A Spatial Dependency and Causality Analysis of Crime in Savannah, Georgia, 2000

Naresh Kumar
Department of Geography
University of Iowa
Iowa City, IA 52242
Email: naresh-kumar@uiowa.edu

Abstract: This article examines the spatial variability in the distribution of crime in the City of Savannah, GA, where a total of 12,458 crimes were reported in 2000. All crimes were geocoded and the same numbers of control locations were generated under the assumption that the spatial distribution of crime is a realization of an inhomogeneous Poisson process (spatially random). The control locations served as a basis of comparison from which individual crime data were modeled as a function of proximity to alcohol-serving establishments and socio-economic data, including, income, race/ethnic segregation and education. As expected, crimes locations were highly clustered and among a host of covariates proximity to alcohol-serving establishments, household income and ethnic diversity emerged important controls of crime incidences in the study area.

Keywords: Spatial analysis, crime, Savannah, alcohol, spatial dependency and causality.

1. INTRODUCTION

Advances in geographic information systems (GIS), which have substituted traditional static pin maps with interactive and flexible mapping capabilities, have revolutionized the field of crime mapping and visualization. Geocoding tools in GIS allow mapping and visualization of crime locations and can help law enforcement agencies and local communities develop an understanding of the spatial patterns of crime and effective allocation of resources. People use this understanding in their routine life; they prefer some places, which pose a lower risk of crime, over others (Eck et al., 2005a). Since crime activities are non-random in time and space, they raise concerns about – (a) their locations and (b) the reasons for their locations (Getis et al., 2000). Mapping and visualization tools can be employed to explore the spatial patterns of crime and to detect hot spots of crime. But spatial-analytical methods are needed to understanding causality behind the locational dependency in the patterns of crimes.

To understand the causality of the spatial distribution of crimes, we need to undertake an ecological analysis, which can allow us to examine the relationship between aggregate estimates of crime and the socio-economic and demographic characteristics of locations. The analysis of this relationship can help us identify the socio-economic, demographic and other conditions that promote crime. Research by (Ceccato and Haining, 2004; Zhu et al., 2004) demonstrates the use of this approach. Both examine the association between aggregate crime rate/ratio and socio-economic, demographic and land-use covariates. By aggregating individual point data to larger geographic units, however, we run in the danger of losing locational details (Sabel et al., 2000), particularly when a crime locations and their proximity to some control(s) is an important covariate. Using a case-control approach and crime data for Savannah, GA this article presents a methodology to model individual crime location (in relation to the established controls) as a function of proximity to alcohol-serving establishments[1] and other census variables in Savannah, GA.

The structure of this article is as follows. First, the background of the research problem is discussed; this includes a review of the relationship between alcohol and violence, place neighborhood characteristics and crime, as well as advances in GIS and spatial analysis of crime. Second, the study area, data and methodology used for the analysis are explained. Then, the results of spatial dependency and causality of crime in the study are presented, which is followed by a discussion and concluding remarks.

2. BACKGROUND

The first systematic study of crime mapping dates back to the turn of the 20th Century (Harries 1999). In one of the earliest attempts, the New York City Police Department (NYPD) used arrays of pushpins on a large paper map to show crime locations. Many other police departments adopted a similar approach to visualize the spatial distribution of crime. Despite its innovation at the time, the pushpins maps were of little use for spatial analysis and modeling. Recent advances in GIS have begun to replace pushpin maps with geocoded information that can be stored, edited, retrieved, modeled and

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[1] Alcohol-serving establishment include pubs/bars and restaurants that serve alcohol.

displayed on demand, thereby providing an opportunity to study the time-space dynamics of crime.

This section reviews background literature in four broad areas, namely (a) links between alcohol and violence, (b) associations among alcohol, place and violence, (c) associations among the location of alcohol-serving establishments, neighborhood context and crime incidences, and (d) the role of GIS and spatial analysis in crime research. Since proximity to alcohol-serving establishments is one of the main controls of crime in the model proposed in this research, three of the four areas, discussed in this section, focus on alcohol and crime.

2.1 Crime, alcohol and socio-economic characteristics

Alcohol use, including alcoholism, is influenced by factors including the genes (i.e., what we inherit), the environment (i.e., where and how we live) and interaction between the two (NIAAA, 2000). Two outcomes of alcohol consumption, health and violence, have been studied at length. A myriad of studies have shown a strong association between alcohol consumption and cancers of the upper aerodigestive tract, including the oral cavity and pharynx (often combined), esophagus and larynx (Corrao et al., 2004; Poschl and Seitz, 2004; Seitz et al., 2004; Zeka et al., 2003). Likewise, numerous studies have demonstrated the effect of alcohol consumption on violence (Bell et al., 2004; Bushman and Cooper, 1990; Frieze and Browne, 1989; Greenberg and Schneider, 1994; Greenberg, 1981; Greenberg et al., 1985; Gustafson, 1991; Hamilton and Collins, 1981; Kantor and Straus, 1987; Tita, 2005; U.S. Department of Justice, 1998).

Researchers have scientifically established that both animals and humans behave more aggressively under the influence of alcohol (Bushman and Cooper, 1990). A cross sectional study in the United States showed that a mere 15 percent increase in alcohol consumption explained a 5.9 percent increase in the rate of assault (Cook and Moore, 1993). Greenberg reviewed 28 studies on the association between homicide and drinking. Fourteen of these studies reported that at least 50 percent of homicides involved drinking of alcohol by the offender or the victim (Greenberg, 1981). In other research, Pernanen observed a similar association, but the range of victims who had consumed alcohol, was between 47 and 68 percent (Pernanen, 1991). With regards to sexual assault, Collins and Messerschmidt argued that most studies estimate that between one-third and three-quarters of sexual assaults involved the consumption of alcohol by one or both parties (Collins and Messerschmidt, 1993). Alcohol consumption is also linked to domestic violence (Frieze and Browne, 1989; Hamilton and Collins, 1981; Kantor and Straus, 1987).

Alcohol and violence have also been examined in association with a number of other socio-economic and demographic variables. Among these, poverty and economic inequality have long been linked with an increase in levels of violence (Blau and Blau, 1982). Parker reports that the consumption of alcohol in association with poverty shows a much stronger impact on homicide rate than the impact of poverty alone (Parker, 1995). With regard to gender, males under the influence of alcohol are disproportionately involved in criminal activities (Goodman et al., 1986; Graham et al., 2002; Shepard et al.,

1989) et al. 2002). In an analysis of 4000 homicides in Los Angeles between 1970 and 1979, Goodman and colleagues found that the proportion of males (0.51), who were under the influence of alcohol and involved in the crime, was two times higher than that of females (0.25) (Goodman et al., 1986).

While the existing literature on violence, alcohol and the race of a victim or an offender has been inconsistent, Gary demonstrates a stronger association between race/ethnicity and homicide (Gary, 1986). He observes that among lower class persons who committed homicide, more than 30 percent were black males under the age of 30 years. Similarly, Goodman and others reported that 38.2 percent of Hispanic homicide victims in Los Angeles had high concentration of alcohol in their blood (Goodman et al., 1986). In assessing economic status, Sampson argues that the economic deprivation, among other factors, has a stronger impact on violent crimes against African-Americans as compared to non-African-Americans (Sampson, 1987). Researchers have also examined the impact of age and alcohol consumption on violent crimes. One research shows that under the influence of alcohol, young adults are more likely to be involved in both sexual and non-sexual assault as compared to people in other age groups (Collins, 1981). The above review clearly demonstrates linkages between alcohol consumption, socio-economic and demographic variables, and violent crime.

2.2 Alcohol, place and crime

Criminal activities are non-random in time and space (Getis et al., 2000). That is why some places experience higher crime incidences than others. A review of the literature suggests that the places, which attract crime include: liquor stores and taverns (Roncek and Bell, 1981; Roncek and Maier, 1991), public housing (Roncek and Bell, 1981) high schools (Roncek and Faggiani, 1985) and certain types of commercial businesses (Walsh, 1986). Since characteristics of places and people who patronize these places generate unique environments, it is important that their effects on alcohol consumption, violence level and crime are captured separately as well as interactively (Block and Block, 1995). Despite the lack of a unified theory of the relationships among alcohol, violence and place, a number of studies provide some insight into these relationships.

