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Examining Naloxone Access: A Spatial Asessment Of Opioid Use In Urban And Rural Contexts

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EXAMINING NALOXONE ACCESS: A SPATIAL ASESSMENT OF OPIOID USE IN URBAN AND RURAL CONTEXTS

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ABSTRACT

Background: Elements of the physical environment have been shown to influence health behaviors including drug use and overdose mortality. Throughout the opioid epidemic in the United States, rural regions have been disproportionately affected by opioid overdose. Although the relationship between the urban built environment and opioid overdose has been established, little is known as to how trends may differ in rural areas.
Methods: Risk terrain modeling was used as a spatial analytical approach to assess environmental features that significantly increase the risk of opioid overdose in Jefferson County, Alabama. Spatial risk assessments were conducted for urban and rural regions as well as for the county as a whole. Criminogenic, opioid-related, and community variables were included and compared across spatial risk models.
Results: Findings indicated that the geographic context, rural or urban, influenced the relationship between environmental features and opioid overdose. In rural areas, community features such as bus stops and public schools were related to the occurrence of opioid overdose. In urban areas, inpatient treatment centers, transitional living facilities, express loan establishments, and liquor vendors were significantly related to the locations of opioid overdose.
Conclusion: Risk terrain modeling can be used to locate high-risk areas for opioid overdose while identifying factors that are contributing to the risk of events occurring in communities. The patterns of overdose risk differ in rural and urban contexts and may be used to inform the placement of treatment and prevention resources.

Keywords: opioid overdose, risk terrain modeling, spatial influence

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INTRODUCTION

For the third consecutive year, fatal drug-related overdoses in the United States have led to a significant decline in life expectancy (Centers for Disease Control and Prevention, 2017d; Hedegaard, Miniño, & Warner, 2018). Of the 72,306 overdose deaths that occurred in 2017, 68% (47,600) involved opioids. For the first time, opioids are the leading cause of fatal overdose in the country and have surpassed car accidents and gun violence as the leading cause of accidental death (Centers for Disease Control and Prevention, 2018c; National Institute on Drug Abuse, 2018). While the gradual escalation in prescription opioid use began in the early 1990s as pharmaceutical companies encouraged prescribers to use opioids to treat non-malignant pain (U.S. Food and Drug Administration, 2018), recent increases in death rates have been driven primarily by the proliferation of highly potent synthetic opioids such as oxycodone, morphine, and fentanyl (National Institute on Drug Abuse, 2018). Prior to this inundation of synthetic analogs, opioids were widely regarded as an urban-centric issue with heroin as the primary drug of choice (DuPont, 1973; Gottschalk, McGuire, Heiser, Dinovo, & Birch, 1979; Ruttenber & Luke, 1984).

The historic concentration of opioid use in urban areas prompted investigations of the contextual determinants unique to urban environments that widely impact health and behavior (Cerda et al., 2013; Galea, Ahern, & Vlahov, 2003; Galea, Nandi, & Vlahov, 2004). Prior research has found the physical, built environment itself to be significantly associated with health outcomes (Casteel & Peek-Asa, 2000; Cozens, 2007; Northridge, Sclar, & Biswas, 2003). Cerda et al. (2013), for instance, found an association between the presence of dilapidated buildings and fatal opioid overdose in New York City neighborhoods. These results added to earlier data from the city suggesting that unclean street conditions, structural fires, and exterior building damage predict overdose mortality (Hembree et al., 2005). In criminology, there is a well-documented relationship between criminogenic locations (features that are thought to engender criminal activity; e.g., liquor vendors, pawn shops, or express loan services) and the occurrence of assault, shootings, and drug sales (Askey, Taylor, Groff, & Fingerhut, 2017; Caplan, Kennedy, & Miller, 2011; E. Groff & Taniguchi, 2019; E. R. Groff & Lockwood, 2013; Irvin-Erickson & La Vigne, 2015; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016; Piza, Feng, Kennedy, & Caplan, 2016). Although these features do not share a direct, causal relationship with crime, their presence creates an environment where crime is more likely. A recent study conducted by Butz and Streetman (2018) found that, in addition to criminogenic locations, spatial proximity to community resources including public parks, schools, and supermarkets also increased the risk of opioid overdose in Providence, Rhode Island.

While spatial associations between the urban physical environment and opioid use have been well-established, little research has examined the role of environmental features in rural areas. As the opioid epidemic has progressed, the largest burden of deaths in which synthetic opioids are implicated has been in rural states (Havens et al., 2007; Paulozzi & Xi, 2008). Between 1999 and 2004, opioid usage in nonmetropolitan counties increased at six times the rate of urban metro areas (Paulozzi & Xi, 2008). A

2015 review of the National Emergency Medicine Service Information System found that the burden of overdose remained 45% higher in rural contexts relative to urban (Faul et al., 2015). Several mechanisms have been cited as contributing to this disparity, including increased rates of prescribing, unique economic stressors, and lower access to healthcare and treatment resources in rural areas (Keyes, Cerdá, Brady, Havens, & Galea, 2013; Paulozzi & Xi, 2008). As consumption patterns differ across rural and urban regions, it is likely that the environmental features that relate to opioid overdose differ as well.

