Linking Public Health, Social Capital, and Environmental Stress to Crime Using a Spatially Dependent Model

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Abstract

This article reports the findings from a localized spatial modeling approach and visual assessment of crime determinants in Flint, Michigan. Factors pertaining to socioeconomic condition, public health, social capital, environmental stress, and neighborhood context were analyzed spatially and statistically using exploratory data analysis, exploratory spatial data analysis (ESDA), ordinary least squares regression (OLS), and geographically weighted regression (GWR). The ESDA indicated that elevated crime densities clustered in legacy residential areas, suggesting the need for a spatially explicit model. The OLS model was able to explain 46 percent of the variation in the model, although the GWR model proved superior, explaining approximately 56 percent. The GWR results largely supported the OLS results, while providing additional insights into the directionality, magnitude, and spatial variation of localized predictors of crime. The factors that contributed positively to crime rates may provide policymakers and law enforcement officials with nuanced information needed for targeted crime-reduction/prevention strategies.

Introduction

Environmental criminology examines how contextual conditions influence criminal behavior throughout space. This strategy allows law enforcement officials to observe the spatial copatterning of criminal events and possible correlates, providing an avenue for more efficient crime-reduction strategies (Phillips and Lee, 2011). The field has surged in popularity because of the availability of robust spatial datasets, advancements in Geographic Information Systems (GISs), and user-friendly spatial analysis tools, allowing for comprehensive spatial analysis of criminal activity (Anselin et al., 2000). Furthermore, environmental criminology and spatial analysis tools have taken root in large part because of the need to account for spatial autocorrelation. Evidence has shown that spatial correlation effects can undermine confidence intervals and significance tests in global regression models such as the ordinary least squares (OLS) model (Matthews et al., 2010). To counter these issues, spatial modeling has evolved to the extent that spatial effects can be minimized, providing a greater understanding of underlying criminal processes (Anselin et al., 2000).

As of the date of this writing, a minimal amount of research has used spatially explicit models to detail significant relationships among crime and its correlates. A few notable studies do exist, however. For instance, a study by Cahill and Mulligan (2007) used a geographically weighted regression (GWR) model to measure invariant local crime correlates throughout Portland, Oregon, and found that local variation of crime predictors was significant. Malczewski and Poetz (2005) used the same method to examine geographical variations of residential burglaries in London, Ontario, Canada. The authors found significant statistical and spatial variations in burglary risk factors such as dwelling value and multifamily housing density. Another important study found that with the use of GWR, crime correlates were spatially and significantly variant throughout an urban area (Graif and Sampson, 2009).

Displaying and interpreting GWR outputs cartographically has historically been complicated at best. Typical outputs from GWR is a choropleth map displaying the *t*-values for each parameter estimated (Mennis, 2006). For example, Graif and Sampson (2009) used classified surface maps of *t*-values to display the statistical significance of each explanatory variable. Using this approach, however, hides the magnitude, directionality, and statistical significance of each estimate on crime. Displaying the parameter estimates in conjunction with their statistical significance can provide more meaningful GWR results, while reducing the volume of maps to interpret (Mennis, 2006). With this concept in mind, one purpose for this research is to build on past studies that have efficiently produced robust GWR visualizations. The specific goals of this research are to (1) demonstrate the advantages of a using a local spatial modeling strategy for crime modeling; (2) institute a progressive cartographic technique that distinguishes among magnitude, directionality, and statistical significance of explanatory factors; and (3) provide a better understanding about the relationships among socioeconomic conditions, public health, social capital, environmental stressors, neighborhood context, and crime. The organization of the article is as follows: the next section, which provides an explanation of the data and preprocessing steps, is followed by a section that presents the modeling approach, and the article concludes with a research summary.

Data and Preprocessing

Reported crime incidence data (26,961 records) from the year 2010 were obtained from the City of Flint Police Department and served as the dependent variable. In this study the crimes selected were aggravated assault, homicide, robbery, and all forms of criminal sexual conduct. The crime incidence data were aggregated and normalized for each U.S. Census Bureau-defined census block group (CBG) because that was the unit level used for analysis.

The explanatory variables were grouped into five categories: socioeconomic condition, public health, social capital, environmental stress, and neighborhood context (exhibit 1). Several socioeconomic status (SES) factors were considered because of their long-standing links to crime (Sampson, 1995). The SES variables were obtained from the U.S. Census Bureau for 2010 at the CBG level.

Social capital factors were obtained from the Speak to Your Health! Survey (STYHS) disseminated to Flint residents in 2007. To ensure that the survey respondents represented all geographic regions of the city of Flint and Genesee County, random samples of households were drawn from Genesee County census tracts. At least 20 residents were obtained for each of the 39 residential census tracts in Flint. The frequency of positive responses per CBG was derived by dividing the number of "yes" responses by the total number of responses because of the ordinal scale of the data.

Public health variables in this study included body mass index (BMI) and nonmotorized mobility safety. BMI was obtained from the STYHS survey, and the average was joined to each CBG. Travel risk factors were obtained from the State of Michigan Department of Transportation for the year 2010.

