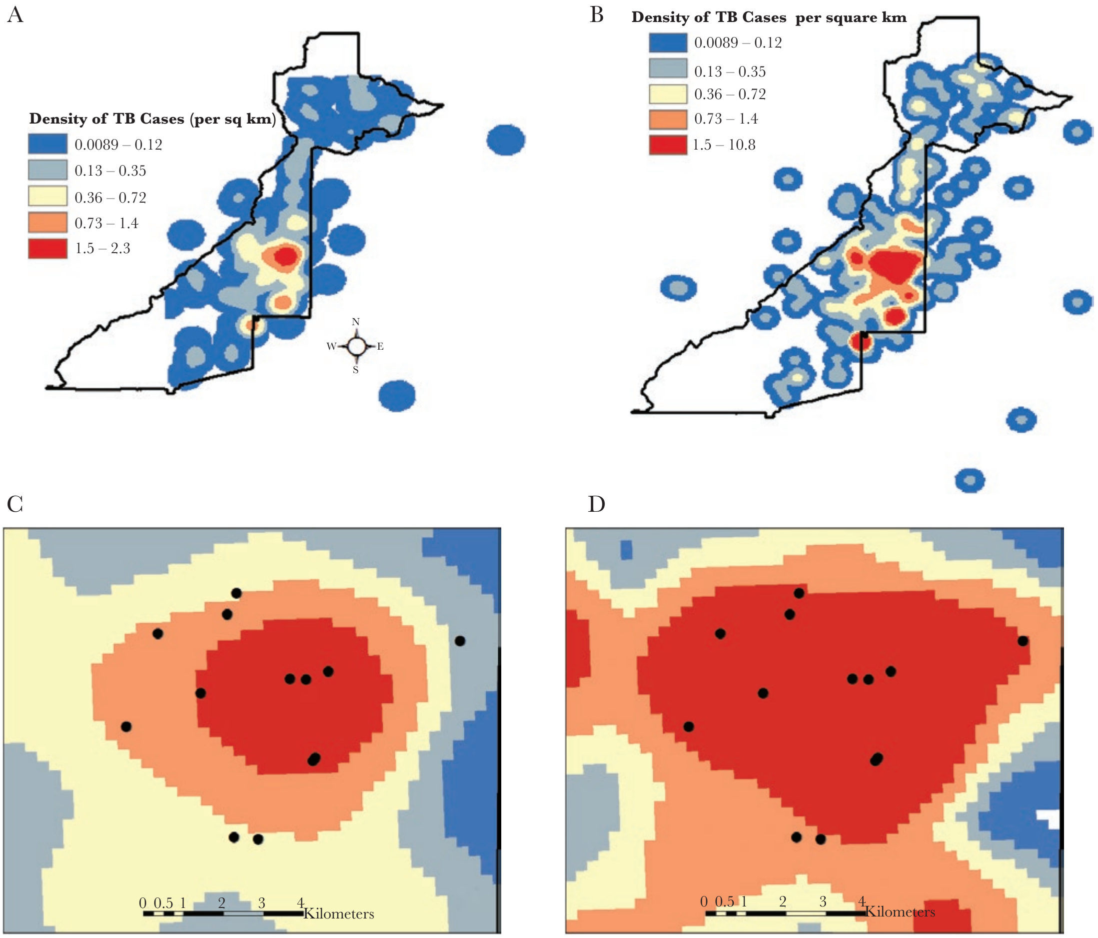

Figure 1. Difference in density of tuberculosis (TB) cases when using a single address versus multiple address for each case, Fulton County, Georgia, 2008–2014. (A) Density map (cases/square mile) of TB cases using a single address versus (B) multiple reported addresses; (C) enlarged area of higest TB case density map overlayed with local homeless shelters when using, for each TB case, single address versus (D) multiple addresses.

of the 13 (85%) reside in one of the areas with the highest density of TB cases in Atlanta (Figure 1D).

Activity Space

From the study sample, 50 cases had 3 or more addresses and were therefore able to be used for activity space analysis. Demographic characteristics of these 47 cases were similar to the overall study cohort (data not shown). Activity space areas (km^2) did not statistically differ based on homeless status or INH drug susceptibility status ($P = .87$ and $P = .41$, respectively; Table 3). However, there was a statistically significant difference in the overlap or intersection of the activity spaces (Table 4). On average, homeless TB cases overlapped with 68% of all activity spaces, whereas non-homeless TB cases overlapped with 30% of all activity spaces ($P < .001$). On average, INH-resistant TB cases overlapped with 68% of all activity spaces, whereas INH-susceptible TB cases overlapped with 46% of all activity spaces ($P = .0025$). Furthermore, we found that homeless cases' activity spaces overlapped with an average 86% of the other homeless cases' activity spaces, whereas non-homeless cases' activity space overlapped on average 29% with other non-homeless cases ($P < .001$). Likewise, INH-susceptible cases' activity spaces overlapped with on average 38% of the other INH-susceptible cases' activity spaces, whereas INH-resistant cases' activity spaces overlapped with on average 81% of other INH-resistant cases ($P < .001$).

DISCUSSION

Spatial analysis incorporating multiple locations for an individual rather than a single residential address allowed us to comprehensively capture and describe the geographic space of a sample of TB-infected persons involved in the 2008–2014 outbreak of INH-resistant TB in Fulton County, Atlanta, Georgia. We observed spatial dispersion of cases that appeared larger when utilizing multiple addresses with involvement of more area homeless shelters than would otherwise be apparent using single address analysis. We also found greater spatial overlap between activity spaces of homeless and INH-resistant cases compared with non-homeless and INH-susceptible cases.

