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Theorizing globally, but analyzing locally: the importance of geographically weighted regression in crime analysis

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Abstract

Theoretical relationships with crime across cities are explicitly or implicitly assumed to be the same in all places: a one-unit change in X leads to a β change in Y. But why would we assume the impact of unemployment, for example, is the same in wealthy and impoverished neighborhoods? We use a local statistical technique, geographically weighted regression, to identify local relationships with property crime. We find that theoretical relationships vary across the city, most often only being statistically significant in less than half of the city. This is important for the development of criminal justice policy and crime prevention, because these initiatives most often work in particular places potentially leading to a misallocation of scarce public resources.

Keywords: Spatial analysis, Spatial nonstationarity, Geographically weighted regression, Property crime

Introduction

Global regression analyses of neighbourhoods in a city estimate one parameter for each explanatory variable to represent an entire study region. Though rarely questioned, having one estimate to represent an entire study area is an assumption. But does one estimate properly represent an entire city? Would one expect a one percent change in unemployment to have the same impact in a wealthy neighbourhood as an impoverished neighbourhood? Certainly not. This has important implications for understanding the nuances of theoretical relationships, but also for criminal justice policy. If a public policy variable only impacts crime in particular areas, this should be known to avoid wasting scarce public resources.

In the early 1990s, research on local spatial statistics began to emerge (Anselin, 1995; Ord & Getis, 1995). In the context of a local regression, geographically weighted regression (GWR) emerged in the mid-1990s to investigate how relationships between variables may vary across space (Brunsdon et al., 1996; Fotheringham et al., 2001, 2002). In GWR, each spatial unit of analysis has its own coefficient to represent its relationship between the explanatory and outcome variable because a regression is estimated for each unit of analysis to estimate local effects. Approximately a decade later, early research in spatial criminology used GWR and found that theoretical relationships do not hold in all places and that theoretical relationships switch signs across the study area (Arnio & Baumer, 2012; Cahill & Mulligan, 2007; Malczewski & Poetz, 2005).

The benefits of this research using local spatial statistics are, primarily, twofold. First, we can identify whether or not theoretical relationships have the same strength across the study region and if the predicted relationship is always in the same direction. In the first case, some places may have a stronger relationship than others and, in the second case, the direction of the theoretical relationship may change across places. As such, the global relationship represents an average effect that may be

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positive, but there may be places where that relationship is negative.

Second, we can identify which spatial units of analysis are driving the global results. It may be that the theoretical relationship under investigation is present in all places, but if that relationship is only present in a subset of the places within the study region, that does not mean that the theory is incorrect, rather that its predicted effects are not omnipresent. This is referred to as spatial nonstationarity, or heterogeneity, in the local results.

We analyze multiple crime types and their explanatory variables, based on social disorganization theory, across Vancouver census tracts (CTs) for 2016. With the working hypothesis being that local effects do not matter, we compare global regression output with GWR output in order to identify local patterns in the data. This shows the utility of using local rather than global spatial statistics to identify local variability in an international (non-US) context. Methodologically, we contribute to the spatial criminology comparing GWR results with the appropriate global spatial regression model, rather than with a non-spatial regression method. More generally, much of the current research uses a limited set of explanatory variables and crime types. We consider a broader set of explanatory variables and five crime types.

Related research

With the development of local regression models in geography during the late 1990s, it was almost 10 years before these methods worked their way into criminological contexts, undertaken by geographers. Overall, this research has proven to be instructive in the contexts of theory and policy, showing the limitations of global statistical methods when trying to understand spatial crime patterns. Specifically, theoretical relationships are not supported in all places.

Analyzing residential burglaries, Malczewski and Poetz (2005) found a different set of explanatory variables remained statistically significant for global and GWR results. Curiously, the signs on coefficients switched in different places or were only statistically significant in particular places: global results showed increases in average dwelling value led to decreases in residential burglaries, but only a relatively small percentage of places had this relationship in the GWR model. In fact, the coefficient switched signs to be positive in places with high levels of rentals and student populations; in other words, relatively more affluent places without a lot of guardianship because of population turnover and young populations not spending a lot of time at home had more residential burglaries. In the context of multi-family dwellings that had a positive global relationship, that relationship was always true at the local level but was not always statistically significant having its strongest effects in an around the city core. In a rural context for theft and residential burglary, Deller and Deller (2012) found that GWR results were almost always consistent with the global results, when statistically significant.

Cahill and Mulligan (2007) found similar types of results in the context of violent crime. With their GWR results, when a variable had some statistically significant effects, only between one- and two-thirds of the units of analysis had statistically significant results. Similar to Malczewski and Poetz (2005), Cahill and Mulligan (2007) had GWR results that were both consistent with global results (when statistically significant) and changing signs in different places across the city: racial heterogeneity, wealth distribution, population density, and single-member households. They also found that variables not statistically significant in the global model were statistically significant in the GWR models; in this case, those areas that were statistically significant had both positive and negative coefficients, likely "cancelling each other out" at the global level. As such, global regression analyses may be masking statistically significant local results because they represent averages of areas across a larger study region.

Considering assault and aggravated assault, Grubesic et al. (2012) found that GWR results were almost always consistent with the global results, when statistically significant, for the relationship between alcohol outlet density, social disorganization, and violence. Disaggregating violence rates by race in the context of structural disadvantage (poverty, unemployment, female head of household, and low education), Light and Harris (2012) found that GWR results all showed statistically significant variation with many of the explanatory variables, including racial diversity and racial groups, switching sign. Specifically, their measure of structural disadvantage is always positive when statistically significant in the GWR model, but most of the (race-specific) control variables switch sign depending on the area: residential instability, percent Hispanic, and young males.

Investigating the relationship between immigration and homicide, Graif and Sampson (2009) showed similar types of changes with their GWR models, but also that the GWR model always showed improvements in goodness-of-fit over global models. In the context of immigration, they found negative results at the global level but varied results when considering GWR results (percent foreign born switched signs from positive to negative depending on the area)—Andresen and Ha (2020) found similar results for a number of property crime types in the context of immigration and crime. Investigating homicide, Becker (2016) found similar results in global and GWR models with regard to statistically significant explanatory variables: concentrated disadvantage, immigrant concentration, and residential stability. Becker (2016) found that immigrant concentration had a negative global effect, but that effect varied in the GWR model, as did concentrated disadvantage. More recently, Becker (2019) found that, when statistically significant, immigrant concentration always has a negative, but spatially varying, effect on homicide; they also find that collective efficacy only partially mediates neighbourhood disadvantage, and that disadvantage becomes spatially stationary when controlling for neighbourhood change. And in an investigation of homicide across Brazilian municipalities, Ingram and da Costa (2017) found spatial variability in all but two of their explanatory variables, with many switching signs from municipality to municipality.

Considering the impact of housing foreclosures on neighbourhood crime rates, Arnio and Baumer (2012) and Zhang and McCord (2014) both found spatial nonstationarity. Moreover, GWR results were statistically significant in different places for different crime types. This has important implications for any crime prevention initiatives and is particularly interesting because the global results show insignificance.