Previous research has also posited that environmental stressors such as lead can have a long-lasting effect on criminal activity (Shaker, Rybarczyk, and Eno, 2009; Wright et al., 2008). Therefore, the average blood lead level (BLL) concentration from 9,000 adolescent people within each census tract was obtained from the State of Michigan Department of Community Health, Childhood Lead Poisoning Prevention Program, for the year 2010. An areal interpolation method was used to join

Exhibit 1

Initial Model Predictor Variables

Socioeconomic condition
- Median household income
- Residents driving to work
- Owner-occupied housing
- Renter-occupied housing
- English-speaking households
- Non-White residents
- Total households
- Households below poverty
- Total families
- Families below poverty
- Residents with diploma or GED

Public health
- Average body mass index, or BMI
- Bicycle crashes
- Pedestrian crashes

Social capital
- Quality of life
- Neighborly visitation
- Neighbors' willingness to help
- Trustworthiness of neighbors
- Neighborhood crime watch participation
- Fear of crime
- Safety during the day
- Safety after dark
- Comparative neighborhood crime
- General health perception
- Satisfaction with health care
- Stress

Environmental stress
- Blood lead levels
- Brownfields

Neighborhood context
- Bus routes
- Bus stops
- Bike trails
- Vacant lots
- Parks
- Railroads
- Schools
- Food outlet diversity
- Food outlets (fast food, liquor stores, convenience stores)
- Zoning variety
- Sidewalks

GED = general equivalency diploma.

these data to the CBGs. The interpolation method is used when the spatial units are not congruent (Flowerdew, Green, and Kehris, 1991). The open and closed leaking underground storage tank, or LUST, dataset served as a proxy for brownfields in this study. The data were obtained from the State of Michigan, Department of Environmental Quality, for the year 2007.

Several neighborhood contextual variables were obtained from the City of Flint, Planning and Engineering Departments. The most recent data were obtained and consisted of transportation routes (bus, bicycle, railroad, and sidewalks), schools, parks, land use, housing type (owner- or renter-occupied), and vacant parcels. Food outlet data were retrieved from the ReferenceUSA database for the year 2010 (http://www.referenceusa.com/). Food outlets were construed as an indicator of neighborhood quality, land use diversity, and opportunistic locations for criminal activity (Gruenewald et al., 2006).

Each explanatory factor in this research was aggregated and then normalized by the area (square feet) of each CBG. This process was used to bring all factors into the same resolution for further spatial analysis and minimize errors associated with the modifiable areal unit problem, or MAUP.

Modeling Approach

To examine relationships among crime, spatial, and aspatial factors within CBGs, we advanced a comprehensive statistical and spatial modeling approach. After cursory descriptive and spatial analysis procedures were conducted, two models were calibrated. The first model, OLS, was developed to detect global crime correlates. A second model, GWR, was then enlisted to highlight significant localized crime explanatory variables.

Exploratory Analysis

Exploratory data analysis (EDA) and exploratory spatial data analysis (ESDA) were conducted to detect for statistical or spatial relationships among crime and potential predictors. The EDA consisted of a Pearson's correlation analysis using SPSS software, version 19 (International Business Machines Corporation, or IBM). The analysis was used to test for linear relations among crime and potential predictors. To further refine potential variable selection, the variance inflation factor (VIF) index was also used to detect for multicolinearity; a threshold of 5 was established as a cutoff value based on previous statistical research (Kutner, Nachtsheim, and Neter, 2004). Exhibit 2 shows the final selection of independent model predictors and their descriptors.

ESDA was imparted in this research to examine spatial associations among all of the factors and to aid with model development. A classic spatial autocorrelation index, Moran's I, was implemented to explore spatial nonstationary effects on crime (Anselin et al., 2000). Exhibit 3 demonstrates that elevated high-high (HH) and low-low (LL) CBG crime densities are clustered throughout space, suggesting the need for a model that accounts for spatial relationships.

Exhibit 2

Selected Independent Variables

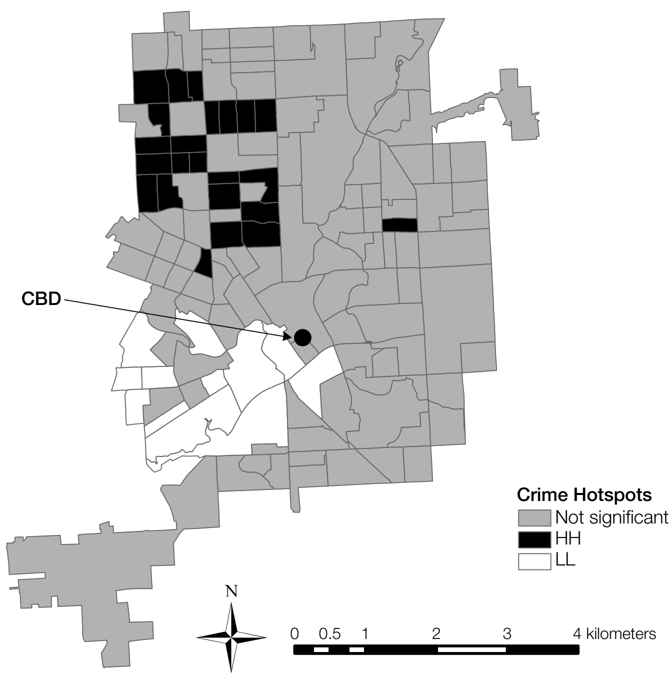
Predictor	Description (normalized by area)	Mean	Std. Dev.	VIF
Blood lead level, or BLL	Predicted BLL	0.0246	0.0173	3.539
Trails	Length of bike trails	0.0016	0.0026	1.313
Vacant lots	Number of vacant lots	0.6483	0.7275	1.396
Railroad	Length of railroads	0.0003	0.0009	1.287
Body mass index, or BMI	Average BMI per block group	0.2852	0.1678	3.193
Sidewalks	Length of sidewalks	113.329	79.9198	2.016
Renter-occupied housing	Number of renter-occupied houses	1.1362	0.6025	2.527
English speaking	Number of English-speaking households	2.6877	1.3175	4.154
Non-White	Number of non-White residents	4.4338	3.1630	3.008
Houses below poverty	Number of households below the poverty level	0.8879	0.6409	2.679
High school diploma or GED	Number of residents with a high school diploma or GED	1.7604	1.0540	2.119
Food outlets	Number of food outlets	0.0087	0.0131	1.098
General health	Attitude toward one's own general health*	0.3329	0.2463	1.138

GED = general equivalency diploma. Std. Dev. = standard deviation. VIF = variation inflation factor.

