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Crime rates and contextual characteristics: a case study in Connecticut, USA

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There is a long-standing interest in the spatial relationship between contextual characteristics and crime rates in the U.S. since such a relationship allows police and stakeholders to design crime prevention programs to better target areas at risk for crime. The objective of this research is to examine the relationships between violent/property crime rates and contextual characteristics at the county-subdivision level in the State of Connecticut. The analysis shows that predictors such as population density, type of housing, education, poverty, and racial/ethnic diversity are significantly associated with violent and property crime rates. The results are discussed in the context of different crime hypotheses, which can explain spatial variations in crime rates. Most importantly, the association between crime rates and the explanatory variables in this study significantly varied over space, highlighting that different crime prevention policies/programs should be implemented in different county subdivisions in Connecticut.

Key Words: ***crime rates, contextual characteristics, Connecticut, geographically weighted regression***

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Introduction

Previous research shows that crime patterns are often not randomly distributed over space and the occurrence of crime tends to be clustered in particular environments (Bernasco & Luykx, 2003; Malczewski & Poetz, 2005). Criminology researchers have long noticed the role of ecological structure and characteristics of crime hot spots in shaping criminal activities since some contextual factors are more conducive to crime than others, and the presence of particular contextual factors either facilitates or constrains crime occurrence (Gonzales et al., 2005). Therefore, identifying which contextual factors contribute to the clusters of crime has been a focal point of research on crime occurrence and patterns since it helps government officials design policies to combat crime. Consequently, as a rich tradition of criminological research, past studies have often focused on the relationship between crime rates and the contextual characteristics of macro-level units (Liska & Bellair 1995; Chamlin & Cochran, 1997). The spatial patterns of crime can be explained by several theories in the criminology field (Brantingham & Brantingham, 1984; Evans, 1989; Hartnagel, 2004, Evans & Herbert, 2013).

Some research suggests that crime patterns can be explained by crime opportunity theory and, consistent with this argument, criminological studies employ the routine activities hypothesis (Cohen & Felson, 1979; Kennedy & Forde, 1990; Koening & Linden, 2004). Routine activity theory presents a framework for explaining crime occurrence when a motivated person meets with a suitable target in the absence of a capable *Guardian*. In other words, the theory emphasizes that the occurrence of crime requires the simultaneous presence of three elements in space: 1) the presence of a motivated offender (such as an unemployed/low-income person), 2) a suitable target (such as a residential dwelling containing goods which could be easily resold) and, 3) the absence of a capable guardian (homeowner, watchful neighbour, friend or relative) (Clarke & Felson, 1993; Knox, 1995; Hackler, 2000). Routine activities theory provides a macro perspective on crime in that it predicts how changes in social and economic conditions influence the overall crime and victimization rate (Cohen & Felson, 1979). In addition, the theory relates the pattern of criminal activities to the daily patterns of social interaction. While a small number of offenders may choose targets or victims far from their homes, most of them tend to commit crimes in areas that they are familiar with (Felson & Cohen,1980; Herbert & Hyde, 1985; Wright et al., 1995; Wiles & Costello, 2000; Ainsworth, 2001; Malczewski & Poetz, 2005). Therefore, it thus offers a frame of reference for concrete and individualized crime analysis and facilitates the application of real policies and practices to alter the necessary elements that make the existence of a crime possible and prevent it (Tilley, 2009).

Another explanation for crime patterns comes from the relative deprivation theory, which suggests that wealthy neighbourhoods/cities tend to have relatively fewer crimes than their disadvantaged counterparts (Kitchen, 2007). Relative deprivation theory was first introduced by Stouffer et al. (1949), and it has traditionally been deliberated via economic measures as a means of empirically assessing one's level of social inequality. From a criminological perspective, relative deprivation may explain why certain people will choose to deviate from societal norms and engage in unlawful behaviour. The basic assumption behind this theory is that individuals may become involved in crimes because they desire items that others possess and which they cannot obtain using legitimate methods. Past research shows that violent crimes (i.e. homicide, assault, robbery) were consistently associated with relative deprivation (income inequality) and indicators of low social capital (Kawachi et al., 1999). Among property crimes, crimes (i.e. burglary and theft) were also associated with deprivation and low social capital (Kawachi et al., 1999). In addition, guided by relative deprivation theory, advantaged areas tend to have a relatively lower crime rate than disadvantaged areas (Sampson & Wooldredge, 1987; Kennedy & Forde, 1990; Miethe & Meier, 1994).

In addition, social disorganization theory links the ecological characteristics of the environment, such as economic disadvantage and ethnic heterogeneity, to crime occurrence and patterns. Shaw & McKay (1942) proposed social disorganization theory in their study of communities with high crime levels in Chicago. Their study shows that crime rates were not randomly distributed throughout the city and that the so-called Zone of Transition, also known as "the least desirable area to live in the city" (Lersch, 2007:57), has the highest crime rate. The Zone of Transition can be described as the melting pot of poor, immigrant, destitute, and criminal (Burgess, 1928). As a result, Shaw & McKay (1942) suggested that the high crime rates were not a function of the personal attributes of the groups residing in the neighbourhoods, but rather that "the structural factors of poverty, high heterogeneity, and high mobility created 'social disorganization', and it was community-level social disorganization that was presumed to cause crime" (Wilcox et al., 2003: 28). Guided by this theory, racially and/or ethnically heterogeneous areas or regions with a high proportion of the economically disadvantaged population are more likely to experience higher crime rates. Additionally, a socioeconomic disadvantage is found to be a strong determinant of crime rates at the neighbourhood level in urban settings or large spatial units such as towns (Halonen et al., 2013; Wang et al., 2019). Specifically, empirical research has found that areas with high crime rates are often associated with higher levels of economic disadvantage, larger proportions of young people, and greater residential instability.