The literature has identified nightlife areas, restaurants, convenience store areas and isolated club or tavern establishments as 'hot spots' or 'clusters' of criminal activities (Block and Block, 1995; Eck et al., 2005b; Sherman et al., 1989). Sherman and colleagues observe that in the city of Minneapolis, Minnesota the 'hot spots, which account for three percent of the neighborhoods the city, explain for more than 50 percent of the total calls for assistance made to the police in a one-year period. His research further demonstrates that among the hot spots of criminal activity, alcohol outlets experience relatively higher incidences of crime per capita.

The 'situation of company' created by the high concentration of inner city males socializing and using alcohol may create a place specific critical mass resulting in violence (Crutchfield, 1989). The effect of situation of company is further confirmed by (Norstrom, 2000) using a time series analysis of data spanning over 38 years, he demonstrates the association between crime type and the setting of place. Two important observations emerge from his analysis. First, the consumption of beer and spirits in bars/restaurant, which are public places, is positively associated with assault and related type of crimes. Second, the consumption of spirits in a private setting, such as the home is linked with the homicide rate. Many other studies that demonstrate linkages between heavy drinking and sexual assault among college age men and women further support the credibility of the effect of situation of company on crime (Miller and Marshall, 1987) (Koss and Dinero, 1989; Nicholson and Min, 1989). In other research, Leppa identified drinking as a risk factor for robbery, because people who have been drinking offer attractive targets for robbery as they are often unable to protect themselves or their judgment is impaired (Leppa, 1974). The recent literature further substantiates strong linkages between alcohol and violent crimes in both licensed and unlicensed environments (Deehan, 2004; Graham and Wells, 2001; Graham et al., 2002).

One particular theory that helps explain the ties between alcohol-serving establishments and crime is the 'routine activity approach'. (Cohen and Felson, 1979) hypothesize crime clustering as a result of routine activities including the convergence in both space and time of motivated offenders, suitable targets, and the absence of capable guardians against a violation. The routine activity theory suggests that the causes of crime may be independent of the social, cultural and economic contexts that are often stressed by other approaches. Under the routine activity theory framework, tavern patronage is clearly an event that brings potential victims and offenders together. In short, routine activities theory hypothesizes that criminal activity is likely to occur where an activity such as the consumption of alcohol takes place. Additional research has shown that nighttime activity is a key factor in crime victimization (Miethe et al., 1987; Sampson and Wooldredge, 1987). Given the increased risks, routine activities like bar and restaurant patronage would logically expose patrons to increased opportunities for victimization. Based on routine activity theory and two other theories, crime pattern and rationale choice theories, new opportunity theory argues that all three theories examine crime opportunities but from three different directions and emphasizes on explaining crime patterns with the aid of place characteristics that facilitate and hinter crime opportunities (Felson and Clarke, 1998.).

2.3 Alcohol Serving Outlet Density and Crime

Alcohol serving outlets, which include restaurant and bar, are commercial activities and their concentration is likely decline with the increasing distance from downtown and/or nodes of economic activities. As mentioned above human and animals acts violently under the influence of alcohol, it can be hypothesized that incidence of crime is likely to be higher in the proximity of alcohol serving establishments, because the frequency of alcohol consumer is likely to be higher in the vicinity of these establishments. These establishments not only connect offenders and victims but also enhance opportunity for criminal activities through violent behavior and impaired senses of both offenders and victims. In addition, the selection of proximity to alcohol-serving establishments also represents proximity to commercial/business activities, which provides relatively higher opportunity for crimes by connecting offenders and victims.

In recent years, researchers have begun to explore the association between the density of alcohol outlets and crime. Scribner and others note that neighborhoods with high densities of off-sale alcohol outlets have higher rates of homicide after controlling for variables including race, unemployment, age, and other social factors (Scribner et al., 1995). In other research, Stevenson explored 178 local government areas in NSW, Australia and observed that high alcohol density alone accounted for 30.4 percent of the variability in assault rate (Stevenson, 1999). In similar research in the City of Los Angeles, Scribner and colleagues noted a significant relationship between both on and off premises alcohol sale and violent assault (Scribner et al., 1995). In a time-series analysis spanning 35 years, Norstrom examined the association between the density of alcohol outlets and violent crime in Norway (Norstrom, 2000). His research revealed that a 12 percent increase in alcohol outlet density was associated with a 6 percent increase in violent crimes during the study period. A study by Gorman and others examined the effect of alcohol outlet density on violet crimes in the 98 census blocks groups of Camden, NJ after controlling for neighborhood social structure (Gorman et al., 2001). While the result of their analysis further confirms the linkage between the density of alcohol outlets and crime, particularly violent crime, their research also observes that the density of alcohol outlets is also associated with physical disorder, such as broken bottles and windows. In addition, design and management of town, city, and business areas and neighborhood characteristic, such as poverty, education, ethnic diversity, can produce major shifts in crime rates (Perry and Simpson, 1987; Peterson et al., 2000; Rosenfeld et al., 2001; Ross and Jang, 2000). For example, it is possible to reduce crime by calming traffic and orienting windows so people can better supervise their own streets.

2.4 GIS, Spatial Analysis and Crime

The geocoding utility in GIS software has revolutionized mapping of data referenced by street addresses and has triggered a revived interest in point pattern analysis. Mapping crime is just one example of this utility (Harries, 1999). Getis and others argue that GIS and spatial analysis have greater potential to fight against crime by informing us about crime hot spots and the locational contexts that govern the time-space dynamics of crime (Getis et al., 2000).

Several software packages have been developed specifically to map, visualize and spatially analyze crime data; CMap (ESRI, 2005), Crimestat III (Ned Levine, 2004) and School COP (Abt Associates Inc., 2005) are some examples. While these software packages have been exploited for crime mapping and visualization, they lack adequate spatial-econometric methods to address causal mechanisms of the spatial patterns of crime. With regard to the use of GIS and spatial analysis, the crime related research can be grouped into two broader categories – (a) mapping and visualization of crime patterns and/or hot spots and (b) ecological analyses of crime patterns.

Numerous studies belong to the first category (Eck et al., 2005b; Goldsmith et al., 2000; Harries, 1999). GIS and specialized tools are widely explored with crime mapping to detect high-crime-density areas known as hot spots. In a recent report, Eck and colleagues have detailed different methods and software used for crime mapping and hot spot detection (Eck et al., 2005b). The second category, ecological analysis, examines aggregate estimates of crime rates in relation to neighborhood characteristics (e.g. census data). The ecological analysis of crime in the United States can be traced back to the classic work by Shaw and McKay (Shaw and McKay, 1942). While there are inherent dangers of ecological fallacies (if used carelessly), researchers continue to use this approach with robust spatial-statistical models (Ceccato and Haining, 2004; Gorman et al., 2001; Krivo and Peterson, 1996; Martin, 2002; Rosenfeld et al., 2001; Ross and Jang, 2000; Sampson et al., 1997; Zhu et al., 2004). The NIAAA report on 'From Genes to Geography: The Cutting Edge of Alcohol Research' and other research has identified the importance of micro environmental characteristics (including cultural, demographic and social factors) in analyzing alcohol related problems (Gruenewald et al., 1996; NIAAA, 2000; Scribner et al., 1999).

The main goal of ecological analysis is to understand why some places witness higher incidences of crime than others, and why certain types of crimes happen in certain locations. One way to answer these questions is to examine the association between crime types in relation to socio-economic, demographic and cultural factors that may differ significantly among geographic areas. Most ecological research relies on aggregate estimates of crime rates and aggregate estimates of neighborhood characteristics, particularly social disadvantage, population density, ethnic/racial composition and residential instability.

Among the studies referenced above, the research by Zhu and others is particularly relevant. They examine the association between alcohol outlet density and violent crimes in 188 and 263 census tracts in Austin and San Antonio, TX, respectively(Zhu et al., 2004). Their analysis involved the use of ordinary least square (OLS) and a spatially autoregressive model (SAM). The results from the SAM model indicate that the alcohol outlet density in association with the neighborhood characteristics explains 71% and 56% of the variance in violent crimes in Austin and San Antonio, respectively.