**Not normalized by area. Instead, measured in frequency of positive responses.*

Exhibit 3

Hotspot Analysis of Crime in the City of Flint, Michigan



CBD = central business district. HH = high-high. LL = low-low.

Model Development

A global regression model was developed using SPSS to determine the generalized causal associations among crime and the explanatory variables. The outputs from this model consist of global predictions of the dependent variable, using several independent variables. The OLS model's strength, coefficients, and residuals served as a comparison with the GWR model. To determine if the OLS model residuals were spatially autocorrelated, a global Moran's I was implemented. Spatially clustered residuals is an indicator of spatial nonstationarity.

A GWR model was developed to measure the magnitude, directionality, and geography of crime predictors for each CBG. The mathematical expression for GWR is similar to the OLS in that local parameters take the place of global parameters, while accounting for distance (Fotheringham, Charlton, and Brunsdon, 2002).

The GWR equation can be expressed as

$$y_i = \beta_0(\upsilon_i, \nu_i) + \sum_k \beta_k(\upsilon_i, \nu_i)\chi_{ik} + \varepsilon_i, \quad (1)$$

where y_i is the dependent variable at location i, $\beta_0(\upsilon_i, \nu_i)$ is the intercept at location i, $\beta_k(\upsilon_i, \nu_i)$ is the estimated kth parameter at location i, χ_{ik} is the independent variable of the kth parameter at location i, and ϵ_i is the error term at location i. The GWR model assumes that the error term is independent and identically distributed (Zhao and Park, 2004).

The GWR model was developed using GWR4 software, developed by Fotheringham, Charlton, and Brunsdon (2002). The GWR model produces parameter estimates for each CBG based on the kernel and the bandwidth selection, producing a continuous surface in return. In this research, a fixed Gaussian weighting scheme was used. The scheme is based on a distance-decay function following a Gaussian curve. The function is adjusted by the bandwidth setting, which dictates the distance that neighborhood parameters from the centroid i will count toward the estimate (Mennis, 2006). The bandwidth setting was set to automatically obtain optimal values to minimize the Akaike Information Criterion (AIC). The setting was chosen to account for the variation in size and quantity of the CBGs. Moreover, the AIC optimization technique assures a robust model, signified by an ideal goodness-of-fit and reduced degrees of freedom coefficients (Graif and Sampson, 2009). The outputs from the GWR model included parameter estimates, R^2 values, and t-values for each CBG.

The directionality, significance, and degree of spatial variability (nonstationarity) of the parameter estimates were assessed using ArcGIS software. The parameter estimates and diagnostics were assessed in accordance with the Mennis (2006) study. Significant relationships between each explanatory variable and dependent variable were obtained by querying t-values at the 90-percent significance level (z-scores ± 1.6565) for each unstandardized parameter estimate. Using a Jenks Natural Breaks sequential classification scheme, an area-class map was produced that grouped the significant estimates into five classes. Those parameter estimates that fell outside the significance threshold were displayed in white.

Results and Discussion

The OLS model coefficients are presented in exhibit 4. The output shows that the densities of English-speaking households and non-White residents are statistically significant ($p < .05$), with English-speaking households negatively affecting crime and non-Whites, by contrast, exhibiting a positive influence. The directionality and influence of these two factors are supported by previous research (Kennedy et al., 1998). The remaining explanatory variables were nonsignificant in this model, despite previous studies that demonstrate otherwise.

The strength of the OLS model is promising, exhibiting an adjusted R^2 of 0.45, which appears to be aligned with previous criminal justice research (Cahill and Mulligan, 2007; exhibit 5). Furthermore, the OLS residuals do not appear to exhibit spatial autocorrelation (exhibit 6). Because more than 50 percent of the model variance is unexplained, however, it is plausible that underlying processes may be affecting crime densities not captured in this assessment.

The GWR model exhibited an adjusted R^2 of 0.54, demonstrating a 19-percent increase in model robustness from the OLS model (exhibit 5). In addition, the AIC increased from -363.11 for the OLS model to -294.78, indicating a better fitting model. The GWR residuals display no significant spatial clustering (exhibit 6). The overall model results disprove that simple linear relationships exist among crime and the independent variables.

Exhibit 4

OLS Model Outputs

Predictor Name	Coefficient	Standard Error	*t*-value	Significance
Blood lead level, or BLL	– 0.133	0.544	– 0.244	0.807
Trails	– 2.508	2.223	– 1.128	0.261
Vacant lots	0.003	0.008	0.397	0.692
Railroad	– 6.222	6.006	– 1.036	0.302
Body mass index, or BMI	0.086	0.053	1.620	0.108
Sidewalks	0.000	0.000	1.876	0.063
Renter-occupied housing	0.017	0.013	1.261	0.210
English speaking	– 0.018	0.008	– 2.359	0.020
Non-White	0.011	0.003	3.934	0.000
Houses below poverty	0.023	0.013	1.798	0.075
High school diploma or GED	0.011	0.007	1.651	0.101
Food outlets	0.531	0.400	1.328	0.187
General health	0.003	0.002	0.153	0.879

GED = general equivalency diploma. OLS = ordinary least squares regression.