To study crime patterns explained by various theories, areal analyses of crime rates and contextual variables across various geographic units (e.g., neighbourhoods, census tracts, cities, states, countries) remain the cornerstone of crime research (Miethe & McDowall, 1993). Although Connecticut has had a dramatic reduction in violent and property crimes over the past decade (FBI, 2017), very little research has been devoted to exploring the geographic relationship between the crime rates and contextual variables at the county subdivision level in Connecticut. Given the various crime theories, empirical research is needed to investigate the spatial differences in crime rates and identify contextual characteristics that underlie existing spatial differences. Accordingly, the objective of this research is to examine the relationship between crime rates and contextual characteristics at the county subdivision level in the state of Connecticut. It should be noted that county subdivisions are better known as cities, towns or municipalities in the U.S.

This article is organized as follows: methodology outlining a description of the study area, variables used in this study, and the local analysis method – Geographically Weighted Regression (GWR); followed by a discussion on the GWR results, which illustrate the relationship between spatial variations in crime rates and contextual variables in Connecticut. The final section presents concluding remarks.

Methodology

Study Area

Connecticut is a U.S. state in southern New England that has 169 county subdivisions and is surrounded by Rhode Island to the east, Massachusetts to the north, New York to the west, and Long Island Sound to the south (Figure 1). Connecticut is part of the New England region, although the southwest part of it is often grouped with New York and New Jersey as the tri-state area. The State of Connecticut is slightly larger than the country of Montenegro, with a land area of 12,559 km^2 and a water area of 1,809 km^2.

Figure 1. Study Area

Economically, it has the highest Human Development Index (0.962) and 7th median household income ($78,444) in the United States (U.S. Census Bureau, 2021). The capital of Connecticut is Hartford, and its most populous city is Bridgeport, with a population of 122,591 and 144,900, respectively, according to the 2018 American Community Survey. Connecticut is the third smallest state by area, the 29th most populous, and the fourth-most densely populated of the fifty states. However, its rural areas and small towns in the northeast and northwest corners of the state contrast sharply with its industrial cities such as Stamford, Bridgeport, and New Haven, located along the coastal highways I-95 from the New York border to New London, then northward up the Connecticut River to Hartford. The Interstate highways in the state are I-95 travelling southwest to northeast along the coast, I-84 travelling southwest to northeast in the centre of the state, I-91 travelling north to south in the centre of the state, and I-395 travelling north to south near the eastern border of the state (Figure 1).

Connecticut's economic output in 2019 as measured by gross domestic product was $289 billion. Finance, insurance and real estate was Connecticut's largest industry in 2018 as ranked by gross domestic product, generating $75.7 billion in GDP that year. However, there is a huge income gap throughout the state. After New York, the study area had the second-largest gap nationwide between the average incomes of the top 1% and the average incomes of the bottom 99% (Sommeiller & Price, 2018).

Connecticut is an important study area for contextual analysis of crime rates due to the following reasons: firstly its violent and property crime rates dropped slightly from 2013 to 2017, while its murder rate jumped significantly after hitting a decade's low in 2016 (FBI, 2017) and major cities in Connecticut such as Hartford, Waterbury, Bridgeport still have much higher crime rates compared to the national average. In addition, the high crime rate led to population loss in major cities in the past (Sauter et al., 2017); secondly, there has been little scholarly research conducted on the area on spatial crime patterns and their relationship to contextual characteristics of county subdivisions.

Data Preparation

This study is based on crime data in the Uniform Crime Report (UCR, 2021) program between 2013 and 2017. The data were collected and managed by the Connecticut Department of Emergency Services and Public Protection (prior to 2011 called the Department of Public Safety). The 5 years crime data is used in this study because it not only provides insights on recently reported offences in Connecticut but also aligns with the most recent American Community Survey (ACS) five-year estimates (2013-2017) released by the US Census Bureau. The data consisted of 414,145 crime incidents that happened in 169 county subdivisions during the 5-years period. Among them, 90,648 (21.9%) are violent crimes and 323,497 (78.1%) are property crimes.

Table 1. Descriptive Statistics for the dependent variables

	Min	Max	Median	Interquartile Range	Standard Deviation
Violent Crime Rates: Violent crime incidents per 100,000 people	2.0	950.8	52.6	62.0	140.3
Property Crime Rates: Property crime incidents per 100,000 people	133.8	3911.1	782.9	1207.0	815.4

In addition, the data table contains violent crime rates and property crime rates which were measured as the number of two types of crimes reported to law enforcement agencies per 100,000 total population. Crime incidents and rates were compiled, calculated and disseminated at the county subdivision level by the Connecticut Department of Emergency Services and Public Protection. The crime incident table was then joined with a shapefile consisting of 169 county subdivisions (Figure 1) based on the unique 10-digit county subdivision FIPS code assigned by the U.S. Census Bureau using ArcGIS 10.6.1 (Esri, 2018) so that violent crime rates and property crime rates can be aligned with contextual variables for further analysis. The descriptive statistics for the dependent variables –violent and property crime rates are shown in Table 1.

This study considers ten socio-economic characteristics as the potential explanatory variables (Table 2). The 11 contextual variables at the county subdivision level were chosen to reflect the key dimensions underlying the variation in the risk of crime as suggested by the theories reviewed in the introduction. The demographic and socio-economic variables such as residential population, age, education, income, employment status, tenure of housing, type of housing, residential mobility, race/ethnicity, and household type were taken from the most recent American Community Survey (ACS) five-year estimates (2013-2017) released by the US Census Bureau through the American FactFinder website (https://factfinder.census.gov/).