Boivin (2018) used GWR and found positive and negative associations between the presence of people and crime. Specifically, Boivin (2018) found statistically significant positive and negative results for residential mobility, work trips, other trips, and mixed land use for an aggregate of crime. This result suggests that places with higher concentrations of people may have guardianship effects, but particularly in places used for shopping, school, and work (Boivin, 2018). Though only considering population density, Maldonado-Guzmán (2020) found that higher population density only predicted property offences; additionally, they found that the presence of temporary lodging (AirBnB) increased both property and violent crimes, varying across space.

Bunting et al. (2018), Louderback and Roy (2018), and Cowen et al. (2019) have investigated global and GWR results for various crime types and context in the Miami-Dade area. These authors consistently found a limited number of places drive the global results and that GWR results often, but not always, switch signs. Similarly, Smith and Sandova (2019) identified spatial heterogeneity of robbery rates across census tracts and block groups in Saint Louis, particularly for relationships involving race, stability, and robbery rates.

Data and methods

Data

Crime incident data for the City of Vancouver are from the Vancouver Open Data Catalogue,[1] that includes commercial burglary, residential burglary, theft from vehicle, theft of vehicle, and other theft[2] (see Table 1). In order to facilitate interpretations, we use the natural logarithm of the counts of all crime types.[3] These ease interpretations because β_i then represents the percentage change in the crime type based on a one-unit change in independent variable i rather than change in a crime rate with no baseline information. Locations of the criminal incidents are not specific to an address, but to the center of their respective street segment and on the appropriate side of the street segment. Because each incident is allocated to the correct side of the street, all incidents are placed in the correct spatial unit of analysis when the count of points in polygons is performed. These crime data are available from 2003 to 2020, but only 2016 crime incident data are used to match the most recent available census data. Figure 1 is provided for neighbourhood context/references in the results, below.

As noted above, GWR research in criminological contexts often considers a limited set of explanatory variables, often using data reduction techniques, such as factor analysis that strives to capture a latent variable/construct through the combination of multiple variables—see Louderback and Roy (2018), Becker (2019), and Maldonado-Guzmán (2020) for recent examples. Though pragmatic because of the volume of statistical output when using GWR, the nuances of theoretical relationships may be shrouded when using formal theoretical constructs rather than the variables used to derive them; this has shown to be of importance in the context of the impact of the economy on crime (Andresen, 2013, 2015). In order to account for these potential nuances, particularly in the context of a relatively new statistical technique, we use the theoretically-informed individual explanatory variables as predictors rather than indices measuring broader theoretical constructs. This can be particularly important from a policy standpoint to develop social programs because not taking a data reduction approach allows for the individual variable driving the policy relevant result to be better identified.

Theoretically informed variables used as predictors in the analyses below are derived from social disorganization theory (Shaw & McKay, 1942). A full review of this empirical literature is beyond the scope of the current paper, but the theoretical approach of social disorganization theory has strong support in the literature (Pratt & Cullen, 2005). According to social disorganization

[1] https://data.vancouver.ca/datacatalogue/crime-data.htm.

[2] Other theft refers to forms of theft not in the other four categories: theft of a mobile phone, computer, purse/wallet, shoplifting, and so on.

[3] The use of crime counts, and their natural logarithm also avoids complications from using inappropriate denominators in crime rate calculations (Andresen, 2011).

Table 1 Descriptive statistics, dependent (rate per 1000) and independent variables

	Mean	Standard deviation	Minimum	Maximum	Variance inflation factor
Commercial burglary	3.89	4.84	0	26.9	
Residential burglary	12.79	9.03	1.11	58.54	
Other theft	7.09	11.52	0	68.68	
Theft from vehicle	17.7	18.98	3.65	135.28	
Theft of vehicle	2.36	1.83	0	10.64	
Unemployment rate	3.8	0.79	2.02	6.73	1.36
Population change, %	7.37	15.94	-9.71	118.91	2.53
Rented, %	24.2	14.64	4.05	59.79	17.33
Major repairs, %	3.23	1.71	0.87	9.53	3.61
Old houses, %	11.6	6.17	0.59	25.82	3.62
Move, 1 year, %	16.67	4.69	7.55	27.71	4.42
Post secondary, %	54.46	12.79	27.24	76.55	20.25
Low income, %	18.48	6.16	9.5	44.37	7.96
Government assistance, %	8.98	4.73	2.2	33.7	11.72
Average dwelling value, 000 s	1213.42	661.13	341.89	3089.16	10.14
Average rent, 00 s	11.34	2.62	4.85	18.01	8.87
Median family income, 000 s	60.11	16.15	14.78	124.08	12.78
Aboriginal, %	2.35	2.45	0	18.11	3.74
Immigrants, %	40.99	12.3	19.39	64.32	33.54
Recent immigrants, %	5.75	2.17	1.31	11.44	3.35
Visible minorities, %	49.21	22.68	10.1	91.01	39.62
Ethnic heterogeneity	57.55	14.11	19.04	80.4	5.64

n = 105

theory, social and economic deprivation, ethnic heterogeneity, and population turnover (residential mobility) lead to increases in crime and delinquency rates; these constructs are listed and italicized, below, to identify the associated variables. In order to account for these constructs a number of variables are derived from the Statistics Canada Census of Population: 13 variables that capture various neighbourhood (census tract) structural characteristics including socio-demographic, socio-economic, housing, income, and land use characteristics are included for analysis. See Table 1 for descriptive statistics.

Population turnover is measured considering the number of residents who have moved into the census tract within the past year (residential mobility), and the percentage of rental units to capture the transient nature of renters when compared to owners (residential mobility). Additional housing characteristics are measured with percentage of dwellings under major repair and percentage of old homes (40 years+), measuring *economic deprivation*. *Social and economic deprivation* include measures of the unemployment rate, the percentage of people with a post-secondary degree/diploma/certificate, the percentage of families that are low income, the percentage of people whose income comes from government assistance (welfare, family allowance, employment insurance, etc.), average dwelling value in thousands of 2006 dollars, average rent in hundreds of 2006 dollars, median income in thousands of 2006 dollars, and median family income in thousands of 2006 dollars—all observations are based on 2016 values but are converted to 2006 dollars in a panel data set, with this being the most recent year available for analysis. Lastly, in the context of ethnic heterogeneity, the percentages of immigrants, recent immigrants (within the past 5 years), and visible minorities are included with the degree of ethnic heterogeneity measured using the Blau (1977) Index. Though conceptually similar, many of these variables measure different phenomena, especially given immigration waves and enclave settlement; for example, some neighbourhoods may have low degrees of ethnic heterogeneity while having high degrees of immigration that are not necessarily visible minorities. Given the importance of immigration shown in the immigration and crime literature, including the use of multiple metrics immigrant,