Exhibit 5

OLS and GWR Model Outputs

	OLS	GWR
Psuedo R^2	0.501	0.796
Adjusted R^2	0.446	0.536
Number of parameters	14.0	58.940
AIC	– 363.112	– 294.788
Sigma	0.057	0.052
Residual sum of squares	0.393	0.161

AIC = Akaike Information Criterion. GWR = geographically weighted regression. OLS = ordinary least squares regression.

Exhibit 6

Global Moran's I Index of OLS and GWR Model Residuals

	OLS	GWR
Moran's I index	0.045392	– 0.037639
Expected index	– 0.007576	– 0.007576
Variance	0.000334	0.000333
z-score	2.897516	– 1.647889
p-value	0.003761	0.099376

GWR = geographically weighted regression. OLS = ordinary least squares regression.

Exhibit 7 uniquely depicts the magnitude, directionality, and geography of crime correlates (unstandardized parameter estimates, β). Exhibits 7a through 7d indicate that SES estimates marginally affect crime. Renter-occupied housing (exhibit 7a) positively affects crime east of the central business district (CBD), while English-speaking residents in the same vicinity have a negative influence (exhibit 7b). Similarly, significant parameter estimates for non-White residents and households living below the poverty level appeared to affect crime in the same general area (exhibits 7c and 7d). The result suggests that these factors have a compounding effect on crime, requiring specific crime-reduction strategies. The SES estimate for educational attainment positively affects crime overwhelmingly in two CBGs south of the CBD (exhibit 7e). Interestingly, the relationship appears counter to previous research that has shown that reduced educational attainment increases crime (Kruger et al., 2007). We can infer from exhibit 7e, however, that criminal activity may be diffusing into this area from nearby locations because the neighborhood is of high SES status.

Exhibit 7f depicts a positive association between crime densities and BMI in several CBGs east of the CBD. The result supports previous research that has shown a link between obesity rates and the probability for criminal arrests (Kalist and Siahaan, 2013). Conversely, self-reported general health shows no significant statistical influence on crime densities (exhibit 7g). The factor is indirectly linked to the fear of crime, which has been purported to affect actual crime. The outcome in this research, however, contains no such linkages (Chiricos, Padgett, and Gertz, 2000). The concentration of BLL appears to negatively affect crime densities among several CBGs in Flint (exhibit 7h). It can be inferred from this result that areas with increased environmental stress do not statistically affect crime, despite prior research indicating otherwise (Needleman et al., 1979).

The neighborhood contextual factors that negatively altered crime densities included recreational trails (exhibit 7i) and railroads (exhibit 7k). The density of trails in the southern portion of Flint appeared to reduce crime. Strong spatial and statistical dependencies between railroads and crime were discovered along the western boundary of Flint (exhibit 7k). One possible inference from this result is that the population density is low in this area, thereby reducing opportunities for victimization. The neighborhood contextual factors that displayed a positive effect on crime included the density of food outlets (fast-food restaurants, liquor stores, and convenience stores) and sidewalks. As evidenced in exhibit 7l, the density of poor-quality food outlets moderately affects crime, with the strongest relationship evidenced in the southeast portion of the city. The positive relationship found in this study is supported by previous research. For example, Gruenewald et al. (2006) found that alcohol establishments had the propensity to accelerate criminal activity. Exhibit 7m exhibits the spatial patterning of significant sidewalk-density estimates on crime, albeit with marginal

Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (1 of 7)