The population density was measured by the number of people per square kilometre. The age variable was calculated by the percentage of the population aged between 20 and 34. The education variable was quantified by the percentage of people aged 25 and above without a college degree or above. The income variable was determined by the median household income. The poverty variable was calculated as the percentage of people living under the poverty line. The employment variable was measured as the percentage of the unemployed population aged 16 years and over. Tenure of housing was quantified by the percentage of renters in the population. The type of housing was calculated by the percentage of multiple-unit dwellings.

Residential mobility was determined by the percentage of movers within the last 12 months. The household type variable was calculated by the percentage of lone-parent families. The racial/ethnic diversity variable was measured using the Shannon equitability index (Shannon & Weaver, 1949) based on eight racial/ethnic groups' populations in county subdivisions in Connecticut, including Hispanic, Non-Hispanic White alone, Non-Hispanic Black alone, Non-Hispanic

Asian alone, Non-Hispanic American Indian and Alaska Native alone, Non-Hispanic Native Hawaiian and Other Pacific Islander alone, Non-Hispanic other race alone, and Non-Hispanic two or more races. Population data for these eight racial/ethnic groups were collected from American Community Survey (ACS) five-year estimates (2014-2018), which were released on the U.S. Census Bureau's website (data.census.gov). Shannon's index, which originated in ecology research, accounts for both abundance and evenness of the species present but also has implications for the relative racial/ethnic heterogeneity of human populations (White, 1986). The Shannon diversity index is calculated using the formula:

$$H = -\sum_{j=1}^{S} p_j \ln p_j$$

Where S is the total number of racial/ethnic groups in the community, p_j is the proportion of the j^{th} racial/ethnic group to the total population.

Then, the Shannon equitability index (E_H) can be then generated by dividing H by H_{max}, which has a value between 0 (no diversity or a county subdivision is completely dominated by one racial/ethnic group) and 1 (perfectly diverse or all racial/ethnic groups are equally represented in a county subdivision). Then, the demographic and socioeconomic datasets were joined with Connecticut county subdivisions file and stored for further analysis using ArcGIS 10.6.1 (ESRI, 2018). The descriptive statistics for each explanatory variable are shown in Table 2.

GWR Model Building

Many early contextual studies on crime patterns are criticized for their use of global regression modelling techniques, such as Ordinary Least Squares or OLS regression (Malczewski & Poetz, 2005) because the regression method violates some basic assumptions (e.g. independence of observations and spatial stationarity of the relationship between independent and dependent variables) when spatial data is used. GWR (Brunsdon et al., 1996; Fotheringham et al., 2002) relaxes these assumptions and enables the analysis of spatially clustered data.

Table 2. Descriptive statistics for the explanatory variables

Variables	Min	Max	Median	Interquartile Range	Standard Deviation
Population density	11.4	2946.3	116.4	291.8	468.2
Age	5.9	41.4	14.6	5.9	5.4
Education	14.7	77.9	51.0	20.2	13.8
Income	33,841	219,868	85,296	29,393	28,102.9
Poverty	0.1	26.8	3.0	3.0	4.4
Employment Status	1.2	16.0	5.6	2.6	2.3
Tenure of housing	2.3	76.2	19.0	15.8	13.7
Type of housing	0.0	80.4	16.4	20.1	16.5
Residential mobility	1.6	18.6	6.6	3.6	3.0
Racial/ethnic diversity	0.130	0.842	0.287	0.197	0.147
Household type	2.9	36.6	12.3	6.4	5.5

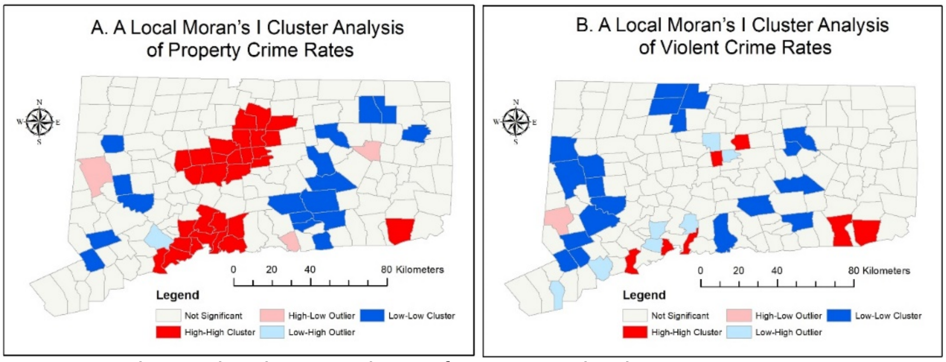

Figure 2. Local Moran's *I* cluster analyses of property and violent crime rates in Connecticut

GWR is often considered as an extension of OLS regression since it allows local parameters instead of global parameters to be estimated, hence making it possible to model spatial variations within the data (Fotheringham et al., 2002). Unlike OLS regression, which produces a single global model across space, GWR simultaneously conducts multiple regressions for different data units so that there is one regression model per spatial data unit (e.g. a county subdivision boundary) (Hipp & Chalise, 2015). In a GWR model, observations near a particular data unit will influence the estimation more than observations distance away (Hipp & Chalise, 2015). Given the weaknesses of OLS regression and the strength of GWR, this research uses GWR for analysing the spatial non-stationarity relationship between dependent variables and contextual characteristics in the study area.

The first step is to examine the two dependent variables: property and violent crime rates and explore their spatial heterogeneity (Figure 2). If the dependent variables are not spatially clustered, there is no need to build a spatially explicit model. The Moran's *I* Index (Anselin, 1995) provided by ArcMap 10.6.1 (ESRI, 2018) was used to identify the clustering of property and violent crime rates across county subdivisions in Connecticut. Moran's *I* ranges from −1.0, perfectly dispersed (e.g. a checkerboard pattern), to a +1.0, perfectly clustered. In this research, Moran's *I* scores (0.561 and 0.132) and *p* value (0.000, 0.003) were generated, indicating property and violent crime rates are spatially clustered, and the results are statistically significant.