The ecological fallacy is another problem with the use of aggregated crime data, particularly when the inferences about the nature of individual crime events are derived from the aggregate data and the crime event locations are to be modeled with reference to proximity to facilities. A recent study presents an example of this approach. They modeled offense patterns in Öresund, a Scandinavian border region that spreads across Sweden and Denmark, at two points of time - before and after the opening of Öresund Bridge. In their model, they included proximity to the bridge (measured by geographic distance) a covariate of the offense rate. The results of their analysis suggest that there have been changes in the levels and the geography of crime after the Öresund Bridge was opened (Ceccato and Haining, 2004) .

Since ecological analyses rely on aggregated data, the size of unit chosen can affect the reliability of the analysis. Choosing an optimal geographic unit is a challenge, because large geographic units can result in too much generalization (Sabel et al., 2000) while small can introduce spatial autocorrelation. One way to address this problem is to analyze individual level crime data. The analysis of spatial dependency and causality of crime in this research extends this individual level approach, and the methodology used to implement it is detailed in the next section.

3. METHODOLOGY

3.1 Study Area: Savannah is a coastal city located in the south east of Georgia (Figure 1); the population of the city declined from 149,245 in 1960 to 131, 510 in 2000 (US Census 2000, Table 1). According to 1997 estimates, 19% of people in the city were living below the poverty line (FedStats, 2001a), while the figure for Georgia was only 14.7%. The Savannah also reported a high crime rate of 9,473 against 5,463 for Georgia and 4,615 for the USA (Table 1). In 1999, the homicide rate in Savannah was 29 per 100,000, which was six times higher than the rate in New York City and 4 times higher than the rate for Georgia. A high crime rate and a diverse demographic profile stimulate interest in the spatial analysis of crime in Savannah.

3.2 Data: Data for the present study was acquired from the Savannah Police Department (SPD) and the Georgia GIS Clearing House. Geo-coded data for 12,458 crime spots and 247 alcohol serving establishments for the year 2000 were procured from the Investigating Division of the SPD (Figure 2). Since 1994, the SPD has used a Record Management System (RMS) that has been tied to their Computer Aided Dispatch (CAD) system. Using this system, the SPD tracks incidences of crime geospatially and records specific attributes of each reported crime. Each crime location has, for example, has several attributes including crime type (UCR Code) and street address. Crime incident locations and alcohol serving establishment locations were available in State Plane coordinates (Georgia East).

Alcohol-serving establishments are grouped into two categories – (a) bars/pubs that serve alcohol and (b) restaurants that serve alcohol. To examine their appropriateness in the statistical model, distances between each crime location and the closest bar/pub and restaurant were computed. Since distances to both facilities showed a significant positive correlation ($\geq$0.77), and have almost the same explanatory power in the analysis of spatial variability in crime distribution, the final model included proximity to either of the two – pub/bar or restaurant (Figure 3).

Roads network data of Chatham County, including Savannah, and land-use data were downloaded from the Georgia GIS Clearing House (http://www.gis.state.ga.us) and were converted to Georgia (East) State Plane Coordinates to make them comparable with the other coverages (Figure 3). To examine the neighborhood context of crime, the 2000 US Census data (particularly SF1 and SF3 files for the state of Georgia) were downloaded from the Census Website (http://www.census.gov), though it may result into the problem of modifiable unit problem (MAUP), which refers to as the differences in inferences of the same data aggregated at different geographic scales/spatial resolutions and shapes (Waller and Gotway, 2004). This problem, however, can be addressed by avoiding aggregation of point data, and multilevel analysis for data at different geographic scales (Subramanian, 2004).

3.3 Methods: Unlike the conventional ecological approach discussed above, the analysis in this research relies on individual crime location data, which allows to computation of precise measures of proximity to potential sources that can be linked with the crime incidences (alcohol-serving establishments in this case). Building on the literature on epidemiological case-control studies, the remaining part of this section details the methodology used to – (a) examine the spatial dependency of crime, (b) generate control points, and (c) examine spatial variability in crime distribution in relation to the selected covariates.

We have a set of spatially distributed crime locations x_i i=1,…,n. The first step in the spatial analysis of point data is to examine if the crime locations are randomly distributed in space or location dependent. The first step in point pattern process is to examine the intensity of spatial dependency in point events. A myriad of test of complete spatial randomness (CSR), such as Clark-Evans, Hopkins and Byth and Ripley are available (Bailey and Gatrell, 1995). For example in the Clark-Evans spatial dependency in point events is estimated by the ratio of actual average distance to the nearest neighbors to the expected average distance $a(x)$ to nearest neighbor distance $e(x)$, and a value of less than one indicates spatial dependency in the point events in question; the lower the value the greater the degree of spatial dependency, and a value of one indicates the realization of a random distribution in a Cartesian space. While most these tests can work effectively under the assumption of homogenous Poisson processes, these fail to compute reliable estimate of $e(x)$ if expected event are the realization of inhomogeneous Poisson processes, for example the intensity of crime is expected to be higher in densely populated areas than in low density areas. Nonetheless, simulation a large number of trials of the expected events using the background probability that guides the inhomogeneous distribution of event can be used to compute $e(x)$ (Schabenberger and Gotway, 2005). In this research, we simulated 11,831 events 100 times to compute expected values within the built-up area, because more than 95% of actual crime locations were in the built-up area. Then another set of 11,831 locations were simulated and tested for their randomness to serve as a control of crime locations, needed for multi-level logistic regression model. A computer application was written in ArcGIS to generate these control locations. The number of locations in each polygon was allocated in proportion to its area. The algorithm used to simulate these a trial is explained below.

The goal of this algorithm is to simulate as many controls (M) as the total number of observed crimes (N) using the built-up area as the background weight. To begin with $\boldsymbol{R_d}$ and non-built up areas ($\boldsymbol{R}$-$\boldsymbol{R_d}$); $\boldsymbol{R_d}$ was further partitioned into discrete subspaces r_i (census block groups in our case) ($i \in (1,2,..., k)$ such that $\bigcup_{i=1}^{k} r_i = R_d$ and $\boldsymbol{p_i} \geq 0$ in every r_i. The probability of a point in each $\boldsymbol{r_i}$ varies in proportion to its area and the number of points ($\boldsymbol{m_i}$) to be allocated to each $\boldsymbol{r_i}$ varies such that, $\boldsymbol{m_i} \geq \boldsymbol{0}$ and $\sum_{i=1}^{k} m_i = N$, where $\boldsymbol{m_i}$ can be defined as $m_i = p_i * M$ such that

$$p_i = \frac{a_i w_i}{\sum_{i=1}^{k} a_i w_i} \qquad (1)$$

where a_i = area of $\boldsymbol{r_i}$
w_i = weight of $\boldsymbol{r_i}$, i.e. the population size in the i^{th} unit.

In order to generate a set of M control locations x_k (k $\in \{1,2,\ldots,K\}$) from Rd such that $x_k \in R_d$, a computer application was written in ArcGIS 9.0 (ESRI, 2005). This application builds on the following strategy with the constraint that $k_i \in m_i$, where k_i is the number of points already sampled from k_i at any point in time.

Repeat until N points are simulated

1. Initialize $k_i=0$ for $i=1,2,\ldots,k$
2. Randomly simulate a point $x_i \in \boldsymbol{R}$ by generating a pair of pseudo random numbers and then project them onto the coordinate system of the geographic extent
3. Identify the container x_k (polygon) for the random point x_i, if the probability of $x_k \in R_d \leq 0$, then **discard** this point and go to step 2
4. If $\boldsymbol{x_k \in R_d}$ (for some i $\in \{1,2,\ldots,k\}$) and $k_i \leq m_i$ then **place** this point, increment $\boldsymbol{m_i}$ by one and go to step 2

A multi-resolution land cover map (downloaded from the Georgia GIS Clearing House) was used to extract the built-up area of Chatham County that included Savannah (Figure 4), and then the block level population data were attached to each polygon of the built up area; these areas serve as container for control locations. Using the population weight for each container, the above algorithm was implemented to generate 11,831 controls (Figure 5), which is equal to the number of crimes reported in the study area in 2000.