Exhibit 7a. Renter-Occupied Housing

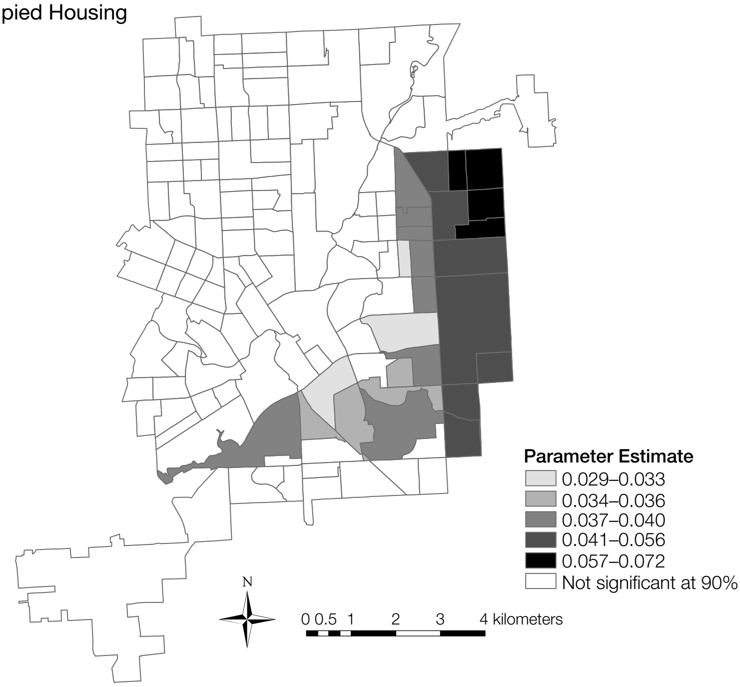


Exhibit 7b. English-Speaking Households

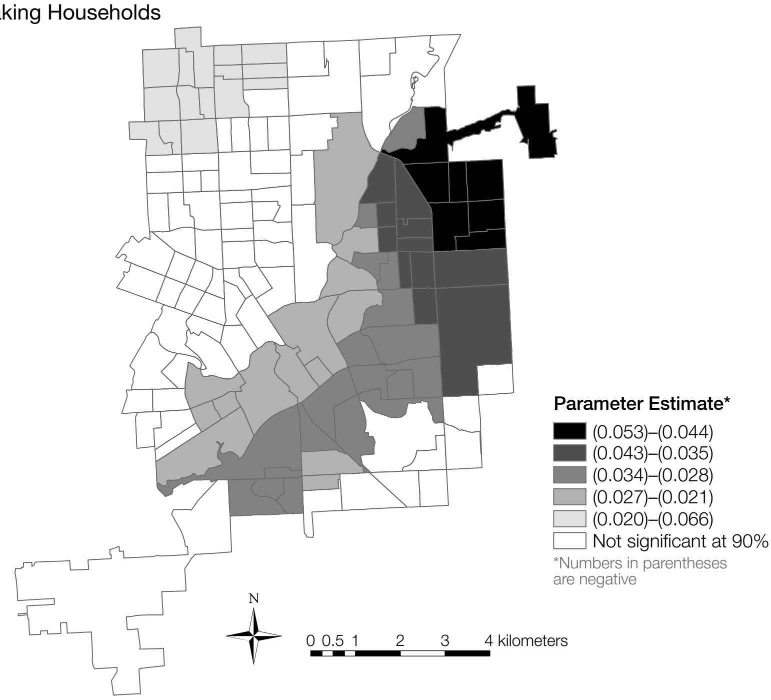


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (2 of 7)

Exhibit 7c. Non-White Residents

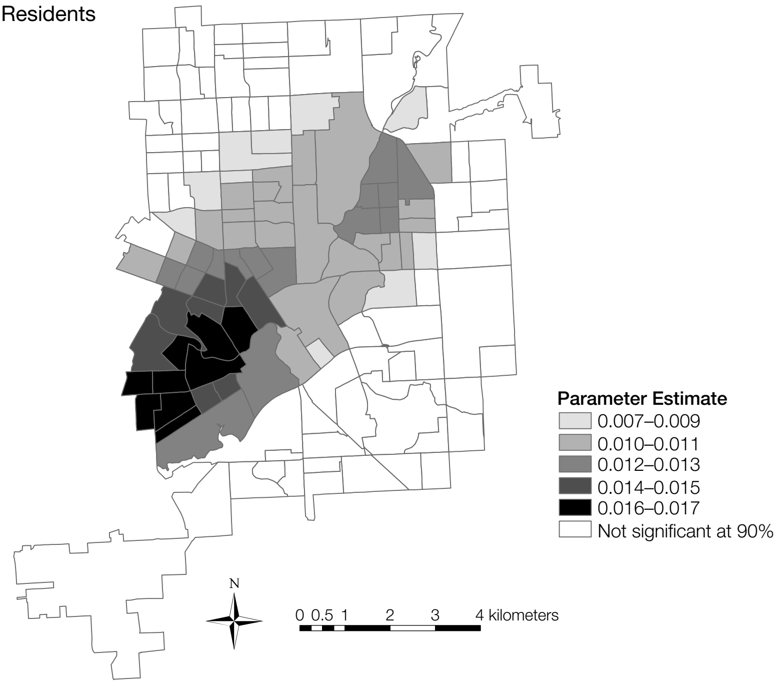


Exhibit 7d. Households Below Poverty

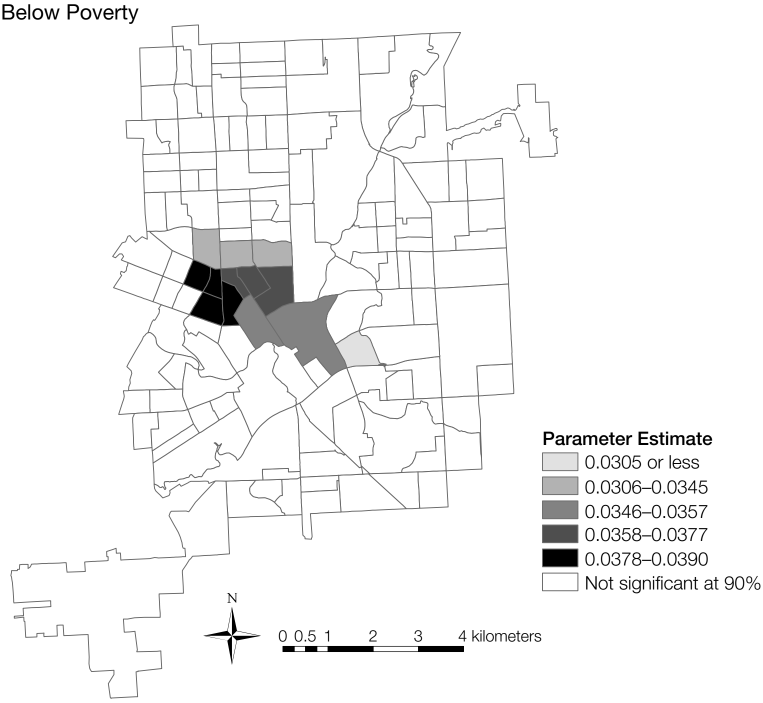


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (3 of 7)