Figure 2 demonstrates five different types of spatial clustering: (1) high-high, for county subdivisions with high crime rates that are in close proximity to county subdivisions with high crime rates; (2) low-low, for county subdivisions with low crime rates that are in close proximity to county subdivisions with low rates; (3) high-low (known as spatial outliers), for county subdivisions with high crime rates, but are proximate to county subdivisions with low rates; (4) low-high (also known as spatial outliers), for county subdivisions with low crime rates, yet are in close in proximity to county subdivisions with high rates; (5) not significant, for county subdivisions where there is no significant spatial clustering. As shown in Figure 2A, low-low spatial clusters were found in county subdivisions s located in the centre-east and west of Connecticut, while high-high spatial clusters were found in or around the New Haven, New London and Hartford metropolitan statistical areas located in southwest, southeast, and the centre of Connecticut.

In other words, the high property crime rates are clustered in or within and around the New Haven, New London, and Hartford metropolitan areas in Connecticut. As shown in Figure 2B, a few low-low spatial clusters were found in county subdivisions located in the centre-east, west, and north of Connecticut, while a few high-high spatial clusters were found in county subdivisions located in the centre, southeast, and southwest of the state. The spatial pattern illustrates that the high violent crime rates are clustered in a few county subdivisions in the New Haven, Hartford, and New London metropolitan areas.

OLS multivariate model (Aiken & West, 1991) in SPSS 25 was then used to conduct initial data exploration and model specification. Two factors motivated the decision to first specify the OLS model: 1) to identify explanatory variables significantly correlated with the dependent variables (property and violent crime rates) before specifying the GWR model; and 2) the GWR software used for spatial analysis does not provide a variance inflation factor (VIF) to measure multicollinearity. If the standard regression equation in the investigation of dependent variables is given by:

$$Y_i = \beta_0 + \sum_k \beta_k x_{ki} + \varepsilon_i$$

where Y_i is the property or violent crime rates at county subdivision i, β_0 is a constant term (i.e. the intercept), β_k measures the relationship between the independent variable x_k and Y for the set of i county subdivisions, and ε_i is the error associated with county subdivision i. It should be noted that $i \in C = \{1,2,\ldots,n\}$ which is the index set of locations of n observations (i.e. all county subdivisions).

It should also be noted that the above equation results in one parameter estimate for each variable included (Cahill & Mulligan, 2007). The summary of the OLS analysis results is presented in Table 3. In the OLS regression, only variables significantly correlated with the dependent variables – property and violent crime rates – were included. The two OLS models are significant (F = 127.103 and 174.952, $p < 0.01$). The adjusted R^2 values are 0.600, 0.806 which mean that the models explained 60% and 80.6% of the variance in county subdivision level property and violent crime rates in Connecticut. The VIF for all variables was less than 5.0, a commonly used cutoff point (Ringle et al., 2015), suggesting no severe multicollinearity issue was detected among the explanatory variables (Table 3).

As shown in Table 3, there is a positive and significant relationship between property crime rates and population density and between property crime rates and the percentage of multiple-unit dwellings. In other words, the higher the population density and percentage of multiple-unit dwellings in a county subdivision, the higher the property crime rate in that county subdivision.

Table 3. Results from ordinary least square model of property and violent crime rates at county subdivision level in Connecticut

Dependent Variable	Independent Variables	β	SE	p-value	VIF
Property crime rates	Intercept	501.720	51.707	< 0.01	-----
	Population density	0.846	0.090	< 0.01	2.359
	Type of housing	16.904	3.704	< 0.01	2.359
Violent crime rates	Intercept	68.152	19.442	< 0.01	-----
	Population density	0.115	0.019	< 0.01	1.431
	Education	0.978	0.414	< 0.05	1.665
	Poverty	8.185	1.894	< 0.01	3.116
	Racial/ethnic diversity	2.685	0.664	< 0.01	4.186

There is also a positive and significant relationship between violent crime rates and population density, percentage of people aged 25 and above without a college degree or above, percentage of families living under the poverty line, and Shannon equitability index. In other words, the higher the population density, percentage of people aged 25 and above without a college degree or above, and percentage of families living under the poverty line in a county subdivision, the higher the violent crime rate in that county subdivision. Additionally, the higher the Shannon equitability index (indicating a more racial/ethnic diversified population) in a county subdivision, the higher the violent crime rate in that county subdivision. The rest of the explanatory variables are insignificantly related to dependent variables in this study. The residuals of the OLS model were spatially auto-correlated (Moran's I = 0.110, 0.146, 0.152; p < 0.05). In other words, the OLS model overestimated crime rates for some county subdivisions, while it underestimated the outcomes for some others.

Then, the same set of variables was used to specify a GWR model using the GWR4 software. GWR is a modelling technique used to explore spatial non-stationarity (Brunsdon et al., 1996). The "main characteristic of GWR is that it allows regression coefficients to vary across space, and so the values of the parameters can vary between locations" (Mateu, 2010:453). In other words, instead of estimating a single parameter for each variable, GWR estimates local parameters. By estimating a parameter for each data location (i.e. a county subdivision) in Connecticut, the GWR equation would only alter the OLS equation as follows:

$$Y_i = \beta_{0i} + \sum_k \beta_{ki} x_{ki} + \varepsilon_i$$

where Yi is the property or violent crime rate at county subdivision i, β_{0i} is the constant term at county subdivision i, x_{ki} is the explanatory variable (i.e. population density, education, racial/ethnic diversity etc.) at county subdivision i, β_{ki} is the value of the parameter for the corresponding explanatory variable at county subdivision i, and ε_i is the error term at county subdivision i. It should be noted that $i \in C = \{1,2,\ldots,n\}$ which is the index set of locations of n observations (i.e. all county subdivisions). GWR becomes useful when "a single global model cannot explain the relationship between some sets of variables" (Brunsdon et al., 1996:281). In the GWR model, a continuous surface of parameter values is estimated under the assumption that locations closer to *i* will have more influence on the estimation of the parameter $\widehat{\beta_i}$ for that location. Consequently, GWR allows researchers to explore "spatial non-stationarity by calibrating a multiple regression model which allows different relationships to exist at different geographical locations" (Leung et al., 2000:1). The GWR model was used to explore the macro-level spatial non-stationarity of the statistical relationship among crime rates and the predictors such as population density, income, racial/ethnic diversity.

