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RELATING ENVIRONMENTAL AND SOCIOECONOMIC STRESSORS TO VIOLENT
CRIME: EVALUATING THREE MAJOR CITIES IN THE UNITED STATES

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1. INTRODUCTION

The idea that environmental and socioeconomic problems affect certain locations and people more than others is still a relatively new concept, albeit the accumulative effects were finally gaining nationwide attention in the late 1980s (Maantay, 2002; Pain, 2000). In terms of violent crime, research shows that risk of being an offender or a victim increases as environmental and socioeconomic stressors accumulate (Blakley, 2006; Wasserman *et al.*, 2003; Borooah and Carcach, 1997; Kemshall, 1997). Studies have shown that these injustices are found disproportionately throughout cities and tend to cluster in communities of color and poor communities (Ratcliffe, 2002; Maantay, 2002; Clarke and Gerlak, 1998).

Wasserman *et al.* (2003) have stated that there is no one factor that will cause someone to be a violent offender, but rather an accumulation of multiple factors. Environmental and socioeconomic conditions are commonly linked to crime rates in the public's mind, and empirical research has supported this (Blakley, 2006; Freeman, 2001). Research has clearly demonstrated that risk factors have a cumulative effect: the more risk factors to which a child is exposed, the greater the likelihood that the child will become a violent offender (Wyrick and Howell, 2004; Elliott *et al.*, 2000; Hawkins *et al.*, 2000). Youth exposed to more than five risk factors by the age of 14 are ten times more likely to commit a violent crime by age 18, compared to those youth with fewer than two risk factors (Herrenkohl *et al.*, 2000).

Research has indicated that economic, family status, education, and health factors are associated to violent crime. Economic deficiency increases the risk that young people will engage in delinquent or violent behavior (Blakley, 2006; Moore and Redd, 2002; Hawkins *et al.*, 2000). Children living with an unmarried mother have been found to be at greater risk for incarceration, poverty, foster care placement, abuse, and neglect (Blakley, 2006; Maynard and Garry, 1997). Academic failure has consistently been identified as a predictor of violent or delinquent behavior (Blakley, 2006; Hawkins *et al.*, 2000; Browning and Huizinga, 1999). Recently, there has been an increased interest in the relationship between health factors and violent crime. Lead, an important environmental health factor, is highly correlated with delinquency and aggressive behavior (Needleman, 2004; Stretesky and Lynch, 2001).

Lead is a significant and relevant ecological and human health risk factor. Research shows that lead exposure is greatest in low-income areas of cities where lead-based paints and lead dust are prevalent (Rasmussen, 2004). That said, lead exposure has primarily been thought of as a socioeconomic stressor in association with crime, but this viewpoint is not ecologically holistic. Lead bioaccumulates and traces can be found almost everywhere. Lead is ingested from house dust, food and water, and taken in via inhalation (Rasmussen, 2004).

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Environmentally, lead exposure has been linked to human health problems in industrial areas (Declercq *et al.*, 2006), where urban airborne lead is prevalent (Meneses-Gonzalez *et al.*, 2006), and where lead in soil leaches into groundwater (Potula *et al.*, 1998).

Most problems associated with mapping risk or injustices are no longer related to data availability or quality, but are in fact spatial analysis knowledge. For proper risk analysis, an understanding of advanced spatial analysis concepts (*e.g.*, modifiable areal unit problem, ecological fallacy) are needed. Mapping risk associated with environmental and socioeconomic factors has been scrutinized and, at times, thought of as misleading. This paradox has been linked to sensitivities of results and their use (Ratcliffe, 2002); findings being contradicted by other spatial analysis (Maantay, 2002); and the idea that no map depicting environmental and socioeconomic injustices can be thought of as objective, because injustices are socially constructed (Dorling and Fairbairn, 1997; Wood, 1992).