The purpose of the current study is to determine what features of the physical and built environment convey risk for opioid overdose in urban and rural regions of Jefferson County, Alabama. Spatial models include environmental features that have been previously associated with drug overdose (e.g. liquor stores, tobacco vendors, and public schools) in addition to several features that are relevant to the current opioid epidemic, chiefly fire stations and pharmacies. Pharmacies are unique as they theoretically convey both risk and protection. For many opioid users, pharmacies are the monthly pick-up site for prescription medications. Additionally, a vast majority of states in the U.S. either allow, or do not expressly prohibit, persons from purchasing syringes from pharmacies without a prescription (Centers for Disease Control and Prevention, 2017c). More recently, country-wide policies have been enacted enabling pharmacies to stock and dispense naloxone (Centers for Disease Control and Prevention, 2018b), a fast-acting opioid antagonist that reverses overdose symptoms within minutes of administration (Coalition, 2018; Wermeling, 2015). In addition to being dispensed from pharmacies, it is becoming commonplace for law enforcement officers and emergency medical services (EMS) to carry naloxone kits. In the event of an opioid overdose, closer proximity to fire stations allows individuals to receive potentially life-saving naloxone faster, while proximity to pharmacies permits easier access for its preemptive purchase.

Few studies have examined the environmental features that geographically associate with rural opioid use and no investigations have, as of yet, compared risk factors in rural and urban regions. The current study sought to fill this gap in the literature by i) producing spatial risk models to forecast high-risk areas of opioid overdoses in the rural and urban areas of Jefferson County, Alabama, as well as a county-wide model, ii) comparing features of the built environment that relate to the occurrence of opioid overdose across models, and iii) examining the specific distribution of pharmacies and fire stations in relation to rural and urban opioid overdoses.

METHODS

Risk Terrain Modeling (RTM)

Risk Terrain Modeling (RTM) is a spatial analysis approach that examines the geographic relationship between the spatial location incidents and features of the environment. This approach can be used to identify areas that are vulnerable to the occurrence of future events. RTM creates a fishnet of grid cells over a defined geography and assigns a risk value to each cell based on the underlying statistical approach automated through RTMDx (discussed further below). Independent variables (i.e., risk factors) are identified based on prior research or hypothesized significance to a given dependent variable (i.e., outcome event). RTM identifies if the risk factors are significantly associated with an outcome through operationalizing spatial risk as a function of proximity or density. That is, risk could be influenced by being within close proximity to a certain factor or if a factor is densely populated in an area, there is a greater association with overdose occurrence. Through the process, the output identifies the influence significant risk factors have on the specified outcome. In short, the greater the risk, the greater the likelihood for the event to occur there in the future. When multiple risk factors have overlapping spatial influences, the risk increases even more since multiple factors are contributing to the relative risk. The product is a composite risk model accounting for the full distribution of risk factors and their contribution to outcome events.

Data and Study Area

The current study examined opioid overdoses in Jefferson County, Alabama, USA. Jefferson County houses Birmingham, Alabama's largest city, and has a population of nearly 660,000 over a 1,111 square mile area (United States Census Bureau, 2018). The county experienced 267 drug overdoses in 2017 and preliminary data from the Jefferson County Coroner/Medical Examiner Office indicates similar numbers for 2018. Since 2015, there have been nearly 1,000 unintentional drug overdoses in the county, the vast majority of which were caused by opioids.

Jefferson County contains both heavily rural and urban regions. The Birmingham metropolitan area, for example, has an estimated 1,443 residents per mi^2 while suburban Homewood houses 3,054 per mi^2 (World Population Review, 2019). Outlying areas such as Adamsville (172 residents per mi^2) and Graysville (123 residents per mi^2), however, are well below the US Census Bureau's criterion for rural areas which are defined as have less than 1,000 persons per mi^2 (United States Department of Agriculture, 2018; World Population Review, 2019). For the purposes of this study, US Census Bureau's designated urbanized area of Jefferson County was utilized for analyses (Ratcliffe, Burd, Holder, & Fields, 2016). The remaining land area of the county was then defined using Esri's ArcGIS Pro 2.2 and classified as the rural area of the county.

In order to account for the "ambiguity of the urban area's edge" noted by Ratcliffe et al. (2016) and to increase power for rural areas analyses, a half mile buffer was added to the defined rural study area and reduced from the urban area. The half mile exchange was only applied to areas on the interior of the county with shared rural-urban boundaries. This process retained the true Jefferson County border while allowing urban fringe areas to be included in the rural study area. This resulted in a rural region of 851.3 mi^2 and urban area of 272.6 mi^2.