While conducting GWR, the adaptive kernel was used, which was produced using the bi-square weighting function. The adaptive kernel uses varying spatial areas but a fixed number of observations for each estimation. It is the most appropriate technique when the distribution of observations varies across space. In this case, observations (i.e. county subdivisions) are much smaller and closer together in the city centre they are at the edge. Finally, a process that minimizes the Akaike Information Criteria (AIC) was used to determine the best kernel bandwidth. The parameter estimates and *t* values produced by the software were exported and mapped using ArcMap 10.6.1 (ESRI, 2018).

Results and discussion

A Local Moran's *I* cluster analysis (Anselin, 1995) was conducted for the residuals of the two GWR models as a diagnostic for the collinearity in GWR residuals. There were no violations of residual independence. The GWR model of property crime rates generated β coefficients for each county subdivision (Table 4, Figure 3A & 3B), local R2 value (Figure 3C), and *t* values for each county subdivision (Figure 4). The GWR model of violent crime rates generated β coefficients for each county subdivision (Table 4, Figure 5A & 5B), local R^2 value (Figure 5C), and *t* values for each county subdivision (Figure 6). The direction of the relationships among the dependent variable and the predictors (Table 4 & 6, Figure 3 & 5) was inconsistent in county subdivisions included in the study.

Table 4. Results from GWR Model of property and violent crime rates in Connecticut

Dependent variable	Independent variables	β coefficients		% of county subdivisions by 95% of t		
		Min	Max	$\lvert t \rvert \leq 1.96$	$1.96 < \lvert t \rvert \leq 2.58$	$\lvert t \rvert > 2.58$
Property crime rates	Intercept	229.195	988.039	-----	-----	-----
	Population density	-0.112	4.353	20.1	58.6	21.3
	Type of housing	-21.393	30.098	65.1	15.4	19.5
Violent crime rates	Intercept	-134.955	16.270	-----	-----	-----
	Population density	-0.043	0.834	47.3	8.3	44.4
	Education	-1.936	2.739	73.4	14.2	12.4
	Poverty	-5.494	32.898	72.8	5.3	21.9
	Racial/ethnic diversity	-7.153	11.674	28.4	16	55.6

* 1.96 and 2.58 are the cutoff values for *t*-test. When $\lvert t \rvert > 1.96$, the β coefficient estimate for a variable is significant at a significance level of 0.05. When $\lvert t \rvert > 2.58$, the β coefficient estimate for a variable is significant at a significance level of 0.01.

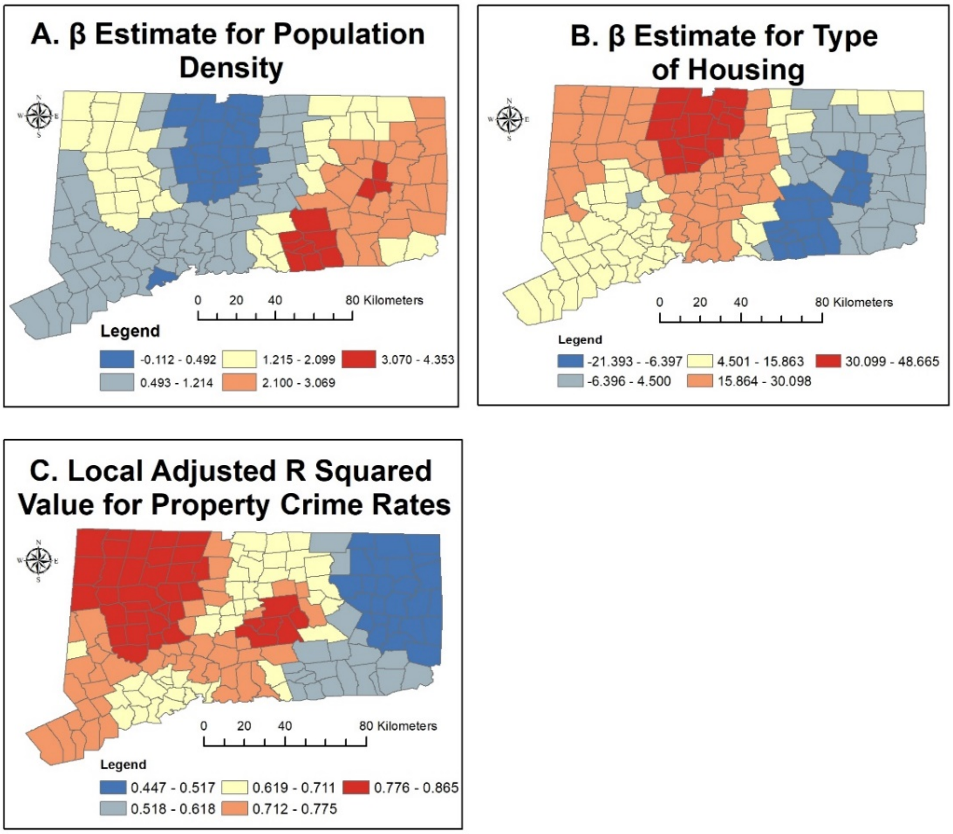

Figure 3. Spatial variations in β coefficient estimates for explanatory variables from the GWR model of property crime rates