Following, Clark-Evans approach, an improved measure of spatial dependency was developed, in which $e(x)$ was replaced by the average distance to the closest neighbor in of 100 trials $s(x)$, and variance (σ^2) was also computed from the results of these trials. This substitution avoids the overestimation in r statistics that is introduced by the assumption of uniformity in the expected point distribution. The improved r statistic is of the form

$$r = a(x)/s(x)) \qquad (2)$$

Once spatial dependency in the point events has been established, understanding the causal mechanism that drives the spatial patterns becomes the main focus of interest. Traditionally, Poisson and OLS regression models are employed to analyze causality of the point counts and aggregated rates derived from the point counts, respectively. Diggle and Rowlingson have proposed parametric point process model for individual case data, in which the risk at point $r(x)$ is modeled using a continuously varying function of distance $f(x)$ from a single source k (of risk, air pollution in their case)(Diggle and Rowlingson, 1994). They further revised this method by adding multiple sources and q spatial reference covariates $z_j(x), j=1,\ldots q$ of the form (Diggle et al., 1997):

$$r(x) = \rho \exp\{\sum_{j=1}^{q} \phi_j z_j(x)\} \prod_{i=1}^{k} f_i(x) \quad (3)$$

Where $f_i(x)$ is an inverse function of distance from the risk source; Lawson also added spatial orientation in the above model, for example wind direction and wind velocity can greatly affect the dispersion and distribution of air pollution from a given source (Lawson, 2001). In crime research, orientation can be useful if the spatial pattern of crime follows any spatial orientation. Diggle and others first estimate the response variable as a ratio of cases in the neighborhood of a given location to the expected number of cases derived using a Poisson estimate, and then regress this ratio as a function of distance from the risk source(s) and covariates (Diggle et al., 1997). The main problem with the suggested approach is that the value of the response variable depends on the way the neighborhood is defined around a given location. We suggest a binary logistic regression model in which the probability of a crime incidence (in relation to the control locations) is a continuous function of distance from the closest alcohol-serving establishment and other covariates of the form:

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha + \delta d^{-k}{}_{ij} + \beta z_i + \varepsilon_i \quad (4)$$

Where p_i = probability of crime at location i
d_{ij} = distance to the closest alcohol outlet, and i is restricted to built-up areas within the study area, Savannah in this case
z_i = covariates at location i
ε_i = residual term, is assumed to have a normal distribution with a 0 mean and variance, σ^2.

$p(x)$, in the above model, never reaches 0 or 1 even if the d_{ij} is beyond the study area. This problem was addressed by restricting the d_{ij} to built-up area within the study area. In the above model, d_{ij}, which is a measure of proximity to a given risk source, can be estimated precisely to street address i and each there will be a unique value for each i. However, the data for the covariates (z_i), which includes socio-economic and demographic contexts at location i, will remain constant for all cases and controls within a census unit (census block and block groups in our case), as census data are available in aggregate form only. As a result, ε_i cannot be expected to have a normal distribution for all cases and controls within a census block. This problem is addressed by introducing a census unit level fixed effect u_k in the above notation (Subramanian, 2004), which will result in unbiased estimates across census blocks.

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha + \delta d^{-k}{}_{ij} + \beta z_i + (u_k + \varepsilon_i) \quad (5)$$

Where u_k is the error cause by assigning the same value of covariates of the k^{th} unit to all cases and controls within the k^{th} unit, block group in this, which is the highest geographic unit of analysis and accounts for intra-block group correlation in the block and point data.

4. RESULTS

The organization this of section is as follows. First, we begin with a descriptive analysis of different crime types in the study area. Then we test whether the distribution of crime is a realization of a spatially random distribution, which is followed by the tabulation of crime and control locations at different distance intervals from alcohol-serving establishments. Finally, using the model discussed above, the spatial distribution of crime is modeled as a function of proximity to alcohol-serving establishments and the selected census variables presented in the table 4.

4.1 Crime classification

Using the Uniform Crime Reporting Code (UCR)[2] a total of 12,458 incidences of crimes, reported in the year 2000, in the City of Savannah can be grouped into 79 crime types (Appendix 1). In order to simplify the analysis, crimes were grouped into four categories (Table 2). The assault and related category was composed to represent crimes of physical violence. The second category contains crimes that are committed mostly for economic purposes, e.g. burglary, theft, robbery, larceny and related crimes, but may also involve violence. Finally, the third category represents the large numbers of motor vehicle theft and related incidents that are manly property crimes. While homicide is a serious crime and requires due attention, it was not included in the analysis because only 18 cases of homicide were reported for the year 2000; this small number may result in unreliable statistical estimates.

4.2 Spatial dependency: The improved Clark-Evans test was employed to compute spatial dependency in the distribution of crime. The results are presented in the table 3. The CSR statistics for the first nearest neighbor is 0.12 ($Z \sim 284$), which indicates high intensity of clustering in the crime distribution in the study area. As apparent from the Figures 6a and 6b the intensity of spatial dependency, however, declines as the number of nearest neighbors used to compute the average distance.

4.3 Causality analysis of crime distribution: The key goal of our analysis is to test the hypothesis that 'the spatial variability in the distribution of crime is a function of proximity to alcohol-serving establishments and the neighborhood environment'. As discussed in the methodology section, a logistic regression with a fixed neighborhood effect (as in equation 5) was employed to this hypothesis. In this model, the response variable included crime and control locations, coded as 1 and 0, respectively, and the seven covariates (or predicting variables) listed in the table 4. Among these seven, the proximity to alcohol-serving establishments, which represents Cartesian distance between the closest alcohol-serving establishments, is one of the important controls of spatial variability in the distribution of crime.

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[2] UCR codes were developed by the U.S. Department of Justice and are the universal standards for crime reporting by law enforcement agencies in the United States. The data obtained from the City of Savannah includes all of the "Group A" crimes, which refer to as the crime represents the most serious crimes against persons, property or society U S Department of Justice, 2000. National Incident Based Reporting System. In: C.J.I.S. Division (Editor). USDOJ.

In the exploratory analysis a host of census variables were downloaded from the 2000 Census, and their associations with crime patterns were examined, and the variables, which showed some meaningful relationship with the crime pattern and needed to control for confounding, were included in the analysis. These variables include population density, diversity index, sex ratio and the ratio of rented to owned households were computed using the census block level data, and for the remaining two variables using census block group data. Six of the seven variables used in the analysis are self-explanatory (Table 4); the only variable that requires explanation is the diversity index. Since using the proportion of multiple races can be correlated, a composite index of race/ethnic diversity (Δ_i^2) was computed for each block as

$$\Delta_i^2 = \frac{\sum_j^k | x_{ij} - x_j |^2}{k} \qquad (6)$$

Where x_{ij} = proportion of j^{th} race/ethnic group in i^{th} block.
x_j = proportion of j^{th} race/ethnic group in the entire study area.
k = the number of race/ethnic groups

The SF1 tables include six racial/ethnic groups. For the sake of simplicity, these were grouped into three categories, namely White, Black and others. In essence, the diversity index is a measure that captures the differences in the proportion of a racial group in a block from the proportion of this racial group in the entire area. If the proportion of different racial/ethnic groups in a given block is the same as their proportion in the entire area, Δ_i^2 will yield a value of 0, while a high value of the diversity index indicates dominance (or segregation) of one or more race/ethnic group(s).

Five of the seven covariates included in the analysis exhibited skewed distributions. Using the measures listed in the Table 4, these variables were transformed to a 'close-to-normal' distribution. Although the unit of analysis is point location (individual crime and control locations), four variables at census block and two variables at census block group level were attached to the point data. This was performed in two steps. First, all blocks within a census block group were assigned the same value for two block group variables, namely high-school graduates and household income. After this exercise, all census blocks have data for the six census variables included in the analysis. Second, census block data were linked with the crime and control locations using a spatial join tool in GIS. All points within an area unit inherit the same attributes of this unit. Using this approach, census block data were linked with the crime and control location data. If two or more than two crime and/or control locations are within a census block, they will inherit the same attributes of this census block. As a result, the selected six covariates assigned to crime and control locations cannot be considered independent if these locations are within a block and within a block group for two variables. This problem was addressed by introducing a block group level fixed effect, which corrects the standard error for clustering within the census blocks and block groups, and produces unbiased estimates(Petersen, 2005; Williams, 2000).

