International Journal of Applied Geospatial Research
Volume 9 • Issue 2 • April-June 2018

Geographic Analysis of Domestic Violence Incident Locations and Neighborhood Level Influences

Rick L. Bunch, University of North Carolina Greensboro, United States

Christine Murray, University of North Carolina Greensboro, United States

Xiaoli Gao, University of North Carolina Greensboro, United States

Eleazer D. Hunt, Greensboro Police Department, United States

ABSTRACT

Domestic violence is an important public health issue, and there is limited research to date that examines community-level influences on this serious form of violence. This article investigates the neighborhood characteristics of domestic violence incidents in the city of Greensboro, North Carolina. US Census block group boundaries and corresponding tables were used as proxies for neighborhoods. The article addresses an important gap in domestic violence research by combining geographic and statistical analyses at the block group level. Geographic data were analyzed using an Optimized Hot Spot Analysis (OHA) along with features selected by penalized Poisson regression model. The OHA was used to identify spatial clusters of high and low values while the penalized Poisson regression model was used to select the important variables from over 7000 candidates. The results of high-dimensional analysis produced six categories and 20 variables that were used to examine the characteristics of spatial clusters.

KEYWORDS

Block Groups, Census, Crime Incidents, Domestic Violence, Geographic Information Systems (GIS), Intimate Partner Violence, Neighborhoods, Penalized Poisson Regression Model

INTRODUCTION

Domestic violence (DV) is a serious public health issue that occurs in all communities, regardless of race, ethnicity, age, gender or socioeconomic status. Victims often suffer unfavorable health outcomes that arise from emotional, physical, and psychological abuse, as well as financial abuse (Bogat et al., 2005; Kessler, Molnar, Feurer, & Appelbaum, 2001). High rates of DV also place significant amounts of pressure on community resources, such as those offered by family service agencies, violence prevention networks, support organizations, and local law enforcement.

A survey conducted by the National Network to End Against Domestic Violence (NNEDV) recorded an astonishing 21,332 hotline calls over a 24-hour period from individuals in the U.S.

DOI: 10.4018/IJAGR.2018040102

who were identified as victims in danger or in need of support (NNEDV, 2015). Likewise, a study conducted by the Centers for Disease Control and Prevention (CDC) reported that an average of 20 people are physically abused by an intimate partner every minute (Black et al., 2011). This equates to over 10 million cases of abuse annually. The high prevalence of DV and its devastating impacts on victims, families, and communities underscore the need for further research that can inform practice, support victims, educate communities, guide law enforcement policies, and reduce rates of abuse.

Recent research on DV has increasingly focused on understanding how the characteristics of neighborhoods can influence and predict rates of DV. A portion of this research has attempted to identify correlates between neighborhood influences and rates of DV, with some being underpinned by social disorganization and contagion theories (Beyer, Layde, Hamberger, & Laud, 2013; Beyer, Wallis, & Hamberger, 2015). Although key to DV research, the delineation of a neighborhood has proven to be a difficult task mostly because the definition is subjective and imprecise (Benson, Fox, DeMaris, & Van Wyk, 2003). To address this problem, several studies have used U.S. Census Tracts as surrogates for neighborhoods (Lee, Zhang, & Hoover, 2013; Raul, Suhasini, & Harris, 2010). Beyer, Layde, Hamberger, and Laud (2015), for example, used U.S. Census Tracts to examine the characteristics of victims (individual-level) in relation to neighborhood demographic variables, such as proportion below poverty, single-parent households, and unemployed.

Surprisingly, there has been very little DV research conducted at the U.S. Census block group level, despite the perceived benefits (Beyer, Wallis, et al., 2015). Murray, Bunch, and Hunt (2016) argued that block group level analysis provides the most promising approach for conducting DV research since data are readily available as geospatial datasets, act as better proxies for neighborhoods, and provide smaller enumeration units for conducting detailed geographic analysis. Additionally, DV studies on rates and neighborhood influences have received far less attention when compared to other health research (e.g., cancer incidence rates, birth defects etc.), and very little work has employed the use of a Geographic Information Systems (GIS) (Beyer, Layde, et al., 2015; Beyer, Wallis, et al., 2015; Murray et al., 2016). Much like other health studies, well established GIS-based crime research has not specifically focused on DV. Many of these studies have opted to wrap DV cases into broader categories such as violent crimes (Law, Quick, & Chan, 2015). However, given the relational patterns that underscore DV, this form of violence warrants special consideration in both research and practice.

The purpose of this study is to examine the distribution of DV incident locations and the characteristics of their neighborhoods in the city of Greensboro, North Carolina (NC). Block group geometry and corresponding attribution from the U.S Census Bureau were used as surrogates for neighborhoods. This study addresses an important gap in DV research by combining geographic and statistical analyses at the block group level (Beyer, Wallis, et al., 2015; Murray et al., 2016). Data were analyzed using an Optimized Hot Spot Analysis (OHA) and a penalized Poisson regression model. The OHA was used to identify spatial clusters of high and low values of DV percentages while, the penalized Poisson regression model, was used to select from over 7000 neighborhood-level variables that influenced DV incident counts. The results were summarized by zone (hot spots and cold spots) and compared using descriptive statistics. The foundation of this research is based upon three research questions. First, are there any statistically significant spatial patterns with respect to the distribution of DV incident locations within the city limits? Second, if spatial patterns exist, what are the characteristics of the underlying neighborhoods? And third, how do the results compare to the larger body of work on DV and neighborhood level influences?

LITERATURE REVIEW

It is important to note that we adopted the term "Domestic Violence" for this paper to broadly capture domestic relationships that suffer from some form of abuse. It is recognized, however, that most cases of DV involve Intimate Partner Violence (IPV) and that the two terms are often used synonymously.

The National Coalition against Domestic Violence (NCADV) provides the definition that will be used throughout this paper:

Domestic violence is the willful intimidation, physical assault, battery, sexual assault, and/or other abusive behavior as part of a systematic pattern of power and control perpetrated by one intimate partner against another. It includes physical violence, sexual violence, threats, and emotional or psychological abuse. (NCADV, 2015, p. 1)

Research on neighborhood characteristics and their influence on DV has produced mixed results (Beyer, Layde, et al., 2015; Beyer, Wallis, et al., 2015; Raul et al., 2010). This may reflect a failure to consider the interactions among neighborhood variables with influences at other levels, such as government policies or family relationships. However, of the studies reviewed on this topic, a majority of the work demonstrated at least some evidence that neighborhood influences are associated with DV (Beyer, Wallis, et al., 2015).

To illustrate the methods used and variables studied in past research, this section includes an overview of key research studies that have examined neighborhood influences on DV. The studies are listed in chronological order to demonstrate how research in this area has evolved over time. In addition, GIS studies within the context of DV, and crime mapping and analysis are also discussed in this section.

Neighborhood Influences on DV

Benson et al. (2003) analyzed data from the first two waves of data (i.e., 1988 and 1994) from the National Survey of Families and Households, combined with data from the 1990 U.S. Census, in order to examine the impact of neighborhood characteristics on DV perpetrated against women. Their findings revealed that, after controlling for violence at the first-time point, the following neighborhood variables impacted violence at the second time point: economic disadvantage, residential instability, male employment instability, and subjective financial strain. Contrary to what the researchers hypothesized, however, higher residential instability was associated with lower rates of DV, which they suggested may be indicative of people in lower income neighborhoods moving less due to fewer economic resources for moving. An advantage of this study was that the data were derived from an anonymous study, rather than police data that require participants to report DV to local authorities.

O'Campo, Burke, Peak, McDonnell, and Gielen (2005) used concept mapping to identify neighborhood domains that impact DV, using a participant sample of 37 women living in Baltimore City, most of whom were African American and at least 30 years old. Many of these women had prior experiences of DV, although it was not required for participation to be a survivor of past abuse. The researchers used three main activities to generate the data: brainstorming groups, sorting and rating groups, and groups to discuss how neighborhood factors were related to experiences of DV. The concept mapping approach identified seven clusters of characteristics of neighborhoods that are linked to DV experiences: deterioration, negative social attributes, violence attitudes and behaviors, stabilization factors, neighborhood monitoring, communication networks, and community enrichment resources. Similarly, Button (2008) demonstrated that neighborhoods in which there are higher levels of crime showed higher levels of approval of DV. In general, people who accepted one form of violence were more likely to have accepting attitudes toward other forms of violence (Button, 2008). The study concluded that attitudes toward different types of family violence can be considered both an individual- and community-level phenomenon.