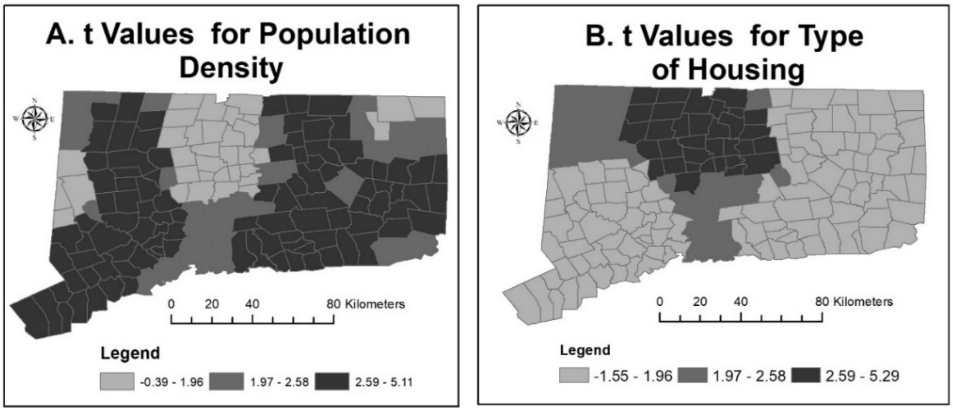

Figure 4. Spatial variations in *t* values for explanatory variables in modeling property crime rates

Note: 1.96 and 2.58 are the cutoff values for *t*-test. When $|t| > 1.96$, the β coefficient estimate for a variable is significant at a significance level of 0.05. When $|t| > 2.58$, the β coefficient estimate for a variable is significant at a significance level of 0.01.

In addition, the property and violent crime rates at the county subdivision level were significantly clustered (Moran's I values: 0.561 and 0.132 and p-value: 0.000 and 0.003). This clustering and the inconsistent direction of the relationships suggest that local contextual variables are associated with property and violent crime rates and that the amplitude of such contexts varies across Connecticut.

As shown in Table 4 and Figure 3A and 5A, population density is largely positively associated with county subdivision level property and violent crime rates across Connecticut. This finding supports previous research, which suggests that the higher the population density, the higher the crime rates (Blau & Blau, 1982; Gibbs & Erickson, 1976; Green et al., 1998). The implication of the relationship between crime rates and population density relates to the practice of comparing different county subdivisions in Connecticut according to their property and violent crime rates.

Based on the findings in this study, the practice of comparing jurisdictional crime rates should be discouraged until one can establish the nature and extent of the relationship between property crime rates and population density or violent crime rates and population density. When a significant positive or negative relationship exists between these variables, comparisons of crime rates among county subdivisions should not be conducted unless adjustments were made for the population density size. The second implication of the relationship relates to crime control/prevention strategies. Under conditions of high population density, capable guardians are not present, or their presence cannot be effectively deployed. As a result, property and violent crime rates can be high in county subdivisions where population density is high. For example, time of day may be a critical factor ignored by many researchers. The population density index was calculated based on the residential population in the ACS data while most residents are away from home at work during daylight hours. Therefore, property or violent crime (i.e. burglary and even murder) may occur virtually undetected among county subdivisions with extensive residential areas in the daytime with a nominally high population density but with a large proportion of the population at work during the day.

As demonstrated in Table 4 and Figure 3B, type of housing is mostly positively associated with county subdivision level property crime rates across the state, although some outliers demonstrate that the predictor is negatively but insignificantly (Figure 4B) associated with the property crime rates in southeastern Connecticut. This finding is consistent with previous research findings, which suggest that residential instability weakens residents' attachment to the area where they live and impedes informal social control and order maintenance. Hence, crime rates are high in areas that have a large portion of multiple-unit dwellings. As shown in Table 4 and Figure 5B and 5C, education and poverty are largely positively associated with the county subdivision level violent crime rates. However, some outliers demonstrate that the predictors are negatively but mostly insignificantly (Figure 6B & 6C) associated with the violent crime rates in southwestern Connecticut.