The results of the logistic regression model are presented in Table 5. When all crimes were regressed on the selected set of covariates, only two – the proximity to alcohol-serving establishment and the median household income - showed a meaningful association with the odds of crime. As expected, both variables experience an inverse relationship with the odds of crime incidence. However the proximity to alcohol-serving establishments shows a stronger association as compared to the median household income. The pseudo-R^2 explains approximately 25 percent of the variability, which means there are a variety of other controls can be responsible for the rest of variability in the spatial distribution of crime in the study area.

It is interesting to note that four of the seven covariates, including proximity to alcohol-serving establishment, income, diversity index and household occupancy type (renter or owner occupied) are significantly associated with the odds of assault, extortion, blackmail and sex related crime. Among these four, three experience an inverse relationship and one a positive relationship. The proximity to alcohol-serving establishments, income and the ratio of renter to owner occupied households are inversely associated with the odds of crime in this category. The association between the odds of physical violence and the first two variables is obvious, but the third requires some explanation. A negative coefficient indicates that the places, which register a high proportion of renter occupied households (and lower proportion of owner occupied households) tends to have lowers odds of physical violence related crimes. The diversity index, a measure of segregation, shows a positive association with the odds of physical violence related crimes, which means that the places with high racial/ethnic segregation are likely to have higher odds of crime as compared to places with mixed ethnic/racial profiles.

The second category of crime that includes burglary, theft, robbery and larceny related crimes, witnesses a significant relationship with just two variables – proximity to alcohol-serving establishments and median household income. The negative association of crimes in this category with the household income indicates that relatively poor neighborhoods experience higher incidences of crimes in this category as compared to rich neighborhoods. It is likely that households in poor neighborhoods may not be equipped with alarm systems, which may leave households vulnerable to burglary, theft, robbery and related crimes.

Among all covariates, proximity to alcohol-serving establishment and household income emerge as two main controls of spatial variability in crime incidence in the study area. In essence, places in the vicinity of alcohol-serving establishments and with relatively low household income are associated with higher odds of crimes. These findings, however, must be interpreted with cautions, as these results may be confounded by the fact that a vast majority of alcohol services establishments are likely to be concentrated in commercial and/or business areas, and we may expect to see the similar relationship between incidence of crime and distance from commercial/business places. In addition to these two variables, racial/ethnic segregation and the ratio of renter to owner occupied households emerge as important controls of spatial distribution in crime. In other words, places with higher racial/ethnic diversity (which can indicate less interaction among people living in a given neighborhood) has the higher probability of crime, particularly assault, extortion, blackmail and sex related crime, as compare to those with less racial/ethnic diversity or people of the same racial/ethnic groups. Income is another important control of spatial dependency in crime distribution. The negative regression coefficient indicates that poor neighborhoods are likely to have higher incidences of crime as compared to richer neighborhoods.

DISCUSSION AND CONCLUSION

This article has demonstrated the importance of GIS, spatial and statistical analysis to examine the spatial variability in crime in relation to proximity to point source of risk and neighborhood characteristics. Unlike the traditional ecological approach, a logistic regression model was adopted to analyze individual level crime data, because it avoids location uncertainty and generalization introduced in the data through the process of aggregation. Although geocoding crime location also involves location uncertainty, the level of uncertainty is much smaller than that in area units, such as census block and census tract level analysis.

When an individual location is known, its precise distance, measured in terms of travel time and cost, to potential risk source(s) can be computed. But when data are aggregated, distance between the centroid of the area unit and source is computed with some degree of uncertainty. Another problem with the aggregation of point data is related to the choice of the size of geographic unit. This is critically important because the degree of generalization and location uncertainty is proportionate to the size of the geographic unit chosen. In reality, it is difficult to find an ideal size of the geographic unit, because the census and jurisdictional boundaries are in irregular shape and their size may vary dramatically, which poses another problem for statistical modeling. Some argue that the level of aggregation should be minimized (Rushton and Lolonis, 1996). In the context of epidemiological research, Sabel and colleagues further stress the need to maintain the data in its original individual form (Sabel et al., 2000).

In this research, not only the crime data were maintained in their original individual form, but also a number of other location and neighborhood attributes were attached to these data. GIS tools were exploited to compute proximity measures, i.e. the distance between crime and control locations and alcohol-serving establishments. A unique aspect of the dataset used in the analysis was that the aggregated census data were attached to individual point data using spatial join tool in GIS; traditionally it is done other way around in which point data are aggregated to area units. Although it posed some statistical challenges, these were resolved by using robust statistical methods as discussed in the methodology section (equation 5). The suggested methodology can be useful to identify spatial contexts that give rise to or discourage the occurrence of criminal activity. In addition, it can also educate local communities about the risk factors of crime in different neighborhoods, and help law enforcement agencies in optimal allocation of resources.

One of the weaknesses of the research is that it lacked a temporal aspect in the analysis. Given the fact that certain criminal activities happen in specific time of the day, the model used for the analysis fails to capture this effect. Furthermore, the introduction of cities of various sizes and demographic composition could strengthen the generalization of relationships between crime and the chosen covariates by separating the effects of unique characteristics of Savannah. Most variables used in the analysis can be associated with crime indirectly, for example proximity to alcohol-serving establishments is an indirect estimate of alcohol consumption that is often linked with violence and crime. The use of some direct measures, such sale of alcohol by each alcohol-outlet and consumption of alcohol by victim and offender, can improve the power of statistical modeling. Finally, the analysis failed to establish linkages between the characteristics of victims and offenders. Since this is an individual level analysis, incorporating the socio-economic and demographic profile of both victim and offender could enhance the explanatory power model used to explain the observed crime pattern.

Given the limitations identified above, an indirect causal link between alcohol-serving establishments and crime was established. This research also demonstrates the potential of GIS, spatial and statistical modeling to analyzing individual crime data. Integration of GIS, spatial analysis and statistical modeling has a great potential to integrate a myriad of information (at different scales – individual to geographic) associated with offense type, victim and offender in addition to the socio-economic, demographic and location contexts to develop a better understanding of their role in explaining crime patterns. As pointed out by NIAAA there is a need to integrate "genes to geographical context"s to understand alcohol problems and associated crimes (NIAAA, 2000).

Among the selected covariates, proximity to alcohol-serving establishments emerges as one of the most important controls of spatial variability in the crime distribution in the study area. The statistical analysis clearly demonstrates that the probability of crime tends to decline as distance from alcohol-serving establishments increases. These findings must be interpreted with caution, because most alcohol serving establishments are likely to be concentrated in commercial/business districts this association may be confounded by proximity to commercial/business activities. Nonetheless, the propensity of people under the influence of alcohol is likely to be higher closer to alcohol serving establishments. Thus, these places are likely to offer higher opportunity for crime, particularly violent crimes.

Median family income, racial/ethnic segregation and household occupancy types also observe statistically significant relationships with the odds of crime. It is important to note that care must be taken while generalizing crime incidences to their neighborhood contexts. While the environment in which a crime is committed can be important in explaining the spatial patterns of crime, there are many confounding variables that can be responsible for human behavior and associated crime. This analysis simply shows a convergence in space and place of activities and persons that leads to increasing risks of criminal activity. The findings of this research are consistent with the other explanations of crime (Cohen and Felson, 1979; Martin, 2002; Sherman et al., 1989; Zhu et al., 2004). The finding of this research can guide us for effective police resource allocation and the crime probability map using the methodology presented in the paper can feed into decision making for activities need to be located in relatively safer area, such as a school location.