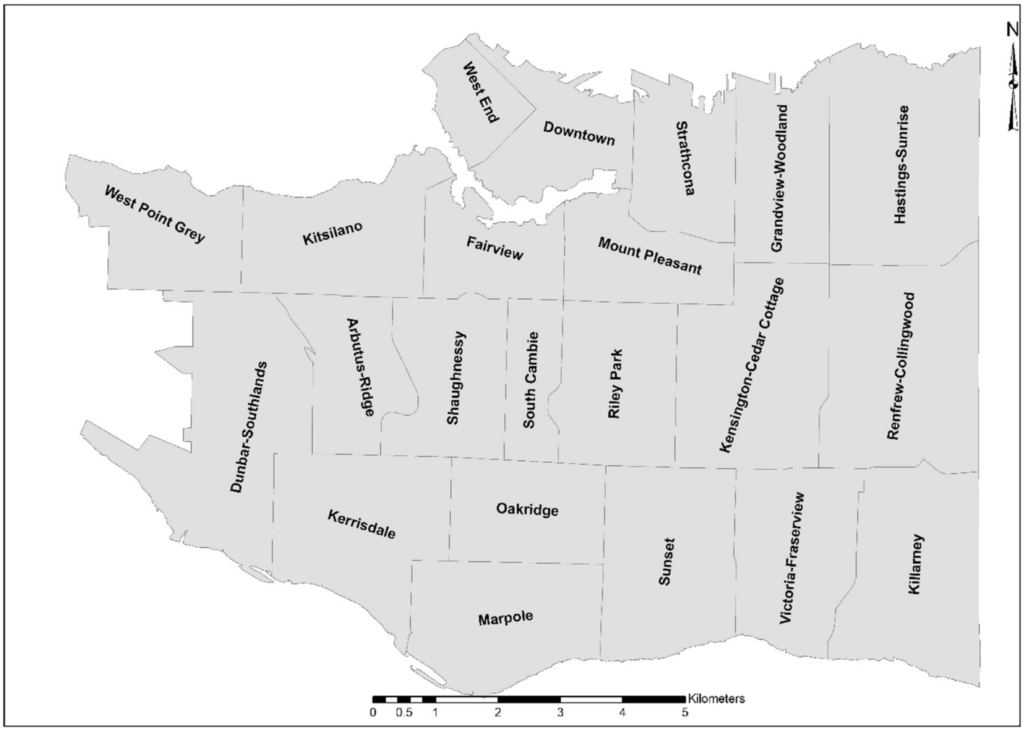

Fig. 1 Vancouver neighbourhoods

ethnic, and visible minority measures (Andresen & Ha, 2020), we consider these variables separately in the analyses below.

All crime and ecological data for Vancouver are aggregated to the census tract level. Census tracts are relatively small and stable geographic areas that tend to have a population ranging from 2500 to 8000, with an average of 4000 persons. There are 105 census tracts in the City of Vancouver. These census tracts typically have boundaries along major roads, but may be along neighbourhood level roads in places with higher population density. As noted above, because the crime data are geolocated on the correct side of the street segment, events are always allocated to the correct census tract. No edge effect corrections have been made to the calculations. Though the crime and place literature is increasingly using micro-places (street segments) as the unit of analysis (Andresen et al., 2017a, 2017b; Braga et al., 2017; Weisburd et al., 2004, 2012) to capture variability within larger units such as census tracts, there are benefits to geographically larger units such as census tracts. There is within census tract variability that cannot be captured here, but the use of census tracts allows for the incorporation of many more socio-demographic and socio-economic variables available through the census. This allows for a better assessment of our spatial theories of crime.

Geographically weighted and global regression analyses

Our global regression analyses begin with ordinary least squares (OLS) and testing for spatial autocorrelation in the residuals using Moran's *I*. If Moran's *I* indicates spatial autocorrelation, there is a choice between a spatial lag and spatial error model: spatial lag models filter out spatial autocorrelation only within the dependent variable whereas spatial error models filter out the spatial autocorrelation in the residuals. Conceptually, the difference between these two models is that the spatial error model is accounting for the unmeasured effect of independent variables, whereas a spatial lag model is accounting for a diffusion process; see Deane et al. (2008) for an excellent articulation of these concepts.

The choice of spatial lag or spatial error models is undertaken using Lagrange Multiplier tests with subsequent tests for remaining spatial autocorrelation in the residuals. In all cases of spatial regression models, first-order Queen's contiguity is sufficient to filter out spatial autocorrelation in the residuals—Rook's contiguity is not considered because we consider census tracts that only connect at a corner to still be contiguous. Because of this, higher order contiguity matrices are not necessary in these analyses. All global regression models use robust standard errors for statistical testing, though tests for heteroskedasticity is only identified in the Other

Theft model using OLS. Global and local (geographically weighted) regression models are compared using AIC values.

Geographically weighted regression can be represented using the following equation:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \quad (1)$$

where y_i represents the value for a crime type at location i, $\beta_0(u_i, v_i)$ represents the constant for location i, $\beta_k(u_i, v_i)$ represents the estimated parameter for independent variable x_k at location i, and ε_i is the independently and identically distributed residual at location i. The vector of parameters is estimated as follows:

$$\widehat{\beta}(u_i, v_i) = \left(X^T W(u_i, v_i)X\right)^{-1} X^T W(u_i, v_i)y \quad (2)$$

where $\widehat{\beta}(u_i, v_i)$ is the vector of estimates for β at all locations i, $W(u_i, v_i)$ is an n x n matrix that has diagonal elements denoting the weighting for all locations for point i (Brunsdon et al., 1996; Fotheringham et al., 2001, 2002). In all cases we use an adaptive kernel. Leung et al. (2000) is used to assess the value of using geographically weighted regression: statistical significance indicated no value in accounting for spatial nonstationarity.

The output from these regressions allows for the mapping of estimated parameters for each independent variable in the regression because a regression is estimated for each unit of analysis. The minimum, maximum, and quartiles are presented in the output table, below, but do not indicate the statistical significance of those estimated parameters. It is critically important to note that any spatial variation identified may not be statistically significant and this should be tested before presenting results. Statistical significance is indicated in the output, along with the percentage of census tracts (if any) that are statistically significant. In order to map both statistical significance and the various magnitudes of the estimated parameters, only estimated parameters statistically significant at the 5 percent level are represented on the maps presented in the discussion, rather than mapping both the spatially varying parameters and z-statistics separately.