Outcome Events

The outcome events examined in the current study are opioid overdoses that occurred in Jefferson County throughout 2015-2018 (N=915). A comprehensive list of drug overdoses for this duration was obtained from the Jefferson County Coroner/Medical Examiner Office, through which all overdoses in the county are processed. Cases were removed if no opioid was detected in the toxicology report or if there were instances of unspecified polydrug overdose (n=180). Additionally, decedents under the age of 18 were excluded (n=2). As the focus of this study is on the locations of opioid overdose, decedents' point of injury (POI) was used for spatial analyses whenever reported. If no POI was available the location where the decedent was found was used instead. If decedents had no address data available (*n*=35), or if the only listed address was the hospital to which they were taken (*n*=5), cases were excluded. Following this data cleaning process, 693 opioid overdoses remained (urban, *n*=508; 73.3%) of which 456 had known POI locations. Considering the United States Census Bureau's 2017 American Community Survey and the 2017 overdose statistics in Jefferson County, the rate of overdose death for rural and urban areas was estimated to be 17.3 and 35.8 per 100,000 people respectively (U.S. Census Bureau, 2017). This rural rate is equivalent to the Centers for Disease Control and Prevention's (CDC) reported average of 17.0 per 100,000 for rural areas in the Unites States (Centers for Disease Control and Prevention, 2017a). The rate of urban opioid overdose deaths in Jefferson County, however, is approximately double the CDC's reported national average for urban areas (16.2 per 100,000).

Risk Factors

Based on prior research and understanding of the current opioid epidemic, 17 risk factors were selected for inclusion (Barnum, Campbell, Trocchio, Caplan, & Kennedy, 2016; Butz & Streetman, 2018; Cerda et al., 2013; Drawve, Thomas, & Walker, 2016; Hembree et al., 2005; McCord & Ratcliffe, 2007; Wheeler, 2017). A list of risk factors, as well as their distribution across the study areas, is included in Table 1. Factors such as liquor stores and pawn shops were included because they are expected to be crime attractors. It is anticipated that a greater number of users will be attracted to these locations because of their affiliations with substance use or monetary acquisition. Of the additional risk factors, several were included due to their inherent affiliation with opioid users (inpatient addiction treatment centers, homeless shelters, pharmacies). Other community locations including public parks, bus stops, and supermarkets are anticipated to be crime generators because of the large volumes of people they serve and have been shown to spatially relate to opioid overdoses in prior studies (Butz & Streetman, 2018). Extant research has also utilized county resources such as 311 complaint sites as indicators of degradation in the physical environment (Barnum et al., 2016; Butz & Streetman, 2018; Wheeler, 2017). Locations of abandoned structures, burned structures, and abandoned vehicles were obtained from the city of Birmingham's 311 Call Center. Because the 311 service is maintained only within the metropolitan area, these variables were only applied to the urban model.

Data on the majority of included risk factors were obtained using RTMDx's geocoding tool. This feature operates by running a successive string of searches using the Google Maps platform. Searches were exhaustively conducted in each of the cities within Jefferson County in order to capture all locations across the study area. The resulting lists were then analyzed to ensure that all of the generated output correctly fell within each risk factor. Of note, tobacco vendors encompass locations that exclusively sell tobacco while vape shops include locations that sell vape supplies but may sell tobacco products as well. Several variables were also obtained from publically available data sources. Homeless and transitional living shelters in the county were gathered through Shelter Listings ("Jefferson County Shelter Listings," 2019), and inpatient drug treatment centers were compiled from Addiction Resource ("Drug and Alcoholism Recovery Centers In

Birmingham," 2019). Additionally, Jefferson County School listings were utilized to compile elementary, middle, and high schools in the study area ("JEFCOED School Directory," 2019).

Model Parameters

Models for the urban, rural, and county-wide areas of Jefferson County were generated using RTMDx, a diagnostic spatial analysis platform developed by the Rutgers Center on Public Security (Caplan & Kennedy, 2013). RTMDx requires the specification of model parameters in order to direct RTM analyses using the selected risk factors and outcome events (Caplan, Kennedy, & Piza, 2013). First, the size of each grid cell must be specified based on the level of gradation desired for assessing the analysis area. For instance, Barnum et al. (2016) selected 213 feet as their cell size as this is half of the average block length in Chicago. This determination is central to the functioning of RTMDx since output from the program is interpreted in the chosen increments. Prior criminal justice research indicates that the spatial influence of environmental features on crime is maximal within 1-3 city blocks (Askey et al., 2017; Groff & Taniguchi, 2019; Groff & Lockwood, 2013; Kennedy et al., 2016; Taylor & Harrell, 1996). Because patterns of drug overdose differ from crime, and because the examined study areas are larger than the city centers often assessed in prior studies, a cell size of 660 feet (.125 mi) was selected (DiMaggio, Bucciarelli, Tardiff, Vlahov, & Galea, 2008). This distance approximates the average length of 1.5 Birmingham city blocks while retaining generalizable mile units. The total number of cells yielded for the county, rural, and urban models were 72,790, 55,966, and 18,316 respectively.