2. MAPPING APPROACH

Crime mapping and analysis, utilizing geographic information systems (GIS), has been at the forefront of criminological research for some time now (Bowers, 1999; Grubestic and Murray, 2001; Harries, 1999). The first attempts to map crime occurred in the early 20th century using paper maps (Harries, 1999). Today's software applications have enabled stakeholders to not only visualize crime patterns, but also to conduct other vital statistical analyses related to types of offences, victim locations, offender locations, incident time, socio-demographic variables, land use conditions, and crime severity (Ackerman and Murray, 2004; Bowers, 1999). A multitude of methods have been used to analyze crime patterns and risk. Visual interpretation, exploratory spatial data analysis (ESDA) choropleth mapping, grid cell analysis, causal models, and spatial autocorrelation (*e.g.*, hot-spot and cluster analysis) are several approaches used in crime analysis (Ackerman and Murray, 2004; Bowers, 1999; Harries, 1990; Messner *et al.*, 1999). For example, Messner *et al.* (1999) utilized ESDA to determine the strength of clustering of homicides in 78 counties in and around St. Louis, Missouri, and it was found that homicides per county were non-random. Ratcliff *et al.* (1999) used hot-spot analysis to uncover the degree of autocorrelation and determined the spatial accuracy between perceived crime clusters and police reported clusters, and Grubestic *et al.* (2001) utilized several hot-spot boundaries to resolve issues related to arbitrary boundary determination. Bowers *et al.* (1999) relied on choropleth and hot-spot maps to visualize selected criteria and crime incidents. Overall, while hot-spot analysis is effective at viewing the spatial affects and patterns of incidents, there remains no clear choice among researchers as to which type of hot-spot analysis is superior, or what determines a significant hot-spot boundary (Grubestic and Murray, 2001). This study attempts to resolve ambiguity by incorporating standardized vector boundaries as the unit of analysis and visualization.

The success of crime risk determination is predisposed to the pitfalls of data aggregation and availability. Crime data are sensitive, highly sought after, and can be at times proprietary and therefore disseminated and aggregated by areal units (Ratcliffe, 2002). As a result of the disparate scale that crime data are typically received by the user, various spatial analysis and statistical techniques have been used to avoid issues related to the modifiable areal unit problem (MAUP) and ecological fallacy. That is, crime data, or any such data that is aggregated at incongruent units, will provide spurious results due to observed spatial patterns not being verified (Fotheringham, 2004; O'Sullivan, 2003; Ratcliffe and McCullagh, 1999). MAUP occurs when data is aggregated at various sized units and when used in statistical analysis reducing robustness. Ecological Fallacy is particularly a problem in crime mapping because the inferences gleaned from individual crime events that are obtained from aggregated auxiliary data can be arbitrary. To circumvent the effects of heterogeneous sized units of analysis, spatial regressive techniques have been used in crime studies. spatial auto regressive (SAR) and geographically weighted regression (GWR) models have been at the forefront of circumventing unclassified spatial dependence among zonal data. SAR models consider the correlation among error terms (spatial error) or model the spatial trend in the error terms

(spatial lag) (Fotheringham, 2004). Similarly, the GWR approach is a Bayesian-modified linear regression technique that utilizes a distance decay weighting philosophy (LeSage, 1999). Both methods have been discovered to be relevant techniques for crime analysis. However, they remain stochastic and cannot assure accuracy. We suggest that a deterministic, rather than stochastic, method be utilized to address issues of spatial data and metric nonstationarity, while at the same time incorporating environmental and socioeconomic variables. Deterministic methods have shown their prominence in studies ranging from biology and physics to the study of disease risk (Bartlett, 1956; Blower and Dowlatabadi, 1994; Colasanti and Grime, 1993; Pitowsky, 1983). Their usefulness is germane to this study because of their exclusion of nonrandom errors and historical significance for the evaluation of risk factors.

In this study, a combination of ESDA, choropleth mapping, and deterministic statistical techniques were used to advance crime mapping analysis and risk determination. Specifically, stochastic and deterministic statistical approaches were used to expose the usefulness of creating a multi-metric index for locating crime risk based on environmental and socioeconomic cues.

3. DATA AND METHODS

A traditional vector boundary method was used for building individual databases for Chicago, Los Angeles, and Philadelphia for statistical analysis. Homicide crime data for all three cities were collected from EveryBlock.com. Property and single mother household data for all three cities were collected from the 2000 US Census. Chicago Blood Lead Level (BLL) data (2003, by community area) were collected from The Chicago Department of Public Health, Childhood Lead Poisoning Prevention website. GIS boundary layer data were downloaded from the Departments of City Planning and corresponding County Planning Agencies for Chicago, Los Angeles, and Philadelphia. Due to BLL data availability, the database for Chicago was aggregated to community area; Los Angeles and Philadelphia databases were aggregated to ZIP code. Community areas and ZIP codes for Chicago are similar in size and number; however, Chicago community areas are more confined by urban design.