The density of alcohol outlets has also been studied as likely influences on neighborhoods and rates of DV. Roman and Reid (2012), for example, were interested in both on-premise alcohol outlets (i.e., restaurants and nightclubs) and off-premise outlets. The findings of their study highlight the importance of making this distinction. Off-premise outlets were significantly associated with higher rates of DV, while on premise outlets were related to decreased rates of DV. More specifically, the increased risk of DV in areas with higher densities of off-premise outlets was present for weekends, but not for weeknights. The researchers propose that these findings suggest that there are different ways that alcohol use may impact perpetrators use of violent, abusive behaviors at different times during the week.

The type and location of community organizations, such as churches, located in and around neighborhood communities have also been studied within the context of DV. Triplett, White, and Gainey (2013) compared the relationships of churches within a neighborhood to rates of street and domestic violence. Churches were theorized to play a stabilizing role within a neighborhood, and they were thought to be present in all types of neighborhoods, so different church characteristics could have unique influences on their surrounding neighborhoods. Their findings showed the exact opposite. More churches in a neighborhood were associated with higher rates of both street crime and domestic violence. However, the researchers stated that there were no known reasons to assume that, as may be the case with alcohol outlets, there was a certain pathway through which churches actually promote violence. Rather, the researchers speculate that churches may be limited in their ability to change the surrounding community with respect to violence.

GIS-Based Studies on DV

Geographic analysis is useful for mapping spatial patterns and analyzing relationships among features. Coy, Kelly, Foord, and Bowstead (2011) provided one of the few studies that used GIS to analyze DV. Their study mapped the female populations and the locations of DV support services throughout England, Scotland, and Wales. When considering the underlying female population, they found that the distribution of DV support services were the highest in urban areas and lowest in areas that were on the edge of urban development. The second part of their study examined the relocation of women fleeing domestic violence by capturing the direction and distance of travel. The study revealed that, on average, relocating women traveled 30.47 miles to obtain services either north to south or east to west of their prior residents. Hetling and Zhang (2010) also used GIS and spatial statistics to examine the locations of DV assault rates, DV serving agencies and levels of poverty using bivariate correlations and testing for spatial patterns. They found a strong correlation between poverty rates and domestic violence assaults. The study also discovered that DV serving agencies were located in more disadvantaged areas with higher rates of overall crime. It is important to note that their study used cities and towns in Connecticut as the geographic unit for the analysis.

A review of the literature clearly demonstrates the major role geography plays in the understanding of the dynamics between neighborhood influences and cases of DV. The literature also highlights the existence of a relatively few studies that have used GIS to address fundamental geographic questions within the context of DV. This opens up a wide range of opportunity for geographic researchers to work collaboratively with those who have expertise in DV (Murray et al., 2016). A major problem for many studies has been centered on acquiring data, since many have had to rely on expensive and time-consuming surveys while some have settled on over generalized data. At least in the U.S., exploiting the rich data from the U.S. Census Bureau at the block group level seems to be a good starting point, especially when considering the maturation of GIS, geospatial datasets, and corresponding methods. The well-established research on crime mapping and analysis provides a solid foundation for studying the influences of neighborhoods on cases involving DV.

Crime Mapping and Analysis

Classic hot spot analysis and mapping studies have operated under the assumption that locations of crime incidents are unevenly distributed across geographic space. Crime incident locations are often scanned by algorithms that take into account the local pattern (a target feature and its neighbors) in relation to the global pattern (all features) within the study area (Chainey & Ratcliffe, 2005). Some algorithms address random and nonrandom point patterns while others focus on spatial autocorrelation by incorporating attributes at locations. Crime incident locations can be aggregated by points (the raw counts of crime incidents at one particular location) or by polygon (e.g., raw counts of crime incidents by Census block group or grid). In some cases, the crime incidents are normalized to produce rates (e.g., per 100,000 people) and used as inputs instead of raw counts. Areas identified as hot spots are often explained in terms of the interaction between victims and offenders as well as the opportunity to commit a crime (Cohen & Felson, 1979). Socioeconomic and demographic factors have also been used to explain high concentrations of crime rates with respect to the underlying population (Wang et al., 2013). The main goals of crime hot spot mapping are to efficiently visualize threats, allocate crime reduction resources, and provide predictive measures (Chainey, Tompson, & Uhlig, 2008; Cohen & Felson, 1979).

There are many approaches to mapping and analyzing crime incident locations (Chainey & Ratcliffe, 2005). Nearest neighbor analysis, for example, is a discrete point pattern technique that examines global patterns to uncover randomness or clustering (Clark & Evans, 1954). However, the method only uses distances between points and does not take into account spatial autocorrelation. Additionally, techniques of simple point and choropleth mapping and density estimations are very useful for visualizing the distribution of crime incidents, but they do not incorporate the capacity to conduct statistical comparisons among clusters of values. Local Indicators of Spatial Association (LISA) is a technique that detects spatial autocorrelation at the local level using Moran's I (Anselin, 1995). The method calculates an index and a Z-Score for each feature, allowing comparisons against the mean. However, the use of the Moran's I does not show whether clustering consists of either low or high values. As an alternative, many crime studies have used the local version of the G-statistic which can make the distinction between clusters of high (hot spots) and low values (cold spots) (Getis & Ord, 1992; Getis & Ord, 1996; Wang et al., 2013). The use of any particular method for analyzing the location of crime corresponds directly with the research questions and needs of those conducting the study. In some cases, it may make sense to analyze crime incident locations as discrete points and use the results for visualization or as inputs for subsequent queries. In other cases, researchers may need to aggregate crime incident locations by a geographic unit to incorporate attributes and tests for spatial autocorrelation (Hart & Zandbergen, 2014).

Census boundaries and fishnets (grids) are commonly used as polygons for aggregating crime incident locations. The use of Census boundaries has a built-in advantage since they provide a wide range of socioeconomic variables that can be used to further explain the relationship between crime and the underlying characteristics of the population. Producing crime rates are also possible since estimates of the population, residents, households and other totals are available. However, aggregating by Census boundaries can be problematic since police jurisdictions and Census boundaries are often not coincident. In this case, areal interpolation can be performed or fishnet polygons can be generated and positioned over crime incident points where counts are produced for each polygon cell. Several researchers have developed methods for computing the appropriate size for fishnet polygons while others have provided methods for adjusting for multiple testing and spatial dependency (Caldas de Castro & Singer, 2006; Chainey & Ratcliffe, 2005; Sun, Reich, Tony Cai, Guindani, & Schwartzman, 2015). The use of the raster data model and corresponding cells rather than polygons to aggregate crime incidents have also been studied in the context of risk surfaces (Kennedy, Caplan, & Piza, 2011).

Risk Terrain Modeling (RTM) was developed as a method for identifying, visualizing, and predicting crime risk (Caplan, Kennedy, & Miller, 2011). The fundamental approach to conducting RTM is to create raster surfaces based on spatial influence for each individual risk factor, and then combine them to produce a composite surface. RTM leverages the concept of map algebra and is similar to the concepts applied to raster based site suitability studies (Nowlin & Bunch, 2016). Caplan et al. (2011), for example, generated point density surfaces for three risks factors that were associated with crime shootings. Each density surface was subsequently reclassified to ordinal rankings (0 – 3) using standard deviation values. The reclassified raster surfaces were summed using a local operation to produce a composite map with the highest values representing the highest risk. Past shooting incident locations were overlaid on top of the composite surface and assessed for accuracy. This work was extended later to include thirteen selected risk factors (e.g., gang hot spots, bus stops, etc.) associated with aggravated assaults, their spatial influences, and a weighted composite surface (Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016). The assessment showed that RTM was able to accurately predict the locations of places that are likely to experience future crime (Kennedy et al., 2016). RTM requires point features and conducts the underlying analysis and rendering using the cells that make up raster surfaces. This limits the inclusion of other attributes and geographic analysis units such as those that capture neighborhood level influences on crime (Drawve, Moak, & Berthelot, 2016).

