

# Geographic Analysis of Domestic Violence Incident Locations and Neighborhood Level Influences

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## 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.

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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.

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