Table 1: Demographic profile of Savannah, Georgia and USA

	Population 2000	Population 1990	% Growth (2000 to 1990)	Crime Rate (Crimes / 100000 Inhabitants)	White, Black, Other (%)
Savannah	131,510	137,812	-4.5	9,473	60.0, 38.0, 2.0
Georgia	8,186,453	6,478,216	26.4	5,463	71.0, 27.0, 2.0
USA	281,421,906	248,709,873	13.2	4,615	75.1, 12.3, 12.6

Source: US Census (2000) & FedStat (2001)

Table 2: Crime classification, Savannah City, GA, USA, 2000

Type of Crime	Crime	
	Frequency	Percentage
1. Assault, Extortion, Blackmail, Sex Related	1,225	9.83
2. Burglary, Theft, Robbery, Larceny Related	5,514	44.26
3. Vehicle Theft and Related	5,675	45.55
Others (not in first three categories)	44	0.35
Total	12,458	100

Table 3: The test of complete spatial randomness (CSR) using Inhomogeneous Point Process

#NN	Nearest Neighbor Distance (Feet)		CSR Statistics		# NN	Nearest Neighbor Distance (Feet)		CSR Statistics	
	Actual	Simulated	Ratio	Z-Value		Actual	Simulated	Ratio	Z-Value
1	43	348	0.12	284	5	120	527	0.23	608
2	63	399	0.16	368	10	202	698	0.29	979
3	83	445	0.19	451	15	282	841	0.33	1322
4	103	488	0.21	531	20	351	970	0.36	1655
5	120	527	0.23	608	25	411	1089	0.38	1973
6	138	565	0.25	682	30	464	1200	0.39	2277
7	156	600	0.26	755	35	512	1306	0.39	2547
8	172	634	0.27	829	40	556	1406	0.40	2785
9	187	666	0.28	904	45	598	1502	0.40	2985
10	202	698	0.29	979	50	641	1594	0.40	3123

Table 4: Covariates included in the model.

Variable Description	Statistical Summary					Transformation used
	Minimum	Mean	Maximum	Standard Deviation	Skewness	
Proximity to Alcohol-serving establishment(distance feet)	4.272	5044	68010	8076.8	2.65	Log
People/mile^2	0.64	6895	594595	15107	21.24	Exp(0.4)
Median Household Income($)	6711	36303	107440	17937	1.07	Square root
Diversity Index	0	0.16	0.22	0.06	-0.74	None
Sex Ratio	10.6	992.4	9000	533.8	5.63	Square root
High school graduates (%)	6.42	28.27	57.14	9.62	0.10	None
Rented Household / Owned Household	0	1.58	351	9.41	21.36	Log

Table 5: Results from the logistic regression model.

Covariates	All Crimes	Assault, Extortion, Blackmail, Sex Related	Burglary, Theft, Robbery & Larceny Related	Vehicle Theft and Related
Log(Distance to the closest alcohol-serving establishment)	-0.955	-0.813	-0.906	-1.036
	(10.56)**	(7.61)**	(9.73)**	(9.99)**
(People/Sq Mile)^0.4	-0.004	-0.001	-0.008	0
	-0.45	-0.1	-0.91	0
Square root of median household income($)	-0.007	-0.008	-0.007	-0.006
	(1.98)*	(2.10)*	(1.99)*	-1.54
Diversity Index	1.916	4.496	2.18	1.183
	-1.37	(3.00)**	-1.54	-0.7
Log (Sex Ratio)	0.006	-0.002	0.007	0.008
	-0.41	-0.07	-0.48	-0.55
High school graduates (%)	0.017	0.025	0.021	0.013
	-1.47	-1.52	-1.88	-0.87
Log(Ratio of renter to Owner occupied Household)	-0.255	-0.464	-0.276	-0.204
	-1.59	(2.03)*	-1.85	-1.15
Constant	6.899	5.61	6.429	7.551
	(5.97)**	(2.87)**	(5.47)**	(6.12)**
Observations	17637	1567	8004	7990
Pseudo-R^2	24.43	20.45	23.56	26.76
Robust z statistics in parentheses; * significant at 5%; ** significant at 1%; Standard errors adjusted for clustering within census block groups				

Appendix 1

UCR Code	Frequency	Percent	Cum. Freq
AGG ASSAULT, FAMILY, GUN	16	0.14	0.14
AGG ASSAULT, FAMILY, OTHE	29	0.25	0.38
AGG ASSAULT, FAMILY, STRO	1	0.01	0.39
AGG ASSAULT, GUN	42	0.35	0.74
AGG ASSAULT, INTIMIDATION	5	0.04	0.79
AGG ASSAULT, NON FAM, GUN	181	1.53	2.32
AGG ASSAULT, NON FAM, OTH	197	1.67	3.98
AGG ASSAULT, NON FAM, STR	27	0.23	4.21
AGG ASSAULT, OFFICER, GUN	3	0.03	4.23
AGG ASSAULT, OFFICER, OTH	5	0.04	4.28
AGG ASSAULT, OFFICER, STR	1	0.01	4.29
AGG ASSAULT, WEAPON	4	0.03	4.32
ARSON PUBLIC BUILDING	1	0.01	4.33
ARSON, BUSINESS	2	0.02	4.34
ARSON, OTHER	25	0.21	4.56
ARSON, RESIDENCE	11	0.09	4.65
ARSON, RESIDENCE ENDANGER	2	0.02	4.67
ASSAULT FREE TEXT	4	0.03	4.7
AUTO THEFT, AUTO	2,146	18.14	22.84
AUTO THEFT, OTHER USE	1	0.01	22.85
AUTO THEFT, OTHER VEH	23	0.19	23.04
AUTO THEFT, RECEIVING STO	2	0.02	23.06
AUTO THEFT, TRUCK/BUS	2	0.02	23.07
BURGLARY, FORCED BUSINESS	498	4.21	27.28
BURGLARY, FORCED RESIDENC	689	5.82	33.11
BURGLARY, NO FORCE, COMME	91	0.77	33.88
BURGLARY, NO FORCE, RESID	437	3.69	37.57
BURGLARY, OTHER	1	0.01	37.58
BURNING OF SEE MIS	1	0.01	37.59
EXTORTION FREE TEXT	75	0.63	38.22
EXTORTION THREAT ACCUSE P	1	0.01	38.23
EXTORTION THREAT DAMAGE P	14	0.12	38.35
EXTORTION THREAT INJURE P	271	2.29	40.64
EXTORTION THREAT OF INFOR	94	0.79	41.43
HOMICIDE, FAMILY, GUN	2	0.02	41.45
HOMICIDE, FAMILY, OTHER W	1	0.01	41.46
HOMICIDE, FREE TEXT	1	0.01	41.47
HOMICIDE, NON FAMI. GUN	12	0.1	41.57
HOMICIDE, NON FAMI.OTHER	2	0.02	41.59
KIDKNAP, ADULT, SEX ASLT	3	0.03	41.61
KIDKNAP, OTHER	7	0.06	41.67
KIDNAP ADULT	4	0.03	41.7
KIDNAP MINOR	2	0.02	41.72
LARCENY, AUTO PARTS	937	7.92	49.64
LARCENY, BICYCLE	226	1.91	51.55
LARCENY, ENTERING AUTO	1,737	14.68	66.23
LARCENY, FROM BANKING TYP	1	0.01	66.24

LARCENY, FROM BUILDING	981	8.29	74.53
LARCENY, FROM COIN MACHIN	23	0.19	74.73
LARCENY, FROM MAIL	42	0.35	75.08
LARCENY, FROM YARDS	282	2.38	77.47
LARCENY, MAIL BOX	35	0.3	77.76
LARCENY, NOT YET CODED	294	2.48	80.25
LARCENY, OTHER	307	2.59	82.84
LARCENY, PICK POCKET	15	0.13	82.97
LARCENY, PURSE SNATCHING	53	0.45	83.42
LARCENY, SHOPLIFTING	1,004	8.49	91.9
LARCENY, US GOV PROPERTY	2	0.02	91.92
RAPE, GUN	3	0.03	91.94
RAPE, OTHER WEAPON	2	0.02	91.96
RAPE, STRONGARM	81	0.68	92.65
ROBBERY, BANK	6	0.05	92.7
ROBBERY, BUSINESS, GUN	115	0.97	93.67
ROBBERY, BUSINESS, OTHER	8	0.07	93.74
ROBBERY, BUSINESS, STRONG	23	0.19	93.93
ROBBERY, FORCE, PURSE	20	0.17	94.1
ROBBERY, OTHER	21	0.18	94.28
ROBBERY, RESIDENCE, GUN	36	0.3	94.58
ROBBERY, RESIDENCE, OTHER	3	0.03	94.61
ROBBERY, RESIDENCE, STRON	19	0.16	94.77
ROBBERY, STREET, GUN	339	2.87	97.63
ROBBERY, STREET, OTHER WE	48	0.41	98.04
ROBBERY, STREET, STRONGAR	179	1.51	99.55
SEX ASSAULT FREE TEXT	27	0.23	99.78
SEX ASSAULT SODOMY BOY ST	4	0.03	99.81
SEX ASSAULT SODOMY GIRL S	1	0.01	99.82
SODOMY, FEMALE	1	0.01	99.83
SODOMY, MALE STRONGARM	1	0.01	99.84
STATUTORY RAPE	19	0.16	100