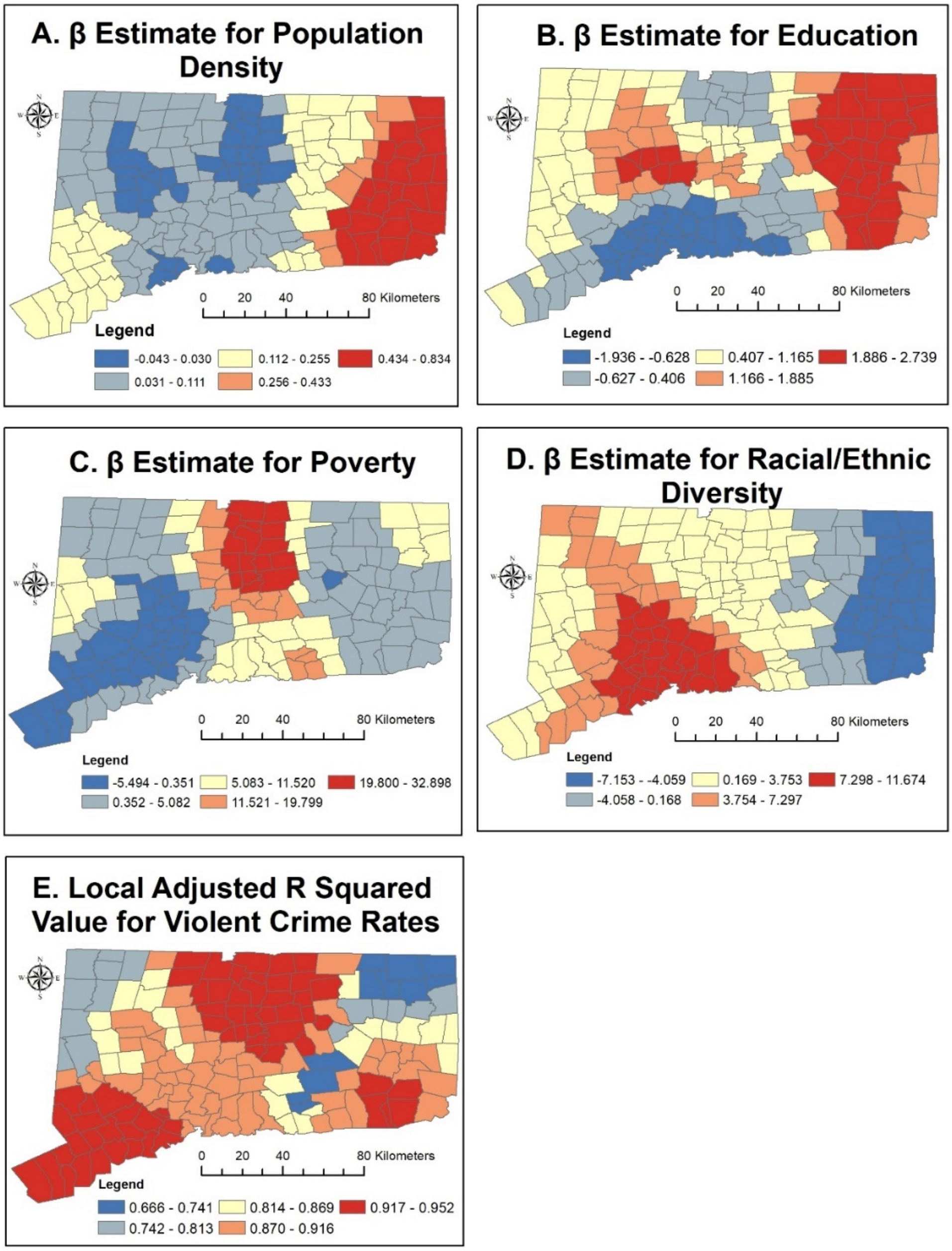

Figure 5. Spatial variations in β coefficient estimates for explanatory variables from the GWR model of violent crime rates

These findings are consistent with previous research showing that education, poverty, and crime have a very intimate relationship that has been verified by researchers from various fields (i.e. criminologists, economists, sociologists) (Graif et al., 2014; Sharkey et al., 2016). The education, poverty, and crime cycle involves many different steps that are always changing. The basis of it, though, is that as people start losing education, they cannot get jobs that pay good wages. As this happens, those people start losing the means to provide for themselves and their families. When people descend into poverty in that way, they begin to turn to criminal activities in an attempt to accommodate for their families and themselves. That criminal activity can take many forms, it can be something as simple as petty theft, or it can escalate to drug trafficking and other severe crimes. Education is the key to *breaking the cycle* as the impoverished people can be motivated to better themselves so that they can obtain a post-secondary education and then find a job with decent paid wages.

As illustrated in Table 4 and Figure 5D, racial/ethnic diversity, defined by the Shannon equitability index, is largely positively associated with the county subdivision level violent crime rates, although there are some outliers demonstrating that the predictors are negatively but mostly insignificantly (Figure 6D) associated with the violent crime rates at eastern Connecticut. This finding confirms that racial/ethnic heterogeneity weakens residents' attachment to the areas where they live and reduces community organization and involvement, so the crime rates are high in areas where the Shannon equitability index is high.

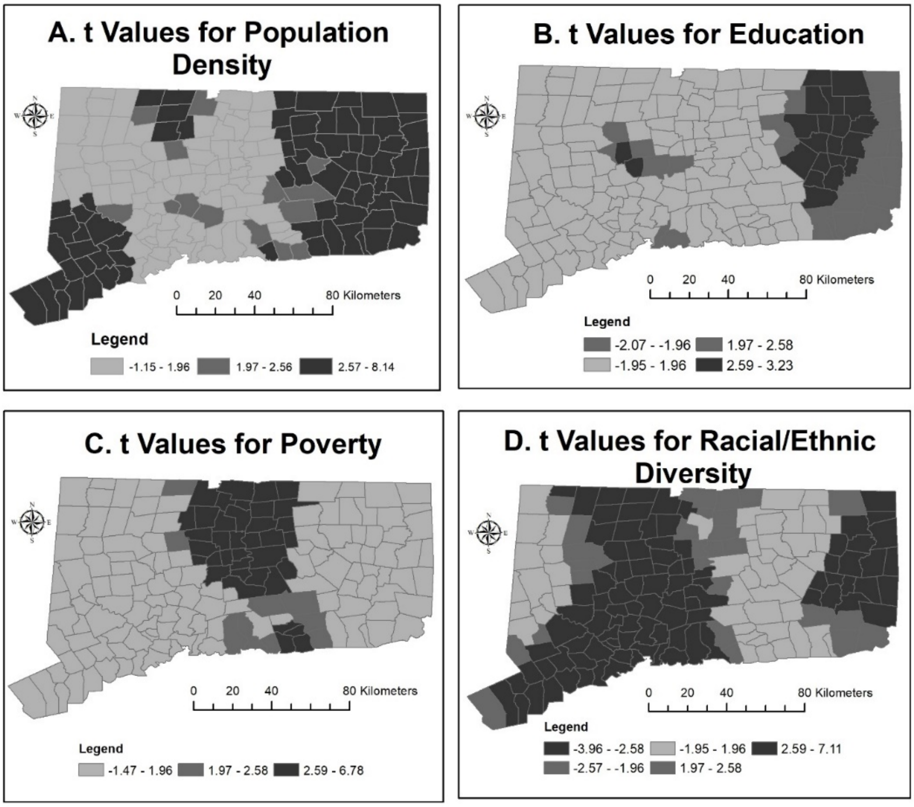

Figure 6. Spatial variations in *t* values for explanatory variables in modeling violent crime rates

Note: 1.96 and 2.58 are the cutoff values for *t*-test. When $|t| > 1.96$, the β coefficient estimate for a variable is significant at a significance level of 0.05. When $|t| > 2.58$, the β coefficient estimate for a variable is significant at a significance level of 0.01.