RTMDx can produce two types of models. Aggravating models assume a positive spatial relationship between risk factor and outcome event locations, while a protective model assumes a negative spatial relationship. Protective models detect factors that buffer against the occurrence of outcome events. The platform also requires the selection of risk factor operationalization. The spatial influence of each variable can be examined as a function of proximity or density. 311 call locations were operationalized by density only as it is expected that only a clustering of these call sites will validate the presence of environmental degradation at these locations (Barnum et al., 2016). The remaining variables were assessed as both proximity and density in order to enable the RTMDx software to illustrate the optimal operationalization for each factor. Risk factors were examined in six, 1.5-block increments for all three models.

Analytic Approach

In order to aggregate four years of opioid overdose data, it was necessary to determine whether overdoses were occurring in similar locations each year. Average nearest neighbor analyses were conducted using Esri's ArcGIS Pro 2.2 in order to validate the creation of one opioid overdose variable to serve as the outcome event in RTM models, as opposed to examining each year of data separately. Average nearest neighbor analyses measure the distance between each variable and its closest neighbor. The values for all of these measurements are averaged and compared to a mean value from a randomly generated series of points. If the former mean is significantly less than the latter, hypothetical distribution, the data are considered clustered.

Aggravating RTMs were produced for rural, urban and county-wide study areas. Following the statistical procedure described by Drawve et al. (2016), RTMDx generated a best fitting model based on the assigned parameters and included variables. The program yielded a list of risk factors that were found to carry significant spatial influence as well as the operationalization for which the pattern was found. The spatial impact is described by two values. The first is the spatial operationalization, proximity or density of factors, and the second is the distance at which the significant risk factors influence opioid overdose occurrence. This process also assigns a relative risk value (RRV) per significant risk factor, determined through the 'best' fitting model factor selection (i.e., lowest BIC value). RRVs indicate the weight that each variable contributes to the final risk model. Composite models are displayed with shaded regions that equate to the relative risk score (RRS) assigned to each cell. RRS are similar to odds ratios in that cells with the lowest odds of an overdose occurring receive a value of one. The greater the expected chance of an outcome event occurring, the greater the RRS. Finally, sensitivity analyses were conducted to examine the stability of results across alternative grid cell sizes and study area buffers.

RESULTS

Average Nearest Neighbor

Average nearest neighbor analyses were conducted using Manhattan distance calculations in order to realistically represent the block-to-block spatial relationship of overdoses. Examining the dispersion of 2015-2018 opioid overdose locations revealed a significant clustering of opioid overdoses throughout the county (nearest neighbor index=.734; $p<.001$). Observed overdoses were separated by a mean distance of 2,640 feet, whereas the expected mean distance if events had randomly occurred was 3,597 feet. When assessing the pattern of exclusively rural and urban overdoses, similar results were found (nearest neighbor index=.717 and .785, respectively; $p<.001$). These results taken together support further analyses that aggregate Jefferson County's 2015-2018 opioid overdose locations.

RTMDx

County, rural, and urban spatial risk models were produced using RTMDx. Fourteen variables were assessed in each, with three additional 311 variables (abandoned structures, abandoned vehicles, burned structures) included in the urban model. A total of 186 variables were generated and tested as potential risk factors for all three models. For the urban area of Jefferson County, seven risk factors emerged as significant, five as a function of proximity and two as density (see Table 2). Being within a 6-block distance of inpatient addiction treatment centers conveyed the greatest risk for opioid overdose (RRV=2.452). Following this, the greatest risk increases were in areas of clustered liquor stores and 311 reported burned structures. These density observations were significant within 4.5 blocks. Additionally, express loan vendors, public parks, fire stations, and transitional housing facilities were related to increased opioid overdose risk. The composite risk map of the urban area had grid cell values ranging from 1-39.3 RRS with an average risk score of 2.135. Figure 1a displays high-risk places in the urban study area of Jefferson County, with darker shaded regions indicating RRS greater than two standard deviations above the mean and lighter shaded regions indicating the top 5% of RRS.

In producing a risk model for Jefferson County's rural area, four variables were found to be significant. RTMDx indicated that bus stop proximity conveyed the greatest risk (RRV=6.744) followed by pharmacies (RRV=2.879). To ease interpretation, being within close proximity of a bus stop is about twice as risky as a place in close proximity to a pharmacy. However, both types of risk factors significantly relate to overdose occurrence. In addition to bus stops, public park density and proximity to schools were shown to relate to opioid overdose occurrences within a .75 mile radius (~ 9 urban blocks).

Spatial analysis for Jefferson County as a whole produced the greatest risk variability amongst cells (1-109.581). The mean RRS value of 2.2 (SD=4.588) was slightly larger than that of the urban model, despite covering an area nearly four times as large. Eight variables were found to be significant in this model, with proximity to public parks producing the greatest risk of opioid overdose (see Figure 2). Seven of the eight risk factors were present in either the rural or urban models, leaving pawn shops the only factor specific to the county model. With a larger study area, and joining the two separate samples, larger, more general relationships could be found, and in the current analysis, pawn shops were a product of this more general analysis. The operationalization, spatial influence, and RRV for all included risk factors across models can be found in Table 2.