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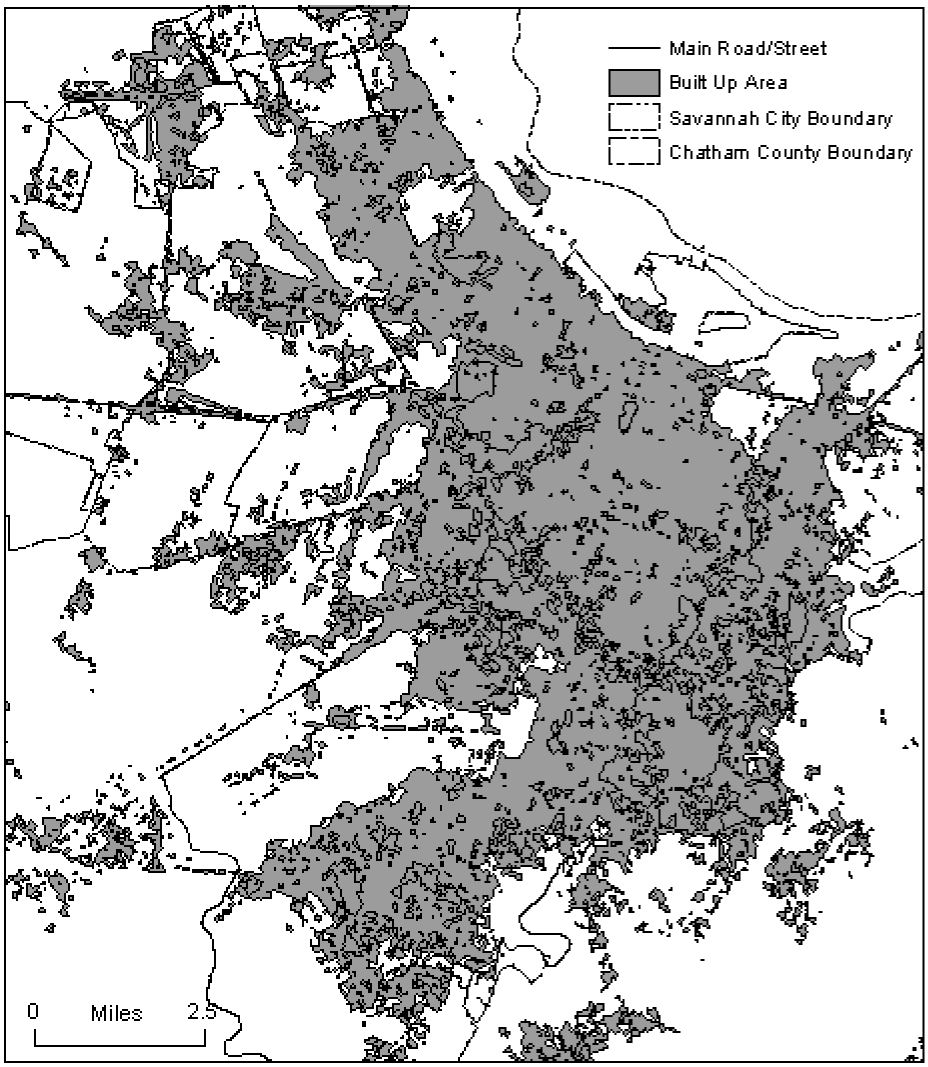

Figure 1: Study area.

Figure 2: Crime locations in the City of Savannah, Georgia, 2000.

Figure 3: Alcohol-serving establishment in the City of Savannah, Georgia 2000.

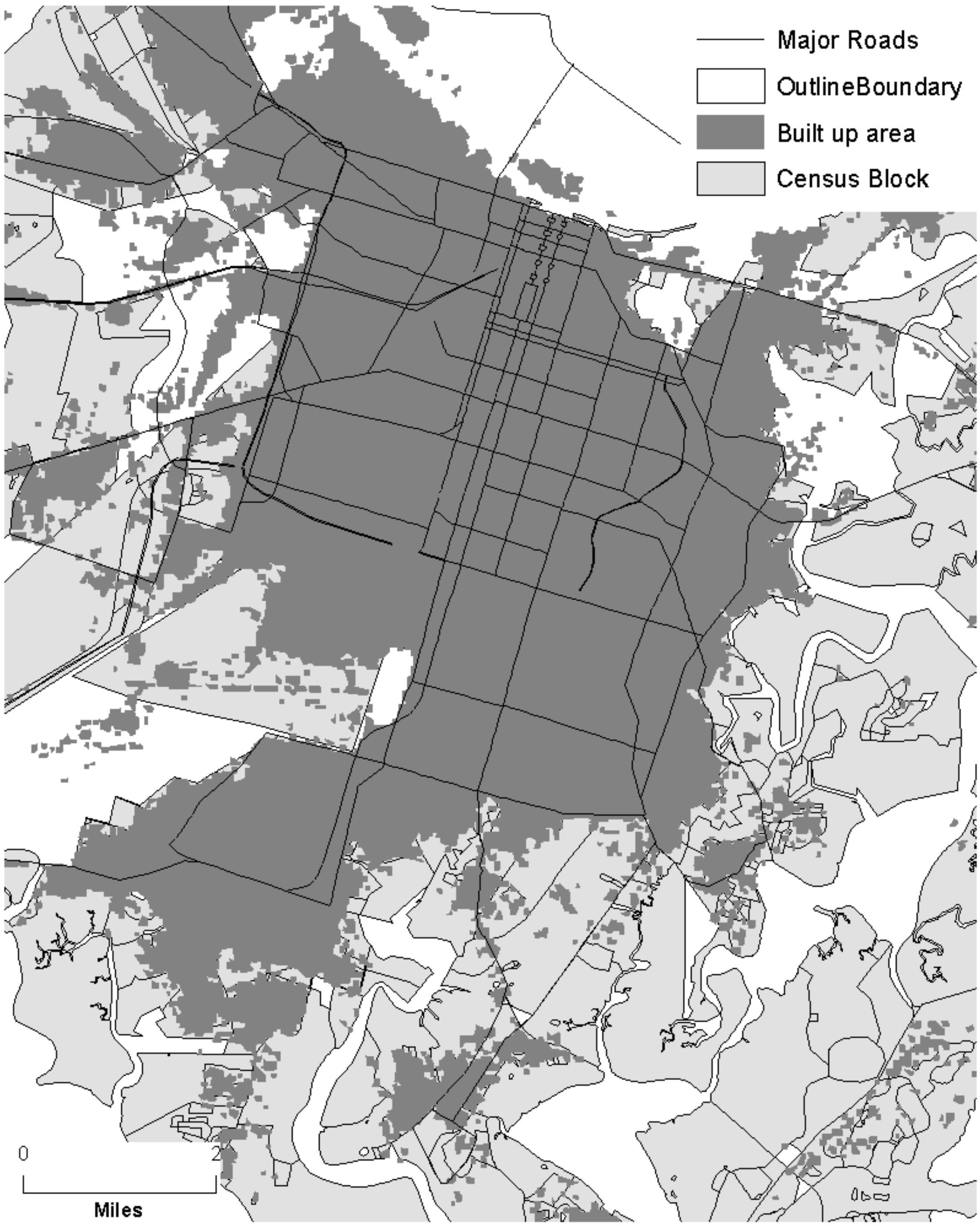

Figure 4: Built up area of Chatham County.