Exhibit 7e. Education

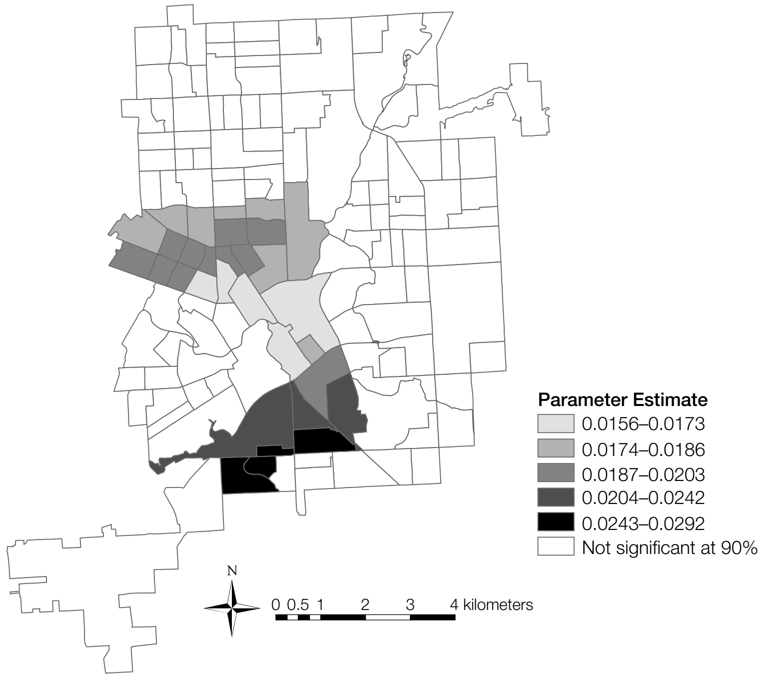


Exhibit 7f. Body Mass Index

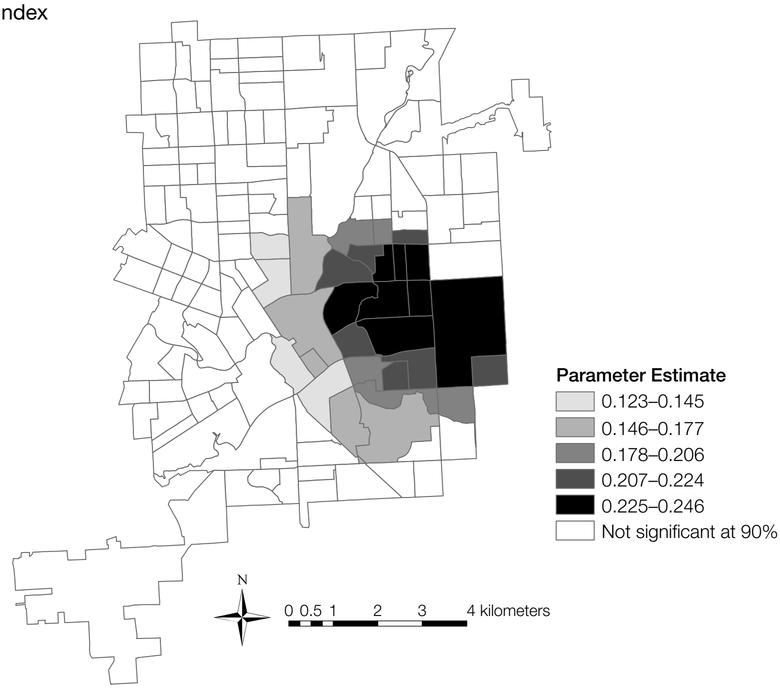


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (4 of 7)

Exhibit 7g. General Health

Exhibit 7h. Blood Lead Level

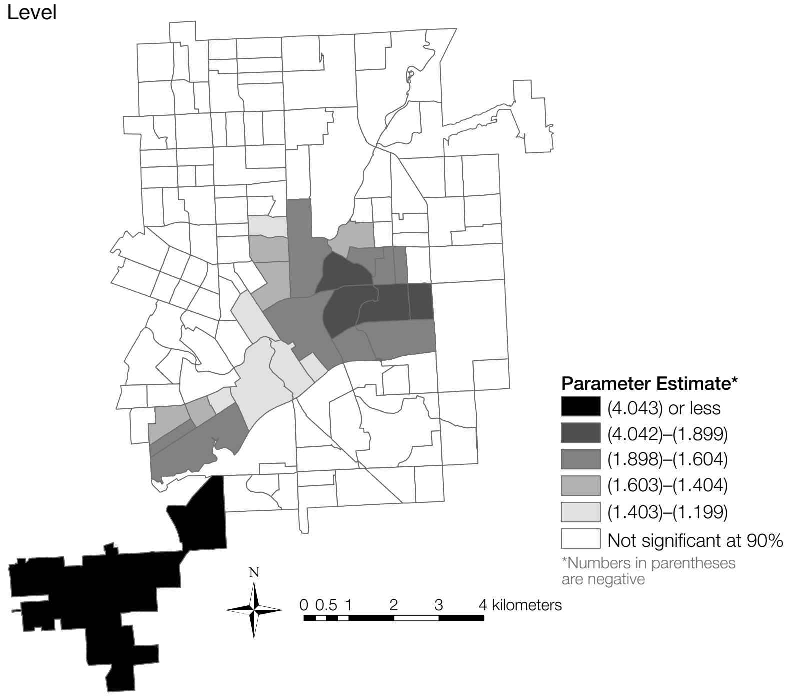


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (5 of 7)