With regard to multicollinearity, Table 2 shows that very few of the independent variables have (nonparametric) correlation coefficients greater than 0.80. Aside from immigrant percent (highly correlated with recent immigrants and visible minorities, expected results), only post-secondary education and government assistance are correlated at a level (marginally) greater than 0.80. Moreover, based on variance inflation factors (VIFs), multicollinearity is generally not shown to be an issue—VIFs are based on a variable's collinearity with all other variables in the regression, with values greater than 10 being a common threshold for concern (O'Brien, 2007). It is important to note that rented, post-secondary, government assistance, average dwelling value, median family income, immigrants, and visible minorities have VIFs greater than 10. However, rented, government assistance, average dwelling value, and median family income are all statistically significant in at least one of the global models with statistically significant results in the local models for the others. In order to test the impact of highly collinear variables, these variables were removed from the analyses and data reduction techniques were investigated. Removing these variables had very little qualitative impact on the results, with no impact on the results reported below. Data reduction techniques did not generate clean components (poor factor loadings, low alpha values, and low variance explained, potentially leading to omitted variable bias) except for those variables that did not impact the results reported below when removed from the analyses. Also, from a practical perspective, theoretical constructs generated using data reduction techniques do not allow for identifying what is actually driving the empirical results. This is problematic for those who wish to use such output for policy formation. Given that testing a specific theoretical construct is not the goal of the present research and that avoiding omitted variable bias is a greater concern (through removing variables or using data reduction), at this point in the analysis there are no general concerns for multicollinearity in the results presented below. Moreover, it is known that geographically weighted regression is not sensitive to multicollinearity, despite this common misconception (Fotheringham & Oshan, 2016).

All analyses are undertaken using R: A Language and Environment for Statistical Computing http://www.r-project.org/, using the *spatialreg* (global regression analyses) and *spgwr* (geographically weighted regression) libraries.

Results

The global and local regression results are presented in Table 3. Goodness-of-fit statistics are presented for both the global spatial and geographically weighted regression results as well as the type of global regression model (spatial error, spatial lag, or OLS) as is the type and order of contiguity matrix. Both R^2 and Adjusted-R^2 values for OLS versions of the global models show significant improvements in variance explained when compared to the local models—the GWR quasi-R^2 values represent the average R^2 for each set of local models; a similar result is present for the local versus global AIC value comparisons. All global models are statistically significant (Wald or F-statistic), and the Leung et al. (2000) test shows that we cannot reject of the null hypothesis

Table 2 Nonparametric correlations, independent variables

	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17
Unemployment rate, X1	0.1	0.33**	0.27**	0.1	0.21*	0.05	0.31**	0.12	0.23*	− 0.19	− 0.41**	0.20*	− 0.16	− 0.04	− 0.17	− 0.16
Population change, X2		0.44**	0.36**	− 0.01	0.32**	0.26**	0.03	− 0.10	− 0.46**	− 0.03	− 0.22*	0.34**	− 0.47**	− 0.30**	− 0.42**	− 0.30**
Rentals, X3			0.73**	0.22*	0.68*	0.57**	0.34**	− 0.15	− 0.78**	− 0.12	− 0.67**	− 0.59**	− 0.64**	− 0.12	− 0.70**	− 0.56**
Major repairs, X4				0.39**	0.46**	0.50**	0.16	− 0.16	− 0.64**	− 0.13	− 0.50**	0.57**	− 0.70**	− 0.30**	− 0.73	− 0.65**
Old houses, X5					0.22*	0.34**	− 0.19	− 0.37**	0.07	0.22*	0.06	0.20*	− 0.58**	− 0.37**	− 0.57**	− 0.56**
Movers, 1 years, X6						0.71**	0.26**	− 0.48**	− 0.43**	0.28**	− 0.36**	0.14	− 0.49**	0.18	− 0.54**	− 0.45**
Post-secondary, X7							0.01	− 0.82**	− 0.28**	0.63**	0.01	0.04	− 0.64**	0.05	− 0.74**	− 0.69**
Low income, X8								0.21*	− .242*	− 0.21*	− 0.69**	0.10	0.16	0.35**	0.04	− 0.04
Government assistance, X9									− 0.14	− 0.84**	− 0.45**	0.26*	0.49**	− 0.04	0.54**	0.53**
Average dwelling value, 000 s, X10										0.42**	0.67**	− 0.74**	0.49**	0.16	0.49**	0.31**
Average rent, 00 s, X11											0.56**	− 0.55**	− 0.16	0.20*	− 0.27**	− 0.33**
Median family income, X12												− 0.51**	0.11	− 0.11	0.15	0.15
Aboriginal, X13													− 0.54**	− 0.45**	− 0.45**	− 0.26**
Immigrants, X14														0.53**	0.95**	0.82**
Recent immigrants, X15															0.41**	0.28**
Visible minorities, X16																0.89**
Ethnic heterogeneity, X17																

* 5% and ** 1% statistical significance

Table 3 Geographically weighted regression and global regression results, all crime types

Variable (expected sign)	Commercial burglary				Residential burglary				Theft from vehicle			
	Min	Max	Global	% sig., GWR	Min	Max	Global	% sig., GWR	Min	Max	Global	% sig., GWR
Unemployment rate (+)	0.020	0.104	0.103	0	−0.139*	0.097	−0.046	11.4%	−0.048	0.116	0.055	0
Population change, % (+)	0.012*	0.021	0.016*	71.4	0.004*	0.015	0.008*	46.7%	0.010*	0.016	0.010**	100
Rented, % (+)	−0.031	−0.009	−0.016	0	−0.059*	−0.040	−0.048**	100%	−0.028*	−0.016	−0.014	7.6
Major repairs, % (+)	−0.206*	−0.130	−0.154*	40.9	−0.115*	−0.074	−0.088*	68.6%	−0.225*	−0.198	−0.163**	100
Old houses, % (+)	−0.041	−0.011	−0.028	0	−0.006*	0.052	0.018	35.2%	−0.005	0.011	0.001	0
Move, 1 year, % (+)	0.001	0.042	0.037	0	−0.009	0.043	0.014	0%	−0.020	−0.004	0.004	0
Post secondary, % (−)	−0.021	0.026	−0.004	0	−0.010	0.031	0.003	0%	−0.004	0.018	−0.003	0
Low income, % (+)	0.035*	0.094	0.021	28.6	0.024*	0.044	0.038*	32.4%	0.046*	0.089	0.031	100
Government assistance, % (+)	−0.133*	−0.060	−0.097	20.9	−0.111*	−0.023	−0.062*	40.9%	−0.102*	−0.044	−0.073**	61.9
Average dwelling value, 000 s (−)	−0.001	0.000	0.000	0	0.000	0.000	0.000	0%	−0.001*	0.000	0.000*	100
Average rent, 00 s (−)	−0.093	0.092	−0.026	0	−0.139*	−0.067	−0.111**	55.2%	−0.047	0.075	−0.017	0
Median family income, 000 s (−)	−0.028	−0.006	−0.023	0	−0.005	0.002	−0.001	0%	−0.013	0.009	−0.003	0
Aboriginal, % (+)	−0.027	0.016	0.034	0	0.021*	0.084	0.055*	15.2%	−0.002	0.029	0.027	0
Immigrants, % (+)	−0.049	−0.002	0.008	0	−0.026*	0.052	0.010	5.7%	−0.047*	−0.027	−0.017	23.8
Recent immigrants, % (+)	−0.072	0.113	0.043	0	−0.058	0.013	0.026	0%	0.015	0.063	0.038	0
Visible minorities, % (+)	−0.040	−0.004	−0.031	0	−0.028	0.018	−0.007	0%	−0.006	0.008	0.001	0
Ethnic heterogeneity (+)	−0.009*	0.040	0.013	28.6	−0.015	0.005	0.000	0%	0.001	0.014	0.002	0
Wald of F-statistic			9.29**				19.9**				36.94**	
Leung et al. (2000)	p-value = 0.31				p-value = 0.17				p-value = 0.21			
AIC	231.2		267.4		74.4		126.9		124.2		145.1	
GWR Quasi-global R^2	0.72				0.76				0.70			
OLS (Adjusted) R^2			0.62 (0.55)				0.60 (0.52)				0.59 (0.51)	
Global model			Lag				Error				Lag	
Spatial weights			1				1				1	
Moran's *I*, residuals p-value	0.15		0.72		0.08		0.38		0.07		0.98	
Koenker's test for heteroskedasticity, p-value			0.59				0.91				0.36	