There is no set standard on which method to use when analyzing crime incident locations for patterns. The spatial element of crime is complex, making it difficult to find one method that addresses all circumstances. Some studies have demonstrated advantages for one method over another in certain instances. Kernel Density Estimation (KDE) and nearest neighbor hierarchical (Nnh), for example, have been shown to outperform several other methods, but results and the appropriate application can vary widely depending on the parameters used, geographic scale, type of crime, and the underlying assumptions made by researchers (Chainey & Ratcliffe, 2005; Chainey et al., 2008; Drawve et al., 2016).

METHODS

The scope of this research is to analyze and identify neighborhood level influences of the DV incident patterns located within the city limits of Greensboro, NC. Block group TIGER/Line files were used as surrogates for neighborhoods, and corresponding detailed tables were acquired to provide attribution. The locations of DV incidents were aggregated using census geometry and analyzed for spatial patterns with an Optimized Hot Spot Analysis (OHA). Attribution derived from ACS 5-years estimates was subjected to a separate statistical analysis as a way to cull the number of variables down to those that likely influence counts of DV incidents. The following provides a discussion on the study area, acquired data, pre-processing procedures, and the analyses.

Study Area

The study area for this research is the City of Greensboro, NC (Figure 1). The city limits of Greensboro is an irregular shaped polygon that covers approximately 137.7 square miles of Guilford County. It is the third largest city in the state, and the largest within the county in terms of population. As of 2015, there were 285,342 people living in the city. Overall, the population of Greensboro is diverse with 47.7% White; 40.6% African American; and 4.5% Asian. The remaining population is a mix of American Indian, Pacific Islander, and some other race. The median household income for residents in the year of 2015 was \$41,628, with 19.3% of persons living in poverty, and 88.7% of the people (age 25 years and over) having at least a high school diploma or equivalent. The total crime rate in the City of Greensboro for 2015 was 4,243 per 100,000 inhabitants, and the violent crime rate was 608 per 100,000 inhabitants.

Acquired Data

All crime incident locations for the year of 2015 were obtained from the Greensboro Police Department (GPD) whose jurisdiction falls within the city limits. Crime incident reports were converted to geospatial datasets by the GPD crime analysis unit. The conversion involves geocoding address locations of reported crimes, and populating the corresponding fields with descriptors about each crime. In this process, the GPD also provides a marker for identifying whether the reported crime involved instances of DV. Crime incidents identified as DV cases ($n = 2,725$) were selected from all crime incidents ($n = 30,655$) and used as input for the analysis (Figure 2).

When considering previous research on neighborhood level influences of DV, demographic composition, educational attainment, and economic conditions of neighborhoods have begun to emerge as common themes (Murray et al., 2016). To examine these themes, the 2010-2014 American

Figure 1. The city limits of Greensboro, NC (delineated by the light orange polygon) is situated in Guilford County

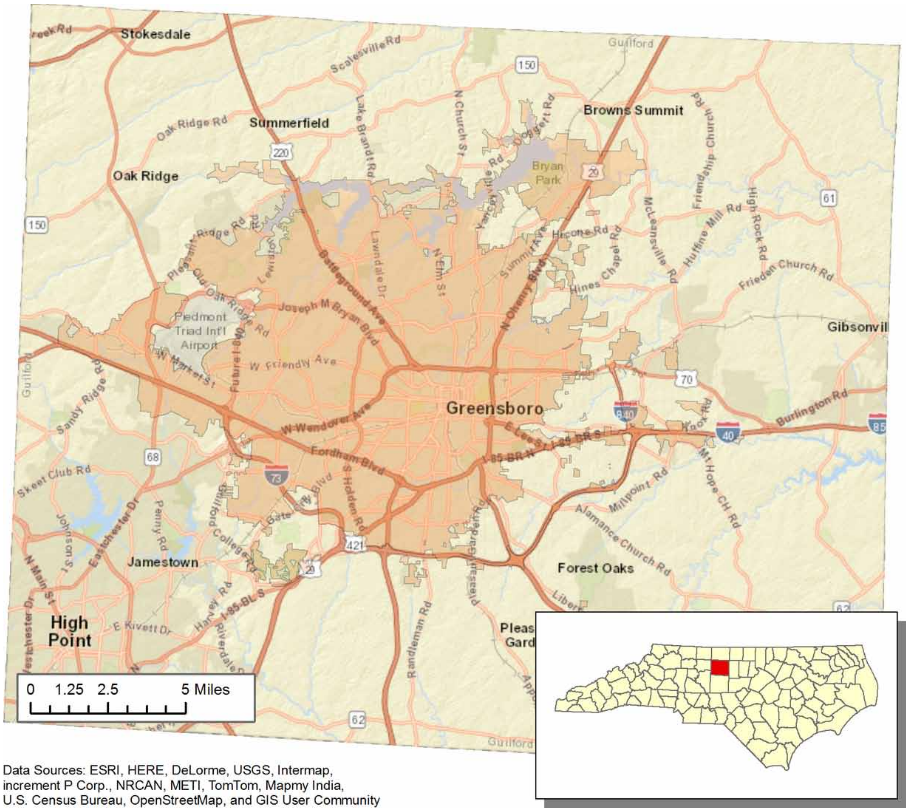
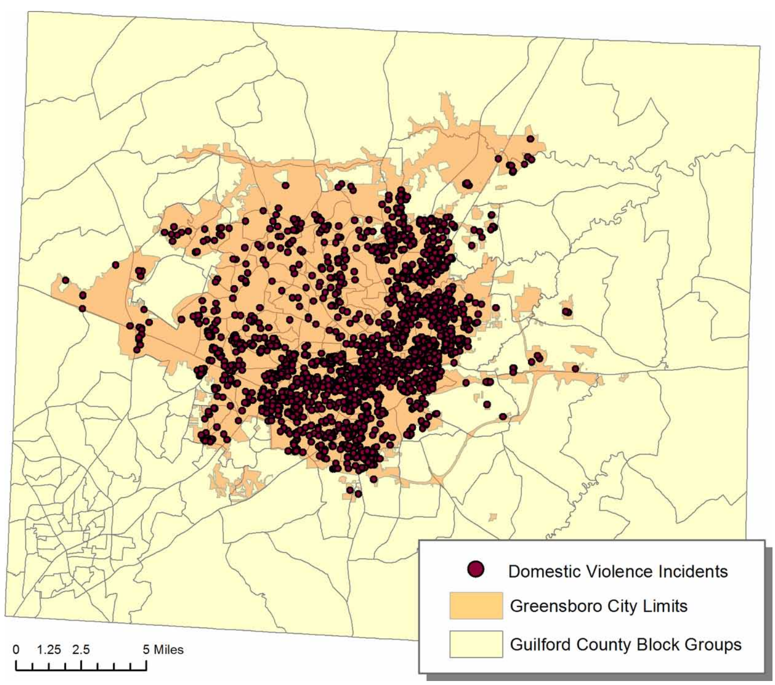


Figure 2. Domestic violence incident locations (n = 2,725)



Community Survey (ACS) 5-year estimates were acquired from the U.S. Census Bureau for Guilford County. These data are designed to be used in GIS, and made available as a geodatabase. The geodatabase was comprised of block group TIGER/Line files and 20 detailed tables containing 7,056 fields collectively. The boundaries and tables can be joined or related by a unique key. Each table and their associated attributes are organized by theme (Table 1). At the time the analysis for this study was conducted, the ACS 2011-2015 5-year estimates and corresponding geodatabases at the block group level were unavailable.