A preliminary exploratory statistical analysis on violent crime location in Chicago (15 June 2007-6 April 2008) revealed that homicides, assault, robberies, and serious offenses involving children were cross-correlated ($R^2 > 0.9$). Due to these results, homicides were chosen as the crime risk response variable for the statistical analyses. Twelve stressors associated with violent crime risk were calculated for the 77 community areas of Chicago. The 12 risk factors initially investigated were percent elevated BLL in children, percent unemployed, percent living below poverty level, single mothers, median income for families, median property values, median income for household, average per capita income, percent not graduating from college, percent vacant housing, median rent cost, and percent not graduating from high school. Pearson correlation and backward stepwise regression (P -value= 0.05 to enter and 0.10 to remove), a multi-metric index comprised of elevated BLL, single mothers, and property values (risk index), was established, showing statistical significance. To meet the assumptions of normality for all variables of parametric tests, we used two types of transformations: log (property values) and arcsine square root (percent elevated BLL, and percent single mothers). All data used in statistical analyses were standardized based on their individual database variances.

The dates and numbers of homicides for Chicago, Los Angeles, and Philadelphia varied by location. For Chicago, from 15 June 2007 through 6 April 2008, there were 340 homicides recorded and aggregated by community area ($n=77$). For Los Angeles, from 15 May 2008 through 27 May 2009, there were 122 homicides recorded for the analyzable ZIP codes ($n=75$). For Philadelphia, there were 973 homicides for the analyzable Zip codes ($n=47$), 1 January 2007 through 27 April 2009.

To test the viability of the newly created multi-metric risk index, standard least squares regression and classical discriminant analysis were conducted using homicides for

Chicago, Los Angeles, and Philadelphia. For the Classical Discriminant Analysis, the number of homicides was grouped equally into three categories—low, moderate, and high risk—for each city. These particular statistical methods have been widely accepted throughout various academic and applied disciplines and will shed light on the applicability of using a multi-metric risk index for mapping crime risk. By using stochastic and deterministic statistical techniques, results can be compared and contrasted based on both probability and presence/absence.

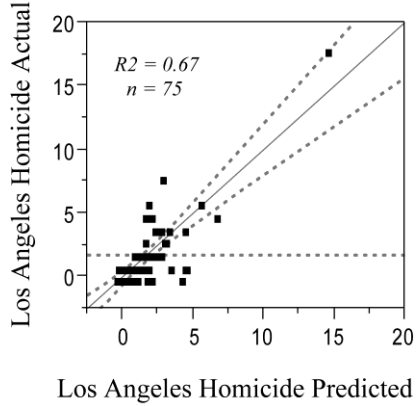
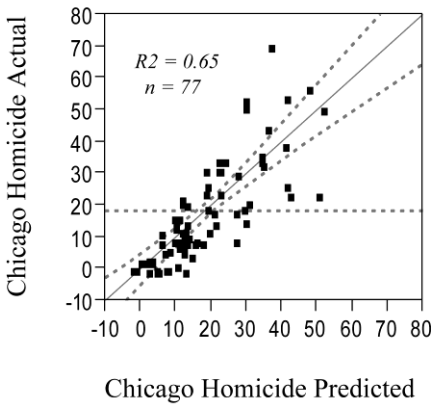
4. RESULTS

4.1 STOCHASTIC STATISTICAL ANALYSIS

The multi-metric risk index proved to be significantly correlated with homicides for Chicago, Los Angeles, and Philadelphia based on the stochastic statistical analysis. Observed versus predicted homicides are shown for all cities (Figure 1). The multi-metric risk index

A. Standard Least Squares Regression of model for Chicago City Community Areas

B. Standard Least Squares Regression of model for Los Angeles City Zip Codes



C. Standard Least Squares Regression of model for Philadelphia ZIP Codes

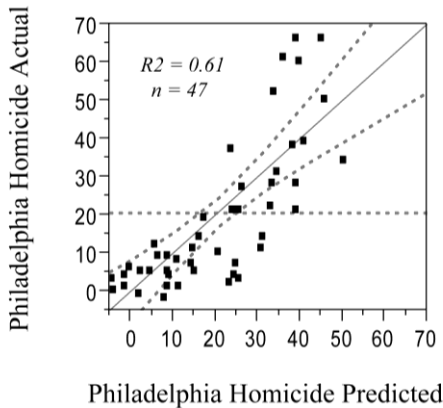


FIGURE 1
STOCHASTIC MODELS: ACTUAL VERSUS PREDICTED HOMICIDES

correlated with homicides for all cities (Chicago $R^2=0.65$, $P<0.001$; Los Angeles $R^2=0.67$, $P<0.001$; and Philadelphia $R^2=0.61$, $P<0.001$). These results show that the multi-metric risk index can be used as a surrogate for actual homicide locations, and thus used in spatially locating and visualizing crime risk. Using the predicted expression from the standard least squares regression analysis, a properly weighted map of predicted crime risk was created for each individual city. A map comparing actual homicides and predicted crime risk was created to visualize the spatial significance for all cities (Figure 2).