Variable (expected sign)	Theft of vehicle				Other theft			
	Min	Max	Global	% sig., GWR	Min	Max	Global	% sig., GWR
Unemployment rate (+)	−0.129	−0.041	−0.073	0	−0.381	−0.150	−0.171	0
Population change, % (+)	0.007*	0.012	0.009**	50.5	0.020	0.025	0.023*	0

Table 3 (continued)

Variable (expected sign)	Theft of vehicle				Other theft			
	Min	**Max**	**Global**	**% sig., GWR**	**Min**	**Max**	**Global**	**% sig., GWR**
Rented, % (+)	−0.027	−0.017	−0.017	0	−0.080	−0.025	−0.051	0
Major repairs, % (+)	−0.105	−0.093	−0.080	0	−0.394**	−0.239	−0.339	40.9
Old houses, % (+)	−0.004	0.007	−0.001	0	0.008	0.060	0.026	0
Move, 1 year, % (+)	−0.006	0.003	0.003	0	−0.024	0.025	0.007	0
Post secondary, % (−)	−0.017	−0.006	−0.015	0	0.020	0.054	0.032	0
Low income, % (+)	0.038*	0.059	0.030	83.8	0.016	0.111	0.064	0
Government assistance, % (+)	−0.098*	−0.063	−0.072**	67.6	−0.199	−0.072	−0.151	0
Average dwelling value, 000 s (−)	−0.001*	−0.001	−0.001**	100	−0.002*	−0.001	−0.001*	39.1
Average rent, 00 s (−)	−0.066	−0.015	−0.029	0	0.069	0.326	0.150	0
Median family income, 000 s (−)	−0.002	0.007	−0.001	0	−0.079*	−0.049	−0.058*	28.6
Aboriginal, % (+)	0.045	0.071	0.055*	0	−0.060	0.114	0.066	0
Immigrants, % (+)	−0.040	−0.025	−0.022	0	−0.108	−0.061	−0.088	0
Recent immigrants, % (+)	0.044	0.056	0.051	0	0.003*	0.271	0.182	3.8
Visible minorities, % (+)	0.011	0.019	0.009	0	0.010	0.076	0.037	0
Ethnic heterogeneity (+)	−0.007	0.001	−0.003	0	−0.042	0.047	0.006	0
Wald of F-statistic			8.49**				F = 3.49**	
Leung et al. (2000)	p − value = 0.43				p − value = 0.46			
AIC	133.6		158.5		376.9		408.9	
GWR Quasi-global R^2	0.62				0.54			
OLS (Adjusted) R^2			0.56 (0.48)				0.41 (0.29)	
Global model			Lag				OLS	
Spatial weights			1				1	
Moran's *I*, residuals p-value	0.13		0.86		0.26		0.17	
Koenker's test for heteroskedasticity, p-value			0.41				0.04	

* p < 0.05, ** p < 0.01. The OLS model for Other Theft reports statistical significance with robust standard errors because of the presence of heteroskedasticity

of GWR being a better fit in all models. The asterisks on the minimum GWR values indicate which variables have some local effects that are statistically significant, not necessarily that the minimum values are statistically significant, allowing for comparisons with the global models. Lastly, the Moran's *I* test for spatial autocorrelation on the final model is reported. As shown in these tables, there is no remaining spatial autocorrelation in these models, with the same result for the geographically weighted regressions.

One of the interesting results shown here, consistent with previous research, is that when a variable is statistically significant in the global model and in the local model, only a subset of the census tracts are statistically significant at the local level. As shown in Table 3, there are some local models in which all census tracts for a variable are statistically significant, but that is not the norm. As such, a subset of the census tracts is driving the results at the global level, having potential impacts for policy development and implementation, discussed above. Additionally, there are a number of results that show statistically insignificant results at the global level but (at least) some statistically significant results at the local level. This shows that global regression model may wash out the effect of a variable when there are only a few of the units of analysis that exhibit statistically significant effects.

The results for commercial burglary show population change, major repairs, and government assistance being statistically significant for the global model; population change has a positive relationship with commercial burglary with major repairs and government assistance having negative relationships. The GWR results have population change, major repairs, and government assistance being statistically significant—see Fig. 2 for mapped output of government assistance and low income estimated parameters with only statistically significant results (at the 5 percent level) being shaded. Additionally, low income and ethnic heterogeneity both have positive relationships with commercial burglary for some census tracts. This ties back to one of the benefits of local spatial statistics being able to identify statistically significant results in a subset of census tracts even when the same variables are not statistically significant at the global level, showing the utility of GWR.

For residential burglary, population change, old houses, low income, and Aboriginal have positive relationships with residential burglary, whereas variables representing rented homes, major repairs, government assistance, and average rent have negative relationships. In addition to all of these variables, the GWR model results showed statistical significance for the unemployment rate (negative) and immigrants (positive)—see Fig. 3 for mapped results of population change and unemployment.

The global results for theft from vehicle retain population change and low income (positive relationships), and major repairs, government assistance, and average dwelling value (negative relationships). Similar to the other crime types, the GWR model maintains the statistical significance and sign of these independent variables as well as rented homes and immigrants, both negative relationships with theft from vehicle—see Fig. 4a for mapped results of major repairs.

Theft of vehicle retains few variables in both the global and GWR models. This may partially be due to the significant drop of this crime type in Vancouver over the past 20 years (Hodgkinson et al., 2016). Regardless, theft of vehicle has differences in the global and GWR results. Variables representing population change and Aboriginal identity have positive relationships with theft of vehicle,[4] whereas major repairs, government assistance, and average dwelling value have negative relationships. In the GWR model, variables representing major repairs and Aboriginal identity are no longer statistically significant in any of the census tracts, but low income is positive and statistically significant in the GWR model. Despite the change in the pattern of retained independent variables, the AIC value for the GWR model still shows a clear improvement over the global model with fewer remaining statistically significant independent variables.

Lastly, there are the global and GWR results for other theft. Only population change has a statistically significant and positive relationship with other theft, whereas major repairs, government assistance, average dwelling value, and median family income have negative relationships. In the GWR model, population change and government assistance are no longer statistically significant for any census tract, with recent immigrants having a statistically significant and positive relationship—see Fig. 4b for mapped results of major repairs. Similar to theft of vehicle, despite the change in the pattern of retained independent variables, the AIC value for the GWR model still shows a clear improvement over the global model with fewer remaining statistically significant independent variables.