Exhibit 7i. Trails

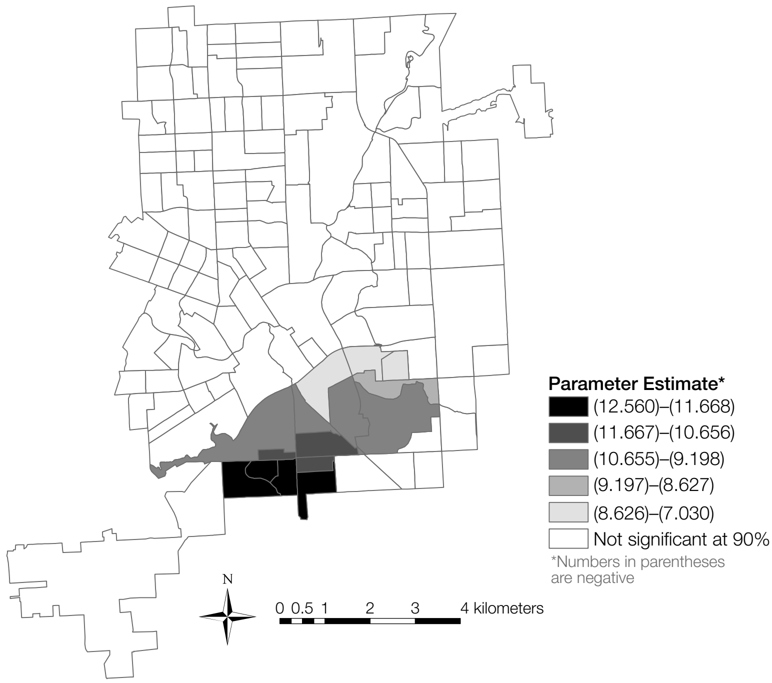


Exhibit 7j. Vacant Lots

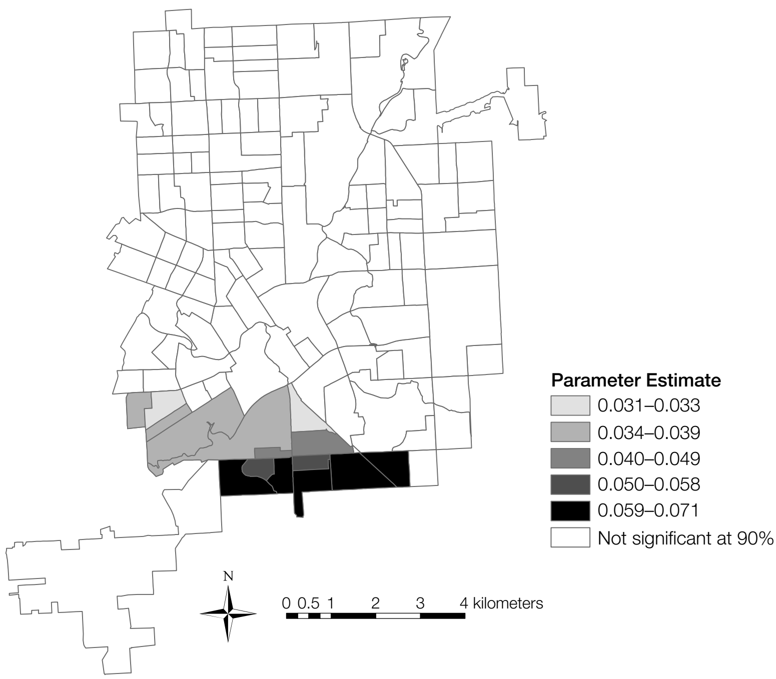


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (6 of 7)