Pre-Processing of Data

City limit geometry for this study was obtained from Greensboro's Planning Department. The city limits are not coincident with the boundaries of Census block groups. To address this issue, a map overlay operation using the intersect method was performed on the block group TIGER/Line files and the city limit boundary (Figure 3). Attributes and metrics for the newly created geometry were recomputed using areal interpolation (Goodchild & Lam, 1980). A proportion was calculated by dividing the area of the new polygons by the area of the original polygons. The resulting proportion was used to update the attribution for the new polygons by multiplying the decimal equivalent by the attribute value of the corresponding original polygon. For example, if the new polygon represented half the area of the original polygon with a population of 200 people, the decimal equivalent of 0.5 was multiplied by 200 to produce a population of 100 for the new polygon. Any block group geometry separated into two features by the intersect overlay operation were re-aggregated using the dissolve

Table 1. U.S. census bureau datasets used for the study

Name	Vintage	Geographic Level
1. Age and Sex	2010-2014 ACS 5-year estimates	Block Group
2. Race	2010-2014 ACS 5-year estimates	Block Group
3. Hispanic or Latino Origin	2010-2014 ACS 5-year estimates	Block Group
4. Migration	2010-2014 ACS 5-year estimates	Block Group
5. Commuting	2010-2014 ACS 5-year estimates	Block Group
6. Children Household Relationship	2010-2014 ACS 5-year estimates	Block Group
7. Household Family Subfamilies	2010-2014 ACS 5-year estimates	Block Group
8. Marital Status and History	2010-2014 ACS 5-year estimates	Block Group
9. School Enrollment	2010-2014 ACS 5-year estimates	Block Group
10. Educational Attainment	2010-2014 ACS 5-year estimates	Block Group
11. Language Spoken at Home	2010-2014 ACS 5-year estimates	Block Group
12. Poverty	2010-2014 ACS 5-year estimates	Block Group
13. Income	2010-2014 ACS 5-year estimates	Block Group
14. Earnings	2010-2014 ACS 5-year estimates	Block Group
15. Veteran Status	2010-2014 ACS 5-year estimates	Block Group
16. Food Stamps	2010-2014 ACS 5-year estimates	Block Group
17. Employment Status	2010-2014 ACS 5-year estimates	Block Group
18. Industry Occupation	2010-2014 ACS 5-year estimates	Block Group
19. Housing Characteristics	2010-2014 ACS 5-year estimates	Block Group
20. Health Insurance	2010-2014 ACS 5-year estimates	Block Group

operation. This ensured that the geometry, even if multipart, contained the one and only record from its original parent block group. The choice to conduct areal interpolation was based on the premise that Census block groups tend to be more homogenous than Census tracts, and that they are designed, with input from the local communities, to be relatively consistent with respect to the distribution of the population, living conditions, and socio-economic status (Iceland & Steinmetz, 2003).

DV counts were computed as an attribute for each block group through a spatial join. The results of spatial join generated the feature class that was used in OHA. All tables from the ACS 5-year estimates were joined to the block groups using a unique key. The resulting 20 tables contained fields populated by the unique block group identifiers, all corresponding ACS 5-year estimates, and counts of DV incidents for each block group. The 20 tables were exported and used in the statistical analysis. There were originally 203 block groups but the number was reduced to 200 since three were removed due to their uniqueness. For example, the city limits covered a portion of one block group that represented the Piedmont Triad International Airport (PTI) where no one lives. The other two encompassed the University of North Carolina Greensboro (UNCG) and North Carolina A&T State University (NC A&T) respectively. UNCG maintains their crime reports through their own police department. The crime records for UNCG are not routinely shared with the GPD, and were not included in the study. Figure 3 provides a summary of the data pre-processing steps.

Analyses

DV incidents for each block group were normalized by dividing counts by the number of households and converting them to percentages. Figure 4 is a choropleth map displaying the percentages of DV incidents by total households for each block group. A crescent shaped pattern emerged along the southwest to the south and southeast and upward into portions of the northeast. Additionally, the northwest portion of the city consisted of relatively low percentages when compared to other regions. The areas denoted by the color of black signify the three block groups that were not included in the analysis. The area to the west is a portion of the PTI airport, and the central and east areas represent the locations of UNCG and NC A&T respectively. Although the choropleth map helps to discern broad patterns, there are no statistical comparisons among local clusters. To examine this issue, spatial statistics were used to identify significant clusters of high and low values.

An Optimized Hot Spot Analysis (OHA) was used to identify statistically significant spatial clusters of hot and cold spots using block group polygons. To test for spatial clustering and significance,

Figure 3. Data pre-processing steps

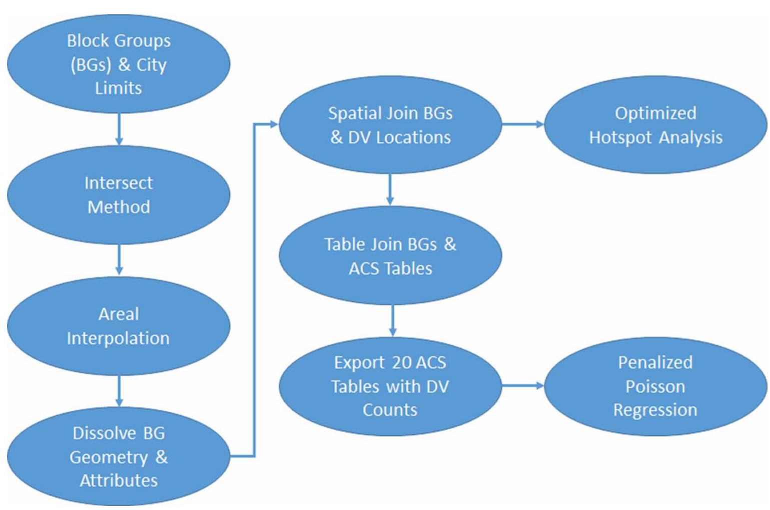
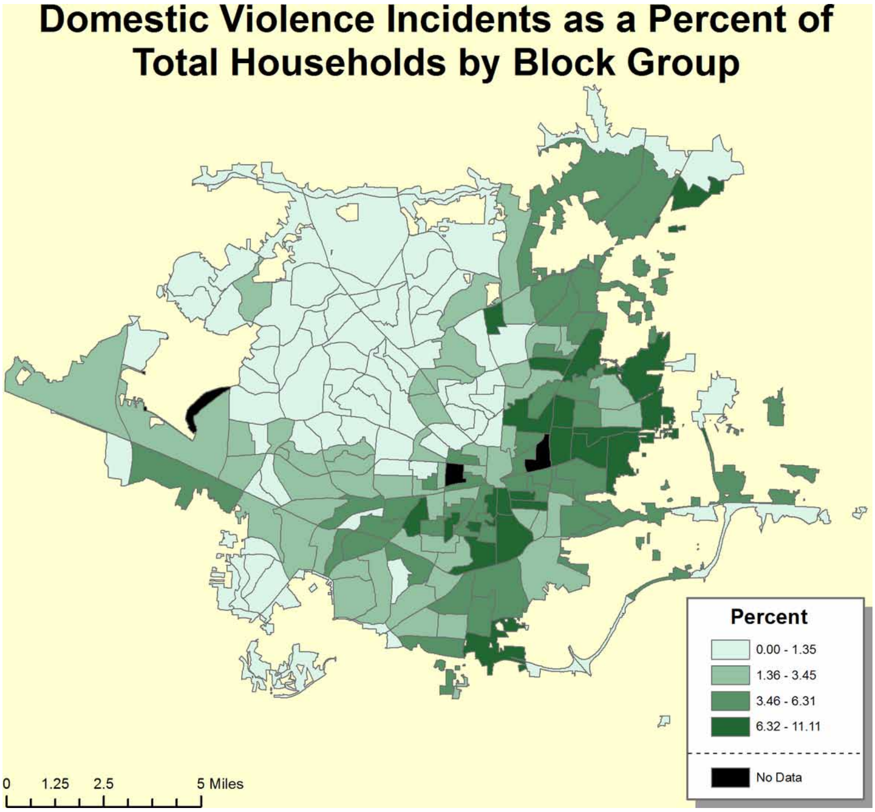


Figure 4. A choropleth map showing domestic violence patterns in the City of Greensboro. The areas denoted by the color of black were excluded from the analysis since they represent the Piedmont Triad International Airport, UNCG and NC&AT (ordered from west to east).



the percentages were used as inputs in the analysis field. The OHA uses the Getis-Ord Gi* statistic and offers optimal methods for computing the appropriate scale of analysis as well as corrections for both multiple testing and spatial dependence (Caldas de Castro & Singer, 2006; Sun et al., 2015). The OHA examines each local pattern (target feature and its neighbors) in relation to global patterns (all features), and renders the results by percent confidence level.