Discussion

The results presented above show the benefits of using GWR when considering spatially referenced crime and ecological data. Overall, the GWR models show an

[4] This result must be taken in the Canadian context as a result of colonialism, institutional racism, and the use of residential schools that have found to be significant risk factors for criminalizing a marginalized population (Monchalin, 2010; Shen & Andresen, 2021).

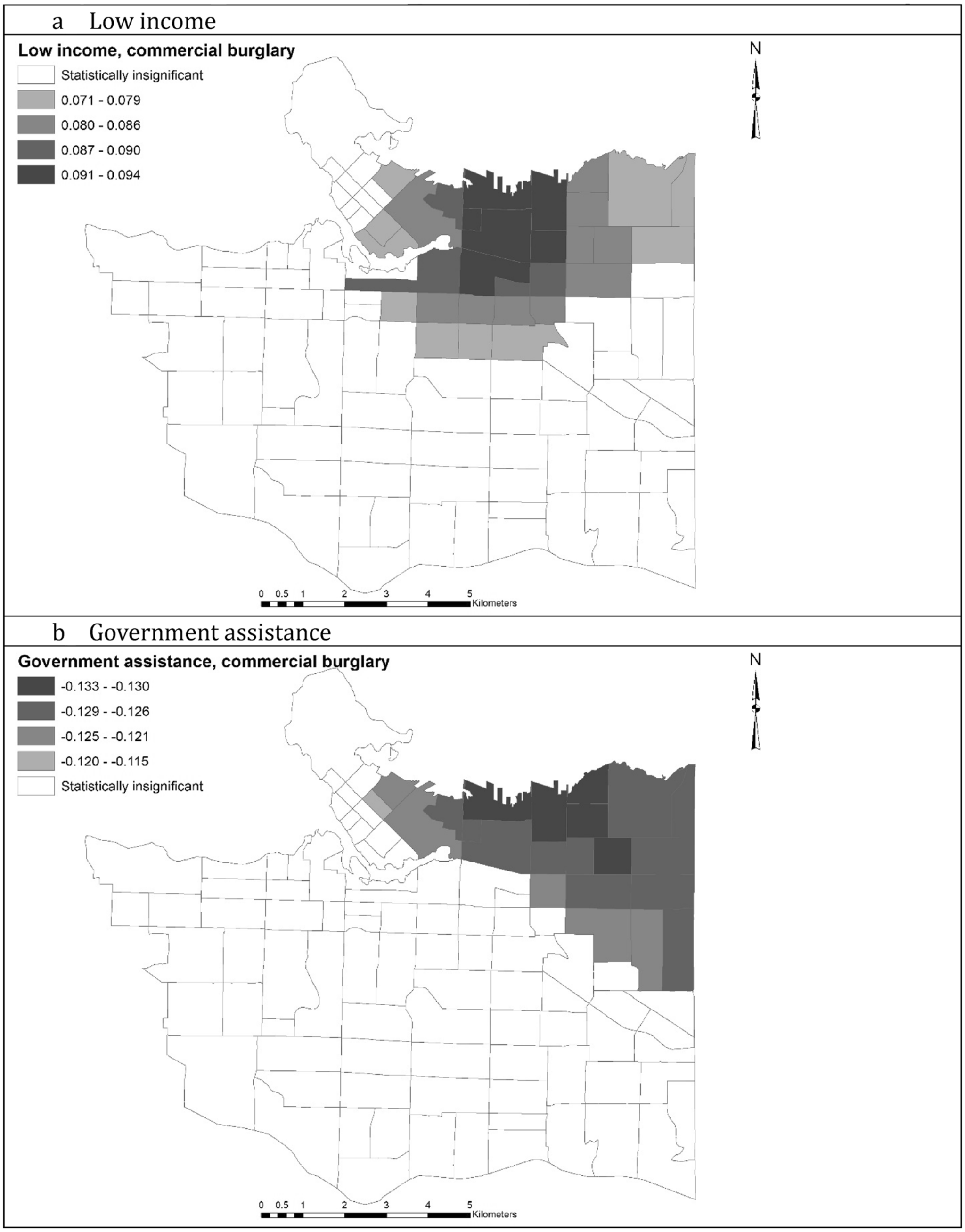

Fig. 2 Geographically weighted regression, local parameters, commercial burglary

improvement over the global models for all property crime types, based on AIC and Leung et al. (2000) statistics. Though there are some changes in the independent variables that are statistically significant in global and GWR models (theft of vehicle and other theft), there are no qualitative changes in the GWR results—there may be some GWR parameters that are opposite in sign when compared to the global parameter, but those GWR parameters are not statistically significant. These overall results are shown in Table 4.

The unemployment rate is only statistically significant for one crime type and only in the GWR model. This alone shows the importance of considering spatial heterogeneity and how the presence of a small number of local relationships can be shrouded when results are only considered in a global context. Population change, rented