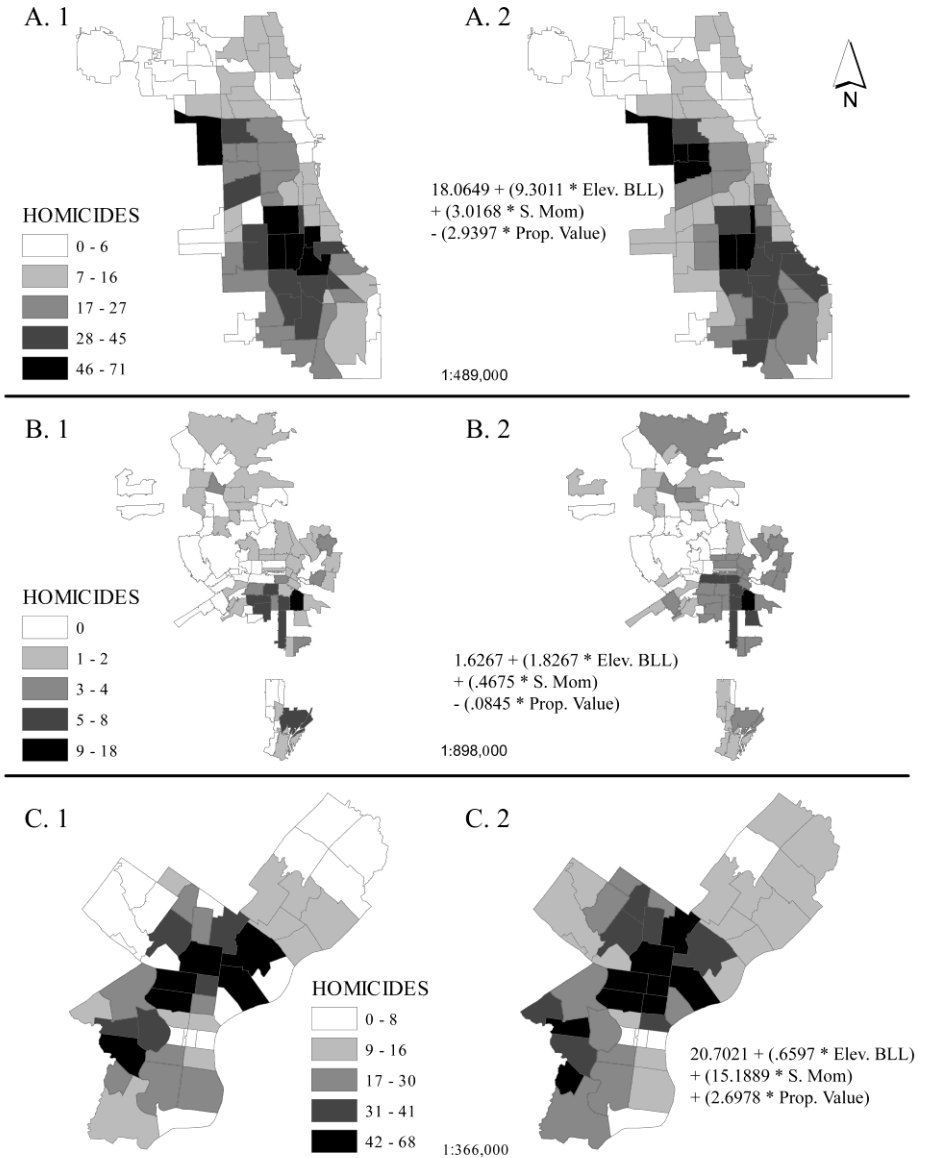


FIGURE 2
 ACTUAL (1) VS PREDICTED (2) HOMICIDES
 FOR CHICAGO (A), LOS ANGELES (B), AND PHILADELPHIA (C)

4.2 DETERMINISTIC STATISTICAL ANALYSIS

The multi-metric risk index proved to be significantly correlated with the low, moderate, and high grouped homicides for Chicago, Los Angeles, and Philadelphia based on deterministic statistical analysis. The multi-metric risk index canonically correlated with homicides in all three cities (Chicago $R_c^2=0.67$, $P=0.000$; Los Angeles $R_c^2=0.83$, $P=0.000$; and Philadelphia $R_c^2=0.81$, $P=0.000$). A jackknifed classification matrix for Chicago, Los Angeles, and Philadelphia reported 78, 77, and 70 percent correct, respectively. A map comparing actual and grouped homicides was created to visualize the spatial significance for all cities (Figure 3).