A statistical analysis was performed to investigate how the average number of domestic violence counts are affected by factors. If the number of factors is small and the variables are not correlated, it was assumed that each variable has a multiplicative effect on the average counts while fixing all other variables, and estimating those multiplicative effects using a Poisson regression model. There were 7,056 features in the ACS 5-year estimates from 200 block groups in total. The large number of features presents a typical high-dimensional problem since the number of variables (7,056) is much larger than the sample size (200 block groups). In general, not all 7,056 features affect the average number of domestic counts importantly and strong correlations exist among the large number of features. We were interested in finding a parsimony model (choose some important variable sets out of 7,056 variables) and investigating their effect on incident counts. Thus, the classical Poisson regression model was not feasible due to the high-dimensionality and multicollinearity of the data.

Instead, a penalized Poisson regression model with elastic net penalty was adopted (Agresti, 2013; Zou & Hastie, 2005) to select a much smaller subset of important variables as a way to investigate their effect on the domestic violence counts. The model assumes that average DV counts are roughly the same as the variability of the DV counts, and that not all features (variables) are important. After performing the high-dimensional count data analysis, we used 1/-1 to indicate either a positive or negative effect on the DV incident counts (dependent variable). Generally, a variable with a positive effect indicates an increasing variable value, causing the average incident count to scale up (with a multiplicative effect being larger than 1), while a variable with a negative effect indicates an increasing variable value, causing the average incident count to scale down (with a multiplicative effect being smaller than 1).

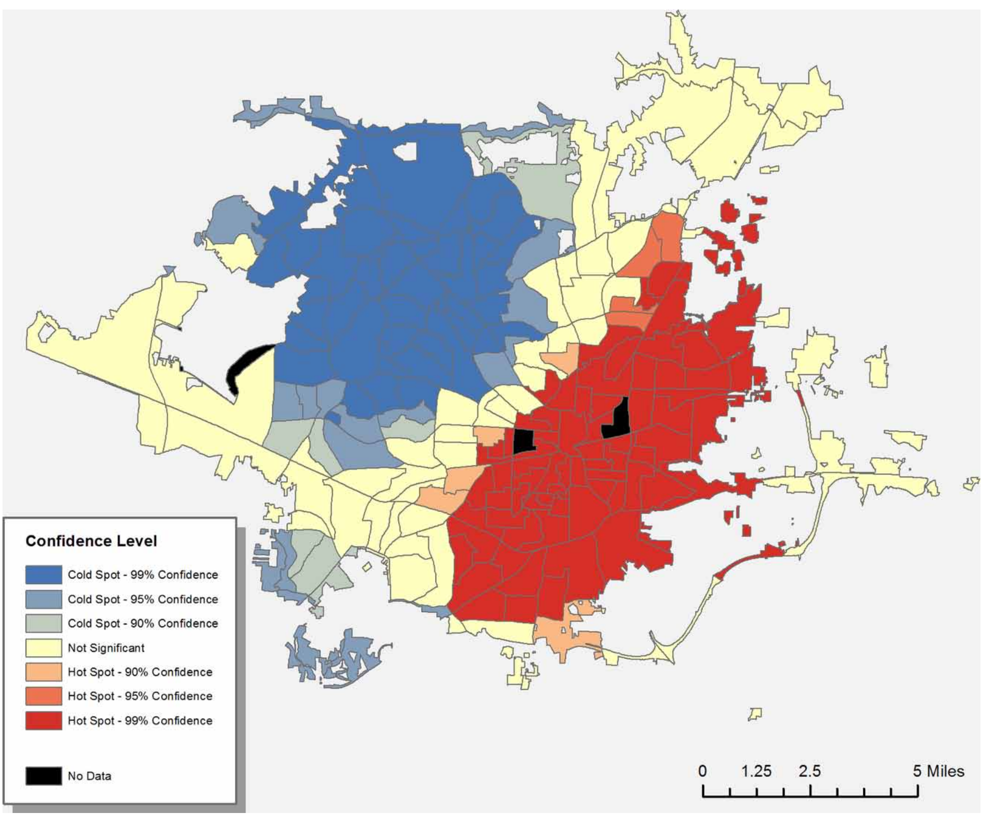
RESULTS

The results of the OHA were used to categorize block groups into two significant zones based upon confidence level. Attribute values representing the selected factors were summarized by zone to produce descriptive statistics and metrics for comparison. This section provides a discussion of the results of OHA and the penalized Poisson regression model, and concludes with a comparison of the two zones using the selected variables and descriptive statistics.

Optimized Hot Spot Analysis

The OHA yielded DV percentages ranging from a minimum of 0.00 to a maximum of 11.11 (*M = 2.68, SD = 2.56, n = 200*). There were a total of 143 features statistically significant at the 90% confidence level and higher. The analysis clearly identified a cold spot region in the northwest portion of the city where low values tended to cluster. Conversely, the analysis also showed a hot spot region in the southeast portion of the city where high values were clustered (Figure 5). These two distinct

Figure 5. The results of the optimized hot spot analysis on domestic violence percentages



zones were examined in combination with the variables selected by the penalized Poisson regression model to better understand the underlying characteristics of the neighborhoods.

Penalized Poisson Regression Model for High-Dimensional Count Data

Based on effect, the penalized Poisson regression model with elastic net penalty selected 20 of 7,056 variables considered in the analysis (Table 2). The 20 variables were represented by the following categories: a) Race, b) Children Household Relationship, c) Household Family Subfamilies, d) School Enrollment, e) Educational Attainment, f) Industry Occupation, and g) Housing Characteristics.

The results of the analysis suggested that variables associated with Race had a negative effect on domestic violence incidents when the population was White alone, White alone or in combination with one or more other races, or Native Hawaiian and Pacific Islander alone or in combination with one or more other races (Table 2). A negative effect was also observed when the variable for Children Household Relationship contained households with spouses but a positive effect when family households was comprised of children with other relatives. There was also a positive effect

Table 2. Results of the penalized Poisson regression model for high-dimensional count data analysis. The table shows the categories and significant variables. Categories are numbered for reference and correspond to Table 1.

Category Name	Variable	Effect
2. Race	1. White alone: Total population	-1
	2. Total: White alone or in combination with one or more other races	-1
	3. Total: Native Hawaiian and Other Pacific Islander alone or in combination with one or more other races	-1
6. Children Household Relationship	4. In households: In family households: Spouse: Total population	-1
	5. In households: In family households: Other relatives: Total population	1
	6. In households: In nonfamily households: Householder: Male: Total population	1
7. Household Family Subfamilies	7. Total: Households with a householder who is Black or African American alone	1
	8. Total: Households with a householder who is Some other race alone	1
	9. Total: Households with a householder who is Hispanic or Latino	1
	10. Total: Population in households with a householder who is White alone, not Hispanic or Latino	-1
9. School Enrollment	11. Total: White alone population 3 years and over	-1
	12. Total: White alone, not Hispanic or Latino, population 3 years and over	-1
10. Educational Attainment	13. Total: Population 25 years and over with a bachelor’s degree or high attainment	-1
18. Industry Occupation	14. Total: Civilian employed Some other race alone population 16 years and over	1
	15. Total: Civilian employed White alone, not Hispanic or Latino population 16 years and over	-1
	16. Total: Civilian employed Hispanic or Latino population 16 years and over	1
19. Housing Characteristics	17. Total: Vacant housing units	1
	18. Renter occupied: Total population in occupied housing units	1
	19. Renter occupied: 1, detached or attached: Total population in occupied housing units	1
	20. Renter occupied: 2 to 4: Total population in occupied housing units	1

when nonfamily households had a male as head of the household. Household Family Subfamilies had variables that showed a positive effect when the householder was African American, some other race alone, or Hispanic or Latino. In the same category, however, there was a negative effect when the householder was White alone, not Hispanic or Latino. School Enrollment had variables that showed a negative effect for children age 3 years and over who were White alone or White alone, not Hispanic or Latino. A negative effect was also observed for Educational Attainment variables when the population 25 years and older had a bachelor's degree or higher. The category of Industry Occupation revealed a positive effect for variables where employed civilians were some other race alone or Hispanic or Latino but a negative effect when the employed civilians were White alone, not Hispanic or Latino. All variables for Housing Characteristics selected by the analysis demonstrated a positive effect for vacant housing units, renter occupied, and tenure of renter occupied housing units (1 year and 2 – 4 years).