Because approximately one third of TB cases in this study were found in homeless individuals, the need to understand

Table 3. Activity Space Areas of Fulton County Tuberculosis Study Case Subset, 2008–2014 (n = 47)

Activity Space Area Analysis	Activity Space Area (km^2)							
	n (%)	Mean	Min	Max	SD	T	*P* Value	95% CI
Total	47	48.3	0.0005	692.9	107.6			
Not homeless	16 (34%)	45.2	1.3	242.1	67.2	−0.17	.87	(−61.1 to 51.5)
Homeless	31 (66%)	49.9	0.0005	692.9	124.5			
INH susceptible	22 (47%)	58.4	0.02	692.9	146.6	0.84	.41	(−39.6 to 94.4)
INH resistant	20 (43%)	30.9	0.0005	168.6	39.9			

Abbreviations: CI, confidence interval; INH, isoniazid; Max, maximum; Min, minimum; SD, standard deviation.

the spatial context is particularly important. Studies typically exclude homeless patients from spatial analyses due to the complexity of utilizing spatial data for transient populations, or studies distill the experience of homeless cases down to a single address [6, 7, 9, 23]. However, excluding homeless cases or only reporting 1 address for those cases would not provide a sufficient picture of the location of TB cases in Fulton County. This also holds true for non-homeless TB cases as well. Although people spend a large amount of time at their place of residence, they also spend time in other locations, including work, school, hangout locations, and church. Using kernel density smoothing, we found that primary address of TB cases have the highest density in the central, downtown region of Atlanta. However, when we perform kernel density including all reported addresses, for instance residential, work, and hangout areas, we found a more dispersed spatial pattern. Thus, people with TB move within a larger area that is incompletely described using primary address alone. Some of these additional locations, particularly work and school, are already targeted for contact tracing purposes; thus, including all locations is a feasible way to describe the spatial context.

The average size of activity spaces among homeless and INH drug resistance cases was not significantly different when compared with non-homeless or INH-susceptible cases. However, we found that the homeless cases' had more shared activity space with other cases than the non-homeless cases, which suggests that transmission patterns can be further explored within these spaces. Such shared spaces among the homeless are likely locations where services are provided to this population, such as homeless shelters and hangout areas, whereas INH resistance activity spaces could suggest areas where transmission of INH-resistant TB occurs. Location data may therefore shed light beyond traditional contact investigations. A prior study using place-based data for TB outbreaks in Houston, Texas identified a unique role of neighborhood gay bars in an outbreak, with the original investigation limited by few name-based contacts identified [17]. Our data support the notion that prospective collection of multiple address/location data and real-time map generation for TB cases allows creation of a relevant and actionable map for targeted education, screening, and public health program activities. By highlighting the dichotomy between this richer map of case activity and traditional single-address surveillance maps, we aim to encourage state and county health departments to routinely and rigorously capture multiple location data as part of standard TB procedures.

This study has several limitations. Due to logistical and funding constraints, we were not able to include all cases of active TB diagnosed during the study period in Fulton County for geographic analysis. In particular, TB cases from 2014 were undersampled for the study. Because data collection started in December 2014, many of the 2014 TB cases were still active and unable to be abstracted. Our restricted sample may also have reduced the degree of spatial overlap compared with an analysis that included all cases, and it may also have led to missed additional key sites or areas of overlap. One hundred thirty-four addresses could not be geolocated and were excluded from the

Table 4. Proportion of Activity Spaces With Intersection or Overlap Among and Within Each Classification (Homelessness and INH Resistance), Fulton County Tuberculosis Study, 2008–2014 (n = 47)

	N	Mean (SD) Activity Space Overlap and Intersection Among All Spaces	*P* Value	N	Mean (SD) Activity Space Overlap and Intersection Within Classification	*P* Value	95% CI
All Spaces	47	0.55 (0.26)	-				
Not homeless	16	0.30 (0.24)	<.001	16	0.29 (0.22)	<.001	
Homeless	31	0.68 (0.15)		31	0.85 (0.17)		
INH susceptible	22	0.46 (0.25)	.003	22	0.38 (0.22)	<.001	
INH resistant	21	0.68 (0.18)		21	0.81 (0.19)		

Abbreviations: CI, confidence interval; INH, isoniazid; SD, standard deviation.

analysis due to insufficient information. Our use of convex hull polygons to characterize routine activity space makes 2 simplifying assumptions: the first is that all points are equally weighted, suggesting a similar amount of time at each; the second is that the area contained by the points is part of the experienced activity space. Future work can consider alternative operationalization of activity space including deviational ellipses of points, mean distance between point pairs, or collection of additional information about visit location frequency, duration, and route of travel. We opted for convex hull polygons because they provide more information about location than paired-distances but operate well with as few as 3 points, whereas deviational ellipses optimally involve more points. Given that only 47 cases were associated with 3 or more addresses, bias may have been introduced into the analysis towards those with more available address data. We found that more intense contact tracing was performed for homeless cases, and, therefore, these cases were more likely to have multiple addresses for analysis. As a result, data may be skewed to their geographic experience. For locations, particularly in homeless cases, lack of detailed description of locations often meant that those addresses were excluded. For instance, "sleeping under a bridge" was common; however, without further identification, the bridge could not be geolocated. Finally, we had insufficient numbers of cases to stratify activity space analysis jointly by homeless status and INH resistance, despite the likelihood that these 2 factors do not operate independently.

CONCLUSIONS

Isoniazid-resistant TB remains a major problem in Fulton County, Georgia. The fact that INH-resistant TB is highly associated with homelessness means that alternative methodologies are necessary for investigating outbreaks. Using geographic as well as traditional epidemiologic analyses may inform meaningful interventions in TB control moving forward. The application of these methods can be used in counties or states across the United States. Furthermore, this methodology is transferable and can be used to investigate other infectious diseases and their possible areas of transmission.

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