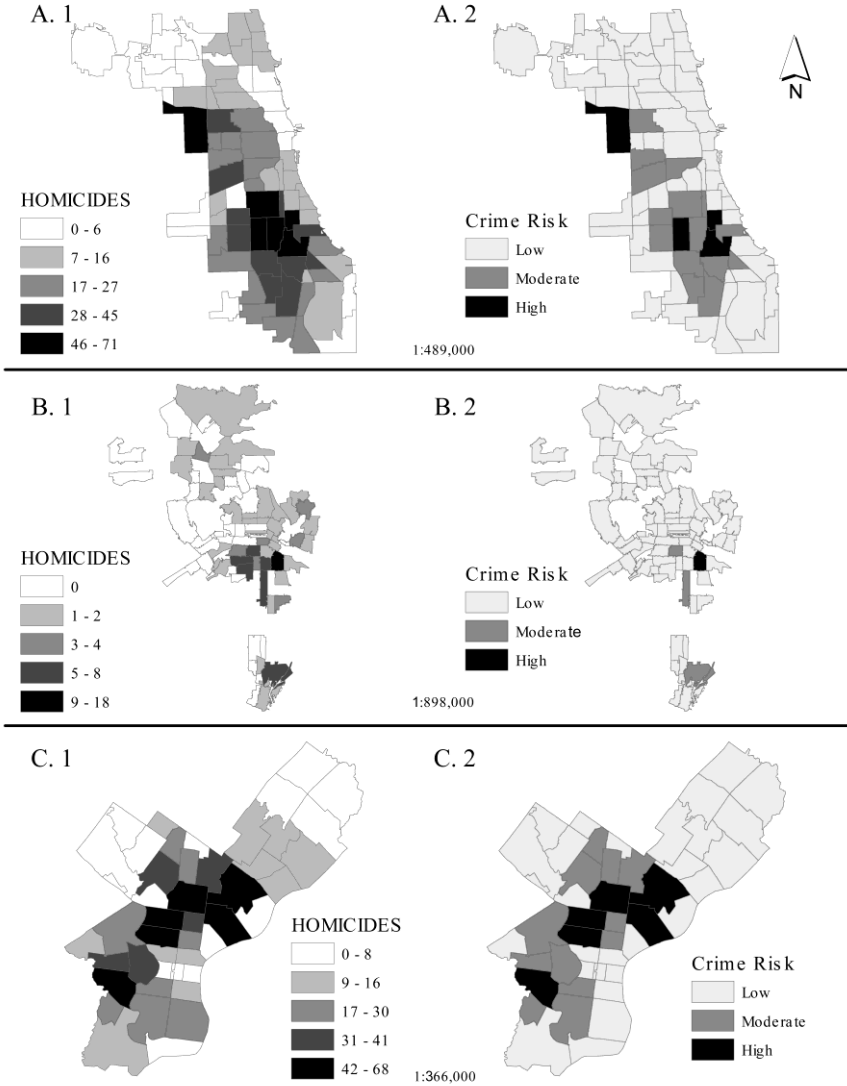


FIGURE 3
 ACTUAL (1) VS GROUPED (2) HOMICIDES
 FOR CHICAGO (A), LOS ANGELES (B), AND PHILADELPHIA (C)

5. CONCLUSION

In conclusion, this paper describes the use of GIS, stochastic, and deterministic statistical methods to visualize a spatial relationship between environmental and socioeconomic stressors and violent crime risk. Significant statistical relationships were found between the created multi-metric risk index (blood lead levels, single mother households, and median property value) and homicides for three major cities in the United States. This study presents and displays an improved process for measuring and mapping crime risk using a multi-metric methodology, and supports consideration of synergistic effects that environmental and socioeconomic stressors have on people and their relevance to violent crime. Since there lacks a consensus on crime mapping methodology and related spatial statistical analysis, this research stands as an example of an objective and quantitatively sound violent crime risk study.

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