Sensitivity Analyses

In order to assess the robustness of these findings, sensitivity analyses were conducted using varying model parameters. While a buffer of .5 miles was determined as optimal to reclassify peripheral suburban areas as rural, analyses using no buffer and a .75 mile buffer were also carried out. In rural analyses, pharmacies registered as the most stable feature, remaining significant in all models. Similar results were found in the urban analyses for fire stations, inpatient treatment centers, and public parks (see Tables 3 and 4).

In addition to the 660 foot cell size used in analyses, models were generated with cell sizes of 330 and 1,320 feet. Changing the cell size impacts both the size of the grid by which the risk maps are partitioned and the search distance from each outcome event to surrounding risk factors. Reducing this parameter in rural models led pawn shops and police stations to become the only significant risk factors in the model. Extending it to 1,320 feet, however, yielded nearly identical results to the primary analyses as schools, public parks, and pharmacies were significantly associated with opioid overdoses. Changing this parameter in urban model had little effect on the output, with express loan lenders, liquor vendors, fire stations, inpatient addiction treatment centers, transitional housing, and 311 burned structure sites conveying significant risk regardless of distance adjustments. The county-wide model also appeared robust with few changes observed in each of the additional models (see Tables 5 and 6).

DISCUSSION

The opioid epidemic in the United States is a continuously shifting public health crisis that has disproportionately affected rural communities (Keyes et al., 2013; Paulozzi, 2006; Paulozzi & Xi, 2008). Alabama in particular has a higher than national rate of opioid overdose and was one of the 23 states to significantly increase in opioid-related deaths (Centers for Disease Control and Prevention, 2018a). Between 2014-2016, Alabama had the most opioid prescriptions per person of any state in the U.S. (Centers for Disease Control and Prevention, 2017a). While the majority of extant research has focused on psychosocial factors unique to rural culture that may be contributing to increased rates, few studies have assessed the impact of the physical, rural context.

To date, RTM has been largely utilized in a policing context in order to preemptively allocate resources to high-crime forecasted locations (Brantingham, 2011; Caplan et al., 2011; Koss, 2015). This study sought to extend that approach by comparing risk-conferring variables in rural and urban areas, and indeed, the profile of environmental features differed greatly across models. Urban overdose risk was predicted by criminogenic and opioid-related features, whereas the threat of future rural overdoses was strongly related to community features. Additionally, the pattern of predicted risk varied greatly between models. In the urban region, high-risk areas coalesced in three predominant clusters surrounding the Birmingham metropolitan area. Risk in the rural region, however, was segmented throughout the suburban boundary in addition to several outlying regions.

In the urban model, express loan vendors, liquor stores, public parks, fire stations, inpatient drug treatment centers, transitional living facilities, and 311 burned structure locations conveyed significant risk for opioid overdose. These results align with Butz and Streetman's (2018) analysis of Providence, Rhode Island which found liquor stores, public parks, and various 311 call complaint sites to geographically associate with opioid overdose in the city. Similarly, studies investigating drug arrest locations have found similar relationships. Liquor stores, public parks, and homeless shelters were associated with the sites of heroin arrests in Chicago (Barnum et al., 2016) while locations of liquor stores, homeless shelters, and drug-treatment centers spatially related to drug arrests in Philadelphia (McCord & Ratcliffe, 2007). Taken together, these findings present a common profile of environmental risk features in urban areas that relate to opioid overdose locations. The ability to accurately forecast areas that are high-risk for opioid overdose has significant treatment and prevention implications. The concentration of risk in urban areas could enable the precision implementation of centralized interventions to reduce opioid overdose and related health concerns. These may include syringe exchange programs, overdose education and naloxone distribution sites (OENDs). (Jarlais et al., 1996; Mueller, Walley, Calcaterra, Glanz, & Binswanger, 2015; Walley, Doe-Simkins, et al., 2013; Walley, Xuan, et al., 2013). Furthermore, the placement of drug treatment centers, methadone clinics, and halfway houses may be informed based on the metropolitan areas expected to have the greatest risk of overdose death.

The rural RTM, on the other hand, presented more diffuse risk areas with less clustering than the urban model. The distribution of high-risk areas in rural regions may not allow for the specificity of resource allocation available in urban areas due to the scattered dispersion of overdose risk. There are, however, opportunities presented given the unique risk factors that forecasted overdose in the model. In addition to several community features, pharmacies emerged as significantly related to the occurrence of opioid overdose. Standing order laws have recently made pharmacies target sites for overdose prevention as they are now able to distribute naloxone to clients at their discretion without requiring an individual prescription (Xu, Davis, Cruz, & Lurie, 2018). As pharmacies are ubiquitous community features, they are a highly accessible venue for treatment resources including naloxone and needle exchange programs; both of which rural users frequently experience barriers in accessing (Browne et al., 2016; Day, Conroy, Lowe, Page, & Dolan, 2006; Sigmon, 2014). As Gonzalez et al. (2009) showed, EMS response times may also be longer in rural areas leading to increased mortality rates. In addition to pharmacies, community features including public parks, bus stops, and public schools all registered as significant in the RTM output. This may be due to the fact that criminogenic and opioid-related features tend to be located in high-density areas and are less common in smaller communities. As such, future spatial risk assessments in rural areas may benefit from focusing on establishments tied to activities of daily living.