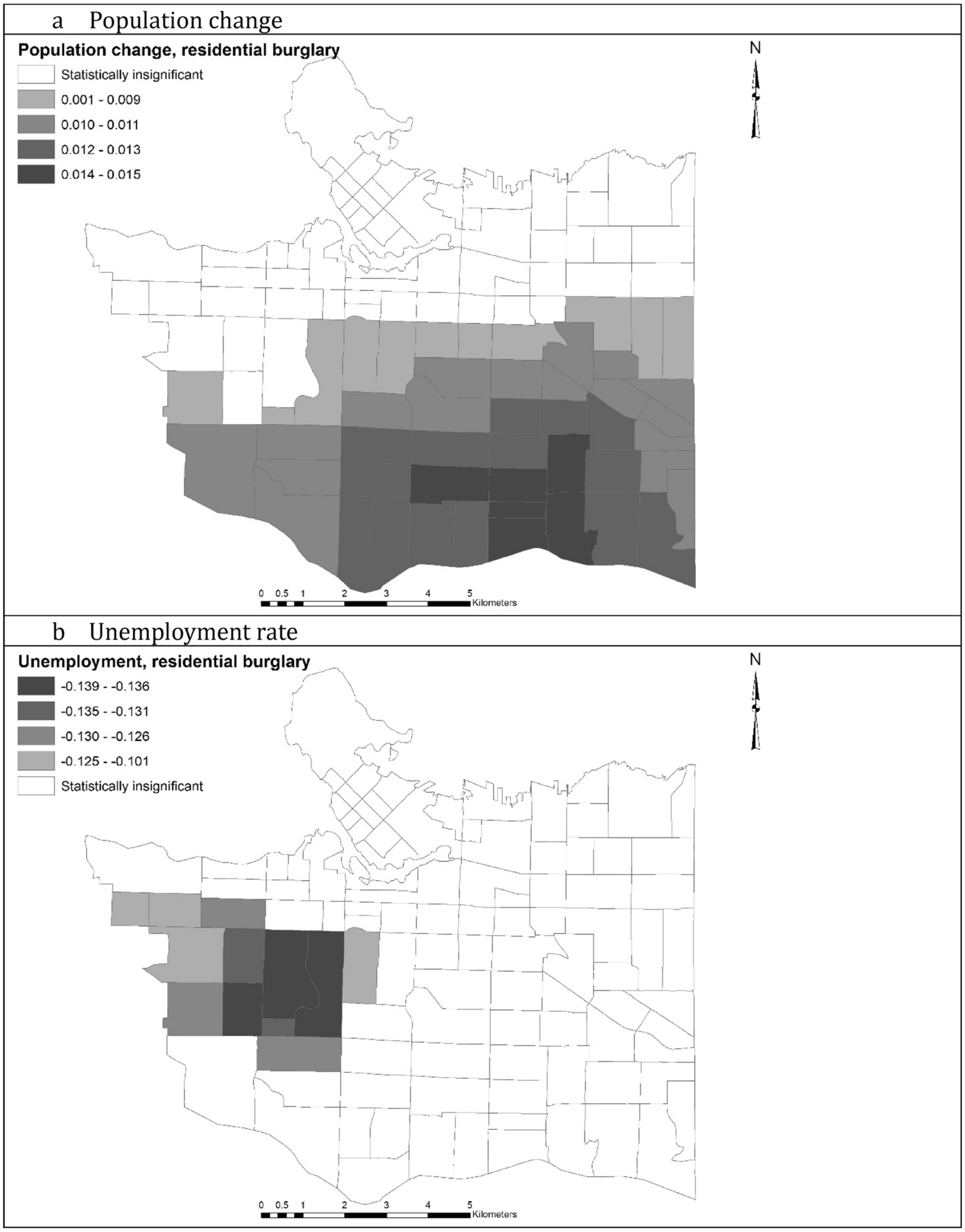

Fig. 3 Geographically weighted regression, local parameters, residential burglary

homes, major repairs, low income, government assistance, and average dwelling value are statistically significant in many of the global and GWR models. Old homes, average rent, median family income, Aboriginal, recent immigrants, and ethnic heterogeneity are statistically significant in at least two of the global or GWR models. Variables representing recent movers, post-secondary education, and visible minorities are not statistically significant in any of the global or GWR models. And only the percentage of immigrants in a census tract switches signs from one crime type to another: local residential burglary (positive) and local theft from vehicle (negative).

When considering the GWR results, it is important to note that the local parameters for a variable are, at times, statistically significant and the same sign in all spatial units of analysis. This is important to note from

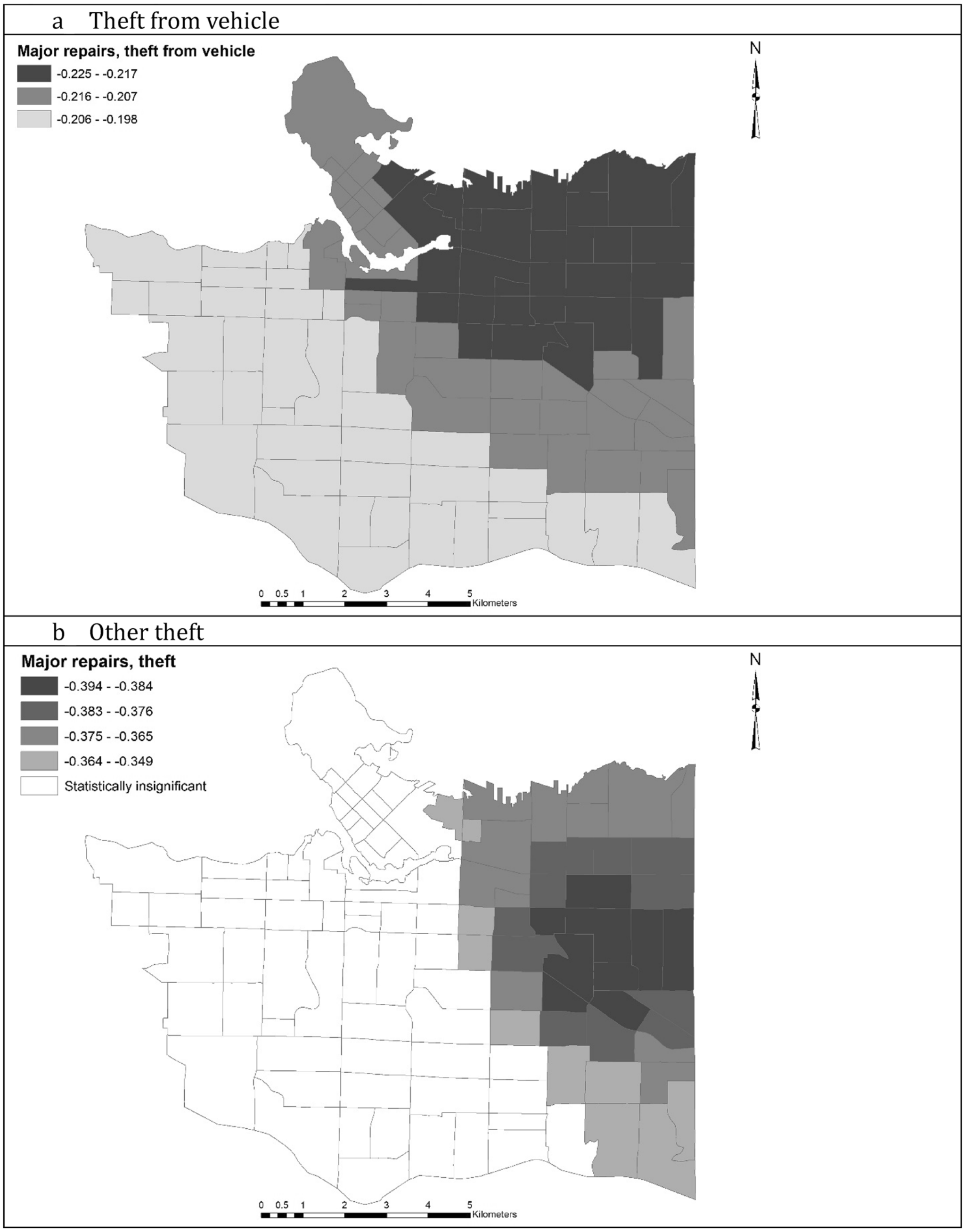

Fig. 4 Geographically weighted regression, local parameters, major repairs

both a theoretical and a policy implementation/evaluation standpoint because whether a potential policy variable impacts an outcome everywhere or only a portion of all places can determine if theoretical relationships hold (even partially) or if a policy intervention was successful in the places it was supposed to be successful. Such a situation is found for population change (theft from vehicle), rented homes (residential burglary), major repairs (theft from vehicle), low income (theft from vehicle), and average dwelling value (theft of vehicle).