Descriptive Statistics

All block groups identified as significant at the 99% confidence level were selected from the results of the OHA, and summarized to compute descriptive statistics using the selected 20 variables displayed in Table 2. The two distinct zones are shown in Figure 6. The Cold Spot zone (blue) consisted of 40 block groups and contained 195 DV incidents ($M = 4.88, SD = 3.24$), and 27,347 households (0.71% of Households). The Hot Spot zone (red) is comprised of 68 block groups, 1,488 DV incidents ($M = 21.88, SD = 13.25$), and 34,011 households (4.38% of Households).

Table 3 represents a summary of all counts from the ACS 5-year 2010-2014 estimates for each significant variable by Hot Spot and Cold Spot zones within the study area of Greensboro, NC. The selected variables associated with Race were found to be important neighborhood characteristics that influence the prevalence of DV. The Cold Spot zone had a higher percentage of White alone population (77.38%) compared to the Hot Spot zone (26.67%). This suggest that regions with higher percentages of White alone populations have relatively lower incidents of DV (negative effect). The

Figure 6. Selected block groups are grouped into two zones for descriptive comparison

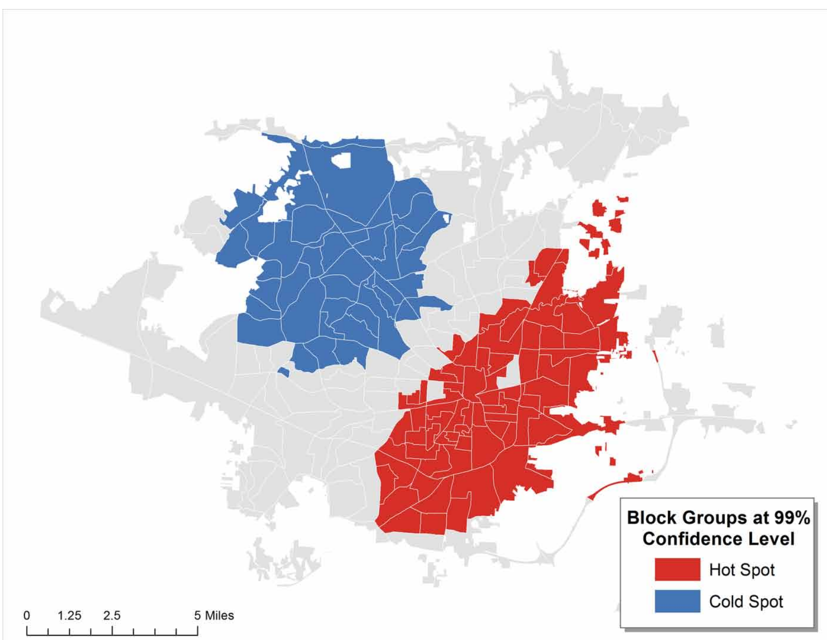


Table 3. Hot spot block groups and cold spot block groups summary statistics and comparison by zone

Category	Variable	Hot Totals[1]	Hot Count	Hot %	Hot (*M*)	Hot (*SD*)	Cold Totals[2]	Cold Count	Cold %	Cold (*M*)	Cold (*SD*)	Effect
Race	1. White alone: Total population	84,733	22,601	26.67%	332.37	274.65	62,223	48,148	77.38%	1203.70	607.25	-1
	2. Total: White alone or in combination with one or more other races	84,733	24,124	28.47%	354.76	277.25	62,223	48,158	77.40%	1229.00	609.69	-1
	3. Total: Native Hawaiian and Other Pacific Islander alone or in combination with one or more other races	84,733	126	0.15%	1.85	9.66	62,223	106	0.17%	2.65	10.12	-1
Children Household Relationship	4. In households: In family households: Spouse: Total population	84,733	8,819	10.41%	129.69	80.00	62,223	12,586	20.23%	314.65	196.19	-1
	5. In households: In family households: Other relatives: Total population	84,733	1,825	2.15%	26.84	32.94	62,223	321	0.52%	8.03	20.42	1
	6. In households: In nonfamily households: Householder: Male: Total population	84,733	6,599	7.79%	97.04	70.92	62,223	3,955	6.36%	98.88	76.68	1
Household Family Subfamilies	7. Total: Households with a householder who is Black or African American alone	34,011	21,519	63.27%	316.46	231.84	27,347	3,937	14.40%	98.43	93.65	1
	8. Total: Households with a householder who is Some other race alone	34,011	584	1.72%	8.59	15.78	27,347	365	1.33%	9.13	25.47	1
	9. Total: Households with a householder who is Hispanic or Latino	34,011	1,703	5.01%	25.04	35.38	27,347	784	2.87%	19.60	28.08	1
	10. Total: Population in households with a householder who is White alone, not Hispanic or Latino	62,208	17,999	28.93%	264.69	234.19	60,517	46,824	77.37%	1170.60	578.82	-1
School Enrollment	11. Total: White alone population 3 years and over	81,127	21,808	26.88%	320.71	263.70	60,479	46,840	77.45%	1171.00	588.37	-1
	12. Total: White alone, not Hispanic or Latino, population 3 years and over	81,127	18,294	22.55%	269.03	245.08	60,479	45,720	75.60%	1143.00	579.02	-1
Educational Attainment	13. Total: Population 25 years and over with a bachelor's degree or high attainment	52,454	12,008	22.89%	176.59	136.60	44,970	25,453	56.60%	636.33	403.96	-1
Industry Occupation	14. Total: Civilian employed Some other race alone population 16 years and over	34,426	816	2.37%	12.00	20.68	31,962	618	1.93%	15.45	51.22	1
	15. Total: Civilian employed White alone, not Hispanic or Latino population 16 years and over	34,426	9,455	27.46%	139.04	148.57	31,962	24,465	76.54%	611.63	307.62	-1
	16. Total: Civilian employed Hispanic or Latino population 16 years and over	34,426	2,472	7.18%	36.35	59.94	31,962	1,159	3.63%	28.98	56.25	1
Housing Characteristics	17. Total: Vacant housing units	39,539	5,538	14.00%	81.44	62.83	29,065	1,717	5.91%	42.93	48.33	1
	18. Renter occupied: Total population in occupied housing units	82,148	48,155	58.62%	708.16	389.23	60,517	1,410	2.33%	453.38	433.93	1
	19. Renter occupied: 1, detached or attached: Total population in occupied housing units	82,148	22,873	27.84%	109.51	126.83	60,517	5,104	8.43%	127.60	121.50	1
	20. Renter occupied: 2 to 4: Total population in occupied housing units	82,148	7,447	9.07%	336.37	207.23	60,517	1,258	2.08%	31.45	52.27	1

same holds true when considering the percentages of the White alone or in combination with one or more races variable (77.40% for the Cold Spot and 28.47% for the Hot Spot) (negative effect). The variable of Native Hawaiian and Other Pacific Island alone or in combination with one or more other races also had a negative effect on DV incidents, although percentage differences were very small (Hot Spot = 0.15%, Cold Spot = 0.17%).

The category of Children Household Relationship revealed that higher percentages of family households with a spouse generally had lower instances of DV cases (negative effect). For example, the Cold Spot zone had 20.23% of family households with a spouse compared to 10.41% for the Hot Spot zone. Conversely, family households with higher percentages of other relatives living in the household tended to have higher cases of DV incidents (Hot Spot = 2.15%, Cold Spot = 0.52%) (positive effect). Percentages of nonfamily households were slightly higher in the Hot spot zone than the Cold Spot Zone (7.79% and 6.36% respectively) when the householder was male (positive effect).

The Household Family Subfamilies category showed that the percentage of African American householder were influential in the prevalence of DV cases (positive effect). The Hot Spot zone, for example, had 63.27% of householders who were African American compared to the Cold Spot where 14.40% of household had African Americans as householders. Households that identified as having a householder as some other race alone demonstrated slightly higher percentages for the Hot Spot zone (1.72%) than the Cold Spot zone (1.33%) (positive effect). The same effect was true when the householder was Latino or Hispanic (Hot Spot = 5.01%, Cold Spot = 2.87%). However, when the householder was White alone, not Hispanic or Latino, the effect on DV instances was negative which suggest that the presence of higher percentages of this cohort resulted in lower incidents (Hot Spot = 28.93%, Cold Spot = 77.37%).