The sensitivity analyses examining the effects of buffer distance highlight the need for well-defined rural, urban, and suburban designations at the county and federal level. Changing this distance traded approximately 100 overdose cases between the rural and urban areas and, consequently, the risk factors to which those overdoses related in each model. While several variables were robust against this change, the significance of others depended on the inclusion or exclusion of overdoses in outlying regions. Further research investigating edge effects in rural and urban environments may improve the predictive validity of future spatial risk analyses. The effect of differing cell sizes and search distances in RTMDx varied by region. It may be that using a smaller distance impedes RTMDx's effectiveness in larger study areas where there is greater scarcity of structural features, overdoses, and longer distances between variables. Using smaller distance parameters in metro areas, however, will offer greater specificity in identifying the associations between variables but may compromise the ability to make comparisons between rural and urban regions. Future analyses may benefit from assuming a greater spatial relationship between environmental features and opioid overdose in order to produce more robust results in rural areas.

A limitation of the current study that may hinder expanded use of RTM is the acquisition of community data. The current study utilized RTMDx's geocoding tool as well as various publicly available data sources. This geocoding process has the practical advantage of capturing the same results a citizen would obtain if they were conducting an online search to locate an establishment in their community. Public data, such as those obtained from a county licensing office, offer a more comprehensive capture of commercial establishments throughout an area of interest. The availability of these data, however, is often limited and may be difficult for researchers to obtain in different states or cities. Furthermore, the data presented herein only describes the spatial influence of environmental features in one city and state. It may be that the relationship between risk factors and overdose sites differs greatly across regions and cities with varying infrastructures, rates of opioid prescriptions, and availability of treatment resources.

Future spatial analyses examining rural regions should expand on the use of physical, environmental features to generate models that include social, demographic, and crime-arrest data. This research may further elaborate the differences in rural and urban opioid use patterns. In order to stem the tide of mortality resulting from the current opioid epidemic it is also critical that treatment initiatives and prevention services consider how an area’s needs may vary by rurality. RTM offers an analysis platform that can identify high-risk areas and inform the allocation of state and federal resources. It is equally important ensure the utility treatment and prevention services that are already in place. Pharmacies for instance, while legally authorized to carry naloxone, often do not stock the drug or maintain a consistent supply (Burrell et al., 2017; Carpenter et al., 2018). Future policy efforts directed towards ensuring naloxone availability in pharmacies may have a significant impact on overdose mortality rates, especially in rural regions.

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Table 1

Environmental features included in rural, urban, and county-wide models.

Risk Factor	*N* (county)	*n* (rural)	*n* (urban)
Criminogenic features			
Express loans	99	3	96
Liquor stores	85	12	73
Pawn shops	39	3	36
Tobacco vendors	58	9	49
Vape shops	41	5	36
Community features			
Bus stops	263	19	244
Police stations	41	7	34
Public parks	111	23	88
Schools	102	41	61
Supermarkets	153	32	121
Opioid-related features			
Fire stations	110	46	64
Inpatient treatment	10	1	9
Pharmacies	241	34	207
Transitional housing	35	1	34
Degradation-related features			
311 Abandoned structures	462	-	462
311 Abandoned vehicles	33	-	33
311 Burned structures	311	-	311

Table 2
RTMDx optimal specifications for significant, risk-predicting features.

Risk Factor	County			Rural			Urban		
	OP	SI	RRV	OP	SI	RRV	OP	SI	RRV
Criminogenic features									
Express loans	P	1,320	1.785		-		P	3,960	1.703
Liquor stores	D	2,640	1.690		-		D	1,980	1.973
Pawn shops	D	3,960	1.712		-			-	
Tobacco vendors		-			-			-	
Vape shops		-			-			-	
Community features									
Bus stops		-		P	3,960	6.744		-	
Police stations		-			-			-	
Public parks	P	3,960	2.498	D	3,960	2.833	D	3,300	1.582
Schools		-		P	3,960	2.581		-	
Supermarkets		-			-			-	
Opioid-related features									
Fire stations	P	3,960	1.750		-		P	1,980	1.625
Inpatient treatment	D	3,300	2.031		-		P	2,640	2.452
Pharmacies	P	3,960	1.911	P	3,300	2.879		-	
Transitional housing	P	3,960	2.141		-		P	3,960	1.857
Degradation-related features									
311 Abandoned structures		-			-			-	
311 Abandoned vehicles		-			-			-	
311 Burned structures		-			-		D	1,980	2.217

*OP = Operationalization, D = Density, P = Proximity; SI = Spatial Influence (ft.), RRV = Relative Risk Valu

Table 3
Sensitivity analysis using no buffer on the rural and urban study areas. RTMDx optimal specifications for significant, risk-predicting features.