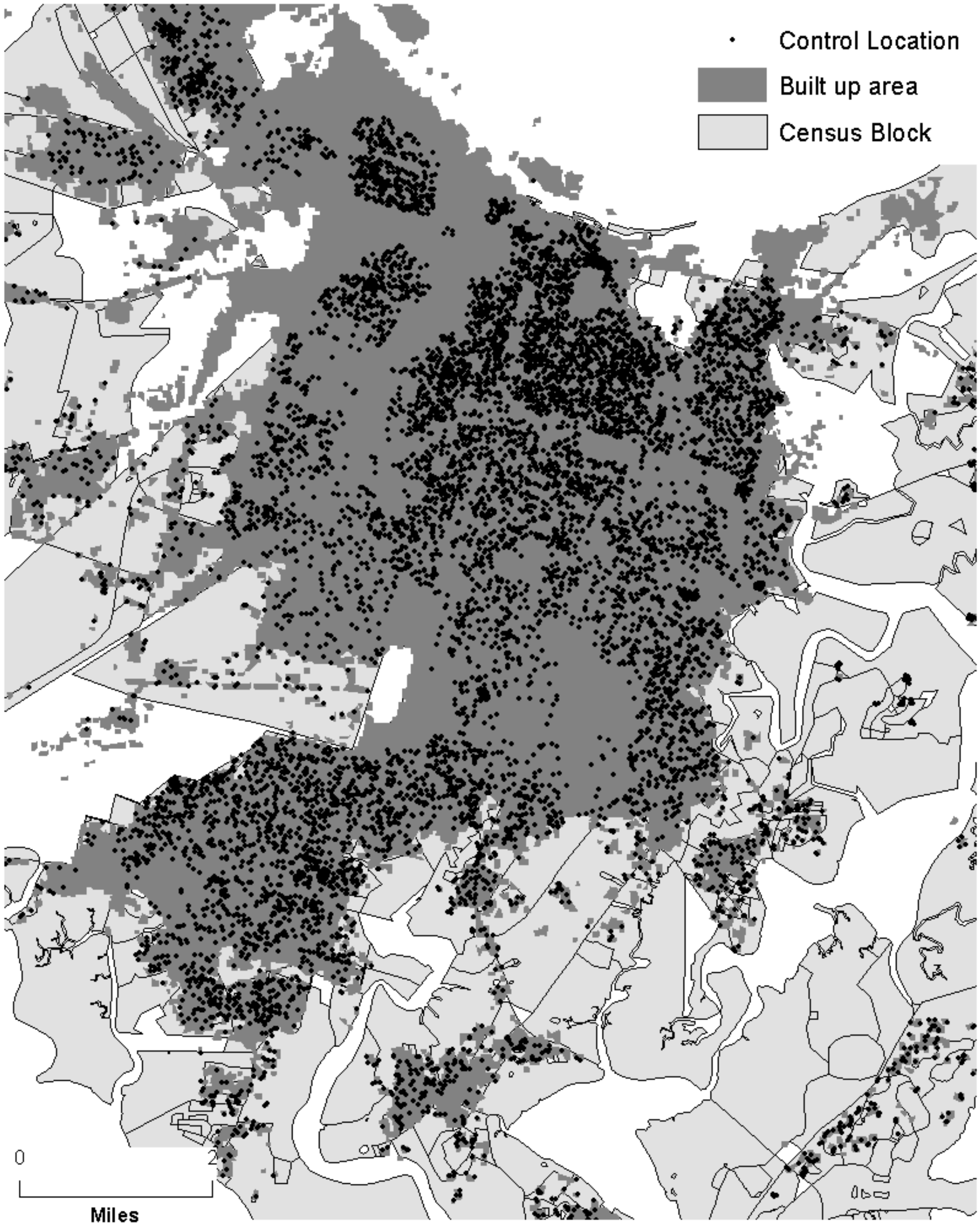

Figure 5: Control locations in the built up area.

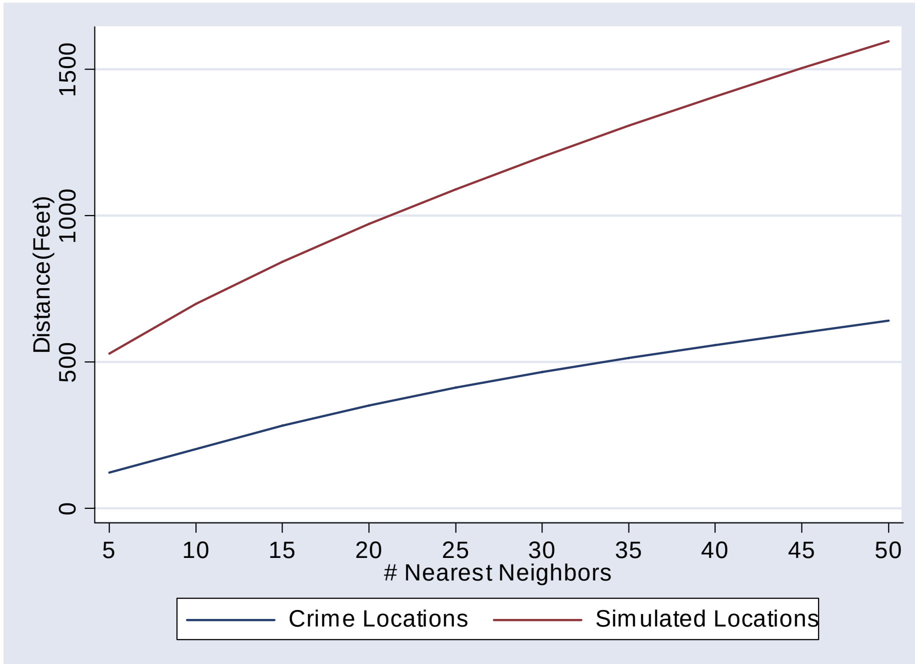

Figure 6a: Actual and Expected Average Distance to the closest 50 neighbors.

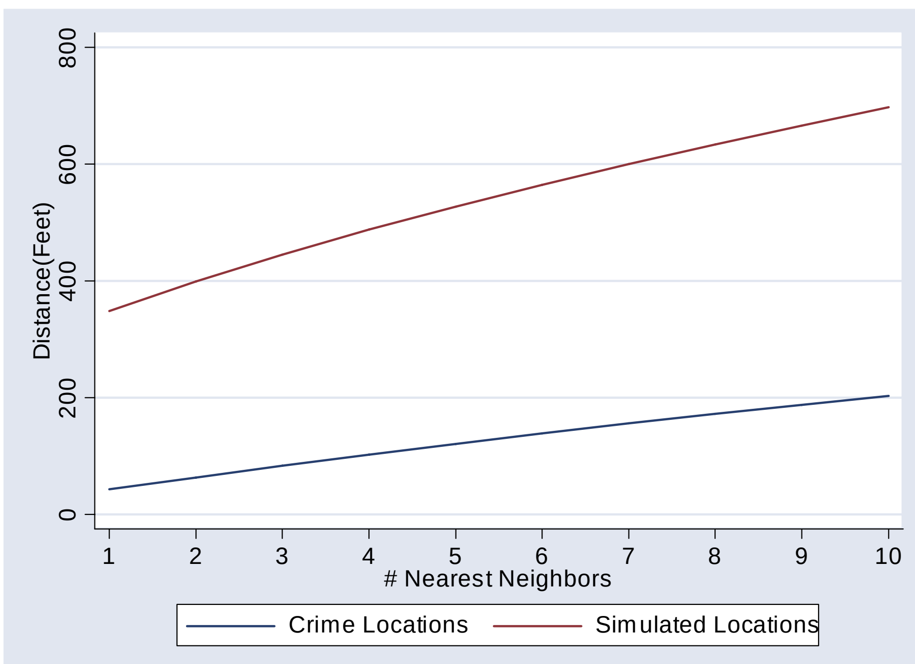

Figure 6b: Actual and Expected Average Distance to the closest 10 neighbors.