Therefore, stakeholders from local communities should first identify crime problems, craft solutions and assess responses to boost social cohesion/control in

Connecticut. Then, intervention measures should focus on county subdivisions with lower social control/cohesion. Finally, the area's general public should be encouraged to participate in neighbourhood watch and related programs (such as citizen patrols) to reduce crime rates.

The GWR results are potentially helpful for the Connecticut Department of Emergency Services and Public Protection in targeting priority county subdivisions for crime prevention and intervention since preventive police strategies should be informed by an understanding of crime's contextual factors. In particular, these factors should be examined locally, and different strategies aimed at preventing and reducing crime should be applied in different county subdivisions in Connecticut. For example, a strategy designed to reduce resident poverty rates may be sufficient to reduce violent crime rates in county subdivisions located in northern and central Connecticut. However, the same approach is unlikely to be effective in those located in eastern Connecticut. In those county subdivisions, violent crime prevention/intervention programs aimed at increasing resident education levels should be considered as tools for preventing and reducing violent crime rates.

As shown in Table 4 and Figures 3 to 6, the change in magnitude and direction of the coefficients suggests spatial non-stationarity of the relationship between the dependent variables (property and violent crime rates) and the predictors. The variation in parameter estimates from GWR suggests the necessity of applying this spatial statistical tool to future crime studies that would be restricted by using global OLS models since GWR provides insights on how a particular explanatory variable influences the crime rates across the study area. The importance of using spatial statistical tools such as GWR in future crime studies can also be confirmed by the local R^2 value (Figure 3C & 5E). The adjusted R^2 for the GWR model of property and violent crime rates ranged from 0.447 to 0.865 and from 0.666 to 0.952, with an average of 0.763 and 0.918, while the adjusted R^2 in the OLS model was 0.600 and 0.806, respectively. The OLS R^2 of 0.600 and 0.806 masks a wide distribution of local associations between the explanatory variables and property and violent crime rates. In other words, without GWR, it would be unable to estimate the variance of local associations. For example, as shown in Figure 3C, in the northwest of Connecticut, the GWR model explained up to 86.5% of the variance in property crime rates. However, among county subdivisions clustered in the east of the state, the model only explains about 44.7% to 51.7% of the variance, a spatial variation that would have been neglected with the OLS model alone.

This study is not without limitations. The first group of limitations is associated with geographic boundary effects, such as Modifiable Areal Unit Problem (MAUP) and edge effect. It should be noted that the statistical relationships drawn from areal data must be carefully interpreted. Robinson (1950) suggested the data scale/boundary problem long ago and clearly explained that inferring individual-level relationships from macro-level correlations is inappropriate. County subdivision boundaries in Connecticut were used in this study, and the relationships between crime rates and contextual characteristics at the county subdivision level cannot be interpreted as and/or applied to individual-level relationships. In addition, the GWR model is restricted by the edge effect, whereby county subdivisions located on the edges of Connecticut do not have the 360° influence of county subdivisions in the state's interior.

The second group of limitations is related to crime data. It should be noted that the crime dataset prepared by the Connecticut Department of Emergency Services and Public Protection may underestimate the crime rates to some extent because only the most severe offence is recorded per incident of crime according to the UCR classification rule. For example, if there were a robbery with a murder involved, the incident would then be classified according to the crime that carried the longest maximum sentence, which would be the murder offence. Such a classification rule results in an underrepresentation of less serious offences such as the robbery in the example. In addition, the local R^2 values accounted for 44.7% to 86.5% and 66.6% to 95.2% of the property and violent crime rates, respectively, which means that other risk factors associated with the property and violent crime rates need to be added to the GWR models.

Conclusions

This research analysed the spatial distribution and correlations of property and violent crime rates in Connecticut. Specifically, this study incorporated contextual correlates with the crime rates. The relationship between the crime rates and predictors, such as population density, education, poverty, education, type of housing, racial/ethnic diversity, is not new (Malczewski & Poetz, 2005), but little research has been done to investigate the spatial heterogeneity of the relationships in the state of Connecticut. This study fills the gap by illustrating that 1) there is a significant correlation between the crime rates and the explanatory contextual variables and 2) this relationship has a spatial but nonstationary association which highlights the need for local and context-specific crime prevention and intervention programs. In other words, using GWR, crime-control researchers and law enforcement can gain an understanding of crime-related issues and respond to the notion that "all crime is local" (Hirst, 2003:6; Jenks and Fuller, 2017:299). The results of this study can also be used by the Connecticut Department of Emergency Services and Public Protection to tailor unique crime control strategies to different targeted county subdivisions. This study presents an initial and exploratory step towards a better understanding of crime in Connecticut. However, much more in-depth work remains before criminology researchers and law enforcement understand why these spatial variations exist and why explanatory factors, such as population density, poverty, education type of housing, racial/ethnic diversity have relatively low explanatory effects in some county subdivisions but explain up to 86.5% and 95.2% of the property and violent crime rates in others.

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