Risk Factor		Rural			Urban	
	OP	SI	RRV	OP	SI	RRV
Criminogenic features						
Express loans		-		D	1960	1.855
Liquor stores		-			-	
Pawn shops		-			-	
Tobacco vendors		-		D	3960	1.559
Vape shops		-		p	3960	1.555
Community features						
Bus stops		-			-	
Police stations		-			-	
Public parks		-		P	3300	1.419
Schools		-			-	
Supermarkets		-			-	
Opioid-related features						
Fire stations		-		P	3960	1.373
Inpatient treatment		-		D	3300	2.188
Pharmacies	D	3,300	8.622		-	
Transitional housing		-		D	3960	2.027
Degradation-related features						
311 Abandoned structures		-		D	1320	1.629
311 Abandoned vehicles		-			-	
311 Burned structures		-		D	2640	2.080

*OP = Operationalization, D = Density, P = Proximity; SI = Spatial Influence (ft.); RRV = Relative Risk Value

Table 4

Sensitivity analysis using a .75 mile buffer on rural and urban study areas. RTMDx optimal specifications for significant, risk-predicting features.

Risk Factor	Rural			Urban		
	OP	SI	RRV	OP	SI	RRV
Criminogenic features						
Express loans		-			-	
Liquor stores		-		D	1,980	1.965
Pawn shops		-			-	
Tobacco vendors		-		D	3,300	1.780
Vape shops		-			-	
Community features						
Bus stops	P	3,960	4.725		-	
Police stations		-			-	
Public parks	P	3,960	3.171	P	3,300	1.434
Schools	P	3,960	2.000	P	3,960	1.480
Supermarkets						
Opioid-related features						
Fire stations		-		D	1,980	1.583
Inpatient treatment		-		D	2,640	2.386
Pharmacies	D	3,300	3.258	P	3,960	1.578
Transitional housing						
Degradation-related features						
311 Abandoned structures		-		D	2,640	2.470
311 Abandoned vehicles		-			-	
311 Burned structures		-			-	

*OP = Operationalization, D = Density, P = Proximity; SI = Spatial Influence (ft.); RRV = Relative Risk Value

Table 5

Sensitivity analysis using 330 foot grid cell size and search increments. RTMDx optimal specifications for significant, risk-predicting features.

Risk Factor	County			Rural			Urban		
	OP	SI	RRV	OP	SI	RRV	OP	SI	RRV
Criminogenic features									
Express loans	D	1,980	3.068		-		D	1,650	1.856
Liquor stores	D	1,980	2.511		-		P	1,980	1.571
Pawn shops		-		D	1,650	15.8		-	
Tobacco vendors		-			-		P	1,980	1.848
Vape shops		-			-			-	
Community features									
Bus stops	P	1,980	2.057		-			-	
Police stations		-		D	1,650	16.59		-	
Public parks	P	1,980	2.320		-			-	
Schools		-			-			-	
Supermarkets									
Opioid-related features									
Fire stations	P	1,980	2.085		-		D	1,650	1.673
Inpatient treatment	D	1,980	2.376		-		D	1,980	2.808
Pharmacies		-			-			-	
Transitional housing	D	1,980	3.531		-		P	1,980	2.196
Degradation-related features									
311 Abandoned structures		-			-		D	1,320	1.796
311 Abandoned vehicles		-			-			-	
311 Burned structures		-			-		D	1,980	1.885

*OP = Operationalization, D = Density, P = Proximity; SI = Spatial Influence (ft.); RRV = Relative Risk Value

Table 6
Sensitivity analysis using 1,320 foot grid cell size and search increments. RTMDx optimal specifications for significant, risk-predicting features.

Risk Factor	County			Rural			Urban		
	OP	SI	RRV	OP	SI	RRV	OP	SI	RRV
Criminogenic features									
Express loans	P	7,920	1.760		-		P	7,920	1.694
Liquor stores	p	2,640	1.461		-		D	1,320	2.778
Pawn shops	P	2,640	1.911		-			-	
Tobacco vendors		-			-		P	6,600	1.534
Vape shops		-			-			-	
Community features									
Bus stops		-			-			-	
Police stations		-			-			-	
Public parks	P	7,920	1.944	P	7,920	2.045		-	
Schools		-		P	3,960	2.517		-	
Supermarkets		-			-			-	
Opioid-related features									
Fire stations	D	7,920	1.825	P	7,960	2.054	D	3,960	1.563
Inpatient treatment	p	5,280	1.745		-		p	2,640	2.190
Pharmacies	P	7,920	2.477	P	7,920	1.991	D	3,960	1.532
Transitional housing	P	3,960	2.155		-		P	3,960	1.716
Degradation-related features									
311 Abandoned structures		-			-			-	
311 Abandoned vehicles		-			-			-	
311 Burned structures		-			-		D	2,640	2.349