With regard to the spatial heterogeneity, there are a number of interesting results. As shown in Fig. 2, government assistance and low income have highly localized effects for commercial burglary. The central northern peninsula at the top of the map is the central business district in Vancouver, with the areas immediately to the

Table 4 Geographically weighted regression results, results summary

	Commercial burglary		Residential burglary		Theft from vehicle		Theft of vehicle		Other theft	
	Global	Local	Global	Local	Global	Local	Global	Local	Global	Local
Unemployment rate				−						
Population change, %	+	+	+	+	+	+	+	+	+	
Rented, %			−	−		−				
Major repairs, %	−	−	−	−	−	−				−
Old houses, %				+						
Move, 1 year, %										
Post secondary, %										
Low income, %		+	+	+		+		+		
Government assistance, %		−	−	−	−	−	−	−		
Average dwelling value, 000 s					−	−	−	−	−	−
Average rent, 00 s			−	−						
Median family income, 000 s									−	−
Aboriginal, %			+	+						
Immigrants, %				+		−				
Recent immigrants, %										+
Visible minorities, %										
Ethnic heterogeneity		+								

east being the Downtown Eastside, the poorest urban neighbourhood in Canada (Barnes & Sutton, 2009). This shows that increases in the percentage of low-income families lead to increases in commercial burglary, but only in places that already have high levels of low income. This in no way implies that increases in low income in other areas does not have an impact on families and their neighbourhoods, but for increases in low income to have an impact on commercial burglary, that impact is only present in places where low income is already at higher levels. This may be some form of a multiplier effect with regard to the impact of poverty in a neighbourhood (Oreopoulos, 2008), or simply shoe the need to consider the interactive nature of constructs within social disorganization theory when understanding crime patterns (Kubrin et al., 2022). The corresponding result here is that the impact of increases in government assistance leads to decreases in commercial burglary in the same places. Moreover, the magnitude impact of increases in government assistance is greater than increases in low income. As such, spatially-targeted government assistance may not only be able to reduce the percentage of low income families, but counter the criminological effects from existing/remaining low income that leads to financial strain for those families.

Two interesting results emerge for residential burglary (see Fig. 3): population change and unemployment. Both of these variables represent aspects of social disorganization theory, with the impact of unemployment on crime also being dependent on the time frame considered, short- versus long-run (Cantor & Land, 1985). Population change over the previous 5 years should capture residential instability and the inability to develop social bonds (Sampson et al., 1997). The positive global parameter supports this, but the fact that the local effects, also positive, are only in the southern and south-eastern portion of the city is instructive. Specifically, only in the places that have lower levels of population change (specifically fewer rental homes) do increases in population turnover lead to increases in residential burglary. As such, areas that tend to systematically have higher levels of population turnover because of being close to a university, in a trendy neighbourhood (Kitsilano), or the central business district do not have impacts from increases in that population turnover, only places that consistently have lower levels of turnover. Moreover, these latter areas have also seen increases in building security in recent years leading to decreases in residential burglary in these areas (Hodgkinson & Andresen, 2019).

Regarding the unemployment rate, increases in unemployment are expected to be related to increases in criminal activity in a social disorganization perspective. However, as put forth by Cantor and Land (1985), and subsequent research (Andresen, 2012, 2013; Phillips & Land, 2012), the short-run effects of increases in unemployment are expected to decrease crime because of increased guardianship through people spending more time at home and spending less money. This is found for residential burglary in Vancouver. In fact, the unemployment rate is only statistically significant for local residential burglary in all of the analyses presented here. As such, because of the relatively low levels of unemployment at the census tract level across Vancouver, its impact on spatial property crime patterns are found to be minimal.

Lastly, though more GWR maps are available to the interested reader, there are the localized effects of major repairs on theft from vehicle and other theft. Houses under major repair are often thought to be an indicator of dilapidated housing and, consequently, representing lower levels of socio-economic status. However, in a city like Vancouver, the presence of major repairs is often related to the refurbishing of older homes in the process of gentrification—see Lees et al. (2007) for a discussion of the process of gentrification. Within Vancouver, gentrification began on the west side of the city and dominantly continued in that area until the turn of the twentieth century (Ley & Dobson, 2008). However, in more recent decades that gentrification has been moving east to relatively more affordable areas of the city.

As shown in Fig. 4a, for theft from vehicle, the local parameters for major repairs are statistically significant and negative for the whole city but the magnitude of the impacts are greater in the eastern areas of Vancouver that are experiencing more recent and, hence, currently greater magnitude levels of gentrification. In the context of other theft, Fig. 4b, the statistically significant and negative effects from increases in major repairs are only present in those areas that are undergoing a lot of gentrification. This shows the importance of understanding local context and a need for future research in this area. This finding of decreases in crime resulting from gentrification processes is known in the criminological literature (MacDonald & Stokes, 2020). However, it is also important to note that the gentrification process has been shown to have negative impacts of the health of marginalized populations living in those areas, specifically in Vancouver (Goldenberg et al., 2020).

Though much of the criminological literature that uses GWR investigates property crime, one of the limitations in the current analyses is that no violent crime types are considered. This limits the generalizability with US-based research. Similar to other research in this area, only one year of data, 2016, are analyzed. A number of our independent variables have high degrees of multicollinearity. However, as discussed, most of these variables prove to be statistically significant in the global and local results, showing the importance of variable inclusion rather than risking omitted variable bias. And, of course, only official police and census data are used in the current analyses. This may be problematic for police data, as it is for all research based on police data, because of the well-known dark figure of crime (Perreault, 2015), but property crime types do have higher reporting rates than violent crime types (Andresen, 2020); however, it may be the case that some of the relationships found here are mediated by under-reporting of crime. In the context of census data, similar to most research in this area, census data are proxies for theoretical constructs, particularly for social disorganization theory (Sampson & Groves, 1989).

Regardless of these limitations, we extend the literature through an international application considering 5 crime types and large number of theoretically informed explanatory variables that allows for a more nuanced investigation of spatial variations in crime patterns. Though there is international research using GWR, cited above, more research in this area is necessary. This is important for (social) science and generalizability, more generally. Though our spatial theories of crime fare well in international contexts, we have shown here that local knowledge is important for understanding the local results. As such, we must be careful when generalizing and need more research in different contexts.

In addition to addressing the limitations, stated above, future research should continue to be applied in other international contexts. Moreover, we need a better understanding of why theoretical expectations are only present in particular places (despite emerging as globally significant). We also need a better understanding of why theoretical relationships change directions in some places despite global relationships being consistent with theoretical predictions; this did not occur in the current research but does occur in this literature, more broadly. Only with a better understanding of these nuances can we move forward with our spatial theories of crime and, potentially, understand why and where they continue to operate as expected and why and where they need to change.

Conclusion

Overall, these analyses show that there is significant local variability in all cases, though that variability has different ranges for different crime types. Similar to previous research in this area, a subset of the areas (CTs) under analysis drive the global results. However, unlike much of the US research, local level results, when statistically significant, are always consistent (same sign) with the global regression output. This shows that the presence of spatial heterogeneity does not necessarily mean that relationships change direction across space, but only their statistical significance and magnitude changes. Moreover, this is shown in a more international (Canadian) context.

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