Exhibit 7k. Railroads

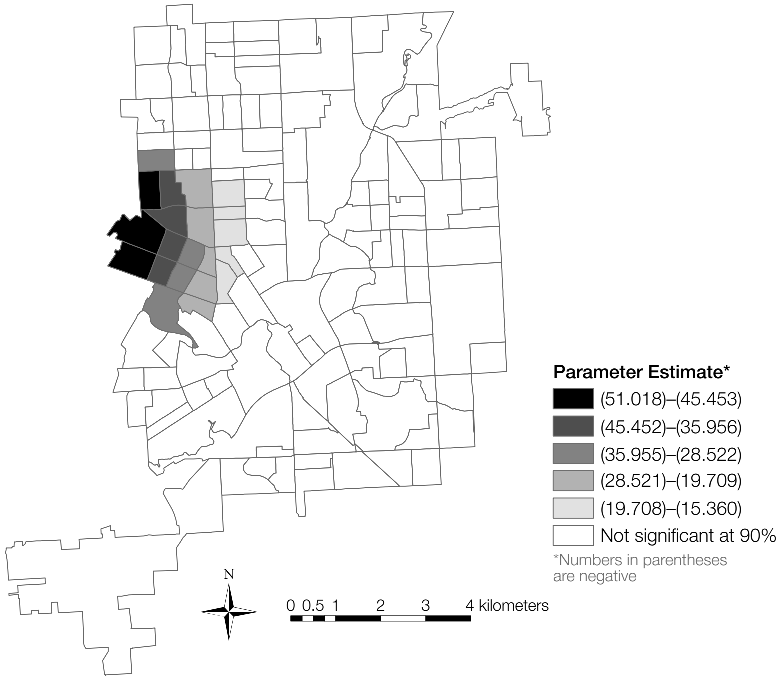


Exhibit 7l. Food Outlets

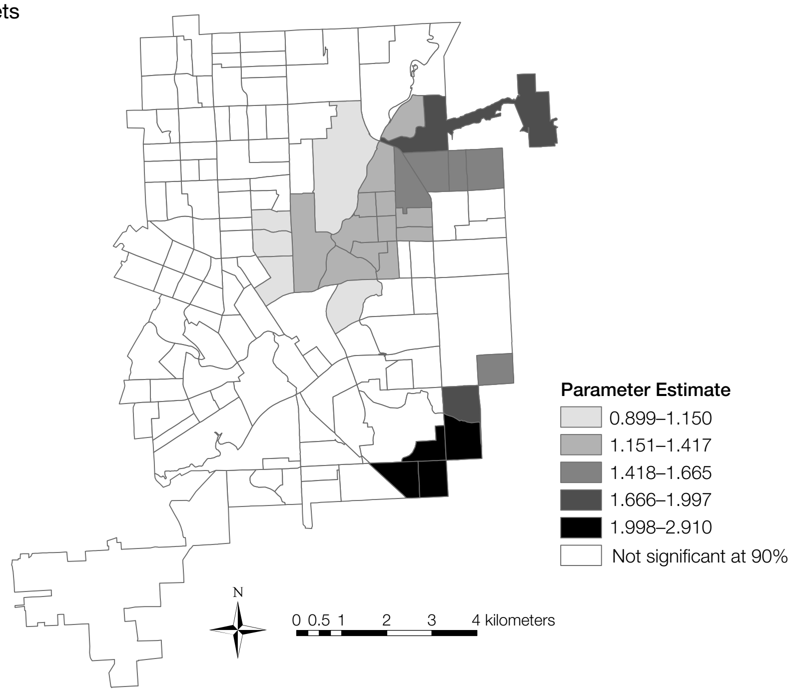
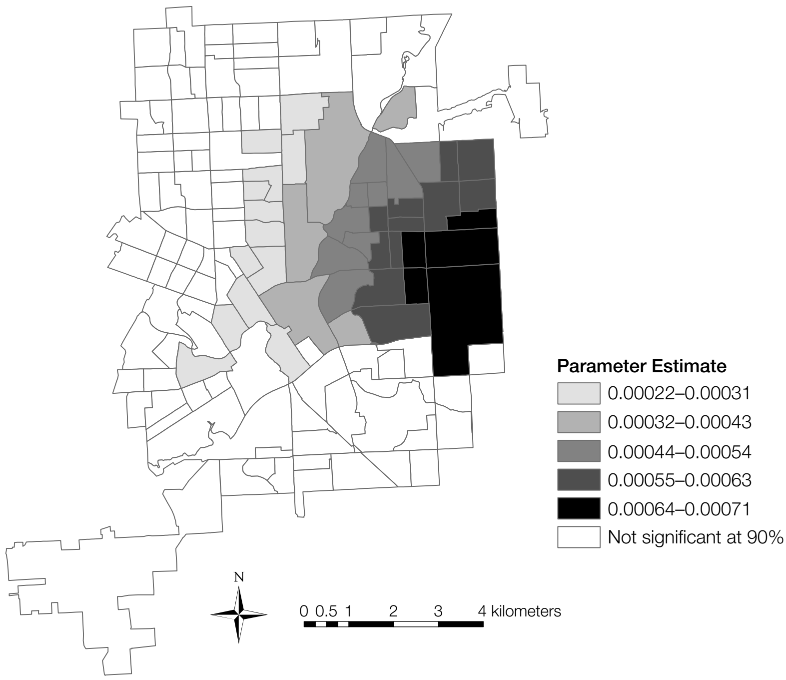


Exhibit 7

Magnitude, Directionality, and Geography of Crime Correlates (7 of 7)

Exhibit 7m. Sidewalks



influence. It is clear from the spatial pattern that sidewalk density may be facilitating criminal activity throughout a large portion of Flint. This result may partly be because sidewalks are vectors for criminal activity. In other words, the increase in pedestrian mobility and exposure may be increasing crime opportunities. The finding here is substantiated by earlier research conducted by Doyle et al. (2006), who found a positive correlation between neighborhood walkability and crime.

Conclusion

The key goal of this article was to critically examine the utility of a spatially explicit model and refined cartographic technique to uncover detailed relationships among crime and important socio-economic conditions, public health, social capital, environmental stress, and neighborhood contextual variables in Flint, Michigan. The objective was reached using a strategic modeling strategy that consisted of EDA, ESDA, global, and localized modeling approaches. The strength and performance of the GWR model were reasonably good in comparison with the OLS model, exhibiting an adjusted R^2 of 0.536. The GWR model provided local coefficients for each CBG, which were integrated into a robust visualization strategy using GIS. The results included several nuanced cartographic outputs that displayed statistically significant relationships between crime and the explanatory factors, which were not evidenced from the OLS model. More importantly, the visualization of the significant GWR coefficients suggest that targeted enforcement strategies should vary based on localized geography and contextual conditions. With a better understanding of how, and to what extent, various factors influence crime at a microscopic scale, law enforcement officials, community planners, and citizenry can develop more insightful crime-prevention/reduction strategies.

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