*OP = Operationalization, D = Density, P = Proximity; SI = Spatial Influence (ft.); RRV = Relative Risk Value

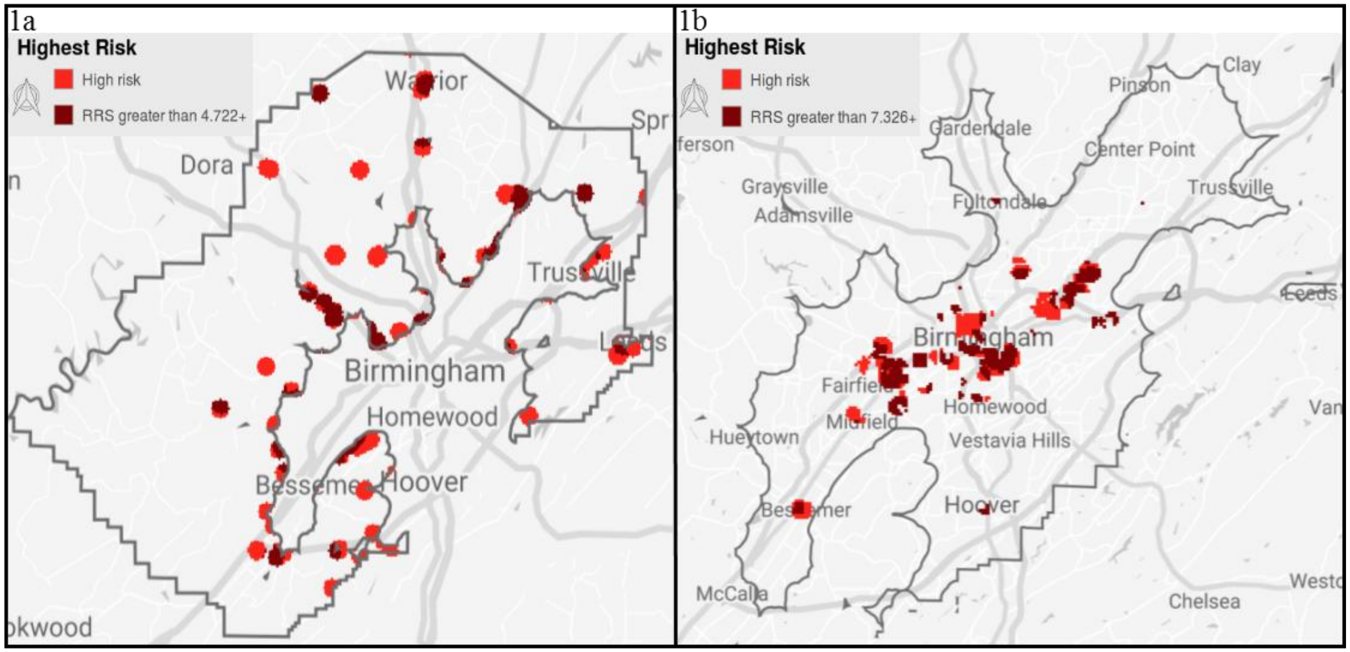

Figure 1. Composite risk terrain maps of the rural (1a) and urban (1b) areas of Jefferson County, Alabama.

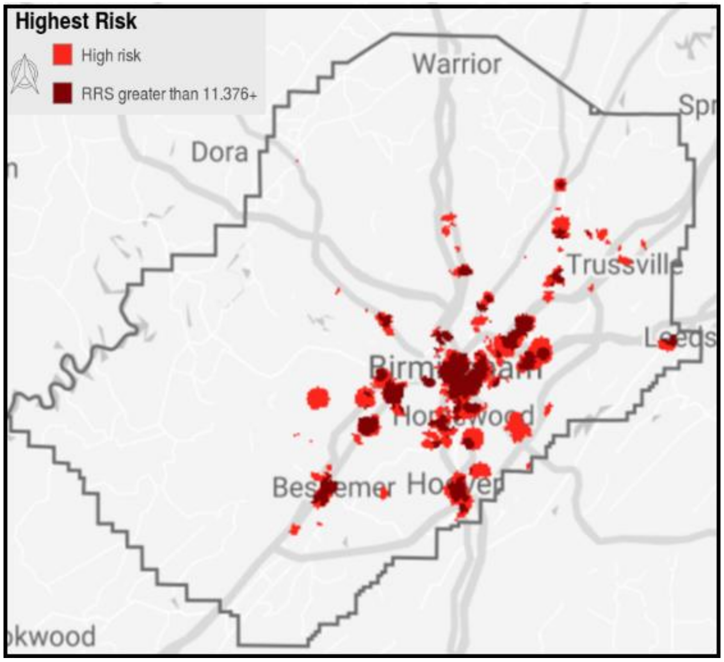

Figure 2. Composite risk terrain map of Jefferson County, Alabama.