Variables for School Enrollment demonstrated a negative effect on DV for both White alone and White alone, not Hispanic for total children of school age (ages 3 years and over). DV incidents were generally lower when percentages of children of school age were higher with respect to White alone (Hot Spot = 26.88%, Cold Spot = 77.45%) and White alone, not Hispanic or Latino (Hot Spot = 22.55%, Cold Spot = 75.60%).

The variable associated with Educational Attainment had a negative effect on cases of DV. For example, the prevalence of DV incidents was lower when higher percentages of the population had a bachelor's degree or higher (Hot Spot = 22.89%, Cold Spot = 56.60%).

Within the Industry Occupation category, the variable of civilian employment (16 years and older) with some other race alone (Hot Spot = 2.37%, Cold Spot = 1.93%) and Hispanic and Latino (Hot Spot = 7.18%, Cold Spot = 3.63%) had a positive effect on the prevalence of DV. White alone, not Hispanic or Latino, however, had a negative effect on DV incidents (Hot Spot = 27.46%, Cold Spot = 76.54%). The Cold Spot zone (76.54%) had higher a percentage of White alone, not Hispanic or Latino people when compared to the same cohort for the Hot Spot zone (27.46%).

CONCLUSION

Several general patterns emerged when considering the variables individually and within the context of their geographic clusters and selected neighborhood characteristics. Race, Educational Attainment, and Housing Characteristics were all found to have significant influences on DV at the neighborhood level. Race had an influence on the prevalence of DV cases, and the trend appeared across multiple variables within several categories. Race appeared as a component in 12 of the 20 variables. All of the variables had a negative effect for neighborhoods with higher percentages of White population and a positive effect for neighborhoods with non-white populations. This includes counts for total population, total population in family households and non-family households, householders, and employed civilians. Other studies have reported no associations among violence against women and residential racial compositions after controlling for multicollinearity. Van Wyck, Benson, and DeMaris (2003), however, did find some evidence but cautioned against grouping people together from all social classes since it may obscure the effects of race. Even though our study did not find direct evidence, income and poverty levels may be more useful as a neighborhood level factor for DV since they impact all population segments (O'Campo et al., 2005).

In addition to race, other neighborhood variables had an impact on rates of DV. For example, neighborhoods with higher populations of residents who have obtained a bachelor's degree or higher tended to have lower prevalence of DV. Educational levels have been found to be an important factor in numerous other studies (Murray et al., 2016). Furthermore, housing characteristics, such as, total vacant units, total population in renter occupied housing units and the short durations of renter occupation all had a positive effect on the number of DV incidents. Overall, these findings suggest that, at least in the city of Greensboro, North Carolina, neighborhoods with generally lower levels of socioeconomic status demonstrated higher rates of DV. These results are in accordance with other studies that have examined social economic characteristics of neighborhoods (Benson et al., 2003).

Despite these results, we issue an important word of caution regarding the interpretation of these findings. Specifically, it is important to remember that the incidents of DV that were analyzed for this study were only those that were reported to the police department. Therefore, these reported incidents are only a proportion of the actual incidents of DV that occurred in the community during the time-frame investigated. Interpersonal violence is significantly underreported in community settings (Benson et al., 2003; Murray et al., 2016; Rennison, 2002). There are a number of reasons why DV may be reported more frequently in neighborhoods that demonstrate lower socioeconomic status levels, such as the closer proximity of housing in rental units and a higher presence of police related to other crimes (Murray et al., 2016). In contrast, residents of neighborhoods with higher socioeconomic statuses may be more inhibited from reporting DV to law enforcement due to greater fear or embarrassment or risk of lost employment due to police involvement (Murray et al., 2016). Therefore, future research examining the geographic distribution of DV in communities should consider alternative methods of identifying cases of DV, such as through community surveys with random samples and records from hospitals and/or family service agencies.

A geographic analysis of DV within communities offers many useful benefits for communities striving to address the problem of DV and prevent future violence (Murray et al., 2016). The identification of higher-risk neighborhoods can offer information to guide law enforcement policies, as well as to support targeted outreach by victim service agencies. The findings from the type of geographic analysis described in this study also can be applied in other communities to identify community-specific risk factors for experiencing abuse. Domestic violence is a complex, significant social issue that carries many negative consequences for individuals and communities. Therefore, it requires comprehensive solutions that account for factors that increase the risk of future violence at multiple levels. Geographic analyses, in particular, offer meaningful findings that can guide future research and practice interventions to work toward the prevention of further violence.

REFERENCES

Agresti, A. (2013). *Categorical data analysis*. Hoboken, N.J.: Wiley-Interscience.

Anselin, L. (1995). Local Indicators of Spatial Association (LISA). *GEAN Geographical Analysis*, *27*(2), 93–115. doi:10.1111/j.1538-4632.1995.tb00338.x

Benson, M. L., Fox, G. L., DeMaris, A., & Van Wyk, J. (2003). Neighborhood Disadvantage, Individual Economic Distress and Violence Against Women in Intimate Relationships. *Journal of Quantitative Criminology*, *19*(3), 207–235. doi:10.1023/A:1024930208331

Beyer, K. M. M., Layde, P. M., Hamberger, L. K., & Laud, P. W. (2013). Characteristics of the Residential Neighborhood Environment Differentiate Intimate Partner Femicide in Urban Versus Rural Settings. *The Journal of Rural Health*, *29*(3), 281–293. doi:10.1111/j.1748-0361.2012.00448.x PMID:23802930

Beyer, K. M. M., Layde, P. M., Hamberger, L. K., & Laud, P. W. (2015). Does Neighborhood Environment Differentiate Intimate Partner Femicides From Other Femicides? *Violence Against Women*, *21*(1), 49–64. doi:10.1177/1077801214564075 PMID:25540251

Beyer, K. M. M., Wallis, A. B., & Hamberger, L. K. (2015). Neighborhood Environment and Intimate Partner Violence: A systematic review. *Trauma, Violence & Abuse*, *16*(1), 16–47. doi:10.1177/1524838013515758 PMID:24370630

Black, M. C., Basile, K. C., Breiding, M. J., Smith, S. G., Walters, M. L., Merrick, M. T., . . . Stevens, M. R. (2011). *The National Intimate Partner and Sexual Violence Survey: 2010 Summary Report*. Retrieved from https://www.cdc.gov/violenceprevention/pdf/nisvs_report2010-a.pdf

Bogat, G. A., Leahy, K., Eye, A., Maxwell, C., Levendosky, A. A., & Davidson, W. S. II. (2005). The Influence of Community Violence on the Functioning of Women Experiencing Domestic Violence. *American Journal of Community Psychology*, *36*(1), 123–132. doi:10.1007/s10464-005-6237-2 PMID:16134049

Button, D. M. (2008). Social Disadvantage and Family Violence: Neighborhood Effects on Attitudes about Intimate Partner Violence and Corporal Punishment. *American Journal of Criminal Justice*, *33*(1), 130–147. doi:10.1007/s12103-008-9033-3

Caldas de Castro, M., & Singer, B. H. (2006). Controlling the False Discovery Rate: A New Application to Account for Multiple and Dependent Tests in Local Statistics of Spatial Association. *GEAN Geographical Analysis*, *38*(2), 180–208. doi:10.1111/j.0016-7363.2006.00682.x

Caplan, J. M., Kennedy, L. W., & Miller, J. (2011). Risk Terrain Modeling: Brokering Criminological Theory and GIS Methods for Crime Forecasting. *Justice Quarterly*, *28*(2), 360–381. doi:10.1080/07418825.2010.486037

Chainey, S., & Ratcliffe, J. (2005). *GIS and crime mapping*. Hoboken, NJ: Wiley. doi:10.1002/9781118685181

Chainey, S., Tompson, L., & Uhlig, S. (2008). The Utility of Hotspot Mapping for Predicting Spatial Patterns of Crime. *Security Journal*, *21*(1-2), 4–28. doi:10.1057/palgrave.sj.8350066

Clark, P. J., & Evans, F. C. (1954). Distance to Nearest Neighbor as a Measure of Spatial Relationships in Populations. *ECY Ecology*, *35*(4), 445–453. doi:10.2307/1931034

Cohen, L. E., & Felson, M. (1979). Social Change and Crime Rate Trends: A Routine Activity Approach. *American Sociological Review*, *44*(4), 588. doi:10.2307/2094589

Coy, M., Kelly, L., Foord, J., & Bowstead, J. (2011). Roads to Nowhere? Mapping Violence Against Women Services. *Violence Against Women*, *17*(3), 404–425. doi:10.1177/1077801211398637 PMID:26086982

Drawve, G., Moak, S. C., & Berthelot, E. R. (2016). Predictability of gun crimes: A comparison of hot spot and risk terrain modelling techniques. *Policing and Society*, *26*(3), 312–331. doi:10.1080/10439463.2014.942851

Getis, A., & Ord, J. K. (1992). The Analysis of Spatial Association by Use of Distance Statistics. *GEAN Geographical Analysis*, *24*(3), 189–206. doi:10.1111/j.1538-4632.1992.tb00261.x

Getis, A., & Ord, J. K. (1996). Local spatial statistics: an overview. *Spatial analysis: modelling in a GIS environment, 374*.

Goodchild, M. F., & Lam, N. S. (1980). Areal Interpolation: A Variant of the Traditional Spatial Problem. *Geoprocessing*, *1*, 293–312.

Hart, T., & Zandbergen, P. (2014). Kernel density estimation and hotspot mapping: Examining the influence of interpolation method, grid cell size, and bandwidth on crime forecasting. *Policing Policing*, *37*(2), 305–323. doi:10.1108/PIJPSM-04-2013-0039

Hetling, A., & Zhang, H. (2010). Domestic Violence, Poverty, and Social Services: Does Location Matter? *Social Science Quarterly*, *91*(5), 1144–1163. doi:10.1111/j.1540-6237.2010.00725.x PMID:21117333

Iceland, J., & Steinmetz, E. (2003). *The Effects of Using Census Block Groups Instead of Census Tracts When Examining Residential Housing Patterns*. Retrieved from https://www.census.gov/housing/patterns/publications/unit_of_analysis.pdf

Kennedy, L. W., Caplan, J. M., & Piza, E. (2011). Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies. *Journal of Quantitative Criminology*, *27*(3), 339–362. doi:10.1007/s10940-010-9126-2

Kennedy, L. W., Caplan, J. M., Piza, E. L., & Buccine-Schraeder, H. (2016). Vulnerability and Exposure to Crime: Applying Risk Terrain Modeling to the Study of Assault in Chicago. *Appl. Spatial Analysis Applied Spatial Analysis and Policy*, *9*(4), 529–548. doi:10.1007/s12061-015-9165-z

Kessler, R. C., Molnar, B. E., Feurer, I. D., & Appelbaum, M. (2001). Patterns and mental health predictors of domestic violence in the United States: Results from the National Comorbidity Survey. *International Journal of Law and Psychiatry*, *24*(4-5), 487–508. doi:10.1016/S0160-2527(01)00080-2 PMID:11521422

Law, J., Quick, M., & Chan, P. W. (2015). Analyzing Hotspots of Crime Using a Bayesian Spatiotemporal Modeling Approach: A Case Study of Violent Crime in the Greater Toronto Area. *GEAN Geographical Analysis*, *47*(1), 1–19. doi:10.1111/gean.12047

Lee, J., Zhang, Y., & Hoover, L. T. (2013). Profiling Weapon Use in Domestic Violence: Multilevel Analysis of Situational and Neighborhood Factors. *Victims & Offenders*, *8*(2), 164–184. doi:10.1080/15564886.2012.749123

Murray, C., Bunch, R., & Hunt, E. D. (2016). Strengthening community-level understanding of and responses to intimate partner violence using geographic information systems (GIS). *Journal of Aggression, Conflict and Peace Research*, *8*(3), 197–211. doi:10.1108/JACPR-01-2016-0209

NCADV. (2015). *Domestic Violence National Statistics*. Retrieved from http://www.ncadv.org/

NNEDV. (2015). *Domestic Violence Counts 2015: A 24-Hour Census of Domestic Violence Shelters and Services (2015)*. Retrieved from http://nnedv.org/downloads/Census/DVCounts2015/DVCounts15_NatlReport.compressed.pdf

Nowlin, J. W., & Bunch, R. L. (2016). A Model for Selecting Viticultural Sites in the Piedmont Triad Region of North Carolina. *International Journal of Applied Geospatial Research*, *7*(3), 38–70. doi:10.4018/IJAGR.2016070102

O'Campo, P., Burke, J., Peak, G. L., McDonnell, K. A., & Gielen, A. C. (2005). Uncovering neighbourhood influences on intimate partner violence using concept mapping. *Journal of Epidemiology and Community Health*, *59*(7), 603–608. doi:10.1136/jech.2004.027227 PMID:15965146

Raul, C., Suhasini, R.-M., & Harris, T. R. (2010). Neighborhood Characteristics as Predictors of Male to Female and Female to Male Partner Violence. *Journal of Interpersonal Violence*, *25*(11), 1986–2009. doi:10.1177/0886260509354497 PMID:20040713

Rennison, C. M. (2002). *Rape and sexual assault: reporting to police and medical attention, 1992-2000*. Retrieved from http://purl.access.gpo.gov/GPO/LPS34215

Roman, C. G., & Reid, S. E. (2012). Assessing the Relationship Between Alcohol Outlets and Domestic Violence: Routine Activities and the Neighborhood Environment. *Violence and Victims*, *27*(5), 811–828. doi:10.1891/0886-6708.27.5.811 PMID:23155728

Sun, W., Reich, B. J., Tony Cai, T., Guindani, M., & Schwartzman, A. (2015). False discovery control in large-scale spatial multiple testing. *RSSB Journal of the Royal Statistical Society: Series B*, *77*(1), 59–83. doi:10.1111/rssb.12064 PMID:25642138

Triplett, R. A., White, G., & Gainey, R. (2013). Churches as Neighborhood Organizations and Their Relationship to Street and Domestic Violent Crime: The Role of Denomination, Stability, and Heterogeneity. *Deviant Behavior*, *34*(10), 803–823. doi:10.1080/01639625.2013.781440

Van Wyck, J. A., Benson, M. L., & DeMaris, A. (2003). Detangling individual-, partner-, and community-level correlates of partner violence. *Crime and Delinquency*, *49*(3), 412–438. doi:10.1177/0011128703049003004

Wang, D., Ding, W., Lo, H., Stepinski, T., Salazar, J., & Morabito, M. (2013). Crime hotspot mapping using the crime related factors—a spatial data mining approach. *Applied Intelligence*, *39*(4), 772–781. doi:10.1007/s10489-012-0400-x

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society. Series B, Statistical Methodology*, *67*(2), 301–320. doi:10.1111/j.1467-9868.2005.00503.x

ENDNOTES

[1] Census totals for the Hot Spot zones were used to compute percentages. Total Population was used for variables 1 - 6; Total Households for variables 7 - 9; Total Population in Households for variable 10; Total Population 3 Years and over for variables 11 - 12; Total Population 25 Years and Over for variable 13; Total Civilian Employed Population 16 Years and Over for variables 14 – 16; Total Housing Units for variable 17; and Total Population in Occupied Housing Units for variables 18 – 20.

[2] Census totals for the Cold Spot zones were used to compute percentages. Total Population was used for variables 1 - 6; Total Households for variables 7 - 9; Total Population in Households for variable 10; Total Population 3 Years and over for variables 11 - 12; Total Population 25 Years and Over for variable 13; Total Civilian Employed Population 16 Years and Over for variables 14 – 16; Total Housing Units for variable 17; and Total Population in Occupied Housing Units for variables 18 – 20.

Rick L. Bunch is a Professor of Geography at the University of North Carolina Greensboro. His research interests are in Geographic Information Science and spatial cognition.

Christine E. Murray, Ph.D., LPC, LMFT, is an Associate Professor in the UNCG Department of Counseling and Educational Development. She is also Director of the Guilford County Healthy Relationships Initiative.

Xiaoli Gao is an Associate Professor of Statistics at the University of North Carolina Greensboro. Her research interests are in High-dimensional Data Analysis and Robust Statistics.

Eleazer D. Hunt is the Director of the Information Services Division for the Greensboro Police Department and Adjunct Faculty in the Department of Geography at the University of North Carolina Greensboro. His research interests are in Geographic Information Science and Criminology.